On Minsky moments in commodity markets

George Dotsis[a] **Anastasios Megaritis**[b]
Athanasios Triantafyllou[c] **and Alexandros Sarris**[a]

[a] *University of Athens, Department of Economics, Greece*
[b] *Keele Business School, University of Keele, UK*
[c] *Essex Business School, University of Essex, UK*

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Motivation - Keynesian Theory and Minsky hypothesis

- Keynesian theory: risk-taking as key source of output fluctuations

- Corollary: Minsky (1977) hypothesis: financial markets are inherently unstable: risk-taking behavior of market participants increases enormously during ‘quiet’ periods (surrounded by a low volatility environment), leading to a sudden market crash: a Minsky moment

- In commodity markets: Minsky moment is the market upheaval (price spike) which often coincides with low commodity inventories

In this Paper

- We search for the mechanism which drives commodity market participants to hold less stocks for lengthy time periods, leaving the respective commodity markets vulnerable to price spikes as the theory of storage suggests
- We follow the **Keynesian** view for the explanation of commodity crises by empirically testing the **Minsky (1977)** hypothesis according to which the excessive stability is destabilizing commodity markets
- Motivated by the Minsky hypothesis, we postulate that the excessively low volatility environment in commodity markets is the key source of increasing risk-taking behavior and subsequent commodity price spikes.
- Our main hypothesis is that unexpected commodity price spikes typically occur after extensive periods of low volatility in the agricultural commodity markets

Relevant literature

- Theory of storage – competitive storage model (Working, 1948; Brennan, 1956; Fama and French, 1987; Bobenrieth et al., 2013; Gordon and Rowenhorst, 2006; Triantafyllou et al. 2020), price spikes occur when the convenience yield for holding physical inventory increases.
- Existence of Minsky moments in equity markets (Dannielson, 2018).
- Our analysis is the first to explain the falling production and inventories as the excessive risk-taking behavior of agricultural market participants

Contribution to the commodity literature

- We show that the low volatility environment predicts rising probability of price spikes of major agricultural, metals and energy commodities like corn, wheat and rice, gold and crude oil for forecasting horizon ranging from 1 up to 5 years.
- Our results are in line with the implications of the theory of storage, according to which falling global production and inventories are associated with agricultural commodity price booms (Working, 1948; Bobenrieth et al., 2013; Triantafyllou et al., 2020).
- Our analysis is the first to explain the falling production and inventories as the excessive risk-taking behavior of agricultural market participants

Data

- Yearly agricultural, metals and energy price series spanning more than 2 centuries (1851-2015).
- Proxy for global demand for commodities: yearly series for global GDP growth rate spanning also from 1851 to 2015.
- Proxy for commodity supply: yearly commodity production series for major agricultural, metals and energy commodities used in our analysis
- Monthly dataset: we additionally conduct the analysis on our monthly time series dataset spanning from January 1987 to May 2019.
- On our monthly time series dataset, except from commodity supply and demand, we control for speculative demand and hedging pressure using CFTC monthly data for commercial and non-commercial traders in commodity futures markets

Monthly and yearly commodity price volatility

- We estimate the GARCH (1,1) yearly conditional volatilities. The model is described in the Equations below

$$X_t = e_t \sigma_t$$
$$\sigma_t^2 = a + b_1 X_{t-1} + c_1 \sigma_{t-1}^2$$

- Where $X_t = \log(\frac{P_{t+1}}{P_t})$ and P_t is the yearly price of the commodity, e_t is i.i.d white noise that is independent from the conditional volatility

- Monthly commodity return volatility: We estimate realized volatilities following Andersen et al. (2001) methodology. Specifically, we calculate the sum of squared 5-minute logarithmic returns filtered through an MA(1) process as shown below:

$$RV_t = \sum_{i=1}^{n} r_i^2$$

Low and high components of commodity price volatility

- We use a Hodrick-Prescott filter (HP filter henceforth). According to the HP filter, the trend of the volatility is the solution of the following optimization problem:

$$\min_{\{\tau_\tau(h)\}_{t=1}^{T}} \left(\sum_{t=1}^{T}[\sigma_t - \tau_t(h)]^2 + h\sum_{t=2}^{T-1}\{[\tau_{t+1}(h) - \tau_t(h)] - [\tau_t(h) - \tau_{t-1}(h)]\}^2\right)$$

where σ_t is the volatility and $\tau_t(h)$ is the trend, whick is a function of parameter h. The choice of the proper h depends on the characteristics of the underlying series. In general, a higher h provides a smoother trend.

- We estimate the trend and cyclical component of the volatility and then we define the low and high volatility components as the negative and positive deviations from the trend respectively

$$\sigma_t^{high}(h)\begin{cases}\sigma_t - \tau_t(h) & if \quad \sigma_t \geq \tau_t(h)\\ 0 & otherwise\end{cases}$$

$$\sigma_t^{low}(h)\begin{cases}\sigma_t - \tau_t(h) & if \quad \sigma_t < \tau_t(h)\\ 0 & otherwise\end{cases}$$

Yearly and monthly probit regression models

- We estimate the probability of occurrence of a boom episode for each commodity, for 5 different predicting horizons (1 to 5 years ahead) using the following predicting model:

$$P\left(boom_{i,t} = 1\right) = F(b_0 + b_1 boom_{i,t-k} + b_2 \sigma_{i,t-k}^{low} + b_3 \sigma_{i,t-k}^{high} + b_4 GDPgrowth + b_5 pgrowth_{\ i,t-k} + \varepsilon_t)$$

- We estimate the monthly regression model shown below:

$$P(S_h = 1) = F(b_0 + b_1 HighVol(12)_{t-h} + b_2 LowVol(12)_{t-h} + b_3 HedgPres(12)_{t-h} + b_4 Spec(12)_{t-h} + b_5 \mathrm{Basis}(12)_{\ t-h} + b_6 GlobEcon(12)_{t-h} + \varepsilon_t)$$

Monthly probit regression results for the corn market

Horizon(h) / MA lags(k)		h=0	h=3	h=6	h=12
Const	Coef.	6.035***	6.423***	2.800*	-1.380
	t-stat	(3.40)	(3.56)	(1.92)	(-1.25)
HighVol(k)	Coef.	722.3***	111.5	-247.2	-51.94
	t-stat	(3.71)	(0.47)	(-1.01)	(-0.30)
LowVol(k)	Coef.	1742.5***	2542.1***	1868.9***	558.6*
	t-stat	(3.71)	(4.94)	(4.59)	(1.81)
HedgPres(k)	Coef.	5.049***	6.279***	4.797***	1.517
	t-stat	(3.83)	(4.21)	(3.90)	(1.60)
Spec(k)	Coef.	-24.13***	-25.75***	-14.11***	-1.684
	t-stat	(-4.39)	(-4.58)	(-3.25)	(-0.55)
Basis(k)	Coef.	0.02***	0.018***	0.005	-0.012
	t-stat	(4.48)	(4.18)	(1.01)	(-1.04)
GlobEcon(k)	Coef.	0.002	-0.0003	-0.001	0.004**
	t-stat	(0.91)	(-0.13)	(-0.54)	(2.26)
% Pseudo R^2		38.5	39.8	29.0	15.0

Monthly probit regression results for the soybeans market

Horizon(h) / MA lags(k)		h=0	h=3	h=6	h=12
Const	Coef.	2.804	2.268	0.343	-1.320
	t-stat	(1.38)	(1.03)	(0.15)	(-0.67)
HighVol(k)	Coef.	-76.09**	-112.7**	-229.2***	-104.5**
	t-stat	(-2.43)	(-2.55)	(-3.03)	(-2.38)
LowVol(k)	Coef.	4.175	8.439	9.82*	62.67***
	t-stat	(0.15)	(0.29)	(1.84)	(3.03)
HedgPres(k)	Coef.	3.615***	4.832***	5.219***	2.907***
	t-stat	(3.79)	(4.36)	(4.69)	(3.78)
Spec(k)	Coef.	-11.73**	-11.14**	-6.968	-2.432
	t-stat	(-2.37)	(-2.06)	(-1.24)	(-0.52)
Basis(k)	Coef.	0.006**	0.004	0.001	-0.001
	t-stat	(2.21)	(1.41)	(0.28)	(-0.23)
GlobEcon(k)	Coef.	0.008***	0.009***	0.009***	0.008***
	t-stat	(4.23)	(4.33)	(4.58)	(4.44)
% Pseudo R^2		31.7	37.6	44.4	33.1

Monthly probit regression results for the wheat market

Horizon(h) / MA lags(k)		h=0	h=3	h=6	h=12
Const	Coef.	0.367	0.128	4.116	-2.563*
	t-stat	(0.25)	(0.07)	(1.47)	(-1.72)
HighVol(k)	Coef.	695.7***	-152.1	-286.7	-5215.1*
	t-stat	(3.52)	(-0.50)	(-0.72)	(-1.84)
LowVol(k)	Coef.	1615.3***	1674.3***	2114.6***	1147.4***
	t-stat	(3.59)	(3.56)	(3.52)	(3.08)
HedgPres(k)	Coef.	2.352**	2.552**	5.925***	1.051
	t-stat	(2.07)	(2.04)	(3.18)	(1.13)
Spec(k)	Coef.	-7.547**	-7.126	-19.84**	0.781
	t-stat	(-2.07)	(-1.55)	(-2.52)	(0.24)
Basis(k)	Coef.	0.0212***	0.0177***	0.00551	0.00501
	t-stat	(4.16)	(3.18)	(0.81)	(0.77)
GlobEcon(k)	Coef.	0.000569	0.00582*	0.0137***	0.00729**
	t-stat	(0.22)	(1.88)	(2.98)	(2.17)
% Pseudo R^2		37.5	36.4	44.5	34.4

Yearly probit regressions on corn market

Corn

Horizon (k)		1year	2year	3year	4year	5year
Constant	coef	-1.219***	-0.808**	-0.823**	-1.099***	-1.462***
	t-stat	(-3.11)	(-2.14)	(-2.07)	(-2.67)	(-3.36)
$boom_{t-k}$	coef	1.334**	-0.399	-1.172	-1.860*	-2.113*
	t-stat	(2.21)	(-0.56)	(-1.34)	(-1.76)	(-1.88)
σ_{t-k}^{low}	coef	53.39	31.13	44.17	83.17*	100.6**
	t-stat	(1.23)	(0.76)	(1.01)	(1.87)	(2.21)
σ_{t-k}^{high}	coef	-37.28	-34.77	-29.75	-5.317	24.25
	t-stat	(-0.84)	(-0.81)	(-0.66)	(-0.14)	(0.78)
$GDPgrowth_{t-k}$	coef	0.721	-9.174	-13.23*	-11.48	-9.615
	t-stat	(0.09)	(-1.20)	(-1.71)	(-1.50)	(-1.22)
$pgrowth_{t-k}$	coef	-14.38***	-4.237	-0.679	0.728	7.070
	t-stat	(-3.27)	(-1.02)	(-0.15)	(0.16)	(1.48)
Pseudo R^2 %		12.5	6.7	6.2	7.3	4.1

Yearly probit regressions on wheat market

Wheat

Horizon (k)		1year	2year	3year	4year	5year
Constant	coef	-1.326***	-1.050***	-1.321***	-1.311***	-1.321***
	t-stat	(-3.54)	(-2.90)	(-3.45)	(-3.46)	(-3.48)
$boom_{t-k}$	coef	1.252**	0.0507	-1.040	-2.199	-1.651
	t-stat	(1.99)	(0.07)	(-1.10)	(-1.42)	(-1.23)
σ_{t-k}^{low}	coef	239.0**	247.9***	267.4**	257.5**	175.5
	t-stat	(2.51)	(2.60)	(2.53)	(2.32)	(1.64)
σ_{t-k}^{high}	coef	25.62	7.814	17.70	24.69	-22.01
	t-stat	(0.57)	(0.14)	(0.25)	(0.29)	(-0.24)
$GDPgrowth_{t-k}$	coef	6.473	-8.386	-15.29*	-13.19*	-8.577
	t-stat	(0.59)	(-1.01)	(-1.95)	(-1.69)	(-1.09)
$pgrowth_{t-k}$	coef	-12.64**	-3.788	-1.720	-3.336	4.133
	t-stat	(-2.10)	(-0.71)	(-0.32)	(-0.62)	(0.79)
Pseudo R^2 %		19.7	9.2	11.3	11.9	9

Yearly probit regressions on barley price spikes

Barley

Horizon (k)		1year	2year	3year	4year	5year
Constant	coef	-1.326***	-1.050***	-1.321***	-1.311***	-1.321***
	t-stat	(-3.54)	(-2.90)	(-3.45)	(-3.46)	(-3.48)
$boom_{t-k}$	coef	0.380	-0.935	-0.754	-0.744	-0.830
	t-stat	(0.64)	(-1.27)	(-1.03)	(-0.99)	(-1.06)
σ_{t-k}^{low}	coef	24.50	22.39	29.70*	27.26*	22.30
	t-stat	(1.45)	(1.37)	(1.83)	(1.67)	(1.38)
σ_{t-k}^{high}	coef	-3.038	-0.651	-4.713	-2.826	-4.198
	t-stat	(-0.31)	(-0.06)	(-0.37)	(-0.24)	(-0.36)
$GDPgrowth_{t-k}$	coef	1.309	-4.258	-0.0302	-4.786	1.992
	t-stat	(0.16)	(-0.50)	(-0.00)	(-0.52)	(0.22)
$pgrowth_{t-k}$	coef	-14.03***	-6.889	-1.418	6.602	0.657
	t-stat	(-2.88)	(-1.43)	(-0.29)	(1.22)	(0.13)
Pseudo R^2 %		12.5	6.7	6.2	7.3	4.1

Yearly probit regressions on copper price spikes

Copper

Horizon (k)		1year	2year	3year	4year	5year
Constant	coef	-2.135***	-1.739***	-1.561***	-1.381***	-1.077***
	t-stat	(-5.11)	(-4.47)	(-4.16)	(-3.84)	(-3.14)
$boom_{t-k}$	coef	1.059*	-1.298	-2.193	-1.093	-0.739
	t-stat	(1.67)	(-1.22)	(-1.64)	(-1.25)	(-1.07)
σ_{t-k}^{low}	coef	112.2**	126.1**	117.4**	69.50	19.69
	t-stat	(2.34)	(2.56)	(2.38)	(1.45)	(0.39)
σ_{t-k}^{high}	coef	-27.10	-30.77	-23.26	-21.80	-20.85
	t-stat	(-0.74)	(-0.67)	(-0.58)	(-0.59)	(-0.66)
$GDPgrowth_{t-k}$	coef	11.93	6.713	5.705	5.056	3.459
	t-stat	(1.34)	(0.82)	(0.72)	(0.64)	(0.44)
$pgrowth_{t-k}$	coef	0.592	-0.936	-2.772	-2.299	-0.380
	t-stat	(0.22)	(-0.34)	(-0.96)	(-0.87)	(-0.17)
Pseudo R^2 %		10.9	13.4	14.1	6.74	2.1

Yearly probit regressions on lead price spikes

Lead

Horizon (k)		1year	2year	3year	4year	5year
Constant	coef	-1.794***	-1.758***	-1.936***	-2.245***	-2.373***
	t-stat	(-5.49)	(-5.75)	(-5.85)	(-5.81)	(-5.75)
$boom_{t-k}$	coef	0.946	-1.691	-1.755	-0.462	-0.0999
	t-stat	(1.44)	(-1.36)	(-1.30)	(-0.55)	(-0.13)
σ^{low}_{t-k}	coef	21.85	44.90**	59.49***	60.34***	52.92***
	t-stat	(1.18)	(2.55)	(3.26)	(3.14)	(2.82)
σ^{high}_{t-k}	coef	-0.682	12.80	8.640	5.198	10.51
	t-stat	(-0.06)	(1.09)	(0.61)	(0.37)	(0.87)
$GDPgrowth_{t-k}$	coef	4.018	1.134	4.716	17.45	23.16**
	t-stat	(0.48)	(0.13)	(0.48)	(1.54)	(1.97)
$pgrowth_{t-k}$	coef	1.345	-0.863	-2.505	-8.332*	-11.40**
	t-stat	(0.32)	(-0.22)	(-0.60)	(-1.82)	(-2.41)
Pseudo R^2 %		4.4	9.9	17.1	21.2	21.2

Yearly probit regressions on steel price spikes

Steel

Horizon (k)		1year	2year	3year	4year	5year
Constant	coef	-2.823***	-2.224***	-2.134***	-1.839***	-2.092***
	t-stat	(-3.82)	(-3.71)	(-3.82)	(-4.02)	(-3.95)
$boom_{t-k}$	coef	1.949**	0.517	0.289	-0.102	0.198
	t-stat	(2.18)	(0.52)	(0.26)	(-0.07)	(0.899)
σ^{low}_{t-k}	coef	18.00*	16.15*	19.78**	20.22**	27.75***
	t-stat	(1.77)	(1.78)	(2.21)	(2.36)	(2.97)
σ^{high}_{t-k}	coef	-1.704	-0.732	-1.654	-3.934	1.453
	t-stat	(-0.40)	(-0.16)	(-0.31)	(-0.53)	(0.16)
$GDPgrowth_{t-k}$	coef	13.65	0.0374	-2.701	-6.933	5.396
	t-stat	(0.84)	(0.00)	(-0.20)	(-0.58)	(0.37)
$pgrowth_{t-k}$	coef	5.345	6.053**	5.069*	2.865	-4.094
	t-stat	(1.62)	(2.00)	(1.69)	(0.94)	(1.14)
Pseudo R^2 %		18.1	12.8	14.1	14.1	17.3

Yearly panel logit for energy, metals and energy price spikes

$$\log it(boom_{i,t}) = b_1 boom_{i,t-k} + b_2\sigma^{low}_{i,t-k} + b_3\sigma^{high}_{i,t-k} + b_4 GDPgrowth_{t-k} + b_5 pgrowth_{i,t-k} + \eta_i + \tau_t + \varepsilon_{i,t}$$

Panel Logit model, with fixed effects

Horizon (k)		1year	2year	3year	4year	5year
$boom_{t-k}$	coef	1.964***	-0.680	-1.750***	-2.044***	-1.558***
	t-stat	(6.27)	(-1.54)	(-3.13)	(-3.36)	(-2.82)
σ^{low}_{t-k}	coef	0.794	2.495	3.914*	4.284*	3.665**
	t-stat	(0.34)	(1.13)	(1.76)	(1.93)	(1.97)
σ^{high}_{t-k}	coef	-1.833	0.0278	-5.928	-10.01	-5.910
	t-stat	(-0.49)	(0.01)	(-0.76)	(-1.09)	(-0.75)
$GDPgrowth_{t-k}$	coef	-0.866	-10.49**	-12.55***	-10.99**	-5.923
	t-stat	(-0.18)	(-2.35)	(-2.82)	(-2.44)	(-1.27)
$pgrowth_{t-k}$	coef	0.318	1.861	2.354**	0.928	-0.271
	t-stat	(0.23)	(1.55)	(1.98)	(0.72)	(-0.19)
Pseudo R^2 %		4	1	2.8	3	1.8

Conclusions

- We empirically show the existence of Minsky moments in commodity markets.
- The low volatility environment predicts subsequent spikes in commodity markets.
- Our results remain robust to the inclusion of commodity demand, supply and speculative demand variables.
- The Minsky hypothesis holds in the short-run (1 to 6 month horizons) and in the long-run (1 to 5 year horizons).
- We show for the first time in the literature the mechanism which drives the excess risk-taking behavior of commodity investors and producers, leading to inventory stock-outs and commodity price spikes.