Market sentiment and the Global Consciousness Projects data

Exploring a surprising link and demonstrating its usability

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Abstract

The Standard & Poor's 500 Volatility Index (VIX) significantly correlates with the data produced by the Global Consciousness Project (GCP). Given the practical implications of this finding, econometric models that either utilize or ignore GCP data are fitted on daily S&P 500 returns. Highly significant interaction terms are found. To address the possibility of P-hacking, the models are tested in an out-of-sample simulation study lasting for a one year. In the simulation, the trader uses S&P 500 tracking instruments and trades in accordance with the model's one-day-ahead forecasts. It is found that GCP data can enhance daily forecasts.

Keywords: Stock market returns, VIX, Global Consciousness Project

JEL-codes: G10, G11, G17

1. Brief Introduction

Prior studies have underscored a noteworthy correlation between the aggregated Global Consciousness Project (GCP) data metric, *Max[Z]*, and daily stock market returns. However, the fundamental reasons behind this correlation have not yet been addressed. This research endeavors to propose a hypothesis suggesting that this connection might be rooted in market sentiment, potentially influenced by events that could be picked up by variations in the GCP data. To examine this hypothesis, an analysis is conducted to investigate the covariation between the Standard & Poor's 500 Volatility Index (VIX), a widely utilized measure of market sentiment, and the daily GCP data metric, *Max[Z]*. Furthermore, this study aims to validate the results through an out-of-sample simulation study and delves into the practical implications that such a correlation could provide for traders.

The structure of this paper is as follows. The subsequent section provides an in-depth discussion of both the VIX measure and the GCP data, including an exploration of their correlations. This is followed by a section in which a connection between the VIX, GCP data, and daily stock market returns is established. Following this, an out-of-sample simulation study is presented, validating the findings by illustrating potential real-world applications of the findings by traders. To conclude, the final section summarizes the results and its implications.

2. The VIX measure and GCP data

Daily stock market returns have demonstrated a correlation with a metric derived from GCP data (Holmberg, 2020, 2021). The driving forces behind this covariation, however, have been left for future research to explore, although it has been suggested that the dependence of daily returns on market sentiment could be a contributing factor. Market sentiment, in turn, may be influenced by events that the GCP data "picks up." Therefore, market sentiment could be considered a potential link between GCP data and stock market returns.[1]

Market sentiment refers to investors' general attitudes and moods toward financial markets. This mood has been shown to correlate with trading volumes and market returns—an association that noise traders tend to acknowledge (So and Lei, 2015). Positive and negative market sentiments could thus drive price movements, even though precisely quantifying market sentiment remains challenging due to its elusive nature. Nevertheless, market participants often

[1] For a more detailed discussion on events impact on market sentiment, refer, for example, to Jordà's (2005) and Fraiberger et al.'s (2018).

consider the CBOE VIX, a measure of the implied volatility of 30-day S&P500 options, as a proxy (Edwards and Preston, 2017). The VIX is also often referred to as the “fear index” due to its historical correlation with market panics. VIX is calculated using the two nearest expiration months of the S&P 500 options to achieve a rolling 30-calendar-day period.

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 (RNGs). The random numbers are generated using physical processes such as avalanching and quantum tunneling, and the hypothesis underpinning the GCP suggests that events triggering widespread emotions or capturing simultaneous attention from large numbers of people may significantly influence the output of the hardware-generated random numbers in a statistically significant way.

Studies conducted by the GCP have yielded results that validate the project’s hypothesis (see, e.g., Nelson et al., 2002; Radin, 2002; Nelson and Bancel, 2011). However, because the possibility that the the random numbers produced by the GCP are affected by such events seems to challenge the current understanding of physics, the results have been criticized (Scargle, 2002), and most scientists demand a high standard of evidence.

It has thus been suggested that the GCP results are due to the experimenter selecting events supportive of the project’s hypothesis, and May and Spottiswoode (2011) suggested that the source of the statistical deviations reported could be attributed to a psi-mediated experimenter effect. Bancel (2011), however, analyzed the data and rejected the simple selection hypothesis with a reasonably high level of confidence. Even though Bancel later did another analysis with results suggestive of that the GCP result is due to a goal-oriented effect (Bancel, 2017), studies conducted on the correlation between the GCP data aggregate *Max[Z]* and daily stock market returns (Holmberg, 2020, 2021), as well its relationship with global internet search trends (Holmberg, 2023), have all produced results supportive of the hypothesis underlying GCP.

A relevant question, however, remains what *Max[Z]* represents and how it is calculated. *Max[Z]* is an aggregate that aims to capture large intraday GCP data values. Let the data produced by an individual physical random number generator (*RNG)* be denoted $RNG_{i,\tau}$ for $i = 1,2, \dots n_{\tau}$, where n_{τ} is the total number of operating *RNGs* during second $\tau \in t$. The *RNGs* used by the

GCP produce a series of 200 bits per second with an expected value of $\mu = 100$ and a variance of $\sigma^2 = 50$ from which n_τ standardized random numbers ($z_{i,\tau}$) can be calculated.

The intraday data is aggregated into daily data, bundling the GCP data into 15-minute (900 seconds) nonnegative data chunks and applying the following formulas to the extracted data:

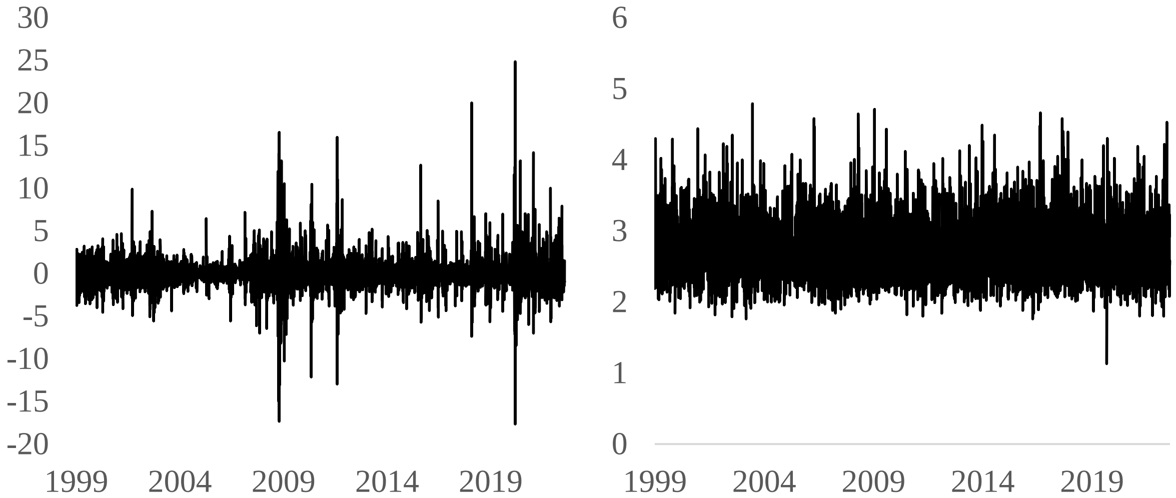
$$Z_\tau = \left| \sum_{\tau-900}^{\tau} z_\tau \Big/ \sqrt{900} \right|, \tag{1}$$

with

$$z_\tau = \left(\sum_i^{N_\tau} RNG_{i,\tau} - N_\tau \mu \right) \Big/ \sqrt{N_\tau \sigma^2}, \tag{2}$$

and were N_τ is the number of active RNGs during τ. Measuring Z_τ at the end of each 15-minute interval, as is done in the daily tables section on the GCP website, 96 daily intraday measurements are obtained, and from these measurements, a daily maximum is calculated. The daily maximum value of Z_τ should conceptually capture large and unexpected values in Z_τ, which in turn could covary with market sentiment measures, such as the VIX index.[2]

Figure 1: Changes in the VIX index and *Max[Z]*



a. ΔVIX *b. Max[Z]*

Note: Daily data (N = 5749) collected between 4 January 1999 and 1 August 2022.
Source: Macrobond, the Global Consciousness Project, and own estimates.

[2] Arguably, other intraday time frames could have also been chosen. However, large measurable intraday movements caused by engaging global events should "show up" in the aggregation procedure regardless of the exact time frame chosen.

Historical data on VIX between 4 January 1999 and 1 August 2022 are aligned with the daily GCP data aggregate *Max[Z]*.[3] Table 1 presents descriptive data on both the ΔVIX and *Max[Z]*, and Figure 1 depicts the two variables.

Table 1: Descriptive statistics, ΔVIX and *Max[Z]*

	ΔVIX	*Max[Z]*
Average	-0.00	2.75
Median	-0.08	2.70
Std. Dev.	1.84	0.41
Minimum	-17.64	1.13
Maximum	24.86	4.79
Skewness	1.48	0.73
Kurtosis	24.27	1.19

Note: Daily data (N = 5749) collected between 4 January 1999 and 1 August 2022.
Source: Macrobond, the Global Consciousness Project, and own estimates.

Observing the data, it becomes evident that there are two notably significant "spikes" in VIX. The first spike occurred during the major financial crisis of 2008, and the second spike followed the COVID-19 pandemic in 2020. Noteworthy spikes also align with other historical events, including the Asian financial crisis in late 1997, the Russian and LTCM crisis in late 1998, the 9/11 terrorist attacks, and the European sovereign debt crisis of 2011-2012. Furthermore, upon visual examination, there are indications that ΔVIX might exhibit heteroskedasticity, a hypothesis later confirmed through statistical analysis. ΔVIX also demonstrates autocorrelation, and *Max[Z]* displays certain prominent "spikes," although their prominence is diminished due to their inherently greater noise. Both variables, however, showcase random fluctuations around their respective means. Consequently, the econometric analysis is deliberately structured to explore whether these variables simultaneously revert back to their mean values and whether the mean reversion process is affected by their covariation.

The hypothesis postulates that *Max[Z]* might encapsulate an undisclosed facet of market sentiment, thus potentially leading to their correlation. Considering the autocorrelation of ΔVIX, the investigation into this correlation is approached using the following linear equation:

$$\Delta VIX_t = \alpha + \beta_1 \Delta VIX_{t-1} + \beta_2 I_t + \sum_i \gamma_i Max[Z_{t-i}] + \sum_j \delta_i (\Delta VIX_{t-1} Max[Z_{t-i}]), \qquad (3)$$

[3] Dates with *Max[Z]* values larger than 5 are removed as well as dates with malfunctioning *RNG*s.

where I_t is an indicator variable equal to unity on Mondays or if the previous day's data has been removed.[4] The significant correlations are tested using the t-statistic on the models' parameters obtained through ordinary least squares (OLS).

Table 2 provides the OLS regression estimates, revealing significant covariance between VIX and several interaction terms (δ_i), thus linking VIX with *Max[Z]*. Specifically, the change in ΔVIX from the previous day demonstrates a significant correlation with the current day's *Max[Z]* as well as its lags for up to three days ($P < 0.01$). This indicates that if an event is detected by the GCP data, resulting in an elevated *Max[Z]* value, market sentiment is influenced for multiple consecutive days.

Table 2: ΔVIX_t model estimates

Variable / Model	Control	1	2	3	4	5	6
Constant	-0.03	0.00	0.21	-0.04	-0.03	-0.26	-0.02
$\boldsymbol{\Delta VIX_{t-1}}$	-0.15^{***}	0.26^{***}	0.07	-0.46^{***}	-0.49^{***}	-0.15	-0.24^{***}
$\boldsymbol{Max[Z_t]}$	-	-0.01	-				-0.01
$\boldsymbol{Max[Z_{t-1}]}$	-	-	-0.09				-0.09
$\boldsymbol{Max[Z_{t-2}]}$	-	-	-	0.00			0.00
$\boldsymbol{Max[Z_{t-3}]}$	-	-	-		0.00		0.01
$\boldsymbol{Max[Z_{t-4}]}$	-	-	-			0.08	0.09
$\boldsymbol{\Delta VIX_{t-1} \times Max[Z_t]}$	-	-0.15^{***}	-				-0.16^{***}
$\boldsymbol{\Delta VIX_{t-1} \times Max[Z_{t-1}]}$	-	-	-0.08^{**}				-0.08^{***}
$\boldsymbol{\Delta VIX_{t-1} \times Max[Z_{t-2}]}$	-	-	-	0.12^{***}			0.11^{***}
$\boldsymbol{\Delta VIX_{t-1} \times Max[Z_{t-3}]}$	-	-	-		0.13^{***}		0.13^{***}
$\boldsymbol{\Delta VIX_{t-1} \times Max[Z_{t-4}]}$	-	-	-			0.00	0.03
$\boldsymbol{I_t}$	0.54^{***}	0.54^{***}	0.54^{***}	0.54^{***}	0.54^{***}	0.54***	0.53^{***}
$\boldsymbol{R^2}$	2.70%	3.05%	2.83%	2.93%	2.95%	2.74%	3.74%

*Significance levels: * 10%, ** 5% and *** 1%.*
Note: OLS estimates on daily data (N = 5749) collected between 4 January 1999 and 1 August 2022.

The sign of the parameters unveils insights into the dynamics: when market sentiment is on the upswing (indicated by a negative ΔVIX_{t-1}), a significant event resulting in a high *Max[Z]* value reverses this trend. This also holds true if the GCP data-affecting event occurred on the very day that market sentiment was improving (day t-1). However, if the event occurred before market sentiment had begun to improve (i.e., during t-2 or earlier), the sign is positive, indicating that the improvement instead was accelerated. This suggests that the event selected by the GCP data affects VIX differently if market sentiment is improving or deteriorating. Note

[4] Some observations are removed due to technical malfunctions distributing in the underlying RNG data used for the *Max[Z]* calculations.

that the outcomes in Table 2 thus harmoniously align with Holmberg's (2021) findings, which show that *Max[Z]* contributes positively to today's returns, only when yesterday's returns were negative and vice versa.

Given that investor sentiment notably influences stock markets (as explored in works such as Brown and Cliff, 2005), the outcomes detailed in Table 2 offer insight into the prior discovery—that daily stock market returns are correlated with *Max[Z]*. Consequently, it appears plausible that *Max[Z]* could capture certain market-affecting information not presently accounted for by VIX. This suggests that the GCP data could be put to practical use by market participants.

3. VIX, *Max[Z]*, and daily stock market returns

The practical implications of the findings in Table 2 are explored by estimating two econometric models on the daily S&P 500 return (r_t). The first model disregards the GCP data ($r_{t,\,without}$), while the second model incorporates its influence ($r_{t,\,with}$). Subsequently, the performance of a GCP data-dependent model is contrasted with the performance of an almost identical GCP data-independent counterpart. Notably, both models are adjusted to account for known influential factors.

A linear time series regression model is specified that allows for autocorrelated returns:[5] Following the insights from Pagan and Schwert (1990), Rogers et al. (1994), and Ghysels et al. (2006), the volatility in returns, a crucial factor in comprehending daily stock market dynamics, is represented by squared lagged S&P 500 returns. To accommodate the observation that investor sentiment affects stock markets, the models are designed to allow returns to be correlated with yesterday's ΔVIX. Recognizing that market sentiment tends to have a global impact, cross-market correlations in returns are also considered.

It is assumed that the Asian market is influenced by the previous day's US return, while European markets are influenced by both the previous day's and the current day's developments in the US, as well as the current day's performance in Asia. Consequently, the models embrace the notion that the S&P 500's behavior is influenced by European and Asian returns, alongside market volatility and market sentiment. Thus, it is assumed that the performance of the US

[5] Serial correlated returns is likely 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; Lo and MacKinlay, 1990 for a more detailed discussion).

markets is not solely autocorrelated but is intricately interlinked with the performance of other markets in ways that are intricate and not always transparent.[6]

In practice, trading activities in Asia are factored into the analysis using two well-established indices: the Japanese Nikkei 225 index, traded at UTC+9, and the Hong Kong Hang Seng index, traded at UTC+8. The European market, which slightly overlaps with the US stock market, is considered through the inclusion of the OMXS-30 index, traded at UTC+1.[7] Furthermore, the well-documented Monday effect (Cross, F. 1973) is addressed by incorporating an indicator variable set to 1 for Mondays. Additionally, the Monday effect is captured through numerous interaction terms involving the indicator variable. The variables' lagged dependencies are determined from the data.

To explore whether and how the GCP data align with daily stock market returns, an analogous econometric model is constructed. Within this model, the variables are permitted to interact with past *Max[Z]* values, enabling an investigation into the potential correlations between the GCP data and daily stock market movements. Both models are designed so that they can be used for one-day-ahead forecasts.[8]

Table 3 presents the model estimates obtained using OLS on data from 4 January 1999 and 1 August 2022. The parameters' significance are tested for using the t-statistic. The "control model" is fitted without any GCP data dependence (i.e., $r_{t,\,without}$), while and the "GCP data model" contains the hypothesized *Max[*Z] dependence (i.e., $r_{t,\,with}$).

The results in Table 3 are highly informative. As expected, the results distinctly demonstrate the autocorrelation of daily returns ($S\&P500_{t-1}$), their dependence on market variance ($S\&P500^2_{t-1}$), and their responsiveness to market sentiment (ΔVIX_{t-1}). Moreover, the returns are influenced by the performance of both the European ($Sweden_t$) and Asian markets ($Hong\ Kong_t$ and $Japan_t$) in addition to being influenced by past returns across global

[6] Since the New York Stock Exchange accounts for about half if the global market capitalization, daily market sentiment can be said to "reset" when markets in the US open for business at 14:30 (UTC). The change in sentiment could thus also affect market prices in Europe, and the intraday trend after US markets open.

[7] The Swedish stock market has a high degree of foreign ownership and closes at UTC 16:00 i.e., about 1.5 hours after the New York Stock Exchange opens (14:30 UTC). It is thus an ideal index as it then also captures a possible "reversal" and "reset" of daily sentiment once the US markets opens.

[8] In Holmberg (2020 and 2021), also todays *Max[Z]* was found to correlate with today's return, an intuitive finding as the GCP data reacts to events affecting daily stock markets directly. However, as the results are validated in an out-of-sample simulation using on one-day-ahead forecasts, only interactions with past values are included.

markets ($Sweden_{t-1}$ and $Japan_{t-1}$). Additionally, it is evident that Monday returns are different, substantiated by the high significance of various interaction terms involving the binary Monday indicator ($P < 0.01$).

Even more intriguing findings emerge when examining the correlation between the GCP data (*Max[Z]*) and S&P 500 returns. Although the significance of lagged *Max[Z]* is absent when considered on its own alongside other variables, it dynamically interacts with OMXS-30 (Sweden) and Hang Seng (Hong Kong) returns and responds to fluctuations in market sentiment (ΔVIX_{t-1}). Notably, some of these interaction terms carry substantial significance ($P < 0.01$). While the interaction term involving Nikkei 225 returns (Japan) is initially non-significant, its significance surfaces when the developments in Hong Kong and Stockholm are excluded. This result implies that the Nikkei 225 index also interacts with *Max[Z]*, albeit in a manner better captured by the other interaction terms. Moreover, the introduction of *Max[Z]* interaction terms amplify the explained variance within the model. This augmentation is highlighted by an increase in the coefficient of determination (R^2) by more than 1 percent. Importantly, this enhanced explanatory power remains evident even after accounting for the additional parameters introduced into the model (R^2_{adj}).

The insights gleaned from Table 3 suggest that daily market movements can be better understood by acknowledging the information contained within the GCP data. Consequently, the results suggest a practical utility for traders in utilizing GCP data. However, it could be claimed that the results are due to data fitting such that the correlations alone are not sufficient to substantiate any assertions. In response to such claims, an out-of-sample simulation study spanning a predefined period of one year was conducted. During the simulation, one-day-ahead forecasts were generated using the parameters in Table 3, and an artificial trader was assumed to operate in alignment with the derived estimates. Thus, the simulation serves as a means to address whether the significant GCP data interactions are valid and to study whether the results can be effectively applied in real-world trading scenarios.[9]

[9] The out of sample simulation was onset in August 2022 and made public continuously on the authors webpage (www.ulfholmberg.info). Preliminary results from the simulation was also presented during a poster session during the TSC 2023 conference in Taormina, Italy (PO-2 (Fri): "*Consciousness, sentiment and stock market returns: Could the GCP data be put to practical use?.*"

Table 3: The S&P500 daily returns models
Standard errors in parentheses

	Without GCP data	With GCP data
$\boldsymbol{Constant}$	$1.380E-04$ $(1.540\text{E}-04)$	$-1.370E-04$ (9.140E-04)
$\boldsymbol{S\&P500_{t-1}}$	-0.312^{***} (0.020)	-0.304^{***} (0.020)
$\boldsymbol{S\&P500^2_{t-1}}$	0.899^{***} (0.271)	0.882^{***} (0.270)
$\boldsymbol{Sweden_t}$	0.437^{***} (0.012)	0.546^{***} (0.068)
$\boldsymbol{Hong\ Kong_t}$	0.062^{***} (0.011)	0.604^{***} (0.078)
$\boldsymbol{Japan_t}$	0.054^{***} (0.013)	-0.071 (0.079)
$\boldsymbol{Sweden_{t-1}}$	0.073^{***} (0.013)	0.072^{***} (0.012)
$\boldsymbol{Japan_{t-1}}$	0.009 (0.011)	0.012 (0.011)
$\boldsymbol{\Delta VIX_{t-1}}$	$-1.440E-05$ $(1.280\text{E}-04)$	$1.074E-03^{*}$ $(5.930E-04)$
$\boldsymbol{Monday_t}$	$-2.740E-04$ (3.450E-04)	$-3.180E-04$ $(3.430E-04)$
$\boldsymbol{Monday_t} \times \boldsymbol{Sweden_t}$	0.118^{***} (0.024)	0.123^{***} (0.023)
$\boldsymbol{Monday_t} \times \boldsymbol{Sweden_{t-1}}$	-0.071^{**} (0.028)	-0.085^{***} (0.028)
$\boldsymbol{Monday_t} \times \boldsymbol{Japan_t}$	0.050^{*} (0.027)	0.050^{*} (0.027)
$\boldsymbol{Monday_t} \times \boldsymbol{Japan_{t-1}}$	0.067^{***} (0.025)	0.060^{**} (0.025)
$\boldsymbol{\Delta VIX_{t-1}} \times \boldsymbol{Japan_{t-1}}$	-0.002 (0.003)	$2.262E-03$ $(3.499E-03)$
$\boldsymbol{\Delta VIX_{t-1}} \times \boldsymbol{Japan_{t-1}} \times \boldsymbol{Monday_t}$	-0.031^{***} (0.006)	-0.031^{***} $(6.301E-03)$
$\boldsymbol{Max}[\boldsymbol{Z_{t-1}}]$	-	1.130E-04 (3.280E-04)
$\boldsymbol{Max}[\boldsymbol{Z_{t-1}}] \times \boldsymbol{Sweden_t}$	-	-0.041^{*} (0.025)
$\boldsymbol{Max}[\boldsymbol{Z_{t-1}}] \times \boldsymbol{Hong\ Kong_t}$	-	-0.200^{***} (0.028)
$\boldsymbol{Max}[\boldsymbol{Z_{t-1}}] \times \boldsymbol{Japan_t}$	-	0.046 (0.029)
$\boldsymbol{Max}[\boldsymbol{Z_{t-1}}] \times \boldsymbol{\Delta VIX_{t-1}}$	-	$-6.940E-04^{***}$ $(2.170E-04)$
$\boldsymbol{Max}[\boldsymbol{Z_{t-1}}] \times \boldsymbol{\Delta VIX^2_{t-1}}$	-	$4.490E-06^{***}$ $(7.800E-07)$
$\boldsymbol{R^2}$	0.341	0.352
$\boldsymbol{R^2_{adj}}$	0.339	0.349

*Significance levels: * 10%, ** 5% and *** 1%.*
Note: OLS estimates on daily data (N = 5749) collected between 4 January 1999 and 1 August 2022.

4. An out-of-sample simulation study

The results in Table 3 suggest that GCP data interact with stock market returns in ways that traders can utilize. To address that it in principle is possible to fit a polynomial to the data until significant correlations are found, even though no true correlation exists, this section presents results from an out-of-sample simulation study lasting for one year. The simulations began on 1 August 2022 and ended on 31 July 2023.[10] Further, the results from the simulations using approximate S&P 500 future prices were made public every week on the author's webpage and, to study the effect from market pricing, the models used were disclosed after 6 months, that is, on 1 February 2023.[11]

The term "out-of-sample" indicates that the models used were fitted on a different sample than the period on which the simulations were made. This therefore addressed the possible problems related to "P-hacking". Thus, if no true correlation exists, the simulations should reveal that no advantage can be gained by utilizing the GCP data. However, if the fund that utilized the GCP data outperforms its GCP data-invariant counterpart, the GCP data's usefulness in an actual trading environment has been demonstrated.[12]

In the out-of-sample simulations, the artificial trader is assumed to either buy and hold an S&P 500 tracking instrument or to trade actively in accordance with expectations aligned with the one-day-ahead forecasts obtained using the parameters in Table 3. If the forecasted return is positive, the trader is assumed to buy (go long), and if the forecast is negative, the trader is assumed to sell (go short). All open positions are closed when the market closes (UTC 21:00). Table 4 summarizes the studied trading strategies.

Table 4: Investment strategies

S&P 500 (B&H)	GCP data fund	Control fund
Buy at start and hold	Long if $\hat{r}_{t,with} \geq 0$	Long if $\hat{r}_{t,without} \geq 0$
	Short if $\hat{r}_{t,with} < 0$	Short if $\hat{r}_{t,without} < 0$

Note: $\hat{r}_t$ is the one-day-ahead model forecast.

Note that the econometric models in Table 3 require a close value from the OMXS-30 index. However, the market in Stockholm closes at UTC 16:00; thus, trades can be made on this market

[10] Since it takes about two days for the daily tables section on the GCP website to update, the simulations used *Max[Z]* values calculated using equation (1) and (2).

[11] www.ulfholmberg.info

[12] It should be noted that it is highly unusual to keep the econometric models constant for a full year. However, as the funds relative performance is studied, this is of little concern.

for another 1.5 hours after the stock market in New York has opened for trade (UTC 14:30). As such, trades made ahead of UTC 16:00 overestimate the simulated returns.

The artificial trader could also wait until the market closes in Stockholm (UTC 16:00), but when doing so, it is assumed that the artificial trader ignores the information embedded during the day in both Europe and Asia. In practice, it is likely that a day trader using the models in Table 3 will trade sometime between S&P 500 open (UTC 14:30) and when markets close in Sweden (UTC 16:00). As such, trades made at the open price (UTC 14.30), as well as trades made at UTC 15:00 and UTC 16:00, were investigated using the S&P 500 futures price.[13] This strategy also allows for studying the potential advantage of early action versus waiting.[14]

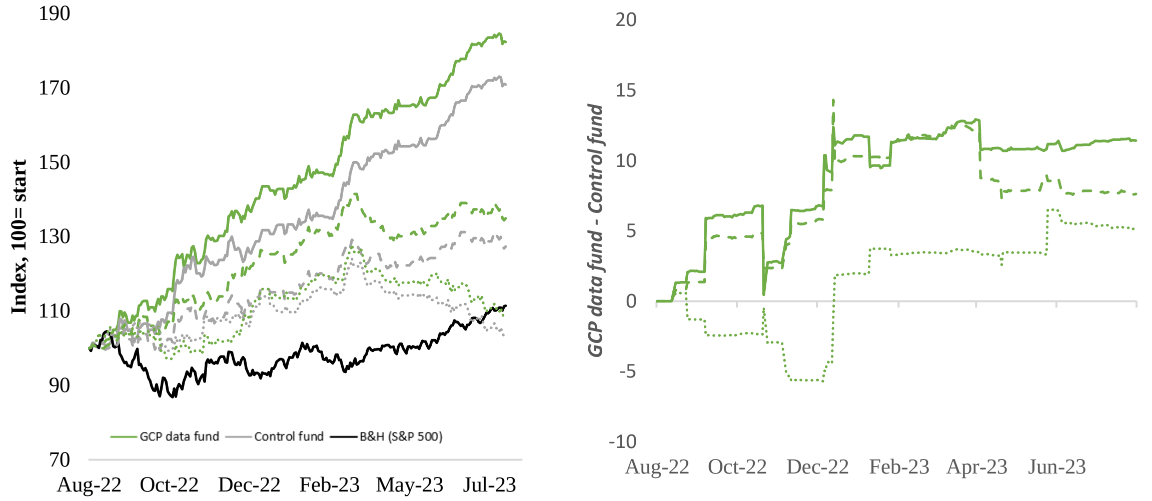
Note, however, that the out-of-sample simulation seeks to investigate if the GCP data can add value to traders by comparing GCP data-dependent trades with a GCP data-invariant counterpart. Since this is investigated by comparing a GCP data-dependent fund with a control fund, the effect on the absolute fund level of trading ahead of UTC 16:00 is of little concern, as the research hypothesis can be addressed through the fund's relative performance.

On 1 August 2022, 100 currency units were made available for investments. The B&H trader immediately invests the full amount in an S&P 500 index-tracking instrument, and the actively traded funds make their first trade on 2 August 2022.[15] Note also that trades were only allowed to be made on dates on which data points exist on the variables needed for making the forecast (i.e., all listed variables in Table 3).

Figure 2 depicts the funds' performance, both in absolute terms (Figure 2a) and in relative terms (Figure 2b). Figure 2a shows that the actively traded funds generally outperform the passive B&H (S&P 500) strategy, except for the simulations in which the trades are made at UTC 16:00 between February and July 2023. Importantly, the GCP data funds' value is in general higher than the control funds, regardless of when the trade is made, which suggests that the GCP data adds value for investors.

[13] E-mini S&P 500 Futures prices from Firstratedata.com at EST 10:00 and EST 11:00 are used.
[14] These issues are of minor concern as the study aims to investigate whether the GCP data can be used in practice, which only requires a comparing with a control fund.
[15] The simulations ignore potential brokerage fees.

Figure 2: Funds' out-of-sample performance



a. Value of artificial funds **b. GCP data funds relative performance (%)**

Note: Solid lines represents the open price (UTC 14:30) simulations, dashed the UTC 15:00 simulations and dotted the UTC 16:00 simulations.

Focusing on the actively traded funds' relative performance (i.e., the value of the GCP data fund after subtracting the value of the control fund), Figure 2b shows that the two funds traded ahead of UTC 16:00 quickly begin to outperform their GCP data-invariant counterparts. Even though the GCP data-dependent funds underperform during the end of October/early November, the GCP data-dependent funds again outperform the control fund from November to January, and during the second half of the simulation period, their performances are mostly identical.

Regarding the relative performance of the UTC 16:00 traded funds, the GCP data-dependent fund underperforms between September and mid-December. However, due to favorable trades made at the end of the year, the UTC 16:00-traded GCP data fund outperform the control fund. When the simulations end on July 31, all three GCP data-dependent funds outperform their control funds by several percentage points.

Table 5: The artificial funds' relative performance

	Relative total return (%)		*Relative hit rate* (%)*	
	Unfiltered	*Filtered*	*Unfiltered*	*Filtered*
Open (UTC 14:30)	*11.4*	*13.9*	*0.5*	*1.5*
UTC 15:00	*7.6*	*12.6*	*1.5*	*2.5*
UTC 16:00	*5.1*	*5.9*	*-0.5*	*0.5*

**Share of trades resulting in positive returns.*

Table 5 presents the actively traded funds' relative performance once the simulations have ended. Here, the results also clearly indicate that GCP data add value to traders. It should, however, be noted that the relative return tends to decrease if the investor waits for the market in Sweden to close (UTC 16:00) and that the relative hit rate, a metric capturing the share of positive return trades, is at its highest if the trades are made at UTC 15:00. This suggests that the GCP data add value during market value uncertainty, a result well aligned with Holmberg's (2021) findings, indicating that *Max[Z]* correlates to a higher degree with stock markets during periods of high market volatility.

In Table 5, a version of the simulations in which the GCP data funds investment decision is conditioned on the size of yesterday's *Max[Z]* is also presented (filtered). In these "filtered" simulations, the GCP data fund trader uses the control funds forecast if *Max[Z]* < $|N^{-1}(1\%)|$. Filtering the *Max[Z]* variable in this manner allows all small and possibly irrelevant GCP data values to be ignored. As shown, filtering the GCP data increases the relative hit by one percent, which in turn increases the relative return by between 0.8 and 4.7 percent.

Table 6: The artificial funds' monthly relative performance (%)

The relative value using the filtered fund is given in parentheses

	Open (UTC 14:30)	***UTC 15:00***	***UTC 16:00***
August, 2022	2.2 (2.2)	1.4 (1.4)	-1.3 (-1.3)
September, 2022	3.6 (3.6)	3.0 (3.0)	-1.1 (-1.1)
October, 2022	-3.9 (-3.9)	-2.5 (-2.5)	-0.6 (-0.6)
November, 2022	3.0 (3.0)	3.0 (3.0)	-2.6 (-2.6)
December, 2022	3.6 (3.6)	3.7 (3.7)	7.8 (7.8)
January, 2023	-0.4 (-0.4)	0.9 (0.9)	1.2 (1.2)
February, 2023	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
March, 2023	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
April, 2023	-1.4 (-0.7)	-3.1 (0.5)	0.0 (0.7)
May, 2023	0.1 (0.1)	0.4 (0.4)	2.6 (2.6)
June, 2023	-0.5 (-0.5)	-0.9 (-0.9)	-0.7 (-0.7)
July, 2023	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
		P values (%)[*]	
Full simulation	31.9 (31.9)	7.9 (0.4)	90.0 (81.4)
From August 2022 to January 2023	12.4 (12.4)	1.0 (1.0)	87.6 (87.6)

[*]*P-values from a standard proportions test on the number of months the funds performed differently.*

Table 6 breaks down the artificial funds' relative performance into monthly contributions, with the results confirming the importance of when the trade is made. If the trade is made at UTC 16:00, the relative performance looks strikingly like chance, but if trades are made slightly after the market has opened (UTC 15:00), the GCP data fund clearly outperforms the control fund. In fact, the GCP data fund produced excess returns in 6 of the 9 months, while the control fund produces excess returns in only 3. This difference is significant at the 10 percent level (P = 7.9%), and if GCP data are filtered, the P value falls to below one percent (P = 0.4%). Further, if the first half of the simulation is analyzed, the fund traded at open (UTC 14:30) performs better than the control fund, and the GCP data fund traded at UTC 15:00 outperforms the control fund in 5 out of 6 months ($P \approx 1\%$). The control fund, however, outperformed the GCP data fund only in October. However, after February 1, when the models were disclosed on the author's webpage, the GCP data fund either underperformed or performed in equivalence with the control fund. [16]

Figure 3 depicts the relative hit rate (i.e., the control funds hit rate subtracted from the GCP data funds hit rate). All GCP data funds outperformed the control funds in August, but in September, the GCP data fund traded at CET 16:00 began to underperform. Both funds traded ahead of markets closing in Stockholm, however, continued to outperform the control funds.

As time progressed, the GCP data funds traded ahead of UTC 16:00 relative performance began to decline. Multiple factors need to be considered when one seeks to understand the declining effect in Figure 3. Below, some notable explanations of these outcomes are listed.

(i) **The results are due to chance.** This explanation seems unlikely as the statistical proportion test on the number of months the GCP data fund outperformed the control fund suggests otherwise. The proportions tests point toward a significance at the 10 percent level if the GCP data is unfiltered and at the 1 percent level if the GCP data is filtered, which is confirmed with a proportions test using the daily data. Furthermore, the GCP data model correctly predicted more trades than the control model, and the final outcome of the simulation's points toward the GCP data adding value to traders (Table 5).

(ii) **Improved market sentiment.** Previous research has found that *Max[Z]* correlates more strongly with daily stock market returns during volatile periods (Holmberg, 2021). As market volatility is related to market sentiment, the declining effect could be the result of VIX beginning to fall during the simulation period. On average, VIX

[16] If the GCP data fund is filtered and if trades made during US Federal reserve decision weeks are ignored, the difference in proportions becomes significant at the 1 percent level over the year, and at the 10 percent level between February and July 2023.

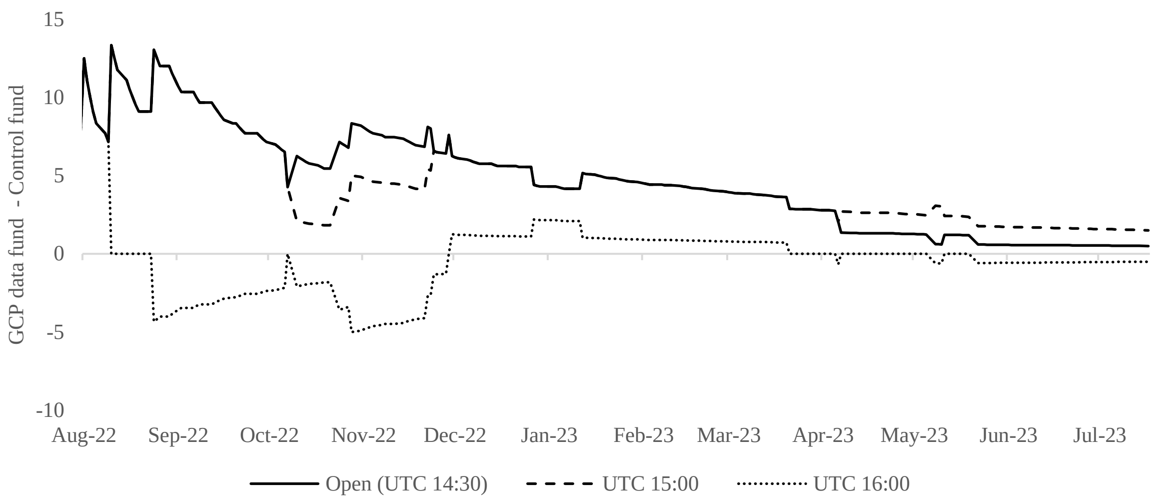
fell from 24.1 during the first half of the simulations to 17.5 during the second half. [17] The decrease in VIX signals a period of more stable returns, and comparing the standard deviation in returns between the first and second half of the simulation period, the standard deviation in returns fell from 1.41 percent to 0.82 percent.

(iii) **No arbitrage**. The no-arbitrage principal suggests that markets do not allow risk-free profits with no initial investment. As with any difference in returns that can be obtained without taking on risk, this will be traded away as prices adjust. Since the models were made public on February, 1 future prices could have been affected, which in turn could have influenced the results.

(iv) **The declining effect.** The *Max[Z]* variable is calculated from the GCP data, and several research papers have found that the Psi effect tends to decline with time (see, e.g., Bierman et al., 2016; Radin, 2006, among others).

(v) **Complex links.** The link between the GCP data, *Max[Z]*, and stock market returns could be more complex than the other links acknowledged. As such, the GCP data-dependent model could need more frequent updates, which, in turn, could have influenced the results.

Figure 3: Relative hit rate (%)



Returning to Figure 4, VIX alone is able to explain between 43 and 58 percent of the observed decline during the year.[18] However, the complex ways in which the GCP data interacts with

[17] The decrease in VIX coincided with the zero-dated options debate in which it was argued that zero-dated options had "broken" VIX. However, as VIX reflects the market's best estimate of SPX volatility over the coming 30 days, this seems unlikely (Sosnicks, 2023).

[18] Simple linear regressions on relative performance of the Open (CET 14:40) and CET 15:00 traded funds suggests that 58 and 43 percent of the model variance can be explained by VIX alone. It is however noted that some of this explained variance could be due to common trends which it is left for future research to explore.

markets as well as the fact that the models were made public after 6 months can both be affecting the results. Thus, the exact reason for the decline is likely to be complex and remains an interesting avenue for future research to explore.

5. Concluding remarks

In this paper, the covariation of GCP data with market sentiment and how this correlation can be put to practical use by market participants have been explored. The paper began by correlating the *Max[Z]* variable, a daily aggregate derived from GCP data, with the commonly used VIX measure. The analysis suggests that not only did today's *Max[Z]* correlate with changes in VIX ($P < 0.01$), but so did several of its lags. As investor sentiment is known to have a measurable impact on stock markets (see e.g., Brown and Cliff, 2005), the results shed light on Holmberg's (2020 and 2021) unorthodox finding—that is, that the GCP data covaries significantly with daily stock market returns.

This is a striking result. Not only does it point toward the validity of the hypothesis underlying the GCP data, but it also suggests that the data can be used in practice by, for example, traders. This practical use is studied by fitting two almost equivalent econometric models on daily S&P 500 returns: one that uses the GCP data and one that does not, where the latter is used as the control model. Both models are designed to allow for one-day-ahead forecasting. The results of the models suggest that *Max[Z]* covaries with daily returns, as yesterday's *Max[Z]* value significantly covaries with today's OMXS-30 returns, with Hang Seng (Hong Kong) returns, and with changes in yesterday's VIX and its variation (ΔVIX_{t-1}^2). Furthermore, approximately one percent of the econometric models' variance is explained by these interaction terms, which suggests that the results can be used to gain a competitive edge in markets.

The potential advantage of using GCP data is studied in an out-of-sample simulation. The simulations are set to last one year, starting on 1 August 2022. Trades made during three different time periods were studied, and when the simulations ended on 31 July 2023, the results clearly showed that the GCP data can be used to inform traders. In fact, if the trades were made when the market opened in New York (UTC 14:30), the GCP data-informed trader achieved between 11.4 and 13.9 percent higher annual returns than their GCP data-invariant counterpart. Furthermore, if the artificial trader waited for half an hour and traded at UTC 15:00, the GCP data could increase the annual returns by 7.6–12.6 percent.

It could, however, be argued that the out-of-sample simulations in which the investment decisions were made at UTC 14:30 or UTC 15:00 overstate the GCP data's contribution to the fund's total return, as OMXS-30 closes at UTC 16:00 such that the artificial trader needs to forecast the OMXS-30 index movements during the final hours of trade. However, as both the GCP data fund and the control fund are subject to this shortcoming, this issue can be ignored such that the results are solid and point toward the usability of the GCP data. For completeness, however, simulations from trades made after the market closes in Stockholm are studied, with results indicating that the GCP data-dependent fund outperforms the control fund.[19]

Taken together, the out-of-sample simulations suggest that investors can gain an edge by acknowledging the information embedded in the GCP data. However, the edge gained decreases with time: as if the trader waits with making the daily trade, the potential gain is reduced. However, considering the results together with Holmberg's (2023) findings—that is, that the GCP data covaries with internet search trends—the results highlight how useful the GCP data can be to forecasters in general.

It is worth noting that the econometric models used in the out-of-sample simulations utilize how yesterday's *Max[Z]* covaries with markets, not today's *Max[Z]*. The results from the analysis presented here also show a correlation between yesterday VIX and today's *Max[Z]*, and previous research reports a correlation between daily returns and today's *Max[Z]*. Thus, it is possible that even more accurate and timely econometric models can be constructed to account for the current day's intraday *Max[Z]* movements. Furthermore, it is possible that more accurate daily GCP data effect measures can be constructed. Such measures may covary even more strongly with markets. How such models or measures can be constructed is as an interesting avenue for future research to explore.

The findings of the present study clearly point in the direction of multiple other avenues for future research. First, they suggest that the data produced by the GCP can be put to practical use by forecasters. Also, as the results validate several claims made by the GCP, they also pave the way for research on alternative theories on e.g., the nature of consciousness. Furthermore, as stock market returns, sentiment, and focused attention tend to be tightly linked to economic

[19] The relative hit rate increases with 0.5 percent such that the relative annual return ends up being between 5.9 and 5.1, using filtered *Max[Z]*) and unfiltered *Max[Z]* respectively.

performance in general, it is also likely that other economic metrics could be better understood by acknowledging the information embedded in the GCP data.

Finally, as with any study, this study has limitations that should be acknowledged. The study does not claim to have established a causal relationship between GCP data and stock market returns, as no theory yet exists that can explain such a link. Nonetheless, the findings suggest that GCP data could be a valuable tool for traders and could provide useful insights into market sentiment dynamics.

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