Testing the inefficient market effect during COVID19

Raffaele Mattera* & Fabrizio Di Sciorio

*University of Naples "Federico II"
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Overview

Summary

- Aim of this paper is to test the effect of market inefficiency on the daily volatility, that we call "Inefficient Markets Effect" (IME).
- We use the multi-fractional Brownian motion (mBm) framework to build a market inefficiency measure based on the time-varying Hurst exponent $H(t)$.
- We investigate IME on three different events: black Monday (1987), Lehman Brothers' default in the 2008 and the COVID19 pandemic shock.
- Whilst before all the shocks we observe a weak explanatory power of inefficiency for volatility, we instead find a strong relationship after them. Then we demonstrate that these events caused higher inefficiency and, therefore, higher volatility.

Motivation (I)

- The concept of efficient market (EMH) is related to the one of randomness. From a mathematical point of view it can be affirmed that the price stocks' variations move as a stochastic process characterized from i.i.d. random variations.
- Volatility has been for long time considered as an indicator of market inefficiency (e.g. Shiller [1981]).
- Also from an historical point of view, of particular interest is conditional volatility (e.g. Földvári and Van Leeuwen [2011]) since the presence of volatility clusters clearly represents a deviation from EMH.
- However, Cochrane [1991] claimed that actually "volatility does not tell us that markets are inefficient but rather that returns are forecastable".
- Is, therefore, market inefficiency generating volatility?

Motivation (II)

- The basic idea of the Efficient Market Hypothesis is that the price variations follows a Geometric Brownian motion (gBm).
- In financial literature there are many empirical evidences, named Stylized Facts (Cont [2001]) characterize the time series of an asset return, that are not explained by such assumption.
- A very useful generalization of Brownian motion is represented by the multi-fractional Brownian motion (mBm) (Peltier and Véhel [1995], Bianchi [2005]) characterize by time varying Hurst [0,1] exponent named regularity function of mBm.
- Multifractality induced by a the time-varying Hurst exponent is related to the idea of long memory. (Lillo and Farmer [2004], Granero et al. [2008])
- Higher values than 0.5 for Hurst exponent indicate persistence of the time series while lower values indicate anti-persistence (e.g. Bianchi and Pianese [2018]). Under efficient markets we have unpredictability and Hurst assumes value if 0.5. (Bianchi and Pianese [2007])

Data

- We consider three different datasets based on adjusted SP500 Index price, the analysis has been conducted by R software (3.5.1).
- The first time series refers to the period from 01/01/1986 to 1/06/1988, where we consider the shock happened at 19/10/1987.
- The second refers to the period from 01/01/2007 to 01/09/2009, where we consider the shock happened at 15/09/2008.
- The last refers to the period 04/09/2019 to 02/03/2020, where we consider the shock happened at 21/01/2020.

Volatility estimation: GED-GARCH(1,1)

- To measure daily conditional volatility we consider fitted values from a standard GARCH(1,1) model (Bollerslev [1986]):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i z_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (1)$$

  For the term $(z_t : t \geq 0)$, a stochastic process with i.i.d. realizations, we assumed a Generalized Error Distribution (Giacalone et al. [2018], Cerqueti et al. [2019]).

- Indeed we tested for the best distributional assumption for modelling returns' volatility (following Mattera and Giacalone [2018], Cerqueti et al. [2020]), finding always the GED as the best parametric specification for all the different datasets.

Inefficiency measure: $I(t)$

- Then we introduce a new measure of market inefficiency $I(t) = 0.5 - H(t)$ given by the difference between theoretical Hurst exponent value of 0.5 under efficient markets and the empirical Hurst value estimated via AMBE method of Bianchi et al. (2013).

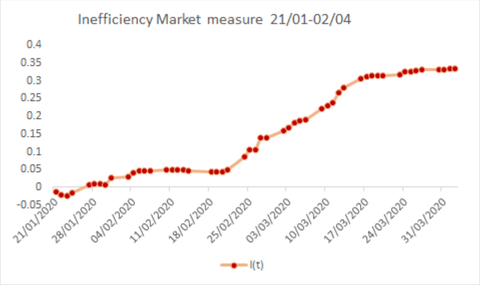

Figure: Inefficiency measure during COVID19 pandemic

Empirical strategy

- Fitst we consider the following linear regression:

$$\sigma_t = \alpha + \beta I(t) + \epsilon_t \tag{2}$$

  where σ_t is the daily conditional volatility obtained from a GED-GARCH(1,1), $I(t)$ the inefficiency measure defined before and ϵ_t the error term.

- Equation (1) is estimated via OLS both before and after the shock happened. We first compare the explanatory power in terms of R^2 of the two regressions and then we compare the fitted values from (1) with the empirical one by computing MSE.
- Then we investigate also the following relationship:

$$\sigma_t = \alpha + \beta I(t) + \gamma D + \delta I(t) * D + \epsilon_t \tag{3}$$

  where D is a dummy variable that takes value of 0 in absence of the shock and 1 otherwise.

Black Monday shock (1987)

Black Monday (1987): results (I)

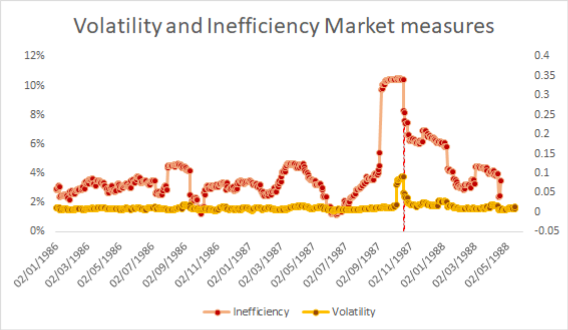

Figure: Volatility vs Inefficiency during "Black Monday" shock

Black Monday (1987): results (II)

- According to regression (1) we get the following results:

	Estimate	S.E.	Estimate	S.E.
α	0.0052564***	0.0003822	0.006321***	0.000543
β	0.0873364***	0.0033755	0.054558 ***	0.003774
F		669.4***		209***
R^2		59%		69%
MSE		1.26%		0.061%

Note: *** means significance at 1%, ** at 5% and * at 10%, S.E. means HAC standard errors. Results to the left refer to regression (1) before the shock, results to the right after it happened.

- We get evidence of both higher R^2 and lower MSE for relationship estimated after the shock.

Black Monday (1987): results (III)

- According to regression (2), instead, we get the following results:

	Estimate	HAC S.E.	t-value	p-value
α	0.0053	0.0003	15.15	0.0000
β	0.0873	0.0031	28.49	0.0000
γ	0.0011	0.0012	0.87	0.3827
δ	-0.0328	0.0087	-3.78	0.0002

- Higher inefficiency generates higher volatility, while the event had not a significant effect on σ_t. What we observe, moreover, is that in presence of the shock inefficiency generated a perverse negative effect on volatility.

Lehman's' Brother default shock (2008)

Lehman Brothers' default (2008): results (I)

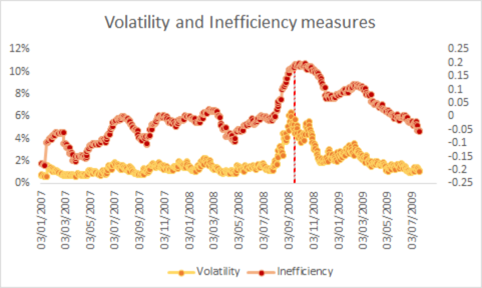

Figure: Volatility vs Inefficiency during 2008 financial crisis

Lehman Brothers' default (2008): results (II)

- According to regression (1) we get the following results:

	Estimate	S.E.	Estimate	S.E.
α	0.0180013***	0.0002589	0.008728 ***	0.001365
β	0.0969826***	0.0034065	0.182667 ***	0.009731
F		810.5***		352.4***
R^2		43.61%		93.68%
MSE		0.93%		0.21%

Note: *** means significance at 1%, ** at 5% and * at 10%, S.E. means HAC standard errors. Results to the left refer to regression (1) before the shock, results to the right after it happened.

- We get evidence of both higher R^2 and lower MSE for relationship estimated after the shock.

Lehman Brothers' default (2008): results (III)

- According to regression (2), instead, we get the following results:

	Estimate	HAC S.E.	t-value	p-value
α	0.0180	0.0002	72.64	0.0000
β	0.0970	0.0033	29.74	0.0000
γ	-0.0049	0.0005	-9.29	0.0000
δ	0.0485	0.0055	8.84	0.0000

- For this sample, inefficiency is again associated to higher volatility levels. Despite the significance of the shock, it had a very weak role in determining levels of σ_t alone, while the strength of this relationship increased of 10 times by considering the role of inefficiency during that period.

COVID19 pandemic shock

COVID19 shock: results

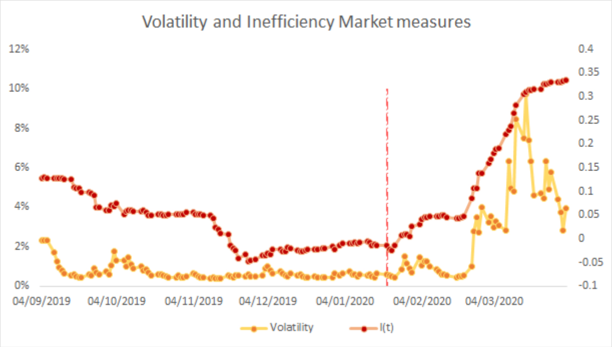

Figure: Volatility vs Inefficiency during COVID19 pandemic

COVID19 shock: results (II)

- According to regression (1) we get the following results:

	Estimate	S.E.	Estimate	S.E.
α	0.006163***	0.001249	0.052382***	0.003095
β	-0.006146	0.010264	0.518782***	0.054044
F		0.3585		92.14***
R^2		23%		87%
MSE		1.01%		0.13%

Note: *** means significance at 1%, ** at 5% and * at 10%, S.E. means HAC standard errors. Results to the left refer to regression (1) before the shock, results to the right after it happened.

- For the third time we evidence of both higher R^2 for relationship estimated after the shock. Moreover, the model is not statistically significant for the considered period before the shock.

COVID19 shock: results (III)

- According to regression (2), instead, we get the following results:

	Estimate	Std. Error	t-value	p-value
α	0.0062	0.0030	2.04	0.0428
β	-0.0061	0.0248	-0.25	0.8045
γ	0.0463	0.0036	12.94	0.0000
δ	0.5298	0.0424	12.50	0.0000

- COVID19 pandemic shock is very peculiar for several reasons. First inefficiency does not seem to play an important role in determining volatility. Then, despite the event generated higher volatility levels, once again the strength of this relationship increases about 10 times if we account for the higher inefficiency generated by the pandemic.

Conclusions

- According to the multifractional Brownian motion framework we developed an inefficiency measure $I(t)$.
- Whilst before all the shocks we observe a weak explanatory power of inefficiency for volatility, we instead find a strong relationship after them for all the three considered financial crisis.
- We provided evidence that these events, if considered alone, have a 10 times lower impact than the case of joint effect with market inefficiency.
- Therefore we conclude that shocks cause higher inefficiency that further increase volatility levels.
- What next? Investigating more shocks, conducting several robustness checks with alternative volatility measures (e.g. VIX) as well as inefficiency measures.

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