The Political Economy of Export Bans and Commodity Price Volatility: *Theory and Evidence from Agricultural Markets*

Michael K. Adjemian, Casey Petroff, and Michel A. Robe*

December 2022

*We are indebted to David Reiffen for numerous insightful discussions. We thank Teah Pelechaty for gathering original-language news stories on commodity export bans and their political context, Bill Liefert for sharing some of his information on agricultural trade restrictions, and Jonathan Wallen, Han Le, and Brent Pruitt for help with market data. We thank Kathy Baylis, Marc Bellemare, Valentina Bruno, Toby Kearn, Matt Kidder, Michael-David Mangini, Gabriel Power, Alessandro Rebucci, Zhiguang Wang, Clay Webb, and seminar participants at Johns Hopkins University, Harvard University, the University of Bonn (Germany), the University of Illinois (UIUC), the International Monetary Fund (IMF), the Inter-American Development Bank (IADB), and the Economic Research Service (ERS-USDA) for helpful comments and suggestions. An early draft was presented under the title "Export Bans and Commodity Price Volatility Expectations" at the 2021 Meeting of the Agricultural and Applied Economics Association (AAEA), the 2021 Meeting of the French Finance Association (AFFI), the 2021 Meeting of the Commodity and Energy Markets Association (CEMA), the first Agriculture Policy Research Group Conference (NIFA-APRG), and the 2022 NCCC-134 Meeting: we thank participants at those conferences for helpful feedback. Our initial research effort was supported by the U.S. Department of Agriculture under ERS Project No. 58-3000-5-0038. Robe gratefully acknowledges further financial support from a NIFA grant (Hatch-Multistate No.1072), and from the Clearing Corporation Charitable Foundation in his capacity as the Clearing Corp. Charitable Foundation Professor in Derivatives Trading at UIUC. Petroff acknowledges the generous support of the James M. and Cathleen D. Stone PhD Fellowship in Inequality and Wealth Concentration. Adjemian and Robe are part-time academic consultants to the U.S. Commodity Futures Trading Commission (CFTC). They used no CFTC resource or information for this project. All opinions, findings, conclusions, or recommendations expressed in this paper are the authors' only and do not necessarily reflect the views of the ERS, the USDA, the CFTC, the leaders of (or other staff at) those institutions, or the U.S. Government. Errors and omissions, if any, are the authors' sole responsibility.

The Political Economy of Export Bans and Commodity Price Volatility: *Theory and Evidence from Agricultural Markets*

Abstract

We show that accounting for political risk helps to explain commodity price dynamics. We propose a simple theoretical model to demonstrate how, over and above the impact of exogenous supply shocks, uncertainty about the future world price of staple foods increases with the likelihood (and is further boosted by the actual imposition) of export bans in top producer countries. To test the model's insights, we provide the first high-frequency empirical analysis of the impact of bans on commodity world price dynamics. We construct a novel daily dataset of major restrictions on agricultural exports announced, adopted, or repealed in 2002-2019. We use daily option-implied volatilities (IVols) as the proxy for commodity market uncertainty. Our empirical framework allows us to control explicitly for known drivers of commodity market uncertainty, including global macro-economic uncertainty and risk aversion (jointly captured by the VIX) and for spot market tightness (including the state of grain inventories) prior the ban. We show that wheat and corn IVols are significantly higher on the day and the week when a ban is first imposed, and also during the whole period when the ban remains in effect. The increase is statistically and economically significant.

Keywords: Export restrictions, Trade policy, Commodities, Price volatility, Uncertainty.

JEL Classification Codes: F10, F14, Q17, Q02, G13, G14, P45.

"We cannot allow domestic grain prices to fall or rise significantly, or for the domestic market to be short of grain. (Since) we live in a market economy, under certain conditions our esteemed exporters may want to export everything. Of course, we cannot allow that."

(Russian Agriculture Minister Dmitry Patrushev, December 2019)

"With the war in Ukraine now entering its fourth month, (we) implore that countries resist unilateral trade policy actions such as imposing export restrictions, which will only (...) prolong the uncertainty in markets, and threaten the most vulnerable around the globe."

(FAO – Joint statement of the outgoing and incoming AMIS Chairs, May 2022)

1 Introduction

Following almost thirty years "during which global agricultural markets were characterized by relatively stable and low prices" (Swinnen 2018, 137), the past two decades have witnessed several periods of elevated commodity price volatility. In the case of staple foods, sharp price run-ups (such as those of 2007–2008, 2010–2011, and 2021–2022) are especially costly for the poor – and they cause political unrest (Bellemare 2015; Hendrix and Haggard 2015; Weinberg and Bakker 2015).

A number of papers analyze how a large, exogenous shock to the world food supply can lead countries to curb agricultural exports in a bid to shield their own citizens from the resulting price shock.[1] In turn, however, implementing trade restrictions to tamp down domestic food prices could feed back into the distribution of world prices. Prior research mostly focuses on the first moment of that distribution, *i.e.*, the extent to which export bans may turbocharge world price *levels*.[2]

[1]See, e.g., Dollive (2008), Bouët and Debucquet (2010), Martin and Anderson (2012), Giordani, Rocha, and Ruta (2016), Pieters and Swinnen (2016), Gouel (2016), Laborde, Lakatos, and Martin (2019), Gawande and Zissimos (2022), and references cited therein. Fulton and Reynolds (2015) and Baylis, Fulton, and Reynolds (2016) ask if a rise in world price volatility might similarly affect trade policy: Bellemare (2015) finds no evidence for such an effect.

[2]See, e.g., Rutten, Shutes, and Meijerink (2013), Anderson (2014), Fulton and Reynolds (2015), Giordani, Rocha, and Ruta (2016), Jensen and Anderson (2017), Porteous (2017), Beckman et al. (2018), and references therein.

Teasing out empirically the extent to which supply shock-driven export bans themselves boost world prices, though, presents several difficulties. For example, unlike for stocks and bonds, there is no model of what commodity price levels or returns should be in a free market – making it hard to get a baseline. Another problem is the endogeneity between commodity price levels and trade policy – an issue made more severe when using monthly, quarterly, or annual data.

In this paper, we attack the question from a different angle. We investigate theoretically the impact of a supply-shock driven export ban on market uncertainty (*i.e.*, on the second moment of the price or return distribution), and we test our model's insights using a novel high-frequency dataset that combines daily information on export bans, market fundamentals, and forward-looking volatility. Our focus on uncertainty is important in its own right. It reflects the latter's relevance to commodity producers' hedging decisions and costs, as well as the first-order harm that price volatility causes to consumer welfare in emerging markets and, even more so, in developing countries (Pallage and Robe 2003).[3]

We start by asking three theoretical questions. First, after a country imposes an export ban, does commodity market uncertainty (precisely, market participants' expectations of future world price volatility) go up? Second, before a ban is even imposed, does an increase in the likelihood that a country *might* restrict international exports drive up world price volatility expectations? Third, what is the link from exogenous supply shocks and domestic political variables, to financial traders' collective view regarding the likelihood of a ban, to forward-looking world price volatility?

To answer these questions, we propose a simple political economy model that identifies conditions under which a combination of a negative supply shock (e.g., a drought or a war) and street or lobbying pressures can bring about export restrictions in a large commodity-exporting country and thereby cause (i) an increase in forward-looking price volatility in

[3] In a widely cited paper, Pallage and Robe (2003) estimate very high welfare costs of business cycles in such countries, even abstracting from the impact that volatility also has on growth. In turn, Borensztein, Jeanne, and Sandri (2013) and Lopez-Martin, Leal, and Fritscher (2019) document several channels through which commodity price uncertainty has a deleterious impact on welfare in commodity-exporting countries.

world commodity markets before a ban is announced as well as (ii) a further increase after it goes into effect. Both results are new; the second result is also counterintuitive, given that our theoretical model abstracts from the possibility of retaliation by other exporting countries – unlike in Giordani, Rocha, and Ruta (2016) – and that the news of a ban therefore resolves all previous uncertainty regarding trade policy.

We then use 2002-2019 data to test empirically our model's main prediction that price uncertainty rises after a ban is imposed.[4] We hand-collect a comprehensive daily dataset of export restrictions imposed by the governments of all major wheat, corn, and soybean producer countries from 2002 through 2019. We combine this information with data on physical fundamentals in agricultural markets, augmented with proxies for the intensity of speculative activity in commodity futures markets and for macroeconomic uncertainty and risk aversion in financial markets. Finally, to measure uncertainty in grain markets, we utilize the forward-looking volatilities implied by the prices of options on commodity futures ("IVols"). Armed with this information, we provide empirical evidence that grain IVols are significantly higher on the day/week when a ban or a major export restriction is first imposed and also during the entire period when a ban or restriction is in effect.[5]

In our theoretical model, the relationship from exogenous commodity price shock to trade restrictions to increased commodity market uncertainty is causal. We search for the bans-uncertainty relationship in the data using the following approach. First, we control for the event-day VIX (which is plausibly exogenous to grain markets) and for a previous-day term futures market-based proxy for grain supply tightness – both of which are known to drive grain IVols in the absence of export bans (Adjemian et al. 2017; Goswami and Karali 2021).

[4] We end our sample at the end of 2019 because, while numerous countries imposed commodity export bans in 2020 (amid COVID-19-related disruptions) and again in 2022 (after the Russian invasion of Ukraine), macroeconomic uncertainty in much of 2020-2022 was exceptionally high and its spillover into commodity markets might obfuscate the link between bans and commodity price uncertainty.

[5] Our empirical analysis does not investigate soybean price uncertainty, because most of the major soybean producers were actively pursuing a pro-export policy (as opposed to mandating restrictions on international trade) during our sample period. We do collect information on soybean export bans, to confirm that our results are robust to accounting for a possible cross-commodity impact of soybean bans in the corn and wheat markets.

Second, we run a placebo analysis in order to show that grain export bans are irrelevant to coffee IVols – suggesting that the grain IVol increase that we attribute to grain export bans are not a mere reflection of some broad-based increase in commodity IVols during the ban periods.

We find that the link between export bans and world price uncertainty is statistically and economically significant. Corn and wheat IVols go up between approximately one and two percentage points on the day when a major grain exporter restricts its commodity exports, and they remain elevated during the entire period when a ban is in effect. Individual grain IVols increase after restrictions imposed on exports of not only that specific commodity but also on other grains or oilseeds. These results hold even though we control for the main financial and physical drivers of grain IVols. Overall, our findings show the importance of taking political risk into account when analyzing forward-looking volatility in agricultural markets.[6]

The paper proceeds as follows. Section 2 discusses our contribution to the literature. Section 3 presents our theoretical model. Section 4 describes our dataset. Section 5 presents our econometric approach and summarizes our empirical results. Section 6 concludes. An Appendix ends the paper.

2 Literature

The present paper weaves together and extends various strands from the political economy and the international, financial, and agricultural economics literatures on trade restrictions and on volatility in the commodity space.

In the international trade literature, most papers on commodity export restrictions are

[6] When prior research on trade restrictions does look at the "volatility" or "instability" of world prices, it typically refers either to short-term price spikes (*i.e.*, price level changes) or to the range of prices over many years (or the dispersion of prices away from a long term trend). In contrast, we are interested in the impact of politically-motivated, temporary export bans on market *uncertainty* regarding future prices, *i.e.*, on forward-looking volatility. Inasmuch as we focus on forward-looking volatility, our perspective is similar to that of Chauveau and Gordon (1988), Zwart and Blandford (1989), and Larue and Ker (1993), who investigate the causal link from farm-support mechanisms or protectionism to world price uncertainty.

concerned with domestic outcomes. In contrast, we analyze the impact of an export ban in one country on the distribution of world benchmark prices. As noted in the Introduction, a number of extant papers also look at world price effects, but most focus on price levels – not price uncertainty.[7] Closer to our paper, therefore, is Ivanic and Martin (2014). Using numerical simulations of a computable general equilibrium model with and without domestic-market insulation measures, that article shows that "[i]nsulation against an *initial* price increase" in world food prices magnifies that increase "while *subsequent* adjustments to the level of protection change the fundamental nature of price volatility" (*ibid.*, p. 272; emphasis added). In contrast, we establish that market expectations of world price volatility are higher following the *one-time* imposition of an export ban by a government. We show, both theoretically and empirically, that the increase is economically significant even in situations where a single large producer imposes an export ban.

In agricultural economics, most of the research on the drivers of commodity price volatility has been empirical, focusing mostly on realized (*i.e.*, past) market volatility – see, e.g., Karali, Power, and Ishdorj (2011), Karali and Power (2013), Rude and An (2015), Bruno, Büyükşahin, and Robe (2017), Tadasse et al. (2016), and references cited therein.[8] In line with the forward-looking perspectives of financial and commodity traders, we focus instead on the market participants' expectations of future volatility that are embedded in the prices of commodity futures options (IVols). Egelkraut, Garcia, and Sherrick (2007) show that grain and oilseed IVols "anticipate realized volatilities and their (seasonal) patterns well" (*ibid.*, p.2). Adjemian et al. (2017) build on those two papers and carry out "the first

[7]For example, Martin and Anderson (2012) quantify the effects of agricultural export restrictions, arguing that they explain 45 (*resp.* 30) percent of the international rice (*resp.* wheat) price jump in 2006-2008. Using a different methodology, Giordani, Rocha, and Ruta (2016) (p. 117) find quantitatively "comparable" results.

[8]Among all those empirical papers, the only one that investigates export restrictions is Rude and An (2015). Using monthly data, those authors conclude that, after accounting for fluctuations in crude oil prices, exchange rates, and interest rates, policies that hampered grains and oilseed exports in 2006-2011 boosted the realized volatility of wheat and rice prices (but not those of corn or soybean) around their respective long-term trends. While Tadasse et al. (2016) also hypothesize that discretionary trade policies might amplify the effects of exogenous supply shocks on price spikes and price volatility, that empirical paper "focuses primarily on exogenous shocks" (*ibid.* p.119) as opposed to endogenous shock amplifiers such as trade policy responses. To the extent that they do look at endogenous amplifiers, their analysis is limited to "the (partly) endogenous factors of speculation and food stocks" (*ibid.* p.119).

empirical analysis of the extent to which grain option-implied volatilities (...) are driven by uncertainty and risk aversion in the broad economy *vs.* by developments specific to the agricultural space" such as seasonalities, weather, and the state of commodity inventories. Our analysis establishes that, over and above those factors, political considerations are highly relevant to grain IVols.

Our prediction that trade restrictions should boost forward-looking price volatility links our paper in turn to several parts of the financial economics literature. First, some recent papers analyze how local supply disruptions can affect the volatility of world commodity prices. Merener (2016), in particular, shows theoretically and empirically that the likelihood of extreme prices movements (precisely, the kurtosis of the return distribution) is increasing in the geographic concentration of a commodity's production (and, hence, its exposure to local shocks). In the same vein, Watugala (2019) documents a positive correlation between production concentration and realized price volatility.[9] Both papers' empirical approach is historical, whereas we focus on market expectations of future volatility. More importantly, neither paper considers the possibility that a link could run from political considerations, to trade restrictions, to world production concentration, to commodity price uncertainty. Our theoretical model shows that such a link should exist and should matter. Our empirical evidence, even if not causal, is consistent with the predictions of the model.[10]

A second set of finance papers investigates how political variables – e.g., governmental policy uncertainty (Boutchkova et al. 2012; Hsu, Li, and Tsou 2022), policy surprises (Pastor and Veronesi 2012) or daily variations in the intensity of street protests (Acemoglu, Hassan, and Tahoun 2018) – directly affect the level and the volatility of financial asset prices. To

[9]Further afield, Gnutzmann, Kowalewski, and Śpiewanowski (2020) provide empirical evidence that, in the highly concentrated potash market, cartelization has reduced the market impact of negative supply shocks.

[10]Anderson (2012) and Anderson (2014) examines the impact of food export bans on realized world price volatility and finds a positive association due to the thinning effect of bans on global markets. Unlike those two papers, our focus is on forward-looking price uncertainty, not on price levels or on price spikes. Furthermore, our empirical approach is different. We do not estimate yearly variations in the intensity of domestic market insulation or exploit such variations to assess short-run and long-run transmission elasticities. Instead, we develop a theoretical model and investigate its predictions using high-frequency (daily) data that allow us to precisely tease out the ban-uncertainty relationship.

our knowledge, however, the financial economics literature to date focuses on equities and ignores commodities. For agricultural staples, we show that domestic political pressures, insofar as they can or do beget short-term trade restrictions, are linked to a substantial increase in the uncertainty regarding future world prices that is reflected in the prices of options on commodity futures.[11]

Finally, our paper follows in the steps of a large political economy literature that seeks to understand why governments may restrict international trade in agricultural products, or why they impose trade-distortionary policies in general. The seminal paper is Grossman and Helpman (1994), whose theoretical framework models interest groups that lobby governments with implicit or explicit contributions in exchange for their preferred trade policies.[12]

We view a government's ban of agricultural exports through the lens of that literature, with the two opposing "lobbying groups" played by agricultural producers (who want to export their crops at the high world prices) and consumers (who demand low domestic prices for staple foodstuffs).[13]

Mitra and Josling (2009) identify circumstances in which this specific political conflict is especially salient, two of which are directly relevant in our model: when commodity prices jump to a very high level compared to domestic consumers' purchasing power, and when the

[11]Brogaard et al. (2020) document that the U.S. political cycle affects international equity prices. They surmise that the channel is from U.S. political uncertainty through investors' aggregate risk aversion. Changes in the risk preferences of financial or commodity market participants play no role in our model.

[12]Numerous papers build upon Grossman and Helpman (1994). For example, Dixit (1996) incorporates non-trade policy instruments into the lobbying framework. Early empirical tests of the model in Grossman and Helpman (1994) include Goldberg and Maggi (1999) and Gawande and Zissimos (2020): using data on U.S. trade barriers and industry-level political lobbying activity, both papers find evidence that supports the model's predictions.

[13]While the food-production sector may lobby (in the traditional sense of the word) the government for its preferred policies, consumers "lobby' ' the government as citizens – either with their votes or, sometimes, through street protest and direct threats to the government's survival. To wit, Weinberg and Bakker (2015) find that food price increases predict civil unrest in a panel of 71 countries. Other studies find a link contingent on institutional qualities of the government. Hendrix and Haggard (2015) find that cities located in democratic countries, which are more permissive of protest but also tend to favor the interests of producers over consumers, tend to experience unrest when food prices increase. Gawande and Zissimos (2020) and Gawande and Zissimos (2022) build political economy models wherein autocratic governments use export policy to satisfy the consumer lobby without having to concede any power; empirically, they find that autocratic countries are more likely to raise export taxes when food prices increase (2020) but that autocrats' success depends on the severity of the underlying output shock (2022).

government wishes to use trade policy to improve its political standing with a given group.[14] In that vein, Abbott (2012) documents cross-country differences in responses to super-high world food prices in 2007-2008: in particular, Russia, Kazakhstan, and Ukraine restricted exports in order to protect consumers, whereas Argentina and Brazil taxed exports in order to boost government revenues.[15]

We contribute to this literature in three main ways. First, we investigate the link between export restrictions and commodity market uncertainty – theoretically and empirically. Second, on the theoretical side, we explicitly integrate political considerations into the analysis of forward-looking staple food price volatility. Third, on the empirical side, we construct a uniquely comprehensive and long (spanning two decades) daily dataset of all export bans for the three major grain and oilseeds (corn/maize, wheat, and soybean), which allows us to tease out the relationship between export bans and forward-looking volatility (and, thus, future price uncertainty).[16]

[14]The other circumstances are when food imports become unreliably volatile, when there is a long gap between crop cycles, and when the government simply wishes to use tariffs to boost government revenues. Thies and Porche (2007) place protectionist policies for agricultural interests in the context of a broader political science literature on special interest groups. They find that these policies can be partially explained by the same institutional factors (for instance, a federalist system that insulates politicians from interest group pressures) that are traditionally used to explain protectionism more broadly – see also Thennakoon (2015) for a model in which trade policy is used to protect producers during downward price spikes.

[15]For a detailed history of government policies regarding grains and oilseed in Argentina and Brazil prior to 2007, see Schnepf, Dohlman, and Bolling (2001) and Deese and Reeder (2008). Gawande and Hoekman (2010) survey the trade policy of a panel of 64 countries over five decades. Among their findings is that countries with a higher share of arable land tend to pursue agricultural trade policies that hurt exporters. They posit that this is because a large share of arable land represents a large investment that, once sunk, cannot be reversed; thus, once crops are planted, the government feels free to extract rents from producers.

[16]Most of the extant datasets on trade restriction are instead much lower-frequency (often annual) in nature, and very few cover many years. For example, Croser, Lloyd, and Anderson (2010) evaluate different measures of the effects of export restrictions and develop trade restrictiveness indices as an alternative to using nominal rates of assistance or consumer tax equivalence. They use these indices in conjunction with an annual database of restrictions to estimate the impact of policy changes on trade and welfare for twenty-eight agricultural commodities. Prompted by the 2007-2008 commodity price boom, a number of other papers construct various datasets of export restrictions and look at various consequences of the latter on international markets. Solleder (2013) finds that export taxes are associated with a sizable decrease in trade, especially when imposed on extractive sectors. The effects are driven by homogeneous goods for which substitutes are more readily available. Finally, Rude and An (2015) update a dataset from Shama (2011) to show that, after accounting for the respective volatilities of crude oil prices, exchange rates, and interest rates, the intensity of export restrictions contributed to the realized volatility wheat and rice prices in 2006-2011 (but not to corn or soybean price volatility). See also Liapis (2013).

3 Model

We focus on agricultural markets characterized by the minimal processing or transformation of the commodity before its final consumption as food.[17] Examples of such staples include wheat in Russia or Egypt; sugar and onions in South Asia; white maize (corn) in Eastern Africa; etc.

World demand for these commodities is price-inelastic in the short term (Roberts and Schlenker 2013; Sayre and Fally 2019). For modeling purposes, we assume that the price elasticity of demand $\eta < 1$ is constant and the same in all countries.

Our objective is to model the impact (in particular, on world price uncertainty) of an export ban that the government of a staple-producing country might impose in reaction to a bad shock to its crop. In our model, a bad weather realization plays the role of the trigger. Our model, however, is more general than this specific choice implies: it encompasses other types of supply shocks, such as the sudden inaccessibility of an exporter country's grain inventories amid a war.

The production cycle of the agricultural commodities that we consider is annual. In a given year, it can be stylized as follows. First, planting takes place, at which point each country's forecasted share α of the expected world harvest (*i.e.*, of the final output) becomes common knowledge. In other words, once planting has taken place, the die is cast: production this year cannot be increased anymore. Next, the weather determines each country's crop progress and condition. Finally, the crops are harvested and international trade takes place. Grain inventories that have been carried over as stocks from previous years are assumed known at all times, and are included in the total quantities available for trading and consumption post-harvest.

Partway through the growing season, the government of a commodity-producing country

[17] For this reason, the model presented in this Section focuses on the tension between the interests of producers and consumers of the commodity whose export is being restricted. We leave for further work political considerations related to possible conflicts between the respective interests of these two types of agents and those of a transformation/refining/manufacturing sector.

("The Country") decides whether to impose an export ban. This decision depends on realized domestic and international weather shocks to date, expected future weather shocks, and domestic political considerations. For tractability, we abstract away from the possibility that other producing countries ("The Rest Of the World" or ROW for short) might impose bans, too.[18]

Figure 1 summarizes the sequence of events in our model. Planting takes place in Period I. Then, the weather impacts the progress and condition of the Country's and ROW crops. Without loss of generality, we assume that the Country's weather is realized first – at the beginning of Period II.[19] Following that first "shock," all market participants view any remaining uncertainty regarding the Country's weather (and thus its harvest this year) as negligible. However, at the beginning of Period III, the Country's government decides whether or not to restrict exports to the ROW. To keep the intuition transparent, we restrict that policy decision to a binary choice between (i) banning exports fully or (ii) allowing international trade to remain completely free of any impediment.[20] Finally, before harvesting starts in Period IV, the ROW experiences its own significant weather shock. Without loss of generality, we assume that the ROW's weather shock is uncorrelated with the Country's.

The remainder of Section 3 proceeds as follows. In Section 3.1, we characterize what the commodity IVol time path would be in a world where in which governments cannot limit or tax international trade. In Section 3.2, we allow for such governmental interventions. We show that the IVol goes up *after* the Country imposes an export ban even though this decision resolves all the prior policy uncertainty. In Section 3.3, we then show how the possibility that such a ban may take place also boosts the commodity IVol *before* the actual ban is announced. Finally, in Section 3.4, we link the likelihood of a ban to political economy variables.

[18]See, e.g., Bouët and Debucquet (2010); Giordani, Rocha, and Ruta (2016); and Jensen and Anderson (2017) for analyses of "beggar-thy-neighbor' ' international policy-response cycles.

[19]The model's predictions remain qualitatively similar if we reverse the order of the weather developments in the Country and in the ROW.

[20]Allowing the government to implement a partial ban or to impose export taxes or quotas complicates the analysis mathematically without adding significantly to the main insights.

3.1 Commodity Price Volatility in a World without Trade Restrictions

As noted above, the weather impacts the progress of crops both in the Country and in the ROW. In this sub-Section, we characterize how the forward-looking volatility of a commodity's world price (IVol) would evolve from Period I through Period IV if it were common knowledge that no country would ever impose any trade restriction.

Let Q^C denote the harvest in the Country and Q^{ROW} denote the harvest in the ROW. The world's total harvest this year is thus $Q^W = Q^C + Q^{ROW}$. For tractability, we assume that the Country's harvest can either be high (Q_H^C) or low (Q_L^C), with *ex-ante* probabilities γ and $(1-\gamma)$ respectively. Likewise, the ROW harvest can be either high (Q_H^{ROW}) or low (Q_L^{ROW}), with *ex-ante* probabilities ρ and $(1-\rho)$ respectively. These probabilities are exogenous and common knowledge.

In this environment, we readily obtain the following results:

- Since the successive weather shocks in the Country and in the ROW are posited to be uncorrelated, the forward-looking variance of world output in Period I (at planting) is:

$$\sigma_{t=1}^2(Q^W) = \gamma.(1-\gamma).[Q_H^C - Q_L^C]^2 + \rho.(1-\rho).[Q_H^{ROW} - Q_L^{ROW}]^2 \tag{1}$$

- At the beginning of Period II, any uncertainty regarding the Country's weather gets resolved. Hence, the forward-looking variance of world output in Period II drops to:

$$\sigma_{t=2}^2(Q^W) = \sigma_{t=2}^2(Q^{ROW}) = \rho.(1-\rho).[Q_H^{ROW} - Q_L^{ROW}]^2 \tag{2}$$

- While $\sigma_{t=2}^2(Q^W)$ is independent of Q^C, the quantity expected to be harvested worldwide is not – and so the percentage standard deviation of the world output is inversely related to Q^C:

$$\frac{\sigma_{t=2}(Q^W|Q^C = Q_H^C)}{E_{t=2}(Q^W|Q^C = Q_H^C)} = \sqrt{\rho.(1-\rho)}.\frac{Q_H^{ROW} - Q_L^{ROW}}{Q_H^C + E(Q^{ROW})} \tag{3}$$

$$< \sqrt{\rho.(1-\rho)}.\frac{Q_H^{ROW} - Q_L^{ROW}}{Q_L^C + E(Q^{ROW})} = \frac{\sigma_{t=2}(Q^W | Q^C = Q_H^L)}{E_{t=2}(Q^W | Q^C = Q_L^C)} \tag{4}$$

- **Lemma 1**: The percentage forward-looking volatility of prices in Period II is higher when the Country's weather is bad ($Q^C = Q_L^C$) than when it is good ($Q^C = Q_H^C$).

While the proof of Lemma 1 is mathematically immediate from the fact that the price-elasticity of demand ϕ is less than 1, it is worth stressing the intuition behind it: a bad productivity shock (in this case, weather) in a commodity-producing country concentrates the remaining output, which brings about an increase in the percentage volatility of world output and, hence, in IVols. The same intuition underpins the following result:

Lemma 2: The forward-looking volatility of world prices is decreasing in the amount of leftover stocks carried over from years past.

Proof: Let $\Delta > 0$ be the fixed, known quantity of worldwide grain stocks carried from prior years that will be available to supplement this year's world harvest in Period IV. From Equation (2), when $\Delta = 0$, the forward-looking volatility of the world output in Period II is $\sigma^2_{t=2}(Q^W) = \rho.(1-\rho).[Q_H^{ROW} - Q_L^{ROW}]^2$. Having $\Delta > 0$ available for world consumption raises the total available supply in Period IV equally in the high (H) and low (L) ROW harvest states. Hence, conditional on $Q_i^C (i = L, H)$, the level uncertainty regarding the total grain supplies that will be available in Period IV is constant $\forall\Delta$ – but the percentage uncertainty, $\rho.(1-\rho).[(Q_H^{ROW} - Q_L^{ROW})/(E(Q^{ROW}) + Q_i^C + \Delta)]^2$, is decreasing in Δ. By definition of a price-inelastic demand, the percentage volatility of prices is greater than the percentage volatility of output. Hence, the world-price IVol is decreasing in Δ. ■

If it is common knowledge that trade will never be restricted, then the IVols are the same in Periods II and III. The next sub-Section explains how this result changes, if a ban is imposed at the start of Period III.

3.2 *Post*-Ban Commodity Price Volatility

The effect of an export ban is to disconnect commodity prices in the Country from those in the ROW. Our specific interest is in how such a ban impacts market participants' uncertainty regarding future world prices, *i.e.*, the IVol in the ROW. In this sub-Section, we focus on how the latter would evolve from Period II to Period III, *i.e.*, following the Country's decision to impose an export ban.

If, absent any trade restrictions, the Country were always a net importer in equilibrium, then the question of the ban's impact would be moot. We therefore assume that, in the world without bans of sub-Section 3.1, the Country is a net exporter in at least one state of the world.

Intuitively, the Country's export ban should have an effect on market uncertainty similar to that of a drop in inventories (Lemma 1): by cutting the total supply available to the ROW in Period IV, it magnifies the relative importance of the (future) ROW weather shock for world prices. The formal proof is slightly less straightforward than that of Lemma 2 because, while inventories carried from the prior year are a known constant, the net exports X^C that would take place from the Country to the ROW in the absence of a ban are not.

Let $X^{C,i}_{ROW,j}$ denote those net exports when its own crop is $Q^C = Q^C_i$ (where $i = H$ or $i = L$) and the ROW's output $Q^{ROW} = Q^{ROW}_j$ (where $j = H$ or $j = L$). $\forall i, X^{C,i}_{ROW,j}$ is a function of the harvest in (and of the state of inventories in) the ROW: *ceteris paribus*, $X^{C,i}_{ROW,L} > X^{C,i}_{ROW,H}$. Thus:

Lemma 3: If it is common knowledge that, *conditional on the domestic weather shock* (*i.e.*, upon learning the future value of Q^C), the Country will impose an export ban, then the IVol after the ban (in Period III) is higher than it would have been under free trade. The magnitude of that increase is (a) inversely related to the price elasticity of demand for the commodity in the ROW, (b) positively related to how badly the ROW's harvest can fail, (c) inversely related to pre-existing stock levels in the ROW, and (d) positively related to the pre-ban share (denoted α) of the Country in the world trade of the commodity.

Proof: Let $\Delta^{ROW} > 0$ be the fixed, known amount of grain stored from prior years in the ROW. This inventory will be available in the ROW to supplement this year's harvest in Period IV. We know from sub-Section 3.1 that the percentage uncertainty in Period III regarding the supply that would be available to the ROW under free trade in Period IV is:

$$\frac{\sigma_{t=3}(Q^{ROW}|Q^{C,i})}{E_{t=3}(Q^{ROW}|Q^{C,i})} = \sqrt{\rho.(1-\rho)}. \frac{[Q_H^{ROW} - Q_L^{ROW}] + [X_{ROW,H}^{C,i} - X_{ROW,L}^{C,i}]}{[\rho Q_H^{ROW} + (1-\rho)Q_L^{ROW}] + [\rho X_{ROW,H}^{C,i} + (1-\rho)X_{ROW,L}^{C,i}] + \Delta^{ROW}} \tag{5}$$

In this setting, there are two possible cases to consider: (I) $X_{ROW,L}^{C,i} > X_{ROW,H}^{C,i} > 0$ (*i.e.*, absent trade restrictions, when $Q^C = Q_i^C$ the Country would always be a net exporter to the ROW) and (II) $X_{ROW,L}^{C,i} > 0 > X_{ROW,H}^{C,i}$ (*i.e.*, absent trade restrictions, if $Q^C = Q_i^C$ then the Country would be a net exporter to the ROW only if the ROW harvest failed).

In case (I), the denominator of Equation (5) is clearly smaller, and its numerator is clearly bigger, when $X_{ROW,L}^{C,i} > X_{ROW,H}^{C,i} > 0$ (no ban) than when $X_{ROW,L}^{C,i} = X_{ROW,H}^{C,i} = 0$ (ban). In case (II), recall that an export ban has bite only if the Country's exports are positive, not if is is a net importer: therefore, the denominator of Equation (5) is again lower, and its numerator is again higher, when $X_{ROW,L}^{C,i} > 0 > X_{ROW,H}^{C,i}$ than when $X_{ROW,L}^{C,i} = 0 > X_{ROW,H}^{C,i}$. Since the price elasticity of the demand for the commodity $\phi < 1$, the percentage volatility of prices is greater than the percentage volatility of output. Hence, the world-price IVol increases after a ban.

The comparative statics are immediate: (a) follows from the definition of an elasticity; (b) and (c) both follow from Equation (5); and (d) follows from the fact that an increase in α is equivalent to an increase in the term $[\rho X_{ROW,H}^{C,i} + (1-\rho)X_{ROW,L}^{C,i}]$ in the denominator of Equation (5).■

3.3 *Pre*-Ban Commodity Price Volatility

In sub-Section 3.1, the world always operated under free trade: there was no possibility that the Country's government might impose an export ban. In this sub-Section, we ask how the IVol would change in Period II if the market were to learn that, at the beginning of Period III, there is instead a probability $\beta > 0$ that the Country's government *might* decide to impose an export ban.

We derive the determinants of β in sub-Section 3.4. In the present sub-Section, we take β as a given exogenous parameter.

Lemma 4: Before exports are banned, the IVol increases with the likelihood β of a ban.

Proof: From sub-Section 3.1, we know that the IVol would be the same in Periods 2 and 3 if the probability of a ban were $\beta = 0$. From Lemma 3 in sub-Section 3.2 we know that, for a given realization of the Country's weather at the beginning of Period II, the IVol rises in Period III after a ban is imposed above what it would have been in the absence of a ban. It follows that the IVol in Period II is increasing in β. $\blacksquare$

Notice what Lemmata 3 and 4 together imply: not only does the forward-looking volatility of (*i.e.*, the uncertainty regarding) the future price of the commodity increase in the probability β of a ban before an actual ban is announced, but the news of the ban itself (*i.e.*, the fact that β becomes 1) further boosts that forward-looking volatility even though it resolves all previous uncertainty regarding the Country's trade policy.

3.4 Political Economy of a Ban

In fall 2019, after a drought that had hurt the previous onion crop and amid exceptionally abundant monsoon rains hurting the new crop amid low inventories, India banned the export of onions (a South Asian diet staple) "with a view to improve domestic availability and control prices."[21] This ban caused consumer angst and fury in several countries that usually import Indian onions, such as Bangladesh. More importantly for our story, it also brought Indian farmers to the streets: indeed, in March 2020, India again allowed onion exports "in the interest of farmers. This decision will increase the income of farmers."[22]

This episode illustrates the domestic political economy trade-off that we seek to capture. Since the agricultural commodities that we model are not substantially processed or transformed between harvest and consumption, the Country's government faces two big domestic constituencies concerned by their prices: producers, who want higher prices; and consumers, who want the opposite.

We could assume that the government maximizes some weighted average of these two domestic constituencies' aggregate expected utilities. Alternatively, we could assume that the government maximizes its expected welfare under the constraint of staying in power – the likelihood of which is influenced by how it responds to these two groups' respective interests. In a seminal paper, Grossman and Helpman (1994) present a model of how special interest groups can use political contributions to influence an incumbent government's trade policy. Rather than write a formal constrained-optimization model of the government's decision-making in the presence of uncertainty regarding future weather developments and thus a ban's impact on post-harvest prices, we build on the findings in that paper (and in the massive literature it has spawned) and simply posit that there exists a world price level in Period II, say P^*, above which the Country's government always imposes a ban because the pressures and political contributions of producers are not able any more to counter the government's fear of removal in upcoming elections (or amid food riots) at the hands of consumers distraught by high prices.

In our model, all participants share the same information as the Country's government about the current and expected future weather and about inventories. In this setting, the

[21] Consumer Affairs Secretary Avinash K. Srivastava as quoted by the Times of India, September 29, 2019.

[22] Indian Commerce and Industry Minister Piyush Goyal tweet as quoted by the Times of India, March 2, 2020.

uncertainty regarding the government's decision (of whether or not to ban exports) arises from the fact that financial traders and other government observers are unsure about the government's utility function, *i.e.*, the effective weight that it puts on the respective expected utilities of consumers *vs.* producers.

Put differently, while the government knows P^* with certainty, the market does not: for any level of $P^W_{t=2}$, the market believes that there is a probability β that the government will impose a ban (if $P^* \leq P^W_{t=2}$) and a probability $1 - \beta$ that it will not (if $P^* > P^W_{t=2}$). Figure 2 plots the probability of an export ban (the shaded area under the curve) as a function of the world price in Period II, $P^* \leq P^W_{t=2}$.

Note that, *ceteris paribus*, P^* is inversely related to Q^C, $E_{t=2}(Q^W)$, and Δ. That is, the Country's government has a greater incentive to impose a ban (a) when $Q^C = Q^C_L$ than when $Q^C = Q^C_H$; (b) when the expected ROW harvest is poor; and (c) when domestic and ROW inventories are low. It follows that:

Lemma 5: The probability β of an export ban is inversely related to Q^C, $E_{t=2}(Q^{ROW})$ and Δ.

Proof: Follows from the fact that β is increasing in $P^W_{t=2}$. ■

We are now in a position to summarize the predictions of our theoretical model.

Proposition: The uncertainty regarding future staple food price levels at harvest time (the commodity IVol) increases following a bad weather shock during the growing season in a large producer Country. The possibility that the Country's government might mandate an export ban boosts the IVol further. Following the adoption of a ban, the IVol increases even more.

Proof: Immediate from Lemmas 1 to 5. ■

4 Data

Our model predicts that price volatility expectations in grain markets are amplified by export bans after they are imposed. To investigate empirically the relationship between bans and market uncertainty, we construct a novel dataset combining market data and political economy information.

Section 4.1 starts by compiling daily information on options-on-futures implied volatilities (IVols) to capture price uncertainty in agricultural markets. Section 4.2 combines this information with data on physical (fundamental) conditions in agricultural markets, and augments it further with proxies for the intensity of speculative activity in grain futures markets and for uncertainty and risk aversion in financial markets. The information gathered is predicated on the findings of Bruno, Büyükşahin, and Robe (2017) regarding the main physical and financial drivers of agricultural IVols at the daily and weekly frequencies.

On the political side, we innovate by hand-collecting high-frequency (daily) information about restrictions on wheat, corn, and soybean exports that were announced, adopted, or repealed between 2002 and 2019. Section 4.3 describes our resulting dataset, covering all substantial export restrictions in major producer countries during that time period.

4.1 Market Data: Commodity IVols, Futures Prices, and Market Activity

We use data from the U.S. markets where the bulk of world price discovery takes place for corn and wheat (Janzen and Adjemian 2017). For each commodity, we construct a daily time series of the term structures of (i) futures prices and (ii) IVols based on Chicago Board of Trade (CME Group) settlement prices for futures and options-on-futures contracts.

We obtain our market data from Bloomberg: term structures for the daily grain futures prices, IVols computed by Bloomberg using the prices of European options on those futures,[23]

[23] Ederington and Guan (2002) and Wayne, Lui, and Wang (2010) establish several technical advantages of using Bloomberg option-implied volatility estimates compared to other estimates. Cao and Robe (2022)

as well as the trading volume and open interest for both futures and option contracts. The Bloomberg IVol series for a given maturity are based on the daily closing prices of the most actively traded option contracts for that maturity, *i.e.*, on at-the-money options for that maturity (Cui 2012).[24]

Our econometric analyses focus on the "nearby" futures and options on futures because near-dated IVols are theoretically the most sensitive to the arrival of new information ((Ederington and Lee 1996). We define the "nearby" futures (and, likewise, options-on-futures) for each commodity as the prompt (*i.e.*, the nearest-dated) contract until the latter approaches expiration and the preponderance of the open interest switches to a deferred contract. Choosing contract roll dates based on open interest (rather than on the closest expiration date) minimizes the likelihood that the "nearby" IVols could artificially jump due to low liquidity around prompt-contract expiration dates or due to transition between contract months with historically very different liquidity levels.[25]

We collect these daily data from Bloomberg for the period 2002-2019. Our sample starts in 2002 because data on export bans in earlier years is spotty – see Section 4.3 below. Some of the commodity IVol drivers identified by Adjemian et al. (2017), which we discuss below, are only available weekly. For weekly analyses that control for those drivers, we sample IVols on Tuesdays. If a given Tuesday is a holiday, then we use the following Wednesday; if that Wednesday is also a holiday, then we use the prior Monday.

---

point out a practical advantage of using Bloomberg IVols: doing so makes analyses easily reproducible.

[24]In the rare occasions when an IVol value (*resp.* futures price) is missing from the Bloomberg dataset for the three first days of a given week even though the relevant options (*resp.* futures) were traded on one or more of those three days, we use interpolation to fill the gap.

[25]Our method almost always amounts to selecting the nearest maturity listed on Standard and Poor's S&P GSCI's investment schedule for a given commodity.

4.2 Physical Market Fundamentals and Global Financial Market Information

Covindassamy, Robe, and Wallen (2017) and Adjemian et al. (2017) document that, in agricultural commodity markets, market expectations of future price volatility rise and fall with a specific set of economic and financial market variables. In order to tease out the relation between commodity IVols and export bans, our empirical analysis must therefore control for those non-political factors.

4.2.1 Daily Data

A key driver of commodity option-implied volatilities is the level of the Chicago Board Options Exchange (CBOE) Volatility Index or VIX, which is constructed using the implied volatilities of options on Standard and Poor's S&P 500 equity index. Intuitively, this is because the VIX jointly captures financial market participants' uncertainty about global macroeconomic conditions (which affect the demand for commodities, in the present case grains) and to investor risk aversion (which permeate both commodity and equity markets) – see Bekaert, Hoerova, and Duca (2013). We obtain daily VIX values from Bloomberg; for the weekly analyses, we sample the VIX on Tuesdays.

Our second daily control variable is commodity-specific. First, as we show theoretically in Section 3 and as Robe and Wallen (2016), Covindassamy, Robe, and Wallen (2017), Adjemian et al. (2017), and Goswami and Karali (2021) establish empirically using data from the mid-1990's to 2019, a commodity's forward-looking price volatility is inversely related to the level of commodity inventories. Intuitively, price volatility is high when stocks are low. Consistent with the forward-looking nature of our analysis, we use market expectations of future storage levels that are embedded in the slope of the term structures of futures price at the market close each day. We follow Bruno, Büyükşahin, and Robe (2017), and express that measure (denoted *Slope*) as an annualized percentage of the nearby futures price and net of interest rate costs (90-day LIBOR). Effectively, *Slope* captures each commodity's net cost of carry (*i.e.*, storage costs minus any convenience yield). We also control for trading volume and time to maturity of the nearby contract. In the physical space, we can control for weather-related supply shocks (summarized through the USDA's weekly progress and condition indices for different crops) and for several one-off exogenous shocks relevant to grain prices (the 2005 biofuel mandate, and the mad cow and swine flu epidemics).

Figures 3 and 4 plot, respectively, the daily nearby CBOT No. 2 corn and soft red winter (SRW) wheat IVols against (i) the VIX and (ii) the commodity's own *Slope*, which is our futures-based proxy for market tightness in that commodity space. Across all days in our 2002-2019 sample, the average IVol is 29.4% for wheat and 27% for corn. It is clear from those two figures that both of these commodity IVols are (i) positively correlated with the VIX, which averages 19% in our sample period, and (ii) negatively correlated with the matching *Slope*.

4.2.2 Weekly Data

In our weekly analyses, we consider some more control variables that are not available at the daily frequency. On the financial side, we use aggregate data on commodity futures trader positions that are published weekly by the market regulator (the CFTC) in order to capture the intensity of speculation in each grain futures market. Precisely, we use the *T Index of Speculative Activity* from Working (1960), a measure that is widely used in the financial and agricultural economics literatures.[26]

To construct those weekly variables, we follow methodologies described in Bruno, Büyükşahin, and Robe (2017). We use public data from the U.S. Commodity Futures Trading Commission (CFTC) and the USDA.

[26] This measure has been widely used in the literature, and Sanders, Irwin, and Merrin (2010) document its continued usefulness in capturing speculation in agricultural futures markets. Büyükşahin and Robe (2014) use non-public CFTC data to document that changes in the T index (computed using the same public CFTC data as in the present paper) capture changes in hedge fund activity.

4.3 Export Bans Data

An important contribution of our paper is the development of a granular database of export restrictions in the past two decades (2002-2019). We build on prior work by a number of authors, and we draw from multiple newspapers and other sources, to create a daily database of all legal restrictions imposed by the governments of major wheat- or corn/maize-producing countries on exports of these commodities. Our dataset is comprehensive, including for instance the day of implementation and the circumstances surrounding the restrictions' implementation.

Among prior studies of export restrictions, we choose three starting points: Shama (2011), the OECD export restrictions database, and the AMIS (Agricultural Management Information System) database. We combine the information from those three sources to start the construction of the part of our database covering 2004 to 2012. Shama (2011) lists restrictions by month of their occurrence, while the other two sources provide an exact day when a measure took effect. For each restriction listed in one or more of these three databases, we then hand-search the Lexis-Nexis archive of news publications for all available English-language sources in order to identify the exact date and time when the restriction comes into effect. We then confirm this English-language information by drawing on local-language sources.

In 2012-2019, as well as in 2002-2004, information from Shama (2011), the OECD, and AMIS is sparser. We therefore run general Lexis-Nexis searches; we draw also on the USDA Foreign Agricultural Service's Grain and Feed Annuals, which summarize trends in agricultural production, consumption, stocks, prices, and trade by country. Again, we complement this information through searches of newspapers in English and local languages.

We focus our efforts on major non-Western grain and oilseed producers and exporters, as identified by USDA: Ukraine, Kazakhstan, Russia, Argentina, Bolivia, Brazil, Paraguay, Uruguay, India, Pakistan, and China. For each country, we focus on major changes in export rules: restrictive export quotas, large export duties (40 percent or higher), official total export bans, and unofficial export stoppages and measures not specifically aimed at stopping exports but which had that effect (such as lawsuits challenging export quotas that led to temporary stoppages). We exclude non-governmental actions that also led to export stoppages, such as labor strikes that affect transportation. Some of our specifications involve the duration of a restriction as well as its date of implementation. We note such durations when a clear end date for the period is available, and when the measure is not superseded by a different restriction.

Some restrictions are announced and immediately implemented. In other cases, a measure might be implemented and then quickly changed or cancelled, or it might be announced well ahead of its date of implementation. We note the announcement date of the measure (in some cases where there is an argument regarding the exact date, we provide the date that we consider to be the most credible); that is, the date when legal hurdles to the measure's implementation seem to have been cleared and after which there are no more changes before implementation.[27]

Table 1 summarizes our export ban dataset. It shows, at least in our sample period, that different countries behave differently with respect to how they use and implement restrictions on exports. For instance, Argentina tends to use quotas to open trade opportunities rather than to close them; a *de facto* restriction on grain exports is generally the default until the government opens a quota for a specific amount of exports. When this quota is exhausted, exports are restricted again until the next quota is imposed. Thus, while quota announcements in Argentina are frequent, we do not include Argentinian quotas in our list of events. Meanwhile, restrictions in Ukraine are typically accompanied by informational noise preceding their actual imposition. In our sample period, different branches of the Ukrainian government (the agricultural ministry, the parliament, the court system, etc.) exhibit different preferences regarding trade restrictions, and an announcement by one branch does not necessarily mean that a restriction will be supported or upheld by the other branches. In

[27]Exploring the impact of information *vs.* implementation is beyond the scope of the present paper.

other cases, exporters will complain of a *de facto* restriction (for instance, cargo ships being kept in ports by government fiat) while the government denies the existence of a *de jure* restriction. In a few cases, this state of affairs makes it difficult to identify an incontrovertible date for the imposition of export restrictions in Ukraine – making it advisable to establish robustness to the choice of date.[28]

5 Empirical Evidence

We use the variables introduced in Section 4 to relate major export restrictions and grain IVols. In all cases, we run estimations for 2002-2019. Section 5.1 discusses our empirical methodology. Section 5.2 summarizes the results. Section 5.3 establishes robustness.

5.1 Econometric Considerations

To study the link between grain IVols and export bans, we need a model of commodity IVols on a day-to-day basis. The model that we use to that effect is inspired by the empirical findings of Adjemian et al. (2017) regarding the drivers of agricultural IVols. In essence, we regress the daily or weekly commodity IVol on the VIX, the state of the physical market implied by the futures cost of carry, and several controls for trading activity in the commodity futures market using the model

$$IVol_t = \alpha + \beta ban_t + \mathbf{X}\gamma + \epsilon_{\mathbf{t}}$$

[28] Two episodes (one in 2006 and one in 2010) are particularly complicated. In 2006, a series of conflicting events complicate our analysis. On September 29 of that year, the Ukrainian government introduced an export licensing requirement for wheat. That measure was formally registered on October 7, but no licenses were actually issued until October 17. Meanwhile, in late September and early October, various government officials discussed the need for a "strategic" grain reserve. On October 12, a quota was announced. A resolution announcing the quota was published on the 17, at which point licenses were issued. However, the legality of the quota was challenged, and exports were halted on November 3. Another quota was announced on December 4 that finally took effect on December 14. In 2010, a quota was planned in August 2010 but was postponed; instead, one was implemented in October of that year. Depending on how credible the market believed the postponement to be, we may or may not expect information to have been incorporated in the intervening two months.

where $IVol_t$ is implied volatility in period t; α is an intercept term; β is the covariate on a dichotomous variable ban_t, which captures information about the timing of an export ban (described below); γ is a vector of covariates on a vector $\mathbf{X}$ of control variables; and ϵ_t is an error term.

We use levels for the independent variables (IVols) and the main explanatory variables (the VIX, and the state of the physical market as proxied by the term structure (*Slope*), and first-differences for two other explanatory variables that capture market activity (Working's T index of speculative intensity, volume, and time-to-maturity of the nearby contract).[29]

We run regression analyses using ordinary least squares (OLS). We run two sets of analyses: daily and weekly. Regressions at the daily frequency allow us to capture the impact of a ban as soon as it happens and, thus, to exploit to the greatest possible extent the granularity of our unique dataset. At the daily frequency, however, some controls are not available because public data regarding crop progress and conditions (USDA) and speculative positions in commodity markets (CFTC) only exist at the weekly frequency. For each specification of our export bans variable (dummies of whether a ban starts or is in effect, and alternative variables that weigh dummies by the world trade share of all countries starting or continuing a ban on a given day), we therefore proceed in two steps. First, we run daily regressions that project each grain IVol on the relevant ban variable as well as the *VIX* (contemporaneously, as agricultural export bans do not drive global macroeconomic uncertainty), the commodity futures term structure *Slope* (lagged one period to avoid possible endogeneity issues), the nearby contract's time-to-expiration (in order to control for the Samuelson (1965) effect), and the first-differenced trading volume (as is typical when volatility is the dependent variable). Second, we run weekly regressions that also control for the level of speculative activity (Working's T). All specifications are shown with robust standard errors following Newey and West (1987).

The main independent variables in the analysis are the initiation or the existence of

[29]Augmented Dickey Fuller (ADF) unit root tests show that all of the variables in our regressions are stationary in our sample period.

an export ban. Using the information gathered in Section 4.3, we start by constructing two dummy variables for each grain. The first dummy, denoted *Start of Ban*, takes the value 1 on the day of the grain export restriction's coming into effect and 0 otherwise. The second dummy, denoted *Ban in Place*, takes the value 1 for the duration of the grain export restriction (starting on the day of the grain export restriction's announcement) and 0 otherwise.

For weekly analyses, we define our *Start of Ban* and *Ban in Place* dummies based on whether the export ban was, respectively, announced or effective as of that week's Tuesday. Intuitively, because we sample weekly data on Tuesdays, market reactions to news may be captured in the week after a restriction is announced if it is announced on a Wednesday through Saturday. Therefore, we time the weekly dummies based on the first Tuesday after a restriction is announced.

Finally, it is intuitive that the impact of an export ban should increase with the magnitude of the trade flow impacted by trade restrictions. We therefore also compute, as an alternative to the above 0-1 dummies, a continuous variable that first multiplies each country's 0-1 *Start of Ban* or *Ban in Place* dummy by that country's 2002 share of world exports (for the commodity impacted by the ban effective that day) and then sums up those products.

5.2 Findings

Consistent with our initial intuition and the prediction of our theoretical model, we find an economically and statistically significant relation between export restrictions (in major producing and exporting countries) and forward-looking commodity price volatility.

Panel A (*resp.* B) of Table 2 reports the results of the daily (*resp.* weekly) OLS regressions of the corn (Models 1 and 2) and wheat (Models 3 and 4) IVols on the *VIX*, on a proxy for the tightness of physical-market supply including inventories (the *Slope* of the commodity's futures term structure), and on a dummy variable *Start of Ban* that equals 1 on the day (Panel A) or week (Panel B) when an exporting country implements a new export ban (see

Table 1) and 0 otherwise. Models (2) and (4) show that the results are robust to including two additional variables: the intensity of financial speculation in futures markets, T, and the change in option trading volume. All models account for the Samuelson (1965) effect by controlling for the time-to-maturity of the options used to compute the commodity IVols. Table 3 carries out the same analysis as in Table 2, but with the dummy variable *Ban in Place*.

In those two commodity markets, Table 3 shows that, in the aftermath of an export ban, the commodity IVols are up significantly by approximately 0.8 (*resp.* 1.43 to 2.05) percentage points on the day (*resp.* week) when the ban is first implemented – which is equivalent to three (*resp.* five to seven) percent of the average IVol in the whole sample period.

Table 3 shows that the commodity IVols remain statistically significantly elevated for the entire duration of the ban: to wit, Panel B of Table 3 shows that corn (*resp.* wheat) IVols are half (*resp.* three quarters) of a percentage point higher during weeks when a grain export ban is in effect, and that this increase is statistically significant at the one percent level of significance regardless of the model specification.

Those results are all the more remarkable that our analysis controls for the tightness of supply (including inventories) in the physical market for each commodity in the immediate runup to the ban, for the contemporaneous intensity of global economic uncertainty and risk aversion (jointly captured by the VIX), and also for lagged values of the commodity IVol.[30] In other words, when market uncertainty is already very high (since bans come about in response to very tight physical market conditions) and thus commodity IVols are already elevated, Tables 2 and 3 establish that a substantial increase in commodity market uncertainty follows governments' policy decisions: the average cost of hedging (for market participants who use options) is up by roughly five to seven percent following a ban.

[30] Consistent with the findings of Adjemian et al. (2017), we find that commodity IVols are statistically significantly positively related to the VIX (a proxy for risk aversion and global economic uncertainty) and lagged volume change (a proxy for information arrival), and inversely related to time-to-maturity (due to the Samuelson 1965 effect).

5.3 Robustness

We establish the robustness of our findings through several exercises.

First, we replace the 0-1 export ban dummies (*Ban in Place* and *Start of Ban*) from Tables 2 and 3 with alternative variables that tally up the number of countries that declare a ban (or have a ban in effect) on a given day or week and weigh that total by each banning country's 2002 share of world exports of the commodity impacted by the ban. Table 4 (*resp.* Table 5) shows that the daily (*resp.* weekly) results are qualitatively similar to those of Table 2 (*resp.* Table 3).

Second, we run a placebo analysis to rule out the possibility that the commodity IVol increase that we tie to grain export bans is not a mere reflection of a generalized increase in commodity market uncertainty (not just grain IVols) during the ban periods. Intuitively, there is no reason why coffee price returns should be related to the onset of a grain export ban (or, for that matter, to a ban on the export of virtually any commodity other than coffee). To that effect, we focus on the coffee market. We therefore repeat the analysis, using a model of coffee IVols proposed by Covindassamy, Robe, and Wallen (2017) that we augment by our ban variables. Table A1 in the Appendix shows that, as expected, coffee IVols are not statistically significantly different when grain export bans are declared or in effect.

6 Conclusion

The present paper provides the first theoretical and empirical investigation of the link between export bans and commodity market uncertainty. We propose a simple model that predicts, and we provide empirical evidence, that uncertainty regarding the future world price of food staples is higher following export bans in top producer countries. In order to investigate empirically our model's predictions, we extract options-on-futures implied volatilities (IVols) to capture price uncertainty in corn and wheat markets. To exploit the high frequency of our market data, we construct a novel, detailed dataset of all major restrictions on agricultural exports that have been announced, adopted, or repealed since 2002 by the world's ten largest grain producers.

Using this daily, country-level information, we document that grain IVols are significantly higher on the day and the week when a ban is first imposed and also during the whole period when the ban is in effect. The increase is statistically and economically significant. The results hold even when we control for global macro-economic uncertainty and risk aversion (jointly captured by the equity VIX) and for supply tightness in the physical market (including the state of grain inventories) prior to the ban. Our results demonstrate the importance of taking political risk into account when analyzing forward-looking volatility in commodity markets.

Our findings suggests several promising venues for further research. First, our model focuses on agricultural staples. For those commodities, very little processing is necessary before consumption, and so the government only needs to weigh the needs of two constituencies: producers and consumers. A natural extension is to commodities that may be used as an intermediate input into the production of another internationally-tradable product (e.g., cotton and other natural fibers that can be exported as raw materials or made into textiles prior to domestic sales and international exports), or when the commodity could be consumed locally or transformed prior to export (e.g., natural gas may be used as such domestically, refined into plastics and fertilizers, or exported in either state of transformation). In such a setting, the government's decision to restrict exports of a raw material must trade off the interests of three groups of domestic constituents: commodity producers, transformers, and consumers. Our analysis, as well as the work of Gawande, Krishna, and Olarreaga (2012) on lobbying competition about import tariffs along the value chain, together point to a possible roadmap for capturing this more complicated environment.

Second, our empirical analysis shows what happens to commodity market uncertainty after an export ban is imposed. *After* a ban is declared, our model predicts that commodity

IVols should rise. *Before* the ban, furthermore, it also predicts that these same IVols should rise (*ceteris paribus*) in line with the perceived probability of a ban. We leave for further research a couple of important questions related to what happens before a ban. On the theoretical side, a natural question is the impact of market participants' doubts regarding the government's policy preferences (in particular, how the government weighs the conflicting interests of its two constituencies), and of the credibility of policy makers' statements regarding future trade policy, on the link between politics, ban likelihood, and *pre*-ban commodity IVols. On the empirical side, the fact that IVols (and, thus, the price of commodity options) should and do rise significantly after a ban is declared means that, prior to the ban, there exist substantial incentives for derivative market participants to trade if they have advance knowledge of the government's intention. Anecdotal evidence suggests that pre-ban bets on policy changes do take place.[31] A fascinating question, which would require regulatory data to answer, is whether there is evidence of informed commodity futures or options trading ahead of new trade restrictions.

7 References

Abbott, Philip C. 2012. "Export Restrictions as Stabilization Responses to Food Crisis." *American Journal of Agricultural Economics* 94 (2): 428–34.

Acemoglu, Daron, Tarek A Hassan, and Ahmed Tahoun. 2018. "The Power of the Street: Evidence from Egypt's Arab Spring." *Review of Financial Studies* 31 (1): 1–42.

Adjemian, Michael K, Valentina Bruno, Michel A Robe, and Jonathan Wallen. 2017. "What Drives Volatility Expectations in Grain and Oilseed Markets?" *Paper Presented at the Annual Meeting of the AAEA, July (Chicago, IL).*

Anderson, Kym. 2012. "Government Trade Restrictions and International Price Volatility." *Global Food Security* 1 (2): 157–66.

———. 2014. "The Intersection of Trade Policy, Price Volatility, and Food Security." *Annual Review of Resource Economics* 6 (1): 513–32.

Baylis, Kathy, Murray E Fulton, and Travis Reynolds. 2016. "The Political Economy

[31] For example, the Financial Times reported in 2011 that the world's largest trader of Russian wheat had "made a speculative bet on rising wheat and corn prices in the early stages of (the 2010) summer's Russian drought." As that company bet on rising prices, its senior traders had "publicly urged Russia to impose a grain export ban. Moscow acted a few days later, triggering a grain rally." (*Glencore reveals bet on grain price rise* – FT, April 24 2011)

of Export Restrictions: The Case of Vietnam and India." In *Food Security in a Food Abundant World*. Emerald Group Publishing Limited.

Beckman, Jayson, Carmen Estrades, Manuel Flores, and Angel Aguiar. 2018. "The Impacts of Export Taxes on Agricultural Trade." National Bureau of Economic Research.

Bekaert, Geert, Marie Hoerova, and Marco Lo Duca. 2013. "Risk, Uncertainty and Monetary Policy." *Journal of Monetary Economics* 60 (7): 771–88.

Bellemare, Marc F. 2015. "Rising Food Prices, Food Price Volatility, and Social Unrest." *American Journal of Agricultural Economics* 97 (1): 1–21.

Borensztein, Eduardo, Olivier Jeanne, and Damiano Sandri. 2013. "Macro-Hedging for Commodity Exporters." *Journal of Development Economics* 101: 105–16.

Bouët, Antoine, and David Laborde Debucquet. 2010. *Economics of Export Taxation in a Context of Food Crisis: A Theoretical and CGE Approach Contribution*. International Food Policy Research Institute (IFPRI).

Boutchkova, Maria, Hitesh Doshi, Art Durnev, and Alexander Molchanov. 2012. "Precarious Politics and Return Volatility." *Review of Financial Studies* 25 (4): 1111–54.

Brogaard, Jonathan, Lili Dai, Phong TH Ngo, and Bohui Zhang. 2020. "Global Political Uncertainty and Asset Prices." *Review of Financial Studies* 33 (4): 1737–80.

Bruno, Valentina G, Bahattin Büyükşahin, and Michel A Robe. 2017. "The Financialization of Food?" *American Journal of Agricultural Economics* 99 (1): 243–64.

Büyükşahin, Bahattin, and Michel A Robe. 2014. "Speculators, Commodities and Cross-Market Linkages." *Journal of International Money and Finance* 42: 38–70.

Cao, An NQ, and Michel A Robe. 2022. "Market Uncertainty and Sentiment Around USDA Announcements." *Journal of Futures Markets* 42 (2): 250–75.

Chauveau, Jean-Marie, and Kathryn M Gordon. 1988. "World Price Uncertainty and Agricultural Policy Formulation Under Rational Expectations." *European Review of Agricultural Economics* 15 (4): 437–56.

Covindassamy, Genèvre, Michel A Robe, and Jonathan Wallen. 2017. "Sugar with Your Coffee? Fundamentals, Financials, and Softs Price Uncertainty." *Journal of Futures Markets* 37 (8): 744–65.

Croser, Johanna L, Peter J Lloyd, and Kym Anderson. 2010. "How Do Agricultural Policy Restrictions on Global Trade and Welfare Differ Across Commodities?" *American Journal of Agricultural Economics* 92 (3): 698–712.

Cui, Changrong. 2012. "Commodity Implied Volatility Surface." *Bloomberg*.

Deese, William, and John Reeder. 2008. "Export Taxes on Agricultural Products: Recent History and Economic Modeling of Soybean Export Taxes in Argentina." *Journal of International Commerce and Economics, U.S. International Trade Commission* 1: 185.

Dixit, Avinash. 1996. "Special-Interest Lobbying and Endogenous Commodity Taxation." *Eastern Economic Journal* 22 (4): 375–88.

Dollive, Kendall. 2008. "The Impact of Export Restraints on Rising Grain Prices." *Office of Economics Working Paper No. 2008-09-A, U.S. International Trade Commission*.

Ederington, Louis H, and Wei Guan. 2002. "Measuring Implied Volatility: Is an Average Better? Which Average?" *Journal of Futures Markets* 22 (9): 811–37.

Ederington, Louis H, and Jae Ha Lee. 1996. "The Creation and Resolution of Market Uncertainty: The Impact of Information Releases on Implied Volatility." *Journal of Financial and Quantitative Analysis* 31 (4): 513–39.

Egelkraut, Thorsten M, Philip Garcia, and Bruce J Sherrick. 2007. "The Term Structure of Implied Forward Volatility: Recovery and Informational Content in the Corn Options Market." *American Journal of Agricultural Economics* 89 (1): 1–11.

Fulton, Murray E, and Travis Reynolds. 2015. "The Political Economy of Food Price Volatility: The Case of Vietnam and Rice." *American Journal of Agricultural Economics* 97 (4): 1206–26.

Gawande, Kishore, and Bernard Hoekman. 2010. "Why Governments Tax or Subsidize Agricultural Trade." In *The Political Economy of Agricultural Price Distortions*, edited by Kym Anderson, 241–77. Cambridge University Press.

Gawande, Kishore, Pravin Krishna, and Marcelo Olarreaga. 2012. "Lobbying Competition over Trade Policy." *International Economic Review* 53 (1): 115–32.

Gawande, Kishore, and Ben Zissimos. 2020. "How Dictators Forestall Democratization Using International Trade Policy."

———. 2022. "Dictators Under the Weather." *University of Exeter (UK) and McCombs School of Business, University of Texas at Austin Working Paper*.

Giordani, Paolo E, Nadia Rocha, and Michele Ruta. 2016. "Food Prices and the Multiplier Effect of Trade Policy." *Journal of International Economics* 101: 102–22.

Gnutzmann, Hinnerk, Oskar Kowalewski, and Piotr Śpiewanowski. 2020. "Market Structure and Resilience: Evidence from Potash Mine Disasters." *American Journal of Agricultural Economics* 102 (3): 911–33.

Goldberg, Pinelopi Koujianou, and Giovanni Maggi. 1999. "Protection for Sale: An Empirical Investigation." *American Economic Review* 89 (5): 1135–55.

Goswami, Alankrita, and Berna Karali. 2021. "Implied Volatility Spillovers in Storable Commodity Markets." *Working Paper, University of Georgia*.

Gouel, Christophe. 2016. "Trade Policy Coordination and Food Price Volatility." *American Journal of Agricultural Economics* 98 (4): 1018–37.

Grossman, Gene M, and Elhanan Helpman. 1994. "Protection for Sale." *American Economic Review* 84 (4): 833–50.

Hendrix, Cullen S, and Stephan Haggard. 2015. "Global Food Prices, Regime Type, and Urban Unrest in the Developing World." *Journal of Peace Research* 52 (2): 143–57.

Hsu, Po-Hsuan, Kai Li, and Chi-Yang Tsou. 2022. "The Pollution Premium." *Journal of Finance, Forthcoming*.

Ivanic, Maros, and Will Martin. 2014. "Implications of Domestic Price Insulation for Global Food Price Behavior." *Journal of International Money and Finance* 42: 272–88.

Janzen, Joseph P, and Michael K Adjemian. 2017. "Estimating the Location of World Wheat Price Discovery." 5. *American Journal of Agricultural Economics*. Vol. 99.

Jensen, Hans G, and Kym Anderson. 2017. "Grain Price Spikes and Beggar-Thy-Neighbor Policy Responses: A Global Economywide Analysis." *The World Bank Economic Review* 31 (1): 158–75.

Karali, Berna, and Gabriel J Power. 2013. "Short-and Long-Run Determinants of Commodity Price Volatility." *American Journal of Agricultural Economics* 95 (3): 724–38.

Karali, Berna, Gabriel J Power, and Ariun Ishdorj. 2011. "Bayesian State-Space Estimation of Stochastic Volatility for Storable Commodities." *American Journal of Agricultural Economics* 93 (2): 434–40.

Laborde, David, Csilla Lakatos, and Will J Martin. 2019. "Poverty Impact of Food Price

Shocks and Policies." *World Bank Policy Research Working Paper*, no. 8724.

Larue, Bruno, and Alan Ker. 1993. "World Price Variability Versus Protectionism in Agriculture: A Causality Analysis." *Review of Economics and Statistics*, 342–46.

Liapis, Peter S. 2013. "How Export Restrictive Measures Affect Trade of Agricultural Commodities." *OECD Food, Agriculture and Fisheries Papers No. 63.*

Lopez-Martin, Bernabe, Julio Leal, and Andre Martinez Fritscher. 2019. "Commodity Price Risk Management and Fiscal Policy in a Sovereign Default Model." *Journal of International Money and Finance* 96: 304–23.

Martin, Will, and Kym Anderson. 2012. "Export Restrictions and Price Insulation During Commodity Price Booms." *American Journal of Agricultural Economics* 94 (2): 422–27.

Merener, Nicolas. 2016. "Concentrated Production and Conditional Heavy Tails in Commodity Returns." *Journal of Futures Markets* 36 (1): 46–65.

Mitra, Siddhartha, and Tim Josling. 2009. "Agricultural Export Restrictions: Welfare Implications and Trade Disciplines." *Position Paper Agricultural and Rural Development Policy, IPC.*

Newey, Whitney K, and Kenneth D West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation." *Econometrica* 55 (3): 703–8.

Pallage, Stephane, and Michel A Robe. 2003. "On the Welfare Cost of Business Cycles in Developing Countries." *International Economic Review* 44 (2): 677–98.

Pastor, Lubos, and Pietro Veronesi. 2012. "Uncertainty about Government Policy and Stock Prices." *The Journal of Finance* 67 (4): 1219–64.

Pieters, Hannah, and Johan Swinnen. 2016. "Trading-Off Volatility and Distortions? Food Policy During Price Spikes." *Food Policy* 61: 27–39.

Porteous, Obie. 2017. "Empirical Effects of Short-Term Export Bans: The Case of African Maize." *Food Policy* 71: 17–26.

Robe, Michel A, and Jonathan Wallen. 2016. "Fundamentals, Derivatives Market Information and Oil Price Volatility." *Journal of Futures Markets* 36 (4): 317–44.

Roberts, Michael J, and Wolfram Schlenker. 2013. "Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate." *American Economic Review* 103 (6): 2265–95.

Rude, James, and Henry An. 2015. "Explaining Grain and Oilseed Price Volatility: The Role of Export Restrictions." *Food Policy* 57: 83–92.

Rutten, Martine, Lindsay Shutes, and Gerdien Meijerink. 2013. "Sit down at the Ball Game: How Trade Barriers Make the World Less Food Secure." *Food Policy* 38: 1–10.

Samuelson, Paul A. 1965. "Proof That Properly Anticipated Prices Fluctuate Randomly." *Management Review* 6 (2).

Sanders, Dwight R, Scott H Irwin, and Robert P Merrin. 2010. "The Adequacy of Speculation in Agricultural Futures Markets: Too Much of a Good Thing?" *Applied Economic Perspectives and Policy* 32 (1): 77–94.

Sayre, Jay, and Thibault Fally. 2019. "Commodity Trade Matters." *NBER Working Paper 24965.*

Schnepf, Randall D, Erik N Dohlman, and H Christine Bolling. 2001. *Agriculture in Brazil and Argentina: Developments and Prospects for Major Field Crops.* US Department of Agriculture Washington, DC.

Shama, Ramesh. 2011. *Food Export Restrictions: Review of the 2007-2010 Experience and*

Considerations for Disciplining Restrictive Measures. FAO Rome.

Solleder, Olga. 2013. "Trade Effects of Export Taxes." *Working Paper No. 08/2013, Graduate Institute of International and Development Studies*.

Swinnen, Johan. 2018. "The Political Economy of Agricultural and Food Policies." In *The Routledge Handbook of Agricultural Economics*, 381–98. Routledge.

Tadasse, Getaw, Bernadina Algieri, Matthias Kalkuhl, and Joachim von Braun. 2016. "Drivers and Triggers of International Food Price Spikes and Volatility." In *Food Price Volatility and Its Implications for Food Security and Policy*, 59–82. Springer, Cham.

Thennakoon, Jayanthi. 2015. "Political Economy of Altering Trade Restrictions in Response to Commodity Price Spikes." *Review of Development Economics* 19 (2): 434–47.

Thies, Cameron G, and Schuyler Porche. 2007. "The Political Economy of Agricultural Protection." *The Journal of Politics* 69 (1): 116–27.

Watugala, Sumudu W. 2019. "Economic Uncertainty, Trading Activity, and Commodity Futures Volatility." *Journal of Futures Markets* 39 (8): 921–45.

Wayne, W Yu, Evans CK Lui, and Jacqueline W Wang. 2010. "The Predictive Power of the Implied Volatility of Options Traded OTC and on Exchanges." *Journal of Banking & Finance* 34 (1): 1–11.

Weinberg, Joe, and Ryan Bakker. 2015. "Let Them Eat Cake: Food Prices, Domestic Policy and Social Unrest." *Conflict Management and Peace Science* 32 (3): 309–26.

Working, Holbrook. 1960. "Speculation on Hedging Markets." *Food Research Institute Studies* 1 (1387-2016-116000): 185–220.

Zwart, Anthony C, and David Blandford. 1989. "Market Intervention and International Price Stability." *American Journal of Agricultural Economics* 71 (2): 379–88.

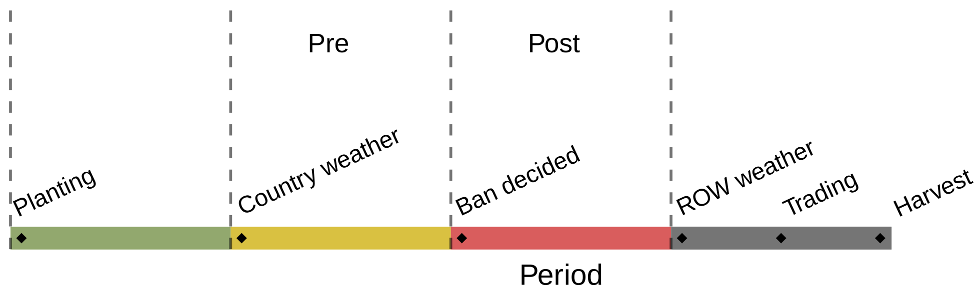

Figure 1: The sequence of events in the model.

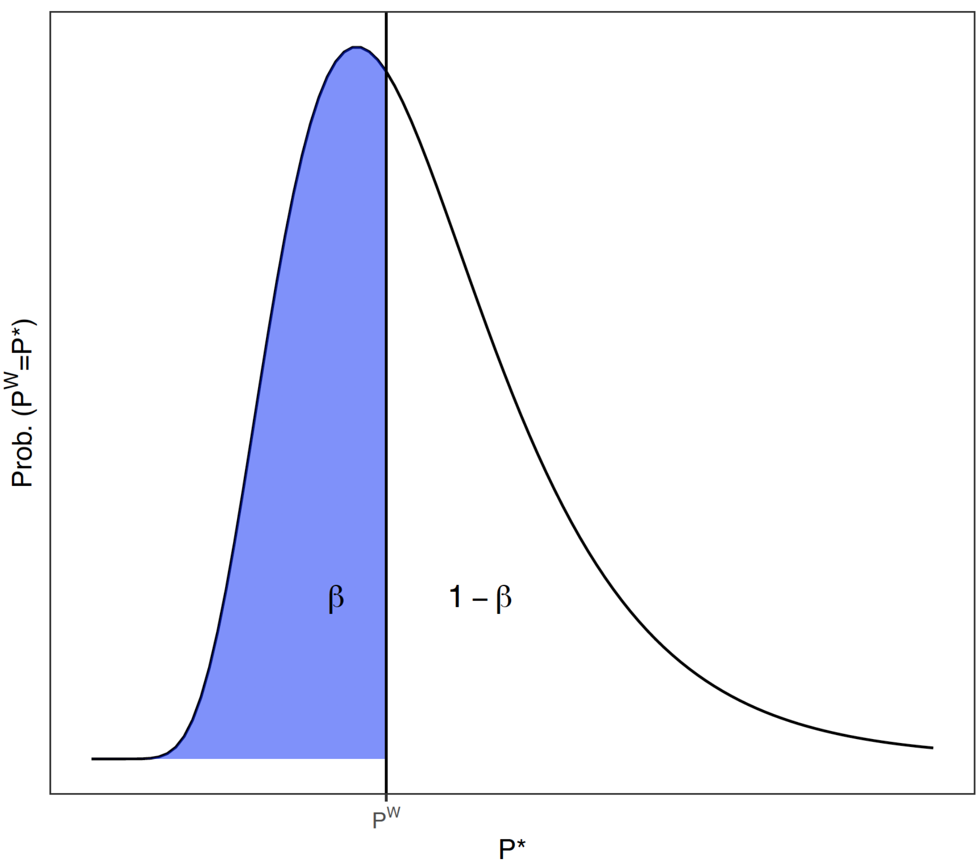

Figure 2: The probability that an export ban will be imposed in Period III as a function of the world price in Period II (see Figure 1).

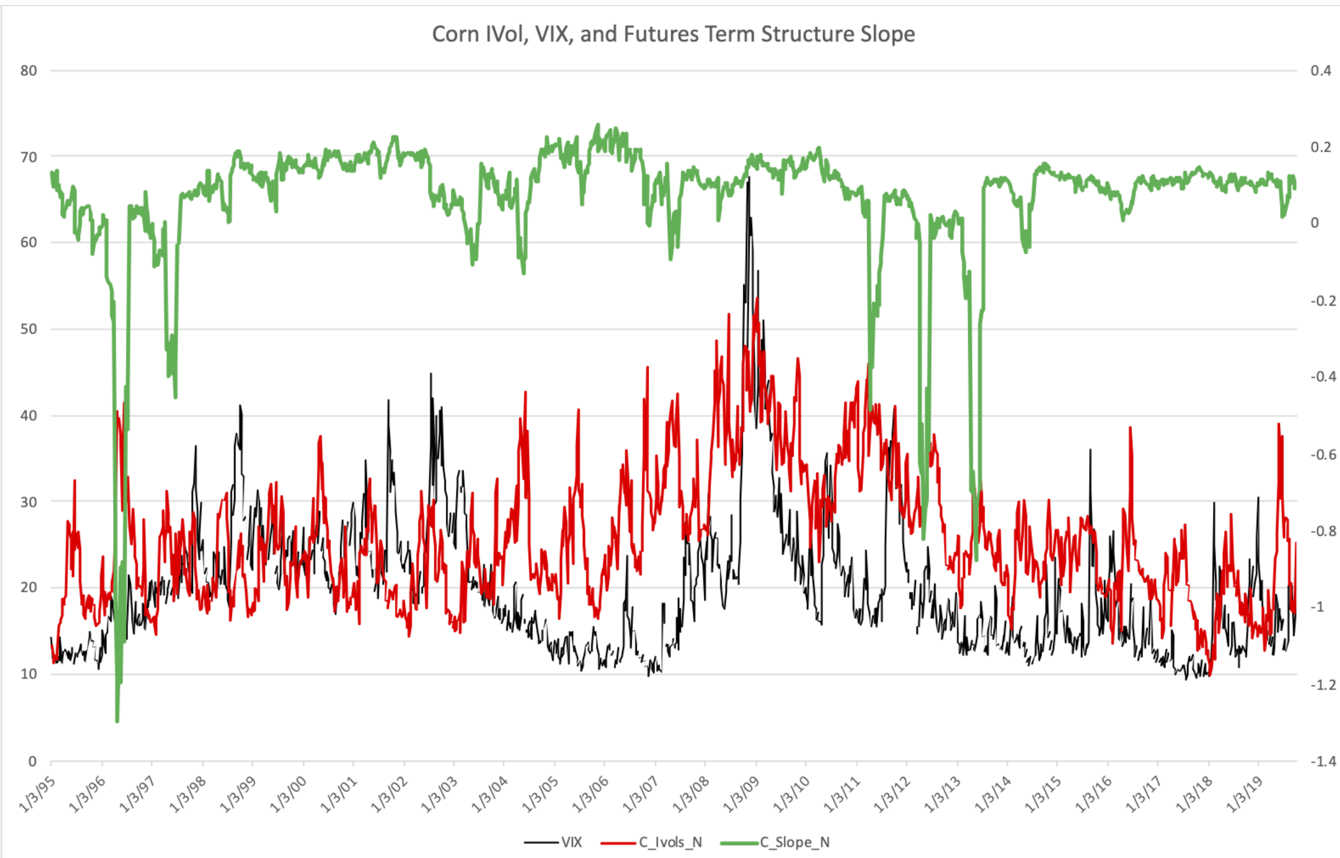

Figure 3: The nearby CBOT No.2 corn option-implied volatility (Corn IVol) together with the VIX index and with a proxy of tightness in the physical corn market: the nearby Slope of the term structure of corn futures prices, expressed as an annual percentage of the corn nearby futures price (net of storage financing costs, proxied by the 90-day LIBOR). Source: Bloomberg, authors' computations.

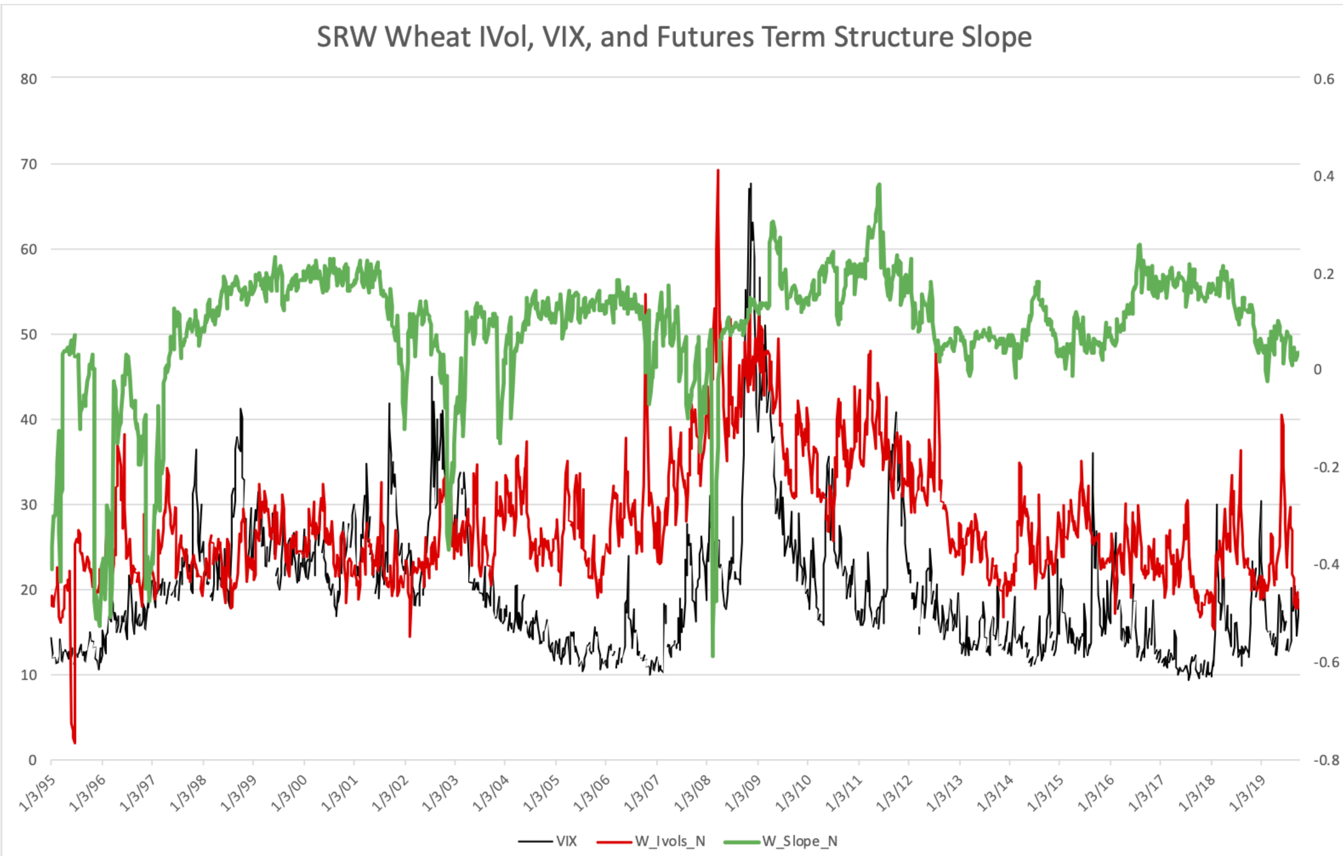

Figure 4: The nearby CBOT soft red winter wheat option-implied volatility (SRW Wheat IVol) together with the VIX index and with a proxy of tightness in the physical wheat market: the nearby Slope of the term structure of SRW wheat futures prices, expressed as an annual percentage of the SRW wheat nearby futures price (net of storage financing costs, proxied by the 90-day LIBOR). Source: Bloomberg, authors' computations.

Table 1: Major Grain Export Bans, 2002-2019. For each major export restriction in one of the ten largest grain exporting countries, the date of the ban's onset and (when it could be ascertained) the date of its removal. Sources: Lexis-Nexis (for English-language news sources) and major Russian-language newspapers

Country	Start	End	Event
Ukraine	2003-09-01		Export duty on corn to make export unprofitable
Kazakhstan	2004-01-23	2004-04-02	Unofficial export ban on wheat
Ukraine	2006-09-26	2006-10-17	Licensing requirement halts corn exports until licenses granted
Ukraine	2006-10-12		Quota of 100,000 tons of corn through end of year
Ukraine	2006-11-03		Temporary ban on wheat due to lawsuit
Ukraine	2006-12-11	2007-05-16	Very tight quota (3,000 tons wheat) implemented
Argentina	2007-03-08	2007-11-01	Licensing requirement creates functional ban on wheat
Ukraine	2007-06-20	2008-04-23	Quota of 3,000 tons of wheat and corn through end of October 2007
Russia	2007-12-28	2008-07-01	40% wheat tax (raised from 10%)
Russia	2008-02-15		Ban on wheat to countries in Customs Union, in addition to tariff
Kazakhstan	2008-04-15	2008-09-01	Export ban on wheat
India	2008-07-03	2008-08-19	Export ban on corn
Russia	2010-08-05	2011-07-05	Export ban on wheat and corn
Ukraine	2010-08-09		Government prevents wheat, grain exports from leaving port
Ukraine	2010-10-07	2010-12-31	Quota of half a million tons of wheat, corn through end of year
Russia	2015-01-16	2015-05-15	$41/per tonne wheat tariff
Ukraine	2015-01-28	2015-06-30	Quota of 2 million tons of corn through June 2015
Russia	2015-06-25	2016-09-02	Wheat tariff of 50% less 5500 rubles/ton
Pakistan	2019-07-17	2019-10-08	Export ban on wheat

Table 2: Impact of ban onset.

	Dependent variable:			
	Wheat		Corn	
	(1)	(2)	(3)	(4)
Panel A: Daily				
Start of ban	0.812*	0.782*	0.779***	0.777***
	(0.430)	(0.474)	(0.227)	(0.248)
IVol(t-1)	0.970***	0.971***	0.976***	0.976***
	(0.004)	(0.006)	(0.003)	(0.004)
VIX	0.017***	0.017***	0.011***	0.011***
	(0.003)	(0.004)	(0.003)	(0.004)
TTM	−0.003**	−0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Slope(t-1)	0.288	0.289	−0.244*	−0.244
	(0.321)	(0.445)	(0.139)	(0.152)
d Volume		−0.00000***		−0.00000
		(0.00000)		(0.00000)
Constant	0.709***	0.716***	0.377***	0.377***
	(0.140)	(0.148)	(0.104)	(0.106)
Observations	4,464	4,463	4,464	4,463
R^2	0.962	0.962	0.965	0.965
Adjusted R^2	0.961	0.962	0.965	0.965
Residual Std. Error	1.540	1.538	1.536	1.537
F Statistic	22,270.900***	18,599.560***	24,392.870***	20,312.150***
Panel B: Weekly				
Start of ban	1.429*	1.469*	2.048**	2.006**
	(0.862)	(0.888)	(0.968)	(0.947)
IVol(t-1)	0.893***	0.893***	0.908***	0.906***
	(0.018)	(0.018)	(0.013)	(0.013)
VIX	0.055***	0.055***	0.043***	0.044***
	(0.012)	(0.011)	(0.012)	(0.013)
TTM	−0.010**	−0.010***	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Slope(t-1)	−0.516	−0.452	−1.004**	−1.122**
	(1.736)	(1.718)	(0.465)	(0.529)
d Volume		−0.00000		0.00000**
		(0.00001)		(0.00000)
d Working T		−4.651		−11.278***
		(3.034)		(3.322)
Constant	2.850***	2.881***	1.571***	1.606***
	(0.469)	(0.471)	(0.430)	(0.439)
Observations	925	924	925	924
R^2	0.861	0.861	0.871	0.873
Adjusted R^2	0.860	0.860	0.870	0.872
Residual Std. Error	2.903	2.903	2.930	2.909
F Statistic	1,136.640***	811.630***	1,236.034***	896.342***

Notes: Significance levels: *p<0.1; **p<0.05; ***p<0.001
Panel A (*resp.* B) of Table 2 reports the results of daily (*resp.* weekly) OLS regressions of the corn (Models 1 and 2) and wheat (Models 3 and 4) IVols on the *VIX*, on a proxy for the tightness of physical-market supply including inventories (the *Slope* of the commodity's futures term structure), and on a dummy variable *Start of ban* that equals 1 on the day (Panel A) or week (Panel B) when an exporting country implements a new export ban (see Table 1) and 0 otherwise. Models (2) and (4) show that the results are robust to including two additional variables: the intensity of financial speculation in futures markets, T, and the change in option trading volume. The OLS models all account for the Samuelson effect by controlling for the time-to-maturity of the options used to compute the commodity IVols. Sample period: January 2002 to September 24th, 2019.

Table 3: Impact of ban period.

	Dependent variable:			
	Wheat		Corn	
	(1)	(2)	(3)	(4)
Panel A: Daily				
Ban in place	0.235***	0.235***	0.151***	0.151***
	(0.066)	(0.058)	(0.053)	(0.053)
IVol(t-1)	0.965***	0.966***	0.974***	0.974***
	(0.004)	(0.006)	(0.003)	(0.004)
VIX	0.020***	0.020***	0.013***	0.013***
	(0.003)	(0.004)	(0.003)	(0.004)
TTM	−0.003**	−0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Slope(t-1)	0.420	0.421	−0.251*	−0.251
	(0.321)	(0.450)	(0.142)	(0.154)
d Volume		−0.00000***		−0.00000
		(0.00000)		(0.00000)
Constant	0.727***	0.734***	0.383***	0.384***
	(0.140)	(0.150)	(0.105)	(0.108)
Observations	4,464	4,463	4,464	4,463
R^2	0.962	0.962	0.965	0.965
Adjusted R^2	0.962	0.962	0.965	0.965
Residual Std. Error	1.538	1.536	1.536	1.536
F Statistic	22,334.930***	18,654.510***	24,409.940***	20,326.480***
Panel B: Weekly				
Ban in place	0.729***	0.749***	0.576***	0.605***
	(0.234)	(0.217)	(0.215)	(0.211)
IVol(t-1)	0.881***	0.880***	0.901***	0.899***
	(0.017)	(0.020)	(0.014)	(0.014)
VIX	0.063***	0.063***	0.047***	0.049***
	(0.012)	(0.014)	(0.013)	(0.013)
TTM	−0.010**	−0.011***	0.002	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Slope(t-1)	−0.251	−0.176	−1.013**	−1.138**
	(1.880)	(1.699)	(0.492)	(0.549)
d Volume		−0.00000		0.00000**
		(0.00001)		(0.00000)
Constant	2.885***	2.918***	1.590***	1.628***
	(0.475)	(0.489)	(0.441)	(0.448)
d Working T		−4.922		−11.727***
		(3.031)		(3.366)
Observations	925	924	925	924
R^2	0.862	0.862	0.870	0.872
Adjusted R^2	0.861	0.861	0.870	0.871
Residual Std. Error	2.894	2.894	2.933	2.911
F Statistic	1,144.799***	817.792***	1,232.583***	894.932***

Notes: Significance levels: *p<0.1; **p<0.05; ***p<0.001
Panel A (*resp.* B) of Table 3 reports the results of daily (*resp.* weekly) OLS regressions of the corn (Models 1 and 2) and wheat (Models 3 and 4) IVols on the *VIX*, on a proxy for the tightness of physical-market supply including inventories (the *Slope* of the commodity's futures term structure), and on a dummy variable *Ban in place* that equals 1 on days (Panel A) or weeks (Panel B) when an export ban is in effect in a major exporting country (see Table 1) and 0 otherwise. Models (2) and (4) show that the results are robust to including two additional variables: the intensity of financial speculation in futures markets, *T*, and the change in option trading volume. The OLS models all account for the Samuelson effect by controlling for the time-to-maturity of the options used to compute the commodity IVols. Sample period: January 2002 to September 24th, 2019.

Table 4: Impact of ban onset (weighted by 2002 crop production share of country imposing ban).

	Dependent variable:			
	Wheat		Corn	
	(1)	(2)	(3)	(4)
Panel A: Daily				
Start of ban (weighted)	14.135*	13.773*	61.909**	61.756**
	(7.374)	(7.881)	(27.530)	(27.693)
IVol(t-1)	0.971***	0.971***	0.976***	0.976***
	(0.004)	(0.006)	(0.003)	(0.004)
VIX	0.017***	0.017***	0.011***	0.011***
	(0.003)	(0.004)	(0.003)	(0.004)
TTM	−0.003**	−0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Slope(t-1)	0.294	0.295	−0.242*	−0.242
	(0.322)	(0.445)	(0.138)	(0.152)
d Volume		−0.00000***		−0.00000
		(0.00000)		(0.00000)
Constant	0.709***	0.716***	0.375***	0.375***
	(0.140)	(0.148)	(0.105)	(0.106)
Observations	4,464	4,463	4,464	4,463
R^2	0.962	0.962	0.965	0.965
Adjusted R^2	0.961	0.962	0.965	0.965
Residual Std. Error	1.540	1.538	1.537	1.537
F Statistic	22,272.870***	18,601.600***	24,379.270***	20,300.880***
Panel B: Weekly				
Start of ban (weighted)	21.773*	22.069*	177.883*	181.125*
	(11.756)	(12.634)	(105.594)	(95.558)
IVol(t-1)	0.894***	0.893***	0.909***	0.907***
	(0.016)	(0.018)	(0.013)	(0.014)
VIX	0.054***	0.054***	0.042***	0.044***
	(0.011)	(0.012)	(0.012)	(0.013)
TTM	−0.010**	−0.011***	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.003)
Slope(t-1)	−0.508	−0.447	−0.992**	−1.113**
	(1.857)	(1.694)	(0.459)	(0.565)
d Volume		−0.00000		0.00000**
		(0.00001)		(0.00000)
Constant	2.868***	2.898***	1.573***	1.609***
	(0.471)	(0.467)	(0.429)	(0.447)
d Working T		−4.490		−11.377***
		(3.002)		(3.277)
Observations	925	924	925	924
R^2	0.861	0.861	0.870	0.872
Adjusted R^2	0.860	0.860	0.869	0.871
Residual Std. Error	2.903	2.904	2.935	2.914
F Statistic	1,136.177***	811.166***	1,230.887***	893.167***

Notes: Significance levels: *p<0.1; **p<0.05; ***p<0.001
Panel A (*resp.* B) of Table 4 reports the results of daily (*resp.* weekly) OLS regressions of the corn (Models 1 and 2) and wheat (Models 3 and 4) IVols on the *VIX*, on a proxy for the tightness of physical-market supply including inventories (the *Slope* of the commodity's futures term structure), and on a variable *Start of ban (weighted)* that multiplies (a) the share of the commodity output impacted by a ban with (b) a dummy variable set equal to 1 on the day (Panel A) or week (Panel B) when an exporting country implements a new export ban (see Table 1) and to 0 otherwise. Models (2) and (4) show that the results are robust to including two additional variables: the intensity of financial speculation in futures markets, T, and the change in option trading volume. The OLS models all account for the Samuelson effect by controlling for the time-to-maturity of the options used to compute the commodity IVols. Sample period: January 2002 to September 24th, 2019.

Table 5: Impact of ban period (weighted by 2002 crop production share of country imposing ban).

	Dependent variable:			
	Wheat		Corn	
	(1)	(2)	(3)	(4)
Panel A: Daily				
Ban in place (weighted)	2.705***	2.704***	9.382**	9.384***
	(0.788)	(0.717)	(3.653)	(3.637)
IVol(t-1)	0.965***	0.965***	0.974***	0.974***
	(0.005)	(0.006)	(0.003)	(0.004)
VIX	0.019***	0.019***	0.012***	0.012***
	(0.004)	(0.004)	(0.003)	(0.004)
TTM	−0.003**	−0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Slope(t-1)	0.382	0.384	−0.261*	−0.261*
	(0.307)	(0.441)	(0.141)	(0.153)
d Volume		−0.00000***		−0.00000
		(0.00000)		(0.00000)
Constant	0.751***	0.758***	0.394***	0.395***
	(0.144)	(0.151)	(0.106)	(0.107)
Observations	4,464	4,463	4,464	4,463
R^2	0.962	0.962	0.965	0.965
Adjusted R^2	0.962	0.962	0.965	0.965
Residual Std. Error	1.538	1.536	1.536	1.537
F Statistic	22,330.930***	18,651.340***	24,400.090***	20,318.290***
Panel B: Weekly				
Ban in place (weighted)	7.718***	7.947***	30.783*	32.946**
	(2.627)	(2.641)	(15.926)	(15.035)
IVol(t-1)	0.881***	0.880***	0.905***	0.903***
	(0.017)	(0.019)	(0.013)	(0.014)
VIX	0.061***	0.061***	0.044***	0.046***
	(0.012)	(0.014)	(0.012)	(0.013)
TTM	−0.010**	−0.010***	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Slope(t-1)	−0.365	−0.294	−1.025**	−1.152**
	(1.697)	(1.599)	(0.477)	(0.575)
d Volume		−0.00000		0.00000**
		(0.00001)		(0.00000)
Constant	2.955***	2.990***	1.629***	1.670***
	(0.479)	(0.492)	(0.439)	(0.453)
d Working T		−4.858		−11.638***
		(2.987)		(3.323)
Observations	925	924	925	924
R^2	0.861	0.862	0.870	0.872
Adjusted R^2	0.861	0.861	0.869	0.871
Residual Std. Error	2.897	2.897	2.938	2.916
F Statistic	1,141.887***	815.610***	1,228.360***	891.670***

Notes: Significance levels: *p<0.1; **p<0.05; ***p<0.001
Panel A (*resp.* B) of Table 5 reports the results of daily (*resp.* weekly) OLS regressions of the corn (Models 1 and 2) and wheat (Models 3 and 4) IVols on the *VIX*, on a proxy for the tightness of physical-market supply including inventories (the *Slope* of the commodity's futures term structure), and variable *Ban in place (weighted)* that multiplies (a) the share of the commodity output impacted by a ban with (b) a dummy variable that equals 1 on days (Panel A) or weeks (Panel B) when an export ban is in effect in a major exporting country (see Table 1) and 0 otherwise. Models (2) and (4) show that the results are robust to including two additional variables: the intensity of financial speculation in futures markets, T, and the change in option trading volume. The OLS models all account for the Samuelson effect by controlling for the time-to-maturity of the options used to compute the commodity IVols. Sample period: January 2002 to September 24th, 2019.

A The Intensity of Financial Speculation in Grain Markets

In Section 5, we test empirically if the intensity of financial speculation in grain markets has an impact on market expectations of future price volatility. As a proxy for that intensity, we employ a version of Working's (1960) T index. This Appendix, reproduced with permission from Adjemian et al. (2017), explains how we construct the T.

A.1 Data

We compute weekly T values from aggregate trader position data published by the U.S. Commodity Futures Trading Commission (CFTC) for corn, soybean, and Chicago wheat futures markets. Precisely, we use the CFTC "Legacy Commitments of Traders Report" (COT) showing the aggregate, long, short, and spread end-of-Tuesday positions of "commercial" and "non-commercial" traders.[32] ^[COT reports also provide data on the positions of non-reporting (*i.e., small) traders.] A trading entity generally gets all of its futures and options positions in a given commodity classified by the CFTC as "commercial" if it is commercially "engaged in business activities hedged by the use of the futures or options markets" as defined in CFTC regulations. The "non-commercial" group includes various types of mostly financial traders including floor brokers, hedge funds, and other types of institutional financial traders.*

A.2 Measuring the intensity of financial speculation

For each grain market in our sample, we use public COT data to compute Working's T every Tuesday. The CFTC data aggregate trader-level positions across all contract maturities. Formally, in the ith commodity market in week T:

$$\textit{Working's } T_{i,t} = \begin{cases} 1 + \frac{SS_{i,t}}{HL_{i,t}+HS_{i,t}} \textit{ if } HS_{i,t} \geq HL_{i,t} \\ 1 + \frac{SL_{i,t}}{HL_{i,t}+HS_{i,t}} \textit{ if } HL_{i,t} \geq HS_{i,t} \end{cases}$$

[32]The CFTC's COT reports started differentiating between "managed money traders" (i.e., hedge funds) and "other non-commercial traders with reportable positions" on September 4th, 2009. The CFTC only makes these more disaggregated data available back to 2006. We therefore rely on the legacy classification scheme, in order to obtain a sufficient time series of trader positions for our entire sample.

B Placebo Exercise

Table A1: Relation between grain ban onset or grain ban duration on coffee IVols (weekly data).

	Dependent variable:			
	Coffee			
	(1)	(2)	(3)	(4)
Start of grain ban	0.096	−0.037		
	(0.713)	(0.799)		
Any grain ban in place			−0.463	−0.575
			(0.343)	(0.365)
VIX	0.028*	0.042**	0.026*	0.040**
	(0.015)	(0.018)	(0.015)	(0.018)
IVol(t-1)	0.786***	0.797***	0.784***	0.795***
	(0.030)	(0.029)	(0.030)	(0.029)
Slope(t-1)	6.844**	9.831***	5.810*	8.646**
	(3.245)	(3.767)	(3.286)	(3.692)
TTM	−0.032***	−0.033***	−0.032***	−0.034***
	(0.009)	(0.009)	(0.009)	(0.009)
d Volume		0.0001**		0.0001**
		(0.00005)		(0.00005)
Constant	8.942***	6.564***	9.310***	6.951***
	(1.483)	(1.462)	(1.542)	(1.473)
Observations	716	716	716	716
R^2	0.671	0.678	0.671	0.679
Adjusted R^2	0.668	0.675	0.669	0.676
Residual Std. Error	4.320	4.273	4.315	4.266
F Statistic	288.977***	248.962***	289.841***	250.127***

Notes: Significance levels: *p<0.1; **p<0.05; ***p<0.001 Table A1 reports the results of weekly OLS regressions of coffee-C IVols on the *VIX*, on a proxy for the tightness of physical-market coffee supply including inventories (the *Slope* of the coffee futures term structure), and variables that capture whether a grain or oilseed export ban was newly initiated (Models 1 and 2) or in place (Models 3 and 4) that week. Models (2) and (4) show that the results are robust to including two additional variables: the intensity of financial speculation in the U.S. coffee futures markets, T, and the change in coffee options-on-futures trading volume. The OLS models all account for the Samuelson effect by controlling for the time-to-maturity of the coffee options used to compute the coffee IVols. Sample period: January 2002 to September 2015.