IMPACTS OF EXPORT RESTRICTIONS ON FOOD PRICE VOLATILITY: EVIDENCE FROM VAR-X AND EGARCH-X MODELS

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Abstract

While export restrictive policy has long been associated with increasing food price volatility, it has received minimal attention in the empirical literature compared to other potential drivers of international food price fluctuations. This paper aims at closing this gap by firstly quantifying the relevant policies in an indicator of export restrictive policy. Subsequently, the effects of that are tested on estimated realized and GARCH volatility in VAR-X models where various wheat price volatilities are allowed to be endogenously determined. In a second step, the impacts of export controls during times of market turmoil are assessed in asymmetric volatility models. This strategy succinctly reveals the effects of export controls along the policy, frequency, country and time dimensions providing a detailed set of evidence. It is found that, most pronounced effects on wheat price volatility stem from long-term quotas. Similarly, longer term prohibitions of some countries have impacted wheat price fluctuation as well. On the contrary, long term tax strategies are shown to not significantly impact wheat price volatility. However, during times of market turmoil all three considered export restrictions have particularly contributed to wheat price volatility. Strengthened and more binding WTO regulation could have led to significantly less food price volatility, especially in times of food price crisis, such as recently experienced during the 2007/08 and 2010/11 episodes.

Keywords

Food Price Volatility; Export Restrictions; GARCH; VAR-X; EGARCH-X

1 Introduction

The identification of volatility drivers in food markets has been a central issue in the aftermath of recent commodity price spikes in 2007/08 and 2010/11. When prices reached record highs of the past 30 years, researchers speculated that volatility of food prices had entered new, fundamentally different dimensions. (Rude & An, 2015). Contrarily, Deaton & Laroque (1992) and Wright (2011) have argued that periods of high and volatile prices are no extraordinary events on commodity and specifically grain markets and ultimately are a result of storage levels. Yet, Gilbert (2010) suggests that long term food price volatility has declined instead of decreased.

The problem has received widespread attention as food price volatility is a major threat to global food security and poverty, and thereby to the achievement of the Sustainable Development Goals (SDG). Since poor households in developing countries spend large shares of their incomes on food, they are particularly vulnerable to fluctuations of prices. (Prakash, 2011). Volatility threatens food secure household's ability to fend off food insecurity, while worsening food insecure household's conditions, leading to increased rates and severity of poverty. For instance, (De Hoyos & Medvedev, 2011) have estimated that the 2006/07 food price surges have pushed 155 million people below the poverty line of 1.25\$ per day. The greater the fluctuations, the greater the proportion and likelihood of households to experience worsened food insecurity.

In recent years, the need to act on volatile global markets has been recognised by the international community. After the second food price spike in 2010/11 the G20 has reacted with the launch of the Agricultural Market Information System (AMIS) aiming at improving market transparency and preventing food price hikes and market instability. Additionally, improved policy coordination has been placed at the heart of responsibilities. Academic researchers have undertaken a wide range of analyses to better understand the dynamics of food price volatility. This has resulted in a broadly comprehensive picture of the forces governing international food price fluctuations. Core problems which are extensively discussed in the literature include low stock levels and biofuels, increasing demand in developing countries, speculative activities and extreme weather events. What is missing is the evaluation of the contribution of policy intervention to international food price movements.

Export restrictions have often been associated with international food price increases and spurred volatility. Yet, In spite of the acknowledged importance, researchers have failed to provide sufficient empirical evidence on the relationship between food price volatility and export controls implemented by national governments. Brümmer, Korn, Schlüßler, Jaghdani, & Saucedo (2013) noticed that no empirical work had been undertaken on the subject. Subsequently, Rude & An (2015) provided initial empirical results.. Nevertheless, export restrictive policy has not received the amount of academic attention it deserves considering its undisputed power to impact international food markets.

In reality, the implementation of export controls has dramatically increased after the 2007/08 food price surges (e.g. Sharma, 2011, AMIS, 2016, Mitra & Josling, 2009). In attempts to isolate domestic prices from international market turmoil, governments have implemented export controls which further exerted pressure on already increasing international prices and their volatility. Simultaneously, export controls remain an area of under-regulation in international agreements (Anania, 2013). In contrast to import policies, export measures are not bindingly disciplined, leaving ample space for countries to restrict exports and consequently pressure international prices. Although several proposals calling for stricter regulation of export controls have been brought to the table, negotiations in the Doha round appear to be stalling and not reaching tangible consensus.

An improved understanding on how export controls impact international food price movements is so critical as, in contrast to volatility drivers on demand or weather-related shocks, they are manageable by national governments through international agreements and treaties, providing one of the few tools to directly control food price fluctuations. Empirical evidence on the effects of export restrictions, in particular with regards to times of crisis when countries respond to increased food prices and volatility, is critical to better coordinate and regulate the implementations of such.

This paper sets out to close this gap and explores empirically the relationship between food price volatility and export restrictions imposed by national governments. Based on conventional volatility measures, a set of Vectorautorgression (VAR) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models with exogenous variables are developed which allow to test the effects of a trade and policy weighted policy indicator along the policy, frequency, country an time dimensions. The main research questions addressed are whether

1. export restrictive policies may be associated with increased food price volatility
2. there are different impacts among the array of different export restrictive measures
3. particular country policies have particularly contributed to food price volatility
4. the timing of such policies matters

In the fourth question it is in particular interesting to examine whether export restrictions have different effects in times of commodity price spikes as experienced in 2007/08 and 2010/11.

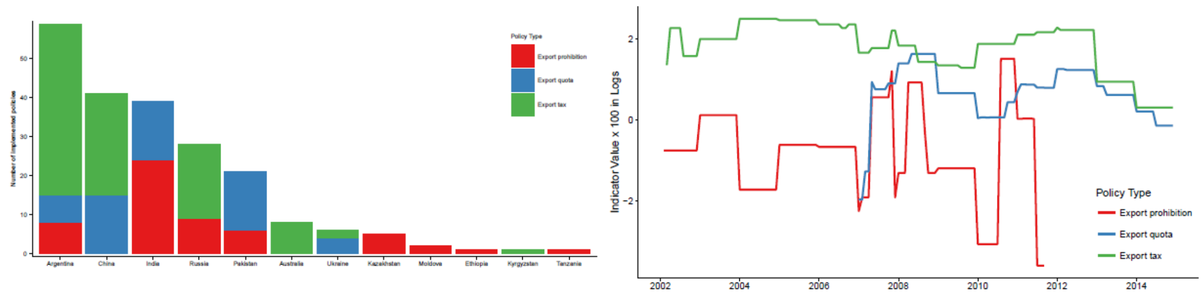
2 Data

2.1 Export Restrictions

Export restrictions data has been drawn from (AMIS, 2016) and the Organization for Economic Development (OECD, 2016). The data include type of restrictions, date of introduction, elimination and motivation as stated in official documents issued by the imposing government. Both data sources have been cross referenced and lay the basis of the dataset used in this analysis. Secondly, as those data list only policies imposed by AMIS and OECD member countries, the data has been extended based on Sharma (2011). For the sake of simplicity, the spectrum of export restrictive instruments has been limited to export taxes, export quotas and export bans, of which a clear distinction will be made throughout the following quantitative analysis.

Figure 1a provides an overview of both the typology of imposed export restrictions and implementing countries during the reference period. Argentina has been applying the highest number of export restrictions and, in addition, is also the only country which has made use of all three types of restrictions with export taxes being the most frequently implemented measure. China exhibits the second highest number of imposed export restrictions and most export bans came into force during both food price crises. However, the 2008 price hikes have led the Chinese government to keep quotas extended into 2015. Similarly, India has introduced quotas and prohibitions in 2007 and left them implemented until late 2011. Quotas which stretch from the first food price spikes until the second period of price hikes and beyond have furthermore been operated by Ukraine and Pakistan. Pakistan has additionally implemented prohibitions prior to 2006. Australia on the other hand has been applying taxes exclusively throughout the period of interest.

Figure 1:



(a) Number of implemented Export Restrictions by country and type, 2002-2014

(b) Export Restrictions Indicators 2002-2015

Building up on Cadot et al. (2015) and Rude & An (2015), three independent indicators for each major export restrictions class are constructed. The starting point is a basic policy dummy variable *p* for a measure of type *j* at time *t*, which can be compiled via unique identification numbers in the data:

$$p_{j,c,t} = \begin{cases} 1 & \text{if implemented} \\ 0 & \text{otherwise} \end{cases}$$

Next, a simple policy count variable *P* for each country can be calculated by summing up all implemented policies of type *j* by country *c*:

$$P_{j,c,t} = \sum_{i=1}^{C} p_{j,c,t} \tag{1}$$

However, some additional features are required to be reflected in each indicator in order to obtain a global indicator which can be used to estimate effects on world market volatility. First, the relative importance of implementing countries needs to be weighted in. Ideally, the trade weight should reflect the exact point in time when a given policy was in place, i.e. the day, week or month. Unfortunately, trade data has not been available at those frequencies and would additionally bring about seasonality in the indicator. On the other hand, annual weights are problematic as they introduce endogeneity. If a country imposes a ban in July and August, the trade weight of that year will already capture some effects of these measures. In order to circumvent this, the indicator is weighted with export shares at *t-1* which is considered to provide the best possible weight of relative market importance at time *t*. The trade weight, or market share, may be expressed as

$$x_{c,t} = \frac{X_{c,t}}{X_{w,t}} \tag{2}$$

Where $x_{c,t}$ is the share of world exports supplied by country *c* at time *t* which naturally is a function of its export quantities $X_{c,t}$ and total world exports $X_{w,t}$.

Secondly, also the policy framework needs to be taken into account. This differers from Rude & An (2015) as they assume a constant an unrelated policy dimension. However, as Anderson & Martin (2011) have pointed out, in particular the combination of many uncoordinated trade policies induce volatile prices. For the sake of taking the overall export restrictive global policy domain into account, the indicator has been policy weighted. Accordingly, a global policy count is calculated similar to equation 1:

$$P_{j,w,t} = \sum_{i=1}^{W} p_{j,w,t} \tag{3}$$

which counts all globally implemented policies of type *j*. Note that here *t* has a different frequency which is in line with that of the trade weight in equation 2.

Finally, the export restriction indicator *ERI*, at point time *t* and for policy *j*, may be expressed as

$$ERI_{j,t} = \sum_{i=1}^{C} \left(\frac{P_{j,c,t}}{P_{j,w,t}} * x_{c,t-1}\right) \tag{4}$$

Where $P_{j,c,t}$ represents a set of policies of the type *j* operated at time *t* by country *c* which is divided by all policies operated in that year. The second part of the equation represents an ordinary trade weight, or market share, at *t-1*. Note that in this study KKRU[1] are aggregated due to their close geographical and trade ties.

The application of the derived policy indicator *ERI* provides three time series which reflect (i) the severity of restrictions (ii) the size of implementing countries relative to others and (iii), the contrast of single policies and the global policy environment and (iv), the timing of implementation which additionally allows for varying the frequency of the series as required. What is more, the indicator may be decomposed to single country policies. Full use of available data is made and no outcome type data is consulted, classifying the indicators as entirely policy based measures. The shortcomings of this approach are for one its limited interpretability. There is no scale or reference to which scores can be compared. While the minimum of the indicator is zero, there is no theoretical maximum of global trade restrictiveness. Hence, the indicator may only be interpreted with regards to time and in

[1] Russia, Ukraine and Kazakhstan have formed a grain union which allows the usage of ports on any of the countries coastline. In spite of the recent political turmoil, countries have expressed continued dedication to the agreement. For further reference see \url{www.timesca.com/index.php/news/12110-kazakhstan-grain-exports-looking-for-new-routes} and \url{www.apk-inform.com/frontend_dev.php/en/news/77336\#.V_31r9HAN0w}. As a landlocked country, Kyrgyzstan is reliant upon ports of its neighbours for their exports.

comparison among countries. Secondly, the indicator does not relate to quantities. In order to grasp the burden of global trade policies in theory the amounts of trade impeded through policy should be reflected.

Figure 1b depicts the policy indicators over time. It is observable that both export bans and export quotas increase during the commodity price hikes in 2007/08 and 2010/2011, which is intuitive as countries react to surging prices in order to stabilize domestic prices. However, export taxes are more pronounced during the pre crisis period form 2002 to 2007. This is connected to the construction of the indicator and reflects the fact that when prices have surged, quotas and bans have been implemented more frequently while taxes have been popular during the whole target period, and with regards to the general policy environment, even more so in tranquil periods.

2.1 Food Price Data

As Wheat remains he most important staple food (USDA, 2016), in this analysis the international wheat price is proxied by two spot prices, namely Hard Red Winter (HRW) and Soft Red Winter (SRW), traded in the U.S. and retrieved from Datastream. All series are available in daily and weekly frequencies and comprise 3373 and 674 observations respectively. Secondly, future contracts of Soft Red Winter are drawn from the same source. SRW and HRW are the most important traded wheat types and are expected to reflect world price behaviour. The advantage of using futures lies in the fact that they are traded much more frequently and therefore are expected to be more sensitive to external shocks which allows the examination of high frequency data.

While spot prices might reveal vulnerability to export controls in higher frequency data, such as monthly or weekly as they are not traded that frequently, futures may react much quicker, also on a daily basis. Choosing the three different prices hence allows a gradual narrowing of the frequency data used and closely analyse whether different frequency models deliver different results.

3 Empirical Strategy

3.1 Volatility estimation

As volatility can not be observed directly, the first step is to derive valid estimates. A dualistic approach is chosen in which one parametric and one non-parametric volatility measures are employed. The reasoning behind this is that different frequency data can be analysed, and secondly comparing effects on distinguished measures of volatility may bring about more confidence in the results or, on the contrary, reveal contradictions, making the overall strategy more robust.

A straightforward model-free way to obtain volatility estimates is the realized volatility as proposed for instance in Poon & Granger (2003).

Defining first the returns *r* from prices *p*,

$$r_t = ln(p_t) - ln(p_{t-1}) \tag{5}$$

volatility can then be calculated as

$$\hat{\sigma} = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(r_t - \bar{r})^2} \tag{6}$$

Here volatility equals the sample variance of returns. *p* denote price and consequently *r* the returns. Since daily price data are available, a monthly volatility time series using daily prices in equation 6 can be constructed. *N* consequently represents the number of days in a month. $\bar{r}$ is the mean return of each month. The obtained results are subsequently annualized through the factor of $\sqrt{12}$. The advantage in calculating a low (monthly) frequency volatility based on high (daily) frequency are mainly twofold: First, as pointed out earlier, stochastic volatility models require more observations than 12 months in 13 years (156 observations), which are available in this framework. Secondly, the approach is non-parametric which means that no a priori assumption on distributions is required. Table 1a provides summary statistics for each compiled volatility series.

Table 1:

(a) Realized Monthly Volatility

	SRW	HRW	Futures
Mean	0.08	0.07	0.06
SD	0.04	0.03	0.02
Min	0.03	0.02	0.02
Max	0.23	0.23	0.14
Skewness	1.33	2.18	1.13
Kurtosis	2.18	6.50	2.07

(b) Weekly GARCH-Volatility

	SRW	HRW	Futures
Mean	0.38	0.35	0.29
SD	0.10	0.04	0.04
Min	0.23	0.27	0.20
Max	0.69	0.49	0.40
Skewness	1.09	0.58	0.55
Kurtosis	1.10	-0.27	-0.42

An alternative parametric option to estimate volatility is that of (G)ARCH models. Pioneered by (Engle, 1982) and (Bollerslev, 1986) they provide standard parametric volatility estimates based on an autoregressive variance process:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{7}$$

The conditional variance is determined by a linear function of q lagged squared residuals and its own p lagged conditional variance. In case of $q = 0$ in equation 7 is equivalent to an ARCH(p) process. Note that α_0, α_i and $\beta_j$are non-negative parameters to ensure positivity of σ^2. Stationarity of the process additionally requires the sum of α-parameters and β-parametes to be smaller than 1. In practice, the GARCH(1,1) has been shown to usually provide the best model choice (Hansen & Lunde, 2005). In this analysis up to GARCH(2,2) models were estimated and ultimately the common GARCH(1,1) was chosen based on AIC and SC.

The results of the estimated ARIMA(52,1,0)-GARCH(1,1) volatilities, which have been annualized by multiplying with $\sqrt{52}$ are depicted in table 1b.

The realized volatility time series entails 156 monthly volatility estimates from January 2002 up to December 2014, while the weekly GARCH volatility provide a volatility series of 624 observations. For both measures, the SRW series is the most volatile among the three price data series. However, monthly realized volatility suggests a much higher standard deviation of those compared to SRW and futures than the estimated GARCH volatility series. Furthermore, both volatility series suggest that futures have been less volatile than both SRW and HRW prices. This is in line with (Kawai, 1983) who found that futures are usually more stable than spot prices.

3.2 The VAR-X model

Choosing an appropriate model to analyse the impacts of export restrictions requires evaluating the properties of the underlying data. In principle, GARCH-X models constitute a good model choice for estimating exogenous effects on volatility. However, as the optimization of parameters in GARCH models is cumbersome, the inclusion of only a limited number of exogenous variables is feasible. Since in this exploratory analysis, the impacts of single country policies are of interest, which implies more than ten variables in most cases, estimating VAR-X models prior to proceeding to GARCH-X models is useful. VAR models appear suitable as volatility series are stationary time series and furthermore, one can safely assume that international wheat price volatilities are somewhat dependent on each other. In the standard framework, the three price volatilities, that is those of SRW, HRW and futures may be estimated endogenously. Spillovers between the volatilities are captured by this model class. Having estimated volatilities of the time series as described in the previous section, a VAR-X model may be formulated where export policies enter the equations as exogenous regressors:

$$y_t = v_0 + v_1 t + A_1 y_{t-1} + ... + A_p y_{t-p} + B_1 x_{t-1} + ... + B_q x_{t-q} + u_t \quad (8)$$

v_0 and v_1 denote parameters for the constant and trends respectively and B are parameter matrices for the exogenous variables x_t

In the case of export restrictions and food price volatility, the endogenous variable vector y_t comprises the three volatility series. Since the estimation of volatility yields stationary data per definition, no further unit root discussion needs to be addressed. According to standard unit root analysis, the export quota and prohibition series are stationary processes, the export taxes series is most likely *I(1)* and consequently enters the equation in first differences.

In this analysis, three specifications of the VAR-X system in equation 8 are estimated. First, realized volatilities are used in the endogenous part of the equation while the three indicator series constitute the exogenous variables. In this model, additional seasonal dummy variables are included to control for seasonality in the price data. Secondly, the weekly ARIMA(52,1,0)-GARCH(1,1) volatilities are endogenously estimated while the exogenous part remains unchanged. Thirdly, while still using the weekly volatilities as endogenous variables, each country policy may be added in the system as an exogenous variable.

Obviously, especially the third VAR-X system yields a model with a large number of regressors. The autometrix algorithm, developed in Doornik (2009) is applied to reduce the original system down to a robust reduced form using the 10% p-value benchmark. However, in case of no instantaneous causality between the endogenous variables, the equations may be treated separately and individual reductions can be performed. (Krolzig, 2001).

3.3 Asymmetric EGARCH-X models

Finally, as it is in particular interesting to understand whether export restrictions might have different impacts at different points in time, EGARCH-X models are employed. More precisely, it is assumed that export restrictive policy measures have different impacts in times of commodity price surges. Admittedly, regime switching models, such as MSGARCH models[2] are also suited to this end, however, as the concerned time periods are known a priori, the models might as well be estimated for each period separately.

Using daily futures data, the scope of estimating EGARCH-X models is threefold: First, having daily price and policy data at hand, a total of 3373 observation allows for analysing different time periods and compare policy effects across time. Secondly, having estimated effects of export policies on monthly and weekly frequency volatility, the impacts on a daily basis is of interest as well. Third, agricultural price volatility is likely to be impacted asymmetrically. That is the size of a 'good news' impact is different than that of a 'bad news' impact on volatility. EGARCH models precisely aim at capturing this asymmetry. (Nelson, 1991):

$$ln(\sigma_t^2) = \omega + \beta ln(\sigma_{t-1}^2) + \gamma \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\epsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (11)$$

where again σ_t denotes the conditional variance of the EGARCH(1,1) and εt is the error term of some underlying mean process. $\frac{\varepsilon_t}{\sqrt{\sigma_t^2}}$ is the standardized shock for period *t*. Large and positive ε imply good news while large negative errors represent bad news. Therefore, γ is a measure of asymmetry. That is the leverage effect and indicates which type of news has larger effects on the conditional variance. A critical advantage of this GARCH formulation is that

[2] Markov switching GARCH

due to the logarithms, the non-negativity restrictions on parameters are removed. Similarly to GARCH models, the EGARCH(1,1) may be augmented using exogenous variables. Adding the three policy indicators on the right hand side, the reference period from 01/01/2002 to 31/12/2014 is subsequently split into five periods. The pre-crisis period before the 2007/08 price spikes stretches from 01/01/2002 to 27/05/2007. The first crisis period covers food price surges from 28/05/2007 up until 01/03/2008. The following period is denoted as the between crisis period which dates from 02/03/2008 to 01/06/2010 in which prices behaved somewhat more stable than in the previous period. The second crisis period has been allocated to the time slot from 02/06/2010 to 27/05/2011, where prices had surged for the second time during the target period. Eventually, the post crisis period is defined as ranging from 28/05/2011 to 13/12/2014. Additionally, the model is also run on the entire period.

Naturally, prices are more volatile in periods of food price surges and equivalently export restrictive measures have been predominantly applied in these periods. However, as countries' policy actions aim at a variety of goals, policies are implemented and withdrawn also in out of crisis periods. The splitting of the time horizon does not just single out periods of volatility and increased incidence of export restrictions but instead makes use of the high frequency data and allows comparing times with different volatility *and* policy regimes.

4 Results

4.1 Aggregate global export restrictive policy

The first VAR-X[3] results, where monthly realized volatilities constitute the endogenous variables, are gathered in table 2. In this model, the impacts of the three major export controls are analysed as global aggregates. The lag order of the model is 3 as suggested by AIC and SC. With regards to spillover effects among the endogenous volatility series, HRW price volatility and futures volatility show some dependency among each other and furthermore are dependent on past SRW volatilities. In particular futures contracts are dependent on past SRW and HRW volatilities which is not surprising as futures contracts are based on spot price information.

With regards to the exogenous variables, export quotas are found to significantly contribute to increased realized volatility of HRW and futures wheat prices. Both export taxes and export prohibitions were not significant at any step of the VAR reduction procedure and are therefore not included in the final model. The SRW volatility series is impacted only by it's own past and a constant.

The second VAR-X model stands in close relation to the first one as they incorporate the same structure of exogenous drivers. In contrast to the first model however, weekly ARIMA(52,1,1)-GARCH(1,1) volatilities constitute the set of endogenous variables. The outcome of the estimation is presented in table 2. AIC and SC suggest a VAR of order 2 to be the best model. Similar to the previous VAR model, export quotas provide the only policy variable found to significantly increase volatility in the HRWand futures contracts markets. In this model, no spillover effects can be detected and the volatility series appear to depend only on their own past.

From the first two VAR-X models it can be derived that, first, as both volatility estimates reveal similar impacts of the exogenous drivers of interest, the likelihood of having detected spurious relationships is reduced. Furthermore, taxes and bans are not found to significantly impact wheat price volatility during the whole target period which is analysed in monthly and weekly frequencies in the aggregate. Export quota policy on the other hand has shown significant impacts in both models. Given the rather extensive time period these models are

[3] In this study the effects of exogenous drivers are of central interest whereas the spillover effects between price volatilities are only of minor importance. Therefore, no impulse response analysis is carried out and the focus lies on the interpretation of exogenous effects.

concerned with, export quotas can be associated with significant long run impacts on wheat price volatility. These results stand in some contrast to Rude & An (2015) who found that taxes increase wheat price volatility to a greater extend than quantitative restrictions.

The fact that prohibitions appear non-significant may seem surprising. Since it is the most powerful policy tool, one might expect to see strongest impacts on price volatility also because their effect on price levels has been shown to be important. (e.g. Mitra & Josling, 2009). However, volatility is a different concept than price levels and high prices might well be theoretically relatively stable. Another explanation would be the actual incidence of export prohibitions. While export prohibitions are the most rigorous policy measure they are equivalently rarely implemented.

4.2 Aggregate global export restrictive policy

The results of the third VAR-X model, where again weekly GARCH volatilities are the endogenous variables in the system, are depicted in table 3. As the system is found to inherit no instantaneous causaliy[4], the model has been reduced on an individual basis.

Here, SRW volatility turns out to be significantly affected by India's export ban policies. HRW volatilities on the other hand have been found to react to export prohibitions introduced by Pakistan and Argentinian export quotas. The futures volatilities are particularly prone to export control measures as Pakistan's bans, Argentina's and KKRU's quotas as well as Australia's export tax polices all turn out to significantly exacerbate volatility of the contract price.

In terms of wheat prices, the results show that futures prices are particularly impacted through export restrictions. This is somewhat intuitive as futures are traded much more frequently and may be expected to be particularly sensitive to external shocks. Although the magnitude of impacts in the first two VAR-X models compare well to each other, five individual country policies have been shown to influence futures contracts volatility.

Surprisingly, prohibition policies of KKRU are not found to have significant effects on volatility, in spite of their relevance concerning food price spikes in 2010/11, whereas KKRU quotas appear to be wheat price volatility increasing. A rather straightforward explanation may be found in the duration of policies. In contrast to export quotas, which within the KKRU were only implemented by Ukraine, bans have been operated only temporarily, that is during some months of food price surges. The significant impact of prohibition policies of India and Pakistan provide further evidence with regards to duration of policy implementation. In contrast to KKRU bans, they have been operational in periods stretching basically over the whole time period.

This argument is further supported through evidence regarding export quotas. While they appear to be powerful volatility drivers during the whole target period, especially KKRU and Argentinian quotas have been shown to individually contribute to international price volatility. Both of which have been in place for several years in the after 2007/08 period instead of being applied only over several months.

4.2 Export restrictions in different volatility regimes

Before examining the individual time periods separately, the model has been run on the entire target period. Table 4 first of all shows the results of the general EGARCH(1,1)-X model from January 1st, 2002 to December 31st, 2014. In line with the VAR-X results, export quotas are found to positively contribute to wheat futures price volatility. Additionally the model exhibits rather high persistence and a positive leverage effect. According to Stigler,

[4] See (Krolzig, 2001)

(2011), these are quite usual characteristics of agricultural price and volatility series[5]. Having confirmed the VAR-X results in a general EGARCH-X model, the specific periods as defined in the previous section can be analysed more closely. Table 5 contains the parameter estimates for the models of each period providing a much more diverse picture of the effects of export restrictions on volatility. Different volatility regimes can clearly be distinguished. The models show higher persistence of volatility during periods of crisis. Interestingly, the leverage effect γ changes sign during crisis periods and becomes negative and thus indicates that during crisis positive shocks, that is larger upward deviations from mean prices, actually generate less volatility than negative ones (price drops). In times of tranquil markets this functions vice versa which again, is in line with the conventional asymmetry feature of agricultural price data. Except for the pre-crisis period and the 2010/11 crisis, α turns out to be insignificant indicating that the absolute size of innovation is not important to the creation of additional volatility and the effects are fully governed by the difference of positive and negative shocks.

Turning now to the exogenous volatility drivers, restrictive export measures have more pronounced effects during periods of price surges. In both crisis periods export taxes appear as statistically significantly volatility increasing with greater magnitude in the first crisis period. During out-of-crisis periods taxes slightly and positively affected wheat futures volatility after the 2011 episode. This result confirms Rude & An (2015) who similarly found tariffs to be important volatility drivers. However, the effects of export taxes may be narrowed down to food price crisis periods and to some extend to the post 2011 period.

Surprisingly, prohibitions show negative effects in the first crisis period while positive effects in the second one. This is likely due to Argentina withdrawing its quotas in November 2007 and additionally introducing a quota for a week only during the same month. At that time, wheat prices where in midst of their surge and volatility was increasing, too.

Quotas exhibit by far the strongest impact but only during the first episode of soaring food prices.

5 Summary and key findings

This paper empirically examined the relationship between export controls and wheat price volatility. To that end, three policy indicators have been compiled which reflect global export restrictiveness in terms of prohibitions, quotas and taxes, and may be decomposed to policies on country levels as well as set up in different frequencies for the period from 2002 to 2014. The effects of the indicators have subsequently been tested over time in VAR-X and EGARCH-X models applying an individual strategy which gradually narrows down the policy measures and levels, the frequency of the data as well as the time period. Moreover, a dualistic approach has been incorporated which entails two particular concepts of volatility which have been subject to the empirical analysis. A novelty emerging from this approach is that (i) specific policy measures, (ii) particular country policy strategies, and (iii) the timing of those may be evaluated with regards to wheat price volatility. Previous studies have placed focus on level impacts, tariff vs. non-tariff measures effects and domestic price volatility.

The key findings from the empirical analysis are:

1. Export restrictive policies have significantly increased wheat price volatility
2. Quotas have had most pronounced effects in comparison to tariffs and prohibitions

[5] In financial econometrics *good news* are referred to as price increases, more precisely large positive error terms in the mean process. Those usually create less volatility than price drops which yields $\gamma < 0$. In agricultural prices good news are low prices, i.e. large negative deviations from the mean which is why $\gamma > 0$ is expected and also usually found empirically. (Stigler, 2011).

3. Long term quota and prohibition policy strategies significantly increased wheat price volatility. In particular prohibitions operated by India and Pakistan, Argentinian and KKRU quota policies as well as export tax policy imposed by Australia and China have significantly increased wheat price volatility
4. All three analysed policy measures have had significantly stronger effects in the price crises periods of 2007/08 and 2010/11 in comparison to more tranquil periods

Within the context of the current WTO regulation and proposals for modification and extensions, the results strongly encourage the introduction of precise conditions for the implementation of emergency measures, with special attention to the time spans of implementation as well as the definition of emergency situations. These concepts have been interpreted very broadly by market participants leading to the imposition of export controls over extensive periods of time and in situations where the presence of an emergency situation is at least questionable. Precisely these longer term quantitative export restrictions are particularly found to contribute to wheat price volatility.

On the other hand, the most ambitious proposal of entirely abolishing export restrictions is linked to somewhat ambiguous results. Truly temporarily introduced export controls have not been found to spur wheat price volatility supporting the current exemption for countries to apply restrictions in times of emergency. Yet, all quantitative export restrictions have had impacts on wheat price volatility either taking the form of individual country policy or then limited to specific periods. Moreover, while export taxes have volatility increasing effects, they are limited to times of market turmoil and may be associated with motivations to increase fiscal revenue instead of protecting domestic consumers. Thus, calls for improved regulation of arbitrary taxes are supported in view of possibilities to moderate food price volatility, while the allowance for temporary emergency measures is challenged only marginally. This is not only supported by the empirical findings, but also by the widespread international recognition of the need of flexibility for food-importing developing countries.

The results from this paper provide nuanced insights on the interaction of trade policy and food price volatility. In summary, long term quantitative restrictions have strongest and most persuasive impacts on food price volatility. Among those, quotas are stronger and more consistent volatility drivers than prohibitions. Export taxes on the other hand are associated with volatility increases in times of stress and long term policy strategies do not translate into higher volatility. In turn, better informed policymaking and international negotiations are enabled to address the problem of increasing food price volatility, which is so critical for the poor and food insecure as well as the advance of the SDGs.

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Appendix: Estimation results tables

Table 2: VAR-X summary of monthly realized volatilities and aggregate policy indicators

	Soft Red Winter	Hard Red Winter	Futures Contracts
SRW_{t-1}	0.18	−0.11	−0.10
	(0.12)	(0.09)	(0.09)
HRW_{t-1}	0.41	0.38	0.30**
	(0.20)	(0.16)	(0.15)
$Futures_{t-1}$	−0.29	−0.14	−0.13
	(0.21)	(0.16)	(0.15)
SRW_{t-2}	0.27**	0.22**	0.24***
	(0.12)	(0.10)	(0.09)
HRW_{t-2}	−0.14	0.03	−0.14
	(0.20)	(0.16)	(0.14)
$Futures_{t-2}$	0.21	−0.06	0.16
	(0.20)	(0.16)	(0.15)
SRW_{t-3}	−0.01	−0.13	−0.08
	(0.12)	(0.10)	(0.09)
HRW_{t-3}	−0.33	−0.35**	−0.35**
	(0.20)	(0.16)	(0.14)
$Futures_{t-3}$	0.23	0.33**	0.41***
	(0.21)	(0.16)	0.15
constant	0.07***	0.09***	0.07***
	(0.02)	(0.02)	(0.01)
Export Quotas	0.01	0.03***	0.02**
	(0.01)	(0.01)	(0.01)

Standard errors in parenthesis. Significance levels are '* * *', '**' and '*' for < 0.1, < 0.05 and < 0.01 respectively
Seasonality is addressed through the inclusion of seasonal dummies which are not reported

Table 3: VAR-X summary of weekly annualized ARIMA(52,1,1)-GARCH(1,1) volatilities and aggregate policy indicators

	Soft Red Winter	Hard Red Winter	Futures Contracts
SRW_{t-1}	0.9713***	0.0005	−0.0077
	(0.0469)	(0.0456)	(0.0212)
HRW_{t-1}	0.0202	0.9187***	0.0190
	(0.0604)	(0.0586)	(0.0273)
$Futures_{t-1}$	−0.0567	−0.2020	0.9353***
	(0.1354)	(0.1314)	(0.0613)
SRW_{t-2}	−0.0144	−0.0027	0.0095
	(0.0472)	(0.0458)	(0.0214)
HRW_{t-2}	−0.0215	−0.1360***	−0.0109
	(0.0567)	(0.0551)	(0.0257)
$Futures_{t-2}$	0.0273	0.2054	−0.0044
	(0.1337)	(0.1298)	(0.0605)
constant	0.0237***	0.0679***	0.0155***
	(0.0097)	(0.0095)	(0.0044)
Export Quotas	0.0029	0.0052***	0.0018**
	(0.0021)	(0.0020)	(0.0009)

Standard errors in parenthesis. Significance levels are '* * *', '**' and '*' for < 0.1, < 0.05 and < 0.01 respectively

Table 4: VAR-X summary of weekly annualized ARIMA(52,1,1)-GARCH(1,1) volatilities and individual country policies

	Soft Red Winter	Hard Red Winter	Futures Contracts
SRW_{t-1}	0.9448^{***}	–	-0.0112
	(0.0150)	–	(0.0074)
HRW_{t-1}	–	0.9189^{***}	0.0296^{**}
	–	(0.0581)	(0.0149)
$Futures_{t-1}$	–	-0.2126^{*}	0.8792^{***}
	–	(0.1249)	(0.0228)
HRW_{t-2}	–	-0.1420^{***}	–
	–	(0.0545)	–
$Futures_{t-2}$	-0.0510	0.2090^{*}	–
	(0.0351)	(0.1220)	–
const	0.0323^{***}	0.0608^{***}	0.0170^{***}
	(0.0096)	(0.0091)	(0.0046)
EP India	0.0013^{**}	–	–
	(0.0005)	–	–
EP Pakistan	–	0.0042^{**}	0.0027^{**}
	–	(0.0020)	(0.0012)
EQ Argentina	-0.0001	0.0025^{***}	0.0013^{***}
	(0.0006)	(0.0009)	(0.0005)
EQ KKRU	–	–	0.0043^{**}
	–	–	(0.0019)
ET Australia	–	–	0.0012^{**}
	–	–	(0.0005)
ET China	–	–	0.0003
	–	–	(0.0002)

Standard errors in parenthesis. Significance levels are '***', '**' and '*' for < 0.1, < 0.05 and < 0.01 respectively
EP, EQ and ET stand for export prohibitions, export quotas and export taxes respectively

Table 5: EGARCH-X results 2002-2014

Parameter	Estimate	Std. Error
ω	-0.1522^{***}	0.0030
α	0.0413^{***}	0.0097
β	0.9818^{***}	0.0002
γ	0.0915^{***}	0.0040
Export Bans	0.0011	0.0007
Export Quotas	0.0073^{***}	0.0022
Export Taxes	0.0222	0.4164

Significance levels are '$***$', '$**$' and '$*$' for < 0.1, < 0.05 and < 0.01 respectively

Table 6: EGARCH-X results for multiple periods

Parameter	Pre-Crisis	07/08 Crisis	Between Crisis	10/11 Crisis	Post-Crisis
ω	-0.8934^{***}	-0.3605^{***}	-1.007	-0.2448^{***}	-0.1898^{***}
α	0.0751^{***}	0.1094	0.1189	0.0828^{***}	0.011
β	0.8945^{***}	0.9671^{***}	0.8743^{***}	0.9754^{***}	0.9777^{***}
γ	0.1123^{***}	-0.1271^{***}	0.0859	-0.1767^{***}	0.1116^{***}
Export Prohibitions	0.0023	-0.015^{***}	-0.0079	0.0004^{***}	-0.0002
Export Quotas	0.0029	0.0686^{***}	0.0396	0.031	-0.0141
Export Taxes	0.0031	0.0222^{***}	0.0113	0.0125^{***}	0.006^{**}

Significance levels are '$***$', '$**$' and '$*$' for < 0.1, < 0.05 and < 0.01 respectively