On the relationship between colour search trends, economic indicators and colour forecasting

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This work explores the relationship between relative search frequencies for colour names using Google Trends and measures of investor sentiment and consumer/business confidence using data between 2004 and 2019. It was found that during periods of economic downturn or negative sentiment, relative search frequencies for black increased and those for yellow decreased. Additionally, we used Granger Causality to show that changes in search frequencies for white and purple may be able to forecast investor sentiment and consumer confidence respectively. The work has implications for the use of data-driven methods for effective colour forecasting.

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Introduction

Colour forecasting is an important process in many manufacturing and retail sectors [1]. The goal of providing consumers with the right colours at the right time and at the right price is driven by the resultant economic benefits for manufacturers and retailers but may also lead to reduced waste and reduced environmental impact [2]. There is some doubt, however, about the effectiveness of current colour-forecasting processes [3]. Existing processes are mostly conducted by colour experts and designers and may be subjective; this raises the question of whether processes based on consumer data would be more effective? Yet it is not easy to quantify performance because it is difficult to even measure the efficacy of colour forecasting. There has been little quantitative evaluation of its accuracy and it may not even be possible to evaluate accuracy; indeed, it is not even clear whether the success of colour forecasts is monitored (often, it appears sufficient that predictions simply are made). Nevertheless, the amount of dead stock (manufactured goods that cannot be sold) that is generated by the textile and fashion industry, for example, suggests that colour forecasting may not be optimal [4]. In this study, consumer data (based on search frequencies for colour names on Google) are collected and used to try to predict investor, consumer and business confidence. If such consumer data about colour can be used to predict confidence or sentiment then we suggest that these data may be able to predict underlying societal trends and the zeitgeist (it is believed that colour forecasting taps into the zeitgeist [5]). Such predictions, if possible, may inspire the use of data-driven or consumer-led colour-forecasting processes in the future. Note that the prevailing economic environment has already been identified as a factor in existing colour forecasting procedures [6]. Figure 1 illustrates the underlying axiom upon which this study is based; that colour name search volumes may be able to predict economic conditions which, in turn, may be one of the factors that drive colour trends.

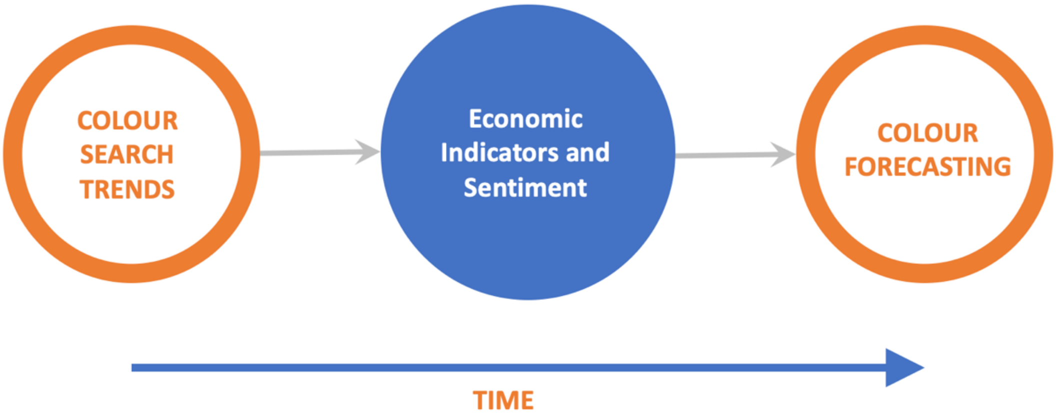

Figure 1: Infographic to show that if colour search trends can predict economic indicators and/or consumer confidence then indirectly they may be able to forecast trend colours in the future or near-future. The arrows represent the direction in which predictions may be made.

Google Trends data have previously been used to make predictions about the present and the near future [7]. This is a form of 'nowcasting' and such contemporaneous forecasting is likely to be valuable in its own right. Google Trends data was first used as a tool to forecast economic statistics relating to the unemployment rate in 2005 [8]. Web-search data has since been used to make predictions in various fields. Researchers have used cancer search data in Yahoo! to estimate the rates of cancer incidence and mortality [9] and job search data in Google to assess the labour market [10]. Google Trends data has also improved prediction performance for global oil consumption [11]. Google Trends data have also been used to show that search volumes for company names are correlated with transaction volumes in the stocks of those companies on a weekly timescale [12]. A related study found that increases in Google search volumes for keywords relating to financial markets can be detected before stock market falls [13]. Huang et al. [14] have used Granger Causality (a statistical test for determining whether one time series is useful in forecasting another) to show that simple linear models can forecast directional movements in the S&P500 financial index with an accuracy of 60% based on search volumes (the number of times a term is searched for) for a number of terms. They argued that search volumes may reflect both investor attention and investor sentiment. Nevertheless, the optimal selection of these terms remains an unsolved issue and there are also examples where predictions can be poor. Sekhavat used search volumes to accurately predict the ranking of mobile games but nevertheless concluded that search volumes can sometimes be affected by events that are unrelated to the things that are being predicted and referred to these as 'noisy' queries [15].

This study builds upon these earlier studies that used consumer search volumes to predict financial movements but explores the possibility that there may be a link between colour search volumes and the underlying economic and societal environment. This is inspired by previous studies that have, for example, suggested that the cyclic variation in colour preferences might be related to the economic environment. For example, Casti noted that there are correlations between economic trends and colour trends [16]. One study found that during an economic recession consumers used darker colours; the use of the colour black increased by 5% during the fall/winter season and by 7% during the spring/summer season [17]. The link between colour trends and the economy has also been reported by the global paint company AkzoNobel who analysed data to conclude that "Analyzing color trends has shown us that during an economic downturn, neutral colors such as black, white and grays are favored for interiors, while more intense colours are used when people feel more confident," [18]. This current work explicitly tests the hypothesis that search volumes for colour names can predict underlying economic conditions and consumer sentiment.

Data retrieval and methods

The Google Trends service was used to download historical monthly search volume data from Google for eleven colour names in English (white, black, red, green, yellow, blue, brown, purple, pink, orange and gray) from January 2004 to December 2019 [19]. We chose these particular colour names because they are the eleven unambiguous colour names according to a number of studies [20]. Google Trends allows users to download a normalised count of the total number of searches related to a specific word (or phrase) over a specific time frame. Search volumes are returned as numbers between 0 and 100 where 100 represents the highest number of searches in that time period. Our colour search data are therefore relative search frequencies. For example, if the search frequency for white is 80 and the search frequency for black is 40 in a given time period, all we know is that twice as many searches were made for white as for black. The data were downloaded for users based in USA since the confidence and sentiment indices also relate to USA.

Several sources were used to obtain data for sentiment and confidence over the same time period. Indices for business confidence (BCI) and consumer confidence (CCI) for the USA market were downloaded from the Organisation for Economic Co-operation and Development [21-22]. Data for investor sentiment (IS) in the USA were collected from Baker and Wurgler's website [23] but note that these data were only available from 2004 to 2018. Table 1 summarises the data (and their sources) used in this paper.

Data Name	**Source**	**Notes**
Colour frequencies	Google Trends [19] USA	Data obtained for each of 11 colour names
Business confidence	OECD [21] USA	Business Confidence Indicator (BCI)
Consumer confidence	OECD [22] USA	Consumer Confidence Indicator (CCI)
Investor sentiment	Baker and Wurgler [23] USA	Investor Sentiment (IS)

Table 1: Summary of Data Sources using in this Study (all data were obtained each month over the period 2004-2019 apart from IS which was only available for the period 2004-2018).

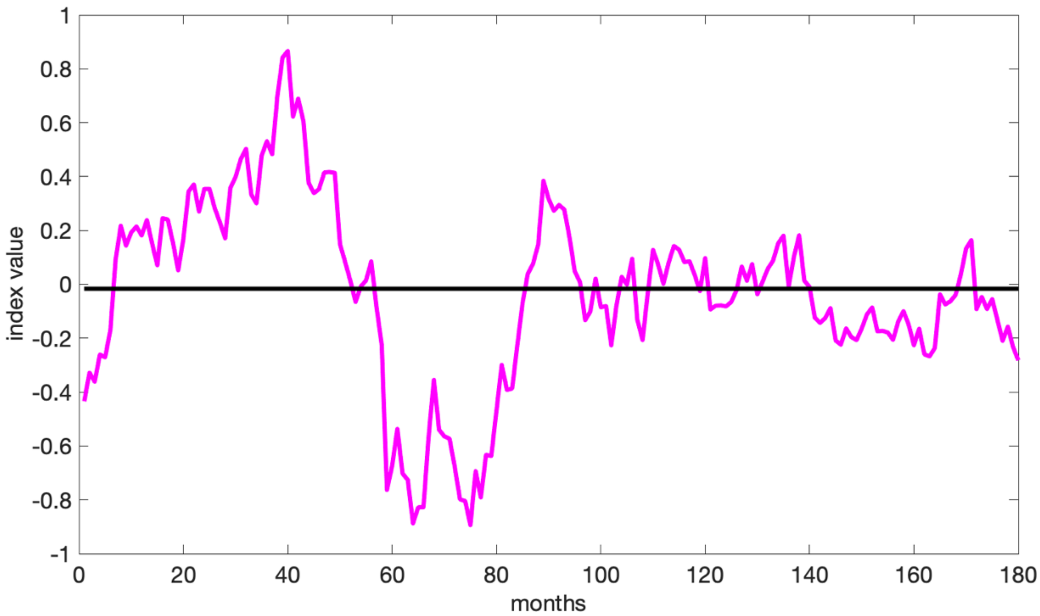

Figure 2: Investor sentiment (IS) over the period 2004-2018 (magenta line) with the median value shown as a black line. We define positive sentiment months as those where the IS value is greater than the median value.

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The relationship between colour relative-frequency data and underlying confidence each month (using the indices BCI, CCI and IS) was investigated. For investor confidence we computed the median value of IS over the whole period and then defined a positive (or negative) sentiment month when the IS was above (or below) its median (see Figure 2).

As Figure 2 illustrates, the median value of IS over the time period is close to zero. The most positive value for investor sentiment occurred after about 40 months (May 2007, just before the financial crash of 2008). IS remained negative (that is, below the median value) from 2008 until early 2012 during the post-crash years.

Figure 3 shows business confidence according to two indices (BCI and CCI) over the period 2004 – 2019 and these data also show low confidence during the period 2008 to 2012. According to the OECD, an uptrend economy is defined when the indices BCI or CCI are above 100 and a downtrend economy is defined when the indices are below 100. Therefore, for these indices we can classify each month in our time period as being positive (uptrend) or negative (downtrend). Notice that after the 2008 crash business confidence recovered more quickly than consumer confidence.

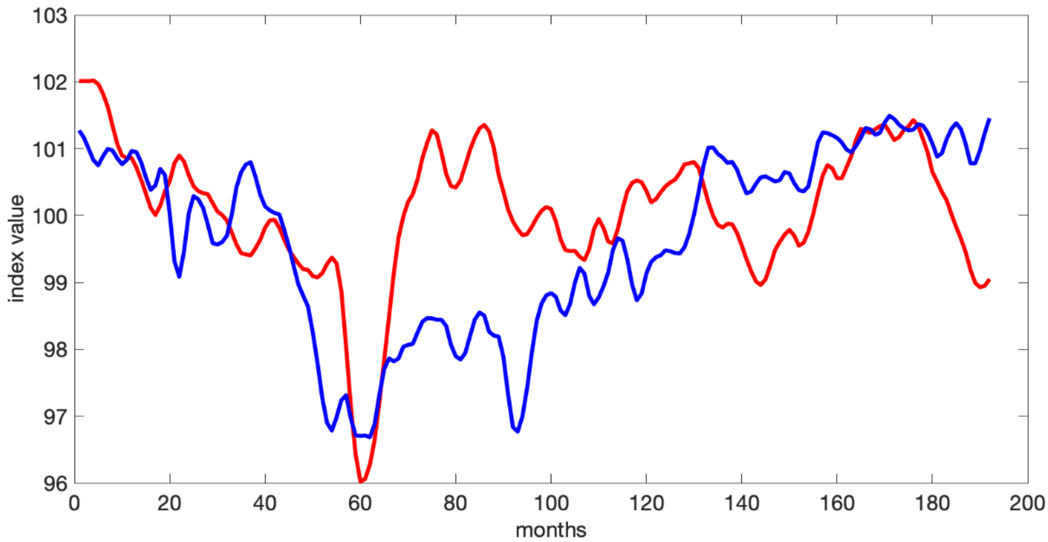

Figure 3: BCI (red line) and CCI (blue line) economic indices each month over the period 2004-2019.

For each colour name, we calculated the mean relative-frequency over each of the positive months (defined by each index) and the mean relative-frequency over each of the negative months. Our first hypothesis (H1) is that colour search frequencies will be different in positive months than in negative months. The null hypothesis is that there is no difference in the colour search frequencies between positive and negative months. To test this, we compare the mean value of the search colour frequencies for the positive and negative months and use a t-test to see if they are different ($p < 0.05$).

Our second hypothesis (H2) is that increases or decreases in relative search frequencies can predict economic and sentiment indicators. The Granger Causality test [24] is a hypothesis for determining whether one time series is useful in forecasting another and has been previously used for financial markets [14] and to test whether relative search frequencies predict mobile game rankings [15]. It allows for a lag parameter so that past values in one time series can predict future values in another. Since our data are collected monthly, a lag of two, for example, tests whether search frequencies in month N can predict confidence in month N+2. We prefer to use the Granger Causality test rather than, for example, correlation for two reasons: (1) we are interested in whether we can predict one set of data from another rather than whether the two data sets are correlated; (2) prediction requires testing whether data points from one data series at one point in time can predict data points for a second data series at a time in the (near) future and therefore the lag aspect in the Granger Causality test was important. Note that with correlation, if times series A is correlated with time series B, then times series B is equally correlated with time series A. However, the Granger Causality test is not symmetrical in this way. Times series A may predict times series B with a certain lag but that does not mean that times series B can predict times series A.

The Granger Causality test was therefore used to calculate an F value; if the F value is greater than the critical value *Fc* (at p=0.05) then the null hypothesis that colour search frequencies do not predict economic indicators is rejected. Table 2 summarises the two hypotheses that were tested in this work and the methods that were used to test them. Note that one of the underlying assumptions of the Granger Causality test is that the data are stationary. A stationary time series is one whose properties do not depend on the time at which the series is observed. Time series data that exhibit trends or have seasonality are not stationary [25]. Before applying the Granger Causality test our data were processed to make them stationary; the process that was applied was to take the value of the time series at month N and subtract from it the value of the time series at month N-1 so that monthly changes were considered. This approximates a first derivative of the time series.

Hypothesis	Method of testing
H1: Relative search frequencies for colour names different in months where investor sentiment, business or consumer confidence is higher or lower.	We use a t-test ($p<0.05$) between the mean of the colour frequencies in positive months and the mean of the colour frequencies in negative months for each colour term and for the indicators CCI, BCI and IS.
H2: Increases or decreases in relative search frequencies can predict economic and sentiment indicators.	The Granger Causality test is used to test ($F>Fc$, $p=0.05$) whether each of the colour search frequencies can predict each of the three indicators CCI, BCI and IS.

Table 2: The two hypotheses tested in this study and the methods that are used to test them.

Results

Tables 3-5 show the mean colour frequency data for the positive and negative months for investor sentiment (Table 3), business confidence (Table 4) and consumer confidence (Table 5). These data are therefore used to test the first hypothesis H1 (see Table 2). From Table 3, there are multiple statistically significant ($p<0.05$) differences in mean search frequencies between months when there are positive and negative investor sentiment. The largest change is for yellow; relative search frequencies for yellow are lower during months of negative sentiment. Relative search frequencies for black are higher during months of negative sentiment. These findings are consistent with Koh's observation that use of black increased during an economic downturn [17]. Koh's work used a different methodology (based on observations of fashion collections rather than google search frequencies). For business confidence (Table 4) we did not find any significant findings. There was some evidence of significant differences for consumer confidence (Table 5) but the differences between positive and negative months were small apart from for gray where a reduction in relative search frequencies was seen during downturn months. In summary we find some evidence to support our first hypothesis though not for all colours and not for all indices.

	positive		negative			
Colour	**mean**	**σ**	**mean**	**σ**	**Δ**	**p-value**
red	51.98	8.80	58.64	8.40	-6.66	0.00
green	71.99	10.63	79.10	11.13	-7.11	0.00
yellow	63.50	22.37	45.70	14.97	17.80	0.00
blue	87.63	4.31	86.34	5.95	1.29	0.10
orange	58.12	8.62	60.93	8.25	-2.81	0.03
pink	69.73	9.73	75.46	13.07	-5.72	0.00
purple	35.59	10.40	45.76	12.43	-10.16	0.00
white	70.55	6.12	73.87	7.46	-3.33	0.00
black	37.71	10.76	45.40	15.28	-7.69	0.00
brown	51.74	9.17	54.18	7.79	-2.44	0.06
gray	39.55	9.49	48.46	12.37	-8.91	0.00

Table 3: USA colour search trends based on 86 positive months and 94 negative months defined by investor sentiment (period 2004-2018).

	upturn		downturn			
Colour	**mean**	**σ**	**mean**	**σ**	**Δ**	**p-value**
red	55.90	10.69	54.91	6.98	0.99	0.48
green	76.18	12.40	75.11	10.17	1.07	0.53
yellow	54.44	22.73	53.91	18.35	0.53	0.87
blue	86.96	5.29	86.95	5.24	0.01	0.99
orange	60.28	8.54	58.73	8.48	1.55	0.22
pink	72.80	13.62	72.63	9.51	0.17	0.93
purple	41.31	12.41	40.40	12.78	0.92	0.63
white	72.98	7.67	71.43	6.11	1.55	0.14
black	42.87	14.85	40.33	12.41	2.54	0.22
brown	52.54	9.00	53.60	7.96	-1.07	0.40
gray	45.55	10.76	42.56	13.08	2.99	0.09

Table 4: USA colour search trends based on 99 upturn months and 81 downturn months defined by BCI (period 2004-2019).

	upturn		downturn			
Colour	**mean**	**σ**	**mean**	**σ**	**Δ**	**p-value**
red	54.92	11.74	55.95	6.02	-1.03	0.46
green	76.56	13.82	74.91	8.70	1.64	0.34
yellow	56.23	25.69	52.35	14.96	3.88	0.21
blue	89.34	4.55	84.78	4.92	4.56	0.00
orange	60.21	9.15	59.01	7.91	1.20	0.35
pink	75.64	14.11	70.05	8.73	5.59	0.00
purple	43.64	16.04	38.39	7.41	5.25	0.00
white	74.02	8.19	70.69	5.33	3.33	0.00
black	43.94	15.92	39.70	11.29	4.24	0.04
brown	52.15	9.39	53.81	7.64	-1.66	0.19
gray	49.57	14.12	39.29	6.34	10.28	0.00

Table 5: USA colour search trends based on 86 upturn months and 94 downturn months defined by CCI (period 2004-2019).

As mentioned in the data retrieval and methods section, in order to apply the Granger Causality test the data were pre-processed to ensure that they were stationary. Figure 4 shows the effect of differencing on two example data sets. The original data are shown at the top and then the differenced data are shown below. Note that in the search data (Figure 4a) there are two aspects that reveal the non-stationary condition; first, there is a general trend that frequencies reduce over the time period of the study; second, there is some evidence of a periodic variation (this may be an annual variation).

Despite the use of differencing the processed data for the yellow search frequencies still show some periodicity (see Figure 4c). To remove this, a second-order differencing process was applied which approximates a second-order differentiation of the data. Figure 5 shows the effect of second-order differencing on the yellow search data and it is evident that the periodicity has been removed. Second-order differencing was applied to all colour search data but first-order differencing was considered to be sufficient for the confidence and sentiment index data.

Table 6 shows the results from the Granger Causality Test. We experimented with different lag values between 1 and 5 months. In Table 6, for each colour and index combination the lag that generates the largest F value are shown; significance is achieved if the F value exceeds the critical value Fc. Note that changes in the relative search frequencies for yellow give quite large F values but do not exceed the critical value of F (Fc = 3.89) and are therefore not significant. Two significant effects are found: firstly, we find that changes in relative search frequencies for white are useful in forecasting Investor Sentiment with a lag of one month; secondly, we find that changes in relative search frequencies for purple are useful in forecasting the Consumer Confidence Index with a lag of three months.

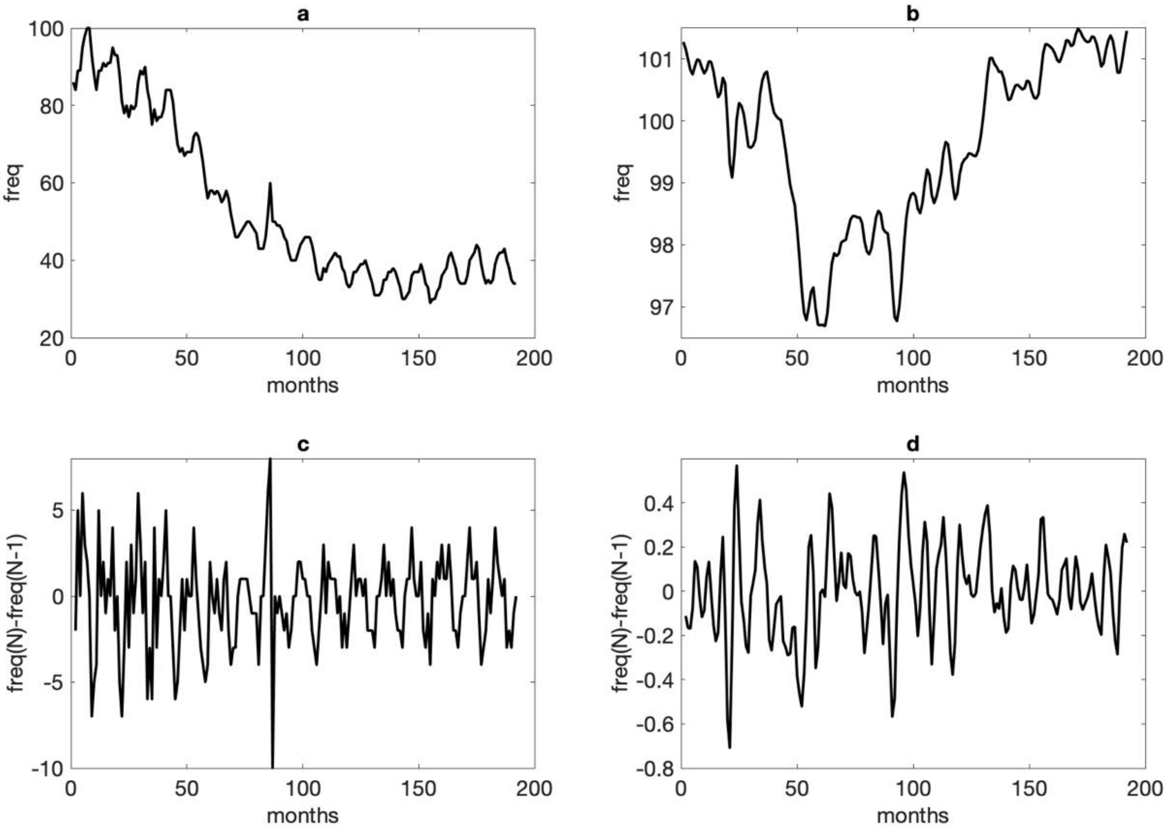

Figure 4: Example processing to ensure that the times series data are stationary: (a) original relative search frequencies for yellow; (b) original CCI data; (c) processed relative search frequencies for yellow; (d) processed CCI data.

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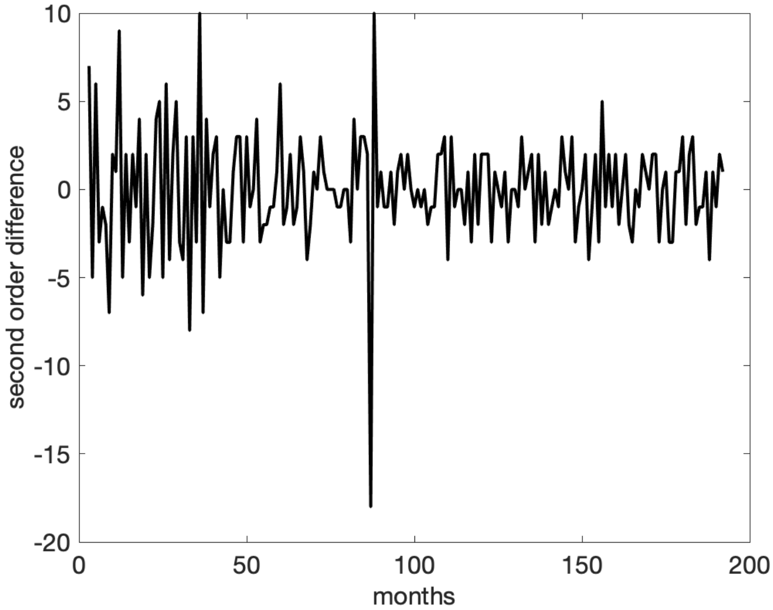

Figure 5: Effect of second-order differencing on the yellow search frequency data in Figure 4a.

	IS		BCI		CCI	
colour	***F***	**lag**	***F***	**lag**	***F***	**lag**
red	0.901	1	1.397	2	1.281	3
green	0.991	1	0.898	2	1.400	3
yellow	2.078	1	2.732	1	2.177	3
blue	1.180	1	2.004	1	1.278	3
orange	0.838	1	0.890	4	2.756	3
pink	0.833	1	0.890	4	1.270	3
purple	0.992	1	0.890	4	**4.489**	3
white	1.274	1	1.205	2	1.316	3
black	1.263	1	2.106	2	2.398	3
white	**4.093**	1	3.403	2	1.235	3
brown	0.890	1	1.018	2	2.165	3

Table 6: Granger Causality test results. For each colour and index the largest F *value is shown and the number of lags that gives this is displayed.* F *values that exceed the critical value (*Fc = *3.89) are underlined and in bold.*

Discussion

We tested two hypotheses: (H1) that relative-frequency search data for colour terms on Google Trends data are different (higher or lower) in months where there is high investor and/or consumer confidence compared to months where there is low investor and/or consumer confidence; (H2) changes in relative-frequency search data for colour terms on Google Trends can forecast indices of economic confidence or sentiment. Our data support both hypotheses although not for every colour search term and not for every index. For H1, notably we found that relative frequencies decrease for yellow and increase for black during months of negative sentiment (this is broadly consistent with some previous work [16, 26]). For H2 we found that IS can be forecast by search frequencies in white with a lag of one month and that CCI can be forecast by search frequencies in purple with a lag of three months. Much further work is needed to explore the implications of the Granger Causality test (H2). For example, in this study we did not explore the nature of the relationship between colour search frequencies and the various indices. Rather, we only identified where there was some evidence that a forecast might be possible.

In this research the search frequencies were for mentions of colour names. However, the colour terms 'yellow' and 'black', for example, may have meanings beyond colour appearance. Google Trends provides data on search volumes in various categories, which may be defined by search region, time, and information on related topics and search terms [38]. We specified 'colour terms' as part of the Google search that generated the data in this work.

It is important to note that the data we used were relative search frequencies; therefore, with our first hypothesis we do not find that people search less frequently using the word yellow during times of economic depression compared to more affluent times; rather, we find that people search relatively less for yellow compared with the other colour search terms that we explored. Of course, it may be that people do actually search less for yellow during times of economic depression. This limitation of using Google Trend data has been noted by Sekhavat [15] who has suggested that the problem may be overcome by using rank aggregation techniques to combine the ranking of results for similar queries rather than combining actual data. It is not clear how this could apply to searches for colour names however.

However, the primary purpose of this work was not to be able to make economic or sentiment predictions from colour search data per se but rather to explore the possibility for a link between colour search trends and the economy (recall Figure 1). Others have suggested that such links exist. For example, Pantone, one of the leading forecasting companies, have stated that there could be a relationship between popular colours and the economy [27] and this has also been suggested elsewhere [28–29]. We find some support for both of our hypotheses in our data although it is difficult to draw clear conclusions. For example, with H1 we found that relative searches for yellow decreased and searches for black increased during negative months. However, with H2 we did not find any Granger-causality between searches for these colours and any of the indices though the F value for yellow was high (whilst not being significant). This work should be seen as a preliminary indication that search frequencies might be able to be used to make early predictions of consumer confidence (which we assume might be related to the popularity of certain colours). Our interest is in being able to make colour nowcasts whereby we are able to predict a few months in advance that certain colours may become more popular.

An increasing number of studies have explored the field of colour forecasting. Although researchers pointed out the potential impact of colour trends on purchasing behaviours, the percentage of influence on colour trends is still unknown. Colour search volumes from Google Trends are not equivalent to colour trends in this study. The colour search trend has recently been suggested as a potential predictor for future colour forecasting. We note that any association between colour trends and colour preferences remains an open question.

One may question whether the ability to make nowcasts would be of practical significance for traditional colour forecasting. Conventional colour forecasting is a relatively slow process that takes place, and makes predictions, over a period of years rather than a period of months. This has been appropriate over many decades given the supply chain management of the textile and apparel industry. However, there is a growing trend [30-31] for individual on-demand produced clothing (also referred to as real-time fashion). As supply chains become much shorter, there is increased pressure on conventional colour forecasting approaches which may not be sufficiently agile to be able to provide information in a timely manner. The industry may need a new approach to colour forecasting that is data-driven and that uses machine-learning approaches [32-35]. This work may provide an impetus for developing such data-driven approaches to colour forecasting. Finally, the work may also contribute to the literature about colour meaning [36-37].

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