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Faraway, so close: the impact of the Russia–Ukraine war on political violence in Asian countries

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Abstract: We show that the Russia–Ukraine-war-induced changes in the international price of wheat affected political violence in Asia. Using data from 13 countries and more than four million cell-level observations, we show that a higher wheat price increases political violence in areas that are more suitable to produce that crop. We interpret this evidence as consistent with a *rapacity effect* being at play: the higher value of agricultural output increases the incentive to violently appropriate it. Our result is robust to a number of falsification and robustness tests. The effect is heterogeneous across countries and cell types: in line with our interpretation of the empirical findings, the effect is larger in countries that are net exporters of wheat and in cells that are rural. We also show that a higher price of wheat increases political violence more in countries that are low-income, fragile, and characterized by the presence of anti-government or terrorist groups, indicating that a higher value of crop production is more likely to fuel violence in areas that are poor or not politically stable.

Key words: Russia–Ukraine war, commodity prices, agricultural trade, agricultural suitability, rapacity effect

JEL classification: F13, F14, Q17, Q54

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1 Introduction

The Russia–Ukraine war began in early 2022 and there are no signs that it will end soon. In addition to the direct dramatic negative effects for the two fighting countries, the war is likely to have negative effects also for *other* countries. In particular, international agencies have called for interventions to mitigate the possible negative impacts on developing economies.

The war-induced change in international prices of the crops produced by the two countries (especially wheat) is one among the possible negative effects for other countries that are raising more concern. Ukraine and Russia are the world's breadbaskets, providing around more than 30% of globally consumed grains (UN 2022). Due to the disruption of the supply chains of Ukraine and the international sanctions imposed on Russia during the war escalation, global grain prices increased consistently in comparison with previous years.

This paper investigates the consequences of wheat price variations during the Ukraine–Russia war on *political violence* in Asian countries. A priori, the expected effect of the change in (international) crop prices on political violence is ambiguous. Higher crop prices could reduce political violence. This is because an increase in the local production of crops would lead to higher wages and hence to a higher *opportunity cost* of fighting, which would reduce violence. At the same time, an increase in crop prices could increase the number of political violent events. This is because of the *rapacity* effect and the asymmetric distribution of the gains from the increased value of crop production (McGuirk and Burke 2020; Amodio et al. 2023). In fact, an increase in wheat price makes the current and future production of this crop more valuable, and as a consequence, the appropriation of this output becomes attractive for combats and terrorists. In locations where the increase of the output value is higher, i.e. in locations more suitable to produce wheat, conflict intensity may thus increase more. Which one of these possible effects prevails is a matter of empirical investigation.

We use information on price changes of wheat (plausibly induced by the Ukraine–Russia war) and data on wheat suitability at very fine spatial resolution (9x9 km) to identify the local-level effect of the war on political violence in Asia. Using data from 13 Asian countries and more than four million cell-level observations, we document that an increase in wheat price increases political violence in areas that are more suitable to produce that crop. This finding is consistent with a *rapacity effect* being at play: political violence increases more in areas where benefits from war-induced price changes of this crop are asymmetrically distributed, profiting disproportionately those endowed with lands most suitable for wheat cultivation and leading to violent actions to seize these gains.

We validate this finding with the results from two falsification exercises and a number of robustness checks. In particular, we show that our results are robust to the use of different price data, a different measure of price shock, and more demanding model specifications. We document that this effect is highly heterogeneous across countries and cell types. In line with our interpretation of the empirical findings, the effect is larger in countries that are net exporters of wheat, excluding that the effect on political violence may be driven by changes in domestic consumers' demand. Moreover, we show that, as expected when violence is directed to appropriate the now more valuable agricultural output, the effect of changes in wheat prices on political violence is driven by rural cells. Finally, we document that the price shock increases political violence more in countries that are low-income, fragile, and characterized by the presence of anti-government or terrorist groups, indicating that a higher value of crop production is more likely to fuel violence in areas that are already poor or not politically stable.

Our paper is related to two main strands of literature. The first one is the literature that exploits changes in commodity prices as a source of exogenous variation to investigate the association of economic conditions and political violence. Two mechanisms predict that higher food prices can favour political violence: (i) the rapacity effect (Dube and Vargas 2013); (ii) relative deprivation (Hendrix and Haggard 2015). According to the former, higher prices increase the appropriable surplus, stimulating violence in turn; while for the latter, unfilled expectations and food insecurity are the main boosting factors of political violence. On the other hand, two mechanisms predict that higher food prices can reduce political violence: (i) opportunity cost effect (Bazzi and Blattman 2014);[1] (ii) tax revenues effect (Besley and Persson 2010).[2] The empirical evidence is also ambiguous. Empirical studies on the effect of food prices volatility on political violence have found different results, both as cross-country (Brückner and Ciccone 2010; Bazzi and Blattman 2014) and at sub-national level (Dube and Vargas 2013; Blair et al. 2021).[3] Some recent studies have provided evidence consistent with a rapacity effect mechanism being at play. Berman et al. (2017) estimate that the rise in mineral prices can explain up to 25% of the average level of violence across African countries. Crost and Felter (2020) show that an increase in the value of major export crops exacerbate violence in the Philippines. Berman et al. (2021), combining information on soil characteristics with worldwide variations of fertilizer prices, show that variations in agricultural productivity increase conflict in sub-Saharan Africa. McGuirk and Burke (2020) show that rising global food prices are associated

[1] According to the opportunity cost effect, higher food commodity prices rise workers' wages and they, in turn, increase the opportunity cost for the marginal workers to abandon their jobs and engage in conflicts.

[2] This latter mechanism applies in the presence of taxable commodities (i.e. oil, minerals) which can increasing government revenues and, in turn, its capacity to cope with, or even prevent, political violence. The more the crop is taxable the more this mechanism is likely to become relevant.

[3] Amodio et al. (2023) document that trade-liberalization-induced increase in economic activity leads to more political violence in areas producing less labour-intensive crops or crops that are locally consumed.

with a higher probability of conflict in cells that produce those crops.[4] We contribute to this literature by providing the first estimate of the effect of a (war-driven and exogenous) change in crop price on political violence in a large sample of Asian countries, which allows us to explore the role of country characteristics in explaining the possible heterogeneous effect of crop price shocks at the local level.

The second literature our paper looks at the possible effect of the Russia–Ukraine war on other countries. Most of these studies have considered the global effect of the war or its impact on the European countries (Caldara et al. 2022; WTO 2023; WPF 2023).[5] Yet, the Russia–Ukraine war is expected to have harsh consequences also on developing countries. International agencies have warned about the possible long-term effect of food prices shocks on food security and peace in these coutries (UNDESA 2023). The projections by FAO et al. (2023) indicate that in vulnerable areas in Africa and Asia, the Russia–Ukraine war will exacerbate the pre-existing food crisis. For instance, McGuirk and Burke (2022) predict that the increase in wheat and maize prices from January to April 2022 (which they assume to be due primarily to the war in Ukraine) will increase inter-group conflict in Africa by 5.3%. Our paper contributes to this effort to understand the possible impact of the Ukraine–Russia war on *other* countries by providing the first rigorous analysis of the possible effect of the war-induced wheat price changes on political violence in a large sample of Asian countries.

This paper proceeds as follows. Section 2 provides some background on the Ukraine–Russia war and the expected effects on wheat world trade and prices and on wheat production and consumption in Asian countries. Section 3 introduces the different data sources employed in the analysis and presents descriptive statistics on the main variable of interest. Section 4 describes the empirical strategy and Section 5 discuss the results. Finally, Section 6 concludes and discusses some policy implications of our analysis.

2 Background

The Russia–Ukraine war On 24 February 2022, Russia military invaded Ukraine as a result of the steep escalation in the tension between the two countries. Prior to the Russian invasion of Ukraine, in March and April 2021 the Russian Armed Forces began massing troops and military equipment near the border with the Ukrainian region of Crimea (Kramer 2021). This mobilization was the largest one since the illegal annexation of Crimea in 2014 (Reuters 2021)

[4] Interestingly, they report that no such effect is detected in areas where production focuses on nonfood crops ('cash crops'). They argue that in this case—because consumers do not buy these crops—higher prices do not reduce real wages of consumers (which would have made them willing to fight more to appropriate the surplus.

[5] Another relevant consequence of the Russia–Ukraine war is the massive inflow of refugees from Ukraine in EU and OECD countries (OECD 2022).

and raised concerns internationally over a potential escalation of the tensions. The troops, identified also by U.S. satellite imagery, have been withdrawn in June 2021, yet leaving all the infrastructures in place (Bielieskov 2021). A second troop massing started in October 2021, with more soldiers and more consistent deployment of forces on new fronts. By December 2021, over 100,000 Russian troops were massed around Ukraine on three sides, including Belarus from the north and Crimea from the south, conducting several military exercises and maneuvers getting closer to Ukrainian borders (Troianovski and Sanger 2022). On 21 February, the Russian President ordered his forces to enter the separatist republics in the eastern region of Ukraine. This is the last military move before the official beginning of the war. As of March 2023, the war is still going on and there is no signal that it will end soon.

Impact of the Russia–Ukraine war on wheat export and price Before the war, Russia and Ukraine were supplying more than one fourth of grains consumed at global level, especially wheat, maize, and barley. One of the consequences of the war has been to halt the possibility for Ukraine to use Black Sea for grain shipping. In addition, Russia has been sanctioned by different countries that have risen export bans against the country. The joint effect of these two circumstances has lead to the disruption of grain supply chains at the global level (McGuirk and Burke 2022) and significantly contributed to a sharp increase in staple food prices (Arezki 2022; Artuc et al. 2022; Porto and Rijker n.d.). At the end of 2022, FAO et al. (2022) estimated that, as consequence of the war, international wheat price was expected to rise between 8.7 and 21.5%.

Wheat consumption and production in Asia Consumption of grains in Asia have increased by more than 30% over the past 10 years (OECD and FAO 2023). While rice remains by far the most grown and consumed grain in the whole region, consumption of wheat-based food staples. Overall, Asian countries are not large importers of wheat or wheat flour (European Commission 2023). Yet, there are large differences across countries. For instance, Bangladesh, Malaysia, Indonesia, Viet Nam, and Yemen are wheat importers, especially from Ukraine and Russia. On the contrary, India and Pakistan have significantly increased domestic wheat production recently (OECD and FAO 2023).

3 Data

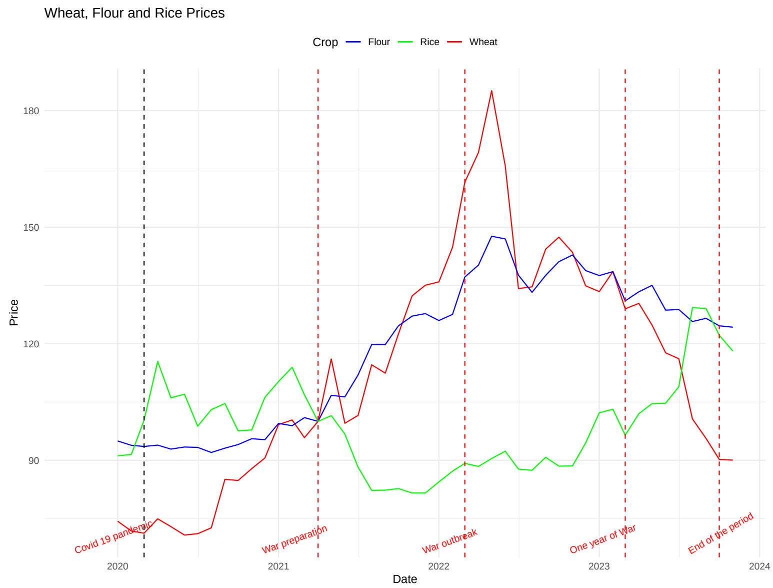
Sample Our sample includes 13 Asian countries: Afghanistan, Cambodia, East Timor, India, Indonesia, Laos, Malaysia, Pakistan, Sri Lanka, Thailand, Viet Nam, and Yemen. They all belong to or border with the Tropical Area (i.e. the geographical area between the Tropic of Cancer and the Tropic of Capricorn) and cover the three main World Bank regions in Asia: East Asia and Pacific (EAP), South Asia (SA), and Middle East and North Africa (MENA).

We conduct our analysis at the sub-national level considering 9km $\times$ 9km cells. These are approximately four million observations.

Prices International wheat monthly prices are derived from the Federal Reserve Bank of Saint Louis (FRED) dataset. From the same source, we derived international monthly prices for wheat flour and rice. In addition, we collected national monthly crop prices from the FAO Food Price Monitoring and Analysis (FPMA) tool. Our data (both global and national prices) cover the period from January 2021 to November 2023.

Figure 1 shows the evolution of these prices during the period 2021–23, taking as reference point prices at the beginning of year 2021. Our period of analysis covers the year preceeding the war (during which there were military activities preparing for the war) and the two years after the beginning of the war (until November 2023). As it clearly emerges from the figure, both the price of wheat and wheat flour are influenced by the different phases of the Ukraine–Russia war. As discussed in Section 2, the period of war preparation can be dated back to spring 2021, and the official beginning of the conflict is 24 February 2022. The prices of wheat and wheat flour began to increase with the rising tension between the two countries (i.e. during war preparation) and continued to do so also after the official beginning of the war. In the same figure, we also report the evolution of the international price of rice. As expected, the evolution of the price of rice during the same period is very different and does not show any increasing trend: this is in line with the fact the war has not (directly) impacted the price of this other crop.

Figure 1: Wheat, wheat flour, and rice international prices (2021–23)

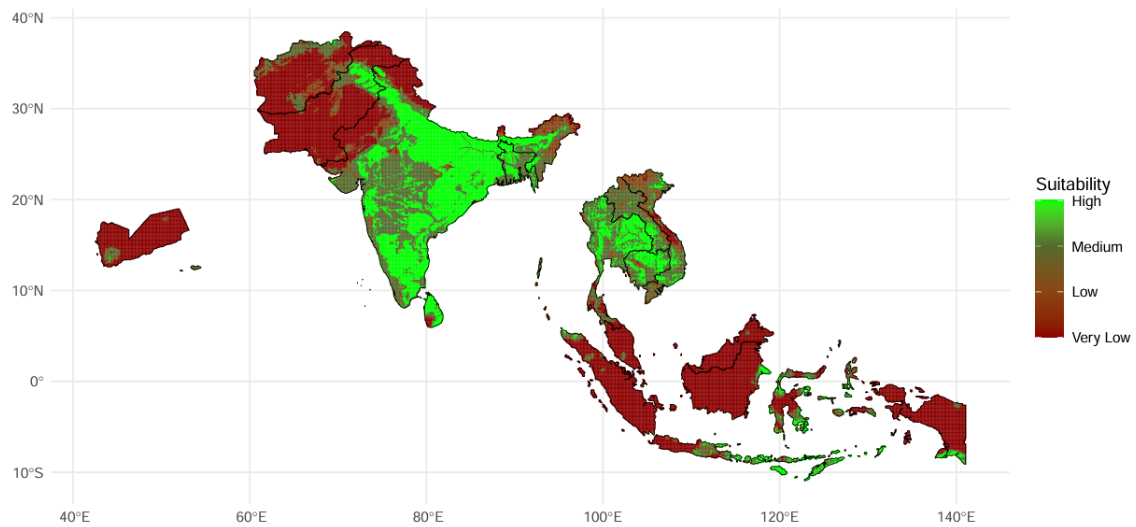


Note: monthly international prices of wheat, wheat flour, and rice are indexed at 01Apr2021.
Source: authors' construction based on data derived from the Federal Reserve Bank of Saint Louis (FRED) dataset.

Crop suitability Data on wheat suitability and potential yields at the sub-national level are from the Global Aero-Ecological Zones (GAEZ Version 3) project (IIASA and FAO 2012). The data provide information on suitability and potential yield for 42 crops at the 9km $\times$ 9km cell level for the whole world.[6] The estimates of potential yields are solely based on agro-climatic conditions (soil and weather characteristics) and are therefore exogenous to any change in agricultural production due to war.[7]

Each crop requires different agronomical characteristics of the terrain. For this reason, some areas are more suitable to farm wheat than to others, i.e. the production potential varies across locations. Table A1 shows descriptive statistics of cell-level suitability of wheat in the full sample of countries. Figure 2 shows the geographical distribution of the cells across the countries of our sample, suggesting large heterogeneity in wheat suitability. The most suitable areas for wheat cultivation are located in India, Sri Lanka, and in some regions of Bangladesh, Cambodia, Laos, Pakistan, Thailand, and Viet Nam. Wheat suitability is instead low in Afghanistan, East Timor, Indonesia, Malaysia, and Yemen.

Figure 2: Wheat suitability in Asian countries



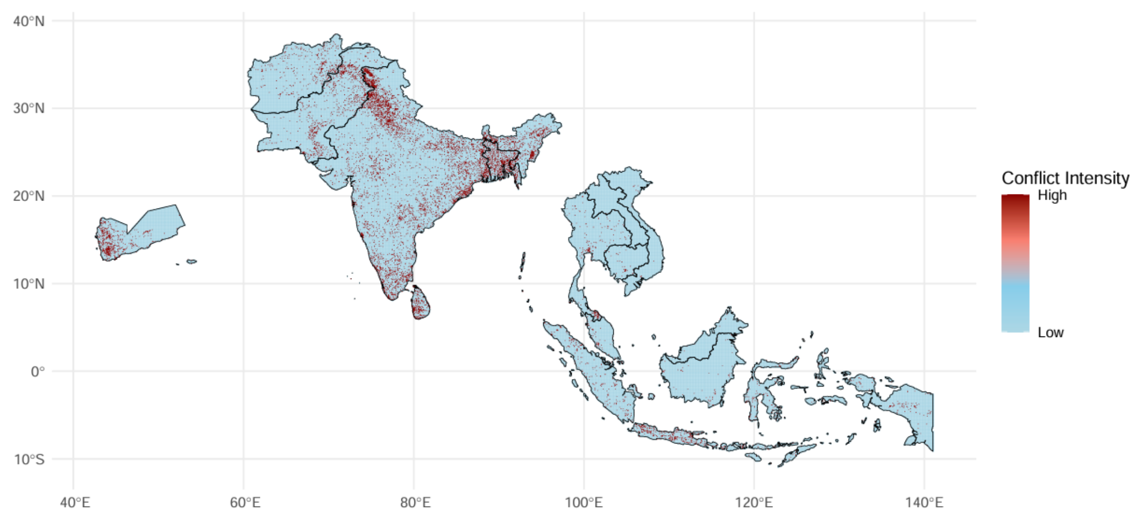
Source: authors' construction based on data from the Global Aero-Ecological Zones (GAEZ Version 3) project (IIASA and FAO 2012).

[6] GAEZ estimates consider two possible scenarios of water supply (rain-fed and irrigation) and three possible levels of inputs (high, medium, and low). It supplies two alternative projections of potential crop yields: one is based on agroecological constraints, which could potentially reflect human intervention, and one is only based on agroclimatic conditions, which are arguably unaffected by human intervention. We consider potential yields based on the scenario considering agroclimatic conditions under rain-fed low-input agriculture.

[7] These data have already been largely used in the economics literature (Costinot and Donaldson 2012, 2016; Costinot et al. 2016; Amodio et al. 2023).

Political violence Data on political violence are from the Armed Conflict Location & Event Data Project database (Raleigh et al. 2010). Events are automatically identified and extracted from news articles, and geo-referenced and time-stamped accordingly. We build our panel dataset of political violence events by considering only those classified as 'Protests', 'Riots', 'Violence against civilians'.[8] We measure the local-level intensity of political violence as the number of violent events that occurred in each cell for each month for the countries in our sample.

Figure 3: Number of political violence events, all countries (after the war begins)



Note: among all the events recognized by ACLED as violent event, we selected only events classified as 'Protests', 'Riots', 'Violence against civilians'. The period after war begins lasts from Jan2022 to Nov2023. Source: authors' construction based on data from the Armed Conflict Location & Event Data Project database (Raleigh et al. 2010).

Table A2 shows the summary statistics of political violence by country, averaged across the FAO-GAEZ 9km $\times$ 9km cells for both measures. Two features stand out. First, and not surprisingly, there is large variation across countries. Second, the number of violent episodes is quite low on average, because many cells do not record any act of violence. The highest conflict intensity is recorded in the cells located in Sri Lanka, Bangladesh, Pakistan, and India.

Other variables In our analysis, we use a number of other datasets to construct our variables. Data on wheat import and export are from the FAOSTAT database (Kasnakoglu 2006). We use data on imported and exported quantities of wheat in 2019 to calculate the net exported quantity.

[8] In practice, we exclude the categories of ACLED events that refer to organized group 'battle'. Our definition of political violence is thus similar to the choice made by McGuirk and Burke (2020) to build their variable *output conflict*—which is intended to capture the conflict events related to the appropriation of surplus—by considering events including riots and violence against civilians from the Armed Conflict Location and Event Dataset (Raleigh et al. 2010). It follows that our definition of political violence also includes unorganized violence by any form of group, including unnamed mobs. This definition captures incidences of food riots, attacks to farms, and crop theft as well as more general rioting and looting. No fatalities are necessary for events to be included in the data.

We define two categories of countries: 'net exporters' if the exported quantity is greater than the imported quantity, 'net importers' otherwise. Per-capita income data are from the World Bank Analytical Classification (GNI per capita in USD, Atlas Methodology). We use data for 2021 to categorize countries between high-income countries (HICs) and non-high-income countries. The Fragile Index is provided by Fund For Peace (2021). We define a country *stable* if its score of Fragility State Index 2021 is ≤ 60 (Malaysia, Viet Nam). A country has a *warning* situation if its score of Fragility State Index 2023 is $[61 \leq \text{x} \geq 80]$ (East Timor, India, Indonesia, Laos, Thailand). A country has an *alert* situation if is score of Fragility State Index 2023 is ≥ 81 (Afghanistan, Bangladesh, Cambodia, Pakistan, Sri Lanka, Yemen). We use MODIS data to define whether a cell is rural or urban (Schneider et al. 2010). However, MODIS data provide this information for cells of a smaller dimension (500x500 m) than those in our sample (9x9 km). Thus, we define a cell as rural if the majority of MODIS cell contained in each cell of our sample is rural, and urban otherwise.

4 Empirical strategy

To explore the effect of the Russia–Ukraine war on Asian countries, we construct a measure of local-level exposure to the war-induced change in the price of wheat. Our main explanatory variable combines the variation over time in the monthly international wheat price with the geographical variation across cells in the suitability to produce wheat. We define $Price\ Shock\ Exposure_{cmt}$ for each cell c at month m in year t as:

$$Price\ Shock\ Exposure_{cmt} = Average\ Wheat\ Price_{(m-3,m-1),t} S_{cw} \tag{1}$$

where $Average\ Wheat\ Price_{(m-3,m-1),t}$ is the average international price of wheat in the previous three months in year t, and S_{cw} is suitability of cell c to produce wheat. Importantly for our identification strategy, while $Average\ Wheat\ Price_{(m-3,m-1),t}$ is specific to each month and year and the same for all cells, S_{cw} is time-invariant but different across geographical areas within countries and it is exogenous (pre-determined) with respect to the preparation or the evolution of the war.[9] By combining changes in the international wheat price (that is exogenous to local conditions in our sample of countries) with a measure of suitability at the cell level (that is by definition not influenced by the war), this measure allows us to causally estimate the effect of (plausibly war-driven) wheat price changes on the local level of political violence.

[9] This measure is similar to the one used in Amodio et al. (2023) to study the effects of trade liberalization episodes on local-level economic activity and political violence.

Regression specification To study the effect of changes in the wheat price on *political violence*, we estimate:

$$Y_{cmt} = \gamma_c + \theta_{mk} + \delta_{tc} + \beta \ Price\ Shock\ Exposure_{cmt} + u_{cmt} \qquad (2)$$

where Y_{cmt} is the number of political violence events in cell c in month m in year t, γ_c is the cell-level fixed effects, θ_{mc} is month-country fixed effects, δ_{tk} is year-country fixed effects, and u_{cmt} is the error term. In order to ease the comparison of our estimates using different samples, in all tables we report the standardized estimated effect of β.[10]

The sign of the estimated effect of the (war-induced) wheat price change on political violence, i.e. β, depends on the spatial distribution and type of agricultural production at the local level, thus providing evidence on whether the *opportunity cost* or the *rapacity* effect prevails in each cell within our sample of Asian countries.

5 Results

We begin by reporting the results of our analysis. We look at the effect of changes in the price of wheat on the local level of political violence for the whole sample of Asian countries. In Section 5.3, we will present our results by country and discuss heterogeneity by country and cell characteristics.

5.1 Main results

Table 1 shows the estimate of the effect of wheat price changes on political violence (as measured by the local number of violent events) for the entire period of conflict tension (column 1) and for the period after the official beginning of the war (column 2).[11] Estimates in column 1 show that an increase in wheat price increases political violence differentially, with a stronger effect in cells more suitable to produce that crop. We interpret the positive effect of an increase in wheat price on political violence as capturing a *rapacity effect*. An increase in wheat price makes more valuable the current and future production of this crop. As a consequence, the appropriation of the produced output becomes attractive for combatants and terrorists. In locations where the increase of the output value is higher, i.e. in locations more suitable to produce wheat, conflict intensity increases more. This result is confirmed when we restrict the period of analysis to the period after the official beginning of the Ukraine–Russia war. Column 2 shows that in this case the magnitude of the effect is twice larger.

[10] We standardize the estimated coefficient using the formula $\frac{sd(Price\ Shock\ Exposure)}{sd(Y)\beta Price\ Shock\ Exposure}$, where $sd(Price\ Shock\ Exposure)$ and $sd(Y)$ indicate the standard deviation of the respective variables.

[11] See Section 2 for a description of the timing of the various phases of the Russia–Ukraine war.

Table 1: Effect of price shock exposure on number of political violence events in Asian countries

	Number of political violence events	
	Entire period (1)	After war begins (2)
Price shock	0.038***	0.074***
	(0.004)	(0.011)
FE cell	YES	YES
FE month-country	YES	YES
FE year-country	YES	YES
Mean	0.021	0.020
Observations	4,089,990	2,693,622

Note: * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The unit of observation is the cell. Standard errors in parentheses are robust. Price shock (denoted in the paper with $Price\ Shock\ Exposure_{cmt}$) is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in prices with cross-sectional variation in crop suitability, as described in Equation 1. The dependent variable is the number of political violent events for the spatial unit in month m, according to ACLED. Among all the events registered in ACLED, we selected those classified as 'Protests', 'Riots' or 'Violence against civilians'. The full sample is composed of 13 countries: Afghanistan, Bangladesh, Cambodia, East Timor, India, Indonesia, Laos, Malaysia, Pakistan, Sri Lanka, Thailand, Viet Nam, Yemen. The entire period of analysis corresponds to the period from Jan2021 to Nov2023. 'After war begins' corresponds to the period from Jan2022 to Nov2023.

Validation

To validate our interpretation of the empirical results as evidence of the *rapacity effect*, we discuss two additional pieces of evidence consistent with the increase in political violence being linked to the war-induced increase in the value of wheat production at the local level.

Falsification We begin by presenting two falsification exercises. In both cases, we construct a modified version of our variable $Price\ Shock\ Exposure_{cmt}$. In the first, we construct the variable measuring the price shock exposure at the local level using the price of rice and the cell-level suitability for rice production (rather than the price of wheat and the cell-level suitability for wheat). As shown in Table A3, columns 1 and 2, results do not hold anymore when we use this alternative variable: if we consider all the conflict period, the sign of the effect of price shock is the opposite of that reported in our main table, while its effect is not statistically significant after the war begins. In the second exercise, we construct the variable measuring the price shock exposure at the local level combining the cell-level suitability for wheat with changes in price of rice. Also in this case, as shown in columns 3 and 4, results do not hold anymore when we use this alternative measure: if we consider all the conflict period, the sign of the effect of price shock is the opposite of that reported in our main table, while if we consider the period after the war begins, the effect is not statistically significant. Taken together, these two falsification exercises indicate that our finding—that wheat price changes drive conflict intensity—is unlikely to be spurious.

Black Sea Grain Initiative Since the beginning of the War, grains exports from Russia and Ukraine have been severely affected (see Section 2). In particular, maritime shipments of Ukrainian grains towards other countries (inside and outside Europe) via the Black Sea have been totally interrupted. In April 2022, an agreement was signed to facilitate the procedures to safely export food (mainly grains) from three Ukrainian ports in the Black Sea. The Black Sea Grain Initiative (BSGI) agreement has been in place since then.[12] According to the European Commission (2023), the BSGI has been crucial for ensuring Ukraine's grain export to global market and to allow the World Food Programme (WFP) to ship grain to support its humanitarian operations in Afghanistan, Ethiopia, Kenya, Sudan, Somalia, and Yemen.

We use this agreement to validate our interpretation of our empirical results. If political violence is driven by rapacity, the BSGI, by increasing the availability of wheat, should reduce its value and thus should lead, for a given increase in the price of wheat, to a smaller increase in the number of violent events (if these are motivated by the attempt to gain control over this resource). To test for this possibility, we look at the potentially heterogeneous effect of an increase in the wheat price in the period before vs the period after the introduction of the BGSI initiative, considering both our full sample and only cells located in Afghanistan and Yemen, which are the only countries of our sample beneficiaries of the WFP initiative connected with the BSGI.

Results are reported in Table A4. The effect of a change in the wheat price on the number of violent events decreases after the introduction of the BSGI for the full sample (column 1 and 3) and also when we only consider Afghanistan and Yemen (column 2 and 4). This finding is confirmed both if we consider the entire period of conflict tension or only after the war begins. In both cases, the effect of the price shock in areas more suitable to produce wheat is smaller after the BSGI, consistent with our interpretation of our main empirical results.

5.2 Robustness checks

Our results are robust to a number of checks, including the use of different data for the price of wheat, a different definition for the price shock variable, and more demanding model specifications.

Alternative measures of wheat price Table A5 reproduces Table 1 with the only difference that the variable *Price Shock Exposure*$_{cmt}$ is now constructed using the international price of wheat flour instead than the price of wheat (see Section 3). Results are virtually unchanged:

[12] The BSGI was set to be initially valid for 120 days. In November 2022, the UN and Ukraine announced an extension of the agreement for further 120 days. Then in March 2023, Turkey and UN additionally extended the agreement until July 2023. By that time, more than 1,000 voyages had successfully left Ukraine, shipping more than 30 million tonnes of grains and other food products towards 45 countries.

an increase in price leads to a higher number of political violence events in areas that are more suitable to produce wheat, suggesting that a rapacity effect is at work.

In our main analysis, we use the international price of wheat to construct our price shock variable. An alternative is to use national prices, because they may better capture changes that occurred at the local level. Yet monthly national wheat prices for countries in our sample only exist for Afghanistan, India, and Yemen. To test the robustness of our results to the use of national wheat prices, we re-calculate our variable $Price\ Shock\ Exposure_{cmt}$ using these prices and estimate Equation 2 only for these countries. Results are reported in Table A6: an increase in the price of wheat leads to higher political violence in cells more suitable to produce wheat.

Table 2 presents a set of additional robustness checks, including an alternative definition for the *Price Shock Exposure* variable, the inclusion of additional fixed effect, and lags and leads for the explanatory variable. Results included in this table are discussed in the following.

Alternative definition for the price shock variable To check the robustness of our results, we estimate Equation 2 using a different measure of exposure to price shocks, modeled as follows:

$$Price\ Shock\ Exposure\ (1\ month)_{cmt} = Wheat\ Price_{(m-1),t} S_{cw} \tag{3}$$

where $Wheat\ Price_{(m-1),t}$ is the price of wheat at month $m-1$ (in the main analysis we use a lag of three months) in yeat t, and S_{cw} is the suitability of cell c to produce wheat. Column 1 of Table 2 shows that results are unchanged with respect to our baseline regression specification 2: a higher price shock increases political violence in cells more suitable to produce wheat.

Additional controls To account for time varying seasonal country-specific characteristics, we augment Equation 2 by including a seasonal (quarter) linear trend for each country in the sample. Column 2 of Table 2 shows that the results do not change.

Lags and leads We use lags and leads to test if we have correctly modeled the timing of the price shock effect. Columns 3 and 4 of Table 2 show the results obtained by including alternatively one lag or one lead, corresponding to 3 months. Column 5 reports the results obtained adding one lag and one lead at the same time. In all cases, the lead has not a statistically significant effect, and the inclusion of the lag does not alter the findings.

Table 2: Effect of price shock exposure on number of political violence events in Asian countries: robustness checks

	Number of political violence events				
	(1)	(2)	(3)	(4)	(5)
Price shock (1 month)	0.056***				
	(0.009)				
Price shock		0.074***	0.063***	0.073***	0.056***
		(0.011)	(0.014)	(0.009)	(0.012)
Price shock (lag)			0.017**		0.022***
			(0.005)		(0.005)
Price shock (lead)				0.004	0.012
				(0.007)	(0.007)
FE cell	YES	YES	YES	YES	YES
FE month-country	YES	YES	YES	YES	YES
FE year-country	YES	YES	YES	YES	YES
Seasonal time trend	NO	YES	NO	NO	NO
Mean	0.020	0.020	0.020	0.020	0.020
Observations	2,693,622	2,693,622	2,693,622	2,693,619	2,693,619

Note: * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is the cell. Standard errors in parentheses are robust. Price Shock (denoted in the paper with $Price\ Shock\ Exposure_{cmt}$) is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in prices with cross-sectional variation in crop suitability, as described in Equation 1. $Price\ Shock\ Exposure_{im}$ is the price-shock exposure of spatial unit in month m that we obtained by combining time variation in prices with cross-sectional variation in crop suitability, as described in Equation 3. The dependent variable is the number of political violent events for the spatial unit in month m, according to ACLED. Among the events registered by ACLED as violent, we select only those classified as 'Protests', 'Riots', 'Violence against civilians'. Price shock lag (lead) corresponds to lag/lead of 3 months in our variable $Price\ Shock\ Exposure_{cmt}$. The full sample includes 13 countries: Afghanistan, Bangladesh, Cambodia, East Timor, India, Indonesia, Laos, Malaysia, Pakistan, Sri Lanka, Thailand, Viet Nam, Yemen. The period of analysis is the one after war begins (Jan2022 to Nov2023).

5.3 Heterogeneity

Results by country

Table 3 shows the results of estimating our main model (Equation 2) country by country. Results indicate that an increase in the price of wheat increases political violence more in areas that are more suitable to produce wheat in Afghanistan, India, Indonesia, Pakistan, and Yemen. Instead, the effect is not statistically different from zero in all other countries, i.e. Bangladesh, Cambodia, East Timor, Laos, Malaysia, Sri Lanka, Thailand, and Viet Nam.

These cross-country differences in the effect of changes in the wheat price on local political violence can be explained by the presence of existing conflict in specific geographic areas of these countries. For instance, Afghanistan, India, Indonesia, Pakistan, and Yemen are all countries in which there are areas characterized by intense activity of terrorist groups. This is in line with our interpretation of our results as evidence of a *rapacity effect* being at work: in areas where anti-government combatants or terrorist groups are active, the higher value of wheat induces an increase in the violence to appropriate the now more valuable agricultural output.[13]

[13] Afghanistan has been recently characterized by an increase of human rights violation. Moreover, in the province of Khorasan, the terrorist group ISIS-K is openly opposing the Taliban regime, through bombing and armed attacks mostly targeting civilians (Human Rights Watch 2023). In India, political violence is mainly concentrated in the areas of Jammu and Kashmir, after the government revoked their constitutional autonomous status and the region split into two federally governed territories (Human Rights Watch 2023). This conflict, that is mainly involving militants versus Indian security forces, has provoked many civilians' deaths, targeted by the active armed militant groups (Bantirani 2023). In addition, this conflict is often affects the bordering Punjab region, in the North-East of Pakistan. While the level of alert in Indonesia is lower than in other countries, the threat of Islamic terrorism has never disappeared (Hart 2023). Moreover, in the West Papua region the tensions are escalating with the terrorist group of the West Papua National Liberation Army (TPNBP) operating with attacks and hostage takings. Pakistan is another example of a country with high-intensity localized political violence. Adding up to the case of Punjab, Tehrik-Taliban Pakistan (TTP), an Islamic armed terrorist group, has been responsible of multiple attacks targeting civilians in the North-Western region of the country. Moreover, in recent times the TTP is gaining influence also in the province of Balochistan, searching for an alliance with the Taliban terrorist group active in the territory, the Baloch Liberation Army (BLA) (Bantirani 2023). In Yemen, the terrorist armed groups (Houti) are active also in the region bordering Saudi Arabia (Ardemagni 2023).

Table 3: Effect of price shock exposure on number political violence events by country (after war begins)

	Number political violence event												
	Afghanistan	Bangladesh	Cambodia	East Timor	India	Indonesia	Laos	Malaysia	Pakistan	Sri Lanka	Thailand	Viet Nam	Yemen
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Price shock	0.020^{***}	-0.026	-0.028	-0.063	0.076^{***}	0.018^{**}	-0.029	-0.001	0.123^{***}	-0.130	$-$ 0.002	0.005	0.191^{***}
	(0.017)	(0.009)	(0.035)	(0.038)	(0.013)	(0.005)	(0.010)	(0.001)	(0.038)	(0.010)	(0.008)	(0.018)	(0.061)
FE cell	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
FE month-country	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
FE year-country	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mean	0.008	0.074	0.003	0.002	0.031	0.009	0.000	0.002	0.040	0.082	0.004	0.000	0.019
Observations	216,016	46,795	53,636	5,106	950,636	569,457	71,415	98,141	283,337	19,734	153,686	101,683	124,016

Note: * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is the cell. Standard errors in parentheses are robust. Price Shock (denoted in the paper with $Price\ Shock\ Exposure_{cmt}$) is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in prices with cross-sectional variation in crop suitability, as described in Equation 1. The dependent variable is the number of political violent for the spatial unit in month m, according to ACLED. Among the all set of violent events registered in ACLED (2023), we selected on three categories: 'Protests', 'Riots', 'Violence against civilians'. The period of analysis is the one after war begins (Jan2022 to Nov2023).

Heterogeneity by country characteristics

In the following, we test the possible heterogeneous effect of the price shock on political violence at the local level along several country characteristics. The categorization of each country is reported in Table A7.

Table 4, column 1, indicates that the induced wheat price shock increases political violence in countries that are net wheat exporters, while its effect is not statistically significant for all the other countries. This is in line with our interpretation of the empirical results: the price shock increases political violence more in countries that are large producers of wheat and in which the consumer demand of this crop is relatively small. This is consistent with a rapacity effect being at play and the demand effect being unlikely to explain our results. Column 2 shows that the magnitude of the effect is larger for countries with a lower economic development, as proxied by per-capita income: the effect is about seven times larger than for countries with higher economic development. This is in line with the idea that any negative shock is likely to have more adverse consequences in countries that are less able to cope with them due to their limited resources. Moreover, the results in column 3 documents that price-shock-induced increase in political violence is larger in countries with socio-political situations which can be defined as alarming or warning, while the effect is much smaller for politically stable countries. Taken together, these results indicate that the increase in political violence crucially depends on the characteristics of the country *before* the price shock: the more developed and the more stable the country, the smaller the probability of an increase in political violence for any given level of price shock.

Table 4: Effect of price shock exposure on number political violence events: heterogeneity by country characteristics (after war begins)

	Number political violence events		
	(1)	(2)	(3)
Price shock (net wheat exporter)	0.089***		
	(0.013)		
Price shock (net wheat importer)	0.004		
	(0.005)		
Price shock (high per-capita income)		0.006***	
		(0.001)	
Price shock (low per-capita income)		0.041***	
		(0.0005)	
Price shock (Fragility Index: stable)			0.002***
			(0.000)
Price shock (Fragility Index: warning)			0.079***
			(0.011)
Price shock (Fragility Index: alert)			0.026***
			(0.009)
FE cell	YES	YES	YES
FE month-country	YES	YES	YES
FE year-country	YES	YES	YES
Mean	0.020	0.020	0.020
Observations	2,515,418	2,693,622	2,569,606

Note: * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. **1. (Net) wheat exporter** A **net exporter** is a country with positive net wheat export value in 2019 (India, Pakistan). All other countries (Afghanistan, Bangladesh, Cambodia, East Timor, Indonesia, Laos, Malaysia, Sri Lanka, Thailand, Viet Nam, Yemen) are **net importers**. **2. Income category** has been identified according to the World Bank Analytical Classification (GNI per capita in USD, Atlas Methodology). **Upper-middle per-capita income** (GNI per capita in 2021 $\geq$ 4,466 & $\leq$ 13,645): Indonesia, Malaysia, and Thailand. **Others**: Afghanistan, Bangladesh, Cambodia, East Timor, India, Laos, Pakistan, Sri Lanka, Viet Nam, Yemen. **3. State fragility** A country is **stable** if its score of Fragility State Index 2021 is $\leq$ 60 (Malaysia, Viet Nam). A country has a **warning** situation if its score of Fragility State Index 2021 is [61 $\leq$ x $\geq$ 80] (East Timor, India, Indonesia, Laos, Thailand). A country has an **alert** situation if is score of Fragility State Index 2021 is $\geq$ 81 (Afghanistan, Bangladesh, Cambodia, Pakistan, Sri Lanka, Yemen).

Rural vs urban cells

A low urbanization rate is a characteristic of most of the countries in our sample. In fact, more than 94% of our cells are rural. This geographical feature of our sample of analysis supports our interpretation of the results: an increase in the fights for the appropriation of wheat production when its value is higher is indeed more likely to occur in rural areas, where agricultural production is more likely to be located.

To further corroborate this interpretation of the results, we test whether the effect of price shock is different in urban vs rural cells. Table 5 indicates that the price effect on conflict intensity is always larger in rural cells, and the effect in urban ones not being statistically different from zero after the war begins. We take the strong rural heterogeneity result as an indication that consumer-side mechanisms are not at play. These results reinforce our reading of our main empirical findings as consistent with a rapacity effect being at work.

Table 5: Effect of price shock exposure on number of political violence events: heterogeneity by rural vs urban cells

	Number of political violence events			
	Entire period		*After war begins*	
	Rural cells	Urban cells	Rural cells	Urban cells
	(1)	(2)	(3)	(4)
Price shock	0.040***	0.025*	0.076***	0.424
	(0.003)	(0.011)	(0.008)	(0.236)
FE cell	YES	YES	YES	YES
FE month-country	YES	YES	YES	YES
FE year-country	YES	YES	YES	YES
Mean	0.016	1.988	0.016	1.988
Observations	4,080,505	9,485	2,685,550	6,072

Note:* p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The unit of observation is the cell. Standard errors in parentheses are robust. Price Shock (denoted in the paper with $Price\ Shock\ Exposure_{cmt}$) is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in prices with cross-sectional variation in crop suitability, as described in Equation 1. The dependent variable is the number of political violent events for the spatial unit in month m, according to ACLED. Among all events registered as violent in ACLED, we selected only those classified as 'Protests', 'Riots', 'Violence against civilians'. A cell is considered urban if the majority of MODIS data cells that it contains are classified as urban, and rural otherwise. The entire period of analysis corresponds to the period from Jan2021 to Nov2023. The period after the war begins corresponds to the period from Jan2022 to Nov2023.

6 Concluding remarks

This paper has provided novel evidence on the effects of the Russia–Ukraine war on political violence in countries that are not directly involved in the conflict. Using data from 13 countries and more than four million cell-level observations, we show that a higher wheat price increases political violence in areas that are more suitable to produce that crop. We interpret this evidence as consistent with a *rapacity effect* being at play: the higher value of agricultural output increases the incentive to violently appropriate it. The effect is significant for Afghanistan, India, Indonesia, Pakistan, and Yemen. Instead, the effect is not statistically different from zero in Bangladesh, Cambodia, East Timor, Laos, Malaysia, Sri Lanka, Thailand, and Viet Nam. Looking at possible explanations of this differential effects, we document that, in line with our interpretation of the empirical findings, the effect is larger in countries that are net exporters of wheat and in cells that are rural. We also show that a higher price of wheat increases political violence more in countries that are low-income, fragile, and characterized by the presence of anti-government or terrorist groups, indicating that a higher value of crop production fuels violence more in areas that are already poor or not politically stable. Our findings show the importance of understanding the conditions under which economic fluctuations induced by the Russia–Ukraine war may affect local political violence also in faraway countries. It is key to informing policies that promote peace.

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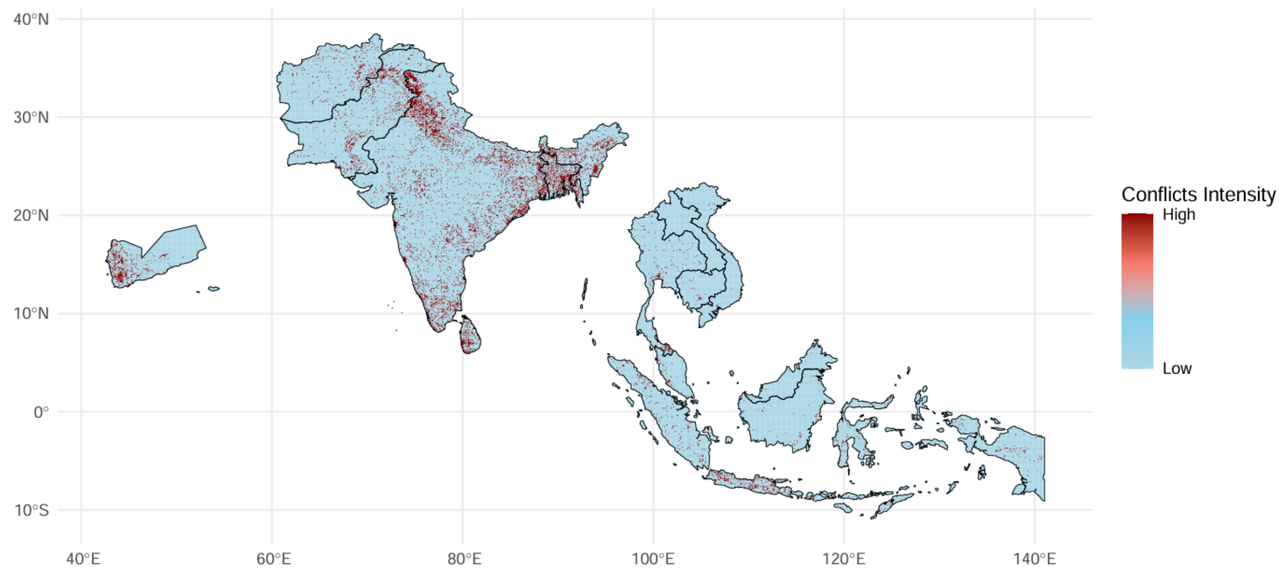
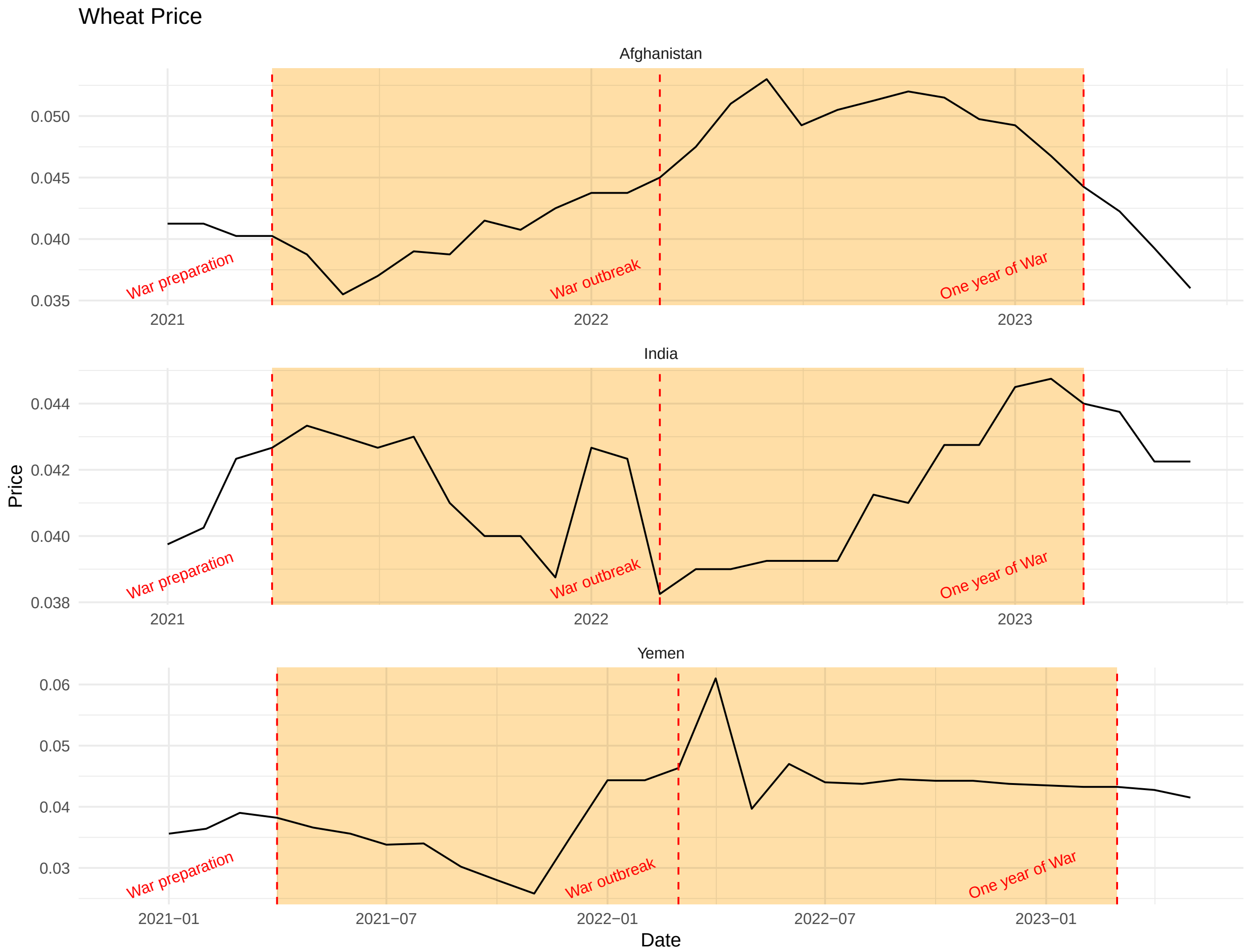
A Appendix figures and tables

Figure A1: Number of political violence event in Asian countries, entire period



Note: among all the events recognized by ACLED as violent events, we selected only events classified as ‘Protests’, ‘Riots’, ‘Violence against civilians’. The entire period lasts from Jan2021 to Nov2023.
Source: authors’ construction based on data from the Armed Conflict Location & Event Data Project database (ACLED) (Raleigh et al. 2010).

Figure A2: Wheat national prices, Afghanistan, India, Yemen



Note: the period of analysis goes from Jan2021 to Nov2023. National prices are expressed in USD/tonnes.
Source: authors' construction based on data from FAO's Food Price Monitoring and Analysis (FPMA) tool.

Table A1: Wheat Suitability Index at cell level, full sample and by country

Country	**Mean**	**SD**	**Obs.**	**Min**	**Max**
Full sample	308.90	418.08	4,098,990	0.00	3,331
Afghanistan	48.97	100.92	216,016	0.00	1,193
Bangladesh	351.00	253.23	46,759	0.00	1,793
Cambodia	439.00	198.05	53,636	0.00	1,192
East Timor	528.81	282.01	5,106	0.00	1,306
India	595.24	489.47	950,636	0.00	3,331
Indonesia	101.54	252.68	569,457	0.00	2,022
Laos	274.53	193.52	71,415	0.00	1,184
Malaysia	6.55	40.70	98,141	0.00	469
Pakistan	90.00	270.04	283,337	0.00	2,900
Sri Lanka	644.69	398.07	19,734	0.00	1,300
Thailand	419.47	226.95	153,686	0.00	1,484
Viet Nam	225.23	209.54	101,683	0.00	1,212
Yemen	16.49	66.44	124,016	0.00	873

Source: authors' based on the Global Aero-Ecological Zones (GAEZ Version 3) project (IIASA and FAO 2012).

Table A2: Number of political violence events registered at cell level in each month of each year, entire period and after the war begins

	Entire period					*After the war begins*				
Country	**Mean**	**SD**	**Obs.**	**Min**	**Max**	**Mean**	**SD**	**Obs.**	**Min**	**Max**
Full sample	0.02	0.43	4,098,990	0.00	84	0.02	0.42	2,693,662	0.00	84
Afghanistan	0.01	0.21	328,720	0.00	33	0.01	0.20	216,016	0.00	33
Bangladesh	0.08	0.97	71,155	0.00	71	0.07	0.84	46,795	0.00	55
Cambodia	0.00	0.12	81,620	0.00	17	0.00	0.14	53,636	0.00	17
East Timor	0.00	0.06	7,770	0.00	3	0.00	0.06	5,106	0.00	3
India	0.03	0.52	1,446,620	0.00	84	0.03	0.51	950,636	0.00	84
Indonesia	0.01	0.19	866,565	0.00	39	0.01	0.20	569,457	0.00	39
Laos	0.00	0.01	108,675	0.00	1	0.00	0.01	71,415	0.00	1
Malaysia	0.00	0.08	149,345	0.00	12	0.02	0.08	91,141	0.00	12
Pakistan	0.04	0.71	431,165	0.00	71	0.04	0.68	283,337	0.00	69
Sri Lanka	0.08	0.79	30,003	0.00	45	0.08	0.84	19,734	0.00	45
Thailand	0.01	0.26	233,870	0.00	42	0.00	0.15	153,686	0.00	20
Viet Nam	0.00	0.01	154,735	0.00	2	0.00	0.01	101,683	0.00	2
Yemen	0.02	0.27	188,720	0.00	22	0.02	0.25	124,016	0.00	21

Note: among all events registered by ACLED as violent, we select only those classified as 'Protests', 'Riots', 'Violence against civilians'. The entire period of analysis corresponds to the period from Jan2021 to Nov2023. The period 'After the war begins' corresponds to the period from Jan2022 to Nov2023.
Source: authors' based on data from the ACLED database (Raleigh et al. 2010).

Table A3: Falsification: Effect of two placebo versions of price shock exposure on number of political violence events

	Number of political violence events			
	Entire period (1)	After war begins (2)	Entire period (3)	After war begins (4)
Price shock (version 1)	-0.025^{***} (0.003)	-0.010 (0.008)		
Price shock (version 2)			-0.058^{***} (0.006)	-0.102 (0.013)
FE cell	YES	YES	YES	YES
FE month-country	YES	YES	YES	YES
FE year-country	YES	YES	YES	YES
Observations	3,990,315	2,622,207	3,990,315	2,622,2072
Mean	0.022	0.022	0.022	0.0222
SD	0.439	0.433	0.439	0.433

Note: * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is the cell. Standard errors in parentheses are robust. $Price\ Shock\ Exposure_{im}(version1)$ is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in rice prices with cross-sectional variation in rice suitability, as described in Equation 1. $Price\ Shock\ Exposure_{im}(version2)$ is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in rice prices with cross-sectional variation in wheat suitability, as described in Equation 1. The dependent variable is the number of political violent events for the spatial unit in month m, according to ACLED. Among all the events recognized by ACLED as violent event, we selected only events classified as 'Protests', 'Riots', 'Violence against civilians'. The full sample is composed by 13 countries: Afghanistan, Bangladesh, Cambodia, East Timor, India, Indonesia, Laos, Malaysia, Pakistan, Sri Lanka, Thailand, Viet Nam, Yemen. The entire period of analysis corresponds to the period from Jan2021 to Nov2023. 'After war begins' corresponds to the period from Jan2022 to Nov2023.

Table A4: Effect of price shock exposure on number of political violence events, before and after the Black Sea Grain Initiative

	Number of political violence events			
	All period		*After war begins*	
	Full Sample (1)	Afghanistan & Yemen (2)	Full Sample (3)	Afghanistan &Yemen (4)
Price shock (before BSGI)	0.008***	0.078*	0.089***	0.891***
	(0.000)	(0.009)	(0.017)	(0.017)
Price shock (after BSGI)	0.005***	0.054*	0.065***	0.653***
	(0.000)	(0.008)	(0.013)	(0.065)
FE Cell	YES	YES	YES	YES
FE month-country	YES	YES	YES	YES
FE year-country	YES	YES	YES	YES
Mean	0.020	0.014	0.020	0.012
Observations	4,098,990	517,440	2,693,622	340,032

Note: * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is the cell. Standard errors in parentheses are robust. Price Shock (denoted in the paper with $Price\ Shock\ Exposure_{cmt}$) is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in prices with cross-sectional variation in crop suitability, as described in Equation 1. The dependent variable is the number of political violent events for the spatial unit in month m events according to ACLED. Among the all set of violent events registered in ACLED (2023), we selected on three categories: 'Protests', 'Riots', 'Violence against civilians'. The full sample is composed by 13 countries: Afghanistan, Bangladesh, Cambodia, East Timor, India, Indonesia, Laos, Malaysia, Pakistan, Sri Lanka, Thailand, Viet Nam, Yemen. The entire period of analysis corresponds to the period from Jan2021 to Nov2023. 'After War begins' corresponds to the period from Jan2022 to Nov2023. **Black Sea Grain Initiative** starts in Jul2022, therefore the period before BSGI is from Jan2022 to Jul2022 and the period after BSGI lasts from Aug2022 to Nov2023.

Table A5: Impact of price shock exposure on number of political violence events: robustness using price of wheat flour

	Number of political violence events	
	Entire period	After war begins
	(1)	(2)
Price shock	0.047^{***}	0.189^{***}
	(0.004)	(0.018)
FE cell	YES	YES
FE month-country	YES	YES
FE year-country	YES	YES
Observations	4,089,990	2,693,622
Mean	0.021	0.020
SD	0.433	0.418

Note: * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is the cell. Standard errors in parentheses are robust. Price Shock (denoted in the paper with $Price\ Shock\ Exposure_{cmt}$) is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in prices with cross-sectional variation in crop suitability, as described in Equation 1. The dependent variable is the number of political violent events for the spatial unit in month m, according to ACLED. Among all the events recognized by ACLED as violent, we selected only events classifies as ‘Protests’, ‘Riots’, ‘Violence against civilians’. The full sample is composed by 13 countries: Afghanistan, Bangladesh, Cambodia, East Timor, India, Indonesia, Laos, Malaysia, Pakistan, Sri Lanka, Thailand, Viet Nam, Yemen. The entire period of analysis corresponds to the period from Jan2021 to Nov2023. ‘After war begins’ corresponds to the period from Jan2022 to Nov2023.

Table A6: Effect of national price shock exposure on number of political violence events: Afghanistan, India, Yemen

	Number of political violence events					
	Entire period			*After war begins*		
	Afghanistan (1)	India (2)	Yemen (3)	Afghanistan (4)	India (5)	Yemen (6)
Price shock	0.014	0.066***	0.046	0.058***	0.075***	0.019***
	(0.009)	(0.005)	(0.022)	(0.017)	(0.013)	(0.061)
FE cell	YES	YES	YES	YES	YES	YES
FE month-country	YES	YES	YES	YES	YES	YES
FE year-country	YES	YES	YES	YES	YES	YES
Observations	328,720	1,446,620	188,720	216,016	950,360	124,016
Mean	0.008	0.031	0.019	0.008	0.031	0.019
SD	0.211	0.518	0.261	0.202	0.207	0.250

Note: * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is the cell. Standard errors in parentheses are robust. Price Shock (denoted in the paper with $Price\ Shock\ Exposure_{cmt}$) is the price-shock exposure of spatial unit in month m that we obtain by combining time variation in prices with cross-sectional variation in crop suitability, as described in Equation 1. The dependent variable is the number of political violent events for the spatial unit in month m, according to ACLED belonging to the categories: 'Protests', 'Riots', 'Violence against civilians'. The entire period of analysis corresponds to the period from Jan2021 to Nov2023. 'After war begins' corresponds to the period from Jan2022 to Nov2023.

Table A7: Characteristics of the countries in the sample

Country	Income category	Net export	Fragility
Afghanistan	LIC	Importer	Alert
Bangladesh	LMIC	Importer	Alert
Cambodia	LMIC	Importer	Alert
East Timor	LMIC	Importer	Alert
India	LMIC	Exporter	Warning
Indonesia	UMIC	Importer	Warning
Laos	LMIC	Importer	Warning
Malaysia	UMIC	Importer	Stable
Pakistan	LMIC	Exporter	Alert
Sri Lanka	LMIC	Importer	Alert
Thailand	UMIC	Importer	Warning
Viet Nam	LMIC	Importer	Stable
Yemen	LIC	Importer	Alert

Note: **1. Income categories** have been identified according to the World Bank Analytical Classification (GNI per capita in USD, Atlas Methodology). **Low per-capita income** (GNI per capita <= 1,135): Afghanistan, Yemen. **Lower-middle per-capita income** (GNI per capita >= 1,136 & <= 4,465): Bangladesh, Cambodia, East Timor, India, Laos, Pakistan, Sri Lanka, Viet Nam. **Upper-middle per capita income** (GNI per capita >= 4,466 & <= 13.645): Indonesia, Malaysia, and Thailand. **2.** A **net exporter** is a country with positive net export value (India, Pakistan). All other countries (Afghanistan, Bangladesh, Cambodia, East Timor, Indonesia, Laos, Malaysia, Sri Lanka, Thailand, Viet Nam, Yemen) are **net importers**.A country is **stable** if its score of Fragility State Index 2021 is $\leq$ 60 (Malaysia, Viet Nam). A country has a **warning** situation if its score of Fragility State Index 2021 is [61 $\leq$ x $\geq$ 80] (East Timor, India, Indonesia, Laos, Thailand). A country has an **alert** situation if is score of Fragility State Index 2021 is $\geq$ 81 (Afghanistan, Bangladesh, Cambodia, Pakistan, Sri Lanka, Yemen).