Article

Revisiting Stock Returns and the Mind: Digging Deeper into the Data

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Abstract

I revisit the findings in Holmberg (2020) and address some of the concerns raised regarding the results. In particular, I analyze the distributional properties of the daily aggregate out of the Global Consciousness Projects data (*Max[Z])*, remove "bad data" due to malfunctioning random number generators and let global stock market returns interact with *Max[Z]* in a more tractable and transparent way. In practice, the "bad data" is removed by the means of truncation and a comparison between the truncated *Max[Z]* variable and computer simulated data reveals that *Max[Z]* deviates from the computer simulations in ways that seem consistent with the global consciousness projects hypothesis. It is also found that *Max[Z]* significantly correlates linearly with global stock market returns and that *Max[Z]:s* stochastic process itself is affected by market volatility. Since meaningful variations in *Max[Z]* suggest that the mind can stretch out of beyond the boundaries of our head, the results put doubt on the prevailing paradigm with regards to consciousness and highlights the need for much more research.

Keywords: Mind, random number generator, Global Consciousness Project, stock market return.

1. Introduction

In Holmberg (2020) it was found that stock market returns covary with variations in the random numbers produced by the Global Consciousness Project (GCP). The covariation was found by correlating the novel *Max[Z]* variable with several well-known stock market index return series and even though the results where strong and robust, concerns were raised with regards to the validity of the results. In this paper, I address these concerns.

The hypothesis underlying the GCP is that events which elicit widespread emotion or draw the simultaneous attention of large numbers of people, may affect the output of the hardware generated random numbers in a statistically significant way. As such, the GCP data hypothesis suggests that the mind can affect matter at a distance. This is a not entirely uncontroversial hypothesis as the possibility that the mind can do so could challenge our current understanding of physics. Most scientists thus demand a very high standard of evidence and to date, published results that seem to validate the GCP data hypothesis are in general regarded as invalid and put to question (see, *e.g.*, Scargle, 2002).[1] The results presented in Holmberg (2020) however appears to validate some of the claims made by the GCP and since the prevailing working hypothesis, in most sciences, is that consciousness is an epiphenomenon of the brain and a result

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+ The author thanks for the comments received by Dean Radin and Roger D. Nelson.

[1] See, *e.g.*, Radin (2002) and Nelson and Bancel (2011) for research supporting the GCP data hypotheses.

of physical arrangements and information processing patters alone, the results suggested that the current paradigm with regards to consciousness needed to be discussed.[2]

After its publication however, the author received several comments and concerns pointing out the fact that the study had included observations affected by malfunctioning random number generators (RNG). Since such malfunctions may result in unreasonably large values on the daily GCP data aggregate studied, concerns were raised with regards to the validity of its results. Furthermore, since an unspecified data driven polynomial was used to link the GCP data aggregate to global stock market returns, criticism was put forward with regards to the complexity of the statistical models used as it made the results unnecessarily opaque.

In this paper I seek to address these concerns as I redo part of the analysis after taking the comments received into consideration. To this end, I begin with analyzing the distributional characteristics of computer simulated data from a data generating process that mimics the process underlying the *Max[Z]* variable. The simulations, together with sound statistical reasoning, are used to find a reasonable truncation point such that the variable is cleansed from "bad data". This truncated *Max[Z]* variable is then linked to global returns linearly such that the results are kept more tractable.

The revised analysis using the truncated variable again shows that global stock market returns significantly correlates with *Max[Z] (*the daily aggregate out of the GCP data). As such, it is concluded that the qualitative implications of the findings in Holmberg (2020) are likely to hold true and in this paper, I also explore the nature of the found correlation. Here it is found that seems to be related to market volatility, a result that could be attributed the finding that the stochastic *Max[Z]* process itself is affected by market volatility.

The paper is organized as follows. The next section discusses consciousness, the GCP data and how and why it should be related to global stock market returns. This is followed by a section discussing the *Max[Z]* variable in Holmberg (2020) in more detail which is followed by a section linking the truncated *Max[Z]* to global stock market returns. The paper ends with a discussion on the results.

2. Consciousness, the GCP and Stock Market Returns

Consciousness is perhaps one of our greatest mysteries as no one knows what it is, what it does or even how it has emerged. The prevailing working hypothesis, in most sciences, is however that consciousness is an epiphenomenon of the brain and a result of physical arrangements and information processing patters (see, *e.g.*, Güzeldere, 1997). This viewpoint rests on the existence of neural correlates (see, *e.g.*, Cotterill, 2001; Llinás, 2002 and Koch, 2004 among others) but how the brain alone can produce our subjective experiences (such as the feeling of warmth, cold or pain) is not yet understood. It is even a philosophical mystery how unconsciousness matter can give rise to sentient beings and this unsolved philosophical conundrum is often referred to as the "hard problem of consciousness" (Chalmers, 1995; 2003).

[2] This especially if its results are seen together with the many results produced by the GCP.

From the above it can be read that our understandings of consciousness are incomplete and that much more research is needed. It could also be understood that most studies on consciousness focus on explaining an individual's consciousness experience and not the will of the many, which arguably is what determines the market price of a good or service (to be studied herein) even though one notable exemption exists namely, the collective consciousness concept within the field of sociology (Durkheim,1893).[3]

There does however exist several alternative theories on consciousness, theories that opens for the possibility of the mind stretching out beyond our heads. It could also be noted that physics allows for this possibility as the so called "observer effect" in quantum mechanics (a well-established physical property of matter) describes that the observation of a quantum phenomenon changes the phenomenon observed and studied. Even though this does not necessarily require a *conscious* observer, the observer effect seems to suggest that only the *measurement* of an object (or event) onsets the transition from the "possible" to the "actual" as the famous "wave function" collapses. A parsimonious interpretation of these results thus suggests that human measurement at a distance affects quantum systems at a distance and the question thus becomes if consciousness itself could be said to be an apparatus of measurement.[4]

That consciousness could have the ability to extend outside a human head and interact with matter has been studied within the research field of parapsychology (see, *e.g.*, Nelson, Jahn and Dunne; 1986; Radin *et. al.*, 2006 and Dunne and Jahn, 2007) and the results from these studies suggests that consciousness indeed has the ability to interact with matter as it was found to affect physical random number generators at a distance. Resting on such findings, Roger D. Nelson developed the Global Consciousness Project (GCP) to investigate if this human machine interaction could pick up the emotional response of a large number of human's coherent attention. Up to date the GCP has produced remarkable results as the projects hardware generated random numbers indeed seem to be influenced by large global emotional events (Nelson and Bancel, 2011).

The GCP is an international and multidisciplinary collaboration project that generates and collects random number data continuously from a network of physical random number generators at up to 70 locations around the world.[5] The random numbers are generated using a quantum tunneling technique and the hypothesis underlying the GCP is that events which elicit widespread emotion or draw the simultaneous attention of large numbers of people, may affect the output of the hardware generated random numbers in a statistically significant way.[6] The idea is thus that if the mind can stretch out beyond our heads and affect random number generators at a distance, it could be true that the mind could do so unconsciously and unintentionally such that large emotional events could affect hardware generated random numbers in a way that gets "picked up" and made visible in the numbers generated from it.

[3] Perhaps the problem with explaining what consciousness originate from the problems faced in the definition of the concept. It could for instance be defined as the state of being aware of and responsive to one's surroundings but since such a definition (or similar versions of it) are imprecise, the term has also been defined in terms of sentience alone e.g. awareness, qualia and subjectivity.

[4] It is noted that this interpretation of the observer effect is controversial within the field of physics.

[5] The exact number of active physical random number generators tend to vary over time.

[6] Please visit https://nooshere.princton.edu/reg for details on the physical RNGs.

Even though the GCP, and the data generated from the project, are subject to much debate one thing is clear: the events that are claimed to be picked up by the GCPs data should also affect daily stock market returns. This since market sentiment affects market prices (Shiller, 2017) and since sentiment is likely to be affected by strong collective emotion and intent. Thus, the global events that are claimed to affect the GCPs data should also, in principal, to some degree covary with changes to global stock market valuations. This was studied for in Holmberg (2020) in which the daily returns from several global stock market indexes where correlated with an aggregate daily GCP data variable labeled *Max[Z]*. In the study, it was indeed found that they did covary.

3. The *Max[Z]* Variable*:* What It Is and What It Measures

Max[Z] is derived out of the huge bulk of second-by-second data provided for and made publicly available by the GCP.[7] The GCP is an international and multidisciplinary collaboration project that generates and collects random number data continuously from a network of physical random number generators (RNG:s). The random numbers are generated using quantum tunneling techniques and the hypothesis underlying the GCP is that events which elicit widespread emotion or draw the simultaneous attention of large numbers of people may affect the output of the hardware generated random numbers in a statistically significant way. As discussed above and as argued for in Holmberg (2020), such events should also affect investor and market sentiment and thus also daily stock market returns. Resting on this insight, the daily *Max[Z]* variable was constructed which made it possible to correlate unexpected GCP data changes with daily stock market returns.

The *Max[Z]* variable is an aggregate measure of daily large and unexpected random values obtained from several RNGs spread out all over the world. In order to get a more precises understanding of it, denote a single random number from an individual RNG at time τ as $RNG_{i,\tau}$ for $i = 1,2, \dots n_\tau$ where n_τ is the total number of operating RNGs at that time. Also acknowledge that each individual RNG produces a random number between 0 and 200 every second and that the random numbers have an expected value of $\mu = 100$ and a variance of $\sigma^2 = 50$. From this, a standardized value can be calculated by simply subtracting the mean and dividing it with the square root of its variance (i.e., its standard deviation).[8] As such, the GCP produces n_τ standardized random numbers ($z_{i,\tau}$) every second (τ). Thus, a method is needed to aggregate the values over time and to this end, I do as the GCP and bundle the data into 15-minute data chunks and derive a 15-minute (900 seconds) non-negative aggregate using Stouffer's Z-score method (Stouffer, 1949):

$$Z_\tau = \sqrt{\sum_{\tau-900}^{\tau} \sum_{i}^{n_\tau} \frac{z_{\tau,i}^2}{n_\tau * 900}}.$$

[7] The data can be downloaded from http://noosphere.princeton.edu/.
[8] More formally, the standardized random numbers are defined as $z_{i,\tau} = \frac{RNG_{i,\tau} - \mu}{\sqrt{\sigma^2}}$.

Since each individual standardized value ($z_{i,\tau}$) should be considered as a random draw from the standard normal distribution and since the aggregation of individual numbers is done using the square root of summed squared standardized values; Z_τ can be viewed upon as the absolute value of a random draw from a standard normal distribution.[9] Measuring Z_τ at the end of each 15-minute interval, 96 intraday measurements are made daily such that the *Max[Z]* is the 24-hour maximum from 96 absolute valued random draws from a standard normal distribution.[10]

Understanding how *Max[Z]* is constructed is useful since knowledge on the data generating process can be used to computer simulate *Max[Z]*:s theoretical distributional properties. Such a distribution can then be used for both identifying unreasonably large observations (bad data) as well as for understanding in which ways, if any, *Max[Z]* deviates from computer simulated data. To this end, I use Excel to produce daily simulated values by simulating 96 random numbers from a standard normal distribution, on which I take the maximum value out of their absolute values.

Table 1 presents descriptive data on 10 000 000 computer simulated such random draws (each draw being the maximum out of 96 individual draws) i.e. a random process constructed to mimic the data generating process underlying *Max[Z]* would be created solely due to chance. As can be seen, the computer simulations indeed suggest that the original *Max[Z]* variable includes very large values and since malfunctioning physical RNGs will produce unreasonably large numbers, such large values should probably be excluded. Why they should be excluded can also be understood from the fact that if the RNGs that produces the numbers malfunctions, they could produce "corner values" and deliver values close to 0 or 200. In such cases, the absolute value out of each standardized random value would be unreasonably large which in turn would influence the aggregate Z_τ variable from which *Max[Z]* is derived. It is thus reasonable to truncate *Max[Z]* in order to cleanse the series from such "bad data".

Table 1. Descriptive data on the computer simulations and *Max[Z]*

	Computer simulated data	*Max[Z]*	Truncated *Max[Z]*
Average	2.73	3.04	2.75
Median	2.68	2.71	2.70
Std. Dev.	0.40	3.99	0.41
Minimum	1.00	1.13	1.13
Maximum	6.06	94.48	5.69
Skewness	0.70	16.39	0.85
Kurtosis	0.90	294.17	1.95

Note: The simulated data results rests on 10 000 000 computer simulated random draws from a process that mimics *Max[Z]*:s construction The *Max[Z]* data is derived out of 7936 daily observations and the truncated *Max[Z]* out of 7849 daily observations between 1999-01-04 and 2020-12-31.

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Noting that a value of 6 is a six-sigma event for $z_{i,\tau}$, it is also acknowledged that obtaining values larger than so is unlikely unless they are the result of malfunctioning RNGs. Thus,

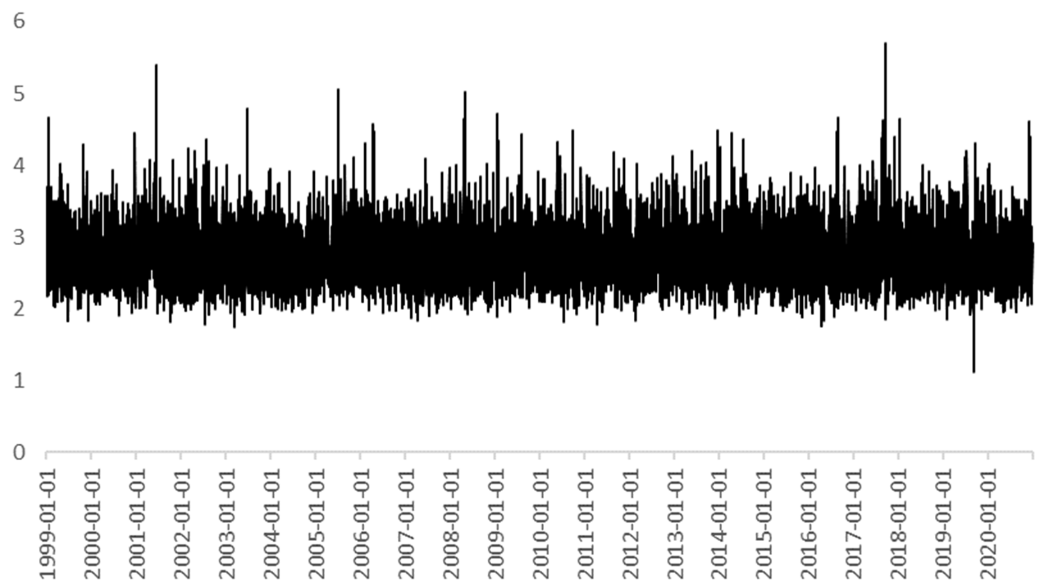
[9] The statistically bewandered could recognise this as a chi distribution.

[10] In practice, the Z-scores are obtained from the column "All Egg Composite" from the Daily Tables section on the GCP webpage.

Max[Z] is truncated at this value and as can be seen in Table 1, the truncated *Max[Z]* variable has distributional properties that closely resembles its computer simulated counterpart even though its average and median values are slightly larger. As it is claimed that the random numbers produced by the GCP will be affected by events "outside" the data generating process discussed above and since such events most likely will result in larger *Max[Z]* values; these distributional characteristics can be said to be consistent with the GCP hypothesis. Note also that truncated *Max[Z]* is both more positively skewed and has a larger kurtosis than the computer simulated data which implies that values larger than the median materialize more often, also this in accordance with the GCP data hypothesis.

Figure 1 depicts the truncated *Max[Z]* variable over time and from the figure it can be seen that the time series is stationary.[11] It is however also found that occasional large values remain but a more detailed analysis of data on the dates on which these observations are retrieved reveals that the RNG:s indeed did function properly during those dates. As such, the observations are regarded as valid and kept for the analysis below.

Figure 1. The truncated *Max[Z]* process



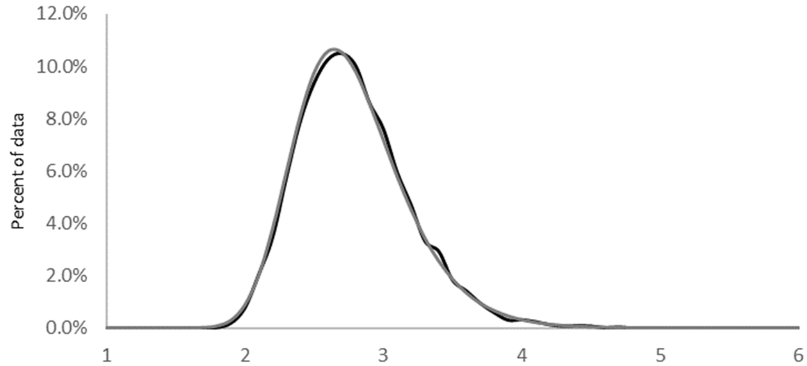
Note: The truncated *Max[Z]* represents 7849 daily values smaller than six between 1999-01-04 and 2020-12-31.

In Figure 2 the truncated *Max[Z]* variables distribution is depicted and compared with the simulated data's distribution. Here it can be seen that they are mostly distributed similarly. But, if the area around the distribution's mode is more closely analyzed, a tendency towards larger values can be seen as distributional mass is "pushed" over from the left side over to the distributions right side. [12] Furthermore, anomalies can also be seen at the "edge" of the distribution and it seems like the truncated *Max[Z]* variable has a tendency to materialize larger

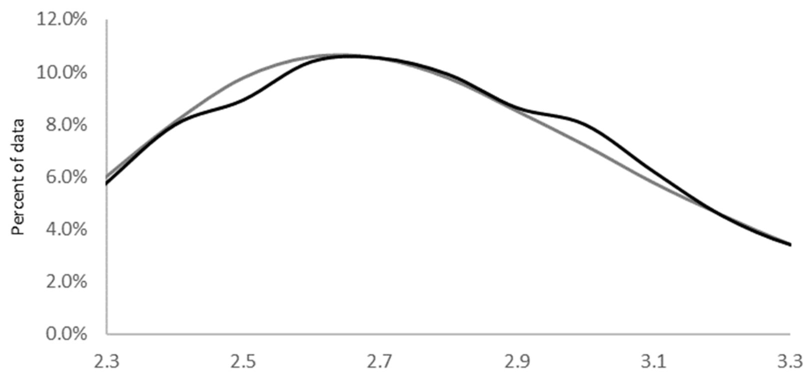
[11] This is confirmed through the Augmented Dickey-Fuller test as the null hypothesis that *Max[Z]* has a unit root is strongly rejected (P-value<0.000).
[12] The mode of a continuous probability distribution is the distributions local maximum value i.e. its peak.

values more often than supported by the underlying data generating process; also this consistent with the GCP hypothesis.

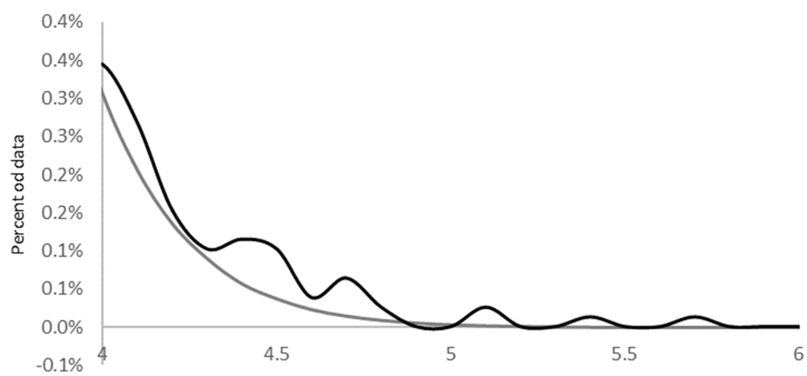
Figure 2. Distribution of the truncated *Max[Z]* and its simulated counterpart



(a) Full distribution



(b) Around the mode



(c) At the edge

Truncated Max[Z] Simulated data

Note: The distributions are approximated from histograms using bins between 1 and 6 in increments of 0.1. The simulated data results rests on 11 20 000 computer simulated random draws from a process that mimics *Max[Z]*:s construction. The truncated *Max[Z]* variables descriptive data is calculated out of the 7849 daily values between 1999-01-04 and 2020-12-31.

Thus, some small differences between the truncated *Max[Z]* variable and its computer simulated counterpart is found, differences that correspond well with what one would expect if the hypothesis underlying the GCP data would be true. The question thus becomes if these differences are the result of coherent attention of a large number of people or if they are simply due to chance. As argued for in Holmberg (2020), market sentiment may also be affected by such events and thus also stock prices.[13] As such, stock market returns can be used for validating the GCP data hypothesis and I thus revisit this topic by analyzing the truncated daily *Max[Z]* variable and its covariation with two well-known global stock market indexes and their daily returns.

4. The Truncated *Max[Z]* and Global Stock Market Returns

It is first acknowledged that no theoretical functional form that links *Max[Z]* with stock market returns yet exists. This can however be bypassed by simply acknowledging that any unknown functional form can be approximated using a polynomial function (Taylor, 1715).[14] In Holmberg (2020), the data was allowed to determine the polynomial but as this resulted in somewhat opaque linkages, I in here keep the results tractable and use the following linear equation:

$$r_t = \alpha + \gamma r_{t-1} + \beta Max[Z_t] + \delta(Max[Z_t] \times r_{i,t-1}) + \epsilon_{i,t}, \tag{1}$$

where r_t is an indexes simple return, γ the autocorrelation coefficient, β returns dependence with the present dates truncated *Max[Z]*, δ the potential interaction effect and where $\epsilon_{i,t}$ is a random error term subject to the usual assumptions.[15] Note that I in Equation (1) allow for autocorrelated returns, a likely outcome since market wide information tends to get incorporated gradually causing serial correlation in the short term (see, *e.g.*, Chordia and Swaminathan, 2000, Sias and Starks; 1997; and Lo and MacKinlay, 1990 for a more detailed discussion). Note also that I study also a version in which the potential interaction effect (δ) is ignored making the linkage completely linear.

I study two global stock market indexes namely the S&P Global 1200 index and the Dow Jones Global index. Even though both these indexes capture the performance of stock markets globally, they are constructed differently and will display slightly different daily return values. The S&P Global 1200 index for instance seeks to capture about 70% of global market capitalization while the Dow Jones Global index focuses on stocks traded globally and targets a 95% coverage of markets open to foreign investment. Table 2 displays descriptive data on the daily returns from both these indexes and as can be seen, they exhibit the usual distributional properties as they both have positive daily averages, are slightly negatively skewed and exhibit large excess kurtosis. The small, yet positive daily average indicates that global equity prices have been subject to trend growth, the negative skewness that returns have been subject to

[13] Shiller (2017) argued for the importance of sentiment as investors' optimistic or pessimistic beliefs about the stock markets may directly influence prices

[14] A Taylor series is a series expansion of a function about a point that allows for an approximation of functional dependence.

[15] I let $r_t = (P_t/P_{t-1}) - 1$ where P is the stock market index value at time t i.e. I use simple returns. As such, the results are comparable with the findings in Holmberg (2020).

frequent small gains and a few extreme losses while the excess kurtosis suggests that returns are leptokurtic with some extreme values.

Table 2. Descriptive data on the global stock market indexes returns

	S&P Global 1200	Dow Jones Global
Mean	0.02%	0.02%
Median	0.06%	0.04%
Std. Dev.	1.04%	1.02%
Minimum	-9.49%	-9.49%
Maximum	9.76%	9.07%
Skewness	-0.37	-0.47
Kurtosis	10.40	10.20

Note: The number of observations for S&P Global is *5599 and 5539 for Dow jones Global*

Equation (1) is estimated using Ordinary Least Squares (OLS) and due to possibly of heteroskedastic and/or autocorrelated residuals, the HAC-Newey-West estimator (Newey and West; 1987) for standard errors is used.[16] Table 3 presents the results and as can be read from the table the results confirm the qualitative findings in Holmberg (2020) since also the truncated *Max[Z]* variable correlates significantly with global stock market returns. In fact, both the S&P Global 1200 and the Dow Jones Global index returns are positively and significantly affected by the present dates (truncated) *Max[Z]* value and by focusing on the "No interaction" model it can be read that a one-units increase in *Max[Z]* tends to increase global returns with between 0.05 and 0.06 percent. Note also that the autocorrelation coefficient is positive and significant and that if the interaction term (δ) is included ("With interaction"), the size of the autocorrelation coefficient increases significantly. The increase is however severely dampened by large *Max[Z]* values since the interaction terms are negative and significant. That *Max[Z]* interacts with past stock markets returns makes the interpretation of the results less obvious and I thus proceed with deriving the marginal effects of the interacting variables.

The marginal effects can be found by taking the partial derivative of Equation (1). By doing so it is found that the marginal effect on daily returns due to changes in past returns is $\partial r_t/\partial r_{t-1} = \gamma + \delta Max[Z_t]$ and that the marginal effect due to a change in *Max[Z]* is $\partial r_t/\partial Max[Z_t] = \beta + \delta r_{t-1}$. Figure 3 illustrates these marginal effects and here it can be seen that past returns adds positively to today's returns only if *Max[Z]* is lower than 3.5 (Figure 3a). As most anomalies found with regards to *Max[Z]* occurred for lesser values then so (Figure 2) it can be said that most events that elevate *Max[Z]* interacts with past returns in a way that results in a positive marginal effect in past yesterday's returns. But if *Max[Z]* is larger than 3.5, a rarity as only about 6.2% of the observations has such large values, yesterday's returns contribute negatively to today's returns. Turning to the "With interaction" models' marginal effect of *Max[Z]* (Figure 3b), it is noted that *Max[Z]* contributes positively to today's returns only if yesterday's returns

[16] The Breush-Pagan Heteroskedasticity Test (Breush and Pagan 1979) strongly rejects that the returns series are homoscedastic.

are negative. It thus seems like *Max[Z]* acts a bit as a "shock absorber" that stabilizes returns within a certain interval.[17]

Table 3. Global stock market index returns and *Max[Z]*

P-values in parenthesis

	S&P Global 1200		Dow Jones Global	
	No interaction	With interaction	No interaction	With interaction
$\boldsymbol{\alpha}$	-0.0015	-0.0016	-0.0012	-0.0013
	(0.0906)	(0.0831)	(0.1652)	(0.1471)
$\boldsymbol{\gamma}$	0.0739	0.3655	0.0948	0.4299
	(0.0141)	(0.0057)	(0.0008)	(0.0009)
$\boldsymbol{\beta}$	0.0006	0.0006	0.0005	0.0005
	(0.0493)	(0.0454)	(0.1008)	(0.0890)
$\boldsymbol{\delta}$	-	-0.1075	-	-0.1235
		(0.0367)		(0.0147)
$\boldsymbol{R^2}$	0.61%	0.81%	0.95%	1.20%

Note: P-values calculated from the t-distribution using HAC standard errors. Estimates based on 5599 (S&P Global) or 5539 (Dow Jones Global) covering the period 1999-01-04 to 2020-12-31

Furthermore, it is noted that the research hypothesis that *Max[Z]* has no effect on global stock returns (i.e. that β =0) is rejected on the ten percent significance level for the Dow Jones Global index (with interaction) and on the five percent level for the S&P Global 1200 (both models).[18] Even though they clearly are significant, between one in ten or one in twenty hypothesis tests using the "No interaction" models can be expected to show a false positive and signal significance even though no true dependence exists. Thus, the results are not strong enough to rule out the possibility that the dependence found is due to chance alone. The practical and philosophical implications of these results thus call for a further investigation on the origins of the found significance.

Keeping the results tractable, the nature of β:s significance in Table 3 is investigated by focusing on the "No interaction" model and by redoing the analyses on chunks of one year data.[19] Thus, the model in Equation (1) is re-estimated without the interaction term on the two global stock market indexes 24 times such that 48 annual estimates on β are retrieved. Figure 4 depicts the β:s *P*-values together with the return's annual standard deviations and by simply "eye bowling" the figure it can be understood that more estimates are significant than what is expected due to chance. In fact, almost 16 percent of the obtained estimates are significant at the

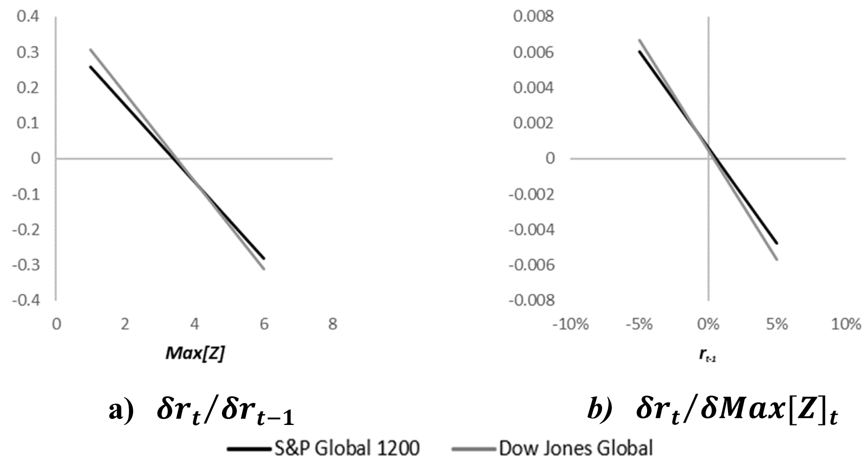
[17] One way of thinking about it is that events that elevate *Max[Z]* also affects investor sentiment such that emotion driven daily valuations becomes less pronounced.

[18] Note that the interaction effect (δ) in general has a lower P-value than β. Since lagged daily returns values already are included in both interaction models, also these P-value can be used for testing for the validity of the GCP data hypothesis. As such, the probability that the GCP data hypothesis is due to chance alone is found to be between 1.5 (Dow Jones Global) and 3.7 (S&P Global 1200) percent.

[19] The annual sample periods always begin on the 1st of January and end on the 31st of December each year.

ten percent level while 9 percent are significant at the five prevent level; results that adds weight to the finding that $\beta \neq 0$.[20]

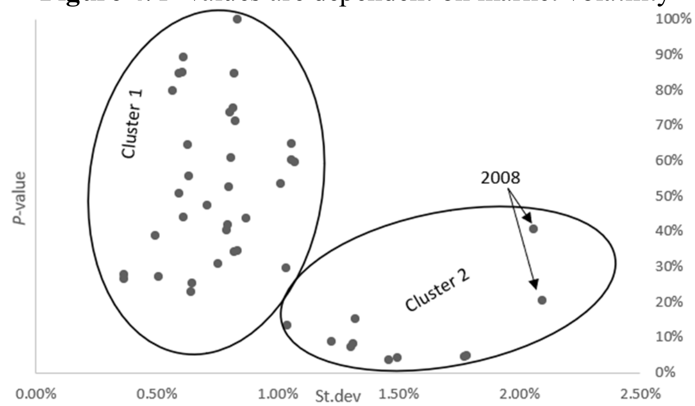
Figure 3. Marginal effects on the model with interaction



Since the *P*-values seem to decrease when standard deviations increase, the results also suggest that *Max[Z]* interacts with global stock market returns only during turbulent times when daily stock market returns are volatile. A cluster analysis on the data in Figure 4 confirms this observation as such an analysis suggests that the estimates can be divide into two distinct clusters. Furthermore, it is found that none of the β estimates in the low standard deviation cluster (Cluster 1) have a low enough *P*-value for significance while 64 percent of the estimates in the cluster for volatile years (Cluster 2) are significant. It also looks like the year 2008 is an "odd fellow" and that this year possibly should be viewed upon as an outlier. This is thus investigated by redoing the regression analysis in Table 3 with the inclusion of an indicator variable on all 2008 observations and from the redone analysis it is found that the indicator variable is significant at the five percent and that all *P*-values decrease. This in turn results in that β becomes significant at the ten percent level for also the Dow Jones Global index for "No interaction" model. The results also seem to point towards that the year 2008 should be viewed as special and if it is excluded from the cluster comparison done above it is found that 78 percent of the estimates in Cluster 2 are significant.

[20] A *P*-value of (say) 10 percent suggests that 10 percent of the hypothesis tests are significant only due to chance. The results in Table 3 are thus considered valid if more than 10 percent of the annual estimates in Figure 3 are significant at the 10 percent level.

Figure 4. *P*-values are dependent on market volatility



Note: Estimates are classified into clusters using the k-means cluster method (MacQueen; 1967) and the *P-values are calculated from the t-distribution using HAC standard errors.*

The results suggest that volatility is an almost a necessary condition for significance and that the year 2008 should be treated as a special year.[21] This opens up to questions with regards to the behavior of the *Max[Z]* process itself and I thus proceed with analyzing the stochastic *Max[Z]* process in more detail.[22] In the analysis of *Max[Z]:s* stochastic process, I acknowledge the need for a daily measure of market volatility if volatility is to be correlated with the *Max[Z]* process. To this end, I use the results in Pagan and Schwert (1990), Rogers et al. (1994) and Ghysels et al. (2006) and proxy daily volatility using squared daily returns. Furthermore, I note that *Max[Z]* is stationary and that its stochastic process can be described using one polynomial for the processes autoregression (AR) part and one for its moving average (MA) part (Shumway and Stroffer; 2010). Thus, the *Max[Z]* process is parsimoniously written as:

$$Max[Z_t] = c + \epsilon_t + \sum_i \varphi_i \; Max[Z_{t-i}] + \sum_i \theta_i \, \varepsilon_{t-i} + \omega_i \sigma_{t-i}^2, \tag{2}$$

where ϵ_i are white noise error terms, φ_i parameters for the autoregressive component, θ_i the moving average parameters and where ω_i is a parameter linking *Max[Z]* to daily stock market volatility (σ_{t-i}^2).

Table 4 presents Maximum Likelihood estimates on the parameters in Equation (2) and as can be seen, the *Max[Z]* variable can be described using its own values as a ARMA(1,1) process. The results in the table also confirm the findings in Figure 3 as it is found that market volatility plays a significant role in explaining *Max[Z]:s* stochastic process. In particular, it is found that *Max[Z]* is influenced by yesterday's and tomorrow's volatility but that it is unaffected by todays volatility. That the *Max[Z]* process is influenced by volatility can possibly be explained by acknowledging that financial markets tend to "pick up" the publics general mood (market sentiment) and adjust prices accordingly. Thus, what should affect *Max[Z]* should also affect market prices (the results in Table 3) which in turn also should affect daily market volatility.

The result that the past and future but not the presents volatility affects the *Max[Z]* process does however require some additional explanation. To this end, assume that an event that results in

[21] In September 2008 the bank Lehman Brothers unexpectedly collapsed which forced the onset of the global financial crisis.
[22] The analysis is done on the truncated *Max[Z]* variable.

changes to coherent attention of a large number of people occurs at time *t*. Assume further that the event gets picked up by the GCP:s RNG:s which in turn results in a slight increase in *Max[Z]*. Recalling that a change in *Max[Z]* will affect global returns in time *t* (Table 3) the event will also affect squared returns which is what is used as a proxy for the present date's volatility. But, as no significant correlation is found with regards to today's volatility on the *Max[Z]* process (Table 4) these results point towards the direction of causality; *Max[Z]* affects market prices while the *Max[Z]* process is unaffected by changes in (squared) returns.

Table 4. The *Max[Z]* process and its dependence with market volatility

P values in parenthesis

	AR(1)	*MA(1)*	*ARMA(1,1)*
c	2.7471	2.7471	2.7471
	(<0.01)	(<0.01)	(<0.01)
φ	0.0273	0.0264	0.8761
	(0.0163)	(0.0206)	(<0.01)
θ	-	-	-0.8514
			(<0.01)
R^2	0.07%	0.07%	0.26%

	S&P Global 1200			**Dow Jones Global**		
	$\hat{\sigma}^2_{t+1}$	$\hat{\sigma}^2_{t}$	$\hat{\sigma}^2_{t-1}$	$\hat{\sigma}^2_{t+1}$	$\hat{\sigma}^2_{t}$	$\hat{\sigma}^2_{t-1}$
c	2.7501	2.7484	2.7498	2.7505	2.7490	2.7498
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
φ	0.8709	0.8740	0.8724	0.8787	0.8809	0.8802
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
θ	-0.8466	-0.8496	-0.8481	-0.8552	-0.8574	-0.8567
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ω_i	-28.327	-11.853	-23.537	-32.304	-16.837	-23.662
	(0.0283)	(0.5136)	(0.0945)	(0.0195)	(0.3742)	(0.1090)
R^2	0.33%	0.27%	0.31%	0.34%	0.28%	0.30%

Note: ARMA Maximum Likelihood using the OPG – BHHH optimization method. Estimates based on 5599 (S&P Global) or 5539 (Dow Jones Global) covering the period 1999-01-04 to 2020-12-31

Since market price affecting information will be incorporated into the price gradually, the events impact on returns is also likely to be carried over to the next day, affecting tomorrow's volatility through the autocorrelation coefficient (γ) in Equation (1). Thus, it is probable that the *Max[Z]* processes dependence on tomorrows volatility originate from the events impact on tomorrows returns. If so, the relative size of returns daily autocorrelation in Table 3 could be used to determine the relative size of the parameter determining the size of the impact of tomorrows volatility in Table 4. This is exactly what is found since γ is 17 percent larger while ω_{t+1} is 14 percent larger for Dow Jones Global compared with for S&P Global 1200. This found dependence could also be why yesterday's returns correlate with today's *Max[Z]* (δ in Table 3), a claim supported by the finding that the index with the lowest *P*-value on δ in Table 3 (Dow Jones Global) also is the index on which tomorrow's volatility interacts the strongest with the *Max[Z]* process

Taken together, the results suggest that it is reasonable to include measures of market volatility in models that seek to disentangle the *Max[Z]* variables effect on global stock market returns. I thus use the findings above and estimate a model that includes lagged squared returns as a proxy for volatility while also acknowledging that the year 2008 can be regarded as a special:

$$r_{i,t} = \alpha_i + \gamma r_{i,t-1} + \beta \, Max[Z_t] + \delta(Max[Z_t] \times r_{i,t-1}) + \theta r_{t-1}^2 + \vartheta I_{2008} + \epsilon_{i,t}. \quad (3)$$

Table 5 presents estimates on Equation (3) using OLS with HAC standard errors and a comparison with Table 3 reveals that the *P*-values again decrease as the model's coefficients of determination (R^2) increases. The findings thus suggest that global stock market returns are affected by the present days *Max[Z]* and that this dependence is strengthened when *Max[Z]*:s dependence with market volatility is accounted for.

Table 5. Global stock market index estimates with volatility measures
P values in parenthesis

	S&P, Global 1200		**Dow Jones, Global**	
	No interaction	Interaction	No interaction	Interaction
$\boldsymbol{\alpha}$	-0.0017	-0.0017	-0.0014	-0.0014
	(0.0624)	(0.0606)	(0.1107)	(0.1041)
γ	0.0770	0.3330	0.1005	0.3936
	(0.0036)	(0.0093)	(0.0000)	(0.0016)
β	0.0007	0.0007	0.0005	0.0006
	(0.0358)	(0.0341)	(0.0750)	(0.0683)
δ	-	-0.0946	-	-0.1083
		(0.0499)		(0.0210)
θ	1.5982	1.4587	1.9469	1.7899
	(0.0032)	(0.0041)	(0.0003)	(0.0005)
ϑ	-0.0026	-0.0026	-0.0028	-0.0028
	(0.0232)	(0.0230)	(0.0184)	(0.0183)
$\boldsymbol{R^2}$	1.11%	1.26%	1.58%	1.78%

Note: P-values calculated from the t-distribution using HAC standard errors. Estimates based on 5599 (S&P Global) or 5539 (Dow Jones Global) covering the period 1999-01-04 to 2020-12-31

5. Concluding remarks

This paper addresses some of the concerns made with regards to the results in Holmberg (2020). The results presented herein confirm its finding that global stock market returns correlate with *Max[Z]* and since the *Max[Z]* variable is derived out of hardware generated random numbers produced by the GCP, the results suggest that consciousness has the ability to stretch out beyond our heads and affect hardware generated random numbers at a distance.

I begin with analyzing the distributional properties of computer simulated data derived from a data generating process that mimics the process underlying the *Max[Z]* variable. From the computer simulated data, a level at which *Max[Z]* should be truncated in order to remove potential "bad data" influenced by malfunctioning RNG:s is found. By comparing the truncated *Max[Z]* variable with its computer simulated counterpart it is found that the truncated *Max[Z]* has both a slightly larger average and median value than it simulated counterpart, is more positively skewed an exhibits larger kurtosis. As the GCP hypothesis suggests that events of coherent attention of a large number of people at times will result in slightly larger *Max[Z]* values, these are statistical properties that resonate well with what could be expected if the hypothesis underlying the GCP would hold true.

Given these results, I redo parts of the analysis in Holmberg (2020) and find that also the truncated *Max[Z]* variable correlates significantly with global stock market returns. Furthermore, the *Max[Z]:s* stochastic process is itself found to be affected by daily market volatility and by including a proxy measure of daily market volatility it is found that the models fit can be improved. This suggest that statistical models can be further developed by simply acknowledging that volatility interacts with *Max[Z]* while *Max[Z]* affects returns. Perhaps *Max[Z]:s* interaction with volatility can be more precisely accounted for using versions of autoregressive conditional heteroscedasticity (ARCH) models; an interesting avenue for future research to explore.

The findings in this paper thus confirms the qualitative results in Holmberg (2020) and adds evidence to the hypothesis underlying the GCP. As the GCP hypothesis suggests that the mind can affect matter at a distance, the results are not supported by our current understandings of consciousness. I am thus left with two unanswered fundamental questions: why and how? What is the mechanism underlying the mind-matter interaction and why does the mind have the ability to do so?

The prevailing working hypothesis with regards to consciousness states that it is an epiphenomenon of the brain and a result of physical arrangements and information processing patters. This explanation does thus not allow for the possibility of mind-matter interaction of the sort suggested by the results in this paper. It is also unlikely that the results can be explained using electromagnetic theories of consciousness (see, *e.g.*, Pocket, 2012 and McFadden, 2002) since the electromagnetic field produced by the brain is not strong enough to affect matter a distance. Thus, one needs to look elsewhere and begin exploring alternative ideas on the nature of consciousness.

Perhaps coherent attention of a large number of people impacts some unexplored consciousness field of sorts and that ripples in this field has the ability to affect matter at a distance; or perhaps the mind projects a field of its own with the ability to affect matter at a distance. Whatever its cause, the results suggest that the prevailing paradigm with regards to consciousness needs to be discussed as the results cannot be understood using our current understanding of consciousness alone.

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