Market Integration and the Impact of Violence on Trade Networks: Evidence from Nigeria

Abstract

Market integration is essential for food security in developing economies, particularly amid socio-political instability. This study examines the dynamics of trade between urban and rural areas, focusing on the role of seasonality and violent conflict in shaping market integration. Using weekly price data from 97 markets across Nigeria, we analyze price adjustments among rural-rural, urban-urban, and urban-rural market pairs.

Our findings indicate that rural-to-rural networks exhibit stronger integration, suggesting effective intra-regional trade that reduces dependence on urban centers. Seasonal variations significantly influence price transmission, with faster adjustments when both markets are in the harvest season and slower adjustments when one market is not, highlighting the role of synchronized production cycles in market efficiency.

Despite frequent violent events, conflict has a limited short-term impact on price transmission. While explosions and riots temporarily slow price adjustments, their effects vary across commodities, and battles and violence against civilians show no systematic influence on market integration. Additionally, fluctuations in conflict intensity do not significantly alter price adjustments, suggesting that markets have adapted to recurring instability. This resilience is particularly evident in markets with stronger trade connections, where broader networks provide alternative trade routes that help mitigate disruptions.

These results emphasize the importance of market connectivity and seasonal synchronization in sustaining trade efficiency. Policies aimed at strengthening rural-urban linkages, securing trade corridors, and improving market connectivity can enhance market resilience and food security.

Keywords:Food Security; Violent Conflict; Agricultural Markets; Crop Trade; Africa

JEL: D40, P25, Q13, O18, H56, E31

I Introduction

Market integration is critical for food security in developing countries where urban food supply depends on strong linkages to producers through rural markets. A well-integrated market system enhances the distribution of goods, facilitates the efficient dissemination of price information, and stabilizes food prices (Badiane and Shively, 1998; Byerlee, Jayne, and Myers, 2006; Kebede, 2024). Market integration makes it more likely that farmers receive fair prices for their produce and helps consumers to access food at lower costs, contributing to poverty reduction and overall food security (Ahmed, Ying, Bashir, Abid, and Zulfiqar, 2017; Olabisi, Obekpa, and Liverpool-Tasie, 2021).

Achieving and maintaining market integration is challenging, particularly in regions affected by seasonal fluctuations and violent conflict. Communal clashes and insurgencies can disrupt economic networks, or threaten food security by raising transaction costs or reducing market access (Minoiu and Shemyakina, 2014; Odozi and Oyelere, 2021, 2022; Hastings, Phillips, Ubilava, and Vasnev, 2022). Disruptions to trade routes and market connections can cause price shocks, affecting both producers and consumers. While previous studies highlight the short-term price volatility caused by violence, research on how conflict influences long-term market integration and price transmission dynamics remains limited.

This paper examines market integration in Nigeria with a focus on price transmission across different market pairs—urban-urban, urban-rural, and rural-rural—while also investigating the effects of seasonality and conflict on price adjustments. Using weekly price data from February 2022 to April 2023 across 97 markets in northern and southern Nigeria, this study provides a comprehensive analysis of trade relationships in a high-frequency setting. We combine market price survey data with information on travel distances, transport costs, violent events (sourced from the ACLED database), and trade networks to investigate the extent to which shocks influence price adjustments. Our empirical strategy follows a dynamic price adjustment model, where price convergence between market pairs serves as an indicator of market integration. The speed of price adjustment—estimated through a first-difference regression framework—allows us to assess how quickly price gaps close over time in response to shocks. We estimate heterogeneous price transmission effects by categorizing market pairs based on (1) their trade relationships (urban-urban, urban-rural, rural-rural) and (2) their seasonal positioning (Harvest to Harvest, Harvest to Non-Harvest, Non-Harvest to Non-Harvest). To assess the impact of violence, we incorporate conflict data at a granular level, examining whether different types of violent events (battles, riots, explosions, and violence against civilians) slow or disrupt price adjustments. Finally, we introduce market connectivity measures to test whether well-connected markets exhibit greater resilience to conflict-induced disruptions.

Guided by a market integration framework, we begin by examining the relative speed of price convergence between market-pairs. Contrary to initial expectations, our results indicate that rural-rural markets adjust prices more quickly than urban-

involved market pairs, suggesting that local trade networks facilitate rapid information flows and price corrections. This aligns with findings from Borno State in Nigeria, where rural markets exhibit strong integration despite regional instability (Onyeka, Olayemi, Kormawa, and Mafimisebi, 2006). Studies in Malawi's maize markets show that private sector participation efficiently moves goods between surplus and deficit regions (Myers, 2013). Studies using data from Ghana, Nigeria, and Madagascar find that transportation costs, infrastructure, and local trading conditions shape market integration and price transmission speeds (Abdulai, 2000; Hatzenbuehler, Abbott, and Abdoulaye, 2016; Moser, Barrett, and Minten, 2009; Minten and Kyle, 1999).

In addition to market structure, we explore how seasonal harvest cycles shape price transmission. Our findings reveal that markets exhibit the fastest price adjustments during the "Harvest to Harvest" period, when both markets are in the harvest season, benefiting from increased supply and active trading. In contrast, price adjustments are slowest when one market is in harvest while the other is not ("Harvest to Non-Harvest"), likely due to mismatches in supply availability and regional production cycles. The seasonal divergence is most evident for locally produced crops like Local Rice and Cowpea, while imported Long-Grain Rice remains unaffected by domestic harvest cycles, reinforcing the role of global supply chains in stabilizing its price adjustments.

Price transmission, a key indicator of market integration, depends on logistics, trader networks, and external shocks like conflict (c.f., Kinnucan, 2019). In Nigeria, recurrent instability challenges market stability, particularly in northern regions affected by insurgencies and communal violence (George and Adelaja, 2022; Odozi and Oyelere, 2022). Conflict disrupts agricultural production, labor markets, and supply chains, disproportionately affecting smallholder farmers, women, and marginalized traders (Adelaja and George, 2019; George, Adelaja, and Awokuse, 2021; Vargas, Reardon, and Liverpool-Tasie, 2023). This paper contributes to the literature, in showing the extent to which market integration is itself disrupted by violence.

Despite the theoretical expectation that violence disrupts market integration, our findings suggest that the impact of conflict on price adjustment is generally weak or inconsistent. While some event types– explosions and riots - introduce temporary frictions, the overall effect on price convergence remains trivial in most cases. Even in situations where conflict appears to slow price adjustments, the impact dissipates over time, suggesting that markets have adapted to recurrent instability. Traders likely anticipate violence and adjust trade routes, pricing strategies, or inventory management practices accordingly, thereby limiting prolonged disruptions.

To better understand why conflict effects appear limited, we examine market connectivity as a potential mitigating factor. Our results indicate that well-connected markets with multiple trade routes experience little to no effect from conflict-related disruptions. In contrast, markets with limited trade options (low-connectivity markets) exhibit slower price adjustments in the presence of violence, particularly for Local Rice. This suggests that conflict effects are highly contingent on market struc-

ture, where traders in isolated locations face greater frictions in adjusting prices. The presence of diverse trade linkages buffers against conflict-induced disruptions, allowing traders to redirect trade flows and stabilize price adjustments.

This study contributes to the literature by expanding on how structural market conditions—such as connectivity and seasonal cycles—shape market integration in the face of instability. Studies show that information frictions, infrastructure, and government policies determine price transmission (Le Cotty, Maitre D'Hotel, and Ndiaye, 2017; Ndiaye, Maître d'Hôtel, and Le Cotty, 2017; Bonilla Cedrez, Chamberlin, and Hijmans, 2020b; Bonilla Cedrez, Chamberlin, Guo, and Hijmans, 2020a; Burke, Bergquist, and Miguel, 2019). Others find that mobile technology adoption improves market efficiency and stabilizes food prices (e.g., Aker, 2010). However, few studies directly assess the interaction between market connectivity, seasonal variation, and conflict in determining trade resilience. Our study addresses this gap by providing a structured analysis of how markets adjust to violence-related shocks, focusing on price movements rather than isolated price levels.

Furthermore, our study builds on research examining how shocks affect market behavior, including studies on the COVID-19 pandemic's impact on food systems and the African Swine Fever outbreak in China (Amare, Abay, and Hatzenbuehler, 2024; Ma, Delgado, and Wang, 2024; Massol, Hache, and Banal-Estañol, 2023). Unlike research that primarily examines price shocks from global markets, our study emphasizes internal trade linkages within Nigeria, showing how market adaptation occurs in response to both seasonality and conflict (Dillon and Barrett, 2016; Dhar, Olabisi, Ogunbayo, Olutegbe, Akano, and Tschirley, 2024).

The paper proceeds as follows: Section II presents the conceptual framework that guides our analysis. Section III describes the data and provides a descriptive analysis of market conditions. Section IV discusses the empirical results, and Section V concludes with policy implications.

II Conceptual framework

In an integrated market system, price differences between locations reflect only transportation costs and other frictions, so that shocks in one market are transmitted to others through arbitrage. The degree to which prices co-move across markets is thus a direct measure of integration. Faster price adjustments to shocks suggest higher levels of integration, while persistent price differences may indicate weak market linkages due to structural barriers.

Violent conflict disrupts market integration by increasing trade frictions and creating uncertainty for traders. One primary channel is the increase in trade costs and physical barriers caused by conflict. Violence damages infrastructure, such as roads and bridges, and leads to blockages through military checkpoints, roadblocks, and curfews. These physical barriers raise transportation costs and force traders to seek alternative, often costlier, routes. As a result, price differences between markets

may widen, and price convergence may slow. Beyond direct cost increases, conflict also discourages traders from traveling along affected routes. Some traders exit the market entirely, while others reduce their trade volumes or reroute trade to safer but potentially less efficient pathways. This leads to market fragmentation, where certain markets become less connected due to the withdrawal of traders, limiting arbitrage opportunities and weakening price transmission. The loss of trade routes and trader participation weakens market linkages, meaning price shocks in one market may not transmit to others in a timely manner. In addition, violence disrupts information flows and supply chains, creating uncertainty about future trade conditions. The unpredictability of conflict may cause erratic supply patterns and increase market inefficiencies, leading to inconsistent price adjustments.

Given these mechanisms, conflict or violence on trade routes should increase price dispersion and slow price convergence when they reduce arbitrage and trader participation in markets. The extent of these effects may depend on the level of market connectivity. Markets with more trade partners may be able to adjust, mitigating the impact of violence events, while markets with fewer alternative trade routes are more vulnerable to disruptions. The effect of conflict on price transmission may also depend on the type of violence. Large-scale, high-intensity events such as explosions may have stronger effects on price adjustment than ongoing, low-intensity violence such as riots or civilian-targeted attacks, as sudden disruptions in infrastructure and security conditions may create greater trade frictions.

This framework guides the empirical analysis by linking conflict exposure to trade frictions, market fragmentation, and price adjustments. The analysis will test whether market pairs exposed to violence exhibit wider price gaps and slower price adjustments compared to unaffected markets. It will also examine whether highly connected markets are more resilient to conflict-related disruptions and whether the type of conflict influences the magnitude of its impact on price transmission in section IV.c.

III Data and Descriptive Statistics

Our study uses four primary data sources: market-to-market relationship data, price data, violence events data, market pairs, and distance data.

Market-to-Market Relationships:

The network data were generated from a comprehensive trader survey conducted in 2022 that covered 140 markets. In each market, we reached out to every trader that could be located on the survey day, with survey participation ranging from 20 to 418 traders per market depending on the market size. One key survey question asked traders to report both the markets from which they purchase products and those to which they sell products. This information was then aggregated at the market level to build a detailed trade network among the markets. Specifically, we defined a market pair as having a direct relationship if a trader in one market named

a trader in the other market as a source or destination. If no direct connection was identified between two markets, but both were connected to a third market, the pair was classified as indirectly connected. Pairs that exhibited both direct and indirect ties were categorized separately, while pairs with no such connections through any third market were classified as unconnected.

Non-response and selection bias are potential concerns because some traders may have been absent or reluctant to report all of their connections. However, we mitigate this risk by surveying at the trader level and then aggregating responses at the market level, thereby reducing the likelihood that entire trade connections are overlooked. Still, certain links may remain unrecorded if no trader from a market pair reported them. Because our main concern is to avoid falsely labeling markets as unconnected, our primary analysis focuses on pairs with at least one explicitly reported link. This approach ensures that we only classify a pair as connected if the data provide direct or indirect evidence of a trading relationship.

The network plot in Figure 1 depicts the trading relationships among the surveyed markets. In this graph, each node symbolizes a market, while the connecting lines (edges) represent the trading connections between these markets. The size of a node illustrates the market's size, serving as an indicator of its importance. To distinguish between urban and rural markets, nodes are color-coded uniquely. Additionally, the transparency of each link reflects the volume of trade reported between markets: a more transparent line signifies a lower volume of trade, making the visualization a tool to easily understand the trading dynamics and market significance based on size, location type, and trading frequency. In Figure 2, we can clearly see that relatively larger markets serve as significant trading hubs, connecting multiple zones and helping trade between different regions of the country. For example, Dawanau – the largest market in Northern Nigeria, has direct links to Bodija – one of the major hubs in the Southwest, and the two have scores of direct and indirect connections to local markets in their respective zones. The network plot looks like the hub-and-spoke pattern observed in other economic sectors and predicted by theoretical papers (e.g., Peng, Yang, Cheng, Lu, and Yuan, 2019; O'Kelly, 1998; Jackson and Watts, 2002; Newman, 2008).

The network diagram depicted in Figure 3 shows the intricate web of trade connections among different market pair types: rural-to-rural, urban-to-urban, and rural-to-urban. It highlights the strong local connectivity among rural markets, which not only are closely interconnected within their immediate vicinity but also play a crucial role as central nodes facilitating trade between various urban and rural markets across different regions. For instance, the large rural market in Tsaragi, located in North Central Nigeria, functions as a crucial hub. It not only connects to nearby rural markets but also links to numerous other markets across the North West and South West regions. Conversely, urban markets exhibit a more constrained pattern of connectivity, characterized by a limited number of direct links to each other. The trade routes connecting rural markets tend to be regional, with occasional inter-regional links. Meanwhile, the connections between rural and urban markets predominantly span across regions, supplemented by a few local linkages. For example, the Mile

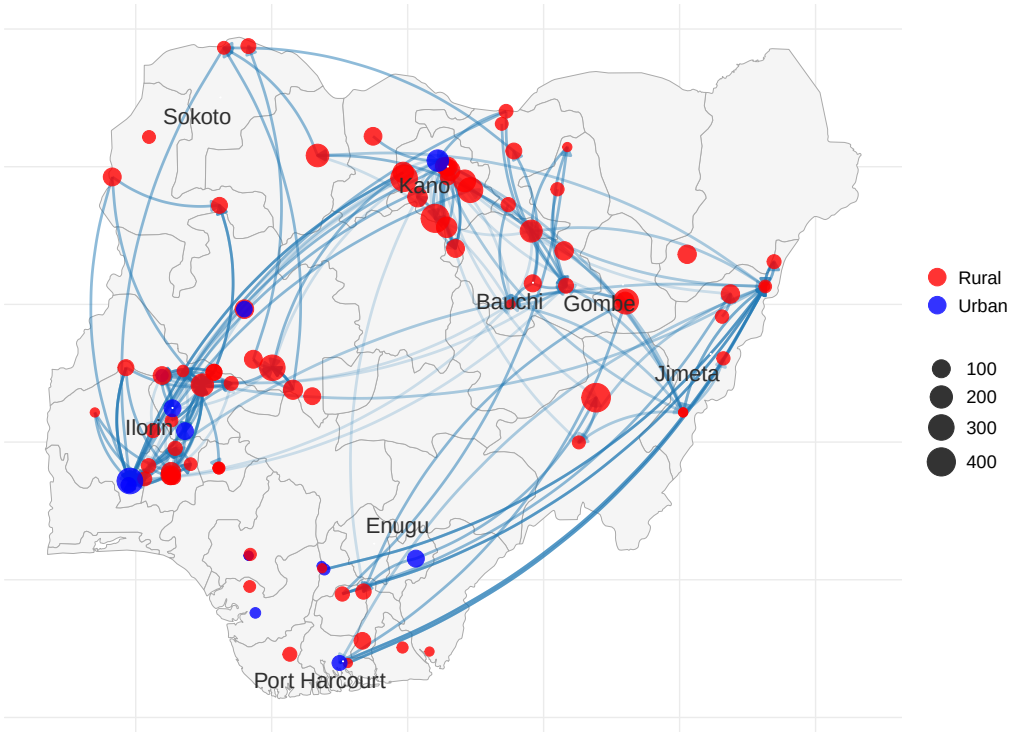


Figure 1: Trade network in Nigeria

Note: Nodes on this graph represent markets and edges indicate trading links between them. Node size corresponds to the market size. Distinct node colors differentiate urban and rural markets. Transparency of the link indicate the number of reported trading between markets, with smaller number to be more transparent. To enhance clarity, self-loops have been excluded from this visualization.

1 market in Port Harcourt, a major urban center in the South South region, connects to several rural markets in the North East, while maintaining only a few local connections.

Price Survey Data: Our main data source is a comprehensive set of weekly prices collected from 97 diverse markets in Nigeria, including 82 rural and 15 urban markets.[1] The 97 markets are those that were included in both the price survey and the trader survey, with each market providing complete information for both surveys. This collection spans across both the northern and southern regions of the country, offering an extensive representation of Nigeria's agricultural market landscape.

Data collection commenced in February 2022, and for the purpose of our analysis, we utilize data spanning until April 2023.[2]

[1]The distinction between rural and urban markets in our study is based on the population size of the local government area (LGA) of each market. A detailed classification of markets into rural and urban is in Appendix Table 14.

[2]The survey is ongoing, but we limit our analysis to data collected up to April 2023 due to the removal of the state fuel subsidy by Nigeria's President Bola Tinubu in May 2023. This policy change could potentially alter transaction costs and complicate our assessment of market integration.

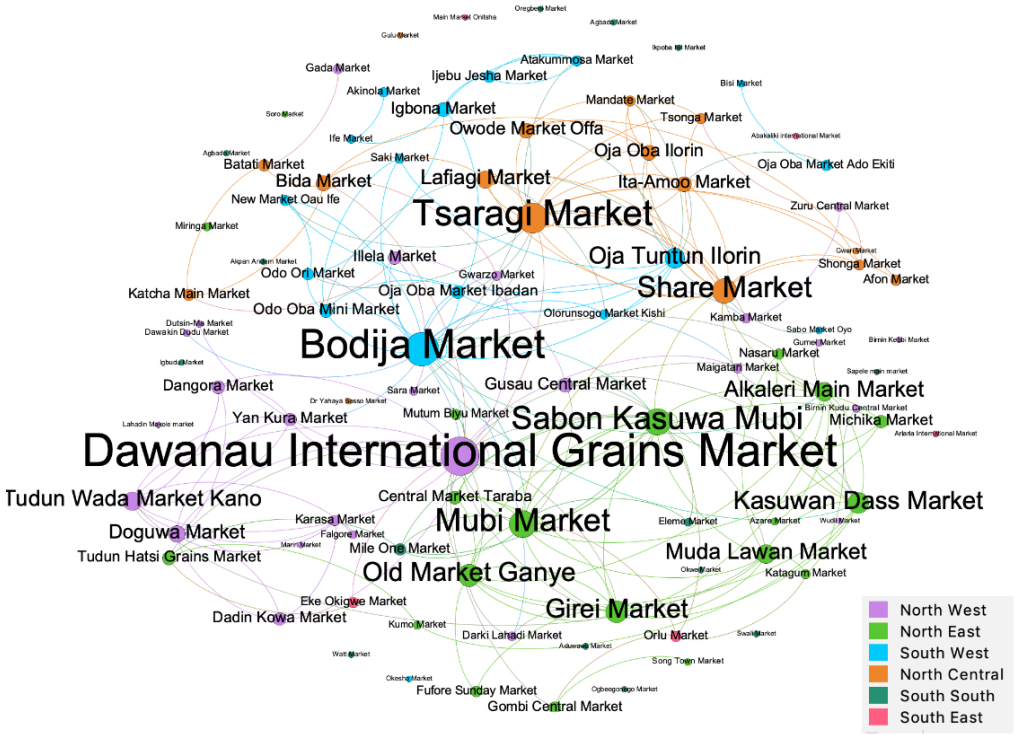


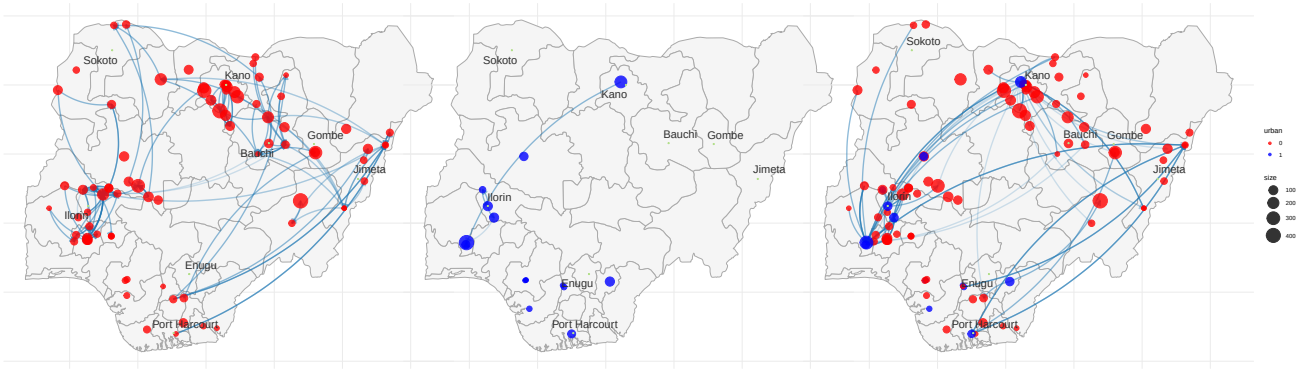
Figure 2: Trade network in Nigeria

Note: Nodes on this graph represent markets and edges indicate trading links between them. Node size corresponds to the market size. Distinct node colors differentiate regions. To enhance clarity, self-loops have been excluded from this visualization.

To gather the data, we deployed enumerators to initially visit each market and collect information on both selling and purchasing prices. Subsequently, these enumerators continued to collect weekly price data via phone calls. We encouraged the enumerators to obtain as many responses as possible from each market location. The total number of responses from each market serves as an estimate of its size. Market sizes range from 20 to 418, averaging at 85 responses [3].

Our survey covered a variety of agricultural commodities, specifically cowpeas, local and long-grain rice, millet, sorghum, groundnuts, soybeans, maize, wheat, cassava, yam, and potatoes. This comprehensive list of products includes the most widely consumed food items in Nigeria. However, in all our analysis, we primarily focus on brown cowpeas, white cowpea, local rice, and long-grain rice, as these represent the four predominant crops in our survey and the Nigerian diet.

[3]The market size is determined by two market surveys that we did in Nigeria, where information is available in both sources, we elect to use the higher value. Recognizing that market sizes can vary considerably, we impose a bottom censoring threshold, setting 20 as the smallest possible size for a market in our study. This approach ensures that the data reflects a realistic range of market sizes while accommodating potential variations and uncertainties in the available information. It is noteworthy that this bottom-censoring of values is a deliberate methodological choice, grounded in our assessment of the data and the context of the markets under investigation.



(a) Rural to rural (b) Urban to urban (c) Rural to urban

Figure 3: Trade network between different market pairs

Post-collection, we filtered out extreme values of reported prices to reduce the potential skewing effect they could have on our analysis. The remaining data were then averaged for each market on a per-week basis for a given crop. This approach enabled us to derive a representative market price for each week in each market.

Table 1 presents summary statistics for the prices of the top four main food items in our survey data: Local Rice, Imported Rice, Brown Cowpea, and White Cowpea. The number of market observations varied slightly among the products, with imported rice having observations from 90 markets, while the other products had observations from 96 to 97 markets. This variation underscores the differing levels of market availability and possibly the demand and supply dynamics for each product. Several patterns of price in the table fit expectations. Local rice is less expensive than the imported rice, while spatial price variation is non-trivial. Urban areas consistently have higher prices across products, while markets in the northern region generally have lower prices compared to rural areas and the southern region, respectively. The price gaps reflect the dynamics of demand from largely urban markets, supply from largely rural areas – predominantly from Northern Nigeria, market competition, and transportation costs.

The data show moderate spatial variation in market prices, highlighted by the average inter-market price gaps, defined as $Mean_t(|P_{ikt} - P_{jkt}|)$. The inter-market price gap serves as a crucial indicator of market integration, reflecting how efficiently prices and information flow between geographically dispersed markets; this often mirrors transaction costs (Baulch, 1997; Negassa and Myers, 2007). A small gap indicates low transaction costs and high market integration, suggesting that goods and information are moving freely across markets. Conversely, a large gap points to high transaction costs and low integration, highlighting barriers to the efficient exchange of goods and information. The average inter-market price gaps for rural-rural market pairs are relatively moderate, with local rice at 82.72 NGN/kg and imported rice at 75.90 NGN/kg, suggesting a notable but not extreme variation in prices within rural areas. This variation could be influenced by factors such as transportation difficulties, access to markets, and localized supply-demand imbalances.

Table 1: Summary Statistics for Product Prices and Price Gaps

Variable	Local Rice	Imported Rice	Brown Cowpeas	White Cowpeas
No. of Market Observations	97	90	96	97
Average Price	489.90	583.14	476.25	437.54
Average Price Urban	617.73	711.18	524.31	491.66
Average Price Rural	465.76	561.49	466.07	425.79
Average Price North	416.29	526.10	451.72	409.99
Average Price South	608.41	682.78	525.34	497.84
Average Inter-Market-Gap (Rural-Rural)	82.72	75.90	61.01	58.83
Average Inter-Market-Gap (Urban-Urban)	60.48	74.00	59.44	47.81
Average Inter-Market-Gap (Urban-Rural)	115.10	103.60	87.42	77.91
Average Inter-Market-Gap (North-North)	56.02	49.53	49.01	44.21
Average Inter-Market-Gap (South-South)	47.79	54.33	75.12	70.05
Average Inter-Market-Gap (North-South)	156.61	137.38	105.02	95.75

Prices are averages in NGN per kg. The most common measure for selling crops in wholesale markets is the 100kg bag, so most of the prices reported above can be understood as wholesale prices when multiplied by 100.
Price gaps too are shown in NGN/kg, as $|P_{ikt} - P_{jkt}|$, for the markets that have trading connections. During the period of our study, the average exchange rate is around 432 Nigerian Naira (NGN) for every US Dollar (USD). Source: Investing.com

Urban-urban market pairs exhibit slightly smaller average price gaps, with local rice at 60.48 NGN/kg and imported rice at 74.00 NGN/kg, indicating a higher degree of price integration within urban centers likely due to better infrastructure and market access.

However, the average inter-market price gaps significantly widen in the urban-rural comparisons, reaching 115.10 NGN/kg for local rice and 103.60 NGN/kg for imported rice. This substantial increase underscores the challenges and inefficiencies in price transmission between urban and rural markets, possibly reflecting the additional costs and logistical complexities of bridging urban and rural economies.

The geographical analysis reveals the smallest average price gaps within the North-North and South-South market pairs, suggesting more cohesive pricing within these regions. However, the North-South price gaps are markedly higher, with local rice showing a gap of 156.61 NGN/kg and imported rice 137.38 NGN/kg. This pronounced disparity between northern and southern markets emphasizes the significant impact of geographical location on market prices, likely reflecting the broader economic, infrastructure, and logistics challenges facing market integration across Nigeria's diverse regions.

Violence Events:

Our analysis draws on violence data sourced from the Armed Conflict Location & Event Data Project (ACLED), widely recognized for its comprehensive coverage of violence events in different regions (Raleigh, Linke, Hegre, and Karlsen, 2010). ACLED's dataset provides detailed information, including the exact date, geographic location, and type of each violence event. We examine the impact of various types of violence on market integration, focusing on those categories with considerable po-

tential to disrupt market dynamics due to their severity and direct impact on civilian populations. Table 2 summarizes the nature and consequences of these incidents.[4] Battles, explosions/remote violence, riots, and violence against civilians—are chosen for our analysis based on their higher likelihood of influencing market dynamics through direct disruptions.

Table 2: Violence types and counts

Type	Total Count	Total Fatalities	Civilian Targeting (%)	Event with Fatality (%)
Battles	1565	7124	0	73
Explosions/Remote violence	259	1939	18	68
Protests	1049	16	3	0.01
Riots	549	280	42	0.30
Strategic developments	427	2	0	0
Violence against civilians	2532	4451	100	52

Note: 1. The table shows the count of violence events observed on the trade route between all market-pairs between Feb 2022 and April 2023. 2. The"Civilian targeting" column specifically identifies the percentage of incidents where civilians are the primary or exclusive targets of violence, excluding events where civilians are incidentally harmed. Source: ACLED (Raleigh et al., 2010).

The selected violence categories, such as battles and explosions/remote violence, are more likely to involve fatalities and civilian targeting, disrupting the normal flow of goods and information crucial for market functions. Riots and violence against civilians are highly visible and directly impact civilian populations, significantly altering economic behaviors and reducing market participation. In contrast, protests and strategic developments, which generally result in fewer disruptions, are excluded from the primary analysis due to their minimal impact on market stability.

For the mapping of trade routes connecting market pairs, we utilize data from OpenStreetMap, a valuable resource for obtaining accurate and up-to-date geographic information. Our analysis specifically targets violence events incidents occurring within a 20km range along these trade routes. Figure 4 illustrates the spatial distribution of these violence events across Nigeria from February 2022 to April 2023, with the size of each circle on the map reflecting the number of violence events. Red circles represent the violence events of interest within the 20km proximity to the trade routes, integral to our analysis. In contrast, incidents denoted by grey circles, which fall outside this specified radius, are not considered in our evaluation.

The geographic analysis reveals a pronounced concentration of violence events in Nigeria's North West and South South regions. This spatial pattern underscores the differential exposure of trade routes to violence events dynamics across various parts of the country, highlighting areas of heightened risk that could potentially disrupt market connectivity and economic activities. Violence along trade routes can often be strategic, targeting these vital paths to disrupt economic stability and exert control. For example, groups like Boko Haram may attack these routes to undermine government authority by creating food insecurity and economic distress. Such disruptions serve multiple tactical purposes: they hinder the supply of essential goods,

[4]The detailed breakdown in appendix table 13 explains and classifies these event.

increasing public dissatisfaction towards government performance, and potentially boost recruitment by exacerbating hardship. Additionally, attacking trade routes allows these groups to seize commodities necessary to sustain their operations (Adelaja and George, 2019).

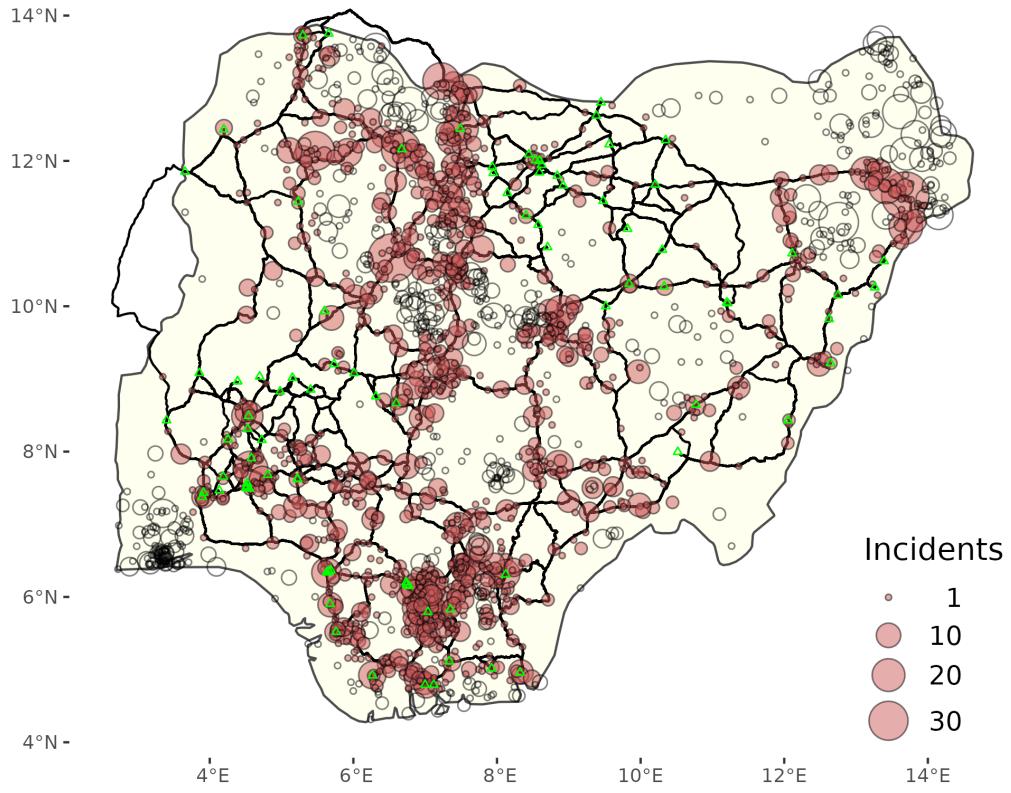


Figure 4: Violence events around trade routes and surveyed markets in Nigeria : Feb 2022-Apr 2023

Note: Mirroring the approach in (Hastings et al., 2022), markets are represented by green triangles, while circles indicate the geographic locations of violence events. The size of each circle corresponds to the number of violence events reported in the ACLED dataset from Feb 2022 to Apr 2023. For our econometric analysis, we focus on violence events occurring within about 20 km of roads connecting markets, depicted by red circles. Incidents represented by grey circles fall outside this scope and are not included in our analysis.

Figure 5 illustrates the distribution of violence event counts on trade routes between markets. The histogram reveals a skewed bimodal distribution, with the majority of trade routes experiencing lower instances of violence, as indicated by the taller bars on the left side of the graph. Specifically, the mode falls within the 0-350

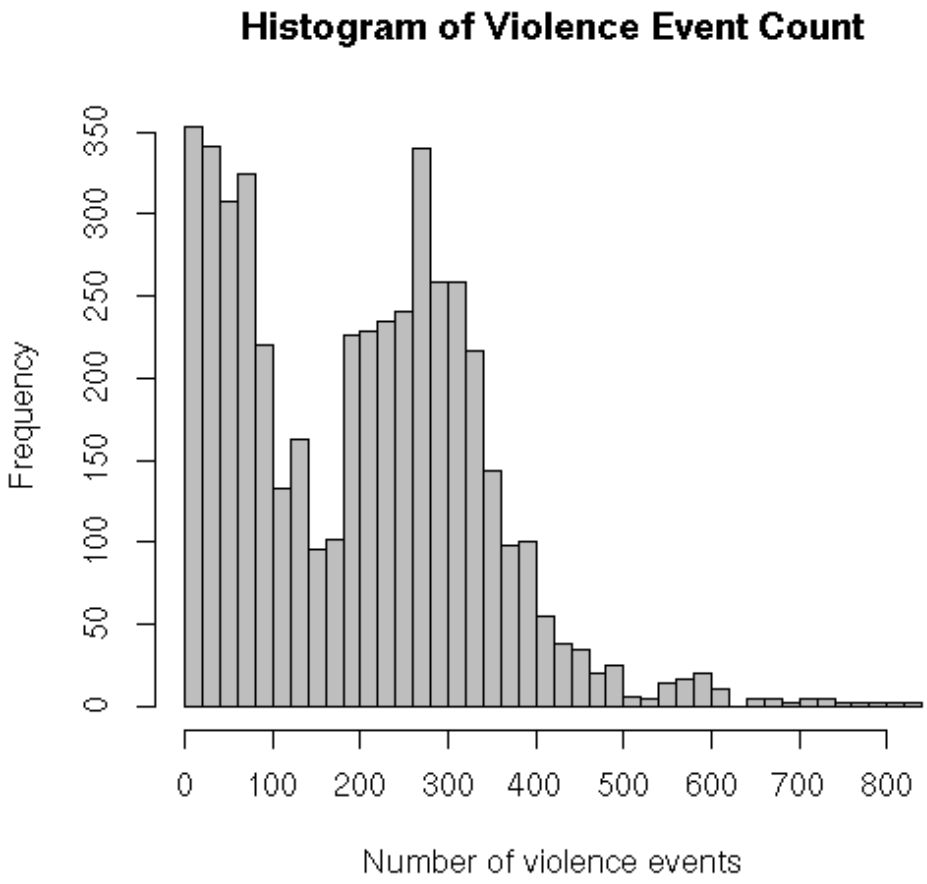


Figure 5: Violence Count on Trade Route between Markets

Note: The Figure shows the count of violence events observed on the trade route between market-pairs between Feb 2022 and April 2023. Source: ACLED (Raleigh et al., 2010).

events range, highlighting that this is the most common occurrence of violence events for the majority of trade routes. The frequency gradually declines as the number of events increases, with significantly fewer trade routes encountering higher levels of violence. Notably, the frequency of routes experiencing between 100 to 200 events is approximately half the frequency of the most common category. Beyond 300 events, the occurrence becomes increasingly rare, suggesting that extremely high counts of violence are not typical for most trade routes.

Table 3 provides a comprehensive summary of violence events, distance, and travel time between market pairs, classified into three distinct categories based on the nature of their connections: with direct connections, with only indirect connections, and with no trade connections. Each category is further subdivided into market pair types: urban to urban, rural to rural, and urban to rural. Observing the data, we can discern patterns that suggest how distance, travel time, and the average number of incidents influence market connections.

Table 3: Summary statistics for violence events, distance, travel time

Pair Type	Number of Pairs	Travel Time (in h)	Distance (in km)	Average No. of Incidents
With direct connections:				
Urban to urban	3	4.59	320.95	119.00
Rural to rural	67	4.22	287.63	45.55
Urban to rural	36	6.58	512.89	129.36
Only indirect connections:				
Urban to urban	6	7.51	582.66	266.17
Rural to rural	166	8.28	627.31	148.40
Urban to rural	67	8.53	647.12	197.63
No trade connections:				
Urban to urban	96	5.54	409.12	176.59
Rural to rural	3088	8.90	678.45	196.21
Urban to rural	1127	8.51	651.79	227.38

Market pairs with direct connections generally exhibit shorter travel times and distances, with urban to urban pairs showing the shortest metrics. This suggests that direct connections are facilitated by proximity and well-established trade routes, which likely contribute to more efficient and resilient market integration. The higher average incidents in urban to rural pairs within this category indicate that while direct connections enhance integration, they also expose markets to more violence, possibly due to higher transaction volumes and urban-specific challenges.

In contrast, market pairs with only indirect connections display significantly longer travel times and distances. This pattern highlights the reliance on major hubs for broader trade routes, which naturally extends the distance and travel time between markets. These indirect connections are associated with higher average incidents of violence, reflecting the vulnerability of longer trade routes to disruptions. The increased exposure to violence in indirectly connected markets underscores the need for enhanced security measures to protect these extended trade networks.

For market pairs with no trade connections, the data shows consistently long travel times and distances, especially in rural to rural pairs. This lack of direct or indirect connections suggests significant barriers to market integration, such as poor infrastructure and limited access to trade networks. The variation in average incidents among these pairs indicates that other factors, beyond travel distance and time, influence market integration challenges. Urban to rural pairs with no trade connections face the highest average incidents, emphasizing the compounded difficulties of violence and isolation in these markets.

IV Empirical Methods and Results

IV.a Descriptive Analysis of Price Differentials

Before analyzing the dynamic adjustment process, we first explore the determinants of baseline price discrepancies between markets. In this descriptive analysis, we regress the logarithmic price differential between market i and market j, defined as

$$y_{ijt} = \ln p_{it} - \ln p_{jt},$$

on several key factors that may affect price formation. Specifically, we include indicators for the pair relationship (distinguishing urban-to-urban, urban-to-rural, and rural-to-rural connections), measures of market connectivity (e.g., connection type), and proxies for geographical and infrastructural barriers such as distance and travel time. In addition, we incorporate a dummy for whether the market pair lies within the same region and include time fixed effects to capture common shocks. Recognizing that conflict can disrupt market operations, we also include a measure of conflict—either as fatalities [5] or event counts—recorded in the previous week. The regression specification is thus given by:

$$\begin{aligned} y_{ijt} = \alpha &+ \beta_1 \ln \text{Distance}_{ij} + \beta_2 \ln \text{TravelTime}_{ij} + \beta_3 \text{SameRegion}_{ij} \\ &+ \delta_1 \text{IndirectConnection}_{ij} + \delta_2 \text{DirectConnection}_{ij} + \delta_3 \text{BothConnections}_{ij} \\ &+ \lambda_1 \text{UrbanToRural}_{ij} + \lambda_2 \text{UrbanToUrban}_{ij} \\ &+ \theta_1 \text{Conflict}_{ijt-1} + \gamma_t + \epsilon_{ijt}. \end{aligned} \tag{1}$$

where γ_t represents time (week) fixed effects and ϵ_{ijt} is the idiosyncratic error term.

[5] please see the table 17 in appendix.

Table 4: Descriptive Regression of Price Differences by Connection Type with Conflict Events

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: *Price Difference* (y)				
Market Characteristics:				
log(Distance)	0.216**	0.057	0.139**	0.114**
	(0.077)	(0.048)	(0.044)	(0.041)
log(Time)	-0.238**	-0.070	-0.096*	-0.093*
	(0.083)	(0.056)	(0.042)	(0.036)
Same Region	0.062***	0.026	0.056**	0.031
	(0.017)	(0.017)	(0.020)	(0.021)
Market Connection Type:				
Only Indirect	-0.047*	0.004	-0.075***	-0.051***
	(0.020)	(0.008)	(0.014)	(0.011)
Only Direct	-0.014	0.065	-0.117**	-0.073*
	(0.107)	(0.072)	(0.038)	(0.029)
Both Direct and Indirect	-0.056	-0.053*	-0.046*	-0.043*
	(0.034)	(0.022)	(0.020)	(0.020)
Conflict Exposure:				
Conflict Events$_{t-1}$	-0.013	-0.007	0.001	0.000
	(0.011)	(0.005)	(0.003)	(0.003)
Trade Relationship Type:				
Urban to Rural	-0.076*	-0.058**	-0.025*	-0.015
	(0.029)	(0.019)	(0.010)	(0.010)
Urban to Urban	-0.016	-0.039	-0.036**	-0.018.
	(0.021)	(0.026)	(0.012)	(0.011)
Week Fixed Effect	Yes	Yes	Yes	Yes
Observations	5,201	4,905	6,906	8,281
R^2	0.099	0.090	0.108	0.052
Within R^2	0.028	0.025	0.043	0.016

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The omitted category for `connection` is "no connection." Specifically:
– `Only Indirect`: Markets share an indirect connection via a third market.
– `Only Direct`: Markets are directly connected but have no indirect links.
– `Both Direct and Indirect`: Markets have both direct and indirect connections.
(3) `log(Distance)` and `log(Time)` are the natural logarithms of market-pair distance and travel time, respectively.
(4) `Same Region` indicates whether both markets are located in the same administrative zone.
(5) The omitted category for `Trade Relationship Type` is Rural-to-Rural trade. Specifically:
– `Urban to Rural`: Trade occurs from an urban to a rural market.
– `Urban to Urban`: Trade occurs between two urban markets.
(6) `Conflict Events`$_{t-1}$ represents the count of violent conflict events in the previous period.
(7) Standard errors (in parentheses) are clustered at the week level. Fixed effects include week dummies.

Table 4 reveals several important insights into the drivers of price differentials across market pairs. For three of the four commodities, the coefficient on ln(Distance)

is positive and statistically significant, indicating that as distance between markets increases, price gaps tend to widen. Interestingly, ln(Time) has a negative and significant effect for the same three commodities, suggesting that once distance is controlled for, longer travel times may in fact correspond to lower price differentials—possibly because markets with slower routes still benefit from consistent trade flows or well-established contractual arrangements. In the case of long-grain rice, neither distance nor travel time exerts a robust effect, hinting that its supply chains may be structured differently, perhaps relying on distinct logistics networks or specialized traders.

The coefficient on "Same Region" is positive, suggesting that market pairs within the same administrative zone exhibit larger price differences. Although this is counterintuitive at first glance, it may reflect localized supply-and-demand imbalances or administrative barriers unique to the region that overshadow reduced transport frictions. If short-distance or higher-frequency trading within a region concentrates particular types of shocks (such as harvest failures or local policy changes), the result may be greater price dispersion than would be expected from purely physical distance. Further investigation into the specific features of these same-zone market pairs—such as local infrastructure quality or idiosyncratic production conditions—could clarify why closer administrative ties do not necessarily minimize price gaps.

Turning to trade connectivity, pairs classified as "Only Indirect" or "Both Direct and Indirect" connections tend to have lower price differentials relative to unconnected markets. This pattern is especially pronounced for brown cowpea and white cowpea, suggesting that denser links—whether direct or indirect—foster more efficient price transmission for those commodities. The effects for local rice and long-grain rice are somewhat less uniform, yet they still generally lean in the direction of tighter links reducing price disparities. Meanwhile, conflict events in the prior period do not show a statistically significant impact on price differentials, implying that short-term shocks from violence may be mitigated by traders rerouting through safer paths or that local markets adjust more gradually to conflict-induced disruptions.

Finally, trade relationship types also matter. Urban-to-rural pairs exhibit systematically smaller price differentials for local rice, long-grain rice, and brown cowpea compared to the omitted rural-to-rural category. This indicates that urban markets, with their larger consumer bases and higher volume of trade, may help anchor or stabilize prices for commodities sourced from nearby rural areas. The negative effect of an urban-to-urban pairing is likewise visible but less consistently significant across commodities, suggesting that city-based market pairs also benefit from more integrated supply chains, though their advantage may vary depending on the product in question.

IV.b Market Integration

Understanding market integration requires examining how price differences between spatially separated markets adjust over time. The classical Law of One Price (LOP)

suggests that in the absence of transaction costs and frictions, prices of the same good should equalize across locations through arbitrage. However, real-world markets are subject to transportation costs, information asymmetries, institutional constraints, and disruptions such as conflict, which can create persistent deviations from the LOP (Barrett and Li, 2002; Fackler and Tastan, 2008). The speed at which these price gaps dissipate provides a measure of market efficiency and resilience, particularly in environments where shocks may hinder arbitrage.

A dynamic adjustment framework is well-suited to capturing these short-run price dynamics. Instead of relying on static price comparisons, this approach models how deviations from price parity evolve over time, explicitly accounting for the persistence of price differences. Dynamic models have been widely used in the market integration literature to estimate price transmission rates and identify structural frictions affecting price adjustments (Ceballos, Hernandez, Minot, and Robles, 2017; Myers and Jayne, 2012; Goodwin and Piggott, 2001). A key advantage of this approach is that it provides a direct measure of the speed of adjustment, offering insights into whether price shocks dissipate quickly or persist due to barriers to arbitrage.

Following the recent literature (Amare et al., 2024; Hastings et al., 2022), we specify a model where price differentials evolve according to the following equation:

$$y_{ijt} = \ln p_{it} - \ln p_{jt}$$

denote the logarithmic price differential between markets i and j at time t. We then specify our model as:

$$\Delta y_{ijt} = \beta_0 \, y_{ijt-1} + \theta_{ijt} + \delta_{ij} + \gamma_t + \epsilon_{ijt}, \tag{2}$$

where Δ represents the first-difference operator, β_0 is the speed-of-adjustment parameter that captures the proportion of the previous period's deviation that is corrected in the current period, θ_{ijt} is a vector of control variables, δ_{ij} denotes market-pair fixed effects accounting for time-invariant heterogeneity, γ_t indicates week fixed effects that capture time-specific shocks common to all market pairs, and ϵ_{ijt} is the idiosyncratic error term.

In this dynamic framework, the lagged term y_{ijt-1} reflects the departure from the long-run equilibrium. Theoretical expectations suggest that β_0 lies between -1 and 0; a value of 0 would indicate no adjustment, while a value closer to -1 implies a rapid return toward equilibrium. Because y_{ijt-1} is predetermined relative to the current change Δy_{ijt}, issues of simultaneity are alleviated—an approach supported in the literature on market integration (see, e.g., Barrett and Li (2002); Negassa and Myers (2007); González-Rivera and Helfand (2001)). This structure is particularly useful when studying conflict-affected markets, where simultaneous shocks to both supply and demand can confound traditional static price comparisons.

While our model focuses on short-term price adjustments, it provides valuable insights into market resilience under external shocks. By estimating how quickly price deviations dissipate, we can assess the role of factors such as transportation

constraints, trade relationships, and conflict exposure in shaping market integration. In the following sections, we extend this baseline model to explore how different types of market connections and external disruptions influence the price adjustment process.

Table 5: Adjustment Speed Estimates with Market-Level Controls

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Lagged Price Difference (y_{ijt-1})	-0.636***	-0.686***	-0.668***	-0.512***
	(0.076)	(0.078)	(0.065)	(0.059)
Estimated Half-Life (Weeks)	0.686	0.598	0.629	0.966
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.690	0.419	0.592	0.493
Within R^2	0.557	0.125	0.359	0.337

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the *first difference of the price gap* between market pairs.
(3) The coefficient on y_{ijt-1} represents the *speed of price adjustment*; a more negative value indicates faster convergence to equilibrium.
(4) For a more intuitive interpretation, we report the half-life, calculated as:

$$\text{Half-Life} = \frac{\log(0.5)}{\log(1+\beta_0)}$$

This represents the number of weeks required for half of a price shock to dissipate.
(5) Market-pair fixed effects account for time-invariant trade relationships, while week fixed effects control for common shocks.
(6) Control variables include interaction terms of y_{ijt-1} with: - log(Distance) (spatial separation), - log(Travel Time) (trade friction), - Same Region (whether markets share an administrative boundary). These controls are included in the regression but omitted from the table for brevity.
(7) Standard errors (in parentheses) are clustered at the market-pair level.

The results in Table 5 confirm that price adjustments occur across all four commodity markets, with the negative and statistically significant coefficients on the lagged price difference (y_{ijt-1}) indicating that deviations from equilibrium gradually correct over time. The consistency in these estimates across different commodities suggests a general pattern of market integration, where arbitrage forces drive price convergence.

To provide a more intuitive interpretation of these adjustment speeds, we calculate the half-life of a price shock, which represents the number of weeks required for half of a price deviation to dissipate. The estimated half-lives are all within a relatively narrow range, suggesting that the pace of price convergence is broadly similar across the sampled markets. This implies that, despite potential differences in trade

infrastructure or storage conditions, the fundamental price adjustment mechanisms function in comparable ways across commodity types.

While these baseline results establish the overall tendency toward price convergence, they do not account for potential heterogeneous effects across different market structures. In the following analysis, we extend the model to explore how trade relationships (rural-to-rural, urban-to-urban, rural-to-urban) and harvest seasons influence the speed of price adjustment. We estimate the following regression equation:

$$\Delta y_{ijt} = \sum_{g} \beta_{1g}(y_{ijt-1} \times \mathbb{1}(\text{Group} = g)) + \theta_{ijt} + \delta_{ij} + \gamma_t + \epsilon_{ijt} \tag{3}$$

The term $\mathbb{1}(\text{Group} = g)$ is an indicator variable that equals one if the market pair ij belongs to group g, and zero otherwise. The groups we consider in this analysis include different types of trade relationships—*rural-to-rural, rural-to-urban, and urban-to-urban*—as well as different seasonal trade patterns—*harvest-to-harvest, harvest-to-non-harvest, and non-harvest-to-non-harvest*. The interaction term $y_{ijt-1} \times \mathbb{1}(\text{Group} = g)$ allows us to estimate the price adjustment speed separately for each group.

Unlike a traditional interaction model where one category is omitted as a baseline, our regression estimates a separate adjustment coefficient for each group. In this specification, the coefficient β_{1g} directly captures the speed of price adjustment within each trade relationship or seasonal category, rather than measuring the difference relative to a reference group. This ensures that each group's price adjustment can be interpreted independently, providing a clearer picture of how market dynamics differ across trade structures and seasonal cycles.

Table 6: Adjustment Speed Estimates for Connected Markets by Market Pair Types

	Local Rice	Long-grain Rice	Brown Cowpea	White Cowpea
Dependent Var.:	Δy_{ijt}	Δy_{ijt}	Δy_{ijt}	Δy_{ijt}
Rural to rural x y_{ijt-1}	-0.760***	-0.668***	-0.758***	-0.555***
	(0.106)	(0.121)	(0.081)	(0.069)
Urban to rural x y_{ijt-1}	-0.560***	-0.723***	-0.531***	-0.397***
	(0.097)	(0.107)	(0.058)	(0.073)
Urban to urban x y_{ijt-1}	-0.539***	-0.582***	-0.565***	-0.609***
	(0.125)	(0.112)	(0.113)	(0.158)
Test:				
Rural to rural = Urban to rural	P=0.069	P=0.725	P=0.003	P=0.064
Rural to rural = Urban to urban	P=0.197	P=0.532	P=0.109	P=0.738
Urban to urban = Urban to rural	P=0.891	P=0.336	P=0.768	P=0.189
Fixed-Effects:				
Market pair	Yes	Yes	Yes	Yes
week	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R2	0.692	0.419	0.599	0.497
Within R2	0.560	0.125	0.370	0.341

Note: (1) *p<0.1; **p<0.05; ***p<0.01.
(2) This analysis includes only market pairs with direct or indirect connections, based on the premise that segregated markets lack mechanisms for price adjustment, rendering them unsuitable for market integration analysis.
(3) Control variables include interaction term of y_{ijt-1} with travel time, travel distance, and if markets are in the region.
(4) Standard errors clustered by market-pairs.

The regression results in Table 6 highlight contrasts in the speed of adjustment—a measure of market integration—across different types of market pairs (urban to urban, urban to rural, and rural to rural) for various commodities (Local Rice, Long-grain Rice, Brown Cowpea, and White Cowpea) within Nigeria's trading landscape. These distinctions provide insights into how market integration dynamics manifest across different geographical and commodity-specific contexts.

For Local Rice, the speed of adjustment demonstrates distinct patterns across market pair types. Rural to rural markets exhibit the fastest adjustment speed (-0.7596, Half-life: 0.49 weeks), suggesting a robust level of market integration and rapid information flow among these pairs. This speed is statistically significantly faster compared to urban to rural markets, which adjust at a slower pace (-0.5596, Half-life: 0.845 weeks). However, the difference between rural to rural and urban to urban markets (-0.5393, Half-life: 0.89 weeks) is not statistically significant (p-value = 0.197), indicating that while rural to rural markets adjust more quickly, this difference is not pronounced enough to suggest significantly better integration relative to urban to urban markets.[6]

[6]For a more intuitive interpretation of the coefficient, we employ the concept of half-life, derived

In the case of Long-grain Rice, the adjustment speed is fastest in urban to rural markets (-0.7229, Half-life: 0.540 weeks), followed by rural to rural markets (-0.6678, Half-life: 0.629 weeks) and urban to urban markets (-0.5824, Half-life: 0.794 weeks). However, the differences in speed across these market pairs are not statistically significant, as indicated by the p-values, suggesting that while there are variations in adjustment speeds, the overall degree of market integration among these pairs does not differ markedly.

These differences in coefficients between imported and local rice across market pairs underscore the varying dynamics of market integration for domestically produced versus imported commodities. The faster adjustment speeds for local rice in rural-to-rural pairs highlight the strong integration within domestic agricultural markets, particularly in rural areas where local rice is a staple. However, the relatively slower adjustment for local rice in urban-to-urban pairs suggests that market integration may weaken as one moves away from rural production centers.

Conversely, the faster adjustment for imported rice in urban-to-rural pairs indicates that the integration of imported commodities might be driven by efficient supply chains that link urban demand centers with rural markets. This efficiency may be supported by more predictable supply routes for imported goods.

For Brown Cowpea and White Cowpea, adjustment speeds are consistently higher in rural to rural markets compared to urban to rural markets, underscoring stronger market integration in rural areas. However, the differences between rural to rural and urban to urban markets are not statistically significant (p-values = 0.109 and 0.738, respectively), indicating similar levels of integration across these market configurations.

The regression results demonstrate that all estimated speeds of adjustment are relatively high, indicating a significant level of market integration for the commodities examined. Particularly, rural to rural markets display a statistically faster speed of adjustment for Local Rice and Cowpea compared to urban to rural markets. However, it is important to note that the differences between rural to rural and urban to urban markets are not statistically significant, which suggests that while rural markets may exhibit quicker adjustments, the overall degree of market integration does not differ significantly across these market pair types.

To better illustrate the spatial variation in harvest timing across Nigeria, Table 15 presents the start and end dates of the harvest season for the key crops across different regions. The timing of harvest varies significantly between the northern and southern regions due to climatic differences, which influence planting and harvesting schedules.

This regional variation in harvest timing implies that market pairs involving interregional trade are more likely to fall into the "Harvest to Non-Harvest" category

using the formula $\frac{\log(0.5)}{\log(1+\beta_0)}$. This metric quantifies the duration required for markets to adjust and correct half of the initial deviations from their equilibrium state. For an in-depth exploration of this methodology, refer to the comprehensive analysis provided in (Goodwin and Piggott, 2001).

at some point in the year. This is particularly relevant for local rice, where harvesting takes place from August to November in the south but from November to January in the north. Similarly, cowpea harvests in the south precede those in the north, meaning that market pairs spanning both regions will frequently involve one market in harvest and the other not.

Given this variation, it follows that a substantial share of weeks will involve trade between markets in different harvest periods. The observed slower price adjustment in "Harvest to Non-Harvest" pairs may therefore be driven by these seasonal misalignments, where supply shocks in one region do not immediately translate into price adjustments in another. This underscores the importance of harvest timing in price dynamics and market integration.

Table 7: Adjustment Speed Estimates for Connected Markets by Season

	Local Rice	Long-grain Rice	Brown Cowpea	White Cowpea
Dependent Var.:	Δy_{ijt}	Δy_{ijt}	Δy_{ijt}	Δy_{ijt}
Harvest to Harvest x y_{ijt-1}	-1.057***	-0.750***	-0.890***	-0.996***
	(0.157)	(0.152)	(0.092)	(0.101)
Harvest to Non-Harvest x y_{ijt-1}	-0.382***	-0.597**	-0.785***	-0.820***
	(0.076)	(0.180)	(0.084)	(0.093)
Non-Harvest to Non-Harvest x y_{ijt-1}	-0.603***	-0.686***	-0.658***	-0.498***
	(0.080)	(0.080)	(0.066)	(0.060)
Test:				
Harvest to Harvest = Harvest to Non-Harvest	P=0.000	P=0.562	P=0.177	P=0.014
Harvest to Harvest = Non-Harvest to Non-Harvest	P=0.002	P=0.681	P=0.002	P=0.000
Harvest to Non-Harvest = Non-Harvest to Non-Harvest	P=0.000	P=0.595	P=0.068	P=0.000
Fixed-Effects:				
Market pair	Yes	Yes	Yes	Yes
week	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R2	0.708	0.419	0.597	0.537
Within R2	0.582	0.125	0.367	0.393

Note: (1) . p<0.1; *p<0.05; **p<0.01; ***p<0.001. (2) This analysis includes only market pairs with direct or indirect connections, based on the premise that segregated markets lack mechanisms for price adjustment, rendering them unsuitable for market integration analysis. (3) Control variables include interaction term of y_{ijt-1} with travel time, travel distance, and if markets are in the region. (4) Standard errors clustered by market-pairs.

The regression results in Table 7 confirm that price adjustment speeds vary significantly across seasonal trade relationships, reinforcing the role of harvest timing in market integration.

For Local Rice, Brown Cowpea, and White Cowpea, market pairs in the "Harvest to Harvest" category exhibit the fastest price convergence, suggesting that when both markets are in the harvest phase, prices adjust more rapidly due to high trading activity, increased supply, and stronger arbitrage opportunities. In contrast, the "Harvest to Non-Harvest" category shows the slowest price adjustments, particularly for Local Rice and White Cowpea. This result aligns with the expectation that

when one market is in harvest and the other is not, price convergence slows due to asymmetries in supply availability and demand responses. The harvest market experiences downward price pressure due to abundant supply, while the non-harvest market maintains relatively stable prices, causing a temporary misalignment that slows adjustment.

Interestingly, for Brown Cowpea, price adjustment is slowest in the "Non-Harvest to Non-Harvest" category, suggesting that trading volumes may decline outside the harvest period, leading to less frequent transactions and delayed price convergence. This pattern suggests that seasonal inactivity, rather than supply-demand asymmetry, could be the dominant factor limiting price adjustments when both markets are out of the harvest season.

Unlike locally produced crops, Long-Grain Rice exhibits no significant differences in price adjustment across seasonal categories. This is expected because Long-Grain Rice is primarily imported, meaning that its price dynamics are more influenced by other factors than domestic harvest cycles. Since supply is not seasonally constrained within Nigeria, price adjustments occur consistently throughout the year, reinforcing the idea that imported goods follow a different pricing mechanism than locally harvested crops.

IV.c The impact of violence and conflict events

To incorporate the impact of violence events on market integration, we extend the model 2 as follows:

$$\Delta y_{ijt} = \beta_0 y_{ijt-1} + \beta_1 (y_{ijt-1} \times \text{Conflict Event}_{ijt-1}) + \beta_2 \text{Conflict Event}_{ijt-1} + \theta_{ijt} + \delta_{ij} + \gamma_t + \epsilon_{ijt}. \tag{4}$$

The interaction term $(y_{ijt-1} \times \text{Conflict Event}_{ijt-1})$ measures whether the speed of price adjustment is altered in the presence of conflict. The inclusion of $\text{Conflict Event}_{ijt-1}$ as a separate term allows us to capture any direct effect of conflict on price differentials, beyond its influence on adjustment dynamics.

The coefficient β_0 represents the baseline speed of price adjustment in the absence of conflict. A negative value for β_0 implies mean reversion in price differences over time. The coefficient β_1 indicates whether and how conflict events affect the speed of adjustment, with a significant and positive β_1 suggesting that conflict slows down market integration. The coefficient β_2 measures the direct effect of conflict on price differentials, capturing any immediate disruptions in market functioning due to conflict events.

Table 8: Impact of Conflict on Price Adjustment (Single Lag)

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Baseline Price Adjustment:				
Lagged Price Difference (y_{ijt-1})	-0.603***	-0.739***	-0.674***	-0.475***
	(0.072)	(0.092)	(0.069)	(0.063)
Conflict Exposure:				
Conflict Events$_{t-1}$	-0.003	0.009	-0.002	0.007*
	(0.006)	(0.009)	(0.004)	(0.004)
Interaction:				
$y_{ijt-1}\times$ Conflict Events$_{t-1}$	-0.023	0.033.	0.003	-0.028
	(0.026)	(0.018)	(0.030)	(0.025)
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.690	0.421	0.592	0.498
Within R^2	0.557	0.128	0.359	0.343

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the first difference in the price gap between market pairs.
(3) The coefficient on y_{ijt-1} represents the speed of price adjustment, where a more negative value implies faster convergence to equilibrium.
(4) Conflict Events$_{t-1}$ represents the number of violent conflict events in the previous period.
(5) The interaction term $y_{ijt-1}\times$ Conflict Events$_{t-1}$ captures how conflict modifies the speed of price adjustment.
(6) Market-pair fixed effects account for time-invariant trade relationships, while week fixed effects control for common shocks.
(7) Control variables include interaction terms of y_{ijt-1} with: - log(Distance) (spatial separation), - log(Travel Time) (trade friction), - Same Region (whether markets share an administrative boundary). These controls are included in the regression but omitted from the table for brevity.
(8) Standard errors (in parentheses) are clustered at the market-pair level.

The regression results presented in Table 8 provide an initial assessment of how conflict events impact the speed of price convergence in market pairs. By limiting the analysis to a single lag of conflict exposure, this model avoids potential multicollinearity and the "bad control" problem that arises when multiple lags of conflict are included simultaneously.

Across all four commodities, the baseline speed of price adjustment remains consistent with prior estimates, as indicated by the coefficients on Lagged Price Difference (y_{ijt-1}). These values are negative and statistically significant, suggesting that price gaps between markets tend to close over time, confirming the presence of market integration mechanisms.

The direct effect of conflict events, as captured by the coefficient on Conflict Events$_{t-1}$, does not show a consistent impact across commodities. While largely

statistically insignificant, a small positive effect is observed for white cowpea, implying that higher conflict exposure is correlated with slightly larger price changes in these markets. However, this effect is economically small, and further tests are needed to confirm its robustness.

The interaction term $y_{ijt-1} \times$ Conflict Events$_{t-1}$ captures how conflict modifies the speed of price adjustment. The coefficients are not statistically significant in most specifications, except for long-grain rice, where a marginally significant positive coefficient suggests that conflict might slow down price adjustments in certain cases. However, given the relatively large standard errors and the fact that the result does not hold consistently across all commodities, this finding should be interpreted with caution.

The effect of different types of violence events

As outlined in our data section, our analysis focuses on types of violence that potentially impact market integration, which including Battles, Explosions/Remote violence, Riots, and Violence against Civilians. For each pair of markets along the trade routes, we counted incidents of each type of violence, and the total fatalities as the measurement of severity. These violent events often do not occur in isolation; rather, they may coincide with one another. Table 18 in appendix shows the average number of each type of event that occurred simultaneously along the trade routes in the same week.

For instance, a significant number of Battles and Violence against Civilians have occurred during the same periods. Similarly, Explosions often coincide with both Battles and Violence against Civilians. Riots, too, frequently occur alongside Battles and Violence against Civilians.

Table 9: Effect of Different Types of Conflict Events on Price Adjustment

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Lagged Price Difference (y_{ijt-1})	-0.599***	-0.746***	-0.702***	-0.464***
	(0.067)	(0.093)	(0.072)	(0.063)
Conflict Event Occurrence:				
Battle Events$_{t-1}$	0.0210	0.0102	-0.0117	-0.0052
	(0.0159)	(0.0170)	(0.0092)	(0.0049)
Violence Against Civilians$_{t-1}$	-0.0081	0.0068	0.0036	0.0173**
	(0.0055)	(0.0079)	(0.0059)	(0.0057)
Explosion Events$_{t-1}$	0.0279	-0.0640.	-0.0492	0.0076
	(0.0227)	(0.0342)	(0.0341)	(0.0249)
Riot Events$_{t-1}$	-0.0588*	0.0424	0.0146	-0.0058
	(0.0251)	(0.0326)	(0.0198)	(0.0144)
Interaction Terms:				
$y_{ijt-1}\times$ Battle Events$_{t-1}$	0.0202	0.0190	-0.1014	-0.0773.
	(0.0900)	(0.0435)	(0.0701)	(0.0423)
$y_{ijt-1}\times$ Violence Against Civilians$_{t-1}$	-0.0434	0.0400	0.0193	-0.0313
	(0.0298)	(0.0346)	(0.0358)	(0.0370)
$y_{ijt-1}\times$ Explosion Events$_{t-1}$	-11.58***	-2.664***	0.3832	0.3431
	(1.970)	(0.488)	(0.347)	(0.281)
$y_{ijt-1}\times$ Riot Events$_{t-1}$	-0.1947	0.1136	0.3309*	0.1549.
	(0.1204)	(0.1314)	(0.1287)	(0.0795)
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.695	0.425	0.599	0.505
Within R^2	0.564	0.134	0.371	0.352

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the *first difference of the price gap* between market pairs.
(3) The coefficient on y_{ijt-1} represents the *speed of price adjustment*; a more negative value indicates faster convergence to equilibrium.
(4) Conflict Events$_{t-1}$ represent the number of specific types of violent events along the trade route.
(5) The interaction terms ($y_{ijt-1}\times$ Conflict Events$_{t-1}$) test whether different types of conflict affect the speed of price convergence.
(6) Market-pair fixed effects control for time-invariant trade relationships, while week fixed effects capture common shocks.
(7) Control variables include interaction terms of y_{ijt-1} with: - log(Distance) (spatial separation), - log(Travel Time) (trade friction), - Same Region (whether markets share an administrative boundary). These controls are included in the regression but omitted from the table for brevity.
(8) Standard errors (in parentheses) are clustered at the market-pair level.

The results presented in Table 9 examine the effect of different types of conflict events on price adjustment dynamics across four key commodities: Local Rice, Long-Grain Rice, Brown Cowpea, and White Cowpea. The estimated coefficients on the lagged price difference (y_{ijt-1}) remain negative and highly significant across all spec-

ifications, consistent with the expectation that price gaps tend to close over time as markets adjust. However, the interaction terms with conflict events provide nuanced insights into how different types of violence influence the speed of price convergence.

The results indicate that battles and violence against civilians generally do not have a strong or systematic effect on market integration. The direct impact of battles (Battle Events$t-1$) is statistically insignificant across all commodities, suggesting that these events may not immediately disrupt trade patterns or supply chains in a way that affects price transmission. Similarly, violence against civilians (VAC$t-1$) only shows a significant direct effect in the White Cowpea market, where it is associated with a small positive price adjustment. This may reflect local market responses, such as traders adapting to periodic violence by diversifying their sourcing or shifting trade routes.

Explosions and riots exhibit more varied effects. The estimated interaction coefficient for explosions ($y_{ijt-1} \times$Explosion Events$_{t-1}$) is highly significant and negative in the Local Rice and Long-Grain Rice markets, indicating that such events slow down price adjustment. This suggests that sudden, large-scale disruptions—such as bombings or remote violence—may create temporary barriers to trade, delaying arbitrage and price convergence. In contrast, the impact of riots appears more commodity-specific. The interaction term for riots is significantly positive for Brown Cowpea, implying that such disruptions may accelerate price adjustments in this market, possibly due to short-term shifts in supply and demand. However, no strong effects are observed for White Cowpea or the rice markets.

Overall, the results suggest that different types of conflict events influence market integration in distinct ways. While explosions seem to create short-term frictions that delay price transmission, riots may have more varied effects depending on market structure and commodity characteristics. Battles and violence against civilians, on the other hand, do not appear to systematically alter price adjustment patterns, at least within the timeframe examined. These findings highlight the importance of considering the specific nature of conflict when assessing its impact on market dynamics.

Extending the analysis to include four lags allows for an assessment of the cumulative effects of conflict on price transmission. The F-tests, which evaluate the joint significance of all four lags for each conflict type, reveal important patterns that were not entirely clear from the one-lag results alone. The impact of battles on price adjustments is more pronounced over time, as shown by the significant joint effect in the Local Rice and White Cowpea markets. While their immediate effect may be minimal, sustained conflict appears to disrupt price convergence, likely due to prolonged insecurity along trade routes. However, battles do not have a significant cumulative impact on Long-Grain Rice or Brown Cowpea, suggesting that these commodities are either sourced from more resilient supply chains or are less sensitive to localized violence. Violence against civilians also shows a significant cumulative effect, particularly for Brown Cowpea and White Cowpea, reinforcing the idea that these markets, which likely rely more on localized, informal trading networks, are

Table 10: F-Test for Joint Significance of Four Lags of Conflict Events

Conflict Event	Local Rice	Long-Grain Rice	Brown Cowpea	White Cowpea
Battle				
χ^2	13.31**	5.95	4.11	27.91***
p-value	(0.0098)	(0.2031)	(0.3914)	(0.00001)
Violence Against Civilians				
χ^2	9.29.	5.17	13.28**	15.82**
p-value	(0.0541)	(0.2702)	(0.0099)	(0.0033)
Explosion				
χ^2	26.96***	48.80***	6.53	1.63
p-value	(0.00002)	(6.44e-10)	(0.1626)	(0.8042)
Riots				
χ^2	4.06	6.65	10.54*	18.34**
p-value	(0.3978)	(0.1558)	(0.0323)	(0.0011)

particularly vulnerable to social instability. This effect was not as clear in the one-lag model, suggesting that the economic consequences of violence against civilians may emerge gradually rather than immediately.

Explosions demonstrate the most severe impact on market integration, with the F-test results indicating a highly significant cumulative effect for Local Rice and Long-Grain Rice. The magnitude and persistence of these effects suggest that large-scale, high-intensity disruptions have lasting consequences for staple food markets. The lack of significance in cowpea markets may reflect differences in supply chain structure, where shorter-distance trade routes provide greater resilience to major infrastructure disruptions. While explosions create barriers to trade that persist over multiple weeks, riots exhibit more varied effects depending on the market. The significant cumulative impact observed in Brown Cowpea and White Cowpea suggests that spontaneous social unrest can disrupt trade in these markets over an extended period. However, the cumulative effects on rice markets remain insignificant, highlighting the greater resilience of these supply chains to temporary unrest.

The combined results suggest that different types of conflict exert distinct influences on market integration over time. Explosions create the most widespread and persistent disruptions, particularly for staple commodities like rice, where long-distance trade and infrastructure dependence amplify the impact. Battles significantly affect price convergence in local commodity markets such as White Cowpea, but their effects take time to materialize. Violence against civilians disproportionately disrupts cowpea markets, possibly due to its effect on informal trade networks, while riots exhibit commodity-specific effects, accelerating price adjustments in some cases while delaying them in others. These findings underscore the importance of distinguishing between different conflict types when analyzing market disruptions and suggest that policy interventions should be tailored not only to the presence of violence but also to the specific form it takes, as the economic consequences vary significantly depending on the nature and persistence of conflict.

The Mechanism

Given that the results suggest that, on average, conflict does not have a robust and significant influence on price adjustment, the next step is to investigate potential mechanisms that may explain this pattern. One possible explanation is that violence events occur with such regularity that traders have already adapted to them, reducing their disruptive impact on market integration. If traders expect violence as a persistent condition rather than an irregular shock, they may have developed strategies to mitigate its effects, such as altering trade routes, maintaining larger inventories, or adjusting pricing strategies preemptively.

To test this hypothesis, we modify our regression equation to replace the total count and fatalities [7] of conflict events with their changes from the previous week. This adjustment allows us to examine whether sudden increases or decreases in violence—rather than its absolute presence—have a more pronounced effect on price adjustments. Specifically, we estimate the following equation:

$$\begin{aligned}\Delta y_{ijt} = \beta_0 y_{ijt-1} + \beta_1 (y_{ijt-1} \times \Delta\text{Conflict Event}_{ijt-1}) \\ + \beta_2 \Delta\text{Conflict Event}_{ijt-1} + \theta_{ijt} + \delta_{ij} + \gamma_t + \epsilon_{ijt}. \end{aligned} \tag{5}$$

Where ΔConflict Event$_{ijt-1}$ denotes the weekly change in the number of conflict events or fatalities along the trade route. The interaction term ($y_{ijt-1} \times \Delta$Conflict Event$_{ijt-1}$ allows us to assess whether unexpected variations in violence alter the speed of price adjustment.

[7] See the appendix table 22

Table 11: Impact of Conflict on Price Adjustment (Change in Conflict Events)

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Baseline Price Adjustment:				
Lagged Price Difference (y_{ijt-1})	-0.6363***	-0.6793***	-0.6726***	-0.4996***
	(0.0756)	(0.0912)	(0.0658)	(0.0599)
Conflict Exposure:				
Change in Conflict Events ($\Delta\text{Conflict}_{ijt-1}$)	0.0007	-0.0069	0.0027	-0.0038
	(0.0063)	(0.0092)	(0.0031)	(0.0028)
Interaction:				
$y_{ijt-1} \times \Delta\text{Conflict}_{ijt-1}$	-0.0048	0.0233.	0.0016	-0.0196
	(0.0234)	(0.0134)	(0.0187)	(0.0149)
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.690	0.422	0.592	0.496
Within R^2	0.557	0.129	0.359	0.340

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the first difference in the price gap between market pairs.
(3) The coefficient on y_{ijt-1} represents the speed of price adjustment, where a more negative value implies faster convergence to equilibrium.
(4) $\Delta\text{Conflict}_{ijt-1}$ represents the change in the number of violent conflict events from the previous period.
(5) The interaction term $y_{ijt-1} \times \Delta\text{Conflict}_{ijt-1}$ captures how fluctuations in conflict modify the speed of price adjustment.
(6) Market-pair fixed effects account for time-invariant trade relationships, while week fixed effects control for common shocks.
(7) Standard errors (in parentheses) are clustered at the market-pair level.

The results presented in Table 11 investigate whether fluctuations in conflict events influence the speed of price adjustment across four key commodities: Local Rice, Long-Grain Rice, Brown Cowpea, and White Cowpea. The estimated coefficients on the lagged price difference (y_{ijt-1}) remain negative and highly significant in all specifications, reinforcing the expectation that price gaps tend to close over time as markets adjust. This finding is consistent with prior results, suggesting that market forces work to reduce price differentials even in the presence of conflict.

However, when examining the impact of changes in conflict intensity, rather than its total count or fatalities, the results indicate that week-to-week variations in conflict events do not systematically alter price adjustment dynamics. The coefficients on $\Delta\text{Conflict}_{ijt-1}$ are small and statistically insignificant across all commodity groups, implying that abrupt increases or decreases in conflict events do not meaningfully disrupt market integration. This suggests that traders may have already internalized the presence of violence and adapted their trade strategies accordingly. If conflict occurs with sufficient regularity, market actors may anticipate fluctuations and adjust trade routes, inventory levels, or pricing mechanisms in a way that limits short-term

disruptions.

The interaction terms between lagged price differences and changes in conflict events provide additional insight into whether unexpected shifts in violence influence price transmission. These interaction effects are largely insignificant across all commodities, indicating that changes in conflict intensity do not substantially alter the speed at which price gaps close. The only marginally significant effect appears in the Long-Grain Rice market, where an increase in conflict events is weakly associated with a slightly faster price adjustment. However, given the lack of a consistent pattern across commodities, this result should be interpreted with caution.

Another crucial mechanism that may help explain the muted effect of conflict on price adjustment is the role of indirect market connections. Many market pairs are not only directly linked to each other but also maintain trade relationships with other markets. This networked structure may provide alternative routes or trading options when violence disrupts a primary connection. If a market is well-connected within the trade network, it may have greater resilience to localized shocks, as traders can adjust their supply chains and shift transactions to alternative routes. In contrast, less-connected markets may be more vulnerable to disruptions, with fewer options to reroute trade when violence occurs.

To investigate this mechanism, we conduct a heterogeneous effects analysis by categorizing market pairs based on their connectivity levels. Specifically, we classify market pairs into four categories based on the total number of additional trade connections each market has. Low Connectivity (connection = 0) includes market pairs where both markets have only one or no additional trade connections beyond their direct link. Moderate Connectivity (connection = 1) comprises pairs where at least one market has between 2 and 5 additional connections. High Connectivity (connection = 2) includes market pairs where at least one market has between 6 and 10 additional connections. Very High Connectivity (connection = 3) consists of pairs where at least one market has more than 10 additional trade connections. By estimating the differential impact of violence across these connectivity levels, we assess whether higher connectivity mitigates the adverse effects of conflict on price adjustment.

Our regression equation incorporates connectivity as an interaction term to explore how price adjustments differ based on the degree of market integration within the broader trade network:

$$\Delta y_{ijt} = \beta_0 y_{ijt-1} + \sum_{c=0}^{3} \Big[\beta_{1c} (y_{ijt-1} \times \text{Conflict Event} ijt - 1 \times \mathbb{1}(\text{connection1} = c)) + \theta_{ijt} + \delta_{ij} + \gamma_t + \epsilon_{ijt}. \tag{6}$$

In this equation, $\mathbb{1}(\text{connection} = c)$ is an indicator function that equals 1 if the market pair falls into connectivity category c (ranging from low to very high

connectivity). The interaction term β_{1c} captures how the speed of price adjustment varies across different levels of market connectivity in response to conflict events.

Table 12: Heterogeneous Effects of Conflict by Market Connectivity

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Baseline Price Adjustment:				
Lagged Price Difference (y_{ijt-1})	-0.5992***	-0.6940***	-0.6690***	-0.4657***
	(0.0750)	(0.0931)	(0.0712)	(0.0626)
Interaction: Conflict and Connectivity				
y_{ijt-1} × Conflict× Low Connectivity	0.1311.	0.2299	-0.0023	-0.1757**
	(0.0730)	(0.1495)	(0.0799)	(0.0667)
y_{ijt-1} × Conflict× Moderate Connectivity	0.0540.	0.1932***	0.0324	-0.0141
	(0.0310)	(0.0516)	(0.0327)	(0.0315)
y_{ijt-1} × Conflict× High Connectivity	-0.0409	0.0026	0.0006	-0.0376
	(0.0317)	(0.0165)	(0.0315)	(0.0230)
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.691	0.424	0.592	0.499
Within R^2	0.559	0.133	0.359	0.343

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the first difference in the price gap between market pairs.
(3) The coefficient on y_{ijt-1} represents the speed of price adjustment, where a more negative value implies faster convergence to equilibrium.
(4) Market connectivity is categorized as follows: - *Low Connectivity*: Both markets in the pair have only one or no additional connections. - *Moderate Connectivity*: At least one market in the pair has 2-5 additional connections. - *High Connectivity*: At least one market in the pair has more than 5 additional connections.
(5) The interaction term y_{ijt-1}× Conflict × Connectivity captures how the effects of conflict vary by market connectivity.
(6) Market-pair fixed effects account for time-invariant trade relationships, while week fixed effects control for common shocks.
(7) Standard errors (in parentheses) are clustered at the market-pair level.

The results presented in Table 12 examine how market connectivity influences the impact of conflict on price adjustment. The interaction terms between conflict and different levels of market connectivity reveal meaningful differences in how conflict affects price transmission across market pairs.

For low-connectivity markets, where both markets in the pair have only one or no additional trade connections, the interaction effect for Local Rice is positive and marginally significant. This suggests that conflict slows down price adjustment in these markets, possibly because traders in isolated locations have fewer alternative trading partners and rely on existing routes despite disruptions. Instead of rapidly adjusting prices in response to shocks, they may experience frictions that prolong

price convergence. However, for Brown Cowpea, no significant effect is observed, and for White Cowpea, the interaction term is negative and significant. While this suggests that conflict accelerates price adjustment in White Cowpea markets, the lack of a similar effect in Brown Cowpea—despite their similarity as commodities—raises concerns that this result may not reflect a systematic pattern but rather an anomaly or statistical noise.

For moderately connected markets, where at least one market in the pair has between 2 and 5 additional connections, the interaction effect is positive and highly significant for Long-Grain Rice. This implies that conflict slows price adjustment in these markets, possibly because traders with multiple trade links have greater flexibility and delay adjustments while considering alternative routes or trade strategies. This effect is not observed for the other commodities, indicating that moderate connectivity does not consistently alter the impact of conflict across all markets.

For highly connected markets, where at least one market in the pair has more than five additional connections, the interaction effects are generally small and statistically insignificant across all commodities. This suggests that these markets are more resilient to conflict-related disruptions. With extensive trade networks, traders have more options to divert trade and absorb shocks, which prevents drastic price adjustments even when conflict occurs.

The findings suggest that market participants have developed resilience to conflict, likely due to both long-term adaptation to persistent violence and the structural advantages provided by broader trade networks. Rather than reacting sharply to short-term fluctuations in conflict, traders may have incorporated expectations of instability into their decision-making, mitigating its impact on trade dynamics. However, the extent of this resilience varies depending on market connectivity. In low-connectivity markets, conflict appears to introduce frictions that slow price adjustment, particularly for Local Rice, suggesting that traders with fewer alternative routes face greater challenges in responding to disruptions. In contrast, in moderate-connectivity markets, conflict significantly slows price adjustment in Long-Grain Rice markets, possibly because traders delay responses while exploring alternative trade options. In highly connected markets, the lack of significant effects suggests that broader trade networks provide a buffer against conflict-induced disruptions, allowing traders to reroute trade and maintain stable price adjustments. These results highlight the dual role of market structure and trader expectations in shaping the impact of conflict on trade. Strengthening market integration may enhance resilience to violence-related shocks by providing traders with more flexibility to adapt, while long-term exposure to instability may have conditioned market participants to incorporate conflict into their decision-making processes.

V Discussion and Conclusion

This study examines market integration in Nigeria, focusing on price adjustments across different trade relationships, seasonal trade patterns, and the impact of conflict on market responses. Our findings highlight the importance of rural markets in maintaining trade stability, as they exhibit faster price adjustments than urban markets due to strong local networks and efficient information flows. Additionally, seasonal asymmetries in harvest timing significantly influence price adjustments, particularly for locally produced commodities.

Our results indicate that price adjustments are fastest when both markets are in harvest ("Harvest to Harvest"), driven by high trading volumes and increased arbitrage opportunities. In contrast, when one market is in harvest while the other is not ("Harvest to Non-Harvest"), price convergence slows significantly, likely due to supply-demand mismatches and regional production cycles. This effect is most pronounced for Local Rice and White Cowpea, where seasonal misalignment leads to temporary frictions in market integration. For Brown Cowpea, however, the slowest price adjustment occurs in the "Non-Harvest to Non-Harvest" category, suggesting that seasonal inactivity, rather than supply disruptions, plays a key role in limiting market efficiency.

In contrast, Long-Grain Rice shows no significant differences in price adjustment across seasons, reinforcing the idea that imported commodities are insulated from local harvest cycles. Since supply is not seasonally constrained within Nigeria, price adjustments occur consistently throughout the year, reflecting global trade patterns rather than domestic production cycles.

When examining the impact of conflict on price adjustment, our findings indicate that conflict events, in general, have a limited and often trivial effect on price convergence. While certain conflict events, such as explosions and riots, initially slow price adjustments, the effects are generally weak and inconsistent across commodities. In contrast, battles and violence against civilians show no systematic impact on price convergence, suggesting that markets have adapted to frequent disruptions. This resilience may be attributed to traders incorporating expectations of instability into their pricing and trade strategies, thereby mitigating the immediate consequences of violence on price transmission.

Furthermore, changes in conflict intensity—rather than the absolute number of events—also fail to systematically alter price adjustment dynamics. This suggests that markets do not respond sharply to week-to-week fluctuations in violence, reinforcing the idea that trade networks have developed adaptive mechanisms to cope with instability.

Despite these adaptations, the structure of market networks plays a key role in determining how markets respond to conflict-related disruptions. In low-connectivity markets, where traders have fewer alternative trade routes, price adjustment is slower, particularly for Local Rice, suggesting that limited trade options amplify in-

efficiencies. In moderately connected markets, Long-Grain Rice markets experience significantly slower price adjustments, potentially due to delayed trade decisions as traders explore alternative routes. However, in highly connected markets, price adjustments remain stable despite disruptions, reflecting the buffering effect of diverse trade linkages that allow traders to reallocate supply and maintain trade flows.

Given the limited impact of short-term violence on price adjustments, policies should focus on improving overall market connectivity and trade infrastructure rather than short-term interventions targeting individual violent events. Ensuring secure and efficient trade routes through better infrastructure, road safety initiatives, and improved logistics could further strengthen market resilience, particularly for local crop markets that rely on intra-regional trade.

Future research could expand the dataset to assess long-term trade resilience and incorporate direct trade flow data to better understand how market linkages evolve in response to shocks. Additionally, exploring the role of informal trade networks and trader expectations in sustaining market activity under conflict conditions could provide further insights into market adaptation strategies.

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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.

References

Abdulai, Awudu (2000), "Spatial Price Transmission and Asymmetry in the Ghanaian Maize Market." *Journal of Development Economics*, 63, 327–349.

Adelaja, Adesoji and Justin George (2019), "Effects of Conflict on Agriculture: Evidence from the Boko Haram Insurgency." *World Development*, 117, 184–195.

Ahmed, Umar Ijaz, Liu Ying, Muhammad Khalid Bashir, Muhammad Abid, and Farhad Zulfiqar (2017), "Status and Determinants of Small Farming Households' Food Security and Role of Market Access in Enhancing Food Security in Rural Pakistan." *PloS one*, 12, e0185466.

Aker, Jenny C (2010), "Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger." *American Economic Journal: Applied Economics*, 2, 46–59.

Amare, Mulubrhan, Kibrom A. Abay, and Patrick Hatzenbuehler (2024), "Spatial Market Integration During a Pandemic: Evidence from Food Markets in Nigeria." *Agricultural Economics*, 55, 86–103.

Badiane, Ousmane and Gerald E Shively (1998), "Spatial Integration, Transport Costs, and the Response of Local Prices to Policy Changes in Ghana." *Journal of Development Economics*, 56, 411–431.

Barrett, Christopher B and Jau Rong Li (2002), "Distinguishing between Equilibrium and Integration in Spatial Price Analysis." *American Journal of Agricultural Economics*, 84, 292–307.

Baulch, Bob (1997), "Transfer Costs, Spatial Arbitrage, and Testing for Food Market Integration." *American Journal of Agricultural Economics*, 79, 477–487.

Bonilla Cedrez, Camila, Jordan Chamberlin, Zhe Guo, and Robert J Hijmans (2020a), "Spatial Variation in Fertilizer Prices in Sub-Saharan Africa." *PLOS One*, 15, e0227764.

Bonilla Cedrez, Camila, Jordan Chamberlin, and Robert J Hijmans (2020b), "Seasonal, Annual, and Spatial Variation in Cereal Prices in Sub-Saharan Africa." *Global Food Security*, 26, 100438.

Burke, Marshall, Lauren Falcao Bergquist, and Edward Miguel (2019), "Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets." *Quarterly Journal of Economics*, 134, 785–842.

Byerlee, Derek, Thomas S Jayne, and Robert J Myers (2006), "Managing Food Price Risks and Instability in a Liberalizing Market Environment: Overview and Policy Options." *Food Policy*, 31, 275–287.

Ceballos, Francisco, Manuel A Hernandez, Nicholas Minot, and Miguel Robles (2017), "Grain Price and Volatility Transmission from International to Domestic Markets in Developing Countries." *World Development*, 94, 305–320.

Dhar, Rahul, Michael Adetayo Olabisi, Iredele Emmanuel Ogunbayo, Nathaniel Siji Olutegbe, Oreoluwa Akano, and David L. Tschirley (2024), "Food Demand Responses to Global Price Shocks: Contrasts in Sub-National Evidence from Nigeria." *(forthcoming in) Food Security*.

Dillon, Brian M and Christopher B Barrett (2016), "Global Oil Prices and Local Food Prices: Evidence from East Africa." *American Journal of Agricultural Economics*, 98, 154–171.

Fackler, Paul L. and Hüseyin Tastan (2008), "Estimating the Degree of Market Integration." *American Journal of Agricultural Economics*, 90, 69–85.

George, Justin and Adesoji Adelaja (2022), "Armed Conflicts, Forced Displacement and Food Security in Host Communities." *World Development*, 158, 105991.

George, Justin, Adesoji Adelaja, and Titus O Awokuse (2021), "The Agricultural Impacts of Armed Conflicts: the Case of Fulani Militia." *European Review of Agricultural Economics*, 48, 538–572.

González-Rivera, Gloria and Steven M Helfand (2001), "The extent, pattern, and degree of market integration: A multivariate approach for the brazilian rice market." *American Journal of Agricultural Economics*, 83, 576–592.

Goodwin, Barry K and Nicholas E Piggott (2001), "Spatial Market Integration in the Presence of Threshold Effects." *American Journal of Agricultural Economics*, 83, 302–317.

Hamilton, James D. (1994), *Time Series Analysis*. Princeton University Press, Princeton, NJ.

Hastings, Justin V., Sarah G. Phillips, David Ubilava, and Andrey Vasnev (2022), "Price Transmission in Conflict-Affected States: Evidence from Cereal Markets of Somalia." *Journal of African Economies*, 31, 272–291.

Hatzenbuehler, Patrick L., Philip C. Abbott, and Tahirou Abdoulaye (2016), "Price Transmission in Nigerian Food Security Crop Markets." *Journal of Agricultural Economics*, 68, 143–163.

Jackson, Matthew O and Alison Watts (2002), "The Evolution of Social and Economic Networks." *Journal of Economic Theory*, 106, 265–295.

Kebede, Hundanol A (2024), "Gains from Market Integration: Welfare Effects of New Rural Roads in Ethiopia." *Journal of Development Economics*, 168, 103252.

Kinnucan, W. (2019), "Forty Years of Price Transmission Research in the Food Industry: Insights, Challenges, and Prospects." *Journal of Agricultural Economics*, 70, 3–25.

Le Cotty, Tristan, Elodie Maitre D'Hotel, and Moctar Ndiaye (2017), "Transport Costs and Food Price Volatility in Africa." *Journal of African Economies*, 26, 625–654.

Ma, Meilin, Michael S. Delgado, and H. Holly Wang (2024), "Risk arbitrage and spatial price relationships: Insights from China's hog market under the African Swine Fever." *Journal of Development Economics*, 166, 103200.

Maddala, G.S. and Shaowen Wu (1999), "A comparative study of unit root tests with panel data and a new simple test." *Oxford Bulletin of Economics and Statistics*, 61, 631–652.

Massol, Olivier, Emmanuel Hache, and Albert Banal-Estañol (2023), "Trade Sanctions and International Market Integration: Evidence from the Sanctions on Iranian Methanol Exports." *The World Economy*.

Minoiu, Camelia and Olga N Shemyakina (2014), "Armed Conflict, Household Victimization, and Child Health in Côte d'Ivoire." *Journal of Development Economics*, 108, 237–255.

Minten, Bart and Steven Kyle (1999), "The Effect of Distance and Road Quality on Food Collection, Marketing Margins, and Traders' Wages: Evidence from the Former Zaire." *Journal of Development Economics*, 60, 467–495.

Moser, Christine, Christopher Barrett, and Bart Minten (2009), "Spatial Integration at Multiple Scales: Rice Markets in Madagascar." *Agricultural Economics*, 40, 281–294.

Myers, Robert J. (2013), "Evaluating the Effectiveness of Inter-Regional Trade and Storage in Malawi's Private Sector Maize Markets." *Food Policy*, 41, 75–84.

Myers, Robert J. and T.S. Jayne (2012), "Multiple-Regime Spatial Price Transmission with an Application to Maize Markets in Southern Africa." *American Journal of Agricultural Economics*, 94, 174–188.

Ndiaye, Moctar, Elodie Maître d'Hôtel, and Tristan Le Cotty (2017), "Remoteness and Maize Price Volatility in Burkina Faso."

Negassa, Asfaw and Robert J Myers (2007), "Estimating Policy Effects on Spatial Market Efficiency: An Extension to the Parity Bounds Model." *American Journal of Agricultural Economics*, 89, 338–352.

Newman, Mark (2008), "The Physics of Networks." *Physics Today*, 61, 33–38.

Odozi, John Chiwuzulum and Ruth Uwaifo Oyelere (2021), "Does Violent Conflict Affect the Labor Supply of Farm Households? The Nigerian Experience." *Agricultural and Resource Economics Review*, 50, 401–435.

Odozi, John Chiwuzulum and Ruth Uwaifo Oyelere (2022), "Violent Conflict Exposure in Nigeria and Household Welfare: What Can We Learn from Panel Data?"

O'Kelly, Morton E (1998), "A Geographer's Analysis of Hub-and-Spoke Networks." *Journal of Transport Geography*, 6, 171–186.

Olabisi, Michael, Hephzibah Onyeje Obekpa, and Lenis Saweda O Liverpool-Tasie (2021), "Is Growing Your Own Food Necessary for Dietary Diversity? Evidence from Nigeria." *Food Policy*, 104, 102144.

Onyeka, UP, JK Olayemi, P Kormawa, and TE Mafimisebi (2006), "Testing Market Integration of Stable Food Stuffs in Borno State, Nigeria." *Nigeria Agricultural Journal*, 37, 11–17.

Peng, Peng, Yu Yang, Shifen Cheng, Feng Lu, and Zimu Yuan (2019), "Hub-and-Spoke Structure: Characterizing the Global Crude Oil Transport Network with Mass Vessel Trajectories." *Energy*, 168, 966–974.

Raleigh, Clionadh, Rew Linke, Håvard Hegre, and Joakim Karlsen (2010), "Introducing ACLED: An Armed Conflict Location and Event Dataset." *Journal of peace research*, 47, 651–660.

Vargas, Carolina M, Thomas A Reardon, and Saweda Liverpool-Tasie (2023), "The Impact of Violent Conflict on Food Supply Chains: the Case of Nigerian Maize Traders." Technical report, Agricultural and Applied Economics Association.

Appendix A: Classification of Violence Events

Table 13: Classification of ACLED Events

Event Types	Sub-Event Types
Battles	Government regains territory
	Non-state actor overtakes territory
	Armed clash
Protests	Excessive force against protesters
	Protest with intervention
	Peaceful protest
Riots	Violent demonstration
	Mob violence
Explosions/Remote violence	Chemical weapon
	Air/drone strike
	Suicide bomb
	Shelling/artillery/missile attack
	Remote explosive/landmine/IED
	Grenade
Violence against civilians	Sexual violence
	Attack
	Abduction/forced disappearance
Strategic developments	Agreement
	Arrests
	Change to group/activity

Source from: ACLED

Our study strategically focuses on three distinct types of violence—battles, violence against civilians, and explosions/remote violence—to evaluate their effects on market integration. In doing this we follow the pattern in previous work (c.f., Hastings et al., 2022). (We marked these in bold in the table). We target these categories because they represent direct and forceful disturbances that can critically affect the core mechanisms of market operations. The classifications detailed below are based on the Armed Conflict Location & Event Data Project (ACLED)'s codebook.

Battles are violent confrontations between organized armed groups at a specified location and time. Such events involve state forces, non-state groups, or external forces engaged in combat, with no minimum fatality threshold required for classification. Instances of civilian harm may occur, categorized as "collateral damage." Within "Battles," specific instances may result in changes in territorial control or

involve simple armed clashes.

Explosions/Remote violence denotes incidents where one party utilizes explosives or long-range destructive weapons. This classification encompasses a wide array of weaponry, from bombs to drones, capable of inflicting widespread destruction, including on civilian populations. When civilians are the primary targets, these events are marked as such.

Violence Against Civilians occurs when organized armed groups violently target unarmed non-combatants. This category includes a spectrum of violence, from physical attacks to forced disappearances, emphasizing the asymmetric nature of such acts—perpetrated by armed individuals against defenseless civilians.

Appendix B: List of the 97 Markets in Our Study

Table 14: List of Markets

	Market	Size	State	Zone	Type
1	Anara/Ngwa	78	Abia	South East	Rural
2	Song	38	Adamawa	North East	Rural
3	Fufore	37	Adamawa	North East	Rural
4	Sabon Kasuwa Mubi	32	Adamawa	North East	Rural
5	Michika	44	Adamawa	North East	Rural
6	Ganye	20	Adamawa	North East	Rural
7	Girei	20	Adamawa	North East	Rural
8	Gombi New Market	108	Adamawa	North East	Rural
9	Mubi North	20	Adamawa	North East	Rural
10	Akpan Andem (Uyo)	24	Akwa-Ibom	South South	Rural
11	Ose Market (Onitsha)	24	Anambra	South East	Urban
12	Azare	37	Bauchi	North East	Rural
13	Alkaleri	54	Bauchi	North East	Rural
14	Nasaru Market	84	Bauchi	North East	Rural
15	Soro	110	Bauchi	North East	Rural
16	Muda Lawan	193	Bauchi	North East	Rural
17	Dass	20	Bauchi	North East	Rural
18	Katagun	20	Bauchi	North East	Rural
19	Swali Market (Yenagoa)	44	Bayelsa	South South	Rural
20	Miringa Market	108	Borno	North East	Rural
21	Etim Ndem(Calabar)	20	Cross-River	South South	Rural
22	Ogbe Ogbogonogo (Asaba)	20	Delta	South South	Urban
23	Oko Market (Delta)	20	Delta	South South	Rural
24	Ogbudu Market (Warri)	22	Delta	South South	Urban
25	Sapele Main Market	27	Delta	South South	Rural
26	International Market (Ebonyi)	83	Ebonyi	South East	Urban

Continued on next page

Table 14 – *Continued from previous page*

	Market	Size	State	Zone	Type
27	Old Market (Enugu)	20	Edo	South South	Urban
28	Oregbeni (Benin)	20	Edo	South South	Urban
29	Lagos Road Market (Benin)	20	Edo	South South	Urban
30	Mission/Aduwawa Market (Benin)	29	Edo	South South	Rural
31	New Market	29	Edo	South South	Rural
32	Oja Oba(Ado Ekiti)	27	Ekiti	South West	Rural
33	Bisi Market	28	Ekiti	South West	Rural
34	Oke Sha Market	20	Ekiti	South West	Rural
35	Kumo	96	Gombe	North East	Rural
36	Tudun Hatsi	281	Gombe	North East	Rural
37	Orlu	47	Imo	South East	Rural
38	Okigwe (Imo State)	59	Imo	South East	Rural
39	Gumel	34	Jigawa	North West	Rural
40	Birnin Kudu Market	46	Jigawa	North West	Rural
41	Maigatari	42	Jigawa	North West	Rural
42	Sara	67	Jigawa	North West	Rural
43	Dawakin Kudu	51	Kano	North West	Rural
44	Dadin Kowa	53	Kano	North West	Rural
45	Yan Kura	85	Kano	North West	Rural
46	Doguwa	99	Kano	North West	Rural
47	Gwarzo	153	Kano	North West	Rural
48	Karasa	113	Kano	North West	Rural
49	Kwanar Dangora	132	Kano	North West	Rural
50	Mariri	143	Kano	North West	Rural
51	Dawanau	178	Kano	North West	Urban
52	Tudun Wada	396	Kano	North West	Rural
53	Darki Market	277	Kano	North West	Rural
54	Falgore Market	153	Kano	North West	Rural
55	Lahadin Makole	338	Kano	North West	Rural
56	Wudil	186	Kano	North West	Rural
57	Dutsinma	96	Katsina	North West	Rural
58	Birnin Kebbi Central Market	34	Kebbi	North West	Rural
59	Zuru Central Market	68	Kebbi	North West	Rural
60	Kamba	99	Kebbi	North West	Rural
61	Itamo	26	Kwara	North Central	Rural
62	Mandate	30	Kwara	North Central	Urban
63	Afon	33	Kwara	North Central	Rural
64	Shonga	68	Kwara	North Central	Rural
65	Tsonga	68	Kwara	North Central	Rural
66	Owode	80	Kwara	North Central	Urban
67	Oja Oba	81	Kwara	North Central	Urban
68	Share	96	Kwara	North Central	Rural
69	Tsaragi	202	Kwara	North Central	Rural

Continued on next page

Table 14 – *Continued from previous page*

	Market	Size	State	Zone	Type
70	Lafiagi	44	Kwara	North Central	Rural
71	Batata (Bida)	99	Niger	North Central	Rural
72	Gwada	113	Niger	North Central	Rural
73	Gulu	81	Niger	North Central	Rural
74	Bosso	63	Niger	North Central	Urban
75	Katcha	125	Niger	North Central	Rural
76	Bida	300	Niger	North Central	Rural
77	Akinola Market (Ipetumodu)	63	Osun	South West	Rural
78	Atakumosa	20	Osun	South West	Rural
79	Ijebu-Jesha	33	Osun	South West	Rural
80	Igbona	46	Osun	South West	Rural
81	Odo Ori Market	49	Osun	South West	Rural
82	Ipetumodu (Ife North)	53	Osun	South West	Rural
83	New Market (Ife)	118	Osun	South West	Rural
84	Oja Oba (Iwo)	127	Osun	South West	Rural
85	Ojaba (Ibadan)	56	Oyo	South West	Urban
86	Odo Oba (ogbomosho)	44	Oyo	South West	Rural
87	Sabo (Oyo)	45	Oyo	South West	Rural
88	Kishi	68	Oyo	South West	Rural
89	Bodija	304	Oyo	South West	Urban
90	Saki	20	Oyo	South West	Rural
91	Eleme	20	Rivers	South South	Rural
92	Port Harcourt Mile 1	55	Rivers	South South	Urban
93	Ilela-Sokoto	34	Sokoto	North West	Rural
94	Gada Market	53	Sokoto	North West	Rural
95	Jalingo	35	Taraba	North East	Rural
96	Mutum Biu	418	Taraba	North East	Rural
97	Gusau	209	Zamfara	North West	Rural

Harvest Season

Table 15: Harvest Timing by Crop and Region in Nigeria

Crops	**Location**	**Start of Harvest**	**End of Harvest**
White cowpeas	South	June	September
White cowpeas	North	August	October
Brown cowpeas	South	June	September
Brown cowpeas	North	August	October
Rice	South	August	November
Rice	North	November	January

Stationarity Test

Table 16: Maddala-Wu Unit-Root Test Results for Crop Prices

Crop Type	Test Statistic (Chi-sq)	Degrees of Freedom	p-value
Local Rice	4616.7	580	$<$ 2.2e-16
Imported Rice	5234.1	542	$<$ 2.2e-16
Brown Cowpea	5334.4	754	$<$ 2.2e-16
White Cowpea	4638.0	978	$<$ 2.2e-16

We conducted the Maddala-Wu Unit-Root Test, a panel data unit root test, to evaluate the stationarity of price differentials across various markets for different crops. Stationarity is crucial in time series analysis, as it implies that the statistical properties of the series, such as mean, variance, and autocorrelation, remain constant over time, which is essential for reliable inference in models focusing on short-term adjustments (Hamilton, 1994).

The results, summarized in Table 16, strongly indicate stationarity for all crops analyzed. For Local Rice, the test statistic is 4616.7 with 580 degrees of freedom, resulting in a p-value of less than 2.2e-16. Similarly, Imported Rice, Brown Cowpea, and White Cowpea exhibit test statistics of 5234.1 (df: 542), 5334.4 (df: 754), and 4638.0 (df: 978), respectively, all with p-values below 2.2e-16. These findings suggest that the price differentials are stationary, which justifies the use of short-term adjustment models in our subsequent analysis (Maddala and Wu, 1999).

Appendix C: Robust Check

Table 17: Descriptive Regression of Price Differences by Crops

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: *Price Difference* (y)				
Market Characteristics:				
log(Distance)	0.2121**	0.0522	0.1416**	0.1146**
	(0.0782)	(0.0460)	(0.0440)	(0.0400)
log(Time)	-0.2383**	-0.0669	-0.0996*	-0.0944*
	(0.0882)	(0.0541)	(0.0419)	(0.0354)
Same Region	0.0618***	0.0257	0.0565**	0.0315
	(0.0163)	(0.0173)	(0.0202)	(0.0207)
Market Connection Type:				
Only Indirect	-0.0461*	0.0043	-0.0750***	-0.0508***
	(0.0192)	(0.0082)	(0.0144)	(0.0107)
Only Direct	-0.0122	0.0657	-0.1171**	-0.0731*
	(0.1067)	(0.0714)	(0.0375)	(0.0291)
Both Connections	-0.0537	-0.0522*	-0.0462*	-0.0430*
	(0.0345)	(0.0220)	(0.0194)	(0.0199)
Conflict Exposure:				
fatality1	-0.0021	-0.0014	0.0003	9.42e-5
	(0.0016)	(0.0010)	(0.0003)	(0.0002)
Trade Relationship Type:				
Urban to Rural	-0.0758*	-0.0585**	-0.0257**	-0.0150
	(0.0290)	(0.0192)	(0.0096)	(0.0096)
Urban to Urban	-0.0167	-0.0406	-0.0360**	-0.0185.
	(0.0216)	(0.0256)	(0.0120)	(0.0109)
Week Fixed Effect	Yes	Yes	Yes	Yes
Observations	5,201	4,905	6,906	8,281
R^2	0.09967	0.09138	0.10813	0.05220
Within R^2	0.02831	0.02584	0.04342	0.01632

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The omitted category for `connection` is "no connection." Specifically:
– `Only Indirect`: Markets share an indirect connection via a third market.
– `Only Direct`: Markets are directly connected but have no indirect links.
– `Both Connections`: Markets have both direct and indirect connections.
(3) `log(Distance)` and `log(Time)` are the natural logarithms of market-pair distance and travel time, respectively.
(4) `Same Region` is an indicator for whether both markets are located in the same administrative zone.
(5) The omitted category for `pair relation` is Rural-to-Rural trade. Specifically:
– `Urban to Rural`: Trade occurs from an urban to a rural market.
– `Urban to Urban`: Trade occurs between two urban markets.
(6) `Fatality1` represents the number of conflict-related fatalities in the previous period.
(7) Standard errors (in parentheses) are clustered at the week level. Fixed effects include week dummies.

Table 18: Cross count of violence events

	Battle	Violence against civilian	Explosion	Riots
Battle	1585	1322	168	690
Violence against civilian	1322	2242	193	930
Explosion	168	193	236	116
Riots	690	930	116	1213

Table 19: Effect of Conflict-Related Fatalities on Price Adjustment Speed

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Lagged Price Difference (y_{ijt-1})	-0.625***	-0.702***	-0.691***	-0.523***
	(0.074)	(0.086)	(0.068)	(0.063)
Conflict Fatalities$_{t-1}$	-0.0006	0.0005	0.0006	0.0024**
	(0.0010)	(0.0012)	(0.0009)	(0.0009)
Interaction: $y_{ijt-1}\times$ Conflict Fatalities$_{t-1}$	-0.0025	0.0021	0.0068	0.0052
	(0.0043)	(0.0035)	(0.0075)	(0.0045)
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.690	0.419	0.593	0.499
Within R^2	0.557	0.125	0.362	0.344

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the *first difference of the price gap* between market pairs.
(3) The coefficient on y_{ijt-1} represents the *speed of price adjustment*; a more negative value indicates faster convergence to equilibrium.
(4) `Conflict Fatalities`$_{t-1}$ represents the number of fatalities in conflict events occurring along trade routes in the previous period.
(5) The interaction term ($y_{ijt-1}\times$ Conflict Fatalities$_{t-1}$) tests whether fatalities modify the speed of price convergence.
(6) Market-pair fixed effects control for time-invariant trade relationships, while week fixed effects capture common shocks.
(7) Control variables include interaction terms of y_{ijt-1} with: - log(Distance) (spatial separation), - log(Travel Time) (trade friction), - Same Region (whether markets share an administrative boundary). These controls are included in the regression but omitted from the table for brevity.
(8) Standard errors (in parentheses) are clustered at the market-pair level.

Table 20: Effect of Conflict Events on Price Adjustment Speed with Four Lags

	Local Rice	Long-Grain Rice	Brown Cowpea	White Cowpea
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Lagged Price Difference (y_{ijt-1})	-0.564***	-0.823***	-0.584***	-0.400***
	(0.162)	(0.112)	(0.078)	(0.079)
Conflict Events:				
Conflict Events$_{t-1}$	0.0033	0.0142	0.0029	0.0112**
	(0.0072)	(0.0123)	(0.0047)	(0.0040)
Conflict Events$_{t-2}$	-0.0063	0.0047	0.0101.	0.0059
	(0.0048)	(0.0054)	(0.0060)	(0.0047)
Conflict Events$_{t-3}$	0.0115.	0.0121	0.0032	-0.0006
	(0.0059)	(0.0097)	(0.0043)	(0.0038)
Conflict Events$_{t-4}$	-0.0134**	0.0001	-0.0086	-0.0098*
	(0.0047)	(0.0040)	(0.0054)	(0.0041)
Interaction Terms:				
$y_{ijt-1}\times$ Conflict Events$_{t-1}$	0.0027	0.0391.	0.0257	-0.0114
	(0.0271)	(0.0228)	(0.0304)	(0.0247)
$y_{ijt-1}\times$ Conflict Events$_{t-2}$	-0.0130	-0.0354	0.0242	0.0304
	(0.0373)	(0.0296)	(0.0299)	(0.0273)
$y_{ijt-1}\times$ Conflict Events$_{t-3}$	0.0005	0.0548.	-0.0104	-0.0462*
	(0.0319)	(0.0317)	(0.0188)	(0.0214)
$y_{ijt-1}\times$ Conflict Events$_{t-4}$	-0.0214	0.0047	-0.0808**	-0.0311
	(0.0468)	(0.0171)	(0.0306)	(0.0267)
Joint Significance Tests (F-Statistics):				
$y_{ijt-1}\times$ Conflict Events$_{t-1}$ to $t-4$	0.2896	4.3193	8.4876	8.6044
	[p-value: 0.9905]	[p-value: 0.3645]	[p-value: 0.07527]	[p-value: 0.07179]
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.694	0.428	0.605	0.507
Within R^2	0.563	0.138	0.379	0.355

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the *first difference of the price gap* between market pairs.
(3) The coefficient on y_{ijt-1} represents the *speed of price adjustment*; a more negative value indicates faster convergence to equilibrium.
(4) `Conflict Events`$_{t-k}$ represents the number of violent events along the trade route at lag $t-k$.
(5) The interaction terms ($y_{ijt-1}\times$ Conflict Events$_{t-k}$) test whether conflict affects the speed of price convergence.
(6) Market-pair fixed effects control for time-invariant trade relationships, while week fixed effects capture common shocks.
(7) Control variables include interaction terms of y_{ijt-1} with: - log(Distance) (spatial separation), - log(Travel Time) (trade friction), - Same Region (whether markets share an administrative boundary). These controls are included in the regression but omitted from the table for brevity.
(8) Standard errors (in parentheses) are clustered at the market-pair level.
(9) The joint significance tests present F-statistics and p-values for the cumulative effect of conflict events and their interactions over four lags.

Table 22: Impact of Changes in Conflict Fatalities on Price Adjustment

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Baseline Price Adjustment:				
Lagged Price Difference (y_{ijt-1})	-0.632*** (0.076)	-0.657*** (0.083)	-0.681*** (0.064)	-0.512*** (0.059)
Change in Conflict Fatalities:				
Δ Fatalities$_{t-1}$	0.0008 (0.0006)	-0.0004 (0.0003)	0.0005. (0.0003)	0.0004 (0.0004)
Interaction:				
$y_{ijt-1} \times \Delta$ Fatalities$_{t-1}$	0.0028* (0.0014)	0.0019 (0.0021)	0.0025 (0.0023)	0.0013 (0.0019)
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.690	0.421	0.595	0.495
Within R^2	0.557	0.127	0.364	0.339

Notes: (1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the first difference in the price gap between market pairs.
(3) The coefficient on y_{ijt-1} represents the speed of price adjustment, where a more negative value implies faster convergence to equilibrium.
(4) Δ Fatalities$_{t-1}$ represents the change in the number of fatalities from conflict events compared to the previous period.
(5) The interaction term $y_{ijt-1} \times \Delta$ Fatalities$_{t-1}$ captures how unexpected increases or decreases in fatalities modify the speed of price adjustment.
(6) Market-pair fixed effects account for time-invariant trade relationships, while week fixed effects control for common shocks.
(7) Standard errors (in parentheses) are clustered at the market-pair level.

Table 21: Effect of Fatalities from Different Types of Violence on Price Adjustment

	Local Rice	**Long-Grain Rice**	**Brown Cowpea**	**White Cowpea**
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Lagged Price Difference:				
y_{ijt-1}	-0.609***	-0.706***	-0.751***	-0.552***
	(0.070)	(0.084)	(0.075)	(0.070)
Fatalities from Violence Events:				
Battle Fatalities$_{t-1}$	0.0056.	-0.0021	-0.0035	-0.00003
	(0.0031)	(0.0017)	(0.0025)	(0.0022)
Violence Against Civilians Fatalities$_{t-1}$	0.0007	0.0010	0.0052*	0.0056**
	(0.0023)	(0.0015)	(0.0021)	(0.0021)
Explosion Fatalities$_{t-1}$	0.0091	-0.0335*	-0.0120	0.0021
	(0.0129)	(0.0141)	(0.0169)	(0.0115)
Riot Fatalities$_{t-1}$	-0.0610**	0.0429	0.0150	-0.0147
	(0.0230)	(0.0309)	(0.0208)	(0.0163)
Interaction Effects:				
$y_{ijt-1}\times$ Battle Fatalities$_{t-1}$	0.0389.	0.00002	-0.0104	-0.0076
	(0.0210)	(0.0075)	(0.0208)	(0.0123)
$y_{ijt-1}\times$ Violence Against Civilians Fatalities$_{t-1}$	-0.0301.	-0.0036	0.0368*	0.0195.
	(0.0159)	(0.0100)	(0.0143)	(0.0109)
$y_{ijt-1}\times$ Explosion Fatalities$_{t-1}$	-2.189**	-0.680***	0.0300	0.0099
	(0.675)	(0.150)	(0.043)	(0.037)
$y_{ijt-1}\times$ Riot Fatalities$_{t-1}$	-0.1123	0.0800	0.1147	0.0308
	(0.0680)	(0.0875)	(0.0815)	(0.0581)
Fixed Effects:				
Market Pair Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	598	593	875	1,002
R^2	0.696	0.424	0.609	0.504
Within R^2	0.566	0.132	0.387	0.351

Notes:
(1) Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.
(2) The dependent variable is the *first difference of the price gap* between market pairs.
(3) The coefficient on y_{ijt-1} represents the *speed of price adjustment*; a more negative value indicates faster convergence to equilibrium.
(4) Market-pair fixed effects account for time-invariant trade relationships, while week fixed effects control for common shocks.
(5) Fatalities refer to the number of deaths resulting from each type of violence event in the previous period.
(6) Control variables include interaction terms of y_{ijt-1} with:
- log(Distance) (spatial separation),
- log(Travel Time) (trade friction),
- Same Region (whether markets share an administrative boundary). These controls are included in the regression but omitted from the table for brevity.
(7) Standard errors (in parentheses) are clustered at the market-pair level.

Table 23: Effect of fatalities caused by different types of violence events on speed of adjustment by products

	Local Rice	Long-grain Rice	Brown Cowpea	White Cowpea
Dependent Variable: Δy_{ijt} (Price Adjustment)				
Baseline Price Adjustment:				
Lagged Price Difference (y_{ijt-1})	-0.7915*** (0.0660)	-0.6566*** (0.0846)	-0.5678*** (0.0716)	-0.6569*** (0.0752)
Interaction:				
y_{ijt-1} × Battle fatality$_{ijt-1}$	0.0275* (0.0112)	-0.0048 (0.0057)	-0.0039 (0.0153)	0.0018 (0.0098)
y_{ijt-1} × Battle fatality$_{ijt-2}$	0.0283 (0.0198)	-0.0073 (0.0119)	0.0071 (0.0121)	0.0392. (0.0210)
y_{ijt-1} × Battle fatality$_{ijt-3}$	0.0011 (0.0111)	0.0062 (0.0097)	0.0125 (0.0094)	0.0122 (0.0095)
y_{ijt-1} × Battle fatality$_{ijt-4}$	-0.0446* (0.0200)	-0.0109 (0.0107)	-0.0136 (0.0146)	0.0034 (0.0123)
y_{ijt-1} × VAC fatality$_{ijt-1}$	-0.0382* (0.0162)	-0.0143. (0.0075)	0.0065 (0.0146)	-0.0050 (0.0111)
y_{ijt-1} × VAC fatality$_{ijt-2}$	0.0155 (0.0110)	0.0086 (0.0055)	-0.0128 (0.0094)	-0.0017 (0.0067)
y_{ijt-1} × VAC fatality$_{ijt-3}$	-0.0064 (0.0071)	-0.0062 (0.0071)	-0.0021 (0.0073)	-0.0092 (0.0065)
y_{ijt-1} × VAC fatality$_{ijt-4}$	0.0192** (0.0066)	0.0077 (0.0049)	-0.0216. (0.0120)	-0.0184 (0.0134)
y_{ijt-1} × Explosion fatality$_{ijt-1}$	-1.925*** (0.2806)	-0.1873 (0.1133)	0.0025 (0.0258)	-0.0181 (0.0203)
y_{ijt-1} × Explosion fatality$_{ijt-2}$	0.0003 (0.0286)	0.0042 (0.0185)	-0.0073 (0.0287)	-0.0895** (0.0293)
y_{ijt-1} × Explosion fatality$_{ijt-3}$	0.0320 (0.0237)	0.1204*** (0.0303)	0.0171 (0.0462)	-0.0227 (0.0273)
y_{ijt-1} × Explosion fatality$_{ijt-4}$	0.5520. (0.2834)	-0.3107. (0.1845)	-0.1382 (0.2020)	-0.1775 (0.3473)
y_{ijt-1} × Riots fatality$_{ijt-1}$	-0.0256 (0.0942)	0.1590** (0.0592)	0.0639 (0.0587)	-0.0055 (0.0478)
y_{ijt-1} × Riots fatality$_{ijt-2}$	-0.0257 (0.0821)	-0.0780. (0.0439)	-0.1346. (0.0809)	-0.0769 (0.0539)
y_{ijt-1} × Riots fatality$_{ijt-3}$	-0.0302 (0.0577)	0.0022 (0.0186)	-0.0288 (0.0269)	-0.0959*** (0.0240)
y_{ijt-1} × Riots fatality$_{ijt-4}$	0.0564 (0.0537)	0.0195 (0.0406)	-0.0020 (0.0363)	0.0072 (0.0698)
Fixed-Effects:				
Market pair	Yes	Yes	Yes	Yes
week	Yes	Yes	Yes	Yes
S.E.: Clustered	by: Market pair	by: Market pair	by: Market pair	by: Market pair
Observations	598	593	875	1,002
R2	0.72750	0.43429	0.59183	0.52210
Within R2	0.61053	0.14806	0.35902	0.37425

Note: (1) . p<0.1; *p<0.05; **p<0.01; ***p<0.001. (2) VAC stands for Violence against civilian. (3) Control variables include interaction term of y_{ijt-1} with travel time, travel distance, and if markets are in the region.