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Covid-19 outbreak and beyond: The information content of registered short-time workers for GDP now- and forecasting.

Sylvia Kaufmann

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Covid-19 outbreak and beyond: The information content of registered short-time workers for GDP now- and forecasting.

Sylvia Kaufmann[*][†]

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Abstract

The number of employees historically filed and registered from January to April 2020 for short-time compensation is used to obtain a nowcast for GDP growth in the first quarter and an outlook until the third quarter 2021. We purge the monthly log level series from the systematic component to extract unexpected changes or shocks to log short-time workers. These monthly shocks are included in a univariate model for quarterly GDP growth to capture timely, current-quarter unexpected changes in growth dynamics. Included shocks explain additionally 24% in GDP growth variation. The model is able to forecast quite precisely the decrease in GDP during the financial crisis. It predicts a mean decline in GDP of 5.7% over the next two quarters. Without additional growth stimulus, the GDP level forecast remains persistently 4% lower in the long run. The uncertainty is large, as the 95% highest forecast density interval covers a decrease in GDP as large as 9%. A recovery to pre-crisis GDP level in 2021 lies only in the upper tail of the 95% highest forecast density interval.

Keywords: Bayesian analysis, Covid-19, two-step regression, forecasting.
JEL-Code: E23, E27, C32, C53

[*]Study Center Gerzensee, Foundation of the Swiss National Bank, Dorfstrasse 2, 3115 Gerzensee, Switzerland, sylvia.kaufmann@szgerzensee.ch

[†]I am grateful to Bernhard Weber from SECO, who provided the most recent numbers of workers pre-registered for short-time work from January 2020 to April 2020. All data and programs are available upon request.

1 Introduction

The Covid-19 pandemic outbreak at the beginning of March 2020 has had negative effects unprecedented since World War II on economic and social life in Switzerland as in other Western European countries. For private people, the lockdown mandated by the Swiss Federal Government on March 13 turned out less restrictive than in neighbour countries like France, Italy and Austria, where people must stay home and needed a permit to move. Nevertheless, economically and socially the imposed restrictions had a huge impact. A large share of the service sector, all personal services with physical contact, tourism and all recreational and cultural businesses were shut down.

Without cash inflows, the restrictions would lead to business insolvencies and mass unemployment. To counteract the disruptive effects, the Federal Government in cooperation with Swiss banks installed a state-guaranteed loan scheme to provide enterprises with lifeline liquidity. Besides, a series of measures shortened administrative procedures to apply for and obtain short-time work compensation, and extended the group of working persons eligible. For example, the number of days in advance of the start of short-time work that employers have to apply and the waiting time, i.e. the number of days between the start of short-time work and the flow of compensation, were reduced to zero. The group of eligible workers newly included among others apprentices, persons employed on an hourly basis, self-employed as well as employed managing staff. Particularly no waiting time between the announcement, the start of short-time work and the flow of compensation provided companies efficiently with emergency liquidity.[1]

The seismic effects of the lockdown and the unbureaucratic procedure lead to a record-high, unprecedented increase in pre-registered short-time workers. In February 2020, roughly 11,000 persons were pre-registered for short-time work, a number slightly above the historical average of around 9,000 (taking into consideration the high volatility in the series). In March, the number increased to above 1.6 million and reached more than 1.9 million in April. This corresponds to nearly 37% of employees. The incredible evolution is plotted in Figure 1 on a logarithmic scale. This increase dwarfs the increase observed during the financial crisis starting at the end of 2008.

Obviously, short-time work directly impacts on GDP. In real-time, the number of pre-registered short-time workers is available more timely and at a higher frequency than a first estimate of quarterly GDP. Therefore, we will evaluate the information content of the number of registered short-time workers for GDP growth, and form a first expectation for GDP prospects over the next one and a half year. The approach is simple, in the spirit

[1] See Eichenauer and Sturm (2020) for an overview (in German) of economic measures taken to counteract the negative effects of the pandemic outbreak.

of Romer and Romer (1989, 2004). There is no horse-race in the paper, as the model is not intended to outperform other, more sophisticated forecasting models. Rather, the approach intends to illustrate that unusual indicators are useful to explore during periods of crisis, also to inform models build and specified during normal periods. The approach is Bayesian. Sequential updating will allow us to evaluate whether the number of registered short-time workers will stay informative as imposed measures will be abolished gradually in the course of the year.
The next section presents the data and introduces the econometric approach. Section 3 discusses the results. Section 4 concludes and provides an outlook.

2 Data and econometric approach

2.1 Data

Figure 1 plots the monthly series of short-time workers (number of employees) on a logarithmic scale and indicates the various sources. The linked, long data series starts in January 2000 and ends in April 2020. The downloaded data (Settled download) from www.amstat.ch starts in January 2004 and runs through January 2020. The series is augmented from January 2000 through December 2003 with observations published in a pdf-file (Settled SECO) on the website of the State Secretariat of Economic Affairs (SECO). I am grateful to Bernhard Weber from SECO, who provided the most recent numbers of workers pre-registered for short-time work from January 2020 to April 2020. The figure highlights in gray past crisis periods and critical monetary policy actions: The dotcom and financial crises, the introduction and the discontinuation of the Swiss franc-euro floor.
The figure illustrates the unprecedented increase in short-time workers during March and April. The number jumped from slightly above 11,000 workers pre-registered in January to 1.6 and 1.9 million in, respectively, March and April 2020, which represents nearly 37% of employees. The level exceeds the historical peak of roughly 90,000 short-time workers in the aftermath of the financial crisis by a factor of 21. Mainly two factors lead to this huge increase. To cut most effectively the Covid-19 infection chain, the Federal Government mandated the shut-down of a large share of the service sector, all personal services with physical contact, tourism and all recreational and cultural businesses. To provide businesses with lifeline liquidity and counteract the disruptive effects that would otherwise lead to mass employment and business failures, the Federal Government abolished the waiting times, namely the number of days in advance of the start of short-time

work that employers have to apply for short-time work and the number of days between the start of short-time work and the flow of compensation. In addition, the group of persons eligible for short-time work compensation was enlarged to, among other, apprentices, workers employed on an hourly basis, self-employed and employed managing staff.

Figure 2 shows additional characteristics of the series. The histogram in Panel (a) shows that the number of short-time workers has been fluctuating between 1,000 and 10'000 most of the time. The cluster of observations below 100,000 refers to numbers recorded in the aftermath of the financial crisis. Excluding the numbers of pre-registered workers in 2020, the historical average has been slightly above 9,000. Panel (b) plots growth rates on a decimal scale, i.e. the first difference of the log level, of the number of persons working short-time and the number of lost working hours. Excluding again the pre-registered data for 2020, both series have a zero mean growth rate and their volatilities (one standard deviation) reach sizeable 0.39 (number of short-time workers) and 0.45 (lost working hours), i.e. 39% and 45%. The correlation between the level series is .97 and growth rates .69. We conclude that both series contain the same information and we could work with either of them. We choose the number of short-time workers in the following.

Figure 3 plots on a percentage scale the series of interest, quarterly growth in real gross domestic product (GDP), as published on the SECO website. We plot along the quarter average of the monthly business cycle index produced and published by the Swiss National Bank (SNB). Given its considerable correlation (.77) with quarterly GDP growth, the index could serve as alternative and allow us to perform the analysis on a monthly basis. However, we observe that in particular since a couple of years before the financial crisis, the index apparently leads the decline in GDP growth. Therefore, we choose to work at the quarterly frequency to analyze and exploit the monthly information contained in the number of short-time workers for real GDP growth.

2.2 Econometric approach

For the analysis, we take the logarithm of the number of short-time workers. Our goal is to form a short- to medium-term forecast of GDP growth (100 times the difference of the logarithmic level) at the end of the observation sample, including information extracted from variation in the number of short-time workers, which is not included already in past systematic GDP growth variation.

We have to address two issues. The first is the inherent endogeneity in historical, i.e. end-revised, time series. Even if the number of short-time workers is available at a higher frequency, the current-quarter monthly variation in this series is reflected in historical current-quarter GDP growth, and vice-versa. The second, less critical issue is to convert the information extracted at the monthly into lower-frequent quarterly information. To tackle the first one, we apply a procedure in the spirit of Romer and Romer (1989) and Romer and Romer (2004) and extract first the unexplained variation in the (log) number of historical, or in-sample, short-time workers, n_t^s:

$$n_t^s = c_n^s + \varphi_1 n_{t-1}^s + \cdots + \varphi_l n_{t-l}^s + \nu_t^s \tag{1}$$

where the superscript s indicates the observations used to estimate the regression, c_n^s is the intercept and ν_t^s is i.i.d. $N(0, \delta^2)$. Given that historical GDP growth figures reflect historical variations in the number of short-time workers, the lagged values n_{t-j}^s in Equation (1) purge current value n_t^s from systematic variation also accounted for by lagged GDP growth. The residuals ν_t^s reflect unexplained variation, i.e. the shock in n_t^s, that we can include as additional information to explain and forecast GDP growth.

There are various possibilities to use or convert the monthly shock series to match the quarterly frequency of GDP growth. We may use each first-, second- or third-month shock, or add up shocks to cumulative quarterly information. We apply the latter approach and include the quarterly cumulated monthly shocks ν_{qt}^s into the regression for quarterly GDP growth:

$$y_t^s = c_y^s + \theta_1 \nu_{qt}^s + \cdots + \theta_k \nu_{q,t-k}^s + \phi_1 y_{t-1}^s + \cdots + \phi_p y_{t-p}^s + \sum_{j=1}^{3} \psi_j D_{jt} + \varepsilon_t^s \tag{2}$$

where c_y^s is the intercept and ε_t^s are i.i.d. $N(0, \sigma^2)$. We allow shocks to have an effect up to k lags, D_{jt} is a set of quarterly dummy variables, $D_{jt} = 1$ if period t corresponds to quarter j and otherwise $D_{jt} = 0$.

We perform inference within a Bayesian framework, see the sampling steps described in the next subsection. Conditional on the model estimate we may draw impulse responses of GDP growth to a shock ν_{qt}^s, for which highest posterior density intervals are available given the Bayesian approach. Forecasts and forecast distributions are available by a posterior predictive analysis. The forecast for GDP growth is then conditioned on timely available information on shocks in the number of short-time workers:

$$y_t^f = \hat{c}_y^s + \hat{\theta}_1 \nu_{qt}^f + \cdots + \hat{\theta}_k \nu_{q,t-k}^f + \hat{\phi}_1 y_{t-1}^f + \cdots + \hat{\phi}_p y_{t-p}^f + \sum_{j=1}^{3} \hat{\psi}_j D_{jt} \tag{3}$$

where $\nu_{qt}^f = n_t^o - n_t^f$ is equal to the one-step ahead forecast error (the difference between observed and forecast values, n_t^o and n_t^f, respectively) or the in-sample error in case $\nu_{qt}^f = \nu_{qt}^s$. Likewise, in-sample values would substitute $y_{t-j}^f = y_{t-j}^s$. Equation (3) can be evaluated at the posterior mean of parameters $\hat{\beta} = E(\beta|\text{Data})$. Evaluating for each draw $m = 1, \ldots, M$ out of the posterior, $\hat{\beta} = \beta^{(m)}$ we obtain draws from the posterior predictive distribution of y_t^f.

2.3 Bayesian inference

Both equations (1) and (2) can generically be represented in a regression matrix format

$$Y = X\beta + \epsilon \tag{4}$$

with Y represents the vector of T left-hand, in-sample observations, X the regressor matrix with right-hand variables ordered in columns and $\epsilon \sim N(0, \kappa I_T)$, with I_T the identity matrix and $\kappa = \{\delta^2, \sigma^2\}$.
We specify standard independent prior distribution for the parameters:

$$\pi(\beta) = N\left(b_0, B_0^{-1}\right), \quad \pi(\kappa) = IG(g_0, G_0)$$

where the normal prior for β is specified in terms of information B_0 and IG represents the inverse Gamma distribution.
Posterior inference on parameters combines the likelihood with prior information

$$\pi(\beta, \kappa|Y, X) \propto L(Y|X, \beta, \kappa)\, \pi(\beta)\, \pi(\kappa) \tag{5}$$

where the likelihood is $L(Y|\cdot) = \prod_{t=1}^{T} f(y_t|x_t, \beta, \kappa)$ with normal observation density $f(y_t|\cdot) = N(x_t\beta, \kappa)$, x_t row t of X.
To obtain a sample out of the posterior (5) we set initial values for β and κ and iterate over the following two steps:

S.1. Draw from $\pi(\beta|Y, X, \kappa) = N(b, B^{-1})$,

$$B = \kappa^{-1}X'X + B_0, \quad b = B^{-1}\left(\kappa^{-1}X'Y + B_0 b_0\right)$$

S.2. Draw from $\pi(\kappa|Y, X, \beta) = IG(g, G)$,

$$g = g_0 + .5T, \quad G = G_0 + .5\,(Y - X\beta)'\,(Y - X\beta)$$

We discard a number of burn-in draws to remove the dependence from initial values and retain M draws for the analysis.

Table 1: Log number of short-time workers. Model choice: Schwarz (BIC) and Akaike (AIC) information criteria. Sample start: January 2001.

l	12	6	4	3	2	1
BIC	-1.82	-1.84	-1.88	-1.91	-1.93	-1.93
AIC	-2.02	-1.94	-1.96	-1.97	-1.97	-1.96

3 Results

3.1 The number of short-time workers

The long observation sample allows us to specify a diffuse prior, i.e. we perform posterior inference without a priori information. For parameters, we set $b_0 = 0$ and $B_0 = 0$, and for δ^2, $g_0 = G_0 = 1$. We iterate 3,000 times over the sampler described in Subsection 2.3, discard the first 1,000 and retain 2,000 for posterior inference.
To decide on the lag length l in Equation (1), we evaluate the Schwarz (BIC) and Akaike (AIC) information criteria on the sample period January 2001 – January 2020. Table 1 summarizes the results. As Figure (1) does not reveal a strong seasonal pattern, we choose a lag length of $l = 3$, which makes a compromise between BIC and AIC. Note that the main results are not sensitive to the choice of the lag length.
We obtain the following posterior inference:

$$\begin{aligned} n_t^s = \underset{(0.15,0.83)}{0.48} \quad \underset{(0.90,1.17)}{+1.02 n_{t-1}^s} \quad \underset{(-0.15,0.22)}{+0.03 n_{t-2}^s} \quad \underset{(-0.24,0.02)}{-0.11 n_{t-3}^s} \quad + e_{\nu t} \\ \sum_{j=1}^{3} \varphi_j = \underset{(0.90,0.98)}{0.94}, \quad \delta^2 = \underset{(0.13,0.18)}{0.16}, \quad R^2 = 0.91 \end{aligned} \tag{6}$$

where the numbers indicate the posterior mean and the 95% highest posterior density interval (HPDI) in parenthesis. The sum of the coefficients indicates that the process is stationary and highly persistent. We explain a large share of data variance as indicated by an R^2 of .91.
Figure 4 plots the data along with the mean fitted values. All draws of error or shock series are plotted at the bottom of the graph, the mean is plotted in red and the black lines indicate the interval of +/- two mean standard errors (0.8). We see the high volatility of shocks during the dotcom crisis and the persistent positive shocks during the financial crisis.

In a second step, we use the model estimate to extract the shocks that affected the series from February to April 2020:

$$
\begin{aligned}
n_t^{f(m)} &= c_n^{(m)} + \varphi_1^{(m)} n_{t-1}^f + \cdots +^{(m)} \varphi_l n_{t-l}^f \\
\nu^{f(m)} &= n_t^o - n_t^{f(m)}
\end{aligned}
$$

where $n_{t-l}^f = n_{t-l}^s$ if the observation is part of the estimation sample and otherwise is the out-of-sample observation. The superscript (m) indicates that we compute one-step ahead forecasts and forecast errors for each of the posterior draws. When $n_t^{f(m)}$ is part of the estimation sample, the forecast errors correspond to in-sample errors, otherwise the errors correspond to out-of-sample forecast errors. Figure 5 plots the data and the mean one-step ahead forecast at the top, and the errors at the bottom. In-sample shocks are plotted in blue, out-of-sample ones in green. The mean is plotted in red. Obiously, the unprecedented increase in March leads to a huge shock, the logarithmic scale means an unexpected increase in short-time workers by a factor of roughly 148. The model accomodates quickly the new level, such that the further incrase in April is attributed largely to the systematic part of the model. Correspondingly, the extracted shock for April is near 0.

3.2 GDP growth

As for the monthly data, we start out with diffuse priors and estimate Equation (2) without prior information. For parameters, we set $b_0 = 0$ and $B_0 = 0$, and for σ^2, $g_0 = G_0 = 1$. We iterate 4,000 times over the sampler described in Subsection 2.3, discard the first 1,000 and retain 3,000 for posterior inference.

The shocks extracted from log short-time workers are cumulated within quarter to match the frequency of GDP growth. Figure 6 plots the cumulated shocks along with GDP growth. The in-sample, negative correlation (-0.59) is substantial. We include the mean of cumulated shocks into Equation (2). We specify the equation in the spirit of Romer and Romer (2004) and, as dealing with quarterly data, we set $k = p = 4$ and include a set of quarterly dummies. Posterior inference yields:

$$
\begin{aligned}
y_t^s = \; & \underset{(0.18,0.83)}{0.50} \; \underset{(-0.91,-0.39)}{-0.66\nu_{qt}^s} \; \underset{(-0.43,0.19)}{-0.12\nu_{q,t-1}^s} \; \underset{(-0.37,0.26)}{-0.05\nu_{q,t-2}^s} \; \underset{(-0.44,0.08)}{-0.19\nu_{q,t-3}^s} \\
& \underset{(-0.21,0.34)}{+0.06\nu_{q,t-4}^s} \; \underset{(0.05,0.65)}{+0.36y_{t-1}^s} \; \underset{(-0.55,0.04)}{-0.27y_{t-2}^s} \; \underset{(-0.49,0.07)}{-0.21y_{t-3}^s} \; \underset{(-0.26,0.26)}{-0.01y_{t-4}^s} \\
& \underset{(-0.19,0.61)}{+0.19D_{1t}} \; \underset{(-0.45,0.39)}{-0.04D_{2t}} \; \underset{(-0.49,0.25)}{-0.15D_{3t}} \; + e_{\varepsilon t}
\end{aligned}
$$

$$
\sum_{j=0}^{4}\theta_j = \underset{(-1.61,-0.29)}{-0.97}, \; \sum_{j=1}^{4}\phi_j = \underset{(-0.66,0.41)}{-0.14}, \; \sigma^2 = \underset{(0.13,0.26)}{0.19}, \; R^2 = 0.50 \quad (7)
$$

where numbers represent the posterior mean with the 95% HPDI in parenthesis. We explain overall 50% of data variation.[2] The information content of contemporaneous shocks is negative and highly significant. A unit shock in log short-time workers leads to a drop in current-quarter GDP growth of .6%. The results reveal that the equation is slightly over-specified. Some lags of shocks, some of the autoregressive lags and dummy variables could be dropped. However, to capture as much systematic data variation as possible, we compute impulse responses and forecasts conditional on the full specification.

3.3 Impulse responses and forecasts

Before further analysing the model and computing a forecast, we may want to evaluate the model's performance, in particular in predicting during crisis periods. Although we only have one observed crisis during the sample, we may use the financial crisis to confront the model with its forecasting ability. We use the same specifications, estimate both equations up to September or the third quarter of 2008, and forecast GDP out-of-sample after the outbreak of the financial crisis, conditional on shocks in log short-time workers observed through February 2009, i.e. the same number of observations available ahead of GDP as currently.

Given the shorter sample period, we specify proper prior distributions by using the posterior moments inferred from the long sample as prior moments in the short sample. Thus, we set $B_0 = 1/M\sum_{m=1}^{M} B^{(m)}$, $b_0 = 1/M\sum_{m=1}^{M} b^{(m)}$ and $G_0 = 1/M\sum_{m=1}^{M} G^{(m)}$. The degrees of freedom are kept at the minimum $g_0 = 3$ to ensure that prior moments exist without inducing to much precision for the error variance. The equations are thus estimated based on the information we accumulated by the beginning of 2020. Figure 7

[2] When shocks to log short-time workers are excluded, the equation explains 26% of data variation.

plots the mean along with the 95% HPDI forecast interval. The forecast declines less than what we observed, -2.9% compared with observed -3.5.%. Nevertheless, the 95% interval includes marginally observed GDP through the first quarter of 2009 and the mean level forecast is nearly on track with observed GDP from the second quarter 2009 onwards. Overall, the model fares well.

We proceed by plotting impulse responses of GDP growth to a shock corresponding to an unexpected doubling in short-time workers. Figure 8, Panel (a) reflects the estimate and plots the impact drop in GDP growth of .46%. Growth returns quickly to zero, there is no hump-shaped recovery. The drop in GDP is persistent, as reflected in Panel (b). The cumulated negative effect on GDP is around -.6%.

Conditional on shocks in log short-time workers observed through April 2020, we compute a forecast for GDP growth from the first quarter 2020 through the third quarter 2021. Figure 9 plots the mean forecast along with the 95% highest forecast density interval. The drop in GDP growth is 3.5% in the first quarter 2020 and GDP growth remains negative during the second quarter. There is a mild, hump-shaped recovery of about 1% forecasted for the first quarter 2021. Panel (b) shows the cumulated effets. The largest decline to -5.7% is reached in the third quarter 2020, while the 95% interval shows that the drop could be as large as 9%. Without any strong positive growth impulses, GDP will remain persistently 4% lower than pre-crisis in the long run. Figure 10 plots the data and forecast of log GDP. Compared with the financial crisis, the drop in GDP could be nearly twice as large this time.

The mean level forecast is in line with the forecasts published by KOF Swiss Economic Institute at ETH on May 15 (-5.5%) and BAK Economics AG on May 7 (-5.3%), and 1% point higher than the forecast released by SECO on April 23 (-6.7%).[3] All institutions forecast a rebound to pre-crisis GDP level for 2021. This level is included only in the upper tail of the 95% highest forecast density interval highlighted in Figure 10.

4 Conclusion

The present paper exploits the information contained in the timely available number of persons registered for short-time work to obtain a now- and forecast in quarterly GDP growth. In a first univariate regression, we purge the log number of short-time workers from the systematic component, to obtain the shock in or the unexpected variation in the series. The observed monthly shocks are cumulated to quarter shocks, and enter

[3]See KOF Swiss Economic Institute (2020), BAK Economics AG (2020), State Secretariat of Economic Affairs (SECO) (2020).

contemporaneously as well in lags the second equation specified for GDP growth. The shocks explain 24% additional data variation. The model forecasts well the decrease in GDP during the financial crisis. The forecast computed for 2020 is in line with the forecasts provided by forecast institutions in Switzerland. However, the recovery to pre-crisis level GDP forecasted by these institutions lies only in the upper tail of the 95% highest forecast density interval provided by the model.

The number of registered short-time workers appears to contain valuable information to obtain a now- and medium-term forecast of GDP. As the crisis phases out and the economy smoothly accelerates, the performance of the indicator may be re-evaluated towards the end of the year.

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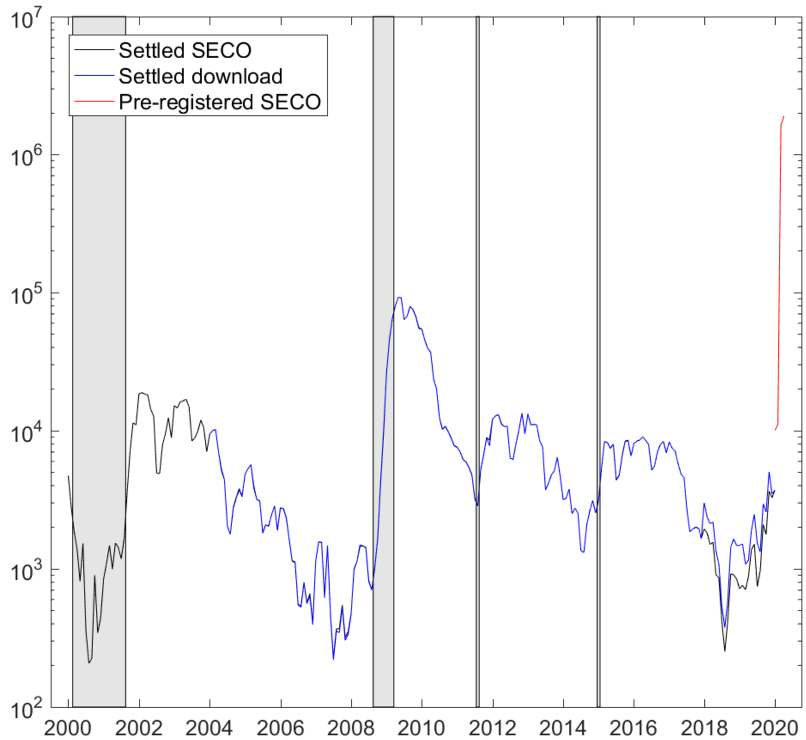
Figures

Figure 1: Short-time workers. Monthly frequency, logarithmic scale. Gray bars highlight the dotcom and the financial crises, the introduction and discontinuation of the Swiss franc-euro floor.

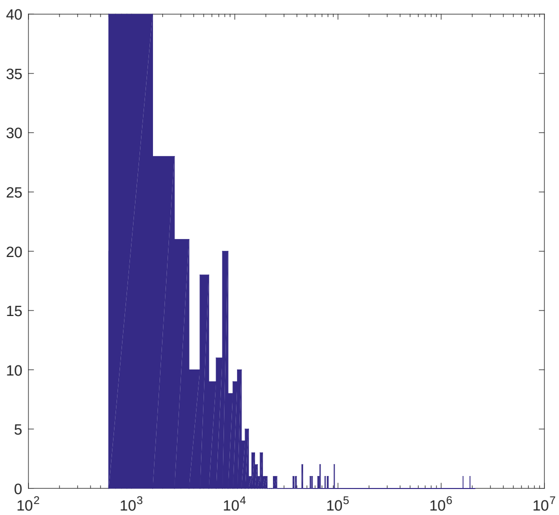


Settled SECO: Published pdf-file* as of May 1, 2020, January 2000 – January 2020; Settled download: Download+ as of May 2, 2020, January 2004 – January 2020; Pre-registered SECO: Obtained by e-mail as of May 1, 2020, January 2020 – April 2020.

* https://www.seco.admin.ch/seco/de/home/Arbeit/Arbeitslosenversicherung/leistungen/kurzarbeits-entschaedigung.html

+ https://www.amstat.ch/v2/index.jsp

Figure 2: Short-time workers and lost working hours. Monthly frequency. Gray bars highlight the dotcom and the financial crises, the introduction and discontinuation of the Swiss franc-euro floor.

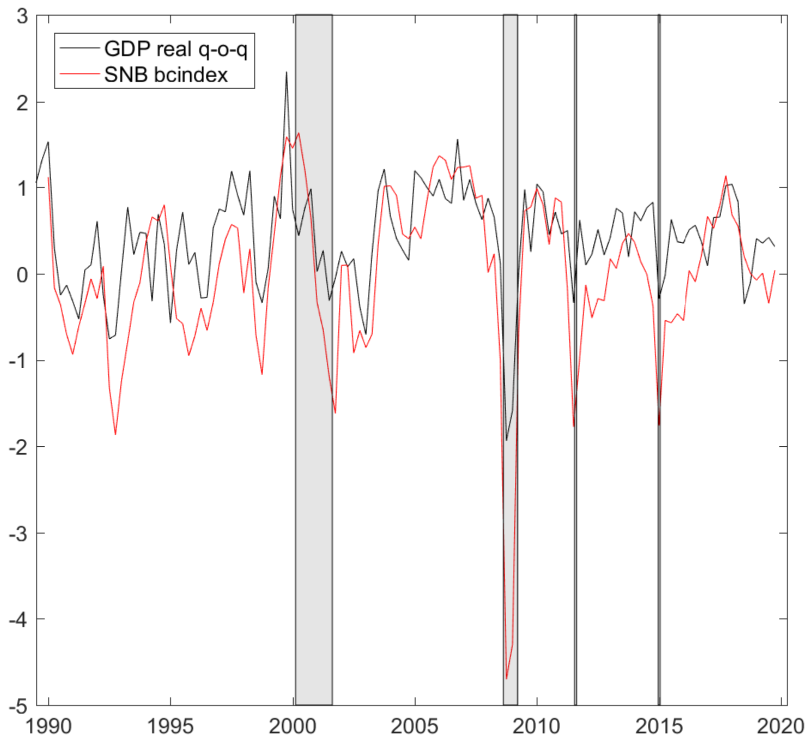


(a) Histogram short-time workers

(b) Growth rates (decimal scale)

Series merged from the three data sources (see footnote to Figure 1), the observation for short-time workers in January 2020 is taken from the e-mail source.

Figure 3: Growth rates (percentage scale). Real GDP* (quarterly frequency) and SNB business cycle index+ (SNB bcindex, quarter average of monthly frequency). Gray bars highlight the dotcom and the financial crises, the introduction and discontinuation of the Swiss franc-euro floor.



* https://www.seco.admin.ch/seco/de/home/wirtschaftslage—wirtschaftspolitik/Wirtschaftslage/bip-quartalsschaetzungen-/daten.html , as of March 3, 2020.

+ https://data.snb.ch/de/topics/snb#!/chart/snbbcich , as of April 21, 2020.

Figure 4: Log short-time workers. Data and mean fitted values, error (shock) series (mean in red). Sample period: April 2000 – January 2020. Gray bars highlight the dotcom and the financial crises, the introduction and discontinuation of the Swiss franc-euro floor.

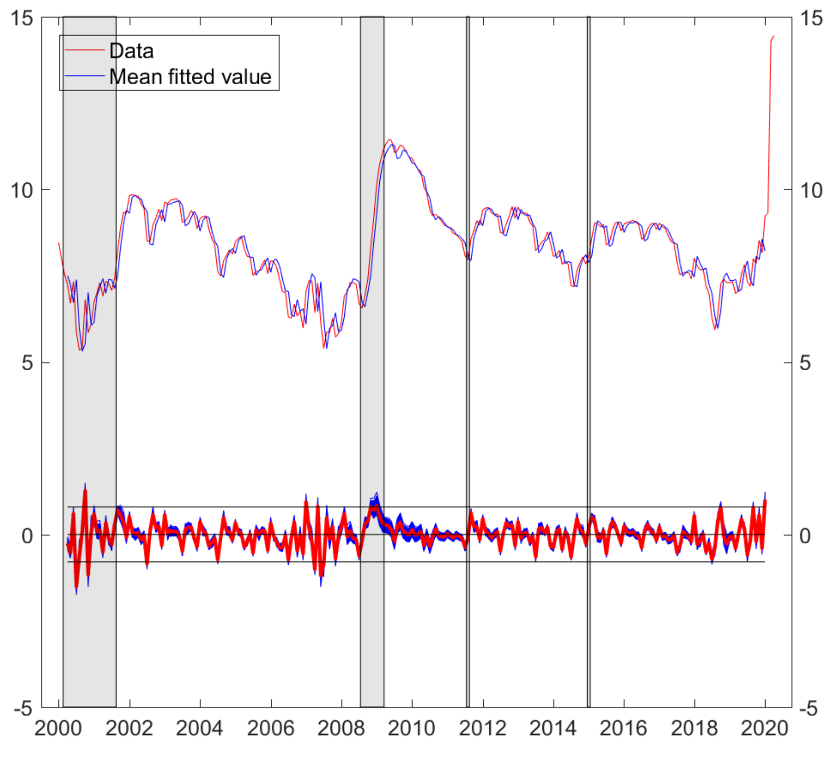


Figure 5: Log short-time workers. Data and mean one-step ahead forecast, one-step ahead error (shock), in-sample (blue), out-of-sample (green), mean (red). Sample period: April 2000 – January 2020.

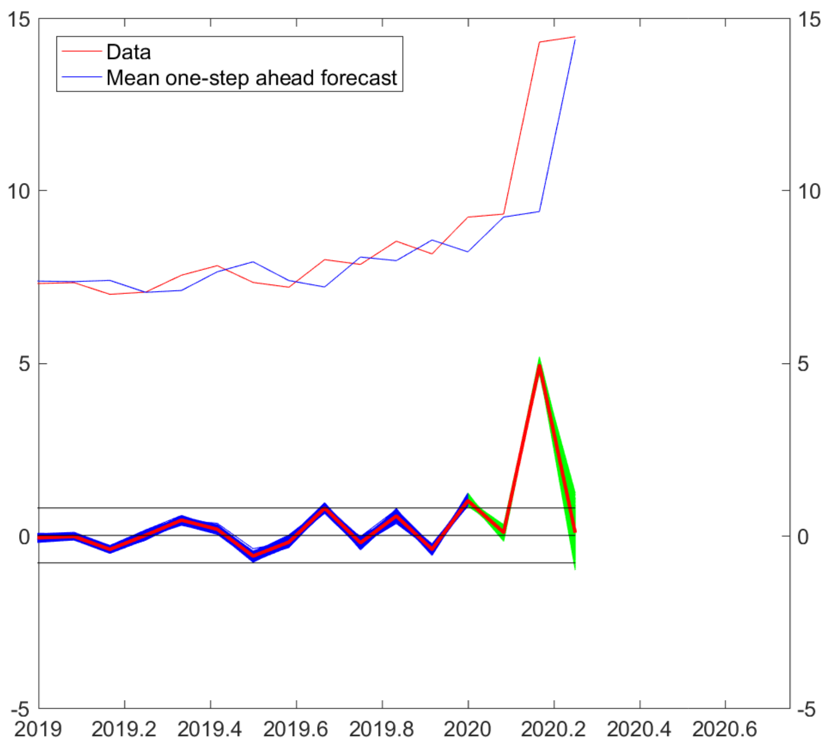


Figure 6: GDP growth and quarter-cumulated shocks in log short-time workers. Sample period: Second quarter 2000 – fourth quarter 2019.

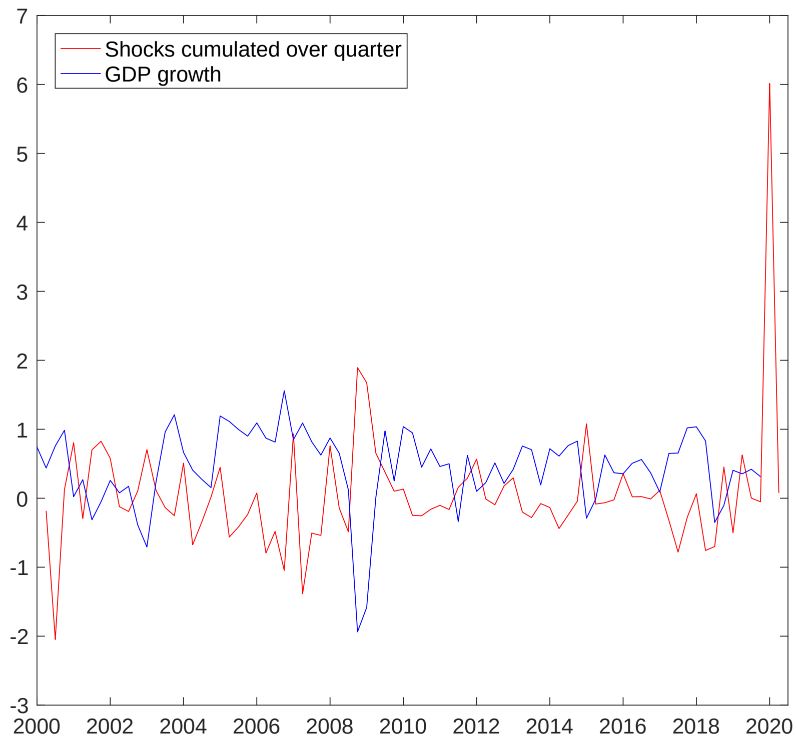


Figure 7: Out-of-sample GDP forecast, mean level forecast with 95% highest forecast density interval in gray. Sample period: Second quarter 2001 – third quarter 2008. Model estimated using as prior information posterior moments obtained for the long-sample estimate. Forecast period: Fourth quarter 2008 – third quarter 2010. Gray bars highlight the financial crisis and the introduction of the Swiss franc-euro floor.

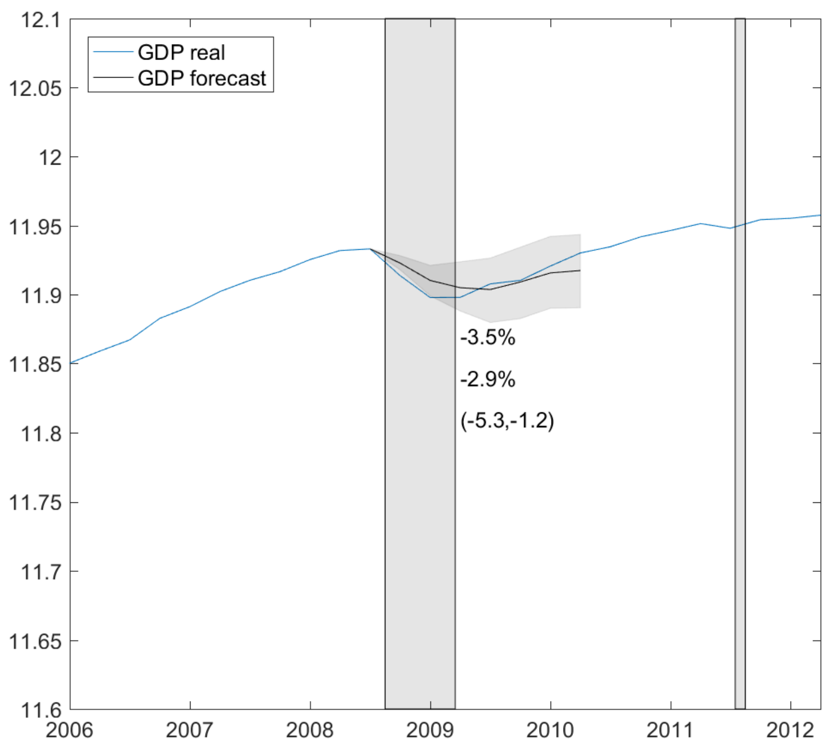
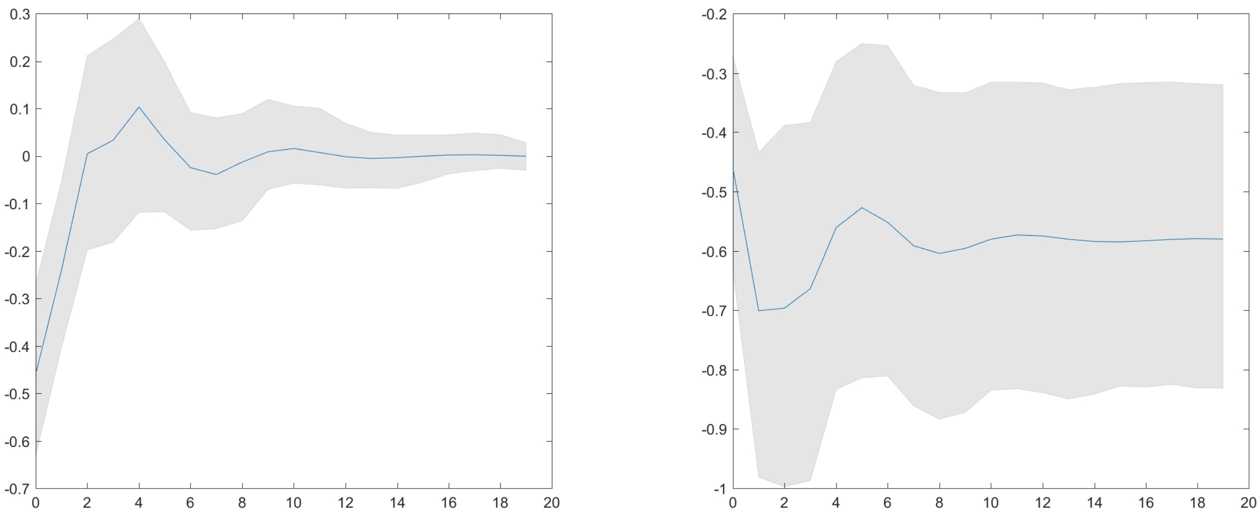


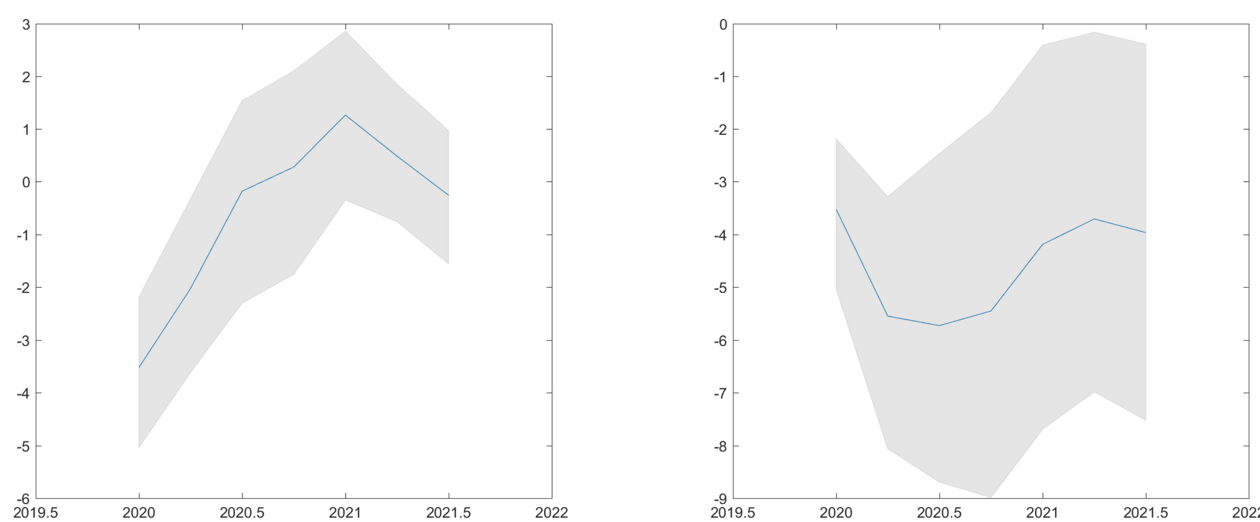
Figure 8: GDP growth. Impulse responses to a unit shock in log short-time workers.



(a) Growth rate

(b) Growth rate cumulated

Figure 9: GDP growth. Forecast period: First quarter 2020 – third quarter 2021. Forecast conditional on shocks in log short-time workers up to April 2020.



(a) Growth rate

(b) Growth rate cumulated

Figure 10: Out-of-sample GDP forecast. Sample period: Second quarter 2001 – fourth quarter 2019. Forecast period: First quarter 2020 – third quarter 2021. Gray bars highlight the financial crises, the introduction and discontinuation of the Swiss franc-euro floor, the red bar indicates the outbreak of the Covid-19 pandemic.