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Measuring economic sentiment using ordinary response options

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Abstract

Economic sentiment is typically measured using ordinary response options. The University of Michigan and the United States Conference Board are two widely used major indexes that have separately established independent consumer sentiment indexes based on three-level ordinary response options: positive, neutral, and negative. Notwithstanding, limited attention has been paid to the structural differences in their built-in formulas, which are referred to the disparate micro scoring schemes applied to an individual question. This paper examines the structural difference of the two indexes and then addresses situations where one is more reliable than the other. Real data from business tendency surveys of the Organization for Economic Cooperation and Development are used to illustrate our points empirically. As a conclusion, it is stressed that the two indexes should be handled with care when applied to economic sentiment comparison studies.

Keywords: Index of Consumer Sentiment, Consumer Confidence Index, micro scoring scheme, neutral response, imbalance

1. Introduction

Economic sentiment is typically measured using ordinary response options for a number of questions because simple qualitative assessments enable the swift evaluation of current economic sentiment. Two popular consumer sentiment indexes used in the United States, the University of Michigan's Index of Consumer Sentiment (ICS) and the Conference Board's Consumer Confidence Index (CCI), are derived from five questions, each having three-level ordinary response options: positive (+), neutral (0), and negative (−). The responses are first converted into scores by question, and then are aggregated into corresponding indexes. So far most investigations concerning the two indexes are associated with the effect of distinct choices of survey questions in measuring the consumer attitude and sentiment toward the general economy, and with the effects of the survey methodology that include sample design, sample size, and interview modes. The indexes' temporal trends and ability to predict consumer spending and/or other macro economic impacts are also often investigated and compared. For example, Bram and Ludvigson (1998) and Ludvigson (2004) conducted an empirical study to determine if there is any significant advantage in forecasting household expenditure by adding either of the two above consumer sentiment indexes to the set of covariates of the baseline linear regression model already containing other well-known economic covariates. They find that the CCI performs better than the ICS in forecasting household expenditure; however, the ICS approach

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and its variants are predominantly adopted by various consumer surveys that include the business tendency surveys (BTSs) conducted by countries in the Organization for Economic Cooperation and Development (OECD) (see, for example, Organization for Economic Cooperation and Development, 2003).

This article focuses on structural differences of the formulas used to obtain each index (or different micro scoring schemes equivalently). The scoring scheme of the ICS considers the imbalance between positive and negative responses versus the CCI that considers the proportion of positive responses among the non-neutral responses. To our best knowledge, the literature has paid limited attention to the structural differences of the formulas. The present study analytically examines the two disparate micro scoring schemes. This study answers questions of how the indexes differ in portraying sentiment in a given data set of responses and when one outperforms the other. In particular, the study answers why the CCI performs better than the ICS in forecasting. Section 2 investigates the two built-in formulas of the ICS and CCI in detail. Section 3 studies the two indexes via statistical quantities, range and precision before answering the previous questions.

2. Index of Consumer Sentiment (ICS) and Consumer Confidence Index (CCI)

2.1. University of Michigan's ICS

The University of Michigan survey (initiated in 1946) is conducted by a telephone interview of a rotating monthly sample of about 500 respondents that represent the adult population living in the continental United States. The ICS comprises five questions: the first two assess present economic conditions and the other three gauge economic expectations. Each question is asked with three response options: positive (+), neutral (0), and negative (−). The index is derived by first adding 100 to the imbalance (or difference) between positive and negative response percentages for each question:

$$m_q = 100\left[1 + \left(p_q^+ - p_q^-\right)\right], \tag{2.1}$$

where p_q^+, p_q^0 and p_q^- denote the proportions of the three corresponding response options and $q = 1, \ldots, Q(= 5)$. The sum of the Q scores of m_qs is then adjusted to make February 1966 the base period (i.e., a value of 100), leading to the ICS:

$$\text{ICS} = \frac{1}{\beta}\sum_{q=1}^{Q} m_q + \alpha, \tag{2.2}$$

where $\beta(= 6.7558)$ is the index value for the base period and $\alpha(= 2.0)$ adjusts for sample design changes implemented in the 1950s. See, for example, Bram and Ludvigson (1998) and Curtin (2002) for detailed discussion.

2.2. Conference Board's CCI

The United States Conference Board has conducted its survey since 1967 for approximately 3,500 respondents among a total of 5,000 household mail-outs. The CCI is based on five questions similar to the ICS with the same three response options. A score for each question is computed as the relative size of the positive responses to the non-neutrals:

$$c_q = 100\left(\frac{p_q^+}{p_q^+ + p_q^-}\right), \tag{2.3}$$

where $q = 1, \ldots, Q(= 5)$. Each score c_q is then divided by the corresponding score c_{q0} from the 1985 survey and all c_q values are aggregated after adjusting for the seasonal variation of the CCI in the form of the arithmetic average:

$$\text{CCI} = \frac{1}{Q}\sum_{q=1}^{Q}\gamma_q\left(100\frac{c_q}{c_{q0}}\right), \tag{2.4}$$

where γ_q are the adjustment factors for the seasonal variation. See, for example, Bram and Ludvigson (1998) and Linden (1982) for more details.

3. Structural differences

Each of the two indexes has its own built-in formula as discussed in Section 2. In this section, we focus on the difference between the two built-in formulas and study the difference analytically. This is done by analyzing the two built-in formulas via statistical quantities, range and precision. To make our comparison efficient and simple, we make three assumptions:

(A1) The index is based on a single question (i.e., $Q = 1$).

(A2) The non-neutral responses are perfectly balanced in the base period (i.e., $\beta = 1$ and $c_{10} = 50$).

(A3) There is no need for sample correction or seasonal adjustment (i.e., $\alpha = 0$ and $\gamma_1 = 1$).

Under the above three assumptions, the two indexes can be much simplified as follows.

Result 1. Assuming (A1)–(A3), the indexes (2.2) and (2.4) can be written, respectively, as

$$\text{ICS} = 100\,[1 + (p^+ - p^-)] := \hat{M}, \tag{3.1}$$

$$\text{CCI} = 200\left(\frac{p^+}{p^+ + p^-}\right) := \hat{C}. \tag{3.2}$$

For ease of notation, we drop the question index q henceforth. Note that (3.1) and (3.2) indicate that, when the indexes are based only on a single question under a set of regularity conditions, we have

$$\hat{M} = m_1 \qquad \text{and} \qquad \hat{C} = 2c_1,$$

where m_1 and c_1 are the two associated micro scores for the question as defined in (2.1) and (2.3), respectively.

3.1. Question range

To understand how the indexes aggregated from the responses to a single question range, Table 1 lists five fictional cases in which the composition of the three response options varies. Note that one case corresponds to one specific composition. Cases 1 and 2 both have equal numbers of positive and negative responses but different numbers of neutral responses (30% and 50%) that result in a perfect positive-negative balance (i.e., $B_n = 0\%$ and $R_n = 50\%$) and yield index values of 100, where $B_n = p^+ - p^-$ denotes the imbalance and $R_n = p^+/(p^+ + p^-)$ the relative size of the positive responses to the non-neutrals. In cases 3 and 4, the imbalances between the two non-neutral response options are the same (i.e., the B_n values are both-28%) but the positive response over the non-neutral option is slightly smaller in size for case 4 (i.e., $R_n = 22\%$) than for case 3 ($R_n = 30\%$). Meanwhile, case 5 has

Table 1: Comparisons of balance, relative size, and index values for five fictional response compositions

Case	Responses (%)			Index			
	Positive	Neutral	Negative	B_n (%)	R_n (%)	$\hat{M}$	$\hat{C}$
1	35	30	35	0	50	100	100
2	25	50	25	0	50	100	100
3	21	30	49	–28	30	72	60
4	11	50	39	–28	22	72	44
5	15	50	35	–20	30	80	60

$B_n = p^+ - p^-$ denotes the balance statistic and $R_n = p^+/(p^+ + p^-)$ denotes the relative size of the positive responses among both positive and negative responses.

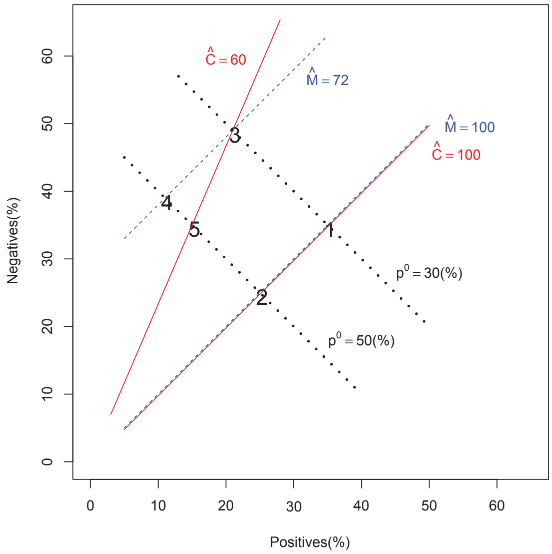


Figure 1: *Contour plot for five fictional cases. $\hat{M}$ and $\hat{C}$ denote the ICS and CCI, respectively, and p^0 represents the proportion of the neutrals. Solid lines connect the response compositions of the same level for the ICS, dashed lines those for the CCI and dotted lines indicate the same proportions of neutrals. ICS = Index of Consumer Sentiment; CCI = Consumer Confidence Index.*

a different imbalance from case 3 but the same relative size. Figure 1 shows the five cases on a two-dimensional plane where the x- and y-axes denote the positive and negative percentage, respectively. This coordinate system is useful to illustrate possible ranges of the two indexes.

In Figure 1, any composition on the line connecting cases 1 and 2 (L_{12}, say) satisfies $p^+ = p^-$, yielding $\hat{M} = \hat{C}$ for various compositions; any composition along the line connecting cases 3 and 4 (L_{34}) represents various $\hat{C}$ values with a fixed value of $\hat{M} = 72\%$; and any composition along the line connecting cases 3 and 5 (line L_{35}) represents various $\hat{M}$ values with a fixed value of $\hat{C} = 60\%$. It is therefore easy to check that L_{12} and L_{34} are parallel and L_{12} and L_{35} have different slopes with the same origin $(0, 0)$. This clearly relates to the different range of the ICS and CCI. The ICS relates to the shift between parallel lines with a fixed slope of 1 according to the value of $\hat{M}$, versus the CCI that relates to the shift between lines circling the origin according to the value of $\hat{C}$. Note that there are other lines that provide useful information about the neutral response; i.e., the line connecting cases 1 and 3 (L_{13}) and the line connecting cases 2 and 4 (L_{24}). It is clear that any composition along the line

L_{13} or L_{24} has a fixed proportion of neutral responses of 30% and 50%, respectively, and that the two lines are parallel. The above discussion can be summarized as follows.

Result 2. Assume that (A1)–(A3) hold. Then,

$$\begin{aligned} L_{\mathrm{ICS}} &: p^- = p^+ + \left(1 - \frac{\hat{M}}{100}\right), && \text{for } 0 \le \hat{M} \le 200, \\ L_{\mathrm{CCI}} &: p^- = \left(\frac{200}{\hat{C}} - 1\right) p^+, && \text{for } 0 \le \hat{C} \le 200, \\ L_{p_0} &: p^- = 100(1 - p^0 - p^+), && \text{for } 0 \le p^0 \le 1. \end{aligned} \tag{3.3}$$

Result 2 indicates that when the line L_{p_0} is given, L_{CCI} has an intersection with L_{p_0} for any value of $0 \le \hat{C} \le 200$, whereas L_{ICS} has an intersection with L_{p_0} when $100p_0 \le \hat{M} \le 100(2 - p_0)$. This then indicates the following result.

Result 3. Assume that (A1)–(A3) hold. Then, for given $0 \le p^0 \le 1$, $100p^0 \le \hat{M} \le 200 - 100p^0$ and $0 \le \hat{C} \le 200$.

Result 3 shows that the range of the ICS varies by the relative size of the neutrals, while that of the CCI does not. Thus, the range of the ICS is smaller than that of the CCI for $p^0 \neq 0$. Note that the range of the CCI has the full span from 0 to 200 regardless of the size of the neutral response.

3.2. Index

To establish the precision of the two indexes $\hat{M}$ and $\hat{C}$ given in (3.1) and (3.2), we require one additional assumption:

(A4) A simple random sample s of size n is selected without replacement from the population U of size N (i.e., the sampling fraction is given as $f = n/N$).

Assumption (A4) is made to provide the indexes with a probabilistic structure and allows a comparison of the precision of the two indexes.

Result 4. Assume that (A1)–(A4) hold. The variance $V(\hat{M})$ is then unbiasedly estimated by

$$v\left(\hat{M}\right) = A_n \left[100^2 \left(1 - p^0\right) + \left(\hat{M} - 100\right)^2\right]. \tag{3.4}$$

Additionally, the variance $V(\hat{C})$ is asymptotically unbiasedly estimated by

$$v\left(\hat{C}\right) = \frac{A_n}{(1 - p^0)} \hat{C} \left(200 - \hat{C}\right), \tag{3.5}$$

where the two variances $V(\hat{M})$ and $V(\hat{C})$ are defined similarly to their estimators $v(\hat{M})$ and $v(\hat{C})$ in (3.4) and (3.5), respectively, but with p^0, $\hat{M}$, and $\hat{C}$ replaced by their population analogues and $A_n = (1 - f)/(n - 1)$ by $(1 - f)/n$, and $f = n/N$ denotes the sampling fraction.

See Appendix for the proof of Result 4. One may now verify the following.

Result 5. Assume that (A1)–(A4) hold. Then, for a given $0 \le p^0 < 1$,

$$v = \left(\hat{M}\right) \le v\left(\hat{C}\right), \quad \text{when } p^+ \in I_{p^0}, \tag{3.6}$$

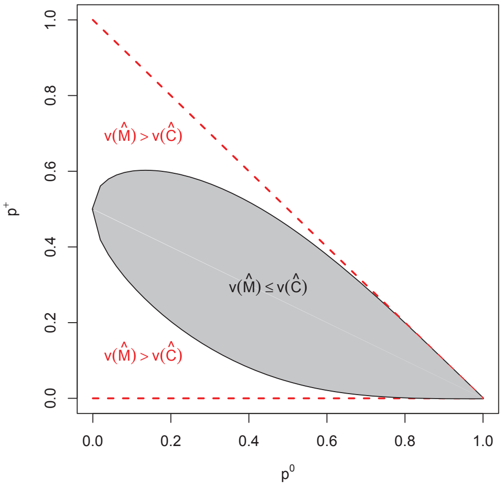


Figure 2: *Division of the region of* (p^+, p^0) *by the equality of* $v(\hat{M})$ *and* $v(\hat{C})$. $v(\hat{M}) \leq v(\hat{C})$ *within the ellipse* I_{p^0}, *but* $v(\hat{M}) > v(\hat{C})$ *outside the ellipse* I_{p^0}.

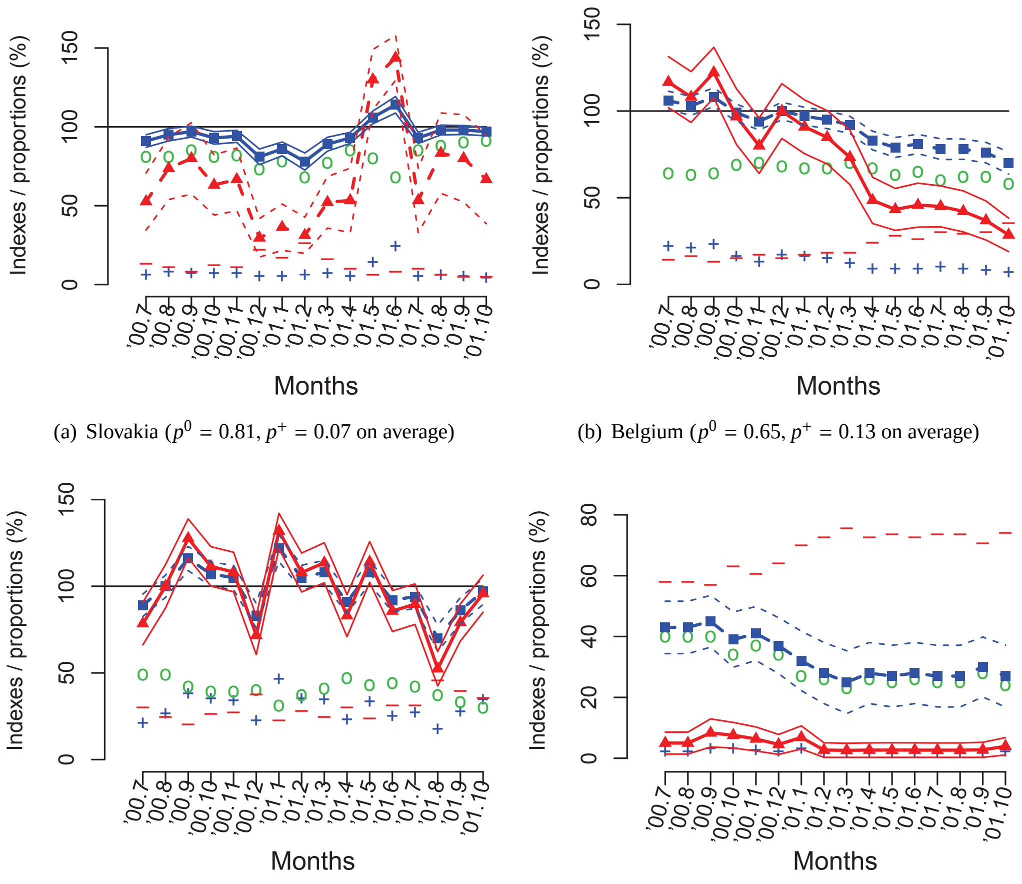
where $0 \leq p^+ \leq 1 - p^0 < 1$ and

$$I_{p^0} = \left[\frac{1-p^0}{2}\left(1 - \sqrt{\frac{p^0}{p^0 + (1-p^0)^2}}\right), \frac{1-p^0}{2}\left(1 + \sqrt{\frac{p^0}{p^0 + (1-p^0)^2}}\right)\right].$$

Figure 2 illustrates I_{p^0} precisely with the interior of an ellipse. Since $v(\hat{M}) \leq v(\hat{C})$ on I_{p^0}, Figure 2 demonstrates that $\hat{M}$ would be more reliable for relatively large p_0 (say, $p^0 \geq 0.6$) and less reliable when relatively small p_0 (say, $p^0 \leq 0.3$) combines with either relatively small p^+ (say, $p^+ \leq 0.2$) or large p^+ (say, $p^+ \geq 0.6$).

3.3. Numerical example

For illustrative purposes, we consider real data examples from OECD's business tendency survey (BTS) during the 16-month period from July 2000 to October 2001: "Judgements on Order Books" for Slovakia, Belgium and Poland and "Total order inflow" for Swiss (see Organization for Economic Cooperation and Development, 2003, p. 34). As in most sentiment surveys, respondents were provided three response options. To simplify our discussion, we assume that a sample size is $n = 500$ with no nonresponse. The average levels of neutral response of the examples vary from 0.81 to 0.30. Figure 3 contains four plots presenting the levels of the three response options in percentage points overlaid with the two indexes for the period for the corresponding BTS examples. Three symbols +, −, and 0 represent the levels of the corresponding response options. The solid line connecting the squares shows $\hat{M}$ values over the period and the dashed line shows $\hat{C}$ values over the period. From three plots (a), (b), and (c) of Figure 3, it is seen that the movements of $\hat{C}$ over time are wider than that of $\hat{M}$, which was a trend also empirically observed by Bram and Ludvigson (1998). Furthermore, the 95% confidence bands show that the variation in $\hat{C}$ is greater over the entire period than that in $\hat{M}$. Plot (d) of Figure 3, however, presents a situation in which the movement of $\hat{C}$ over time is narrower than that of $\hat{M}$. The average values of p^0 and p^+ in plot (d) are 0.30 and 0.02, respectively, which belong to the region where $\hat{C}$ is less variable (or more reliable) then $\hat{M}$ as indicated in Figure 2. The



(a) Slovakia ($p^0 = 0.81$, $p^+ = 0.07$ on average) (b) Belgium ($p^0 = 0.65$, $p^+ = 0.13$ on average)

(c) Swiss ($p^0 = 0.40$, $p^+ = 0.29$ on average) (d) Poland ($p^0 = 0.30$, $p^+ = 0.02$ on average)

Figure 3: *Comparisons of the ICS-type ($\hat{M}$) and CCI-type ($\hat{C}$) indexation results from business tendency surveys of the Organization for Economic Cooperation and Development on "Judgements of Order Books" for Slovakia (a), Belgium (b), and Poland (d) and "total order inflow" for Swiss (c) from July 2000 to October 2001. Three symbols* $+$, 0, *and* $-$ *represent the levels of the corresponding response options. The squares connected with a dotted line represent the movement of* $\hat{M}$. *The triangles connected with a solid line represent the movement of* $\hat{C}$. *The dashed lines represent the 95% confidence bands of* $\hat{M}$, *while the solid lines represent those of* $\hat{C}$.

numerical examples indicate that the index values (and hence their confidence intervals) might give quite different signals even when the schemes are applied to the same response composition.

4. Concluding remarks

4.1. Treatment of neutrals

The two predominant consumer sentiment indexes ICS and CCI are different in many aspects including questionnaire composition, survey mode, sample design and size. Above all, the methods of treating the neutrals are basically different in computing the corresponding micro scores for individual questions that are used to derive the indexes. The ICS reflects the neutrals in its micro score, while the CCI does not. The following expressions rewritten from (3.1) and (3.2), respectively show how the neutral answers are treated in $\hat{M}$ and $\hat{C}$:

$$\hat{M} \propto \frac{(1)n^+ + (0)n^0 + (-1)n^-}{n^+ + n^0 + n^-}, \qquad \text{and} \qquad \hat{C} \propto \frac{n^+}{n^+ + n^-},$$

where n^+, n^0 and n^- are the numbers of sampled people giving the corresponding answers. $\hat{M}$ gives a zero weight to the neutrals in the aggregation versus $\hat{C}$ that does not take the neutrals into account, by simply ignoring them in the aggregation. As a result, when the neutral answers are dominant, the CCI becomes more sensitive to a relatively small imbalance between the positives and negatives than the ICS. When the neutral answers are not that dominant, the ICS becomes sensitive in the sense that it has a wider range as seen in Result 3. However, Result 5 shows that the relative size of the neutral answers also influences the reliability of the two indexes. Therefore, the relative size of the neutrals is informative for each index's relative standing and stability, even in the case of the ICS.

4.2. Generalization

Several variants of the ICS micro scoring scheme have been used by adopting different response weights for the three or more response options. Let G denote the total number of response options given to a respondent. A generalized version of the ICS micro score (say, $\hat{M}$ in (2.1)) can then be defined as

$$\hat{E} = a_0 + \sum_{g=1}^{G} a_g p_g, \tag{4.1}$$

where a_0 is a constant, and (a_g, p_g) is a pair of the weight and the sample proportion for the gth response category from $g = 1, \dots, G$. For example, the ICS is a special case of $\hat{E}$ with $G = 3$ and $(a_0, a_1, a_2, a_3) = 100(1, 1, 0, -1)$, and is the most commonly used. However, there is a lack of a variant or generalization because the CCI is rarely adopted by surveys (except for the Conference Board). Like (4.1), the CCI can be generalized with $G = 2L + 1$ according to

$$\hat{J} = 100 \left(\frac{\sum_{l=1}^{L} \frac{l}{L} p_l}{\sum_{l=-L}^{L} \frac{|l|}{L} p_l} \right), \tag{4.2}$$

where p_l denotes the lth response category and $l = -L, -(L-1), \dots, 0, L-1, L$. The generalized versions of (4.1) and (4.2) may reduce the effect of the neutrals in evaluating the sentiment. The validity of (4.1) and (4.2) as the most discriminant sentiment indexes can be further pursued but remains an open research question (e.g., Stangl, 2006).

4.3. Forecasting accuracy

Results 1–5 indicate that it i possible to infer that $\hat{C}$ might have a notable advantage over $\hat{M}$ in (correct) forecasting. What is behind this is that (i) $\hat{C}$ has desirable-for-prediction sensitivity due to its invariant range regardless of p_0 (Results 2 and 3 on range). (ii) $I^c_{p^0}$ (the unshaded area in Figure 2 between the two dashed lines where $\hat{C}$ is expected to be more reliable than $\hat{M}$) is the region where it is easier to make correct forecasts, relative to I_{p^0}, i.e., p^0 is relatively small and p^+ (and hence p^-) tends to be close to either 0 or 1 on $I^c_{p^0}$ (refer to Results 4 and 5 on precision). Note that (i) and (ii) together imply that $\hat{C}$ is equipped with desirable sensitivity to imbalance between the non-neutrals regardless of the neutrals whenever significant difference exists between p^+ and p^-. This appears to be the key reason behind better prediction performance of CCI over ICS and explains the findings by Bram and Ludvigson (1998). Note that prediction might be made better by ICS where there is no significant difference between p^+ and p^-.

As discussed above, the two indexes are designed to evaluate economic sentiment *per se*. However, their different micro scoring schemes might indicate different signals which are mainly attributable to their different treatments of the neutrals in forming the micro scores and indexes. The ICS is accompanied by many historical developments such as the Carson-Parkin framework (see, e.g., Seiler, 2013), while the CCI is not. The imbalance in (2.1), for example, can be assumed to be constructed with answers on a 3-level Likert scale that are affected by a cycle function $g(t)$ of time t with random errors by respondents. Such a cycle function might be viewed as a target parameter for the imbalance statistics; therefore, the ICS are to estimate. It would be also desirable to discuss the parameters for the two indexes that are used for estimation and the meaning of those parameters as recommended by one of the referees; however, this is beyond the scope of the current paper. In closing, it is important to stress that the two indexes be handled with care or combined when applied to economic sentiment comparison studies.

Appendix: Proof of Result 4

Proof of (3.4): Let y_i denote the value of the survey question for the i^{th} sampled person with respect to the three response options. If we let three numeric values −1, 0, and 1 denote positive, neutral, and negative answers, respectively, from each sampled person, then y_i can be rewritten as $y_i = \sum_l a_{yl} I_i(l)$, where $I_i(l)$ is the response indicator of the i^{th} person for category l, $a_{yl} = l$ is the corresponding response weight and $l = -1, 0, 1$. Letting $p_l = n^{-1}\sum_{i=1}^n I_i(l)$ denote the sample proportion of the lth response category, we have $\bar{y} = n^{-1}\sum_{i=1}^n y_i = \sum_{l=-1}^1 a_{yl} p_l = p^+ - p^-$, where $p^+ = p_1, p^0 = p_0$ and $p^- = p_{-1}$. Note that $\hat{M} = 100(1+\bar{y})$. Following basic sampling theory (e.g., Park, 2015; Särndal *et al.*, 1992, pp. 46–47), an unbiased estimator of the variance of $\hat{M}$ is given as $v(\hat{M}) = 100^2 v(\bar{y})$, where $v(\bar{y}) = A_n(n^{-1}\sum_{i=1} y_i^2/n - \bar{y}^2)$, $A_n = (1-f)/(n-1)$ and f denotes the sampling fraction. Since $I_i(l)I_i(l') = I_i(l)$ for $l = l'$ or $= 0$ for $l \neq l'$, we have $y_i^2 = \sum_l a_{yl}^2 I_i(l)$ and $n^{-1}\sum_{i=1}^n y_i^2 = \sum_l a_{yl}^2 p_l = p^+ + p^-$. Thus,

$$A_n^{-1} v(\bar{y}) = (p^+ + p^-) - (p^+ - p^-)^2 = (1 - p^0) - \left(\frac{\hat{M}}{100} - 1\right)^2,$$

completing the proof of (3.4). □

Proof of (3.5): Define $x_i = \sum_l a_{xl} I_i(l)$ and $u_i = \sum_l a_{ul} I_i(l)$ for each sampled person i, where $a_{xl} = 1$ for $l = 1$ and $= 0$ for $l = 0$ and $= -1$ for $l = -1$; thus, $a_{ul} = |a_{yl}|$ for any $l \in \{-1, 0, 1\}$. We then note that $\hat{C} = 200(\bar{x}/\bar{u})$, where $\bar{x}$ and $\bar{u}$ denote the sample means of x_i and u_i, respectively. Using Taylor's linearization technique, an approximate unbiased estimator of the variance of $\hat{C}$ is given as $v(\hat{C}) = 200^2 v(\bar{z})$, where $v(\bar{z})$ is defined similarly to $v(\bar{y})$ for a variable $z_i = (\bar{u})^{-1}[x_i - (\bar{x}/\bar{u})u_i] = \sum_l a_{zl} I_i(l)$ and $a_{zl} = (1/\bar{u})[a_{xl} - (\bar{x}/\bar{u})a_{ul}]$. By noting $(1-p_0)(a_{z,-1}, a_{z0}, a_{z1}) = (1 - \hat{C}/200, 0, -\hat{C}/200)$, $\bar{z} = \sum_l a_{zl} p_l = 0$, and $z_i^2 = \sum_l a_{zl}^2 I_i(l)$, we have

$$A_n^{-1} v(\bar{z}) = \sum_{i=1}^n \frac{z_i^2}{n} = \frac{1}{1-p_0}\left(\frac{\hat{C}}{200}\right)\left(1 - \frac{\hat{C}}{200}\right),$$

completing the proof of (3.5). □

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