Three Centuries of Swiss Economic Sentiment*

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Abstract

There is a lack of consistent and well-measured Swiss business cycle indicators over long historical episodes. This paper fills this gap by constructing a business cycle indicator on quarterly frequency spanning from 1820 to 2021. Using textual data such as historical company records, newspapers, and business association reports, I develop a business cycle indicator, drawing on sentiment and count-based measures related to key economic concepts. This approach involves extensive data collection, surpassing existing datasets in scope and historical coverage. The composite indicator demonstrates strong correlations with real economic activity, effectively capturing historical downturns and expansions. I also employ it to estimate recession probabilities, shedding light on Switzerland's economic history. This paper contributes by introducing a comprehensive business cycle indicator, assembling a rich textual dataset, presenting innovative text mining methods, and establishing the first business cycle dating for Switzerland in the 19th and early 20th centuries.

Keywords: 19th century, 20th century, business cycles, Switzerland, qualitative coincident indicators, textual analysis, sentiment analysis

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1 Introduction

> "The farther backward you can look, the farther forward you are likely to see."
>
> — Winston Churchill

Churhill's insight resonates profoundly with the objective of this paper, which takes on the challenge of uncovering Switzerland's economic history. A story not fully told due to a lack of well-measured economic data for the 19th and early 20th centuries. In the first instance, consistent and well-measured gross domestic product (GDP) statistics are missing. There is only a tentative estimate of annual GDP since 1851 and no information before that (see Historische Statistik der Schweiz HSSO, 2012k; Stohr, 2016). Moreover, real GDP estimates suffer from error-prone deflators that bias econometric estimates and descriptive statistics (Kaufmann, 2020).

Within the last three centuries Switzerland transformed from a group of farming regions to a leading global economic player (Church & Head, 2013). To shed light on this transformation, this paper introduces a business cycle indicator covering long historical episodes, created from a diverse mix of historical documents. This approach breaks new ground by using written narratives to fill in the gaps where traditional economic data is missing or inaccurate.

Because hard data is difficult to measure retrospectively, in this paper, I address this challenge by using textual data to develop a quarterly business cycle indicator for Switzerland, spanning the 19th, 20th, and 21st centuries. Given the impossibility of asking people and businesses from the past about their financial and economic situation, I rely on alternative sources like business reports, association documents, and newspapers to construct a qualitative historical perspective. The method is inspired by the work of Burri (2023), combining several sentiment and count-based indicators drawn from key economic concepts relevant to Swiss economic history. The approach involves extensive data work, including manually collecting sources from archives and converting them into a machine-readable format. This work has resulted in an immense and unique textual database for the construction of the indicator (refer to Table 1 for a complete list of sources).

The developed indicator effectively captures key economic downturns, including the major recessions of the late 20th and early 21st centuries, as well as historical crises like the two world wars and the Great Depression. Notably, the indicator also sheds light on lesser-known economic disturbances in the 19th century, such as the Sonderbund War and the Franco-Prussian War. The indicator's ability to mirror real economic activity in Switzerland, especially in recent decades, validates its accuracy and underscores its ability as a tool for economic analysis.

Furthermore, the paper provides a first business cycle chronology for Switzerland in the 19th and early 20th centuries, a period previously lacking systematic economic analysis. My research reveals that Swiss recessions have become less frequent over time, aligning with broader European economic trends (Broadberry & Lennard, 2023). However, contrary to the commonly held belief, the duration of recessions does not exhibit a significant decrease over the studied periods. This finding challenges some prevailing narratives about the nature of economic cycles. Additionally, the paper confirms that Switzerland's economic cycles have increasingly synchronized with those of its neighboring countries in the 20th century.

The foundational work of Thorp (1926) and Burns and Mitchell (1946) serves as a basis for my approach of utilizing textual data to create a business cycle indicator and chronology. Thorp (1926), utilized narrative accounts to describe the business cycle, highlighting the importance of qualitative data when hard data is missing. Burns and Mitchell (1946) further developed this field by introducing a more systematic and empirical approach to identifying economic cycles, emphasizing the analysis of a wide range of economic indicators. This paper bridges these methodologies by integrating advanced computational techniques to convert textual records (qualitative business annals) into a quantifiable time series akin to Burns and Mitchell's (1946) methodology.

The importance of stories and public discourse in shaping economic trends was emphasized by Shiller (2017, 2019). Narratives, often rooted in credible business and media sources, serve dual purposes: they reflect the economic conditions of their time and can influence future economic decisions and policies. Shiller's insights into the power of narratives underscore the potential of textual data as a rich source of economic information, paving the way for its application in diverse economic analyses.

The paper is related to a growing body of research that uses textual data to measure economic activity and sentiment.[1] The study by Kabiri et al. (2022), which develops

[1] Textual data are also used for a variety of other purposes in economics, such as predicting stock returns (Hirshleifer et al., 2023; Tetlock, 2007), measuring economic policy uncertainty (Ardia et al., 2021; Baker et al., 2016; Larsen, 2021), identifying monetery policy shocks (Aruoba & Drechsel, 2022; Ter Ellen et al., 2022), and measuring inflation expectations (Angelico et al., 2022; Binder, 2016; Larsen et al., 2021). Ash and Hansen (2022) and Beach and Hanlon (2022) provide an extensive review.

a monthly sentiment index for the United States from 1920 to 1934, is most closely aligned with this paper in its historical approach. For more contemporary periods, Burri and Kaufmann (2020), Bybee et al. (2020), Larsen and Thorsrud (2019), Shapiro et al. (2020), and Thorsrud (2020) have utilized text mining and machine learning to analyze newspaper articles, creating leading indicators and business cycle measures. Complementing these efforts, studies by Ardia et al. (2019), Barbaglia et al. (2022), Burri (2023), Ellingsen et al. (2021), and Kalamara et al. (2022) demonstrate the effectiveness of textual data in predicting various economic variables.

This paper distinguishes itself from existing studies in several key aspects. While previous research, primarily focused on contemporary data over short periods, this paper ventures into uncharted territory by applying similar methodologies to long historical episodes. Another difference lies in the source and scope of the textual data used. Unlike studies that primarily rely on well structured and often categorized newspaper articles, this paper employs a broader range of historical documents, including business reports, association documents, and archival material. This unique and diverse corpus not only enriches the analysis but also makes it more complex, and thus requiring adequate methodology.

My contribution to this body of research is multifaceted. Firstly, I introduce a business cycle indicator that stands as the most extensive record of Swiss economic activity to date. This indicator is unique in its quarterly frequency, offering a more detailed perspective. Secondly, I assemble an extensive and unique textual dataset by systematically gathering and digitizing a wide range of sources relevant to Swiss economic history. Thirdly, I present an innovative method for extracting meaningful insights from noisy and heterogenous historical text sources. Lastly, I establish the first business cycle dating for Switzerland in the 19th and early 20th centuries.

The remainder of this paper is organized as follows. In the next section, I describe what textual data I use and how I convert it into machine readable format. Moreover, I discuss the variables that I use for validating the indicator. Section 3 explains the methodology. Results are discussed in section 4. I use the developed indicator to identify phases of recession in Swiss economic history in section 5. In section 6 I conduct a series of robustness checks. The last section concludes.

2 Data

I follow Burri (2023) in developing qualitative business cycle indicators for hand-selected economic concepts using textual analysis of company records, business association reports, and newspapers. Therefore, I collected a vast amount of textual data from various archives and libraries. The text data is either already digitized by the data provider or by myself. In this section, I first discuss how I put some structure on this unstructured pile of texts. That is, how I process the scanned images and put them into machine readable format as well as how I parse their layout. Moreover, I discuss the data used for validating the indicators.

2.1 Textual data

The indicators for measuring business cycle fluctuations are based on textual analysis of historical documents.[2] Therefore, I have put a substantial effort into collecting and digitalizing historical documents relevant for business cycle fluctuations. Annual reports of companies, and reports of national and regional business associations stem largely from the Wirtschaftsarchiv Basel, whereas newspapers primarily stem from e-newspaperarchives.ch and scriptorium.bcu-lausanne.ch. Most of the newspapers are already in machine-readable format. Therefore, I only had to apply optical character recognition (OCR) to the documents that I have scanned myself and to those where the OCR is of poor quality. Already digitized data are either in PDF or METS/ALTO format.[3] In total we collected 107 sources in German and French language. The raw data size of these almost 100 millions of texts is close to 7 Terabyte.

2.1.1 Scanning documents

I only selected documents to scan that likely comprise information about the business cycle. These either concern a textual description of a company's own situation (largely annual reports of companies) or a description of the state of the economy in different sectors (largely reports of business associations). Figures 1-2 show examples of scanned pages from the annual report of the Chambre vaudoise du commerce et de l'industrie

[2] See table 1 in the Appendix for a comprehensive list of all data sources. Figure 7 provides information on how many sources were available for each period.

[3] METS/ALTO files are types of digital files used to store information about documents, such as books or articles, in a structured way. METS describes the structure of the document, like its chapters or pages, while ALTO contains the actual text of the document along with details about its layout, formatting, and coordinates of each element on the page. Especially for larger documents with many pages, these files can be resource-intensive to process with statistical software. As a result, loading METS/ALTO files can take a long time. I developed R routines to read METS/ALTO files in parallel which might be useful to researchers. Find more informations here: https://marcburri.github.io/posts/2023/09/11/mets-alto-r/.

(1923) and the insurance company Helvetia (1860). From a substantive point of view, the paragraphs comprise a discussion of the weak industry sector and an assessment of the business situation conditional on the difficult political situation of the insurance company. Thus, firms and business associations regularly judged the economic situation in their writing.

2.1.2 Image pre-processing

After scanning these reports, the files have to be prepared for text recognition. I therefore set up an image pre-processing procedure that ameliorates the quality of the scans and makes it easier to convert the documents into machine-readable format. This step includes cropping the images, turning them into black and white (eventually erasing shimmering text from the back side), removing the curvature of the text (stemming from bent book pages), removing speckles, and sharpening the contrast of the documents.[4] Figures 1-2 show that the quality of the pre-processed image is improved, which in turn improves the following OCR.

2.1.3 Optical text recognition (OCR)

Converting the images into machine-readable text format is a key step. Therefore, I use the Abbyy FineReader software based on machine-learning techniques which is widely used for larger-scale digitizing projects. Figures 1 - 2 show the recognized text with that software. From a technical point of view, they demonstrate that it is possible to recognize text in high quality from different fonts and languages. It is evident that we can readily convert normal font and gothic type into machine-readable text. However, the examples are not perfect. In particular, the software has trouble recognizing the punctuation marks correctly. But this is not a serious problem, because they will be deleted in a further step anyway. Overall, these examples demonstrate, however, that it is possible to convert the images of the scanned documents into text quite accurately.

2.1.4 Layout parsing

We have different types of publications. Therefore the length of texts differ. Annual reports might potentially be several hundred pages long. On the other side newspaper articles seldom exceed one page. Moreover there are advertisements and tables that do not contain valuable information. Therefore I also use the Abbyy software for parsing the layout of publications for which this has not been done before. Figure 3 shows an example of a parsed layout. It is obvious that title, paragraphs as well as tables can be

[4]Mostly I used the CamScanner application for mobile devises to conduct these steps. In a few cases I also used ScanTailor.

easily identified. This has several advantages. First, long texts from annual reports can be split into shorter paragraphs. Many of these do not contain any useful information. Second, tables and figures can be identified and filtered out.

2.2 Validation data

Validating the indicator is difficult, especially for the 19th century when data on real economic activity is scarce and inaccurately measured. Nevertheless, I collect as much real activity data as possible covering the 19th century to calculate correlations and validate the accuracy of the indicator. In this section I briefly describe the collected data for validation and explain why it should be correlated with the business cycle indicator. An extensive overview and data sources are listed in Table 2 in the Appendix.

2.2.1 Data on real activity

The indicator developed in this paper is a measure of the business cycle. Therefore, it should be correlated with real economic activity. Real GDP is one of the most widely used measure of real economic activity. However, GDP growth rates only provide a snapshot of how much the economy has grown from one period to the next, but not whether that growth is above or below the economy's potential. Therefore, I mainly use the output gap as a validation measure. The output gap is the difference between actual and potential GDP. It is a measure of the extent to which the economy is operating above or below its potential. The output gap is a useful indicator of the health of the economy and the degree of inflationary pressures.

The output gap is calculated as suggested by Hamilton (2018). That is I estimate an OLS regression of GDP in logs, y_{t+h}, on a constant and the $p = 2$ most recent values of y as of date t,

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + v_{t+h}$$

where the residuals

$$\hat{v}_{t+h} = y_{t+h} - \hat{\beta}_0 - \hat{\beta}_1 y_t - \hat{\beta}_2 y_{t-1}$$

offer a reasonable way to construct the cyclical component, that is the output gap. As suggested by Hamilton (2018), $h = 2$ for annual data.

For Switzerland, annual GDP data in real and nominal terms for the 19th century is presented in Historische Statistik der Schweiz HSSO (2012k). The authors state that some sector estimates of value added have "the characteristics of a rough estimate at best". For instance, in relation to estimates of the wholesale and retail value added, they "did not have sufficient data to reliably estimate the value added of this important branch". Based on this dataset, Stohr (2016) estimates an improved GDP series by refining the estimation of certain branches.[5] This estimate serves as a crucial reference point for the business cycle indicator. As the reference series, I use Stohr's (2016) single-deflated estimate from 1851-1890 and the double-deflated estimate for the period from 1890 to 1947.[6] For the period from 1948 to 2022, I use the official GDP figures from the Swiss Federal Statistical Office (FSO).

Because Swiss GDP is not accurately measured for the 19th century and business cycles tend to be international in nature, I also compare the business cycle indicator to estimates for real GDP growth and the output gap of various countries. In particular, to Switzerland's neighboring countries as well as the USA and England. The data is taken from the Maddison database (Bolt & van Zanden, 2020). Finally, I also use world GDP, Swiss GDP per capita, data on trade, and data on the Swiss labor market as validation measures.

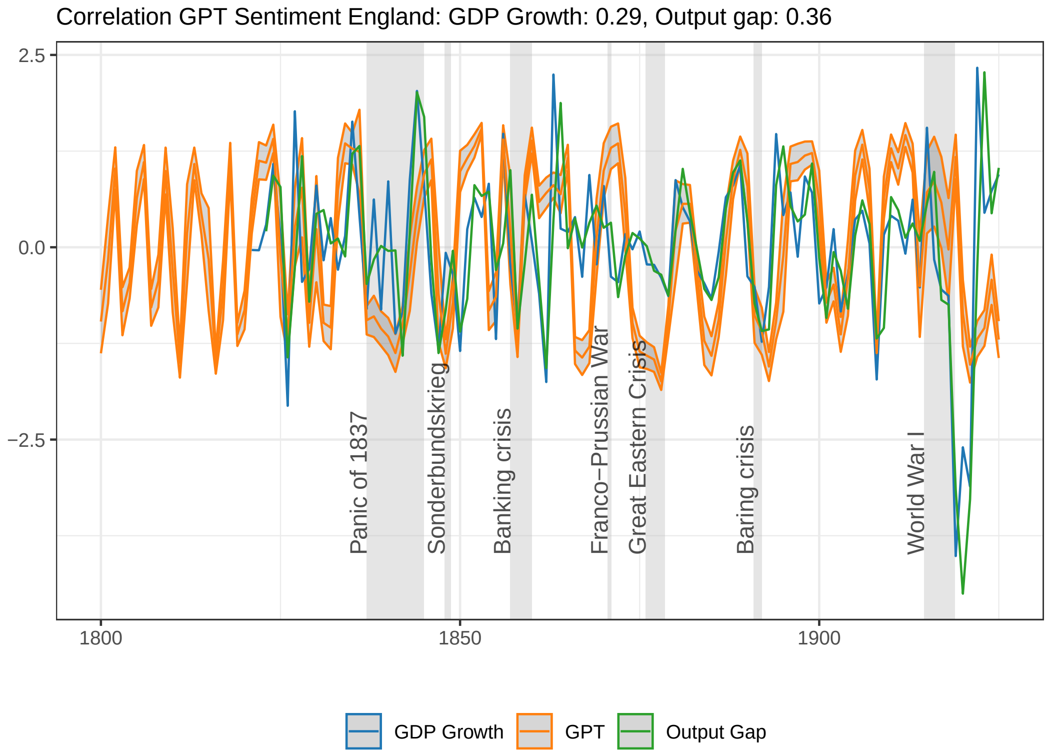
2.2.2 Thorp GPT Sentiment

The validation indicators discussed above are hard data, likely measured with error in the early periods. The proposed business cycle indicator in contrast, is a qualitative indicator based on sentiments from textual analysis. There is, however, no existing qualitative indicator for the 19th century that I can use for validation. In his book, Thorp (1926) provides a detailed narrative account of the busines cycle in selected countries for every single year up to 1925. He describes the business cycle in terms of the state of the economy, the financial situation, and the state of the labor market. I therefore use his account to create a qualitative sentiment indicator for Switzerlands neighboring countries as well as for England and the USA using large language models (LLM) and use them as validation measures.[7] In particular, I use OpenAI's (2023) GPT-3.5 model and repeatedly feed it with ten years of Thorp's (1926) descriptions and ask it to rate the state of the economy in a given year from -5 to 5. The mean over all ratings serves as the sentiment indicator. I provide more details on the creation of these sentiment indicators in Appendix B

Figure 1 shows this sentiment indicator for England (orange line) together with one standard deviations confidence bands. These bands are rather narrow, suggesting the model is quite confident about its predictions. Only during World War I, the confidence bands are wider indicating that the model is less confident about the state

[5]This series is available in the Maddison project database (Bolt & van Zanden, 2020).
[6]See Stohr (2016) and Stohr (2017) for more information about single- and double-deflated GDP
[7]Unfortunately Thorp (1926) does not provide a narrative account for Switzerland.

Figure 1 — Thorp GPT sentiment indicator for England



Notes: This graph shows the normalized sentiment indicator (in orange) based on Thorp's (1926) texts and OpenAI's (2023) GPT-3.5 model together with one standard deviation confidence bands. In blue real GDP growth and in green the output gap calculated from the series provided by Bolt and van Zanden (2020). Gray shaded areas represent crises.

of the economy. From a narrative viewpoint, it is evident that the sentiment indicator is correlated with the business cycle. There is a decrease of the sentiment for all major crises during that period. Moreover, the correlation between the sentiment indicator and the output gap is 0.36. The results look similar for the other countries.[8]

3 Methodology

The methodology for constructing the business cycle indicator is combining tools from several fields. First, I use natural language processing (NLP) techniques to extract information from the textual data. Second, I use methods from time series econometrics to correct for anomalies in the data. Finally, I use machine learning techniques to combine the different indicators into a composite indicator of the business cycle. In this section I describe the methodology used to extract information from text, to create

[8]See Figure 16 in the Appendix for the sentiment indicators for the other countries.

topic-specific indicators, and ultimately to create a composite indicator of the Swiss business cycle.

3.1 Extracting economic signals from text

The texts contain a lot of information that is not relevant for the business cycle indicator. For instance, advertisements, tables, and figures do not contain information about the business cycle. Therefore, I use the layout parsing described above to identify and remove these elements. Moreover, I remove punctuation marks, numbers, and special characters like Extensible Markup Language (XML) and Hypertext Markup Language (HTML) tags. I also remove stopwords, that is words that are not informative, typically conjunctions such as "or" and "if". The stop words for both French and German are provided by Feinerer and Hornik (2019). Moreover, for each text I count terms appearing in a German-French lexicon available from dict.cc, containing roughly 60'000 words. If a text is supposed to be in French, I only keep it if 20% of its terms are contained in the French lexicon and more French than German words are identified. This serves as a filter to remove texts with poor OCR quality or texts that are not in German or French.

Only a fraction, however, of the remaining texts contain information about the business cycle. In the literature it is common to use a topic modelling algorithm to classify texts into topics to further refine the selection (see e.g. Thorsrud, 2020). However, with the amount of textual data at hand, this is not feasible. Therefore, I use a simple keyword-based method proposed by Burri (2023) to create indicators for hand-selected economic topics. This method creates indicators by using two different approaches. First, a count-based approach where the indicator is given by simply counting terms related to certain topics. And second, a keyword-in-context (KWIC) approach in which topics are defined by keywords and a sentiment is extracted from a few words surrounding the keywords (Luhn, 1960).[9] I apply these two approaches to create indicators for each topic and for each source.

The keywords for eleven topics (3 count-based and 8 KWIC-based) are carefully selected by reading through business association reports for all available time periods.[10] This is important, especially for the 19th century when language might have been very different from today and the same topics were described by different terms. Reading the texts makes sure I capture potentially changing language over time. The French

[9] Some papers also refer to this method as aspect-based sentiment analysis (see e.g Barbaglia et al., 2022).

[10] The full list of topics with selected keywords is available in Tables 3 and 4 the Appendix. Moreover, I provide information about the number of identified keywords over time in Figure 7.

keywords are obtained by translating the German keywords using ChatGPT, as well as reading French texts. Using these keywords I create a new text corpus in which each document is given by a keyword and its 15 preceding and the 15 following words.

I create quarterly (mostly newspapers) and yearly (mostly business reports) indicators for every topic and source. The count-based indicator measures the number of documents associated with a specific topic. To calculate sentiment scores I use a simple methodology that resembles business cycle indicators based on firm surveys. I classify all words into positive, neutral, and negative words, using existing dictionaries. Then I compute the "sentiment score" for each document, that is, the share of positive minus the share of negative words.

To define positive and negative words, I follow Shapiro et al. (2020) and combine existing dictionaries, that are proven to capture economic sentiment. The German lexicon combines the dictionaries "SentiWS" developd by Remus et al. (2010) (see e.g. Burri & Kaufmann, 2020) and a translation of the Loughran and McDonald (2011) lexicon (see e.g. Ardia et al., 2019). The French lexicon consist of translations of the same two dictionaries as well as the "FEEL" dictionary by Abdaoui et al. (2017).

More formally, let $\mathcal{K}_j$ be the list of keywords for topic j, $\mathcal{P}$ the list of positive and $\mathcal{N}$ the list of negative words. Then $w_{t,d,j} = (w_{t,d,j,-15}, w_{t,d,j,-14}, \ldots, w_{t,d,j,0} \in \mathcal{K}_j, \ldots, w_{t,d,j,15})$ denotes the list of terms in document d at date t for topic j. The count-based indicators are then calculated as

$$S_{t,j} = \sum_d \mathbb{1}(w_{t,d,j,0} \in \mathcal{K}_j)$$

The document-level sentiment score is given by

$$S_{t,d,j} = \frac{\sum_n \mathbb{1}(w_{t,d,j,n} \in \mathcal{P}) - \sum_n \mathbb{1}(w_{t,d,j,n} \in \mathcal{N})}{|w_{t,d,j}|}$$

where $N_{t,d,j}$ is the number of terms in the document. Figure 4 in the Appendix provides a more intuitive example of how the document-level sentiment score is being calculated. Finally, KWIC-based indicators, $S_{t,j}$, for a given topic j are calculated as a simple average of the sentiment scores

$$S_{t,j} = \frac{\sum_d S_{t,d,j}}{|S_{t,d,j}|}$$

3.2 Topic-specific indicators

The created source-level indicators suffer from a number of deficiencies. First, the quality of the OCR often changes over time. This is particularly relevant for the 19th and early 20th centuries, for which the archives often received the records from various sources in varying quality. This can also be interpreted as a change of the measurement error - the higher the quality of the OCR, the lower the measurement error. Second, the publication frequencies of the sources change over time - increased publication frequency means a higher information density, and therefore, lower measurement error. Third, due to advancements in technology, the length of the articles and reports tends to increase over time. Finally, some indicators contain missing values and most sources are only available for a limited time period. These points potentially lead to indicators with trends and structural breaks in mean and variance. To address these issues, a six-step procedure is proposed to rectify anomalies in the data. Given the myriad of methods available for this purpose, this aspect is not heavily emphasized.[11] A comprehensive description of the procedure is provided in Section C of the Appendix.

1. If the frequency is annual, interpolate missing observations.
2. Detrend the indicator.
3. Detect structural breaks in mean and variance.
4. Normalize each segment.[12]
5. If the frequency is annual, temporally disagregate the indicator to quarterly frequency.
6. Remove outliers (observations more than 3 standard deviations away from the mean).

Finally, I aggregate the corrected source-level indicators to an overall indicator for each topic. To effectively summarize the information content of the data and eliminate idiosyncratic noise, I estimate a factor model in static form:

$$X = F\Lambda + e$$

The model comprises N variables and T quarterly observations. Therefore, the data

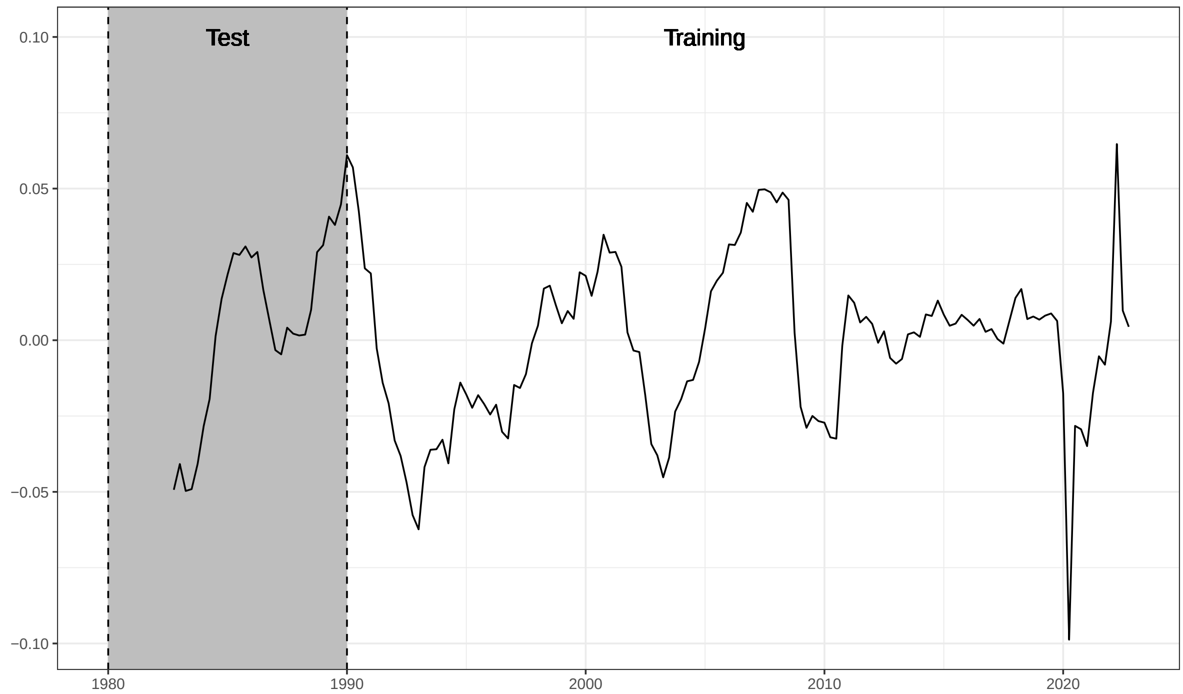
[11] Alone for the detrending step there are numerous possibilities (Canova, 1994, 1998).

[12] I show in Appendix D that with time-varying measurement error, this is preferable to not normalizing.

matrix X is $(T \times N)$, the common factors F are $(T \times r)$, the factor loadings Λ are $(r \times N)$, and the unexplained error term e is $(T \times N)$. The advantage of using a factor model is that it allows for summarizing the information in a large data matrix X with a small number of common factors r. Factors and loadings can be estimated through principal components, under the assumption that the idiosyncratic components are only weakly serially and cross-sectionally correlated (Bai & Ng, 2013; Stock & Watson, 2002).[13] The obtained topic-specific indicators are depicted in Figures 5 and 6 in the Appendix.

3.3 Composite indicator

Figure 2 — Quarterly output gap split into training and test set



Notes: The black line represents quarterly output gap estimated with Hamilton's (2018) method. The trianing set is used to etimate elastic net models with different combinations of hyperparameters. The gray shaded area is the test set used to evaluate the models. Data source: SECO

The final step is to combine the indicators for different topics into one composite indicator for the business cycle. Following Bybee et al. (2021) I use shrinkage methods to do this. Specifically, I use elastic net regression to connect the indicators with the

[13] I interpolate missing values using an EM-algorithm (Stock & Watson, 2002), after standardizing the data to have zero mean and unit variance. I choose a relatively large number of factors for interpolating the data ($r = 4$). Finally, I use the first principal component of the interpolated data set.

output gap and then backcast the indicator's values going back to 1820.[14] A primary strengths of elastic net lies in its ability to effectively handle collinearity. In such cases, traditional regression methods can struggle to provide stable and reliable coefficient estimates. Elastic net, however, combines L1 (Lasso) and L2 (Ridge) regularization techniques, creating a balance that not only addresses collinearity but also encourages sparsity in the model. This means it can automatically select a subset of relevant predictor variables while shrinking the coefficients of less important ones towards zero. By doing so, elastic net enhances the interpretability of the model and improves its predictive performance by reducing overfitting. The objective function of the elastic net is given by

$$\text{Minimize:} \quad \frac{1}{2n}\sum_{i=1}^{n}(y_i - x_i^T\beta)^2 + \lambda\sum_{j=1}^{p}\left(\alpha|\beta_j| + \frac{1-\alpha}{2}\beta_j^2\right)$$

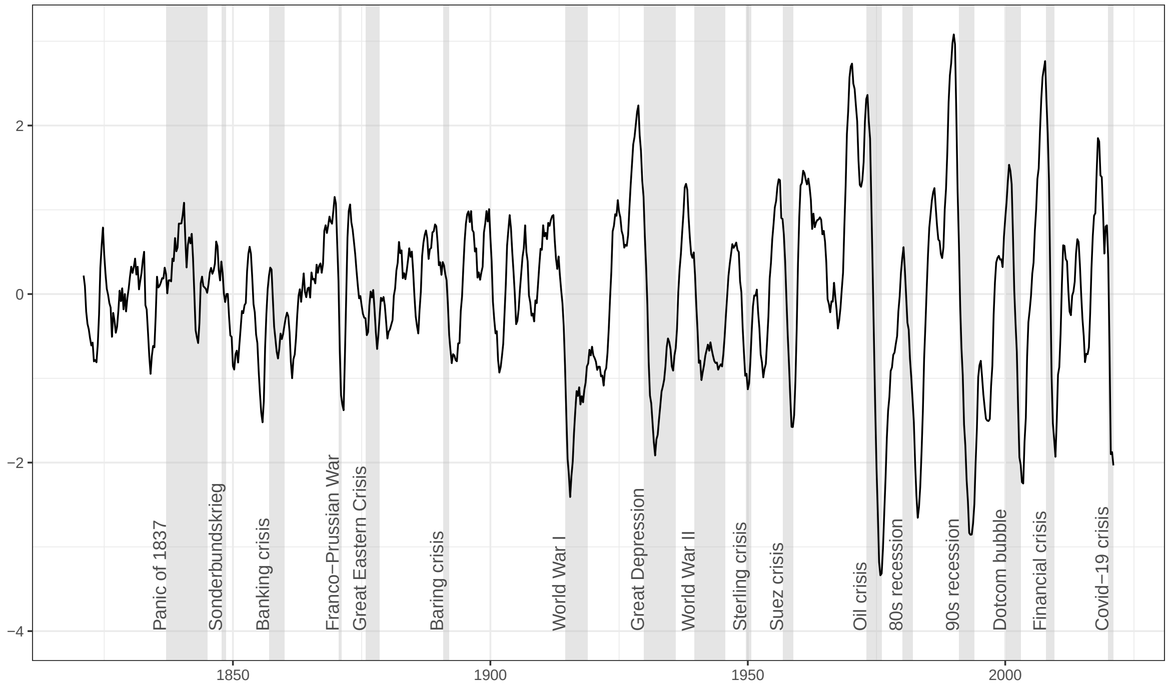
where y_i is the output gap, x_i is the vector of indicators, β is the vector of coefficients, λ is the penalty parameter, and α is the mixing parameter. The mixing parameter α controls the relative weight of the L1 and L2 penalties. When $\alpha = 0$, the penalty is an L2 penalty (ridge regression) and when $\alpha = 1$, it is an L1 penalty (lasso regression). The elastic net penalty is a convex combination of the L1 and L2 penalties. Figure 2 illustrates how optimal values of λ and α are chosen. I perform a grid search over a range of λ and α values, estimate a model on a training set and select the combination that minimizes the mean squared error (MSE) on a test set. The test set spans the years 1980 - 1990 and the training set 1991-2022.

4 Results

The composite indicator is depicted with the black solid line in Figure 3. A few observations stand out. First, the indicator tracks economic downswings, given by the gray shaded areas, very well. It captures all the major recessions the Swiss economy faced in the last decades, like the oil crisis from 1974, the recessions from the beginning of the 80s and 90s, the great financial crisis and the Covid–19 crisis. Moreover, the indicator responds to the two world wars as well as to the great depression. It is also able to capture crises in the 19th century like the Sonderbund War from 1847, the Franco-Prussian war from 1870 and the Baring crisis from 1890.

[14]To create a quarterly output gap, I use Hamilton (2018) filtered real GDP estimates from the State Secretariat for Economic Affairs (SECO). For robustness, I also use estimate of the output gap provideed by the SECO and the SNB. The results are very similar.

Figure 3 — Composite indicator



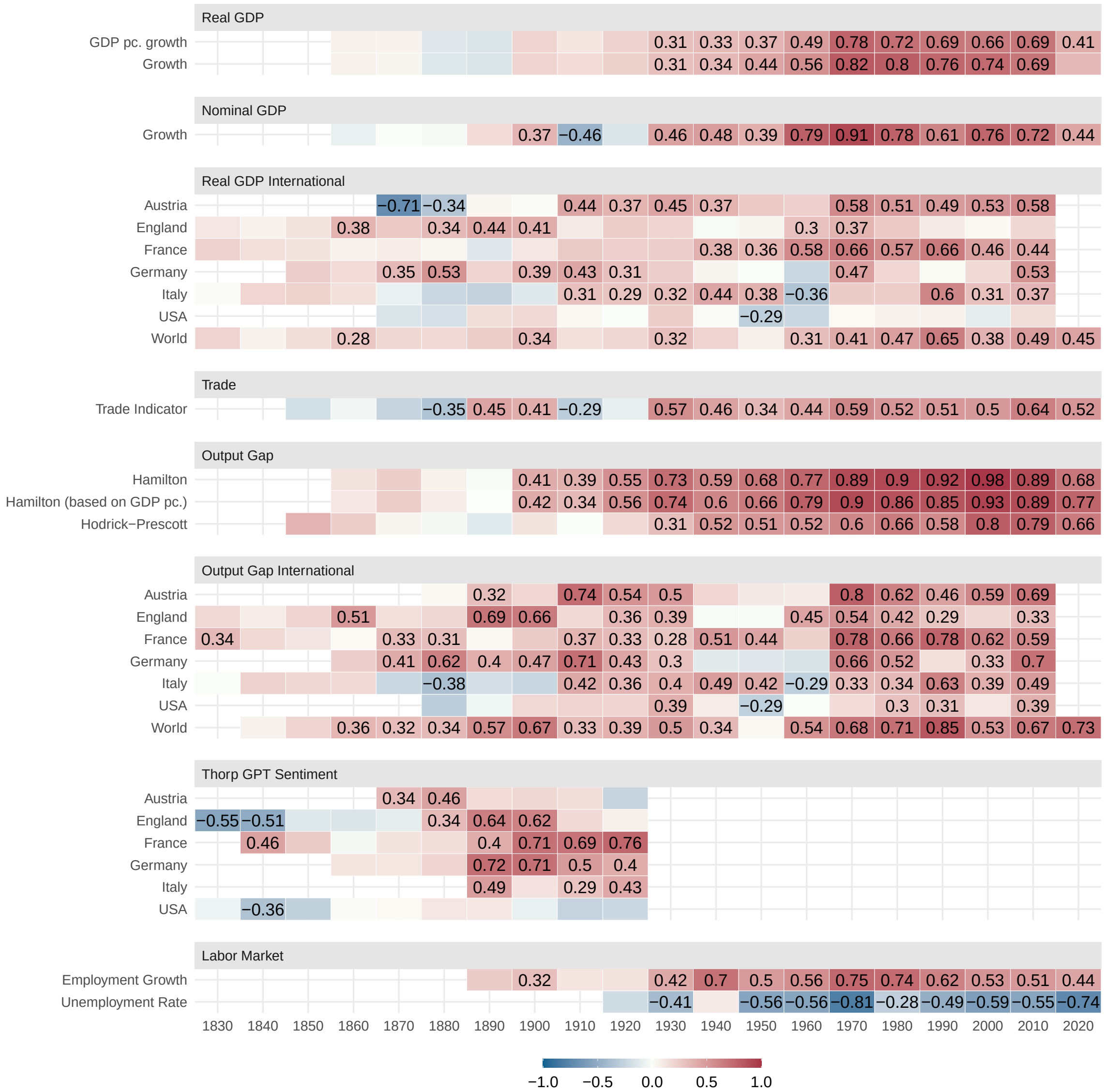
Notes: The black line represents the composite historical business cycle indicator. Gray shaded areas indicate global and Swiss crises, recessions and wars.

Second, the indicator gets more volatile over time. This may seem counterintuitive given that the overall economy, including GDP growth, exhibited reduced volatility during the "great moderation" period. However, this discrepancy can be explained. First, the indicator serves as a qualitative measure of the business cycle, assessing the economy's state in comparison to nearby timeframes. Consequently, it's most meaningful when evaluated within a range of a few decades. Second, the earlier data may contain higher measurement errors leading to lower volatility by construction. In practical terms, when standardizing the identified segments of the source-level indicators as outlined earlier, a higher noise-to-signal ratio in the early data can lead to a more pronounced reduction of the signal during normalization. This results in a dampened signal in the averaged indicator, where some of the noise is effectively canceled out. Appendix D provides a more detailed explanation of this phenomenon.

Figure 4 shows the rolling correlations between the indicator and a selected set of variables with a fixed window size of 20 years. The indicator is highly correlated with the output gap, with an overall correlation of around 0.5. The correlation is highest during the late 20th and 21st centuries, with a correlation coefficent of around 0.9. The correlation is lower during the early 20th century, but with around 0.5 still substantial. For the 19th century there is still some correlation but it is not statistically differnt from zero. A similar picture emerges for labor market data, trade, and real and nominal GDP growth. The correlation is high during the late 20th and 21st centuries and lower for the 19th and early 20th centuries. This is what would be expected given the data limitations for Switzerland in the 19th century.

In the late 20th and early 21st centuries, the indicator shows a correlation with the output gap and real GDP growth of neighboring countries. This correlation is less pronounced in the USA and England, yet remains substantial. In contrast, during the 19th century, the correlation diminishes for all countries but maintains statistical significance in France, Germany, and England. This pattern indicates a higher synchronization of the Swiss business cycle with international trends in the 20th century compared to the 19th century. These observations align with the findings of Broadberry and Lennard (2023), who report increasing synchronization of business cycles over time. Specifically, they note that 25% of the potential correlations between European countries' GDP growth were significantly positive from 1870 to 1950. This proportion rose to 66% from 1950 to 2000.

Figure 4 — Rolling correlations with 20 year window



Notes: The graph shows rolling correlations with a fixed window size of 20 years between the indicator on the left and the composite indicator. The time period considered is given by the year on the x-axis plus and minus ten years. Only statistically significant (on 10% level) correlations are labeld. Correlations with fewer than 10 observations are not shown.

The broad picture can also be confirmed by the correlations with the sentiment indicators based on Thorp's (1926) description of the state of the economy. For all considered countries except the USA, there is substantial correlation with the business cycle indicator. The strongest correlations are observed for Germany, France and England.

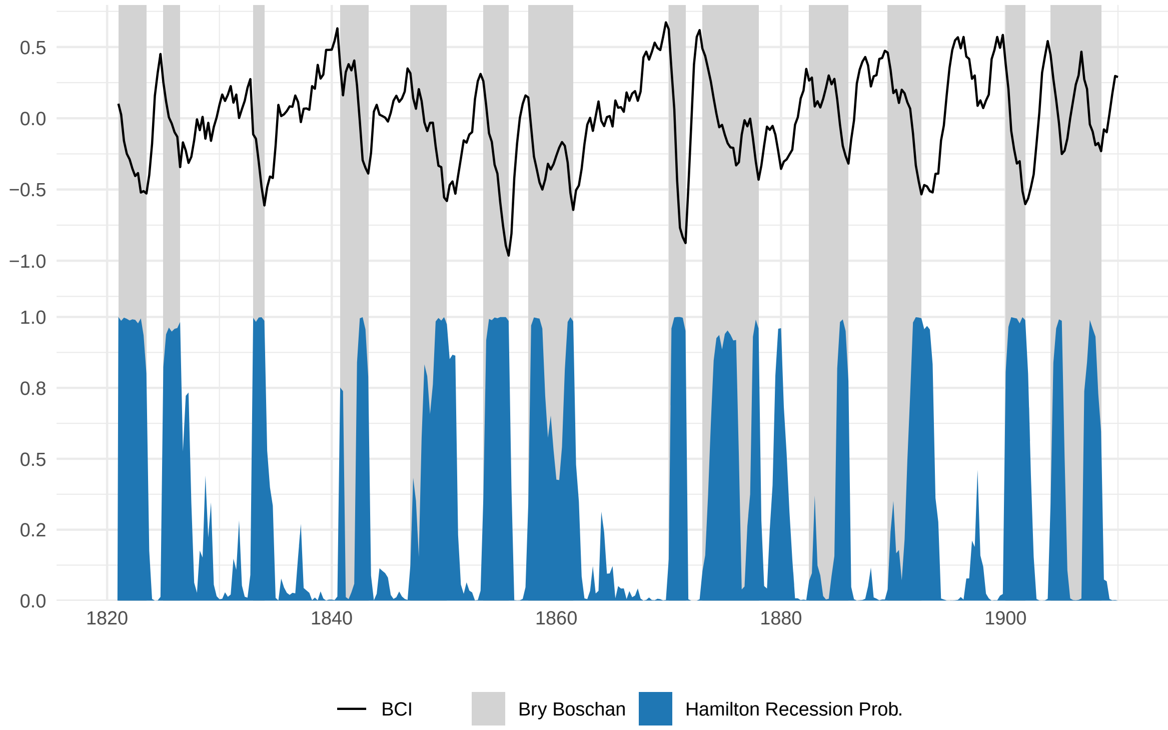
Before 1850 there are a few significant positive corrrelations with variables from France. This makes sense since France still had political influence on Switzerland during this period. When Napoleon's forces entered Switzerland in 1798, it led to the end of the centuries-old Swiss Confederacy and the establishment of the Helvetic Republic (1798-1803), a French client state. However, there are no positive significant correlations with variables from other countries. This divergence could be explained by unique internal political and social conflicts following the Congress of Vienna in 1815. The period until foundation of modern Switzerland in 1848 was characterized by pronounced divisions between liberal and conservative cantons, culminating in the Sonderbund War of 1847. These internal disputes, centered on governance, federal authority, and religious differences, fostered a climate of economic uncertainty and a focus on domestic concerns. Moreover, the absence of a common currency until the Coinage Act of 1850 posed significant challenges to Switzerland's economic development during this period. Consequently, economic sentiment in Switzerland might have been insulated from broader European trends during this period. (See e.g. Church & Head, 2013)

5 Business cycle dating

It is generally acknowledged that the modern business cycle features long expansions combined with short recessions (see e.g. Romer & Romer, 2020). Due to data limitations, systematic data-driven analysis of business cycles could until recently be only conducted on very modern data (Broadberry & Lennard, 2023). With the progress in the quantification of economic activity, however, Broadberry and Lennard (2023) analysed the nature of business cycles of nine European countries. Their main finding is that recessions got less frequent and shorter over time.

How do these findings compare to the Swiss business cycle? For the 18th and early 19th centuries, there is, to the best of my knowledge, no business cycle chronology available. Since 1956 the Economic Cycle Research Institute (ECRI) provides a chronology of business cycle turning points for Switzerland. The ECRI chronology is more a judgemental measure, considering a number of indicators, including output, employment, income, and sales (Glocker & Wegmueller, 2020). Moreover, Siliverstovs (2011) uses an approach based on Markov-switching models and Glocker and Wegmueller (2020) use a Markov-switching dynamic factor model (MS-DFM) to date business cycle turning points for Switzerland starting in 1980. Both identify turning points that are largely consistent with those determined by the ECRI. Therefore, I mainly

Figure 5 — Indicator and recession classification 1820 - 1910



Notes: The graph shows the composite indicator given by the black solid line together with smoothed recession probabilities obtained by Hamilton's (1989) Markow-Switching autoregression model. The gray shaded areas indicate recessions obtained by an adapted Bry and Boschan (1971) algorithm.

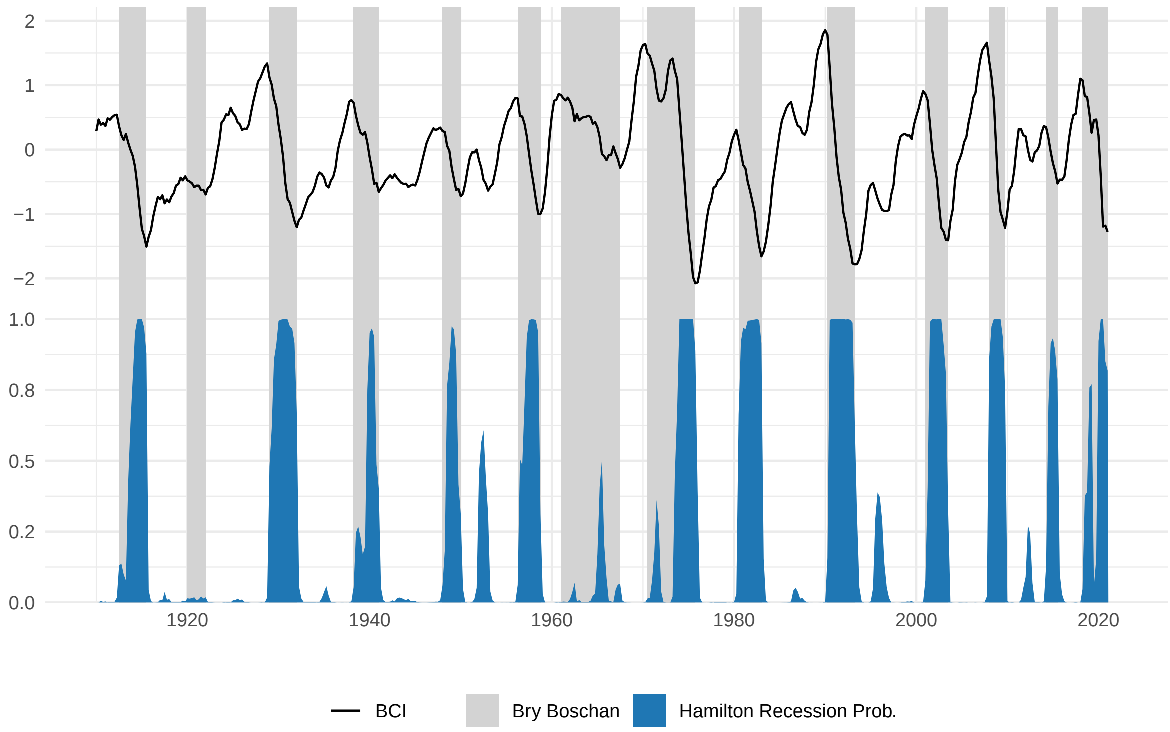
use the ECRI chronology for comparison.

To address the lack of a business cycle chronology for Switzerland during the 18th and early 19th centuries, this section utilizes the developed business cycle indicator to identify and date business cycle turning points. As Romer and Romer (2020) explain, recessions are not simply random categorizations of macroeconomic outcomes. Instead, they represent critical moments in the macroeconomy, characterized by a rapid and significant deviation of economic activity from its normal state. Establishing a business cycle chronology for the 18th and early 19th centuries is thus crucial for understanding these pivotal economic shifts.

I use the Markov-Switching autoregression model proposed by Hamilton (1989). This is inline with Romer and Romer (2020) who show that "recession periods emerge clearly from a Markov-switching model". The model is given by

$$y_t = \mu_{s_t} + \phi y_{t-1} + \varepsilon_t$$

Figure 6 — Indicator and recession classification 1910 - 2021



Notes: The graph shows the composite indicator given by the black solid line together with smoothed recession probabilities obtained by Hamilton's (1989) Markow-Switching autoregression model. The gray shaded areas indicate recessions obtained by an adapted Bry and Boschan (1971) algorithm.

with $\varepsilon_t \sim N(0, \sigma^2)$ and where s_t is the realization of a two-state Markov chain with

$$\Pr(s_t = j | s_{t-1} = i, s_{t-2} = k, \ldots, y_{t-1}, y_{t-2}, \ldots) = \Pr(s_t = j | s_{t-1} = i) = p_{ij}$$

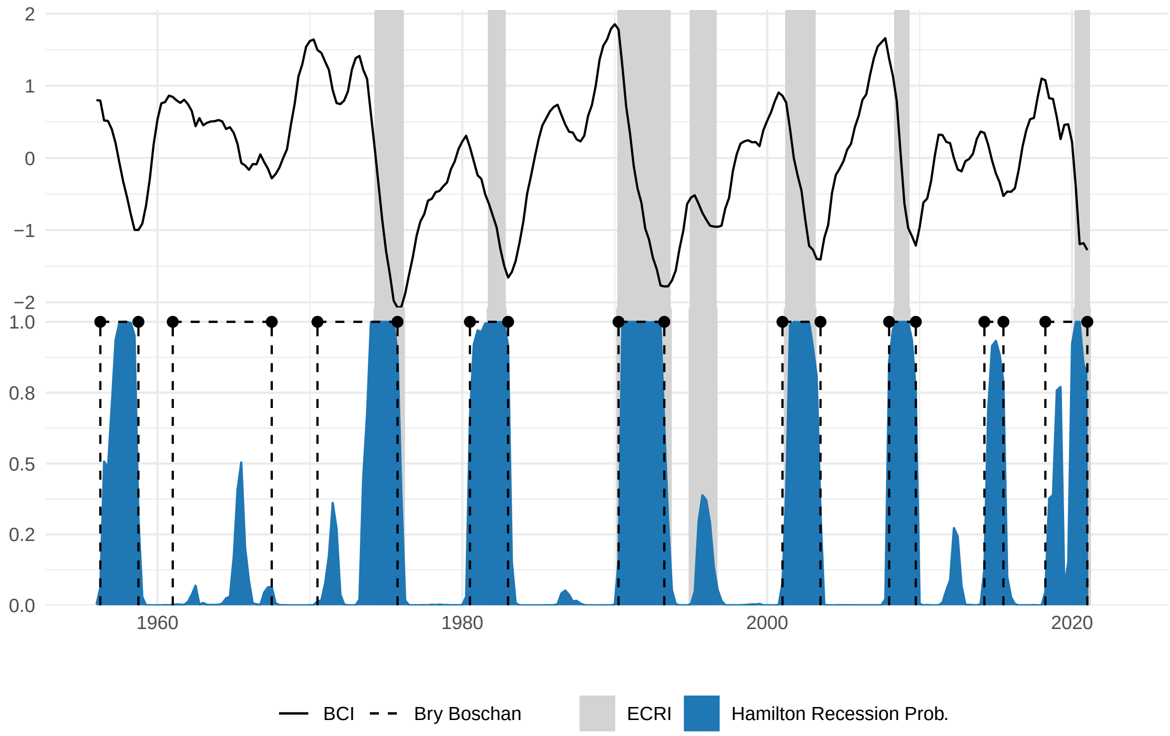
where $i, j = 0, 1$. Within this framework, one can label s_t = 0 and s_t = 1 as the expansion and recession states at time t. Because the indicator is less volatile in the 19th century, I estimate the model on two samples. First, from 1820 to 1910 and second, from 1910 to 2021.[15]

For robustness, I also use the nonparametric algorithm proposed by Harding and Pagan (2002) to date business cycle turning points. The algorithm is a quarterly adoption of Bry and Boschan's (1971) algorithm for monthly data. However, since the algorithm is designed for data in levels, I increase the the number of quarters within which a local

[15] It is not uncommon to estimate the model on different samples. For example, Romer and Romer (2020) estimate the model with data from 1929 to 1947 and 1948 to 2019.

maximum or minimum has to occur to 10 quarters.[16]

Figure 7 — Comaprison with ECRI dating



Notes: The graph shows the composite indicator given by the black solid line together with smoothed recession probabilities obtained by Hamilton's (1989) Markow-Switching autoregression model. The black dashed lines indicate recessions obtained by an adapted Bry and Boschan (1971) algorithm. The gray shaded areas are recession dates obtained from ECRI.

An issue when utilizing detrended data arises because it tends to categorize "growth recessions" as contractions. In the literature, these are not generally recognized as true recessions (Broadberry & Lennard, 2023). To address this, I refine the identified recession periods, ensuring that their entire duration aligns with negative values in the business cycle indicator. The censored business cycle dating is very similar to the original one. All recessionary episodes identified using the Markov-switching model are listed in table 7 in the Appendix.

[16]This aligns with the general understanding that business cycles can vary but often fall within a 2 to 10-year range. See Harding and Pagan (2002) for more details on the algorithm.

Table 1 — Frequency, duration, and number of Swiss business cycles

	Algorithm	Recession (Peak to trough) 1820-1910	1911-1950	1951-2022	Expansion (Trough to peak) 1820-1910	1911-1950	1951-2022
Frequency	Hamilton (1989)	32.5	17.5	25.3	67.5	82.5	74.7
	Bry and Boschan (1971)	50.6	40.0	38.8	49.4	60.0	61.2
	BL2023 (Swiss GDP)	25.4	45.0	15.3	74.6	55.0	84.7
	ECRI			19.3			80.7
	OECD			39.0			61.0
	Technical recession			15.7			84.3
Duration	Hamilton (1989)	6.5	7.0	7.1	13.8	34.5	21.3
	Bry and Boschan (1971)	14.0	12.8	12.1	14.1	20.4	19.4
	BL2023 (Swiss GDP)	5.0	8.0	6.3	13.5	10.5	34.3
	ECRI			7.4			29.9
	OECD			22.5			33.2
	Technical recession			2.7			13.5
Number	Hamilton (1989)	18.0	4.0	10.0	18.0	4.0	10.0
	Bry and Boschan (1971)	13.0	5.0	9.0	13.0	5.0	9.0
	BL2023 (Swiss GDP)	12.0	9.0	7.0	12.0	9.0	7.0
	ECRI			7.0			7.0
	OECD			13.0			13.0
	Technical recession			10.0			10.0

Notes: Frequency is the share in percent of quarters in a given phase. Duration is the average number of quarters in a given phase. The ECRI dating starts in 1956, OECD dating starts in 1960, and quarterly GDP to calculate technical recessions is available from 1980. Broadberry and Lennard (2023) (BL2023 Swiss GDP) classify recessions as negative real annual GDP growth. Annual real Swiss GDP growth is available from 1852.

The results of the estimated recessionary episodes are depicted in Figures 5 and 6. I associate those values of the regime probability with a recession which are above 0.5.[17] The two regimes identified appear to correspond with phases of recessions and expansions, with the model's high recession probability periods showing considerable alignment with the recessions delineated by the Bry-Boschan algorithm. However, the Bry-Boschan procedure tends to overestimate recessions' duration.

Figure 7 presents a comparison between the derived classification and the recession episodes as identified by the ECRI. There is a significant overlap between the recessionary regime probabilities (illustrated in blue) and the ECRI's recession dating (indicated by the gray shaded area). The Hamilton model exhibits a tendency to classify recessions more liberally. It additionally identifies with high probability recessions in 1958, known as the Eisenhower recession, and in 2015, coinciding with the SNB's termination of the minimum exchange rate. Additionally, the model suggests with

[17] The recession threshhold of 0.5 is arbitrary and chosen to be inline with Hamilton (1989). However, using different threshholds like e.g. 0.8 proposed by Romer and Romer (2020) would not change the results significantly because the estimated probability is typically close to either 0 or 1.

less certainty another brief recessionary period in the 1960s.[18] This suggests that the Markov-switching model reliably identifies recessions.

How does the modern Swiss business cycle compare to the business cycle in the 19th century? Table 1 shows frequency, duration, and number of identified recessions and expansions for periods 1820 to 1910, 1911 to 1950, and 1951 to 2022. Recessions in the 19th century were more frequent than in the 20th and 21st centuries. The share of quarters in recession decreases no matter which classification is used. However, the duration of recessions does not change significantly over the periods considered. Expansions in contrast get longer over time. The average duration of expansions increases from 13.8 quarters in the period up to 1910 to 21.3 quarters since 1951. Tables 5 and 6 in the Appendix compare these numbers to the European (Broadberry & Lennard, 2023) and the british business cycle (Broadberry et al., 2023). The results on the frequency and the expansions are inline with the findings on the European business cycle, albeit less pronounced. However, the duration of recessions is not. Broadberry and Lennard (2023) find that the duration of recessions in Europe decreases over time. On the other hand, Broadberry et al. (2023) confirm that the duration of recessions in the UK stays constant over time. Therefore, the widespread believe, that recessions got shorter, is not fully supported by the data.

6 Sensitivity analysis

In this section, I perform a comprehensive series of robustness checks. In particular, I show that the proposed keyword-based algorithm delivers similar results as a rating based on OpenAI's (2023) LLM GPT-3.5. Moreover, I analyze the sensitivity with respect to different aggregation techniques, as well as different subsets of the data. All corresponding figures can be found in Appendix A.

6.1 Keyword-based algorithm

Given the emergence of LLMs, it naturally raises the question as to why these models are not employed for extracting information from texts. There are two main reasons. First, the cost of utilizing these models is a significant factor. For instance, OpenAI's (2023) GPT-3.5 model incurs a charge of 0.001 USD per 1000 tokens[19]. With a conservative

[18] I also compare my classification to the recession dates provided by the Organisation for Economic Co-operation and Development (OECD), recessionary episodes based on the technical definition for recessions (two consecutive quarters of negative GDP growth), and the definition by Broadberry and Lennard (2023) - classifying periods with negative annual GDP growth as recessions. The classifications show a high degree of overlap and are depicted in Figures 8, 9 and 10 in the Appendix.

[19] This corresponds to approximately 750 words.

estimate of the average text length being only 20 tokens, processing 100 million texts would approximate a total expense of around 2 million USD. Second, it would take a significant amount of time to process all the texts. Nevertheless, for future research it would be interesting to compare the proposed keyword-based algorithm with LLMs.

Due to the high costs associated with LLMs, their use for analyzing the gathered text corpus is not feasible. Nonetheless, to ascertain the efficacy of the proposed keyword-based algorithm, it is also applied to Thorp's (1926) work on business cycles. I then compare the obtained sentiment indicators to the indicators derived with GPT-3.5 as described in section 2 and B in the Appendix. To be precise, GPT-3.5 based indicators are using the texts in English. For the keyword-based algorithm, the English texts are first translated to German and French.[20] I then use the methodology outlined in section 3 to create a sentiment indicator.

As shown in Figure 11 in the Appendix, the correlation between the GPT-3.5 based indicator and the keyword-based indicator is between 0.5 and 0.8. This suggests that the proposed keyword-based algorithm delivers similar results as LLMs, with the difference of being cheap and fast. The question whether one or the other method is superior is beyond the scope of this paper and should be addressed in future research. However, the results suggest that the keyword-based algorithm is a viable alternative to LLMs.

6.2 Aggregation techniques

There are countless possibilities to construct a business cycle indicator from textual data. To check that the indicator is not sensitive to the aggregation technique, I compare the baseline indicator to several alternatives.

Other aggregation methods to composite indicator. Instead of using an elastic net model to aggregate the topic-specific indicators to the composite indicator, I use a

- Weighted average based on keyword importance in each topic:

$$S_t = \sum_{j=1}^{P} \omega_{j,t} s_{j,t}$$

  where S_t denotes the composite indicator in quarter t, P is the total number of topics. $\omega_{j,t}$ and $s_{j,t}$ represent the weight derived by the number of identified keywords and the topic-specific indicator, respectively, for topic j in quarter t.

[20] To translate the texts, I use ChatGPT.

- Markov-Switching Dynamic Factor Model (MS-DFM) brought forward by C.-J. Kim (1994), Diebold and Rudebusch (1996), M.-J. Kim and Yoo (1995) and Chauvet (1998).[21] In these models the common component is governed by an unobservable regime-switching variable.[22] The model comprises one factor (based on screeplot in Figure 12) and 5 lags (based on Bayesian Information Criterion (BIC)).[23] Using a MS-DFM not only allows to check sensitivity of the indicator but also the sensitivity of the business cycle dating.

Other aggregation methods to topic-specific indicators. Instead of using a static factor model to aggregate the sources to a topic-specific indicator, I use a

- Weighted average based on keyword importance in each source:

$$S_{j,t} = \sum_{i=1}^{N_t} \omega_{j,i,t} s_{j,i,t}$$

  where $S_{j,t}$ denotes the topic-specific indicators. N_t is the total number of sources available in quarter t. $\omega_{j,i,t}$ and $s_{j,i,t}$ represent the weight derived by the number of identified keywords and the source-level indicator, respectively, for a specific topic j and source i in quarter t.

- fixed effects regression model à la Shapiro et al. (2020). I estimate the quarter fixed effects and use these as the indicator ($S_{j,t} = \hat{f}_{j,t}$) from the following regression

$$s_{j,i,t} = f_{j,t} + f_{j,i} + f_{j,l} + f_{j,f} + f_{j,i} * f_{j,p} + \varepsilon_{j,i,t}$$

  where $s_{j,i,t}$ is the sentiment score in quarter t for a specific topic j and publication i. $f_{j,t}$ is a sample quarter fixed effect, $f_{j,i}$ a source fixed effect, $f_{j,l}$ a language fixed effect, $f_{j,f}$ a frequency fixed effect, $f_{j,i} * f_{j,p}$ a source*type fixed effect. Type is either a report or a news article. Allowing for all these other fixed effects besides the quarter fixed effects ensures that the index is independent of changes over time in the composition of the sample across newspapers and reports versus regular articles. Moreover, it controls for differences in the sentiment scores across sources, languages, and frequencies. This might be important because the sentiment scores differ considerably across sources, types, frequencies, and languages.

[21] I thank Philipp Wegmüller for providing his programs to estimate MS-DFMs.

[22] Camacho et al. (2015) show that performing the estimation in one step is superior to estimating a Markov-switching process on the factor in a sequential step.

[23] See section E in the Appendix for more details.

Other adjustment methods. Instead of adjusting the source-level indicators according to the procedure described in section 3.2, I

- do not scale the sentiment-based indicators. I still identify structural breaks but only demean each segment. I do not change the calculation of the count-based indicators. See section C in the Appendix for more details.
- do not substract a trend.

Subsets of data. Instead of using all available data, I calculate the indicator

- only based on German texts.
- only based on French texts.
- only using sentiment-based indicators.
- only using count-based indicators.

As shown in Figures 14 and 15, the alternative indicators are very similar. However, there is some more dispersion before World War I. Nevertheless, all alternative indicators capture major downturns like the Franco-Prussian war from 1870 or the Baring crisis from 1890. There is substantial correlation between the alternative indicators and the baseline indicator. The correlation between the alternative indicators and the output gap is similar to the correlation between the baseline indicator and the output gap. Finally, the recession probabilities obtained with the MS-DFM in Figure 13 show substantial overlap with the dating obtained using Hamilton's (1989) model. These analyses demonstrate that the indicator is not overly sensitive to specific aggregation techniques or data limitations.

7 Conclusions

This paper presents a pioneering approach to study Switzerland's economic dynamics across three centuries. By meticulously compiling and analyzing an extensive collection of textual data, including company reports, business association documents, and newspapers, I construct a comprehensive business cycle indicator on quarterly frequency for Switzerland from 1820 to 2021. This indicator serves as a tool for economic analysis, particularly for periods where traditional data sources are scarce or non-existent.

The key findings of the paper are multifaceted. The composite business cycle indicator exhibits a strong correlation with known economic fluctuations and real activity in Switzerland, particularly in the latter half of the 20th century and the early 21st century. This correlation, although somewhat weaker, extends to earlier periods, indicating the indicator's reliability across different historical contexts. Notably, the indicator successfully captures major economic downturns, including the two world wars, the Great Depression, and various financial crises. Additionally, the indicator correlates with economic variables in neighboring countries, suggesting its effectiveness in capturing broader European economic dynamics.

A novel contribution of this research is the establishment of a business cycle chronology for Switzerland in the 19th and early 20th centuries, a period for which such data was previously unavailable. The results show that Swiss recessions have become less frequent over time, aligning with trends observed in other European nations. Interestingly, the duration of Swiss recessions does not show a significant reduction, offering a nuanced view of economic cycles and challenging some conventional beliefs about their evolution.

The paper makes a substantial contribution to Swiss economic history. It not only provides a valuable tool for understanding historical economic fluctuations but also sets a benchmark for future research in the field.

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A Supplementary material

Table 1 — Textual data sources

Publication	Name	Source	Availability	Lang.	Freq.	# texts
AGB	Zeitschrift Schweizer Arbeitgeber	SWAB	1907 - 2014	de	M	124.94
ARC	ArcInfo	e-newspaper archives.ch	2018 - 2021	fr	D	143.05
AWP	AWP Financial News	AWP	2001 - 2020	de	D	1860.85
BAN	Briger Anzeiger	e-newspaper archives.ch	1899 - 1933	de	BW	204.22
BAZ	Basler Zeitung	Tamedia	2000 - 2021	de	D	323.94
BEOL	Berner Oberländer	Tamedia	2018 - 2021	de	D	76.22
BILA	Bilan	Tamedia	1996 - 2021	fr	D	18.08
BNN	Bündner Nachrichten	e-newspaper archives.ch	1885 - 1892	de	D	50.42
BR_DE_GB	Annual Report Swiss Confederation	Swiss Confederation	1849 - 2018	de	Y	306.57
BR_de_SR	Annual Report Government Account	Swiss Confederation	1849 - 2021	de	Y	3193.07
BR_FR_GB	Annual Report Swiss Confederation	Swiss Confederation	1848 - 2018	fr	Y	3170.38
BU	Der Bund	Tamedia	1995 - 2021	de	D	800.47
BUR	Bote vom Untersee und Rhein	e-newspaper archives.ch	1900 - 2018	de	BW	620.46
BZ	Berner Zeitung	Tamedia	1996 - 2021	de	D	1051.75
CMV	Aktiv : CMV/FCOM : Gemeinsames Gewerkschaftsmagazin	e-newspaper archives.ch	1930 - 1998	de	BM	40.83
CS_BUL	Credit Suisse Bulletin	Swiss National Library	1895 - 2016	de	Y	3121.80
DBB	Der Bund	e-newspaper archives.ch	1850 - 1994	de	D	2865.65
Démocrate	Le Démocrate	Scriptorium	1855 - 1999	fr	D	4141.31
DMR	Der Murtenbieter	e-newspaper archives.ch	1854 - 2010	de	BW	651.18
EDP	Engadiner Post	e-newspaper archives.ch	1893 - 1930	de	TW	92.23

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Table 1 – continued from previous page

Publication	Name	Source	Availability	Lang.	Freq.	# texts
EIZE	Eidgenössische Zeitung	e-newspaper archives.ch	1838 - 1864	de	D	73.19
EXR	FAN - L'express : feuille d'avis de Neuchâtel	e-newspaper archives.ch	1738 - 2018	fr	D	8410.07
FAAV	Feuille d'avis du district d'Avenches	Scriptorium	1882 - 2010	fr	D	5750.28
FCS	Feuille commerciale de Sierre et du district	e-newspaper archives.ch	1918 - 1930	fr	BW	50.74
FDV	Journal et feuille d'avis du Valais	e-newspaper archives.ch	1903 - 1968	fr	TW	1311.36
FUW	Finanz und Wirtschaft	Tamedia	2000 - 2021	de	D	93.47
FZG	Freiburger Nachrichten	e-newspaper archives.ch	1864 - 2006	de	D	2638.32
GAV	Gazette du Valais	e-newspaper archives.ch	1855 - 1922	fr	TW	258.07
GBL	Geschäftsblatt für den obern Teil des Kantons Bern	e-newspaper archives.ch	1876 - 1938	de	BW	339.40
GDB	Gazette de Berne	e-newspaper archives.ch	1692 - 1797	fr	BW	69.08
GTR	Grütlianer	e-newspaper archives.ch	1852 - 1925	de	BW	229.89
HAZ	Handels-Zeitung	SWAB	1861 - 1894	de	D	36.38
HEU	24 Heures	Tamedia	1996 - 2021	fr	D	535.01
IMP	L'impartial	e-newspaper archives.ch	1881 - 2018	fr	D	7102.04
IND	L'indicateur = Der Anzeiger	e-newspaper archives.ch	1914 - 1923	fr	W	48.32
ISB	Intelligenzblatt für die Stadt Bern	e-newspaper archives.ch	1834 - 1922	de	D	579.98
JC	Journal du district de Cossonay	Scriptorium	1899 - 2007	fr	D	3353.52
JM	Journal de Morges	Scriptorium	1894 - 2017	fr	D	9032.77
KK_CA	Reports Kommission für Konjunkturbeobachtung	SNB	1953 - 1983	de	Y	7.81
KK_ES	Econmic Situation report Kommision für Konjunkturbeobachtung	SNB	1932 - 2001	de	Y	47.15

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Table 1 – continued from previous page

Publication	Name	Source	Availability	Lang.	Freq.	# texts
KK_MIT	Mitteilungen Kommission für Konjunkturbeobachtung	SNB	1933 - 2007	de	Y	145.69
LAT	Langenthaler Tagblatt	Tamedia	2019 - 2021	de	D	26.99
LB	Der Landbote	Tamedia	1998 - 2021	de	D	446.08
LBP	Le bien public	e-newspaper archives.ch	1879 - 1888	fr	TW	70.05
LCE	Le confédéré	e-newspaper archives.ch	1861 - 2009	fr	W/BW	701.46
LCG	Le confédéré de Fribourg	e-newspaper archives.ch	1848 - 1907	fr	BW	169.57
LCR	Le chroniqueur	e-newspaper archives.ch	1854 - 1881	fr	TW	96.29
LEJ	Le Jura	e-newspaper archives.ch	1852 - 1970	fr	BW	182.35
LES	L'essor	e-newspaper archives.ch	1906 - 2015	fr	M	51.82
LFM	Le Franc-Montagnard	e-newspaper archives.ch	1898 - 2020	fr	BW/TW	533.68
LGE	La Gruyère	e-newspaper archives.ch	1882 - 1930	fr	TW	158.79
LLE	La liberté	e-newspaper archives.ch	1871 - 2012	fr	D	6975.28
LSL	La Suisse libérale	e-newspaper archives.ch	1881 - 1982	fr	W	304.98
MIG	Construire : hebdomadaire du capital à but social	e-newspaper archives.ch	1944 - 2004	fr	W	399.06
MIM	Wir Brückenbauer : Wochenblatt des sozialen Kapitals	e-newspaper archives.ch	1943 - 2004	de	W	479.30
NVB	Nidwaldner Volksblatt	e-newspaper archives.ch	1866 - 1991	de	BW	236.52
NVE	Le nouvelliste	e-newspaper archives.ch	1904 - 2016	fr	D	7505.93
NZG	Neue Zuger Zeitung	e-newspaper archives.ch	1846 - 1891	de	BW	25.10
NZN	Neue Zürcher Nachrichten	e-newspaper archives.ch	1895 - 1991	de	D	1412.94
NZZ	Neue Zürcher Zeitung	e-newspaper archives.ch	1780 - 2020	de	D	3698.76

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Table 1 – continued from previous page

Publication	Name	Source	Availability	Lang.	Freq.	# texts
OIZ	Die Gewerkschaft : das Magazin der Gewerkschaft Textil, Chemie, Papier	e-newspaper archives.ch	1901 - 1992	de	BM	51.08
OTB	Oberländer Tagblatt	e-newspaper archives.ch	1909 - 1961	de	D	371.66
SGZ	St. Galler Zeitung	e-newspaper archives.ch	1831 - 1881	de	D	173.81
SLB	Seeländer Bote	e-newspaper archives.ch	1850 - 1904	de	TW	75.30
SMZ	SMUV-Zeitung / Schweizerischer Metall- und Uhrenarbeitnehmer-Verband	e-newspaper archives.ch	1902 - 2001	de	M	44.69
SNB_GB	Annual Report SNB	SNB	1908 - 2018	de	Y	736.58
SNB_GMB	Money Market Report SNB	SNB	1945 - 1985	de	Y	58.09
SNB_QB	Quarterly Report SNB	SNB	1967 - 2019	de	Q	46.70
SWA_BER_Vorort	Annual Report Vorort	SWAB	1878 - 1976	de	Y	2063.75
SWA_GB_BCG	Annual Report Banque du Commerce Geneve	SWAB	1845 - 1907	fr	Y	85.54
SWA_GB_BCN	Annual Report Banque cantonale Neuchâteloise	SWAB	1883 - 1989	fr	Y	166.83
SWA_GB_BCV	Annual Report Banque cantonale vaudoise	SWAB	1854 - 1949	fr	Y	25.48
SWA_GB_BCVL	Annual Report Banque cantonale du valais	SWAB	1856 - 1871	fr	Y	11.27
SWA_GB_BDG	Annual Report Banque de Genève	SWAB	1858 - 1930	fr	Y	36.24
SWA_GB_BGG	Annual Report Banque Glane/Gruyere	SWAB	1888 - 1960	fr	Y	4.45
SWA_GB_BHCG	Annual Report Banque hypothécaire du canton de Genève	SWAB	1848 - 1950	fr	Y	108.56
SWA_GB_BPG	Annual Report Banque populaire de la Gruyère	SWAB	1864 - 1968	fr	Y	58.07

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Table 1 – continued from previous page

Publication	Name	Source	Availability	Lang.	Freq.	# texts
SWA_GB_CAIB	Annual Report Crédit agricole et industriel de la Broye	SWAB	1867 - 1965	fr	Y	103.68
SWA_GB_CCIG	Annual Report Chambre de Commerce de Genève	SWAB	1865 - 1930	fr	Y	80.12
SWA_GB_CEB	Annual Report Caisse d'epargne de Bassecourt	SWAB	1883 - 1988	fr	Y	59.58
SWA_GB_CECL	Annual Report Caisse d'epargne et de crédit Lausanne	SWAB	1878 - 1956	fr	Y	35.91
SWA_GB_CEPL	Annual Report Caisse d'Epargne et de Prévoyance de Lausanne	SWAB	1905 - 1960	fr	Y	7.80
SWA_GB_CF	Annual Report Credit foncier vaudois	SWAB	1901 - 1956	fr	Y	41.84
SWA_GB_CHCF	Annual Report Caisse Hypo Fribourg	SWAB	1854 - 1909	fr	Y	4.58
SWA_GB_CHCV	Annual Report Caisse hypothécaire Cantonale vaudoise	SWAB	1860 - 1900	fr	Y	34.26
SWA_GB_CME	Annual Report Caisse Mutuel pour l'Epargne	SWAB	1874 - 1920	fr	Y	17.42
SWA_GB_CVCI	Annual Report Chambre vaudoise du commerce et de l'industrie	SWAB	1904 - 1929	fr	Y	2.90
SWA_GB_Helveti	Annual Report Helvetia	SWAB	1859 - 1957	de	Y	4.18
SWA_GB_SLKB	Annual Report Spar- und Leihkasse Bern	SWAB	1858 - 1960	de	Y	46.59
SWA_GB_SwissRe	Annual Report Swiss RE	SWAB	1864 - 1960	de	Y	33.26
SWA_GB_ZVAO	Annual Report Arbeitgeberverband	SWAB	1910 - 1960	de	Y	94.63
TA	Tages-Anzeiger	Tamedia	1996 - 2021	de	D	994.33
TAA	Täglicher Anzeiger für Thun und das Berner Oberland	e-newspaper archives.ch	1877 - 1907	de	D	68.06

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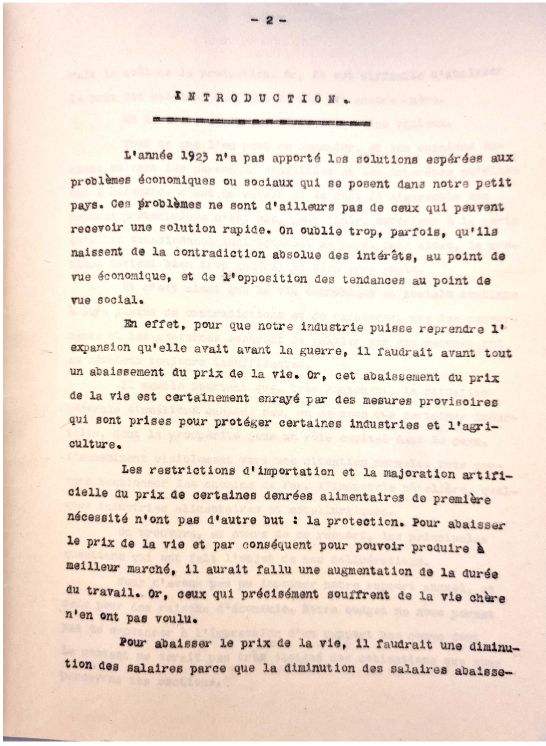
Table 1 – continued from previous page

Publication	Name	Source	Availability	Lang.	Freq.	# texts
TCP	FTCP : organe de la Fédération du personnel du textile, de la chimie et du papier	e-newspaper archives.ch	1951 - 1979	fr	BM	23.40
TDG	Tribune de Genève	Tamedia	1996 - 2021	fr	D	592.38
THT	Thuner Tagblatt	Tamedia	2019 - 2021	de	D	28.61
TSB	Tagblatt der Stadt Biel	e-newspaper archives.ch	1865 - 1900	de	D	115.44
VHT	VHTL-Zeitung / Gewerkschaft Verkauf, Handel, Transport, Lebensmittel	e-newspaper archives.ch	1904 - 2004	de	W/BM	21.98
WAB	Walliser Bote	e-newspaper archives.ch	1861 - 2008	de	D	2494.40
ZFZ	Zürcherische Freitagszeitung	e-newspaper archives.ch	1705 - 1914	de	W	53.95
ZGN	Zuger Nachrichten	e-newspaper archives.ch	1886 - 1900	de	TW	18.80
ZHUL	Zürcher Unterländer	Tamedia	2011 - 2021	de	D	179.52
ZKB_GB	Annual Reports Zürcher Kantonalbank	ZKB	1870 - 2016	de	Y	733.79
ZSZ	Zürichsee-Zeitung	Tamedia	2001 - 2021	de	D	549.34
ZVB	Zuger Volksblatt	e-newspaper archives.ch	1861 - 1900	de	BW	32.11
ZWB	Zürcherisches Wochenblatt	e-newspaper archives.ch	1801 - 1842	de	BW	33.43

Notes: Publications with source SWAB were digitized by ourselves (except AGB and HAZ).
Frequencies: D: daily, TW: three a week, BW: twice a week, W: weekly, BM: twice a month, M: monthly, Q: quarterly, Y: yearly.
Number of texts is in thousands.

Figure 1 — Scanned page, a pre-processed image, and the OCR text: Chambre vaudoise du commerce et de l'industrie, 1923.



- 2 -

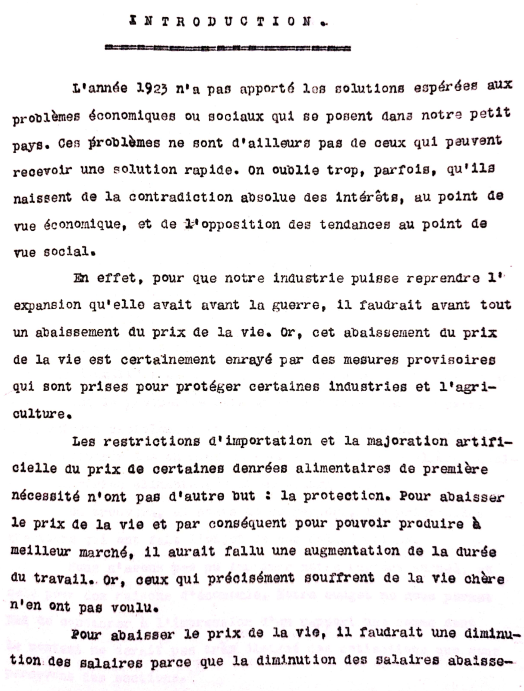
INTRODUCTION.

L'année 1923 n'a pas apporté les solutions espérées aux problèmes économiques ou sociaux qui se posent dans notre petit pays. Ces problèmes ne sont d'ailleurs pas de ceux qui peuvent recevoir une solution rapide. On oublie trop, parfois, qu'ils naissent de la contradiction absolue des intérêts, au point de vue économique, et de l'opposition des tendances au point de vue social.

En effet, pour que notre industrie puisse reprendre l'expansion qu'elle avait avant la guerre, il faudrait avant tout un abaissement du prix de la vie. Or, cet abaissement du prix de la vie est certainement enrayé par des mesures provisoires qui sont prises pour protéger certaines industries et l'agriculture.

Les restrictions d'importation et la majoration artificielle du prix de certaines denrées alimentaires de première nécessité n'ont pas d'autre but : la protection. Pour abaisser le prix de la vie et par conséquent pour pouvoir produire à meilleur marché, il aurait fallu une augmentation de la durée du travail. Or, ceux qui précisément souffrent de la vie chère n'en ont pas voulu.

Pour abaisser le prix de la vie, il faudrait une diminution des salaires parce que la diminution des salaires abaisse-



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Notes: Source: Schweizerisches Wirtschaftsarchiv Basel.

Result from OCR of figure 1
INTRODUCTION*.

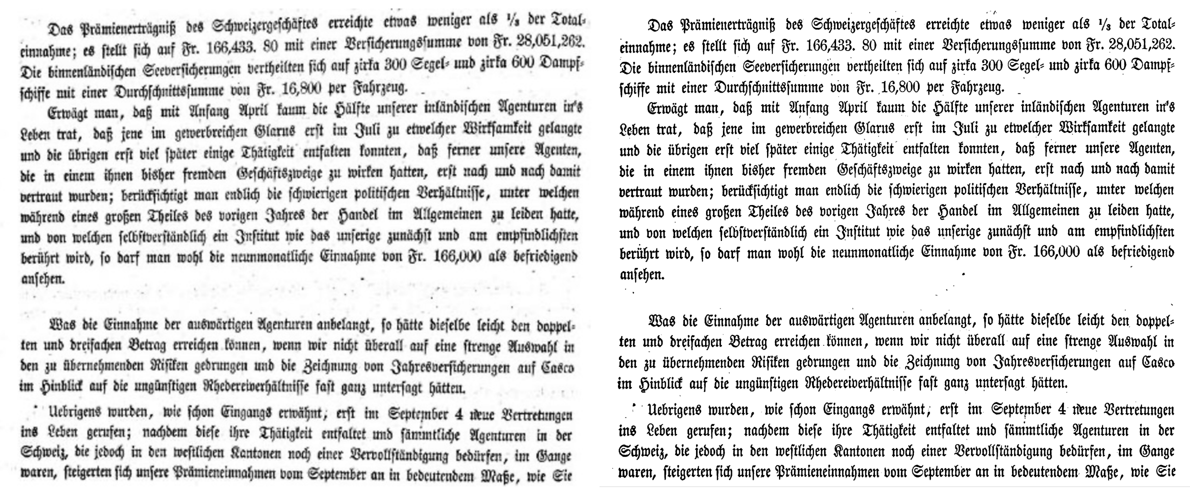
L'année 1923 n'a pan apporté les solutions espérées aux problèmes économiques ou sociaux qui so posent dans notre petit pays* Ces problèmes ne sont d'ailleurs pas de ceux qui peuvent recevoir une solution rapide, on ou'olie trop, parfois, qu'Ils naissent de la contradiction absolue des intérêts, au point de vue économique, et de *3?'opposition des tendances au point de vue social»

En effet, pour que notre industrie puisse reprendre l'expansion qu'elle avait avant la guerre, il faudrait avant tout un abaissement du prix de la vie. Or, cet abaissement du prix de la vie est certainement enrayé par des mesures provisoires qui sont prises pour protéger certaines industries et l'agriculture.

Les restrictions d'importation et la majoration artificielle du prix de certaines denrées alimentaires de première nécessité n'ont pas d'autre but : la protection. Pour abaisser le prix de la vie et par conséquent pour pouvoir produire à meilleur marché, il aurait fallu une augmentation de la durée du travail. Or, ceux qui précisément souffrent de la vie chère n'en ont pas voulu.

Pour abaisser le prix de la vie, il faudrait une diminution des salaires parce que la diminution des salaires abaisse-

Figure 2 — Scanned page, a pre-processed image, and the OCR text: Erster Geschäftsbericht, Helvetia, 1860.



Das Prämienerträgniß des Schweizergeschäftes erreichte etwas weniger als ⅓ der Totaleinnahme; es stellt sich auf Fr. 166,433. 80 mit einer Versicherungssumme von Fr. 28,051,262. Die binnenländischen Seeversicherungen vertheilten sich auf zirka 300 Segel- und zirka 600 Dampfschiffe mit einer Durchschnittssumme von Fr. 16,800 per Fahrzeug.

Erwägt man, daß mit Anfang April kaum die Hälfte unserer inländischen Agenturen in's Leben trat, daß jene im gewerbreichen Glarus erst im Juli zu etwelcher Wirksamkeit gelangte und die übrigen erst viel später einige Thätigkeit entfalten konnten, daß ferner unsere Agenten, die in einem ihnen bisher fremden Geschäftszweige zu wirken hatten, erst nach und nach damit vertraut wurden; berücksichtigt man endlich die schwierigen politischen Verhältnisse, unter welchen während eines großen Theiles des vorigen Jahres der Handel im Allgemeinen zu leiden hatte, und von welchen selbstverständlich ein Institut wie das unserige zunächst und am empfindlichsten berührt wird, so darf man wohl die neunmonatliche Einnahme von Fr. 166,000 als befriedigend ansehen.

Was die Einnahme der auswärtigen Agenturen anbelangt, so hätte dieselbe leicht den doppelten und dreifachen Betrag erreichen können, wenn wir nicht überall auf eine strenge Auswahl in den zu übernehmenden Risiken gedrungen und die Zeichnung von Jahresversicherungen auf Casco im Hinblick auf die ungünstigen Rhedereiverhältnisse fast ganz untersagt hätten.

Uebrigens wurden, wie schon Eingangs erwähnt; erst im September 4 neue Vertretungen ins Leben gerufen; nachdem diese ihre Thätigkeit entfaltet und sämmtliche Agenturen in der Schweiz, die jedoch in den westlichen Kantonen noch einer Vervollständigung bedürfen, im Gange waren, steigerten sich unsere Prämieneinnahmen vom September an in bedeutendem Maße, wie Sie

Notes: Source: Schweizerisches Wirtschaftsarchiv Basel.

Result from OCR of figure 2

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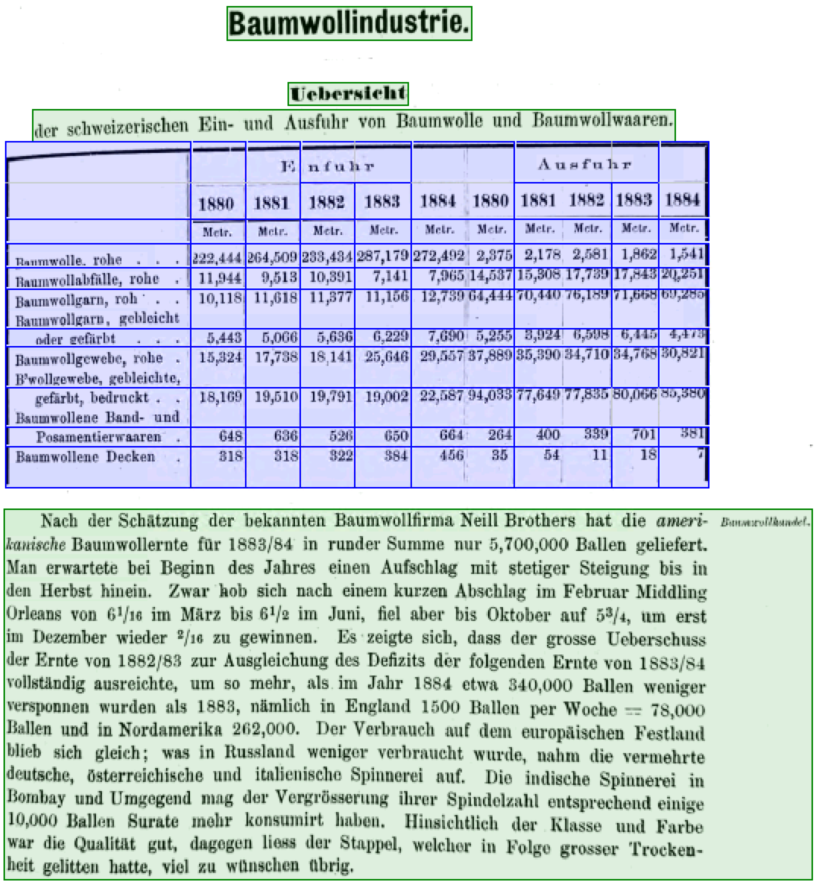
Figure 3 — Parsing the layout: Handels- und Industrieverein Vorort, 1923



Baumwollindustrie.

Uebersicht

der schweizerischen Ein- und Ausfuhr von Baumwolle und Baumwollwaaren.

	Einfuhr					Ausfuhr				
	1880	1881	1882	1883	1884	1880	1881	1882	1883	1884
	Metr.	Metr.	Metr.	Metr.	Metr.	Metr.	Metr.	Metr.	Metr.	Metr.
Baumwolle, rohe . . .	222,444	264,509	233,434	287,179	272,492	2,375	2,178	2,581	1,862	1,541
Baumwollabfälle, rohe .	11,944	9,513	10,391	7,141	7,965	14,537	15,308	17,739	17,843	20,251
Baumwollgarn, roh . .	10,118	11,618	11,377	11,156	12,739	64,444	70,440	76,189	71,668	69,285
Baumwollgarn, gebleicht oder gefärbt . . .	5,443	5,066	5,636	6,229	7,690	5,255	3,924	6,598	6,445	4,473
Baumwollgewebe, rohe .	15,324	17,738	18,141	25,646	29,557	37,889	35,390	34,710	34,768	30,821
B'wollgewebe, gebleichte, gefärbt, bedruckt . .	18,169	19,510	19,791	19,002	22,587	94,033	77,649	77,835	80,066	85,380
Baumwollene Band- und Posamentierwaaren .	648	636	526	650	664	264	400	339	701	381
Baumwollene Decken .	318	318	322	384	456	35	54	11	18	7

Baumwollhandel.

Nach der Schätzung der bekannten Baumwollfirma Neill Brothers hat die *amerikanische* Baumwollernte für 1883/84 in runder Summe nur 5,700,000 Ballen geliefert. Man erwartete bei Beginn des Jahres einen Aufschlag mit stetiger Steigung bis in den Herbst hinein. Zwar hob sich nach einem kurzen Abschlag im Februar Middling Orleans von 6 1/16 im März bis 6 1/2 im Juni, fiel aber bis Oktober auf 5 3/4, um erst im Dezember wieder 2/16 zu gewinnen. Es zeigte sich, dass der grosse Ueberschuss der Ernte von 1882/83 zur Ausgleichung des Defizits der folgenden Ernte von 1883/84 vollständig ausreichte, um so mehr, als im Jahr 1884 etwa 340,000 Ballen weniger versponnen wurden als 1883, nämlich in England 1500 Ballen per Woche = 78,000 Ballen und in Nordamerika 262,000. Der Verbrauch auf dem europäischen Festland blieb sich gleich; was in Russland weniger verbraucht wurde, nahm die vermehrte deutsche, österreichische und italienische Spinnerei auf. Die indische Spinnerei in Bombay und Umgegend mag der Vergrösserung ihrer Spindelzahl entsprechend einige 10,000 Ballen Surate mehr konsumirt haben. Hinsichtlich der Klasse und Farbe war die Qualität gut, dagegen liess der Stappel, welcher in Folge grosser Trockenheit gelitten hatte, viel zu wünschen übrig.

Notes: This figure illustrates that it is possible to parse the layout (i.e. titles, tables and paragraphs) of a given text. Source: Schweizerisches Wirtschaftsarchiv Basel.

Table 2 — Validation data sources

Publication	Name	Source	Availability	Freq.
HSSODEF	Real GDP (deflator-adjusted)	Historische Statistik der Schweiz HSSO (2012k)	1851 - 1890	Y
HSSOCPI	Real GDP (CPI-adjusted)	Historische Statistik der Schweiz HSSO (2012k)	1851 - 1890	Y
HSSO	Nominal GDP	Historische Statistik der Schweiz HSSO (2012k)	1851 - 1890	Y
HSSO16A	Real and nominal GDP	Historische Statistik der Schweiz HSSO (2012c)	1890 - 1948	Y
HSSO16B	Real and nominal GDP	Historische Statistik der Schweiz HSSO (2012d)	1948 - 2005	Y
MADDISON	Real GDP	Bolt and van Zanden (2020)	1820 - 2018	Y
FSOGDP	Real and nominal GDP	Federal Statistical Office (FSO)	1948 - 2021	Y
SECOGDP	Real and nominal GDP	State Secretariat for Economic Affairs (SECO)	1980 - 2022	Q
CHAINR	Chained real GDP	Maddison, HSSO, FSO, SECO	1851 - 2021	Y
CHAINN	Chained nominal GDP	HSSO, FSO, SECO	1851 - 2021	Y
RGDPWORLD	Real GDP world		1830 - 2022	Y
RGDPCapita	Real GDP per capita	HSSO	1851 - 2021	Y
OutputGapHP	HP-filtered CHAINR	see CHAINR	1851 - 2021	Y
OutputGapHam	Hamilton-filtered CHAINR	see CHAINR	1851 - 2021	Y
GDPSTOHR	Real and nominal GDP	Stohr (2016)	1851 - 2008	Y
RGDPINT	Real GDP international (Austria, England, France, Germany, Italy, USA)	Bolt and van Zanden (2020)	1851 - 2020	Y
IMPVOL	Import volumes	Historische Statistik der Schweiz HSSO (2012e)	1851 - 1913	Y
EXPVOLBAI	Export volumes index (Bairoch)	Historische Statistik der Schweiz HSSO (2012a)	1851 - 1913	Y
EXPVOLBER	Export volumes index (Bernegger)	Historische Statistik der Schweiz HSSO (2012a)	1851 - 1913	Y
IMPVAL	Import values	Historische Statistik der Schweiz HSSO (2012b)	1886 - 1992	Y
EXPVAL	Export values	Historische Statistik der Schweiz HSSO (2012b)	1886 - 1992	Y

Continued on next page

Table 2 – continued from previous page

Publication	Name	Source	Availability	Freq.
IMPVOLM	Import volumes	Historische Statistik der Schweiz HSSO (2012i)	1924 - 1987	M
EXPVOLM	Export volumes	Historische Statistik der Schweiz HSSO (2012g)	1924 - 1967	M
IMPVALM	Import values	Historische Statistik der Schweiz HSSO (2012j)	1924 - 1992	M
EXPVALM	Export values	Historische Statistik der Schweiz HSSO (2012h)	1924 - 1992	M
IMPVALEZV	Import values	Federal Office for Customs and Border Security (FOCBS)	1988 - 2022	M
EXPVALEZV	Export values	Federal Office for Customs and Border Security (FOCBS)	1988 - 2022	M
TradeIndicator	First principal component of trade related indexes	HSSO, FOCBS	1851 - 2022	Y
THORPGPT	Created sentiment indicators (Austria, England, France, Germany, Italy, USA)	Thorp (1926), GPT-3.5	1800 - 1925	Y
HSSOUNEMP	Unemployment rate	Historische Statistik der Schweiz HSSO (2012l)	1913 - 1995	Y
HSSOEMP	Employment growth	Historische Statistik der Schweiz HSSO (2012f)	1890 - 2005	Y
FSOUNEMP	Unemployment rate	FSO	1970 - 2021	M
FSOEMP	Employment growth	FSO	1998 - 2021	M
ECRIREC	Recession indicator	Economic Cycle Research Institute (ECRI)	1956 - 2022	M
OECDREC	Recession indicator	Organisation for Economic Co-operation and Development (OECD), Fred: CHEREC	1960 - 2022	M

Notes: This table shows sources, available periods and frequency of the validation data. Most series are further spliced to a long time series spanning as many periods as possible.

Table 3 — Keywords defining economic concepts in German

Topic	Keywords (based on readings)	Method
Real activity	wirtschaft ware absatz nachfrage geschäft konsum waare fabrikant erlös umsatz markt industrie branche käufer unternehmer ernte ergebniss konjunktur kundschaft verkauf produktion dienstleistung verarbeitung gewerbe ertrag einnahmen ausgaben fabrikation bestellung versorgung materialbeschaffung einkäufer verlust konkurrenten fabrizieren fabrikat besteller werth neugründung materialien betriebsmittel materialeinkäufe jahresresultat geschäftsperiode werkstätten erfolg bestellungen eigenkosten produkte rohmaterialien einbusse fabric fabrik herstellung geschäftsgang wirtschaftsleben wirtschaftlich nachfrage geschäftslage marge angebot erträgnis rendite produzent vertrieb volkswirtschaft konjunkturrückgang verkaufsziffern kauflust kaufunlust geschäftsjahr kleinbetrieb bautätigkeit verbraucher konkurrenz erzeugnis konsum profit fremdenverkehr dienste dienstleistungen investition versorgungsmöglichkeit versorgungslage versorgungsschwierig bruttoinlandprodukt bruttosozialprodukt realwachstum wertschöpfung	KWIC
Trade	eingangszölle eingangszoll konkurrenzverhältnisse konkurrenzverhältnis einfuhr ausfuhr export import sendungen aussendung importeure exporteure handelsstatistik absatzfeld wettbewerb absatzgebiet zwischenhandel handel importhaus zollverhältnisse zollverhältnis handelsbilanz waarenverkehr warenverkehr waarenausfuhr warenausfuhr waareneinfuhr wareneinfuhr importhandel handelsverkehr zoll zolleinnahmen zölle weltbedarf fracht exportziffern gesammtexport gesamtexport taxen verkehrserleichterung bezugsquelle ausland generaltarif tarif einfuhrverbote zufuhren zufuhr grosshändler seefracht wasserweg welthandel weltverkehr güterstrom güteraustausch güterumschlag umschlagverkehr wagenverkehr	KWIC
Capacity	lager kornspeicher speicher ueberproduktion überproduktion vorräthe vorräte liefertermine lieferfrist vorrat vorrath aufträge lieferfristen lagerware lager depots bestellungen lieferungen wagenmangel	KWIC
Labor	arbeit erwerb beruf erwerbende arbeiter aufsichtspersonal arbeiterin angestellte arbeitskräfte beschäftigung arbeitszeit arbeitgeber arbeiterschaft ueberzeit überzeit arbeitstag arbeitsleistung ausbildung lehrlinge ueberzeitarbeit überzeitarbeit streik arbeitseinstellung arbeitsfeld thätigkeit tätigkeit arbeiterinnen personal	KWIC

Continued on next page

Table 3 – continued from previous page

Topic	Keywords (based on readings)	Method
Inflation	preis getreidepreise theuer teuer preisfall kostenpreise wechselkurs silberpreis preisaufschlag silberkurs preisbasis kurs preissturz baumwollpreise preisnotierung preisnotirung waarenpreise warenpreise kursschwankungen kostenpreis preissteigerung schleuderpreise abschlag materialpreise maschinenpreise unterbietung preisvorteile preisvortheile verkaufspreise rohpreise preiserhöhung entwerthung entwertung goldkurs geldvertheuerung geldverteuerung geldwerth geldwert vertheuerung verteuerung wechselkurse pari preise teuerung kaufkraft aufschlag inflation inflatorisch	KWIC
Wages	entgelt lohnerhöhung arbeitslöhne löhne arbeitslohn kaufkraft lohnverhältnisse lohnsätze lohnansätze stundenlöhne stundenlohn akkordlöhne akkordlohn akkord tagesverdienst löhnungen löhnung lohnverhältnis verdienstverhältnisse verdienstverältnis einkommen lohnniveau lohnstopp lohnpolitik	KWIC
Credit	kreditverhältnisse banknoten münzen einleger guthaben einzahlung rückzahlung prämien renten kapitalien verzinsung amortisation wechsel geldmarkt zinsen zins rendite diskontsätze disconto discontsätze diskontosätze diskontosatz diskontsatz geldkraft zinsfuss wechselgeschäft wechselkverkehr zinssätze zinssatz diskontopolitik geldinstitute lombardvorschüsse notenemission vorschüsse kontokorrent kreditwirtschaft kredit schuldbriefe kreditwesen leihmarkt emissionsbanken diskonto geldbedarf diskonti diskontoverkehr geldsuchenden emissionen geldverteuerung liquidität geldknappheit geldstand lombardsatz geldleihpreis geldmärkte kapitalmarkt anleihen hypothek depositen darlehen pfandbrief geldpolitik geldmenge	KWIC
Financial	kapitalvermehrung emissionskurs tageskurs agio kurse dividenden emittirt emittiert obligationen rentabilität konversion börsengeschäft kapital werthpapiere wertpapiere titelverkäufe papiere kurssteigerung portefeuille tratten ueberspekulation überspekulation entwerthung entwertung finanzcrisis finanzkrisis börse emission gründung aktie actie aktien kurs effekten märkte wechselkurs devisen valoren dividende wertschriften	KWIC
Recession	crisis krise rezession recession finanzcrisis finanzkrisis spekulationskrise krach krisis zahlungsfähigkeit fallimente bankerottir liegenschaftenkrisis konkurse schaden konjunkturrückgang weltbrand notstand valutasturz depression valutaschwierigkeit wirtschaftskatastrophe schäden liquidation liquidier hemmnisse zusammenbruch notlage katastrophe baisse	Count
Boom	hausse aufschwung hochkonjunktur prosperität erholungsperiode boom	Count

Continued on next page

Table 3 – continued from previous page

Topic	Keywords (based on readings)	Method
War	krieg konflikt putsch	Count

Notes: The table contains keywords used to identify economic concepts in German. The most right column indicates the method used to identify the keywords. KWIC stands for keyword-in-context, which means that a sentiment score is calculated from the words surrounding the keyword. Count indicates that the indicator is created by counting the appearances of these keywords. Terms embedded in \b are used to avoid counting words that contain the keyword, but are not the keyword itself. For example, \bertrag\b (in english: revenue) is used to avoid counting the word "ertragen" (endure) as a keyword. For the other words, wildcards are used, which means that all words containing e.g. "import" are counted as a keyword.

Table 4 — Keywords defining economic concepts in French

Topic	Keywords (based on readings)	Method
Real activity	économie marchandise vente \bdemande\b affaire consommation marchandis fabricant revenu horlogerie marchand industrie branche acheteur entrepreneur récolte marcheé conjoncture clientèle production \bservice\b \bachat\b rendement recettes dépenses fabrication commande approvisionnement perte concurrents fabriquer produit commanditaire matériaux achats commandes \bcoûts\b produits fabriq usine fabric économique demande récoltes marge \boffre\b \bmarché\b producteur distribution economie ventes economique \bacheter\b fiscal entreprise consommateur concurrence profit tourisme revenus services investissement produite pib \bcroissance\b	KWIC
Trade	importation exportation export import importateurs exportateurs commerc commerce douani marchandises douane fret taxes tarif approvisionnements approvisionnement grossistes marchandise transbordement	KWIC
Capacity	entrepôt silo stockage surproduction réserves livraison réserve commandes marchandise dépôts livraisons \bstock\b	KWIC
Labor	travail gain métier travailleurs ouvrier personnel ouvrière employée main-d'œuvre emploi employeur formation apprentis grève activité ouvrières	KWIC
Inflation	prix taux cours rabais dévalorisation monétaire renchérissement parité majoration inflation inflationniste	KWIC
Wages	rémunération salaire salaires salariaux accord rémunérations revenu	KWIC
Credit	crédit banque monnaie déposants solde versement remboursement primes rentes capitaux intérêt amortissement change monétaire intérêts rendement taux escompte lombard émission \bavances\b créance argent émissions liquidité capital emprunts hypothèque dépôts prêts	KWIC
Financial	capital spéculation \bémission\b cours agio dividendes émis obligations rentabilité conversion bourse titres papiers portefeuille trattes sur-spéculation dévalorisation financière financi émission fondation action actions \bcours\b effets \bmarchés\b devises valeurs dividende	KWIC
Recession	crise récession krach solvabilité faillites faillite dommages conflagration dépression catastrophe liquidation liquider effondrement baisse	Count
Boom	hausse expansion prospérité rétablissement boom	Count

War	guerre conflit putsch	Count

Notes: The table contains keywords used to identify economic concepts in French. The most right column indicates the method used to identify the keywords. KWIC stands for keyword-in-context, which means that a sentiment score is calculated from the words surrounding the keyword. Count indicates that the indicator is created by counting the appearances of these keywords. Terms embedded in \b are used to avoid counting words that contain the keyword, but are not the keyword itself. For example, \bdemande\b (in english: demand) is used to avoid counting the word "demander" (asking) as a keyword. For the other words, wildcards are used, which means that all words containing e.g. "import" are counted as a keyword.

Figure 4 — Document-level sentiment score

Lead text of FUW from March 6, 2020

Before cleaning

Das Coronavirus trifft die Schweizer Wirtschaft ab dem Frühjahr mit voller Kraft. Volkswirte stimmen auf ein schwaches zweites Quartal ein. Konsum, Tourismus und Exportindustrie leiden bereits. Der Bundesrat sollte die Kurzarbeit ausweiten.

After cleaning

coronavirus trifft schweizer wirtschaft frühjahr voller kraft volkswirte stimmen schwaches zweites quartal konsum tourismus exportindustrie leiden bereits bundesrat kurzarbeit ausweiten

---

In English

Before cleaning

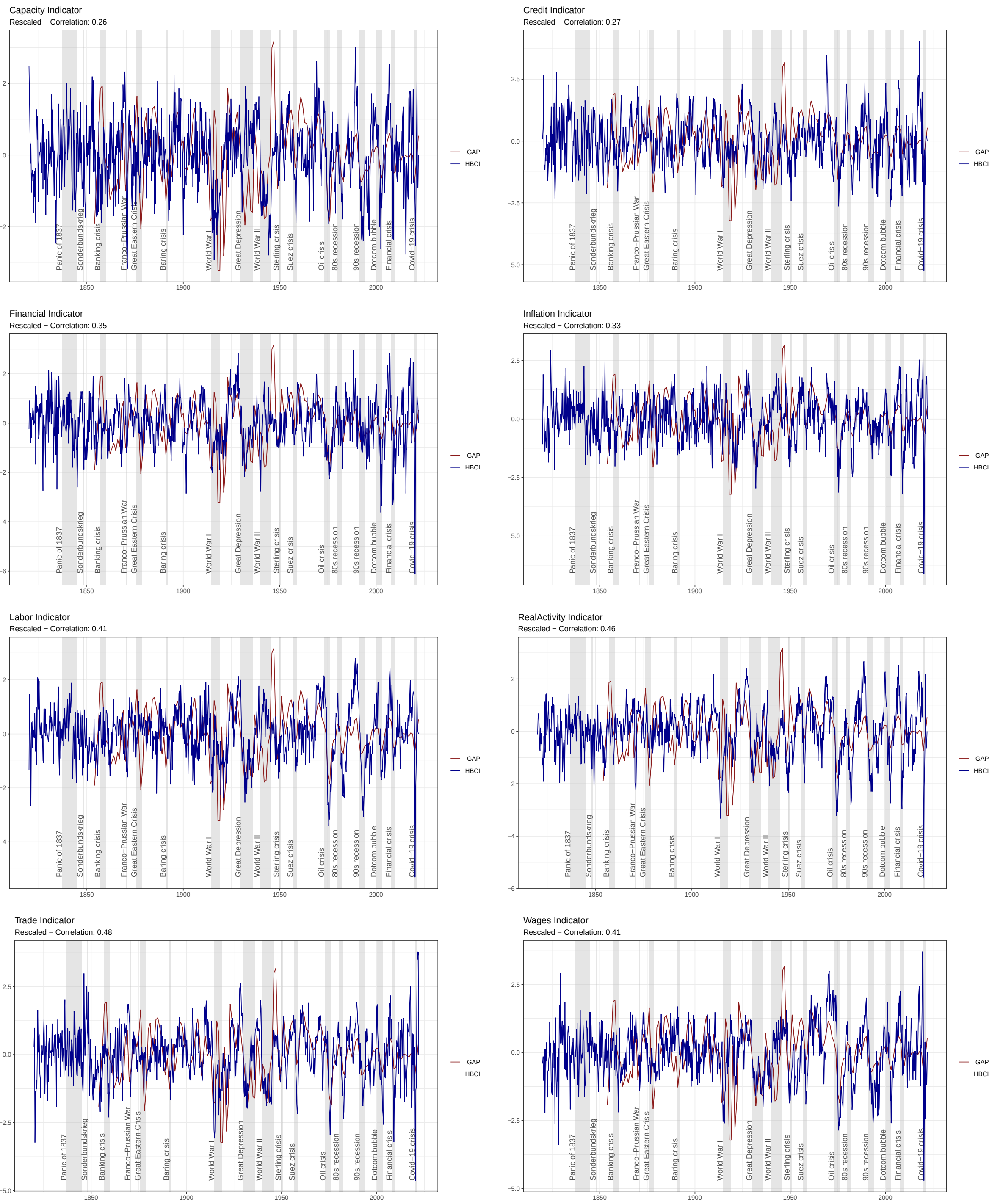
The corona virus is hitting the Swiss economy with full force from the spring. Economists are predicting a weak second quarter. Consumption, tourism and the export industry are already suffering. The Federal Council should extend short-time work.

After cleaning

corona virus hitting swiss economy spring full force economists predicting weak second quarter consumption tourism export industry already suffering federal council extend short time work

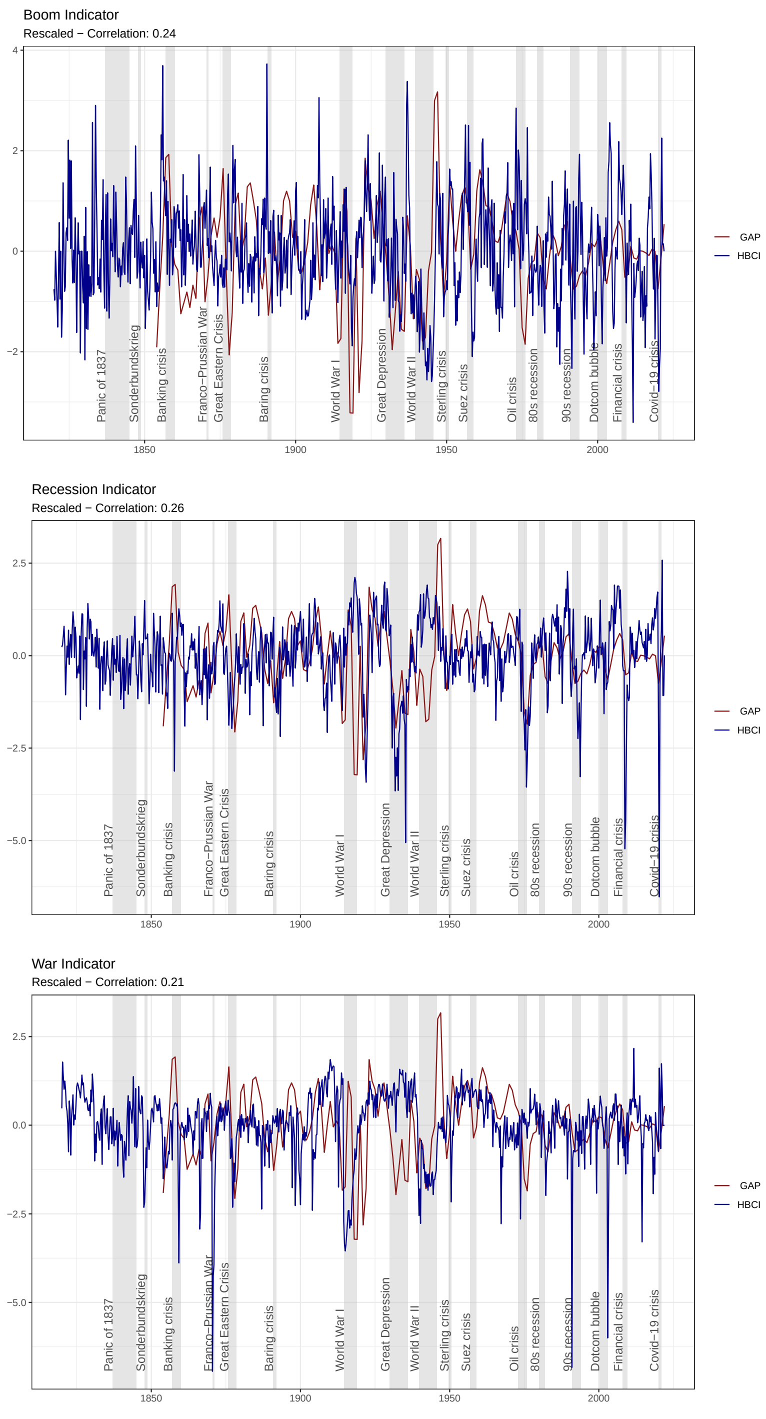
Notes: Example of how document-level sentiment scores for two topics are calculated based on a article teaser from FUW. For the general economy topic that is defined by the keyword (in blue) *wirtschaft*, the number of negative words (in red) is subtracted from the number of positive words (in green) within the ten preceding and following words from the keyword, and this result is divided by the total number of words. In this case, the sentiment score is $S_{t,d,\text{economy}} = (1-1)/14 = 0$. Note that there are only 14 words in the denominator because the keyword is close to the beginning of the text. The same method is applied to calculate the sentiment score for other topics, such as the industry topic, which in this example is given by $S_{t,d,\text{industry}} = (1-2)/19 = -0.05$.

Figure 5 — Sentiment-based topic-specific indicators



Notes: These graphs show sentiment-based topic-specific indicators together with the output gap.

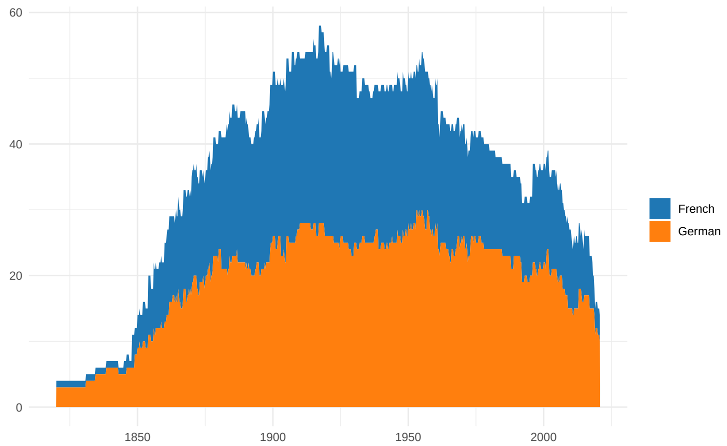
Figure 6 — Count-based topic-specific indicators



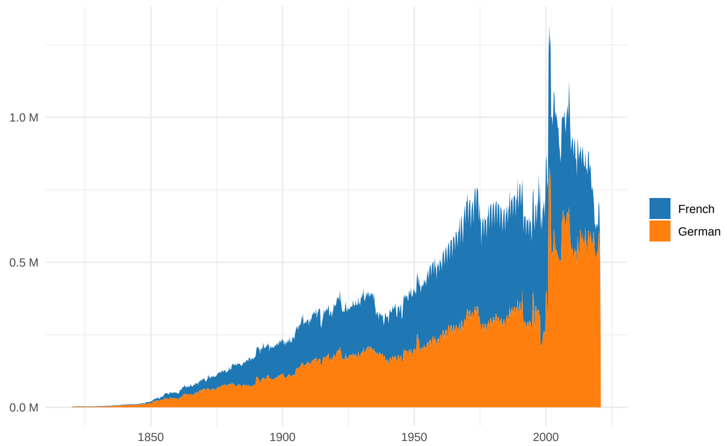
Notes: These graphs show count-based topic-specific indicators together with the output gap. Indicators are scaled to have a positive correlation with the output gap.

Figure 7 — Available sources and identified keywords

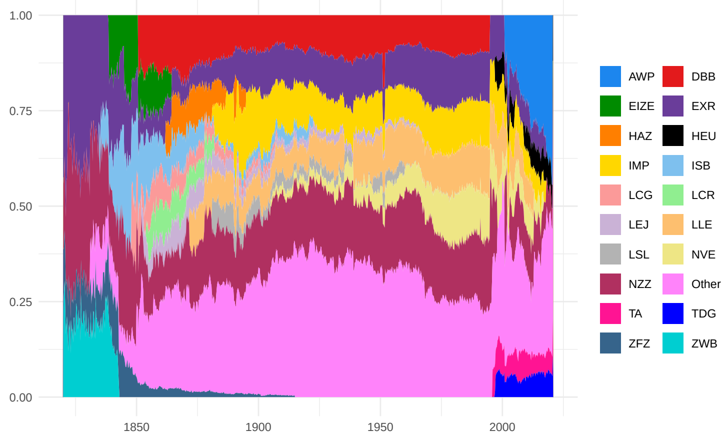
a) Number of available sources



b) Number of identified keywords



c) Most important sources



Notes: The graph shows number of available sources and identified keywords for each language in Panels a) and b), respectively. Panel c) shows the most important (by most identified keywords) sources and their share.

Table 5 — Frequency, duration, and number of Swiss compared to European business cycles

		Recession (Peak to trough)			Expansion (Trough to peak)		
	Algorithm	1800-1870	1870-1950	1950-2000	1800-1870	1870-1950	1950-2000
Frequency	Hamilton (1989)	32.3	25.3	21.5	67.7	74.7	78.5
	Bry and Boschan (1971)	49.3	45.9	36.5	50.7	54.1	63.5
	BL2023 (Swiss GDP)	35.0	32.5	14.0	65.0	67.5	86.0
	ECRI			19.2			80.8
	BL2023 (European GDP)	38.0	28.4	5.9	62.0	71.6	94.1
Duration	Hamilton (1989)	7.6	6.5	7.2	17.0	19.6	23.0
	Bry and Boschan (1971)	11.4	15.1	14.4	14.6	16.9	21.8
	BL2023 (Swiss GDP)	5.6	6.5	7.0	9.6	13.2	36.0
	ECRI			8.7			32.1
	BL2023 (European GDP)	6.4	7.2	4.0	9.6	17.2	54.8
Number	Hamilton (1989)	8.0	13.0	6.0	9.0	12.0	6.0
	Bry and Boschan (1971)	7.0	11.0	5.0	8.0	10.0	6.0
	BL2023 (Swiss GDP)	5.0	16.0	4.0	5.0	16.0	4.0
	ECRI			4.0			4.0

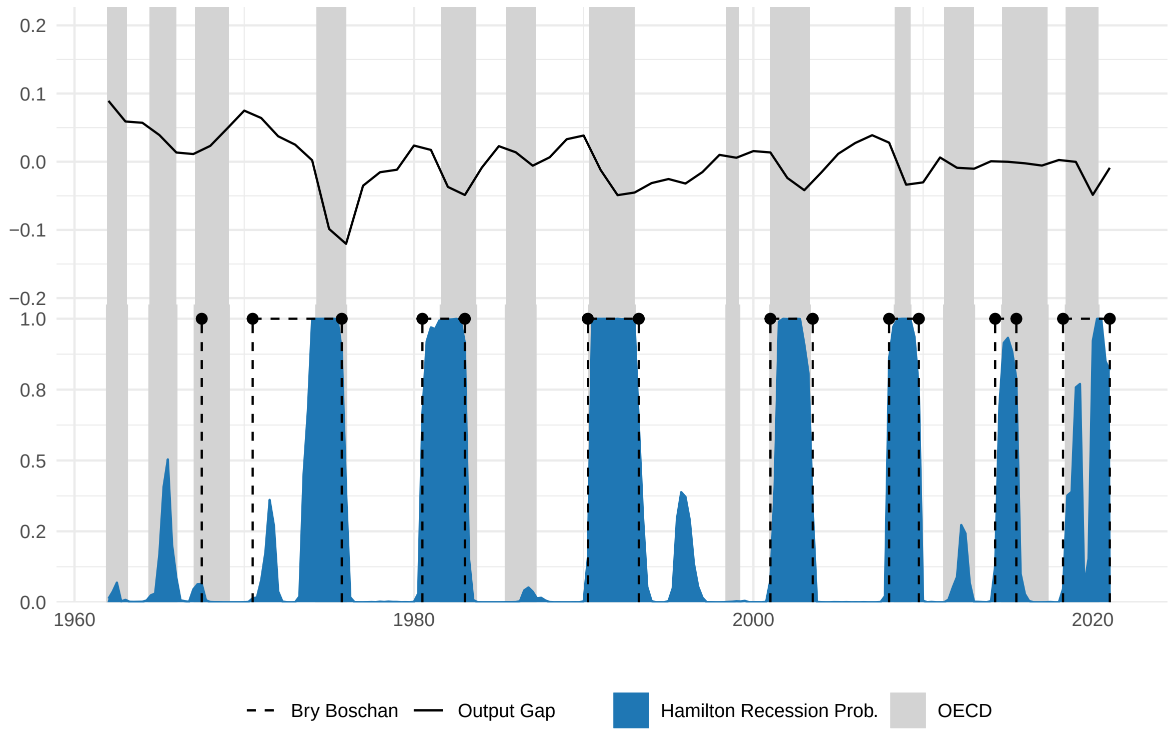
Notes: Frequency is the share of quarters in a given phase in percent. Duration is the average number of quarters in a given phase. Dating based on Hamilton (1989) and Bry and Boschan (1971) starts in 1820, real Swiss GDP growth is available from 1852, and the ECRI dating starts in 1956. Broadberry and Lennard (2023) (BL2023 European GDP) classifiy recessions as negative GDP per capita growth.

Table 6 — Frequency, duration, and number of Swiss compared to UK business cycles

		Recession (Peak to trough)			Expansion (Trough to peak)		
	Algorithm	1817-1908	1909-1947	1948-2009	1817-1908	1909-1947	1948-2009
Frequency	Hamilton (1989)	33.4	13.5	27.4	66.6	86.5	72.6
	Bry and Boschan (1971)	51.6	35.9	39.9	48.4	64.1	60.1
	BL2023 (Swiss GDP)	25.9	43.6	17.7	74.1	56.4	82.3
	ECRI			21.9			78.1
	B2023 (UK GDP)	22.8	25.6	11.3	77.2	74.4	88.7
Duration	Hamilton (1989)	6.9	7.0	7.6	14.6	35.7	23.2
	Bry and Boschan (1971)	14.0	13.5	12.6	14.1	20.4	21.1
	BL2023 (Swiss GDP)	5.0	8.5	6.3	13.7	10.7	33.3
	ECRI			7.9			27.7
	B2023 (UK GDP)	5.2	10.0	7.2	17.6	29.2	55.2
Number	Hamilton (1989)	17.0	3.0	9.0	17.0	3.0	9.0
	Bry and Boschan (1971)	13.0	4.0	8.0	13.0	5.0	7.0
	BL2023 (Swiss GDP)	12.0	8.0	7.0	12.0	8.0	7.0
	ECRI			6.0			6.0
	B2023 (UK GDP)	16.0	4.0	4.0	16.0	4.0	4.0

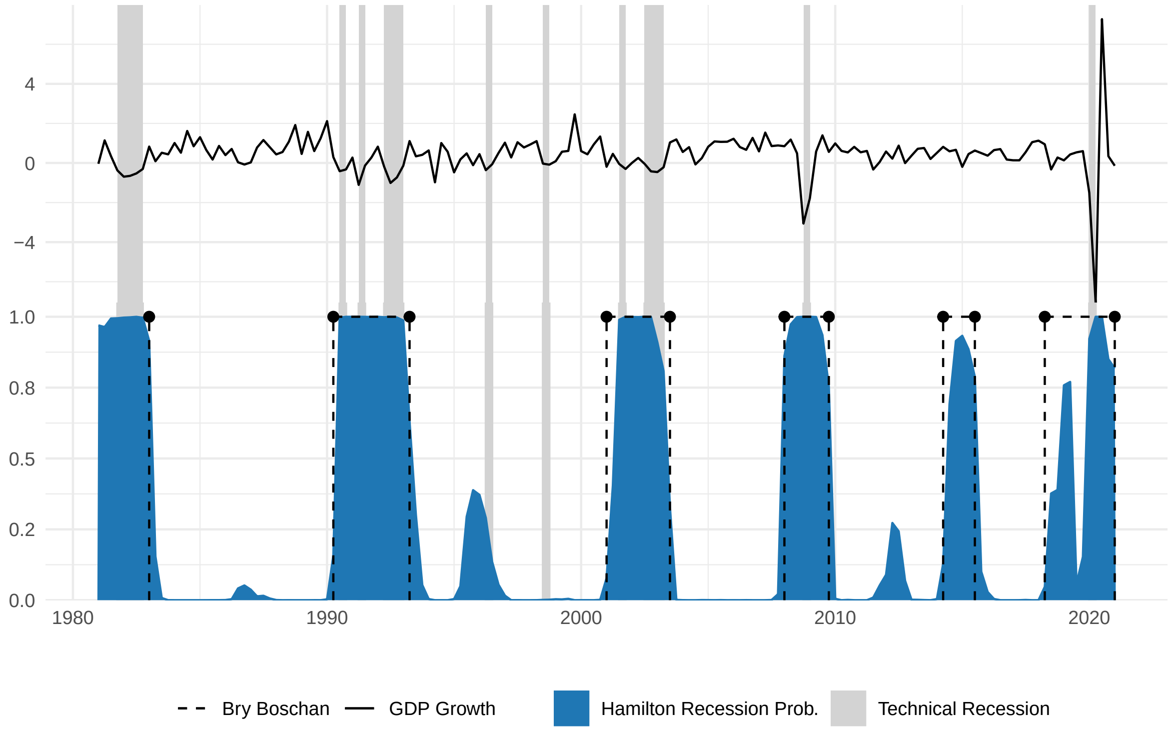
Notes: Frequency is the share of quarters in a given phase in percent. Duration is the average number of quarters in a given phase. Dating based on Hamilton (1989) and Bry and Boschan (1971) starts in 1820, real Swiss GDP growth is available from 1852, and the ECRI dating starts in 1956. Broadberry et al. (2023) (B2023 UK GDP) use discretion to classify phases in economic activity. BL2023 classifies recessions as negative GDP per capita growth.

Figure 8 — Comaprison with OECD dating



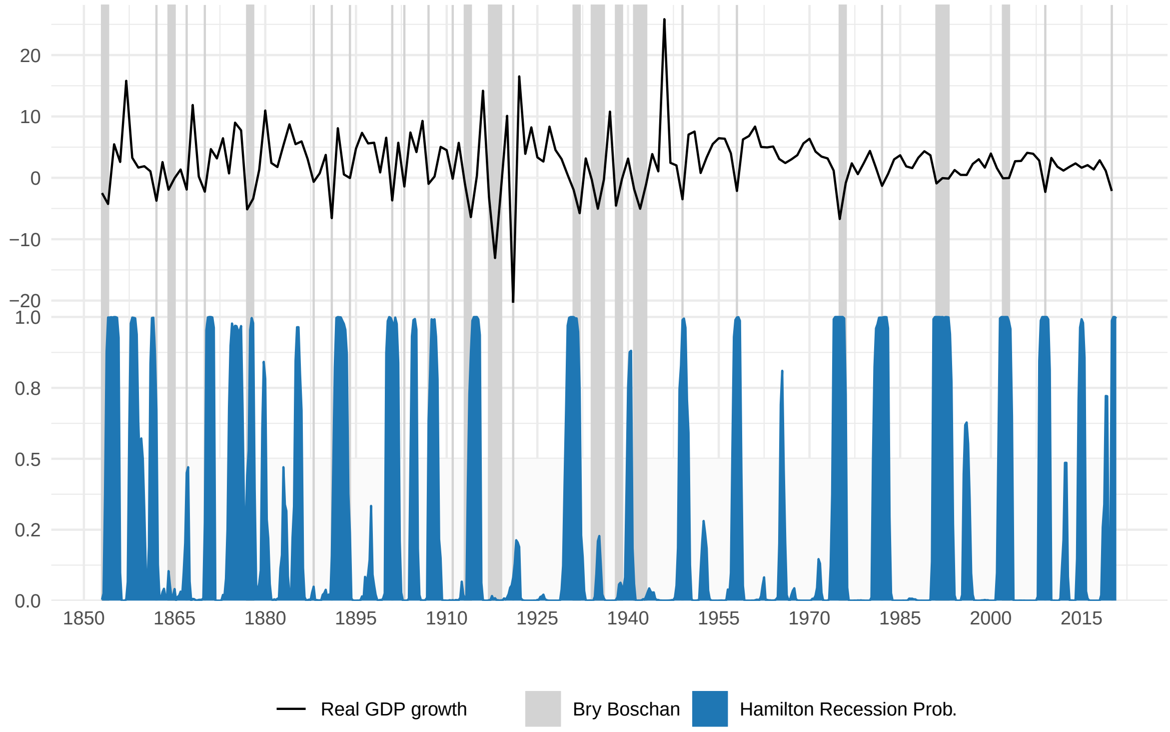
Notes: This graph shows the output gap given by the black solid line together with smoothed recession probabilities obtained by Hamilton's (1989) Markow-Switching autoregression model. The black dashed lines indicate recessions obtained by an adapted Bry and Boschan (1971) algorithm. The gray shaded areas are recession dates obtained from OECD.

Figure 9 — Comaprison with technical recession



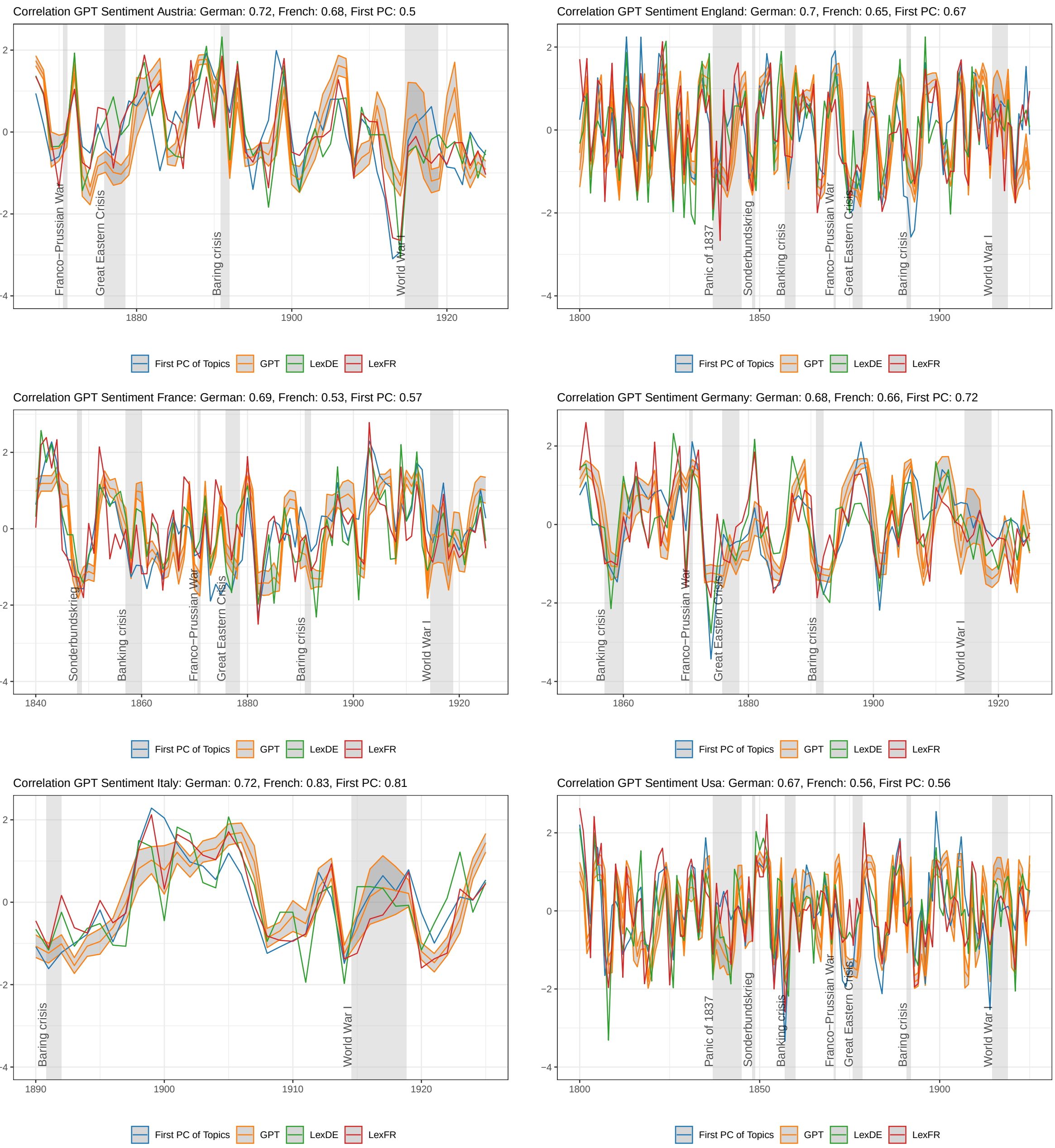
Notes: This graph shows quarterly real GDP growth given by the black solid line together with smoothed recession probabilities obtained by Hamilton's (1989) Markow-Switching autoregression model. The black dashed lines indicate recessions obtained by an adapted Bry and Boschan (1971) algorithm. The gray shaded areas indicate technical recessions.

Figure 10 — Comaprison with BL2023 algorithm based on annual GDP growth



Notes: This graph shows annual real GDP growth given by the black solid line together with smoothed recession probabilities obtained by Hamilton's (1989) Markow-Switching autoregression model. The gray shaded areas indicate contractions obtained with the algorithm proposed by Broadberry and Lennard (2023).

Figure 11 — Comparison of lexicons and methods



Notes: These graphs show several text based sentiment indicators based on Thorp's (1926) description. In orange the normalized sentiment indicator based on OpenAI's (2023) GPT-3.5 model together one standard deviation confidence bands. In green, the sentiment indicator based on a German translation of Thorp (1926) and the German lexicon. In red, the sentiment indicator based on a French translation of Thorp (1926) and the French lexicon. In blue, the first principal component from indicators based on both translations and the proposed keyword-based algorithm. Gray shaded areas represent crises.

Table 7 — Quarterly turning points in Switzerland, 1821 - 2021

Censored

Peak	Trough
1821 Q1	1823 Q3
1825 Q1	1826 Q3
1833 Q1	1833 Q4
1842 Q2	1843 Q2
1848 Q1	1850 Q2
1853 Q4	1855 Q4
1857 Q3	1859 Q1
1859 Q3	1859 Q4
1861 Q1	1862 Q1
1870 Q2	1871 Q3
1874 Q1	1876 Q2
1877 Q2	1878 Q1
1879 Q3	1880 Q1
1885 Q1	1886 Q1
1891 Q3	1893 Q3
1900 Q1	1902 Q1
1904 Q2	1905 Q1
1907 Q1	1908 Q3
1913 Q4	1915 Q3
1929 Q4	1932 Q1
1940 Q1	1940 Q3
1948 Q3	1950 Q1
1957 Q2	1958 Q3
1965 Q2	1965 Q3
1974 Q1	1976 Q1
1980 Q4	1983 Q1
1990 Q3	1993 Q3
1995 Q4	1996 Q2
2001 Q2	2003 Q3
2008 Q1	2009 Q4
2014 Q3	2015 Q3
2020 Q1	2021 Q1

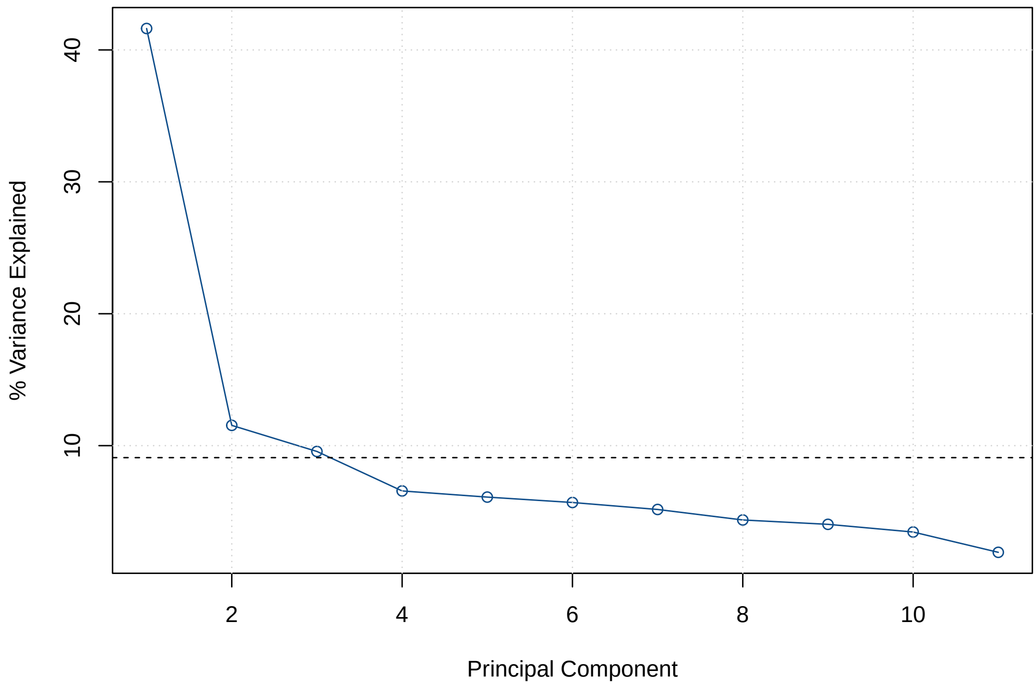
Notes: Quarterly truning points of Swiss business cycles obtained from Hamilton's (1989) Markov-switching autoregression model and smoothing. See section 5 for details.

Not censored

Peak	Trough
1821 Q1	1823 Q3
1825 Q1	1826 Q3
1833 Q1	1833 Q4
1842 Q2	1843 Q2
1848 Q1	1850 Q2
1853 Q4	1855 Q4
1857 Q3	1859 Q1
1859 Q3	1859 Q4
1861 Q1	1862 Q1
1870 Q2	1871 Q3
1874 Q1	1876 Q2
1877 Q2	1878 Q1
1879 Q3	1880 Q1
1885 Q1	1886 Q1
1891 Q3	1893 Q3
1900 Q1	1902 Q1
1904 Q2	1905 Q1
1907 Q1	1908 Q3
1913 Q4	1915 Q3
1929 Q4	1932 Q1
1940 Q1	1940 Q3
1948 Q3	1950 Q1
1957 Q2	1958 Q3
1965 Q2	1965 Q3
1974 Q1	1976 Q1
1980 Q3	1983 Q1
1990 Q3	1993 Q3
1995 Q4	1996 Q2
2001 Q2	2003 Q3
2008 Q1	2009 Q4
2014 Q3	2015 Q3
2019 Q1	2019 Q2
2020 Q1	2021 Q1

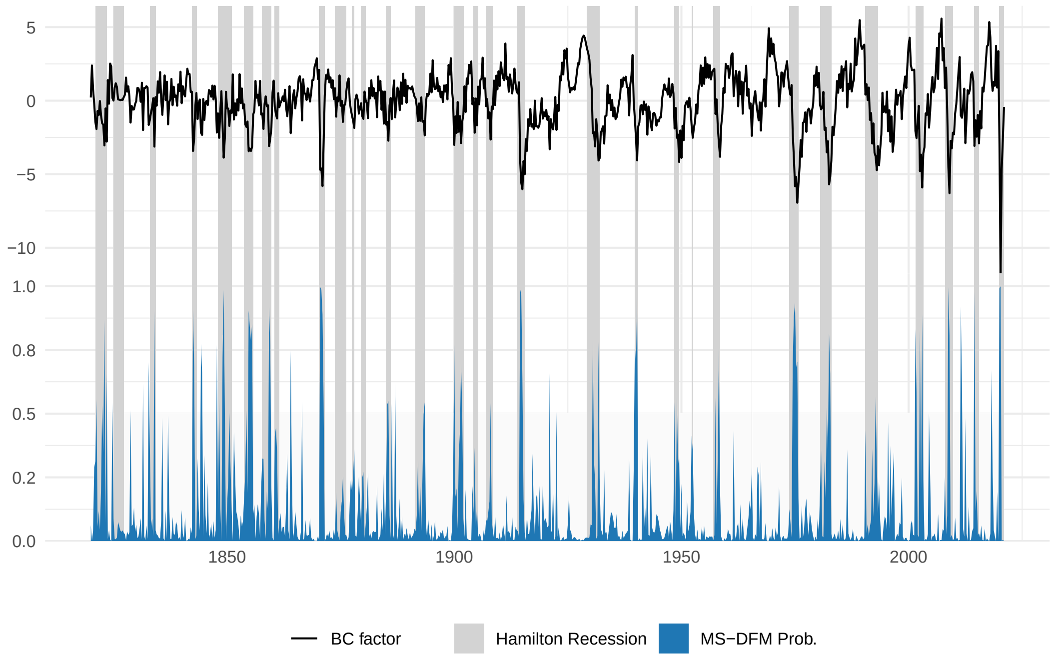
Notes: Quarterly truning points of Swiss business cycles obtained from Hamilton's (1989) Markov-switching autoregression model. See section 5 for details.

Figure 12 — Scree plot for MS-DFM used for sensitivity analysis



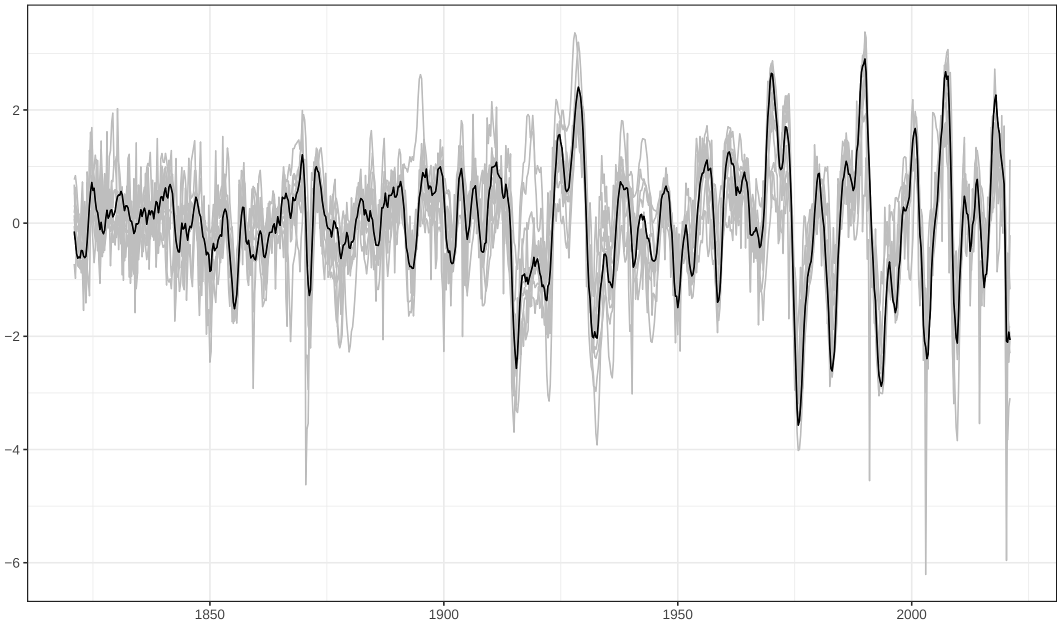
Notes: This graph shows marginal contribution of each aditional factor to R^2.

Figure 13 — Recession probabilities derived from MS-DFM



Notes: This graph shows the business cycle factor (black solid line) together with smoothed recession probabilities (blue) obtained with the MS-DFM. The gray shaded areas indicate recessions obtained with Hamilton's (1989) Markow-Switching autoregression model with the baseline indicator.

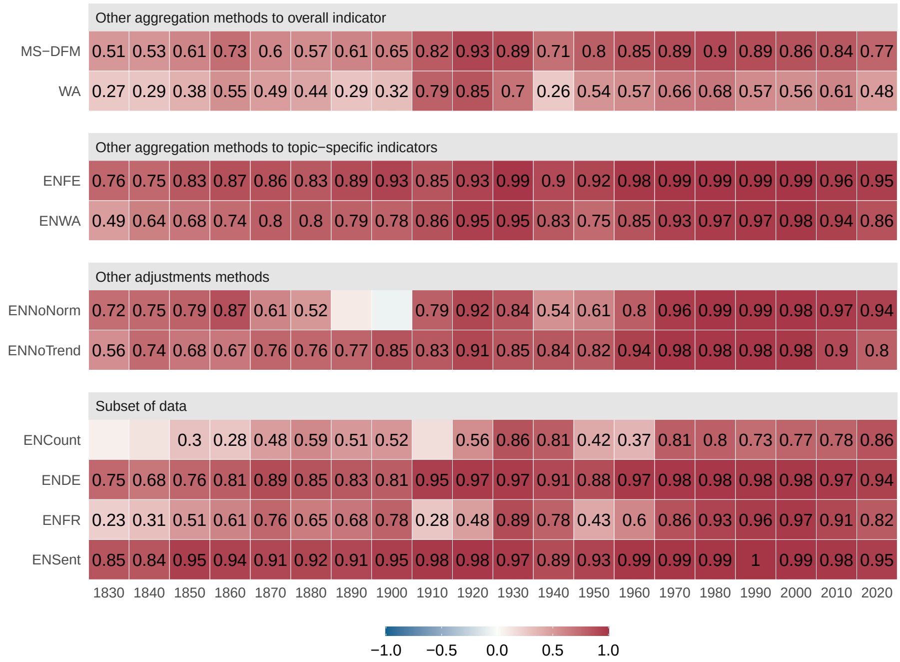
Figure 14 — Comparison to indicators based on other aggregation techniques, adjustments methods and subsets of data.



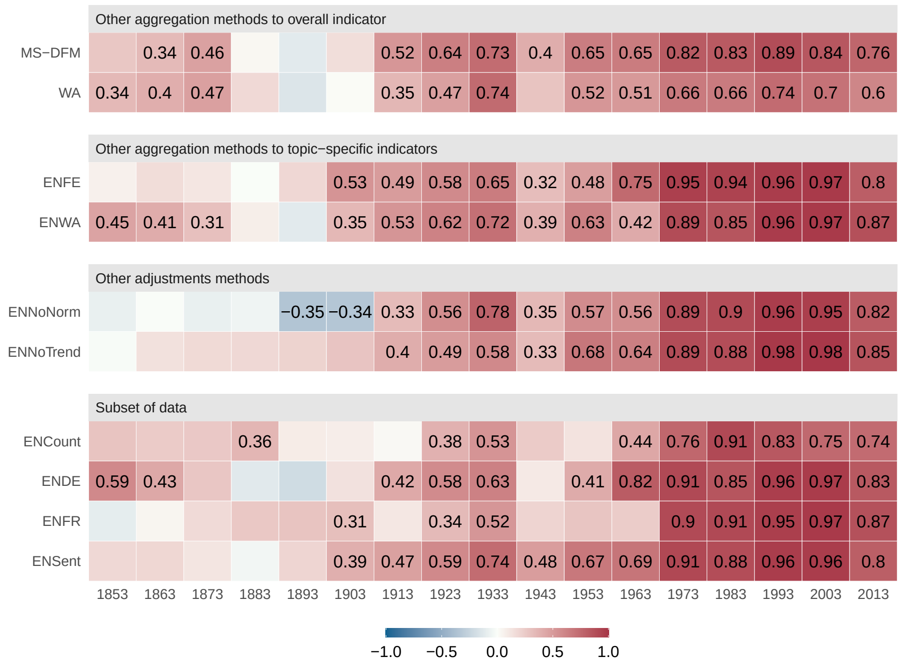
Notes: This graph shows the baseline indicator (black solid line) together with several indicators based on other aggregation techniques, adjustment methods, and subsets of data (gray lines). See section 6 for more details.

Figure 15 — Correlations of alternative indicators

a) Correlation with baseline composite indicator



b) Correlation with output gap



Notes: The graph shows rolling correlations with a fixed window size of 20 years between the indicator on the left and the composite indicator (in panel a) and the output gap (in panel b). The time period considered is given by the year on the x-axis plus minus ten years. Only statistically significant (on 10% level) correlations are labelled.

B GPT-3.5 meets Business Annals: A new take on 19th century sentiments

Qualitative business cycle indicators based on consumer or business surveys became popular in the mid-20th century. Before, however, there were no systematic attempts to measure the business cycle using surveys. To overcome this, I propose to use Thorp's (1926) description of the state of the economy together with OpenAI's (2023) GPT-3.5 language model to construct economic sentiment indicators for several countries in the 19th and early 20th centuries. In this section, I show step-by-step how this can be done.

Thorp's (1926) book "Business Annals" is a seminal work in the field of financial history and economic analysis. In this book, Thorp (1926) meticulously compiles and analyzes historical data related to business cycles, financial situation, and economic fluctuations. His aim is to provide a comprehensive record of business conditions and their impact on financial markets. He provides a detailed narrative account of the business cycle in selected countries for every year from around 1830 to 1925. Thorp's work laid the foundation for the systematic study of economic business cycles (Burns & Mitchell, 1946). I therefore use his account to create a qualitative sentiment indicator for Switzerlands neighboring countries as well as for England and the USA.

GPT (Generative Pre-trained Transformer) models are a type of artificial intelligence model used for natural language understanding and generation tasks. GPT models work by pre-training on a large corpus of text to learn the patterns, grammar, and semantics of language. During pre-training, they learn to predict the next word in a sentence, which helps them capture contextual information. They generate text by probabilistically predicting the most likely next word based on the input context and the knowledge they've learned during pre-training (Brown et al., 2020).

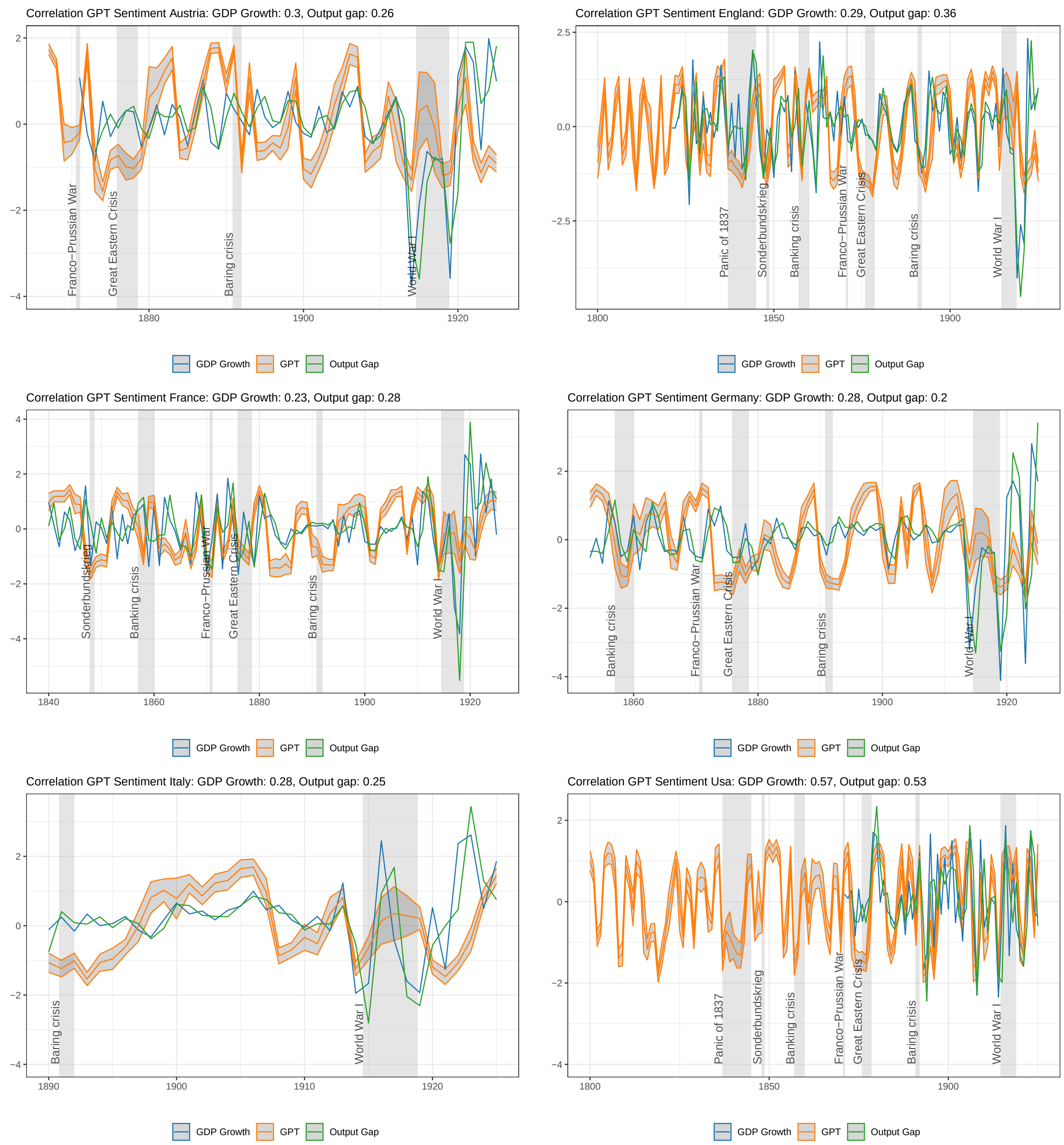
> **Prompt**:
> Given the short economic descriptions from the year {start_year} to {end_year}, rate the state of the {country} economy from the text below on a scale of -5 (worst) to 5 (best). Take into account the surrounding years for relative judgment. Return a JSON with the year and your rating only. Text: {texts}

To create the sentiment indicators, I ask the model to rate the state of the economy on a scale of -5 (worst) to 5 (best) for every year until 1925 whereby it should take the surrounding years into account for relativ judgment. The exact prompt is depicted above. However, GPT-3.5 has a limited context window of 4'096 tokens. This means that the model can roughly take into account the last 3'000 words when generating the next word. Therefore, it is not possible to use the model in one batch because the text of Thorp's (1926) book is too long. Instead, I split the text into chunks of ten years and move forward by five years. Hence, I get two ratings for every year. The average of the two ratings is the final rating for the year.

Prompting the model exactly the same twice, does not necessarily lead to the same output. This behaviour is governed by the parameter 'temperature' which controls the randomness of the output. With value of zero, the model becomes deterministic. I use the defualt value of one which leads to a more diverse output. To get a more robust rating, I prompt the model 20 times and take the average of the 20 ratings. Figure 16 shows the normalized sentiment indicator (in orange) together with one standard deviation confidence bands. Using everytime the same degree of randomness allows to interpret the confidence bands as a measure of uncertainty. Most often the model is quite confident about the state of the economy. However, during World War I the confidence bands become wider.

Moreover, I compare the created GPT sentiment indicators with real GDP growth (blue line) and the output gap (green line) calculated from the series provided by Bolt and van Zanden (2020). The correlation between the sentiment indicator and real GDP growth is goes from 0.23 to 0.57, and with the output gap from 0.2 to 0.53. The correlation with neighboring countries is somewhat lower than with USA or England. This might be because these two countries have a lot of good quality data available for the 19th century. The sentiment indicator is less erratic than real GDP growth and the output gap, and therefore serves as a good alternative measure to vaildate the historical business cycle indicator.

Figure 16 — Comparison with GDP growth and output gap

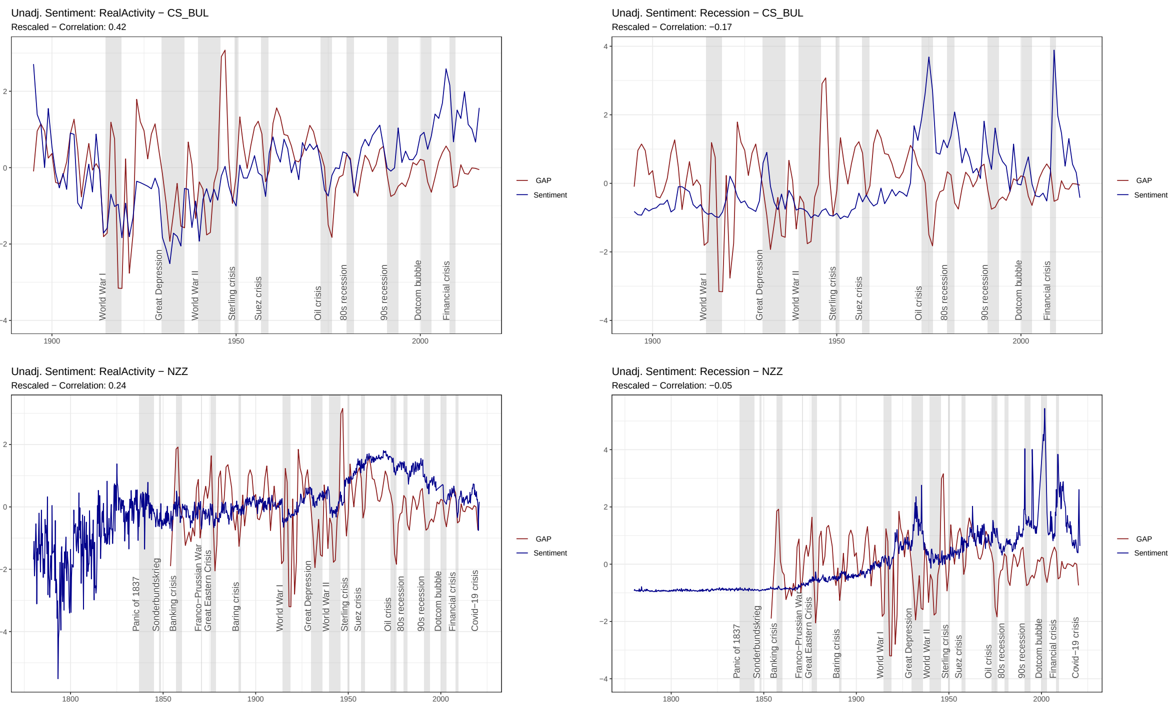


Notes: These graphs show the normalized sentiment indicator (in orange) based on Thorp's (1926) texts and OpenAI's (2023) GPT-3.5 model together with one standard deviation confidence bands. In blue real GDP growth and in green the output gap calculated from the series provided by Bolt and van Zanden (2020). Gray shaded areas represent crises.

C Source-level indicator anomaly correction

In this section I explain the six steps of the procedure to correct for anomalies in the source-level indicators in more detail. I use examples of the indicator based on the *Credit Suisse Bulletin* (CS_BUL) published annually and the *Neue Zürcher Zeitung* (NZZ) published daily. To illustrate the procedure I show the sentiment-based real activity, and the count-based recession topics. The same procedure is applied to all other source-level indicators. The following are the six steps:

Figure 17 — Unadjusted source-level indicators



Notes: These graphs show the unadjusted source-level indicator (in blue) together with the output gap (in red). Gray shaded areas represent crises. Credit Suisse Bulletin at the top, NZZ at the bottom. Left the real activity topic, right the recession topic.

0. Removing texts where less than 20% of words that are identified in a German-French lexicon. Then, aggregate the remaining texts to quarterly or annual frequency. Texts from sources that are published more frequently than once per quarter are aggregated to quarterly, whereas texts from sources with a publication frequency that falls between quarterly and annually are aggregated to annual frequency.

1. If the frequency is annual, interpolate missing observations using Stinemann

interpolation (Stineman, 1980). This step is needed to make sure it is a regular time series before temporally disaggregating annual data to quarterly frequency.

2. Detrend the indicator using Locally Estimated Scatterplot Smoothing (LOESS) with a bandwidth or span of 0.7 (Cleveland, 1979). LOESS is a statistical method used to create a smooth line through a scatterplot. It works by taking a small section of the data points and fitting a model, like a straight line or a curve, to these points. This process is repeated for each section of the data, with the fitted lines or curves changing to adapt to the data in that particular section. The bandwidth is typically a value between 0 and 1 and represents the fraction of the total data points that are included in each local fit. A small bandwidth will lead to a more wiggly line, and a large bandwidth will lead to a smoother line. The bandwidth of 0.7 is a good compromise between a smooth line and a line that follows the data points closely.

3. Detect structural breaks in mean and/or variance using a binary segmentation algorithm.[24] This algorithm originates from the work of Edwards and Cavalli-Sforza (1965), Scott and Knott (1974) and Sen and Srivastava (1975). The multiple parameter changepoint problem has been discussed by Horvath (1993) or Picard et al. (2005). The process initiates with a single changepoint test applied across the entire dataset to detect significant changes in mean and/or variance. Upon identifying a changepoint, the data is split into two at the changepoint location. This test is then recursively conducted on each segment, continually splitting them at newly identified changepoints. The procedure repeats until no further significant changepoints are detected, adhering to criteria such as a predefined maximum number of changepoints or a minimum length for the segments. The final outcome of this method is a division of the dataset into segments. The objective function the algorithm minimizes is given by

$$\sum_{i=1}^{m+1} \left[\mathcal{C} \left(y_{(\tau_{i-1}+1):\tau_i} \right) \right] + \beta m \tag{1}$$

where m is the number of breakpoints, $\mathcal{C}$ is a cost function (here the negative log likelihood), and βm is a linear penalty function. τ_i is the position of the i-th changepoint in the data. I assume the segments are normally distibuted. Moreover, I allow a maximum of one breakpoint every ten years, with an overall cap of five

[24] I use the implementation of Killick and Eckley (2014).

breakpoints. Additionally, each segment is constrained to a minimum length of five years. This approach is based on the premise that the OCR quality of texts changes infrequently. The ability to incorporate such prior information into the algorithm enhances its suitability for this particular application.

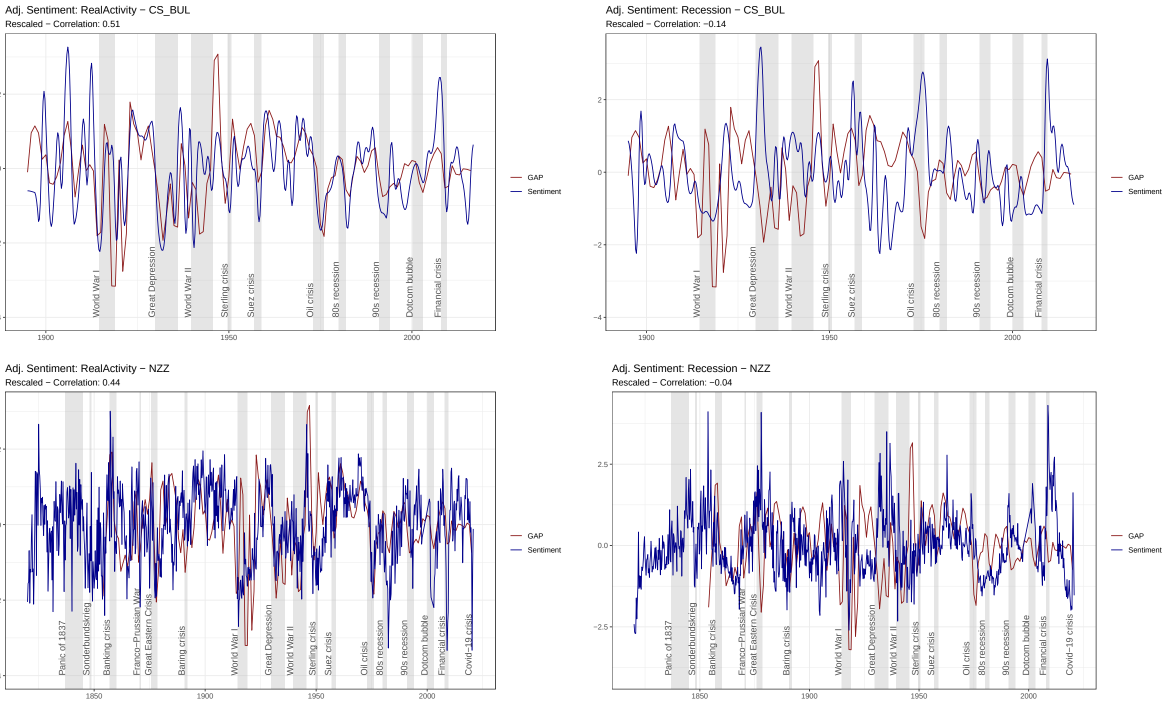
4. Normalize each identified segment.[25] The normalization is done by subtracting the mean and dividing by the standard deviation of the segment.

5. If the frequency is annual, temporally disagregate the indicator to quarterly frequency using the method developed by Dagum and Cholette (2006) which is based on work by Denton (1971). I employ a straightforward method that does not require an indicator series. This method executes basic interpolation, adhering to the temporal additivity constraint as outlined by Sax and Steiner (2013). The temporal additivity constraint applied in this study mandates that for count-based indicators, the sum of the series at a lower frequency must equal the corresponding series at a higher frequency. For sentiment-based indicators, it is the mean.

6. Remove outliers (observations more than 3 standard deviations away from the mean).

[25] I show in Appendix D that with time-varying measurement error, this is preferable to not normalizing.

Figure 18 — Adjusted source-level indicators



Notes: These graphs show the adjusted source-level indicator (in blue) together with the output gap (in red). Gray shaded areas represent crises. Credit Suisse Bulletin at the top, NZZ at the bottom. Left the real activity topic, right the recession topic.

D Normalization of time-series with breaks

In this section, I show that it is benefitial to normalize data around identified breaks within the context of the dataset at hand, particularly when dealing with a small number of available sources at the beginning of the sample.

The availability of data sources varies over time, with earlier periods having fewer digitized sources compared to later ones. Moreover, the measurement error associated with these source level indicators is not static - it changes over time and tends to be larger in earlier periods. In most cases, the changes in the measurement error are abrupt and lead to structural breaks in the series. For instance, due to a sudden change of the optical character recognition (OCR) quality or because the frequency of the publication changes - increased publication frequency means a higher information density, and therefore, lower measurement error. This makes it essential to normalize the source-level indicators around these structural breaks.

The following section explains the challenges of normalization in the presence of time-varying measurement error through a simplified illustration.

D.1 Simplified illustration

Suppose that the true but unobservable sentiment is determined by a stochastic process. For simplicity, I consider this process to be independent and identically distributed (iid), although it could also follow a different pattern such as an AR(1):

$$s_t = u_t \quad u_t \sim iid(\mu, \sigma_s^2)$$

The sentiment observed from source i at time $t = 1, \ldots, T$, denoted $\hat{s}_{t,i}$, comprises the true sentiment plus some measurement error, which is also assumed to iid:

$$\hat{s}_{t,i} = s_t + v_{t,i} \quad v_{t,i} \sim iid(0, \sigma_t^2)$$

For simplicity, I first assume a constant magnitude for measurement error across all sources. However, let's consider that from a certain time point, T_b, onwards, the magnitude of measurement error diminishes due to improvements in OCR quality or changes in publication frequency, for instance:

$$\sigma_t^2 = \begin{cases} \sigma_h^2 & \text{if } t \leq T_b \\ \sigma_l^2 & \text{if } t > T_b \end{cases}$$

Here, σ_h^2 represents the higher measurement error variance before time T_b, and σ_l^2 is the lower variance thereafter. Overlooking this breakpoint and simply averaging out the indicators from all sources would lead to a higher variance in the high measurement error regime.

$$Var\left(\frac{1}{n}\sum_{i=1}^{n}\hat{s}_{t,i|t\leq T_b}\right) = \sigma_s^2 + \frac{1}{n}\sigma_h^2 > Var\left(\frac{1}{m}\sum_{i=1}^{m}\hat{s}_{t,i|t>T_b}\right) = \sigma_s^2 + \frac{1}{m}\sigma_l^2$$

In this expression, n signifies the number of sources prior to T_b, and m the number post T_b, typically with $m > n$. If both, m and n are would be larg enough, the difference in variance would be negligible. However, in the context of this project, the number of sources is limited especially for the early sample, and the difference in variance is substantial. It follows that the level of the aggregated indicator is not comparable pre and post break.

If this is the case a nice property of the indicator would be to have the same variance across time, for instance for an application of business cycle dating utilizing a markov-switching model. One potential strategy is to normalize the indicators from the pre- and post-T_b periods separately before combining them.

$$\begin{gathered}
Var\left(\frac{1}{n}\sum_{i=1}^{n}\frac{\hat{s}_{t,i|t\leq T_b} - \mu}{\sqrt{\sigma_s^2 + \sigma_h^2}}\right) < Var\left(\frac{1}{m}\sum_{i=1}^{m}\frac{\hat{s}_{t,i|t>T_b} - \mu}{\sqrt{\sigma_s^2 + \sigma_l^2}}\right) \\
\frac{n^2\sigma_s^2 + n\sigma_h^2}{n^2(\sigma_s^2 + \sigma_h^2)} < \frac{m^2\sigma_s^2 + m\sigma_l^2}{m^2(\sigma_s^2 + \sigma_l^2)} \\
\frac{\sigma_s^2}{\sigma_s^2 + \sigma_h^2} + \frac{\sigma_h^2}{n(\sigma_s^2 + \sigma_h^2)} < \frac{\sigma_s^2}{\sigma_s^2 + \sigma_l^2} + \frac{\sigma_l^2}{m(\sigma_s^2 + \sigma_l^2)}
\end{gathered}$$

But still then, depending on the specific parameters, the resulting pre- and post-break variance of the combined indicator could differ substantially. A significant disparity between m and n, coupled with a large $\frac{\sigma_h^2}{\sigma_l^2}$ ratio, results in a higher post-breakpoint variance. The intuition behind this result is that a large pre-break noise-to-signal ratio causes a more substantial downscaling of the signal during normalization, leading to a muted signal in the averaged indicator where some noise is canceled out.

D.2 Correlation with true sentiment

The ultimate goal is to end up with an indicator that is correlated as much as possible with the true sentiment over the full sample. In the setup of the simple illustration above, the true sentiment is known. Therefore, I can calculate the correlation between the true sentiment and the aggregated indicator for different normalization strategies. If no normalization is applied before aggregation the correlation is given by

$$\begin{aligned}
\rho_{\text{NN}} &= Corr\left(s_t, \frac{T_b}{T}\frac{1}{n}\sum_{i=1}^{n}\hat{s}_{t,i|t\leq T_b} + \frac{T-T_b}{T}\frac{1}{m}\sum_{i=1}^{m}\hat{s}_{t,i|t>T_b}\right)\\
&= \frac{\sigma_s^2}{\sigma_s\sqrt{\sigma_s^2 + \frac{T_b}{T}\frac{1}{n}\sigma_h^2 + \frac{T-T_b}{T}\frac{1}{m}\sigma_l^2}}
\end{aligned}$$

where $\frac{T_b}{T}$ and $\frac{T-T_b}{T}$ are the weights of the pre- and post-break period, respectively.

If normalization is applied to both segments individually before aggregation, the correlation is given by

$$\begin{aligned}
\rho_{\text{SN}} &= Corr\left(s_t, \frac{T_b}{T}\frac{1}{n}\sum_{i=1}^{n}\frac{\hat{s}_{t,i|t\leq T_b}}{\sqrt{\sigma_s^2+\sigma_h^2}} + \frac{T-T_b}{T}\frac{1}{m}\sum_{i=1}^{m}\frac{\hat{s}_{t,i|t>T_b}}{\sqrt{\sigma_s^2+\sigma_l^2}}\right)\\
&= \frac{\sigma_s^2/\sqrt{\sigma_s^2 + \frac{T_b}{T}\frac{1}{n}\sigma_h^2 + \frac{T-T_b}{T}\frac{1}{m}\sigma_l^2}}{\sigma_s\sqrt{\frac{T_b}{T}\left(\frac{\sigma_s^2}{\sigma_s^2+\sigma_h^2} + \frac{\sigma_h^2}{n(\sigma_s^2+\sigma_h^2)}\right) + \frac{T-T_b}{T}\left(\frac{\sigma_s^2}{\sigma_s^2+\sigma_l^2} + \frac{\sigma_l^2}{m(\sigma_s^2+\sigma_l^2)}\right)}}
\end{aligned}$$

The question is whether normalization pays off, that is whether $\rho_{\text{SN}} > \rho_{\text{NN}}$. This condition can be simplified to

$$\begin{aligned}
&\rho_{\text{SN}} > \rho_{\text{NN}}\\
1 &> \frac{T_b}{T}\left(\frac{\sigma_s^2}{\sigma_s^2+\sigma_h^2} + \frac{\sigma_h^2}{n(\sigma_s^2+\sigma_h^2)}\right) + \frac{T-T_b}{T}\left(\frac{\sigma_s^2}{\sigma_s^2+\sigma_l^2} + \frac{\sigma_l^2}{m(\sigma_s^2+\sigma_l^2)}\right)
\end{aligned}$$

The right-hand side of this condition is a weighted average, therefore, the weights sum up to one. If the terms in brackets are lower than one it is benefitial to normalize the segments.

$$\begin{aligned} 1 &> \frac{\sigma_s^2}{\sigma_s^2 + \sigma_h^2} + \frac{\sigma_h^2}{n(\sigma_s^2 + \sigma_h^2)} \\ n(\sigma_s^2 + \sigma_h^2)^2 &> (n\sigma_s^2 + \sigma_h^2)(\sigma_s^2 + \sigma_h^2) \\ \sigma_s^2 + \sigma_h^2 &> \sigma_s^2 + \frac{1}{n}\sigma_h^2 \end{aligned}$$

Hence, if $n > 1$ the left bracket is lower than one as well. The same holds true for the second bracket if $m > 1$. In the early sample of the dataset used for this paper there are at least 5 sources available. These findings suggest that it is benefitial to normalize the segments before aggregation.

D.3 Simulation

To substantiate these findings, I carried out a simulation exercise. In this exercise, I compare the two aggregation methods discussed above. To mirror what is observed in the actual dataset, I employed the following parameter values:

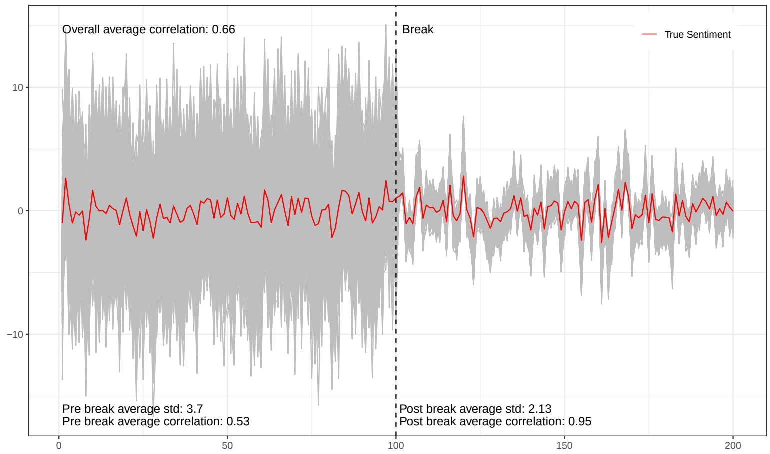
$$\begin{aligned} &\sigma_s = 1, && \sigma_h = 10, && \sigma_l = 2, && n = 15, \\ &m = 95, && t = 1, \dots, 200, && T_b = 100. \end{aligned}$$

I ran 1000 iterations to compute the average indicator for a set of 110 time series, conducting the procedure once without any normalization and once with normalization. The outcomes are graphically represented in Figure 19: Panel (a) illustrates the scenario without normalization, where each of the 1000 simulations is represented by a gray line, and the true underlying series is traced in red. As anticipated, on average the variance of the composite indicator is notably higher in the pre-break phase compared to the post-break phase.

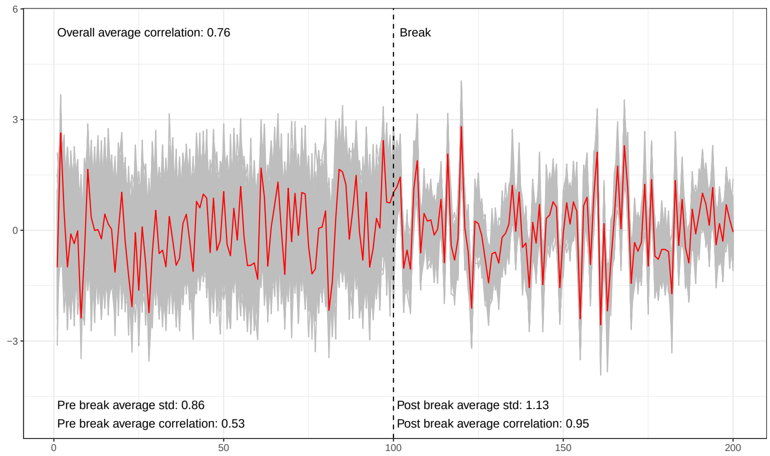
Panel (b) of Figure 19 displays the results when the normalization is employed.The simulations reveal a compelling aspect: while the average correlation with the true

Figure 19 — Simulation

(a) Without normalization



(b) With normalization



series is largely the same for both pre-break and post-break periods regardless of normalization, it is considerably higher across the entire timeline when the data is normalized. This enhancement in correlation serves as an extra argument to normalize the data.

E Markov-Switching Dynamic Factor Model

In this section I describe details of the MS-DFM used in the sensitivity analysis section.[26] MS-DFMs are pioneered by C.-J. Kim (1994), Diebold and Rudebusch (1996), M.-J. Kim and Yoo (1995) and Chauvet (1998). The model here closely follows Chauvet (1998). Estimating DFMs operate on the principle that an observed time series vector X_t can be split into two separate and orthogonal elements. First, the common components, often referred to as latent factors (f_t), which encapsulate the joint movements among the observed variables in X_t. Second, the idiosyncratic component (u_t). These idiosyncratic components emerge from measurement errors and unique characteristics inherent in the data. The MS-DFM reads as follows:

$$X_t = \Lambda f_t + u_t \tag{2}$$

$$f_t = \mu_{s_t} + \sum_{p=1}^{P} A_p f_{t-p} + \eta_t \quad \eta_t \sim N(0, I) \tag{3}$$

$$u_t = \sum_{q=1}^{Q} C_q u_{t-q} + \varepsilon_t \quad \varepsilon_t \sim N(0, \Sigma) \tag{4}$$

where P is the lag number of the factor and Q is the lag order of the idiosyncratic component. s_t is the realization of a two-state Markov chain with

$$\Pr(s_t = j | s_{t-1} = i, s_{t-2} = k, \ldots, y_{t-1}, y_{t-2}, \ldots) = \Pr(s_t = j | s_{t-1} = i) = p_{ij}$$

where $i, j = 0, 1$. Within this framework, one can label s_t = 0 and s_t = 1 as the expansion and recession states at time t.

The specific MS-DFM in this application has 1 unobserved factor (See also scree plot 12) which is assumed to follow an AR(5) process (i.e. $P = 5$, based on Bayesian Information Criterion). The innovations are assumed to be independent (so that Σ is a diagonal matrix) and the error term associated with each equation, is assumed to follow an

[26] See e.g. Mariano and Murasawa (2010) and Stock and Watson (1989, 2016) for prominent examples and further information on DFMs.

independent AR(2) process (i.e. $Q = 2$). Therefore, the specification considered here is:

$$x_{i,t} = \lambda_i f_t + u_{i,t} \tag{5}$$

$$f_t = \mu_{s_t} + a_1 f_{t-1} + a_2 f_{t-2} + a_3 f_{t-3} + a_4 f_{t-4} + a_5 f_{t-5} + \eta_t \quad \eta_t \sim N(0, \sigma_f^2) \tag{6}$$

$$u_{i,t} = c_{i,1} u_{i,t-1} + c_{i,2} u_{i,t-2} + \varepsilon_{i,t} \quad \varepsilon_{i,t} \sim N(0, \sigma_i^2) \tag{7}$$

where i denotes one of the $n = 11$ indicators ($i = 1, \ldots, n$). For identification reasons the variance of η_t, σ_f^2, is given by unity. For estimation the model is cast into state-space representation and estimated using the Kalman filter.

$$y_t = H\xi_t + w_t \qquad w_t \sim NID(0, R) \tag{8}$$

$$\xi_t = \mu(s_t) + F\xi_{t-1} + v_t \qquad v_t \sim NID(0, Q) \tag{9}$$

I use the following definitions:

$$y_t = [x_{1,t}, \ldots, x_{n,t}]' \tag{10}$$

$$w_t = 0_{(n\times 1)} \tag{11}$$

$$R = 0_{(n\times n)} \tag{12}$$

$$\xi_t = [f_t, \ldots, f_{t-P}, u_{1,t}, \ldots, u_{n,t}, u_{1,t-1}, \ldots, u_{n,t-1}]' \tag{13}$$

$$H = \begin{pmatrix} \lambda_1 & 0_{(1\times P-1)} & 1 & 0 & \ldots & 0 & 0_{(1\times n)} \\ \lambda_2 & 0_{(1\times P-1)} & 0 & 1 & \ldots & 0 & 0_{(1\times n)} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \lambda_n & 0_{(1\times P-1)} & 0 & 0 & \ldots & 1 & 0_{(1\times n)} \end{pmatrix} \tag{14}$$

$$v_t = [\eta_t, 0_{(1\times P-1)}, \varepsilon_{i,t}, \ldots, \varepsilon_{n,t}, 0_{(1\times n)},]' \tag{15}$$

$$diag(Q) = [\sigma_f^2, 0_{(1\times P-1)}, \sigma_1^2, \ldots, \sigma_n^2, 0_{(1\times n)}]' \tag{16}$$

$$F = \begin{pmatrix} a_1 & \ldots & a_P & 0_{(1\times n)} & 0_{(1\times n)} \\ I_{P-1} & \ldots & 0_{(P-1\times 1)} & 0_{(P-1\times n)} & 0_{(P-1\times n)} \\ 0_{(n\times P)} & \ldots & 0_{(n\times P)} & diag(c_{i,1}) & diag(c_{i,2}) \\ 0_{(n\times P)} & \ldots & 0_{(n\times P)} & I_n & 0_{(n\times n)} \end{pmatrix} \tag{17}$$

$$\mu(s_t) = [\mu_{s_t}, 0_{(1\times P-1)}, 0_{(1\times 2n)}]' \tag{18}$$

$$\tag{19}$$

The estimation of the dynamic factor model with regime switching is carried out by maximizing its likelihood function. For estimating this model, I utilize the techniques developed by C.-J. Kim (1994) and Chauvet (1998).