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Stock Returns and the Mind

An Unlikely Result that Could Change Our Understanding of Consciousness

Abstract: *Emotions and feelings affect economic systems. This is well known as e.g. stock markets tend to react to sudden political and emotional events. However, the link between emotions, consciousness, and economic systems at a deeper level than the aggregate resulting action of people at large is yet to be explored and understood. In this paper, a first building block is presented as it is shown that a variable derived from the random numbers obtained by the Global Consciousness Project is statistically related to various well-known stock market index returns. The relationship is shown to be non-linear and that variations in the variable, to some extent, predate the underlying trade. The results presented are found to be robust and qualitatively unaffected by the removal of outliers. Apart from the pure economic value of these findings, the results have truly baffling implications. This is the case as they confirm some previous unorthodox research suggesting that consciousness stretches out beyond the locally confined space of our heads and that consciousness can affect hardware-generated random numbers at a distance. Thus, these results put doubt on the existing paradigm with regards to consciousness and highlight the need for further research.*

1. Brief Introduction

This paper shows that random numbers generated by the Global Consciousness Project (GCP) significantly correlate with stock market returns. This topic is investigated since market prices are the result of

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investors' collective decisions on worth and thus should be affected by events similar to the events that are claimed to affect the GCP data. This suggests that there could exist some correlation between the GCP data and stock market returns which is empirically tested for with highly significant results. The relationship found is shown to be non-linear as it can be approximated using a second- or third-degree polynomial. Also, and somewhat surprisingly, variations in the GCP data variable seem to predate the underlying trade. The paper ends with a section discussing these results and suggests future research.

2. Economics, Market Prices, and the Will of the Many

Within the field of economics, the market price is a term that refers to the price at which an asset or service can be bought or sold. Economic theory further suggests that the market price converges to the 'clearing market price', which is the point where the forces of supply and demand meet. Since the market price depends on the demand and supply of a good or service, it is also likely to change regularly in order to adapt to events that may affect the underlying demand and supply functions.

Sudden and unexpected macroeconomic and political occurrences could be classified as such events and arguably such events could cause the market price to be re-evaluated and changed. This since the events could affect consumers (demand side shifts), producers (supply side shifts), or even change the 'rules of the game' (i.e. regulatory changes). However, in the absence of such events, the market price could be viewed as stable and as an emergent result of the 'spontaneous coordination of the plenty'.[1] But for the coordination to occur, economic agents need to 'know what they want', have preferences, and be able to order and rank the choices presented to them (see e.g. Mas-Colell, Whinston and Green, 1995). All these factors thus implicitly assume that some form of conscious behaviour as consumers, for instance, maximizes some underlying utility function while firms simply seek to maximize profits (and have the cognitive ability to do so).[2] The maximization procedures referred to above are

1 For a discussion on the emergent properties of market prices see Wang *et al*. (2018).

2 Even though such views on economic agents could be said to grossly oversimplify the complexity of human behaviour, it should be noted that the underlying economic theory is flexible enough to accommodate other important aspects of human will. Within e.g.

also likely to occur with 'one's own self-interest' first in mind and, as famously stated by Adam Smith (1776) in his work *The Wealth of Nations*, '[markets are] led by an invisible hand to promote an end which was no part of his intention'. Thus, the individual's conscious behaviour is likely to play an important part in the determination of market prices.

It should, however, be noted that there exists no agreement within the field of economics as to how the underlying functions that economic agents seek to maximize should be formalized. Most economists would, however, agree that a 'consumer preference set' of some sort is needed and that parts of such a preference set could be shared with other economic agents.[3] From this it could be understood that market prices are partly dependent on a collective preference set and that this also should be true for stock market prices. However, it is noted that stock market prices, at least in theory, are only sensitive to investors' beliefs about future firm profits and dividends (Sharpe, 1978). But, since profits and dividends are dependent on the individual's choice to consume, consumer preferences will implicitly determine future firm profits. This is a mechanism that (theoretically) should be understood and considered by investors when they form their expectations about the future and set a firm's price. Thus, also, stock market prices are dependent on a collective preference set. But what about *daily* stock market price movements?

An individual's opinion, or some aggregate of such opinions, is often referred to as sentiment. Sentiment can thus be thought of as a subset of the drivers of market prices and thus possibly part of some collective preference set that determines the market price of a firm. Acknowledging this, I lean on the large bulk of empirical research that shows that investor and market sentiment is indeed related to daily stock market returns and note that the idea that market sentiment may affect daily stock price movements has a long history within the field of economics.[4] As an example, Keynes (1936) associated the stock market with a 'beauty contest' where participants devote their efforts not to judging the underlying concept of beauty, but instead to

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behavioural economics, economists seek to understand the motivations and reasons *behind* individuals' decisions.

3 Examples of this are that prices should be non-negative and that consumers value having a good higher than not having a good at all.

4 Fisher and Statman (2003) and Daszyńska-Żygadło, Szpulak and Szyszka (2014) find a positive relationship between investor sentiment and market returns.

'anticipating what average opinion expects the average opinion to be'. Also, Shiller (2017) argued for the importance of sentiment as investors' optimistic or pessimistic beliefs about the stock markets may directly influence prices. The interested reader could consult the excellent introduction in Lansing and Tubbs (2018) for a more detailed discussion on sentiment and stock market prices while I in this paper simply acknowledge that sentiment affects stock market prices and that sentiment may be affected by daily stock market beliefs.

The above reasoning suggests that changes to the collective preference set are likely to affect daily stock price movements. The above also suggests that e.g. emotional and engaging world events could affect the collectively decided worth of a firm. As it is claimed that the GCP data also may be affected by such events, it is argued that daily stock market returns and the GCP data could be correlated. This is an unexplored research avenue and, since the inclusion of the GCP data rests on some unorthodox research on the nature of consciousness, a supporting discussion on consciousness follows in the sections below.

3. A Brief Discussion on Consciousness

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 solely the result of physical arrangements and information processing patterns (see e.g. Güzeldere, 1997). This viewpoint rests on the existence of neural correlates (see e.g. Cotterill, 2001; Llinás, 2002; 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 non-conscious 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).

From the above it can be read that our understandings of consciousness are incomplete and that much more research is needed. However, it could also be understood that most studies on consciousness focus on explaining an individual's conscious experience and not the will of the many.[5] Thus aspects related to collective decision making are often ignored even though one notable exemption exists, the collective consciousness concept within the field of sociology.

In sociology, a set of shared beliefs, ideas, attitudes, and knowledge that is common to a social group or society is defined as a society's collective consciousness (Durkheim, 1893/1997). As consumers are individuals, and as individuals act and consume within social groups and economies, it could be argued that the collective consciousness *à la* Durkheim affects the collective preference set of consumers and, through it, market prices. Perhaps this is a concept of consciousness that can be used for understanding changes in the collective consumer preference set in economics. Perhaps it could also be said that the collective consciousness of Durkheim should be correlated with the GCP data, at least if the society is defined in a way that is aligned with the definition underlying the GCP data (i.e. globally). However, the GCP data is special as it rests on the assumption that human consciousness can stretch out beyond our heads and affect random number generators at a distance. As this idea is not part of the most prevalent theories on consciousness, a discussion on alternative theories is provided in the following section.

4. Alternative Theories on Consciousness and the GCP Data

There exist several alternative theories of consciousness that allow the possibility that the mind stretches out beyond our heads and it should also be noted that physics permits this possibility. This 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) initiates the transition from the 'possible' to the

5 Perhaps the problem with explaining what consciousness is originates from the problems faced in the definition of the concept. Consciousness 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) is imprecise, the term has also been defined in terms of sentience alone, e.g. awareness, qualia, and subjectivity.

'actual' as the famous 'wave function' collapses.[6] This thus suggests that human measurement done at a distance affects quantum systems at a distance.[7] That consciousness can extend outside a human head and interact with (say) a random number generator has also been studied within the research field of parapsychology by, for example, Nelson, Jahn and Dunne (1986), Radin *et al*. (2006), and Dunne and Jahn (2007). The results from their studies suggest that consciousness can do so and, taken together, it is noted that some research results allow for the possibility of consciousness stretching out beyond our heads.

Thus, some research findings suggest that consciousness has properties that cannot be described purely using reductionist material sciences alone, at least not as they are understood to date. Such findings have thus resulted in several alternative hypotheses and theories of consciousness, theories that attempt to 'close the gap' between philosophy and material sciences. In, for example, Donald Hoffman's 'conscious agents' theory (2008; 2014), consciousness, rather than space-time and physical objects, is fundamental. Even though Hoffman is thought of as a consciousness realist, this is a theory of consciousness shared by many modern philosophical idealists (see e.g. Kastrup, 2018). Other notable examples include electromagnetic theories of consciousness (see e.g. Pockett, 2012; McFadden, 2002)[8] and quantum brain dynamics theories (see e.g. Atmanspacher, 2004; Van den Noort, Lim and Bosch, 2016).[9]

Some, but not all, of these alternative theories allow for consciousness stretching out beyond the human head and some view consciousness as fundamental, putting consciousness studies at the forefront of academic exploration. From this it is noted that some of the alternative

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6 Physicists have found that even passive observation of quantum phenomena can change the measured result (see e.g. Buks *et al.*, 1998).

7 It is noted that this interpretation of the observer effect is controversial within the field of physics.

8 Electromagnetic theories of consciousness branch off into a 'Cemi' version and a 'quantum mind' version. The former proposes that digital information from neurons is integrated to form a conscious electromagnetic information field in the brain (see e.g. McFadden, 2002), and the latter that electric dipoles of water molecules constitute a quantum field, referred to as the cortical field, with corticons as the quanta of the field. Thus, the two alternative theories are linked in a sense.

9 One viewpoint here is that the brain may be viewed as a 'quantum computer' and that all psychological phenomena, including consciousness, can be explained using the processes of quantum computing (e.g. Penrose, 1994).

theories allow for the possibility of consciousness affecting matter at a distance and that machines harvesting quantum technology could be affected by consciousness from a distance. Resting on such findings, Roger D. Nelson developed the Global Consciousness Project (GCP) to investigate if this human–machine interaction also could be true on a global scale.

The GCP is an international and multidisciplinary collaboration that generates and collects random number data continuously from a network of physical random number generators at 70 locations around the world. The random numbers are generated using quantum tunnelling 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. 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 and that large emotional events will thus affect hardware-generated random numbers in a way that gets 'picked up' and made visible in the numbers generated from it. The GCP has produced remarkable results as the random numbers seem to be influenced by large global emotional events (Nelson and Bancel, 2011). 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 GCP hardware could also affect consumers' collective preference set and thus also stock market prices and stock market returns.

5. A Suggestive Link between Stock Markets and the GCP Data

From the above it could be argued that stock market prices and the data collected by the GCP should covary since the GCP data, as claimed, is affected by large global emotional events and since such events should also affect stock market prices and the returns obtained from them. Thus, I here seek a 'non-interaction-based' statistical codependence between the data obtained from these seemingly unrelated sources.

However, the way in which the GCP has conducted their studies would not answer the research question posted herein. This since the GCP studies rely on large global emotional events (such as disasters, war, or political events) to get measurable effects. But as pointed out by its critics, this has been one of the project's weaknesses since the events chosen could be selected in order to fit the data. This criticism has been addressed by the GCP as they have constructed a predefined protocol on how to choose the events to be studied. For this study, however, such criticism is irrelevant as I seek a time series correlation that does not rely on the importance of single large emotional events.

I chose to study daily stock market returns which thus also requires the need for a daily aggregate variable from the GCP data. The aggregate GCP data variable derived relies on the the large bulk of publicly available GCP data (collected every second) and converts it into daily observations that aims to capture significant deviations from what should be expected from random numbers. To this end, I use the unfiltered *Z*-scores calculated every 15 minutes, and derive a daily observation by taking the 24-hour maximum of these *Z*-scores. Such a measure should arguably capture any large shifts in the random numbers since even subtle unexpected shifts in the data would be captured in the measure.[10]

Note that the number of active random number generators tends to vary over time but that this is of little concern as I utilize the information from the *Z*-scores obtained from the column 'All Egg Composite' from the Daily Tables section on the GCP webpage.[11] This data retrieval process results in a time series of maximum daily *Z*-scores spanning from the 9th August 2019 all the way back to the 1st January 1999. Note also that all 'bad data' are removed.[12]

The aggregated daily GCP variable is labelled *Max*[*Z*] and if the GCP data are affected by events disturbing the will of the many, it will (arguably) be captured in the *Max*[*Z*] variable. Also, and as discussed above, such events should affect stock market returns which thus suggests that stock returns and *Max*[*Z*] could be correlated. A statistically significant correlation could also suggest that there is some underlying quantity determining both stock market returns and the *Max*[*Z*] series as illustrated in Figure 1 (in the figure, the postulated

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10 Most GCP studies use XOR filtered data in their studies. Such a filtering procedure will exclude events that could cause spurious effects (e.g. temperature changes) but, as the procedure removes some possibly important data, I here use its unfiltered version.

11 Note that the 15-minute intervals underlying the maximum *Z*-score calculations begin at 00:00:00 UTC. Please visit the GCP website for further details http://noosphere.princeton.edu/.

12 In particular, all dates with reported bad data are removed. Also, three dates with unusually high maximum, minimum, and average values are removed.

correlation between the two variables is illustrated by the intersection between stock market returns and GCP data effects).

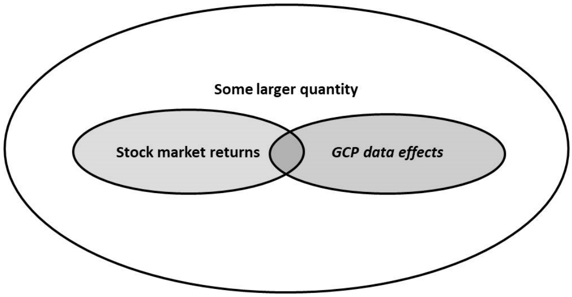

Figure 1. The GCP data and stock market returns could have a testable intersection.

But how could such an intersection be formalized? This is as yet unexplored territory and no known functional form linking *Max*[*Z*] and stock market returns exists. In the absence of a functional form, I lean on the Taylor theorem (Taylor, 1715) which allows for an approximation of any functional relationship with a polynomial linear function.[13] Here, it is thus only postulated that *Max*[*Z*] could have an effect on stock market returns in some unknown way, and that equation (1) can be used as an approximation of this relationship:

$$r_{i,t} = \alpha_i + \Sigma_j \Sigma_k (\gamma_{i,j,k} r^k_{t-j} + \beta_{i,j,k} Max[Z]^k_{t-j}) \quad (1)$$

where r_t is stock returns, *Max*[*Z*] is the maximum value over 24 hours, i are different stock market indexes, and where $k = (1,2,\ldots K)$ is the number of polynomial terms while j is the lag structure under study. The best fit and order of the polynomial in equation (1) is an empirical question and treated as such.

6. Results

In this section, the relationship between *Max*[*Z*] and stock market returns (r) is analysed, i.e. the intersection in Figure 1.[14] The returns are obtained from the Dow Jones Global Equity Index as this index is

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

14 Returns are defined as $r_t = (P_t - P_{t-1})/P_{t-1}$ where P_t is the price/index value at time t.

ideal for capturing global stock market movements and daily changes in global sentiment. In other words, this index is a good fit for testing the existence of an intersection as in Figure 1.[15]

Requiring the data to be balanced, missing data are excluded such that only dates on which there are both *Max*[*Z*] values and some activity on the Dow Jones Global Equity Index are used. In Table 1 below, descriptive data for the variables used are displayed and, as can be seen, stock market returns exhibit the 'usual' stock market return properties while *Max*[*Z*] is largely skewed and exhibits excess kurtosis.

	***Max*[*Z*]**	**Open**	**Close**
Mean	3.0197	0.0002	0.0002
Median	2.7100	0.0000	0.0004
Maximum	82.1000	0.0665	0.0907
Minimum	1.7600	–0.0861	–0.0713
Std. Dev.	3.9546	0.0098	0.0098
Skewness	15.9442	–0.7297	–0.2778
Kurtosis	273.2198	12.2483	10.7302

Note: The number of observations (N) for all variables is 5236.

Table 1. Descriptive of the data.

As discussed in the previous section, the exact functional form describing the relationship between stock market returns and *Max*[*Z*] is not known, but a polynomial as in equation (1) can be used to proxy such a relationship. The return series (r) used in this study are derived both from daily 'close' values (the last reported value of the day, which is the usual reporting standard within the industry) but also on daily 'open' values (from the first observation every day). This since I want to allow for the possibility that *Max*[*Z*] could predate stock market returns.

After significant statistical trials, a second- and third-degree polynomial function seems to fit the data best, dependent on if the analysis is done on today's or yesterday's *Max*[*Z*]. The obtained estimates are derived using Ordinary Least Squares (OLS) and, due to the possibility of heteroskedastic and/or autocorrelated residuals, the HAC-Newey-West estimator (Newey and West, 1987) for standard

15 The index measures the performance of stocks that trade globally, targeting 95% coverage of markets open to foreign investment. It is float market cap weighted and quoted in USD.

errors is used.[16] All significance tests are performed using the t-statistic together with HAC standard errors and in Table 2 the results using the full sample stretching back to March 1999 are presented.[17]

In Table 2, γ_r is the coefficient describing dependence on previous stock market returns (the autocorrelation component) and the β:s the dependence with *Max*[*Z*] as in equation (1). As expected, the auto-correlation component (γ_r) is highly significant but so is the *Max*[*Z*] dependence for both daily 'open' and 'close' returns. Also, both return series are affected by the present date's *Max*[*Z*] *and* yesterday's *Max*[*Z*] such that changes in *Max*[*Z*] (partly) seem to *predate* actual stock market returns. This even after possible additional 'excluded variable bias' is investigated by letting both return series be dependent on an additional autocorrelation component. Apart from the implication the results have on our understanding of consciousness (it appears to confirm the validity of the GCP data), this is a profound result in the face of the 'no arbitrage' assumption in economics.

What is meant by the no arbitrage assumption is that economic systems have an implicitly built-in non-arbitrage property and that all true arbitrage profits are 'removed' as soon as the market becomes aware of them. This has been observed in the past, and the Monday/ Weekend effect (Cross, 1973) is probably the most famous. This was a phenomenon in financial markets in which stock returns on Mondays were often significantly lower than those of the immediately preceding Friday. The prevalence of the phenomenon is much debated as it disappeared when the results where made public (as price mechanisms corrected) but later re-emerged. Regardless, the results presented herein are derived from publicly available data and the estimates can thus be found and derived by anyone. If arbitrage profits can be made from these results, this quantified effect should be traded away as soon as the results are made public as they can only exist because no one yet knows about the effect.

16 Note that if the usual standard errors are used the qualitative nature of the results is unaffected.

17 Data on the Dow Jones Global Equity Index began during March 1999.

	Open on $Max[Z]_t$	Open on $Max[Z]_{t-1}$	Open on $Max[Z]_t$ and $Max[Z]_{t-1}$
α	–0.0016**	–0.0011***	–0.0027***
γ_r	0.0781***	0.0782***	0.0779***
$\beta_{Max[Z]t}$	0.0007***	–	0.0007***
$\beta_{Max[Z]t}{}^2$	–2.13E-05**	–	–2.14E-05**
$\beta_{Max[Z]t}{}^3$	1.60E-07**	–	1.71E-07**
$\beta_{Max[Z]t-1}$	–	0.000463***	0.000457***
$\beta_{Max[Z]t-1}{}^2$	–	–6.11E-06***	–6.11E-06***
R^2	0.73%	0.81%	0.90%
	Close on $Max[Z]_t$	**Close on $Max[Z]_{t-1}$**	**Close on $Max[Z]_t$ and $Max[Z]_{t-1}$**
α	–0.0012**	–0.0006	–0.0018***
γ_r	0.1297***	0.1297***	0.1314***
$\beta_{Max[Z]t}$	0.0005**	–	0.0005**
$\beta_{Max[Z]t}{}^2$	–1.57E-05*	–	–1.64E-05**
$\beta_{Max[Z]t}{}^3$	1.09E-07	–	1.23E-07*
$\beta_{Max[Z]t-1}$	–	0.0003**	0.0003*
$\beta_{Max[Z]t-1}{}^2$	–	–4.31E-06**	–3.83E-06*
R^2	1.79%	1.78%	1.91%

*Significance levels: * 10%, ** 5%, and *** 1%.*
Note: The sample size (N) is 5237.

Table 2. Estimates for r_t.

Returning to the results in Table 2, it is noted that the predating effect obtained can also be found from the significant results from the 'open' series on the current date's *Max*[*Z*]. This as the open return series is obtained directly when stock markets open in New York, while the *Max*[*Z*] result is obtained several hours later during the day and first when the 24h time period has passed.[18] Furthermore, looking at the coefficient of determination (the R^2 value) it is found that about 1% for daily open values and just below 2% of daily close values can be explained using the specifications in Table 2. Not much, but well in line with previous research with regards to the autocorrelated nature of stock market returns. However, and more importantly given the research hypothesis, the R^2 value increases between 0.2% and 0.3% after the inclusion of the *Max*[*Z*] dependence. This result is obtained by comparing the coefficient of determination with and without the polynomial structure describing the $Max[Z]_t$ and $Max[Z]_{t-1}$ depend-

18 The 15-minute intervals, from which the daily maximum *Z* value is calculated (the *Max*[*Z*] variable), begins at 00:00:00 UTC and ends 24 hours thereafter.

ence but, as most variance still remains unexplained, the results open up an obvious avenue for future research. Note also that the significant dependence on *Max*[*Z*] is unaffected by the inclusion of the lagged returns and that this variable is only included for the residuals to be well behaved (and in order to reduce missing variable bias).

The results presented in Table 2 also carry with them some clues regarding the shape between *Max*[*Z*] and stock market returns. This since it is found that the polynomial in equation (1) has a positive first term and a negative second term, a result that holds true for both the $Max[Z]_t$ dependence as well as for $Max[Z]_{t-1}$. Also, if the current date's *Max*[*Z*] dependence is studied, both on a stand-alone basis and in conjunction with $Max[Z]_{t-1}$, a third and positive polynomial term is found. This can be seen from the first and last column in Table 2. The results also suggest that small to moderate values of *Max*[*Z*] coincide with positive returns, which is a result that corresponds nicely to the small but positively observed trend growth in stock market returns (the first row for the second and third columns in Table 1). But, if *Max*[*Z*] increases to large enough values, there is a negative effect on stock market returns, possibly due to large negative global emotional events that also have a large impact on the GCP data. As *Max*[*Z*] grows even larger, the effect on stock market returns turns positive again and the results also suggest that this third polynomial term effect rapidly loses its ability to affect stock market returns as no significant term is found on yesterday's *Max*[*Z*].

But, as shown in the descriptive data in Table 1, the *Max*[*Z*] variable is both skewed and exhibits large kurtosis which could result in non-normal residuals if the parameters are obtained through OLS. However, it is noted that OLS estimates are still a reasonable estimator in the face of non-normal errors. In particular, the Gauss-Markov Theorem states that the ordinary least squares estimate is the best linear unbiased estimator of the regression coefficients as long as the errors have zero mean, are uncorrelated, and have constant variance. This seems to be the case for the estimates underlying the results in Table 2.[19] Also, heteroskedasticity and autocorrelation consistent standard errors (HAC) have been used when testing for significance such that the results could be considered robust to such issues.

However, as 'outliers' could drive the qualitative nature of the results, only dates on which $Max[Z] < 10$ are considered in a separate

19 Best meaning optimal in terms of minimizing mean squared error.

analysis.[20] The statistical results excluding such large values are presented in Table 3 and, as can be seen, significant correlations remain. The ‘open’ return series maintains its dependence on $Max[Z]_t$ while its dependence on $Max[Z]_{t-1}$ shifts and becomes linear. Also, a combined specification suggests such dependence on the ‘open’ series, while for the ‘close’ series the predating dependence vanishes. These results thus suggest that large $Max[Z]$ values could, in part, be the cause of the non-linearity and also that the results support the qualitative conclusion that a statistical dependence between these variables exists.

	Open on $Max[Z]_t$	**Open on $Max[Z]_{t-1}$**	**Open on $Max[Z]_t$ and $Max[Z]_{t-1}$**
α	–0.00126**	–0.0013	–0.0146**
γ_r	0.0784***	0.0780***	0.0780***
$\beta_{Max[Z]t}$	0.0096**	–	0.0099**
$\beta_{Max[Z]t^2}$	–0.0021**	–	–0.0022**
$\beta_{Max[Z]t^3}$	0.0001**	–	0.0001**
$\beta_{Max[Z]t-1}$	–	0.0005**	0.0005*
$\beta_{Max[Z]t-1^2}$	–	–	–
R^2	0.77%	0.67%	0.84%
	Close on $Max[Z]_t$	**Close on $Max[Z]_{t-1}$**	**Close on $Max[Z]_t$ and $Max[Z]_{t-1}$**
α	–0.0013*	–	–
γ_r	0.1321***	–	–
$\beta_{Max[Z]t}$	0.0005*	–	–
$\beta_{Max[Z]t^2}$	–	–	–
$\beta_{Max[Z]t^3}$	–	–	–
$\beta_{Max[Z]t-1}$	–	–	–
$\beta_{Max[Z]t-1^2}$	–	–	–
R^2	1.82%	–	–

*Significance levels: * 10%, ** 5%, and *** 1%.*
Note: The sample size (N) is 5207.

Table 3. Estimates for r_t given that $Max[Z] < 10$.

Summing up, the results in Table 3 confirm the qualitative nature of the results in Table 2 as they suggest that the estimates are not driven by outliers and that they are statistically sound. Also, both tables suggest that an increase in $Max[Z]$ in general is affiliated with increased returns, but that larger $Max[Z]$ values signal negative returns

[20] A $Max[Z]$ value of 10 is highly unlikely and thus a good proxy for extreme value and outlier detection.

to come. It is also found that large changes in *Max*[*Z*] predate stock price movements and it is noted that this last point could have obvious market implications. In addition to the above, these results seem to confirm the validity of many GCP studies and suggest that random numbers, at least if generated using quantum tunnelling techniques, can be influenced by intention and global emotions at a distance.

The results presented so far herein suggest that the intersection argued for in Figure 1 is likely to exist. But perhaps the results are due to some spurious and causal relationship or due to chance? The former could be true, as the intersection illustrated in Figure 1 also suggests that an underlying larger quantity could determine both stock market returns and the *Max*[*Z*] series. In fact, as the term spurious correlation is generally understood in statistics, it describes a non-causal correlation that can be spuriously created by an antecedent which (in this case) causes both *Max*[*Z*] and *r*. Thus, this is of little concern as it could be argued that such an underlying variable could exist and should be explored in future research. The second point could, however, be a source of concern, even though the likelihood of the results being due to chance is well below 1/100 based on the significance tests made.[21]

This latter concern is adequately addressed by applying the same statistical techniques on a wide range of well-known equity indexes all around the globe. The dependence structure follows equation (1) and is inspired by the obtained dependence in Table 2 but modified in the spirit of parsimony. Returns are calculated using the indexes' 'close' value and, as can be seen in Table 4, significant correlations are again found with regards to the relationship between daily stock (*r*) returns and *Max*[*Z*]. In fact, almost all stock market return series (11 of the 12 studied) are found to be significantly correlated with *Max*[*Z*], which supports the results presented in Table 2. Notably, the 'timing' of the variable's dependence is found to differ, which possibly could be attributed to the index's geographical location and thus reflects the difference in UTC closing times. This expiation is supported by the findings as different geographical 'blocks' are subject to the same dependence structure at large. The pure American return indexes (S&P, Dow Jones, Nasdaq, and Ibovespa) correlate with the current day's *Max*[*Z*] while the European stock market indexes and most

21 The tables lowest P-value related to *Max*[*Z*] is for 'open' returns on $Max[Z]_{t-1}$. Here, the P-value is about 0.0003, i.e. a one in 3,333.333 result if due to chance.

Asian indexes correlate with $Max[Z]_{t-1}$.[22] The Japanese Nikkei 225 is an exception but, taken together, these dependences hint towards the importance of time.

		USA, S&P 500	USA, Dow Jones	USA, Nasdaq	Brazil, Ibovespa
α	Americas	–0.0003	–0.0003	–0.0003	–0.0018
γ		–0.0707***	–0.0663***	–0.0329*	–0.0103
$\beta_{Max[Z]t}$		0.0002	0.0002	0.0003	0.0009**
$\beta_{Max[Z]t^2}$		–3.60E-06*	–3.73E-06*	–4.23E-06*	–3.40E-05**
$\beta_{Max[Z]t^3}$		–	–	–	2.81E-07**
R^2		0.55%	0.52%	0.14%	0.01%
		UK, FTSE 100	**France, CAC 40**	**Germany, CDAX**	**Switzerland, SIX**
α	Europe	–0.0011**	–0.0009	–0.0012*	–0.0011***
γ		–0.0360**	–0.0272	0.0013	0.0344*
$\beta_{Max[Z]t-1}$		0.0005***	0.0004*	0.0005**	0.0005***
$\beta_{Max[Z]t-1^2}$		–6.22E-06***	–6.05E-06**	–6.84E-06**	–6.51E-06***
R^2		0.26%	0.16%	0.12%	0.28%
		Singapore, SGX	**Hong Kong, Hang Seng**	**China, Shanghai**	**Japan, Nikkei 225 +**
α	Asia	–0.0004	–0.0007	0.0005	–0.000706
γ		0.0395**	–0.0108	0.0137	–0.029901
$\beta_{Max[Z]t-1}$		0.0002	0.0004*	–4.65E-05	0.000309**
$\beta_{Max[Z]t-1^2}$		–3.47E-06*	–5.24E-06**	–3.36E-07	–3.27E-06*
R^2		0.21%	0.70%	0.05%	0.16%

*Significance levels: * 10%, ** 5%, and *** 1%.*
Note that + indicates that the regression was done on non-lagged values of Max[Z]. Note also that the sample size (N) per regression is 5236.

Table 4. Estimates for r_t on alternative indexes.

7. Conclusions and Future Research

In this paper, it was shown that the random numbers generated by the GCP covary with global stock market returns. This topic was investigated after it was claimed that such a dependence should exist since stock market returns are the result of investors' collective decisions of the worth of firms. As such a collective decision should follow the usual market pricing mechanisms in economics, it was argued that stock market prices should be affected by events similar to events that are claimed to affect the GCP data. In an empirical part of this paper,

[22] $Max[Z]$ is calculated using a fixed 24h rolling window.

such a dependence was found to exist for several different world stock market indexes.

The relationship was found using a newly defined variable, derived from the GCP data. This new variable was constructed in a way that captures large changes in the GCP data over the past 24 hours. This variable was labelled $Max[Z]$ and was found to be correlated with global stock market returns, as well as various local well-known stock market indexes. It was also shown that the relationship between $Max[Z]$ and stock market returns can be approximated with a second- and third-degree polynomial and that the polynomial dependence is dependent on whether today's $Max[Z]$ values are used or if the $Max[Z]_{t-1}$ is studied. The results thus suggest that yesterday's GCP data can be used to describe today's stock market movements, which is a profound result as it could open up arbitrage profit opportunities. How the market will react to this new information will thus be interesting to follow.

The results also validate some of the claims made by the GCP, and since the GCP data rest on the assumption that consciousness stretches out beyond our heads and can affect hardware-generated random numbers at a distance, the current paradigm with regards to consciousness needs to be discussed. The results actually invite a discussion on alternative theories of consciousness as the results presented herein cannot be understood using the prevailing scientific understanding of consciousness alone. Perhaps the results are better understood through the lens of some alternative theories as some of these theories allow for the possibility of consciousness stretching out beyond our heads. Furthermore, since the random numbers collected by the GCP use quantum tunnelling techniques to obtain the random numbers, quantum brain dynamics theories or electromagnetic theories of consciousness are obvious candidates in a pursuit of a deeper understanding of the results. Here, this is left as an interesting avenue for future research.

On a less grandiose level, a better formalization of the functional form linking large random numbers and stock market returns could be studied and better daily GCP data variables could be constructed and tailored to fit individual markets. Also, a more thorough study of the relationship between different indexes could be done and such a study should also adjust for time differences in reporting and possible exchange rate effects. Furthermore, pure market sentiment and market volatility could be related to the $Max[Z]$ variable and could be studied, and so could any relationships found between different markets. If these dependences can be found, a latent and underlying hidden factor could possibly be obtained and, if this were the case, research that seeks to explain such a latent hidden variable could be conducted. The importance of time also adds to future research dimensions and it would be interesting to see if financial futures markets are affected by $Max[Z]$ and, if so, at which point in time. Finally, various macro-economic variables could be constructed and possibly correlated with variables aggregated out of the GCP data. In short, these novel findings open multiple avenues for future research.

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