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# A daily fever curve for the Swiss economy

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**Abstract**

**Abstract**: Because macroeconomic data is published with a substantial delay, assessing the health of the economy during the rapidly evolving Covid–19 crisis is challenging. We develop a fever curve for the Swiss economy using publicly available daily financial market and news data. The indicator can be computed with a delay of one day. Moreover, it is highly correlated with macroeconomic data and survey indicators of Swiss economic activity. Therefore, it provides timely and reliable warning signals if the health of the economy takes a turn for the worse.

**JEL classification**: E32, E37, C53

**Keywords**: Covid–19, Leading indicator, Financial market data, News sentiment, Forecasting, Switzerland

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# 1 Introduction

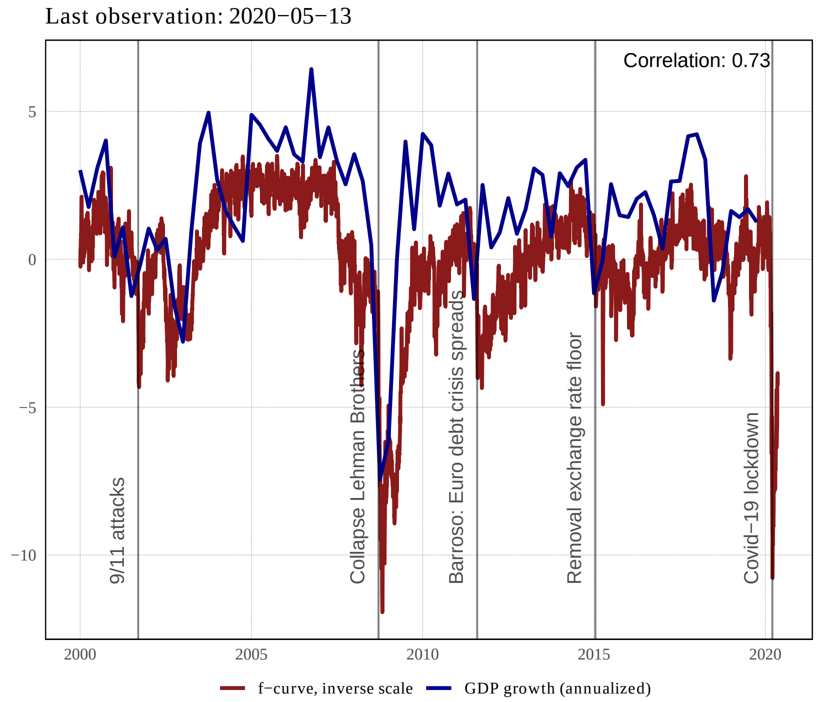
Because macroeconomic data is published with a substantial delay, assessing the health of the economy during the rapidly evolving Covid–19 crisis is challenging. Usually, policy makers and researchers rely on early information from surveys and financial markets to construct leading indicators and forecasting models (see, e.g., OECD, 2010; Abberger et al., 2014; Kaufmann and Scheufele, 2017; Galli, 2018; Wegmüller and Glocker, 2019; Stuart, 2020, for Swiss applications). Most of those indicators, however, are published with a delay of one to two months.[1] Because the Covid–19 crisis requires policy decisions on a daily basis, we need high-frequency information to assess the economic impact of stricter or looser health restrictions, as well as economic aid measures.

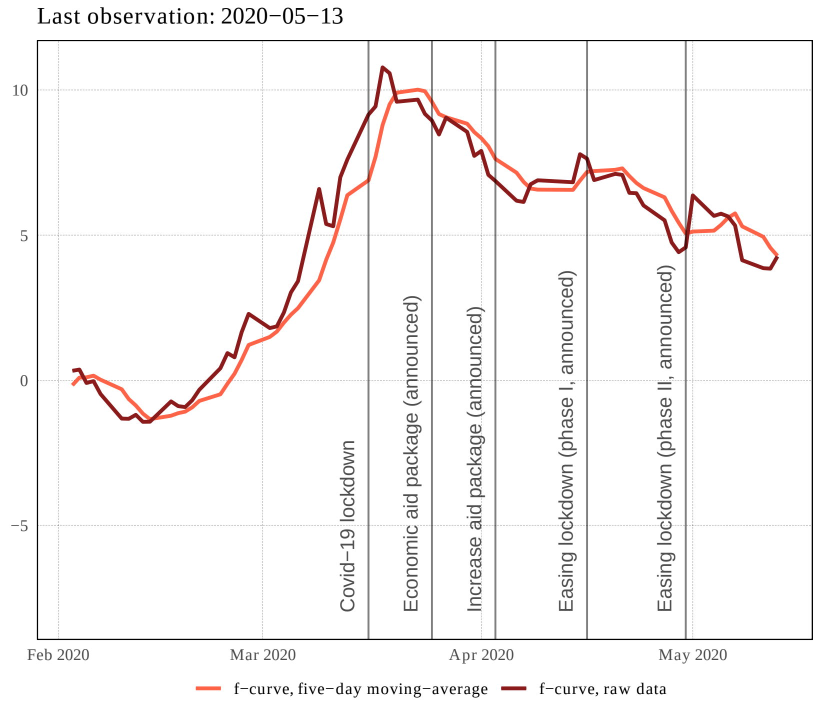
We develop a novel daily fever curve ($f$–curve) for the health of the Swiss economy using publicly available financial market and news data. We construct risk premia on corporate bonds, term spreads, as well as stock market volatility indices starting in 2000. In addition, we collect short economic news from online newspaper archives. We then estimate a composite indicator which has the interpretation of a fever curve: As for monitoring the condition of a patient, an increase of the fever curve provides a reliable and timely warning signal if health takes a turn for the worse.

The upper panel of Figure 1 shows the $f$–curve (on an inverted scale) jointly with real GDP growth: the indicator closely tracks economic crises. It presages the downturn during the Global Financial Crisis, responds to the removal of the minimum exchange rate, as well as to the euro area debt crisis. The $f$–curve also responds strongly to the Covid–19 crisis (see lower panel). The indicator starts to rise in late February. By then, it became evident that the Covid–19 crisis will hit most European countries; in Switzerland, the first large events were canceled. It reaches a peak shortly after the lockdown. Afterward, the fever curve gradually declines with news about economic aid measures and gradual loosening of the lockdown. The last values up to 13 May 2020 suggest the Swiss economy is in a severe recession, with a GDP growth rate at -3.8%, and a probability of GDP growth below -1% of 96% in Q2 2020. So far, the depth of the

[1] The main reason is that monthly survey data has to be processed, as well as, it takes time to estimate models and report the forecasts. See Table A.1 for publication lags of some important macroeconomic data and leading indicators.

Figure 1 — A fever curve for the Swiss economy




*Notes:* The upper panel compares the fever curve (on an inverse scale) to quarterly GDP growth. The lower panel gives daily values of the fever curve along with important policy decisions.

recession is comparable to the Global Financial Crisis. However, the speed of the recession is unprecedented.

The indicator has several advantages we hope will make it useful for policy makers and the public at large. The methodology of the $f$–curve is simple; the data selection process is based on economic theory and intuition; the data sources are publicly available and we provide the program codes and daily updates on github.com/dankaufmann/f-curve.[2] Finally, additional daily indicators that track economic activity are easily integrated in our modeling framework.

There are various initiatives in Switzerland and abroad to satisfy the demand for reliable high-frequency information on the economic impact of the crisis. Becerra et al. (2020) use internet search data to assess the dynamics of the Covid–19 crisis. Brown and Fengler (2020) provide early information on Swiss consumption based on publicly available payment data. Eckert, Florian (2020) develops a daily mobility index for monitoring the impact of the lockdown. For the U.S., economists at the Federal Reserve Bank of New Work estimate a weekly index of economic activity based on retail sales, unemployment insurance claims, as well as other rapidly available production, price and employment data (Lewis et al., 2020). Moreover, Buckman et al. (2020) create a daily news sentiment indicator that leads U.S. consumer sentiment. Our paper is the first, to the best of our knowledge, to combine daily information from newspapers and financial market data in a daily measure of economic activity for Switzerland.

In what follows, we describe the data and methodology. Then, we provide an analysis of the impact of the Covid–19 crisis, a decomposition of the $f$–curve into domestic and foreign factors, as well as an evaluation. The last section concludes.

## 2 Method

This section discusses how we construct daily financial market data and news sentiment indicators. Then, we explain the method to summarize these data in a composite indicator.

[2] We plan to continuously extend the indicator. We therefore welcome suggestions for improvements and extensions.

### 2.1 Data

We use publicly available bond yields underlying the SIX Swiss Bond Indices® (SIX, 2020a). These data are available on a daily basis and with a delay of one day. Because many bond yields start only around 2007, we extend the series with a close match of government and corporate bond yields from the SNB (see Table A.1 and Figure A.2 in the Online Appendix).[3] Then, we compute various spreads that should be correlated with economic activity: a government bond term spread (8Y - 2Y), the interest rate differential vis-à-vis the euro area (1Y), and risk premia of short- and long-term corporate debt. Besides interest rate spreads for Switzerland, we compute risk premia of foreign companies that issue debt in Swiss franc for short- and long-term debt. We also include term spreads for the U.S. and for the euro area. For the latter, we use short-term interest rates in euro (European Central Bank, 2020) and long-term yields of German government debt (Deutsche Bundesbank, 2020). In addition, we include two implied volatility measures of the Swiss and U.S. stock market. Swiss data stem from SIX (2020b) and are published with a delay of one day. U.S. data stem from Chicago Board Options Exchange (2020).

These financial market data should be related to the Swiss business cycle. Stuart (2020) shows that the term spread exhibits a lead on the Swiss business cycle.[4] Kaufmann (2020) argues that a narrowing of the interest rate differential appreciates the Swiss franc and thereby weights on economic activity. Finally, risk premia should be positively correlated with the default risk of companies, which should increase during economic crises. Moreover, recent research documents an increase in uncertainty during economic downturns (Baker et al., 2016; Scotti, 2016). There are various ways to measure uncertainty (Dibiasi and Iselin, 2016). Because we aim to exploit quickly and freely available financial market data, we prefer a measure of stock market volatility to proxy uncertainty.

We complement the financial market data with sentiment indicators based on Swiss newspapers. Therefore, we extract headlines and lead texts from the online archives of *Tages-Anzeiger*, the *Neue Zürcher Zeitung* and the *Finanz und Wirtschaft*. We focus on the headline

[3] Data from the SNB are published with a longer delay. Therefore, these bond yields cannot be used to track the economy on a daily basis.

[4] We therefore move forward all term spreads by half a year.

and lead text as these are publicly available and often contain the key messages of the articles. To narrow down the relevant articles, and to decompose the sentiment indicator into a domestic and foreign part, we use our own search queries (See Table A.3 in the Online Appendix for a detailed description).

Then, we use the lexical methodology to calculate a sentiment indicator (see, e.g., Thorsrud, 2020; Shapiro et al., 2017; Ardia et al., 2019). First, we filter out irrelevant information.[5] Second, we identify positive and negative words using the lexicon delevoped by Remus et al. (2010). Finally, we calculate for each article $n$ and each day $t$ a sentiment score:

$$S_{t,n} = \frac{\#P_{t,n} - \#N_{t,n}}{\#T_{t,n}} ,$$

where $\#P_{t,n}, \#N_{t,n}, \#T_{t,n}$ represent, for each article and each time period, the number of positive, negative, and total words, respectively. Finally, we compute a simple average over all articles to obtain daily indicators for articles about the domestic and foreign economy.

News sentiment indicators receive more and more attention for forecasting economic activity. Buckman et al. (2020) show that during the Covid–19 pandemic, news sentiment indicators provide reliable and early information on the economy, even compared to quickly available survey data. Ardia et al. (2019) show that news sentiment helps forecast U.S. industrial production growth. Finally, Becerra et al. (2020) show that sentiment indicators based on internet search engine queries track the Global Financial Crisis and the Covid–19 downturn in Switzerland.

### 2.2 Estimation

The financial market data and news indicators are quite volatile but are also correlated with each other. To parsimoniously summarize the information, and clean the indicators from

[5]This includes html tags, punctuation and numbers. Also, we remove so-called stop-words. These are words like (e.g. the German words *der*, *wie*, *ob*). We use the stop-words provided by Feinerer and Hornik (2019). Finally, we transform all articles to lowercase.

idiosyncratic fluctuations, we estimate a factor model in static form:[6]

$$X = F\Lambda + e$$

The model comprises $N$ variables and $T$ daily observations. Therefore, the data matrix $X$ is $(T\times N)$, the common factors $F$ are $(T\times r)$, the factor loadings $\Lambda$ are $(r\times N)$, and the unexplained error term $e$ is $(T \times N)$. The advantage of a factor model is that we can parsimoniously summarize the information content in the large data matrix $X$ with a relatively small number of common factors $r$.

Assuming that the idiosyncratic components are only weakly serially and cross-sectionally correlated, we can estimate the factors and loadings by principal components (Stock and Watson, 2002; Bai and Ng, 2013).[7] Our main indicator is the first principal component of the static factor model.[8]

Because this factor has no clear economic interpretation, we decompose its fluctuations into a contribution from domestic and foreign fluctuations. Suppose for that there are only two factors driving the variables. One factor captures foreign fluctuations. The other factor captures domestic fluctuations. We allow for spillovers from abroad the domestic economy, but not vice versa. Under these assumptions, the factor model reads:

$$\begin{bmatrix} X & X^* \end{bmatrix} = \begin{bmatrix} f & f^* \end{bmatrix} \begin{bmatrix} \lambda_{11} & 0 \\ \lambda_{21} & \lambda_{22} \end{bmatrix} + e$$

where $X, X^*$ denote the data matrix with domestic and foreign variables, respectively. In addition $f, f^*$ represent the domestic and foreign factors and $\lambda_{11}, \lambda_{21}, \lambda_{22}$ are loading matrices for which the dimension depends on the number of foreign and domestic variables.

To estimate this factor model, we can use an iterative procedure inspired by Boivin et al.

[6]The news indicators are much more volatile than the financial market data (see Figure A.1 in the Appendix). We therefore compute one-sided five-day moving averages before including them in the composite indicator.

[7]To account for missing values, we compute the indicator only if at least three underlying data series are observed. Moreover, we remove all weekends. Then, we interpolate few additional missing values using an EM-algorithm (Stock and Watson, 2002), after normalizing the data to have zero mean and unit variance. For interpolation, we choose a relatively large number of factors for interpolating the data ($r = 4$). Finally, we estimate the $f$–curve as the first principal component of the interpolated data set.

[8]An interesting extension would be to examine whether more than one factor comprises relevant information for Swiss economic activity. We leave this extension for future research.

(2009); Kaufmann and Lein (2013). First, we estimate the foreign factor only on foreign data. This imposes that foreign variables only load on the foreign factor. Second, we estimate the domestic factor on $\tilde{X}$, where

$$\tilde{X} = X - \lambda_{21} f^* ,$$

removes variation explained by the foreign factor. We can estimate $\lambda_{21}$ for every indicator comprised in $X$ in a regression on the domestic and foreign factor. Because this regression depends on the value of the domestic factor, we repeat this step 50 times (see Boivin et al., 2009; Kaufmann and Lein, 2013, for more details). Finally, we can estimate a decomposition by regressing the *f*–curve on the domestic and foreign factors. This procedure does not guarantee that the decomposition adds up exactly to the overall factor. However, the unexplained rest turns out to be small. The decomposition involves additional estimation steps that may reduce the forecast accuracy; therefore, we only use this decomposition for interpretation, but not for forecasting.

# 3 Analysis

The *f*–curve should primarily be used to quickly detect turning points of the business cycle. As such, it is correlated or leading many important macroeconomic variables (see Figure A.4 in the Online Appendix).[9] In its current form, we have not optimized the indicator to track any particular measure of economic activity. To illustrate the usefulness of the indicator, however, we focus the analysis on the predictive ability for GDP growth.

## 3.1 How severe is the economic impact of the Covid–19 crisis?

We use the indicator in the following direct forecasting model:

$$y_{\tau+h} = \alpha_h + \beta_{h,1} f_{\tau|t} + \beta_{h,2} f_{\tau-1} + \nu_{\tau+h}$$

where $y_\tau$ denotes quarterly GDP growth, $h$ is the forecast horizon, $\tau$ gives time in quarterly

[9] Using this information to estimate a higher frequency GDP would be an interesting avenue for future research.

frequency, and $t$ denotes time in daily frequency. $f_{\tau|t}$ is our best guess of the $f$–curve for the entire quarter based on daily information at time $t$. We compute $f_{\tau|t}$ and $f_{\tau}$ as the simple average of available daily observations for a given quarter. Finally, $\nu_{\tau+h}$ is an error term.

Table 1 — Forecasts

(a) Real GDP growth

| | Point forecast | 90% interval forecast | Probability of growth $< -1\%$ |
|---|---|---|---|
| 2019 Q4 | 1.3 | - | - |
| 2020 Q1 | -0.5 | [-3, 2] | 0.37 |
| 2020 Q2 | -3.8 | [-6.3, -1.3] | 0.96 |
| 2020 Q3 | -1.1 | [-4.7, 2.4] | 0.53 |
| 2020 Q4 | 0.6 | [-3.1, 4.3] | 0.23 |

(b) Nominal GDP growth

| | Point forecast | 90% interval forecast | Probability of growth $< -1\%$ |
|---|---|---|---|
| 2019 Q4 | 1.1 | - | - |
| 2020 Q1 | 0.1 | [-3.1, 3.2] | 0.28 |
| 2020 Q2 | -3.7 | [-6.8, -0.6] | 0.92 |
| 2020 Q3 | -1.1 | [-5.2, 3.1] | 0.51 |
| 2020 Q4 | 0.1 | [-4.2, 4.4] | 0.35 |

*Notes:* Point, interval, and probability forecasts of seasonally adjusted and annualized quarterly GDP growth. Data observed until 2019 Q4. The interval forecast shows the range in which the actual GDP growth rate will lie with a probability of 90%. The last column shows the probability of a severe recession, that is, a growth rate smaller than -1% annualized.

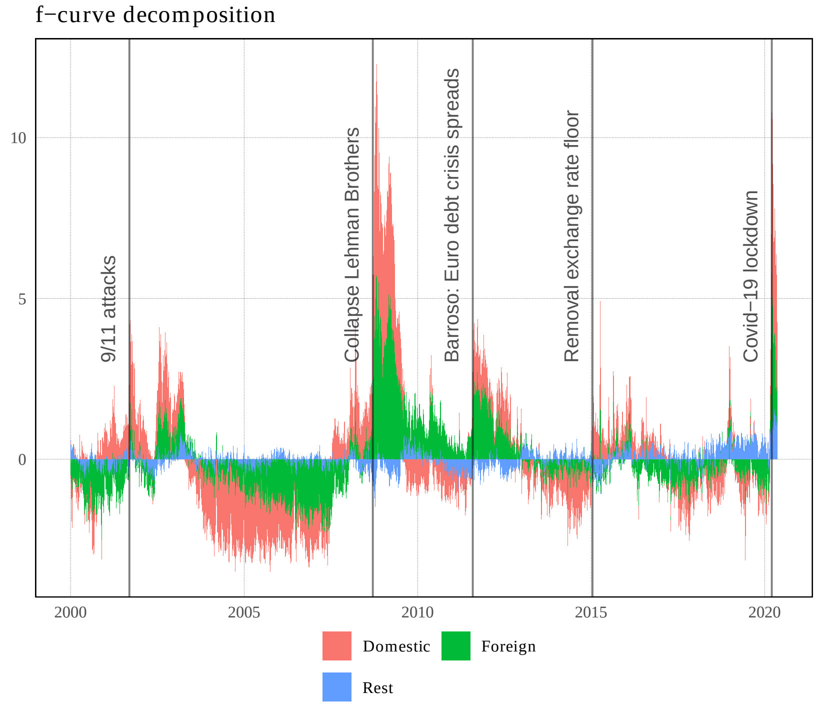
At the time of our last update, $\tau$ = 2020 Q2 and $t$ = 13 May 2020. Because of publication lags, we start with a "backcast" of real GDP growth in Q1 2020 (see Table 1). The model suggests real GDP growth in Q1 2020 fell by 0.5% (Panel a). The probability of a GDP growth rate below $-1\%$ is still relatively low (37%). In Q2 GDP declines at a 3.8% annualized rate. The probability of a growth rate below $-1\%$ amounts to 96%. In Q3 GDP will decline once more. The probability of a GDP decline of more than 1% falls to 53%.

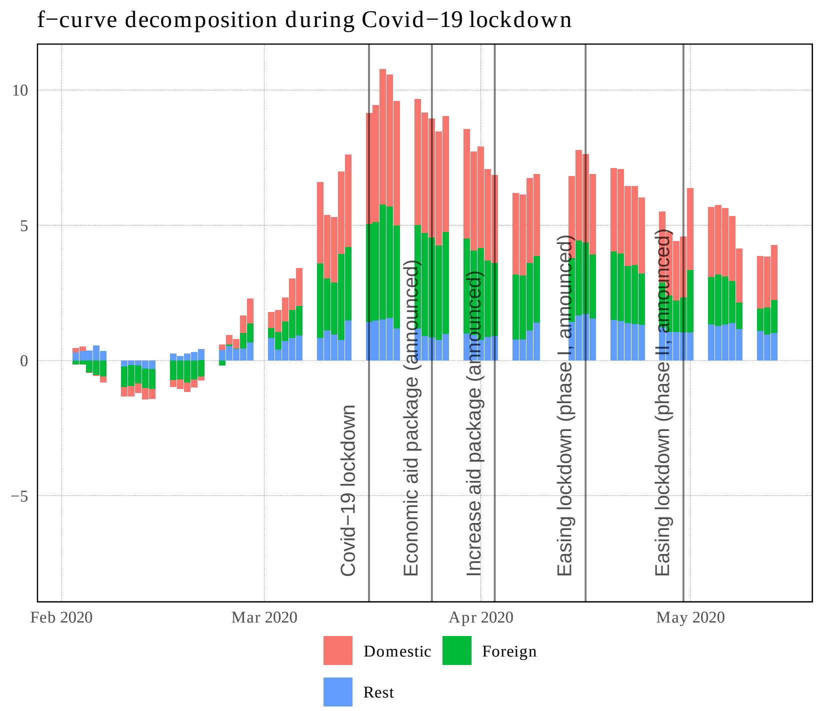
Panel (b) reports forecasts for nominal GDP. Nominal GDP is more relevant for assessing whether firms can repay their debt. This is particularly relevant for the the Covid–19 bridging credits that are granted at a 0% interest rate (Swiss Confederation, 2020). If firms' nominal revenues decline strongly and permanently, it will be more difficult to repay debt even with a 0% interest rate. The forecast uncertainty is larger. The probability that nominal GDP will decline by more than 1% in Q2 2020 is still 92%. In addition, nominal GDP growth will likely remain subdued for the rest of the year.

### 3.2 Is the Covid–19 crisis driven by foreign or domestic factors?

The factor model allows decomposing the indicator into contributions from foreign and domestic variables. The upper panel of Figure 2 shows that the foreign contribution rises after the collapse of Lehman Brothers, but also, during the euro area debt crisis. By contrast, the domestic contribution rises after the removal of the minimum exchange rate in 2015, but also, during the Covid–19 crisis. Focusing on the Covid–19 crisis, the lower panel shows the indicator rose already in the last week of February, before the actual Covid–19 lockdown. It reaches a peak in the first week of the lockdown and declines somewhat thereafter. Half of the increase in the indicator can be traced back to foreign developments. Although the domestic lockdown is important, the $f$–curve suggests the Swiss economy would have suffered even in the absence of these restrictions. During the last four weeks, the contribution from foreign variables declines. The domestic contribution, however, remains elevated. Therefore, while the negative foreign demand shock seems to become less important, the model suggests economic activity will remain subdued also due to domestic headwinds.

Figure 2 — Decomposition domestic and foreign variables




*Notes:* Decomposition of the *f*–curve into foreign factors, domestic factors, and an unexplained rest.

### 3.3 How reliable is the *f*–curve?

We evaluate the forecast performance of the indicator in a pseudo real-time exercise using the real-time data set for quarterly GDP vintages by Indergand and Leist (2014).[10] We then conduct a forecast based on the state of information when a new quarterly GDP vintage is published by SECO. This yields 69 (68) nowcasts (one-quarter-ahead forecasts) observations. In addition, we compare our forecasts to two benchmarks. First, we use an AR(1) model estimated on the real-time vintage for GDP growth. Second, we compare the forecasts to the first quarterly release of GDP growth for the corresponding quarter. Because quarterly GDP is substantially revised ex-post, we treat the initial quarterly GDP release as a forecast of the true GDP figure. To compute the forecast errors, we use the last available release of quarterly GDP from 3 March 2020.

Table 2 panel (a) shows the RMSE of the *f*–curve is slightly smaller than the one of the first official GDP release. In addition, the $p$-value of a test of equal predictive accuracy is 0.5. That is, we do not reject the null of equal predictive ability, suggesting that the indicator yields an accurate prediction of the current state of the economy. The advantage of the *f*–curve is, of course, that its value for the entire quarter is available about 2 months earlier than the first GDP release. In addition, we compare the *f*–curve to a standard AR(1) model. Panel (b) shows we outperform the AR(1) benchmark. The RMSE is 25% lower for the current quarter. Moreover, the difference in forecast accuracy is statistically significant. For the next quarter, however, the *f*–curve does not provide a more accurate forecast than the AR(1) model.

Panels (c) and (d) shows the indicator performs worse for forecasting nominal GDP growth. Therefore, the indicator primarily comprises more information on real economic activity than nominal aggregate demand. Still, the indicator significantly outperforms the AR(1) model for the current quarter at the 10% level.

It is beyond the scope of this study to compare the predictive accuracy of the *f*–curve to

[10]The evaluation is not strictly a real-time forecast evaluation because we use three types of in-sample information. First, the *f*–curve is constructed based on knowledge of the business cycle in the past, in particular, the Global Financial Crisis. Second, the link of the underlying indicators with new data is based on inspecting whether different data sources are highly correlated. Third, the normalization of the indicators in the factor model may introduce revisions that we do not account for in the forecast evaluation. Arguably, using this in-sample information in the evaluation makes sense if the goal of the evaluation is to show whether the indicator is useful going forward, rather than whether the indicator would have been useful in the past.

Table 2 — Pseudo real-time evaluation

(a) Real GDP growth: First release vs. $f$–curve

| | RMSE First release | RMSE $f$–curve | Rel. RMSE first release/$f$–curve | DMW-test ($p$-value) First release $<f$–curve |
|---|---|---|---|---|
| $h=0$ | 1.83 | 1.81 | 1.01 | 0.557 |
| $h=1$ | 1.81 | 2.35 | 0.77 | 0.055 |

(b) Real GDP growth: $f$–curve vs. AR(1)

| | RMSE $f$–curve | RMSE AR(1) | Rel. RMSE $f$–curve/AR(1) | DMW-test ($p$-value) $f$–curve$<$ AR(1) |
|---|---|---|---|---|
| $h=0$ | 1.81 | 2.41 | 0.75 | 0.032 |
| $h=1$ | 2.35 | 2.43 | 0.97 | 0.413 |

(c) Nominal GDP growth: First release vs. $f$–curve

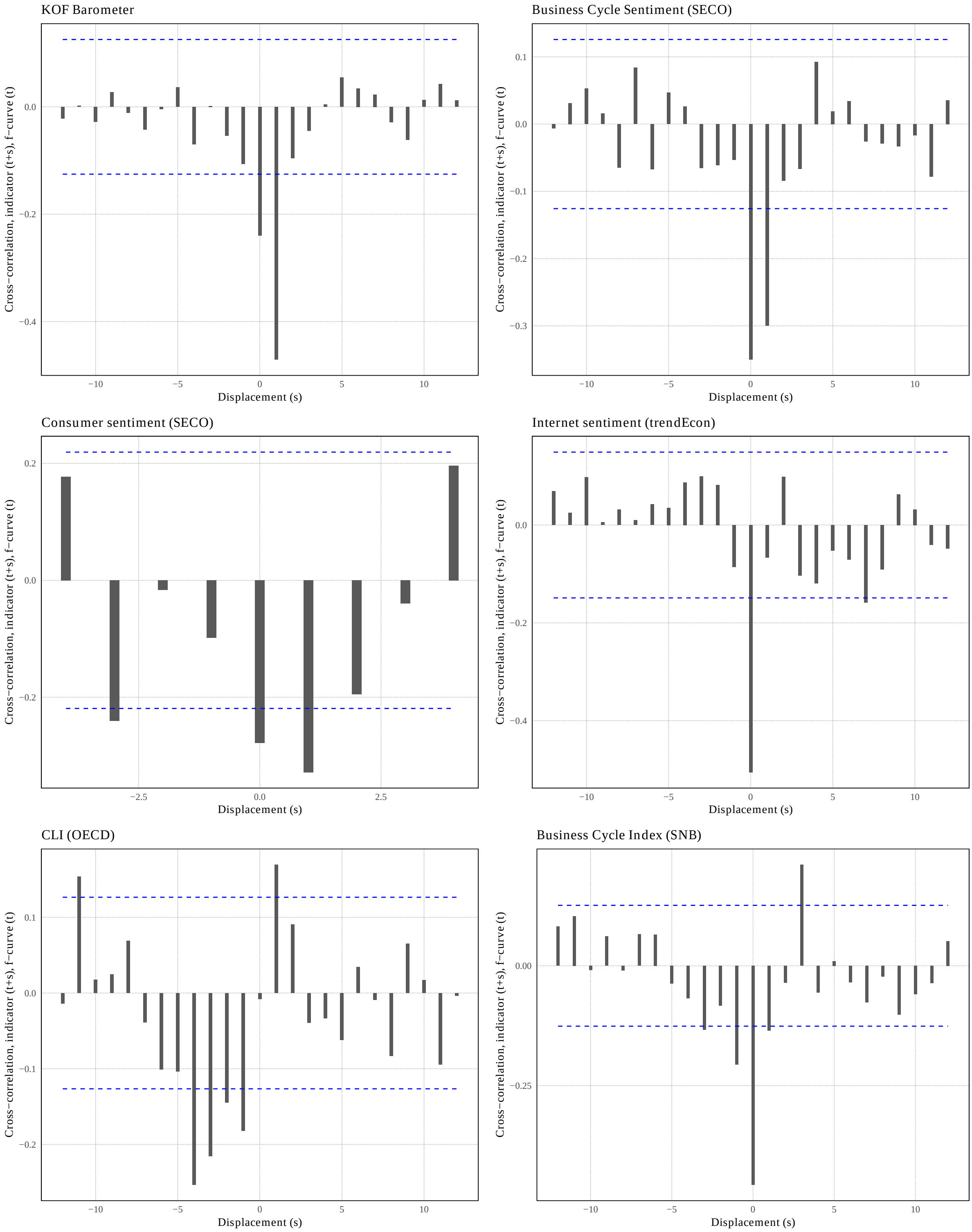
| | RMSE First release | RMSE $f$–curve | Rel. RMSE first release/$f$–curve | DMW-test ($p$-value) First release $<f$–curve |
|---|---|---|---|---|
| $h=0$ | 2.1 | 2.36 | 0.89 | 0.082 |
| $h=1$ | 2.11 | 2.88 | 0.73 | 0.006 |

(d) Nominal GDP growth: $f$–curve vs. AR(1)

| | RMSE $f$–curve | RMSE AR(1) | Rel. RMSE $f$–curve/AR(1) | DMW-test ($p$-value) $f$–curve$<$ AR(1) |
|---|---|---|---|---|
| $h=0$ | 2.36 | 2.8 | 0.84 | 0.058 |
| $h=1$ | 2.88 | 2.84 | 1.02 | 0.555 |

*Notes:* Root-mean-squared errors (RMSE) for forecasts on days with a new quarterly GDP release. All growth rates measured in seasonally adjusted annualized rates. A lower RMSE implies higher predictive accuracy. $h=0$ ($h=1$) denotes the forecast for the current (next) quarter. We use two different benchmarks. First, we use the first quarterly release of the corresponding GDP growth rate (panels a and c). Second, we use a simple AR(1) model (panels b and d). The DMW-test provides a $p$-value for the null hypothesis of equal predictive accuracy against the alternative written in the column header (Diebold and Mariano, 2002; West, 1996). We assume a quadratic loss function.

Figure 3 — Cross-correlation with other indicators




*Notes:* Cross correlation between the *f*–curve and other prominent leading and sentiment indicators. We either aggregate all data either to quarterly frequency (consumer sentiment) or monthly frequency (remaining indicators). The dashed lines give 95% confidence intervals. A bar outside of the interval suggests a statistically significant correlation between the indicators. In addition, before computing the cross-correlation the series have been pre-whitened with an AR(p) model (see Neusser, 2016, Ch. 12.1). The lager order has been determined using the Bayesian Information Criterion.

other indicators.[11] Instead we perform a cross-correlation test (see Neusser, 2016, Ch. 12.1). Figure 3 shows a substantial correlation between the $f$–curve and many prominent leading indicators. There are two exceptions. Our indicator is lagging the OECD CLI. However, this indicator is smoothed ex-post. For example, it declines already before the removal of the minimum exchange rate, which is an artifact of the smoothing procedure (see Figure A.3 in the Online Appendix). Second, the relationship with consumer confidence is less clear. Overall, these results still suggest the $f$–curve provides sensible information comparable with other existing indicators that are published with a relevant delay, or are available on a shorter time period.

## 4 Concluding remarks

We develop a new daily indicator of Swiss economic activity. A major strength of the Indicator is that it can be updated with a delay of only one day. An evaluation of the indicator shows that it is not only correlated with other business cycle indicators but also accurately tracks Swiss GDP growth. Therefore, the $f$–curve provides an accurate and flexible framework to track Swiss economic activity at high frequency.

Having said that, there is still much room for improvement. We see six promising avenues for future research. First, the news sentiment indicators could exploit other publicly available news sources, in particular, newspapers from the French- and Italian-speaking parts of Switzerland. Second, we could use a topic modelling algorithm, instead of our own search queries, to classify news according to countries, sectors, and economic concepts (see e.g. Thorsrud, 2020). Third, the lexicon could be tailored specifically to economic news (see e.g. Shapiro et al., 2017). Fourth, we could examine the predictive ability of multiple factors and for other macroeconomic data. Fifth, the information could be used to disaggregate quarterly GDP and industrial production into monthly or even weekly series. Finally, it would be desirable to collect and exploit the information from many different daily indicators that are currently

[11]Such information would require accurate real-time information, which is hard to come by for business cycle indicators. It is noteworthy, however, that other indicators are estimated or smoothed such that they undergo substantial revisions over time; moreover, they are published with significant delays (see Table A.1); finally, some are based on lagged data (see, e.g., OECD, 2010).

developed into one single composite indicator or indicator data set. Exploiting all this new information will likely further improve our understanding of the temperature and pulse of the Swiss economy at high frequency.

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# A Online Appendix

Table A.1 — Macroeconomic data and leading indicators

| | Type | Publication | Frequency | Source | Comments |
|---|---|---|---|---|---|
| GDP | Target | +9 weeks | Quarter | SECO | First publication subject to further revisions |
| Employment | Target | +9 weeks | Quarter | SFSO | |
| Registered unemployment | Target | +1 week | Month | SECO | |
| ILO unemployment | Target | +6 weeks | Month | SFSO | |
| Output gap | Target | $>$ +4 months | Quarter | SNB | |
| SNB Business Cycle Index | Indicator | $>$ +2 months | Month | SNB | |
| Internet search sentiment | Indicator | +1 day | Day | trendEcon | Indicator based on internet search engine |
| KOF Barometer | Indicator | +0 days | Month | KOF | Some underlying data probably missing at the end of the sample |
| Consumer sentiment | Indicator | +4 weeks | Quarter | SECO | Survey during first month of quarter. Indicator published at beginning of second month |
| OECD CLI | Indicator | $>$ +1 week | Month | OECD | Many underlying data are lagged two months |

*Notes:* Publication lags between the last day of the variable frequency (i.e. last day of the quarter or last day of the month) and the publication date of a recent release. Therefore, all publication lags are approximate and may change over time.

Table A.2 — Data underlying $f$–curve

| | Type | Publication | Frequency | Source | Comments |
|---|---|---|---|---|---|
| Term spread CH | $f$–curve | +1 day | Day | SIX, SNB | 8Y – 2Y. SNB data used before SIX data available. Maturity of SIX data is approximate |
| Term spread USA | $f$–curve | +1 day | Day | Fed Board | 10Y – 2Y |
| Term spread Europe | $f$–curve | +1 day | Day | Buba, ECB | 10Y Germany – 1Y euro area. 1Y EUR Libor used before 2004 |
| Risk premium CH | $f$–curve | +1 day | Day | SIX, SNB | 8Y AAA-AA – 8Y government. SNB data for debt issues by banks used before SIX data available. Maturity of SIX data is approximate |
| Short-term risk premium CH | $f$–curve | +1 day | Day | SIX | 1-3Y AAA-BBB – 1-3Y government. Start in 2008 |
| Risk premium foreign | $f$–curve | +1 day | Day | SIX, SNB | 8Y Foreign corp. – 8Y government. SNB data used before SIX data available. Average of various credit ratings |
| Short-term risk premium foreign | $f$–curve | +1 day | Day | SIX | 1-3Y AAA-AA – 8Y government. Start in 2008 |
| Stock market volatility CH | $f$–curve | +1 day | Day | SIX | |
| Stock market volatility USA | $f$–curve | +1 day | Day | CBOE | |
| Interest rate differential | $f$–curve | +1 day | Day | SIX, SNB, ECB | 1-3 year government bonds CH – 1 year government bond yields euro area. 1Y EUR Libor used before 2004 |
| Domestic news sentiment | $f$–curve | +1 day | Day | FuW, NZZ, TA | More details in Table A.3 |
| Foreign news sentiment | $f$–curve | +1 day | Day | FuW, NZZ, TA | More details in Table A.3 |

Table A.3 — Queries underlying news indicators

| | URL | Keywords |
|---|---|---|
| | **Domestic news sentiment** | |
| FuW | fuw.ch/unternehmen/<br>fuw.ch/makro/ | We use all articles listed in *Makro* and *Unternehmen* and select those containing the word *schweiz** in either lead text, tag or cateogry. |
| NZZ | zeitungsarchiv.nzz.ch | [*konjunktur** OR *wirtschaft** OR *rezession**] AND *schweiz** |
| TA | tagesanzeiger.ch/zeitungsarchiv-930530868737 | [*konjunktur* OR *wirtschaft* OR *rezession*] AND *schweiz* |
| | **Foreign news sentiment** | |
| FuW | fuw.ch/unternehmen/<br>fuw.ch/makro/ | We use all articles listed in *Makro* and *Unternehmen* and select those containing [*ausland* OR *eu* OR *euro** OR *deutsch** OR *us** OR *amerika**] in either lead text, tag or cateogry. |
| NZZ | zeitungsarchiv.nzz.ch | [*konjunktur** OR *wirtschaft** OR *rezession**] AND [*ausland* OR *eu* OR *euro** OR *deutsch** OR *us** OR *amerika**] |
| TA | tagesanzeiger.ch/zeitungsarchiv-930530868737 | [*konjunktur* OR *wirtschaft* OR *rezession*] AND [*ausland* OR *eu* OR *euro* OR *europa* OR *deutschland* OR *us* OR *usa* OR *amerika*] |

*Notes:* Since the *Finanz und Wirtschaft* is a business newspaper, we do not restrict the search with keywords related to the economy. The asterisk (*) represents a wildcard search operator. E.g. the query *schweiz** matches also *schweizerische*. Wildcards are allowed only in the NZZ archive.

Figure A.1 — Daily indicators for $f$–curve

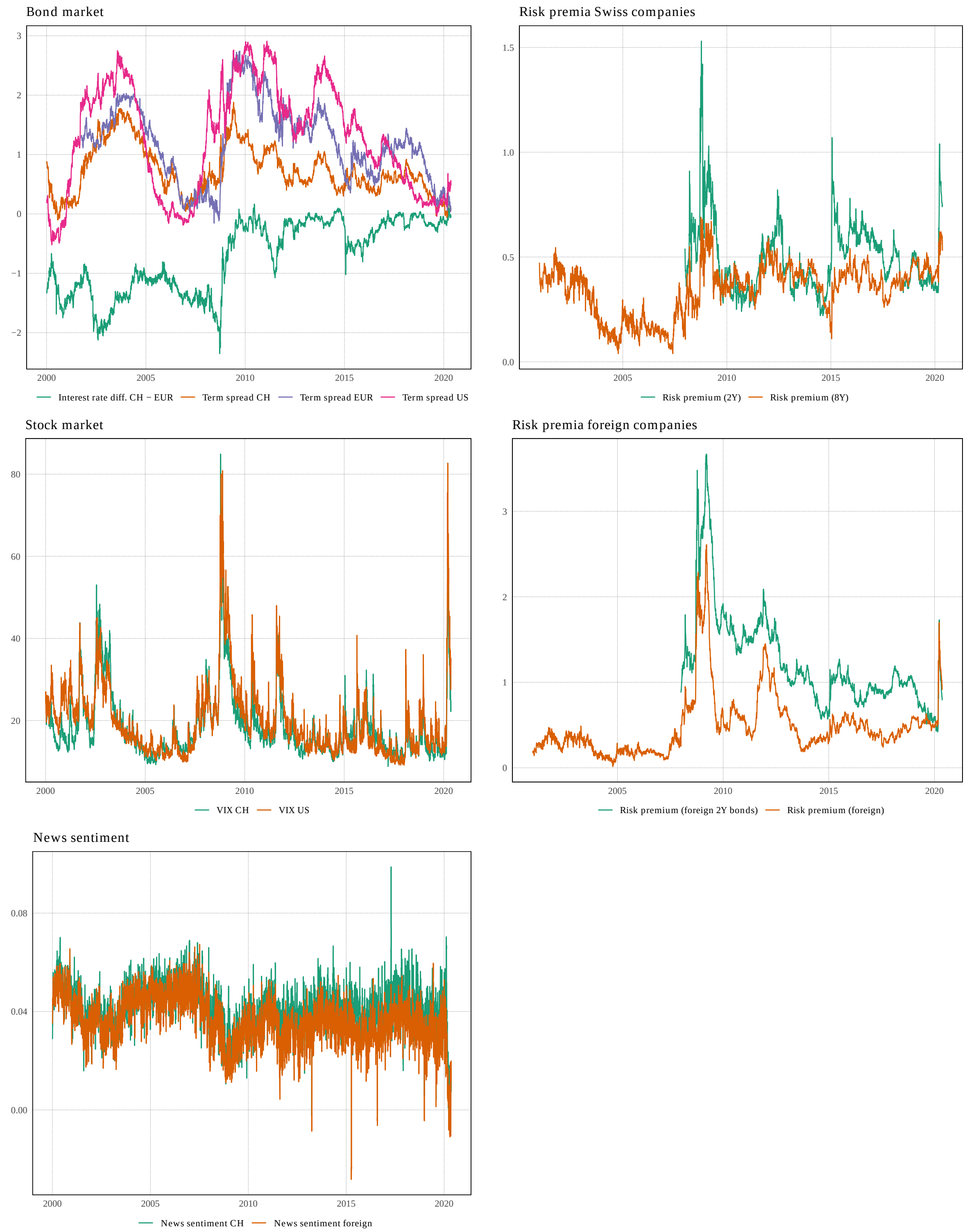
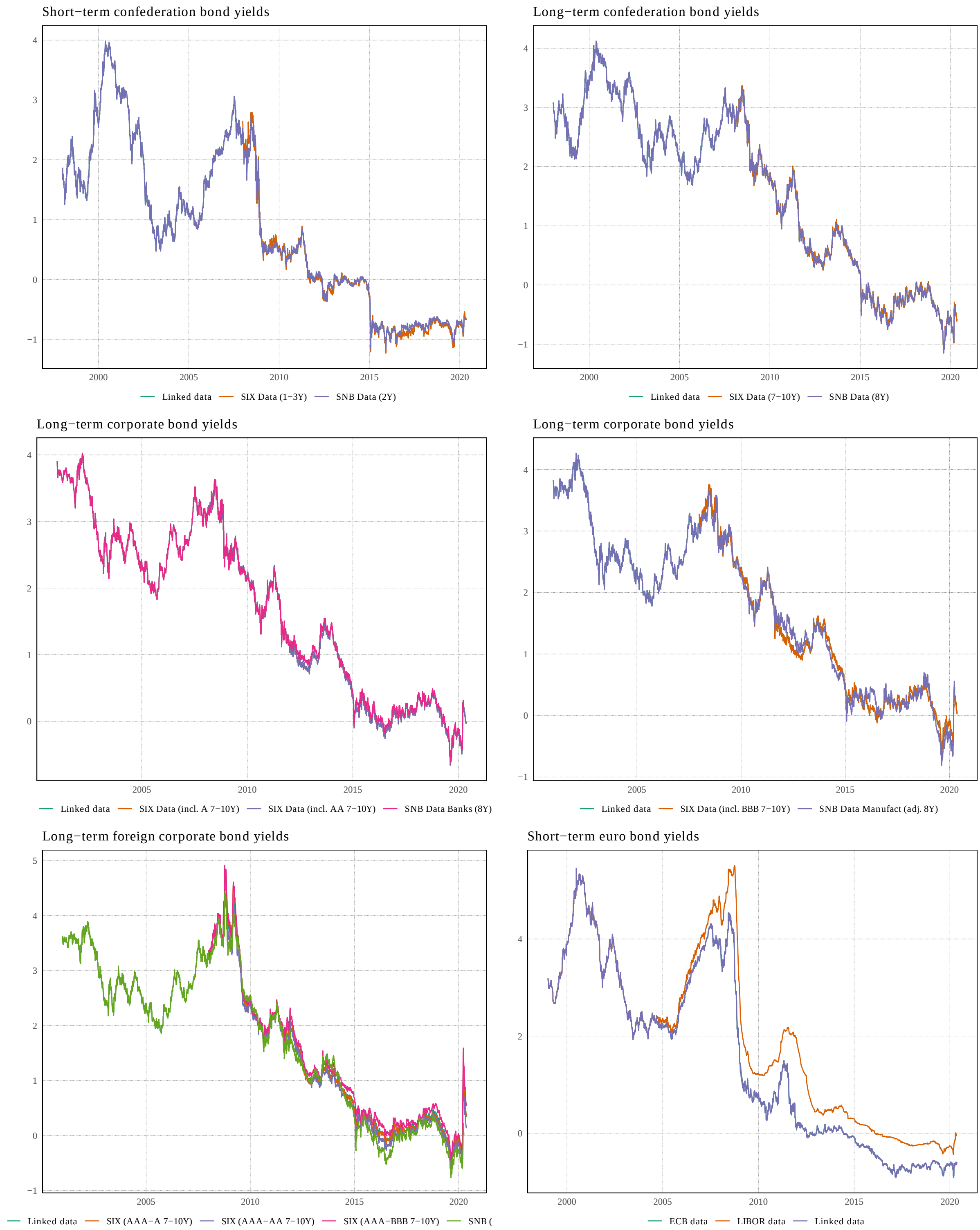
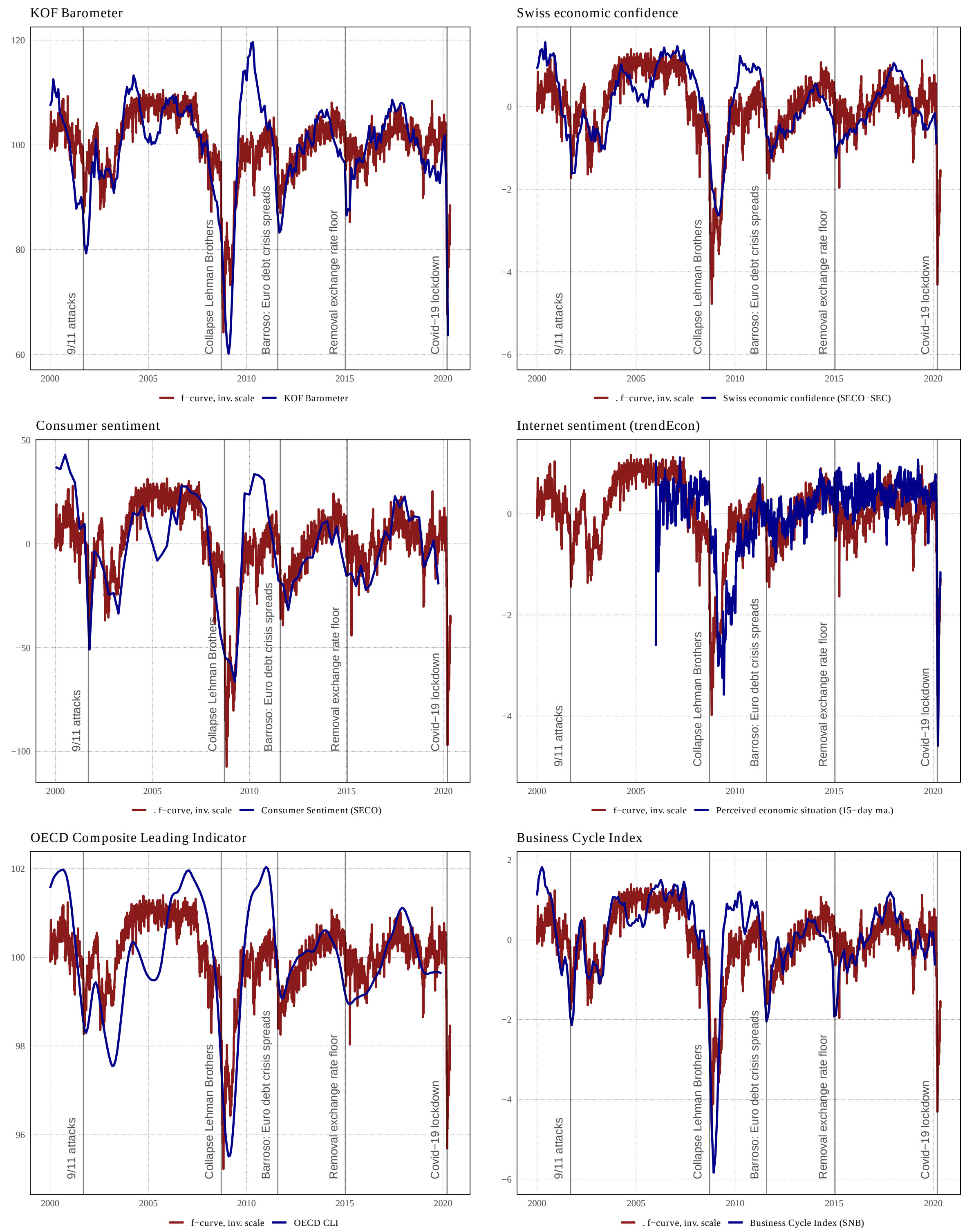


Figure A.2 — Spliced data underlying $f$–curve

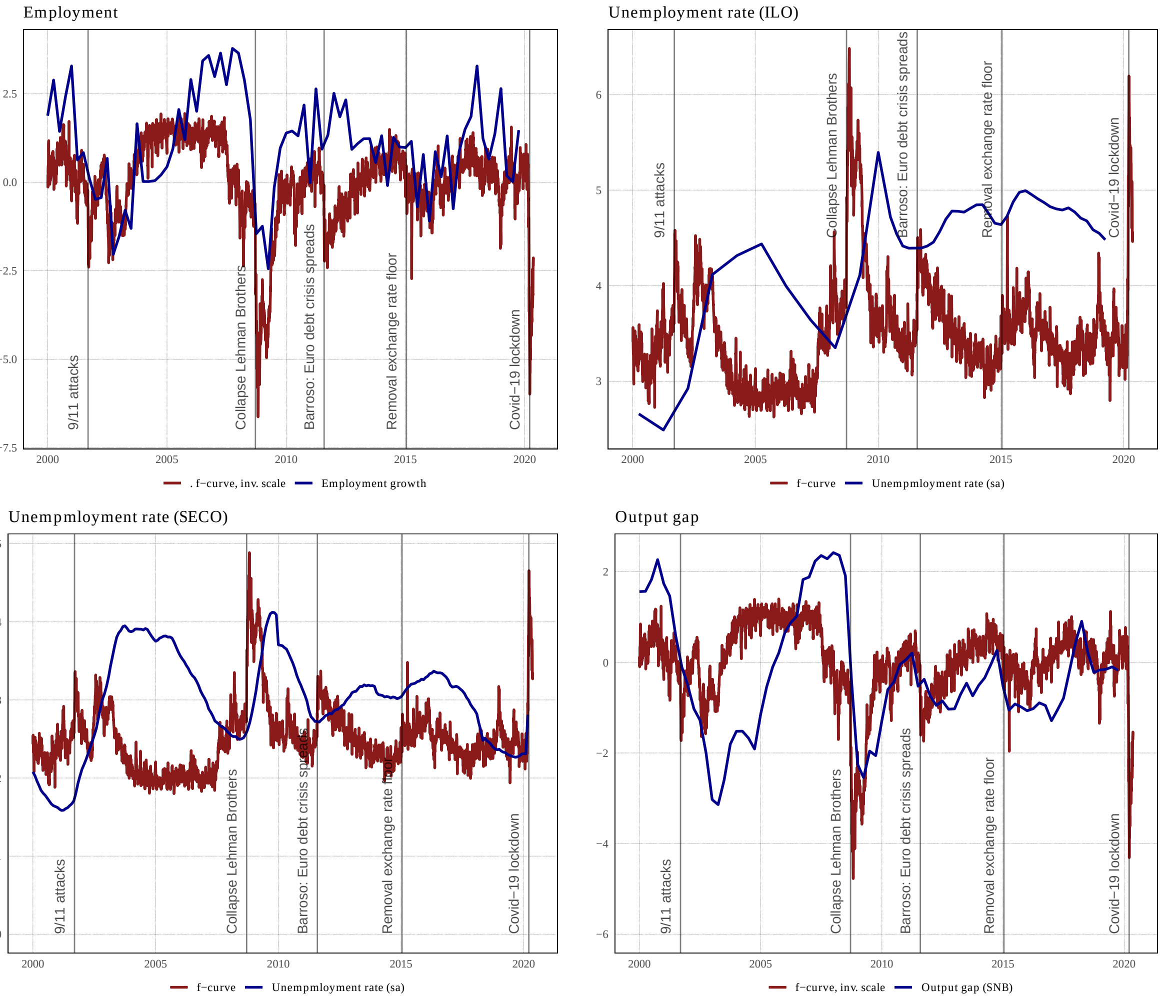


## Figure A.3 — Comparison with other indicators




*Notes: f*–curve rescaled such that it roughly matches the mean and volatility of the other data series.

Figure A.4 — Comparison with other macroeconomic data




*Notes: f*–curve rescaled such that it roughly matches the mean and volatility of the other data series.