Testing the efficient market hypothesis in Ukraine

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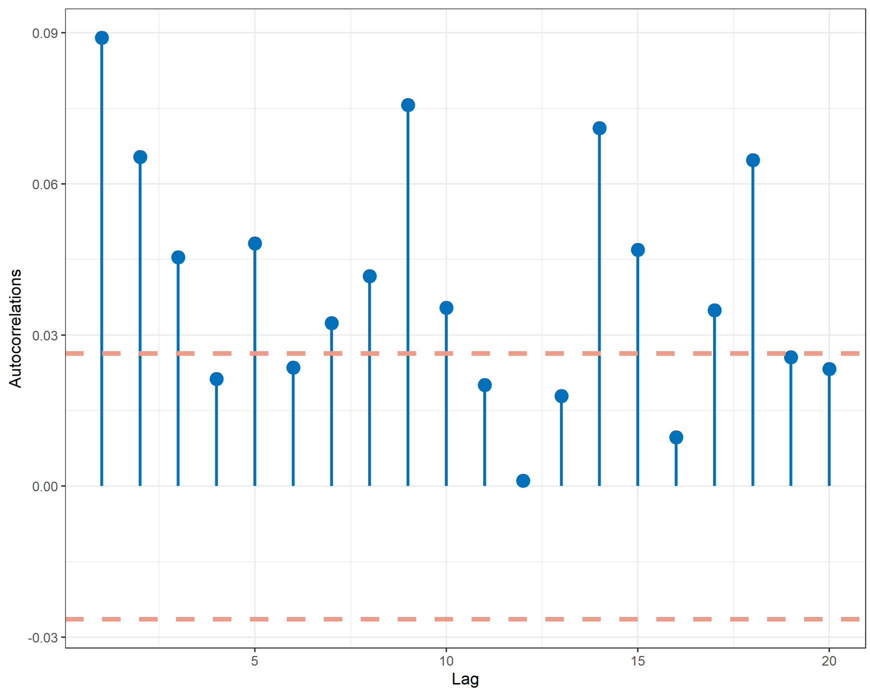
I study the Ukrainian stock market index (PFTS) from 1999 to 2022 (before Russia's invasion) to try and determine if the market is efficient.

Log returns are used for this exercise because they are time additive and are unbounded from below (i.e. consistent with unbounded random variables). For this section, I will analyse the ACF and conduct variance ratio (VR) tests to test the EMH using i.i.d. standard errors (RW1).

Figure 1 shows the first 20 autocorrelation coefficients against the Bartlett intervals of 95% confidence bands (in pink). One method for testing the EMH is using the correlogram here – only 8 out of the first 20 lags fall within the 95% confidence interval, and the rest are highly significant under the i.i.d. assumption. Additionally, all the coefficients are positive, implying high persistence in the series and evidence against the weak-form EMH.



Bartlett intervals: $[\frac{-z_{\alpha/2}}{\sqrt{T}}, \frac{z_{\alpha/2}}{\sqrt{T}}]$

Figure 1: ACF of the PFTS, RW1

Separately, I conduct the VR test for this series. This test exploits the fact that under the EMH, returns are uncorrelated and therefore under the null of efficient markets, we have:

$$\mathrm{VR}(q) = \frac{\mathrm{Var}(r_{t:t+q})}{q\mathrm{Var}(r_t)} = 1 \tag{1}$$

In practice, the VR test for lag q is constructed as:

$$\hat{\mathrm{VR}}_j(q) = \frac{\hat{\sigma}^2_{Lj(q)}}{q\hat{\sigma}^2_H}, \quad \text{for } j = N, O \tag{2}$$

$\hat{\sigma}^2_{LN}$ is the low-frequency non-overlapping sample variance, $\hat{\sigma}^2_{LO}$ is the low-frequency overlapping sample variance, and $\hat{\sigma}_H^2$ is the sample mean. The overlapping method has greater efficiency but uses duplicated observations. I compute the test statistic for both cases for completeness. Table 1 reports the VR test results for the commonly used $q = 5$, i.e. weekly returns. The VR for both overlapping and non-overlapping cases are similar – both tests reject the null hypothesis of no predictability (i.e. efficient markets) at the 1% significance level. Furthermore, the test statistic $Z_j(5)$ is positive for both cases, suggesting a positive autocorrelation in returns.

Table 1: Variance ratio test results for $q = 5$, RW1

	VR $VR_j(5)$	Test statistic $Z_j(5)$
Non-overlapping sample	1.307108	8.062672
Overlapping sample	1.265863	9.010956

$j = N,\ O$. N refers to non-overlapping sample and O refers to overlapping sample

Overall, results from both the autocorrelation plots and VR tests suggest that the market may not be efficient and there may be predictability in returns. In particular, there is a strong positive autocorrelation present in the series. However, there are several key underlying assumptions. Standard errors are assumed to be i.i.d., the trading time hypothesis is assumed (no weekend effects), and finally, the underlying market characteristics are assumed to be constant over the sample period (i.e. there are no structural breaks over time). Some of these assumptions are hard to reconcile with stylised facts, so I will relax them in later parts of this exercise.

Rolling window mean and the rolling window standard deviation

Next, we calculate the rolling window mean and the rolling window standard deviation for the daily logarithmic return on this index.

The first step in this exercise is to determine the duration of the window. A commonly used duration is the "annual window", which varies between 243 and 251 days across the sample period for the PFTS index. Here, I use the mid-point between the two, 247 days. The rolling window mean for daily log returns, M_t^k, is calculated as follows:

$$M_t^k = \frac{X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-(k-1)}}{k} \tag{3}$$

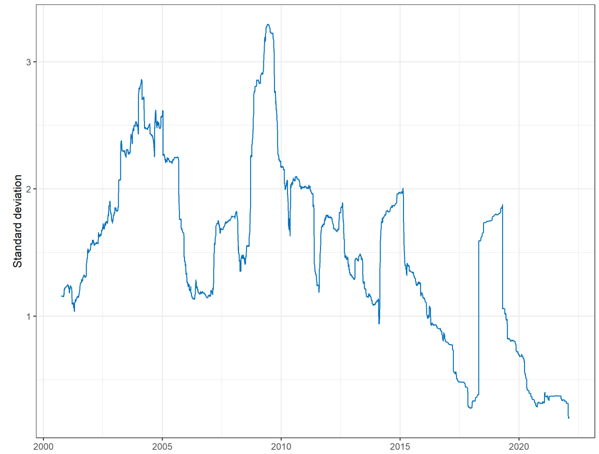
Here, $k = 247$ and X_t is the log returns at date t. Using the same principle, the rolling window standard deviation for daily log returns, S_t^k, is calculated as follows:

$$S_t^k = \sqrt{\frac{\sum_{i=0}^{k-1} (X_{t-i} - \mu_t)^2}{k}}, \quad \mu_t = \frac{1}{k}\sum_{i=0}^{k-1} X_{t-i} \tag{4}$$

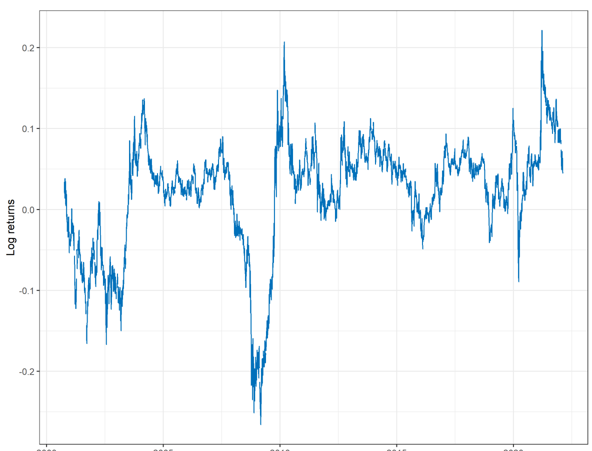
The two series are plotted in panels 2a and 2b. Both series exhibit a high degree of time variation. In particular, the mean appears to be increasing from 2000 to 2008, around the time of the Global Financial Crisis (GFC), before sharply dropping and rebounding through 2010, and finally settling down to a lower level post-crisis. The rolling standard deviation is consistent with stylised facts in that returns exhibit a high degree of heteroscedasticity - high during periods of financial crises and low during economic booms. As reference, the analogous annual window plots for the S&P 500 are plotted for the same time period in panels 2c and 2d. Remarkably, the S&P and PFTS are very similar. The rolling mean tracks closely across markets, especially prior to 2010, but the PFTS mean drops more aggressively than the S&P post

2010, possibly because of its greater exposure to the Eurozone crisis and the annexation of Crimea in the early 2010s. Patterns observed in the PFTS also appear to lag the S&P slightly - suggesting a great level of interconnected between markets, and it would be interesting to investigate if there are lead-lag effects between the two markets.

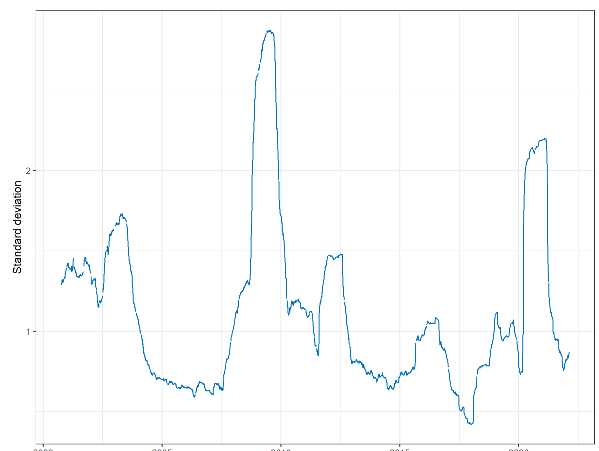
(a) Rolling window mean of log returns, PFTS (k=247)



(b) Rolling window standard deviation of log returns, PFTS (k=247)



(c) Rolling window mean of log returns, S&P 500 (k = 252)



(d) Rolling window standard deviation of log returns, S&P 500 (k = 252)

Figure 2: Rolling window mean and standard deviation for PFTS and S&P 500

Challenging the i.i.d. error innovations assumption

It is well established that returns are highly heteroscedastic and follow higher moment dependence. In particular, there is significant volatility clustering in most returns series, including that of the Ukrainian stock market (Hoffmann and Neuenkirch, 2017). Furthermore, as discussed above, there is clear time variation in the standard deviation of returns for the PFTS. Therefore, assuming that the error innovations ε_t are i.i.d. does not appear to be consistent with empirical and theoretical findings.

Instead of the i.i.d. assumption, a first step may be to more appropriately assume that ε_t follow a martingale difference sequence, MDS (RW2.5). This allows us to capture the fact that $\mathrm{Var}(\varepsilon_t)$ may be time-varying, and construct the corresponding heteroscedastic robust standard errors, outlined in Equation 5.

$$\sqrt{\frac{\left(\sum_t \tilde{r}_t^2\right)^2}{\sum_t \tilde{r}_t^2 \tilde{r}_{t-j}^2}}\rho(j), \quad \text{where } \tilde{r}_t = r_t - \bar{r}_t \tag{5}$$

Using the RW2.5 assumption, we can perform the above tests with updated standard errors (and confidence intervals). Figure 3 plots the same autocorrelation plot as in Figure 1, but now with heteroscedastic robust confidence intervals in pink. Under RW2.5, there are still a number of lags (1st, 2nd, 9th, 14th, 18th) that appear to be significant, though much less so than under the RW1 assumption.

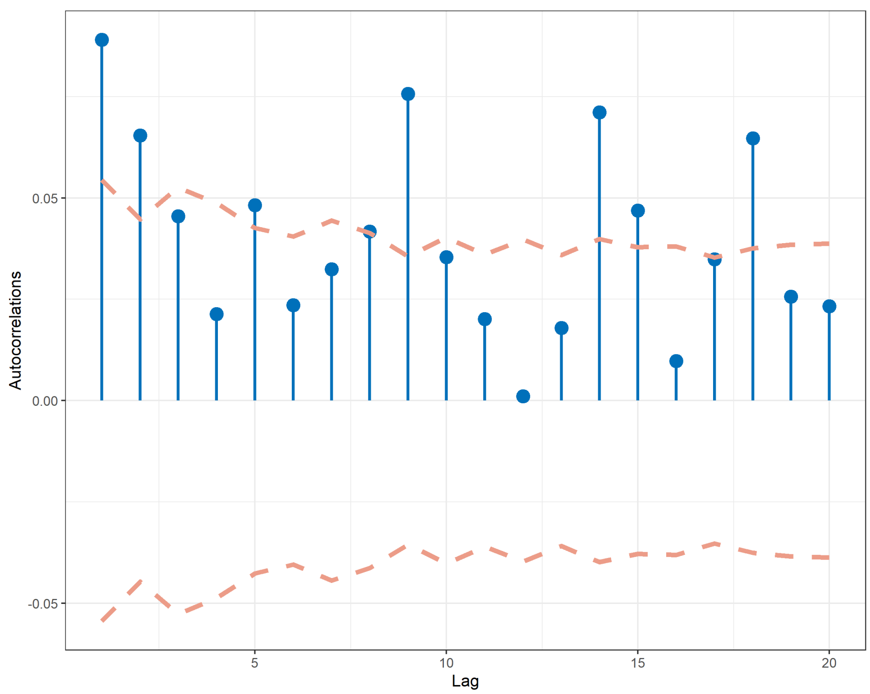


Figure 3: ACF of the PFTS, RW2.5

As for the VR statistic, the corresponding consistent estimator of its asymptotic variance is given by

$$\hat{V}_{O3}(q) = 4\sum_{j=1}^{q-1}\sum_{k=1}^{q-1}\left(1-\frac{j}{q}\right)\left(1-\frac{k}{q}\right)\frac{\sum_{t=1}^{T}\tilde{r}_{t-j}\tilde{r}_{t-i}\tilde{r}_t^2}{\sum_{t=1}^{T}\tilde{r}_t^2} \tag{6}$$

VR test results in Table 2 are still largely similar to that found previously: the test statistic is 4.016 and the null of no predictability is rejected at the 1% level.

Table 2: Variance ratio test results for $q = 5$, RW2.5

	VR	Robust standard errors	Test statistic
	$VR_O(5)$	$\sqrt{\hat{V}_{O3}(5)}$	$Z_{O3}(5)$
Overlapping sample, full period	1.266	0.066	4.016

Overall, there is strong evidence that the i.i.d. assumption needs to be relaxed for the PFTS data. However, simply changing the assumption to MDS errors is insufficient to overturn the rejection of the weak-form

EMH. This is not surprising – as seen in panel 2a, the sample mean of log returns appear to have an upward trend prior to 2008, before stabilising around a lower average post-GFC. The difference between the two periods is potentially driven by a structural break. Therefore, an analysis of the entire period may yield inconclusive results.

Discussion

To say that the underlying structure behind PFTS returns has not changed over 20 years is a strong assumption. Unfortunately panels 2a and 2b do not build confidence in that assumption. Therefore, to investigate the potential for structural break, I first compute summary statistics for log returns in Table 3. Separate statistics are calculated for (i) the full sample, (ii) pre-2010, and (iii) post-2010 – the choice for this breakpoint stems from what is observed in panel 2a. The log returns series is significantly different pre-2010 compared to post-2010. In particular, post-2010, the average returns are lower, excess kurtosis is larger, and the distribution has a greater positive skew – this implies that large abnormal events are much more likely to happen and that the distribution has a fatter right tail. Interestingly, the positive skewness of the returns series is inconsistent with findings in the existing literature (Albuquerque, 2012).

Table 3: Sample statistics for PFTS log returns

	Mean	Standard deviation	Skewness	Kurtosis
Full Sample	0.052	1.644	0.737	26.225
Pre-2010	0.118	1.981	0.142	15.007
Post-2010	-0.003	1.292	2.196	57.145
Pre-2008	0.182	1.800	0.320	17.600

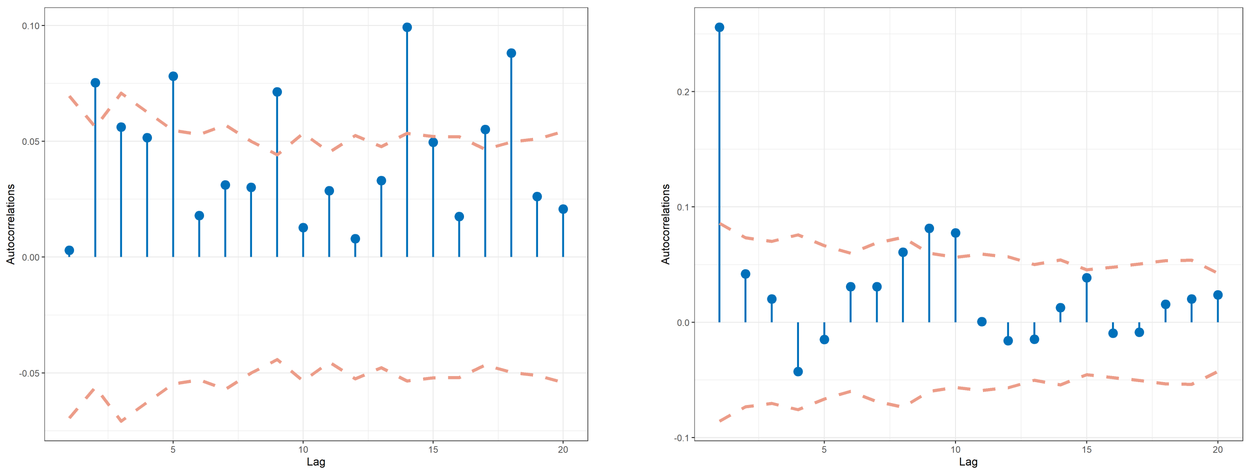
In light of the above, I test the EMH for each period separately. From Figure 4, it is clear that the autocorrelation structure is quite different across periods. Pre-2010, lags 2, 5, 9, 14, and 18 are significant, albeit not strongly. Post-2010, only the first lag autocorrelation is significant. Results of the VR tests for the split samples are reported in Table 4. The null hypothesis of no predictability of returns is rejected at the 1% significance level for the post-2010 period, and weakly significant at a 10% level pre-2010. Contrasted to my initial findings, evidence of linear dependence of daily returns here is much less obvious, especially pre-2010.

As a final exercise, I drop observations during the GFC (2008-2010) and test the EMH pre-crisis. The ACF is plotted in Figure 5 and VR test results are in Table 4. The returns pre-2008 has a statistically significant but economically non-meaningful negative first order autocorrelation, and a VR less than one. There is insufficient evidence to reject the null of efficient markets. These findings closely resembles the findings in the US markets (Campbell et al., 1997).

Table 4: Variance ratio test results for $q = 5$, RW2.5

	VR	Robust standard errors	Test statistic
	$VR_O(5)$	$\sqrt{\hat{V}_{O3}(5)}$	$Z_{O3}(5)$
Pre-2010	1.16	0.08	1.93
Post-2010	1.45	0.11	4.19
Pre-2008	0.91	0.08	-0.9 9

Overlapping sample used for calculations



(a) ACF of the PFTS pre-2010, RW2.5

(b) ACF of the PFTS post-2010, RW2.5

Figure 4: ACF plots of the PFTS, split by time period

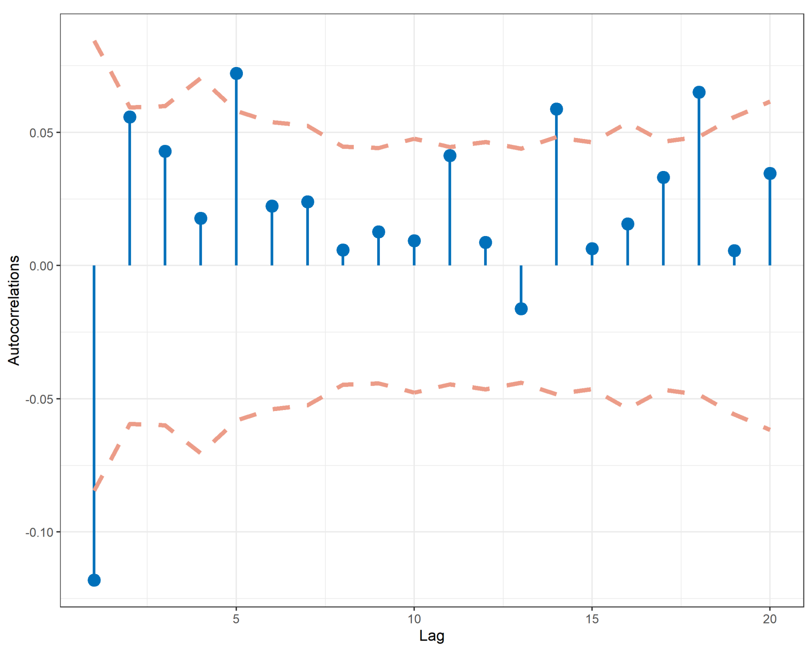


Figure 5: ACF of the PFTS pre-2008, RW2.5

Overall, there appears to be a structural break occurring sometime around 2010. This can be formally tested using the Chow test. I propose two potential explanations for this. First, the GFC from 2008-2010 is a major global event that could have potentially caused a structural break post-crisis. Second, the economic instability brought by the Eurozone crisis and annexation of Crimea in the early 2010s could have contributed to -among other things- higher risk in the overall Ukrainian economy and changed the structure of the returns series. The evidence presented here suggest that the market appears to be relatively efficient prior to the GFC but has since become less so. As an extension, it may be useful to conduct the VR test for different lag lengths.

References

Albuquerque, R. (2012). Skewness in Stock Returns: Reconciling the Evidence on Firm Versus Aggregate Returns. *Review of Financial Studies*, 25(5):1630–1673.

Campbell, J. Y., Lo, A. W., and MacKinlay, A. C. (1997). *The Econometrics of Financial Markets*. Princeton University Press, Princeton, N.J.

Hoffmann, M. and Neuenkirch, M. (2017). The pro-Russian conflict and its impact on stock returns in Russia and the Ukraine. *International Economics and Economic Policy*, 14(1):61–73.