BOX ARTICLE 1.1

Box 1.1: Economic Sentiments in Singapore

Many macroeconomic data series, including Gross Domestic Product (GDP), are published with a lag. The problem of data lag is partially mitigated by the use of more regular activity-based indicators such as the monthly industrial production and retail sales indices. Such indicators are further complemented by survey-based sentiment indices[1] which measure economic agents' perception of the outlook of the economy in the near future.

In this study, we tap on unconventional data sources to obtain a higher-frequency and more real-time measure of economic sentiments in Singapore. This is part of our effort to expand the use of high frequency, real-time data to complement traditional indicators for better monitoring of the health of the Singapore economy.[2]

Role of economic sentiments in understanding the health of the economy

Economic sentiments play a role in influencing economic outcomes (Throop, 1992). For example, the level of optimism in the economy can affect consumers' saving and spending activities, business owners' hiring and capital expenditure plans, and the amount of credits available to businesses. Both activity-based indicators and economic sentiments are thus important barometers for assessing the overall health of the economy and can offer new insights to policymakers (Exhibit 1). For instance, when both economic sentiments and activity-based indicators are positive (negative), they may reinforce each other to increase the likelihood of an improving (deteriorating) economy. On the other hand, mixed signals could suggest that the economy is at a turning point.

Exhibit 1: Sentiment-based and Activity-based Economic Indicators

		Economic Activity	
		Positive	**Negative**
Economic Sentiments	**Positive**	Sentiments and real economic activity are aligned (i.e., self-reinforcing a favorable economic outcome)	Recovery expected in the coming months
	Negative	Weakness expected in the coming months	Sentiments and real economic activity are aligned (i.e., self-reinforcing a negative economic outcome)

[1] For example, the Department of Statistics' / Economic Development Board's Services and Manufacturing Business Expectation Surveys, SBF-DP SME index and Thomson Reuters/INSEAD Asia Business Sentiment Survey provide a gauge of the level of optimism among business owners.

[2] In 2013, MTI economists leveraged on Google searches to improve Singapore's visitor arrivals forecast (see Goh & Leong (2013)). In the following year, MTI economists text-mined local newspapers to measure economic policy uncertainty in Singapore (see Feng (2014)). The MTI Economics Division is also developing a suite of other high frequency, activity-based indicators using data such as electricity consumption to complement traditional indicators for better monitoring of the health of the Singapore economy.

Measuring economic sentiments in Singapore using non-survey based information

As far as we are aware, almost all sentiment-based indices in Singapore rely on purpose-built surveys to gather the sentiments of consumers or businesses.

However, another possible source of data on economic sentiments is the news media. This is particularly since the news media is the primary source of information on the latest economic events and developments for many economic agents (i.e., consumers and businesses). The tone used in economic reporting thus not only reflects current sentiments, but could also prompt the economic agents to revise their sentiments. Increasingly, text analytics techniques have been used overseas to mine sentiments from the news media. For example, studies overseas have focused on using text-derived sentiments to predict stock market movements (Schumaker & Chen, 2009; Garcia, 2013), labour market outcomes (Levenberg, Pulman, Moilanen & Simpson, 2014) and economic growth (Ormerod, Nyman & Tuckett, 2015).

Here, we construct the Singapore News Economic Sentiment Index (SNES) to measure economic sentiments as portrayed by the local newspapers, and also assess the extent to which it correlates with the performance of the Singapore economy.

To construct the SNES, economic-related articles published in the local newspapers[3] between January 2001 and June 2016 were first identified.[4] In total, more than 217,300 economic-related articles were identified for the construction of the SNES.

Next, the economic-related articles were analysed at the sentence-level using a proprietary polarity lexicon[5] to determine the semantic orientation of the sentence (i.e., whether the sentence is positive, negative or neutral). Specifically, from each sentence, polarised words were tagged and context clusters of words around the polarised words were extracted to identify any contextual valence shifters. The valence shifters affect the polarity of a sentence through negation (e.g., 'not' and 'no'), amplification (e.g., 'very' and 'extremely'), or de-amplification (e.g., 'barely' and 'slightly'). Taking the number of polarised words and the valence shifters into consideration, a numerical score that reflects whether the sentence conveyed positive (i.e., larger than 0), negative (i.e., smaller than 0) or neutral (i.e., equal to 0) sentiments was assigned to each sentence. The scores of all the polarised sentences (i.e., sentences with at least one polarised word) were averaged across all the articles published within the day, month or quarter to form the daily, monthly or quarterly SNES. The SNES index was then normalised to range from -1 to 1. A value larger than 0 indicates the overall economic sentiment is positive.

The advantage of using the SNES is two-fold. First, the SNES is not based on surveys, and as such, avoids the traditional limitations of surveys.[6] Second, it is high-frequency and close to real-time, which allows policymakers to obtain an immediate sensing of economic sentiments in Singapore.

[3] Six local newspaper publications were used, namely The Straits Times, The Business Times, The Edge Singapore, Today (Singapore), MyPaper and The New Paper. Other text sources (e.g., economic reviews by professional bodies) could also be included in future work to augment the SNES.

[4] Local newspaper articles were pre-selected using the keywords 'Singapore' and any of the following five words: 'econom', 'busin*', 'industr*', '*employ*', and 'inflation', where the asterisk represents truncation character used to replace one or more characters. A list of over 700 economic-related terms (e.g., 'export', 'gross domestic product/GDP', 'fiscal policy', etc.) were used to determine the proportion of economic-related terms in each article. Based on an analysis of a sample of articles, a threshold on the proportion of economic-related terms that ought to appear in an article before the article could be classified as economic-related was determined. Using this reference threshold, 25% of the pre-selected articles were dropped from the construction of the SNES. An audit of a random sample of the dropped articles indicated that only a minority were incorrectly dropped.*

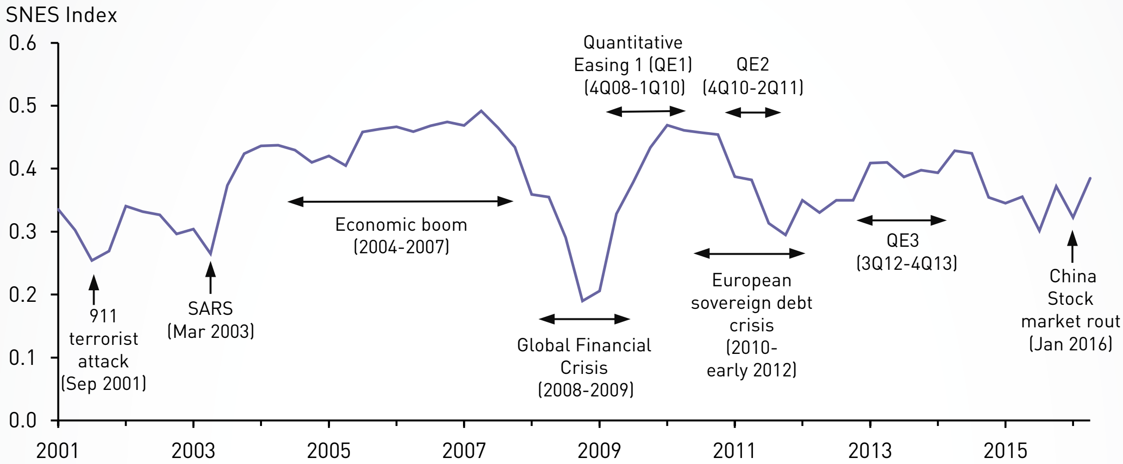
[5] The polarity lexicon consists of 1,794 emotionally-charged words, of which 1,209 words are negatively-charged (e.g., 'hopeless', 'worsen', etc.), and 585 words are positively-charged (e.g., 'bullish', 'prosperous', etc.).

[6] The quality of the data elicited from surveys is a common concern. For instance, respondents may not answer survey questions accurately. Many surveys also do not track particular individuals through time, making it difficult to measure changes in attitude over time. In addition, the choice of words and questions can have unintentional effects on the responses. Lastly, surveys may be subject to sampling and data recording errors.

The SNES correlates well with economic events

The SNES generally correlates well with significant economic events that have occurred since 2001 (Exhibit 2). For instance, the SNES tumbled during the 11 September 2001 terrorist attack in the United States and the SARS outbreak in 2003. This was followed by an upward swing which was sustained throughout the period of economic boom between 2004 and 2007. The SNES then fell to a new low during the 2008-2009 Global Financial Crisis (GFC), but rebounded strongly in the second quarter of 2009. Subsequently, the SNES experienced various troughs on the back of events such as the European sovereign debt crisis in September 2011 and the China stock market rout in January 2016.

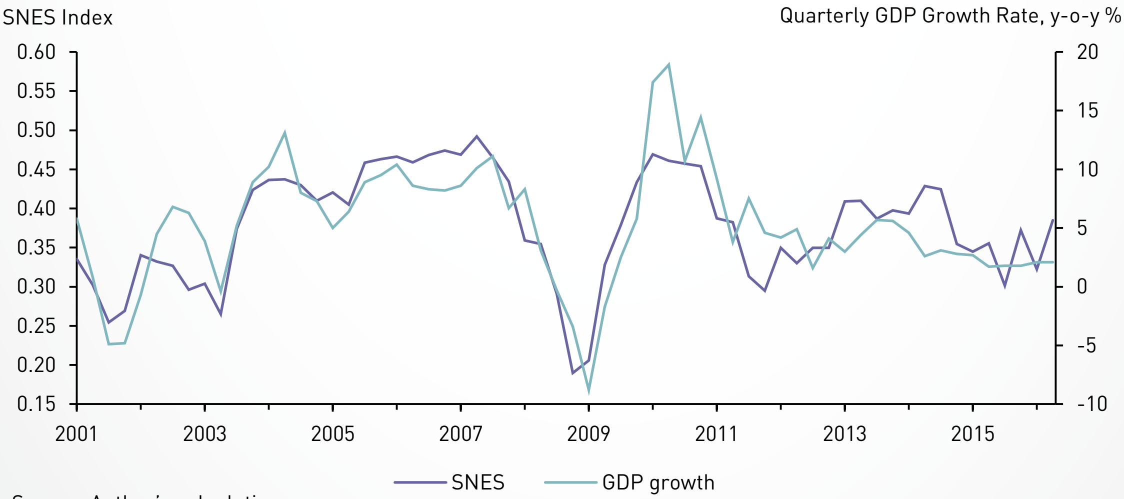
Exhibit 2: The SNES Index for Singapore (1Q01-2Q16)



Source: Author's calculations

To assess the SNES's contemporaneous correlation with respect to key economic indicators, we used the quarterly GDP growth rate as the reference indicator. We found that through the years, the quarterly SNES and GDP growth rate moved closely together (Exhibit 3). In particular, both series exhibit a strong contemporaneous correlation of 0.79.

Exhibit 3: The SNES and GDP Growth Rate (1Q01 – 2Q16)



Source: Author's calculations

Incorporating the SNES helps to explain variations in GDP growth

The informational value of the SNES is also evaluated by assessing how much of the variation in the quarterly GDP growth rate can be explained by the SNES. A benchmark Autoregressive Distributed Lag (ADL) model as represented by equation (1) was first estimated.[7]

$$GDP\ growth_t = \beta_0 + \beta_1\ GDP\ growth_{t-1} + \beta_2\ GDP\ growth_{t-4} + \epsilon_t \tag{1}$$

where $GDP\ growth_t$ is the quarterly GDP growth rate in quarter $t \in \{1,2,\ldots,T\}$.

We then extended the benchmark model by including the contemporaneous SNES as represented by equation (2) to test if its inclusion improved the model.

$$GDP\ growth_t = \beta_0 + \beta_1\ GDP\ growth_{t-1} + \beta_2\ GDP\ growth_{t-4} + \alpha_0\ SNES_t + \epsilon_t \tag{2}$$

where $SNES_t$ is the quarterly SNES in quarter t.

The benchmark and extended models were estimated using data for the period of January 2001 to June 2016. The coefficient estimates in both models were all statistically significant at the 1% level and the positive sign of α_0 indicates that the SNES was positively associated with the GDP growth rate (Exhibit 4). In addition, the adjusted R^2 of the extended model was 0.77, higher than that for the benchmark model. This suggests that the SNES provides useful information to explain variations in the GDP growth rate.

Exhibit 4: Model estimates and goodness of fit of the benchmark and extended model

	Benchmark Model	Extended Model
	Coefficients	
β_0	2.88*** (0.85)	-8.10*** (2.01)
β_1	0.77*** (0.06)	0.50*** (0.06)
β_2	-0.27*** (0.11)	-0.23*** (0.08)
α_0		31.76*** (6.14)
	Goodness of fit	
Adjusted R^2	0.64	0.77

Source: Author's calculations

Note: The asterisks *** denote statistical significance at 1% using a 2-sided t-test. The heteroscedasticity-autocorrelation robust standard errors of the estimated coefficients are given in parenthesis. The goodness of fit was assessed by adjusted R^2. The larger the adjusted R^2, the better the model fit.

Unconventional data sources offer the potential for higher-frequency, real-time sensing of the performance of the Singapore economy

The use of text analytics to derive economic sentiments expands our effort to tap on unconventional data sources to monitor the health of the Singapore economy. In particular, the SNES enables us to measure economic sentiments in Singapore on a higher frequency and close to real-time basis. Our analysis shows that the SNES correlates well with Singapore's economic performance, and can hence be used to complement other indicators to improve our sensing of the health of the Singapore economy.

[7] Higher order autoregressive models were also estimated, but they do not offer any advantage over the selected benchmark model.

Contributed by:

Lam Yan Tung, Economist
Economics Division
Ministry of Trade and Industry

References

Feng, S. Y. (2014). Economic policy uncertainty in Singapore. Economic Survey of Singapore, Third Quarter 2014.

Garcia, Diego (2013). Sentiment during recessions. Journal of Finance, 68: 1267–1300.

Goh, S. L., & Leong, C. H. (2013). Can the volume of queries on search engines forecast Singapore's visitor arrivals? Economic Survey of Singapore, Third Quarter 2013.

Levenberg, A., Pulman, S., Moilanen, K., & Simpson, E. (2014). Predicting economic indicators from web text using sentiment composition. International Journal of Computer and Communication Engineering vol. 3, no. 2, 109-115.

Ormerod, P., Nyman, R., & Tuckett, D. (2015). Measuring Financial Sentiment to Predict Financial Instability: A New Approach based on Text Analysis. arXiv:1508.05357. Retrieved from http://arxiv.org/abs/1508.05357.

Schumaker, R. P., & Chen, H. (2009). Textual analysis of stock market prediction using breaking financial news: The azfin text system. ACM Transactions on Information Systems, Vol. 27, no. 2, 12:1-12:19.

Throop, A. W. (1992). Consumer sentiment: its causes and effects. Federal Reserve Bank of San Francisco Economic Review 1, 35-59.