Sources of domestic food price volatility: An empirical investigation using structural gravity of maize markets

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1 Introduction

More frequent extreme weather events are expected to increase the volatility of crop yields affecting the income stability of farmers and sectors that rely on agricultural products as their main inputs. World markets are an important source for stabilizing prices. However, the extent to which international markets are a reliable source for stabilizing agricultural commodity prices depends on the degree to which weather-driven supply shocks are uncorrelated across countries. Intuitively, trade stabilizes markets via the movement of products from where they are abundant to where they are relatively scarce. Thus, regions with positive correlation of supply shocks would simultaneously experience abundance or scarcity reducing the scope for international trade to stabilize prices. Despite the early theoretical recognition of the crucial role that weather correlation between locations has on bilateral trade patterns (Williams and Wright, 1991), most studies on trade and price stability assume that weather-driven supply shocks are independently distributed over time and space (Bigman, 1985). This at odds with the fact that worldwide climates are correlated, typically over thousands of kilometers, through the so-called climate "teleconnections" such as El Niño/Southern Oscillation (Rosenzweig and Hillel, 2008). Moreover, global climate models project increases in the frequency of extreme events occurring simultaneously in several growing regions of the world (Diffenbaugh and Scherer, 2011).

Against this background, this paper investigates the extent to which correlated weather-driven supply shocks matter for domestic price formation around the world. We focus on maize, a widely produced and traded commodity. The main challenge for this research is that comprehensive and consistent cross-country price data for enough years to calculate reliable estimates of variances and covariances, on either producer or consumer prices, are largely unavailable.

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In this work we attempt to circumvent this difficulty using the so called "structural gravity" framework established in seminal work of Anderson and Van Wincoop (2003). The gist of the empirical strategy is to use the variation in price data *implicit* in the matrix of bilateral trade flows to infer supply prices consistent with a Constatnt Elasticity of Substituion (CES) demand system. The CES is a workhorse to analyse international trade flows and, as demonstrated below, it also allows for convenient closed form expressions for relating the variance of supply prices to the covariance of cross-country supply shocks.

2 Theorethical Framework

The goal of this section is to develop formulae for pinning down the relationship between domestic price variability, international trade flows, and domestic and foreign supply shocks. Start with th CES Utility function defined over all sources:

$$U_j = \left(\sum_i q_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

Which when maximized subject to a budget constraints:

$$\sum_j p_{ij} q_{ij} \leq E_j \tag{2}$$

gives demands:

$$q_{ij} = \frac{\beta_{ij} E_j}{p_{ij}^{\sigma} P_j^{1-\sigma}}. \tag{3}$$

where:

- q_{ij}: quantity exported from country i to j.
- β_{ij}: CES preference parameter:
- p_{ij}: price of i's product on j's market.
- P_j: CES price index.
- E_j :expenditures.

The CES price index of country j is given by:

$$P_j = \left[\sum_i \beta_{ij}^{\sigma} p_{ij}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{4}$$

where:

$$p_{ij} = (c_i z_i \tau_{ij}). \tag{5}$$

is the price of the good produced by country i in country j. This price is determined by marginal unit costs (c_i), a productivity parameter, z_i and the costs of transporting the good from i to j. The productivity parameter captures weather shocks. As written, $z_i > 1$ would be associated with bad weather because it causes prices to increase (it amplifies marginal costs.) $z_i < 1$ will reduce marginal costs, reducing the price, thus making i more competitive.

The objective is to see how the correlation of supply shocks among trading partners relates to prices. To do this, note that P_j is determined by the four random variables β_{ij}, c_i, z_i, and τ_{ij}. Therefore, we can decompose the variance of P_j into the variance of β_{ij}, c_i, z_i, and τ_{ij}. As a matter of notation, we use $a_{j[i]}$ to denote the i^{th} element of:

$$\boldsymbol{a}_j = [\boldsymbol{\beta_{1j}}, ..., \boldsymbol{\beta_{Nj}}, \boldsymbol{c_1}, ..., \boldsymbol{c_N}, \boldsymbol{z_1}, ..., \boldsymbol{z_N}, \boldsymbol{\tau_{1j}}, ..., \boldsymbol{\tau_{Nj}}] \tag{6}$$

a vector of the 4N random variables entering the CES price index P of country j. Each $a_{j[i]}$ is a time series, e.g. $a_{j[1]} = \boldsymbol{\beta_{1j}} = \beta_{1j,t=1}, ..., \beta_{1j,t=T}$ with sample mean $\bar{a}_{j[1]} = T^{-1}\sum_t^T a_{j[1,t]}$. The vector of the sample means of each element in $\boldsymbol{a}_j$ is given by:

$$\bar{\boldsymbol{a}}_j = [\bar{\beta}_{1j}, ..., \bar{\beta}_{Nj}, \bar{c}_1, ..., \bar{c}_N, \bar{z}_1, ..., \bar{z}_N, \bar{\tau}_{1j}, ..., \bar{\tau}_{Nj}]. \tag{7}$$

The variance of the first order Taylor series expansion around sample means is given by:

$$Var(P_j) = \sum_i \left(\frac{\partial P_j}{\partial a_{j[i]}}\right)^2 \Bigg|_{\boldsymbol{a}_j=\bar{\boldsymbol{a}}_j} var(a_{j[i]}) + \sum_i \sum_{k\neq i} \frac{\partial P_j}{\partial a_{j[i]}} \frac{\partial P_j}{\partial a_{j[k]}} \Bigg|_{\boldsymbol{a}_j=\bar{\boldsymbol{a}}_j} cov(a_{j[i]}, a_{j[k]}). \tag{8}$$

The derivatives $\dfrac{\partial P_j}{\partial a_{j[i]}}$ for $\boldsymbol{c_i}, \boldsymbol{z_i}$, and $\boldsymbol{\tau_{ij}}$—known as sensitivity terms in the error propagation literature —are given by:

$$\frac{\partial P_j}{\partial a_{j[i]}} = P_j^\sigma \beta_{ij}^\sigma (p_{ij})^{1-\sigma} a_{j[i]}^{-1} \Bigg|_{a_j=\bar{a}_j}. \tag{9}$$

And the derivatives for $\boldsymbol{\beta_{ij}}$ is given by:

$$\frac{\partial P_j}{\partial \beta_{ij}} = \frac{\sigma}{1-\sigma} P_j^\sigma \beta_{ij}^\sigma (p_{ij})^{1-\sigma} \beta_{ij}^{-1} \Bigg|_{a_j=\bar{a}_j}. \tag{10}$$

All evaluated at the sample means $\bar{a}_j$.

The sensitivity terms indicate that the effect of an increase in the variance of the supply shock in any country i affects the variance of the CES price index P_j in direct proportion to the contribution of country i's price to j's overall price, or said otherwise, the larger the market share, the most sensitive the cost of living in country j is to increases in the volatility of shocks in country i.

Two interesting situatiosn are revealed by expression 8. First, if covariances are zero, the variance of any given supply shock is diluted through the trade shares. It is possible then that this dilution decreases total variance. In this sense, trade acts as a risk sharing agreement, a point made, for instance, in Bigman (1985). However, if the covariances are positive, the variance price would be amplified relative to no covariation assumption.

Getting an empirical measure of the relative effects of variances and covariances along the lines in 8 can be achieved by getting measures of the CES price, which are unobserved. But we can construct them using structural gravity. When we do so, we also get measures of the supply prices. These series of modeled or estimated prices have some advantages such as: country and time coverage as well as the reference against to which to measure real prices. This is the task to which we turn next.

3 Structural Gravity and Estimation

Following Anderson and Van Wincoop (2003), structural gravity is derived by summing all the bilateral demands (in equation 3) from country$i$:

$$\begin{aligned} Q_i &= \sum_j q_{ij}, \\ &= \sum_j \frac{\beta_{ij} P_j^{\sigma-1} E_j}{p_{ij}^{\sigma}}, \\ &= \frac{1}{p_i^{\sigma}} \sum_j \frac{\beta_{ij} E_j P_j^{\sigma-1}}{\tau_{ij}^{\sigma}}, \\ &= \frac{\Pi_i}{p_i^{\sigma}}. \end{aligned} \tag{11}$$

And then solving for the supply price in i as:

$$p_i = \left(\frac{Q_i}{\Pi_i}\right)^{-\frac{1}{\sigma}}. \tag{12}$$

where $\Pi_i = \sum_j \frac{\beta_{ij} E_j}{\tau_{ij}^{\sigma} P_j^{\sigma-1}}$ is Anderson and Van Wincoop (2003)'s index of *outward multilateral resistance*, a summary measure of the ease with with country i can access export markets.

The supply prices in 12 can be used to rewrite the CES demand equation 3 so that it is now a function of the outward multilateral resistance indices:

$$q_{ij} = \beta_{ij} \left(\frac{Q_i}{\Pi_i}\right) \left(\frac{1}{\tau_{ij}}\right)^{\sigma} \left(\frac{E_j}{P_j^{1-\sigma}}\right). \tag{13}$$

Moreover, by substituting the supply price in 12 into the CES price index 4 we obtain:

$$P_j^{1-\sigma} = \sum_i \beta_{ij}^{\sigma} \left[\left(\frac{Q_i}{\Pi_i}\right)^{-\frac{1}{\sigma}} \tau_{ij}\right]^{1-\sigma}. \tag{14}$$

This version of the CES price index is Anderson and Van Wincoop (2003)'s index of *inward multilateral resistance*, a summary measure of the ease with which exporters can sell in country j. A main insight of Anderson and Van Wincoop (2003) is that both P_i and Π_i are simultaneously determined, a fact that, as discussed shortly, is central to our empirical strategy.

By adopting astructural view of the gravity model of trade we are able to combine the simplicity of fixed-effect estimation with the clear mapping from data to prices suggested by the CES functional form. In particular, we can estimate the demand equations 13 by using importer and exportes fixed effects, m and e:

$$q_{ij} = \exp\left(e_i - \sigma \log(\tau_{ij}) + m_j\right) \varepsilon_{ij} \tag{15}$$

where $\exp(m_j) = \dfrac{E_j}{P_j^{1-\sigma}}$, which we can use to solve for $P_j^{1-\sigma} = \dfrac{E_j}{\exp(m_j)}$. Likewise, $\exp(e_i) = \dfrac{Q_i}{\Pi_i}$, from which we obtain $\Pi_i = \dfrac{Q_i}{\exp(e_i)}$. An additional complication arising from working with quantities is that we do not directly observe expenditures E_j, which are in value because they are derived from the budget constraint, $\sum_j p_{ij} q_{ij} = E_j$. The q_{ij} are bilateral trade flows, and are observed. For getting th eunobserved prices, we can use estimates of τ_{ij} p_i to get them. The estimates of τ_{ij} are straightforward:

$$\widehat{\tau_{ij}^{-\sigma}} = (DIS\tau_{ij}^{\hat{\gamma}_1} \exp \sum_{k=2}^{K} \hat{\gamma}_k ind_k), \tag{16}$$

As for the prices p_i, equation 12 indicates that we require three pieces: (i) an estimate of the elasticity of substitution σ, (ii) the output Q_i in each country, and (iii) an estimate of Π. Our estimate of σ comes from Hertel et al. (2007). Q_i is the sum of domestic sales plus bilateral exports minus imports, all data that is used in estimation. The price indices $P_j^{1-\sigma}, \Pi_i$ are recovered from the fixed effects, after propeer normalization (Fally, 2015). In particular:

$$\Pi_i = \frac{Q_i}{Q_0 \exp(e_i)} \tag{17}$$

will normalize $\Pi_i = 1$ when $j = 0$ because $\exp(e_o) = 1$. The CES price index will be:

$$P_j^{1-\sigma} = \frac{Q_0 E_j}{\exp(m_j)} \tag{18}$$

So, now knowing $\widehat{\Pi_i}$ we can easily get p_i for every country i, $\widehat{\tau_{ij}}$ for every country pair, which combined with the observed quantities q_{ij}, can be used to recover expenditures $\widehat{E_j}$, which in turn are used to recover $\widehat{P_j^{1-\sigma}}$ using 18[1].

[1] An important issue is that by normalizing in the U.S., we are wipe out the variability in the US along the dimension of normalization—therefore variation in other prices is relative to the U.S. One way of making

4 Data and Estimation Steps

In terms of procedure, for each year in 1962-2009, we estimate a gravity equation by regressing bilateral maize import volumes (from COMTRADE) and domestic sales (from FAOSTAT) on internal and bilateral distances and a set of variables on bilateral cultural, geographical, and economic proximity (from CEPII), as well as applied tariffs on maize imports (from TRAINS). The dataset covers 75 countries encompassing + 90% of production and maize trade. We use the parameter estimates of the gravity equation to calculate bilateral trade costs using standard procedures in the literature . The estimated trade costs and country fixed effects are used to calculate country-level CES price indices and CES supply prices. This procedure generates consistent CES price indices and supply prices for 75 countries, from 1962 to 2009. We also use the estimated prices and other parameters to calculate the sensitivity terms that capture the sensitivity of the CES price index to supply shocks. These sensitivities are than used to construct sensitivity-weighted variances and covariances of domestic and foreign supply shocks. As proxy variables for the supply shocks we use year-to-year changes in growing season temperature and precipitation (CRU TS3) aggregated using global crop calendars. We also use a drought index as well as detrended yields from FAOSTAT. Note that by using variables within the growing season of each marketing year, we are explicitly taking into accounts differences in hemispheric seasons. The final step is to determine the relative importance of domestic and foreign climate variances, as well as covariances between domestic and foreign production. For this we regress the variance of the estimated CES price indices and supply prices on the sensitivity weighted variance and covariance matrices of weather shocks.

5 Results

Figure 6 shows the CES price indices and supply prices for few countries representative of each major region of the world (sub-Saharan Africa, Latin America, Asia, and North America). Few regularitties are worth noting. First, in most countries the CES price indices are lower and less variable than domestic supply prices. This can be taken as preliminary evidence of the stabilizing role of international trade as the swings in the domestic supply prices are diluted when they are averaged with the prices of other suppliers. Second, the time series capture the stylized behavior documented elsewhere of relatively long periods of low and stable prices, interrupted by sharp spikes, the most recent of which ocurred in the late 2000s.

Figures 6 and 6 compare the coefficients of variation of the two price series for the periods 1962-2009 and 1990-2009. During the longer period, it is difficult to observe any definite

these variations "absolute" is to use a normalization that in each year produces the p_i observed in the U.S. For instance: say that $p_i = 2$, then we can find the Π_{US} that satisfies this: $2 = \left(\frac{Q_{US}}{\Pi_{US}}\right)^{-\frac{1}{\sigma}}$ then we find the term K that satisfies: $\Pi_{US} = \frac{Q_{US}}{Kexp(e_{US})}$, and use that K to normalize 17 and 18. This normalization can be done at two levels. One, with nominal prices, and the other with US real prices. This normalization ensures that the variance of the model-estimated US price will match the observed variance.

relationship between these two price series. If anything, the coefficients of variation lie close to the 45 degrees line, with the exception of some countries in Southern Africa. However, when we reduce the periof of analysis to 1990-2009, the CES supply prices seem much more variable than the CES price indices, suggesting again that the effect of domestic supply shocks is diluted as world trade in agricultural products became slightly less distorted in the mid 1990s, after the adoption of the WTO Agreement on Agriculture.

Using the CES price indices and supply prices we now regress their variance on the variance of four different sources of supply shocks: the variance of a dought index constructed as in Babcock and Yu. The variance of temperature and precipitation, and the variance of yield deviations from trend. The main result here is that the variance of the CES supply prices are not correlated with the variances of the supply shocks,. However when we look at the supply prices, we find a richer story. A first result is that the higher the variance of the source of domestic supply shocks, the higher the variance of the domestic supply prices. Interestingly, we also find that correlated supply shocks are associated with greate price volatility. Meanwhile, variation in the partner countries, in itself, is not a source of increased price volatility. This is a subtle buy interesting message insofar countries may be vulnerable to foreign shocks insofar they are correlated; this is a qualitative different story of simple vulnerability. (I think the terms are correlations. adjust the text accordingly.

6 Conclusions

Our preliminary results indicate that supply prices are much more unstable than the CES price indices, which suggests that exposure to trade reduces price volatility. The volatility of the CES price indices appear uncorrelated with variations in several proxies for weather supply shocks. In contrast, the variability of CES supply prices increases when countries have correlated supply shocks. Very preliminary, the results suggest that the theoretical recognition of the crucial role that weather correlation between locations has on bilateral trade patterns, and the climatic evidence on worldwide climate correlations, global studies on trade and price stability would benefit by considering the possibility of supply shocks.

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Tables and Figures

Table 1: The effects of own variance and covariance with partners on the variability of CES price indices

	Dependent variable:			
	Coefficient of variation of CES price indices			
	Drought Index	Temperature	Precipitation	Yields
	(1)	(2)	(3)	(4)
own.var	−0.058	−1.435	−0.344	0.060
	(0.143)	(4.210)	(0.543)	(0.385)
cov.with.partners.var	0.041	0.020	0.137	−0.121
	(0.223)	(0.153)	(0.217)	(0.198)
partners.own.var	−0.042	−1.313	−0.327*	−0.113
	(0.030)	(0.824)	(0.192)	(0.136)
cov.between.partners	−0.085	−0.258	0.959	−0.116
	(0.292)	(0.519)	(1.034)	(0.382)
Constant	0.559***	0.562***	0.562***	0.553***
	(0.017)	(0.017)	(0.016)	(0.017)
Observations	68	68	68	68
R^2	0.200	0.212	0.208	0.191
Residual Std. Error (df = 63)	0.099	0.098	0.098	0.099
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2: The effects of own variance and covariance with partners on the variability of supply prices

	Dependent variable:			
	Coefficient of variation of CES supply prices			
	Drought Index	Temperature	Precipitation	Yields
	(1)	(2)	(3)	(4)
own.var	0.953^{***}	25.827^{***}	2.945^{***}	1.961^{***}
	(0.112)	(3.389)	(0.465)	(0.390)
cov.with.partners.var	1.148^{***}	0.397^{***}	1.188^{***}	1.046^{***}
	(0.174)	(0.123)	(0.186)	(0.201)
partners.own.var	0.014	0.395	0.148	0.196
	(0.024)	(0.663)	(0.165)	(0.138)
cov.between.partners	0.258	0.437	−1.109	−0.616
	(0.228)	(0.418)	(0.886)	(0.387)
Constant	0.111^{***}	0.118^{***}	0.137^{***}	0.139^{***}
	(0.013)	(0.014)	(0.014)	(0.017)
Observations	68	68	68	68
R^2	0.695	0.681	0.637	0.481
Residual Std. Error (df = 63)	0.077	0.079	0.084	0.101
Note:				*p<0.1; **p<0.05; ***p<0.01

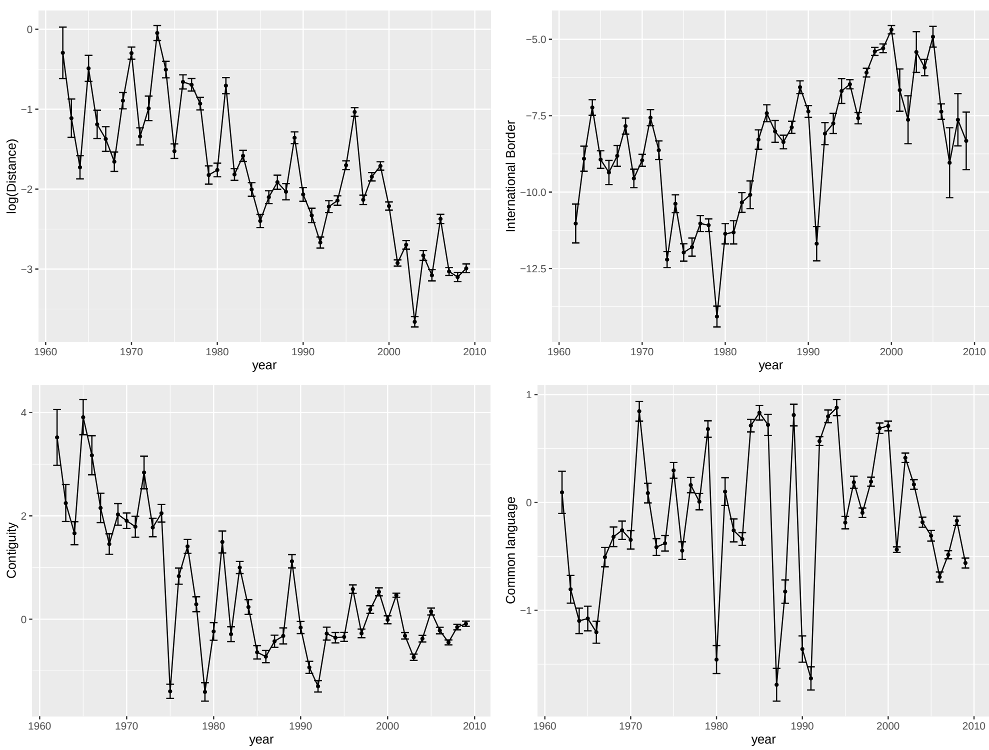

Figure 1: Parameter estimates

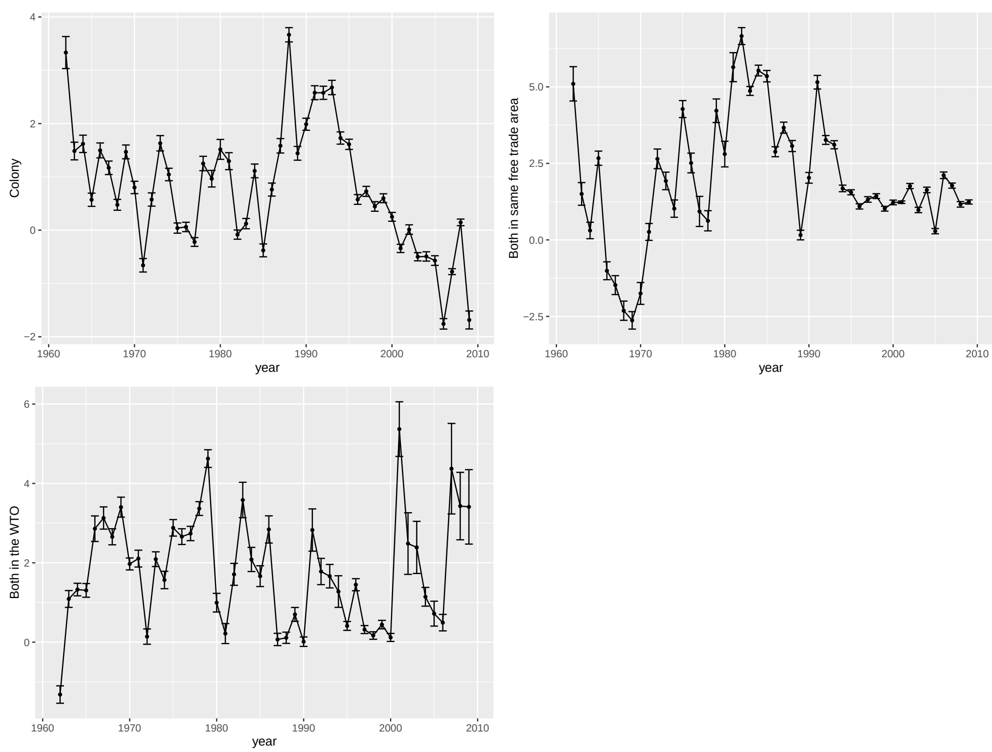

Figure 2: Parameter estimates (cont)

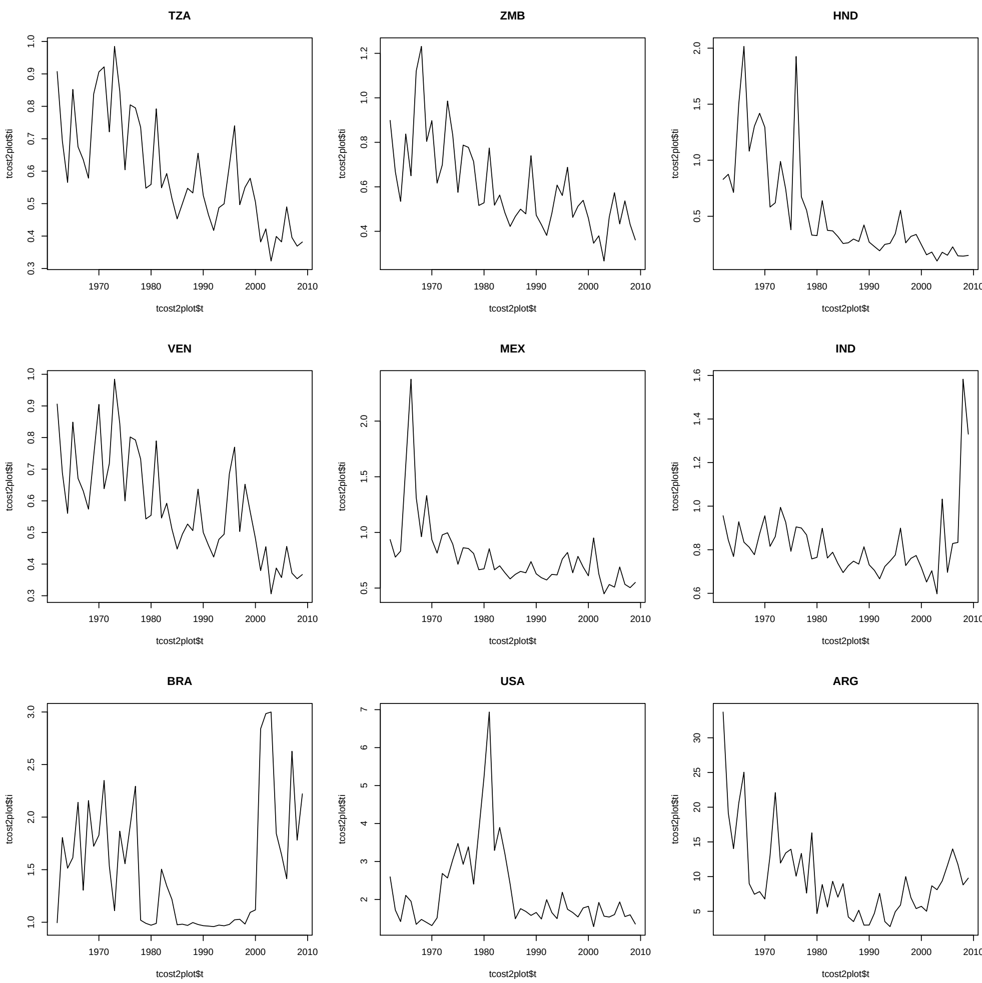

Figure 3: Trade costs for selectedcountries

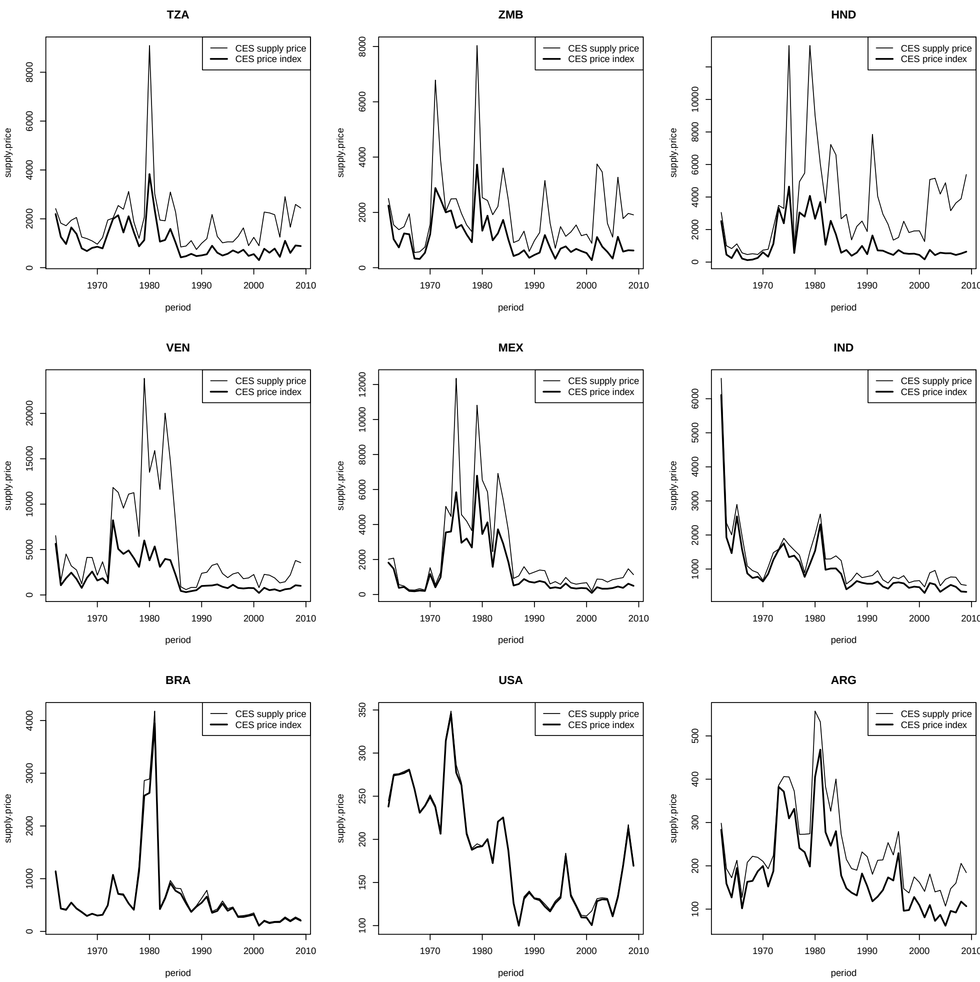

Figure 4: CES Prices (relative to U.S. real prices

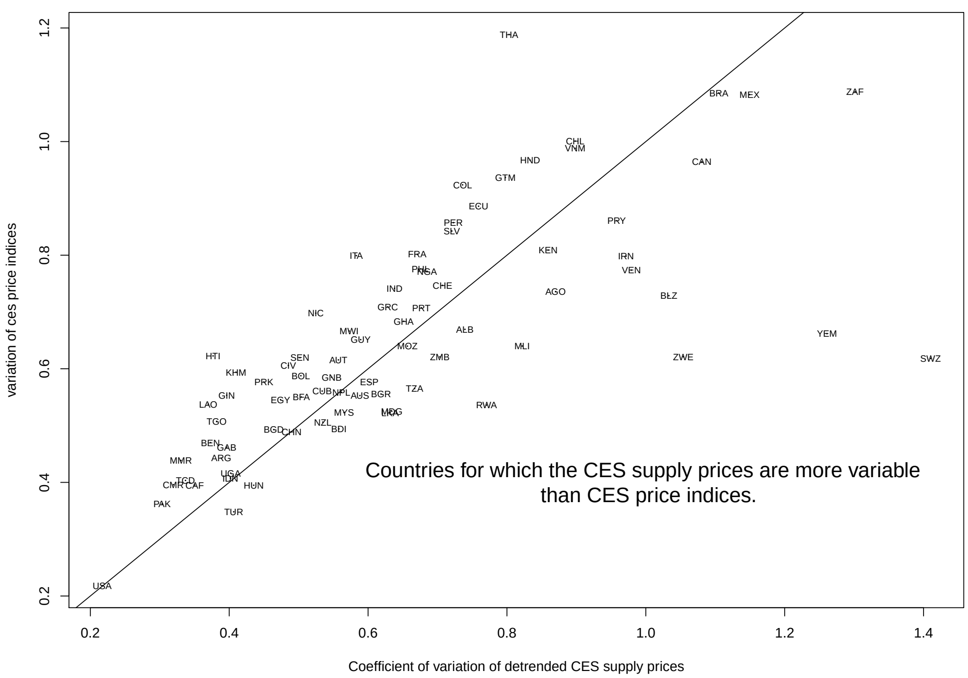

Figure 5: Variability of CES prices (1962-2009)

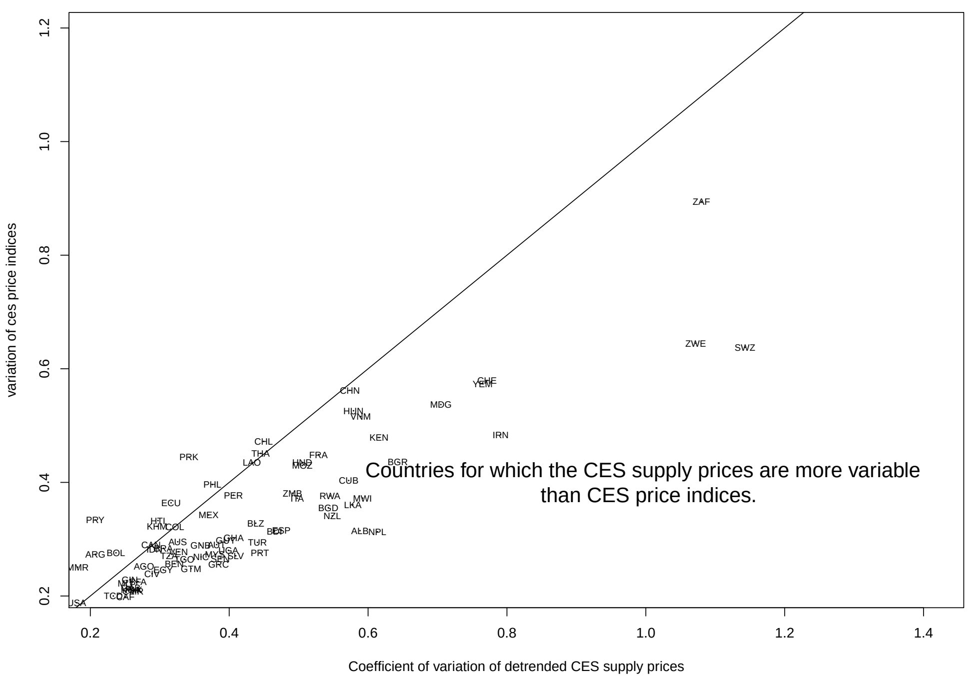

Figure 6: Variability of CES prices (1990-2009)