

FINANCIAL SPECULATION IMPACT ON AGRICULTURAL COMMODITY PRICE VOLATILITY: TGARCH APPROACH

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Abstract. Motivated by agricultural commodity price fluctuations and spikes in the last decade, we investigate whether financial speculation destabilizes the price of agricultural commodities. The aim of this research is to assess the impact of financial speculation on agricultural commodity price volatility. In our study we use weekly returns on wheat, soybean and corn futures from Chicago Mercantile of Exchange. To measure this impact, we apply autoregressive conditional heteroskedasticity (ARCH) technique. We also propose a model with seasonal dummy variables to measure if financial speculation impact on price volatility differs among seasons. The results of our research indicate that financial speculation as an exogenous factor has either no effect or reduces the volatility of the underlying futures prices. Therefore, we conclude that the increase of non-commercial market participants does not make the agricultural commodity prices more volatile or this link is at least questionable.

Keywords: financial speculation, agricultural futures, price volatility, commodity futures markets.

JEL code: C58, G13, Q02

Introduction

Agricultural commodity exchange markets are used to distribute the price risk between agricultural producers and consumers. In the last two decades, major commodity exchange markets became more open to index funds and other investors that do not participate in the underlying agricultural activities. On the one hand, this indicates speculative activity that can potentially affect the prices and cause bubbles. On the other hand, these investors provide the necessary liquidity for these markets to function. The problem whether financial speculation (best described by index funds' net positions) distorts the prices of agricultural commodities have drawn a lot of attention in the recent academic literature. Although many of these studies differ in price measures and other variables used, there is no consensus among authors if financial speculation makes the commodity markets more unstable (Haase et al., 2016). Many authors argue that an increase in non-commercial positions does not disrupt agricultural commodity markets, nor it causes spikes in price levels. Etienne et al. (2017) who used Granger causality tests to analyse Chicago Board of Trade wheat, soybean, and corn markets between 2004 and 2015, provide little evidence that grain futures prices experienced large and prolonged bubbles and that the index investments were causing them. Similar results were achieved by Sanders and Irwin (2010) who used regression models to analyse the relationships between futures returns and long positions of index fund investors in twelve US agricultural commodity markets between 2006 and 2008. On the other hand, these studies lack the emphasis on price volatility and its modelling. A study by Dawson (2015) highlights a high volatility persistence and structural breaks in London International Financial Futures and Options Exchange wheat futures prices between 1996 and 2012. However, it is not clear whether the change in volatility structure is a result of financial speculation. Therefore, the aim of this research is to assess the impact of financial speculation on agricultural commodity price volatility. To achieve this, we first describe the methodology to measure the price volatility and financial speculation, then we analyse the underlying impact of financial speculation on volatility and its clustering.

The complex and non-linear relationships between variables requires advanced techniques in order to achieve more detailed results. Many studies on commodity futures markets use

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autoregressive conditional heteroskedasticity (ARCH) approach (Gupta and Rajib, 2012). According to Silveira et al. (2017) ARCH methods allow to model financial data which do not follow a normal distribution. ARCH methods are primarily used to forecast volatility in futures markets. However, these models can also be used to explain the factors responsible for volatility and its clusters. In our research we apply modified ARCH techniques to estimate the impact of financial speculation on the volatility of prices. Another important factor within agricultural markets is the seasonality as prices become more volatile prior to harvest times (Karali and Thurman, 2010). Therefore, we also add seasonality to our modelling to see if the effect of financial speculation differs among seasons.

Methodology

Our research consists of three models: preliminary generalized autoregressive conditional heteroskedasticity (GARCH) model, main threshold generalized autoregressive conditional heteroskedasticity (TGARCH) model and a proposed TGARCH model that uses financial speculation as a multiple seasonal variable. We start our analysis by defining the variables for all three models. First, we generate price return series as the natural log of futures prices:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100. \quad (1)$$

where: R_t is price returns on futures, P_t is futures price, t is time period, \ln is natural logarithm.

To measure financial speculation in agricultural commodity markets we apply Working T index of excess speculation (Working, 1960). The Working's T index measures the excess of non-commercial positions (index funds positions) relative to commercial positions (agricultural producers' and consumers' positions) and is used in the research on futures markets (Buyuksahin and Robe, 2014). The value of this index cannot be less than 1. If it is equal to 1, then all positions in the market are commercial. According to the methodology originally described by Working (1960), we generate a time series of speculative activity index:

$$T_t = \begin{cases} 1 + \frac{SS_t}{HL_t + HS_t} & \text{if}(HS_t \geq HL_t), \\ 1 + \frac{SL_t}{HL_t + HS_t} & \text{if}(HL_t > HS_t). \end{cases} \quad (2)$$

where: T_t is working T index for financial speculation, SS_t are non-commercial short positions, SL_t are non-commercial long positions, HS_t are commercial short positions and HL_t are commercial long positions, t is time period.

Next, we perform a test if time series are stationary. In ARCH modeling stationary time series are required in order to obtain consistent parameter estimates (Buyuksahin and Robe, 2014). We perform Augmented Dickey–Fuller test if the data used in our research is stationary - H_0 : unit root is present; H_1 : alternative hypothesis. Next, we define our preliminary model with 1 time period AR lags GARCH (1,1). ARCH models consist of two segments: mean and variance equations. We place speculation index in our variance equation:

Mean equation:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + u_t. \quad (3)$$

Variance equation:

$$h_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 h_{t-1}^2 + \beta_3 T_{t-1}. \quad (4)$$

where: the mean equation consists of returns R_t as an autoregressive process with parameters α_0 , α_1 and an error term u_t with a variance of h_t^2 . The conditional variance h_t^2 is provided in the variance equation, where β_0 is the constant, $\beta_1 u_{t-1}^2$ is the residual (ARCH) effect, $\beta_2 h_{t-1}^2$ is the variance

(GARCH) effect. We also use an external variable $\beta_3 T_{t-1}$ in the variance equation to assess the direct effect of speculation index on conditional volatility.

As an extension to our previously described GARCH model, we use a Threshold Autoregressive Conditional Heteroskedasticity (TGARCH) approach for our main model. In this approach a binary variable is added to estimate the negative return impact on volatility and whether this relationship is asymmetric (Hadsell, 2006). In order to assess the seasonal volatility, time seasons are also added to the variance equation. To avoid multicollinearity, we only use 3 seasons: spring, summer and autumn. Next, we specify our main model based on TGARCH methodology proposed by Zekoian (1994):

Mean equation:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + u_t. \quad (5)$$

Variance equation:

$$h_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 h_{t-1}^2 + \beta_3 T_{t-1} + \beta_4 u_{t-1}^2 d_{t-1} + \beta_5 DP_{t-1} + \beta_6 DS_{t-1} + \beta_7 DA_{t-1}. \quad (6)$$

where: $\beta_4 u_{t-1}^2 d_{t-1}$ is the asymmetric component, the parameter $d_t = 1$ if $u_{t-1} < 0$ and $d_t = 0$ otherwise. If $\beta_4 \neq 0$, then a threshold effect exists, when $\beta_4 > 0$, the return impact on volatility is asymmetric. $\beta_5 DP_{t-1}$ is the seasonality parameter to measure the effect of spring, $DP_t = 1$ if time period t is spring and $DP_t = 0$ otherwise. $\beta_6 DS_{t-1}$ is the summer effect. $\beta_7 DA_{t-1}$ is the autumn effect. Other parameters described in preliminary model (formula 3 and 4).

We also propose an alternative TGARCH model with an additional variable to model financial speculation as a multiple component with seasonal dummy variable. This model allows to assess the season weighted financial speculation and its impact on price volatility. We select spring as the most volatile season for agricultural futures markets. Next, we specify our proposed model:

Mean equation:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + u_t. \quad (7)$$

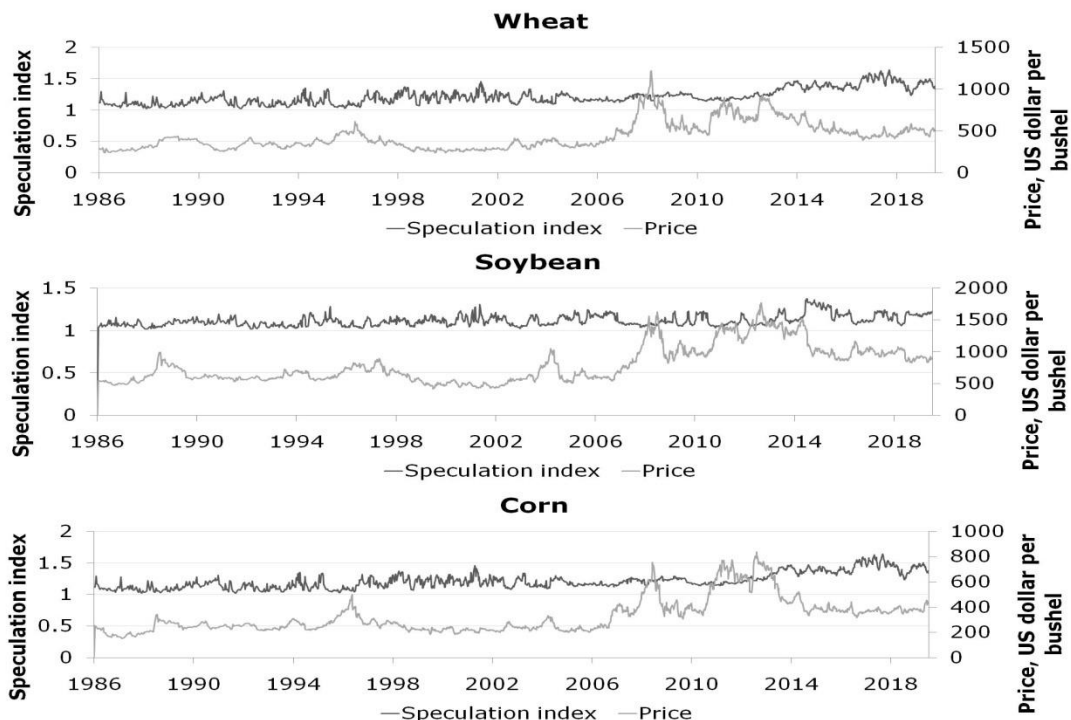
Variance equation:

$$h_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 h_{t-1}^2 + \beta_3 T_{t-1} + \beta_4 u_{t-1}^2 d_{t-1} + \beta_5 DP_{t-1} + \beta_6 T_{t-1} DP_{t-1}. \quad (8)$$

where: $\beta_6 T_{t-1} DP_{t-1}$ is the multiple effect of speculation index T_{t-1} and season spring effect DP_{t-1} . Other parameters described in preliminary and main model (formula 3, 4, 5 and 6).

Data

In our research we use weekly data for wheat, corn and soybean continuous contracts from Chicago Mercantile of Exchange. The prices for these commodity futures are quoted in US cents per bushel. In our research we cover the time period from January 1986 to July 2019. In total, our analysis covers 1563 weekly observations. We use data on commercial and non-commercial positions to generate the time series of Working T index of speculative activity (Figure 1).



Source: author's calculations based on Chicago Mercantile Exchange data, 2019

Fig. 1. Prices and speculation index for wheat, soybean and corn futures (January 1986–July 2019)

Research results and discussion

We start our analysis by providing descriptive statistics for wheat, corn and soybean futures from Chicago Mercantile of Exchange (Table 1). We split our time series into two subsamples covering, respectively, 1986–2002 ($n=698$) and 2003–2019 ($n=865$). The volatility of returns described by standard deviance is larger in the time period of 2003–2019 for all three agricultural commodities. Jacque-Bera test results meet the significance criteria of q -value <0.05 and thus show that sample data have the skewness and kurtosis matching a normal distribution.

Table 1

Descriptive statistics of weekly price returns of agricultural commodity futures

	Wheat			Soybean			Corn		
	1986-2019	1986-2002	2003-2019	1986-2019	1986-2002	2003-2019	1986-2019	1986-2002	2003-2019
Mean	0.03	0.01	0.05	0.03	0.01	0.05	0.03	-0.01	0.07
Median	-0.07	-0.06	-0.10	0.14	0.09	0.21	0.00	0.00	0.05
Minimum	-17.18	-17.18	-15.78	-24.19	-24.19	-21.20	-19.98	-19.98	-17.68
Maximum	18.78	18.78	16.84	13.94	13.94	11.34	21.23	20.91	21.23
Std. deviation	3.93	3.50	4.25	3.38	3.24	3.49	3.89	3.71	4.03
Skewness	0.29	0.35	0.26	-0.56	-0.57	-0.56	-0.10	-0.25	-0.01
Kurtosis	1.49	2.99	0.73	3.98	6.24	2.57	4.13	6.07	2.94
Jacque-Bera	167.6**	273.3**	28.9**	1113.0**	1169.8**	282.6**	1115.5**	1077.0**	310.9**

Notes: Estimates with p -value less than 0.05 are flagged with one asterisk (*), with p -value less than 0.01 are flagged with two asterisks (**).

Source: author's calculations based on Chicago Mercantile Exchange data, 2019

Our next step is to test the hypothesis for data stationarity. We provide estimates for ADF statistics for each commodity used in our study (Table 2). Hypothesis H_0 of unit root can be rejected for both returns and speculation in all cases, except for speculation index of wheat (-2.93) in 2003–

2019. The results confirm that further ARCH technique is appropriate for modelling volatility of selected time series.

Table 2

Augmented Dickey Fuller Test

	Wheat			Soybean			Corn		
	1986-2019	1986-2002	2003-2019	1986-2019	1986-2002	2003-2019	1986-2019	1986-2002	2003-2019
Price	-2.57	-2.53	-2.49	-2.90	-3.00	-2.03	-2.96	-2.95	-2.11
Return	-40.41**	-27.01**	-30.04**	-40.03**	-12.30**	-28.87**	-18.35**	-25.59**	-15.82**
Speculation index	-4.68**	-7.18**	-2.93	-8.47**	-8.39**	-4.76**	-7.75**	-5.81**	-5.74**

Notes: Estimates with p-value less than 0.05 are flagged with one asterisk (*), with p-value less than 0.01 are flagged with two asterisks (**).

Source: author's calculations based on Chicago Mercantile Exchange data, 2019

In order to measure the time-varying impact of speculative activity on agricultural futures price volatility, we provide estimates for the preliminary GARCH (1,1) model (Table 3). All three commodities have highly significant volatility (GARCH) effects implying volatility clusters. Residual (ARCH) effect is present in all cases except for whole sample of wheat (0.0744) and corn (0.0632) in 2003–2019. The existence of volatility clustering allows the further modelling of exogenous factors for futures price volatility. However, speculation index is a significant explanatory factor only in case of corn futures (-0.0214 with p-value less than 0.05 in 1986–2019, -0.0363 with p-value less than 0.01 in 2003–2019, Table 3). However, negative estimate of financial speculation indicates that financial speculation has a reverse effect and reduces the price volatility of corn futures.

Table 3

Preliminary GARCH model estimates for agricultural commodity returns

Period	Wheat			Soybean			Corn		
	1986-2019	1986-2002	2003-2019	1986-2019	1986-2002	2003-2019	1986-2019	1986-2002	2003-2019
Mean Equation									
constant	-0.0113	-0.0233	-0.0107	0.0701	0.0387	0.0955	0.0910	0.0430	0.1699
Return	-0.0163	-0.0203	-0.0118	-0.0338	-0.0397	-0.0177	-0.0269	-0.0155	-0.0372
Variance Equation									
constant	0.0038	0.0913	0.0390	0.0136	0.0018	0.0251*	0.0332**	0.0297	0.0503**
Residual	0.0744	0.1388**	0.1148**	0.1387**	0.1721**	0.1089**	0.1167**	0.1621**	0.0632
Volatility	0.8754**	0.4254**	0.7826**	0.8084**	0.7329**	0.8418**	0.8273**	0.7714**	0.8877**
Speculation index	0.0031	-0.0331	-0.0157	-0.0061	0.0079	-0.0164	-0.0214*	-0.0178	-0.0363**

Notes: Estimates with p-value less than 0.05 are flagged with one asterisk (*), with p-value less than 0.01 are flagged with two asterisks (**).

Source: author's calculations based on Chicago Mercantile Exchange data, 2019

Next, the asymmetry and seasonality effects are obtained through the estimation of the threshold generalized autoregressive conditional heteroskedasticity (TGARCH) model which is used as the main model for our research. Table 4 results indicate the presence of volatility clusters in both soybean and corn returns as residual and volatility estimates are highly significant similarly to the results of our previous model. The effect of financial speculation on volatility is only present in corn (-0.0120 with p-value less than 0.05 in 2003–2019). The further results suggest that there is a strong evidence for an asymmetric effect of volatility shocks of soybean (-0.6100 with p-value less than 0.01 in 2003–2019) and wheat (-0.5355 with p-value less than 0.01 in 2003–2019). The asymmetry effect in corn futures was only present between 1986 and 2002 (-0.4366 with p-value less than 0.01). However, in all cases the asymmetry estimate is negative, meaning that a positive return increases volatility at a greater extent than a same size negative return. Dummy variables for seasonality indicate that returns on futures prices were significantly more volatile during spring compared to other seasons.

However, the only exception is soybean futures that were also volatile during summer (0.0054 with p-value less than 0.01 in 2003–2019).

Table 4

Main TGARCH model estimates for agricultural commodity returns

Period	Wheat			Soybean			Corn		
	1986–2019	1986–2002	2003–2019	1986–2019	1986–2002	2003–2019	1986–2019	1986–2002	2003–2019
Mean Equation									
constant	0.0038	-0.0848	0.0700	0.1560**	0.0978	0.1935	0.1708**	0.1332	0.2207**
Return	-0.0280**	-0.0244	-0.0242	-0.0373	-0.0494	-0.0094	-0.0519*	-0.0141	-0.0606**
Variance Equation									
constant	0.0011	0.0055	0.0023	0.0012	0.0027	0.0009	0.0003	-0.0004	0.0145
Residual	0.0405**	0.0375	0.0476	0.0489**	0.0402**	0.0534**	0.0430**	0.0336**	0.0409**
Volatility	0.9550	0.9453**	0.9461**	0.9511**	0.9492**	0.9494**	0.9594**	0.9606**	0.9470**
Asymmetry	-0.3652*	-0.0529	-0.5355**	-0.5913**	-0.6393**	-0.6100**	-0.2438	-0.4366**	0.0958
Speculation index	0.0004	-0.0030	0.0000	-0.0010	-0.0017	-0.0012	-0.0013	-0.0004	-0.0120*
Spring	0.0048**	0.0061**	0.0047**	0.0033**	0.0039**	0.0029*	0.0104**	0.0115**	0.0096**
Summer	-0.0013	0.0004	-0.0021	0.0047**	0.0045*	0.0054**	0.0004	0.0004	0.0021
Autumn	-0.0022	-0.0025	-0.0005	-0.0031**	-0.0040**	-0.0019	-0.0016	-0.0020	-0.0008

Notes: Estimates with p-value less than 0.05 are flagged with one asterisk (*), with p-value less than 0.01 are flagged with two asterisks (**).

Source: author's calculations based on Chicago Mercantile Exchange data, 2019

Next, Table 5 shows the results of our proposed modified TGARCH model that includes the product of seasonal dummy variable and financial speculation. An estimate for the ARCH processes indicates similar results as in previous models, the volatility and residual effects are present in all cases except for wheat. The asymmetry between returns and volatility is present and negative in soybean and wheat futures in time period after 2003. The product of financial speculation and seasonal dummy variable has a statistically significant and negative effect on volatility in wheat (-5.4768 with p-value less than 0.01 in 1986–2002) and soybean (-1.9046 with p-value less than 0.01 in 1986–2019, -2.0884 with p-value less than 0.05 in 2003–2019). However, in case of wheat the non-multiple speculation effect was also significant but positive (1.2722 with p-value less than 0.01 in 1986–2002). This can indicate that an increase in non-commercial positions reduces the volatility during more volatile spring season.

Table 5

Proposed TGARCH model estimates for agricultural commodity returns

	Wheat			Soybean			Corn		
Period	1986-2019	1986-2002	2003-2019	1986-2019	1986-2002	2003-2019	1986-2019	1986-2002	2003-2019
Mean Equation									
constant	-0.0006	-0.0692	0.0499	0.1474**	0.0812	0.1620	0.1689**	0.1289	0.2088*
Return	-0.0277	-0.0280	-0.0207	-0.0235	-0.0375	0.0002	-0.0500*	-0.0074	-0.0606*
Variance Equation									
constant	-0.3498	-1.2307*	1.0732	-0.4197	-0.4989	-0.7707	-0.2379	-1.0537	1.1668
Residual	0.0390**	0.0159	0.0622	0.0399**	0.0402**	0.0297*	0.0421**	0.0356**	0.0393**
Volatility	0.9537**	0.9496**	0.9160**	0.9644**	0.9556**	0.9779**	0.9601**	0.9571**	0.9539**
Asymmetry	-0.4445*	-0.6814	-0.4675*	-0.5972**	-0.4869*	-0.9071*	-2.2576	-0.4237*	0.0892
Speculation index	0.3362	1.2722**	-0.4670	0.2838	0.3924	0.5597	0.0520	0.8344	-1.0102
Spring	2.2654*	7.3280**	-1.2809	2.7780**	3.2436	2.8739**	2.3437**	5.4632**	0.7818
Speculation * Spring	-1.2763	-5.4768**	1.4042	-1.9046**	-0.2121	-2.0884*	-1.0347	-3.7467	0.2074

Notes: Estimates with *p*-value less than 0.05 are flagged with one asterisk (*), with *p*-value less than 0.01 are flagged with two asterisks (**).

Source: author's calculations based on Chicago Mercantile Exchange data, 2019

In the following, we conclude that realized futures return can be modelled by using ARCH techniques. Time series are stationary, both residual and volatility effects are present in most of cases. Furthermore, we estimate a negative asymmetry effect meaning that an increase in returns is more related to further increase in volatility than vice versa. Our preliminary GARCH model indicates that the presence of financial impact on agricultural futures volatility is only present in corn. However, this impact is negative, meaning that an increase in non-commercial futures positions reduces the underlying price volatility. Similar results are present in our main TGARCH model, only corn futures have a significant but negative effect on volatility. The main model also allows to assess the effect of seasonality on futures price volatility indicating that all agricultural commodities were more volatile during spring, soybean futures were also volatile during summer. In our proposed modified TGARCH model the negative effect of season weighted financial speculation on volatility is mostly present in soybean futures. The effect of financial speculation on wheat is positive and statistically significant, however, the effect is negative for season weighted financial speculation and was only present during time period of 1986–2002. Eventually, we are unable to find the destabilizing effect of financial speculation on underlying futures price volatility. Our study gives the following results: financial speculation as an exogenous factor either had no effect or reduced the volatility or increased the volatility only in time period before 2003. The further investigation on financial speculation impact on price volatility can be expanded by using months instead of seasons, more detailed time periods, also involve more commodity futures.

Conclusions, proposals, recommendations

- 1) In our research we analyse the volatility of three agricultural commodities, adopting extended autoregressive conditional heteroskedasticity (ARCH) models. We use realized weekly returns on wheat, soybean and corn futures from Chicago Mercantile of Exchange. The results from analysis show that time series are stationary and include volatility clustering, thus further modelling of exogenous variables using ARCH techniques is available. In our research we also indicate that futures prices are more volatile during spring as compared to other seasons.

- 2) The results of our main and preliminary model analysis show that financial speculation impact on volatility is only present in corn futures. However, this effect is negative, meaning that the increase in non-commercial positions is associated with lower price volatility. In addition, our proposed threshold autoregressive conditional heteroskedasticity (TGARCH) model with financial speculation as multiple factor with seasonality shows that speculation impact on volatility is present in soybean futures but is also negative.
- 3) The results of our research have important policy implications. Financial speculation is a concern for regulators of futures commodity exchanges to apply a limit on non-commercial positions. Our analysis similarly to other authors indicates that the influence of financial speculation on price level and price volatility in the agricultural markets is at least questionable or in some cases can be opposite as an increase in non-commercial positions can be followed by less volatile prices. However, we also provide evidence that non-commercial positions can make the price more stable or reduce the volatility during the more volatile spring periods.

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