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Nowcasting Private Consumption in Switzerland using a Mixed-Frequency Dynamic Factor Model with High-Frequency Data

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Abstract

Various empirical papers have provided evidence that dynamic factor models and the use of high- and mixed-frequency data yield good estimates for nowcasts. This thesis uses the dynamic factor model framework of Giannone et al. (2008) with daily, weekly, and monthly data to nowcast private consumption in Switzerland. The specific target indicator is the growth rate of the Swiss retail trade turnover index. In addition to traditional macroeconomic data, also payment transaction data as well as mobility and search engine data at daily frequency are used. Using daily payment transaction data improves the performance accuracy over a simple benchmark model and a model that only employs monthly data. The results indicate that high-frequency data can improve the nowcast estimates for Switzerland.

Keywords: Nowcasting, Private consumption, Dynamic factor model, Mixed-frequency, High-frequency data, Kalman filter, Switzerland
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1 Introduction

The ongoing Covid-19 pandemic has led to a renewed demand for real-time monitoring of the economy and highlighted the problem of timely estimation of macroeconomic variables. Economic policy makers need to make real-time decisions based on their judgment of current and future economic conditions using incomplete data. Understanding where the economy is in real-time delivers valuable information to policy makers since official publications of economic indicators often lack timeliness and are released with a substantial time-lag. Estimating the present is called *nowcasting* and is the modern approach to monitoring current economic conditions (as defined by e.g. Doz et al. (2011)). The demand for timely information resulted in new high-frequency[1] data being collected and made available to the public for research. Amongst others these include payment card data. The availability of these data give rise to the question to which extent such high-frequency indicators, specifically payments data, can support the prediction of macroeconomic variables such as consumption.

Motivated by the issue of timely information and the publication of a new type of data, this thesis estimates a nowcast of the *retail trade turnover index* in Switzerland, which is one part of private consumption. The retail trade turnover index is a monthly statistic on a national level and contains sales from different subgroups like petrol stations, food, beverages, tobacco products, information and communication technology, household appliances, sports goods, clothing and footwear.[2] For the purpose of this research, the overall calendar and seasonally adjusted statistic is analysed. The official publication by the Federal Statistical Office has an approximate lag of one to two months (the maximal delay observed after the reference period is around 60 days). Private consumption accounts for more than 50% of gross domestic product (GDP) in Switzerland[3] and is the biggest part of the national income identity. GDP is still one of the most important measures of economic activity and, therefore, the economy strongly depends on consumption. Aggregate private consumption consists of various components of which this thesis focuses on one specific part, that is the retail trade turnover.[4]

Three reasons were decisive for the choice of the retail trade turnover index. First, the majority of the nowcasting literature has focused on GDP rather than its components. Therefore, GDP, which is a quarterly aggregate statistic, has been amply analysed. By focusing on one component

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[1] In this thesis high-frequency data refer to daily data.

[2] The retail trade turnover statistic is based on a mandatory survey with approximately 4000 Swiss enterprises that are active in the retail trade sector. More details on the index can be found in Subsection 4.1.

[3] According to the State Secretariat for Economic Affairs SECO (`www.seco.admin.ch`).

[4] The expenditures of Swiss households and the different components of consumption are summarized in Table B9 in Appendix B. The retail trade turnover is the sum of various consumption components.

of the aggregate statistic only, I investigate a barely researched indicator. Second, the availability of appropriate indicators and their frequency is decisive too. Since the high-frequency data have a short time span (e.g. most daily series used in this thesis are available only since 2019), a quarterly indicator would have too few observations (only around eight). Third, early estimates of retail sales help to anticipate developments in that sector and to make informed policy decisions. Information about private household spending is important to assess and predict overall economic activity.

Consumption is not determined by a single indicator but rather by the dynamics and interactions of many indicators. Therefore, a great number of different economic variables will be used (see Section 4 for an overview). The employed model will account for different release dates of the data and incorporate data at mixed (daily, weekly, and monthly) frequencies. The use of high-frequency data adds timely information to the model and, thus, might improve the nowcasting accuracy. Besides mobility data and search engine data, the model also contains newly available daily payment transaction data for Switzerland. The model that will be used is an exact mixed-frequency dynamic factor model (MF-DFM) based on Giannone et al. (2008), which accounts for the different frequencies of the time series data. This framework helps to reduce the dimension of the model by extracting only a few common factors. The main questions investigated in this thesis are whether and how well payment data and other traditional macroeconomic data can nowcast the retail trade turnover and to what extent high-frequency data can improve the performance of the model.

This thesis contributes to the existing nowcasting literature in three manners. First, to my best knowledge it is the first study that estimates a nowcast of the growth rate of the seasonally adjusted Swiss retail trade turnover. Compared to other nowcasting studies for Switzerland, the focus was never on only one part of aggregate private consumption but mostly on GDP and GDP growth. Second, the scope of research using daily payment data for Switzerland is limited, as the data have only recently become available. This thesis complements existing research in this field.[5] In contrast to most of these research projects, this thesis does not create a new index but nowcasts an existing index. Third, this thesis analyses the extent to which high-frequency data help in nowcasting and adds to the discussion on the usefulness of these data. Since the focus has mainly been on nowcasting quarterly variables until now, my research also adds to the literature that nowcasts monthly indicators compared to quarterly indicators. Moreover, compared to big indices such as GDP, it will help understand how well smaller indices can be nowcasted with a dynamic factor model.

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[5] See e.g. Guggia et al. (2021); Alvarez and Lein (2020), and Eckert and Mikosch (2020). For a full overview of research projects that use the Swiss payment data please visit `www.monitoringconsumption.com`.

The three main results are the following. First, the use of the factor model to nowcast the growth rate of the retail trade turnover index in Switzerland improves the overall performance upon a simple benchmark model. During pre-Covid-19 pandemic times, the factor models were not able to yield significantly better results than the benchmark, but as soon as the growth rate started to become more volatile, the factor models outperformed the benchmark. Second, high-frequency data are adding relevant and timely information and improve the performance accuracy over a model specified with only traditional monthly indicators. Third, payment transaction data for Switzerland on a daily basis add significant information and support the nowcast estimation of the retail trade turnover growth rate.

The remainder of this thesis is structured as follows. Section 2 offers a review of the relevant literature. Section 3 will introduce in detail the model. Section 4 explains the data and in Section 5 the results will be reported and discussed. Section 6 concludes.

2 Literature review

The following section briefly summarises important research on nowcasting, the model that is used, the use of high-frequency data and payment data, and the case of Switzerland. The nowcasting literature is still relatively young. Two of the early papers that can be related to the topic are the papers of Mitchell and Burns (1938) and Stock and Watson (1989). They write about leading indicators and construct synthetic indicators of the real economy. However, the literature has been growing in the last couple of years where most of the macroeconomic nowcasting focuses on GDP. Recent research has been done on India (Bragoli and Fosten, 2018), Mexico (Caruso, 2018), the Euro Area (Hindrayanto et al., 2016; Marcellino et al., 2016; Angelini et al., 2011; Rünstler et al., 2009), Brazil (Bragoli et al., 2015), China (Giannone et al., 2013), Germany (Schumacher and Breitung, 2008), and the USA (Stock and Watson, 2002b). Some important findings so far are that the nowcasting results provide good accuracy for preliminary estimates of the official figures. Moreover, the nowcast gets better the closer one gets to the end of the nowcasting period and the more data is included. This strongly supports the approach of including timely data. However, nowcasting is subjective to the indicators used and which statistic is being predicted. Compared to the above mentioned papers which focus on GDP in big economies or currency areas, this thesis looks at a small economy and a specific subcomponent of GDP.

The model that is used in this thesis is a dynamic factor model. The technical model was developed by Sargent et al. (1977); Geweke (1977) and has, amongst other fields, been applied for forecasting. More specifically, the model will be used with the two step-procedure including principal component analysis and the Kalman filtering techniques, which is theoretically outlined by Doz et al. (2011) and based on the seminal paper in the nowcasting literature of Giannone et al. (2008). However, although Giannone et al. (2008) use data with various frequencies (monthly indicators and quarterly target variable), they aggregate the monthly common factors to quarterly frequency to nowcast GDP in the USA. They use principal component analysis and the dynamic factor model (DFM) for the estimation. Amongst other studies, this approach was used by Aastveit and Trovik (2012) for Norway, Angelini et al. (2011) for the Euro area, Barhoumi et al. (2010) for France, Matheson (2010) for New Zealand, and Rünstler et al. (2009) for the European countries. Furthermore, Siliverstovs and Kholodilin (2010) build upon this model too and apply it to Switzerland. They find that the factor model improved the performance of the now- and forecast of GDP growth and that a single factor model performed the best. Compared to the above mentioned studies, this thesis will use higher frequency data and will nowcast a monthly indicator instead of a quarterly statistic. In addition to that, it will also differentiate between stock and flow variables and adjust the temporal aggregation accordingly by also taking into account how the variables were transformed before entering the model. Besides academic research, also several central banks (Bank of England, Norges Bank, Federal Reserve Bank) have used the DFM for now- and forecasting purposes.

The use of mixed-frequency data is becoming more common, but the majority of studies to date only use monthly and quarterly data. However, the inclusion of high-frequency variables has resulted in improved performance for various nowcasting models. The study of Modugno (2013) reports that high-frequency data improve the accuracy of the nowcast for inflation. Similarly, Bańbura et al. (2013) note that performance has improved for inflation nowcasting but has not contributed much to the GDP growth nowcast. There are also various projects that emerged in recent times which focus on using high-frequency data to monitor economic development in real-time and which report that including these variables improved the accuracy (Guggia et al., 2021; Fenz and Stix, 2021; Lewis et al., 2020; Eraslan and Goetz, 2020; Rua et al., 2020). In contrast to these projects, Carriero et al. (2020) find that weekly data are less informative than monthly data. The conclusion regarding the inclusion of high-frequency data in the nowcasting of macroeconomic variables is not yet final. Thus, the results are not conclusive and it is difficult to make an educated guess about whether these data can improve the nowcasting model for the Swiss retail trade turnover index. Other frequently employed models include e.g the mixed-data-sampling (MIDAS) regression suggested by Ghysels et al. (2007) or the mixed frequency vector autoregressive model (MFVAR) (see e.g. Foroni and Marcellino (2016)).[6] However, these approaches suffer from the curse of dimensionality. For a comparison of different models see e.g. Foroni and Marcellino (2013) and Jansen et al. (2016).

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[6] For a brief overview of other models see Table B10 in Appendix B.

An increasing amount of studies also use payment transaction data or Google and search engine data in their models. Galbraith and Tkacz (2018) include debit card payment data to nowcast GDP and retail sales growth in Canada. They find that the inclusion substantially improves the accuracy of the estimation. However, in contrast to the research at hand, their paper aggregates the payment data to monthly frequency. Gil et al. (2018) nowcast quarterly private consumption in Spain using a monthly mixed-frequency model and also find the data to add valuable information. These results are in line with the findings of Carvalho et al. (2020) and Conesa et al. (2015). Further, Carlsen and Storgaard (2010) and Esteves et al. (2009) also find evidence that payment data are useful to nowcast retail sales and quarterly private consumption, respectively. Compared to this thesis, they use the MIDAS regression approach and aggregate the payment data to a lower frequency. Duarte et al. (2017) also adopt a MIDAS regression approach but employ both daily and aggregated monthly payment transaction data. They find that in most of the model specifications the aggregated monthly payment data perform better than the daily counterpart. The inclusion of debit card payment data and payment data in general seem to add important information and improve the performance of the timely nowcast. Regarding the inclusion of search engine data to nowcast economic activites, Vosen and Schmidt (2011) compare Google Trends data versus survey data and find that the Google Trends data analysis outperforms the survey data. Niesert et al. (2020) look at the out-of-sample performance of such indicators and conclude that they are useful for predicting unemployment, but less so for the consumer price index or consumer confidence. For further research related to Google and search engine data see amongst others also Ferrara and Simoni (2019); Smith (2016); Choi and Varian (2012), and McLaren and Shanbhogue (2011). In general these data seem to be a promising new source to now- and forecast macroeconomic variables such as private consumption. In this research I also include Google Trends data as well as payment data. The difference is that the data will not be aggregated and included at their respective frequency (daily).

Aggregate private consumption in Switzerland is being forecasted by several institutions. The State Secretariat for Economic Affairs (SECO), the KOF Swiss Economic Institute, the UBS, the Institute of Applied Economics from the University of Lausanne (Créa), and BAK Economics (BAK) produce yearly forecasts that are updated quarterly or monthly, and Credit Suisse (CS) produces quarterly forecasts.[7] However, currently none of these institutions do a nowcast. Related studies that focus on Switzerland are Galli (2018) and Galli et al. (2017) who compares factor models with different specifications and a mixed-frequency dataset to nowcast GDP. Siliverstovs and Kholodilin (2010) use a DFM to now- and forecast GDP growth. Both, however, do not include data at a daily frequency and focus on the quarterly GDP statistic.

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[7] For an overview of existing forecast on total private consumption in Switzerland see Table B11 in Appendix B.

In summary, payment data can be promising indicators for nowcasting the Swiss retail trade turnover. In general however, it seems that non-aggregated high-frequency (daily) data are not necessarily improving the performance and might add more noise than actual information. The fact that weekly and daily indicators contain a lot of noise is a major challenge. Previous studies have also shown that mixed-frequency data used in a DFM can provide accurate estimates. This thesis employs an existing framework but uses newly available data. It investigates the performance of the model in a different setting and applied to a rather small target statistic at monthly frequency.

3 Methodology

3.1 Mixed-frequency dynamic factor model (MF-DFM)

This thesis will use a parametric dynamic factor model (DFM) cast into state space representation to estimate the nowcast. A factor model exploits the fact that relevant data series of a high-dimensional vector of time-series variables co-move quite strongly so that their dynamics can be captured by a few common unobserved or latent factors. Two seminal papers on this approach are Sargent et al. (1977) and Stock and Watson (1989). That extracting common factors for a macroeconomic dataset with many variables works, is shown by e.g. Watson (2004) and Giannone et al. (2004). It is assumed that the target variable depends on common factors and not on individual dynamics specific to certain variables. Compared to a full model which would reduce the degrees of freedom substantially (curse of dimensionality), the DFM allows for a more parsimonious model. Despite its technical complexity, it is purely model-driven and transparent.

One challenge is that the information set, denoted as Ω, contains data sampled at a wide range of frequencies, from daily to monthly.[8] Due to the real-time estimation of the model, new data points are available each time the model is estimated. The newly available observations contain new information and increase the information set. Therefore, the notation of the data vintage, Ω_v, is introduced, where v is a specific date. The information set contains all the variables and is defined as follows: $\Omega_v = \{Y_{i,t_i}; t_i = 1, ..., T_{i,v}; i = 1, ..., N\}$, where $T_{i,v}$ is the last available observation of series i in the data vintage v. The fact that $T_{i,v}$ is different for the series reflects

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[8] Another challenge is the revision of the data (see e.g. Croushore (2011); Croushore and Stark (2001) or Bouwman and Jacobs (2011)). This will, however, not be incorporated in this thesis. Therefore, some of the data are to a certain extent *pseudo* real-time and the thesis follows a stylized publication agenda (explained in Section 5). However, Schumacher and Breitung (2008) and Bernanke and Boivin (2003) show that the impact of data revision on the estimation of the factors cancel out.

the non-synchronous data releases and implies the so-called *ragged* edge problem. This basically means that not all series are published at the same time and/or for the same period. Nowcasting the target variable, y_t^{IND}, is the linear projection of y_t^{IND} on the available information Ω_v, which is

$$\mathbb{P}(y_t^{IND}|\Omega_v) = \mathbb{E}(y_t^{IND}|\Omega_v) \tag{1}$$

where $\mathbb{P}$ stands for the projection.

3.2 Technical model explanation

The model follows the paper of Giannone et al. (2008) who use the methodology outlined in Doz et al. (2011). In the following subsection, the model is illustrated in technical terms. The DFM explains each series in terms of two orthogonal unobserved stationary stochastic processes. The first part is the latent variable that captures the joint dynamic of the time series (common shocks), and the second part are the idiosyncratic disturbances (series specific shocks or dynamics). The fact that these two parts are orthogonal follows from the assumption that the factors, f_t, and idiosyncratic components, u_t, are uncorrelated at all leads and lags, i.e.

$$Cov(f_{it}, u_{js}) = 0, \quad t, s \in \mathbb{Z}, i = 1, ..., r, j = 1, ..., n. \tag{2}$$

The following equation shows the representation of the DFM

$$Y_t = \Lambda f_t + u_t, \quad u_t \sim i.i.d. \quad N(0, \Sigma_u) \tag{3}$$

where Y_t is an $n \times 1$ vector of data that contains all of the variables (n equals the number of variables which also includes the target variable y_t^{IND}), Λ is an $n \times r$ matrix of loadings with r being the number of factors, f_t is an $r \times 1$ vector of unobserved common components (factors), and u_t is an $n \times 1$ vector of series specific idiosyncratic components. It is assumed that u_t is cross-sectionally orthogonal white noise (zero cross-correlation) and, hence, $\mathbb{E}(u_t u_t') = \Sigma_u = diag(\sigma_1, ..., \sigma_N)$.[9] Since all variables will later be standardized, the unconditional means μ are not included in Equation

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[9] This implies that Y_t follows an exact factor model (see e.g. Stock and Watson (2016, p.423)). The assumption that Σ_u is diagonal is quite strong but Doz et al. (2011); Stock and Watson (2002a) show consistency for the factor estimation for weakly cross-correlated idiosyncratic components. Banbura et al. (2010) show that the idiosyncratic errors can also be modelled as an AR(p) process.

(3). The next equation is the VAR(p) law of motion for the factors

$$f_t = \underset{r \times r}{\Phi_1} f_{t-1} + ... + \underset{r \times r}{\Phi_p} f_{t-p} + \epsilon_t, \quad \epsilon_t \sim i.i.d. \quad N(0, \Sigma_\epsilon) \tag{4}$$

where f_t are the latent common factors from Equation (3), Φ are $r \times r$ matrices of autoregressive coefficients, and ϵ_t is an $r \times 1$ vector. The values of the latent parameter matrices Λ, Σ_u, Φ, and Σ_ϵ, are determined from the r latent common factors f_t.

3.2.1 Model estimation steps - *"Two-step procedure"*

The *two-step procedure* combines principal component analysis with the Kalman filter in order to account for the missing values due to the ragged edge problem. The Kalman smoother is used to recursively estimate the common factors.[10] The model is defined on a daily basis with the underlying assumption that the economy evolves at a daily frequency and that the monthly and weekly variables are related to the daily factors. Therefore, the lower-frequency variables have to be appropriately aggregated.

In a preparatory step the time aggregation relationship needs to be defined. This is an issue that arises due to the use of mixed-frequency data. In addition, one needs to differentiate between flow and stock variables. Assume e.g. that the low-frequency variable is y_t^{LF} (LF = **l**ow **f**requency) and its corresponding daily representation y_t^{LF*}. Stock variables are observed at a specific point in time and the relation can be defined as

$$y_t^{LF} = \begin{cases} \dfrac{1}{D_i} \sum_{j=0}^{D_i - 1} y_{t-j}^{LF*} & \text{if } y_t^{LF} \text{ is observed} \\ \text{missing} & \text{otherwise} \end{cases} \tag{5}$$

where D_i is the number of days of the respective period i (week, month).[11] For flow variables the intra-period sums of the respective unobserved daily values are taken,

$$y_t^{LF} = \begin{cases} \sum_{j=0}^{D_i - 1} y_{t-j}^{LF*} & \text{if } y_t^{LF} \text{ is observed} \\ \text{missing} & \text{otherwise.} \end{cases} \tag{6}$$

The low frequency data are treated like high frequency data with periodically missing values. This

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[10] Doz et al. (2011) have shown the consistency of the two-step procedure. An alternative to the two-step approach is to use the Expectation Maximization (EM) algorithm to obtain the maximum likelihood estimates (see e.g. Doz et al. (2012); Bańbura and Modugno (2014)).

[11] Another approach would be to assign the observed value to the last day of the respective period. I follow Galli (2018) and use the average.

aggregation is consequently adjusted depending on the transformation of the variable before it enters the model. For untransformed stock variables (level) the average of the factors over the last period is used. For (log-) differenced stock or untransformed flow variables (level) the factors are summed up over the last period. And for (log-) differenced flow variables the weighted sum over the last two periods is used. The weights are as in Mariano and Murasawa (2003) (see also Equation (15) below and Bańbura et al. (2013, pp.200-202) for more details). This aggregation is applied to the daily factors in order to estimate the loadings of Λ.

The estimation of the model broadly follows two steps:

- Estimate the common factors with principal component analysis (PCA),[12] while using a balanced data set of all indicators on a daily frequency. The balanced dataset is obtained by only using the data up to the date where the least recently available data are observable. Variables with more than 30% missing values over the period are omitted and not included in the first estimation step. The periodically missing values of the lower frequency data are replaced with splines.[13] The parameters (loadings and variances for each factor) are estimated by a simple OLS regression on the previously obtained factors where the factors are aggregated as outlined above. Given the estimates of the factors that were obtained by the PCA, $\hat{f}_t$, the VAR coefficients Φ and the variance-covariance matrix Σ_ϵ are estimated with the following OLS regression

$$\hat{f}_t = \sum_{i=1}^{p} \Phi_i \hat{f}_{t-i} + \epsilon_t. \tag{7}$$

- The second step uses the Kalman filter and smoother on the entire information set Ω_v to consistently re-estimate (update) the factors $\hat{f}_t$ for a given vintage date v. The Kalman filtering method deals with missing values and only weights information that is available at the specific date.

In order to use the Kalman filter and smoother, the DFM is cast into state space form. Due to the state space representation, the Kalman filter and smoother can retrieve the conditional expectation of the value of the factors (state vector)

$$\hat{f}_{t|\Omega_v} = \mathbb{E}(f_t|\Omega_v; M) \tag{8}$$

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[12] PCA is a least-squares method for estimating the unobserved factors nonparametrically.

[13] There are other approaches, such as only using the highest frequency data (see e.g. Galli (2018)) or aggregating the daily and weekly data to monthly frequency and then estimating the PCA with the monthly data. I also estimated the PCA using only the highest frequency data, but the results did not improve.

and the uncertainty related to the estimate

$$\widehat{P}_{t|\Omega_v} = \mathbb{E}[(f_t - \hat{f}_{t|\Omega_v})(f_t - \hat{f}_{t|\Omega_v})^\top; M]. \tag{9}$$

where M stands for the underlying model.

3.3 Temporal aggregation & state space representation

The model is estimated at the highest frequency and, therefore, as a daily MF-DFM. This implies that lower frequency data enter the model as daily series with periodically missing values, where the observed value corresponds to the last day of the respective period.[14] After grouping the variables by their frequency we obtain the vector of observables

$$Y_t = \begin{bmatrix} y_t \\ y_t^{IND} \end{bmatrix} = \begin{bmatrix} y_t^D \\ y_t^W \\ y_t^M \\ y_t^{IND} \end{bmatrix}; \quad Y_t^* = \begin{bmatrix} y_t^* \\ y_t^{ind*} \end{bmatrix} = \begin{bmatrix} y_t^D \\ y_t^{W*} \\ y_t^{M*} \\ y_t^{ind*} \end{bmatrix} \tag{10}$$

where y_t^D is a $n_D \times 1$ vector, y_t^W is a $n_W \times 1$ vector, y_t^M is a $n_M \times 1$ vector, Y_t^* is the unobserved daily equivalent of Y_t, and IND stands for the target variable that is nowcasted. Since the target variable is monthly, it will henceforth be included in the vector for monthly variables. It is assumed that the unobserved daily equivalent of the weekly and monthly data follow the same model as outlined above. Therefore, these lower-frequency variables can be expressed as a function of the daily common factors. However, in order to estimate the loadings, the factors have to be appropriately aggregated.

The state space representation of the MF-DFM looks as follows

$$Y_t = \Lambda_t f_t + u_t \tag{11}$$

$$f_t = A f_{t-1} + \epsilon_t \tag{12}$$

$$\text{where} \quad \begin{bmatrix} u_t \\ \epsilon_t \end{bmatrix} \sim N\left(0, \begin{bmatrix} R & 0 \\ 0 & Q \end{bmatrix}\right). \tag{13}$$

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[14] For weekly data it is Sunday, for monthly data it is the last day of the month (e.g. January 31st).

The covariance matrix R and the covariance matrix Q of the VAR estimation are

$$R = \underbrace{\begin{bmatrix} \Sigma_u^D & \mathbf{0}_{n_D \times n_W} & \mathbf{0}_{n_D \times n_M} \\ \mathbf{0}_{n_W \times n_D} & \Sigma_u^W & \mathbf{0}_{n_W \times n_M} \\ \mathbf{0}_{n_M \times n_D} & \mathbf{0}_{n_M \times n_W} & \Sigma_u^M \end{bmatrix}}_{n \times n}; \qquad Q = \underbrace{\begin{bmatrix} \Sigma_{\epsilon\, r\times r} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}}_{(r*pC)\times(r*pC)}. \tag{14}$$

where pC is the number of lags (latent variables) that are included in the model. For the model with monthly flow variables, $pC = 59$. This follows from the time aggregation step and is shown in the equations below. The measurement equation can be written in matrices as follows (assuming that the data contain weekly and monthly flow and stock variables)

$$\underbrace{\begin{bmatrix} y_t^D \\ y_t^{W_a} \\ y_t^{W_s} \\ y_t^{W_w} \\ y_t^{M_a} \\ y_t^{M_s} \\ y_t^{M_w} \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} \Lambda^D & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \frac{1}{7}\Lambda^{W_a} & \frac{1}{7}\Lambda^{W_a} & \cdots & \frac{1}{7}\Lambda^{W_a} & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \Lambda^{W_s} & \Lambda^{W_s} & \cdots & \Lambda^{W_s} & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 1\Lambda^{W_w} & 2\Lambda^{W_w} & \cdots & 7\Lambda^{W_w} & 6\Lambda^{W_w} & \cdots & 1\Lambda^{W_w} & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \frac{1}{30}\Lambda^{M_a} & \frac{1}{30}\Lambda^{M_a} & \cdots & \frac{1}{30}\Lambda^{M_a} & \frac{1}{30}\Lambda^{M_a} & \cdots & \frac{1}{30}\Lambda^{M_a} & \frac{1}{30}\Lambda^{M_a} & \cdots & \frac{1}{30}\Lambda^{M_a} & 0 & \cdots & 0 \\ \Lambda^{M_s} & \Lambda^{M_s} & \cdots & \Lambda^{M_s} & \Lambda^{M_s} & \cdots & \Lambda^{M_s} & \Lambda^{M_s} & \cdots & \Lambda^{M_s} & 0 & \cdots & 0 \\ 1\Lambda^{M_w} & 2\Lambda^{M_w} & \cdots & 7\Lambda^{M_w} & 8\Lambda^{M_w} & \cdots & 13\Lambda^{M_w} & 14\Lambda^{M_w} & \cdots & 30\Lambda^{M_w} & 29\Lambda^{M_w} & \cdots & 1\Lambda^{M_w} \end{bmatrix}}_{\Lambda} \underbrace{\begin{bmatrix} f_t^D \\ f_{t-1}^D \\ \vdots \\ f_{t-6}^D \\ f_{t-7}^D \\ \vdots \\ f_{t-12}^D \\ f_{t-13}^D \\ \vdots \\ f_{t-29}^D \\ f_{t-30}^D \\ \vdots \\ f_{t-59}^D \end{bmatrix}}_{f_t} + \underbrace{\begin{bmatrix} u_t^D \\ u_t^{W_a} \\ u_t^{W_s} \\ u_t^{W_w} \\ u_t^{M_a} \\ u_t^{M_s} \\ u_t^{M_w} \end{bmatrix}}_{u_t} \tag{15}$$

where $y_t^{i_a}$ stands for a stock variable in level where the aggregation is just the average (subscript a) and i stands for W = weekly or M = monthly, $y_t^{i_s}$ stands for a (log-) differenced stock or a flow variable in level. For these variables the sum (subscript s) is taken. $y_t^{i_w}$ stands for a (log-) differenced flow variable which is aggregated by the weighted sum (subscript w) over the last two periods.[15]

The inclusion of flow variables creates a high-dimensional state vector, which is challenging from a computational point of view and results in long calculations of the second estimation step. The

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[15] The weight starts at 1 at time t and subsequently increases until $t - D_i$ and then decreases again. For a weekly variable this would be $w = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 6 & 5 & 4 & 3 & 2 & 1 \end{bmatrix}$.

transition equation looks as follows

$$\underbrace{\begin{bmatrix} f_t^D \\ f_{t-1}^D \\ f_{t-2}^D \\ \vdots \\ f_{t-58}^D \\ f_{t-59}^D \end{bmatrix}}_{f_t} = \underbrace{\begin{bmatrix} \Phi_1 & \Phi_2/\mathbf{0} & \Phi_3/\mathbf{0} & \cdots & \Phi_{p-1}/\mathbf{0} & \Phi_p/\mathbf{0} \\ I_r & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & I_r & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & I_r & \mathbf{0} \end{bmatrix}}_{\text{A}} \underbrace{\begin{bmatrix} f_{t-1}^D \\ f_{t-2}^D \\ f_{t-3}^D \\ \vdots \\ f_{t-59}^D \\ f_{t-60}^D \end{bmatrix}}_{f_{t-1}} + \underbrace{\begin{bmatrix} \epsilon_t^D \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}}_{\epsilon_t} . \tag{16}$$

The $\mathbf{0}$ in matrix A above are $r \times r$ matrices of zeros and the notation $\Phi_p/\mathbf{0}$ implies that it can either be a matrix of autoregressive coefficients or a zero matrix, depending on the value of p. Moreover, $f_t^D = \begin{bmatrix} f_1 & f_2 & \cdots & f_r \end{bmatrix}^\top$ contains all r common factors and Φ are $r \times r$ matrices of autoregressive coefficients for the daily factors.

The Kalman filtering specifications are based on Aruoba et al. (2009). The filter takes as input Λ, R, A, Q, and the initial values for the latent states, i.e. the expectation and the variance for each latent state: $f_1 \sim N(a_1, P_1)$. Since the dataset will contain many missing values due to the ragged edge problem, the filter is constructed so that it does not weigh the missing values for the estimation of the common factors.

3.4 Nowcast

Finally, as the last step the nowcast can be computed as

$$\widehat{y^{IND}}_t = \beta^\top \widehat{f^D}_{t|\Omega_v} \tag{17}$$

where β is a vector that contains the loadings from matrix Λ of the target variable and $\widehat{f^D}_{t|\Omega_v}$ is a vector of the r daily factors and the lags obtained from the Kalman filter and smoother.[16] As mentioned above, most of the variables are transformed before entering the model so that all the variables are stationary series. Stochastic and deterministic trends are removed by first-differencing and seasonal components are also controlled for. Before using the data in the estimation, each variable is standardized. After estimating the nowcast, the standardization is reverted. Therefore,

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[16] In order to compute the nowcast in Equation (17), some paper reestimate the coefficients using an ordinary OLS regression (Siliverstovs and Kholodilin, 2010; Giannone et al., 2008). I compared the two approaches and they yield the same results.

the mean is added again and the value is multiplied by the standard deviation. Depending on the transformation of the target variable, one could also revert the transformation. For a log-differenced version, z, of the variable y one would do the following

$$\begin{aligned}
\hat{y}_{t+1} &= y_t + \hat{z}_{t+1} \\
\hat{y}_{t+2} &= y_t + \hat{z}_{t+1} + \hat{z}_{t+2} \\
&\dots \\
\hat{y}_{t+H} &= y_t + \textstyle\sum_{i=1}^{H} \hat{z}_{t+i}.
\end{aligned} \tag{18}$$

In a next step the series would be transformed by the exponential function.

4 Data & variables

The following section presents the underlying data sample for the estimation, which spans the period from January 1, 2015, until April 30, 2021. In a first step possible target indicators are analysed and then the explanatory variables are discussed. All the data are time series data with different frequencies. The highest frequency is daily and the lowest is monthly, some indicators have weekly frequency. Yearly and quarterly data are not included due to their low frequency and high publication lag.[17] The target variable is monthly. The main data sources include the State Secretariat for Economic Affairs (SECO), the Federal Statistical Office in Switzerland (FSO), the Swiss National Bank (SNB), and the KOF Swiss Economic Institute. However, also more "modern" data such as payment transaction data, Google Trends data,[18] and mobility data are used. Ideally the variables included in the model are available in a timely manner and are robust during volatile times. Similarly, it would be advantageous if the data were not revised too much in retrospect. However, there is a trade-off between timeliness and stability. Due to the Covid-19 crisis, many institutions started to gather and publish timely data on various subjects. These data are highly informative and readily available but the time period of the series is potentially short and the number of observations rather small. Compared to monthly variables they are a lot more volatile. Below both the target variable and the predictor variables are discussed.

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[17] Another reason for not including quarterly variables is the technical aspect. The state space would explode if the model is defined on a daily basis and quarterly indicators are included. This problem is exacerbated if flow variables are incorporated, as these inherently generate high-dimensional state vectors already.

[18] Google Trends offers a representative data sample of search queries regarding certain keywords. Thus, keywords can be put in context and the relative importance of each keyword can be observed over a period of time. For more information visit `https://support.google.com/trends/answer/4365533?hl=en`.

4.1 Target variable

Several consumption indicators for Swiss households exist. Table 1 provides an overview of the most prominent indicators published by FSO, SECO, and KOF. These capture different parts of household consumption and the overall sentiment in the market. Depending on the indicator they are available at monthly, quarterly or yearly frequency.

Table 1: Private consumption indicators

Variable	Freq.[a]	Elmts. priv. cons.[b]	Publ. lag[c]	Source
Retail trade turnover (DHU)	M	a, b, c, e	1-2 M	FSO
Turnover in the tertiary sector[d]	Q	a, b, c, e & wholesale commodity	2Q	FSO
Private consumption (as part of GDP)[e]	Q	a-j	1Q	SECO
Economic sentiment indicator	M	-	1M	KOF
Swiss economic confidence	M	-	0M	SECO
Consumer confidence index	Q	-	0Q	SECO
Expenditures for housing	Y	d	3Y	FSO
Consumption expenditure by purpose	Y	indiv. components	2Y	FSO

[a] D = daily, M = monthly, Q = quarterly, Y = yearly

[b] Detailed information on the letters can be found in Table B9 in Appendix B

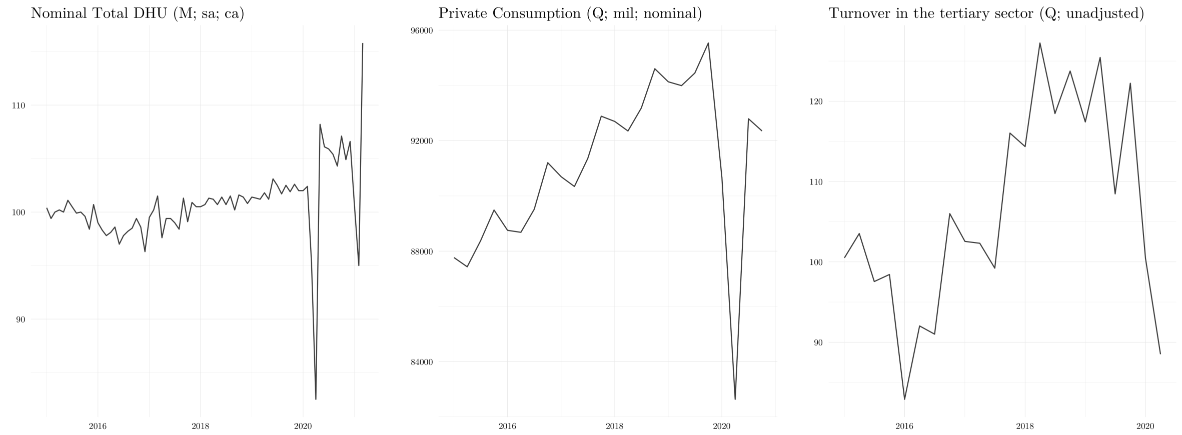
[c] Max delay observed after reference period

[d] DHU is one part of this series

[e] Household consumption is reported according to the national concept; including final consumption of private non-profit organizations (Endverbrauch der privaten Organisationen ohne Erwerbscharakter - POoE).

The *retail trade turnover index* and the *turnover in the tertiary sector* indicators are from the supply/producer side. They are published by the FSO and capture the turnover of the retail sector, and the wholesale trade and service sector, respectively. SECO releases the *private consumption* indicator which is from the demand/consumer side and captures the aggregate consumption of Switzerland. Figure 1 depicts these three indicators for the timespan of the data sample. Confidence and sentiment indices are published by different institutions, but are "only" mood indices, therefore, they are less suitable for a nowcast and are used as an input to estimate the target variable. It has been shown that consumer sentiment measures can add additional timely information and improve the forecast performance of consumption related variables (Wilcox, 2007). Moreover, their publication lag is zero months, which makes a nowcasting redundant. As mentioned above, yearly and quarterly indices are not of great interest either due to their low frequency. Private consumption can be split up in different categories according to the UN's COICOP classification (Classification of

Figure 1: Possible target variables



Notes: This figure shows the development of the three target variables that were deemed appropriate for the nowcast exercise. The abbreviations in the graph titles stand for the following: *sa* = seasonally adjusted, *ca* = calender adjusted, *M* = monthly, *Q* = quarterly, and *mil* = million.

Individual Consumption According to Purpose), but for Switzerland there are no indices reflecting a single category with a frequency higher than yearly.[19]

The most suitable indicator is the *retail trade turnover index*, short DHU for "Detailhandelsumsatz" in German. The DHU represents the demand for products procured by households in the retail sector and is an important component of private consumption. According to the HABE[20] it is approximately 11.4% of total household expenditure. However, if only the *consumer spending* and not *compulsory transfers* are considered, it increases to around 21.8% and, hence, quite an important part (see Table B9 in Appendix B for more information of the different shares). The monthly economic statistic is published by the FSO. In this thesis, I look at the monthly change in the index. This key figure gives an indication of whether retail sales are developing positively or negatively. Since the variable is seasonally adjusted, it is possible to compare the value with the previous month.[21] For this reason, the first difference of the logarithmised DHU multiplied by 100 is nowcasted. The DHU has mostly moved sideways with some ups and downs until recently when the Covid-19 pandemic started and preventive measures were implemented. There was a huge plunge due to the March 2020 lockdown with a strongly negative growth rate. The subsequent readjustment

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[19] See the following link for yearly data `www.bfs.admin.ch/statistiken`

[20] HABE stands for *Household Budget Survey* (Haushaltsbudgeterhebung) and can be found here `www.bfs.admin.ch/HABE`.

[21] For the seasonal adjustment, the FSO uses the SAS software and the X-12-ARIMA method. For the calendar adjustment they calculate an average weight of the individual days of the week for each series and then apply this to each month. The X-12-ARIMA reference manual can be found here `https://www.census.gov/ts/x12a/v03/x12adocV03.pdf`.

was even more pronounced, overshooting the pre-lockdown level. The measures imposed by the government strongly impacted retail sales, especially in the non-food sector.[22] Gastro and cultural establishments were completely closed, while grocery shops were allowed to be open. Goods are increasingly bought online, which makes the current crisis more of a service sector crisis compared to previous crises such as the 2008/2009 financial crisis. However, as this sector can rebound relatively quickly, a V-shaped recovery can be observed. The last observed month in the sample, March 2021, experienced a strong increase. According to FSO (2021), all sectors were growing strongly. First and foremost, however, the sectors "household appliances" and "information and communication technology".

4.2 Predictor variables

The dataset consists of around 180 variables from three categories: hard/quantitative data, indices and price indices, and soft/qualitative information (surveys). The dataset summary statistic can be seen in Figure 2, Table 2, and Table B12 in Appendix B.[23] Almost all indicators are either monthly or daily.[24] The *Data Categories* pie chart in Figure 2 shows the different topics to which the variables can be related. The last pie chart shows the number of *hard*, *soft*, and *indices* data. The exact number of variables in the model varies over time. This is the case because not all indicators have a long history and can only be included for more recent estimates. Thus, depending on the data vintage and model specification, not all variables are included. The monthly variables have around 76 observations and are available from the start of the sample (January, 2015). For the daily variables the number of observations strongly varies with a maximum of 2300 for the Google Trends data and a minimum of 368 for a car traffic indicator measured in Zurich. The variables with the fewest observations are the weekly mobility data with only 68 observations (data from a joint project of the ETH Zurich and the University of Basel).

Financial variables such as stock indices or exchange rates have timely information but tend to be quite volatile and if enough macroeconomic variables are included they have a limited role in the nowcasting (Bok et al., 2018). Knotek II and Zaman (2019, p.1709) conclude that including only a few financial variables "may reflect idiosyncratic financial market fluctuations that are unrelated to contemporaneous economic conditions" and, hence, worsen the short-term forecast. Including a

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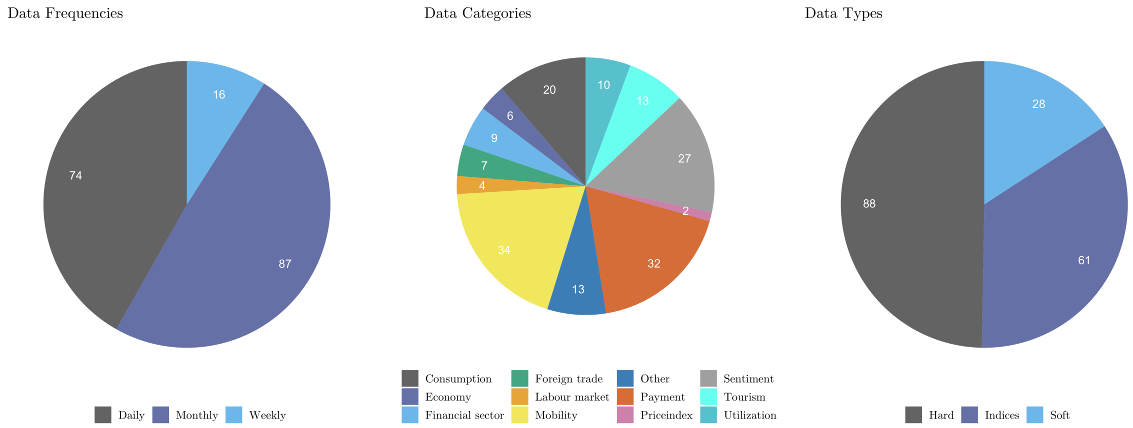
[22] For an overview of all measures and ordinances implemented by the Swiss government please visit `www.bag.admin.ch`.

[23] Table B12 shows more details on each variable (transformed) such as the mean, the standard deviation, and the number of observations.

[24] Most of the high-frequency data are available at `https://kofdata.netlify.app` and at `https://statistik.zh.ch/`.

Figure 2: Data summary charts



Notes: This figure shows summary statistics of the predictor variables in the dataset. The numbers are representative for the model that includes all variables (ALL).

great number of indicators may reduce that risk. However, an advantage of financial data is that they are not revised. Therefore, this thesis includes the Swiss Market Index, but no single stock titles and also refrains from including the exchange rates with the US dollar and the Euro.[25] Another type of data are survey data. These provide important information because, on the one hand, they are timely and, on the other hand, they reflect the opinion of market participants who themselves act as now/forecasters by using all available information to form an opinion. As Wilcox (2007) (cited in Vosen and Schmidt (2011, p.567)) put it, "macroeconomic variables indicate consumer's ability to spend and survey-based indicators try to capture consumer's willingness to spend, the Google indicator intends to provide a measure for consumer's preparatory steps to spend." The survey data included in the dataset are the KOF business tendency surveys, the Purchasing Manager's Index (PMI), and the sentiment variables.

All variables are seasonally adjusted by using the X-13ARIMA-SEATS procedure,[26] made stationary by differencing or log-differencing, and are standardized.[27] The standardization prevents overweighting series with large variances in the determination of common factors. Some of the daily variables were also transformed to represent the 7- or 30-days-rolling mean, since they still displayed some seasonality and were too noisy (see Table 2 for more details on the transformation of the vari-

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[25] See e.g. Andreou et al. (2013) for a discussion of financial variables. They include daily financial indicators in their MIDAS regression and find improvements in the forecasting performance. I also included more financial indicators such as the exchange rates, but the results did not improve.

[26] For daily and weekly series the X-13ARIMA-SEATS approach does not work and, therefore, this thesis relies on Taylor and Letham (2018)'s approach.

[27] As suggested by Siliverstovs and Kholodilin (2010) the PMI and the KOF business tendency survey are not transformed but also standardized.

ables). Some recently published mobility and utilization capacity variables are only available for Zurich. It is assumed that this region is representative for the whole of Switzerland.

4.2.1 Payment transaction data

In the wake of the Covid-19 crisis, Worldline and SIX Payment Services have made anonymized and aggregated transaction and payment data available so that they can be used in academic research. The data are made public by the Monitoring Consumption Switzerland project.[28] This is a great opportunity to integrate timely and stable data into the modelling process to nowcast the DHU. It is essentially a measure of consumption in real-time since the data capture a broad range of spending activities. This thesis uses the *acquiring data* which start on January 1, 2019. The data differentiate the payment method (credit cards, debit cards, and mobile payment), the cardholder origin (domestic versus foreign), the channel (e-commerce and point-of-sale (POS)), and between the amount of the transaction and the number of transactions per day.[29] The reported payment transactions were carried out with merchants in Switzerland. Figure 3 shows the development of three variables from the payment dataset during the Covid-19 crisis. A study undertaken by Trütsch et al. (2019)[30] finds that debit cards are still the most used means of payment in Switzerland, but mobile payment is increasing. This is confirmed by Figure 3. Moreover, there is a significant drop in the number of transactions after the implementation of the first lockdown (March 17, 2020). A highly similar development can be observed for the amount per transaction. After the initial drop the curves go back to the pre-lockdown level, whereas the mobile payments overshoot the pre-lockdown value. With the intensification of the protective measures on December 22, 2020, and the subsequent lockdown, there is another dive. However, this time not as severe. The benefit of including such timely data has been shown by e.g. Galbraith and Tkacz (2018) who find that payment system data improved the nowcast for GDP and retail sales growth. Since the data are quite volatile and demonstrate a big seasonal pattern, the thesis controls for weekdays, months, Christmas period, and Black Fridays. In addition, the 30-days-rolling mean is taken. This process will smooth the series. Since the target variable (DHU) is monthly and retail sales are not really volatile, it makes sense to have a series that has some degree of correlation with the target variable.

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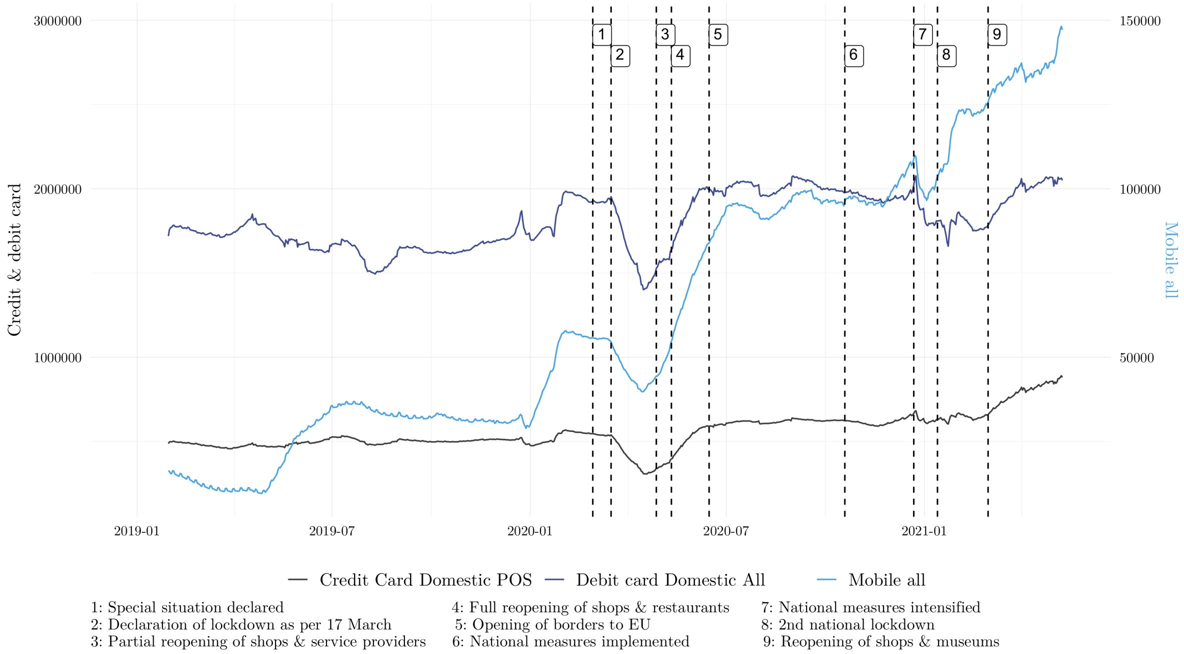
[28] `https://monitoringconsumption.com/project/`

[29] The mobile payment include payments that are debited directly to the bank account, e.g. TWINT. The data can be downloaded here: `https://monitoringconsumption.com/data/`

[30] See their website `https://www.swisspaymentmonitor.ch` for more information.

Figure 3: Payment transaction data (number of transactions)



Notes: This figure shows the 30-days rolling mean of the payment data from Worldline and SIX Payment Services. On the left hand side is the scale for the credit and debit card data and on the right hand side is the scale for the mobile payment data.

4.2.2 Search engine & mobility data

Another type of high-frequency data that is included in the model are search engine data. Google Trends data have already been used to forecast private consumption by e.g. Woo and Owen (2019) who found that it provides additional information to the model. Search engine data are timely and depict what market participants are currently looking for. Compared to traditional variables, these indicators provide forward-looking information beyond what is already captured in the macroeconomic indicators. This thesis uses data provided by trendEcon which are based on Google Trends data.[31] I also created three basic Google Trends indicators based on simple keywords related to the food sector, online shopping, and names of big retail stores.[32] The Google Trends time series index provides the volume of search queries entered into Google by users based on the IP address. The maximum in the specified time period is normalised to the value 100.

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[31] trendEcon is a collaboration between economists from the KOF Swiss Economic Institute, the economic forecast division of the State Secretariat for Economic Affairs (SECO), the Swiss Federation of Trade Unions (SGB), cynkra, and the University of St. Gallen (see `https://www.trendecon.org`).

[32] The keywords used for the three trends are the following; food sector: Coop, Migros, Aldi, Denner, Spar, Volg, Lidl; retail stores: Manor, Globus, Jelmoli, Mediamarkt, Ochsnersport, Orell Füssli; online shopping: Zalando, Digitec, Galaxus, Coop@home, leshop, Amazon.

Depending on the frequency, Google allows you to display a longer or shorter time period. For daily frequency one can choose a time span of at most nine months. In order to get a daily index for a longer period, the daily Google Trends data are collected for different subsets of nine months and then aggregated by properly adjusting them.[33] In addition to this, also the OWID Google mobility trends data are used.[34] These indices use anonymized data provided by apps, e.g. Google Maps, and measure the number of visitors to certain locations.

4.2.3 Further data

To complete the dataset, also traditional economic indicators are used. Table 2 shows all sources of the explanatory variables. The table shows the frequency, the approximate publication lag, and also the transformation of the variables. The additional variables include e.g. the number of bankruptcies on a daily basis. An increase in bankruptcies might indicate an economic slowdown which could manifest in lower consumption. Especially during the current crisis this might be a valuable indicator. However, there was no special increase in bankruptcies during the start of the Covid-19 pandemic (Eckert et al., 2020). This is probably also due to the support of the government. The number of bridging loans skyrocket at the beginning of the pandemic.[35] Others are the PMI, Consumer Price Index (CPI), and Swiss foreign trade. As Switzerland is a small open economy, the country is strongly influenced by the world, which is why variables that capture external economic activity are also included (Swiss foreign trade). Figure 4 shows the development for a selection of explanatory variables over the period from the beginning of 2019 until now compared to the target variable (seasonally adjusted but not transformed). Most of the indicators show similar developments and a strong correlation. Except *unsecured utilisation loans* does not follow the DHU at all (excluded from the dataset). Some other variables seem to react with a small lag, such as the *KOF activity index* or the *trendEcon mobility index*. The quick rebound of the DHU is not matched by several other indicators such as *overnight stays total* or *flights from the airport Zurich*. These stay below the pre-pandemic level for a longer time. Especially high correlations can be observed for the indicators *car registrations* or as well *credit card domestic POS*. Interesting is also that the *confederation bond yield* anticipated the plunge in March 2020. As already mentioned above, not all of the variables are available before 2020 or 2019. Therefore, there are different

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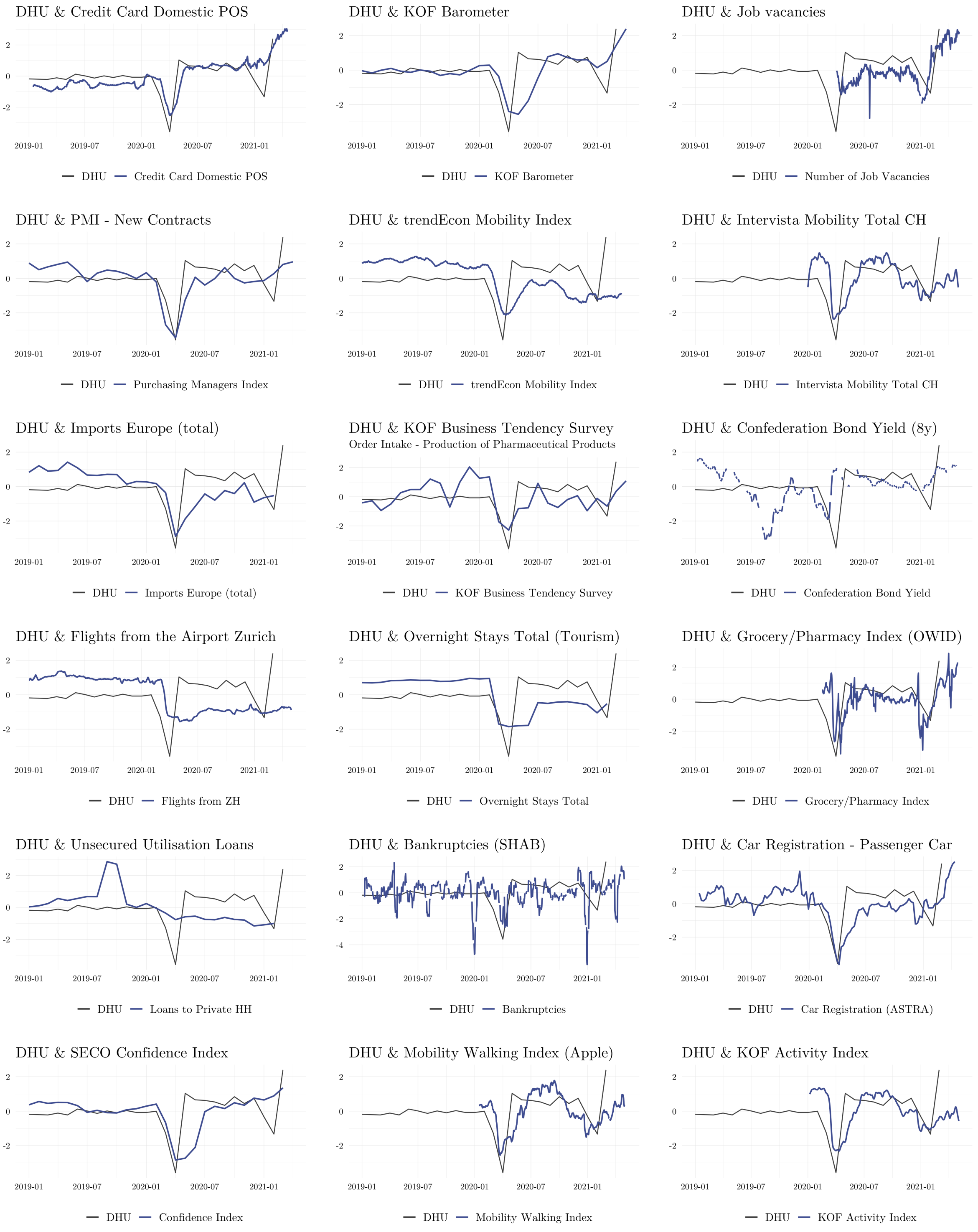
[33] Weekly frequency data are available for the past five years and for monthly frequency it goes back to 2004 (which is when these data were offered for the first time). Therefore, one can use lower frequency data to adjust the index. The methodology used can be found here: `https://github.com/dballinari/GoogleTrends-Scraper`.

[34] OWID stands for *Our World in Data* and the data can be found here: `https://ourworldindata.org/covid-mobility-trends` (or also on the Google website `https://www.google.com/covid19/mobility/`). The indices show the change to a baseline period in January and February 2020 and represent the 7-day-rolling mean.

[35] See `https://covid19.easygov.swiss/fuer-medien/`

Figure 4: Target variable and a selection of explanatory variables



Notes: The graphs show the standardized series over the timespan from 2019 - 2021 compared to the target variable.

Table 2: Overview of the explanatory variables

Variable	Freq.[a]	Publ. lag[b]	Category	Approx. timing (last update)	Transform[c]	Source
Indicators based on Google searches	D	0D	Consumption	-	Δ, log, sa, 30d	trendEcon
Watches and jewellery					$reg(t)$, sa	
Mobility					sa	
Travel abroad					log, sa	
Cultural events					sa	
Gardening and home improvement					$reg(t)$, sa	
Clothing and shoes					$reg(t)$, sa	
Food delivery					$reg(t)$, sa	
Retail					log, sa	
Google mobility trends	D	8D	Mobility	-	Δ	OWID
Retail and Recreation						
Grocery and pharmacy stores						
Public transport stations						
Parks and outdoor spaces						
Workplace visitors						
Time spent at home						
Google Trends data[d]	D	2D	Sentiment	-	$reg(t)$, sa, 30d	Google
Apple mobility data	D	1D	Mobility	-	log-Δ, sa, 7d	Apple
Drive						
Transit						
Walking						
Unemployment rate	M	1M (31D)	Labour market	begin following month	sa	FSO
KOF Barometer	M	0M (25D)	Economy	begin following month	Δ	KOF
Activity index	D	0D	Economy	-	Δ	KOF
Mobility index	D	7D	Mobility	-	Δ, sa	FSO/intervista
Index of weekly economic activity	W	2W (13D)	Economy	begin following week	sa	SECO
Mobility by means (avg trip dist & # trips)	W	2W (13D)	Mobility	begin following week	Δ	ETH/Uni BS
Employment data			Labour market		Δ, sa	AMSTAT
Vacancies	D	0D		-		
Jobseekers	D	0D		-	7d	
Businesses	D	2D	Economy	-	7d	SHAB
Bankruptcies					sa	
Debt enforcement					log, sa	
New companies					sa	
Car registration	W	0W (7D)	Utilization	end following week	sa, yoy	ASTRA
Hotels & spas (supply/demand)	M	2M (60D)	Tourism	begin month after next	sa	FS0
Overnight stays (tourism)	M	3M (96D)	Tourism	end of month	Δ, sa	FSO (SNB)
Use of services	D	7D	Utilization	-	7d	Statistics ZH
# of train arr/dep. at ZH HB					Δ, sa	SBB
Freq. of pers. passing at Hardbrücke					log-Δ, sa	
Usage online learning platform					log-Δ, sa	
KOF business tendency survey data	M	0M (21D)	Sentiment	begin following month	sa	KOF
Credit card transactions (**n**umber & **a**mount)	D	3D	Payment	-	30d	SIX
ATM withdrawal					log-Δ, sa	
Credit domestic E-commerce					Δ, sa	
Credit domestic POS					log-Δ, sa	
Credit foreign E-commerce					n=Δ, sa	
Credit foreign POS					Δ, sa	
Debit domestic					n=log-Δ, sa	
Debit foreign					n=Δ, sa	
Mobile					$reg(t)$, sa	
Number of payment cards	M	2M (85D)	Payment	end of month after next	Δ, sa	SNB
Payment and cash withdrawals	M	2M (85D)	Payment	end of month after next	various, sa	SNB
Loans (mortgages & credits)	M	2M (85D)	Financial sector	end of month after next	Δ, sa	SNB
10 year gov bond rate	D	31D	Financial sector	-	Δ, 7d	SNB/BIS
Consumer Price Index	M	0M (50D)	Price index	end following month	Δ	FSO
PMI (Industry & service)	M	0M (31D)	Sentiment	begin following month		Procure/CS
Swiss Foreign Trade (EU, GER)	M	2M (85D)	Foreign trade	end of month after next	Δ	FCA[e](SNB)
Swiss Market Index	D	1D	Financial sector	-	Δ	yahoo

[a] D = daily, M = monthly, Q = quarterly, Y = yearly

[b] Max delay observed after reference period.

[c] log = logarithmised; Δ = first difference; $reg(t)$ = regressed on time; sa = seasonally adjusted; 7d = 7-days-rolling mean; 30d = 30-days-rolling mean; yoy = year-on-year

[d] See e.g. (Gil et al., 2018. p.14) who use Google data in their research.

[e] Federal Customs Administration (FCA)

variables in the period before and after 2019/2020. In addition, several variables were excluded due to a lack of correlation with the DHU, whereby the estimation results could be improved. These include *shortwork*, daily *bridging loans* or daily *Covid-19 cases* which had explosive patterns largely unrelated to the DHU index and where only available for a short period. Moreover, all quarterly indicators such as job market statistics or quarterly gastro revenues were excluded due to their low frequency.

5 Empirical application

This section employs the methodology described in Section 3, explains the nowcasting exercise for the different model specifications, and discusses the results of the estimation. Several specifications of the model are compared in order to determine whether payment and high-frequency data can improve the nowcasting performance and its accuracy in the case of Switzerland.[36] The list below shows the various model specifications where the basic univariate model (AR(1)) and the random walk model (RW) are used as benchmarks (using $p = 1$ for the autoregressive model is typical in the literature).

- A factor model that includes all data (monthly, weekly, and daily) and is estimated at a daily frequency (ALL);
- a factor model where only monthly indicators are included, estimated at a monthly frequency (MO);
- a factor model where only daily indicators are included, estimated at a daily frequency (DO);
- a factor model where only daily payment indicators are included, estimated at a daily frequency (PO);
- a factor model with only a small selection of variables, estimated at a daily frequency (SO);
- the above mentioned models where the number of factors is restricted to one (*ALLF1*, *MOF1*, *DOF1*, *POF1*, *SOF1*);
- a naïve random walk model (RW);
- an AR(1) model (*AR1*).

The reason for implementing a model with pre-selected variables is because Boivin and Ng (2006) show that a model based on a smaller subset of data can outperform a large-scale factor model.

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[36] The models in this thesis do not include autoregressive components of the target variable as predictors and, thus, follow the approach of Giannone et al. (2008). This would be possible and the literature uses both approaches, see e.g. Jansen et al. (2016) who show that including lags improved the nowcast performance for GDP growth. In order to capture some momentum or autoregressive components one could also just use the lags of the factors.

Moreover, also M. Modugno suggested to perform a preliminary selection (personal communication, May 4, 2021). For Switzerland however, Galli et al. (2017) conclude that a small selection performs inferior in monitoring economic activity. The selection in this thesis includes 12 indicators, which is similar to Camacho and Martinez-Martin (2014) who use 11 variables in their research. The indicators are selected based on their statistical correlation, their timeliness, and their economic meaning. In order for the selection to be representative of the mixed-frequency approach and, thus, comparable with the other model specifications, the indicators also represent the three frequencies (monthly, weekly, and daily). For two variables this thesis follows the selection of Galli et al. (2017) (KOF survey data and PMI). Eventually, this led to the following choice of variables: (1) number of credit card transactions at point-of-sale (domestic) (D) and (2) amount of debit card payments (domestic) (D). Both variables are highly relevant and are directly related to the DHU index. They display a strong correlation with the target variable and debit cards are the primary means of payment in Switzerland (see Figure 3). In order to represent the physical cash usage, also the (3) cash withdrawal (credit cards) (M) are included. From a survey perspective, the (4) PMI - new contracts (M) and (5) KOF business survey (order intake - production of pharmaceutical products) (M) are included. These have a high importance in Switzerland, are timely available, and strongly forward-looking. (6) OWID grocery & pharmacy index (D), (7) KOF sales activity index (D), and (8) trendEcon social index (D) record the visitors going to grocery and pharmacy stores, the daily compound sales and buying activity of the Swiss population, and the cultural events sector. All three indicators have a high economic meaning related to the DHU and are also quite relevant during the Covid-19 pandemic. In order to reflect the average mobility of the population, this thesis includes the (9) Apple walking index (mobility) (D) which uses the requests for direction in Apple maps and the (10) trendEcon mobility index (D) which analyses requests for ground transportation in general. To round up the selection, also two weekly indicators are included which are the (11) car registrations (private car) (W) and the (12) SECO weekly activity index (W) which measures the overall growth of the Swiss economy.

5.1 Estimation & nowcasting exercise

The data sample spans just under five and a half years over the period from January 2015 to April 2021. The reasons for the rather short time-period are changes in the collection methods of various variables and some structural breaks before 2015.[37] Moreover, almost all high-frequency data are only available since 2019/2020. The first out-of-sample nowcast is estimated for January 2019 and subsequently for each month until April 2021. The nowcast is updated each week. Hence,

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[37] These variables include e.g. the loans indicator or the number of payment cards and ATMs.

the initial parameters stay constant for the weekly updates during the month and are estimated in-sample. The updates of the nowcast are out-of-sample. Every time there are new data available, the information set Ω increases and the latent states (factors) can be updated using the Kalman filter and smoother. The news coming from the newly available data are expected to affect the accuracy of the estimation. This method makes it possible to update the nowcast every day and the model allows for a real-time estimation.

In order to reconstruct the real-time data flow and estimation, different data-vintages were created where the ragged edge and the publication delays were replicated by following a stylized publication calender. The assumption that the publication dates do not change too much over time is common in the literature (see e.g. Giannone et al. (2008)).[38] The data vintages include also revised data and, therefore, it is essentially a *simulated pseudo real-time nowcasting exercise*. As mentioned in Section 4, many of the high-frequency variables are only available later in 2019 or 2020. This implies that these indicators only enter the model when they are available (i.e. they are not included in the initial PCA estimation for the estimates in early 2019). To illustrate the nowcast estimate, suppose it is towards the end of May (May 25) and the last release date of the DHU data was in early May where the March value was released (see Figure 5a for an illustration). Hence, the official values for April and May are not yet published and, thus, not observed. This implies that there are two months that can be predicted, the current month (nowcasting) and the previous month (backcasting). Many other indicators are already available for days or weeks within these two months, and some monthly indicators are observed for one or both months. These new datapoints are used to reestimate the common factors which are then used to nowcast the target variable. As time moves on, more and more datapoints will be available for April and March, the months in-between the current date and the date where the target variable, DHU, was last observed. The models that include daily indicators will give an estimate of the DHU for each day. Thus, for the ongoing month always the last available estimate is taken. The monthly model (MO) only yields estimates for the previous month. This is because the data are not published as frequently and timely as the higher frequency variables, i.e. there are no monthly indicators published for a month in that same month. The newly estimated factors only go up to the most recently observed variables.

Figure 5b shows how the prediction changes over the period of two months (here February, 2020 is chosen as an example). The first four updates are estimated in real-time (actual-month estimations), the last four updates are from the weeks in the following month (therefore essentially backcasts or previous-month estimations). The official number is not observed for the whole period of the two

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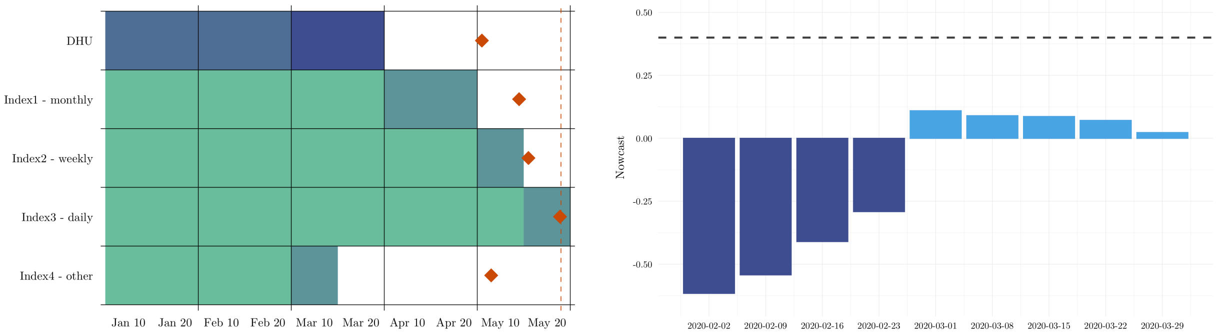
[38] To reconstruct the availability of the data at the respective days, February 2021 is used as a reference month for the stylized calender (the four Sundays where February 7^{th}, 14^{th}, 21^{st} and 28^{th}).

Figure 5: Delays, publication dates, and evolvement of the nowcast



(a) Simulated delays and publication dates.

(b) Development of the nowcast over time.

Notes: Subfigure (a): The red points show the publication date of the respective series. The darker part for each series (row) shows the most recently published data and the red dashed line is the current date (today or with respect to the example, May 25). Subfigure (b): This subfigure shows the evolution of the nowcast value for one example month. The dashed line represents the actual value for that month. The dark blue bars represent the current-month estimations and the light blue bars represent the previous-month estimations. The available information increases over time. The month shown is February 2020 and the estimations are from the model *PO*.

months. The figure shows the improvement of the nowcast over time as more information becomes available, which intuitively makes sense. However, the nowcast gets slightly worse towards the end. Although this observation is generally true, this development is not always the case and sometimes the nowcast deteriorates over time.

The number of common factors, r, is determined according to criterion IC_2 from Bai and Ng (2002) but with a maximum of 5 factors. This ensures parsimony and reduces the risk of overfitting the model. In addition, the number of observations at the beginning of the sample is rather small (e.g. 48 for the model MO). The number of lags, p, for the transition equation is chosen to be 1 and 2. The assumption that $p = 1$ is common in the literature (see e.g. Banbura et al. (2010) or Bańbura and Modugno (2014) who use 1 and 2 lags).[39] Moreover, Kuzin et al. (2013) suggest that pooling over different specifications, rather than selecting one model, yields a more stable nowcast accuracy over time. Therefore, also the averages over the different model parametrization are reported and compared to the other models. These variations not only help to find the best model but also allow to check the robustness of the models with respect to the parametrization.

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[39] Alternatively one could use an information criterion such as the BIC (Galli, 2018).

5.2 Results & performance measures

As explained above in Section 3, the nowcast is obtained as a projection of the target variable on the common factors. The models are evaluated by looking at the out-of-sample nowcasting performance during the period from January 2019 to April 2021. These are in total 28 months. Different data vintages are used to mimic the real-time data flow which implies that the performance measure of the out-of-sample nowcast happens in pseudo real-time. Figure 6 shows the in-sample fit of this projection for the above mentioned models.[40] The figure shows that the models do not perfectly replicate the DHU growth rate over the period from 2015 to 2021. Especially the decline and subsequent increase in turnover after the first lockdown due to the Covid-19 pandemic in early 2020 is underestimated a lot. During this volatile period the models *MO* and *PO* have the best in-sample fit. The R^2 values for the in-sample fits are shown in Table 3. Especially the monthly model with four factors closely follows the development of the growth rate. The high R^2 value for *MO* might be attributable to the fact that this model contains less unrelated noise. The 1-factor model performs equally well or better than using multiple factors for the models *POF1* and *SOF1*. For the models *ALLF1, MOF1* and *DOF1* it performs worse.

Table 3: In-sample R^2

	ALL	MO	DO	PO	SO	ALLF1	MOF1	DOF1	POF1	SOF1
R^2	0.1943	0.9622	0.0128	0.2549	0.1728	0.0360	0.1913	0.0066	0.4440	0.2967

Notes: This table shows the R^2 of the in-sample fit for the different models.

However, more important is the prediction accuracy and the out-of-sample performance of the models. Figure 7 shows the different rolling out-of-sample nowcasts for the models specified according to their best performing parametrization.[41] The out-of-sample nowcast performance is measured using the root mean squared error (RMSE) and is applied to the overall rolling out-of-sample estimation of the models. All models perform more accurately when specified with more than one factor. The majority of models achieve the best RMSE with 5 factors. With respect to the order of the AR(p) of the transition equation, some models perform better with $p = 1$, others with $p = 2$. In Figure 7 it can be seen that all models except the monthly model have similar prediction paths.

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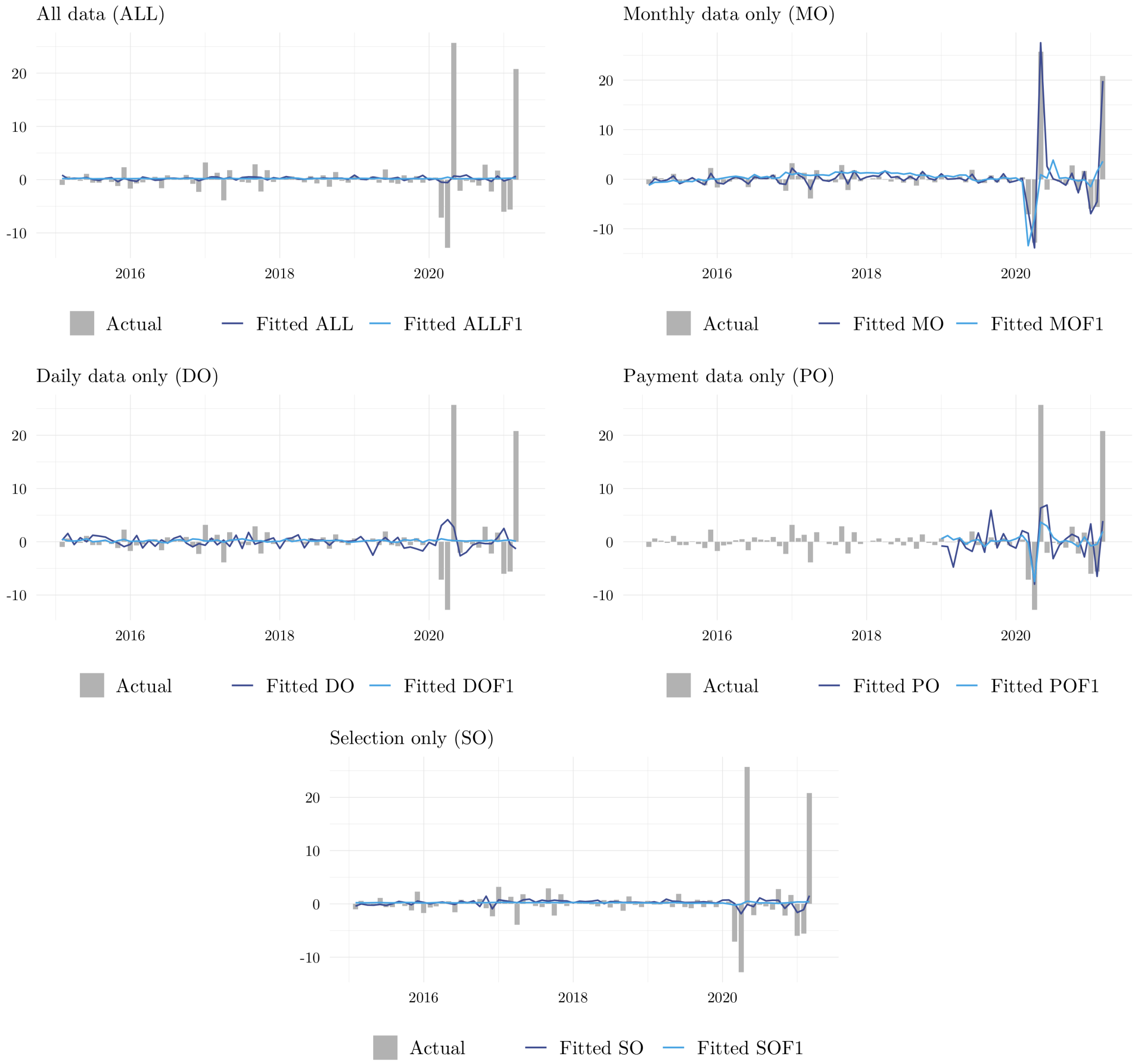
[40] For the in-sample fit at daily frequency for the models *ALL, DO, PO*, and *SO*, see Figure A2 in Appendix A. Figure A3 in Appendix A shows the in-sample fit comparison in a joint graph.

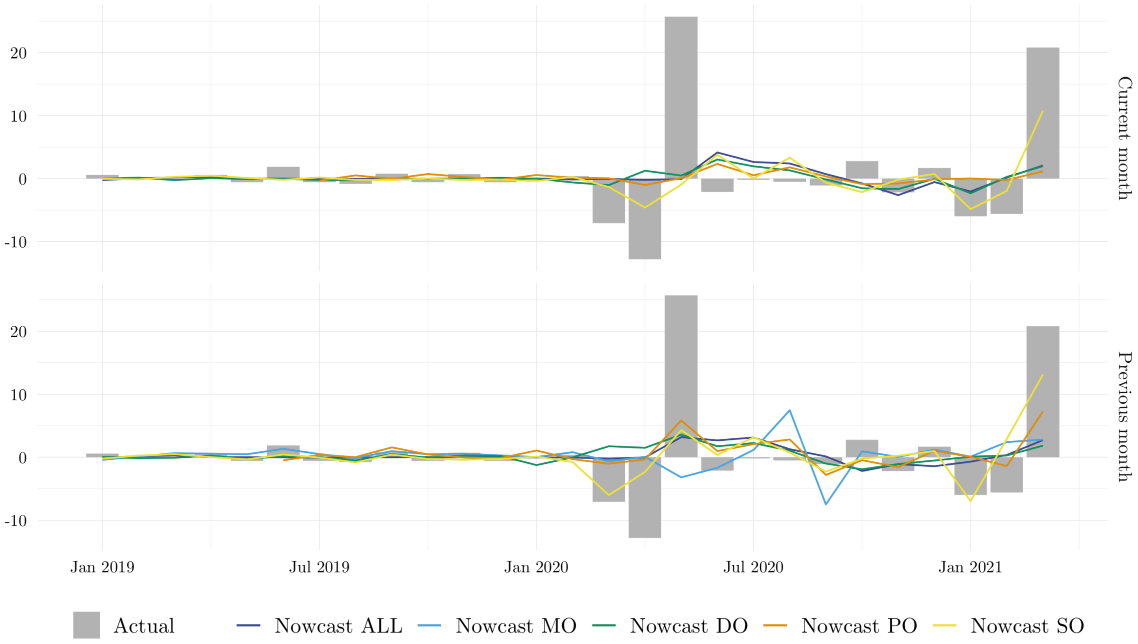
[41] The best root mean squared error (RMSE) results were obtained for the following specifications: *ALL*: $p = 2$, $r = 3$ for the current-month estimation and $p = 1$, $r = 2$ for the previous-month estimation; *MO*: $p = 1$, $r = 5$; *DO*: $p = 2$, $r = 5$ current-month and $p = 2$, $r = 3$ previous-month; *PO*: AVG (average over all specifications) current-month and $p = 2$, $r = 5$ previous-month; *SO*: $p = 1$, $r = 5$ for both months. Further illustrations showing the out-of-sample nowcast for each model and the individual weeks can be found in figures A5, A6, A7, A8, and A9 in Appendix A.

Figure 6: In-sample fit for the five different models



Notes: The in-sample fits are estimated using the parameters $p = 1$ and $r = 4$, where p stands for the number of lags in the transition equation and r for the number of common factors. For the model *PO*, the fit starts only in 2019 since the data are only available starting from then.

Figure 7: Rolling out-of-sample nowcast - comparison best RMSE models



Notes: This figure shows the out-of-sample nowcast using the best performing model specifications according to the RMSE. These are the following: ALL: current-month = $(p2, r3)$, previous-month = $(p1, r2)$; MO: $(p1, r5)$; DO: current-month = $(p2, r5)$, previous-month = $(p2, r3)$; PO: current-month = (AVG) (average over all specifications), previous-month = $(p2, r5)$; SO: current- and previous-month = $(p1, r5)$, where p stands for the number of lags in the transition equation and r for the number of common factors. For this illustration the average across the weekly updates are used for each model.

The model *SO* also slightly deviates from the common prediction. Moreover, the nowcast improves as more information becomes available since the prediction for the previous month is more accurate than for the current month. The drop in retail sales turnover during the first lockdown in March 2020 was not anticipated well by the models, except for the model *SO* which captures some of the downturn. The subsequent recovery shortly after in May 2020 is nowcasted more accurately. The development of the growth-rate is especially well captured by the model *SO*. For a graphical illustration of the out-of-sample results for the simple 1-factor models see Figure A4 in Appendix A. The model *DOF1* improves its prediction along the nowcasting period for the current-month nowcast estimation substantially. For the most recent months (November 2020 - March 2021) the predictions were quite accurate. Moreover, the model *MOF1* nowcasts the drop in March 2020 with a lag of approximately two months. In general, the growth-rates of the DHU tend to be more volatile than what the models predict. This can also be observed by looking at the standard deviation of the actual growth rates versus the predicted growth rates (see Table 4).

Table 4: Out-of-sample standard deviation

	DHU	ALL	MO	DO	PO	SO	ALLF1	MOF1	DOF1	POF1	SOF1	AR1	RW
							Current month						
SD	7.326	1.253	-	1.119	0.805	2.767	0.862	-	0.677	0.585	0.493	3.611	6.014
							Previous month						
SD	7.326	1.09	2.358	1.001	3.649	3.436	0.927	1.848	0.786	1.858	0.832	4.436	6.108

Notes: This table shows the standard deviation of the out-of-sample estimation for the different models. For the calculation of the values, the best-RMSE model specifications were used. These are the following: *ALL*: current-month = $(p2, r3)$, previous-month = $(p1, r2)$; *MO*: $(p1, r5)$; *DO*: current-month = $(p2, r5)$, previous-month = $(p2, r3)$; *PO*: current-month = (AVG) (average over all specifications), previous-month = $(p2, r5)$; *SO*: current- and previous-month = $(p1, r5)$, where p stands for the number of lags in the transition equation and r for the number of common factors. For the calculation the average across weeks is used.

Varying the parametrization does not significantly change the qualitative performance of the out-of-sample nowcast. The results for different values of p and r show that the models are robust with respect to changes in these parameters.[42] Table 5 shows the RMSE values for each model and each weekly update. The RMSE is reported relative to the *AR1* benchmark model, therefore, a value below one implies that the model performs better than the *AR1*.[43] The choice to compare the results to the *AR1* and not to the *RW* is because the *AR1* outperforms the *RW*. As a statistical

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[42] Tables B4, B5, B6, B7, and B8 in Appendix B show all performance measures which include the root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), and mean absolute error (MAE).

[43] For a qualitative result of the benchmark performance see Figure A1 in Appendix A which shows the one- and two-periods ahead rolling out-of-sample predictions. The current-month nowcast is essentially a two-period ahead forecast while the previous-month backcast is a one-period ahead forecast.

test to compare the models to the benchmark, the Diebold and Mariano (1995) (DM) test is used.[44] The loss function is defined as the squared errors. The table shows that the models *ALL, DO, PO, POF1* and *SO* have a statistically significantly different nowcast accuracy from the *AR1* benchmark model for some or all of the weeks for the current-month nowcast. For the previous-month estimation this is true for the models *PO, POF1* and *SO*. The RMSE decreases over time as more information becomes available, which is graphically illustrated in Figure 8. This implies that the information increase over time improves the nowcast and the uncertainty related to the estimation decreases. Hence, intra-month publications convey new information that matters. There is a substantial difference in the RMSE for the current-month nowcast and the previous-month backcast with a better performance accuracy for the previous month. The RMSE also tends to improve after each weekly update, but not as much as between the months.

Table 5: Nowcast evaluation (RMSE)

	Current month				Previous month			
Model	Week 1	Week 2	Week 3	Week 4	Week 1	Week 2	Week 3	Week 4
ALL	0.8622*	0.8446*	0.8382*	0.8267*	0.746	0.7612	0.7598	0.7607
ALLF1	0.8744	0.8648	0.8557	0.8444	0.8088	0.8108	0.8109	0.8113
MO	-	-	-	-	0.8719	0.8582	0.8715	0.8815
MOF1	-	-	-	-	0.9195	0.9273	0.9429	0.9088
DO	0.8422*	0.8576	0.845*	0.8365*	0.7627	0.7659	0.7675	0.7693
DOF1	0.8643	0.8738	0.8764	0.8684	0.7826	0.7827	0.7802	0.7818
PO	1.0457	0.9984	0.9381*	0.8938*	0.7391**	0.6962**	0.6684**	0.6721**
POF1	1.0297	1.008	0.9616	0.9161*	0.7701*	0.7511*	0.7271*	0.7283*
SO	0.8486	0.7725	0.6926*	0.7329*	0.5998**	0.598*	0.6002**	0.6035**
SOF1	0.8682	0.8638	0.8622	0.8599	0.795	0.7867	0.7844	0.7842

Notes: This table shows the RMSE of the different models at different times. The model specifications are the following: *ALL*: current-month = $(p2, r3)$, previous-month = $(p1, r2)$; *MO*: $(p1, r5)$; *DO*: current-month = $(p2, r5)$, previous-month = $(p2, r3)$; *PO*: current-month = (AVG) (average over all specifications), previous-month = $(p2, r5)$; *SO*: current- and previous-month = $(p1, r5)$. For the 1-factor models it is just $(p1, r1)$, where p stands for the number of lags in the transition equation and r for the number of common factors. The different columns titled *week x* represent the week of the month, so *week 1* implies the first week of the month, i.e. the first weekly update. The reported values are relative to the benchmark RMSE. The asterisks indicate whether the predictive ability of a specific model is significantly different than the *AR1* benchmark. This is measured using the Diebold and Mariano (1995) (DM) test (modified version proposed by Harvey et al. (1997) is used). ***, **, and * stand for a rejection of the null hypothesis with a p-value smaller than 1%, 5%, and 10%, respectively.

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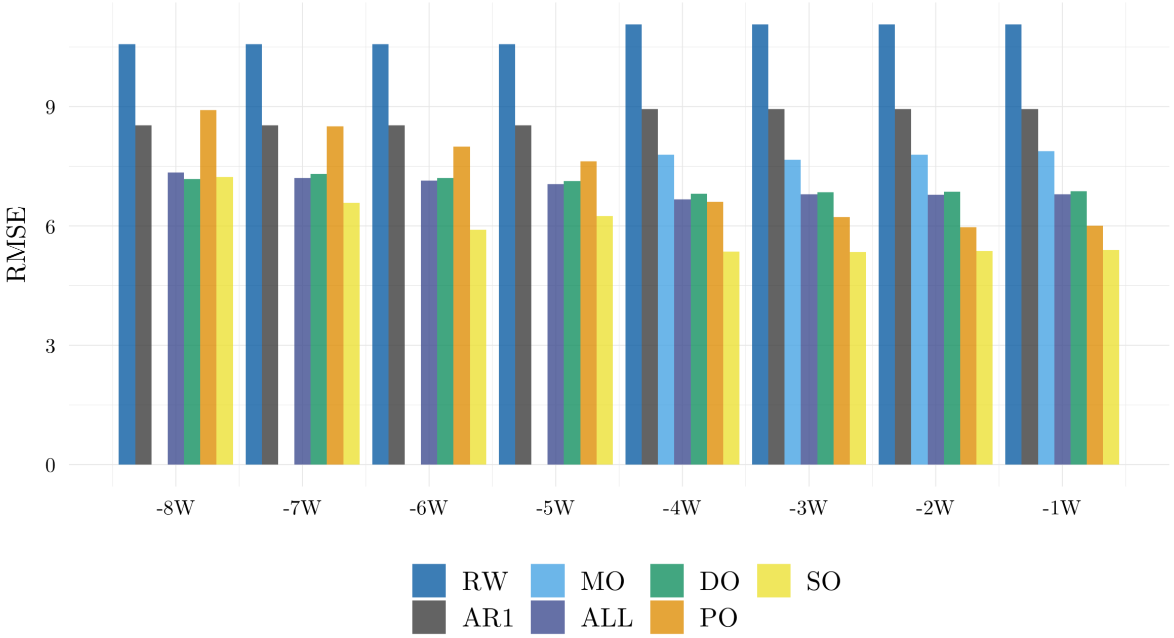
[44] For more DM test results where all models are compared against each other see Table B3 in Appendix B.

Figure 8: Development of the RMSE



Notes: This figure shows how the RMSE changes over time. The markers on the x-axis indicate how many weeks before the publication date of the actual figures the estimate was made. For each model the best performing parametrization in terms of RMSE was chosen. These are the following: ALL: current-month = $(p2, r3)$, previous-month = $(p1, r2)$; MO: $(p1, r5)$; DO: current-month = $(p2, r5)$, previous-month = $(p2, r3)$; PO: current-month = (AVG) (average over all specifications), previous-month = $(p2, r5)$; SO: current- and previous-month = $(p1, r5)$, where p stands for the number of lags in the transition equation and r for the number of common factors.

In addition to the overall out-of-sample nowcast performance analysis, the performance before and after the begin of the Covid-19 pandemic is analysed. The results are presented in Table B1 in Appendix B. The model accuracy is strongly affected by the crisis and the RMSE values increase a lot for the estimation starting in March 2020. All multi-factor models perform worse compared to the *AR1* benchmark for the pre-crisis estimation. This is not true for the 1-factor models, which manage to slightly outperform the *AR1* benchmark (except for the model *DOF1*). In the period after the Covid-19 pandemic started, all models outperform the benchmark significantly, including all 1-factor models. Compared against the *RW* benchmark, all models provide better estimation performance for the pre- and post-crisis period. The multi-factor models perform slightly worse in the pre-crisis period than their 1-factor counterpart. However, during the crisis the multi-factor models significantly outperform the 1-factor specification. The fact that the performance is better for the post-Covid-19 estimation, i.e. during the crisis, could be related to the circumstances that more variables are available. As discussed above, several high-frequency indicators are only available since 2020.

Since the performance of the models is similar in terms of RMSE and across time, it is difficult to determine the "best" performing model. In order to do so, Hansen et al. (2011)'s model confidence set (MCS) is employed. The MCS has an interpretation similar to a confidence interval and yields a *model confidence set* which contains the best models with a certain confidence level. In the case where all models are included in the set, the data were either not informative or all models belong to the best models (with a certain confidence level). The main result of the MCS statistic are the MCS p-values. Intuitively, the MCS p-value represents the highest confidence level at which a model is still included in the model confidence set. Table 6 shows the MCS statistics for the different models. The MCS is estimated using 15000 bootstrap replications, the t.max statistic, and the squared error is chosen for the loss function. For the current-month estimation the MCS puts all models in the $\widehat{\mathcal{M}}^*_{90\%}$ except for the model *RW*. The $\widehat{\mathcal{M}}^*_{60\%}$ contains nine models. Not included are the two benchmark models, the average specifications of the models *ALL* and *DO*, and the model *DOF1*. For the previous-month estimation the $\widehat{\mathcal{M}}^*_{90\%}$ contains all models whereas the $\widehat{\mathcal{M}}^*_{60\%}$ contains only two models. These are the multi-factor models *SO* and *PO*. The best performing models according to the RMSE are also the models with the highest MCS p-values. The inference that can be drawn from the results in Table 6 is the following. Since most of the models are included in the $\widehat{\mathcal{M}}^*_{90\%}$, they have a similar performance. The best nowcast for the current-month estimation is provided by the multi-factor model *SO* while the second best performance is achieved with several other models including the models with only payment data. For the previous-month estimation the best model is the multi-factor model *PO* while the second best is the multi-factor model *SO*.

Table 6: Model confidence set results

Model	Current month		Previous month	
	RMSE	p_{MCS}	RMSE	p_{MCS}
ALL				
Average	7.2427	0.2077*	6.9255	0.3079*
ALLF1	7.3194	0.426**	7.2341	0.2041*
Mult. factors	7.1673	0.426**	6.7537	0.3079*
MO				
Average	-	-	7.8933	0.3079*
MOF1	-	-	8.2398	0.2777*
Mult. factors	-	-	7.818	0.2041*
DO				
Average	7.3427	0.2077*	6.9097	0.3079*
DOF1	7.4441	0.2077*	6.9836	0.3079*
Mult. factors	7.1739	0.426**	6.8399	0.3079*
PO				
Average	8.2159	0.426**	6.4519	0.3079*
POF1	8.3026	0.426**	6.6275	0.3079*
Mult. factors	8.2159	0.426**	6.2522	1**
SO				
Average	7.0329	0.426**	6.5738	0.3079*
SOF1	7.3595	0.426**	7.0364	0.3079*
Mult. factors	6.2442	1**	5.3458	0.6667**
Benchmark				
AR1	8.5248	0.2077*	8.9359	0.3079*
RW	10.5658	0.0931	11.0665	0.2041*

Notes: This table shows the model confidence set statistics based on Hansen et al. (2011). The * and ** behind the p_{MCS}-value indicates that the model is in the $\widehat{\mathcal{M}}^*_{90\%}$ and $\widehat{\mathcal{M}}^*_{60\%}$, respectively. For the multiple factor models, the best performing RMSE model specification were used, which are: *ALL*: current-month = $(p2, r3)$, previous-month = $(p1, r2)$; *MO*: $(p1, r5)$; *DO*: current-month = $(p2, r5)$, previous-month = $(p2, r3)$; *PO*: current-month = (AVG) (average over all specifications), previous-month = $(p2, r5)$; *SO*: current- and previous-month = $(p1, r5)$.

5.3 Discussion of the results

The results clearly indicate that including timely data improves the performance accuracy for the nowcast of the Swiss retail trade turnover index growth rate compared to the simple benchmark models. Furthermore, all models with high-frequency data manage to outperform the monthly model *MO*. The actual point estimates are, however, not extremely precise. A major reason is the structural break in the target variable at the beginning of the Covid-19 pandemic. The significant drop and subsequent spike explain much of the increase for the post-Covid-19 RMSE. Although the RMSE is much lower in the pre-Covid 19 period, the performance of the models in this period is worse than the *AR1* benchmark. This suggests that in ordinary times the models were unable to extract relevant information to nowcast the change in the DHU index more accurately than a simple benchmark model. However, the poorer performance prior to Covid-19 can be partly explained by the fact that the actual growth rate series experienced very little change before the outbreak of the pandemic. A prediction of zero growth for this period would in itself have resulted in a small error, and outperforming the benchmark is therefore inherently difficult. When analysing the data, it becomes clear that many high-frequency variables are only available from early 2019 or 2020 and did not provide any additional information in the pre-pandemic period. This in turn reinforces the argument that timely data contain valuable additional economic signals. Moreover, all models outperform the benchmark models once the growth rate of the retail turnover index becomes more volatile. Consequently, once a nowcast actually starts to provide valuable information, the model is able to deliver superior results compared to the benchmark. Another reason for the rather poor point estimate accuracy is the following: high frequency data move much more than the monthly target variable. Since this thesis includes the variables at their original frequency, the additional volatility could hide economically relevant information. Aggregating the high-frequency variables to a lower frequency is an alternative that has been used by several other studies and in some cases has improved the estimates.

In Figure 8 above we saw that the RMSE is lower for the previous-month backcast compared to the current-month nowcast. One possible explanation is that at the beginning of each month important data are released for the past month, i.e. for the month that is being backcasted. These include the PMI, the KOF business survey, the KOF economic barometer, and the KOF economic sentiment indicator. All of these variables are forward-looking and add relevant information to the model.[45] Each week there are new data released from the daily and weekly variables. Therefore, the higher

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[45] Further monthly publications are the following. For the second weekly update, unemployment data are newly available. In the third week new observations of the SECO confidence index, foreign activity numbers, and several other data from the Swiss National Bank related to payments and loans are published. In the fourth week the CPI data are released.

frequency indicators add new information on a regular basis. This explains the steady improvement of the RMSE over time.

The results of the RMSE performance measure and the MCS statistics strongly indicate that the best models are *PO* and *SO*. Both are based on a selection of indicators. *PO* includes only high-frequency payment data and the model *SO* uses only a small sample of 12 variables. Unlike *PO* and *SO*, the model *ALL* includes all available indicators. The probability that some of the information is not related to the DHU growth rate is therefore higher than in the models that extract the factors only from information that is closely related to consumption in Switzerland. For example, payment data are directly related to retail sales in the Swiss market. As a consequence, one reason why the models with fewer variables perform better than the large models seems to be that the common factors contain less noise that is unrelated to the development of the DHU. Although the monthly model *MO*, which is based on more traditional macroeconomic variables, provided the best in-sample fit, its out-of-sample results did not perform as well. These findings suggest that future nowcast modelling should incorporate timely data. In contrast to the model with only monthly data, *DO* includes only high-frequency indicators. Both approaches were outperformed by using a mixture of frequencies or a selection of variables. Monthly data tend to lag behind, whereas daily data, while timely, evolve at a much higher frequency than the monthly retail turnover growth rate. By limiting the data set to only one of these categories, information is lost. Furthermore, the observed results possibly stem from the fact that the target variable at hand is a rather small index compared to GDP. Since the statistic is specific to one area and covers fewer sectors, it is also influenced by less indicators. Therefore, it could be that smaller indices require fewer and more carefully selected variables. However, if the model is to be used for nowcasting a broader range of indicators, the more general models might outperform the specific models.

The results of this thesis are partly in line with the results of Modugno (2013), who finds that the inclusion of daily high-frequency variables improved the nowcast. More specifically, he notes that using high-frequency indicators improved the nowcast for CPI indicators, but that the data did not help for whichever target indicator. Bańbura et al. (2013) find that the inclusion of high-frequency data does not improve the nowcast significantly. Furthermore, the findings that payment data add important information is in line with Galbraith and Tkacz (2018). However, in their analysis they do not aggregate the payment data. Probably the most comparable study in terms of research question and country is Duarte et al. (2017). They compare the performance of MIDAS regression models with daily and aggregated monthly payment data and find that the aggregated payment data outperform the daily counterpart. Similar to my explanations, they conclude that the daily data are a lot nosier and hamper the extraction of relevant information. Therefore, it would be interesting to investigate whether the aggregation would change the nowcast performance for the study at hand. In contrast to Galli (2018) who finds that for Switzerland it is important to use a broad range of variables, this thesis finds that for the specific index at hand, a smaller subset actually yields a better nowcast performance, since both the PO and the SO outperform the other models.

6 Conclusion

This thesis has used a mixed-frequency dynamic factor model specified at a daily frequency to nowcast the growth rate of the DHU in Switzerland. A key benefit of this model is the possibility to estimate the index in real-time and update the nowcast as soon as new data are available. The framework makes it possible to observe the effect that new information has on the estimate, since the RMSE can be calculated for each update. Further, it allows to use data at their respective frequency and it is not required to aggregate them to the lower frequency of the target variable. The model efficiently deals with asynchronous release dates and the ragged edge. Real-time monitoring of economic activity is a challenge that yields valuable information for various stakeholders. This study complements ongoing research in this area and provides results for the MF-DFM approach for Switzerland.

The main question of this thesis addressed the extent to which high-frequency data, and especially payment data, can be exploited to now- and backcast a consumption related variable in Switzerland. The estimations have shown that daily data improve the nowcasting performance of the MF-DFM. Moreover, payment transaction data are relevant indicators for consumption related target variables. For policy makers and practitioners this is important information as they cannot only rely on traditional macroeconomic variables, but also use other timely data to form opinions and get early indications on the direction of the economy. The potential usefulness of this newly available data type has a great potential in supporting future now- and forecasting.

A potential weakness of this study is the short sample period and the associated relatively small number of observations. In the future, when more observations are available, payment data can be expected to be an even more relevant source of information for the development of retail sales. Although high-frequency data can improve the nowcast accuracy, it is important which variables are used and how they enter the model. Appropriate transformations and data preparations are crucial. Moreover, this thesis does not include indicators related to changes in the behaviour with respect to consumption or demographics. Some of these variables are either not or only available on a much lower frequency. While variables controlling for mobility and payment behaviour are included, proxies for behavioural changes are not. However, in times of crises, mechanisms tend to change as well as behaviours. This could be important to take into consideration (see e.g. Alexander and Karger (2020) who look at how the lockdowns affected the consumer behaviour). Another possible limitation is the extent of external and internal validity of the results. The analysis was conducted for Switzerland, which is a small open economy. Therefore, the results cannot be directly compared or applied to bigger economies. However, the results could be generalised to other small open economies that have similar characteristics to Switzerland. The time period over which the nowcast is estimated includes both ordinary times and a major crisis. Due to the rather short prediction period, the internal validity could be questioned. In these extraordinary and unprecedented times, indicators and the economy in general might follow market mechanisms that are different from ordinary times. It would be important to run the model over a longer time-period to test its internal validity for Switzerland. In addition, one could apply the model to other consumption related variables such as quarterly aggregate consumption.

Last but not least, there are several aspects that could be explored in future research and would be worth analysing. The framework presented here has some limitations and can be extended. The following paragraph discusses some of these aspects. The approach of this thesis was to include relevant data and extract common factors. A further refinement of the factor specification could be to estimate factors that are specific to groups of variables (block structure) (Banbura et al., 2010). Moreover, the data-revision process is not taken into account. The data vintages used to replicate the real-time flow are pseudo-real-time. However, some indicators are strongly adjusted in the retrospect. These revisions change the informational content and the impact of the revision on the nowcast could be studied. Since each series and the release of new data contains a signal of current economic activity, a more profound analysis of the informational content of different macroeconomic data releases would be interesting. This thesis also refrains from modelling the individual idiosyncratic dynamics separately. In a future study it could be tested how the nowcast is affected when an autoregressive model for the idiosyncratic components is specified. In addition, comparing other models such as Ghysels et al. (2007) MIDAS methodology or a Bayesian approach to the MF-DFM would be interesting.

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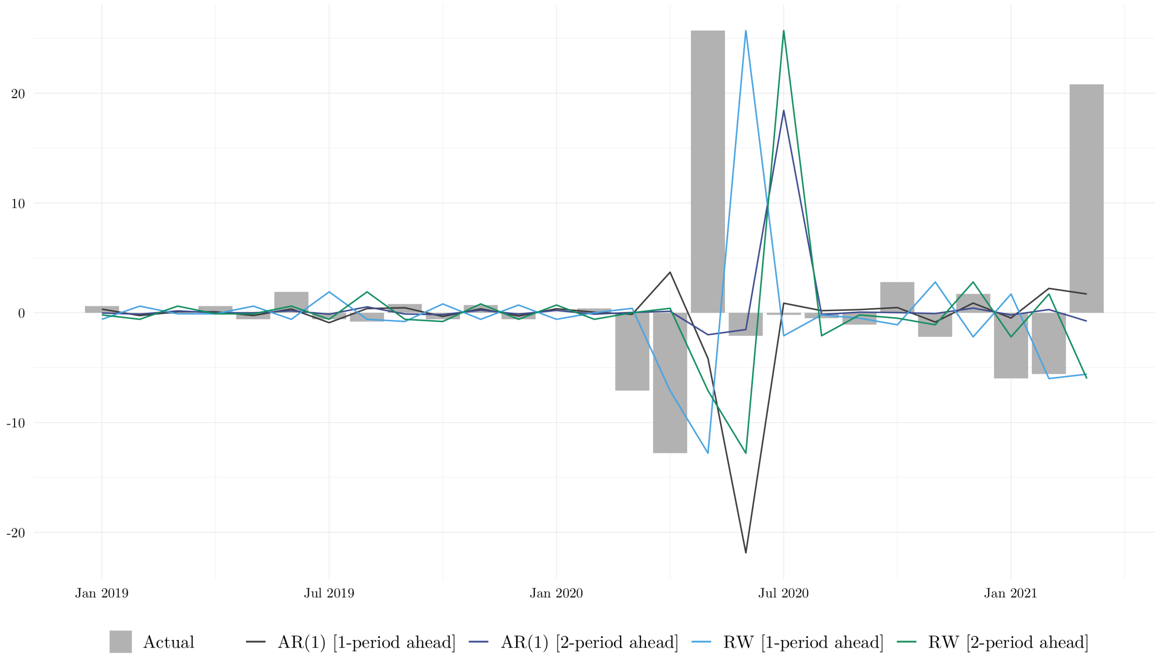
Appendix

A Additional figures

This section contains several additional figures related to the estimation results.

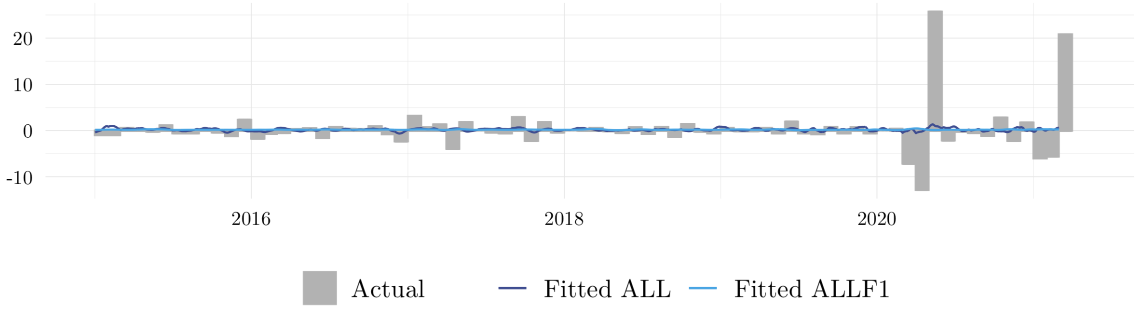
Figure A1: Benchmark models results - out-of-sample nowcast



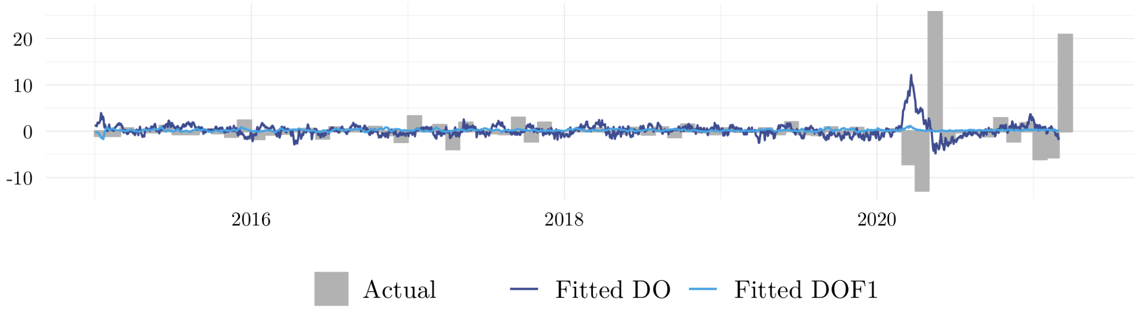
Notes: This figure shows the rolling out-of-sample nowcast starting in January 2019 for 1- and 2-period-ahead predictions, for the benchmark models. The 1-period ahead prediction is essentially the previous-month estimation whereas the 2-period ahead prediction is the current-month estimation.

Figure A2: In-sample fit across models (at daily frequency)

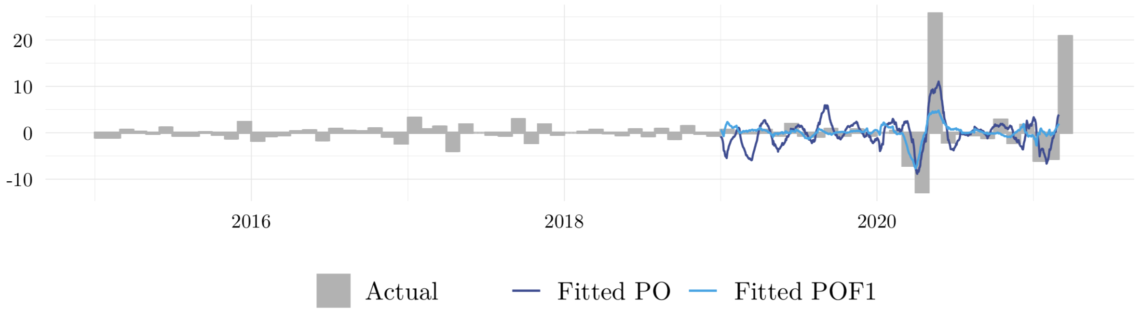
All data (ALL)



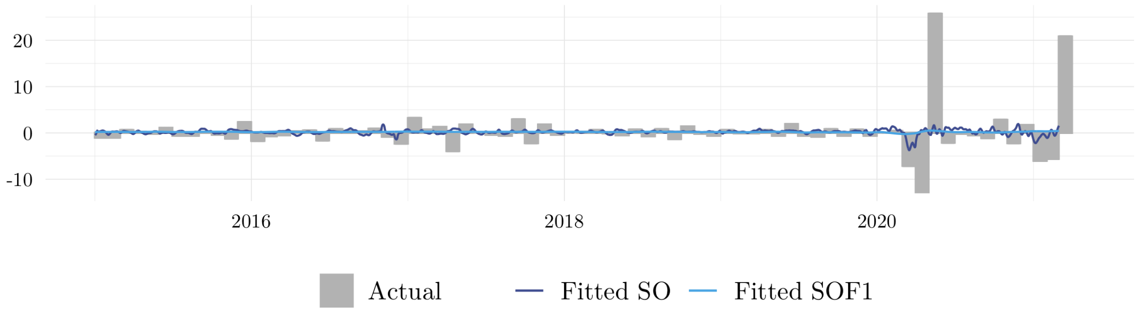
Daily data only (DO)



Payment data only (PO)



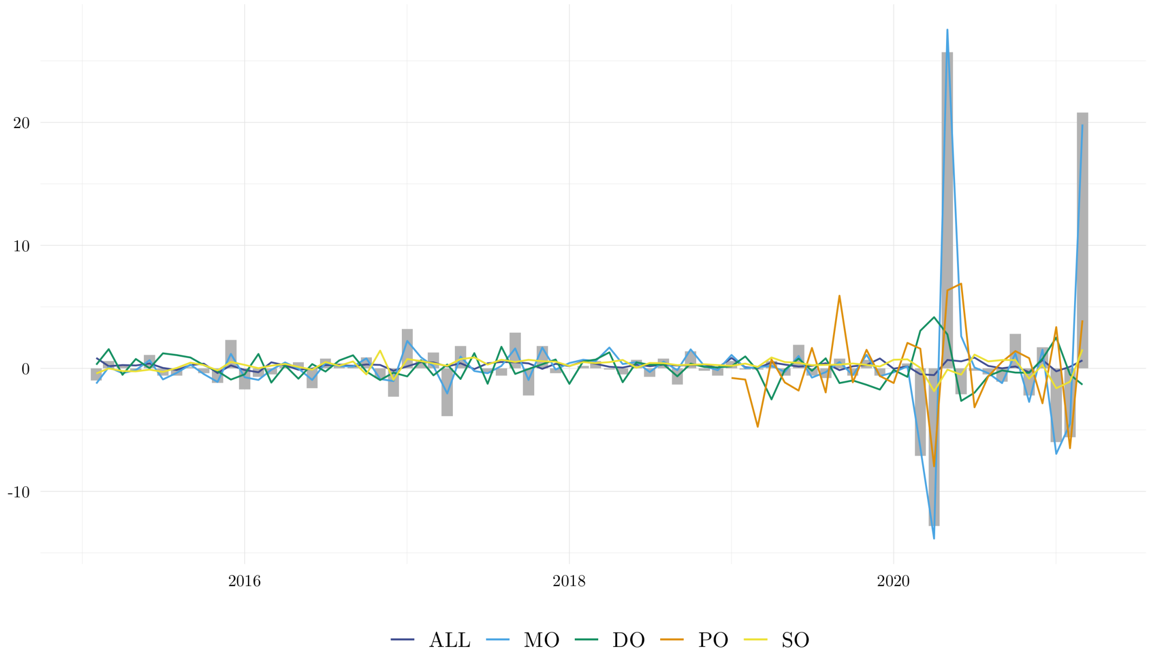
Selection only (SO)



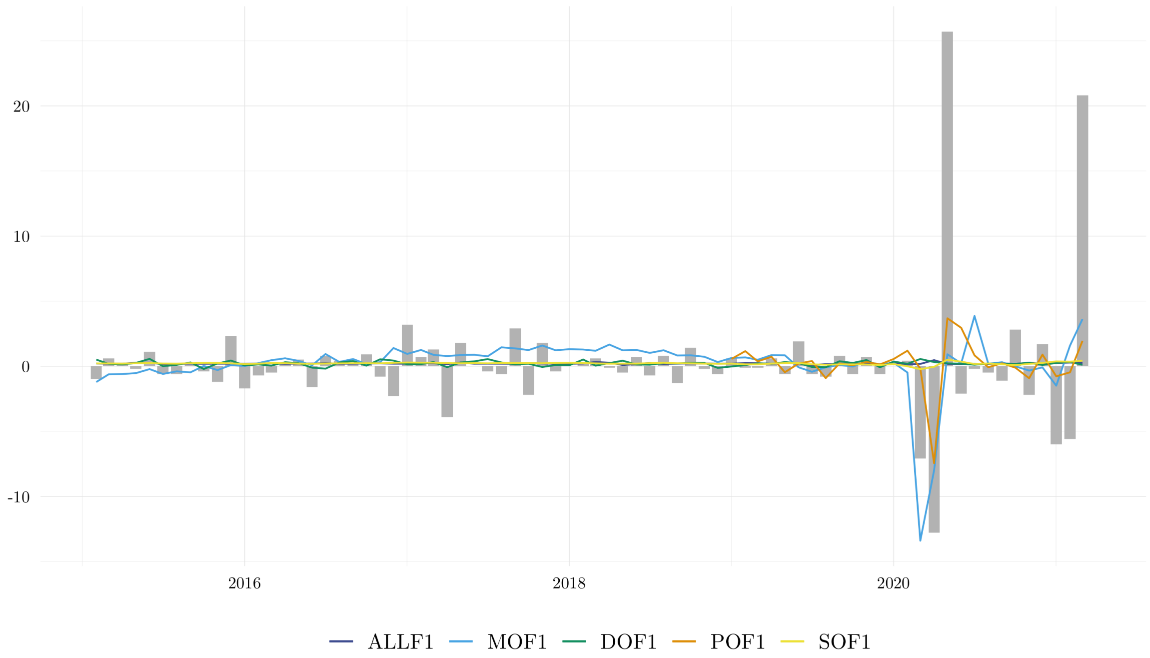
Notes: This figure shows the in-sample fit on a daily basis (not available for the monthly model MO). The model specifications are $(p1, r4)$, where p stands for the number of lags in the transition equation and r for the number of common factors.

Figure A3: In-sample fit across models - comparison

Comparison (p1, r4)



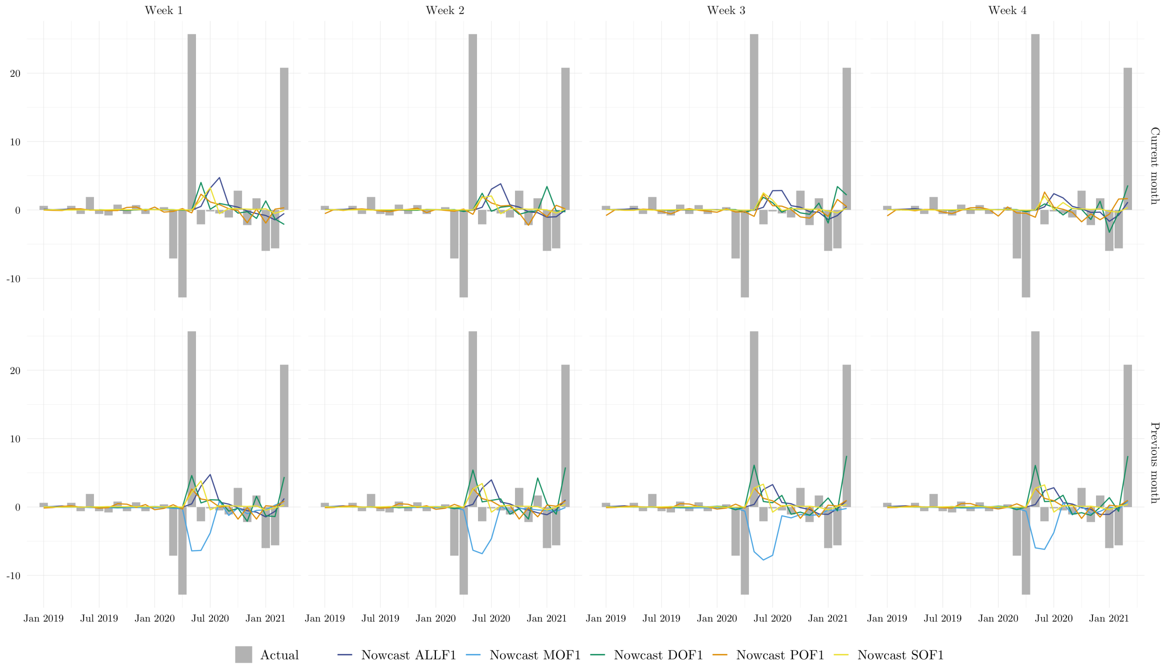
Comparison (r1, p1)



Notes: This figure shows the in-sample fit where the 1-factor in-sample fits are compared to the multi-factor in-sample fits. p stands for the number of lags in the transition equation and r for the number of common factors.

The following figures show the rolling-out-of sample nowcast. The week number on the horizontal axis indicates in which week of the month the nowcast was made. Therefore, it depicts how the predictions evolve over time (increasing information set). "Current" and "previous" month refer to whether the estimation was made for the current (on-going) month or the previous month.

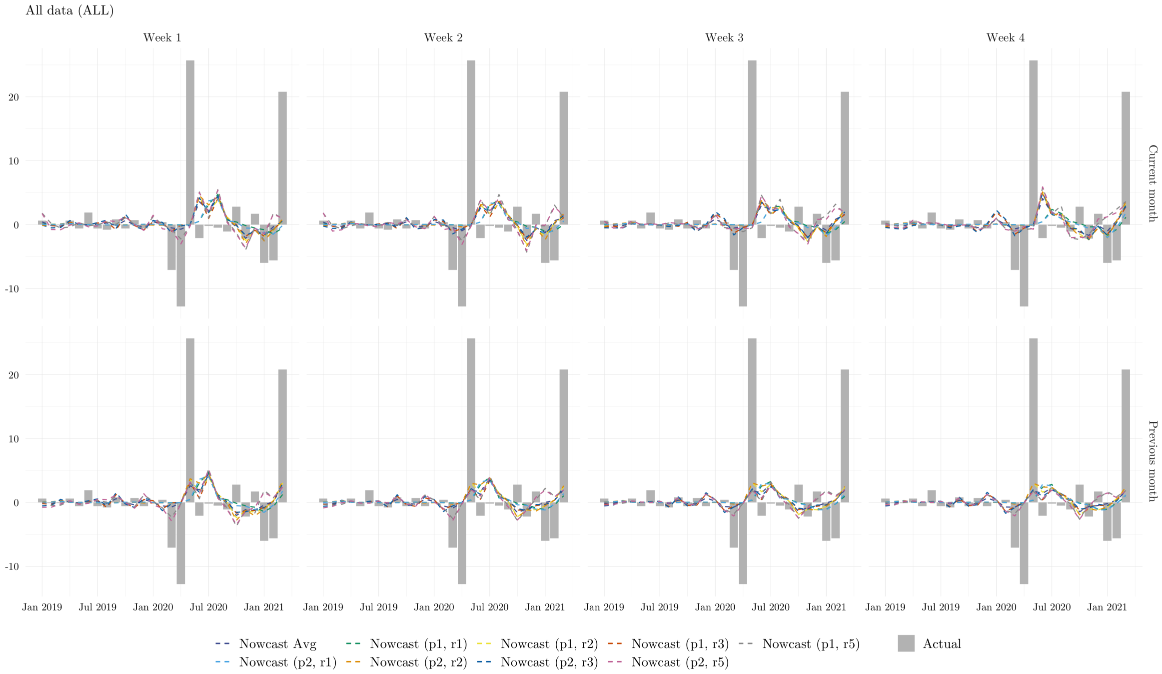
Figure A4: Rolling out-of-sample nowcast - 1-factor models



Notes: This figure shows the rolling-out-of sample nowcast for the different models specified with only one factor $(p1, r1)$. The week number indicates in which week of the month the nowcast was made. "Current" and "previous" month refer to whether the estimation was made for the current (on-going) month or the previous month.

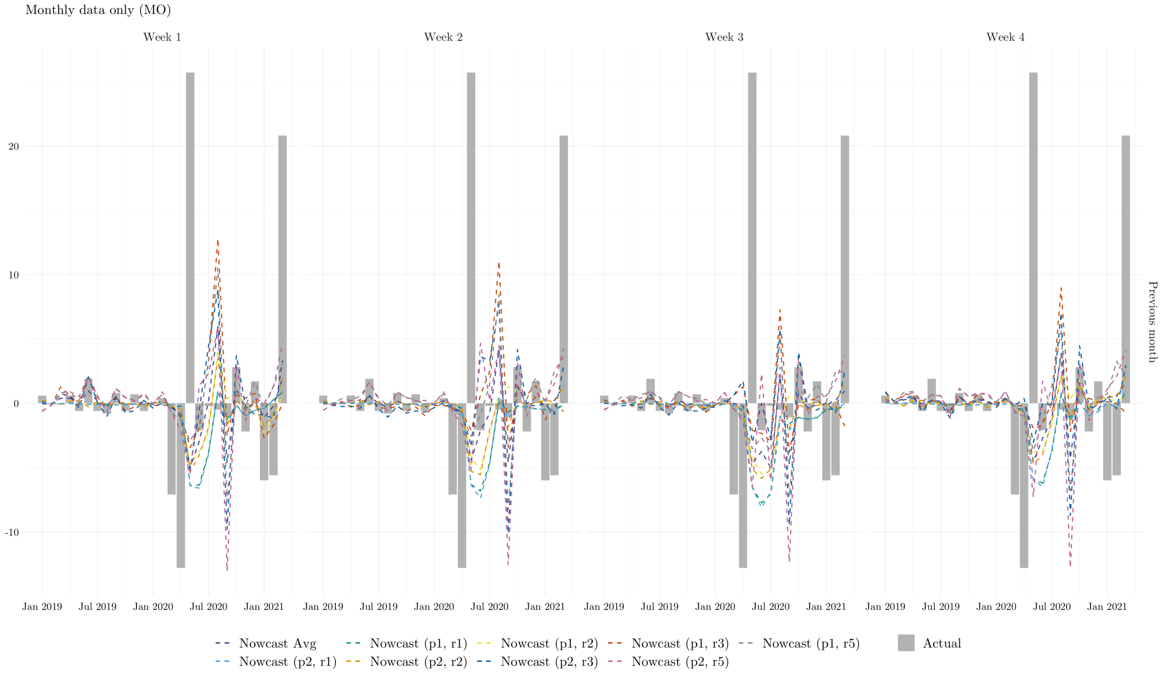
Below are the figure for the models *ALL, MO, DO, PO*, and *SO*. They show the nowcast for each combination of the specification of the parameters p and r.

Figure A5: Rolling out-of-sample nowcast - *ALL*



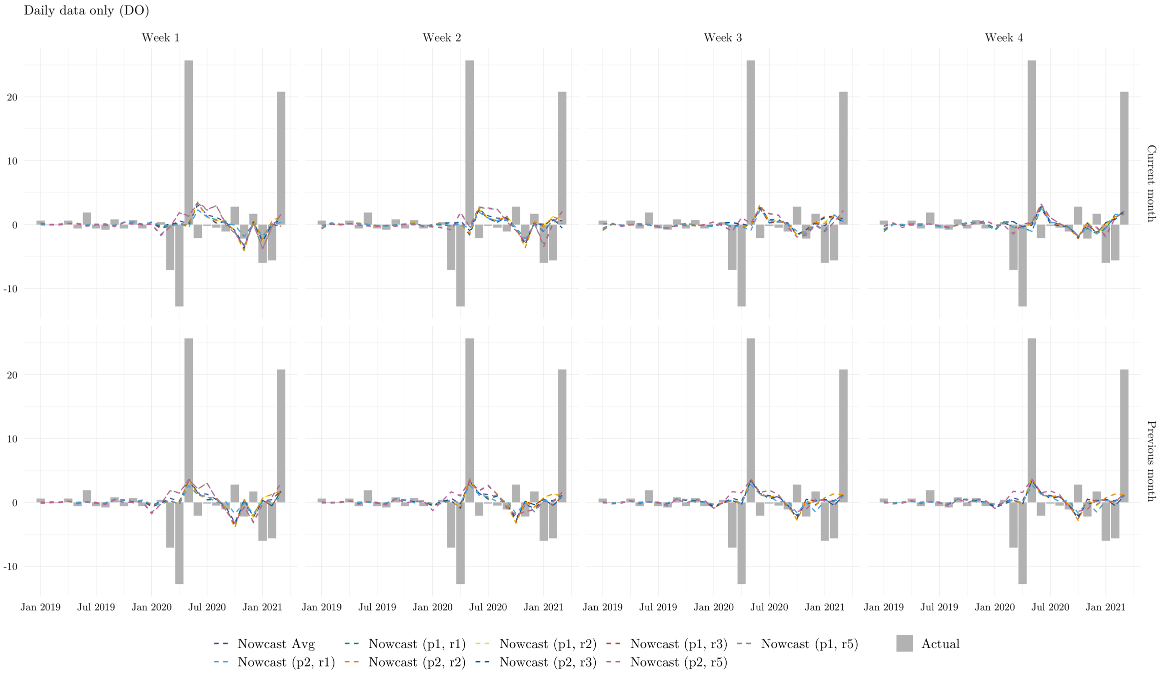
Notes: This figure shows the rolling-out-of sample nowcast for the model *ALL*.

Figure A6: Rolling out-of-sample nowcast - *MO*



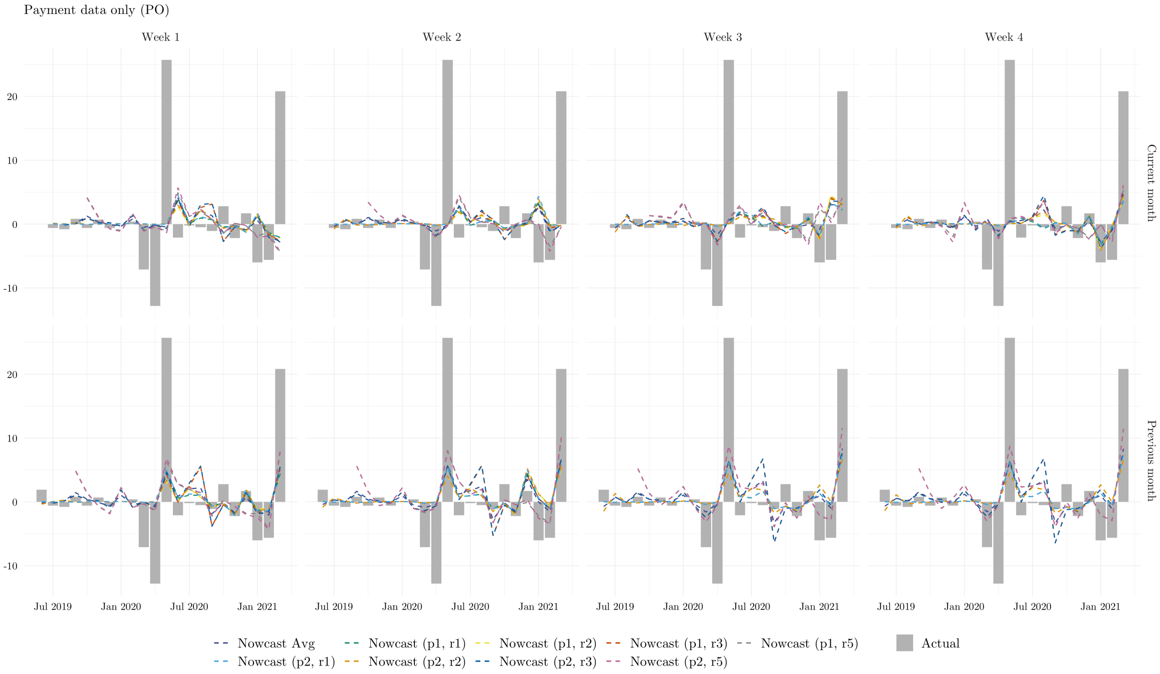
Notes: This figure shows the rolling-out-of sample nowcast for the model *MO*.

Figure A7: Rolling out-of-sample nowcast - *DO*



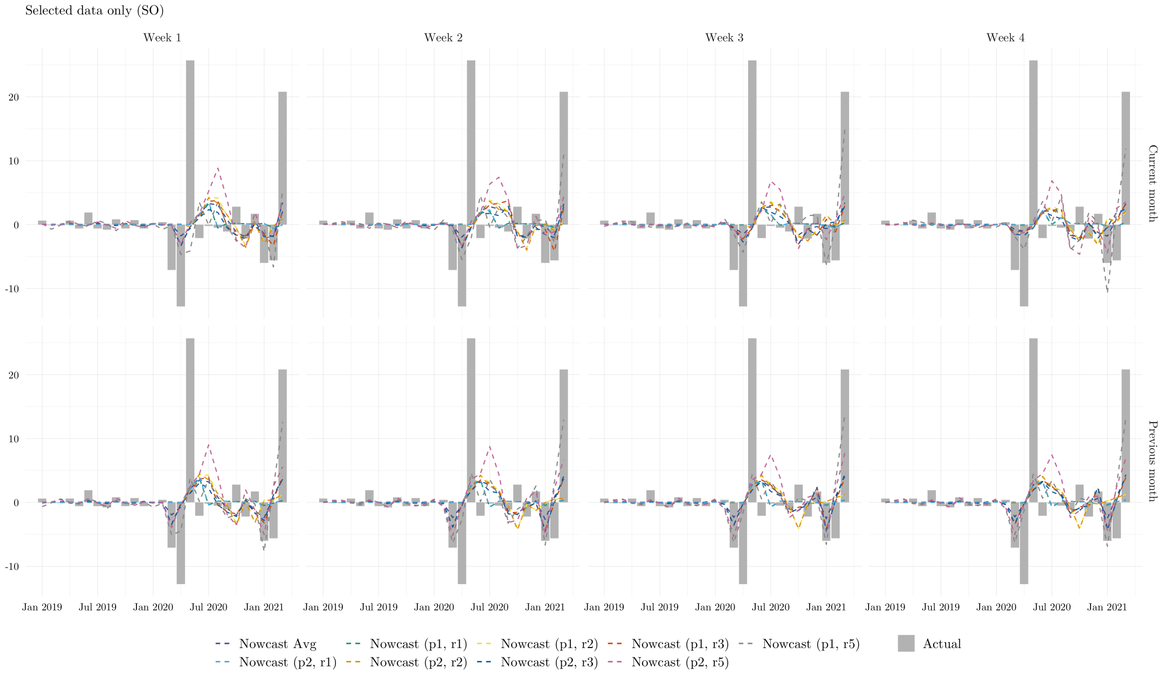
Notes: This figure shows the rolling-out-of sample nowcast for the model *DO*.

Figure A8: Rolling out-of-sample nowcast - *PO*



Notes: This figure shows the rolling-out-of sample nowcast for the model *PO*.

Figure A9: Rolling out-of-sample nowcast - *SO*



Notes: This figure shows the rolling-out-of sample nowcast for the model *SO*.

B Additional tables

Appendix B contains additional tables with performance measure results and tables with general information. The perfomance measure MAPE is slightly adjusted due to one value of the actual series being 0. This value is dropped in both, the actual and the estimated series. Therefore, this measure needs to be interpreted with caution.

Table B1: RMSE pre/post Covid-19 pandemic

Multi-factor

Model	Current month		Previous month	
	Pre	Post	Pre	Post
Absolute RMSE values				
ALL	0.9628	10.0902	0.774	9.5197
MO	-	-	0.7293	11.0322
DO	0.8149	10.1126	0.7455	9.6443
PO	0.8236	10.1727	1.3821	7.1084
SO	0.8274	8.7918	0.7251	7.5252
Values relative to the *AR1* RMSE				
ALL	1.2337	0.8387	1.2528	0.7542
MO	-	-	1.1805	0.874
DO	1.0442	0.8406	1.2067	0.7641
PO	1.0553	0.8456	2.2371	0.5632
SO	1.0602	0.7308	1.1737	0.5962
Values relative to the *RW* RMSE				
ALL	0.9242	0.6769	0.5643	0.6106
MO	-	-	0.5317	0.7076
DO	0.7822	0.6784	0.5435	0.6186
PO	0.7905	0.6825	1.0076	0.456
SO	0.7942	0.5898	0.5286	0.4827

(a) Multi-factor models (best RMSE)

1-factor

Model	Current month		Previous month	
	Pre	Post	Pre	Post
Absolute RMSE values				
ALLF1	0.7583	10.3233	0.7727	10.2013
MOF1	-	-	0.7749	11.627
DOF1	0.7871	10.4981	0.7692	9.8462
POF1	0.6446	10.2872	0.9076	8.3932
SOF1	0.7712	10.3793	0.77	9.9211
Values relative to the *AR1* RMSE				
ALLF1	0.9716	0.8581	1.2507	0.8082
MOF1	-	-	1.2543	0.9212
DOF1	1.0086	0.8726	1.2451	0.7801
POF1	0.826	0.8551	1.4691	0.665
SOF1	0.9882	0.8627	1.2463	0.786
Values relative to the *RW* RMSE				
ALLF1	0.7279	0.6926	0.5633	0.6543
MOF1	-	-	0.5649	0.7458
DOF1	0.7555	0.7043	0.5608	0.6316
POF1	0.6187	0.6901	0.6617	0.5384
SOF1	0.7402	0.6963	0.5614	0.6364

(b) 1-factor models $(p1, r1)$

Notes: These tables show the RMSE in the period before the Covid-19 pandemic started (January 2019 - February 2020) compared to the period during the pandemic. For each model the best performing parametrization in terms of RMSE was chosen (best RMSE over the whole out-of-sample estimation). These are the following: *ALL*: current-month = $(p2, r3)$, previous-month = $(p1, r2)$; *MO*: $(p1, r5)$; *DO*: current-month = $(p2, r5)$, previous-month = $(p2, r3)$; *PO*: current-month = (AVG) (average over all specifications), previous-month = $(p2, r5)$; *SO*: current- and previous-month = $(p1, r5)$, where p stands for the number of lags in the transition equation and r for the number of common factors.

Table B3: Diebold and Mariano test results

	Current month							Previous month						
	ALL	MO	DO	PO	SO	AR1	RW	ALL	MO	DO	PO	SO	AR1	RW
ALL	-	-	-0.009	-0.455	1.114	-1.857	-1.753	-	-1.205	-0.527	1.823	1.552	-1.668	-1.586
	-	-	(0.504)	(0.673)	(0.138)	(0.963)	(0.954)	-	(0.88)	(0.699)	(0.041)	(0.066)	(0.946)	(0.938)
MO	-	-	-	-	-	-	-	1.205	-	1.037	1.747	1.867	-1.174	-1.499
	-	-	-	-	-	-	-	(0.12)	-	(0.155)	(0.048)	(0.037)	(0.874)	(0.927)
DO	0.009	-	-	-0.566	1.111	-1.804	-1.731	0.527	-1.037	-	1.756	1.416	-1.56	-1.562
	(0.496)	-	-	(0.711)	(0.138)	(0.921)	(0.952)	(0.301)	(0.845)	-	(0.047)	(0.084)	(0.935)	(0.935)
PO	0.455	-	0.566	-	1.052	-1.68	-1.732	-1.823	-1.747	-1.756	-	-0.292	-2.14	-1.854
	(0.327)	-	(0.289)	-	(0.153)	(0.921)	(0.951)	(0.959)	(0.952)	(0.953)	-	(0.613)	(0.978)	(0.961)
SO	-1.114	-	-1.111	-1.052	-	-1.847	-1.833	-1.552	-1.867	-1.416	0.292	-	-2.083	-1.765
	(0.862)	-	(0.862)	(0.847)	-	(0.962)	(0.961)	(0.934)	(0.963)	(0.916)	(0.387)	-	(0.976)	(0.955)
AR1	1.857	-	1.804	1.68	1.847	-	-1.644	1.668	1.174	1.56	2.14	2.083	-	-1.379
	(0.037)	-	(0.041)	(0.054)	(0.038)	-	(0.944)	(0.054)	(0.126)	(0.065)	(0.022)	(0.024)	-	(0.91)
RW	1.753	-	1.731	1.732	1.833	1.644	-	1.586	1.499	1.562	1.854	1.765	1.379	-
	(0.046)	-	(0.048)	(0.049)	(0.039)	(0.056)	-	(0.062)	(0.073)	(0.065)	(0.039)	(0.045)	(0.09)	-

Notes: This table shows the Diebold and Mariano test (modified test proposed by Harvey et al. (1997)). In each column it tests the hypothesis whether the column-model is more accurate than the row model. The values in brackets are the p-values. A value of the DM-statistic above the standard critical values from a normal distribution implies that the null hypothesis can be rejected. The model specifications are based on the best-RMSE models and are the following: *ALL*: current-month = $(p2, r3)$, previous-month = $(p1, r2)$; *MO*: $(p1, r5)$; *DO*: current-month = $(p2, r5)$, previous-month = $(p2, r3)$; *PO*: current-month = (AVG) (average over all specifications), previous-month = $(p2, r5)$; *SO*: current- and previous-month = $(p1, r5)$. p stands for the number of lags in the transition equation and r for the number of common factors

Table B4: All performance measures - parametrization robustness analysis (*ALL*)

		Model: *ALL*								
WOM, h[a]	Perf. measure	M $(p1, r1)$	M $(p1, r2)$	M $(p1, r3)$	M $(p1, r5)$	M $(p2, r1)$	M $(p2, r2)$	M $(p2, r3)$	M $(p2, r5)$	AVG[b]
WOM = 1, h = 0	RMSE	7.4545	7.3833	7.3559	7.3784	7.3868	7.3651	7.3501	7.3554	7.3472
WOM = 1, h = 0	MAPE	202.6698	176.5165	169.8351	204.2243	202.908	205.0289	211.5355	251.0182	183.3339
WOM = 1, h = 0	MASE	0.6956	0.6959	0.6955	0.7265	0.6858	0.7023	0.7092	0.7379	0.6915
WOM = 1, h = 0	MAE	4.0068	4.0082	4.0062	4.1848	3.9504	4.0452	4.0849	4.2506	3.9828
WOM = 2, h = 0	RMSE	7.3724	7.2824	7.2408	7.3912	7.2912	7.2481	7.2	7.3142	7.2643
WOM = 2, h = 0	MAPE	193.4796	173.9667	176.5692	208.0013	192.9398	200.9019	213.3386	252.8824	182.274
WOM = 2, h = 0	MASE	0.6846	0.6893	0.6848	0.7401	0.6747	0.6946	0.6922	0.7349	0.6862
WOM = 2, h = 0	MAE	3.9432	3.9706	3.9445	4.2631	3.8863	4.0009	3.9869	4.2332	3.9524
WOM = 3, h = 0	RMSE	7.2951	7.2411	7.2031	7.4945	7.2146	7.2205	7.1451	7.4419	7.2574
WOM = 3, h = 0	MAPE	182.1733	170.4863	173.67	183.6838	177.0116	190.1635	196.2804	193.9987	163.7887
WOM = 3, h = 0	MASE	0.6718	0.6832	0.6789	0.7236	0.6617	0.687	0.6761	0.712	0.679
WOM = 3, h = 0	MAE	3.8697	3.9353	3.9104	4.1678	3.8116	3.9572	3.8943	4.101	3.9108
WOM = 4, h = 0	RMSE	7.1986	7.1494	7.103	7.353	7.1135	7.1185	7.0477	7.3736	7.1498
WOM = 4, h = 0	MAPE	166.6283	159.3214	175.7562	179.7542	154.8437	165.7136	186.1771	184.6211	150.2775
WOM = 4, h = 0	MASE	0.6568	0.6723	0.6676	0.7169	0.6442	0.6687	0.6586	0.7023	0.6653
WOM = 4, h = 0	MAE	3.7833	3.8727	3.8456	4.1292	3.7104	3.8519	3.7936	4.0452	3.8319
WOM = 1, h = 1	RMSE	7.2272	6.666	6.742	6.8735	7.1828	6.6963	6.743	6.8652	6.849
WOM = 1, h = 1	MAPE	211.4356	203.3671	220.9918	245.8542	203.147	219.2845	246.7042	255.0889	212.2323
WOM = 1, h = 1	MASE	0.6853	0.6618	0.6677	0.6926	0.6865	0.6788	0.6802	0.6948	0.6762
WOM = 1, h = 1	MAE	3.9475	3.8117	3.8462	3.9892	3.9541	3.9101	3.9179	4.0019	3.8947
WOM = 2, h = 1	RMSE	7.2456	6.8024	6.8833	7.0269	7.2178	6.8275	6.8818	7.001	6.9648
WOM = 2, h = 1	MAPE	197.7001	196.0051	207.9188	215.2885	193.2436	209.2342	223.203	214.264	196.6468
WOM = 2, h = 1	MASE	0.685	0.669	0.6671	0.6811	0.6863	0.6808	0.6735	0.6785	0.6748
WOM = 2, h = 1	MAE	3.9453	3.8533	3.8427	3.9233	3.9529	3.9215	3.8791	3.908	3.8867
WOM = 3, h = 1	RMSE	7.2463	6.7891	6.8962	7.0097	7.218	6.7944	6.8854	6.989	6.9607
WOM = 3, h = 1	MAPE	184.9242	183.7702	192.8841	182.5831	181.522	191.1304	198.368	182.0572	178.4345
WOM = 3, h = 1	MASE	0.6821	0.6647	0.6664	0.6735	0.6818	0.6712	0.6661	0.6684	0.6702
WOM = 3, h = 1	MAE	3.9291	3.8287	3.8387	3.8794	3.9273	3.8659	3.8365	3.85	3.8603
WOM = 4, h = 1	RMSE	7.25	6.7978	6.9246	7.0267	7.2223	6.7962	6.9085	7.0096	6.9744
WOM = 4, h = 1	MAPE	176.5019	173.1974	185.662	175.897	176.1172	180.287	189.7245	173.368	169.6372
WOM = 4, h = 1	MASE	0.6802	0.6622	0.6677	0.673	0.6802	0.6677	0.6649	0.666	0.6686
WOM = 4, h = 1	MAE	3.9178	3.8144	3.8459	3.8763	3.9182	3.8461	3.8296	3.836	3.8512

[a] WOM = week of month, h: $h = 0$ stands for current-month estimation, $h = 1$ stands for previous-month estimation.

[b] AVG = average (average across all model specifications).

Notes: This table reports the four performance measures for the different model specifications (different number of lags in the transition equation p and different number of common factors r) for the model *ALL*. AVG stands for average.

Table B5: All performance measures - parametrization robustness analysis (MO)

Model: MO

WOM, h[a]	Perf. measure	M $(p1, r1)$	M $(p1, r2)$	M $(p1, r3)$	M $(p1, r5)$	M $(p2, r1)$	M $(p2, r2)$	M $(p2, r3)$	M $(p2, r5)$	AVG[b]
WOM = 1, h = 1	RMSE	8.2165	7.8828	8.1011	7.7912	8.2281	7.8386	8.06	8.0478	7.8609
WOM = 1, h = 1	MAPE	171.0927	156.3646	292.3186	288.7039	177.8083	146.1661	289.4974	244.9419	157.4097
WOM = 1, h = 1	MASE	0.7141	0.6747	0.7107	0.74	0.7215	0.6689	0.7454	0.7473	0.6777
WOM = 1, h = 1	MAE	4.1131	3.8864	4.0935	4.2623	4.1559	3.853	4.2937	4.3043	3.9036
WOM = 2, h = 1	RMSE	8.2865	7.9839	7.9601	7.6685	8.2973	7.9717	7.8946	8.0536	7.8241
WOM = 2, h = 1	MAPE	186.2405	147.8788	232.9321	220.7774	191.3385	135.7151	242.8932	174.2951	135.0717
WOM = 2, h = 1	MASE	0.7233	0.7014	0.7328	0.7244	0.7282	0.6885	0.7636	0.7412	0.6726
WOM = 2, h = 1	MAE	4.1665	4.0401	4.2208	4.1724	4.1943	3.9656	4.3981	4.2691	3.8744
WOM = 3, h = 1	RMSE	8.4259	8.0429	8.0747	7.7881	8.4239	7.9631	7.9176	8.3262	7.9863
WOM = 3, h = 1	MAPE	235.7039	203.8088	203.597	242.2728	233.7949	195.1248	199.919	274.86	209.5784
WOM = 3, h = 1	MASE	0.753	0.7156	0.7321	0.7306	0.7561	0.7049	0.7386	0.7833	0.7159
WOM = 3, h = 1	MAE	4.3374	4.1221	4.2167	4.2085	4.3553	4.0604	4.2541	4.512	4.1236
WOM = 4, h = 1	RMSE	8.1212	7.7497	7.8842	7.8772	8.127	7.7674	7.7718	8.399	7.8497
WOM = 4, h = 1	MAPE	167.7484	132.8621	175.805	221.4432	169.6462	123.0092	171.7155	191.0378	146.5241
WOM = 4, h = 1	MASE	0.7036	0.6627	0.6889	0.7319	0.709	0.6562	0.7147	0.7579	0.6762
WOM = 4, h = 1	MAE	4.053	3.8171	3.9681	4.216	4.0838	3.7798	4.1165	4.3654	3.8951

[a] WOM = week of month, h: $h = 0$ stands for current-month estimation, $h = 1$ stands for previous-month estimation.

[b] AVG = average (average across all model specifications).

Notes: This table reports the four performance measures for the different model specifications (different number of lags in the transition equation p and different number of common factors r) for the model MO. AVG stands for average.

Table B6: All performance measures - parametrization robustness analysis (DO)

Model: DO

WOM, h[a]	Perf. measure	M $(p1, r1)$	M $(p1, r2)$	M $(p1, r3)$	M $(p1, r5)$	M $(p2, r1)$	M $(p2, r2)$	M $(p2, r3)$	M $(p2, r5)$	AVG[b]
WOM = 1, h = 0	RMSE	7.3677	7.2575	7.4361	7.1842	7.3643	7.2682	7.4346	7.1795	7.2983
WOM = 1, h = 0	MAPE	125.7682	134.7949	137.0832	187.5899	125.6466	134.4328	136.0658	192.1874	146.4179
WOM = 1, h = 0	MASE	0.6534	0.6652	0.6759	0.684	0.6528	0.6665	0.6731	0.6861	0.6686
WOM = 1, h = 0	MAE	3.7635	3.8314	3.893	3.94	3.7601	3.8389	3.8773	3.9518	3.8509
WOM = 2, h = 0	RMSE	7.4494	7.5413	7.7277	7.327	7.4489	7.5478	7.7317	7.311	7.4981
WOM = 2, h = 0	MAPE	124.9509	132.9542	136.5584	171.8999	126.1593	134.8731	138.8545	176.5303	142.8476
WOM = 2, h = 0	MASE	0.6628	0.689	0.7008	0.6745	0.6626	0.6873	0.6975	0.672	0.6808
WOM = 2, h = 0	MAE	3.8177	3.9687	4.0364	3.8853	3.8164	3.9586	4.0175	3.8706	3.9214
WOM = 3, h = 0	RMSE	7.4713	7.4452	7.5032	7.2171	7.4614	7.4368	7.5068	7.2032	7.3976
WOM = 3, h = 0	MAPE	120.3497	120.3633	115.815	152.0227	119.7392	120.905	116.3256	156.8367	125.9547
WOM = 3, h = 0	MASE	0.6734	0.6858	0.6925	0.6663	0.6716	0.6833	0.6916	0.6646	0.6783
WOM = 3, h = 0	MAE	3.8789	3.9503	3.989	3.838	3.8685	3.9355	3.9834	3.8282	3.9071
WOM = 4, h = 0	RMSE	7.4032	7.2849	7.2492	7.1344	7.4046	7.2778	7.2274	7.1309	7.258
WOM = 4, h = 0	MAPE	119.4229	117.803	109.7223	146.5851	119.5111	119.4473	110.1212	149.655	118.9672
WOM = 4, h = 0	MASE	0.6796	0.6837	0.6804	0.6593	0.6798	0.6841	0.6782	0.6594	0.6743
WOM = 4, h = 0	MAE	3.9143	3.938	3.9191	3.7977	3.9156	3.9404	3.9062	3.7982	3.884
WOM = 1, h = 1	RMSE	6.9929	6.9063	6.8366	6.973	6.9933	6.8894	6.8153	6.9655	6.9074
WOM = 1, h = 1	MAPE	130.1597	134.1821	124.8208	168.396	130.3039	134.1036	124.1297	167.7019	139.0303
WOM = 1, h = 1	MASE	0.6661	0.6827	0.6641	0.693	0.6667	0.6799	0.661	0.6919	0.6753
WOM = 1, h = 1	MAE	3.8366	3.9323	3.8253	3.992	3.8402	3.9162	3.8074	3.9854	3.8898
WOM = 2, h = 1	RMSE	6.9942	6.8955	6.8506	6.9806	6.9929	6.8917	6.8441	6.9707	6.9169
WOM = 2, h = 1	MAPE	129.1837	135.5638	123.5713	151.0272	129.5165	134.7969	121.6689	146.7051	133.9135
WOM = 2, h = 1	MASE	0.6655	0.6736	0.653	0.6664	0.6661	0.6716	0.6504	0.6626	0.6636
WOM = 2, h = 1	MAE	3.8331	3.8799	3.7611	3.8384	3.8366	3.8685	3.746	3.8164	3.8224
WOM = 3, h = 1	RMSE	6.9721	6.8836	6.8665	6.9748	6.9711	6.8798	6.8585	6.9752	6.9127
WOM = 3, h = 1	MAPE	126.8499	131.4988	119.53	133.9951	126.9693	130.2234	117.1602	132.2199	124.6475
WOM = 3, h = 1	MASE	0.6628	0.6685	0.65	0.6503	0.6633	0.6664	0.6474	0.6477	0.6566
WOM = 3, h = 1	MAE	3.8179	3.8506	3.7443	3.7459	3.8208	3.8383	3.729	3.731	3.7821
WOM = 4, h = 1	RMSE	6.9861	6.8967	6.8824	6.9758	6.9852	6.8931	6.8746	6.9779	6.9239
WOM = 4, h = 1	MAPE	126.4297	131.5159	122.8759	131.6463	126.7111	130.445	120.643	130.1535	124.7521
WOM = 4, h = 1	MASE	0.6633	0.6693	0.653	0.649	0.6639	0.6673	0.6504	0.6466	0.6574
WOM = 4, h = 1	MAE	3.8205	3.8551	3.7612	3.7382	3.8242	3.8436	3.7463	3.7246	3.7864

[a] WOM = week of month, h: $h = 0$ stands for current-month estimation, $h = 1$ stands for previous-month estimation.

[b] AVG = average (average across all model specifications).

Notes: This table reports the four performance measures for the different model specifications (different number of lags in the transition equation p and different number of common factors r) for the model DO. AVG stands for average.

Table B7: All performance measures - parametrization robustness analysis (PO)

Model: PO

WOM, h[a]	Perf. measure	M ($p1, r1$)	M ($p1, r2$)	M ($p1, r3$)	M ($p1, r5$)	M ($p2, r1$)	M ($p2, r2$)	M ($p2, r3$)	M ($p2, r5$)	AVG[b]
WOM = 1, h = 0	RMSE	8.7777	8.7493	9.2141	9.9665	8.8114	8.7609	9.2414	10.0483	8.9141
WOM = 1, h = 0	MAPE	128.262	128.9001	171.926	222.7637	132.9013	133.6599	175.1489	230.5701	152.1215
WOM = 1, h = 0	MASE	0.7129	0.7094	0.7518	0.7526	0.7204	0.7122	0.7547	0.7573	0.7317
WOM = 1, h = 0	MAE	5.118	5.0928	5.6883	6.2653	5.1715	5.113	5.7104	6.3043	5.2529
WOM = 2, h = 0	RMSE	8.5927	8.6213	8.753	9.0847	8.6562	8.6264	8.7498	9.1032	8.5108
WOM = 2, h = 0	MAPE	110.7635	135.1073	153.9848	171.0655	113.6006	138.2082	159.0411	174.9762	136.9168
WOM = 2, h = 0	MASE	0.6971	0.714	0.7137	0.6688	0.7063	0.7134	0.7126	0.668	0.6984
WOM = 2, h = 0	MAE	5.0042	5.1254	5.4003	5.5679	5.0708	5.1217	5.3919	5.561	5.0137
WOM = 3, h = 0	RMSE	8.1975	8.2218	8.1426	8.5604	8.1803	8.1579	8.0809	8.5353	7.9974
WOM = 3, h = 0	MAPE	125.0504	144.5356	162.5816	154.6566	136.5442	152.3292	176.5272	167.2004	144.4878
WOM = 3, h = 0	MASE	0.6522	0.6748	0.6621	0.6774	0.6538	0.6731	0.6648	0.6824	0.6665
WOM = 3, h = 0	MAE	4.682	4.8442	5.01	5.6397	4.6937	4.8318	5.0302	5.6813	4.7847
WOM = 4, h = 0	RMSE	7.8094	7.8041	7.7973	8.1779	7.7968	7.74	7.7491	8.0907	7.6194
WOM = 4, h = 0	MAPE	97.8978	133.1079	168.397	177.3432	99.3431	140.5987	180.8218	196.4219	135.8902
WOM = 4, h = 0	MASE	0.5851	0.6	0.6001	0.6269	0.5828	0.5973	0.6	0.6298	0.597
WOM = 4, h = 0	MAE	4.2007	4.3073	4.5406	5.2188	4.184	4.2877	4.5398	5.2428	4.2861
WOM = 1, h = 1	RMSE	6.8816	7.1534	7.0832	6.7643	6.8013	7.0729	7.0113	6.6047	6.6984
WOM = 1, h = 1	MAPE	121.3612	145.4756	216.5994	228.0217	126.0657	153.7206	228.386	236.7455	163.9618
WOM = 1, h = 1	MASE	0.5617	0.582	0.6023	0.5866	0.5586	0.5796	0.6005	0.5783	0.5713
WOM = 1, h = 1	MAE	3.9007	4.0418	4.3238	4.6442	3.8793	4.0255	4.3108	4.5785	3.9675
WOM = 2, h = 1	RMSE	6.7115	7.077	6.8865	6.2936	6.7036	7.0457	6.859	6.2216	6.4924
WOM = 2, h = 1	MAPE	127.7766	164.044	244.6398	214.197	131.5281	167.5798	251.4763	212.0053	176.7012
WOM = 2, h = 1	MASE	0.5775	0.62	0.6322	0.558	0.5834	0.6217	0.6344	0.5489	0.5904
WOM = 2, h = 1	MAE	4.0108	4.3056	4.5383	4.4179	4.0517	4.318	4.5546	4.346	4.1005
WOM = 3, h = 1	RMSE	6.4977	6.9604	6.818	5.9848	6.4908	6.956	6.8165	5.9729	6.3403
WOM = 3, h = 1	MAPE	124.0324	176.0386	277.7499	241.9972	124.7775	176.2544	278.5622	242.8726	194.3765
WOM = 3, h = 1	MASE	0.5719	0.6312	0.6453	0.5349	0.5716	0.6307	0.6452	0.5342	0.595
WOM = 3, h = 1	MAE	3.972	4.3834	4.6324	4.2353	3.9697	4.3804	4.6317	4.2293	4.1324
WOM = 4, h = 1	RMSE	6.5078	6.9636	6.8472	6.016	6.5023	6.96	6.846	6.006	6.3565
WOM = 4, h = 1	MAPE	129.7676	177.8866	282.7086	252.3262	129.8683	178.0455	283.298	252.7672	199.2185
WOM = 4, h = 1	MASE	0.5741	0.6295	0.6473	0.5358	0.5739	0.6295	0.6476	0.5357	0.5957
WOM = 4, h = 1	MAE	3.9869	4.3721	4.6467	4.2424	3.986	4.3719	4.6493	4.2416	4.1374

[a] WOM = week of month, h: $h = 0$ stands for current-month estimation, $h = 1$ stands for previous-month estimation.

[b] AVG = average (average across all model specifications).

Notes: This table reports the four performance measures for the different model specifications (different number of lags in the transition equation p and different number of common factors r) for the model *PO*. *AVG* stands for average. The calculations for the performance measures for the parametrization with $r > 2$, are based on a smaller sample due to the loss of more degrees of freedom.

Table B8: All performance measures - parametrization robustness analysis (SO)

Model: SO

WOM, h[a]	Perf. measure	M ($p1, r1$)	M ($p1, r2$)	M ($p1, r3$)	M ($p1, r5$)	M ($p2, r1$)	M ($p2, r2$)	M ($p2, r3$)	M ($p2, r5$)	AVG[b]
WOM = 1, h = 0	RMSE	7.4012	7.3904	6.9768	7.234	7.4024	7.3527	6.8053	7.0885	7.1271
WOM = 1, h = 0	MAPE	163.0869	221.09	200.655	153.7633	168.8061	213.8999	158.8539	283.714	187.1907
WOM = 1, h = 0	MASE	0.6752	0.6958	0.6388	0.6328	0.6768	0.6902	0.6099	0.7118	0.6566
WOM = 1, h = 0	MAE	3.8892	4.0077	3.6793	3.6449	3.8982	3.9757	3.5128	4.1001	3.7823
WOM = 2, h = 0	RMSE	7.3634	7.5018	7.0217	6.5858	7.3569	7.4721	6.8744	7.016	7.0592
WOM = 2, h = 0	MAPE	140.3637	210.3293	198.6194	156.6573	146.0235	200.8942	152.3853	302.0547	184.421
WOM = 2, h = 0	MASE	0.6667	0.7204	0.6618	0.6073	0.6686	0.7147	0.6319	0.716	0.665
WOM = 2, h = 0	MAE	3.8404	4.1497	3.8119	3.4981	3.8509	4.1168	3.6395	4.1241	3.8302
WOM = 3, h = 0	RMSE	7.3499	7.5479	7.1597	5.9039	7.3376	7.525	7.1162	6.9825	7.0189
WOM = 3, h = 0	MAPE	131.7521	200.2065	194.0893	153.1865	134.8692	190.9689	156.4779	291.401	180.0351
WOM = 3, h = 0	MASE	0.6675	0.7233	0.6999	0.5242	0.6676	0.7185	0.6776	0.6997	0.67
WOM = 3, h = 0	MAE	3.8449	4.1663	4.0315	3.0196	3.8451	4.1387	3.9032	4.0304	3.8591
WOM = 4, h = 0	RMSE	7.3303	7.4164	7.1185	6.2475	7.3156	7.3925	7.1959	7.2152	7.046
WOM = 4, h = 0	MAPE	111.6829	183.7373	171.7156	152.2008	113.6694	173.0898	145.5714	288.9908	163.6505
WOM = 4, h = 0	MASE	0.6619	0.7185	0.6833	0.6182	0.6617	0.7124	0.6816	0.7261	0.6691
WOM = 4, h = 0	MAE	3.8126	4.1387	3.9361	3.5609	3.8112	4.1037	3.9263	4.1822	3.8542
WOM = 1, h = 1	RMSE	7.1045	7.2634	6.7242	5.3597	7.0936	7.2521	6.7672	6.8607	6.6963
WOM = 1, h = 1	MAPE	107.6717	210.6752	182.1145	186.3152	107.4615	198.1667	149.7833	332.718	179.5243
WOM = 1, h = 1	MASE	0.6547	0.737	0.6324	0.5045	0.6544	0.7352	0.6332	0.7029	0.6483
WOM = 1, h = 1	MAE	3.7711	4.2454	3.6425	2.9061	3.7691	4.2346	3.647	4.0488	3.734
WOM = 2, h = 1	RMSE	7.0301	7.2369	6.6215	5.3435	7.0155	7.2271	6.5795	6.5301	6.5789
WOM = 2, h = 1	MAPE	114.0072	189.1429	175.2191	192.0262	112.9643	178.5707	149.6338	325.1674	170.7913
WOM = 2, h = 1	MASE	0.6526	0.7225	0.6109	0.489	0.6516	0.72	0.6018	0.6549	0.6274
WOM = 2, h = 1	MAE	3.7589	4.1617	3.5189	2.8165	3.7531	4.1473	3.4663	3.7723	3.6136
WOM = 3, h = 1	RMSE	7.0093	7.1499	6.5789	5.3629	6.9941	7.1391	6.5079	6.3104	6.5178
WOM = 3, h = 1	MAPE	113.3647	181.6287	164.449	193.7231	112.0424	173.1153	144.4023	303.3462	165.0164
WOM = 3, h = 1	MASE	0.6518	0.7109	0.5986	0.4778	0.6504	0.7084	0.5878	0.6255	0.6168
WOM = 3, h = 1	MAE	3.7546	4.095	3.4478	2.7521	3.7464	4.0803	3.3856	3.6029	3.5526
WOM = 4, h = 1	RMSE	7.0076	7.1397	6.5709	5.3926	6.9909	7.1306	6.523	6.4236	6.5398
WOM = 4, h = 1	MAPE	113.1431	177.198	160.3629	192.5554	110.9534	170.2159	143.5922	303.0017	163.2392
WOM = 4, h = 1	MASE	0.6516	0.7087	0.5976	0.4843	0.6495	0.7067	0.5894	0.6419	0.6185
WOM = 4, h = 1	MAE	3.7534	4.0821	3.4419	2.7896	3.7412	4.0703	3.3947	3.6971	3.5627

[a] WOM = week of month, h: $h = 0$ stands for current-month estimation, $h = 1$ stands for previous-month estimation.

[b] AVG = average (average across all model specifications).

Notes: This table reports the four performance measures for the different model specifications (different number of lags in the transition equation p and different number of common factors r) for the model SO.

Table B9: Private consumption categories

HABE (Household income and expenditure)	%	*COICOP Classification*
Compulsory transfer exp.	28.4%	
1 Social security contr.	10.2%	
2 Taxes	11.7%	
3 Health insurance (basic insurance)	6.5%	
Monetary transfer to other hh	1.7%	
Other insurance, fees & transfers	5.6%	
4 Health insurance (add. insurances)	1.5%	
5 Other insurance premiums	1.8%	
6 Fees	0.7%	
7 Donations, made gifts	1.6%	
Consumer spending		
8 Food and non-alc. beverages	6.3%	a Food and non-alc. beverages
9 Alc. beverages and tobacco products	1.0%	b Alc. beverages and tobacco products
10 Guest houses and lodging	5.8%	
11 Clothing and shoes	1.9%	c Clothing and shoes
12 Housing and energy	14.4%	d Housing, water, electricity, gas
13 Furnishing & ongoing housekeeping	2.2%	e Furniture, interior decoration, hh appliances and objects
14 Health care expenditure	2.4%	f Health Care
15 Traffic	7.4%	g Transport and communication
16 Communication	1.8%	h Leisure and culture and education
17 Entertainment, recreation and culture	5.4%	i Restaurants and Hotels
18 Other goods and services	3.7%	j Other goods and services

Notes: The table shows the different components of private consumption and their share for Swiss households. Percentages are according to the *household income and expenditure* statistics of the FSO. COICOP classification stands for *Classification of Individual Consumption According to Purpose.*

Table B10: Overview of other models used in nowcasting

Approach	Model	Example paper
Classic approach		
	Mixed frequency vector autoregressive model (MFVAR)	Foroni and Marcellino (2016)
	Dynamic factor model such as Factor Augmented VAR (FAVAR)	Bok et al. (2018)
Bayesian approach		
	Bayesian Structural Time Series (BSTS)	Niesert et al. (2020)
	Bayesian vector autoregression (BVAR)	Bloor and Matheson (2011)
Mixed frequency		
	Temporal aggregation.	
	Bridge equation model:	
	The bridge equations are specified at a higher frequency than the variable that is nowcasted, enabling a bridge between, say, monthly and quarterly data. This approach is already somehow outdated though. It is also a partial model and only captures a limited aspect of the nowcasting.	Bańbura et al. (2013)
	Mixed-data sampling model (MIDAS):	
	MIDAS is a refinement of the bridge equation model. In a MIDAS-type model the predictors are included in the regression at their original observation frequency. However, the MIDAS equations suffer from the curse of dimensionality problem and can include only a handful of variables.	Ghysels et al. (2007)

Notes: This table shows an overview of employed models in the nowcasting literature. See also Jansen et al. (2016) for a comparison of several approaches and Schumacher (2014) for a comparison of the MIDAS approach and the bridge equations.

Table B11: Existing private consumption forecasts in Switzerland

Institution	Variables in Model	Forecast period	Updates	Source
SECO	Retail sales, overnight stays, car registrations, national consumer price index, number of passengers in air and train traffic, unemployment figures, employment figures, income trends and population growth, and survey data	Yearly	Quarterly	*www.seco.admin.ch*
KOF	Disposable income of private households, long-term interest rate	Yearly	Quarterly	*www.kof.ethz.ch*
UBS	Top-down & Bottom-up approach	Yearly	Quarterly	*www.ubs.com*
CS	Savings rate, consumer sentiment, labour market, population trends (migration), services-PMI, retail trade (bottom-up)	Quarterly	Quarterly	*www.credit-suisse.com*
Créa[a]	Disposable income, unemployment rate, interest rates, measure of wealth	Yearly	Semi-annually	*www.unil.ch*
BAK	*No answer*	Yearly	Monthly	*www.bak-economics.com*

[a] Institute of Applied Economics from the University of Lausanne

Table B12: Summary statistics of all indicators

Begin of Table

Indicators	n	Mean	S.D.	Min	Max
activ.tot	490.00	0.00	1.58	-8.72	4.18
amount.chf.credit.domestic.e.comm	830.00	4444.79	82064.55	-382078.46	320480.23
amount.chf.credit.domestic.pos	1195.00	0.04	1.06	-5.93	5.02
amount.chf.credit.foreign.e.comm	830.00	482.97	75504.72	-791333.25	774235.01
amount.chf.credit.foreign.pos	830.00	-6150.08	101795.15	-495889.96	338753.89
amount.chf.debit.domestic.all	830.00	12518.74	898080.63	-5186650.32	4392319.53
amount.chf.debit.foreign.all	830.00	-363.03	21485.27	-111439.86	79726.47
amount.chf.mobile.all.all	830.00	6448.03	34748.80	-217509.01	192472.94
AMOUNTCHF.ATM.WITHDRAWAL	1195.00	0.09	1.54	-6.51	6.62
aufkommen.fussverkehr.indexiert.stadt.zurich	480.00	-0.03	4.63	-19.96	22.57
aufkommen.miv.indexiert.stadt.zurich	488.00	0.04	1.37	-7.63	6.21
aufkommen.veloverkehr.indexiert.stadt.zurich	480.00	0.10	5.98	-23.58	23.53
clothing.sa	2294.00	0.98	0.21	-0.04	1.71
coop.migros.aldi.denner.spar.volg.lidl	2285.00	30.61	2.08	25.82	40.17
driving	472.00	0.02	1.51	-6.78	5.37
E.confederation.yield.8years	1061.00	0.00	0.01	-0.08	0.06
erwerbstaetig.sa.ch	494.00	0.01	0.35	-1.80	1.13
fluege.zrh.zrh	2307.00	-0.05	1.68	-14.03	11.22
fooddelivery.sa	2293.00	0.00	0.02	-0.09	0.11
garden.sa	2293.00	0.00	0.02	-0.11	0.16
grocery.and.pharmacy	446.00	-2.24	7.99	-29.43	20.14
ilias.nutzung.zh	599.00	0.41	7.30	-41.67	40.57
in.ausbildung.sa.ch	494.00	0.01	0.41	-2.38	1.10
jbCand.immediate.tot	757.00	2.58	1708.14	-12662.71	12702.71
jbCand.tot.tot	908.00	0.04	0.16	-0.42	0.59
jbVac.tot.sa	387.00	38.02	1230.50	-12186.88	9065.69
konkurse.sa	486.00	0.03	10.21	-57.21	51.83
luxury.sa	2293.00	0.00	0.03	-0.11	0.15
manor.globus.jelmoli.mediamarkt.ochsnersport.orell.fussli	2285.00	6.77	0.53	4.76	9.12
mobil	490.00	0.01	1.90	-9.96	5.59
mobility.sa	2293.00	0.00	0.02	-0.08	0.08
neueintrag.handelsregister	486.00	0.54	9.33	-41.71	42.29
nicht.erwerbstaetig.sa.ch	494.00	0.01	0.30	-0.91	0.95
number.of.transactions.credit.domestic.e.comm	830.00	70.22	853.24	-3904.83	4507.12
number.of.transactions.credit.domestic.pos	830.00	0.07	0.88	-4.54	4.37
number.of.transactions.credit.foreign.e.comm	830.00	3.52	178.89	-1330.53	1307.21
number.of.transactions.credit.foreign.pos	830.00	-22.58	953.76	-5008.04	3007.73
number.of.transactions.debit.domestic.all	830.00	0.02	0.77	-4.15	4.44
number.of.transactions.debit.foreign.all	830.00	-5.19	290.18	-1309.83	863.91
number.of.transactions.mobile.all.all	830.00	157.68	632.88	-3576.06	3294.65
oev.freq.hardbruecke.stadt.zurich	489.00	0.02	2.88	-14.43	12.80
oneYear.bond.i	1061.00	0.00	0.01	-0.10	0.04

Continuation of Table B12

Indicators	n	Mean	S.D.	Min	Max
P.mortgage.bond.inst.yield.8years	1355.00	-0.02	0.20	-0.66	0.39
parks	446.00	30.69	41.17	-26.86	149.43
residential	445.00	0.02	0.51	-2.00	2.71
retail.and.recreation	445.00	-0.07	1.74	-10.00	6.28
sales	490.00	-0.01	1.34	-5.89	3.65
schuldbetreibungen.sa	608.00	347.97	59.45	146.37	454.70
smi.index	1242.00	0.30	93.56	-882.06	572.53
social.sa	2293.00	0.00	0.03	-0.21	0.13
tages.distanz.100pluskm.sa.ch	495.00	0.00	0.19	-0.80	1.22
tages.distanz.2.10km.sa.ch	495.00	0.00	0.16	-0.41	0.87
tages.distanz.20.50km.sa.ch	495.00	0.01	0.24	-2.19	0.76
tages.distanz.mittelwert.erwerbstaetig.sa.ch	494.00	0.01	0.46	-2.42	1.07
tages.distanz.mittelwert.kinder.ja.sa.ch	494.00	0.00	0.48	-2.34	1.14
tages.distanz.mittelwert.modus.andere.vkm.sa.ch	494.00	0.00	0.02	-0.07	0.07
tages.distanz.mittelwert.modus.miv.sa.ch	494.00	0.01	0.32	-1.48	0.83
tages.distanz.mittelwert.modus.oev.sa.ch	494.00	0.00	0.13	-0.83	0.44
tages.distanz.mittelwert.sa.ch.land	494.00	0.02	0.49	-2.67	1.12
tages.distanz.mittelwert.zweck.andere.sa.ch	494.00	0.00	0.02	-0.13	0.11
tages.distanz.mittelwert.zweck.einkauf.sa.ch	494.00	0.00	0.10	-0.58	0.22
tages.distanz.mittelwert.zweck.freizeit.sa.ch	494.00	-0.01	0.39	-1.94	1.33
tages.distanz.mittelwert.zweck.pendeln.sa.ch	494.00	0.02	0.25	-0.85	1.91
tenYear.bond.i	1061.00	0.00	0.01	-0.07	0.07
total.sa.ch	494.00	0.01	0.33	-1.75	0.88
training.mathematik.lmvz.global	449.00	0.19	8.47	-46.79	35.97
training.mindsteps.deutschschweiz	476.00	0.16	11.00	-55.22	63.31
transit	472.00	-0.02	2.15	-14.04	4.49
transit.stations	445.00	-0.06	1.34	-7.14	4.28
travel.sa	2293.00	-0.03	0.89	-5.93	4.11
trendecon.sa	2293.00	0.00	0.98	-8.61	7.69
walking	472.00	0.02	2.15	-11.89	7.78
workplaces	445.00	-0.04	1.78	-9.86	8.29
zalando.digitec.galaxus.coop.home.leshop.amazon	2284.00	0.00	0.09	-0.63	0.61
Bicycle.avg.daily.dist	69.00	6.85	346.75	-763.19	829.63
Bicycle.avg.trip.distance	69.00	7.91	875.11	-1938.23	1619.01
Bus.avg.daily.dist	69.00	-2.10	121.92	-575.41	375.76
Bus.n.trips.daily	69.00	0.00	0.03	-0.12	0.09
Car.avg.daily.dist	69.00	-17.58	2065.98	-11115.72	5155.98
Car.n.trips.daily	69.00	0.00	0.14	-0.73	0.25
Train.avg.daily.dist	69.00	-21.22	1002.71	-5650.81	1561.12
Train.n.trips.daily	69.00	0.00	0.03	-0.19	0.04
Walk.avg.daily.dist	69.00	1.53	205.82	-724.93	447.85
Walk.avg.trip.distance	69.00	-1.85	91.78	-177.33	330.46
WWA	324.00	0.03	0.57	-2.87	3.48
x01.personenwagen	168.00	3.40	1346.33	-4786.25	3185.00

Continuation of Table B12

Indicators	n	Mean	S.D.	Min	Max
x10.leichter.motorwagen.nur.wohnwagen	162.00	-0.25	14.44	-45.75	56.25
x30.lieferwagen	168.00	2.22	119.28	-504.50	314.25
x35.lastwagen	168.00	0.32	24.29	-154.00	101.00
x60.motorrad.nur.roller	168.00	9.07	100.32	-161.75	294.75
A.DE.VVP	74.00	1.06	9.30	-19.30	22.60
A.EUROPE.T.VVP	74.00	0.32	6.73	-20.00	12.20
A.EUROZONE.T.VVP	74.00	0.63	7.68	-20.90	18.20
ankunfte.6	73.00	-3790.72	148633.93	-1046733.09	573609.86
Auftragsbestand.Index.sa	76.00	54.04	8.50	16.93	69.50
Auftragsbestand.Index.sa.2	76.00	53.97	8.42	33.75	76.40
bargeldbezug.creditcards.amountMil	73.00	-0.12	4.69	-24.50	18.70
bargeldbezug.creditcards.transactionsT	74.00	330.34	21.85	218.15	366.71
bargeldbezug.Emoney.amountMil	73.00	-0.05	0.42	-1.90	1.60
bargeldbezug.Emoney.transactionsT	73.00	-0.14	2.17	-12.75	6.60
Beschaeftigte.Index.sa	76.00	49.14	4.49	36.79	58.59
Beschaeftigte.Index.sa.2	76.00	51.12	5.52	39.37	65.99
bruttobetten.auslastung5	73.00	0.00	0.04	-0.28	0.14
bruttozimmer.auslastung4	73.00	0.00	0.04	-0.31	0.17
Cardnotpresent.creditcards.amountMil	73.00	5.88	27.15	-95.94	91.77
Cardnotpresent.creditcards.transactionsT	73.00	99.76	378.23	-2745.24	580.85
Cardnotpresent.debitcards.amountMil	73.00	1.11	4.29	-17.31	23.01
Cardnotpresent.debitcards.transactionsT	73.00	16.11	46.40	-329.14	98.62
Cardnotpresent.Emoney.amountMil	73.00	3.21	4.74	-9.96	27.69
Cardnotpresent.Emoney.transactionsT	73.00	3.62	4.03	-11.59	21.44
ch.kof.inu.ng08.fx.sector.2d.10.q.ql.chg.order.in.pmppm.balance.d11	76.00	3.07	22.87	-44.26	58.94
ch.kof.inu.ng08.fx.sector.2d.10.q.ql.exp.chg.order.in.n3m.balance.d11	76.00	10.53	11.32	-27.00	41.13
ch.kof.inu.ng08.fx.sector.2d.11.q.ql.chg.order.in.pmppm.balance.d11	76.00	-2.93	31.79	-70.52	92.63
ch.kof.inu.ng08.fx.sector.2d.11.q.ql.exp.chg.order.in.n3m.balance.d11	76.00	23.43	23.35	-28.89	87.61
ch.kof.inu.ng08.fx.sector.2d.14.q.ql.chg.order.in.pmppm.balance	74.00	2.80	51.63	-100.00	96.40
ch.kof.inu.ng08.fx.sector.2d.14.q.ql.exp.chg.order.in.n3m.balance	74.00	5.19	24.08	-71.46	80.38
ch.kof.inu.ng08.fx.sector.2d.21.q.ql.chg.order.in.pmppm.balance.d11	76.00	5.07	18.14	-50.27	40.03
ch.kof.inu.ng08.fx.sector.2d.21.q.ql.exp.chg.order.in.n3m.balance.d11	76.00	18.93	11.82	-14.50	49.37
DZ2.anz.E.geld.karten.mit.kontaktlos.zahlfunk	73.00	16432.40	34812.87	-186872.01	183577.41
E.DE.VVP	73.00	0.15	5.52	-21.20	12.10
E.EUROPE.T.VVP	73.00	0.04	7.04	-20.40	14.50
E.EUROPE.T.WMF	73.00	5.71	536.37	-2451.72	982.11
E.EUROZONE.T.VVP	74.00	-0.58	9.36	-29.70	19.10
ecoBarometer	76.00	97.73	11.63	51.69	134.02
ecoSent.ch	75.00	96.90	8.72	60.67	107.07
ecoSent.eu	76.00	103.41	9.20	69.07	113.93
Einkaufsmenge.Index.sa.2	76.00	51.36	8.06	33.88	72.60
Einkaufspreise.Index.sa	76.00	53.35	10.41	14.28	75.30
Einkaufspreise.Index.sa.2	76.00	54.15	12.26	13.58	83.60
erfasste.betriebe2	74.00	4816.76	158.59	4581.38	5105.04

Continuation of Table B12

Indicators	n	Mean	S.D.	Min	Max
GA.arrivals.foreign	73.00	-7.96	61.25	-443.11	136.91
GE.secured.utilisation.loan.private.hh	73.00	124.18	375.67	-760.00	1996.00
Geschaeftstaetigkeit.Index.sa	76.00	57.61	8.44	18.14	72.93
GS0.arrivals.swiss	73.00	0.99	99.60	-482.84	499.66
H.mortgage.utilisation.loan.private.hh	73.00	3097.38	494.14	1825.99	4471.26
Lagerbestaende.Einkauf.Index.sa.2	76.00	49.05	3.60	40.90	57.31
Lagerbestaende.Verkauf.Index.sa.2	76.00	47.87	3.27	39.89	56.28
LD2010100.national.ind.cpi	74.00	0.00	0.15	-0.33	0.31
Lieferfristen.Index.sa.2	76.00	59.64	10.59	45.93	85.80
logiernachte.7	73.00	-12656.54	323107.93	-2363155.04	1179488.62
Neuauftraege.Index.sa	76.00	55.74	8.82	15.48	73.28
PMI.SA.2	76.00	54.11	6.52	41.18	69.50
PMIS.SA	76.00	54.38	7.25	21.84	67.80
Produktion.Index.sa.2	76.00	55.36	7.71	28.97	71.30
DHU.47.ohne.473.total.ohne.tankstellen	75.00	100.86	3.58	81.21	114.73
DHU.47.total.detailhandel	74.00	0.21	4.50	-12.80	25.70
DHU.4711.472.mit.nahrungsmitteln.getr.nken.tabakwaren	74.00	0.26	2.58	-6.33	12.26
DHU.473.mit.tankstellen	74.00	-0.14	3.51	-15.10	11.50
DHU.474.mit.informationstechnik	74.00	0.69	6.02	-13.87	27.12
DHU.475.mit.haushaltsgerate.textilien	74.00	0.44	11.00	-26.20	60.30
DHU.478.479.verkaufsstand.internet.detailhandel	74.00	0.56	3.56	-4.80	14.60
DHU.bekleidung.schuhe	74.00	-0.01	15.06	-49.70	76.50
DHU.nahrungsmittel.getr.nke.tabak	74.00	0.19	1.85	-5.90	6.60
DHU.total.ohne.treibstoffe	74.00	0.23	4.68	-12.60	26.90
DHU.treibstoffe	74.00	-0.11	4.25	-20.00	9.40
seco.ecoConf	75.00	-0.10	0.65	-2.35	0.97
T0.anz.kk.tot	73.00	27109.75	36992.51	-11801.71	220571.98
T0.arrivalis.tot	73.00	-3.79	148.63	-1046.73	573.61
T0.total.utilisation.loan.private.hh	73.00	3206.81	677.09	1510.20	5197.56
T1.anz.debitk.tot	74.00	10514774.28	82451.24	10410401.95	11003216.24
T1.overnight.stay.tot.foreign	73.00	-18.23	150.06	-1178.10	302.64
T2.anz.E.geld.karten.tot	73.00	18264.07	37595.50	-106598.67	102450.30
T2.total.other.loan.utilisation.private.hh	73.00	116.01	555.88	-1562.00	1695.00
T3.anz.ATM.tot	73.00	1.52	58.29	-196.65	244.57
T3.overnight.stay.tot	73.00	-12.66	323.11	-2363.16	1179.49
total.unempl.rate	74.00	0.00	0.09	-0.13	0.51
TotalPayments.debitcards.amountMil	74.00	3912.66	240.18	2862.48	4537.33
TotalPayments.Emoney.amountMil	73.00	1.97	3.21	-12.32	13.02
TotalPayments.Emoney.transactionsT	73.00	2.43	3.81	-22.42	18.75
Verkaufspreise.Index.sa	76.00	49.37	7.27	25.37	66.10
vorhandene.betten3	73.00	51.62	808.66	-579.32	5029.98
vorhandene.zimmer3	73.00	6.40	481.31	-1894.46	1902.30
yoy.change.cpi	74.00	0.00	0.20	-0.55	0.51
ZahlungenPraesenz.creditcards.amountMil	73.00	-0.55	109.15	-372.13	682.24

Continuation of Table B12					
Indicators	n	Mean	S.D.	Min	Max
ZahlungenPraesenz.creditcards.transactionsT	73.00	92.97	1109.74	-4356.18	6281.96
ZahlungenPraesenz.Emoney.amountMil	73.00	0.37	3.06	-12.61	17.76
zimmernachte.8	73.00	-8579.74	188895.70	-1366929.72	715375.97
End of Table					