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Global shocks and local sellers: Kenyan fertilizer markets' response to the fuel-fertilizer-food price crisis☆

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ABSTRACT

Global fertilizer prices doubled during the 2020–2022 fuel-fertilizer-food crisis, pushing an additional 210 million people into acute food insecurity. We use transaction-level data from agro-dealers to analyze how this global shock transmitted through Kenyan retail markets. How global price shocks spread across rural markets to affect firms and farmers in low-income countries remains poorly understood. We show that retail fertilizer prices in Kenya rose 81% on average during the crisis, with remarkable spatial variation ranging from 5% decreases to 138% increases across shops. We use dyadic panel analysis to identify changes in price transmission and in market integration across Kenyan fertilizer retailers and to evaluate the effects of government policy intervention. We find evidence of asymmetric price transmission; agro-dealer prices responded faster to import price increases than decreases. We show that larger shops and major agricultural production zones experienced faster price transmission and stronger integration with import markets relative to high-poverty areas. Kenya's National Fertilizer Subsidy Program slowed price transmission but may have prolonged higher fertilizer retail prices. Our results imply that farmers do not benefit as rapidly from input price reductions as they would under symmetric transmission. Our results also demonstrate that global shocks transmit unevenly across markets, suggesting effective stabilization policies should account for heterogeneity in market conditions and variable pass-through behavior.

1. Introduction

At the peak of the global fuel-fertilizer-food crisis between March 2020 and March 2022, fertilizer prices doubled in international markets, contributing to a global food crisis that pushed an additional 210 million people into acute food insecurity (USAID, 2022; World Bank, 2022; World Food Programme, 2024). Smallholder farmers, essential to the global food system, are particularly vulnerable to input price shocks (Hishigsuren, et al., 2014). Limited data with adequate temporal and spatial detail has prevented a clear understanding of how international input price shocks are transmitted to farmers in low-income countries. We address this gap by studying how agro-dealers in Kenya responded to surging fertilizer prices and we assess how shop- and county-level socioeconomic characteristics influenced price transmission patterns. We also analyze how subsidies implemented by the Kenyan government in response to the crisis may have impacted price dynamics.

We introduce a transaction-level dataset from agro-dealer sales, offering unprecedented detail to explore spatial price dynamics in Kenyan fertilizer markets. We document how these dynamics shifted during the rapid fertilizer price increases of 2021 and 2022. The dataset includes monthly sales data from 1,308 agro-dealers over 42 months: July 2020 to December 2023. The panel comprises 37,244 total observations, tracking the monthly sales of each diammonium phosphate (DAP) product sold by each agro-dealer. Our analysis shows that fertilizer

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prices in Kenya increased sharply during the global fuel-fertilizer-food crisis, but increases were uneven across the country. While the average price change across shops was 81%, changes ranged from −5% to +138%. We show that the crisis period coincided with rising spatial price dispersion and a shift toward a negatively skewed price distribution, indicating lower prices relative to the median occurred more frequently.

We study how price transmission changed during the global price shock, focusing on both Kenya's import-to-retail links and variation among local retail markets. We characterize how transmission and price dispersion changed across agro-dealers over the course of the crisis. In competitive markets, the law of one price suggests trade arbitrages away spatial price differences until only transaction costs remain (Fackler and Goodwin, 2001). The speed of correction towards this spatial equilibrium indicates the level of market integration and shock exposure. We first use dyadic panel analysis to study how local retail prices adjust to the import price, given Kenya's heavy reliance on imports. We then study price dispersion within Kenya using a dyadic panel that analyzes price transmission across domestic shops.

Our base model employs a difference-in-differences estimator to analyze whether domestic fertilizer markets experienced price increases more fully than decreases in response to the global fuel-fertilizer-food crisis. We study heterogeneity in price transmission by interacting global fertilizer price increases with agro-dealer and county-level characteristics. We further investigate how the National Fertilizer Subsidy Program (NFSP) changed price dynamics by incorporating interaction terms and controlling for subsidy exposure based on a shop's proximity to government fertilizer distribution centers. To mitigate bias from omitted variables, we include region and year fixed effects.

We find evidence of slow and asymmetric price transmission between import and retail markets in Kenya. Only 23% of price declines are transmitted to internal markets within a month, while 34% price increases are transmitted in the same period. Overall, results suggest a low degree of integration with international markets. Price transmission is relatively faster within domestic retail markets, with retail-retail price spreads adjusting 45% to 52% in one month, potentially due to greater within-country competition. The speed of price transmission has important implications from an economic welfare perspective. First, integrated markets tend to be more competitive. Second, understanding how price shocks travel through markets can help researchers and policy makers understand how and when farmers will face higher input prices, with consequences for agricultural productivity and food security.

Together, asymmetric price transmission, NFSP exposure, and variability in price adjustment speed help explain Kenya's rise in spatial price dispersion during the global fuel-fertilizer-food crisis. Counties with higher maize output and fertilizer application rates experience faster price transmission during the crisis, while counties with higher poverty rates experience slower price transmission. Faster price transmission implies greater integration with import markets and, consequently, greater potential shock exposure. However, potentially higher price elasticities in poor counties could make their farmers more vulnerable to price shocks (Boysen, 2015; Muhammad, et al., 2017; Rudder, 2023; Assefa, et al., 2024). Larger shops adjust to price increases faster than smaller shops. The NFSP slowed price transmission between import and retail markets, especially for shops near distribution points. The subsidy – which bypassed retailers in favor of government depots – likely contributed to slower price transmission by artificially reducing prices and displacing commercial sales. Dealers had already sourced their stocks for the agricultural season at high market prices and proved reluctant to drop prices; instead, they held their stocks (Opiyo, et al., 2023).

Our paper makes four primary contributions. First, we contribute to the literature on market integration in developing countries. We use transaction data from agro-dealers to study the functioning of a market critical for economic growth and food security. Research has found mixed evidence of integration within and across countries and markets in Sub-Saharan Africa (Minot, 2011; Amikuzuno and Ogundari, 2015; Greb, et al., 2016). Some studies suggest that Kenyan input and staple cereal commodity markets are highly integrated (Chamberlin and Jayne, 2013; Nzuma, 2014), while others find limited cointegration between domestic and international markets and that domestic market integration weakens with distance (Brenton, et al., 2014; Nzuma, 2014; Gitau and Meyer, 2018). However, most of these findings come from relatively small samples that may not represent Kenya's overall market system. By studying integration across a wider set of markets, we provide reliable evidence that Kenyan fertilizer markets are characterized by slow and asymmetric price transmission.

Second, we explore how key shop and county characteristics relate to price transmission during price shocks, revealing heterogeneous price dynamics. We use time series panel methods to estimate price transmission between 84 import-retail market pairs and 3,486 retail-retail market pairs. Previous papers applying a similar approach typically use a much smaller set of 200–600 market pairs (Salazar, et al., 2023; Amare, et al., 2024). Our more comprehensive spatial market model better represents the overall market and captures spatial variation in price transmission across Kenya. We document important heterogeneity in how the crisis affected price dynamics. Larger shop size and county-level maize output and fertilizer applications rates are correlated with faster price transmission. County-level poverty rates are correlated with slower price transmission. These findings provide insight into which regions of Kenya were most affected by the global crisis, highlighting how market structure and local economic conditions shape price transmission dynamics.

Third, while research on price transmission and market integration in low-income countries often focuses on staple grain output markets, we examine an important agricultural input: fertilizer. Few papers have studied cointegration and price transmission in fertilizer markets in Sub-Saharan Africa. Bonilla Credez et al. (Bonilla Cedrez, et al., 2020) use the World Bank Living Standards Measurement Study (LSMS) data to document fertilizer price dispersion in Sub-Saharan Africa but do not study market integration. Agbahey et al. (2015) find that Ethiopian fertilizer retail markets are well integrated with import and global markets. We fill this gap by showing Kenyan fertilizer markets experience slow and asymmetric price transmission. This asymmetry implies that farmers in Kenya do not benefit as quickly from an input price reduction as they would under symmetric price transmission.

Fourth, we build on a growing literature linking price transmission in low-income countries to global shocks. The degree and speed of price transmission informs how global commodity price shocks affect farmer welfare (Nakelse, et al., 2018). Previous research suggests that significant shocks such as the COVID-19 pandemic (Amare, et al., 2024) and regional conflicts (Hastings, et al., 2022) tend to weaken market integration, while drought (Salazar, et al., 2023) can accelerate price transmission. Vos et al. (2025) found that the recent fertilizer price shock transmitted unevenly across Sub-Saharan Africa, with mixed impacts on domestic prices, consumption, and simulated yields. However, the authors also noted that limited data made it challenging to quantify how global shocks transmit to local markets and identify what factors may mitigate or exacerbate these shocks. Our focus on global input price shocks contributes to this literature. We find that rising global fertilizer prices are linked to faster price transmission between import and retail markets. Our analysis accounts for the Kenyan government's introduction of the NFSP in September 2022. We show that the NFSP is associated with slower price transmission between import and retail markets for shops most exposed to the subsidy. Our results suggest that while the NFSP may have helped protect farmers from price increases, it also may have contributed to persistently high commercial fertilizer prices in Kenya even as global prices fell.

The remainder of this paper is structured as follows. Section 2 provides a background on Kenyan fertilizer markets and the global fuel-fertilizer-food price crisis. Section 3 describes the data used. Section 4 presents the empirical model used to study price transmission in Kenyan

fertilizer markets. Section 5 documents the spatial and temporal price trends we observe as global fertilizer prices rose. Section 6 presents and discusses our main results, outlines key policy recommendations, and identifies limitations to our study. The final section concludes.

2. Background

2.1. Kenyan fertilizer markets

Agriculture is central to Kenya's economy, employing up to 50% of the population (World Food Programme, 2022a). Most of Kenya has a bimodal production calendar, with a primary long rains growing season from March to June and a secondary short rains season from October to December. Fertilizer use is relatively high in Kenya compared to other countries in Sub-Saharan Africa: between 55% and 88% of farmers use fertilizer in maize production, a crucial staple crop (Olwande et al., 2009a,b; Muindi, et al., 2016; Jena, et al., 2020). Ninety-five percent of Kenya's smallholders grow maize, accounting for 85% of national production. In 2020, nearly half (49%) of total fertilizer imports were applied to maize, followed by potatoes at 10%, sugarcane at 9%, and tea at 8% (AfricaFertilizer, 2025). However, the average application of 60 kg/ha remains well below recommended rates (The World Bank, 2024).

Diammonium phosphate (DAP) is the most intensively and extensively used fertilizer in Kenya. It comprises 33% of total annual fertilizer imports and is applied by 60% of farmers (Ministry of Agriculture and Livestock Development, 2024; AfricaFertilizer, 2025). The next most-used fertilizer, calcium ammonium nitrate (CAN), comprises 18% of total annual imports and is applied by 49% of farmers. Kenya imports all fertilizer through the Mombasa port, incurring transactions costs such as clearing, bagging, and transportation to warehouses before distribution to retailers. The importation process introduces delays: our cross-correlation analysis shows that retail prices are most strongly correlated with import prices from four months prior (Appendix A, Fig. A1). Retail prices also tend to exceed import prices due to these transaction costs. From January 2016 to January 2020, the average price differential between import and retail prices was 13 KSH/kg but ranged from 2 KSH/kg to 23 KSH/kg. The average retail price was 71 KSH/kg.

2.2. The global fuel-fertilizer-food crisis and Kenyan government response

Global fertilizer prices began to rise in June 2020 after the COVID-19 pandemic disrupted supply chains. Increasing fuel prices, geopolitical conflict, and persistent high demand exacerbated global fertilizer shortages and consequent price increases (Hebebrand and Laborde, 2022). For example, the price of natural gas, a key ingredient in nitrogen (N) fertilizers, spiked in Europe and Asia starting in June 2021 (Gilbert, et al., 2021). Similarly, the price of coal, a key ingredient in the production of phosphate-based fertilizers, rose in China, leading the government to impose fertilizer export restrictions in October 2021 and extend them in July 2022. The Ukraine-Russia War and subsequent economic sanctions further disrupted supply chains and contributed to rising fuel and fertilizer prices. As Russia and Belarus are major exporters of nitrogenous and potash fertilizers, the war contracted global fertilizer supply. Global fertilizer prices peaked in April 2022 before steadily decreasing (Vos, et al., 2025).

The majority of countries in Sub-Saharan Africa (SSA) are net importers of fertilizer, exposing them to price shocks in the global market (African Export-Import Bank, 2023). Kenya imports 100% of its fertilizer (AfricaFertilizer, 2025). Farmers reduce fertilizer application when prices rise, decreasing crop yields and affecting income and food security (Hebebrand and Laborde, 2022; World Food Programme, 2022b).[1] In Kenya, the recent period of high fertilizer prices was associated with significant reductions in total maize production. Between the 2020/2021 and 2022/2023 growing seasons, Kenya's total cultivated maize area contracted by 11% while aggregate maize production and yields dropped by 24% and 17%, respectively (U.S Department of Agriculture, 2024). These statistics are consistent with predictions from the World Food Program (WFP) in September 2022 that Kenya's 70% increase in fertilizer prices would decrease maize yields by 12% and push an additional 3 million Kenyans into acute food insecurity (World Food Programme, 2022b).

In response to the fertilizer price increases, the Kenyan government launched the National Fertilizer Subsidy Program (NFSP) in September 2022 to support farmers and address food security concerns (Ayalew, et al., 2024). Prior to September, the government had used an e-voucher based system to distribute fertilizer through agro-dealers. In September 2022, the government changed the structure of the program from the previous e-voucher retailer-based system to distribution through National Cereal and Produce Board (NCPB) depots and last-mile selling centers. The government procured 472,500 MT of NPK and urea fertilizer in late 2022 that it subsidized at rates between 41–55%. The government first piloted the subsidy program in 12 major maize-producing counties in February 2023, before expanding to an additional 29 counties in March 2023 (Opiyo, et al., 2023; Ayalew, et al., 2024). The NFSP program distributed 37% of the imported 472,500 MT of fertilizer during the 2023 long rains, with the remainder distributed during the following two seasons.

An assessment of the NFSP in 2023 by the International Food Policy Research Institute (IFPRI) found significant limitations to Kenya's fertilizer subsidy program (Ayalew, et al., 2023). The assessment notes that many farmers are located closer to agro-dealers than NCPB distribution centers and argue that the transition from the e-voucher system therefore served to *decrease* accessibility while increasing transaction costs. The IFPRI study also found that the chemical composition of subsidized fertilizer deterred farmer adoption. Due to soil acidity concerns, the government subsidized the NPK fertilizers over DAP fertilizers that are the most popular in Kenya. Moreover, the NFSP was an untargeted national program, focusing neither on the most affected areas nor on vulnerable populations. The program has been found to have disproportionally benefited larger and wealthier farmers over smaller and poorer ones (Njagi, et al., 2024; Ricker-Gilbert, et al., 2024a). Despite these limitations, evidence suggests that the NFSP successfully and cost-effectively boosted maize production during this period (Ayalew, et al., 2024; Ricker-Gilbert, et al., 2024a).

Finally, the NFSP has important consequences for the private sector. The subsidy displaced commercial fertilizer purchases and led to a 22% to 57% crowding-out effect (Ayalew, et al., 2024; Ricker-Gilbert, et al., 2024a). The program likely decreased the volume of fertilizer handled by commercial distributors and sold by last-mile agro-dealers in 2023 by 22% and 34%, respectively (Njagi, et al., 2024). The major maize producing counties received the bulk of subsidized fertilizer and may have experienced the greatest disruption to commercial markets. The NFSP program likely impacted commercial fertilizer prices and markets across Kenya. Our analysis therefore examines the impact of global fertilizer prices on market integration while controlling for the NFSP.

3. Data

Our primary dataset is a three-year (July 2020 – December 2023) panel of 1,308 small, medium, and large agro-dealers in Kenya. AgNexus, a research consultancy firm specializing in agricultural markets, developed and manages this panel. This agro-dealer-by-month dataset tracks monthly sales volume and price for each DAP product sold by each agro-dealer. All recorded sales are retail sales to customers and do not include the government subsidy for fertilizer. While the dataset does not track individual customers, AgNexus reports that most customers served by these agro-dealers are smallholder farmers.

The panel dataset was based on AgNexus's prior census study

[1] Estimated own-price elasticities for fertilizer range from −0.12 to −0.92 (World Food Programme, 2022; Komarek, et al., 2017; Olwande, et al., 2009).

conducted with 10,034 retail outlets in Kenya. AgNexus used stratified, purposive, and disproportional sampling to create a sample representative of the larger sales environment. Larger agro-dealer shops – in terms of annual revenue – are relatively few but make up a disproportionate share of total sales in Kenya.[2] Disproportional sampling was used to ensure these larger shops were included in the sample given their importance in the overall market. While small shops comprise 48% of the sample, they represent only 13% of DAP sales by weight. In contrast, medium shops comprise 38% of the sample and represent 48% of DAP sales by weight; large shops comprise 8% of the sample and represent 19% of sales; and x-large shops comprise 5% of the sample and represent 16% of sales.

AgNexus enumerators visit each agro-dealer monthly to collect price and quantity data for each stock keeping unit (SKU) sold. In some cases, enumerators collect these data from the agro-dealer's inventory management system. In others, enumerators collect data manually. Data cleaners use a mixture of manual and machine learning methods to code sales by standardized units and categories. These data are linked with product and agro-dealer libraries that contain basic information on every shop and product in the sample. We use a subset of this full AgNexus dataset: our panel comprises 37,244 unique DAP observations from 1,308 agro-dealers.

We focus on DAP for our descriptive and empirical analysis for two primary reasons. First, DAP is the most intensively and extensively used fertilizer in Kenya (Ministry of Agriculture and Livestock Development, 2024; AfricaFertilizer, 2025). Second, the spatial and temporal data availability is highest for DAP in the full AgNexus dataset.[3] The panel time series method we use to estimate price transmission requires a balanced panel with no gaps. Panels for the other fertilizer types would require significant interpolation that would make our results less reliable.

We use data from the NCPB to account for the possible relationship between the NFSP and changes in price transmission in commercial fertilizer markets. The NCPB shared a list of 265 depots and selling centers that participated in the national subsidy program. We match 258 of these locations to GPS coordinates using name, county, and NCPB depot. We calculate the distance between each NFSP distribution point and each retailer in our sample to identify how close shops are to NCPB depots that distribute subsidized fertilizer (Luxen and Vetter, 2011).

To study heterogeneity in price transmission across markets in Kenya, we collect additional data including: the monthly global price of DAP (U.S. Gulf F.O.B) from the World Bank (The World Bank, 2014); Kenya monthly import and retail fertilizer price data from AfricaFertilizer (AfricaFertilizer, 2025); data on county-level maize production, crop farming, and fertilizer use from the Kenyan Ministry of Agriculture and Livestock Development (Ministry of Agriculture and Livestock Development, 2024); data on county-level poverty rates from the Kenya National Bureau of Statistics (KNBS, 2023); and travel time data to the port from the Food and Agricultural Organization of the United Nations (FAO, 2020).

We use import price data to study price transmission between retail and import markets. For the import price data, AfricaFertilizer partnered with the Mombasa Port Authority to calculate the cost build-up after import, which incorporates the cost of bagging, CIF, clearing, finance, and warehousing. Assuming market integration, the law of one price implies that any remaining price spread between the Mombasa port and agro-dealers is due to transaction costs, as trade would arbitrage away other differences.

We observe that the AgNexus fertilizer quantity data contain more outliers than the fertilizer price data. AgNexus confirmed that outliers likely reflect sales from larger to smaller agro-dealers, rather than sales to farmers. To control for these quantity outliers, we remove observations above the 95th percentile or below the 5th percentile.[4] Prices have fewer outliers; furthermore, many outliers above the 95th percentile are likely due to rising fertilizer prices during the sample period. We remove transactions for prices above the 99.5 percentile or below the 0.5 percentile. This process removes 1,869 observations based on quantity and 414 observations based on price: 6% of total DAP observations. The number of shops present in the panel by month remains the same.

The number of shops present in the panel varies by month from between 211 and 700. AgNexus reduced the size of the sample in June 2021 to manage costs. Some shops also decided to stop participating, typically due to survey fatigue or lack of interest. AgNexus later added new shops to the sample to replace those they dropped or that stopped participating. Finally, due to firm exit and seasonality of operations, not all shops report agricultural input sales in every month.

We conduct an attrition analysis of our unbalanced panel to identify factors that predict whether a shop is dropped from the panel or stops participating and report the results in Appendix B. In summary, we find that dropped shops are likely to be smaller, further from major markets, and located in counties that produce a larger share of national maize output. It makes sense for AgNexus to include larger and more accessible shops in the panel as it likely reduces data collection costs. Attrition could impact the external validity of our results if price dynamics across the remaining shops are different from dropped shops. However, AgNexus preserved their sampling frame when dropping shops. They maintained stratification by region and shop size to ensure the remaining sample was representative of the prior census and larger sales environment. Large shops also represent a disproportionate share of total sales. While we use region fixed effects when studying import-retail market pairs, this analysis is also robust to using dyad fixed effects that control for time-invariant shop characteristics, such as shop size and average county-level maize output. We also control for heterogeneity in price transmission for these predictors in our import-retail analysis. Finally, we use dyad fixed effects when studying retail-retail market pairs to control for shop characteristics. Thus, we expect our descriptive and empirical findings to still be informative of general market dynamics.

We convert all monthly prices into real Kenya Shilling (KSH) per kilogram (kg), using the Kenya National Bureau of Statistics consumer price index (CPI) with a base year of 2020 to adjust for inflation. Commercial DAP consumption is seasonal, with the majority of DAP purchased and applied at planting during the long and short rains growing seasons. We define relevant the window for long rains DAP purchases as February to April and the relevant window for short rains DAP purchases as August to October. We use these windows when aggregating prices over time. Both temporal and spatial price aggregation rely on a weighted average by quantity sold (kg).

4. Empirical methods

4.1. Empirical analysis

We begin by examining the time series properties of the import and retail price data using panel- and pair- specific tests. First, we test for stationarity of the individual price series to explore whether the prices are cointegrated, indicating a long-term equilibrium relationship. Second, we introduce our base dyadic panel model to estimate changes in price transmission as global fertilizer prices rise. Third, we extend this

[2] Shop sizes are defined by annual turnover – revenue – in sales (KSH): small is X < 1,000,000; medium is 1,000,000 < X < 5,000,000; large is 5,000,000 < X < 10,000,000; x-large is 10,000,000 < X; and outlier is 40,000,000 < X.

[3] The full AgNexus fertilizer dataset tracks sales of all fertilizer types and contains 221,703 unique observations at the SKU-shop-month level. This full dataset contains 37,244 DAP transactions, 26,888 CAN transactions, 19,980 NPK transactions, and 9,964 urea fertilizer transactions.

[4] We remove these observations instead of winsorizing them as they likely reflect sales to smaller agro-dealers, not to farmers.

model with interaction terms to control for NFSP operations. Finally, we expand the model to capture heterogeneity in the speed of adjustment to price increases based on key shop characteristics. We estimate these models using a panel of import-retail and domestic retail-retail market pairs.

4.1.1. Testing for panel unit roots and cointegration

We perform the Im et al. (2003), Levin et al. (2002), Harris and Tzavalis (1999), Breitung (2000), and Fisher-type Choi (2001) unit root tests on the price data. Since prices are likely to contain a unit root, we perform these tests on both price levels and their first differences to ensure stationarity after first differencing. Given the presence of unit roots in price series, we apply panel cointegration tests to the import and retail prices, including Kao (1999), Pedroni (2004), and Westerlund (2005). Based on Engle and Granger's cointegration approach, these tests treat price spreads as residuals from the equilibrium parity, with unit root tests checking for stationarity. Stationary residuals indicate cointegration, while non-stationary residuals suggest prices are not cointegrated.

For robustness, we also apply the unit root tests to the import-retail price spreads. Rejection of a unit root process in the price spread indicates import and retail prices are cointegrated. We further implement the cross-sectionally augmented IPS (CIPS) test which tests the joint null hypothesis of a unit root (homogenous non-stationary) against the alternative hypothesis of at least one stationary series in the panel (Pesaran, 2007). This test accounts for potential cross-sectional dependence between price series, and we apply it to the import-retail price spread.[5]

4.1.2. Estimating price transmission in Kenyan fertilizer markets

After confirming our price spreads are stationary and cointegrated, we conduct dyadic panel analysis to estimate how the speed of adjustment between fertilizer import and retail prices changed during the global crisis. Following previous literature, we assume that price spreads are equal to transaction costs when markets are in long-run equilibrium (Amare, et al., 2024). In this context, the speed of adjustment is interpretable as the amount of a deviation adjusted in one month as markets move back toward an equilibrium where price spreads equal transaction costs.

We use global fertilizer price increases as an indicator of the intensity of the crisis, as they drive rising import and retail prices in Kenya (Hebebrand and Laborde, 2022; Rice and Vos, 2024). We include an interaction term between the speed of adjustment and the variable *DapRise* which takes the value of 1 when global fertilizer prices are rising, and 0 otherwise. This term allows us to test whether the speed of adjustment changes when global fertilizer prices are rising compared to when they are falling. We treat global fertilizer prices as a plausibly exogenous variable to explore price transmission dynamics between import and retail prices, as we do not expect domestic fertilizer prices in Kenya to affect U.S gulf prices.[6]

We estimate the following (difference-in-difference) dyadic panel regression:

$$\Delta Y_{ijt} = \beta_0 Y_{ijt-1} + \gamma DapRise + \beta_1 Y_{ijt-1}{}^{*}DapRise + \alpha_{ij} + \delta_t + \varepsilon_{ijt} \quad (1)$$

where $Y_{ijt} = Ln(P_{it}) - Ln(P_{jt})$ is the price spread calculated as the difference in log prices between markets i and j, Δ is the first-difference operator, and Y_{ijt-1} is the lagged price spread. The term γ reflects the changes in the price spread as the global price of DAP rises. $\beta = [\beta_0, \beta_1]$ is a vector measuring the short-run speed of adjustment to deviations from the long-run equilibrium, where β_0 represents the adjustment as global fertilizer prices are falling and β_1 represents the additional increase or decrease in speed of adjustment when global fertilizer prices are rising. In theory, we expect β_0 and $\beta_0 + \beta_1$ to be bounded by zero and negative one $(-1 < \beta_0, \beta_0 + \beta_1 < 0)$, which suggests that prices are cointegrated (Hastings, et al., 2022; Amare, et al., 2024). We study integration between import and retail markets by estimating equation (1) where $(i = 0)$ is the import price in Mombasa and $(j = 1, \cdots, N)$ is the price at each retailer. We also include region (α_{ij}) and year (δ_t) fixed effects to reduce bias from possible omitted variables and confounders.[7]

NFSP should have affected price spreads and their dynamics, in particular for those shops most exposed to the subsidy. Government first rolled-out the NFSP in 12 major agricultural production counties in February 2023 before expanding to an additional 29 counties in March 2023 (Opiyo, et al., 2023). We define *SubAct* as a binary variable equal to 1 when the subsidy program is active from either February or March 2023 to December 2023, and 0 otherwise.[8] The variable *DepotDist* is defined as the distance, in minutes, from each shop to its closest NCPB depot or selling center. We rely on *DepotDist* as a plausibly exogenous indicator of exposure to the subsidy program, with exposure decreasing in distance to the nearest distribution point. We extend equation (1) to control for the effect of the NFSP on price transmission for shops most exposed to the subsidy:

$$\Delta Y_{ijt} = \beta_0 Y_{ijt-1} + \gamma_1 DapRise + \gamma_2 SubAct + \beta_1 Y_{ijt-1}{}^{*}DapRise + \beta_2 Y_{ijt-1}{}^{*}SubAct + \beta_3 Y_{ijt-1}{}^{*}SubAct{}^{*}DepotDist + \alpha_{ij} + \delta_t + \varepsilon_{ijt} \quad (2)$$

In this model $\beta = [\beta_0, \beta_1, \beta_2, \beta_3]$ is a vector measuring the short-run speed of adjustment to deviations from the long-run equilibrium. β_0 represents the adjustment as global fertilizer prices are falling and the subsidy program is inactive, and β_1 to β_3 represent the additional increase or decrease – or change – in adjustment under different conditions. β_1 represents the change in adjustment when global fertilizer prices are rising; β_2 represents the change in adjustment when the NFSP is active; and β_3 represents how the speed of adjustment changes when the NFSP is active as the distance between retailers and the closest NCPB depot grows.

While one may be concerned about collinearity between *DapRise* and *SubAct*, the timing of the global fertilizer price crisis and the subsidy program is relevant. As discussed in Section 2.2, the NFSP launched in September 2022 and did not start to distribute subsidized fertilizer until February and March of 2023, after global and import fertilizer prices started to fall. This timing is also visible in Appendix C, Fig. C1. Indeed, the estimated correlation coefficient between these two variables is 0.05. Out of caution, we also run an alternative specification that only includes the subsidy indicator variables and find that the coefficients are consistent in magnitude, direction, and significance. These regression results are reported in Appendix C, Table C1, column (2).

We then explore heterogeneity in the adjustment of spreads between import and retail prices during global price increases. This analysis provides additional context regarding the relationship between changes in price spreads and retailer characteristics including shop size, distance to the port, market accessibility, and the characteristics of the county where the retailer operates: average annual maize output, percent of households farming, fertilizer application rate in 2020, and poverty rate

[5] We also run the Engle-Granger test on each dyad separately in addition to these panel cointegration tests.

[6] In 2020, global fertilizer consumption was 201.94 million metric tons (mt). Of this, Kenya imported a negligible 834,549 mt, or 0.41%.

[7] Our results are consistent in direction, magnitude, and significance if we use dyad fixed effects instead of region fixed effects.

[8] February 2023: Trans-Nzoia, Uasin Gishu, Nakuru, Narok, Migori, Nyandarua, Elgeyo Marakwet, Kericho,Kakamega, Bungoma, Bomet and Nandi. March 2023: Baringo, Busia, Embu, Garissa, Homa Bay, Isiolo, Kajiado, Kiambu, Kilifi, Kirinyaga, Kisii, Kisumu, Kitui, Kwale, Laikipia, Lamu, Machakos, Makueni, Meru, Murang'a, Nyamira, Nyeri, Mombasa, Taita Taveta, Tana River, Tharaka Nithi, Siaya, Vihiga, and West Pokot.

Table 1
Retailer Characteristics.

Characteristic	Variable	Description
Shop-Level Characteristics		
Population Density (people/km^2)	PopDen	Number of people per km^2
Time to Mombasa Port (hr)	Port	Driving time to Mombasa port in hours
Time to 20 k Market (hr)	Market	Driving time to closest market of at least 20,000 people in hours
Small Shop	Small	Annual turnover less than 1,000,000 KSH
Medium Shop	(Omitted)	Annual turnover between 1,000,000 KSH and 5,000,000 KSH
Large	Large	Annual turnover greater than 5,000,000 KSH
Duration (hr)	Duration	Driving time between each retailer pair in hours (*this variable is only used in the retail-retail market pair panel analysis)*
County-Level Characteristics		
Fertilizer Application Rate (kg/ha)	FertRate	Average fertilizer application rate in 2020
Maize Production (mt)	MaizeProd	Average annual maize production from 2016 to 2020
% Households Crop Farming	PerFarmers	Percent of households crop farming
Poverty Rate	Poverty	Poverty headcount rate in 2020

Note: This table describes the retailer characteristics used to explore heterogeneity in price adjustment between import and retail prices. Some characteristics are available only at the county-level. We assign county-level characteristics to shops within each county and express their indices at the retailer (i,j) level. For the shop-level analysis we include shop size as binary variables, omitting medium as the reference category.

in 2020 (see Table 1). We assign county-level characteristics to shops within each county and express their indices at the retailer (i,j) level.

To test whether adjustment varied across key shop and county characteristics we estimate the following dyadic panel regressions:

$$\begin{aligned}\Delta Y_{ijt} &= \beta_0 Y_{ijt-1} + \gamma_1 DapRise + \gamma_2 SubAct + \beta_1 Y_{ijt-1}{*}DapRise \\ &+ \beta_2 Y_{ijt-1}{*}SubAct + \beta_3 Y_{ijt-1}{*}SubAct{*}DepotDist \\ &+ \beta_4 Y_{ijt-1}{*}DapRise{*}Characteristic_j + \alpha_{ij} + \delta_t + \varepsilon_{ijt} \end{aligned} \quad (3)$$

$$\begin{aligned}\Delta Y_{ijt} &= \beta_0 Y_{ijt-1} + \gamma_1 DapRise + \gamma_2 SubAct + \beta_1 Y_{ijt-1}{*}DapRise \\ &+ \beta_2 Y_{ijt-1}{*}SubAct + \beta_3 Y_{ijt-1}{*}SubAct{*}DepotDist \\ &+ \sum_{x=1}^{X} \beta_{3+x} Y_{ijt-1}{*}DapRise{*}Characteristic_{jx} + \alpha_{ij} + \delta_t + \varepsilon_{ijt} \end{aligned} \quad (4)$$

We estimate equation (3) separately for each of the shop characteristics. We then estimate equation (4) as a joint regression that includes all shop characteristics x, *for* $x = 1, \cdots, X$. We are primarily interested in what factors may have mitigated or exacerbated shop exposure to the global price shock and limit our focus to triple interactions. We follow previous literature and in equations (3) and (4) and interact shop $Characteristic_{jx}$ with Y_{ijt-1} and *DapRise* (Amare, et al., 2024). This allows us to estimate how different shop characteristics may affect the adjustment coefficient as prices rise.

Finally, we study domestic market integration by estimating equation (1) where $(i.j = 1, \cdots, N, and i \neq j)$ for each of the domestic retailer price pairs and α_{ij} are dyad fixed effects. Equation (5) explores possible heterogeneity in price transmission as prices rise based on the driving distance between retailer market-pairs.

$$\begin{aligned}\Delta Y_{ijt} &= \beta_0 Y_{ijt-1} + \gamma DapRise + \beta_1 Y_{ijt-1}{*}DapRise \\ &+ \beta_2 Y_{ijt-1}{*}DapRise{*}Duration_{ij} + \alpha_{ij} + \delta_t + \varepsilon_{ijt} \end{aligned} \quad (5)$$

4.2. Panel Creation

We build the panel of retail shops to study price transmission. Panel time series analysis requires a balanced panel, but only 10 shops report sales every month. We restrict the sample to shops reporting fertilizer sales in at least 75% of months and missing no more than two consecutive months of data. We use this approach to maximize the sample size and minimize interpolation of missing data. This process generates a final subsample of 84 shops, compared to the total sample of 1,308. The average shop in this subsample reports fertilizer sales in 90% of months. We use linear interpolation to fill in the missing data. We create two dyadic panels: the "import-retail" and the "retail-retail." We use the "import-retail" panel to explore how price transmission changed between import and retail markets as global fertilizer prices rise. This dataset comprises 84 monthly price pairs linking each shop and the import price. The "retail-retail" panel comprises 3,486 monthly market pairs linking each shop to the remaining 83, allowing us to explore domestic market integration during the global crisis by assessing the price spreads between retailers.

Alongside our attrition analysis, we explore which characteristics predict if we include a shop in the dyadic panel. As shown in Table B1 in the Appendix, the dyadic panel has a greater share of large shops and fewer small shops than the full sample. This is expected, as the dyadic panel requires consistent observations over time. These are more likely to be larger shops that sell throughout the year. To check the robustness of our results, we create a third panel aggregating to the subcounty level.[9] While aggregation reduces variation, it allows us to include more retailers, including smaller shops. For each subcounty and month, we compute weighted averages of prices and numerical characteristics (Table 1) across shops using shop sales as weights. For the categorial variables measuring shop size, we calculate the percent of shops within a subcounty that are small, medium, or large in each month. The county-level characteristics remain the same, as each subcounty is within a county. We limit our sample to subcounties reporting fertilizer sales in 75% of months and missing no more than two consecutive months of data. We use linear interpolation to create the final dyadic panel of 80 subcounty-level average retail prices and the import price.

A map showing the shops selected for dyadic panel analysis is included in Fig. C2 in the Appendix. Balance tables comparing dropped shops to constant shops or shops added later by AgNexus are also available in Appendix B.

5. Descriptive results

We begin this section by characterizing spatial and temporal trends in fertilizer prices before, during, and after the global fuel-fertilizer food crisis. In the next section, our econometric analysis explores how rising global fertilizer prices are linked to changes in price transmission across regional markets in Kenya. Fig. 1 presents Kenya's national average DAP import and retail prices from July 2020 to December 2023, spanning the pre-crisis, crisis, and post-crisis period. In the pre-crisis period, we observe relatively stable DAP retail prices with a mean of 66 KSH/kg between the 2020 short rains and 2021 long rains.[10] Import prices started to rise sharply by February 2021, but retail prices did not significantly increase until September 2021. In Kenya, it takes several months for imported fertilizer to reach domestic markets with retail prices lagging import prices by four months as shown in the cross-correlation analysis in Fig. A1, Appendix A. Fig. 1 shows how this delayed price transmission altered the relationship between import and retail prices during the global fuel-fertilizer-price crisis, reversing the price spread starting in January 2021.

Table 2 presents summary statistics of retail DAP prices and percent changes during the sample period. The table is divided into three panels: the top panel shows real DAP prices in KSH/kg, the middle panel

[9] Kenya is comprised of 47 counties and 291 subcounties. We choose to aggregate to the subcounty-level over the county-level to increase the number of observations in the panel.

[10] Paired T-Test confirm no statistically significant difference in DAP prices between the two periods (Difference is −0.3, T-value is −1.11).

Fig. 1. Import and Retail Prices for DAP Fertilizer in Kenya (July 2020 to December 2023). *Note: This figure presents the monthly national average retail (blue line) and import (orange line) price of DAP fertilzer from July 2020 to December 2023. The figure uses vertical dotted lines to identify significant events that contributed to the global fuel-fertilizer-food price crisis and to show when the Kenyan government announced the National Fertilizer Subsidy Program (NFSP). Retail price data is from AgNexus panel of 1,308 shops. Import price data is from AfricaFertilizer. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).*

Table 2
Changes in DAP Prices During the Crisis Across Shops.

	N	Mean	SD	Median	Min	Max	CV
Real Prices (KSH/kg)							
2020 SR	846	65.88	7.54	65.00	50.00	100.00	0.11
2021 LR	837	65.79	5.82	65.23	49.74	93.85	0.09
2021 SR	451	75.25	6.92	75.08	52.56	93.85	0.09
2022 LR	413	103.37	15.41	105.63	48.85	133.33	0.15
2022 SR	338	117.34	10.51	117.75	55.82	143.92	0.09
2023 LR	439	105.20	8.97	105.00	51.69	129.39	0.09
2023 SR	452	100.45	11.13	100.21	51.69	145.38	0.11
Season-on-Season Percent Change							
SR 20 – LR 21	628	1.58	10.36	1.15	−39.43	53.58	6.54
LR 21 – SR 21	384	15.68	11.66	15.56	−30.00	59.10	0.74
SR 21 – LR 22	370	36.55	19.94	38.87	−12.60	99.16	0.55
LR 22 – SR 22	288	8.31	7.80	8.33	−24.40	35.99	0.94
SR 22 – LR 23	292	−9.82	7.25	−9.96	−31.51	22.35	−0.74
LR 23 – SR 23	355	−4.29	8.43	−3.70	−29.11	43.06	−1.97
Year(s)–on-Year(s) Percent Change							
LR 21 – 22	350	59.80	24.82	65.86	−10.33	111.36	0.42
SR 20 – 22	246	84.93	20.48	86.91	−0.32	133.29	0.24
SR 21 – 22	283	53.42	17.22	52.66	−11.01	132.35	0.32
SR 22 – 23	264	−14.73	8.54	−15.46	−36.50	20.38	−0.58

Note: The table presents the summary statistics of DAP prices and percent changes from July 2020 to December 2023. The table is divided into three panels: the top panel shows DAP real prices in KSH/kg, the middle panel presents season-to-season changes, and the bottom panel shows year-to-year changes. The long rains (LR) and short rains (SR) are the primary growing seasons in Kenya. Data is from AgNexus panel of 1,308 shops.

presents season-to-season changes, and the bottom panel shows year-to-year changes. During the crisis, the mean price of DAP climbed 16% between the 2021 long and short rains; 37% between the 2021 short rains and 2022 long rains; and 8% between the 2022 long and short rains. The national average price of DAP peaked during the 2022 short rains at 117 KSH/kg compared to 66 KSH/kg before the crisis – a percent change of 77%.

However, these national trends mask significant spatial heterogeneity in prices and price changes across Kenya during this period. In the following paragraphs, we show how the global fuel-fertilizer-food price crisis influenced price dispersion (Figs. 2 and 3) and shifts in the price distribution over time (Fig. 4).

Fig. 2 presents the distribution of percent price changes across the long and short rains, the key agricultural seasons in Kenya. The left boxplot depicts the distribution for 350 shops between the 2021 and 2022 long rains. The right boxplot depicts the distribution for 264 shops between the 2022 and 2023 short rains. During the 2022 long rains, farmers saw an average price increase of 60%, though with considerable spatial variation. Eight percent of shops (27 of 350) exhibited falling prices, while others had increases up to 110%. Frequent incidences of low prices resulted in a negative skew of −1.44. After the crisis peaked in August 2022, Kenyan fertilizer prices steadily declined although at a

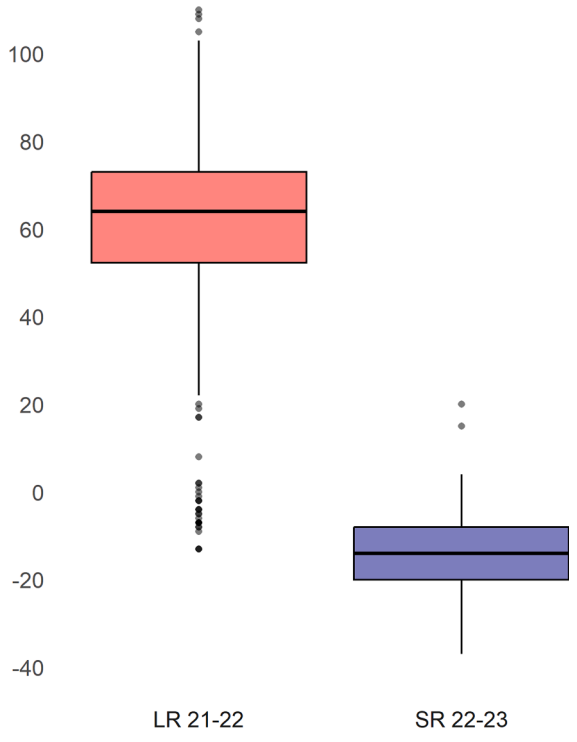

Fig. 2. Boxplot Distributions of Price Changes Between the 2021 and 2022 Long Rains & the 2022 and 2023 Short Rains. *Note: This figure depicts two boxplots. The left boxplot (orange) depicts the distribution of percent change in price for 350 agro-dealer shops between the 2021 and 2022 long rains. For the left boxplot the IQR is 21%, the median is 66%, and skew is −1.44. The right boxplot (purple) depicts the distribution of the percent change in price for 264 shops between the 2022 and 2023 short rains. For the right boxplot the IQR is 9%, the median is −15%, and the skew is 0.35. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).*

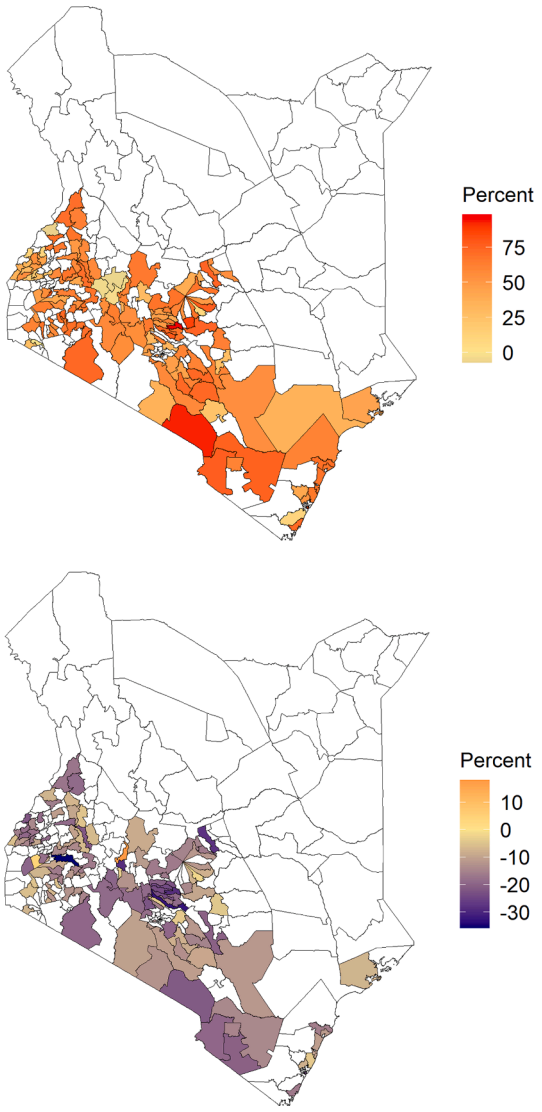

Fig. 3. Percent Change in DAP Prices by Subcounty Between the 2021 and 2022 Long Rains & the 2022 and 2023 Short Rains. *Note: The figure presents the percent change in DAP across growing seasons. The left panel shows the average percent change across 134 subcounties between the 2021 and 2022 long rains. The national average percent change during this period was 60% with a standard devation of 25%. The right panel shows the average percent change across 107 subcounties between the 2022 and 2023 short rains, after global prices began to decline. The national average percent change during this period was −15%, with a standard deviation of 9%. Data is from AgNexus panel of 1,308 agro-dealer shops.*

slower rate than they increased. Between the 2022 and 2023 short rains the average DAP price fell 15%. While 97% of shops (263 of 270) experienced declining prices, a few shops saw price increases ranging from 4% to 20%. Comparing the boxplots in Fig. 2, we observe more spatial variation during the crisis: the IQR was 21% with a median of 66%, compared to an IQR of 9% and a median change of −15% after the crisis. The distribution also shifted to a slight positive skew.

Fig. 3 depicts the percent change in DAP prices by subcounty as the crisis peaked and fell during Kenya's main agricultural seasons. The left panel shows the percent change for 134 subcounties between the 2021 and 2022 long rains, while the right panel shows the percent change across 107 subcounties between the 2022 and 2023 short rains. The figure uses weighted averages by quantity sold to aggregate data to the subcounty-level and is color-coded in shades of orange and purple, where orange reflects a positive and purple reflects a negative percent change. Darker colors represent a large percent change, whereas lighter colors represent a small percent change. While the percent changes varied widely across subcounties, no clear spatial patterns emerge and price changes do not correlate with distance to the port. While a few subcounties that experienced large price increases during the crisis also experienced large price decreases afterward, this pattern is not consistent across subcounties.[11] In the next section, Empirical Results and Discussion, we study heterogeneity in price transmission to better understand the spatial dispersion observed in Fig. 3.

Fig. 4 shows how price dispersion changed in Kenya over time. The solid and dotted blue lines represent the median and mean DAP price across all shops. The shaded area shows the interquartile range (IQR), while dashed black lines indicate the whiskers. Between July 2020 and September 2021, the average IQR was 7 KSH/kg. Between September 2021 and September 2022, the average IQR doubled to 15 KSH/kg. The increase in spatial price dispersion persisted after prices fell with an average IQR of 13 KSH/kg, indicating lasting market instability. The global fuel-fertilizer-food crisis also coincided with a shift toward a negatively skewed price distribution. Prices generally rose between

[11] The correlation coefficient between subcounties that experienced an above average price change between the 2021 – 2022 long rains and subcounties that experienced an above average price change between the 2022 – 2023 short rains is only 0.1.

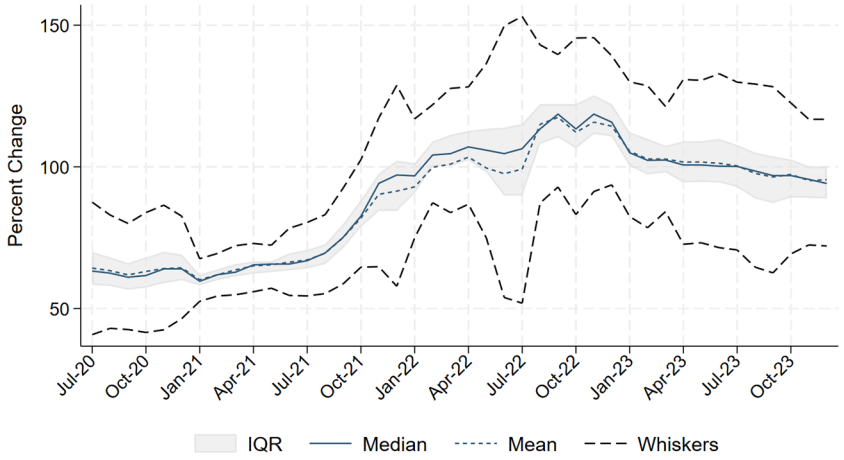

Fig. 4. DAP Prices and Price Dispersion in Kenya from July 2020 to December 2023. *Note: The figure shows how price dispersion changed in Kenya from July 2020 to December 2023. The solid and dotted blue lines represent the median and mean DAP price across all shops. The shaded area shows the interquartile range (IQR), while dashed black lines indicate the whiskers, with the bottom whisker as (25th- IQR*1.5) and the top whisker as (75th + IQR*1.5). Data is from AgNexus panel of 1,308 shops. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).*

Table 3
Panel Unit Root Test Results.

Panel Unit Root Test	$Ln(P_{it})$		$\Delta Ln(P_{it})$		$Ln(P_{it}) - Ln(P_{jt})$ Import − Retail		$Ln(P_{it}) - Ln(P_{jt})$ Retail − Retail	
	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value
Im-Pesaran-Shin	1.251	0.895	−53.919	0.000	−5.029	0.000	−140.000	0.000
Levin-Lin-Chu	−4.996	0.000	−50.587	0.000	−4.227	0.000	−110.000	0.000
Harris-Tzavalis	0.935	0.723	−0.163	0.000	0.847	0.000	0.516	0.000
Breitung	1.150	0.875	14.820	0.000	−-8.775	0.000	−57.953	0.000
Fisher-Type (DF)	1.386	0.917	−34.053	0.000	−-4.382	0.000	−100.273	0.000

Note: This table presents the results of a suite of panel unit root tests. We apply the tests to log prices, first differenced prices, the log price spreads between import and retail prices (where (i = 0) is the import price and (j = 1,…,N) is the price at each retailer), and the log price spreads between domestic retail prices (where (i,j = 1,…,N, and i ≠ j) for each of the domestic retailer price pairs. When applicable, we use the BIC to select the optimal lag. The tests' hypotheses are as follows; (Im-Pesaran-Shin, 2019) null: all series in panel contain a unit root, alternative: some series panels are stationary, allowing for heterogeneity in AR process; (Levin et al., 2002) null: all series in panel contain a unit root, alternative: all series in panel have homogeneous stationary process; (Harris and Tzavalis, 1999) null: all series in panel contain a unit root, alternative: all series in panel are stationary; (Breitung, 2000) null: all series in panel contain unit roots, alternative: all series in panel are stationary; and (Fisher-type, 2001) null: all series in panel contain unit roots, alternative: at least one panel is stationary.

September 2021 and 2022, but remained lower in some areas pulling the mean price below the median as indicated in Fig. 4.[12]

These results suggest that during and after the global crisis, farmers encountered a wider range of fertilizer prices across markets, evidence of potential disparities in how the shock affected input affordability within Kenya. Market integration provides a useful framework for understanding these dynamics. In integrated markets, the margins between market *i* and market *j* reflect transaction costs in long-run equilibrium. When a shock, such as a rise in import prices in market *i*, occurs, market actors will adjust this disequilibrium in subsequent periods through arbitrage. However, if there is heterogeneity in the speed of adjustment across different shops, differential price transmission may lead to increased price dispersion. In the next section, we study changes in price transmission and market integration to better understand the increase in price dispersion and shift to a negatively skewed price distribution within Kenyan fertilizer markets.

6. Empirical results and discussion

In this section, we first examine the time series properties of our price data. We then explore how price transmission between import and retail markets and across domestic retail markets changed when global fertilizer prices rose. We explore how the NFSP may have affected price transmission in Kenya. We also identify shop- and county-level characteristics linked with faster or slower transmission as fertilizer prices rose. Finally, we discuss our key policy recommendations and limitations.

6.1. Panel unit root and cointegration results

We first use panel unit root and cointegration tests to show that our

Table 4
Panel Cointegration Tests.

Panel Cointegration Tests	$Ln(P_{it}), Ln(P_{jt})$ Import − Retail		$Ln(P_{it}), Ln(P_{jt})$ Retail − Retail	
	Statistic	P-Value	Statistic	P-Value
Kao (ADF)	−1.280	0.100	−77.480	0.000
Pedroni (ADF)	4.437	0.000	−159.815	0.000
Pedroni (Phillips–Perron)	3.747	0.000	−156.165	0.000
Westerlund (Ho: Some panels)	8.062	0.000	−44.236	0.000
Westerlund (Ho: All panels)	1.959	0.025	−40.382	0.000

Note: This table presents the results of panel cointegration tests. When applicable, we use the BIC to optimally select the lag. (Kao, 1999) null: no cointegration, alternative: cointegration in all panels; (Pedroni, 2004) null: no cointegration, alternative: cointegration in all panels; (Westerlund, 2005) null: no cointegration, alternative: 1) cointegration in some panels, or 2) cointegration in all panels.

[12] In Appendix C, Fig. C.3, we also discuss how price dispersion changed between the three main growing seasons in Kenya from 2021 to 2023: the 2021, 2022, and 2023 long rains.

Table 5
Regression Estimates for Shop-Level Import-Retail Market Pairs.

	(1)	(2)	(3)
Y_{ijt-1}	−0.233***	−0.208***	−0.208***
	(0.013)	(0.012)	(0.012)
DAP Rise	0.012***	0.032***	0.032***
	(0.003)	(0.003)	(0.003)
Y_{ijt-1}*DapRise	−0.109***	−0.197***	−0.247***
	(0.014)	(0.015)	(0.070)
SubAct		−0.141***	−0.142***
		(0.007)	(0.007)
Y_{ijt-1}*SubAct		0.111***	0.112***
		(0.024)	(0.023)
Y_{ijt-1} *SubAct*DepotDist		−0.001**	−0.001***
		(0.000)	(0.000)
Y_{ijt-1}*DapRise*PopDen			0.000
			(0.000)
Y_{ijt-1}*DapRise*Port			−0.004
			(0.004)
Y_{ijt-1}*DapRise*Market			−0.006
			(0.012)
Y_{ijt-1}*DapRise*Small			0.054***
			(0.013)
Y_{ijt-1}*DapRise*Large			−0.029*
			(0.015)
Y_{ijt-1}*DapRise*FertRate			−0.000
			(0.000)
Y_{ijt-1}*DapRise*MaizeProd			−0.000
			(0.000)
Y_{ijt-1}*DapRise*PerFarmers			0.019
			(0.072)
Y_{ijt-1}*DapRise*Poverty			0.003**
			(0.002)
Observations	3444	3444	3444
Adjusted R^2	0.249	0.336	0.337

Note: This table presents the regression estimates for the shop-level import-retail panel and follows equations (1), (2), and (4). Column (1) presents the base model. Column (2) accounts for the effect of the NFSP on shops most exposed to the subsidy based on their distance to distribution depots. We define SubAct as a binary variable equal to 1 when the subsidy program is active from February or March 2023 to December 2023 and 0 otherwise. The variable DepotDist is defined as the distance in minutes each shop is from its closest NCPB depot or selling center. We rely on DepotDist as a plausibly exogenous indicator of exposure to the subsidy program, with exposure decreasing in distance to the nearest distribution point. Column (3) accounts for heterogeneity in the speed of adjustment during global fertilizer price increases. For additional details on the shop characteristics refer to Table 1. All models included region and year fixed effects. Standard errors are in parentheses and are clustered at the market-pair level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

price series are stationary and cointegrated. Cointegration implies there is a long-run relationship between markets, enabling us to estimate the speed of adjustment to deviations from the long-run equilibrium. We use these estimates to study how price transmission changed between import and retail markets and across domestic retail markets in the following subsections.

As outlined in Section 4.1.1, we test for stationarity in logarithmic prices, first differenced prices, the log price spreads between import and retail prices, and the log price spreads between domestic retail prices using panel and specific market-pair unit root tests. In Table 3 we present the results of the panel unit root tests. We generally detect a unit root in log prices, but we strongly reject the null hypothesis of a unit root in first differenced prices and log price spreads. For the log price spreads, failure to reject the null hypothesis would imply there is no cointegration or long-run relationship between import and retail prices or between domestic retail prices.

Table 4 presents the results of the panel cointegration tests, which generally reject the null hypothesis of no cointegration. For import-retail price spreads we estimate the CIPS test statistic of −4.087, below the critical value of −2.17 at the 1% significance level. This finding aligns with the unit root tests in Table 3 and the panel cointegration tests in Table 4, confirming that most import-retail and retail-retail market pairs

Table 6
Regression Coefficients for Shop-Level Retail Market Pairs.

	(1)	(2)
Y_{ijt-1}	−0.452***	−0.452***
	(0.028)	(0.028)
DapRise	−0.005	−0.005
	(0.004)	(0.004)
Y_{ijt-1}*DapRise	−0.047*	−0.073**
	(0.027)	(0.033)
Y_{ijt-1}*DapRise*Duration		0.006
		(0.005)
Observations	142,926	142,926
Adjusted R^2	0.227	0.227

Note: This table presents the regression estimates for shop-level retail-retail panel and follows equations (1) and (5). Column (1) presents the base model while column (2) accounts for heterogeneity in adjustment based on the distance in hours between retail market pairs. Both models include dyad and year fixed effects. Standard errors are in parentheses. We clustered standard errors at the market-pair level, where clusters are each retail location, using the two-way cluster robust estimator to account for likely dependence between observations arising from the dyadic structure (Cameron, 2011). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

are stationary and cointegrated.

In the Appendix C1 we present the results of the individual import-retail market pair Engle-Granger tests. While we fail to reject the null hypothesis of no-cointegration for all market pairs, this may due to low power when using individual time series with structural breaks (Campos, et al., 1996). Furthermore, our unit root and cointegration tests consistently show that the import-retail price spreads follows a stationary process and are cointegrated. Given this we believe our results hold but should be treated cautiously. After confirming the panel is cointegrated, we estimate the speed of adjustment to deviations from the long-run equilibrium using the dyadic panel regression. Results are presented in the next subsection.

6.2. Spatial market integration in Kenyan fertilizer markets during the global fuel-fertilizer-food crisis

In this section, we use dyadic panel regression to study how price transmission between retail and import markets changed during the fuel-fertilizer-food price crisis. We pay special attention to the speed of adjustment parameters (β) in equations (1) – (5) and how these changed during the global DAP fertilizer price increases.

First, we focus on the panel of import-retail market pairs. We estimate the base model in equation (1) and its extensions (2) and (4) that control for the NFSP and key shop characteristics. We check the consistency of our findings by re-estimating the model for the panel of subcounty-level import-retail market pairs and report the results in Appendix C3, Table C3 and Table C4. Second, we estimate how domestic market integration changed between retail market pairs within Kenya.

6.2.1. Price transmission between import and retail markets

Table 5 reports the results of import-retail market pairs. The base model is presented in column (1). Column (2) presents the model controlling for exposure to the NFSP based on retailer proximity to fertilizer distribution depots. Column (3) presents the full model incorporating all interactions to control for heterogeneity in adjustment during global fertilizer price increases. In Appendix C2, Table C2, we also report the results from equation (3) where we estimate each interaction separately.

The base model (column 1) suggests that market dynamics correct 23% to 34% of a disequilibrium in one month, depending on whether global fertilizer prices are falling or rising. While we find evidence of spatial market integration, the low speed of adjustment indicates slow price transmission across import and retail markets and a slow return to the long-run equilibrium. This result is consistent with the cross-correlation analysis in Fig. A1 that shows retail prices typically lag import prices by four months. Nzuma (2014) found similar speeds of

adjustment between world and domestic maize markets in Kenya, ranging from 29% to 31%.

The minimal transformation of fertilizer imports, characterized by low added value in the supply chain, may promote symmetric price transmission. Yet we find evidence of asymmetric transmission, with import-retail price spreads responding 11% to 25% faster to price increases than decreases. Our results are consistent with Serra and Goodwin (2003) who also find evidence of asymmetries in low added value supply chains. This research also aligns with previous findings of asymmetric price transmission in commodity markets. Ngare et al. (2013) found that maize price increases were transmitted 6% to 10% faster than decreases across Kenyan highland markets. While Ngare et al. (2013) documented regional price transmission between retailers, our analysis shows asymmetries in vertical price transmission. This asymmetry represents a shift in welfare distribution as consumers temporarily transfer welfare to retailers, preventing smallholder farmers from benefiting promptly from price reductions (Meyer et al., 2004).

While identifying the causes of asymmetric price transmission exceeds our scope, several commonly cited factors may apply to our context. Previous literature tends to link imperfect competition to asymmetric price transmission, although whether it leads to positive or negative asymmetries depends on context and market structure (Meyer et al., 2004; Lloyd, 2016; Cramon-Taubadel and Goodwin, 2021). While Kenya has a competitive fertilizer retail market, the upstream value chain is more concentrated with seven to ten primary fertilizer importers and 135+ secondary distributors (Ricker-Gilbert, et al., 2024b). In 2023, nine companies blended and wholesaled 90% of the fertilizer distributed in Kenya. Market power in the upstream value chain may be leading to relatively slower and more asymmetric price transmission between import and retail markets, although we cannot test this possibility with our data.

Asymmetric price transmission can also arise in competitive markets due to multiple factors, including menu costs, imperfect information, and search costs (Meyer et al., 2004; Cramon-Taubadel and Goodwin, 2021). When price shocks show serial correlation amid consumer information gaps, firms may respond asymmetrically (Tappata, 2009). In this model, consumer search intensity is lower when prices rise and price dispersion decreases, reducing willingness to search as potential gains diminish. Contrary to Tappata's (2009) predictions, we find price dispersion increases during price hikes. However, search costs and information frictions remain relevant in our context and are exacerbated by increased fuel costs during the global crisis. High search costs likely diminished search intensity despite greater potential savings. Per Tappata's model, this differential search behavior may have affected the agro-dealers' elasticity of demand, contributing to the asymmetric price transmission.

Import-retail fertilizer markets in Kenya exhibit slow and asymmetric price transmission, with the NFSP program further slowing transmission, particularly for shops near distribution centers. Column (2) in Table 5 suggests that the NFSP reduces the speed of price transmission between import and retail markets through the term Y_{ijt-1}*$SubAct$. However, distinguishing its effects from rising global fertilizer prices may be challenging as they are consecutive, national market shocks. We rely on the plausible exogeneity of *DepotDist* to confirm these results. The interaction Y_{ijt-1}*$SubAct$*$DepotDist$ shows that adjustment speed increases with distance to fertilizer distribution centers. Shops near NCPB depots, which are more exposed to the NFSP, experience slower price transmission than distant, less exposed shops. This applies to both price increases and decreases during the period of the subsidy. This implies that while the NFSP may have initially sheltered farmers from price increases, it also prolonged higher commercial fertilizer prices.

The NFSP may have slowed price transmission by disrupting private sector operations and distorting price signals. As discussed, multiple studies argue that the subsidy displaced the private sector and made it challenging for agro-dealers to offload existing stock, resulting in sticky fertilizer prices and slow price transmission even as global fertilizer prices fell (Opiyo, et al., 2023; Njagi, et al., 2024). Recent literature quantifies this crowding out effect at 22% to 57% (Ayalew, et al., 2024; Ricker-Gilbert, et al., 2024a). This is consistent with previous research that finds that subsidy programs lead to crowding out, particularly when programs exclude the private sector and/or target areas where the private sector is already active and fertilizer demand is high (Ricker-Gilbert, et al., 2011; Mason and Jayne, 2013; Mather and Jayne, 2018). In Kenya, there is a robust market of agro-dealers supplying fertilizer, but operations are characterized by narrow margins, highly seasonal sales, and limited financing (Rutsaert et al., 2021a). In this context, the presence of subsidized fertilizer may have created a price ceiling for retailers, limiting their ability to adjust prices in response to global price changes. Additionally, the program may have contributed to market fragmentation and slowed the passthrough of price signals from import to retail markets.

Column (3) of Table 5 reveals important heterogeneity in price transmission during fertilizer price increases. Large shops adjust prices faster, while small shops and shops in high poverty counties are associated with slower price transmission. Market accessibility, as proxied by Y_{ijt-1}*$DapRise$*$Market$, does not have a statistically significant relationship with changes in price transmission. While the parameters Y_{ijt-1}*$DapRise$*$FertRate$ and Y_{ijt-1}*$DapRise$*$MaizeProd$, are negative but not statistically significant in Table 5, they become significant when estimated separately in Appendix C2, Table C2. This suggests that county-level fertilizer application rates and maize production are linked to faster price transmission.

Shop size plays an important role in price transmission: relative to medium-sized shops, larger shops have faster price transmission and smaller shops have slower price transmission as global fertilizer prices rise. This is intuitive given the fertilizer market structure in Kenya. Importers and distributors generally sell fertilizer directly to large hub agro-dealers who sell fertilizer to customers and smaller retailers (IFDC and Afap, 2018). Given the role of large agro-dealers in the fertilizer supply chain, we would expect larger shops to experience faster price transmission due to their greater integration with import markets.

Higher county-level maize output and fertilizer application rates are associated with faster price adjustment (Appendix C2, Table C2). This indicates that areas of intensive agricultural production may be more strongly integrated with import markets, potentially due to higher fertilizer demand, more frequent fertilizer restocking, and stronger links to fertilizer supply chains. This greater integration implies that these shops may have experienced the price shock sooner and to a greater extent than other retailers. As these counties produce a larger share of national food production, this has important food security implications.

The county-level poverty rate is correlated with slower price transmission as global fertilizer prices rise. This indicates retail markets in poor counties may be less connected to import markets, with uncertain welfare implications for farmers. Slower price transmission implies that it took longer for the global crisis to affect poor counties potentially insulating them from the price shock. However, previous literature finds that households in poor and rural areas have higher own-price elasticities for food and for fertilizer (Boysen, 2015; Muhammad, et al., 2017; Rudder, 2023; Assefa, et al., 2024). Consequently, price sensitive farmers in poor counties may have demanded less fertilizer as prices rose, potentially affecting local prices and slowing adjustment to import markets. More elastic demand translates into reduced fertilizer application when prices rise – with consequences for income and food security (Hebebrand and Laborde, 2022; World Food Programme, 2022b). Consequently, while poorer counties experienced slower price transmission, this may be more of an indicator of their vulnerability than their insulation from the crisis.

The combination of asymmetric price transmission, exposure to the NFSP, and heterogeneity in the speed of adjustment by key shop- and county-level characteristics may have led to differential price

transmission across shops during the global fuel-fertilizer-food crisis, helping to explain the rise in spatial price dispersion that we observe in Section 5.

Finally, in Appendix C3 we re-estimate equations (1) – (4) using the subcounty-level panel of import-retail markets pairs. We find that coefficients are generally consistent in direction and magnitude but not necessarily in significance. We expect this, as aggregation increases the representativeness of the panel at the cost of shop-level variation and precision. We are cautious in assuming that our shop-level results represent the full sample. However, we expect our findings to characterize dynamics in the larger market due to the robustness of the subcounty-level analysis and the disproportionate importance of large shops in total sales.

6.2.2. *Price transmission within retail markets*

This section explores how price transmission within local Kenyan retail markets changes as global fertilizer prices rise, with the results presented in Table 6 following equations (1) and (5). Rather than examining how each shop relates to the Mombasa market, this analysis focuses on understanding local dynamics during the crisis by showing how shops transmit shocks to one another.

We find that domestic retail markets have faster price transmission than import-retail markets: fertilizer retail markets adjust 45% to 52% of a disequilibrium in one month. We again find evidence of positive asymmetric price transmission although its magnitude is smaller. Previous research finds that distance between markets generally weakens spatial market integration (Minot, 2011; Brenton, et al., 2014; Gitau and Meyer, 2018). We do find that distance between markets is correlated with slower price transmission, but the coefficient is statistically insignificant. These findings suggest that domestic DAP markets may be more integrated internally than with external import markets.

One possible explanation behind greater domestic market integration and more symmetric price transmission relates to competition. Rutsaert et al. (2021b) found that input prices increased with decreasing competition, even controlling for transportation costs. Rudder (2023) found that greater competition in commodity retail markets increased price passthrough. As previously discussed, asymmetric price transmission can be linked to the presence of market power (Meyer et al., 2004; Cramon-Taubadel and Goodwin, 2021). While the upstream value chain is more concentrated, the fertilizer retail market in Kenya is vibrant and competitive with more than 10,000 agro-dealers. Greater competition may lead to faster and more symmetric price transmission among domestic retailers.

Another possible explanation relates to our empirical design. We use a network structure when studying price transmission among domestic markets, where each retailer is connected to the remaining retailers in the panel, including retailers in close proximity. This design captures how price shocks are transmitted within the local market, emphasizing the interconnection between shops. This may cause market integration to appear larger when considering the full network of shop interactions, rather than just the direct link between each shop and Mombasa.

6.3. *Policy implications*

Our results suggest four implications for policy.

First, our results illustrate a central tension for policymakers: market integration has long run benefits including higher incomes and lower trade costs, but it also exposes domestic markets to global shocks. Faster price transmission is generally linked to market efficiency (Cramon-Taubadel and Goodwin, 2021) and research suggests that policymakers can enhance market integration by investing in infrastructure and removing distortionary policies (Nzuma, 2014; Gitau and Meyer, 2018; Salazar, et al., 2023). However, we find that weak market integration and slow price transmission between import and retail markets initially shielded Kenyan farmers from rising fertilizer prices, though variably so. While import prices started to rise sharply in February 2021, retail prices did not follow until after the 2021 main growing season. In the long-term, policymakers should balance investments in market integration with those that bolster domestic resilience to shocks, such as social safety nets or strategic grain reserves. In the short-term, delayed price transmission may give developing countries time to prepare for global price shocks before they impact domestic markets.

Second, price stabilization policies should recognize that farmers may experience shocks differently across space, depending on market structure, retailer characteristics, and local socioeconomic conditions. Regions with faster price transmission are generally more exposed to shocks, but exposure alone does not determine vulnerability. To enhance food security, the government may want to target fertilizer subsidies to support smallholder farmers in poor counties and implement alternative policies to assist consumers with high food prices. The NFSP aimed to provide relief to farmers and ensure food security during the crisis. Our results show that intensive agricultural production areas exhibit faster price transmission, making them more exposed to external price shocks. These areas received the bulk of subsidized fertilizer under the NFSP, potentially boosting maize production and enhancing national food security cost-effectively (Ayalew, et al., 2024; Ricker-Gilbert, et al., 2024a). However, faster transmission does not necessarily mean greater vulnerability. We find that poorer, food-insecure counties experience slower price transmission, possibly due to high price elasticities that reduce fertilizer consumption and increase agro-dealer stocks. These areas, often net food buyers, may have benefitted from the NFSP subsidies to major production areas (Ariga and Jayne, 2011). However, the NFSP disproportionally benefited larger and wealthier farmers over smallholders in poorer areas (Ricker-Gilbert, et al., 2024a; Njagi, et al., 2024).

Third, the government should evaluate returning to the e-voucher system to distribute fertilizer through the private sector as a means of minimizing market distortions and increasing the response of agro-dealers to price signals. The NFSP may have led to market fragmentation and fertilizer stockholding, slowing price transmission between import and retail markets. While this slower transmission may have protected the country from fertilizer price spikes, it also slowed adjustment after global fertilizer prices started to fall, keeping domestic retail prices higher for longer. Furthermore, in the medium term the NFSP may drive smaller shops out of business, reducing competition and increasing prices and costs for farmers (Ricker-Gilbert, et al., 2024a). This reduced competition may lead to lower market integration in domestic retail markets. The government could help minimize these market disruptions by returning to the e-voucher system and leveraging the private sector. However, evaluations of previous voucher system programs in the region such as the National Agricultural Input Voucher Scheme (NAIVS) in Tanzania or the Agriculture Cluster Development Programme (ACDP) in Uganda highlight challenges with these programs as well including logistical challenges, delayed payments, and vouchers not reaching the poorest households (Aloyce, et al., 2014; World Bank, 2014; Donovan, et al., 2024).

Fourth, data collection on farming systems and poverty has primarily relied on farmer surveys at limited points in time due to the high costs and logistical challenges. Investing in supply-side data that tracks commercial input markets over time would provide better insights into market changes that may impact farmer livelihoods (Dillon, et al., 2025). In most European countries and the United States, supermarket data are well monitored and provide valuable indicators of wealth and consumer demand. Setting up similar systems in the global south would allow development programs as well as governments or private companies to make data-driven decisions when responding to market changes.

6.4. *Limitations*

We acknowledge several important limitations to our study. First, we focus on heterogeneity in the speed of adjustment as fertilizer prices rise

to better understand how the global fuel-fertilizer-food price crisis relates to changes in market integration in Kenya. Several shop characteristics described in Table 1 were only available at the county-level, leading to less variation and less precision in our estimations. Consequently, some characteristics may be correlated with changes in price transmission even if we cannot detect them statistically. In addition, our panel is relatively short, with considerable observations but only 13 months before retail fertilizer prices began to rise in Kenya, and no data before global and import prices started to rise (big n small t). Future research could refine our model by covering a longer time period and incorporating additional shop-level characteristics.

Second, our model has considerable attrition given AgNexus's decision to drop shops and the methods we use to construct the panel for dyadic regression analysis. Our analysis in Appendix B shows that attrition is correlated with shop characteristics, raising questions about the degree to which our findings represent the full sample of shops. Although our results should be interpreted with caution, they likely reflect dynamics in the larger fertilizer market. First, AgNexus preserved its stratified sampling frame when it dropped shops. Second, while smaller shops were more likely to be dropped from the sample, medium and large shops represent a disproportionate share of total *sales* in the market. Finally, we use fixed effects and heterogeneity analysis to control for shop characteristics.[13] These allow us to be transparent about how effects vary across shop characteristics and account for unobserved characteristics that may correlated with both attrition and the outcomes of interest.

Third, we make several assumptions about NFSP implementation due to limited information about the exact timing and geography of program rollout. First, we assume that the program is active from February or March 2023 to December 2023, though it may not have operated between the main growing seasons from July to August 2023. Second, we assume subsidized fertilizer was sold at all the NCPB depots and selling centers. However, it is unclear whether the NFSP distribution began at NCPB depots before expanding, or if both channels operated simultaneously. These assumptions are conservative because the subsidy program should have limited or no effect on price transmission when it is not active or when it has not been rolled out at a given depot. Hence, our results may underestimate the true effect of the NFSP on price transmission. However, we do not have access to county-by-month subsidized fertilizer distribution data and cannot tell for which months the subsidy was active in a given county. In Table C5 to Table C7 in Appendix C4, we re-estimate the models presented in Table 5 and adjust these assumptions. We find that the coefficient on Y_{ijt-1}*$SubAct$*$DepotDist$ is consistently negative in direction, similar in magnitude, and generally significant at the 10% level or lower.

Finally, we assume proximity to NFSP depots serves a proxy for exposure to the subsidy program. In reality, actual exposure likely depends both on proximity and the amount of fertilizer distributed at a given depot which varied based on the number of nearby farmers registering their land in the NFSP (Ricker-Gilbert, et al., 2024a). Data suggests that more fertilizer was distributed in major maize producing counties (Ayalew, et al., 2024; Njagi, et al., 2024). Consequently, some agro-dealers near a distribution center may have received limited subsidized fertilizer. Hence, using distance as a proxy may overestimate exposure for some closer shops and underestimate it for other shops. These opposing effects complicate predictions on this proxy may impact our results. However, we expect underestimation to have a stronger impact, given fertilizer distribution was concentrated in certain counties and depots. This suggests our results may be conservative. Unfortunately, we lack access to depot-level fertilizer allocations and cannot explore this other dimension of NFSP exposure.

[13] For our import-retail analysis we use regional and year fixed effects, but our results robust to using dyad fixed effects instead. For our retail-retail analysis we use dyad fixed effects, given the difficulty of controlling for shop characteristics through heterogeneity analysis.

7. Conclusion

The 2020–2022 global fuel-fertilizer-food crisis led to a rapid but uneven rise in fertilizer prices and pushed millions of people into acute food insecurity. However, limited data makes it challenging to understand how global shocks transmit to local markets and what factors may mediate these shocks. To address this gap, we investigate how price transmission changed between import and retail markets and among domestic retail markets in Kenya during the global crisis. We contribute to the literature on market integration in developing countries and provide insight into how spatial price dynamics changed. By exploring how price transmission varied by shop and county characteristics, we identify markets where farmers may have been most exposed to the shock. We also evaluate how the NFSP impacted price transmission from import to retail markets in Kenya. These findings can help inform policy to mitigate the adverse effects of global price shocks while minimizing market distortions.

Overall, we find evidence of slow price transmission between import and retail markets in Kenya, with the speed increasing during the crisis. Markets correct 34% of a disequilibrium during the crisis compared to 23% after. We observe faster price transmission in domestic retail markets, where retail-retail market pairs adjust 45% to 52% of a disequilibrium in one month, potentially due to greater domestic retail competition. We show that the NFSP may have slowed price transmission and disrupted market integration between import and retail markets, particularly for shops most exposed to the subsidy based on their proximity to distribution points. While this slower price transmission may have helped protect farmers from price shocks, it also likely prolonged higher commercial fertilizer prices through displacement of the private sector.

We consistently find asymmetric price transmission across both import-retail and retail-retail market pairs during the global fuel-fertilizer-food crisis, with import-retail market pairs adjusting 11 to 25% faster to price increases than decreases. We also document important heterogeneity in the speed of adjustment during the crisis. In particular, we find that large shop size is correlated with faster price transmission. Intensive agricultural production – as proxied by pre-crisis county-level maize output and fertilizer application rates – is also correlated with faster price transmission. Finally, we find that county-level poverty rates are linked to slower price transmission. Our results underscore how uneven price transmission across regions can widen disparities in input access and affordability during global crises.

Taken together, asymmetric price transmission, exposure to the NFSP, and heterogeneity in the speed of adjustment during price increases are strongly associated with the rise in spatial price dispersion and the shift to a negatively skewed price distribution during the global crisis and which persisted a year after prices started to decline.

Future studies could complement and build on our analysis in several ways. First, our panel is relatively short. In the future, it would be valuable to explore price transmission dynamics in Kenya or similar countries with data that covers a longer time period. This would allow us to test whether our results hold in the long-run. A longer time period in analysis would also allow us to better understand how domestic fertilizer markets might react to future global shocks. Other important sources of heterogeneity by shop and county might be studied, including competition, infrastructure, or cellular phone network connectivity. While we control for possible omitted variables and confounders and identify several exogenous sources of variation, our analysis is still descriptive in nature. Future research could incorporate causal identification methods to unearth mechanisms driving changes in price transmission. Finally, our analysis could be extended through application to other countries or other types of critical agricultural production inputs.

Our analysis demonstrates the value of new kinds of data – especially

data on the operations of the supply side of agricultural input markets – to provide insight into longstanding questions in agricultural development and policy. We find that Kenya fertilizer retail markets are characterized by slow and asymmetric price transmission, and that price transmission varies across markets due to intermediary characteristics and policy intervention. Based on these findings, we recommend that policymakers carefully weigh the trade-offs of market integration and protective measures such as subsidies. Where feasible, targeted instruments should be used to cushion farmers and consumers against price shocks while minimizing broader market distortions. In Kenya specifically, we recommend that the government consider reinstating the e-voucher system for subsidized fertilizer distribution.

CRediT authorship contribution statement

Hanna S. Willwerth: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Conceptualization. **Colleta N. Khaemba:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Teresa Serra:** Writing – review & editing, Methodology. **Hope C. Michelson:** Writing – review & editing, Methodology, Conceptualization. **Pieter Rutsaert:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Jason Donovan:** Writing – review & editing, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Appendix A discusses the correlation between DAP import and retail prices over time. Appendix B presents the results of the attrition analysis for our unbalanced panel. In Appendix C, we first present several figures related to panel design and our empirical model. We then report the results of individual import-retail market pair cointegration tests in Appendix C1. Sections Appendix C2 – Appendix C4 report additional regression models related to our main model in Table 5, including several robustness checks.

Appendix A

Appendix A presents information on the correlation between DAP import and retail prices. Fig. A1 presents the cross-correlation between DAP import and retail prices and shows that retail prices are most strongly correlated with import prices four months before with a correlation coefficient of 0.79.

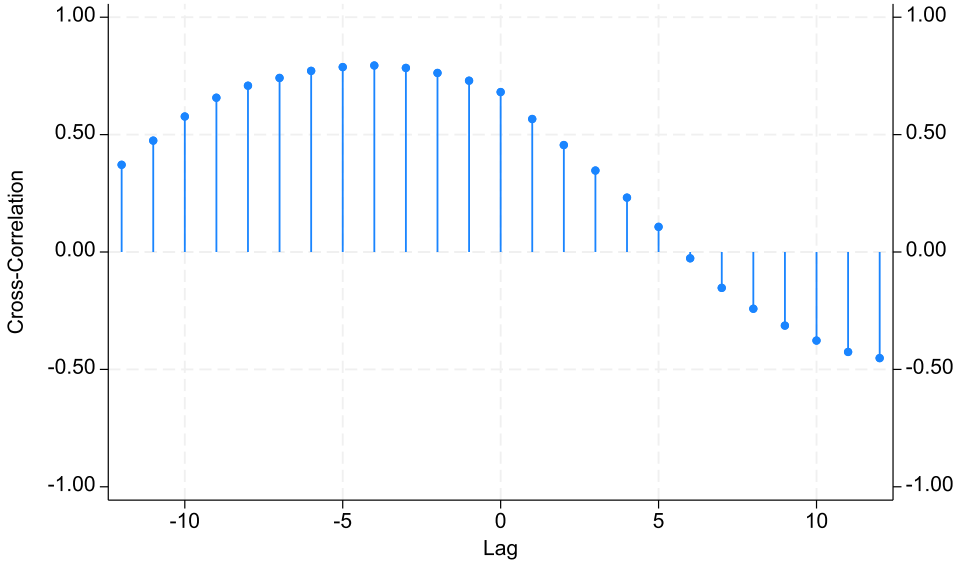

Fig. A1. Cross-Correlation Between Import and Retail DAP Prices. *Note: This figure presents the cross correlation between DAP import and retail prices and shows that retail prices are most strongly correlated with import prices four months before at 79 %.*

Appendix B

This section analyzes and compares the unbalanced original agro-dealer panel and the dyadic panel used in our econometric analysis. Table B1 columns (1) – (3) presents the results of our attrition analysis and investigates characteristics that effect the likelihood of a shop dropping from the panel, stopping, or closing. AgNexus dropped shops from the sample part way through the panel to manage survey costs. Some shops also decided to stop participating. According to AgNexus, this was primarily due to: survey fatigue; that the shop did not see value in participating; or that the shop wanted real time rather than monthly information. Table B1 column (4) explores what characteristics are correlated with a shop being selected for our dyadic regression analysis.

A total of 1,308 shops appear in the full sample but the number of shops present in a given month varies between 211 and 700. This is partially due

to the seasonality of agriculture as not all shops report agricultural input sales in every month. AgNexus also dropped 587 shops part way through the panel to reduce survey costs. The majority – but not all – of the dropped shops were dropped in April 2021, and a smaller number were dropped in July 2022. While AgNexus preserved the stratified sampling design, they did not provide additional criteria to explain why specific shops were dropped. An additional 154 shops decided to stop participating. Finally, 26 shops closed or stopped operating during the panel. Later, as AgNexus secured additional funding, they increased the sample size by adding an additional 44 shops.

We study how rising global fertilizer prices affected price transmission between import and retail markets and across retail markets in Kenya. This analysis requires a balanced time series of DAP sales for each retail market. However, only 10 shops in the panel report sales in every single month. To accomplish this, we restrict our sample to shops reporting sales in at least 75 % of months and missing no more than two months of data in a row. We then use linear interpolation to fill in missing data. This approach maximizes the sample size while limiting the amount of interpolation required.[14] Our strategy generates a final panel of 84 shops which we use in our dyadic regression analysis.

In Table B1 we explore what characteristics predict shop attrition and shop inclusion into the dyadic regression analysis. In column (1) the dependent variable is the probability of AgNexus dropping a shop from the sample. In column (2) the dependent variable is the probability a shop decides to stop participating in the panel. In column (3) the dependent variable is the probability a shop closes during the panel. Finally, in column (4) the dependent variable is the probability we include a shop in the dyadic regression analysis. We regress all dependent variables on the key shop characteristics described in Section 4, Table 1.

Table B1
Regression Results Predicting Attrition and Inclusion in the Dyadic Panel Using Shop Characteristics.

	(1)	(2)	(3)	(4)
	Dropped	Stopped	Closed	Dyadic Panel
PopDen	−0.000*	0.000***	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Port	−0.002	0.014**	0.004	−0.013***
	(0.008)	(0.006)	(0.003)	(0.005)
Market	0.054***	0.022	0.003	0.004
	(0.018)	(0.014)	(0.006)	(0.011)
Small	0.481***	−0.074***	−0.005	−0.092***
	(0.028)	(0.023)	(0.010)	(0.018)
Large	−0.209***	−0.044	−0.006	0.116***
	(0.038)	(0.031)	(0.014)	(0.024)
FertRate	0.000	−0.001***	−0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
MaizeProd	0.000***	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
PerFarmers	0.081	−0.155**	−0.004	0.223***
	(0.088)	(0.072)	(0.032)	(0.056)
Poverty	0.006***	−0.001	−0.001	−0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	1029	1029	1029	1029
Adjusted R^2	0.362	0.039	−0.003	0.094

*Note: This table presents the results of regressing the probability AgNexus drops a shop (column 1), the probability a shop decides to stop participating in the panel (column 2), the probability a shop closes during the panel (column 3), and the probability we include a shop in the dyadic regression analysis (column 4) on key shop characteristics. More information on the shop characteristics can be found in Section 4, Table 1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Several characteristics are statistically significant predictors of whether AgNexus drops a shop from the sample, a shop decides to stop participating, and we include a shop in the dyadic panel analysis. We find that time to the nearest 20 k market, small shop size, county-level maize output, and county-level poverty rate are positively correlated with the likelihood AgNexus drops a shop from the sample (column 1). Large shop size is negatively correlated with the likelihood a shop is dropped. This is sensible as it is likely easier and less expensive to collect data on larger, more accessible shops. Table B1, column (2) shows that smaller shops are less likely to stop participating while shops located in denser areas and further from the port are more likely to stop participating. We find that the county-level fertilizer application rate and percent of households farming are negatively correlated with the likelihood a shop decides to stop participating. In column (3) we do not observe any statistically significant predictors of a shop closing during the panel.

In Table B1, column (4), we explore what characteristics are correlated with our decision to include a shop in the dyadic regression analysis. We find that distance from the port is negatively correlated with the probability of inclusion. The percent of households farming in a given county is positively correlated with the likelihood of inclusion. This may be because counties with a larger share of farmers have more consistent demand for agricultural inputs throughout the year. We find that shop size is an important predictor of whether we include a shop in the dyadic regression analysis. We find small shops are significantly less likely and large shops are significantly more likely to be included relative to medium shops. We expected this to be the case, as we require shops in the dyadic panel to report sales in the majority of months. These are more likely to be larger shops for several reasons. First, AgNexus was more likely to drop smaller shops. Second, smaller shops are more likely operate seasonally with sales concentrated during the main growing seasons. In contrast, larger shops are more likely to sell throughout the year.

Despite this limitation, we still expect that large shops represent overall market dynamics well. In their census of agro-dealers in Kenya, AgNexus confirmed that larger shops are more heterogenous and represent a large share of total agricultural input sales despite being a relatively small share of the total number of shops. Furthermore, while we use region fixed effects when studying retail-import market pairs, this analysis is also robust to using dyad fixed effects that control for time-invariant shop characteristics − such as shop size and average county-level maize output. We also control for

[14] When developing this approach, we explored relaxing and tightening the criteria (e.g., missing at most one month in a row, missing no more than three months in a row, etc.). We find our results are robust to adjusting the criteria.

heterogeneity in price transmission for these predictors in our analysis. Finally, we use dyad fixed effects when studying retail-retail market pairs to control for shop characteristics. Thus, we expect our findings to still be informative of general market dynamics.

B.1. Balance tables

We investigate the results of our attrition analysis in Table B1 by including balance tables to test for statistically significant differences between shop characteristics. We compare shops that are dropped, stopped participating, or are included in the dyadic regression analysis to shops that remain constant in the panel or are added later by AgNexus. AgNexus defines constant as shops that are not dropped from the panel and do not decide to stop participating or close. Note, this means that constant shops may still not appear in every month due to the seasonality of agricultural input sales. Table B2 presents the balance table for shops AgNexus dropped, Table B3 presents the balance table for shops that decided to stop participating, and Table B4 presents balance table for shops that we included in the dyadic regression analysis.

Table B2
Balance Table Comparing Dropped Shops to Constant or Added Shops.

	Dropped		Constant or Added Later		Difference	
	N	Mean	N	Mean	Diff	T-Stat
PopDen	558	2,413.96	539	2,847.30	433.34	2.53
Port	558	6.71	540	6.17	−0.54	−4.37
Market	455	0.87	410	0.82	−0.05	−1.02
Small	558	0.70	541	0.26	−0.43	−15.91
Medium	558	0.26	541	0.48	0.21	7.51
Large	558	0.04	539	0.26	0.22	10.67
FertRate	554	143.22	531	139.84	−3.38	−1.73
MaizeProd	554	140,157.97	531	98,860.68	−41,297.29	−6.28
PerFarmers	554	0.62	531	0.61	−0.01	−0.85
Poverty	554	33.27	531	32.22	−1.05	−2.27

Note: This table is a balance table that comparing shops AgNexus decided to drop from the sample to shops that remain constant in the panel or were added later. The balance table reports the number of observations and mean for each category, and then tests for statistically significant differences. AgNexus defines constant as shops that are not dropped from the panel and do not decide to stop participating or close. Note, this means that constant shops may still not appear in every month due to the seasonality of agricultural input sales. More information on the shop characteristics can be found Section 4, Table 1.

While time to nearest 20k market and county-level poverty rate are statistically significant predictors of whether AgNexus drops a shop from the sample, Table B2 shows that the absolute difference is relatively small. However, we do see large, statistically significant differences in size. We observe that 70% of dropped shops are small, compared to 26% of shops that are constant or added later. Similarly, large shops comprise 4% of dropped shops whereas they comprise 26% of constant or added shops. We find that there is a substantial difference in county-level maize output between dropped shops and shops that are constant or are added later.

Our descriptive analysis explores how prices changed across seasons, such as between the 2021 and 2022 long rains. The attrition from dropped shops may mean our findings are not representative of the full sample if we expect prices to have changed differently across counties of high vs. low maize output or across shop size. If so, the average effects we observe may be due to a larger share of constant shops in the panel after AgNexus decided to reduce the sample size in April 2021. However, AgNexus did preserve the stratified sampling when they reduced the sample size to ensure the panel represented the prior census. Consequently, we expect our findings to be representative of the larger fertilizer market.

Table B3 compares shops that decided to stop participating to shops that remain constant in the panel or are added later. We do see that shops that stopped participating are located further from the nearest 20 k market and have a lower percent of households farming although the differences are relatively small in magnitude. We also see a statistically significant difference in county-level fertilizer rates. While population density, small shop size, and county-level poverty rate are statistically significant predictors of a shop stopping in Table B1, we do not observe statistically significant differences in these variables on average.

Table B3
Balance Table Comparing Stopped Shops to Constant or Added Shops.

	Stopped		Constant or Added Later		Difference	
	N	Mean	N	Mean	Diff	T-Stat
PopDen	154	2,904.49	539	2,847.30	−57.19	−0.23
Port	153	6.18	540	6.17	−0.00	−0.02
Market	133	0.99	410	0.82	−0.17	−2.07
Small	154	0.27	541	0.26	−0.00	−0.05
Medium	154	0.56	541	0.48	−0.09	−1.93
Large	154	0.17	539	0.26	0.09	2.25
FertRate	150	128.34	531	139.84	11.50	3.73
MaizeProd	150	86,507.83	531	98,860.68	12,352.84	1.49
PerFarmers	150	0.58	531	0.61	0.03	2.14
Poverty	150	33.31	531	32.22	−1.10	−1.43

Note: This table is a balance table comparing shops that decided to stop participating to shops that remain constant in the panel or were added later. The balance table reports the number of observations and mean for each category, and then tests for statistically significant differences. AgNexus defines constant as shops that are not dropped from the panel and do not decide to stop participating or close. Note, this means that constant shops may still not appear in every month due to the seasonality of agricultural input sales. More information on the shop characteristics can be found in Section 4, Table 1.

Table B4 compares shops that we decided to include in the dyadic regression analysis to shops that are constant in the panel or are added later and are not included in the dyadic panel. In Table B1 column (4) we observe shop size, time to the Mombasa port, and the county-level percentage of households farming are statistically significant predictors of whether we include a shop in the dyadic regression analysis. Table B4 confirms these

results. We find that the dyadic panel has a substantially lower share of small shops (1% vs. 30%) and higher share of large shops (45% vs. 23%).

Table B4
Balance Table Comparing Dyadic Shops to Constant or Added Shops.

	Dyadic Panel		Constant or Added Later			
	N	Mean	N	Mean	Diff	T-Stat
PopDen	84	2,414.05	469	2,945.21	531.17	1.62
Port	84	5.63	470	6.24	0.61	2.54
Market	80	1.00	343	0.80	−0.20	−2.32
Small	84	0.01	471	0.30	0.29	5.74
Medium	84	0.54	471	0.47	−0.07	−1.12
Large	84	0.45	469	0.23	−0.23	−4.42
FertRate	84	137.75	461	139.75	2.01	0.52
MaizeProd	84	90,120.33	461	100,164.19	10,043.86	0.92
PerFarmers	84	0.65	461	0.60	−0.05	−2.84
Poverty	84	32.17	461	32.24	0.07	0.08

Note: This table is a balance table comparing shops we decided to include in the dyadic regression analysis to shops that remain constant in the panel or were added later and are not included in the dyadic panel. The balance table reports the number of observations and mean for each category, and then tests for statistically significant differences. AgNexus defines constant as shops that are not dropped from the panel and do not decide to stop participating or close. Note, this means that constant shops may still not appear in every month due to the seasonality of agricultural input sales. More information on the shop characteristics can be found Section 4, Table 1.

Appendix C

This section contains additional information related to the descriptive and empirical analysis sections of the main paper. First, we describe several figures related to our empirical approach, including a map of the agro-dealers used the dyadic panel analysis and a figure documenting global, import, and retail DAP prices over time. In Appendix C1 we complement the panel unit root and cointegration tests discussed in Section 6.1 by reporting the results of our individual market-pair cointegration tests. In Appendix C2 we estimate equation (3) separately for each characteristic in Table 1. In Appendix C3 we re-estimate Table 5 in the main paper and Table C2 in the Appendix at the subcounty-level as a robustness check. Finally, in Appendix C4 we re-estimate Table 5 in the main paper while adjusting our assumptions about NFSP rollout.

Our empirical model uses the global price of DAP as a plausibly exogenous indicator of the intensity of the crisis. Fig. C1 presents the retail, import, and global DAP price (KSH/kg) over time. As shown below, the 2021–2022 rise in global fertilizer prices largely corresponds to the time period when the import-retail price spread in Kenya reversed.

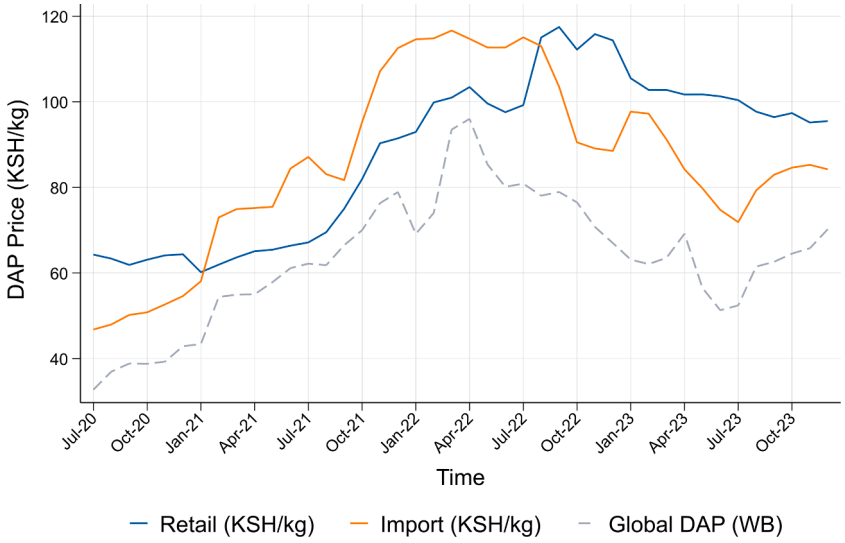

Fig. C1. DAP Retail, Import, and Global Prices (KSH/kg) over Time. *Note: The figure presents the retail (solid blue line), import (solid orange line), and global (dashed grey line) DAP price (KSH/kg) over time.*

Fig. C2 presents the spatial distribution of shops used in the dyadic regression analysis to study price transmission between import and retail markets and among retail markets in Kenya.

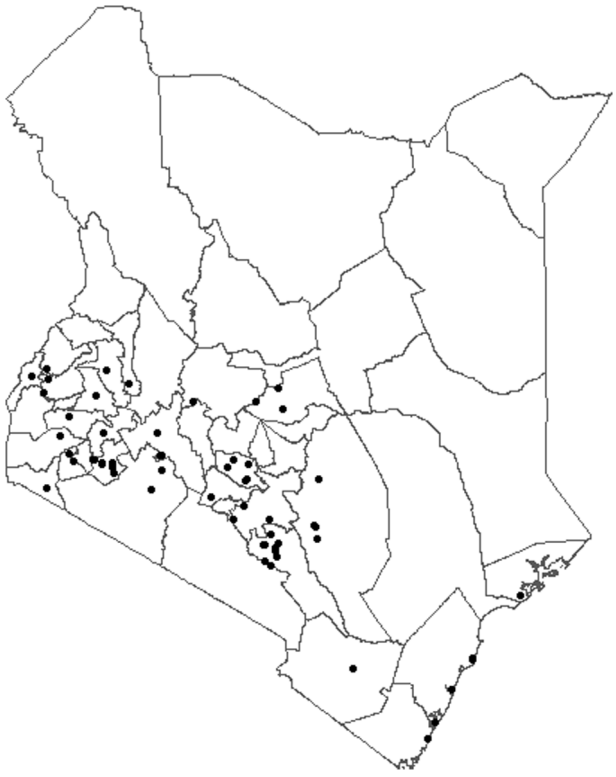

Fig. C2. Retailer Locations for Shops Used in the Dyadic Regression Analysis. *Note: This figure presents the spatial distribution of shops used in the dyadic regression analysis to study price transmission between import and retail markets and across retail markets in Kenya. Shop location are indicated as black dots on a map of Kenya that includes county outlines.*

Fig. C3 depicts the boxplots of DAP prices during three main growing seasons in Kenya from 2021 to 2023: the 2021, 2022, and 2023 long rains. This figure shows how the spatial dispersion in prices changes before, during, and after the global fuel-fertilizer-food crisis. During the 2021 long rains prices are clustered within a relatively narrow interquartile range of 5.27 although there outliers above and below the whiskers. The IQR doubles to 10.45 and number of outliers increases during the 2022 long rains, indicating greater price variability. We also observe a notable change in the price distribution as it shifts from a positive skew during the 2021 long rains to significant negative skew during the 2022 long rains. These trends persist as prices fall. During the 2023 long rains the IQR increases to 12.48, although there are fewer outliers at both ends of the price distribution.

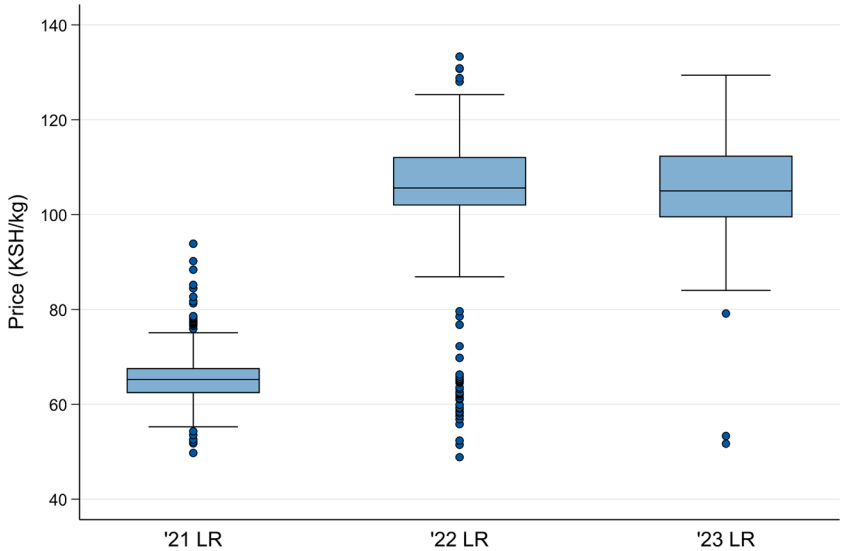

Fig. C3. Dap Prices and Price Dispersion in Kenya: Boxplots of Prices Across the 2021–2023 Long Rains. *Note: The figure presents the boxplots of DAP prices during the 2021, 2022, and 2023 long rains. The shaded blue area represents the interquartile range (IQR), the solid line in the middle represents the median price, the whiskers represent 1.5*IQR, and the blue dots represent outliers. The IQR is 5.27 during the 2021 long rains, 10.45 during the 2022 long rains, and 12.48 during the 2023 long rains. The skew is 1.71 during the 2021 long rains, −1.76 during the 2022 long rains, and −0.75 during the 2023 long rains. Data is from AgNexus panel of 1,308 shops.*

C.1. Individual Import-Retail market pair cointegration test

We complement the panel unit root and panel cointegration tests reported in Table 3 and Table 4 in Section 6.1 by applying the Engle Granger test to the individual import-retail market pairs. We fail to reject the null hypothesis of no-cointegration for all of the individual market pairs. This would imply there is no long-run relationship between import and retail prices and that our subsequent speed of adjustment estimates are not valid. However, this finding may due to low power when using individual time series with structural breaks (Campos, et al., 1996). Furthermore, our unit root and cointegration tests consistently show that the import-retail price spreads follows a stationary process and are cointegrated. Given this we believe our results hold but should be treated cautiously.

C.2. Import-Retail market pair regression estimates

In Section 4.1.2, we discuss the issue of possible collinearity between *DapRise* and *SubAct*. We show that these are consecutive events with a low estimated correlation coefficient of 0.05. Out of caution, we run an alternative specification that only controls for the effect of the NFSP, excluding the *DapRise* interactions. These results are reported below in Table C1, column (2).

The base model is presented in column (1). Column (2) presents the model controlling for exposure to the NFSP based on retailer proximity to fertilizer distribution depots, excluding the *DapRise* interactions. Column (3) expands the base model by controlling for exposure to the NFSP. Column (4) presents the full model incorporating all interactions to control for heterogeneity in adjustment during global fertilizer price increases. We find that the coefficients are consistent in magnitude, direction, and significance.

Table C1
Regression Estimates for Shop-Level Import-Retail Market Pairs (Controlling Only for NFSP).

	(1)	(2)	(3)	(4)
Y_{ijt-1}	−0.233***	−0.309***	−0.208***	−0.208***
	(0.013)	(0.010)	(0.012)	(0.012)
DAP Rise	0.012***		0.032***	0.032***
	(0.003)		(0.003)	(0.003)
Y_{ijt-1}*DapRise	−0.109***		−0.197***	−0.247***
	(0.014)		(0.015)	(0.070)
SubAct		−0.096***	−0.141***	−0.142***
		(0.007)	(0.007)	(0.007)
Y_{ijt-1}*SubAct		0.055**	0.111***	0.112***
		(0.022)	(0.024)	(0.023)
Y_{ijt-1} *SubAct*DepotDist		−0.001**	−0.001**	−0.001***
		(0.000)	(0.000)	(0.000)
Y_{ijt-1}*DapRise*PopDen				0.000
				(0.000)
Y_{ijt-1}*DapRise*Port				−0.004
				(0.004)
Y_{ijt-1}*DapRise*Market				−0.006
				(0.012)
Y_{ijt-1}*DapRise*Small				0.054***
				(0.013)
Y_{ijt-1}*DapRise*Large				−0.029*
				(0.015)
Y_{ijt-1}*DapRise*FertRate				−0.000
				(0.000)
Y_{ijt-1}*DapRise*MaizeProd				−0.000
				(0.000)
Y_{ijt-1}*DapRise*PerFarmers				0.019
				(0.072)
Y_{ijt-1}*DapRise*Poverty				0.003**
				(0.002)
Observations	3444	3444	3444	3444
Adjusted R^2	0.249	0.276	0.336	0.337

Note: This table presents the regression estimates for the shop-level import-retail panel and follows equations (1), (2), and (4). Column (1) presents the base model. Column (2) accounts for the effect of the NFSP on shops most exposed to the subsidy based on their distance to distribution depots, excluding the DapRise interactions. We define SubAct as a binary variable equal to 1 when the subsidy program is active from February or March 2023 to December 2023 and 0 otherwise. The variable DepotDist is defined as the distance in minutes each shop is from its closest NCPB depot or selling center. We rely on DepotDist as a plausibly exogenous indicator of exposure to the subsidy program, with exposure decreasing in distance to the nearest distribution point. Column (3) extends the base model while accounting for the effect of the NFSP. Column (4) accounts for heterogeneity in the speed of adjustment during global fertilizer price increases. For additional details on the shop characteristics refer to Table 1. All models included region and year fixed effects. Standard errors are in parentheses and are clustered at the market-pair level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In Section 6.2.1, we explore heterogeneity in the speed of adjustment as global fertilizer prices are rising. In the main paper, we estimate equation (4) where we include interactions for all the key shop characteristics outlined in Table 1. In this section, we estimate equation (3) separately for each characteristic and report the results below in Table C2.

Table C2
Regression Estimates for Shop-Level Import-Retail Pairs (Equation (3)).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Y_{ijt-1}	−0.233***	−0.208***	−0.208***	−0.207***	−0.208***	−0.237***	−0.208***	−0.208***	−0.208***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
DAP Rise	0.012***	0.032***	0.032***	0.032***	0.032***	0.033***	0.032***	0.032***	0.032***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Y_{ijt-1}*DapRise	−0.109***	−0.202***	−0.167***	−0.203***	−0.191***	−0.082**	−0.178***	−0.196***	−0.317***
	(0.014)	(0.017)	(0.026)	(0.021)	(0.016)	(0.039)	(0.017)	(0.036)	(0.048)
SubAct		−0.141***	−0.141***	−0.141***	−0.141***	−0.150***	−0.141***	−0.141***	−0.142***
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Y_{ijt-1}*SubAct		0.111***	0.113***	0.111***	0.112***	0.085***	0.111***	0.111***	0.109***
		(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)
Y_{ijt-1} *SubAct*DepotDist		−0.001**	−0.001**	−0.001**	−0.001***	−0.001***	−0.001**	−0.001**	−0.001**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Y_{ijt-1}*DapRise*PopDen		0.000							
		(0.000)							
Y_{ijt-1}*DapRise*Port			−0.005						
			(0.004)						
Y_{ijt-1}*DapRise*Market				0.007					
				(0.012)					
Y_{ijt-1}*DapRise*Small					0.082***				
					(0.012)				
Y_{ijt-1}*DapRise*Large					−0.017				
					(0.016)				
Y_{ijt-1}*DapRise*FertRate						−0.001***			
						(0.000)			
Y_{ijt-1}*DapRise*MaizeProd							−0.000**		
							(0.000)		
Y_{ijt-1}*DapRise*PerFarmers								−0.001	
								(0.045)	
Y_{ijt-1}*DapRise*Poverty									0.004***
									(0.001)
Observations	3444	3444	3444	3444	3444	3444	3444	3444	3444
Adjusted R^2	0.249	0.336	0.336	0.336	0.336	0.344	0.336	0.336	0.337

Note: This table presents the regression estimates for shop-level import-retail market and accounts for heterogeneity in the speed of adjustment following equation (3). Column (1) presents the base model. Columns (2) – (9) estimate the regression for each of the characteristics included in Table 1. We define SubAct as a binary variable equal to 1 when the subsidy program is active from February or March 2023 to December 2023 and 0 otherwise. The variable DepotDist is defined as the distance in minutes each shop is from its closest NCPB depot or selling center. We rely on DepotDist as a plausibly exogenous indicator of exposure to the subsidy program, with exposure decreasing in distance to the nearest distribution point. All models included region and year fixed effects. Standard errors are in parentheses and are clustered at the market-pair level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C2 shows that our estimates of the key paramaters Y_{ijt-1}, Y_{ijt-1}*$DapRise$, and Y_{ijt-1}*$SubAct$*$DepotDist$ are generally consistent across columns (1) through (9) and with the main model presented in Table 5, Section 6.2.1. When heterogeneity in the speed of adjustment during price increases is estimated separately for each characteristic, we find that small shop size remains statistically significant at the 1% level and is of similar magnitude. Small shops experience 8% slower price transmission than medium shops during price increases. Large shop size is no longer statistically significant. However, we do observe that county-level fertilizer application rate and maize output are correlated with a faster speed of adjustment at the 5% level. Finally, we find that the county-level poverty rate is correlated with slower price transmission at the 1% level. We discuss these results in Section 6.2.1.

C3. Import-Retail market pair regression estimates (Subcounty-Level)

In our main regression in Table 5, we estimate the impact of rising global fertilizer prices on price transmission using the shop-level panel of import-retail market pairs. In Table C3 and Table C4, we re-estimate the regressions using a subcounty-level panel of import-retail market pairs. By aggregating to the subcounty level, we increase the representativeness of the panel at the expense of shop-level variation and precision. We then check if our estimates are robust to aggregating to the sub-county level.

Table C3
Regression Estimates for Subcounty-Level Import-Retail Market Pairs.

	(1)	(2)	(4)
Y_{ijt-1}	−0.278***	−0.255***	−0.255***
	(0.018)	(0.019)	(0.018)
DAP Rise	0.020***	0.041***	0.043***
	(0.004)	(0.004)	(0.004)
Y_{ijt-1}*DapRise	−0.035	−0.085***	−0.143
	(0.023)	(0.027)	(0.181)
SubAct		−0.174***	−0.178***
		(0.010)	(0.011)
Y_{ijt-1}*SubAct		−0.067*	−0.081*
		(0.040)	(0.047)
Y_{ijt-1}* SubAct*DepotDist		−0.001	−0.001
		(0.001)	(0.001)
Y_{ijt-1}*DapRise*PopDen			0.000

(*continued on next page*)

Table C3 (*continued*)

	(1)	(2)	(4)
			(0.000)
Y_{ijt-1}*DapRise*Port			0.007
			(0.005)
Y_{ijt-1}*DapRise*Market			0.008
			(0.015)
Y_{ijt-1}*DapRise*Small			0.156
			(0.163)
Y_{ijt-1}*DapRise*Medium			0.041
			(0.146)
Y_{ijt-1}*DapRise*Large			0.030
			(0.140)
Y_{ijt-1}*DapRise*FertRate			−0.000
			(0.001)
Y_{ijt-1}*DapRise*MaizeProd			−0.000*
			(0.000)
Y_{ijt-1}*DapRise*PerFarmers			−0.077
			(0.103)
Y_{ijt-1}*DapRise*Poverty			0.002
			(0.001)
Observations	3280	3092	2939
Adjusted R^2	0.204	0.260	0.269

Note: *This table presents the regression estimates for subcounty-level import-retail market and follows equations (1) (2), and (4). Column (1) presents the base model. Column (2) accounts for the effect of the NFSP on shops most exposed to the subsidy based on their distance to distribution depots. We define SubAct as a binary variable equal to 1 when the subsidy program is active from February or March 2023 to December 2023 and 0 otherwise. Column (3) accounts for heterogeneity in the speed of adjustment during global fertilizer price increases. Each characteristic is the average value across shops in a given subcounty in a given month. For example, DepotDist is the average distance from the closest NCPB depot across shops in a given subcounty in each month. PopDen is the average population density across shops in a given subcounty in each month. Shop size would be the percent of shops within a subcounty that are small, medium, or large in each month. For additional details on the shop characteristics refer to Table 1. All models included dyad and year fixed effects. Standard errors are in parentheses and are clustered at the market-pair level.* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C4
Regression Estimates for Subcounty-Level Import-Retail Market Pairs (Equation (3)).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Y_{ijt-1}	−0.278***	−0.255***	−0.255***	−0.255***	−0.255***	−0.254***	−0.254***	−0.255***	−0.255***
	(0.018)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
DAP Rise	0.020***	0.041***	0.041***	0.042***	0.041***	0.041***	0.041***	0.041***	0.041***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Y_{ijt-1}*DapRise	−0.035	−0.097***	−0.074**	−0.093**	−0.150	0.008	−0.059**	−0.075	−0.168**
	(0.023)	(0.025)	(0.032)	(0.035)	(0.126)	(0.051)	(0.025)	(0.057)	(0.065)
SubAct		−0.174***	−0.174***	−0.177***	−0.175***	−0.175***	−0.175***	−0.174***	−0.175***
		(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Y_{ijt-1}*SubAct		−0.069*	−0.065	−0.083*	−0.068*	−0.068*	−0.066	−0.067	−0.069*
		(0.040)	(0.040)	(0.044)	(0.040)	(0.040)	(0.040)	(0.041)	(0.040)
Y_{ijt-1}*SubAct*DepotDist		−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Y_{ijt-1}*DapRise*PopDen		0.000							
		(0.000)							
Y_{ijt-1}*DapRise*Port			−0.002						
			(0.006)						
Y_{ijt-1}*DapRise*Market				0.013					
				(0.017)					
Y_{ijt-1}*DapRise*Small					0.115				
					(0.150)				
Y_{ijt-1}*DapRise*Medium					0.069				
					(0.130)				
Y_{ijt-1}*DapRise*Large					0.038				
					(0.124)				
Y_{ijt-1}*DapRise*FertRate						−0.001			
						(0.000)			
Y_{ijt-1}*DapRise*MaizeProd							−0.000		
							(0.000)		
Y_{ijt-1}*DapRise*PerFarmers								−0.016	
								(0.094)	
Y_{ijt-1}*DapRise*Poverty									0.002
									(0.002)
Observations	3280	3092	3086	2950	3076	3092	3092	3092	3092
Adjusted R^2	0.204	0.260	0.259	0.267	0.260	0.261	0.261	0.260	0.261

Note: This table presents the regression estimates for subcounty-level import-retail market and accounts for heterogeneity in the speed of adjustment following equation (3). Column (1) presents the base model. Columns (2) – (9) estimate the regression for each of the characteristics included in Table 1. We define SubAct as a binary variable equal to 1

when the subsidy program is active from February or March 2023 to December 2023 and 0 otherwise. Each characteristic is the average value across shops in a given subcounty in a given month. For example, DepotDist is the average distance from the closest NCPB depot across shops in a given subcounty in each month. PopDen is the average population density across shops in a given subcounty in each month. Shop size would be the percent of shops within a subcounty that are small, medium, or large in each month. For additional details on the shop characteristics refer to Table 1. *All models included dyad and year fixed effects. Standard errors are in parentheses and are clustered at the market-pair level.* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

When we aggregate to the subcounty level, the coefficients are generally consistent in direction and similar in magnitude to the coefficients estimated using the shop-level import-retail market pairs. For example, we find that the subcounty-level import-retail price spread adjusts 28 % of a disequilibrium in one month when global fertilizer prices are falling. Rising global fertilizer prices are associated with 4 % – 17 % faster price transmission. The coefficients on Y_{ijt-1}*SubAct*DepotDist* are generally consistent in magnitude and direction across specifications but are statistically insignificant. When testing for heterogeneity in adjustment, we find that the county-level characteristics (*FertRate*, *MaizeProd*, *PerFarmers*, and *Poverty* are consistent in magnitude and direction, although only maize production is statistically significant in Table C3. The shop-level characteristics (*PopDen*, *Port*, *Market*, *Small, etc.)* are somewhat consistent in magnitude and direction, although all are statistically insignificant. We expect this, as aggregation increased the representativeness of the panel at the cost of shop-level variation and precision.

The consistent direction and magnitude of our coefficients suggest that while the composition of the shop-level dyadic panel is different from the full sample, the sample may have experienced similar changes in price transmission. However, given many of the estimated coefficients are statistically insignificant at the subcounty-level, we are cautious in assuming our shop-level result represent the full sample. Nevertheless, we expect our findings to be characteristic of changes in the larger market as medium and large shops represent a disproportionate share of total sales.

C.4. Relaxing NFSP assumptions

In our empirical model we make several assumptions about NFSP implementation due uncertainty about the exact timing and geography of its rollout. First, we assume that the program is active from February or March 2023 and onward. However, it is possible the program was not active between the main growing seasons, such as from July to August 2023. Second, we assume that subsidized fertilizer was sold at all the NCPB depots and selling centers. However, it is unclear if the NFSP first distributed through NCPB depots and later expanded into selling centers, or if the program operated through both channels from the beginning. We expect these assumptions to be conservative, given that the subsidy program should have limited or no effect on price transmission when it is not active. In this section we check the robustness of our main results in Table 5 by re-estimating equations (1), (2), and (4) and modifying these assumptions. First, in Table C5 we assume that distribution only occurs through NCPB depots, not through last mile selling centers. Second, in Table C6 we assume that the subsidy program is only active during the main growing seasons (February/March – June 2023 and September – November 2023). Finally, in Table C7, we combine both of the aforementioned assumptions.

We find that the coefficient on Y_{ijt-1}*SubAct*DepotDist* is generally consistent in direction, magnitude, and significance across Table 5 and Table C5 to Table C7. The coefficients on the other terms are also consistent in direction, magnitude, and significance. This suggests our results are robust to relaxing and strengthening our assumptions about the implementation of the NFSP program.

Table C5
Regression Estimates for Shop-Level Import-Retail Market Pairs – Assuming Distribution Only Occurs through NCPB Depots.

	(1)	(2)	(3)
Y_{ijt-1}	−0.233***	−0.208***	−0.208***
	(0.013)	(0.012)	(0.012)
DAP Rise	0.012***	0.032***	0.032***
	(0.003)	(0.003)	(0.003)
Y_{ijt-1}*DapRise	−0.109***	−0.197***	−0.237***
	(0.014)	(0.015)	(0.069)
SubAct		−0.141***	−0.142***
		(0.007)	(0.007)
Y_{ijt-1}*SubAct		0.115***	0.116***
		(0.024)	(0.024)
Y_{ijt-1} *SubAct*DepotDist		−0.001**	−0.001***
		(0.000)	(0.000)
Y_{ijt-1}*DapRise*PopDen			0.000
			(0.000)
Y_{ijt-1}*DapRise*Port			−0.004
			(0.004)
Y_{ijt-1}*DapRise*Market			−0.007
			(0.011)
Y_{ijt-1}*DapRise*Small			0.052***
			(0.014)
Y_{ijt-1}*DapRise*Large			−0.030*
			(0.015)
Y_{ijt-1}*DapRise*FertRate			−0.000
			(0.000)
Y_{ijt-1}*DapRise*MaizeProd			−0.000
			(0.000)
Y_{ijt-1}*DapRise*PerFarmers			0.017
			(0.073)
Y_{ijt-1}*DapRise*Poverty			0.003*
			(0.001)
Observations	3444	3444	3444
Adjusted R^2	0.249	0.336	0.337

Note: This table presents the regression estimates for the shop-level import-retail panel and follows equations (1), (2), and (4). Column (1) presents the base model. Column (2) accounts for the effect of the NFSP on shops most exposed to

the subsidy based on their distance to distribution depots. We define SubAct as a binary variable equal to 1 when the subsidy program is active from February or March 2023 to December 2023 and 0 otherwise. The variable DepotDist is defined as the distance in minutes each shop is from its closest NCPB depot (we exclude last-mile selling centers). We rely on DepotDist as a plausibly exogenous indicator of exposure to the subsidy program, with exposure decreasing in distance to the nearest distribution point. Column (3) accounts for heterogeneity in the speed of adjustment during global fertilizer price increases. For additional details on the shop characteristics refer to Table 1. All models included region and year fixed effects. Standard errors are in parentheses and are clustered at the market-pair level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C6
Regression Estimates for Shop-Level Import-Retail Market Pairs – Assuming Subsidy Program is Only Active During Main Growing Seasons.

	(1)	(2)	(3)
Y_{ijt-1}	−0.233***	−0.236***	−0.236***
	(0.013)	(0.012)	(0.012)
DAP Rise	0.012***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)
Y_{ijt-1}*DapRise	−0.109***	−0.098***	−0.172**
	(0.014)	(0.014)	(0.069)
SubAct		−0.036***	−0.037***
		(0.007)	(0.007)
Y_{ijt-1}*SubAct		0.089***	0.087***
		(0.029)	(0.028)
Y_{ijt-1} *SubAct*DepotDist		−0.001***	−0.002***
		(0.000)	(0.000)
Y_{ijt-1}*DapRise*PopDen			0.000
			(0.000)
Y_{ijt-1}*DapRise*Port			−0.003
			(0.004)
Y_{ijt-1}*DapRise*Market			−0.003
			(0.011)
Y_{ijt-1}*DapRise*Small			0.041***
			(0.015)
Y_{ijt-1}*DapRise*Large			−0.027*
			(0.016)
Y_{ijt-1}*DapRise*FertRate			−0.000
			(0.000)
Y_{ijt-1}*DapRise*MaizeProd			−0.000
			(0.000)
Y_{ijt-1}*DapRise*PerFarmers			0.043
			(0.076)
Y_{ijt-1}*DapRise*Poverty			0.003**
			(0.001)
Observations	3444	3444	3444
Adjusted R^2	0.249	0.268	0.268

Note: This table presents the regression estimates for the shop-level import-retail panel and follows equations (1), (2), and (4). Column (1) presents the base model. Column (2) accounts for the effect of the NFSP on shops most exposed to the subsidy based on their distance to distribution depots. We define SubAct as a binary variable equal to 1 when the subsidy program is active from February/March to June 2023 and September to November, and 0 otherwise. The variable DepotDist is defined as the distance in minutes each shop is from its closest NCPB depot or selling center. We rely on DepotDist as a plausibly exogenous indicator of exposure to the subsidy program, with exposure decreasing in distance to the nearest distribution point. Column (3) accounts for heterogeneity in the speed of adjustment during global fertilizer price increases. For additional details on the shop characteristics refer to Table 1. All models included region and year fixed effects. Standard errors are in parentheses and are clustered at the market-pair level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C7
Regression Estimates for Shop-Level Import-Retail Market Pairs – Assuming Distribution Only Occurs through NCPB Depots & Subsidy Program is Only Active During Main Growing Seasons.

	(1)	(2)	(3)
Y_{ijt-1}	−0.233***	−0.236***	−0.236***
	(0.013)	(0.012)	(0.012)
DAP Rise	0.012***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)
Y_{ijt-1}*DapRise	−0.109***	−0.098***	−0.167**
	(0.014)	(0.014)	(0.069)
SubAct		−0.037***	−0.038***
		(0.007)	(0.007)
Y_{ijt-1}*SubAct		0.096***	0.093***
		(0.030)	(0.029)

(*continued on next page*)

Table C7 (*continued*)

	(1)	(2)	(3)
Y_{ijt-1} *SubAct*DepotDist		−0.002***	−0.002***
		(0.000)	(0.000)
Y_{ijt-1}*DapRise*PopDen			0.000
			(0.000)
Y_{ijt-1}*DapRise*Port			−0.003
			(0.004)
Y_{ijt-1}*DapRise*Market			−0.003
			(0.011)
Y_{ijt-1}*DapRise*Small			0.041***
			(0.015)
Y_{ijt-1}*DapRise*Large			−0.028*
			(0.016)
Y_{ijt-1}*DapRise*FertRate			−0.000
			(0.000)
Y_{ijt-1}*DapRise*MaizeProd			−0.000
			(0.000)
Y_{ijt-1}*DapRise*PerFarmers			0.042
			(0.076)
Y_{ijt-1}*DapRise*Poverty			0.003*
			(0.001)
Observations	3444	3444	3444
Adjusted R^2	0.249	0.268	0.268

Note: This table presents the regression estimates for the shop-level import-retail panel and follows equations (1), (2), and (4). Column (1) presents the base model. Column (2) accounts for the effect of the NFSP on shops most exposed to the subsidy based on their distance to distribution depots. We define SubAct as a binary variable equal to 1 when the subsidy program is active from February/March to June 2023 and September to November, and 0 otherwise. The variable DepotDist is defined as the distance in minutes each shop is from its closest NCPB depot (we exclude last-mile selling centers). We rely on DepotDist as a plausibly exogenous indicator of exposure to the subsidy program, with exposure decreasing in distance to the nearest distribution point. Column (3) accounts for heterogeneity in the speed of adjustment during global fertilizer price increases. For additional details on the shop characteristics refer to Table 1. All models included region and year fixed effects. Standard errors are in parentheses and are clustered at the market-pair level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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