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Róbert Ambriško *

Abstract

Macroeconomic data are published with a time lag, making room for nowcasting macroeconomic variables using fiscal data. This is because a) monthly and daily fiscal data are available from the state budget in a very timely manner and b) many fiscal data are the function of macroeconomic variables. I employ two nowcasting models, bridge equations and MIDAS regressions, which link quarterly macroeconomic variables to monthly fiscal data for the Czech Republic. Bridge equations are found to be particularly suitable for nowcasting the wage bill using social contributions, achieving a 2% improvement in the root mean square error (RMSE) of one-quarter recursive forecasts compared to historical CNB forecasts. Further, I propose a tractable method for incorporating daily data into the nowcasting models, relying on STL decomposition by Cleveland et al. (1990). Depending on the timing, the RMSE for the wage bill can be up to 4% lower when the available daily data on social contributions are taken into account in the nowcasting models too.

Abstrakt

Makroekonomická data jsou publikována s časovým zpožděním, což vytváří prostor pro krátkodobou prognózu („nowcasting“) makroekonomických proměnných pomocí fiskálních dat, a to z těchto důvodů: a) měsíční a denní fiskální data jsou velmi včasně dostupná ze státního rozpočtu, b) mnoho fiskálních dat je funkcí makroekonomických proměnných. Používám dva krátkodobé modely, můstkové rovnice a MIDAS regresi, které propojují čtvrtletní makroekonomické proměnné s měsíčními fiskálními daty pro Českou republiku. Můstkové rovnice se ukazují jako obzvlášť vhodné pro krátkodobou prognózu objemu mezd a platů pomocí sociálních příspěvků; přinášejí 2% zlepšení střední kvadratické odchylky chybovosti čtvrtletních rekurzivních prognóz oproti historickým prognózám ČNB. Dále navrhuji schůdnou metodu pro včlenění denních dat do krátkodobých modelů, která se spoléhá na dekompozici STL od Cleveland a kol. (1990). V závislosti na načasování může být střední kvadratická odchylka chybovosti prognóz pro objem mezd a platů až o 4 % nižší, pokud jsou dostupná denní data o sociálních příspěvcích také zohledněna v krátkodobých modelech.

JEL Codes: C53, C82, E37.
Keywords: Bridge equations, daily data, fiscal, midas, nowcasting, real-time data, short-term forecasting, STL.

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1. Introduction

Nowcasting, the prediction of the current state of the economy or its very recent past, is of key importance to central banks and other institutions which produce economic forecasts. The current state of the economy heavily influences the macroeconomic forecast in the long-term, which is relevant for the central bank when making the correct monetary policy decisions in the present. Thus, it is essential for the central bank to devise and employ nowcasting models, which minimize the errors of prediction for the relevant macroeconomic variables.

The main macroeconomic variables from national accounts (e.g. GDP, wage bill) are available quarterly and are published with a substantial time delay. In the Czech Republic, the figure for the current quarter is usually published at the beginning of the third month of the following quarter.[1] Thus, the current state of the macroeconomic variable must always be estimated and a "nowcast" is produced. Moreover, in the first two months of the current quarter, the figure for the previous quarter is still missing, and it has to be estimated too.

Various nowcasting models can be employed to estimate the current state of the macroeconomic variable concerned. One common feature of these models is that they link the macroeconomic variable to the relevant indicator or to a set of several indicators, which are able to explain the movements in the underlying macroeconomic variable. Often these indicators are available in higher frequencies (monthly, weekly, daily etc.) than the underlying quarterly macroeconomic variable.

Several suitable indicators for macroeconomic variables can be taken from fiscal data. The economic reasoning for this is the following: Many fiscal data are the function of macroeconomic variables, also known as macroeconomic bases. For instance, personal income tax and social contributions depend on wages and salaries. Further, value added tax is a function of consumption or more broadly of gross domestic product (excluding exports). Generally, fiscal data are readily available in higher frequencies, on a monthly or even daily basis. As opposed to the main macroeconomic variables from national accounts, fiscal data from the cash fulfillment of the state budget are published in a very timely manner, e.g. the monthly fiscal figures are available on the first working day after the end of the month. Moreover, daily fiscal data, published also with a lag of one working day, are available internally at the CNB and the Ministry of Finance (MF).

A faster availability of fiscal data compared to macroeconomic data means that the inverse relationship between macroeconomic and fiscal variables can be utilized. In other words, more timely fiscal data can be used to predict relevant macroeconomic variables, which are published with a greater delay. Thus, there is some room for nowcasting macroeconomic variables using more timely fiscal data.

This paper presumably represents the first attempt to comprehensively assess the ability of Czech fiscal data for nowcasting selected macroeconomic variables. Another important contribution is methodological: I propose employing a suitable method of utilizing daily data to further improve the predictions of monthly nowcasting models. More specifically, my method relies on extracting the trend from the daily series using STL decomposition (Cleveland et al., 1990) to forecast missing monthly figures.

[1] There is one exception: the initial preliminary release of real GDP is published in the second month of the following quarter. The preliminary release of real GDP for 2020 Q2 was already available at the end of July 2020 (the first month of the following quarter).

The main results of the paper are as follows: The best nowcasting performance is found for the wage bill using social contributions, modelled with bridge equations. This brings a 2% improvement in the root mean square error of one-quarter recursive forecasts compared to the CNB's historical wage bill forecasts. Furthermore, the CNB's historical forecast for real GDP is outperformed by nowcasting real GDP with value added tax using bridge equations estimated by robust least squares. By including daily fiscal data, nowcasting models can be improved further. It is shown that, depending on the timing, the root mean square error of one-quarter recursive forecasts for the wage bill can be up to 4% lower (i.e. the forecasts are more precise) when the available daily data on social contributions are taken into account. Another important lesson from the nowcasting exercise is to use real-time (historical) data instead of pseudo real-time (the last vintage) data, as the errors of recursive forecasts are affected by frequent revisions of the macroeconomic time series.

This paper is structured as follows: Section 2 reviews the relevant literature. Section 3 presents the macroeconomic and fiscal data used. Section 4 provides nowcasting models and their evaluation. Section 5 discusses the results and their robustness. The last section summarizes my findings and puts forward several ideas for future research.

2. Related Literature Review

The literature on economic nowcasting has focused predominantly on real GDP. Common references include, for instance, Giannone et al. (2008) and Banbura et al. (2013). Nowcasting real GDP has been covered by several authors from the CNB in the past (Arnostova et al., 2011; Benda and Ruzicka, 2007; Franta et al., 2016; Rusnak, 2016). In addition, a few papers have devoted their attention to nowcasting other macroeconomic variables, such as foreign GDP (Adam and Novotny, 2018), the trade balance (Kucharcukova and Bruha, 2016) and inflation (Havranek et al., 2010).

Nevertheless, the literature on nowcasting macroeconomic variables using high-frequency fiscal data is relatively scarce. A number of authors argue that intra-annual fiscal data for several euro area countries should be incorporated into the models to improve the forecasts of annual fiscal aggregates (Asimakopoulos et al., 2020; Perez, 2007; Pedregal and Perez, 2010; Onorante et al., 2010). Moreover, Asimakopoulos et al. (2020), using the MIDAS approach, found that the subcomponents of aggregated fiscal series should be taken into account to increase the accuracy of annual fiscal aggregates. Another important feature of the models employing intra-annual fiscal data is their potential to detect economic turning points early, as emphasized by Pedregal and Perez (2010).

High-frequency data, especially daily data, are subject to high volatility and noise, and therefore smoothing techniques are to be applied prior to any meaningful analysis, which may follow, for instance, the proposals set out in Misch et al. (2017). In a similar manner, I construct 21-business day rolling sums of daily data as a proxy for a monthly fiscal series, since the average monthly number of business days in the Czech Republic is about twenty-one.

Real-time daily fiscal data are available for many countries, but are rarely, if ever, used. According to Misch et al. (2017), the benefits of using daily fiscal data include improved fiscal surveillance and nowcasting economic activity. For example, during the course of the year, additional daily fiscal data can indicate whether yearly forecasts are reasonable or some fiscal criteria will be met. Furthermore, nowcasting economic activity using fiscal data might be a good option for countries in which national accounts statistics are of poor quality.

The seasonal adjustment of daily fiscal data is not straightforward, since daily data usually contain multiple seasonalities (e.g. weekly, monthly and yearly patterns) and the number of observations varies between months and years. Popular seasonal adjustment techniques, such as X-13 and Tramo-Seats, are currently being implemented for quarterly or monthly data only. Nonetheless, one can resort to other available techniques in order to seasonally adjust daily data. One of them is Seasonal-Trend decomposition using Loess (LOcal regrESSion) smoothing, in short STL decomposition, proposed by Cleveland et al. (1990). STL decomposition can handle any type of seasonality and is robust to outliers, but it does not take into account the trading day or any variation in the calendar. This method was recently enhanced by Ollech (2018) to handle the effect of moving holidays.

Another way of seasonally adjusting daily data is to employ structural time series models. The Prophet toolbox, developed by Facebook (Taylor and Letham, 2018), uses the Bayesian approach and Fourier periodic functions to estimate the seasonal component of time series. Koopman and Ooms (2003) built an unobserved components model for daily tax revenues, where the issue of the unequal number of observations per month is resolved with time transformation and the inclusion of missing values. The TBATS[2] method, also based on an unobserved components model, was proposed by Livera et al. (2011), and further utilized, for instance, by Ardizzi et al. (2019) to seasonally adjust daily payment data.

Nowcasting models often deal with mixed frequency variables because some of the independent variables are available in higher frequencies (e.g. monthly, weekly or daily) than the dependent variable (usually specified in quarterly or yearly frequency). Therefore, suitable econometric models are needed. For this purpose, the econometricians tend to start with simple models, such as bridge equations, introduced by Klein and Sojo (1989) or MI(xed) DA(ta) S(ampling) regression, devised by Ghysels et al. (2004). The advantage of these models is that they can be applied relatively easily and their results can be interpreted clearly. This is the reason I have employed them in this paper. More complicated models, which are commonly used for nowcasting, include dynamic factor models and mixed frequency VAR models.

3. Data

In this section selected relationships between macroeconomic and fiscal data are described and illustrated. The relationship between wage bill and social contributions is found to be the closest, followed by the relationships between GDP and value added tax, and between private consumption and value added tax. These relationships are thus the subject of the nowcasting exercise.

3.1 Wage Bill vs. Social Contributions

The relationship between wage bill and social contributions is naturally very close, since part of social contributions is collected in the wage bill. In the Czech Republic, social contributions (including health insurance) are paid both by employees and employers. The part that is paid by employees is contained in the wage bill, while the part paid by employers is not (it is included in the total compensation of employees, which is a different statistical category).

Social contributions paid by employees currently account for 11% of the wage bill, while social contributions paid by employers are calculated at a rate of 33.8% on the top of the wage bill. Unfortunately, disaggregated data about social contributions paid by employees and employers are not available at a higher frequency than quarterly. Nevertheless, in the nowcasting exercise it is possible

[2] [T]rigonometric seasonality, [B]ox-Cox transformation, [A]RMA errors, [T]rend and [S]easonal components

to relate the wage bill to total social contributions, but social contributions need to be netted out for the structural changes to social contributions paid by employers and are not, by definition, reflected in the wage bill. For example, a change in the employer social contribution rate is not reflected in the wage bill, and thus this effect should be removed prior to the analysis.

The social contribution rates are fairly stable in the Czech Republic, and have only been changed on few occasions. In 2009, total social contribution rates dropped from 47.5% to 45%, more specifically from 12.5% to 11% for employees and from 35% to 34% for employers. More recently, in July 2019, the social contribution rate for employers decreased slightly from 34% to 33.8%.

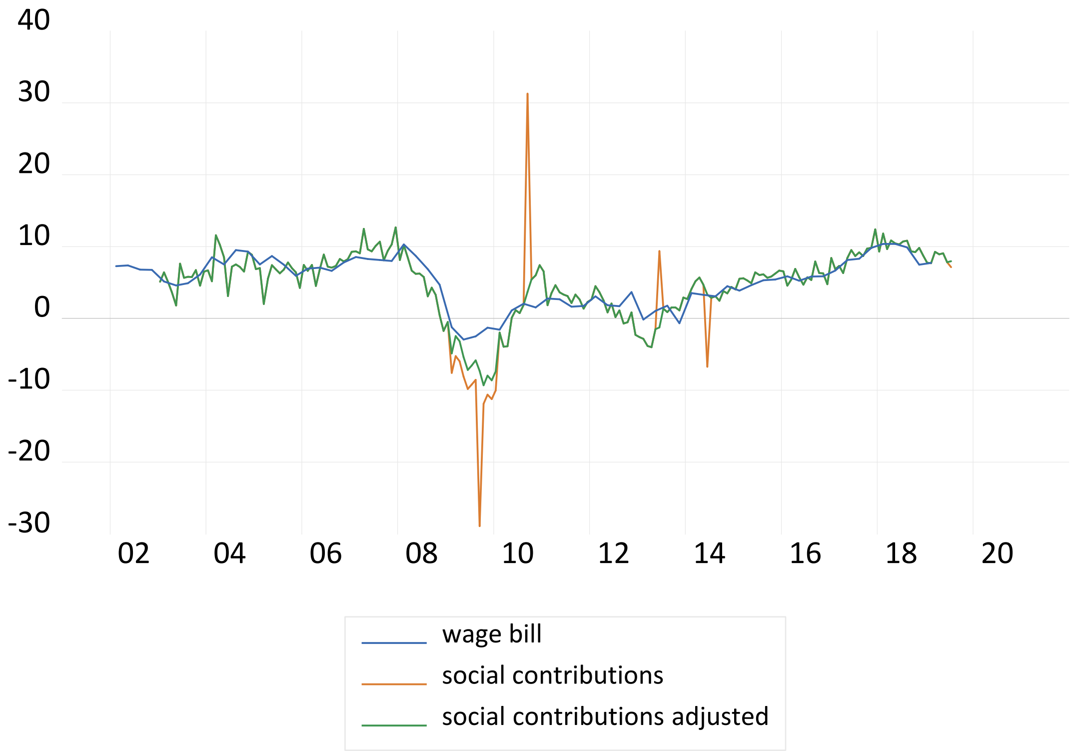
Wage bill data are seasonally adjusted and published quarterly and in accrual terms by the Czech Statistical Office (CZSO).[3] Social contribution data are monthly, recorded in cash methodology, provided by the MF and seasonally adjusted by the X-11 algorithm. It is important to note that social contributions in cash methodology are recorded with a one-month delay, reflecting the delay in paid wages and salaries. The CNB's summer 2019 forecast is the cut-off date for data, (i.e. the last wage bill observation is 2019 Q1) and the cut-off date for social contributions is July 2019. Time series for monthly social contributions begin in January 2002. A real-time database is created for the wage bill, with historical data vintages from 2014 onwards. The revisions to social contributions are minor and occur only in the month of publication; thus the last vintage of data is used in the nowcasting exercise.

The original and adjusted social contributions for tax changes in employers' rates and outliers, together with the wage bill, are shown in Figure 1. There are two outliers in the level data, one in September 2009, and the other in June 2013. These are substituted by the average value of the previous and subsequent value for the corresponding outlier. Next, social contributions are adjusted for the change in the employer tax rate in January 2009, when employer contributions fell from 35% to 34%. I create hypothetical social contributions where the social contribution rate is assumed constant (at 34%) over the entire sample, by scaling social contributions from January 2009 by a factor of 34/35. It is worth noting that the annual growth rate of adjusted social contributions (illustrated by the green line) is higher in 2009 than in the original unadjusted series, reflecting the drop in social contribution rates from 2009 onwards. After the adjustment, social contributions evolved more in line with the wage bill in 2019. This makes sense because – as mentioned above – changes in the employer social contribution rate are not incorporated into the wage bill. There is also a minor difference between the original and the adjusted social contributions at the end of the sample owing to a small positive systematic revision of data usually made by the MF in the second half of the month. My motivation to consider this systematic revision is in ex-ante anticipation of the final monthly figure for social contributions, which should result in a more precise nowcasting of the wage bill.

The wage bill and the adjusted social contributions in levels are depicted in Figure A1 in the Appendix. Next, Figure A2 compares the wage bill and accrualized social contributions (i.e. shifted one month back in time and with monthly observations summed into quarters). Visually, these two series share common dynamics. This is also confirmed by the correlation measured between wage bill and social contributions, which is close to 1. This means that social contributions are a brilliant candidate for nowcasting the wage bill, which will be demonstrated later in the results. Furthermore,

[3] An indirect approach is used internally within the CNB. More specifically, the industry components of the wage bill are seasonally adjusted using the Tramo-Seats procedure which takes into account the trading day effect, and are consequently aggregated.

Figure 1: Wage Bill vs. Social Contributions (annual changes in %)



the wage bill and social contributions are cointegrated with one cointegrated vector. Therefore, it is possible to estimate the nowcasting equations directly in levels.[4]

Daily social contributions are also included in the cash fulfillment of state budget, which is available internally within the CNB. These are published with a one working day lag. The selected sample of daily social contributions is shown in Figure A12 in the Appendix, covering 2019 until mid-August. One can notice that this daily data exhibits high volatility and possibly contains multiple seasonalities (e.g. weekly, monthly and yearly). Despite these difficulties, I propose a tractable method of handling daily data for nowcasting. My method consists of several steps. First, 21-business day rolling sums are constructed from daily data as a proxy for monthly fiscal series. Next, the trend from daily rolling sums is extracted using STL decomposition (Cleveland et al., 1990) and prolonged with the ARMA forecast. Afterwards, this trend is utilized to forecast the missing monthly social contribution figures, where daily observations are only partially available (e.g. do not yet include the whole month).

An alternative indicator that may be suitable for nowcasting the wage bill is the monthly data on industrial wages and salaries. This indicator is constructed internally within the CNB, and its dynamics, along with the wage bill and adjusted social contributions, are depicted in Figure A3 in the Appendix. Social contributions and industrial wages and salaries co-move similarly, but there are also a few periods with a higher wedge between them, especially in 2011 and 2019. Further-

[4] I tried this specification, but there is still some residual autocorrelation in the estimated equations. This autocorrelation issue can be remedied by assuming AR(1) residuals in the specification. Unfortunately, nowcasting the performance of such specification turned out worse than the specification in growth rates, and is thus omitted in the results.

more, social contributions are less jittery and cover a longer time span compared to industrial wages and salaries. This is a relevant issue for the estimation of a nowcasting model. Altogether, social contributions seem to be a more appropriate candidate for wage bill nowcasting.

One may argue that personal income tax is also a relevant indicator for wages, as personal income tax is a tax levied on wages. Unfortunately monthly and daily time series for personal income tax, recorded in cash methodology, are very volatile in the Czech Republic. Moreover, there are significant cash-accrual adjustments that influence cash data for personal income tax. To be more specific, the March and June tax liability settlements for the previous calendar year have a significant impact on personal income tax collection, and the exact amount of these settlements is not available. Therefore, the usage of personal income tax for nowcasting is rather limited. For the sake of this analysis, I tried to nowcast the wage bill with personal income tax, but the forecasting performance turned out to be inferior to nowcasting the wage bill with social contributions, and thus these results are not presented in this paper.

3.2 Macroeconomic Data vs. Value Added Tax

Value added tax (VAT) can be related to private consumption or GDP. This relationship arises because VAT is a tax imposed on the consumption of goods and services. More broadly VAT reflects overall evolution in GDP, since the majority of its expenditure components are subject to VAT (except for exports, which are excluded from VAT in the domestic economy).

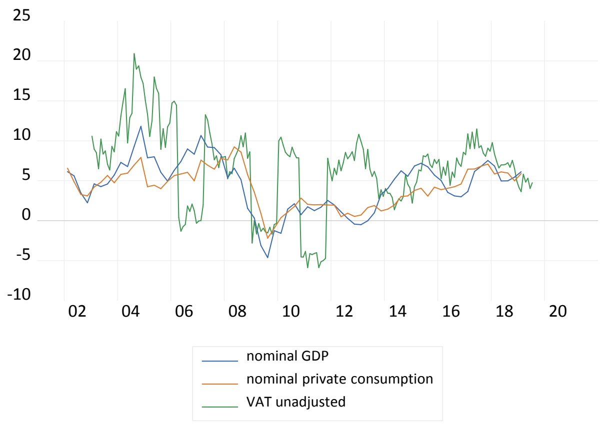
The analysis of VAT with respect to private consumption or GDP is complicated in the Czech Republic by the fact that the government makes relatively frequent changes to the VAT rate. The changes in VAT gradually transmit into price deflators (e.g. a consumption or GDP deflator), which implies that the VAT changes have different impacts on nominal and real macroeconomic variables. For example, assuming the immediate pass-through of VAT changes to prices, a change in the VAT rate would appear in nominal private consumption, but not in real private consumption. Thus, in the nowcasting exercise, it is preferable to relate nominal private consumption or nominal GDP to unadjusted VAT, whereas real private consumption or real GDP should be linked to VAT netted out for tax changes.

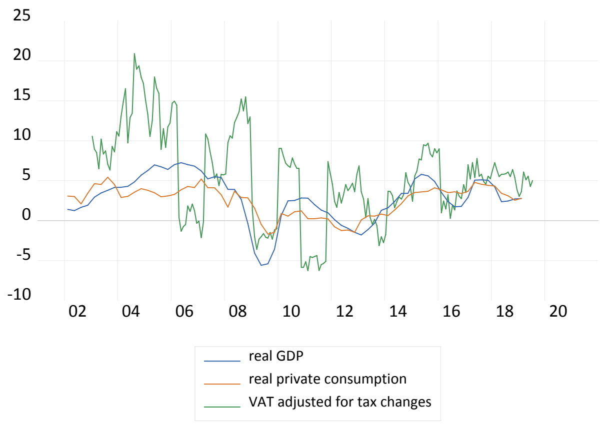
In order to nowcast real macroeconomic variables using VAT, I construct an auxiliary time series for VAT, which is expertly adjusted for relevant past tax changes. The estimated yearly budgetary impacts of the VAT changes are adopted from official government documents, such as the Fiscal Outlook, the Convergence Programme, the State Budget, the explanatory notes to the laws etc., and are presented in Table A1 in the Appendix. For simplicity, it is assumed that the annual impacts of the changes in VAT are equally distributed into the months in which they were valid. Otherwise stated, if some of the VAT changes came into effect during the year (and not as of the beginning of the year), this would also have to be taken into account in the adjusted series for VAT. Using algebra, the annual VAT growth rate is adjusted for past tax changes according to the following formula:

$$vat_t^{adj} = vat_t - \frac{IMP_t^P + IMP_t^T - IMP_{t-12}^T * (1 + \frac{vat_t}{100})}{(VAT_{t-12} - IMP_{t-12}^T)} * 100, \qquad (1)$$

in which vat_t^{adj} is the adjusted accrualized annual growth rate of VAT in monthly frequency expressed in percentage points, vat_t is an original unadjusted accrualized annual growth rate of VAT, VAT_t denotes the level of unadjusted accrualized VAT, and IMP_t^P, IMP_t^T are accrual budgetary impacts of permanent and temporary VAT measures in CZK. In this adjustment process it is important to match accrual budgetary impacts with corresponding VAT cash collection (because VAT is

Figure 2: GDP, Private Consumption vs. VAT (annual changes in %)





recorded with a one-month delay). Therefore VAT data are accrued – shifted one month back in time.

The original unadjusted and adjusted VAT rates for the past tax changes are depicted in Figure A4 in the Appendix or with green lines in Figure 2. For a better understanding of these figures, several episodes with significant VAT changes can be highlighted. There was an increase in the reduced VAT rate from 10% to 14% in 2012, followed in 2013 by an additional increase in the reduced VAT rate from 14% to 15% and the standard rate from 20% to 21%. If there had been no increase in the VAT rate in 2012 and 2013, then VAT collection would have risen more slowly (see its approximate estimates in the VAT series adjusted for tax changes). From the adjusted VAT series, the changes in VAT are netted out, and therefore adjusted VAT represents hypothetical VAT collection when the VAT changes did not occur in the past.

Data for private consumption and GDP are quarterly, seasonally adjusted and published by the CZSO in accrual terms. In cash methodology, data for VAT are monthly, come from the MF and are seasonally adjusted. VAT is recorded with a 1 month delay, reflecting the due date of VAT (the 25th of the month following the tax return period). The tax system is further complicated due to VAT refunds, which are paid with a two-month delay. This additional delay in VAT refunds complicates nowcasting due to the need for an additional forecast for the missing independent observations to produce the nowcast. Moreover, the time series of VAT netted out for the effect of VAT refunds is found to be very volatile. Thus, I have left the role of VAT refunds out of my analysis. The time series for monthly VAT start in January 2002. The last observation for quarterly data (private consumption and GDP) is 2019 Q1, and for VAT it is July 2019. A real-time database is created for private consumption and GDP, both in real and nominal terms, beginning in 2014 for the purposes of recursive forecasts. VAT data are not revised ex-post; therefore the last vintage of data is used.

GDP, private consumption and accrualized VAT are shown in Figures A5 and A6 in the Appendix. Figure A5 presents variables in nominal terms, whereas Figure A6 presents variables in real terms and with VAT adjusted for past tax changes. There are some comovements between GDP and VAT, and private consumption and VAT, but according to the Johansen cointegration test, these two relationships do not seem to involve cointegrated variables. Thus, these two relationships are then modelled on growth rates.

The correlation between private consumption and VAT and between GDP and VAT (expressed in annual growth rates) is moderate, reaching around 0.4–0.5. Inspecting these relationships visually in Figure 2, a more stable relationship can be identified from 2014 onwards. The results will show that there is some potential for nowcasting private consumption or GDP using VAT.

4. The Models

4.1 Bridge Equations and MIDAS Regression

Two different models are employed to nowcast quarterly macroeconomic variables using monthly fiscal data – bridge equations and MIDAS regression. The bridge equations have the following specification:

$$y_{t_Q} = \alpha + \beta_1 y_{t_Q-1} + \beta_2 X^Q_{t_Q} + \varepsilon_{t_Q}, \tag{2}$$

where y_{t_Q} is the annual growth rate of the selected macroeconomic variable in quarterly frequency (denoted by the time index t_Q), and $X^Q_{t_Q}$ is the quarterly average of monthly fiscal data, α is the constant, the β_1 parameter captures the persistence of the macroeconomic variable, the β_2 parameter reflects the contribution of fiscal data in explaining the selected macroeconomic variable, and the error term ε_{t_Q} is assumed to follow normal distribution with zero mean. The quarterly average of monthly fiscal data is computed as follows:

$$X^Q_{t_Q} = \frac{1}{3}\sum_{j=0}^{2} X^M_{3t_Q-j}, \tag{3}$$

where $X^M_{3t_Q-j}$ is the annual growth rate of fiscal data in monthly frequency in the $(3-j)$-th month of the t_Q quarter, for $j \in \{0,1,2\}$. The superscript Q or M indicates that fiscal data are either in quarterly or monthly frequency. In other words, quarterly fiscal data are approximated[5] by the average monthly fiscal data. This way, in bridge equations the macroeconomic variable is linked to quarterly fiscal data, which is made from three monthly observations. It is sensible from an economic point of view to work only with an aggregator for fiscal monthly data which takes into account exactly three months; for instance, exactly three monthly social contributions should be reflected in the wage bill for a given quarter. Bridge equations are estimated by an ordinary least square estimator.

The second model utilized for nowcasting is a MIDAS regression, which has the following specification:

$$y_{t_Q} = \alpha + \beta_1 y_{t_Q-1} + \beta_2 \sum_{j=0}^{2} \omega_j X^M_{3t_Q-j} + \varepsilon_{t_Q}, \tag{4}$$

where the weights ω_j add up to one and depend on unknown parameters, which are estimated. The explanation of other variables and parameters stay the same as for bridge equations. Similar to bridge equations, monthly fiscal data are aggregated over exactly three months. One can notice that the MIDAS regression resembles the bridge equation. The difference lies in the weighting scheme of the high-frequency variable. In bridge equations, there is equal weighting across monthly data

[5] This approximation is due to the fact that both quarterly and monthly fiscal data are expressed in annual growth rates.

(1/3), whereas in the MIDAS regression, the weighting of monthly data, given by the weights ω_j, is allowed to be more flexible. Of the several algorithms available to estimate these weights, an unrestricted U-MIDAS was chosen. These two estimated models are then used to nowcast the macroeconomic variables using fiscal data.

4.2 Timing and Forecasting of Incomplete Monthly Data

The timing of the nowcasting exercise is of key importance to understanding what macroeconomic and fiscal data enter the model. For a formal explanation, Q0 denotes the current quarter for which the forecast for the macroeconomic variable is to be made. Q1 is the quarter following Q0. The forecast can be made in the first month (labeled as M0), the second month (M1) or the third month (M2) of a given quarter (either Q0 or Q1). The aim is to forecast the macroeconomic variable for quarter Q0. The forecast of the macroeconomic variable for Q0, which is conducted in any month of the same quarter (Q0), represents the nowcast, whereas the macroeconomic variable forecast for Q0, which is conducted in the following quarter (Q1), is called the backcast (e.g. forecasting the past observation, which is yet to be published). Three different nowcasts can be computed in the Q0 for each of its months. Only two backcasts are calculated in Q1, one for the first month and the other for the second. The backcast for the third month is omitted, as the figure for the macroeconomic variable for quarter Q0, which is the subject of the prediction, is finally published at the start of the third month. It is important to note that nowcasting the macroeconomic variable for Q0 in the first or second month of quarter Q0 is further complicated by the fact that the figure for the macroeconomic variable for the previous quarter (Q(-1)) is yet to be published, and thus has to be estimated as well.

As regards independent monthly fiscal data, observations are often missing, which have to be forecasted before the nowcast (or the backcast) of the macroeconomic variable can be produced. To elaborate more on this forecasting of monthly data, imagine a situation in which the nowcast for a macroeconomic variable is to be calculated in the first month (M0) of the current quarter (Q0). The latest available monthly fiscal data is for the third month (M2) of the previous quarter (Q(-1)). Additionally, there has to be an accrual adjustment of the monthly fiscal data (e.g. shifted back in time), which is recorded in cash methodology with some delay. In the case of social contributions and value added tax, this delay is one month, meaning that the latest available monthly observation at the beginning of the current quarter (Q0) corresponds to the second month (M1) of the previous quarter (Q(-1)) in economic terms. Hence, in order to produce the nowcast of a macroeconomic variable for quarter (Q0), it is necessary to forecast the four missing monthly data from the first month (M0) of the current quarter (Q0) to the first month (M0) of the following quarter (Q1). Now, imagine a different situation in which the backcast for a macroeconomic variable is to be made at the beginning of the quarter (Q1). The latest monthly fiscal data is for the third month (M2) of the previous quarter (Q0), which, after accrualization, corresponds to the second month (M1) of the previous quarter (Q0). In this situation, there is only one missing monthly observation (for the first month M0 of the current quarter Q1), which has to be forecasted in order to compute the backcast. Similar logic applies for the remaining timings of the nowcast/backcast.

Missing monthly data are extended using several techniques. Traditional simple time series models, which include random walk (the last observed growth rate) or autoregressive moving average model (ARMA), are utilized. Moreover, as a novel approach, I apply STL decomposition to extract the trend from the daily series in order to forecast missing/future monthly figures.

4.3 The Evaluation of the Models

The models are validated by several means. First, both pseudo real-time and real-time recursive out-of-sample forecasts are produced. In the pseudo real-time forecasts the last vintage of macroeconomic data is used, whereas the macroeconomic data first released enters the real-time forecast.

The sample used in the initial evaluation covers the period from the beginning of 2003 until the end of 2013. The models are estimated on this sample and out-of-sample forecasts are computed. The evaluation sample is then extended into the future by one month. Again, the models are estimated and out-of-sample forecasts are calculated. The recursive estimation continues until the last considered observation, which is from July 2019. By construction, the evaluation period for the models is flexible and increases with each additional iteration.

The evaluation of the models which also use daily data is slightly more complicated. Besides rolling over months in recursive forecasts, there are additional iterations which loop over 21 business days. To illustrate, one can construct such recursive forecasts which reflect exactly 10 business days in the first month of any quarter in the evaluation sample.

Subsequently, root mean square errors (RMSE) are computed for out-of-sample one-quarter-ahead forecasts. Twenty out-of-sample forecasts are made, gradually covering the period 2014 Q2–2019 Q1, and these enter into the calculation of the RMSEs. In addition, RMSEs are distinguished for their different possible timings over the months (reflecting 3 nowcasts and 2 backcasts), or for daily data also within one month (21 business days). RMSEs are compared with usual benchmark models, including random walk (the last observed growth rate of a macroeconomic variable) and ARMA forecasts, and also against historical forecasts from models used at the CNB. Finally, the performance of alternative forecasts as against historical CNB forecasts is also checked using the Diebold-Mariano test [6].

5. The Results

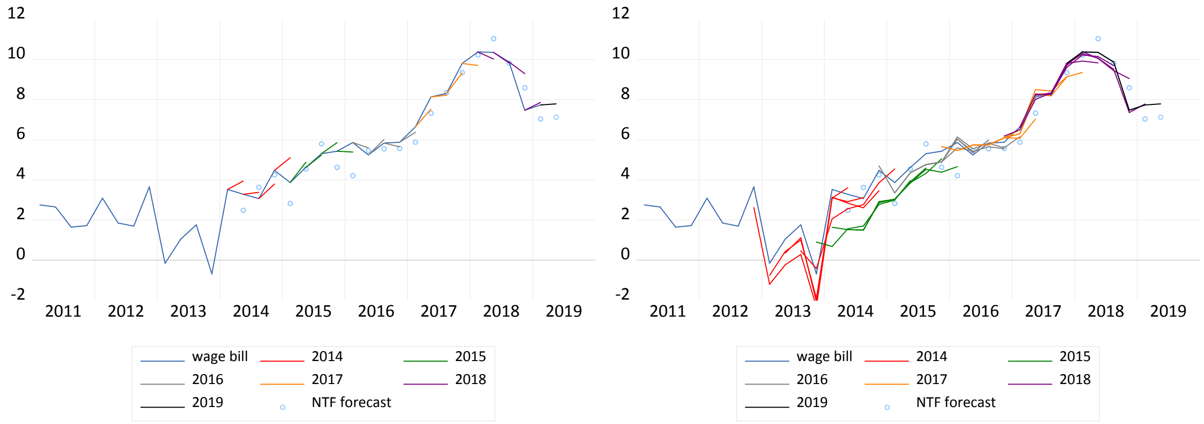
At the beginning of this section, selected recursive out-of-sample forecasts are depicted to visually inspect the performance of nowcasting models. Afterwards, several nowcasting models, which link macroeconomic variables (wage bill, gross domestic product and private consumption) to fiscal data (social contributions and value added tax), are evaluated using root mean square errors. Next, the robustness of the results is reviewed with respect to the alternative quarterly specifications for nowcasting models. Lastly, the performance of nowcasting models, which relate the wage bill to daily data on social contributions, is assessed.

5.1 Recursive Forecasts

The performance of nowcasting models is checked by plotting selected recursive out-of-sample forecasts, focusing on the closest relationship found between the wage bill and social contributions. To make graphs more readable, not all recursive forecasts are shown, only those which correspond to the timing of the macroeconomic forecast at the CNB. The CNB's macroeconomic forecast is completed in the first month of the quarter, meaning that the subject of the nowcasting exercise is to backcast the macroeconomic variable for the previous quarter. Given this timing, there are three monthly observations of fiscal data available for the previous quarter. Due to the fiscal accrualization of fiscal data (i.e. reflecting the one-month delay in recording social contributions and VAT), one

[6] Devised by Diebold and Mariano (1995)

Figure 3: Bridge Equations: Pseudo and Real-time Recursive 1-period Forecasts for the Wage Bill using Forecasted Social Contributions



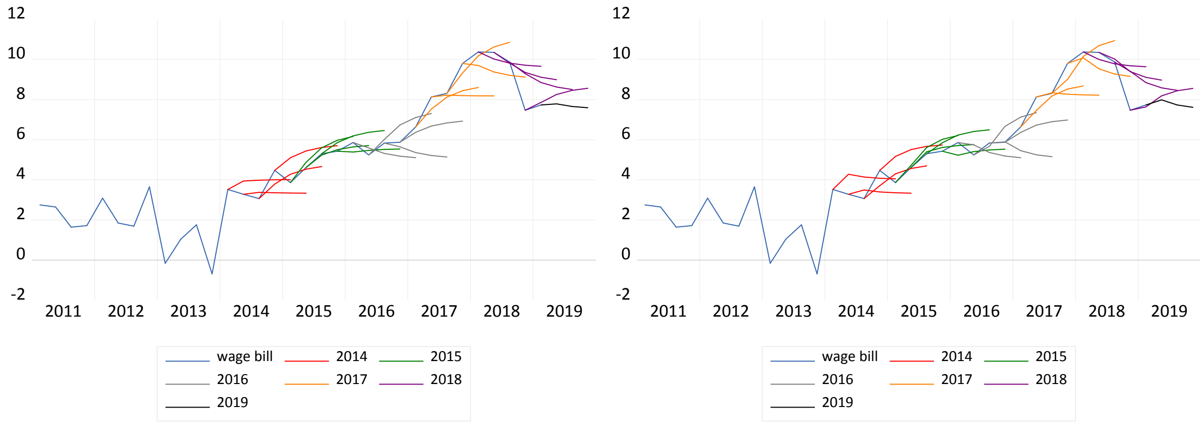
monthly fiscal observation is missing, which has to be forecasted in order to complete the backcast of the macroeconomic variable.

Employing bridge equations, recursive backcasts for the wage bill using social contributions are depicted in Figure 3. The left-hand graph shows pseudo real-time forecasts using the last vintage of wage bill data (as available in the CNB's summer 2019 forecast, with the last observation for 2019 Q1). On the right-hand graph there are real-time forecasts which are based on the first releases of wage bill data. Real-time forecasts also include 4 historical observations which make data revisions visible over time. One missing monthly observation for social contributions is forecasted with the random walk model (e.g. the last observed annual growth rate is propagated). Recursive forecasts are distinguished by colors, signaling the year of the last observation for wage bill data that enters the model. In these graphs, the wage bill is expressed in annual growth rates. The blue circles represent the CNB's historical wage bill forecasts for one-quarter ahead.

Recursive backcasts show that bridge equations for the wage bill using social contributions perform better than the CNB's historical forecasts. The left-hand graph in Figure 3 shows that pseudo real-time backcasts for the wage bill are on average more precise than the CNB's historical forecasts. This result can be partially attributed to past data revisions of the wage bill. Pseudo real-time backcasts have the advantage of working with the latest vintage of data, whereas the CNB's historical forecasts were based on real-time data, and associated deviations of historical forecasts from revised data may naturally be higher. Therefore, it is strongly recommended that real-time backcasts are also checked. By inspecting the right-hand graph in Figure 3, it is difficult to judge whether real-time backcasts are more successful than the CNB's historical forecasts. Calculated RMSE for real-time backcasts is around 0.7 percentage points, which is roughly the same for the CNB's historical forecasts[7]. The situation is different for pseudo real-time forecasts, where bridge equations have a slightly lower RMSE (0.6) compared to the CNB's historical forecasts (0.7). Nevertheless, the results of the Diebold-Mariano test, shown in Table A7 in the Appendix, cannot reject the null hypothesis that both forecasts (from bridge equations and the CNB's historical forecast) have the same accuracy, which holds for both real-time and pseudo real-time forecasts.

[7] If a different error statistic is used for the evaluation, then some improvement is noticeable when bridge equations are used. For example, the mean average error (MAE) for bridge equations is 0.49, compared to 0.55 for the CNB's historical forecast.

Figure 4: Pseudo Recursive 4-period Forecasts for the Wage Bill using Forecasted Social Contributions



A few episodes can be identified in which bridge equations seem more suitable for making backcasts for the wage bill than the CNB's historical forecasts. For instance, bridge equations seem to be better in capturing the turning point in the wage bill which occurred in 2018 Q2. More recently, the backcast of the wage bill for 2019 Q1, produced by bridge equations, was more successful than the CNB's near-term forecast.

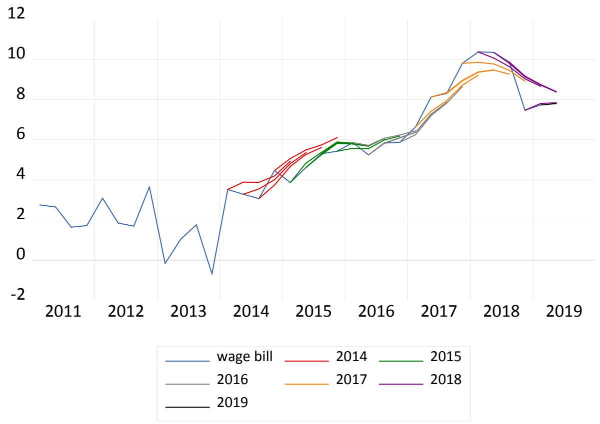
Pseudo recursive forecasts for the wage bill using social contributions, which utilize both bridge equations and MIDAS regression, are shown in Figure 4. The left-hand graph in this figure shows bridge equations, while the one on the right illustrates the MIDAS regression. The forecast horizon is larger in these recursive forecasts and equals 4 quarters. The timing of recursive forecasts is kept the same as in the previous case, i.e. the forecasts are made in the first month of the quarter. In order to complete the forecasts, the underlying fiscal monthly data are extended into the future using a random walk model. Given the similarities of the two models, there are some minor differences in their recursive forecasts. This is also confirmed by the average RMSE, which attains the same value of 0.95 pp for both models. The RMSE is higher than the recursive backcasts, (which are 1-period forecasts), due to the longer forecast horizon.

Simulating the recursive forecasts in which realized observations are plugged into an independent variable is another way of assessing the performance of the nowcasting model. It means that missing monthly data are not forecasted, as was the case in previous recursive forecasts, but realized observations are used to complete the forecasts. In the example considered, the observed social contributions are utilized to predict the wage bill. Such pseudo recursive forecasts modelled with bridge equations are available in Figure 5. The forecast horizon is 4 quarters, making the timing consistent with previous recursive forecasts (the first month of the quarter). Qualitatively, the model performs well in predicting the wage bill. Nevertheless, its ability to detect turning points (e.g. in 2018) has some limitations, especially for longer forecasting horizons. The average RMSE of pseudo recursive forecasts is 0.65 pp, which is intuitively lower than for when social contributions are forecasted (0.95 pp).

5.2 Nowcasting Performance using Monthly Data

The ability of fiscal data for nowcasting selected macroeconomic variables is assessed with the root mean square errors of recursive forecasts. Several relationships between quarterly macroeconomic

Figure 5: Pseudo Recursive 4-period Forecasts for the Wage Bill using Realized Social Contributions



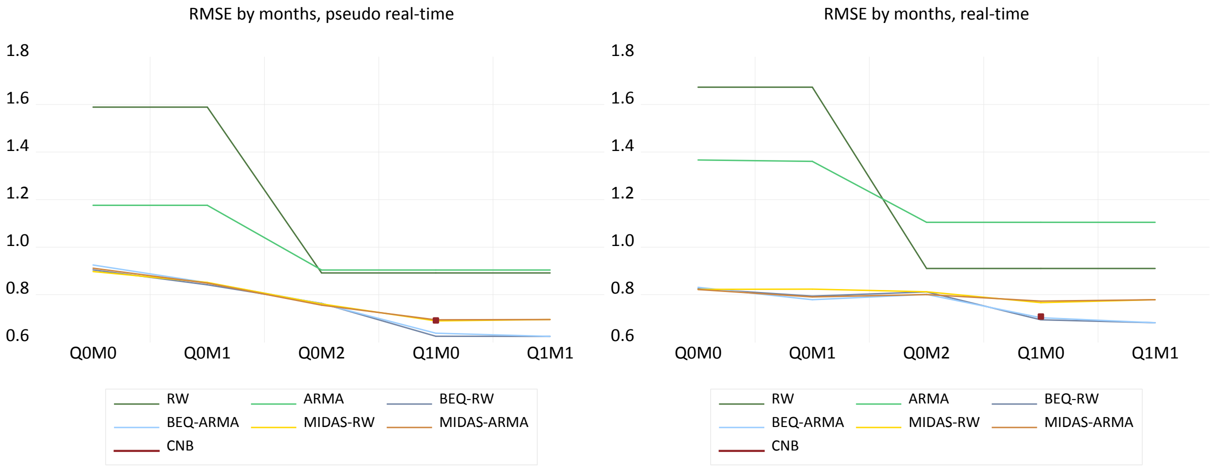
variables and monthly fiscal data are scrutinized, including the wage bill vs. social contributions, gross domestic product vs. value added tax, and private consumption vs. value added tax. RMSEs for recursive forecasts are computed for different timings in the quarters, which correspond to three possible nowcasts and two backcasts. Both bridge equations and MIDAS regression are utilized for nowcasting, further divided into two variants where missing monthly observations are forecasted either with the random walk or ARMA model. For benchmarking purposes, recursive forecasts are also calculated for so-called naive models, which do not incorporate any data other than those for a dependent macroeconomic variable (e.g. no fiscal data are included). These benchmark models include the random walk or ARMA model. The backcasts from nowcasting models are compared with historical CNB macroeconomic forecasts, suggesting the importance of fiscal data in nowcasting selected macroeconomic variables.

5.2.1 Nowcasting Wage Bill with Social Contributions

The relationship between the wage bill and social contributions is the most promising in terms of nowcasting performance. The results for this relationship are graphically presented in Figure 6 (and in Table A2 in the Appendix), utilizing both pseudo real-time (left-hand graph) and real-time data (right-hand graph). Generally, I favor focusing my attention on the results obtained using real-time data rather than pseudo real-time data, since the results for pseudo real-time data might be blurred by frequent historical revisions of macroeconomic (wage bill) data. In addition, it is certainly not appropriate, or fair, to compare historical forecasts with alternative models which use solely the last vintage of data. As a reminder, the purpose of the nowcasting exercise is to predict the quarterly wage bill for Q0 for different timings (months) in the current quarter Q0 or in the following quarter Q1.

As regards naive benchmark models, for instance the random walk or ARMA model, depicted here in dark and light green, there is a significant drop in RMSE occurring in the third month of the current quarter (labeled using the time index Q0M2). This drop stems from the fact that the figure for the macroeconomic variable (in this case the wage bill) for the previous quarter Q(-1) is published, and thus the precision of the naive model, with its forecast for the current quarter Q0, increases. The wage bill for the previous quarter Q(-1) has to be estimated in the first or second month of the current quarter Q0, consequently making the nowcast of the wage bill for the current quarter Q0 less accurate. In the first and second months of the following quarter (Q1M0 and Q1M1), the RMSEs

Figure 6: Nowcasting the Wage Bill with Social Contributions



are stable for naive models, since there is no new data from which these models could benefit. Naive models are very simple time series models, which use only data for dependent variables. It is worth noting that the results for the third month of Q1 (timing Q1M2) are omitted. This is because the wage bill for Q0 is finally released in this period, and it makes no sense to predict it.

The CNB forecast is produced in the first month of Q1 (Q1M0), and the root mean square error for the CNB historical forecast for the wage bill is represented in Figure 6 by a brown dot. Bridge equations, represented by blue lines, achieve the best results, or the least errors, for this timing. Nonetheless, the improvement in bridge equations compared to the CNB forecast is relatively small, achieving a 2% improvement in the RMSE of one-quarter recursive forecasts. This small gain is reflected in the Diebold-Mariano (D-M) test, which suggests that both forecasts are equally accurate (for details see the results in Table A7 in the Appendix). There is, however, an interesting result showing that an additional improvement (of up to 4% in the case of the RMSE) in the prediction of the wage bill is possible when the daily data on social contributions is reflected as well, as demonstrated later in Section 5.4.

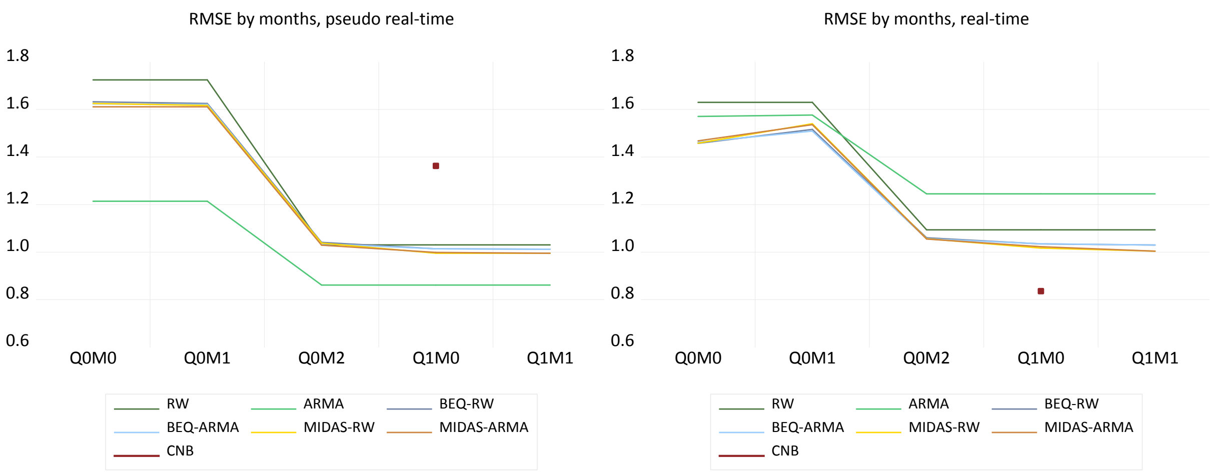
For nowcasting periods (timings from Q0M0 to Q0M2), the performance of bridge equations and MIDAS regression in predicting the wage bill is roughly similar with respect to the RMSEs recorded. As for the backcasts (timings Q1M0 and Q1M1), bridge equations produce the least errors.

5.2.2 Nowcasting GDP with Value Added Tax

As discussed earlier, VAT is a suitable candidate for nowcasting GDP because the majority of expenditure components of GDP are subject to VAT (except for exports). In nowcasting models, nominal GDP is related to unadjusted VAT, whereas real GDP is linked to VAT netted out for past tax changes, since VAT changes are more likely to be reflected in the GDP deflator than in the real GDP.

As regards the results presented here, it is important to note that historical data for GDP are not initial preliminary releases, published in the second month of the quarter, but official first releases, which are available at the beginning of third month of the quarter. The results for the relationship between nominal GDP and VAT are displayed in Figure 7 or in Table A3 in the Appendix. For

Figure 7: Nowcasting Nominal GDP with Value Added Tax



all models, there is an intuitive drop in the RMSE occurring in the third month of the current quarter (timing Q0M2), which arises from the inclusion of new GDP observations into the estimated models. In the case of pseudo real-time data, none of the nowcasting models that involve VAT is better than the simple ARMA model (light green). All the models have a lower RMSE for recursive forecasts than the historical CNB forecast (with timing Q1M0). However, this seems to be mainly due to the historical revisions of data, which is supported by the results using real-time data (see the right-hand graph). Employing real-time data, none of the models is strong enough to improve the accuracy of historical CNB forecasts.[8] This is likely due to the fact that the CNB forecast of GDP is conducted on disaggregated components, which utilize a set of various indicators, whereas these nowcasting models rely just on one particular indicator (VAT). Nevertheless, bridge equations and MIDAS regression achieve lower RMSEs compared to the naive models (random walk or ARMA model).

The RMSE for recursive forecasts for the relationship between real GDP and VAT adjusted for past tax changes are displayed in Figure 8 or in Table A4 in the Appendix. Qualitatively, the general conclusions are very similar to those for the relationship between nominal GDP and unadjusted VAT. Using real-time data, none of the alternative nowcasting models are capable of improving on the historical CNB forecast. Nonetheless, the good news is that bridge equations and MIDAS regressions bring at least some improvement to the accuracy of the forecasts with respect to the naive models.

5.2.3 Nowcasting Private Consumption with Value Added Tax

Besides GDP, value added tax can be used for the nowcasting of private consumption as well. Private consumption is subject to VAT, and thus there is theoretically the potential to exploit high-frequency VAT data for nowcasting private consumption. The results are divided for both nominal and real private consumption, which are linked to unadjusted VAT and VAT adjusted for past tax changes, respectively.

The results for the relationship between nominal private consumption and unadjusted VAT are depicted in Figure 9 or in Table A5 in the Appendix. Concerning pseudo real-time data, the ARMA

[8] The D-M test, presented in Table A7 in the Appendix, shows that the accuracy of historical CNB forecasts for GDP significantly differ only from the ARMA model in real-time.

Figure 8: Nowcasting Real GDP with Value Added Tax

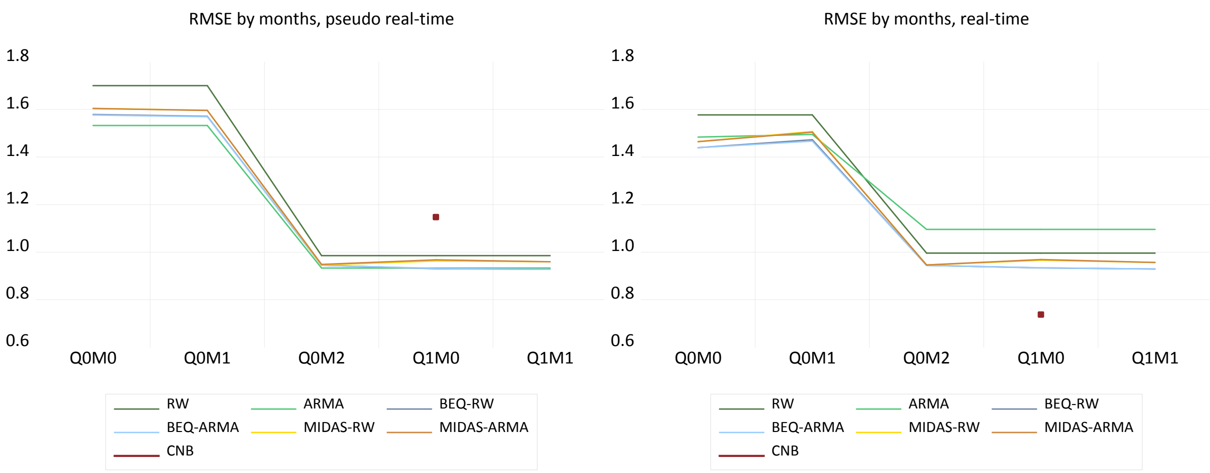
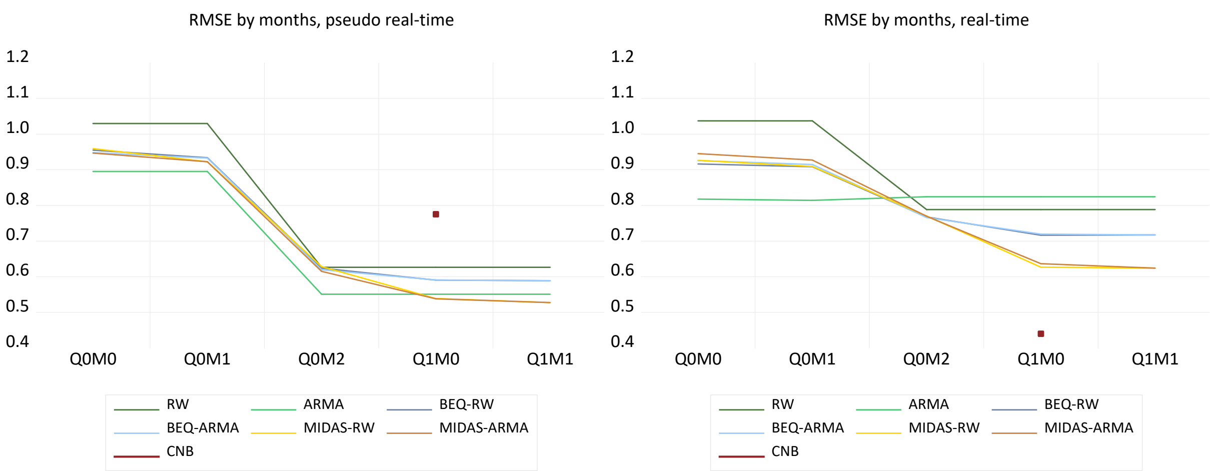


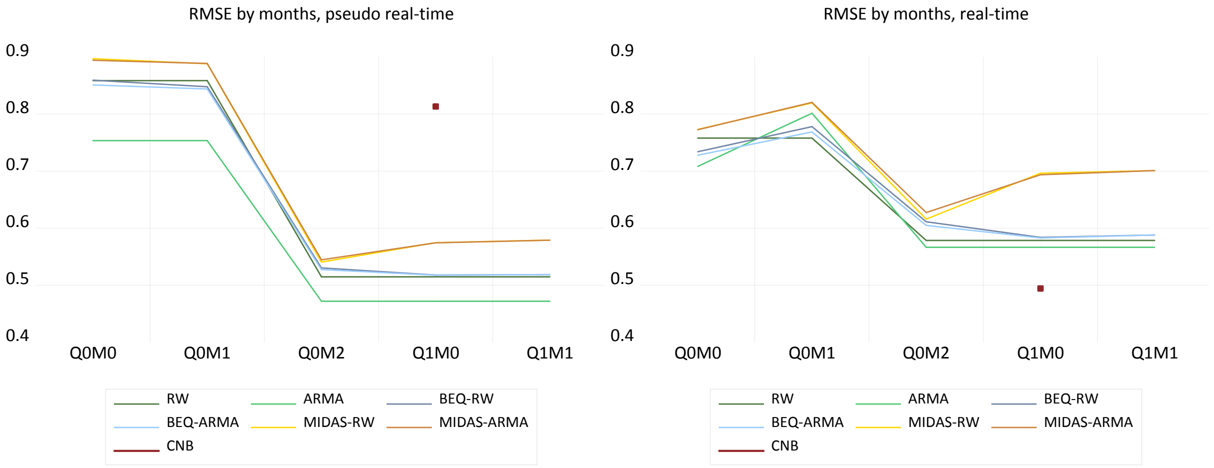
Figure 9: Nowcasting Nominal Private Consumption with Value Added Tax



model records the lowest RMSE for nowcasting periods, whereas a MIDAS regression with an ARMA extension of the missing observations seems appropriate for backcasting periods. All the models outperform the historical CNB forecast, but this can again be somewhat attributed to the frequent revisions of private consumption. If real-time data for private consumption is used, then the results on the right-hand graph show that none of the models perform better than the historical CNB forecast. The D-M test also confirms that the historical CNB forecast has better forecasting accuracy, see Table A7 in the Appendix. This result suggests that VAT is not a very reliable indicator for nowcasting private consumption, compared to the current CNB practice. Surprisingly, in the first and second month of Q0 the ARMA model produces the most precise backcast. For later timings (from Q0M2 onwards), MIDAS regression gives the lowest RMSE.

The results for the relationship between real private consumption and VAT adjusted for past tax changes are shown in Figure 10 or in Table A6 in the Appendix. Bridge equations and MIDAS regressions perform worse than naive models for both pseudo real-time and real-time data. Hence, there is no potential for VAT to improve the nowcasting of real private consumption. Similar to previous cases, pseudo-real time data perform better than the historical CNB forecast, but the situation

Figure 10: Nowcasting Real Private Consumption with Value Added Tax



is reversed when the real-time data for real private consumption are considered. This reversal likely arises from the historical revisions of data on private consumption. Nevertheless, the D-M test, in the last column of Table A7, is not powerful enough to prove any significant difference between the forecasting accuracy of the historical CNB forecast and alternative models in real-time.

An important lesson from the analysis provided is that the use of real-time data is essential for nowcasting. Results derived solely from pseudo real-time data may be biased and the corresponding policy prescriptions may be completely reversed after using real-time data. This is precisely what I demonstrated for the relationships between VAT and GDP/private consumption, showing that the historical CNB forecast is superior to alternative nowcasting models, which are estimated on real-time data. This outcome is the opposite for pseudo-real time data, however.

5.3 Robustness: Quarterly Specification

As a robustness check, I also estimate previous relationships using the quarterly transformation of variables. The underlying motivation to perform such estimation reflects an issue connected with the baseline annual specification, which is specified in annual growth rates. Annual specification implies that the error term has a moving-average structure, which can lead to inefficient estimates. Furthermore, annual specification might not be practical for forecasting/nowcasting purposes due to base effects. Therefore, I also proceed as follows with alternative quarterly specifications:

$$y_{t_Q} = \alpha + \beta_1 X^Q_{t_Q} + \varepsilon_{t_Q}, \tag{5}$$

where y_{t_Q} is the quarterly growth rate of the selected macroeconomic variable in quarterly frequency, and $X^Q_{t_Q}$ is the quarterly average of monthly fiscal data, α is the constant, the β_1 parameter reflects the contribution of fiscal data in explaining the dependent variable, and ε_{t_Q} is the error term. The quarterly average of monthly fiscal data is defined as:

$$X^Q_{t_Q} = \frac{1}{3}\sum_{j=0}^{2} X^M_{3t_Q-j}, \tag{6}$$

where $X^M_{3t_Q-j}$ is the quarterly growth rate of fiscal data in monthly frequency in the $(3-j)$-th month of the quarter t_Q, for $j \in \{0,1,2\}$. Notice that the quarterly specification resembles the baseline annual specification in Equation 2. Main difference is that the autoregressive part is omitted in the quarterly specification because it is not significant, and relevant variables are expressed in quarterly growth rates. Besides OLS estimation of the quarterly specification, a robust least squares (RLS) estimation is also carried out. RLS estimation is designed to be less sensitive to outliers. Of the several approaches available in RLS, I chose an S-estimation by Rousseeuw and Yohai (1984), which focuses on outliers in the regressor variable, and tackles possible high volatility in fiscal series. In addition, the MIDAS regression is run with the following quarterly specification:

$$y_{t_Q} = \alpha + \beta_1 \sum_{j=0}^{2} \omega_j X^M_{3t_Q - j} + \varepsilon_{t_Q}, \tag{7}$$

where ω_j are the weights, and the explanation of other variables and parameters stay the same as in Equations 5–6. In order to have comparable results for the quarterly specification and the annual specification, the forecasting evaluation of quarterly models is checked with RMSE in which nowcasts/backcasts are expressed as year-on-year growth rates, and are computed ex-post from quarterly figures.

The results for quarterly specifications, along with annual specifications, are depicted in Figures A7–A11 in the Appendix. All the results presented are solely for real-time data due to their relevancy. The panels on the left show the results for bridge equations, whereas the panels on the right show those for MIDAS regression. The blue lines represent annual specifications, while the other colors are used for quarterly specifications.

When you examine Figure A7, it is evident that nowcasting the wage bill with the quarterly specification does not bring any improvement compared to the annual specification. Nowcasting nominal GDP with value added tax in the quarterly specification is more precise than the forecast made with the annual specification (see Figure A8). Both MIDAS regression and bridge equations perform better in the quarterly specification. Nevertheless, the quarterly specification does not beat the historical CNB forecast of the nominal GDP in the relevant period (Q1M0). The results for nowcasting real GDP with VAT are shown in Figure A9. Quarterly specifications outperform annual specifications for both MIDAS regression and bridge equations. The lowest RMSEs are recorded for bridge equations, which bring some improvement over historical CNB forecasts. This improvement is distinct for the robust least squares estimation of bridge equations, presented with green lines. Nowcasting nominal private consumption with the quarterly specification is worse than the baseline annual specification for all considered quarterly specifications (check Figure A10). Finally, nowcasting real private consumption with the quarterly specification is superior to the annual specification, as can be seen from Figure A11. Bridge equations are associated with the lowest RMSEs, especially when estimated using the RLS approach. Nonetheless, none of the nowcasting models is able to outperform historical CNB real private consumption forecasts.

To summarize the results of the robustness check, the quarterly specification is more successful in nowcasting macroeconomic variables than the annual specification in some cases. This concerns the results for nowcasting GDP (both in nominal and real terms) and real private consumption. In one case, the historical CNB forecast is outperformed by the bridge equations for real GDP estimated by robust least squares.

5.4 Nowcasting Performance using Daily Data

Forecasting the accuracy of nowcasting models which relate the wage bill to social contributions can be further improved by incorporating daily data. Daily fiscal data from the cash fulfillment of the state budget are available in timely manner, with a lag of one working day. A short sample of daily social contributions is illustrated in Figure A12 in the Appendix. The underlying idea to work with daily data is that several days of daily data in a given month should provide some indication as to the possible monthly outcome. In other words, one should be able to forecast the missing monthly figures, where daily observations are available only partially (e.g. do not yet cover the whole month). Ideally, the forecast of monthly figures should become more precise with each additional daily observation taken into account in a given month.

Nevertheless, there are a few complications when making a forecast of monthly figures using daily data. First, daily data is highly volatile. Second, daily data may contain nontrivial patterns of seasonality, possibly occurring in multiple frequencies (weekly, monthly, or yearly).

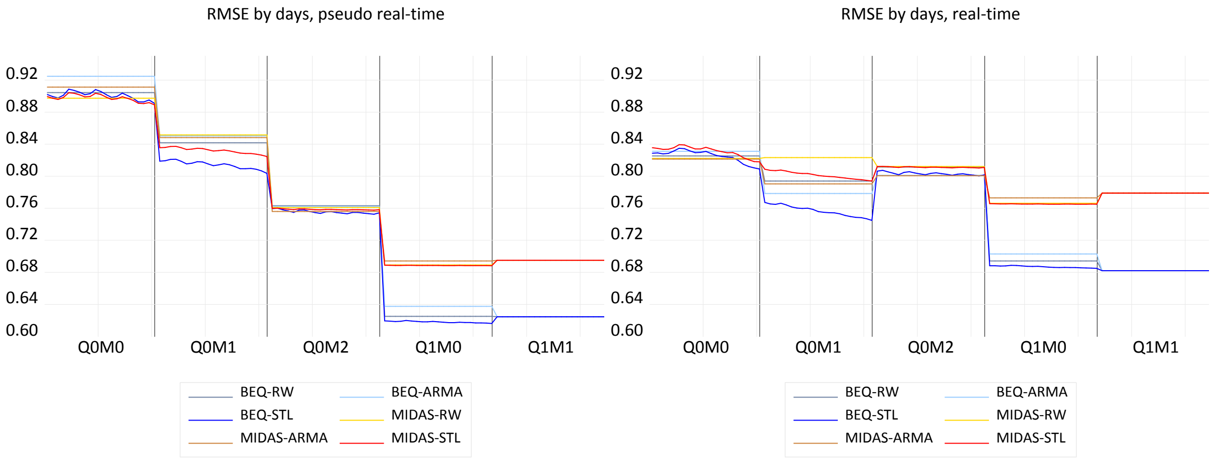
To overcome the first issue of high volatility, daily data are aggregated to monthly sums. There is on average 21 working days in a month, thus rolling 21-day sums are constructed as a proxy for a monthly series. In the case of social contributions, this statistic is depicted in Figure A13 in the Appendix. These rolling 21-day sums, calculated to the last day of each month, can be compared with the officially published monthly data, which is provided in Figure A14 in the Appendix. Both time series have been evolving roughly in concert since 2011, whereas in the more distant history, i.e. before 2010, the rolling 21-day sums were more volatile compared to the officially published monthly data.

To tackle the second issue, i.e. the seasonality of daily data, it is possible to apply those models which can forecast the missing daily data in a month while allowing for seasonal patterns, or alternatively seasonally adjust the daily data. First, I employed seasonal ARIMA models to forecast the missing daily observations in a month, but the results were unsatisfactory. Although forecasted daily data can capture seasonal patterns, aggregating daily data to monthly figures imply unrealistic annual growth rates, involving sudden spikes or drops. Similar problems, with unrealistic annual growth rates of forecasted monthly data, have arisen by applying Facebook's Prophet model (Taylor and Letham, 2018) to daily data. Nonetheless, promising results have been obtained with the STL decomposition (Cleveland et al., 1990) of daily data to extract seasonal and trend components.

Using STL decomposition, the trend from the daily rolling sums of social contributions is extracted, as illustrated by the green line in Figure A15 in the Appendix. This daily series can be transformed into monthly series by taking the last observations in each month and comparing them to the officially published monthly data on social contributions, see Figure A16 in the Appendix. The STL trend from daily social contributions evolves roughly in line with official monthly data. Therefore, this STL trend is a suitable candidate to forecast the missing monthly figures for social contributions.

My proposed method of nowcasting macroeconomic variables using daily data consists of the following steps. First, 21-business day rolling sums are constructed from daily data as a proxy for a monthly series. Second, the trend from daily rolling sums is extracted using STL decomposition and prolonged over the forecasting horizon with an ARMA forecast. For daily social contributions, this ARMA extension is illustrated by the orange line in Figure A15 in the Appendix. Third, this STL trend with the ARMA extension is used to forecast the missing monthly figures, which are necessary to complete the nowcast of the macroeconomic variable. To be more specific, a daily series with STL trend including its ARMA extension is transformed into a monthly series by taking the last observations in each month. This transformed series for social contributions is illustrated by orange lines in Figures A16–A17 in the Appendix. Notice that Figure A17 is just a zoomed version of Figure A16, showing only data from 2018. The official monthly series, which are present in the nowcasting models, are then prolonged with the ARMA extension of the STL trend in a manner

Figure 11: Nowcasting Wage Bill with Social Contributions



illustrated by the green line in Figure A16 in the Appendix. It means that the changes in the prolonged STL trend are propagated at the end of the available official monthly series, e.g. the orange and green lines are parallel in the same figure. This blue-green line then enters into the nowcasting models.

The advantage of this nowcasting method is that it can be applied to any business day during a given month. Once more daily observations are available, the nowcasting procedure described can be updated. Does this daily nowcasting significantly improve the results? An evaluation of the models which relate the wage bill to social contributions shows that there are some gains in using daily data for nowcasting.

The evaluation of the models which also use daily data is a bit more complicated than for monthly models. Besides rolling months in recursive forecasts, as was the case in Section 5.2, there are additional iterations which loop over 21 business days. Therefore, RMSEs are distinguished for different possible timings over 5 months (reflecting 3 nowcasts and 2 backcasts) and because of daily data there are also 21 possible recursive forecasts calculated for each business day during the 5 months under consideration.

The results for the relationship between the wage bill and daily social contributions are depicted in Figure 11. To recap, the aim of the nowcasting exercise is the prediction of the quarterly wage bill for Q0 for different timings (in this case business days) in the current quarter Q0 (for months M0 till M2) or in the following quarter Q1 (for months M0 and M1). The end of each month is highlighted with vertical black lines. For benchmarking purposes, RMSEs for monthly models are illustrated in this figure with horizontal lines. These lines correspond to the results shown for the monthly models in Figure 6, using the same color scheme. Naive monthly models are omitted, since their nowcasting performance is worse than that of bridge equations or MIDAS regression.

Focusing on the results obtained using real-time data (see right-hand graph in Figure 11), there is some improvement at the end of the month using daily data in the first month of the current quarter (timing Q0M0). Starting from the 17$^{\text{th}}$ business day, bridge equations with a daily STL extension (blue line) achieve lower RMSE than MIDAS regression with an ARMA extension (golden line). However, this improvement is difficult to interpret, as data on social contributions from the first month of the current quarter still belong in accrual terms to the previous quarter, reflecting the delays in paid wages and salaries. Therefore, daily social contributions in the first month of the current quarter should not contain relevant signal for the outcome of the wage bill in the current quarter.

An important result is that bridge equations with daily data bring the best improvement over the monthly models in the second month of the current quarter (timing Q0M1). This makes sense because the monthly models do not yet incorporate any relevant data on social contributions, which belong in accrual terms to the wage bill in the current quarter (i.e. social contributions in the first month still belong in accrual terms to the previous quarter). On the other hand, daily social contributions available in the second month of the current quarter belong in accrual terms to the wage bill in the current quarter, and therefore have some "advantage" or "lead" over the monthly data. Note that the recorded RMSE is already lower when data on social contributions for the first business day is considered. There is an initial 1.3% improvement in the RMSE with respect to bridge equations with an ARMA extension, and the percentage improvement rises to 4.3% by the end of the month. RMSEs for daily data tend to decrease during the month, which is a desirable property. It means that having more daily data in the month makes the nowcast more precise. Nevertheless, there is still some artefact of weekly seasonality present in the data after applying the STL decomposition, since there are four small visible humps in RMSEs (for the blue line). Thus, day-on-day changes in the RMSE may occasionally worsen (be positive) or hover around zero, but the differences in RMSEs over several days improve the results (achieve a lower RMSE).

In the third month of the current quarter (timing Q0M2), bridge equations with daily data perform worse than monthly MIDAS regression or bridge equations with an ARMA extension. Nonetheless, bridge equations with daily data are still better than monthly MIDAS regression or bridge equations with a random walk extension. What is surprising is that the lower bound of RMSEs in the third month of the current quarter is larger than RMSEs in the second month of the current quarter, even though more recent data are included in the nowcasting models.

In the first month of the quarter Q1 (timing Q1M0), in which a backcast for the previous quarter Q0 is made, bridge equations with daily data record the lowest RMSEs, beating monthly bridge equations with random walk extensions. RMSEs for this timing are slowly decreasing over the course of the month, including more daily observations in the bridge equations. As a reminder, this timing is relevant for the CNB forecast, since its forecast is being regularly finalized in this period. Therefore, compared to common monthly models, daily data on social contributions can further improve the accuracy of backcasting the wage bill, albeit by a small margin. To be more specific, the percentage improvement in RMSE over bridge equations with a random walk extension increases from 0.8% (when the first daily observation is included) to 1.3% (at the end of month, when daily data for 21 business days are included).

In the second month of Q1 (timing Q1M1), bridge equations with daily data do not lead to any improvement in RMSE. This result is intuitive and correct because daily observations available in this timing already belong in accrual terms to the wage bill for Q1, whereas the purpose is to predict the wage bill for Q0. In this timing, the monthly figure for the previous month (Q1M0) is known, and this is exactly the last monthly observation necessary to complete the backcast of the wage bill for Q0. By definition of used nowcasting models, additional more recent data (from Q1M1) are irrelevant for the backcast computed for Q0. This is also apparent from the figure, showing that RMSEs for bridge equations or MIDAS regression coincide, irrespective of the type of extension used to forecast missing monthly observations (i.e. these monthly observations are not missing in this timing).

As regards pseudo real-time data (see left-hand graph in Figure 11), the results for daily data are qualitatively similar. The best improvement in RMSE occurs for bridge equations with STL extension in the timings Q0M1 and Q1M0, as was the case for real-time data. In addition, there is some minor improvement in RMSE for timing Q0M2; the RMSE for bridge equations with STL extension is lower than MIDAS regression with ARMA extension roughly from the second half of the month. The importance of these results for pseudo real-time data should not be overstated because, as mentioned earlier for monthly models, these results may be biased due to frequent revisions of macroeconomic data. Anyway, for the sake of completeness, these results are presented in this paper to illustrate the differences between using real-time data and pseudo real-time data.

Overall, nowcasting performance using daily data can bring some improvement over purely monthly models, as demonstrated in this section for the relationship between the wage bill and social contributions. Perhaps, this improvement may not be deemed large enough to outweigh the costs of making traditional nowcasting models more complicated.

6. Conclusion

In this paper, high-frequency fiscal data are used to near-term forecast (nowcast and backcast) selected macroeconomic variables for the Czech Republic. Many fiscal data, such as personal income tax, value added tax and social contributions, are a function of macroeconomic variables (e.g. wage and salaries, private consumption and GDP). Fiscal data are available in a very timely manner as opposed to macroeconomic data, which are published with a substantial time lag. Therefore, the inverse relationship between macroeconomic variables and fiscal data can be grasped in order to nowcast macroeconomic variables using more timely fiscal data.

I employ two kinds of commonly used models for nowcasting: bridge equations and MIDAS regression, which link quarterly macroeconomic variables to monthly fiscal data. The forecasting of incomplete monthly data, which are necessary to complete the nowcast/backcast in most timings, follows traditional naive models (random walk and autoregressive moving average models) or, in the proposed novel method, relies on the extraction of the STL trend (Cleveland et al., 1990) from available daily fiscal data.

For comparison purposes, the root mean square error (RMSE) of one-quarter recursive forecasts is computed and compared to historical CNB forecasts. For the relevant timing of the CNB forecast, which is the first month of the quarter (when a backcast for the previous quarter is made), a 2% improvement in RMSE is found for the nowcasting model which relates the wage bill to social contributions as against the historical CNB forecasts. Furthermore, nowcasting real GDP with value added tax, which utilizes bridge equations estimated by robust least squares, is able to slightly outperform the CNB's historical forecast.

Incorporating daily data on social contributions into the nowcasting models can further reduce the RMSE of the wage bill. In terms of the timing of the CNB forecast, this represents a roughly 1% improvement in RMSE on the best performing monthly nowcasting model. The maximum improvement in RMSE is found for different timings: in the second month of the current quarter, the improvement in RMSE is around 1% at the beginning of the month with respect to the best monthly model, and gradually rises to approximately 4% by the end of the month when more daily social contributions are taken into account.

An important recommendation arising from the performed analysis is to use real-time historical data instead of pseudo real-time data (the last vintage); otherwise RMSE is likely affected by frequent revisions of the macroeconomic time series, and corresponding policy implications might be overstated or indeed the exact opposite.

Overall, there is some benefit in nowcasting macroeconomic variables using more timely fiscal data. The forecasts can be improved by employing daily fiscal data, albeit at the expense of making nowcasting models more complicated. Generally, reflecting daily data in nowcasting models can reduce forecast errors in other economic fields as well, which might be especially relevant for finance or trading. Hence, the method I have proposed for incorporating daily data into the nowcasting models can serve as a good starting point for further research, devoted to the wider usage of daily data for forecasting.

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Appendix

Figure A1: Wage Bill vs. Social Contributions (in CZK bn, native frequency)

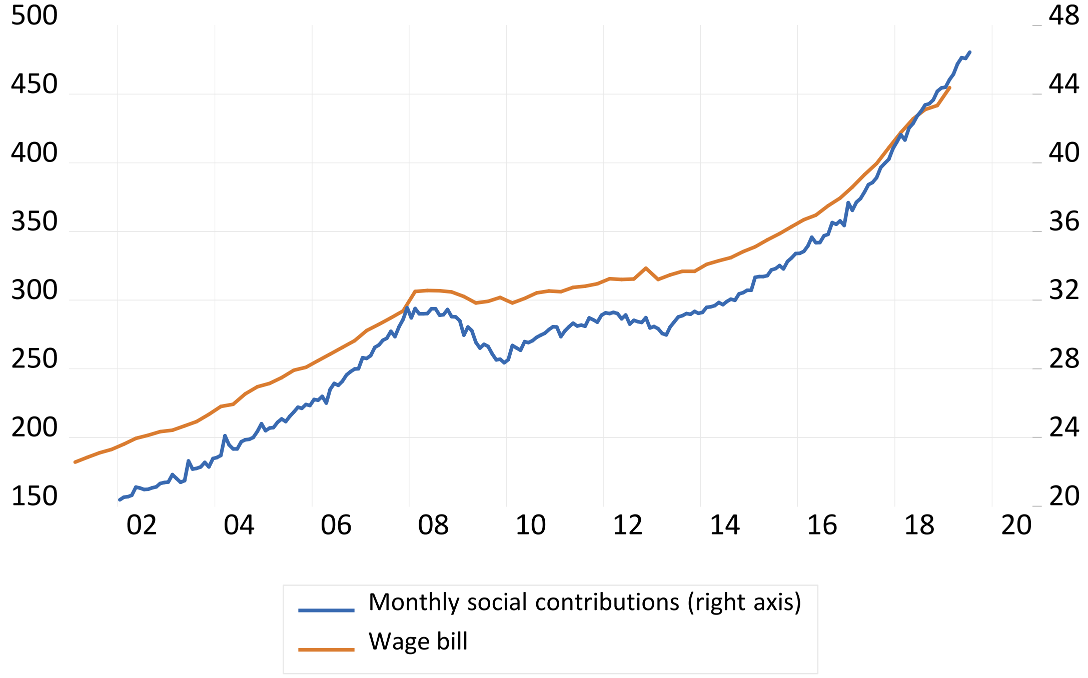


Figure A2: Wage Bill vs. Accrualized Social Contributions (in CZK bn, quarterly frequency)

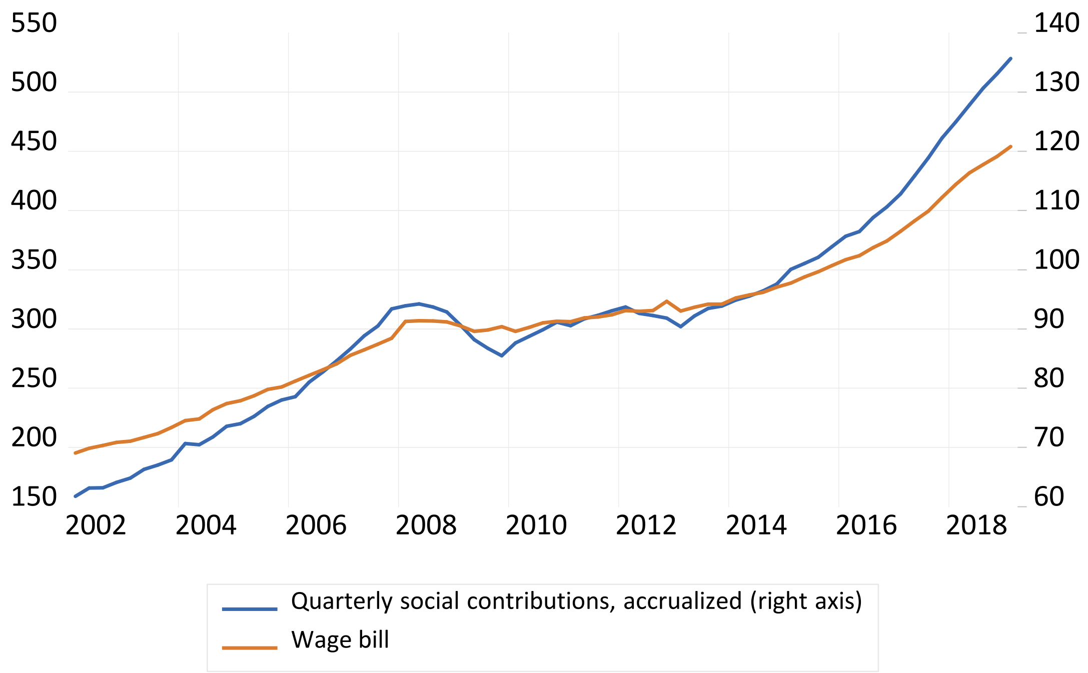


Figure A3: Wage Bill, Social Contributions, Industrial Wages and Salaries (annual changes in %)

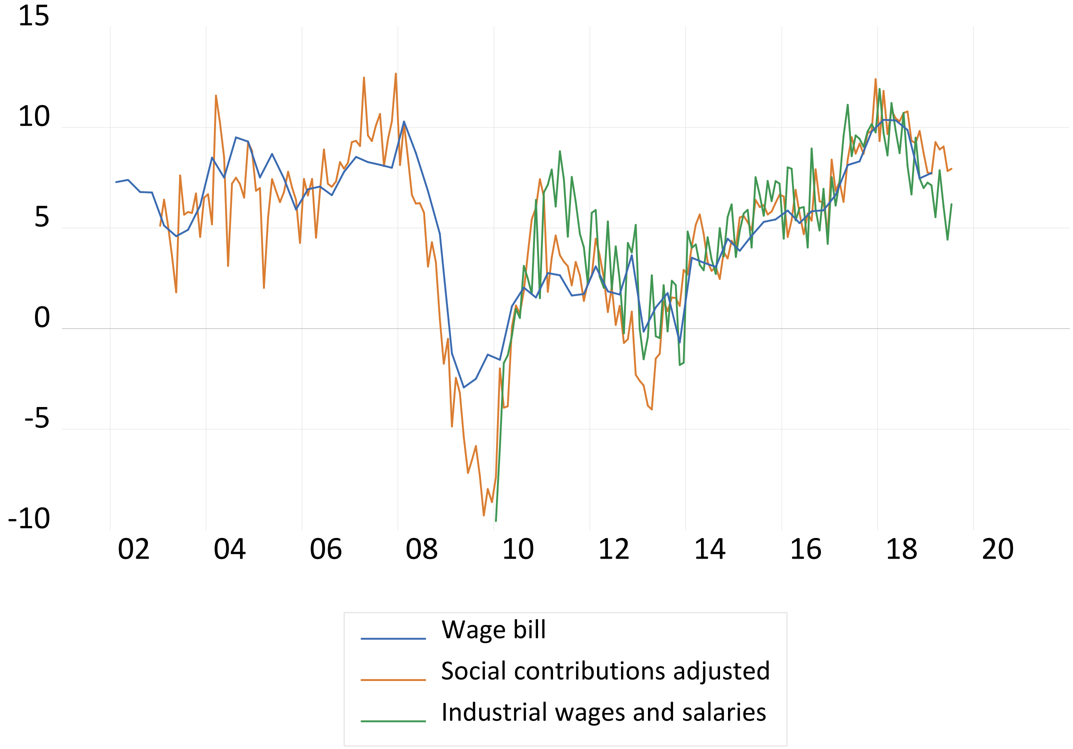


Figure A4: Unadjusted and Adjusted Value Added Tax (annual changes in %)

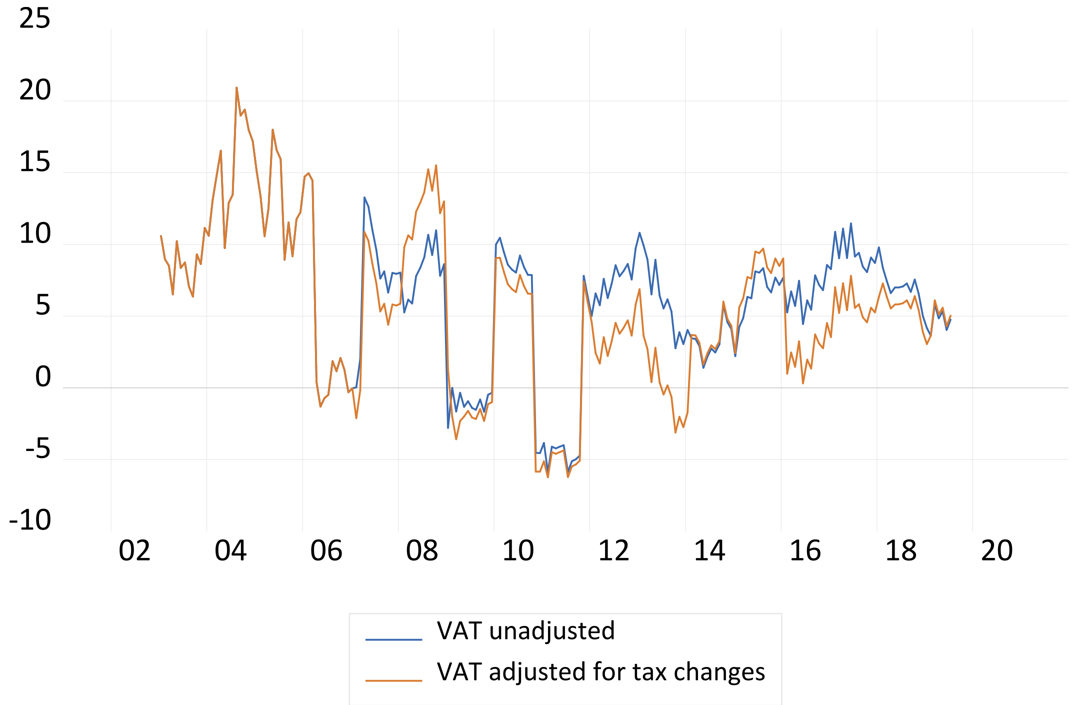


Figure A5: Nominal GDP, Private Consumption vs. Accrualized VAT (in CZK bn, quarterly frequency)

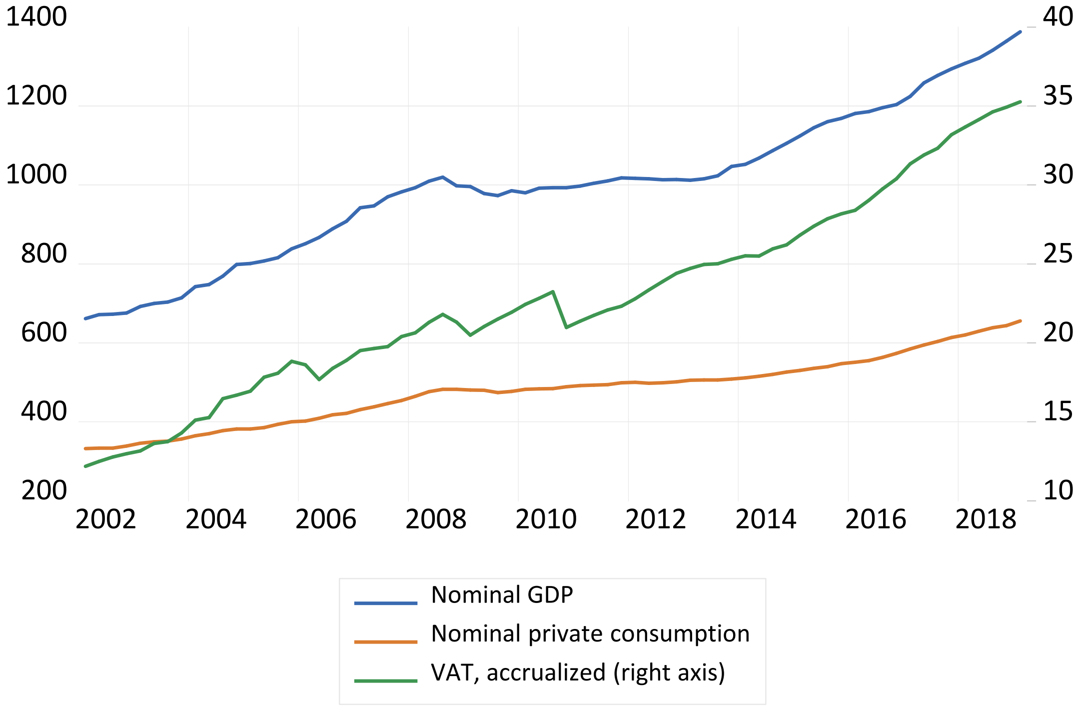


Figure A6: Real GDP, Private Consumption vs. Accrualized VAT (in CZK bn, quarterly frequency)

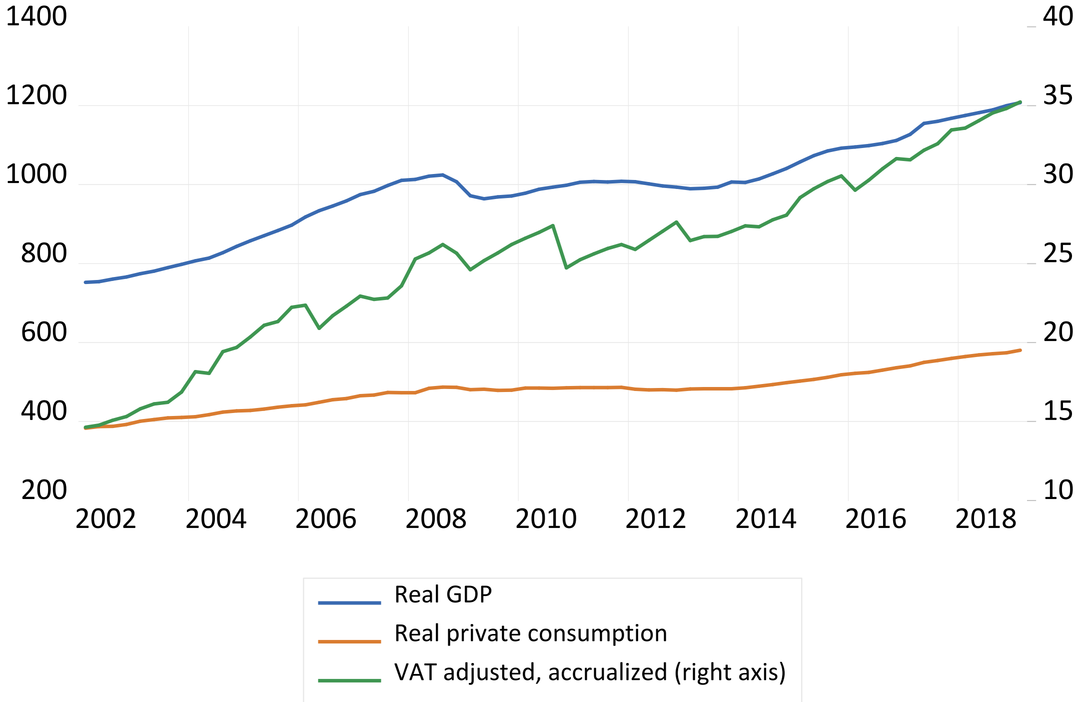


Table A1: VAT Measures and Their Budgetary Impacts (in CZK bn)

VAT measure	Implemented	2001	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Extended VAT refund	Jan-01	0.5													
Impact of the frontloading of goods before an increase in VAT rate	Jan-07		5.0	-5.0											
2009 stimulus package: extended VAT deduction on cars	Apr-09				-2.4	0.4									
2010 austerity package: increase in both VAT rates (by 1%)	Jan-10					3.0									
Antisolar energy power package: increase in VAT rate	Jan-11						1.0			-0.7					
Increase in reduced VAT rate (from 10% to 14%)	Jan-12							10.5							
Increase in reduced VAT rate (from 14% to 15%) and standard VAT rate (from 20% to 21%)	Jan-13								17.0						
Books, medical products and baby food moved from the 1st reduced VAT rate (15%) to the 2nd reduced VAT rate (10%)	Jan-15										-4.2				
Introduction of sales VAT reporting	Jan-16											13.7	8.0	3.0	
Introduction of electronic records of sales	Dec-16 (1st phase), Mar-17 (2nd phase)											0.2	6.0	1.5	
Food-related service moved to the 1st reduced VAT rate (15%)	Dec-16												-0.5		
Newspapers and magazines moved to the 1st reduced VAT rate (from 15% to 10%)	Jan-17												-0.5	-0.3	
Extended VAT refund for public broadcasters (television and radio)	Apr-17												-0.3	-0.1	
Public transport fares moved to the 2nd reduced VAT rate (10%)	Feb-19														-1.0

Note: All measures are permanent except for the "Impact of the frontloading of goods before an increase in VAT rate" from 2007, which is a temporary measure.

Table A2: Root Mean Square Errors for Wage Bill

	Nowcast			Backcast	
Model	M0	M1	M2	M0	M1
Pseudo real-time					
RW	1.589	1.589	0.891	0.891	0.891
ARMA	1.176	1.176	0.903	0.903	0.903
BEQ-RW	0.904	0.842	0.763	0.625	0.625
BEQ-ARMA	0.925	0.850	0.762	0.638	0.625
MIDAS-RW	0.897	0.852	0.761	0.689	0.695
MIDAS-ARMA	0.911	0.848	0.756	0.694	0.695
CNB	NA	NA	NA	0.692	NA
Real-time					
RW	1.673	1.673	0.910	0.910	0.910
ARMA	1.367	1.361	1.104	1.104	1.104
BEQ-RW	0.825	0.794	0.811	0.694	0.682
BEQ-ARMA	0.831	0.778	0.801	0.703	0.682
MIDAS-RW	0.822	0.823	0.812	0.766	0.779
MIDAS-ARMA	0.821	0.790	0.801	0.773	0.779
CNB	NA	NA	NA	0.708	NA

Table A3: Root Mean Square Errors for Nominal GDP

	Nowcast			Backcast	
Model	M0	M1	M2	M0	M1
Pseudo real-time					
RW	1.724	1.724	1.030	1.030	1.030
ARMA	1.214	1.214	0.861	0.861	0.861
BEQ-RW	1.633	1.625	1.041	1.014	1.012
BEQ-ARMA	1.624	1.621	1.035	1.014	1.012
MIDAS-RW	1.626	1.617	1.038	0.995	0.995
MIDAS-ARMA	1.612	1.611	1.029	0.999	0.995
CNB	NA	NA	NA	1.363	NA
Real-time					
RW	1.630	1.630	1.094	1.094	1.094
ARMA	1.571	1.576	1.245	1.245	1.245
BEQ-RW	1.458	1.516	1.060	1.034	1.030
BEQ-ARMA	1.462	1.509	1.056	1.035	1.030
MIDAS-RW	1.458	1.540	1.056	1.017	1.004
MIDAS-ARMA	1.468	1.537	1.055	1.023	1.004
CNB	NA	NA	NA	0.836	NA

Table A4: Root Mean Square Errors for Real GDP

	Nowcast			Backcast	
Model	M0	M1	M2	M0	M1
Pseudo real-time					
RW	1.701	1.701	0.985	0.985	0.985
ARMA	1.533	1.533	0.933	0.933	0.933
BEQ-RW	1.579	1.571	0.945	0.931	0.929
BEQ-ARMA	1.576	1.570	0.945	0.932	0.929
MIDAS-RW	1.604	1.596	0.946	0.963	0.959
MIDAS-ARMA	1.603	1.596	0.949	0.967	0.959
CNB	NA	NA	NA	1.148	NA
Real-time					
RW	1.577	1.577	0.996	0.996	0.996
ARMA	1.484	1.495	1.095	1.095	1.095
BEQ-RW	1.440	1.473	0.945	0.934	0.930
BEQ-ARMA	1.440	1.468	0.945	0.935	0.930
MIDAS-RW	1.465	1.507	0.946	0.966	0.957
MIDAS-ARMA	1.465	1.504	0.947	0.969	0.957
CNB	NA	NA	NA	0.737	NA

Table A5: Root Mean Square Errors for Nominal Private Consumption

	Nowcast			Backcast	
Model	M0	M1	M2	M0	M1
Pseudo real-time					
RW	1.030	1.030	0.626	0.626	0.626
ARMA	0.895	0.895	0.551	0.551	0.551
BEQ-RW	0.955	0.934	0.624	0.590	0.589
BEQ-ARMA	0.948	0.933	0.619	0.591	0.589
MIDAS-RW	0.959	0.922	0.628	0.539	0.528
MIDAS-ARMA	0.947	0.922	0.615	0.538	0.528
CNB	NA	NA	NA	0.775	NA
Real-time					
RW	1.037	1.037	0.788	0.788	0.788
ARMA	0.817	0.814	0.824	0.824	0.824
BEQ-RW	0.916	0.908	0.768	0.716	0.717
BEQ-ARMA	0.926	0.915	0.766	0.719	0.717
MIDAS-RW	0.926	0.909	0.770	0.627	0.624
MIDAS-ARMA	0.945	0.927	0.770	0.637	0.624
CNB	NA	NA	NA	0.440	NA

Table A6: Root Mean Square Errors for Real Private Consumption

	Nowcast			Backcast	
Model	M0	M1	M2	M0	M1
Pseudo real-time					
RW	0.859	0.859	0.515	0.515	0.515
ARMA	0.753	0.753	0.472	0.472	0.472
BEQ-RW	0.859	0.848	0.531	0.518	0.519
BEQ-ARMA	0.851	0.844	0.528	0.518	0.519
MIDAS-RW	0.897	0.888	0.541	0.574	0.578
MIDAS-ARMA	0.894	0.888	0.544	0.573	0.578
CNB	NA	NA	NA	0.813	NA
Real-time					
RW	0.758	0.758	0.578	0.578	0.578
ARMA	0.708	0.801	0.566	0.566	0.566
BEQ-RW	0.734	0.778	0.612	0.584	0.588
BEQ-ARMA	0.727	0.769	0.605	0.583	0.588
MIDAS-RW	0.773	0.819	0.616	0.695	0.700
MIDAS-ARMA	0.772	0.820	0.627	0.692	0.700
CNB	NA	NA	NA	0.494	NA

Table A7: The Results of the Diebold-Mariano Test

Model	Wage Bill	Nominal GDP	Real GDP	Nominal Private Consumption	Real Private Consumption
Pseudo real-time					
RW	-0.723	0.896	0.457	1.746	2.776
	(0.48)	(0.38)	(0.65)	(0.10)	(0.01)
ARMA	-1.260	1.645	0.184	1.572	3.429
	(0.22)	(0.12)	(0.86)	(0.13)	(0.00)
BEQ-RW	0.980	0.893	0.676	2.164	3.230
	(0.34)	(0.38)	(0.51)	(0.04)	(0.00)
BEQ-ARMA	0.930	0.896	0.676	2.153	3.233
	(0.36)	(0.38)	(0.51)	(0.04)	(0.00)
MIDAS-RW	0.611	0.881	0.509	2.944	2.557
	(0.55)	(0.39)	(0.62)	(0.01)	(0.02)
MIDAS-ARMA	0.536	0.892	0.507	2.925	2.553
	(0.60)	(0.38)	(0.62)	(0.01)	(0.02)
Real-time					
RW	-0.988	-0.912	-1.754	-2.989	-0.376
	(0.34)	(0.37)	(0.10)	(0.01)	(0.71)
ARMA	-1.999	-2.946	-2.414	-3.427	0.040
	(0.06)	(0.01)	(0.03)	(0.00)	(0.97)
BEQ-RW	0.491	-0.914	-1.343	-2.812	-0.689
	(0.63)	(0.37)	(0.20)	(0.01)	(0.50)
BEQ-ARMA	0.447	-0.908	-1.349	-2.808	-0.681
	(0.66)	(0.38)	(0.19)	(0.01)	(0.50)
MIDAS-RW	-0.162	-0.959	-1.731	-2.009	-1.733
	(0.87)	(0.35)	(0.10)	(0.06)	(0.10)
MIDAS-ARMA	-0.229	-0.936	-1.731	-2.036	-1.726
	(0.82)	(0.36)	(0.10)	(0.06)	(0.10)

Note: The CNB's historical forecast and the selected alternative model forecast are two competing forecasts. The test statistic is based on the absolute difference between the forecast and the actual observation. The p-values are listed in parentheses. The null hypothesis is that both forecasts are equally accurate, whereas the alternative hypothesis states that one forecast differs in accuracy from the second forecast. The negative values of the test statistic indicate that the alternative model is less accurate than the CNB's historical forecast.

Figure A7: Nowcasting Wage Bill with Social Contributions: Yearly vs. Quarterly Specification

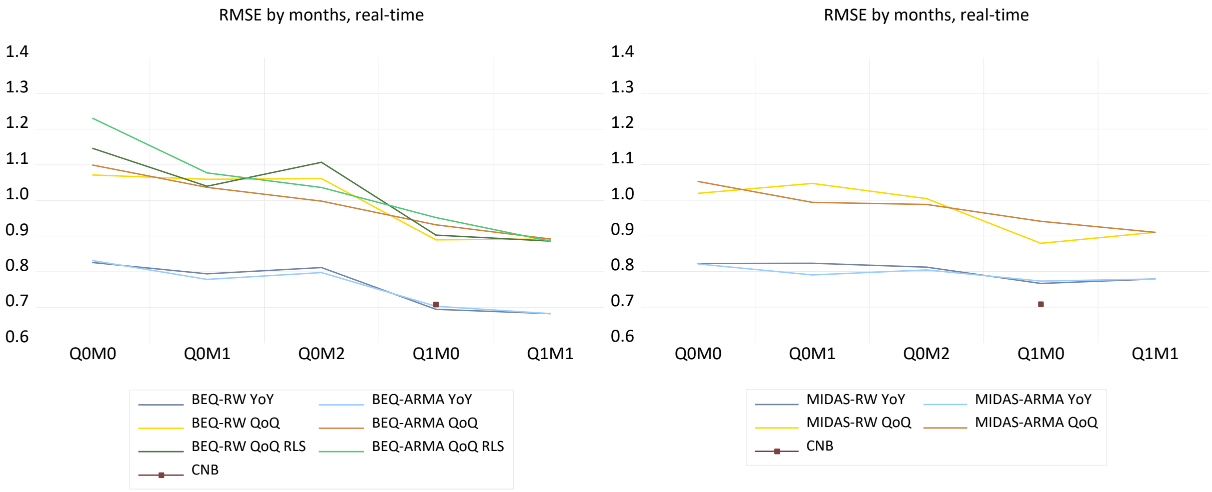


Figure A8: Nowcasting Nominal GDP with Value Added Tax: Yearly vs. Quarterly Specification

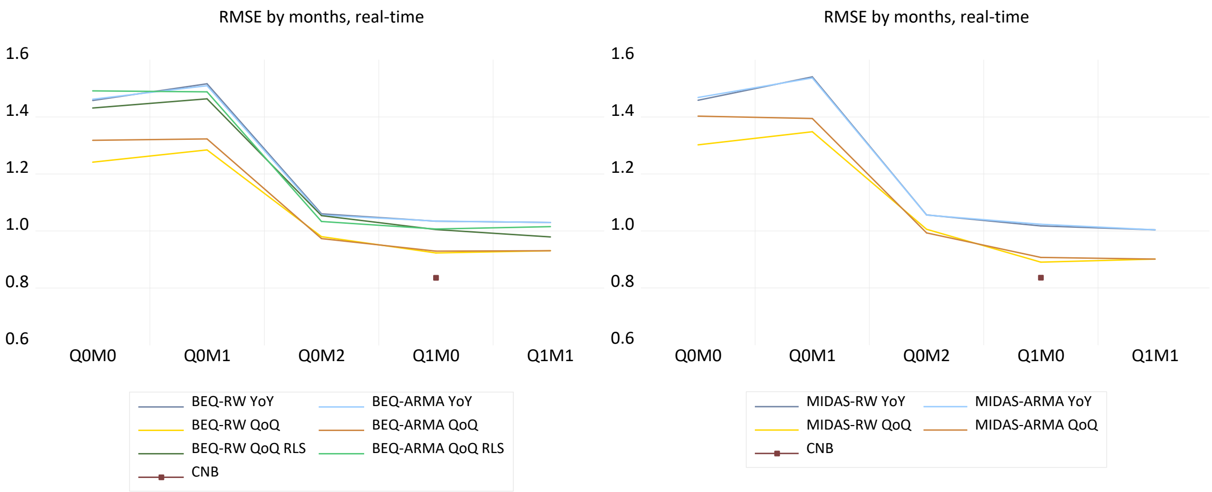


Figure A9: Nowcasting Real GDP with Value Added Tax: Yearly vs. Quarterly Specification

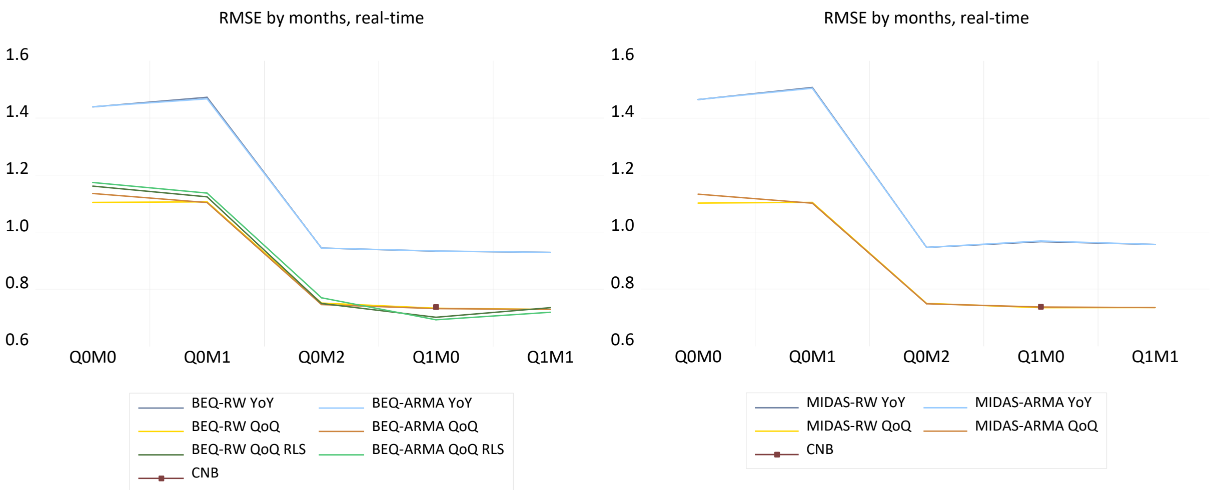


Figure A10: Nowcasting Nominal Private Consumption with Value Added Tax: Yearly vs. Quarterly Specification

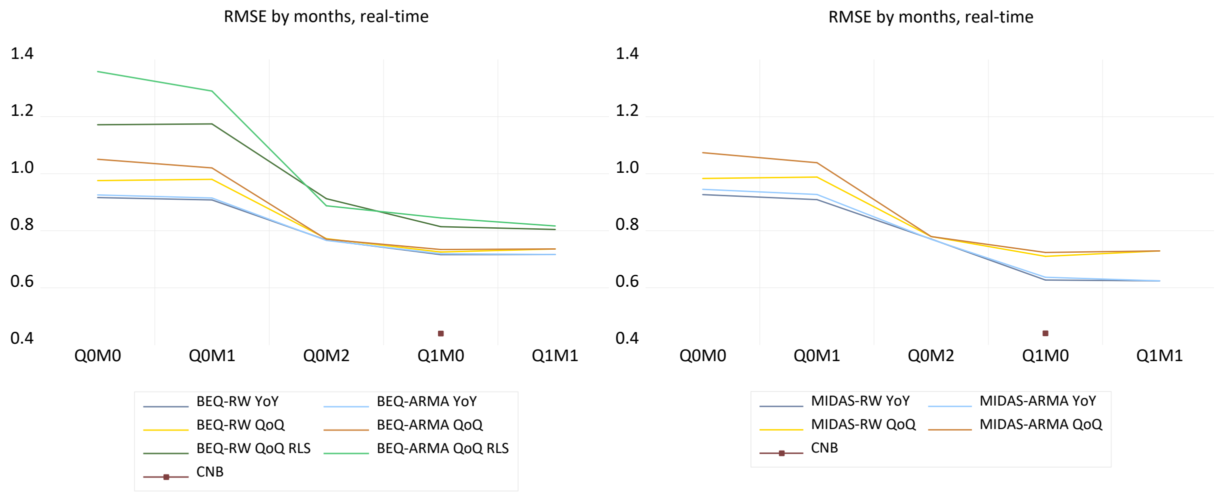


Figure A11: Nowcasting Real Private Consumption with Value Added Tax: Yearly vs. Quarterly Specification

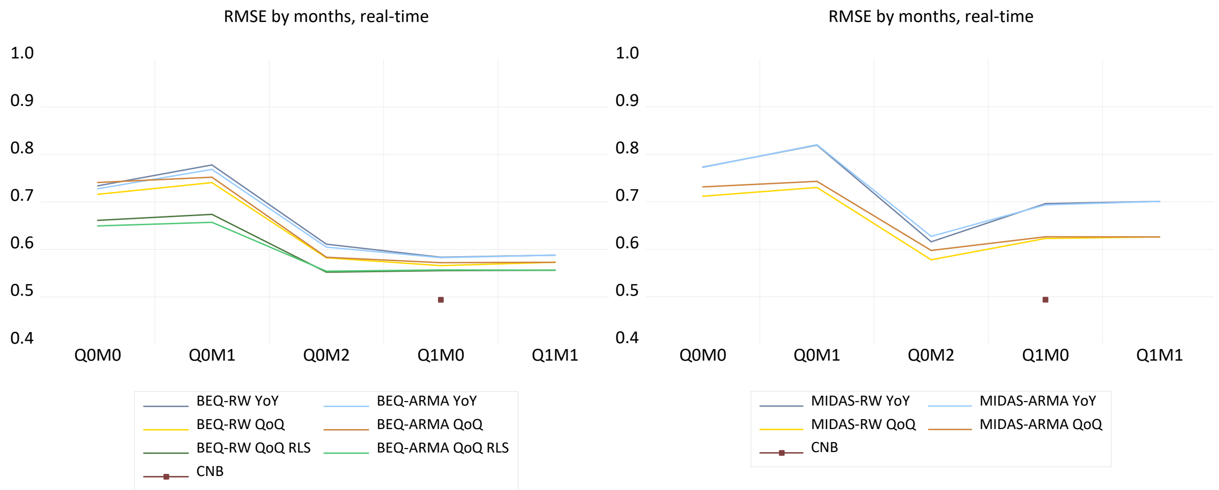


Figure A12: Daily Social Contributions (in CZK bn)

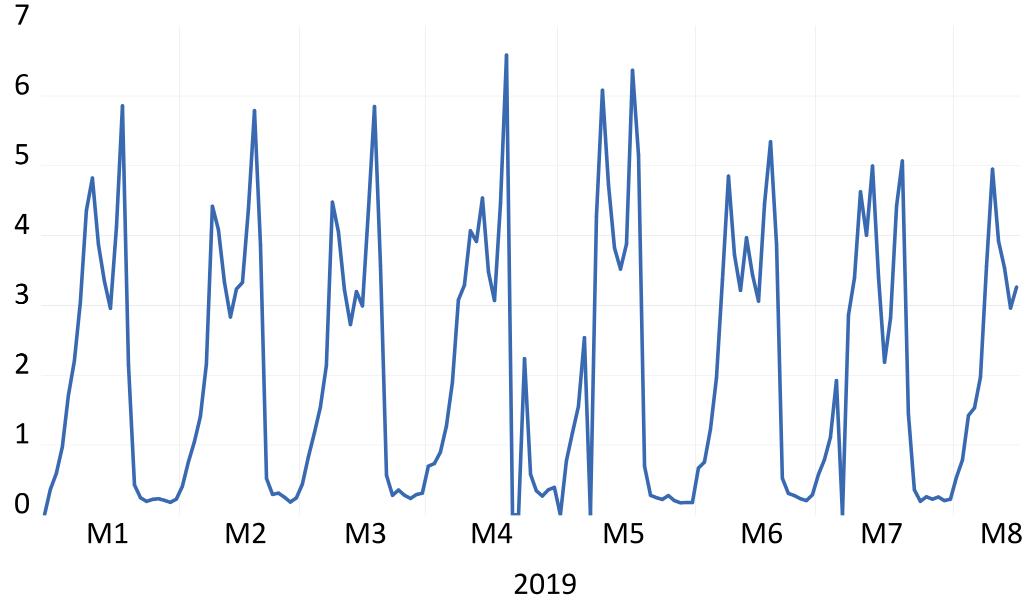


Figure A13: Daily Social Contributions, Rolling 21-day Sums (annual changes in %)

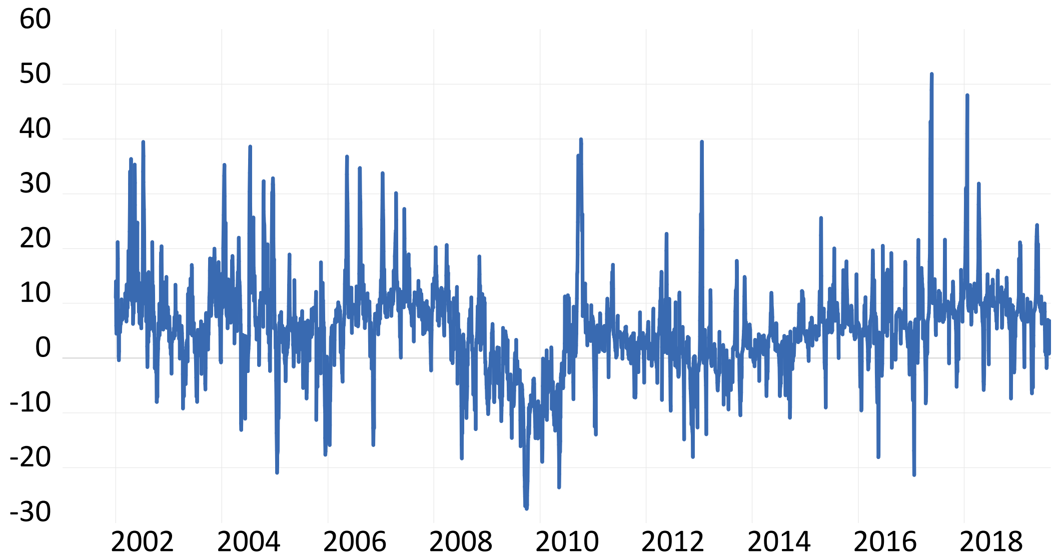


Figure A14: Monthly Social Contributions (annual changes in %)

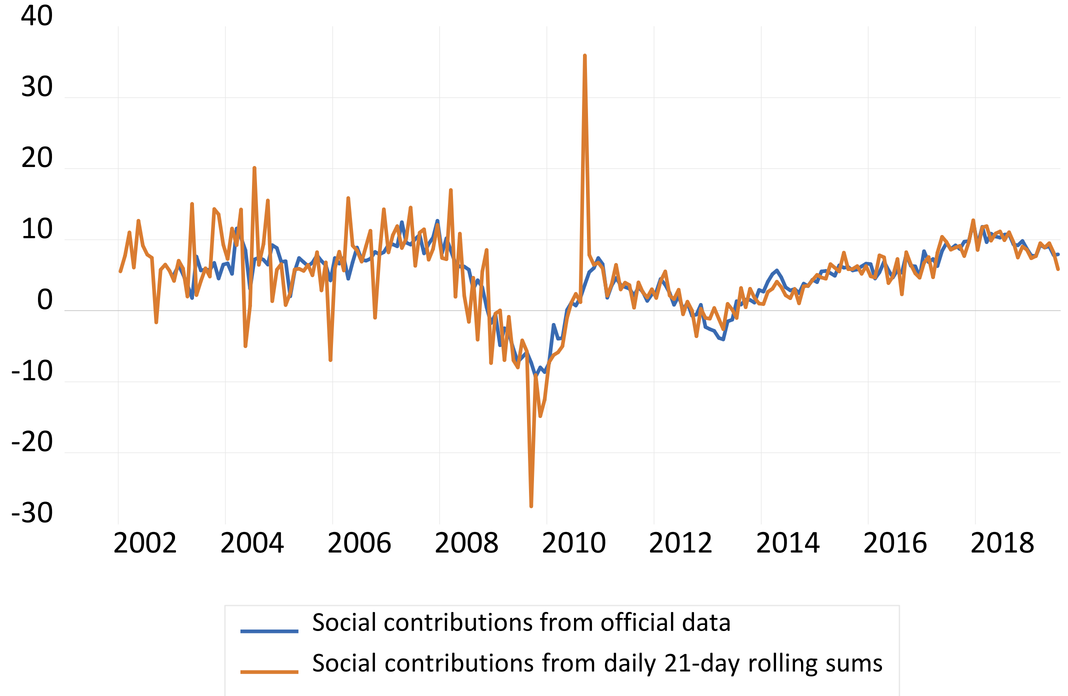


Figure A15: Daily Social Contributions, Rolling 21-day Sums (annual changes in %)

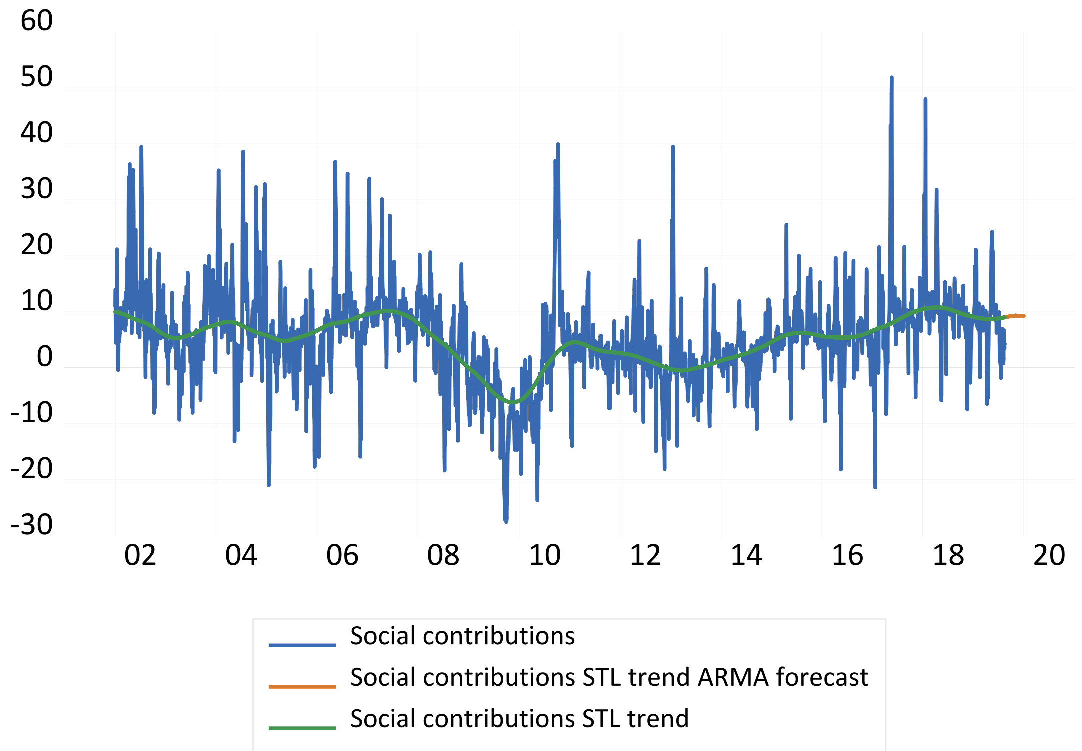


Figure A16: Monthly Social Contributions (annual changes in %)

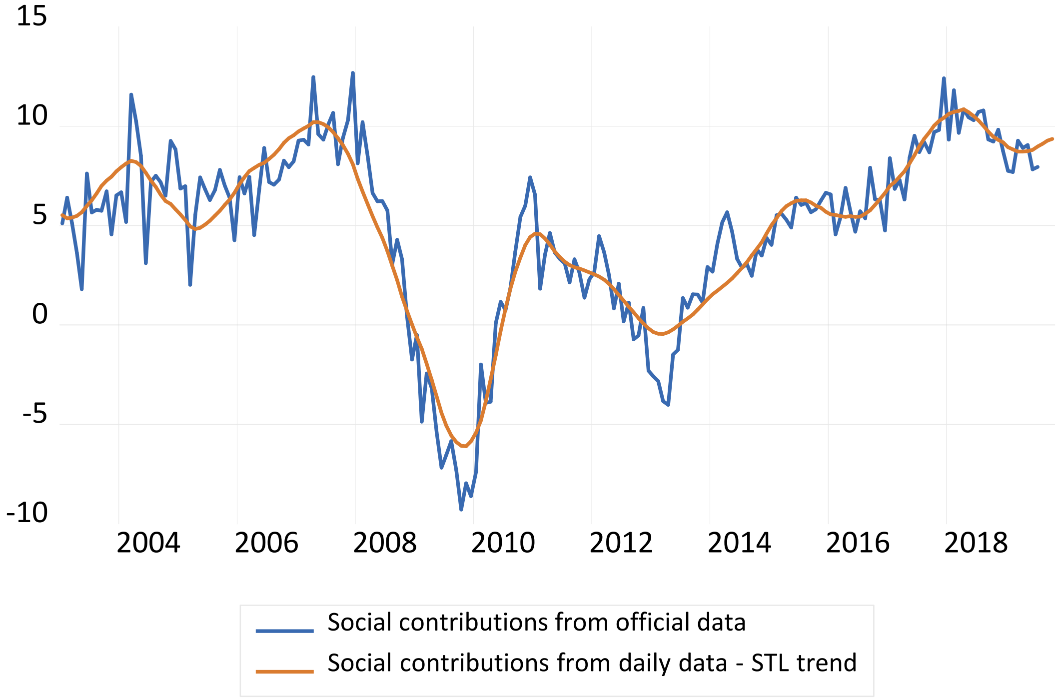
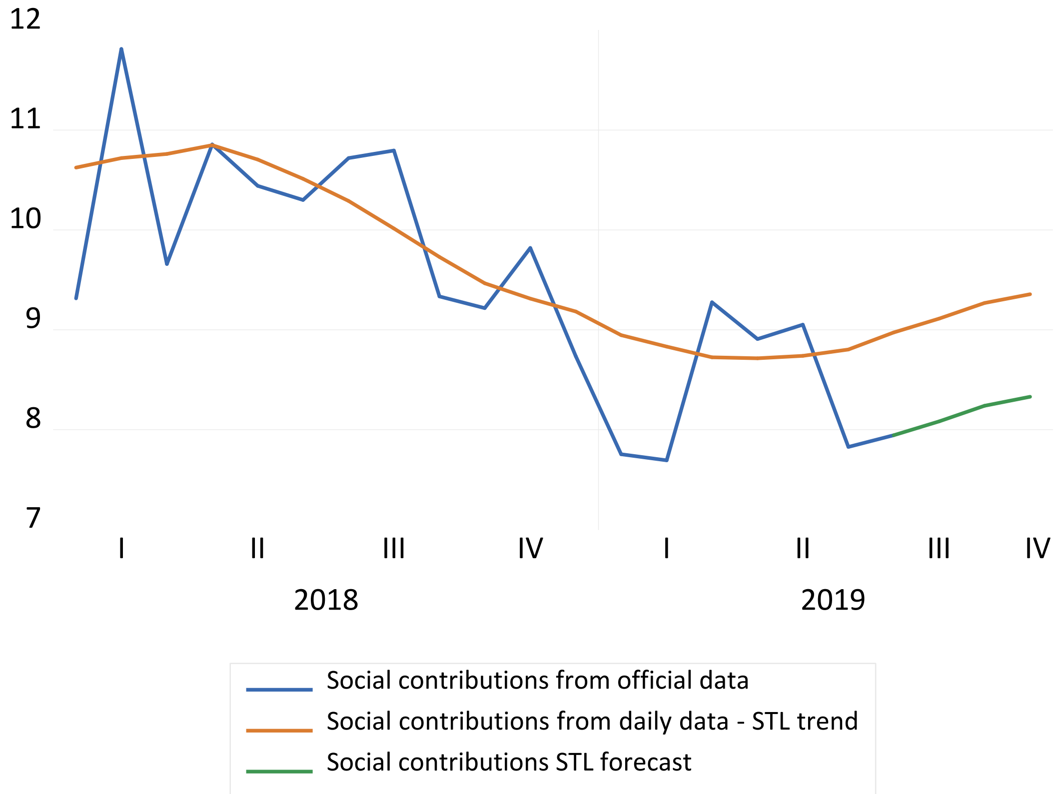


Figure A17: Monthly Social Contributions (annual changes in %)



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