Discussion paper

The methodology of the Dutch consumer confidence survey during the corona crisis

Jan van den Brakel
Sabine Krieg and
Marc Smeets

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Content

Summary

The Dutch Consumer Survey (CS) is a monthly survey that measures the consumer confidence in the Netherlands. The estimation procedure is based on a structural time series model. By means of this model information from the past and the relations between the five questions that are used to construct the consumer confidence index, is used to improve the accuracy of the estimates.
In the Netherlands the corona crisis started in February 2020, causing a sharp decline in the consumer confidence not long after. The corona crisis changed the volatility of the five variables that are used to measure consumer confidence as well as the relations between these variables. As a result the structural time series model was temporarily misspecified, since the structure of the model was based on the past, while the past was very different from the period during the corona pandemic. This paper describes how the model is adapted to take the rapid changes in the consumer confidence into account.

The regular CS is carried out in the first half of every month and the monthly figures are published shortly afterwards. Due to the increased volatility of the consumer confidence in the first months of the corona crisis and the great need for timely information of the impact of corona on the economy, a second measurement in the second half of the months April, May and June of 2020 was planned. In this paper a structural time series model is described which was used to estimate the consumer confidence of the second half of the month during this period.

Keywords

Small area estimation, structural time series model, corona crisis

Reviewers

Rob Willems

1. Introduction

The Dutch Consumer Survey (CS) measures the consumer confidence in the Netherlands. The CS is a monthly survey of around 1000 persons. Since 2017 a structural time series model has been applied to estimate the trend of the consumer confidence which is published instead of seasonally adjusted figures (Van den Brakel et al. 2021). By means of this model information from the past and the relations between the five questions that are used to construct the consumer confidence index, is used to improve the accuracy of the estimates.

In the Netherlands the corona crisis started in February 2020, causing a sharp decline in the consumer confidence not long after. The corona crisis changed the volatility of the five variables that are used to measure consumer confidence as well as the relations between these variables. As a result the structural time series model was temporarily misspecified, since the structure of the model was based on the past, while the past was very different from the period during the corona pandemic. This paper describes how the model is adapted to take the rapid changes in the consumer confidence into account. The corona crisis affected other surveys as well, for example the Labour Force Survey and the Health Survey. How the methods and structural time series models were constructed and adjusted for these surveys is described in Van den Brakel et al (2022), Gonçalves et al. (2022) and Van den Brakel and Smeets (2023).

The regular CS is carried out in the first half of every month and the monthly figures are published shortly afterwards. Due to the increased volatility of the consumer confidence in the first months of the corona crisis and the great need for timely information of the impact of corona on the economy, a second measurement in the second half of the months April, May and June of 2020 was planned. In this paper a structural time series model is described which was used to estimate the consumer confidence of the second half of the month during this period.

The paper focuses predominantly on the first lockdown during the corona pandemic. In the subsequent lockdowns similar adjustments as described in this paper were applied. In the production process of the CS, there are only a few days available for data analysis. In this paper, the solution developed and implemented at the start of the pandemic is described and compared with some alternative approaches that were developed afterwards. The method finally chosen has been applied during the initial phase of the Russian invasion of Ukraine as well, since this crisis had a similar impact on the volatility of the consumer confidence.

The paper is organized as follows. In Section 2, the development of the corona crisis in the Netherlands is described as background information. In Section 3, the survey design of the CS is described as well as the multivariate structural time series model that is used for estimating monthly figures. For the second measurements in the months in the second quarter of 2020, an adapted version of the structural time series model was required. This is described in Section 4. The different possibilities to account for the extreme developments of the consumer confidence are discussed in Section 5. In Section 6, the model estimates under the different options are compared. In Section 7 it is described how the model used for the production of official publications is used during the corona crisis as well as the escalation of the Russian invasion in 2022. The discussion and conclusion can be found in Section 8.

2. The corona crisis in the Netherlands

The corona crisis had a large effect on society in the Netherlands, like in many other countries. Since the rules aimed at reducing covid-19 transmission during the lockdown and the economic policy interventions are different in each country, a short summary of the events in the Netherlands is provided as background information in this section. This overview is not meant to be a complete economic or historical analysis. Only the most important dates and events, as they presumably influence the development of the consumer confidence are described. This summary is based on available sources on the internet, especially https://www.rivm.nl/ and https://nl.wikipedia.org/wiki/Coronacrisis_in_Nederland .

The first infection with covid-19 in the Netherlands was reported on February 27, 2020. In the first days of March the number of infected people increased slowly. At that time the official policy was that the infection was under control and that no strong measures were needed. This policy changed about mid-March. March 15 was the first day with more than 100 people hospitalized within 24 hours. Also the number of patients in intensive care increased rapidly. Despite expanding the Intensive Care Unit (ICU) capacity, there were some doubts whether it would be sufficient. Therefore, the government introduced many extra measures, like forbidding large events, closing restaurants, schools and hair salons. People were asked to work at home as much as possible, and for many people their work stopped completely. Shops were allowed to stay open, but many shops closed their doors anyway, just to be safe. This was called the intelligent lockdown. In these weeks corona was the only important issue in the news.

The intelligent lockdown showed to be effective quite soon. The largest number of hospitalized persons within one day was reached on March 27, namely 611. Around the same time, the increase of the number of ICU patients slowed down, and from April 7 the number of ICU patients was decreasing.

The relaxation of the lockdown started on May 11, 2020 with the opening of primary schools. At the same date hairdressers and other contact professions were allowed to work again. Restaurants opened on June 1, 2020. Nevertheless, life was still not back to normal. There were still many limitations, for example the number of guests in a restaurant or theater was restricted. Furthermore, many people were afraid to get infected and for this reason they did not use the possibilities to go out and spend money. So for many companies the ability to make profit was still limited.

The government decided to support the economy with large amounts of money. Companies could continue to pay the salary of their employees almost completely with public money. Also self-employed people obtained some support. Nevertheless, some people lost their jobs, especially young people with flexible contracts. A big majority remained employed, partly because there was still work, partly because of the payment with public money. These people were not affected financially by the crisis directly. But as the crisis lasted longer and the financial support by the government became subject to stricter requirements, more people lost their jobs during the summer months. Furthermore, the limitations of the lockdown influenced the possibilities and the feelings in the Netherlands. On the other hand, there were also some economic sectors with increasing profits during the crisis, for example supermarkets and web shops.

Despite the relaxation of the measurements in June, the infection rate stayed low during the summer. In September the covid transmission rate started to grow again quickly. Due to a dramatic increase of the infection rate, a second lockdown started on October 14. First, the measures were less strict, but this proved insufficient and therefore new and stronger measures were introduced during the subsequent months. On December 15 all non-essential shops and the practice of non-medical contact professions were closed. Furthermore, a curfew was introduced in January 2021. After some relaxations of measures in spring 2021, the government ended the lockdown on June 5, 2021. The number of infections and hospital admissions dropped significantly in June and vaccination coverage increased to the extent that a so-called opening plan could be put in place on June 26: society effectively reopened in compliance with the measure to keep a distance of 1.5m. Due to the further decline in the number of infections in August, most of the measures were abandoned on September 25 and converted into just an advice, including the 1.5m measure. The corona ticket, which states that a person is vaccinated, has had a covid infection or recently tested negative, went into effect for every catering visit, festivals and other events, theatres, concerts or cinema visit, and all professional sports matches.

In October, it became clear that vaccinations were less effective when infected with the delta variant than with the alpha variant. The corona infections continued to rise. Due to concerns about the new omikron variant, a new lockdown went into effect on December 19, 2021 as a precautionary measure, with quite strict rules. In 2022, the corona measures were slowly relaxed after the lockdown. On February 25, 2022, several measures expired, such as the 1.5m measure and the corona ticket. The support package for companies changed a few times during the corona period and was finally terminated at that time. Finally, the last measures expired in March 2022, such as the obligation to wear a face mask on public transport. In the months that followed, the Netherlands was hardly concerned with the coronavirus. There was a greater focus on long-term policy and corona recovery, for example, in the cultural sector.

3. Consumer confidence before corona

A summary of the survey design and the estimation process of the CS is provided in this section. See Van den Brakel et al. (2021) for more details. The CS is a monthly survey that measures the consumer confidence in the Netherlands. Each month a stratified two-stage sample of 2150 persons is drawn. Data collection is based on a sequential mixed-mode design that starts with web interviewing (WI). After three reminders, non-respondents are approached by means of computer assisted telephone interviewing (CATI). With a response rate of about 47%, this results in a monthly net response that is slightly larger than 1000 persons. Data collection takes place in the first two weeks of the month and the monthly figures of the CS are published a few days later. The survey is carried out following the joint harmonized EU Consumer Survey (European Commission, 2014).

The consumer confidence is derived from five variables that are based on the following questions:
- opinion about changes in the general economic situation of the country over the last 12 months (ESL12),
- expectations of changes in the general economic situation of the country over the next 12 months (ESN12),
- opinion about changes in the financial situation of the household over the last 12 months (FSL12),
- expectations of changes in the financial situation of the household over the next 12 months (FSN12),
- whether it is the right moment for people to make major purchases (MP).

For the first four questions there are two positive and two negative answer options (“a lot better”, “a little better”, “a lot worse”, “a little worse”). Furthermore, there are the options “the same” and “do not know”. For the fifth question there is one positive and one negative answer option (“yes, it is the right moment now”, “no, it is not the right moment now”). Furthermore, there is a neutral option (“it is neither the right moment nor the wrong moment”) and the possibility to answer “do not know”. The percentages of positive, negative and neutral answers (as percentage points of the total answers) p_i^+, p_i^-, p_i^0 and the differences $y_i = p_i^+ - p_i^-$ in positive and negative answers are computed for each question $i = 1, \dots ,5$. Finally, consumer confidence is calculated as the mean over these five differences y_i.

The publication of monthly figures started in 1986. Until 2016 both the original figures and seasonally adjusted figures of the indicator series were published. Furthermore, the underlying series of the percentages were also published. Since 2017 a structural time series model has been applied to compute the trend of the indicator series which is published instead of the seasonally adjusted figures. In January 2017 the survey process of the CS was redesigned, which caused discontinuities in the series. In Van den Brakel et al (2021) it is discussed how these discontinuities are quantified and how to account for these discontinuities in the estimation process. The direct estimates $y_1, \dots, y_5$ for the period 1986 – 2016 are corrected for this discontinuity. The corrected figures are used as input of the time series model. This implies that there is no need to take these discontinuities into account in the model itself.

As mentioned before, the estimation procedure of the CS is based on a multivariate structural time series model, see Harvey (1989) and Durbin and Koopman (2012) for technical details. Ssfpack 3.0 (Koopman et al., 1999, and Koopman et al., 2008) in combination with Ox (Doornik, 2007) is used for the computations.

Each month t the general regression (GREG) estimator (Särndal et al. 1992) is applied to the observed responses to obtain a GREG estimate $y_{i,t}$ for the five questions of the CS. As a result, a vector $\mathbf{Y}_t = (y_{1,t}, y_{2,t}, y_{3,t}, y_{4,t}, y_{5,t})'$ is observed, which gives rise to a vector of time series that can be modelled as

$$\mathbf{Y}_t = \mathbf{L}_t + \mathbf{S}_t + \mathbf{e}_t. \tag{3.1}$$

Here $\mathbf{L}_t = (L_{1,t}, L_{2,t}, L_{3,t}, L_{4,t}, L_{5,t})'$ is a vector of the trends of the five series, $\mathbf{S}_t = (S_{1,t}, S_{2,t}, S_{3,t}, S_{4,t}, S_{5,t})'$ is a vector of the seasonal patterns of the five series and $\mathbf{e}_t = (e_{1,t}, e_{2,t}, e_{3,t}, e_{4,t}, e_{5,t})'$ is a vector of the measurement errors in all five series.

The trend $L_{i,t}$ $(i = 1, \dots, 5)$ is modelled with the so-called smooth trend model:

$$\begin{aligned} L_{i,t} &= L_{i,t-1} + R_{i,t-1}, \\ R_{i,t} &= R_{i,t-1} + \eta_{R,i,t}. \end{aligned} \tag{3.2}$$

with $R_{i,t}$ the slope parameter of series i. The disturbance terms $\eta_{\mathrm{R},i,t}$ are normally distributed with

$$\begin{aligned} &\mathrm{E}(\eta_{\mathrm{R},i,t}) = 0, \\ &\mathrm{Cov}(\eta_{\mathrm{R},i,t}, \eta_{\mathrm{R},i',t'}) = \begin{cases} \sigma^2_{\mathrm{R},i} & \text{if} \quad i = i' \text{and } t = t' \\ \varsigma_{\mathrm{R},i,i'} & \text{if} \quad i \neq i' \text{and } t = t' \\ 0 & \text{if} \qquad t \neq t' \end{cases}. \end{aligned} \tag{3.3}$$

Using this model, information from the past about the long-term development is used to improve the estimates. By modelling the covariance between the slope disturbances, the precision of the estimates is improved with the information from the other variables. A positive correlation is observed since the five indices y_i measure related economic and financial variables.

The so-called trigonometric seasonal model is used to model the seasonal component $S_{i,t}$ ($i = 1, \dots, 5$). For details about this component see Durbin and Koopman (2012), Ch.3. Since the seasonal components are almost time invariant, it makes no sense to model the covariances between the seasonal disturbance terms (Van den Brakel et al., 2021).

It is assumed that the measurement errors of the five series are correlated:

$$\mathrm{E}(e_{i,t}) = 0,$$
$$\mathrm{Cov}(e_{i,t}, e_{i',t'}) = \begin{cases} \sigma^2_{\mathrm{e},i} & \text{if} \quad i = i' \text{and } t = t' \\ \varsigma_{\mathrm{e},i,i'} & \text{if} \quad i \neq i' \text{and } t = t' \\ 0 & \text{if} \qquad t \neq t' \end{cases}. \tag{3.4}$$

In this way, the model accounts for the fact that the five questions are all answered by the same respondents, which introduces dependency between the five sample estimates. By (3.3) and (3.4) it is assumed that the variances and covariances are constant over time. See Van den Brakel, Krieg and Smeets (2021) for a more detailed discussion about the necessity to account for this covariances. The general way to fit a structural time series model is to put it in state-space form. Subsequently the Kalman filter can be applied to fit the model. The Kalman filter assumes that the variance and covariance parameters of the state disturbance terms are known. These parameters, often referred to as hyperparameters, are unknown. Estimates for these hyperparameters, are obtained with maximum likelihood using a numerical optimization procedure. The Kalman filter is a recursive algorithm that also requires starting values for the state variables. Since all state variables are non-stationary, a diffuse initialization is used for the Kalman filter, which implies that all state variables are initialized with a value equal to zero and a large value for its standard error. The Kalman filter recursions provide optimal estimates for the trends and seasonal components including their standard errors. The parameters of interest are trends $L_{i,t}$ and signals that are defined as the sum of the trend and the seasonal component: $L_{i,t} + S_{i,t}$. The model-based estimate of the consumer confidence is computed as mean of the estimates of the trends and signals for the five series. The model-based estimates for the different consumer confidence indices are therefore automatically consistent.

4. Changes of the model due to extra measurements

Statistics Netherlands decided for the months April, May and June of 2020 to conduct an extra survey in the second half of these months. Whereas the regular survey is conducted as a mixed-mode design (around 80% WI and 20% CATI), the second survey was conducted with WI only. There are two problems with this second measurement. First, the time series model for the regular publications is developed for time series with a monthly sampling frequency. These additional measurements require a model for series with a sampling frequency of 24 observations per year. This requires a model with a different volatility for the trend component and a seasonal component with 24 time periods instead of 12 months. Since the data collection of the regular survey takes place in the first two weeks of the month, the seasonal pattern of the regular survey is equal to the seasonal pattern in the first half of the months of the time series model for two observations per month. However, we do not know the seasonal pattern in the second half of the months. The second problem is that the additional surveys do not use CATI data collection. This will introduce relative bias compared to the measurements of the regular survey due to differences in mode dependent selection effects and measurement errors.

These issues are solved by developing a time series model for seasonally adjusted direct estimates. The model only contains a trend that is defined at a frequency of 24 observations per year. In addition an adjustment is applied to three direct estimates for the second part of April, May and June 2020 to correct for the missing CATI responses.

As a first step, an input series of seasonally adjusted direct estimates is constructed. The seasonal component in time series model (3.1) is time dependent. Figure 4.1 shows the seasonal effects of the five series, estimated with the structural times series model (3.1) using the regular direct estimates observed in the first two weeks of the month. These estimates are computed with data until March 2020, and are therefore not affected by the extreme developments of the corona crisis. We see that the seasonal pattern is quite small compared to the month-to-month changes of the target variables, at least in the considered period, as shown in the right panel of Figure 4.2 and 4.3.

A series of seasonal adjusted direct estimates for the series observed in the first two weeks of the months is obtained by subtracting the smoothed estimates for the seasonal component from the direct estimates for the entire period used in the analysis. The seasonal components for the direct estimates for the second half of April, May and June 2020 are approximated by taking the mean of the pattern of the first half of the same month and the next month. This is a strong assumption, but since the seasonal patterns are small in the considered period, the possible bias introduced by not meeting this assumption probably is relatively small.

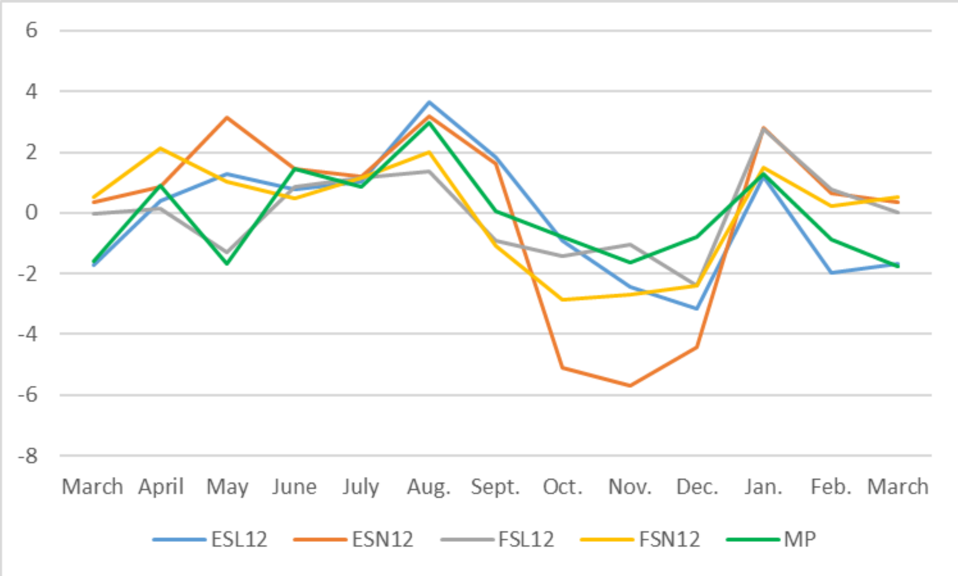


Figure 4.1 Seasonal pattern for period March 2019 – March 2020

In a next step, a simple adjustment is applied to the direct estimates of the second half of April, May and June 2020 to correct for the relative bias that is the result of not having CATI data collection. Explorative data analyses showed that CATI respondents prefer the neutral option more often than the WI respondents (for all variables), which motivates the corrections as proposed hereafter. To analyze the effect of not using CATI as a data collection mode, the series of direct estimates are recalculated using the WI response only for the period January 2018 until March 2020. The left panel of Figure 4.2 shows the difference of the estimates based on the regular survey with and without the CATI respondents included for the two economic variables ESL12 and ESN12. The right panel shows the series of direct estimates based on the complete response of WI and CATI. The figures show the data up to and including June 2020. Note that at the time when the figures about April and May were published, only shorter time series were available.

For the variable ESN12, the left panel of Figure 4.2 shows that from January 2020 on there is a clear upward trend in the difference between the estimates with and without the CATI respondents. For the same period there is a strong downward trend in the direct estimates based on the complete response, as can be seen the right panel of Figure 4.2. Therefore, it was decided to use the mean of a very short recent period to compute the correction term to correct for the missing CATI response. This was the mean of March and April for the correction of April, the mean of April and May for the correction of May and the mean of April, May and June for the correction of June. After evaluating all data (when it became known) we concluded that it had been better to not correct the value of April as explained above, but to just use the value itself. But at that time, there were doubts about it because of the volatility of the series.

For the variable ESL12, the crisis started to influence the results in May. In April it was only visible that the differences between the estimates with and without the CATI respondents is lower in 2018 than in 2019 (left panel of Figure 4.2)which seems to coincide with the lower level of the target variable in 2019 (right panel of Figure 4.2). Therefore, the correction term for April was computed as the mean of the differences over 2019 and 2020 (as far as available). In May the value of the target variable dropped, with no clear effect on the differences. Then the same choice was made. In June, the target variable was very low again, and now, the difference had the largest value ever. Therefore, the mean of April, May and June was used for the correction of June.

Similar results for the other three variables are shown in Figure 4.3. Here it is concluded that the differences are small and volatile without a clear trend. Therefore, it was decided to use the mean over the entire period as correction term.

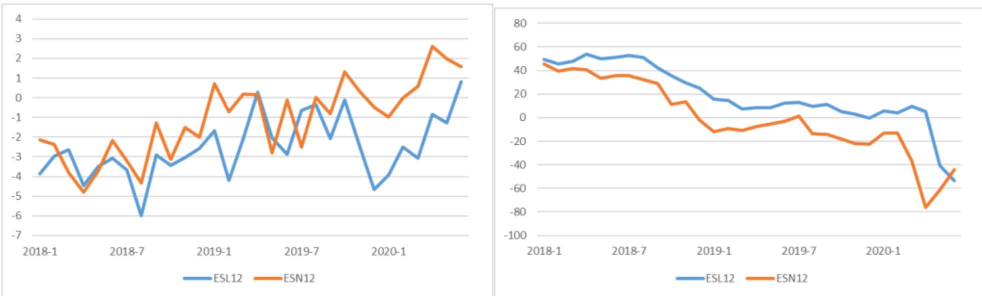


Figure 4.2 Left: Difference of estimates with and without CATI respondents; right: estimates with CATI respondents included; for the variables ESL12 and ESN12

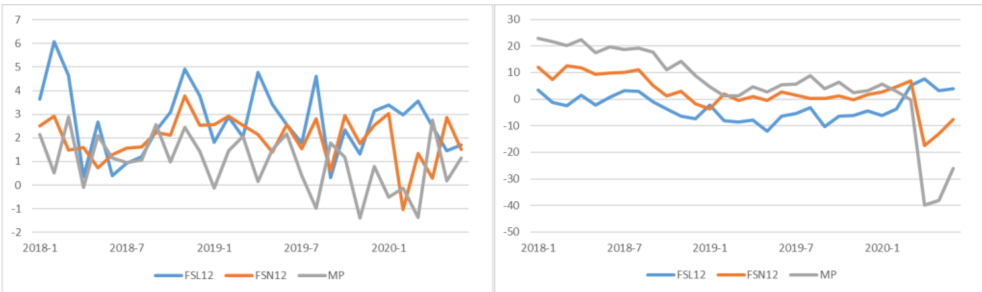


Figure 4.3 Left: Difference of estimates with and without CATI respondents; right: estimates with CATI respondents included; for variables FSL12, FSN12 and MP

Table 4.1 shows the value of the correction terms which are applied in the production process. The correction terms are small compared to the developments of the target variables and the influence of the choices how to compute them is small as well. The corrected estimates for April, May and June 2020 are obtained by subtracting the differences in Table 4.1 from the direct estimates that are based on the WI responses.

	ESL12	ESN12	FNSL12	FSN12	MP
April	-2.08	1.59	2.77	1.94	1.00
May	-2.02	2.18	2.72	1.96	0.97
June	-0.42	2.05	2.69	1.95	0.98

Table 4.1: correction terms for survey without CATI

Finally, the direct estimates obtained with the aforementioned steps are combined in one series that is defined at a frequency of 24 observations per year. The observations for the first half of the month are completely observed, since they come from the regular survey. The observations for the second half of the month are only observed for April, May and June 2020. For all other periods, these observations are defined as missing. In this way the vector $\mathbf{Y}_t = (Y_{1,t}, Y_{2,t}, Y_{3,t}, Y_{4,t}, Y_{5,t})'$ is observed and is modelled similarly as in Section 3, but without a seasonal component:

$$\mathbf{Y}_t = \mathbf{L}_t + \mathbf{e}_t. \tag{4.1}$$

The trend $\mathbf{L}_t$ and the measurement error $\mathbf{e}_t$ are similar as in Section 3, with the exception of the variance structures. The corona crisis affected only three of the five questions in April. Therefore it can be expected that the correlations of these model components based on the relations observed in the past, are no longer valid. It was, therefore, decided to set the correlations between the slope disturbance terms in (3.3) and the measurement errors in (3.4) equal to zero.

5. Adapting the model to increased volatility

The corona crisis has had a dramatic impact on the consumer confidence variables. In April 2020 a strong decrease of the direct estimates was observed for three of the five questions (ESN12, FSN12, MP, see also Figure 6.1). This resulted in a temporal misspecification of the time series model (3.1). Note that real month-to-month developments in the population parameter are modelled in (3.1) with the trend and the seasonal component. The flexibility of both components to pick up month-to-month changes in the population parameter are defined by the variance of the slope disturbance terms and the variance of seasonal disturbance terms. At the start of the corona crisis, these variances are based on the size of the month-to-month changes in the input series observed in the past. As a result, the model is not able to accommodate the large increase of the month-to-month changes in the variables ESN12, FSN12, and MP. This temporal misspecification was in particular visible in the standardized innovations. Innovations are the one-step-ahead prediction errors, which play a crucial role in the evaluation of structural time series models (Durbin and Koopman, 2012). Under a correctly specified model, the standardized innovations are standard normally and independently distributed. The standardized innovations for the three variables in April had values close to -5, which are far outside the 95% confidence interval of (-2,2). Also a comparison of the model estimates with the direct estimates showed that the model failed to adequately pick up the increased volatility of the input series.

When the direct estimates for April became available, it was decided to adapt model (3.1) to avoid publishing strongly biased trend figures for consumer confidence. The time available for data analysis and inference in the production process of the Dutch CS is limited to three or four days. In this period it was decided to increase the flexibility of the trend by temporarily increasing the variance of the slope disturbance terms, i.e. $\sigma^2_{\mathrm{R},i}$ in (3.3). This approach is described in this section and compared with other alternatives that are analyzed afterwards. All possible changes adapt or interfere with the trend component of model (3.1). It is possible that the corona crisis also influences the seasonal pattern. It was, however, not possible to estimate new seasonal patterns in that time. Therefore, it is assumed that the seasonal pattern does not change, as recommended by Eurostat, (2020), and this part of the model is not adapted.

Three of the five variables of the CS were affected in April 2020. This also invalidates the assumption that the correlations between the slope disturbance terms and the measurement errors are similar to the correlations based on the series observed in the past. Therefore, as a first change the correlations between the slope disturbance terms of the slopes in (3.3) and between the measurement errors in (3.4) are set equal to zero, similarly as for the model in Section 4.
Six different ways to adapt model (3.1) to the increased volatility in the input series are compared. The options can be applied both for the once-per-month model and for the twice-per-month model.

Option 0: Model (3.1) where the correlations between the slope disturbance terms and the measurement errors are set equal to zero, as in all other options.
Option 1: Model (3.1) where the trend is made more flexible by temporarily increasing the variance of the slope disturbance terms, $\sigma^2_{\mathrm{R},i}$, in (3.3). This achieved by multiplying $\sigma^2_{\mathrm{R},i}$ with a factor $f_{i,t}$, i.e.

$$\mathrm{Cov}(\eta_{\mathrm{R},i,t}, \eta_{\mathrm{R},i',t'}) = \begin{cases} f_{i,t}\sigma^2_{\mathrm{R},i} & \text{if} \quad i = i' \text{ and } t = t' \\ 0 & \text{otherwise} \end{cases}.$$

These factors $f_{i,t}$ are equal to one before the beginning of the corona crisis and have to be chosen by hand during the crisis. This approach is also applied in a similar context by Van den Brakel et al. (2022, 2023) and Gonçalves et al. (2022). Increasing the variance until the model sufficiently follows the observed series, makes the procedure somehow subjective. In order to avoid this, the values for $f_{i,t}$ were chosen such that the standardized innovations take values just outside the interval (-2,2). Another objective criterion is the maximum likelihood (ML) estimate of $\sigma^2_{\mathrm{R},i}$. It is preferred that this estimate does not change too much if new observations become available. If the trend component of model (3.1) is not adapted, then the ML estimates for $\sigma^2_{\mathrm{R},i}$ will gradually increase during the corona crisis. Choosing the values for $f_{i,t}$ such that the ML estimates for $\sigma^2_{\mathrm{R},i}$ remain more or less equal to values obtained before the start of the corona crisis, is another way to set the values for $f_{i,t}$. Note that increasing the value of $f_{i,t}$ influences the slope disturbance term in period t and therefore the slope in period $t+1$ and the level of the trend in period $t+2$.

The interpretation of this approach is that increasing the variance of the trend results in a model estimate that gives more weight to the observed direct estimate of the input series and less weight to the model prediction that is based on the information observed in the past. An advantage of Option 1 is that with relatively small factors $f_{i,t}$ it is possible to borrow at least some information from the past.

Option 2: Model (3.1) where the variance of the trend is made time varying by defining two different variance components for the slope disturbance terms; one for the observations outside the corona crisis and one for the observations during the corona crisis, i.e.

$$\mathrm{Cov}(\eta_{\mathrm{R},i,t}, \eta_{\mathrm{R},i',t'}) = \begin{cases} \sigma^2_{\mathrm{R},i} & \text{if} \quad i = i' \text{and } t = t' \text{and } t < T_{C,i} \text{ or } t > T_{E,i} \\ \sigma^2_{\mathrm{R,C},i} & \text{if} \quad i = i' \text{and } t = t' \text{and } T_{C,i} \leq t \leq T_{E,i} \\ 0 & \text{otherwise} \end{cases} .$$

Here $T_{C,i}$ is the period where the corona crisis started to affect question i, and $T_{E,i}$ is the last month of this crisis. As in Option 1 it has to be taken into account that the moment that the variance changes from $\sigma^2_{\mathrm{R},i}$ to $\sigma^2_{\mathrm{R,C},i}$, affects the level of the trend with a delay of two periods. The parameters $T_{C,i}$ and $T_{E,i}$ have to be chosen accordingly. An advantage of this method is that the ML estimates for $\sigma^2_{\mathrm{R},i}$ and $\sigma^2_{\mathrm{R,C},i}$ are based on an objective likelihood criterion. An important disadvantage is that $\sigma^2_{\mathrm{R,C},i}$ cannot be estimated at the beginning of the crisis, when only a few periods are available for this estimate. Furthermore, it is not known beforehand whether one constant variance component for the entire period of the crisis is sufficient. Finally, the choices of $T_{C,i}$ and $T_{E,i}$ are somehow subjective.

Option 3: The model is extended with a level intervention component to accommodate the large jump in the input series caused by the corona crisis. Equation (3.1) is extended to

$$\mathbf{Y}_t = \mathbf{L}_t + \mathbf{S}_t + \boldsymbol{\Delta}_t\mathbf{B} + \mathbf{e}_t,$$

with $\boldsymbol{\Delta}_t = \mathrm{diag}(\delta_{1,t}, \delta_{2,t}, \delta_{3,t}, \delta_{4,t}, \delta_{5,t})$ a diagonal matrix containing dummy indicators $\delta_{i,t}$ that switches from zero to one at time period, say τ_i, when the corona crisis started to affect indicator i, i.e.

$$\delta_{i,t} = \begin{cases} 0 & \text{if} \quad t < \tau_i \\ 1 & \text{if} \quad t \geq \tau_i \end{cases}, \; i = 1, \dots, 5.$$

Furthermore, $\mathbf{B} = (b_1, b_2, b_3, b_4, b_5)'$ denotes a vector of regression coefficients describing the effect of the corona crisis on indicator i.

This model would be appropriate when an indicator is affected by the corona crisis in one period (in the beginning of the corona crisis) and subsequently develops in a similar way as before the start of the corona crisis. This was, however, not the case, but this was not known in the beginning of the crisis. Another major drawback of this approach is that a sufficient number of periods with $\delta_{i,t} = 1$ are required to obtain stable estimates for the regression coefficients. In a production process, this is not the case. As a result, the estimates for $\mathbf{B}$, obtained when only the first period under the corona crisis was available, will be subject to large revisions once more periods with $\delta_{i,t} = 1$ become available. This results in revisions of the same order in the parameter estimates of the CS.

Option 4: This option is similar as Option 3, except that now the effect of the corona crisis on the index is determined outside the model. This value is used in the time series model as a fixed value known without error. This option is considered to avoid that the Kalman filter estimates for $\mathbf{B}$ and the parameter estimates of the CS are subject to large revisions as more and more observations during the corona crisis become available. This option requires additional information to choose this value accurately, which is generally not available. This option was, however, considered for the model with two observations per month (Section 4). With the model for one observation per month (Section 3), figures are estimated for the first half of the month using one of the other options. Then the model for the second half of the month is applied. With a well-chosen value for $\mathbf{B}$, the estimates are forced to be at the right level for the (at that moment known) first half of the month.

Option 5: All periods during the corona crisis are considered as outliers. This is another way to circumvent the revisions for the estimates for $\mathbf{B}$ and the parameter estimates of the CS during the first months of the corona crisis under Option 3. The model is extended with a term to model these outliers. So equation (3.1) is replaced by

$$\mathbf{Y}_t = \mathbf{L}_t + \mathbf{S}_t + \sum_{\tau=1}^{\mathrm{T}} \boldsymbol{\Delta}_t^{\tau} \boldsymbol{\gamma}_{\tau} + \mathbf{e}_t,$$

with $\boldsymbol{\Delta}_t^{\tau} = \mathrm{diag}(\delta_{1,t}^{\tau}, \ \delta_{2,t}^{\tau}, \ \delta_{3,t}^{\tau}, \ \delta_{4,t}^{\tau}, \ \delta_{5,t}^{\tau})$ diagonal matrices containing dummy indicators $\delta_{i,t}^{\tau}$ that are equal to one if for period t an outlier is required for indicator i and zero for all other periods, i.e.

$$\delta_{i,t}^{\tau} = \begin{cases} 1 & : \quad \text{for period } t \text{ an outlier for index } i \text{ is required} \\ 0 & : \quad \text{otherwise} \end{cases}.$$

Furthermore $\boldsymbol{\Gamma}_{\boldsymbol{\tau}} = (\gamma_{1,\tau}, \gamma_{2,\tau}, \gamma_{3,\tau}, \gamma_{4,\tau}, \gamma_{5,\tau})'$ for $\tau = 1, \dots, \mathrm{T}$, are vectors of regression coefficients with the estimates of the outliers, and T the periods of the corona crisis where outliers were required. Under this model, the predictions for period t are equal to the direct estimates in the input series if this period is defined as an outlier. It is understood that $\delta_{i,t}^{\tau}$ is not necessarily equal to one for all indicators during the entire corona crisis. For indicators that are not or only partially affected, $\delta_{i,t}^{\tau}$ can be equal to zero for all or particular periods. Outlier detection methods can be used to select significant outliers only.

6. Results

Figure 6.1 shows the direct estimates of the five series for July 2019 – September 2020. The series are presented as twice-per-month series, with missing values in the second half of the month except for the second quarter of 2020. Three of the five series (FSN12, MP, and ESN12) decrease considerably in the first half of April. These series are slowly increasing almost directly afterwards, with a decrease in

August (except for FSN12). De decrease of ESL12 starts a little later, but continues until (at least) September 2020. The series FSL12 stays on the same level until and including the first half of June.

The series of the direct estimates (including the periods starting from 1986) are the input of the time series models of Section 3 and 4, with the appropriate periods selected. Furthermore, the models are estimated in real time, which means that the last periods in Figure 6.1 were not known when the models were applied in the production process in the months before September 2020.

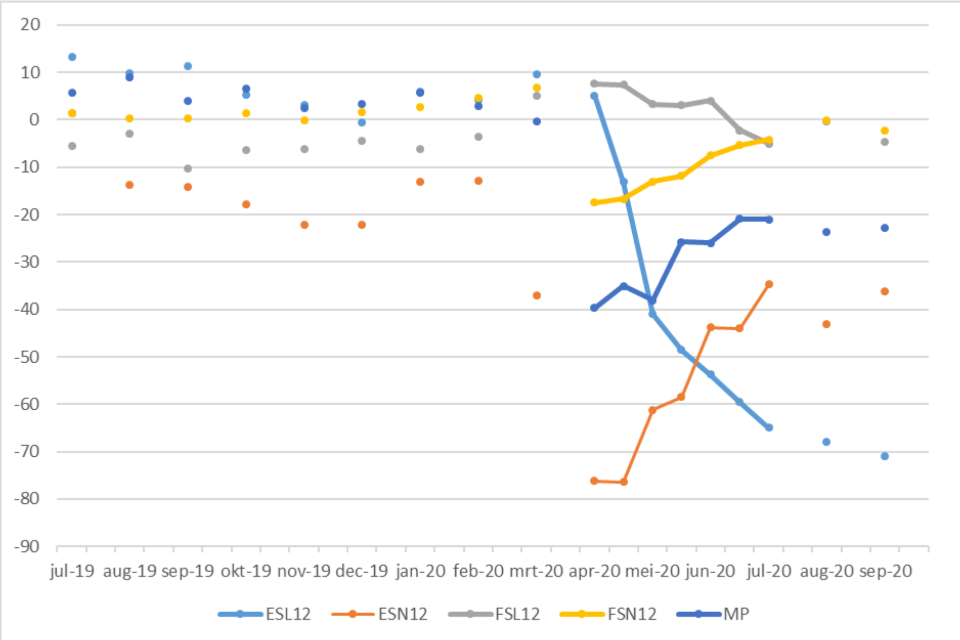


Figure 6.1: direct estimates for five series, July 2019 – September 2020

In Section 6.1 it is described which model changes were applied in the production process of the CS for the regular monthly figures based on the data collection in the first two weeks of the month. In Section 6.2 the final model for the production of the additional figures for the second halves of April, May and June 2020 is presented. In Section 6.3 and 6.4 we compare estimates based on different solutions described in Section 5.

6.1 Model changes for the one observation per month model

For the model for one observation per month, Option 1 is applied in all periods. Due to the sharp decline in April of the variables ESN12, FSN12 and MP, the first model adjustments were necessary in this month for these three variables. Table 6.1 shows the factors $f_{i,t}$ used to temporarily increase the variance of the slope disturbance terms, that are applied in the months January – July 2020. The factors of month t affect the estimates for the trend in month $t+2$. With these factors, the standardized innovations are -2.7, -2.8 and -3.6 and the estimated trends are -68.7, -15.8 and -37.9 (ESN12, FSN12, MP, April). Almost the same results are found with factors equal to 1 for January (and the same factors as in the table for February). With factors all equal to 1 in January and February, it would have been -

3.6, -5.1 and -8.5, and the trend estimates -61.8, -5.8 and -21.6. The values for $f_{i,t}$ are chosen such that standardized innovations are reduced to an acceptable irregularity, since they might now and then exceed the critical value of 2 in absolute terms. Increasing the variance of the slope disturbance terms for MP, shrunk the standardized innovation from -8.5 to -3.6. Although this value is still large, the attained reduction was considered to be a reasonable compromise between the size of the factor $f_{i,t}$ and the value of the innovation. With the chosen factors, the differences between the trend and signal estimates versus the direct estimates were in line with the differences observed in the past. The standardized innovations might indeed exceed the 95% confidence intervals in 5% of the cases after all.

	ESL12	ESN12	FSL12	FSN12	MP
January	1	1	1	10	10
February	1 - 10 (*)	10	1	100	100
March	10	50	1	75	75
April	5	25	1	25	50
May	5	1	50	1	1
June	1	25	1	1	1
July	1	1	1	1	1

Table 6.1: factors $f_{i,t}$ to increase the variance of the slope disturbance terms in model (3.1) combined with Option 1 for the regular publications. (*): this factor was 1 for the estimates of April and changed to 10 for the estimates of May.

6.2 Model changes for the two observations per month model

Model (4.1) in combination with one of the options described in Section 5 was applied three times in the production process. The first time was in April. Then two periods during the crisis were available. Figure 6.1 shows that ESN12, FSN12 and MP are on the same level in these two periods after the decline in the first half of April. Therefore it was decided to apply Option 4 (level interventions with known values for the regression coefficients) for these variables. The regression coefficients were set to -20 (ESN12), -19 (FSN12) and -36 (MP). In this way the model-based estimates for the first half of April could be reproduced reasonably well. The variance of the slope disturbances was not temporarily increased for these variables. The variable ESL12 shows a sharp decline in the second half of April. This was modelled using Option 1 where the variance of the slope disturbance terms was multiplied with factor 100. Finally, the variable FSL12 was not affected by the crisis in this period and no model changes were necessary. With these changes the standardized innovations were within the interval (-2,2) for all five variables.

In the second half of May it turned out that the series ESN12, FSN12 and MP were increasing, and that the model with the discontinuity applied in April was no longer valid, at least for ESN12 and MP. Therefore, it was decided to apply Option 1 for all variables, which is also appropriate for ESL12. For FSL12 no changes are needed because the variable is still not affected by the crisis. Table 6.2 shows the chosen factors (the factors of May were not applied then).

In the second half of June the increase of the variables ESN12, FSN12 and MP had continued in a usual way. ESL12 still decreased. FSL12 showed a (for this variable quite strong) decrease for the first time. Option 1 was applied again with the factors specified in Table 6.2.

	ESL12	ESN12	FSL12	FSN12	MP
January-1	1	1	1	10	1
January-2	1	1	1	10	1
February-1	1	10	1	100	10
February-2	1	100	1	100	10
March-1	10	100	1	100	100
March-2	10	100	1	100	100
April-1	10	10	1	10	100
April-2	10	10	1 - 10 (*)	10	100
May-1	25	1	20	1	100
May-2	10	1	10	1	10

Table 6.2: factors applied in the second half of May and June in model (4.1) combined with Option 1. (*): this factor was 1 in the second half of May and 10 in the second half of June

6.3 Comparison models for one observation per month

The factors used to increase the variance of the slope disturbance terms in Option 1 are specified in Table 6.1. Under Option 2, the period for the second value of the slope disturbance variances started in April 2020 for ESN12, FSN12 and MP and in May 2020 for ESL12. For FSL12 only one value for the slope disturbance variance is defined. For Option 3 the level interventions started in May for variable ESL12 and in April for the other variables. Under Option 5, outliers are defined for all months from April until September for all five variables.

Figure 6.2 compares the filtered trend estimates of model (3.1) combined with different options, defined in Section 5, with each other and with the direct estimates for ESL12. In Option 1, the factors of Table 6.1 are used. Option 4 is not applied here, since there is no external information about the values of the regression coefficients of the level interventions. This option is only considered for the model for two observations per month (see Section 5). The estimates under Option 1, 2, 3 and 5 are quite similar to each other and to the input series. Only Option 0 is different. The trend is not flexible enough to follow the sharp decline in the input series in May. Large negative values for the slope come with a delay of a few time periods. This also results in a small underestimation in August and September.

Figure 6.3 shows filtered trend estimates for ESN12. Option 3 (level intervention in April) picks up the strong decrease in the input series in April (see Figure 6.1).

Under this option the variance of the slope disturbance terms remains unaffected. As a result this model is not capable to pick up the recovery of ESN12 in May and June. The predictions under Option 1, 2 and 5 are much closer to the direct estimates.

Figure 6.4 shows filtered trend estimates for the variable FSL12. Options 2 and 3 are not shown because the decline for this variable started only in July. The estimation of two different variances for the slope disturbance terms (Option 2) would be unstable, due to the small number of observations for the period for which a different variance for the slope disturbance terms is defined. Modelling the effect of covid with a discontinuity is, for the same reason, also less useful. Option 5 defines outliers for the months from April until September, which results in the most flexible model with filtered trend estimates that are close to the direct estimates. Under Option 1 the model prediction still removes some sampling error resulting in more smooth predictions for FSL12.

Figure 6.5 and 6.6 compare the filtered trends for FSN12 and MP respectively. It follows that Option 0 cannot follow the development of the direct estimates. It misses the sharp decline in April as well as the increase directly afterwards. There are smaller differences between the other options. It is questionable whether the trend under Option 3 (and Option 1 in Figure 6.5) should be more or less flexible (the trend under the other options are too flexible). The differences are, however, small and all estimates would be acceptable.

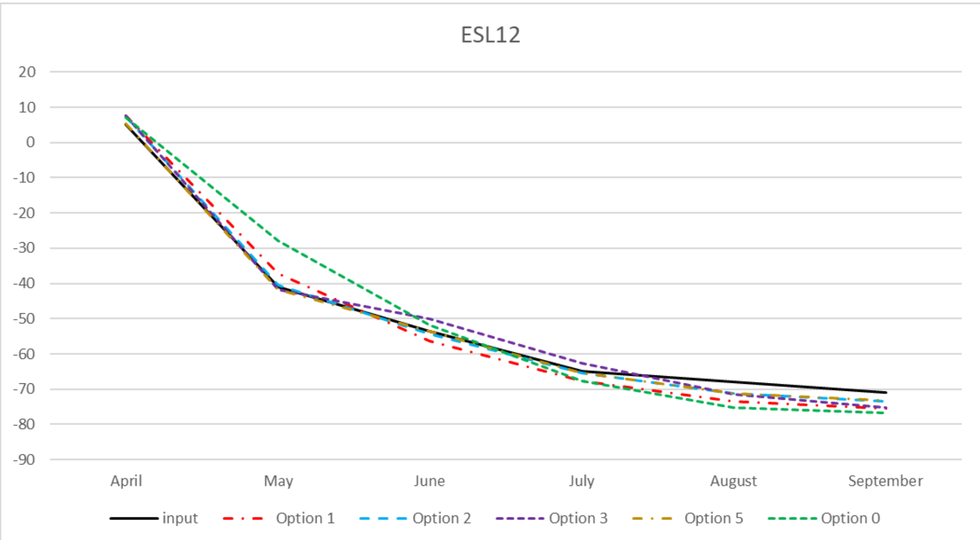


Figure 6.2: direct estimates and filtered trend estimates for ESL12

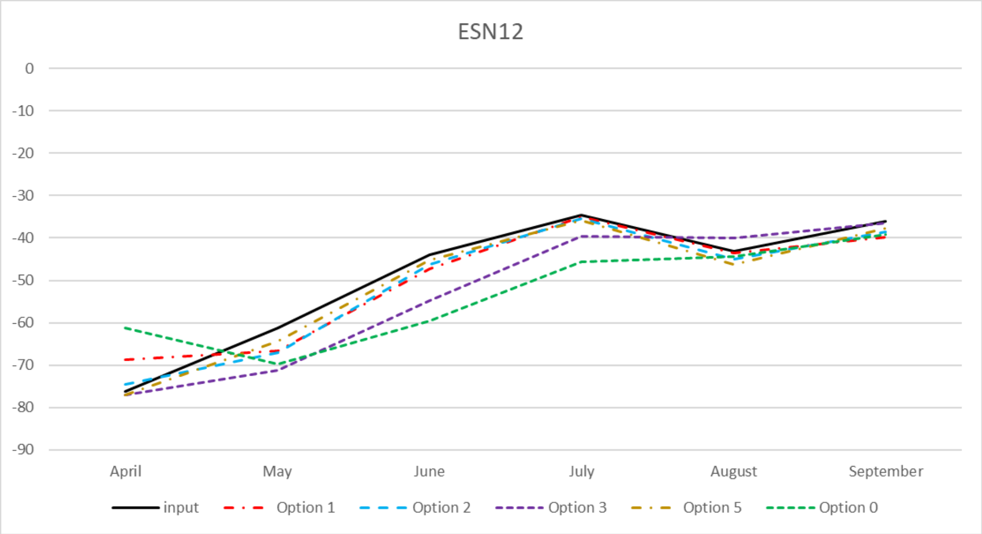


Figure 6.3: direct estimates and filtered trend estimates for ESN12

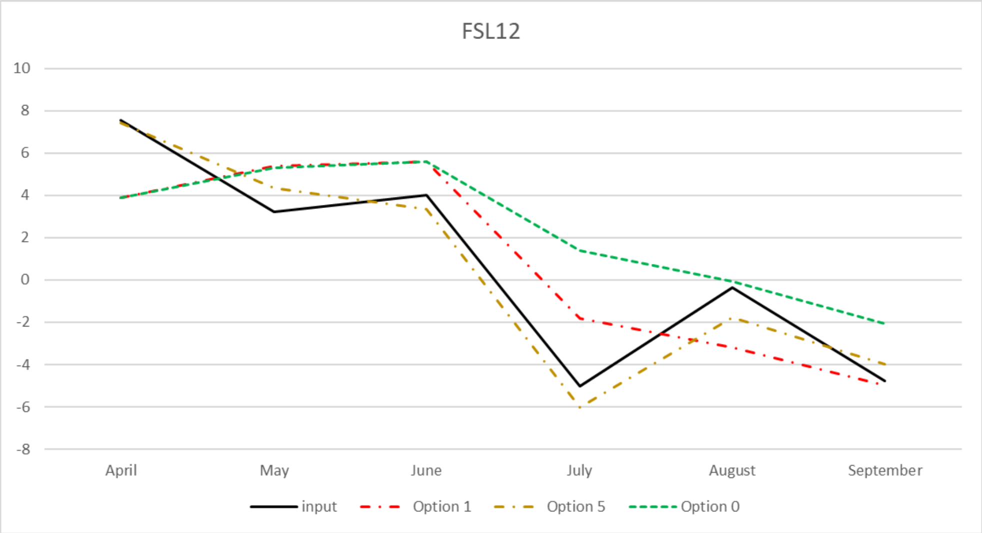


Figure 6.4: direct estimates and filtered trend estimates for FSL12

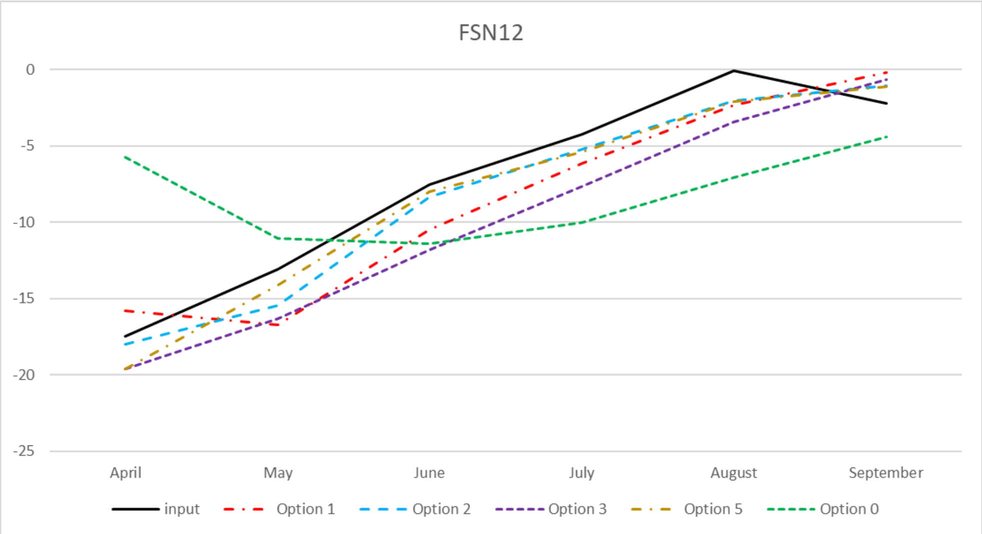


Figure 6.5: direct estimates and filtered trend estimates for FSN12

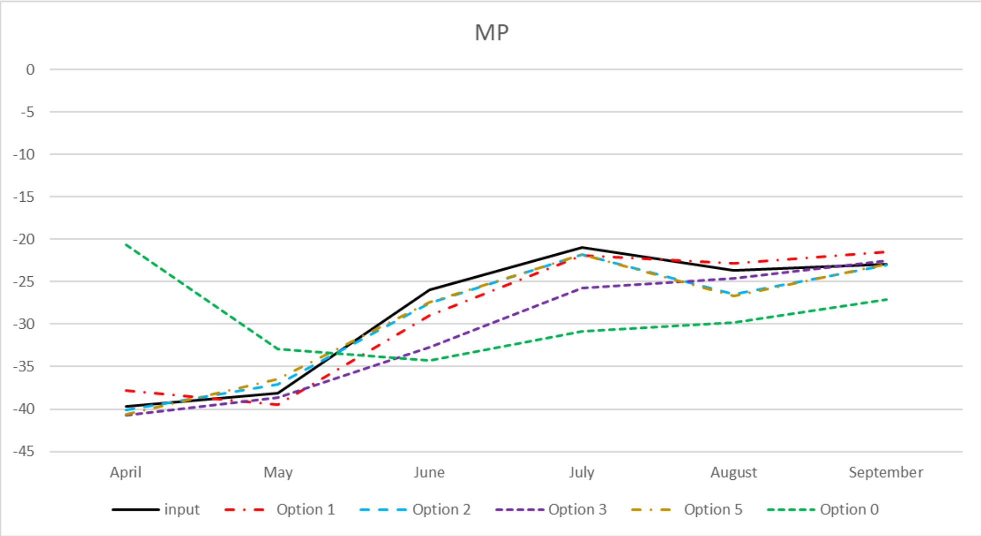


Figure 6.6: direct estimates and filtered estimates for MP

6.4 Comparison models for two observations per month

In this section different options for model (4.1) for two observations per month are compared. The factors used in Option 1 to increase the variance of the slope disturbance terms are specified in Table 6.2. Note that the published estimates for the first half of every month are computed with the monthly model, Option 1. The published series are called Option 4/1, as for publication first Option 4 was applied and later Option 1 (see Section 6.2).

Results for variable FSL12 are not presented as this variable is quite stable for the considered period. Figures 6.7 – 6.10 compare results for Options 0, 1, 2, and 4/1 (published). The results for Options 3 and 4 (both with level interventions) are compared in Figures 6.11 – 6.13. This is only done for ESN12, FSN12 and MP, since for these variables Option 4 was applied in the production process. We do not show estimates under Option 5 here, as these estimates are very similar to the input series, which was already shown in the previous subsection.

The figures 6.7 – 6.10 show similar results as we have seen in the previous section: without changes of the model (= Option 0) the trend is not sufficiently flexible to follow the development of the input series. The differences between the other options are small.

The options with a level intervention (Figure 6.11 – 6.13) are acceptable for FSN12 and MP. For ESN12, however, the trend is not sufficiently flexible to follow the increasing development after the sharp decline in April.

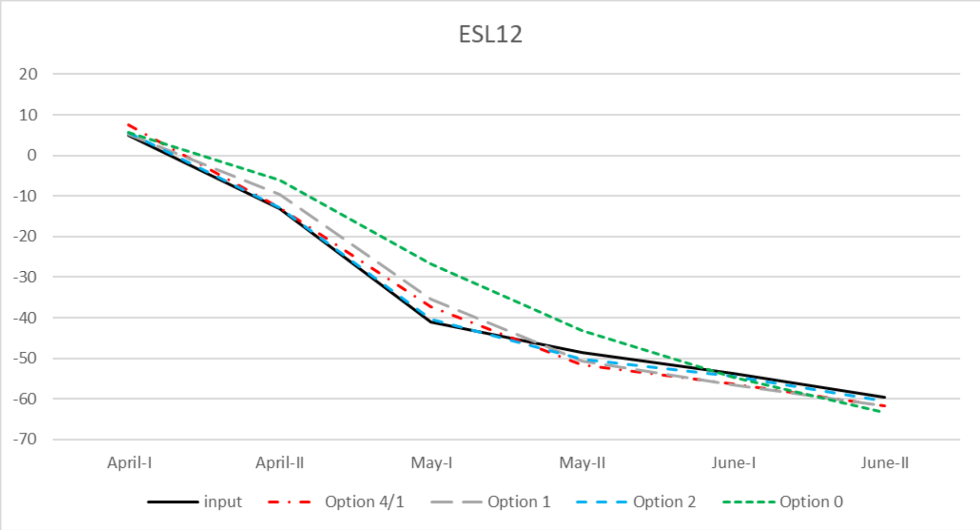


Figure 6.7: direct estimates and model estimates for ESL12

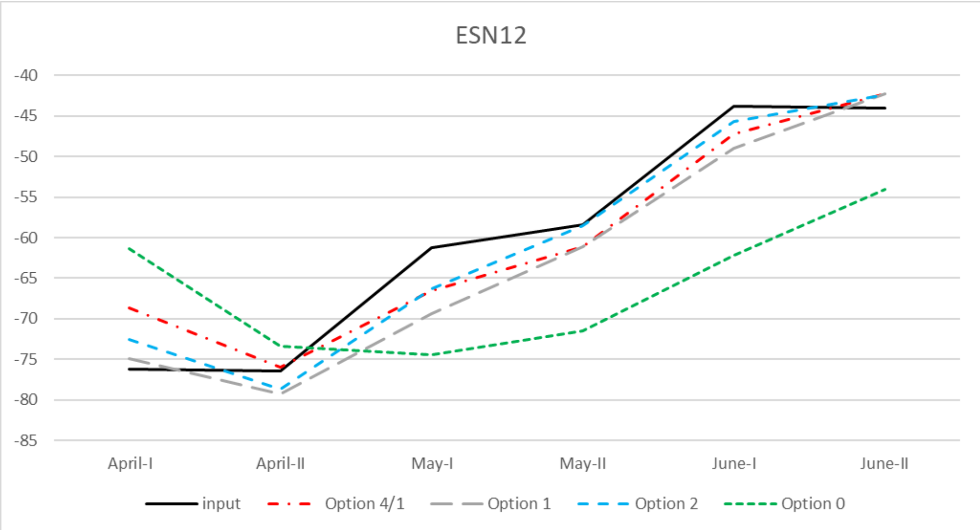


Figure 6.8: direct estimates and model estimates for ESN12

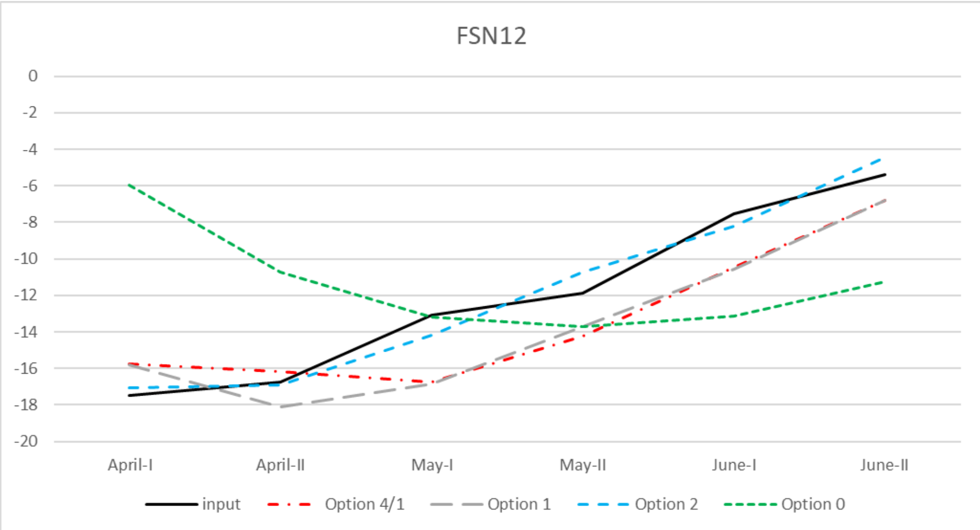


Figure 6.9: direct estimates and model estimates for FSN12

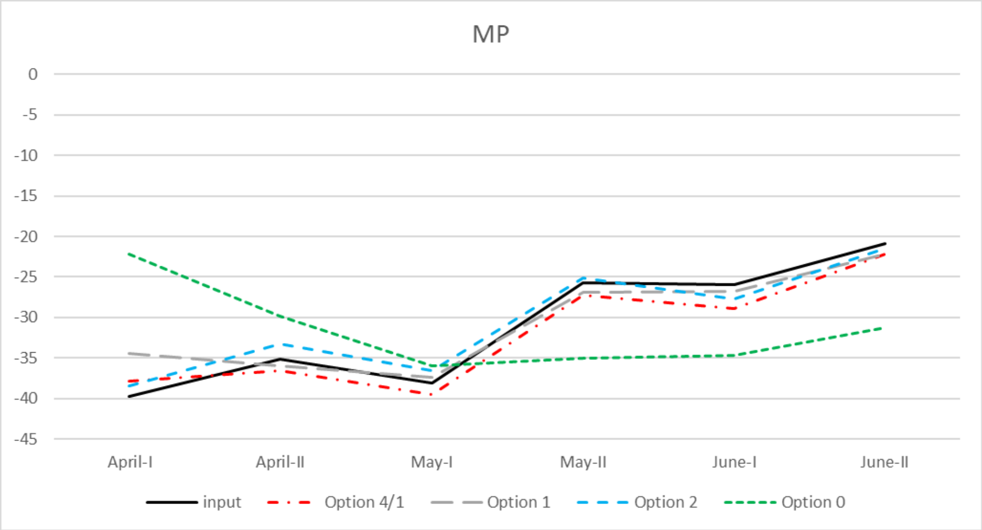


Figure 6.10: direct estimates and model estimates for MP

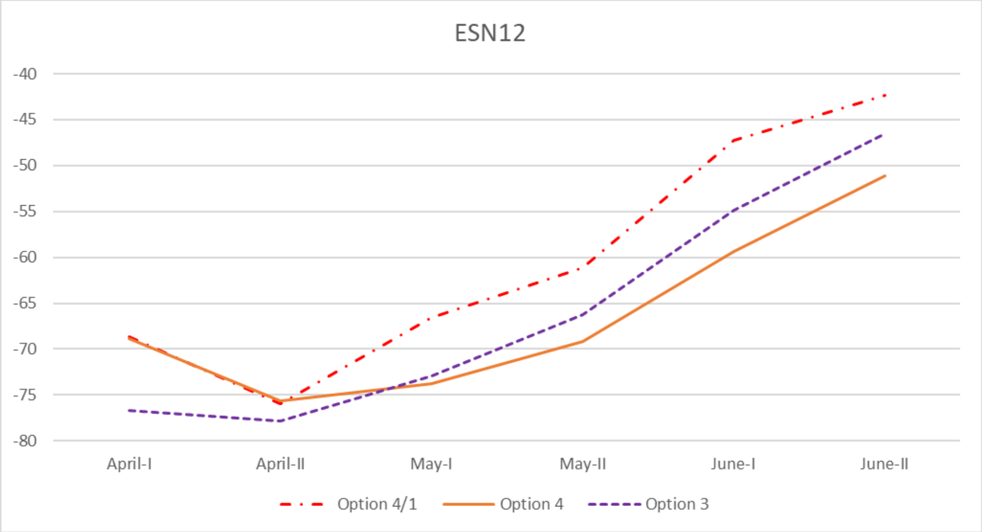


Figure 6.11: direct estimates and model estimates for ESN12

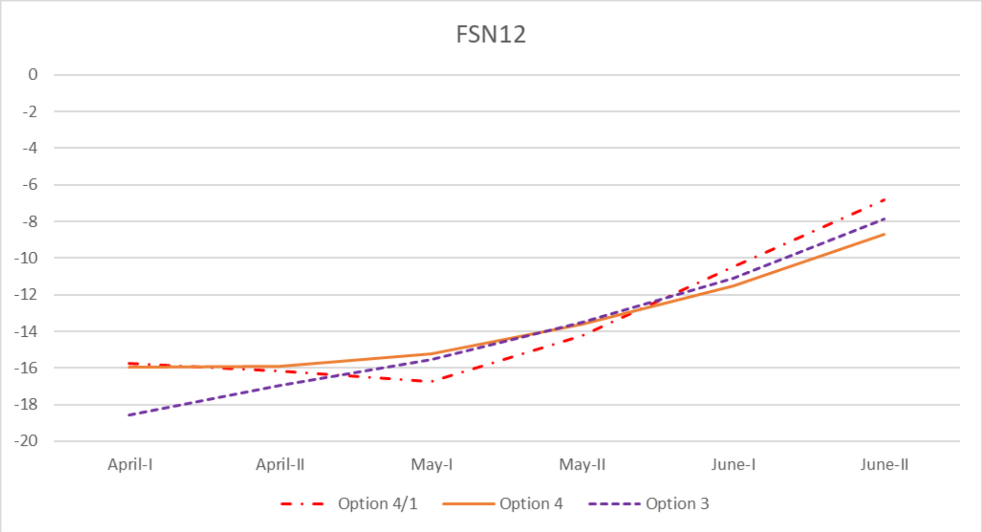


Figure 6.12: direct estimates and model estimates for FSN12

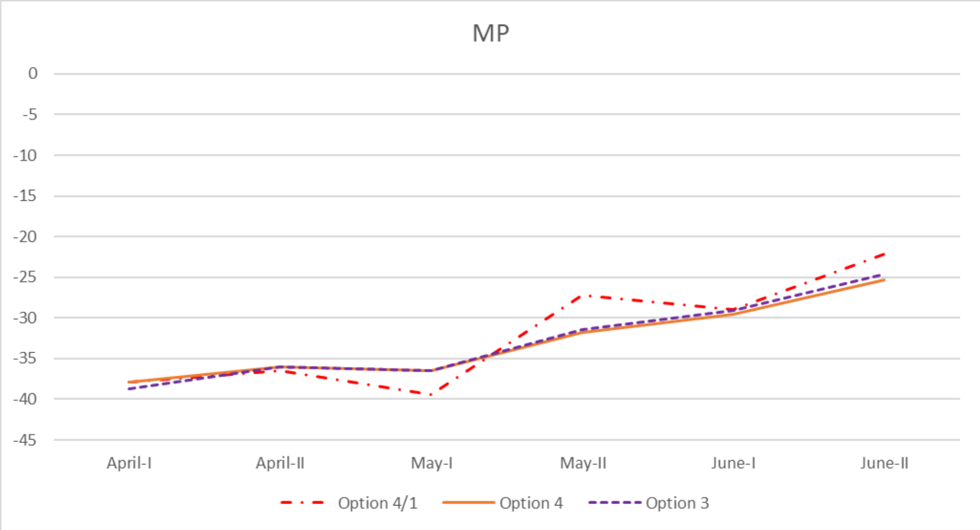


Figure 6.13: direct estimates and model estimates for MP

6.5 Summary results

The corona crisis resulted in extreme period-to-period changes for the parameters of interest. For the model used for the regular monthly publications this caused a temporal model mis-specification, which required an adjustment of the model. To this end different model specifications have been tested. A separate model is developed to produce estimates for the second halves of April, May and June. Also for this model different specifications are considered to accommodate the increased volatility of the parameters of interest during the corona crisis. The model estimates found with the different adjustments are more or less similar in most of the considered examples. In summary the following advantages and disadvantages of the different options can be noticed.

Option 1: the model estimates seem to be plausible as they follow the direct estimates quite well and the signs of model misspecification in terms of extremely large innovations are solved. There is some subjectivity in the choice of the factors used to inflate the variance of the slope disturbance terms of the trend. The model predictions, however, are very similar to those obtained with Option 2, where a more objective value for the variance of the slope disturbance terms during the corona crisis is obtained once sufficient data are available. Option 1, however, is particularly appropriate in an ongoing production process, since it does not require a minimum amount of observations under the corona crisis. Another advantage is that the variance can gradually decrease back to the normal situation, once the corona crisis diminishes. The major disadvantage is that for each period the factors have to be tuned manually in a production process that generally has very limited amount of time for data analysis and inference.

Option 2: the model estimates are plausible, for similar reasons as mentioned under Option 1. A major advantage of this approach is that a more objective likelihood criterion is used to estimate the variance for the trend disturbance terms during the corona crisis. The method, however, is not applicable in an ongoing production process, since a minimum number of observations under the corona crisis are required to obtain a sufficiently stable maximum likelihood estimate for the variance of the trend component. Another difficulty is to make an informed decision for which periods a separate value is required. On top of that, it is not known in advance whether one hyperparameter for the entire corona period is sufficient.

Option 3: This option assumes that the impact of the corona crisis on the population parameters concentrates in one period and that from that point on the volatility of the input series turns back to normal. This assumption was clearly not met for several indicators. Another major drawback of this approach is that the regression coefficients of the level intervention are subject to large revisions directly after the start of the corona crisis when the level intervention is switched on.

Option 4: This option is proposed to circumvent the large revisions of the regression coefficients of the level intervention under Option 3. This option is only applicable in a specific situation like the one in this paper where there is external information to fix a value for these regression coefficients.
Option 5: This option results in the most flexible model in the sense that the model predictions will be very close to the direct estimates. The major disadvantage is that under this option the model does not smooth any survey errors from the direct estimates. The only added value of the model is the seasonal correction. Another issue is to decide which periods are considered as outliers, although outlier detection methods can be used for this purpose.

Our evaluation emphasizes that Option 1 was the most appropriate approach for an ongoing production process. If there are no requirements to publish figures directly after the start of a crisis and time is available to collect more observations under the corona crises, then Option 2 would be a good alternative.
The fact that the factors have to be chosen manually every month under Option 1 can be seen as a disadvantage. One could consider to automatize this process. It is, however, understood that adapting the model specification with an automated procedure increases the risk of introducing model misspecification.

7. Official statistics for consumer confidence during and after corona

Option 1, which increases the flexibility of the trend using variance inflation factors in combination with defining the covariances for the slope disturbance terms and the measurement errors equal to zero, is implemented in the production process since the beginning of the corona crisis. After the first lockdown, the factors were mostly set to 1 again, except for a few times during the following corona waves. In February 2022, Russia invaded Ukraine. This strongly influenced the Dutch consumer confidence and it was necessary to increase the variances of the slope disturbance terms again for some months. Finally it was decided to define a full covariance matrix for the slope disturbance terms and the measurement errors from June 2022 on. As a result the production model (3.1) now has two time varying covariance structures for the trend and the measurement errors:

$$\mathrm{Cov}(\eta_{\mathrm{R},i,t}, \eta_{\mathrm{R},i',t'}) = \begin{cases} f_{i,t}\sigma^2_{\mathrm{R},i} & \text{if} \quad i = i' \text{and } t = t' \\ \delta^c_t \varsigma_{\mathrm{R},i,i'} & \text{if} \quad i \neq i' \text{and } t = t'. \\ 0 & \text{if} \quad t \neq t' \end{cases} \tag{7.1}$$

$$\mathrm{Cov}(e_{i,t}, e_{i',t'}) = \begin{cases} \sigma^2_{\mathrm{e},i} & \text{if} \quad i = i' \text{and } t = t' \\ \delta^c_t \varsigma_{\mathrm{e},i,i'} & \text{if} \quad i \neq i' \text{and } t = t'. \\ 0 & \text{if} \quad t \neq t' \end{cases} \tag{7.2}$$

with $f_{i,t}$ the variance inflation factors as specified in Table 7.1 and δ^c_t a dummy indicator that switches off the covariances in (7.1) and (7.2) during the corona crisis:

$$\delta^c_t = \begin{cases} 1 & \text{if} \quad t \notin [\text{Jan. } 2020 - \text{June } 2022] \\ 0 & \text{if} \quad t \in [\text{Jan. } 2020 - \text{June } 2022] \end{cases}.$$

Year	Month	ESL12	ESN12	FSL12	FSN12	MP
2019	Until Dec.	1	1	1	1	1
2020	January	1	1	1	10	10
2020	February	1 - 10	10	1	100	100
2020	March	10	50	1	75	75
2020	April	5	25	1	25	50
2020	May	5	1	50	1	1
2020	June	1	25	1	1	1
2020	July	1	1	1	1	1
2020	August	1	1	1	1	1
2020	September	1	10	1	1	1
2020	October	1	1	1	1	1
2020	November	1	10	1	1	1
2020	December	1	1	1	1	1
2021	Jan-July	1	1	1	1	1
2021	August	1	10	1	1	1
2021	Sept. – Nov.	1	1	1	1	1
2021	December	1	5	1	5	1
2022	January	1	10	1	25	1
2022	February	10	25	50	10	1
2022	March	1	10	0	50	1
2022	From April on	1	1	1	1	1

Table 7.1 Variance inflation factors $f_{i,t}$ for covariance matrix (7.1).

In this section two additional options are compared with the options from Section 5 and 6.

Option 6: The production model is unchanged. Thus the model allows for non-zero correlations between the slope disturbance terms and measurement errors during the entire period, also during the lockdowns. There are no variance inflation factors to accommodate the increased period-to-period changes during the lockdowns and the Russian invasion.

Option 7: The production model is changed to the new proposed model with time varying correlations between the slope disturbance terms and measurement errors as defined in (7.1) and (7.2) and variance inflation factors as defined in Table 7.1.

The maximum likelihood estimates for the correlation matrices of the slope disturbance terms and measurement error disturbance terms are given in Table 7.2 for Option 6 and Table 7.3 for Option 7. Since there are some differences between the correlations under both options, it can be concluded that the corona crisis violated the assumption that the covariances matrices are constant over the entire period. The differences are, however, relatively small. Since the length of the crisis is small compared to the length of the entire series, the effect on the correlations under Option 6 is small.

Trend	ESL12	ESN12	FSL12	FSN12	MP
ESL12	1				
ESN12	0.796	1			
FSL12	0.614	0.453	1		
FSN12	0.820	0.932	0.704	1	
MP	0.511	0.526	0.734	0.702	1

Measurement error	ESL12	ESN12	FSL12	FSN12	MP
ESL12	1				
ESN12	0.410	1			
FSL12	0.148	-0.077	1		
FSN12	0.138	0.407	0.140	1	
MP	0.107	0.325	-0.070	0.226	1

Table 7.2: Correlation matrices for the slope disturbance terms (top table) and measurement error disturbance terms (bottom table) under Option 6 (unadjusted production model)

Trend	ESL12	ESN12	FSL12	FSN12	MP
ESL12	1				
ESN12	0.849	1			
FSL12	0.630	0.402	1		
FSN12	0.861	0.873	0.603	1	
MP	0.399	0.372	0.586	0.514	1

Measurement error	ESL12	ESN12	FSL12	FSN12	MP
ESL12	1				
ESN12	0.575	1			
FSL12	0.104	-0.050	1		
FSN12	0.212	0.379	0.227	1	
MP	0.232	0.216	-0.016	0.072	1

Table 7.3: Correlation matrices for the slope disturbance terms (top table) and measurement error disturbance terms (bottom table) under Option 7 (new production model with time varying correlations defined in (7.1) and (7.2))

Figure 7.1 compares the filtered trend estimates under Option 6 and 7 with the direct estimates for consumer confidence for the period January 2012 until April 2023. It is understood that the filtered trends under Option 0 are very similar to Option 6 and that the filtered trends under Option 1 are very similar to Option 7. This is illustrated in Figure 7.2, which compares Options 0, 1, 6 and 7 for the period January 2020 until April 2023. The reason for this result is that the trend is mostly influenced by the variance inflation factors. Since Option 0 and 6 do not use these factors they have a very similar trend pattern. The same applies to Option 1 and 7 that both use the same variance inflation factors. The main differences between the trends under Option 6 and 7 occur around the start of the first lockdown. The filtered trends under Options 0 and 6, which do not increase the flexibility of the trend, show substantial larger deviations from the series of the direct estimates. This is further illustrated in Figures 7.3 and 7.4 where the filtered trends under Option 0, 1, 6 and 7 are compared with the direct estimates for two of the five underlying series ESN12 and FSN12, respectively.

Figure 7.1 shows the evolution of consumer confidence over the last 11 years starting in 2012, which is around the end of the financial crisis of 2007 – 2011. The consumer confidence stays low for two years and starts to increase around 2014. Note that the low value of consumer confidence in 2022 is the lowest value since the start of the series in 1986. Also note that the month-to-month change from March to April 2020 is the largest drop in consumer confidence that occurred since the start of the series. The use of the variance inflation factors has the strongest visible impact on this series in 2020 during the first lockdown.

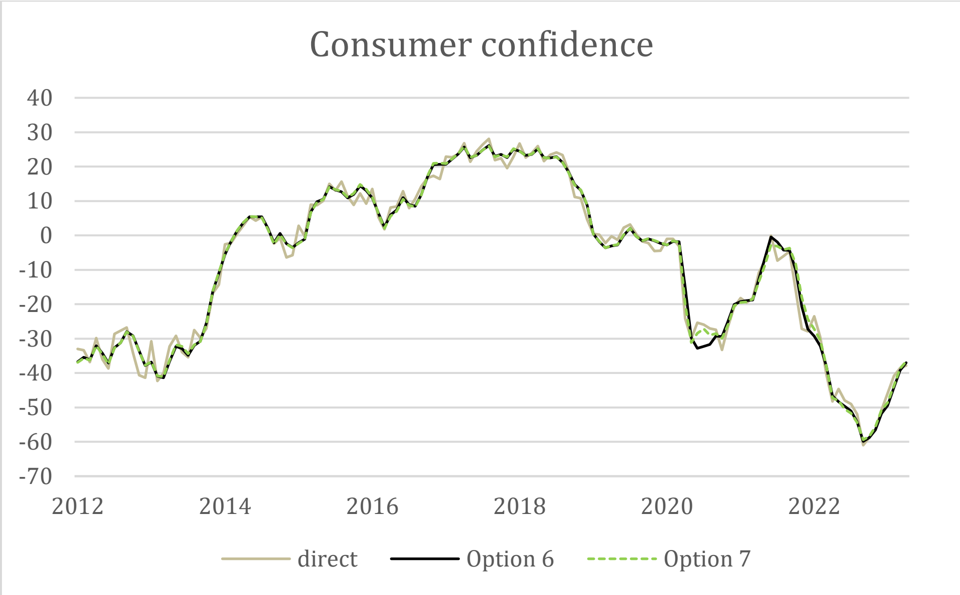


Figure 7.1: direct estimates and filtered trends consumer confidence under Option 6 and 7

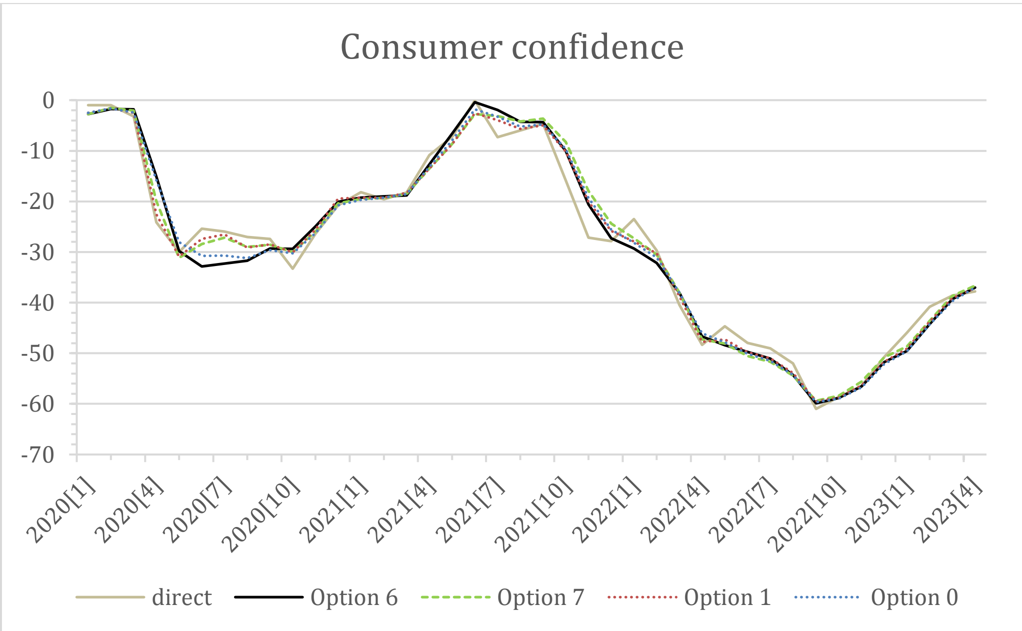


Figure 7.2: direct estimates and filtered trends consumer confidence under Option 0,1,6 and 7

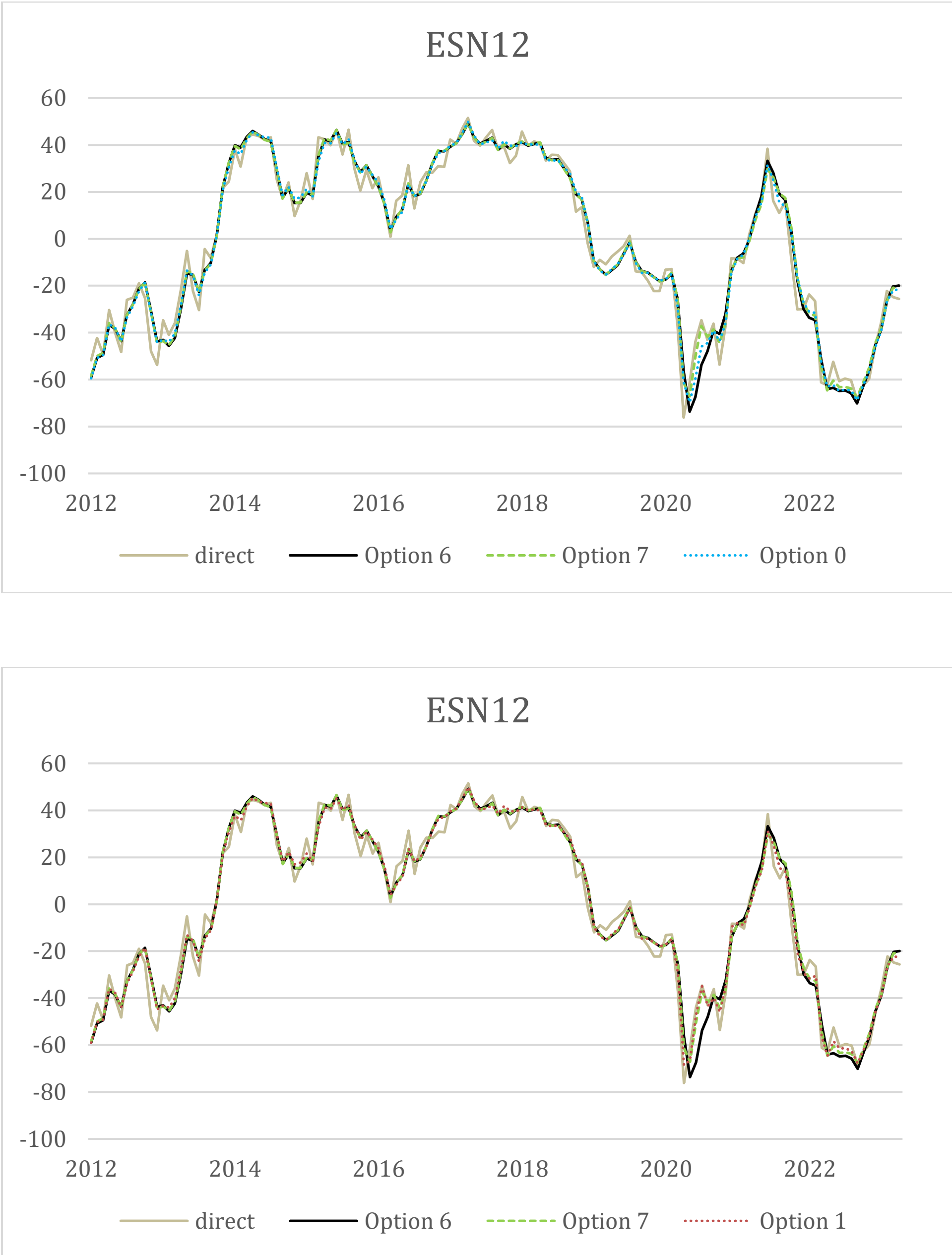
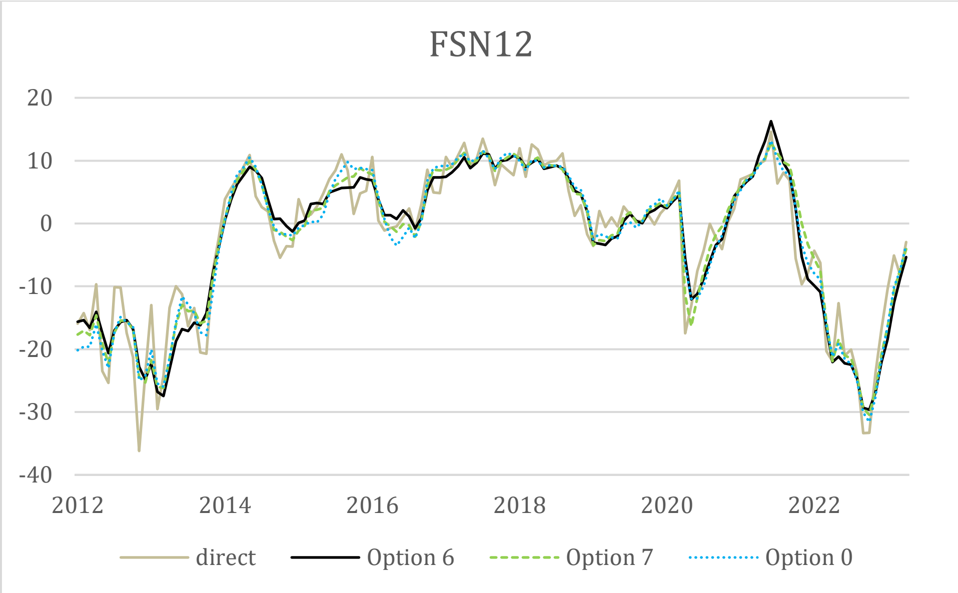


Figure 7.3: direct estimates and filtered trends ESN12 under Options 0, 6 and 7 (top panel) and Options 1, 6 and 7 (bottom panel).



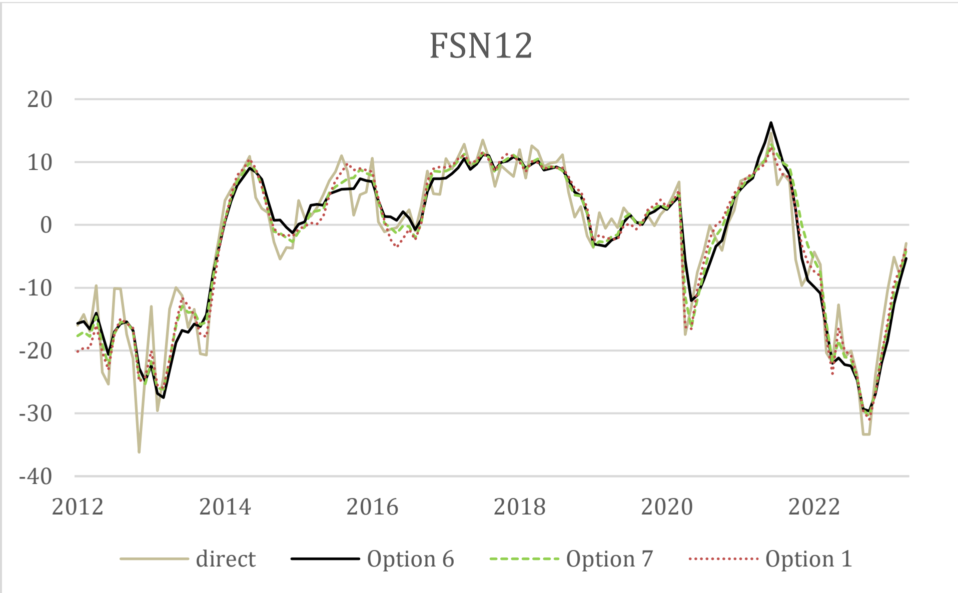


Figure 7.4: direct estimates and filtered trends FSN12 under Options 0, 6 and 7 (top panel) and Options 1, 6 and 7 (bottom panel).

Figure 7.5 compares the standard errors for the filtered trend of consumer confidence under Option 0, 1, 6 and 7. Under Option 0, which does not allow non-zero correlations for the slope disturbance terms and measurement error, the filtered trend has a constant standard error around 1.6. Under Option 0, the strong decrease of the series in 2020 and 2022 results in larger estimates for the variance of the slope disturbance terms. This results in larger standard errors for the filtered trend for the entire period. Under Option 1, this is prevented because the variance of the slope disturbance terms is temporarily inflated with the larger factors during the corona crisis. As a result the standard errors of the filtered trend are smaller during the pre-corona period under Option 1. The variance inflation factors, however, result in larger standard errors for the filtered trend during the lockdowns and the initial phase of the invasion in Ukraine.

The standard errors under Option 6 are also constant over time and clearly large compared to Option 0. This is the result of modelling correlations between the measurement errors. As argued in Van den Brakel et al. (2021) the time series model should account for correlation between the measurement errors, since, some events, e.g. good or bad news about the economy, influence the answers to all questions in a similar way. Ignoring these correlations underestimates the uncertainty of the filtered trend.

The standard errors under Option 7 are outside the period where the correlations are set equal to zero, equal to the standard errors under Option 6. During the corona period without non-zero correlations and variance inflation factors for the slope, the standard errors are smaller and equal to the standard errors under Option 1. As argued before, it can be expected that ignoring the correlations between the measurement errors underestimates the uncertainty of the filtered trends. Therefore the standard errors before the period where the correlations are defined to be zero is a more realistic estimate for the level uncertainty.

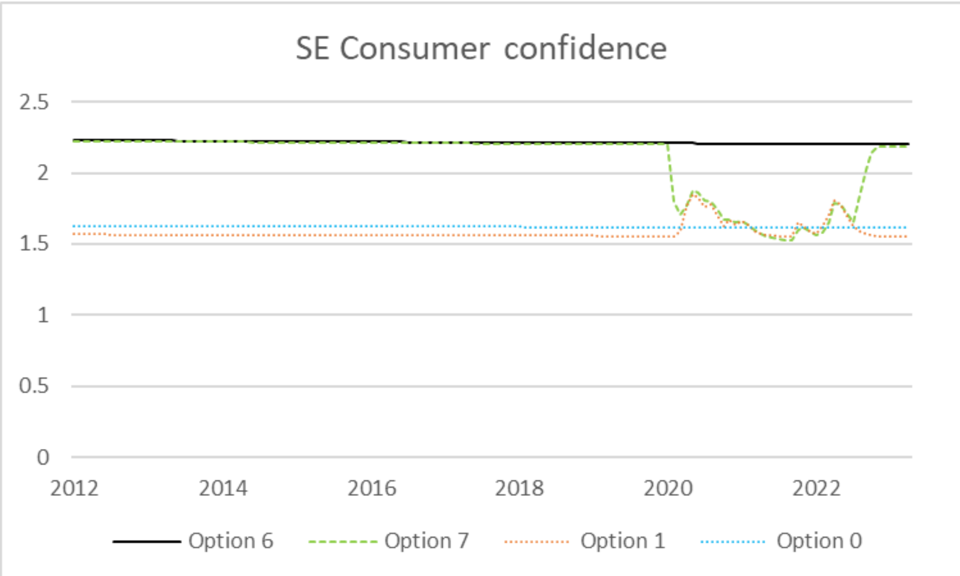


Figure 7.5: SE of filtered trends consumer confidence

8. Conclusion

Since 2017 the estimates of the Dutch Consumer Survey have been computed with a structural times series model. By means of this model, information from the past is used to improve the accuracy of the estimates. The corona crisis in 2020 led to extreme developments of the target variables of the Dutch Consumer Survey. This resulted in a temporary misspecification of the time series model used to produce monthly consumer confidence figures. At the same time there was an increased demand for timely figures about the impact of the corona crisis on the economy.

To account for the sudden increase in the month-to-month changes of the consumer confidence indicators, it was necessary to increase the flexibility of the trend components. This is achieved by increasing the variance of the slope disturbance terms of the trend using variance inflation factors. In this paper, this approach is compared with alternative solutions. One alternative is to define separate variance components for the slope disturbance terms during the corona period and estimate them using maximum likelihood. This approach, however, requires a minimum amount of observations under the corona period and is therefore not applicable in a production process at the start of the corona crisis. Another alternative is to model the shock in the indicators with a level intervention. This approach, however, assumes that the impact of the corona crisis on the consumer confidence indicators is concentrated in one period or at the most in a few periods.

The original production model allows for non-zero correlations between the slope disturbance terms and also between measurement errors of the consumer confidence indicators. Modelling the correlations between the measurement errors is in particular important, since some events, e.g. good or bad news about the economy, influence the answers to all questions in a similar way. Ignoring these correlations underestimates the standard errors of the filtered trend of the consumer confidence index.

The linear state space models considered in this application assumes that correlations are time invariant. The corona crisis changed the correlations between the measurement errors of the input series. To avoid model misspecification it was necessary to switch to a model that does not allow for non-zero correlations between the measurement errors and neither between the slope disturbance terms. A side effect of this adjustment is that the standard errors of the filtered trends are underestimated during the period that the correlations are switched to zero. The standard errors for the filtered trend before the start of the corona crisis are probably a more realistic approximation.

To produce more timely figures about consumer confidence, it was decided to collect additional data for the second halves of April, May and June of 2020. Data collection for these three additional surveys was based on WI only. There was no budget or field capacity for a non-response follow-up using CATI. Simple adjustments, based on the observed differences between estimates based on the full response and the WI response in the period before the start of the corona crisis, are applied to the WI estimates for the second half of these three months to correct for mode effects. A separate model, defined at a frequency of two estimates per month, is developed to produce estimates for the second halves of April, May and June. Also for this model different specifications are considered to accommodate the increased volatility of the parameters of interest during the corona crisis.

The Russian invasion in Ukraine influenced the consumer confidence in a similar way as the corona crisis, making model adjustments necessary again. It appears that after April 2022 the behavior of the consumer confidence indicators has stabilized such that the covariance structures as used before the start of the corona crisis can be used in the model again.

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Telephone +31 88 570 70 70, fax +31 70 337 59 94
Via contactform: www.cbs.nl/information