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SJES DATA STREAM

Capturing Swiss economic confidence

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Abstract

Survey data can offer timely information on the current state of the economy and its short-term outlook. In this paper, we propose a "Swiss Economic Confidence Index" (SEC). This is a monthly indicator based on aggregating a selection of individual survey indicators, which we show to have favorable leading properties. Applying simple criteria, we select those surveys from a set of currently more than 250 sentiment indicators. We show that the SEC index provides useful signals on GDP growth in a number of real-time out-of-sample forecasting exercises.

Keywords Business cycle index, Economic sentiment, Switzerland, Nowcasting

JEL Classification C32, C38, C53, C55, E32

1 Introduction

Business cycle analysis is an important task for economists to understand the fluctuations in economic activity and hence for economic policy decision making. Among the various types of indicators used for this purpose, survey-based leading indicators (also referred to as *soft* indicators) have gained increasing importance in recent decades. These indicators are derived from surveys conducted among businesses, households, or other economic agents, and provide valuable insights into their expectations and sentiment about the near term course of the economy.[1]

This paper's contribution revolves around the identification, collection, and examination of survey-based data pertaining to the Swiss economy. These surveys cover various aspects, including investor, business, and household confidence as well as their expectations. The availability of such data has increased significantly over the past quarter of a century, in particular since the financial crisis of 2008/2009. One challenge we face is that these survey-based indicators may have different reporting frequencies, with some available on a monthly basis and others on a quarterly basis, resulting in a mixed frequency dataset. We synthesize the information from these indicators into a single composite indicator—hereafter referred to as the SEC index—that captures the sentiment tendency of economic agents as reflected in the surveys.

Our objective in constructing a monthly composite indicator is to provide an overall measure of the sentiment tendency of domestic economic agents as reflected in the surveys, while mitigating the impact of quality deficiencies in individual survey-based indicators. To achieve this, we adopt a variable selection approach that enables us to identify the most appropriate indicators to be used in the SEC index. This approach enables to adapt the composition of the SEC index over time and hence allows us to continuously update and refine our indicator selection, ensuring the accuracy and reliability of our composite indicator in tracking the dynamics of the Swiss economy. The data are made available to the public

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[1] See for instance Milgrom and Roberts (1990), Ball and Romer (1991), Farmer (1999).

on the website https://www.seco.admin.ch/sec. The index is updated monthly with a delay of around 15 days.[2]

The attractiveness of survey-based indicators results primarily from their timely availability and the forward-looking insights they allow for (compare Baffigi et al., 2004, for instance) covering a wide range of sectors and activities. However, the value of such survey data ultimately depends on the extent to which they convey reliable information about real economic activity. In particular, they may be prone to subjectivity or data quality problems, rendering less precise their signals compared to *hard*, that is, measurable and objective economic indicators. While the subjective and qualitative soft indicators reflect expectations, sentiment and alike, hard indicators in turn state what happened as concerns real economic activity. The most prominent example is the Gross Domestic Product (GDP), which measures value added of companies and the public sector generated in a specific time period. Hence, hard indicators provide more accurate and reliable information about current economic conditions but may have limitations in terms of timeliness and forward-looking information. Apart, hard data are often revised after the initial release. These disadvantages of hard indicators shape the increasing reliance on soft indicators, for the purpose of business cycle analysis.

However, the proliferation of survey-based leading indicators in recent decades has also raised concerns about their quality and reliability. Despite their timeliness and ability to capture the sentiment of economic agents in real time, these indicators often suffer from inadequacies that impair their accuracy for providing reliable business cycle signals. From the point of view of a single indicator, one common challenge is the presence of quality deficiencies, such as measurement errors or subjective assessments, which can introduce noise and uncertainty into the indicator's signals. Moreover, survey-based indicators are often relatively new compared to hard indicators, which gives rise to shorter time series relative to hard ones. This may impair their ability to conduct sophisticated time series analysis and hence their usefulness as leading indicators. From a more general point of view, a challenge arises when different leading indicators give conflicting signals. This can leave policymakers and analysts in a dilemma as to which indicator to trust and which signals to consider as most reliable (compare Frale et al., 2010b, among others). In such situations, it becomes crucial to identify appropriate indicators that provide consistent and robust signals for tracking the course of the economy.

We explore three different use cases for the SEC index and its underlying survey-based dataset. In the first, we examine the practical utility of survey-based indicators and the SEC index, focusing on their use from a practitioner's perspective in times of pronounced economic turmoil. The second use case assesses the now- and forecasting capabilities of the SEC index, shedding light on its effectiveness in this regard. The third use case explores the prospect of using the survey-based indicators that make up the SEC index to establish a sentiment-based measure of subjective uncertainty.

A notable advantage of the SEC index is its ability to mitigate weaknesses associated with specific indicators, such as the impact of strong fluctuations or irregular response rates in surveys. This feature enhances the reliability and accuracy of the SEC index, providing a more robust assessment of Swiss economic sentiment. Moreover, despite a more than doubling of the available indicators since 2000 and the evolving information content of individual sentiment indicators over time, the selection of indicators has remained relatively constant. However, it is important to note that a limitation of our composite sentiment index, when compared to individual assessments of surveys, is that the information set is completed sequentially on a monthly basis. This means that not all indicators are published simultaneously, resulting in delays. For example, the composite indicator for the fourth quarter of 2022 was not complete until the seventh working day of the following month, January 11. Despite this drawback, survey data have consistently demonstrated its forward-looking properties by capturing respondents' views on future conditions, which are not readily available through timely hard data, as highlighted by Baffigi et al. (2004).

With a view to alternative indicators, Switzerland boasts several publicly available business cycle indices. For instance, Galli (2018) employs a large and broad set of monthly and quarterly indicators to condense in a business cycle index with favorable nowcasting properties (SNB-BCI).[3] Additionally, the KOF Barometer (Abberger et al., 2018) is an established indicator for Swiss business cycle developments. These indices typically blend hard and soft data sources to derive their findings. Recently, Wegmüller et al. (2023) introduced an index for Swiss economic activity based solely on hard data, on a weekly frequency, and Kugler and Sheldon (2023) proposed a method to predict GDP growth based on a forward-looking measure of unemployment. However, our work distinguishes itself from these previous studies by focusing

[2] It should be noted that the published SEC index, as provided on the homepage, consists of 30 survey indicators, as selected by our procedure in November 2019. An update of the set of indicators occurs only periodically for user-friendliness. The next update is planned together with the revision of the quarterly Swiss GDP data in September 2024.

[3] In a similar vein, Glocker et al. (2020) used a small set of mixed-frequency indicators to construct an index for recession dating (SECO-DFM).

Table 1 Set of indicators

Source	Survey	Sector	Freq.	Obs.	*N*	Std.	Pers.
UBS & CFA Society	Financial market survey	Investors	M	179	14	28.3	0.86
Manpower	Employment Outlook Survey	Whole Economy	Q	71	1	7.2	0.91
Procure.ch & UBS	Purchasing Managers' Index	Manufacturing	M	339	8	8.4	0.90
		Services	M	111	7	8.9	0.80
SECO	Consumer Confidence Survey	Consumers	Q	104	11	23.8	0.94
Sentix	Economy Index	Investors	M	171	6	20.6	0.81
KOF	Business Tendency Surveys	Whole Economy	M	168	1	10.5	0.92
			Q	113	3	10.1	0.97
		Construction	M	239	32	14.3	0.96
			Q	74	24	7.4	0.93
		Manufacturing	M	311	22	12.2	0.89
			Q	96	23	10.0	0.94
		Services	M	158	12	12.4	0.85
			Q	65	45	14.6	0.92
		Trade	M	265	15	17.3	0.81
			Q	84	28	14.9	0.93

Abbreviations: Obs: Average number of observations per group, N: Number of indices per group, Std.: Standard deviation, Pers: Persistence in terms of AR(1)-coefficient.

Sources: KOF: KOF Swiss Economic Institute, SECO: Swiss State Secretariat for Economic Affairs

solely on survey data instead. Specifically, our coincident index captures the sentiment of various sectors and economic actors, akin to aggregate survey indicators like the Purchasing Managers' Index (PMI), the consumer sentiment index or the SENTIX overall index. Notably, Frale et al. (2010a) proposed a monthly measure for the euro area GDP based on a small-scale factor model featuring two factors, including the contribution of survey indicators. What sets our work apart to these contributions, however, is its simplicity and transparency in index construction.

The paper is structured as follows: In Sect. 2, we provide an overview of survey data describing economic sentiment of economic agents in Switzerland. The sections additionally describe the methodology employed to construct the composite index. Section 3 presents the new index and its in-sample properties. In Sect. 4, we carry out the three use cases. Lastly, we conclude in Sect. 5.

2 Data, indicator assessment, and selection

We collect data from various sources which conduct surveys. Their aim is to capture the perception of economic agents such as households and firms.[4] Table 1 presents the sources of the indicators used in our analysis. The final set of indicators comprises a total of 252 variables, with 117 at a monthly frequency and 135 at a quarterly frequency. Monthly surveys are typically released toward the end of the month or in the first few days of the following month, while quarterly surveys may be published within the corresponding quarter or with a substantial delay.

The surveys used in our analysis cover a wide range of economic agents and sectors. Of the 252 indicators, 32 address either investor or consumer sentiment, 42 cover domestic trade activity (retail and wholesale trade), 56 focus on construction activity (including project engineering), 64 relate to services such as banking and insurance, hotel and catering, and 53 are related to the manufacturing sector. The remaining five indicators pertain to activities that are not specific to any sector.[5]

In addition to capturing the sentiment and confidence of economic agents across different sectors, surveys also encompass a range of questions. For example, the consumer sentiment survey asks households to assess the current economic situation in the country as well as their expectations for the next 12 months. To classify each indicator, we distinguish between those that measure the current situation and those that measure expectations. Surveys not only vary in terms of their target sector, timing, and publication delay, but also in their statistical properties. On average, monthly indicators have a slightly

[4] One prominent example is the manufacturing survey conducted by the KOF Swiss Economic Institute, see https://kof.ethz.ch/en/surveys/business-tendency-surveys/konjunkturumfrage-industrie.html for more information on how the survey is run.

[5] For reasons of brevity and precision, we do not consider indices for subdivisions, size of enterprises, or any other possible dimensions of distinction from the different KOF Business Tendency Surveys. For instance, for the construction sector, we do not consider indices for civil engineering, construction of buildings, or special construction activities separately.

higher standard deviation than quarterly surveys. There is also considerable heterogeneity across sectors. Investor and consumer sentiment are highly volatile, while surveys targeting manufacturing, services, or the overall economy exhibit less noise. This pattern also holds for persistence, with investor surveys displaying relatively low levels of auto-correlation, while consumer and business sentiment surveys for construction, trade, manufacturing, and services show higher degrees of persistence.

2.1 Examining the informational content with cross-correlation analysis

To assess the informational content of survey indicators for real economic activity, we compare them directly with the growth rate of GDP. The choice of GDP as the reference variable is made because it is the most commonly used variable to capture the business cycle. In accordance with Gyomai et al. (2016), we follow the classical definition of a business cycle, which is based on real GDP index values. Periods of positive growth (expansion) and negative growth (classical contraction) are used to define the business cycle.[6] Although there are several other hard indicators that could be used as a target/reference measure for real economic activity (e.g., the output gap or inflation), we choose to focus on GDP, and in particular its growth rate, in line with a large body of literature investigating the effectiveness of leading indicators (compare Claveria et al., 2018, Frale et al., 2010b, Carrington et al., 2000. Even though GDP includes information that goes beyond the business cycle, it is still the most important and reliable coincident business cycle indicator for policymakers and analysts worldwide, as it is a harmonized measure which builds on a standardized methodological framework. We use the quarter-on-quarter growth rates of quarterly real GDP, which is seasonally, calendar, and sport-event adjusted, as our target variable.[7] We obtain real-time vintages from 2000-Q1 to 2023-Q2 from Indergand and Leist (2014) and from internal data at SECO.

Although foreign sentiment can be relevant to the Swiss business cycle, we exclude it on purpose as we only want to capture the characteristics of domestic sentiment. Additionally, we exclude aggregate headline indices as for instance, the Swiss manufacturing purchasing managers index (PMI) or the KOF Barometer, as they are constructed coincident indices themselves.[8]

As we are faced with a large number of domestic survey indicators, we begin our analysis by examining their cross-correlations with GDP, our target variable. This allows us to make an initial assessment of the lead-lag relationship between GDP and the survey indicators, as well as to determine whether an indicator is pro-cyclical or counter-cyclical (or a-cyclical in which case it would be dropped from the subsequent analysis).

The cross-correlation coefficient, given by $\rho_{XY}(\tau) = \frac{\mathrm{Cov(X(t),Y(t-\tau))}}{\sqrt{\mathrm{Var(X)Var(Y)}}}$, measures the similarity between two series X and Y at different time lags. A high correlation of indicator Y with the reference series X at $\tau > 0$ indicates that it is a *leading* indicator, while a high correlation at $\tau < 0$ indicates that it is a *lagging* indicator and thus less useful for forecasting. We rely on the robust estimator proposed by Dalla et al. (2022) to test the significance of the pairwise correlations, using the robust $\tilde{t}_{xy,k}$ statistic.[9] There are, of course, many alternative approaches for examining the ability of survey-based indicators in tracking real economic activity. Claveria et al. (2018) provided an overview in this context and they propose a pure data-driven approach based on genetic programming.

To conduct the cross-correlation analysis, it is necessary to adjust all variables to the same frequency. However, since GDP is based on a quarterly frequency, while half of the survey data is based on a monthly frequency, we have to adjust the monthly data to a quarterly frequency before calculating the pairwise cross-correlations. For a first descriptive analysis of cross-correlations, we take the average of the three months corresponding to a specific quarter.

Table 2 presents the cross-correlations between the survey indicators and real GDP. The sample covers the period from 1995-Q1 to 2023-Q2, based on the last available GDP vintage from 2023-Q2. Due to the disruptions by the COVID-19 crisis in 2020-Q2 and 2020-Q3, we

[6] We explicitly focus on the business cycle defined by the GDP growth rate. An alternative would be to focus on the growth cycle, but that would require the estimation of an accurate long-term trend. Growth cycle estimates are conditional on the chosen detrending or trend estimate methods and thus sensitive to the model specification. See (Mazzi et al., 2017) for more details.

[7] Since 2018, in addition to the standard adjustment of GDP for calendar and seasonal effects, SECO adjusts Swiss GDP for effects related to international sports events. Several major international sports federations have their headquarters in Switzerland, including the World Football Association FIFA, the European Football Association UEFA, and the International Olympic Committee IOC. In accordance with applicable international standards, namely the European System of Accounts (ESA) 2010, the value added by Swiss-domiciled companies is included in the gross domestic product (GDP) of Switzerland. In the case of international sports federations, their sales and intermediate consumption are mainly related to the organization and marketing of major sports events. Since these take place periodically, they cause regular fluctuations in the data. From a business cycle perspective, GDP should be adjusted for these fluctuations in the spirit of seasonal effects. For more details consider www.seco.admin.ch/GDP.

[8] Detailed information on the KOF Barometer is provided in Abberger et al. (2018), information on the Swiss Purchasing Managers Index can be found here: https://www.procure.ch/en/about-us/service/pmi/.

[9] It is important to note that tests for the absence of cross-correlation may be invalid when the time series are not independent and identically distributed. Refer to Dalla et al. (2022) for more information on how to establish a robust estimator.

Table 2 Cross-correlations with real GDP

	Lag		Contemporary		Lead	
	Mean	**Range**	**Mean**	**Range**	**Mean**	**Range**
Sector/Actor						
Construction	0.17	(0.00, 0.41)	0.08	(0.00, 0.24)	0.13	(0.00, 0.39)
Consumers	0.24	(0.02, 0.56)	0.16	(0.00, 0.44)	0.15	(0.02, 0.25)
Investors	0.25	(0.01, 0.49)	0.29	(0.02, 0.57)	0.19	(0.02, 0.45)
Manufacturing	0.36	(0.00, 0.65)	0.27	(0.00, 0.62)	0.13	(0.00, 0.39)
Services	0.23	(0.00, 0.60)	0.18	(0.00, 0.43)	0.13	(0.00, 0.29)
Trade	0.27	(0.03, 0.59)	0.17	(0.01, 0.44)	0.12	(0.00, 0.32)
Whole Economy	0.26	(0.03, 0.45)	0.15	(0.08, 0.27)	0.12	(0.01, 0.06)
Assessment						
Current situation	0.23	(0.00, 0.59)	0.17	(0.00, 0.62)	0.13	(0.00, 0.39)
Expectations	0.31	(0.01, 0.65)	0.23	(0.01, 0.60)	0.14	(0.00, 0.45)

Correlations in absolute terms. Mean corresponds to average cross-correlation of survey indicators for a particular group. Reference is the vintage 2023-Q2 of real, seasonally and Sport-events adjusted GDP, starting in 1995. *Lag/lead* indicates that the indicator is lagging/leading GDP by one quarter. Monthly indicators are aggregated to quarterly frequency by taking the mean of the corresponding months

drop these two quarters from the analysis.[10] This decision is rooted in the recognition that these time periods were influenced by biases in real economic activity stemming from the implementation of lockdown policies. Our choice aligns with the rationale put forth by Lenza and Primiceri (2022), who contend that their findings support the validity of this ad hoc approach for the purpose of parameter estimation.

Instead of reporting individual correlations, we group the indicators by sector and type of survey, and show their average correlations with GDP. Our analysis reveals several key findings. First, the correlation between the survey indicators and GDP tends to increase as more information becomes available, with the highest correlation typically observed at a one-quarter lag. However, the investor surveys show the highest correlation once data for the current quarter are complete. Second, investor sentiment has the highest average contemporaneous correlation with GDP, followed by manufacturing surveys. The other sectors exhibit relatively low contemporaneous correlations with GDP. Third, the construction surveys contain limited information for GDP growth. Fourth, expectations surveys exhibit a higher correlation with GDP than surveys assessing the current situation. Finally, expectations surveys do not show strong leading properties; their correlation with GDP is comparably low and peaks at one month after the current quarter. An explanation of this is given in Juodis and Kučinskas (2023). Expectations can be wrong either because of bias (systematic errors) or noise (unsystematic errors). Using data from professional forecasters, Juodis and Kučinskas (2023) find that the magnitude of noise is large (10–30 % of the forecast MSE) and comparable to the bias, which attenuates the correlation of expectations surveys with GDP.

Upon examining individual survey indicators, we observe that certain indicators have a strong correlation with real GDP. However, no single indicator performs markedly better than the others. Notably, several indicators from the manufacturing and investor surveys exhibit an average contemporaneous correlation exceeding 0.6 with GDP, whereas survey indicators tailored for the service sector demonstrate comparatively lower correlation, with an average contemporaneous correlation at best of 0.5. This trend poses a growing challenge for business cycle analysis, given the service sector's increasing significance resulting from structural changes. Additionally, the correlation of most sentiment indicators with the target variable improves as more information becomes available, with the indicators being either concurrent or lagging rather than leading.

2.2 Indicator selection

As reported in Table 2, among the 252 survey indicators, there is a bulk of series which only contain little or no information for explaining fluctuations in GDP.[11] While those indicators might provide a useful signal for the development in a particular sector, for the analysis of the business cycle in general they are only of limited

[10] This is equivalent as setting separate dummies for these two quarters in a linear regression of GDP on the respective survey indicator.

[11] We are aware that different forms of variable selection are possible, see Kim and Swanson (2018) for a survey on shrinkage. We want to keep things as simple as possible. Our approach is related to the regularization technique LASSO (Least Absolute Shrinkage and Selection Operator), as not selecting an indicator because of low correlation to the target is similar to setting its coefficient to zero.

usefulness. Therefore, we set up a selection scheme to extract those indicators which explain most of the variation in GDP. Prior to the selection process, all variables are seasonally adjusted and standardized to have zero mean and unit variance. To construct a timely monthly indicator, we exclude quarterly surveys with a publication lag exceeding 30 days. Swissmem and Deloitte surveys are excluded due to this criterion.

Each indicator has to meet the following *three* selection criteria:

1. It exhibits at least five years of observations, in order to avoid spurious correlations.
2. Indicators at quarterly frequency should have a publication delay of at most 30 days after the end of the respective quarter.
3. Based on the robust $\tilde{t}_{xy,k}$ statistic, its contemporaneous correlation with GDP is significant at the 5% level and at least 0.35 in absolute terms.

Averaging the monthly indicators to obtain quarterly series would result in a loss of information for the present case. Instead, for the selection algorithm applied here, we adopt the blocking approach proposed by Carriero et al. (2015). This method involves splitting the high-frequency information into multiple low-frequency time series. Specifically, we distribute the monthly observations of a given time series into three quarterly series. The first quarterly series collects observations from the first months of each quarter (i.e., January, April, July, and October), the second one collects observations from the second months (i.e., February, May, August, and November), and the last one assembles the observations from the third months (i.e., March, June, September, and December).

3 The SEC index

Once the subset of promising indicators is determined, we condense the information contained therein into one single sentiment index. Following the recommendations in Carriero et al. (2017) and Ozyildirim (2019), we calculate the arithmetic, unweighted average in each quarter from the selected indicators.[12] Similar simple and transparent approaches are also used by the Conference Board, the OECD and Eurostat to construct their respective Composite Leading Indicators.[13]

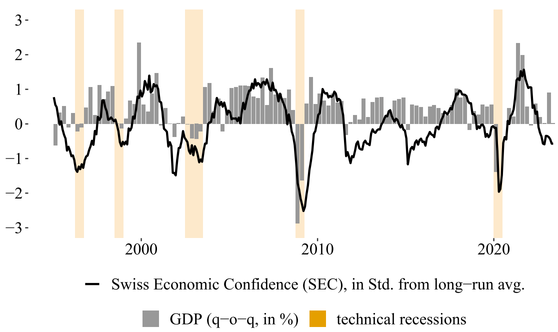

Fig. 1 Swiss economic confidence—SEC

The resulting sentiment index for the Swiss economy (SEC) is shown in Fig. 1. For illustrative purposes, 2020-Q2 and 2020-Q3 are not displayed. It comprises 40 survey indicators: 1 consumer sentiment, 9 investor sentiment, 21 covering manufacturing, 2 trade and 7 services. Twenty-four indicators capture expectations, 16 the current economic situation.[14]

As can be seen in the figure, the index adequately captures the different phases of the Swiss business cycle. Notably, the index leads by several months the beginning of a recession indicated by the shaded areas.[15] Economic sentiment was most pessimistic during the financial crisis of 2008. For a shorter time, sentiment also dropped significantly in the wake of the COVID-19 pandemic in spring 2020. For an extended period, it remained below its long-term average in the wake of the Dot-Com crisis of 2002 and during the European debt crisis in 2012.

As shown in Fig. 1, the sentiment indicator is remarkably in line with the trajectory of GDP growth. Yet, there are several episodes where real economic activity experienced strong positive growth, while economic sentiment remained sluggish. Notably, sentiment fell sharply with the removal of the Swiss Franc lower bound versus the Euro at the beginning of 2015. It took more than a year

[12] Albeit simple, “non-model based cyclical composite indicator (CCI) for the European countries, which are averages of standardized selected single coincident variables, yield in general similar results as more complicated methods” (Carriero et al., 2017). We acknowledge that more sophisticated methods such as a dynamic factor models constitute an interesting alternative approach, however, at the cost of concurrently increasing the extent of complexity (See also Illing & Liu, 2006, among others) for similar simple approaches. Our methodology, based on unweighted averages, also favors notable advantages over principal component analysis (PCA), especially in

Footnote 12 (continued)

handling ragged edges caused by missing observations at series beginnings and ends. This makes PCA less viable in our context, as it would necessitate excluding entire time series with incomplete data, resulting in significant changes to remaining variable factor loadings. While PCA has its merits, our approach excels in addressing the complexities of missing data, highlighting its pragmatic utility in the presence of real-world data imperfections.

[13] See Joint Research Centre-European Commission (2008) for a survey.

[14] A full list of the indicators is shown in Table 5 on page 28 in the appendix.

[15] As Switzerland has no official recession dating committee, we define a technical recession as two consecutive quarters of decline in real GDP, but at the same time, expansion gets 0 only when two consecutive quarters will show increase.

Table 3 Regressing GDP on SEC index

	I	II	III	IV	1%	10%
$SEC_q^{quarterly}$	0.85***				0.84***	0.77***
	(0.10)				(0.10)	(0.10)
$SEC_q^{m_1}$		0.79***	−0.42	−0.77*		
		(0.12)	(0.33)	(0.31)		
$SEC_q^{m_2}$			1.16***	0.14		
			(0.30)	(0.34)		
$SEC_q^{m_3}$				1.29***		
				(0.26)		
F-test: $\beta_i^m = 0$		18.32 (0.00)	13.52 (0.00)	12.45 (0.00)		
F-test: $\beta_1^m = ... = \beta_i^m$			4.85 (0.03)	7.08 (0.01)		
SER	0.46	0.36	0.44	0.55	0.44	0.44
Adj. R^2	0.43	0.33	0.41	0.52	0.42	0.52
Num. obs.	108	108	108	108	108	108

Note: All regressions include four lags of quarter-over-quarter GDP. Results are significant at the $***p < 0.001; **p < 0.01; *p < 0.05$ levels. Estimation sample is 1995:Q1–2023:Q2 using the latest vintage of SEC and GDP data. Data for 2020:Q2 and 2020:Q3 are neglected. Standard errors are given in parentheses for coefficients, and p values are given in parentheses for F-statistics

for the sentiment to recover, while GDP growth turned positive after just one quarter. In general, we observe that it takes time for economic sentiment to recover following a recession, whereas growth of value added recovers swiftly. There are several possible reasons for the discrepancies between sentiment and GDP growth: First, GDP is a very broad measure for economic activity. While the cyclical manufacturing sector is broadly covered by surveys, there are many sectors (e.g., real estate, transport, public administration, education, among others) which are not.[16] Second, sentiment exhibits more persistence than GDP, which is due to the inertia of households and firms in adjusting their judgements. Third, sentiment in a particular sector might decrease due to a particular event and bring down the overall index, albeit economic activity in other sectors performing well.

3.1 Relationship between the SEC index and GDP

We now explore in more detail the in-sample properties of the SEC index. In a first step, we assess the relationship between the SEC index and GDP as our target variable. We consider a linear regression to this purpose with data from 1995-Q1 to 2023-Q2. For robustness purposes, we omit the data for 2020-Q2 and 2020-Q3.[17] Importantly, the SEC index is based on a monthly frequency, while GDP growth on a quarterly. We first regress the quarter-over-quarter GDP growth on the quarterly, average SEC index, following

$$\Delta GDP_q = c + \beta SEC_q^{\text{quarterly}} + \sum_{s=1}^{4} \delta_s \Delta GDP_{q-s} + e_q, \tag{1}$$

where ΔGDP_q is the quarter-over-quarter real GDP growth (calendar, seasonally and sports events adjusted) in quarter q and $SEC_q^{\text{quarterly}}$ is the quarterly average SEC index. The results in Column (I) of Table 3 show that the quarterly SEC is a significant predictor of GDP growth, with 46% of variation explained (31% without lagged GDP growth), roughly 45 days before the release.

We then regress the quarter-over-quarter growth rate on the flow of information from the SEC, starting with the SEC for just the first month of the quarter, and so on, following

$$\begin{aligned}\Delta GDP_q =& c^m + \sum_{i=1}^{m} \beta_i^m SEC_q^{m_i} \\ &+ \sum_{s=1}^{4} \delta_s^m \Delta GDP_{q-s} \\ &+ e_q^m, \quad m = 1, 2, 3,\end{aligned} \tag{2}$$

in which $SEC_q^{m_i}$ is the monthly SEC index for the i-th month of quarter q. Columns (II–IV) report the results. The most recent month's SEC is a significant positive predictor of growth, with the adjusted R^2 rising from 0.36 to 0.55. In other words, every additional data point adds information for the current quarter. Apart, the

[16] We take the unweighted average across surveys on purpose, because it is a priori not clear how sentiment from consumers or investors would be weighted against the sentiment from manufacturing and services.

[17] Results including these two quarters are available from the authors upon request.

coefficients on monthly SEC index are jointly significant for all specifications. We conclude that a strong signal for GDP growth is available already from the first month of the quarter, nearly four months before the GDP release.

We have tested the robustness of our results with respect to the assumptions established in Sect. 2.2 to select appropriate indicators extensively. Lowering the significance threshold to the 10% level yields a wider set of selected indicators (around 45). Raising instead the significance level to 1% lowers the amount of selected indicators further (around 20). As shown in columns 5 and 6 of Table 3, the relationship between the resulting indices and GDP is qualitatively similar, especially for the index constructed with a 1 % threshold. The three indicators show a consistently similar temporal profile, which is also reflected in their high correlation to each other (>0.95 in each case). We interpret this result in favor of the robustness of our approach with respect to alternative threshold values (see also Sect. for further details).[18]

3.2 Indicator selection over time

So far we presented results based on the indicators chosen with the latest available GDP data. However, as the relation between survey indicators and real economic activity might change over time, the set of possible indicators in the index should be updated periodically. We thus carry out an assessment of the temporal stability of the set of selected indicators. To do so we make use of real-time GDP data starting as early as 2000-Q1. Concerning the survey indicators, we use their final available vintage. The exercise can still be regarded as real time since revisions in survey data are generally negligible.[19] Instead of applying the selection algorithm presented in Sect. 2.2 in every of the possible 94 quarters, we evaluate only every second quarter of the year, resulting in a total of 24 quarters. The reasons to do so are twofold: (i) quarterly Swiss GDP gets benchmarked to the new annual values in August every year and updated with the publication of Q2 data; (ii) the business cycle in general and GDP growth in particular exhibit enough inertia such that a periodic update once per years should be sufficient.[20]

We report the composition of the index over time in Fig. 2. Remarkably, while the number of available survey

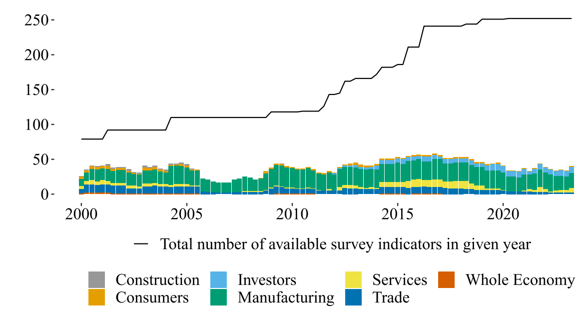

Fig. 2 Selected indicators quarter-by-quarter

indicators has steadily increased from 79 in 2000 to 252 in 2023, the number indicators satisfying the above criteria has been fairly stable. On average, 39 indicators were selected. The maximum was reached in 2016 with a total of 56 indicators. In 2006, a minimum of only 18 indicators satisfied the selection criteria above. Indicators from the manufacturing surveys are selected frequently, 10 indicators satisfy the above criteria in all of the 24 simulated quarters, and 24 are chosen at least half of the time. However, indicators from the other surveys are more prone to instabilities in the correlation pattern: only eight other indicators are chosen more than half of the time.

Since the financial crisis of 2008, substantial effort has been undertaken to improve the quality of survey data. Apart, investor sentiment surveys were introduced. This is reflected in the recovered stability of the composition by 2009. Since then, the amount of indicators in the index has been constantly hovering around 40. Apart from the improved measurement of survey data and introduction of new surveys following the financial crisis, another explanation for variations in the indicator composition is the fact that the relationship between sentiment surveys and the economy in general can change over time. For example, the manufacturing PMI is considered a reliable indicator for developments in the manufacturing sector and, due to this sector's high share in aggregate production, also for the economy as a whole. However, due to structural change, the share of the manufacturing sector in the overall economy is slowly declining. Moreover, in Switzerland the share of the business cycle in-sensitive chemical and pharmaceutical industry has increased substantially since 2000. These are possible reasons why the correlation between the industrial PMI and other sentiment indicators and GDP has also weakened over time.[21]

The temporal stability of selected indicators as shown in Fig. 2 has implications for the real-time path of the aggregate sentiment index. Overall, our sentiment indicator

[18] Figure 6 in the Appendix displays the course of alternative SEC indicators, each with a different choice of threshold value for statistical significance in the sub-indicator selection process.

[19] As we use seasonally adjusted survey data, revisions could stem from changes in seasonal adjustment.

[20] The results presented here are qualitatively robust to applying the selection procedure once per quarter. More details are available from the authors upon request.

[21] See https://dievolkswirtschaft.ch/de/2019/10/indergand-11-2019/ and Gayer and Marc (2018) for some evidence.

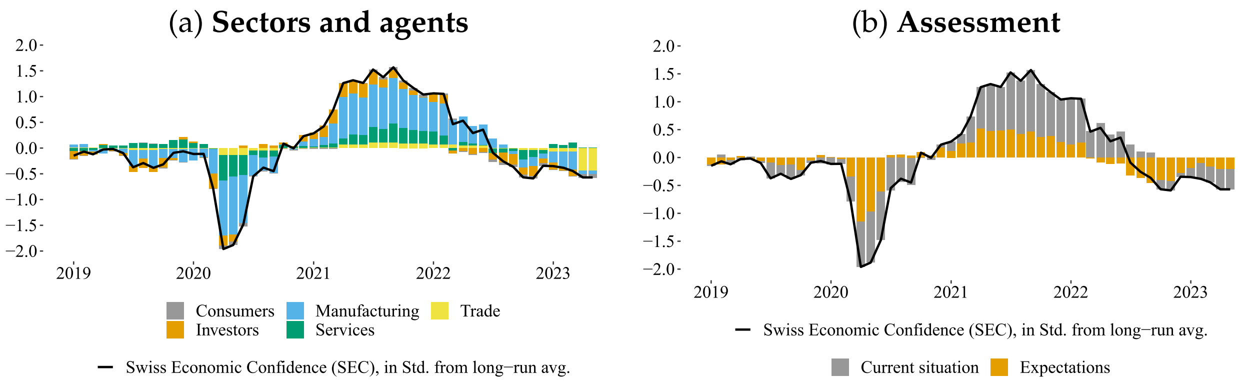

Fig. 3 Growth contributions to sentiment index

displays remarkable in-sample stability and is not subject to major historical revisions. For instance, when comparing the SEC index as it would have been constructed in real time with the last available vintage, then the mean absolute revision amounts to 0.14 index points over all months since 1995 (See Fig. 7 in the Appendix.). Several reasons can be brought forward to explain these revisions: First, volatility of GDP has decreased over time, as the share of the service sector gained weight. Second, prior to the financial crisis, the index was less balanced across sectors and actors, as investor sentiment and service surveys were not available at the time or only spanning over a short sample. Third, as some indicators with high correlations to GDP are selected every time, an underlying structural pattern of the index is given in any period. Qualitatively, the index clearly indicated the business cycle turning points at all times. This is good news for the main purpose of the index: what is detrimental from the perspective of a policymaker or analyst is not the level of the index, rather it is its direction.

4 Use cases

The choice of indicators and their aggregation into a composite index opens up several practical applications. In the following sections, we will delve into three specific use cases in greater depth.[22]

4.1 Drivers of the SEC index

One feature of the SEC index is that it can be decomposed along two dimensions: (1) by type of sectors and agents, and (2) by type of assessment (namely current situation and expectations). In order to obtain feature contributions, we first compute the respective weights of each group of indicators in any given month and then multiply it by the mean value of the surveys pertaining to that group.

For instance, the user could be interested in explaining the behavior of sentiment during the COVID-19 recession of 2020 and the energy crisis of 2022. To this purpose, Fig. 3a displays the contributions of the distinct sub-indicators to the SEC index. Economic sentiment sharply deteriorated in February and March 2020 with the outbreak of the pandemic, but recovered quickly by June 2020 along with the easing of containment measures. Although the Swiss government imposed a second lockdown between January and April 2021, sentiment did not deteriorate again. This is mainly due to the prompt recovery in manufacturing activity (light blue bars) given the strong demand for goods from abroad. With the economic recovery gaining speed throughout 2021, sentiment broadly improved. With rising inflation rates amid the energy crisis and the heightened uncertainty following the Russo–Ukrainian conflict, sentiment deteriorated swiftly in the second half of 2022. In particular, investor and consumer sentiment first contributed negatively to the development of the SEC index. With increase in interest rates and sluggish growth in 2023, also sentiment in the manufacturing sector deteriorated gradually.

Figure 3b distinguishes among the type of assessment: current and expected development. We observe an improvement in expectations already by mid-2020, while the assessment of the current situation was sluggish until the end of 2020. Expectations gradually deteriorated in 2022 and did not recover since. In the following, also the assessment of the current situation declined steadily.

4.2 Predicting GDP with the SEC index

In Sect. 3.1, we highlighted the usefulness of the SEC index to provide early signals for movements in GDP. In the following, we evaluate the informational content of the selected indicators' ability in this context. To this purpose, we rely on the composite indicator and establish out-of-sample GDP forecasts. We compare the suitability of the composite indicator with various alternative

[22] A fourth use case is presented in the Appendix, where we apply the Sahm rule to the SEC index (See Fig. 8).

commonly used indicators in Switzerland to assess the quality of our indicator and evaluate its inherent information content. The main challenge in this context concerns the choice of an appropriate statistical framework which allows to analyze jointly data of different sampling frequencies; in our case this applies to the (monthly) composite index or alternative monthly business cycle indicators on the one hand and quarterly GDP figures on the other.

A popular statistical framework in this respect is offered by means of so-called bridge equations. These have been used extensively to compute forecasts from mixed frequency data, as in Ingenito et al. (1996), Rünstler and Franck (2003), Baffigi et al. (2004), and Diron (2008).[23] The univariate bridge equation is given by:

$$y_{t_q} = \alpha + \gamma y_{t_q-1} + \beta(L)x_{t_q} + u_{t_q}, \tag{3}$$

in which y_{t_q} is quarterly GDP growth. The bridge equation contains a constant, α, and potentially an auto-regressive term, γy_{t_q-1}. The lag polynomial is given by $\beta(L) = \sum_{i=0}^{p} \beta_{i+1} L^i$, with $Lx_{t_q} = x_{t_q-1}$. The predictor x_{t_q} is our monthly SEC index $x_{t_{\{m\}}}$ aggregated to the quarterly frequency via the function $x_{t_q} = \sum_{j=0}^{3} \omega_j L^{j/\{3\}} x_{t_{\{m\}}}$, in which $\omega_j = 1/3$. This is an indirect forecasting procedure as it involves two steps: (1) forecasting the monthly indicator with auto-Arima such that the reference quarters are predicted; (2) time aggregation to obtain the quarterly prediction. Time aggregation is generally done by a simple arithmetic mean. We consider two distinct econometric models for the assessment: (i) bridge equations and (ii) bridge equations with auto-regressive elements (AR-Bridge), where the lag order is determined by BIC.

We mimic the regular forecasting routine as the practitioner would experience. Nevertheless, the forecast exercise is considered *pseudo* real time: (1) we draw real-time vintages for GDP growth from Indergand and Leist (2014) and an internal database; (2) we abstract from potential data revisions in the sentiment indicators; (3) we use the real-time constructed SEC index as it would have been constructed based on the information set available at the time of the prediction (see Sect. 3.2 for details and Fig. 7 in the Appendix).

Given this setup, we assess the usefulness of our proposed SEC index presented in Sect. 3 to forecast quarterly real GDP growth. We consider a horizon of (i) one quarter ahead (nowcasts) for which we distinguish among the first, second, and third month of a quarter and (ii) two quarters ahead (forecasts). Our forecasting exercise comprises a total of 268 months or 90 quarters of GDP to be predicted in the period 2001:M3-2023:M6. Following our definition of technical recessions used in Section 3, we exclude the quarters 2002:Q3–2003:Q2, 2008:Q3–2009:Q1, and 2020:Q1–2020:Q2 to account for the subsample without recessions. In addition, we exclude 2020:Q3 as it was shaped by the relaxation of containment measures in the wake of the COVID-19 pandemic. The estimation sample is recursively expanded over time.

4.2.1 Benchmarking

We calculate the relative root-mean-squared error (RMSE) to measure the predictive accuracy. As a benchmark, we estimate an AR(1)-model on the real-time vintages of quarterly (quarter-over-quarter) GDP growth.[24] Forecast errors are calculated relative to the first release of GDP.[25] The horizon refers to the number of months until the release of the quarterly GDP figure. For instance, in March 2023, GDP was available until the fourth quarter of 2022, while the monthly indicators were available until February 2023. We are interested in both the nowcast and the forecast. The former refers to the current quarter (i.e., January to March), while the latter refers to the next quarter (i.e., April to June). The GDP for the first quarter of 2023 will be published in June 2023, i.e., with a lag of two months with respect to the reference period. The forecast horizon is thus one quarter and three months before publication. For the forecast, GDP for the second quarter will be published in September 2023, i.e., with a lag of five months relative to the reference period.

We provide the results of this exercise in Table 4. In the first row, we report the RMSE of the benchmark univariate AR(1)-model. The second and third rows display the relative RMSE of two alternative models each containing our monthly SEC index: (i) a Bridge- and (ii) an AR-Bridge model. The relative RMSEs are shown together with significance levels from the modified Diebold–Mariano test,[26] where we test the hypothesis that the forecasts

[23] Other commonly used approaches are MIDAS (mixed data sampling) models (Ghysels et al., 2004, 2007) and the state-space approach in which the Kalman filter is run for the purpose of parameter estimation and forecasting (Rünstler and Franck, 2003; Bai et al., 2013). For brevity and simplicity, we do not compare a vast amount of different modeling approaches. We leave this for possible future work.

[24] Our results are qualitatively robust to other benchmarks such as random walk or an AR(p)-model with lags determined by the BIC. Results are available from the authors upon request.

[25] The results are qualitatively robust to calculating forecast errors relative to the final of GDP.

[26] Diebold and Mariano (1995) provide a pairwise test to analyze whether the differences between two or more competing models are statistically significant. As there is potentially a short-sample problem, we apply the modified version of the Diebold–Mariano test according to Harvey et al. (1997). We assessed the robustness of these results using the fixed-*b* test of Coroneo and Iacone (2020), in order to control for the presence of serially correlated errors and the small sample size. In the majority of pairwise comparisons, the results of the Coroneo and Iacone (2020) test confirm those of the modified Diebold–Mariano. The results are available upon request from the authors.

Table 4 Out-of-sample predictive accuracy relative to benchmark

	Full sample						**Without recessions**					
	Nowcasts			**Forecast**			**Nowcasts**			**Forecast**		
Horizon	1	2	3	4	5	6	1	2	3	4	5	6
Root mean squared errors												
AR(1)-model	15.30	15.3	15.30	13.00	12.90	12.90	3.57	3.57	3.57	6.10	6.08	6.08
Relative performance of SEC index												
SEC Bridge	0.644*	0.644*	0.620*	0.767*	0.855*	0.898	0.909	0.907	0.835*	0.514*	0.519	0.527
SEC AR-Bridge	0.820*	0.820*	0.772*	0.791**	0.882*	0.917	1.013	1.011	0.988	0.641*	0.686	0.650
Relative performance of alternative monthly indicators												
KOF Barometer	0.476	0.476	0.470	0.666	0.860	1.101	1.221	1.220	1.256	0.778	0.689	0.674
PMI Manufacturing CH	0.686	0.685	0.688	0.818*	0.867	0.889	1.157	1.149	1.081	0.571	0.556	0.536
PMI Manufacturing Foreign	0.631	0.631	0.620	0.711*	0.795*	0.884	1.118	1.116	1.059	0.579	0.551	0.542
SNB-BCI	0.410*	0.410*	0.369	0.386*	0.563	0.962	0.944	0.944	0.854	0.502*	0.672	0.834

Modified Diebold–Mariano test: the alternative hypothesis states that the monthly indicator is more accurate than the benchmark. Significance levels: *p value*: ***< 0.01, ** < 0.05, *< 0.1 of the modified Diebold–Mariano test (Harvey et al., 1997). Horizon refers to months until the GDP release of the respective quarter. For the target variable—GDP—the real-time vintages are used. Forecast errors are with respect to the first release. The estimation sample spans from 2001:M3-2023:M6 for the full sample. For the subsample without recessions, we exclude the quarters 2002:Q3–2003:Q2, 2008:Q3–2009:Q1 and 2020:Q1–2020:Q3

improve when using the SEC index; that is, the forecasts of any of the two Bridge models outperform the univariate AR(1)-benchmark model.

Table 4 presents the results: First, the two Bridge models with our SEC index give rise to a RMSE smaller than the benchmark model in most cases—the relative RMSE is only for the AR-Bridge model at horizons 1 and 2 months in the restricted sample above unity; second, the difference across the two Bridge models (Bridge versus AR1-Bridge) is negligible; third, in the full sample case, the statistical evidence is strong. The models with the monthly SEC index significantly outperform the univariate benchmark up to five months ahead; fourth, once considering normal episodes (without recessions), then the predictions of the SEC index are only at horizons three and four months statistically superior to the benchmark; fifth, the gain in predictive accuracy applies in both samples for both nowcasting and (short-term) forecasting GDP growth. In the sample without recessions, the gain from using the SEC index is particularly strong at high horizons: this is an indication of the leading property the SEC index contains due to the high amount of surveys featuring expectations.

4.2.2 Horse-race against other indicators

The previous discussion has underlined the gain in predictive accuracy when using the SEC index. A key question in this regard, however, concerns the gain in predictive accuracy of the SEC index relative to the gain of alternative monthly indicators. To this purpose, we challenge the predictive content not only against simple benchmarks, but also against well-established monthly business cycle indicators for the Swiss economy: (i) KOF Economic Barometer,[27] (ii) the manufacturing PMI, (iii) the export-weighted manufacturing (foreign) PMI, (iv) the Business Cycle Index of the Swiss National Bank (SNB-BCI). For this purpose, we use the previous Bridge model, now alternating on the monthly indicator to forecast GDP growth.[28]

The results are displayed in rows four to six of Table 4. As regards the full sample, the SEC index exhibits a somewhat lower RMSE in particular at short horizons than the SNB-BCI, and also against the KOF Barometer. In the restricted sample, the performance of the SEC index relative to these two alternatives improves substantially.[29] With respect to both manufacturing PMIs, there is strong evidence that the SEC index has superior predictive accuracy. At most horizons, the RMSE is lower, and the PMIs do not display significantly higher predictive accuracy than the benchmark most of the times.

[27] The KOF Economic Barometer is a leading composite indicator that shows how the Swiss economy is likely to develop. The database consists of over 500 indicators, of which only a subset is used, which though changes over time (Abberger et al., 2018)

[28] The analysis could be extended for yet other indicators, as for instance, financial market stress indicators (Cook and Taeyoung, 2021; Glocker and Kaniovski, 2014), uncertainty indicators (Poncela and Senra, 2017) and alike; we leave this open for future research in this respect.

[29] Note that the SNB-BCI is published with a significant lag and contains several hundred sub-indicators, among others, also many hard indicators.

To summarize, we find clear evidence that the SEC index is a powerful alternative for GDP nowcasting and forecasting relative to commonly used monthly business cycle indicators. This in turn implies that our SEC index is a valuable enrichment to the existing set of monthly business cycle indicators. Our index provides an adequate picture of real economic activity. Moreover, given the subsample stability of our results, the SEC index is useful for nowcasting and forecasting GDP growth during both recessionary and tranquil economic times.

4.3 Dispersion across the SEC index's constituent series as an uncertainty measure

Dispersion in economic sentiment, employed as a gauge of uncertainty, pertains to the extent of variability or divergence in sentiment and confidence levels voiced by individuals, businesses, or other economic actors within an economy or market (Girardi and Reuter, 2017). This concept holds significant utility in economic analysis and forecasting for assessing the degree of uncertainty prevailing in economic conditions (Born et al., 2023).

Our methodology is readily applicable for this purpose. It involves the examination of cross-sectional dispersion among the sentiment indicators that constitute the SEC index. This approach is akin to the one presented in Girardi and Reuter (2017), who measure dispersion across four distinct survey questions related to expectations (business conditions, production, employment, and order books) to construct an uncertainty measure. Building upon this example, we formulate a measure for uncertainty by considering all the sub-indicators employed in the SEC index and quantify the dispersion as one standard deviation (std.) from the mean of the indicators at each point in time. The resulting dispersion-measure hence captures the extent of variations among the constituent survey-based indicators in our sample which offers a valuable means of quantifying uncertainty.

The resulting uncertainty measure is displayed in Fig. 4. Evidently, uncertainty was particularly high during the COVID-19 pandemic in 2020 and 2021. Some heightened uncertainty can also be observed in the wake of the financial crisis of 2008–09. A particular spike can be detected at the beginning of 2015, when the SNB removed the lower bound on the Swiss Franc versus the Euro exchange rate. Further, Fig. 5 compares the level of the SEC index and the measure of uncertainty by means of a scatter plot. The figure illustrates the relationship

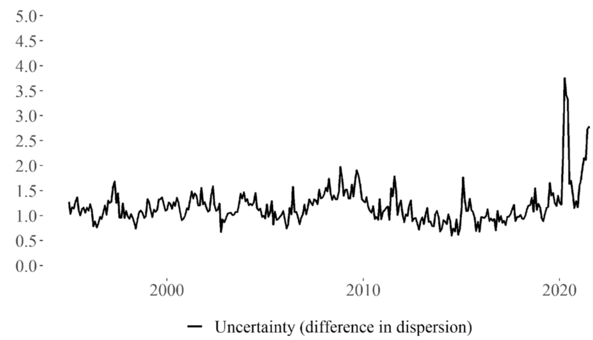

Fig. 4 The uncertainty measure

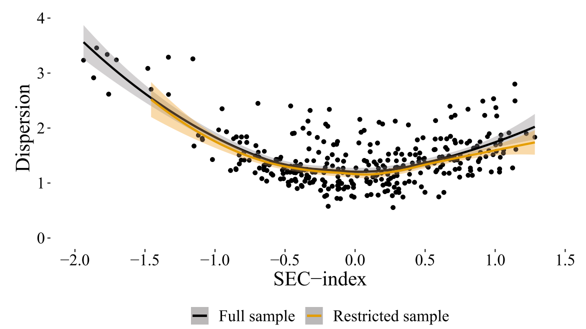

Fig. 5 The SEC index and uncertainty

between the level of the SEC index, depicted on the x-axis, and the uncertainty measure, depicted on the y-axis. The scatter plot comes along with a Local Polynomial Regression Fitting (LOESS), following Cleveland et al. (2017). We use the default degree of smoothing $\alpha = 0.75$, implying that around a point x, the fit is made using 75 % of the data in the neighborhood of x. We plot the fitted values along with a 95 % confidence interval. The restricted sample excludes the years 2002, 2009, 2020, and 2021.

It reveals a convex relationship, indicating that elevated levels of uncertainty correspond to both low and high values of the SEC index. Notably, uncertainty is particularly pronounced when the SEC index reaches extremely high or low values. Potential reasons for the observed convex pattern include information asymmetries and psychological factors, among other contributing factors. Information asymmetry suggests that as the SEC index strays from the norm (i.e., its mean value), the reliability and interpretability of the underlying data may diminish, thus contributing to heightened uncertainty. On the other hand, psychological factors suggest that extreme values within the SEC index could evoke fear or exuberance within certain sentiment indicators, consequently amplifying uncertainty across the entirety of sentiment indicators.

In principle, the uncertainty indicator can also serve as a tool for economic forecasting, much alike what was demonstrated with the SEC index in Sect. 4.2. However, we abstain from pursuing this endeavor, as it falls outside the primary scope of this study. Instead, we direct interested readers to Glocker and Hölzl (2022), who evaluate the out-of-sample forecasting performance of various uncertainty measures.

5 Conclusions

This paper's primary contribution revolves around the identification, collection, and examination of survey-based data pertaining to the Swiss economy. These surveys cover various aspects, including investor, business and household confidence and expectations, for which we observe a significant increase in the availability of such data over the past quarter of a century.

We synthesize the information from these indicators into the *SEC index*, a single monthly composite indicator which captures the sentiment tendency of economic agents as reflected in the domestic surveys. By providing such an overall measure, the impact of quality deficiencies of individual survey-based indicators can be mitigated. This is established by imposing only a handful of transparent and widely agreeable constraints on the survey indicators co-movement with real GDP.

We discuss the practical possibilities of the SEC index in the context of three use cases. First, we examine the use of the SEC index and its constituent series from a practitioners point of view during an episode of pronounced economic turmoil. Second, we study the composite indicator's forecast accuracy for real GDP. We show that the SEC index performs well in predicting GDP growth in real time and even outperforms commonly used monthly business cycle indicators as for instance, the PMI and alike. Finally, the third use case discusses the use of the selected survey indicators as the key ingredients for measuring economic uncertainty in Switzerland.

In conclusion, the organization of a collection of survey-based indicators in the form of our SEC index represents a valuable enhancement to the current array of monthly business cycle indicators. It offers a comprehensive representation of actual economic activity and demonstrates superior nowcasting and forecasting capabilities for GDP growth compared to existing monthly indicators. This development stands to greatly benefit analysts and policymakers in their efforts to promptly and accurately assess the prevailing state of the Swiss economy's business cycle.

Appendix

See Table 5, Figs. 6, 7 and 8.

Table 5 Final set of indicators comprised in SEC index

Source	Sector/Agent	Survey	Index
SECO	Consumers	Consumer sentiment	Expected General Economic Situation, SA, Index
UBS & CFA Society	Investors	Credit Suisse & CFA Society	Short-Term Interest Rates, Balance
UBS & CFA Society	Investors	Credit Suisse & CFA Society	Export Expectations, Balance
UBS & CFA Society	Investors	Credit Suisse & CFA Society	Current Economic Situation, Balance
UBS & CFA Society	Investors	Credit Suisse & CFA Society	Inflation Rate , Balance
UBS & CFA Society	Investors	Credit Suisse & CFA Society	Unemployment Rate, Balance
UBS & CFA Society	Investors	Credit Suisse & CFA Society	Economic Expectations, Balance
Sentix	Investors	Economic Indices	Headline Index (Expectations)
Sentix	Investors	Economic Indices	Institutional Investors (Expectations)
Sentix	Investors	Economic Indices	Individual Investors (Expectations)
KOF	Manufacturing	Manufacturing	Incoming Orders, Change Previous Month Compared to Same Month of Previous Year, Balance, SA
KOF	Manufacturing	Manufacturing	Foreign Order Backlog, Assessment, Balance, SA

Table 5 (continued)

Source	Sector/Agent	Survey	Index
KOF	Manufacturing	Manufacturing	Order Backlog, Change Previous Month Compared to Month Before, Balance, SA
KOF	Manufacturing	Manufacturing	Incoming Orders, Change Previous Month Compared to Month Before, Balance, SA
KOF	Manufacturing	Manufacturing	Production, Change Previous Month Compared to Month Before, Balance, SA
KOF	Manufacturing	Manufacturing	Production, Change Previous Month Compared to Same Month of Previous Year, Balance, SA
KOF	Manufacturing	Manufacturing	Stock of Intermediate Goods, Assessment, Balance, SA
KOF	Manufacturing	Manufacturing	Stock of Final Goods, Assessment, Balance, SA
KOF	Manufacturing	Manufacturing	Profit Situation, Change Past 3 Months, Balance, SA
KOF	Manufacturing	Manufacturing	Purchase of Intermediate Goods, Expected Change Next 3 Months, Balance, SA
KOF	Manufacturing	Manufacturing	Production, Expected Change Next 3 Months, Balance, SA
KOF	Manufacturing	Manufacturing	Incoming Orders, Expected Change Next 3 Months, Balance, SA
KOF	Manufacturing	Manufacturing	Number of Employees, Expected Change Next 3 Months, Balance, SA
KOF	Manufacturing	Manufacturing	Exports, Expected Change Next 3 Months, Balance, SA
KOF	Manufacturing	Manufacturing	Business Situation, Expected Change Next 6 Months, Balance, SA
Procure.ch & UBS	Manufacturing	Purchasing Managers' Index	Output, SA, Index
Procure.ch & UBS	Manufacturing	Purchasing Managers' Index	Backlog of Orders, SA, Index
Procure.ch & UBS	Manufacturing	Purchasing Managers' Index	Quantity of Purchases, SA, Index
Procure.ch & UBS	Manufacturing	Purchasing Managers' Index	Purchase Prices, SA, Index
Procure.ch & UBS	Manufacturing	Purchasing Managers' Index	Suppliers' Delivery Times, SA, Index
Procure.ch & UBS	Manufacturing	Purchasing Managers' Index	Employment, SA, Index
KOF	Services	Business Situation	Financial Services, SA
KOF	Services	Financial & Insurance Service Sectors	Business Situation, Assessment, Balance, SA
KOF	Services	Financial & Insurance Service Sectors	Business Situation, Change Past 3 Months, Balance, SA
KOF	Services	Financial & Insurance Service Sectors	Demand, Change Past 3 Months, Balance, SA
KOF	Services	Financial & Insurance Service Sectors	Business Situation, Expected Change Next 6 Months, Balance, SA
KOF	Services	Service Sectors	Business Situation, Expected Change Next 6 Months, Balance, SA
KOF	Services	Service Sectors	Demand, Expected Change Next 3 Months, Balance, SA
KOF	Trade	Wholesale Trade	Volume of Stock, Assessment, Balance, SA
KOF	Trade	Wholesale Trade	Business Situation, Expected Change Next 6 Months, Balance, SA

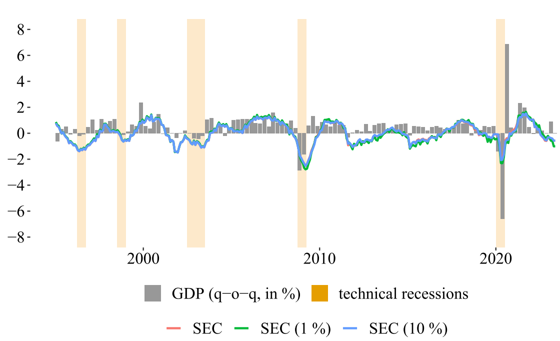

Fig. 6 Quarterly Swiss economic sentiment—different thresholds

Fig. 7 Swiss economic confidence—SEC

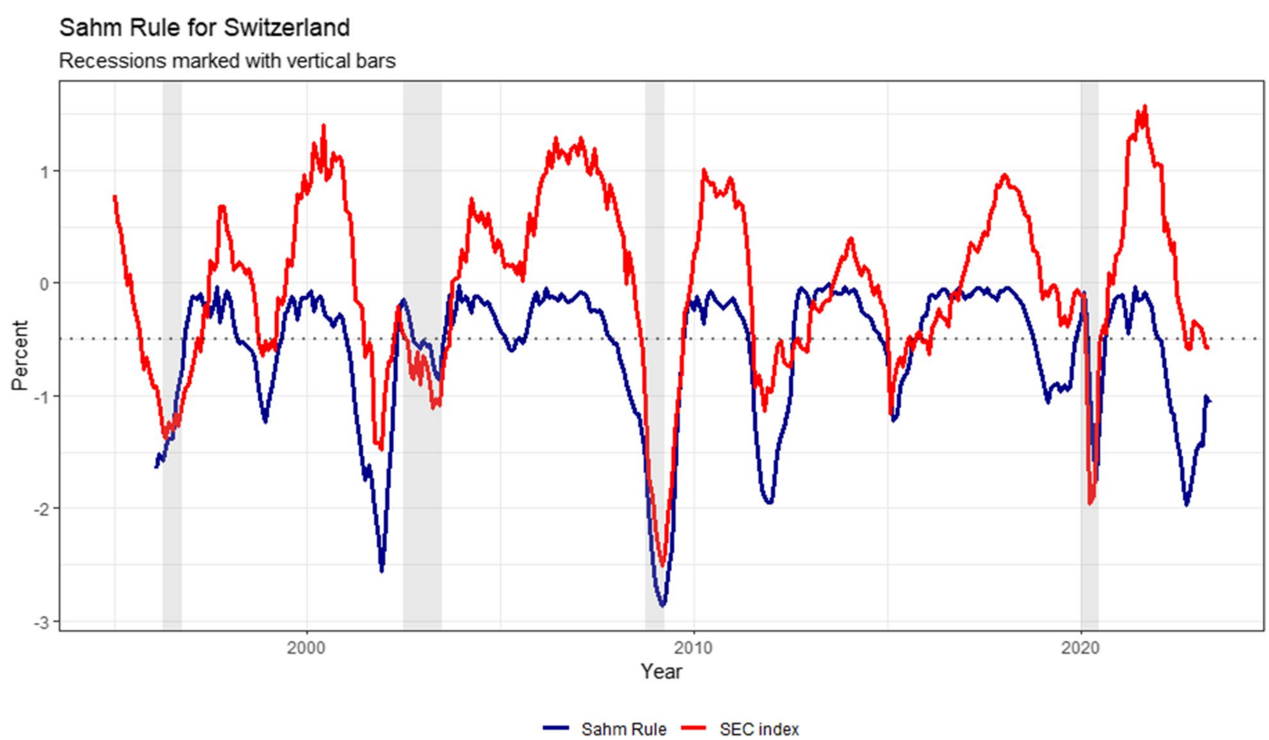

Fig. 8 Sahm rule for SEC index

We also benchmarked our index against the so-called Sahm rule. The Sahm Recession Indicator signals the start of a recession in the USA when the three-month moving average of the national unemployment rate (U3) rises by 0.50 percentage points or more relative to the minimum of the three-month averages from the previous 12 months. This implies that the Sahm rule is in fact a lagging indicator, meaning it tells you there is a recession after the recession has already started. We applied the same logic to the SEC index. However, note that we have to invert the rule, meaning a deterioration of sentiment goes along with a slowdown of economic activity. The result is illustrated in Fig. 1. The indicator aligns well with the recessionary periods, except for the COVID19-period.

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Author contributions
All authors jointly developed the idea, conducted data analysis, interpreted the results, and were major contributors in writing the manuscript. All authors proof-read and approved the manuscript.

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Data availability
The data are made available to the public on the website https://www.seco.admin.ch/sec. The index is updated monthly with a delay of around 15 days. Codes for replication are available from the authors upon request. It should be noted that the published SEC index, as provided on the homepage, consists of 30 survey indicators, as selected by our procedure in November 2019. An update of the set of indicators occurs only periodically for user-friendliness. The next update is planned together with the revision of the quarterly Swiss GDP data in September 2024.

Declarations

Competing interests
The authors declare that they have no competing interests.

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References

Abberger, K., Graff, M., Siliverstovs, B., & Sturm, J.-E. (2018). Using rule-based updating procedures to improve the performance of composite indicators. *Economic Modelling, 68*, 127–144.
Baffigi, A., Golinelli, R., & Parigi, G. (2004). Bridge models to forecast the euro area GDP. *International Journal of Forecasting, 20*(3), 447–460.
Bai, J., Ghysels, E., & Wright, J. H. (2013). State space models and MIDAS regressions. *Econometric Reviews, 32*(7), 779–813.
Ball, L., & Romer, D. (1991). Sticky prices as coordination failure. *The American Economic Review, 81*(3), 539–552.
Born, B., Dovern, J., & Enders, Z. (2023). Expectation dispersion, uncertainty, and the reaction to news. *European Economic Review, 154*, 104440.
Carriero, Andrea, Marcellino Massimiliano, and Mazzi Gian Luigi (2017) 'Definitions and taxonomy of indicators.' *Handbook of Cyclical Composite Indicators for Business Cycle Analysis* 75–95
Carriero, Andrea, Todd E Clark, and Massimiliano Marcellino (2015) 'Realtime nowcasting with a Bayesian mixed frequency model with stochastic volatility.' *Journal of the Royal Statistical Society. Series A,(Statistics in Society)* 178(4), 837
Carrington, William J, John L Eltinge, and Kristin McCue (2000) 'An Economist's Primer on Survey Samples.' Working Papers 00-15, Center for Economic Studies, U.S. Census Bureau, September
Claveria, O., Monte, E., & Torra, S. (2018). A data-driven approach to construct survey-based indicators by means of evolutionary algorithms. *Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement, 135*(1), 1–14.
Cleveland, William S, Eric Grosse, and William M Shyu (2017) 'Local regression models.' In 'Statistical models in S' (Routledge) pp. 309–376
Cook, Thomas R., & Doh, Taeyoung. (2021). To improve the accuracy of gdp growth forecasts, add financial market conditions. *Economic Bulletin, 1*(2), 1–5.
Coroneo, L., & Iacone, F. (2020). Comparing predictive accuracy in small samples using fixed-smoothing asymptotics. *Journal of Applied Econometrics, 35*(4), 391–409.
Dalla, V., Giraitis, L., & Phillips, P. C. B. (2022). Robust tests for white noise and cross-correlation. *Econometric Theory, 38*(5), 913–941.
Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics, 13*(3), 253–263.
Diron, M. (2008). Short-term forecasts of Euro area real gdp growth: dn assessment of real-time performance based on vintage data. *Journal of Forecasting, 27*(5), 371–390.
Farmer, Roger EA (1999) *The macroeconomics of self-fulfilling prophecies* (mit Press)
Frale, C., Marcellino, M., Mazzi, G. L., & Proietti, T. (2010). Survey data as coincident or leading indicators. *Journal of Forecasting, 29*(1–2), 109–131.
Frale, C., Marcellino, M., Luigi, G. M., & Proietti, T. (2010). Survey data as coincident or leading indicators. *Journal of Forecasting, 29*(1–2), 109–131.
Galli, A. (2018). Which indicators matter? Analyzing the swiss business cycle using a large-scale mixed-frequency dynamic factor model. *Journal of Business Cycle Research, 14*(2), 179–218.
Gayer, Christian, Marc, Bertrand, et al. (2018). 'A 'new modesty'? level shifts in survey data and the decreasing trend of normal'growth.' Directorate General Economic and Financial Affairs (DG ECFIN), European Comission: Technical Report.
Ghysels, E., Sinko, A., & Valkanov, R. (2007). Midas regressions: Further results and new directions. *Econometric Reviews, 26*(1), 53–90.
Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov (2004) 'The midas touch: Mixed data sampling regression models.' Technical Report, Working paper, UNC and UCLA
Girardi, A., & Reuter, A. (2017). New uncertainty measures for the Euro Area using survey data. *Oxford Economic Papers, 69*(1), 278–300.
Glocker, Christian, & Wegmueller, Philipp. (2020). Business cycle dating and forecasting with real-time Swiss GDP data. *Empirical Economics, 58*, 73.
Glocker, C., & Kaniovski, S. (2014). A financial market stress indicator for Austria. *Empirica, 41*(3), 481–504.
Glocker, C., & Hölzl, W. (2022). A direct measure of subjective business uncertainty. *German Economic Review, 23*(1), 121–155.
Gyomai, G, N Ahmad, and R Astolfi (2016) 'The OECD System of Composite leading indicators.' *Eurostat Handbook on cyclical composite indicators*
Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting, 13*(2), 281–291.
Illing, M., & Liu, Y. (2006). Measuring financial stress in a developed country: An application to canada. *Journal of Financial Stability, 2*(3), 243–265.
Indergand, R., & Leist, S. (2014). A real-time data set for Switzerland. *Swiss Journal of Economics and Statistics, 150*(4), 331–352.
Ingenito, Robert, Bharat Trehan et al. (1996) 'Using monthly data to predict quarterly output.' *Economic Review* pp. 3–11.
Joint Research Centre-European Commission (2008) *Handbook on constructing composite indicators: methodology and user guide* (OECD publishing)

Juodis, A., & Kučinskas, S. (2023). Quantifying noise in survey expectations. *Quantitative Economics, 14*(2), 609–650.
Kim, H. H., & Swanson, N. R. (2018). Mining big data using parsimonious factor, machine learning, variable selection and shrinkage methods. *International Journal of Forecasting, 34*(2), 339–354.
Kugler, Peter, & Sheldon, George. (2023). A monthly leading indicator of swiss gdp growth based on okun's law. *Swiss Journal of Economics and Statistics, 159*(1), 11.
Lenza, M., & Primiceri, G. E. (2022). How to estimate a vector autoregression after March 2020. *Journal of Applied Econometrics, 37*(4), 688–699.
Mazzi, G. L., Ozylidririm, A., & Mitchell, J. (2017). *Alternative detrending methods*. Handbook on cyclical composite indicators for business cycle analysis: Eurostat.
Milgrom, P., & Roberts, J. (1990). Rationalizability, learning, and equilibrium in games with strategic complementarities. *Econometrica, 58*(6), 1255–1277.
Ozyildirim, Ataman (2019) 'Compiling cyclical composite indexes: The conference board indicators approach.' *Business cycles in BRICS* pp. 303–313
Poncela, P., & Senra, E. (2017). Measuring uncertainty and assessing its predictive power in the euro area. *Empirical Economics, 53*(1), 165–182.
Rünstler, Gerhard, & Franck Sédillot (2003) 'Short-term estimates of euro area real GDP by means of monthly data.' Technical Report, ECB working paper
Wegmüller, P., Glocker, C., & Guggia, V. (2023). Weekly economic activity: Measurement and informational content. *International Journal of Forecasting, 39*(1), 228–243.

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