Nowcasting Norwegian Household Consumption with Debit Card Transaction Data [*]

Knut Are Aastveit[†] Tuva Marie Fastbø [‡] Eleonora Granziera[§]

Kenneth Sæterhagen Paulsen[¶] Kjersti Næss Torstensen [‖]

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Abstract

We use a novel data set covering all debit card transactions for Norwegian households to nowcast quarterly household consumption in Norway. These card payments data are free of sampling errors and are available weekly without delays, providing a valuable early indicator of household spending. To account for mixed-frequency data, we estimate various mixed-data sampling (MIDAS) regressions using predictors sampled at monthly and weekly frequency. We evaluate both point and density forecasting performance over the sample 2011Q4-2020Q1. Our results show that MIDAS regressions with debit card transaction data improve both point and density forecast accuracy over competitive standard benchmark models that use alternative high-frequency predictors. Finally, we illustrate the benefits of using the card payments data by obtaining a timely and relatively accurate nowcast of the first quarter of 2020, a quarter characterized by heightened uncertainty due to the COVID-19 pandemic.

Keywords: Debit Card Transaction Data, Nowcasting, Forecast Evaluation, COVID-19

JEL classification: C22, C52, C53, E27

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[†]Norges Bank & BI Norwegian Business School; email: Knut-Are.Aastveit@Norges-Bank.no

[‡]Norges Bank; email: Tuva-Marie.Fastbo@Norges-Bank.no

[§]Norges Bank; email: Eleonora.Granziera@Norges-Bank.no

[¶]Norges Bank; email: Kenneth.Paulsen@Norges-Bank.no

[‖]Norges Bank; email: Kjersti-Ness.Torstensen@Norges-Bank.no

1 Introduction

Accurate knowledge of current economic conditions is essential for forecasting and economic policy making. However, key macroeconomic time series aggregates are released with a significant lag. Therefore, policy makers have to rely on early estimates of macroeconomic aggregates, or "nowcasts". These early assessments are often based on indicators which are highly correlated with the variable of interest, available at a higher frequency and released without delays (Evans, 2005; Giannone et al., 2008; Banbura et al., 2011).

The recent shutdown of significant portions of the worldwide economy, in order to restrain the outbreak of the coronavirus, has triggered a global recession. The uncertain consequences of the rapid spread of the virus and the induced infection control measures have made it extremely challenging for forecasters and policymakers to quantify and assess the current and future outlook of the economy. This has raised a renewed interest in the search for reliable high-frequency indicators that can track the real economy in a timely matter. Recent work by Carriero et al. (2020) and Lewis et al. (2020) have emphasized the importance of incorporating information from various weekly indicators, covering labour market conditions, the production side of the economy and financial markets, to track the real economy during the COVID-19 pandemic.[1] While these are clearly important indicators for tracking the real economy, there is a lack of reliable and timely indicators that capture the demand side of the economy, which may be of particular importance during the current pandemic. As highlighted in a recent paper by Guerrieri et al. (2020), economic shocks associated with the COVID-19 epidemic can be thought of as supply shocks that trigger changes in aggregate demand that are larger than the shocks themselves. They argue that when shocks are concentrated in certain sectors, as they are during a shutdown in response to an epidemic, there is greater scope for total spending to contract.[2]

In this paper, we document that debit card transaction data serve as an early and reliable indicator for household consumption in Norway. We use data provided by BankAxept, which records all domestic debit card transactions by Norwegian bank account holders.[3] The data is a proxy for household spending, is available without delays and without sampling errors. Debit card transactions currently account for more than 35% of the total value of all household consumption expenditures. While this paper focus on the case of Norway, we expect debit card transactions data to also be useful for real time monitoring of consumption in other countries, particularly for countries where card payments account for a high share of consumption expenditures.

The card payment data are available at the weekly frequency, while consumption is sampled at the quarterly frequency.[4] To account for the frequency mismatch, we estimate Mixed Data

[1] The importance of using predictors that are sampled at a higher frequency than monthly observations, have also been earlier emphasized by Andreou et al. (2013) and Aastveit et al. (2017), using daily financial data and weekly activity and financial conditions indices, respectively.

[2] The standard mechanism is that when workers lose their income, due to the shock, they reduce their spending. However, what makes the shutdown situation so peculiar, is the fact that now some goods are no longer available making it less attractive to spend in general. Guerrieri et al. (2020) argue that one interpretation is that the shutdown increases the shadow price of goods in affected sectors, making current consumption more expensive and thus discouraging it.

[3] Although we can observe each individual payment, this project will make use of aggregate transactions.

[4] The data is available at the weekly frequency since January 2006 and at the daily frequency since January 2019. Due to the short sample of data available at the daily frequency we limit our analysis to the use of card

Sampling (MIDAS) regressions which exploit the difference in sampling frequencies explicitly.[5] MIDAS models were introduced by Ghysels et al. (2004) as a flexible and parsimonious approach to relate low frequency data with high frequency variables.[6] The model specification is based on distributed lag polynomials and generates a direct forecast of the low-frequency variable. MIDAS models differ on the functional form of the polynomial characterizing the coefficients associated with the high frequency variables. Foroni et al. (2015) shows that if the difference in sampling frequency is not large, as in our case, it is not necessary to use distributed lag functions and that an unrestricted model performs comparable to the non-linear models, but has the advantage that can be estimated with OLS. For these reasons, we prefer the Almon lag polynomial which restrict the number of parameters to estimate but does not require non-linear estimation.

In our empirical application, we compute recursive point and density nowcasts from the various MIDAS regressions for quarterly household consumption growth in Norway for the evaluation period 2011Q4-2020Q1. For the BankAxept data, we consider specifications that use both the volume of transactions as well as the value of payments as high-frequency predictors. We compare forecasts from the MIDAS models using BankAxept data with various alternative benchmark models, such as a simple AR model and various ARDL and MIDAS models that use alternative high-frequency predictors for consumption such as the unemployment rate, retail sales, an uncertainty index[7] based on Norwegian newspaper data (Larsen, 2017), a Norwegian financial news index (FNI) (Larsen and Thorsrud, 2019; Thorsrud, 2020) and total returns from the benchmark index at the Oslo Stock Exchange. For monthly frequency predictors, we evaluate the forecasts performance of the models at three points in time during the quarter, just after the 1st, 2nd and 3rd month, respectively, while for weekly predictors we obtain a nowcast for each week in the quarter. In our evaluation, we focus on both point and density nowcasts. The relative forecasting performance of the different models is assessed in terms of root mean squared errors (RMSE) for point forecasts and the logarithmic score (LS) for the density forecasts.

We have three main findings. First, debit card transactions data are useful for nowcasting household consumption. Compared with the alternative benchmark models, we finds gains both in terms of improved point and density nowcasts performance, from MIDAS models that include debit card transactions data. The gains are sizeable and statistically significant. This holds true at all three points in time during the quarter for the monthly debit card data and starting from week 5 for the weekly data. In fact, while most of the alternative models are either performing at par or slightly worse than a simple AR model, models that incorporate BankAxept data provide gains in the magnitude of almost 60% compared with the simple AR model at the end of the

payment data at the weekly frequency.

[5] Alternative approaches that also exploit differences in sampling frequencies range from bridge equation models (Angelini et al., 2011), factor models (Giannone et al., 2008; Banbura and Modugno, 2014) and mixed-frequency VAR models (Kuzin et al., 2011; Schorfheide and Song, 2015)

[6] MIDAS models is a popular way of dealing with mixed-frequency data and have been extensively used for nowcasting macroeconomic variables, see among others, Andreou et al. (2010, 2013), Clements and Galvão (2008, 2009), Kuzin et al. (2011), Marcellino and Schumacher (2010) and Ferrara and Marsilli (2019).

[7] Motivated by the large literature documenting that large changes in uncertainty may cause severe negative impacts on the economy, see e.g. Bloom (2009) and Baker et al. (2016), we include a Norwegian specific news-driven measure of uncertainty. In a recent paper, Baker et al. (2020) have argued that forward-looking uncertainty measures, such as a newspaper based uncertainty measure, are particularly useful for assessing the impact of the COVID-19 crisis on the economy.

quarter (approximately 6 weeks prior the quarterly national accounts are released).[8]

Second, for MIDAS models which contain BankAxept data, we find a gradual improvement of the nowcasting performance throughout the quarter, both for the volume and value predictors. Already after four weeks we obtain considerable gains in terms of improved nowcasts compared to the alternative benchmark models.

Finally, we document that a MIDAS model that includes the number of BankAxept transactions provide a strikingly accurate nowcast of the first quarter of 2020. As many other countries, Norway implemented drastic restrictions as a response to the coronavirus outbreak in the second week of March, two weeks after its first registered coronavirus case, including closing many shops and establishments. The shutdown had severe consequences for the economy where the unemployment rate rose from 2.7 percent in February to 10.7 percent at the end of March. Similarly, output and spending fell drastically. Despite such an extreme event, we show that a MIDAS model that includes the number of BankAxept transactions, provides a density nowcast at the very end of the first quarter that is almost centered around the actual value of -10.2 percent! As a comparison, the actual value of consumption for 2020Q1 either fall outside or lies in the tail of the density nowcasts provided from all the alternative benchmark models.

Our paper contributes to the large and growing literature on nowcasting. While most of the earlier papers focus on point nowcasts of GDP growth, we differ on two important aspects. First, instead of nowcasting GDP growth, we focus on household consumption growth. Household consumption consists of about 45 percent of GDP and has played a key role in the early parts of the current COVID-19 crisis. Second, we focus on both point and density nowcasts. Policymakers and forecasters are increasingly interested in forecast metrics that require density forecasts of macroeconomic variables, as complete probability distributions of outcomes provide information helpful for making economic decisions, see e.g. Tay and Wallis (2000), Garratt et al. (2003), Gneiting (2011) and Clark (2011). Accordingly, several central banks, including the Bank of England, Norges Bank and Sveriges Riksbank have committed to publishing density or interval forecasts for macroeconomic aggregates in recent years. However, despite the flourishing theoretical and empirical literature on the use of various mixed-frequency approaches for nowcasting, the focus has so far mainly been on point forecasts, Aastveit et al. (2014), Mazzi et al. (2014), Carriero et al. (2015), Aastveit et al. (2017) and Aastveit et al. (2018) being notable exceptions. The COVID-19 pandemic has triggered a massive spike in uncertainty, making the value of probabilistic forecasts more important than ever. As highlighted above, we document how our density nowcasts of household consumption provide important insights during the first quarter of 2020.

While most earlier studies in the nowcasting literature analyze the US economy, we focus on Norway. Nowcasting of the Norwegian economy has so far targeted output: Aastveit et al. (2011) describe Norges Bank's system for averaging models (SAM) which generates density forecasts for Norwegian Mainland GDP by combining vector autoregressive models, leading indicator models and factor models. Aastveit and Trovik (2012) estimate a dynamic factor model on

[8] One exception is MIDAS models which includes monthly retail sales data. For these models, we obtain gains of about 50%, compared with the simple AR model, when data for all three months of the quarter are available. However, in contrast to the BankAxept data which have no publication delay, retail sales data have a publication delay of close to 1 month and are subject to revisions.

a large database and find that unemployment, industrial production, and asset prices improve accuracy for the nowcasts of Norwegian GDP. Luciani and Ricci (2014) document that a Bayesian dynamic factor model outperforms simple univariate benchmark models both in terms of point and density forecast. Differently from this literature, our paper focuses on private household consumption which represents an important input to policy decision, given that it constitutes one of the main components of gross domestic product. Moreover, we explore the role of high frequency indicators for nowcasting.

The increased availability of electronic payments data has spurred a recent literature on real time forecasting of economic activity and its components using these electronic transactions. Duarte et al. (2017) obtain nowcast and one step ahead forecasts of Portuguese private consumption by combining data from ATM and POS terminals. Carlsen and Storgaard (2010) investigates whether electronic payments by card (Dankort) provides a useful indicator for the nowcast of monthly retail sales in Denmark. Verbaan et al. (2017) analyse whether the use of debit card payments data improves the accuracy of the nowcast and one quarter ahead forecast of Dutch private household consumption. Barnett et al. (2016) estimate a mixed frequency dynamic factor model which includes data on credit card transaction volumes to obtain a measure of US monthly GDP. Galbraith and Tkacz (2018) generate nowcast of Canadian GDP and retail sales using electronic payments data, including both debit card transaction and cheques clearing through the banking system. Finally, Aprigliano et al. (2019) assess the ability of a wide range of retail payment data to accurately forecast Italian GDP and its main domestic components. All these papers document an improvement in *point* forecast accuracy when using transaction data relative to simple benchmark models. Our paper differs from these studies in two important ways: first, we evaluate the performance of data transaction for both point and *density* forecasts and second we illustrate the use of transaction data during the highly uncertain and tumultuous environment generated by the COVID-19 pandemic.

Finally, we are related to the growing number of papers on forecasting economic aggregates during the COVID-19 pandemic. Carriero et al. (2020) focus on US GDP, Cascaldi-Garcia et al. (2020) on Euro-Area GDP. Lahiri and Yang (2020) nowcast U.S. state revenues. Aaronson et al. (2020) target US unemployment insurance, while Foroni et al. (2020) forecast GDP growth for G7 countries.

The paper is organized as follows: section 2 describes the debit card transaction data, the other variables included in the analysis and the models used to conduct our investigation. Section 3 outlines the forecast evaluation results over the whole sample while section 4 illustrates the nowcast exercise during the COVID-19 pandemic. Section 5 concludes.

2 Data and Methodology

2.1 Debit Card Transaction Data

Norway is a near cashless economy: as shown in figure 1, the share of cash withdrawals relative to total card usage has fallen from 20 percent in 2011 to 8 percent in 2019. [9] This

[9] Due to large fees charged by banks when taking out cash directly from an account, most cash withdrawals are done with cards.

makes Norway an ideal economy in which to use electronic payments data to study household consumption.

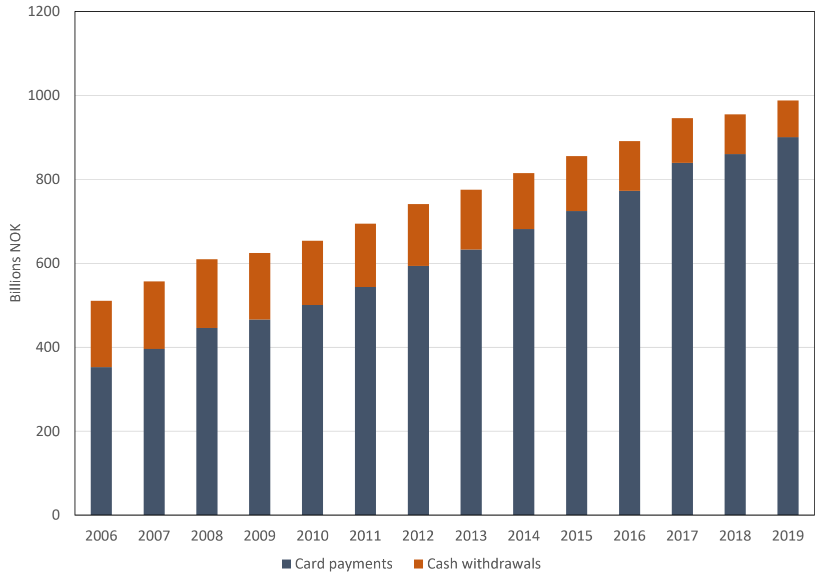


Figure 1: Value of Card Usage

The debit card data are provided by the Norwegian retail clearing institution, Nets Branch Norway, for the years 2006 to 2018, and by Vipps AS for the years 2019 to 2020. The observations spanning the years 2006 to 2018 are sampled at the weekly frequency, whereas the observations for 2019 and 2020 are daily. The data covers all debit card transactions via BankAxept, which is the national payment system in Norway owned by the Norwegian banks. Typically, all debit card payments in physical domestic stores are BankAxept, whereas payments abroad, online or mobile payments are paid through credit cards, VISA or Mastercard. Note that in Norway online shopping represents only 3 percent of quarterly consumption.

BankAxept debit card ownership and usage is well spread among age groups: figure 2 shows for different age groups the percentage of people that have completed at least one transaction using a BankAxept debit card in 2018. This percentage is close to 100 for all age groups. Therefore, our data is not capturing spending by a specific age group.

Among card payments, debit card is the dominant means of payment in Norway throughout the sample period, as shown in figure 3. On average from 2006 to 2019 eight out of ten card transactions were BankAxept, accounting for 71 percent of the total value. However, the share of BankAxept transactions has somewhat fallen over the sample period. In 2006 BankAxept accounted for 85 percent of the transactions and 78 percent of the value, whereas it accounted for 64 percent of the transactions and 58 percent of the value in 2019. Debit card data are used for smaller value transactions than credit card data, with an average value of 340NOK for BankAxept versus 640NOK for credit card.

Still, the total value of quarterly debit card transactions represents about one third of total household consumption, as shown in figure 4, panel (a). Moreover, panel (b) of 4, which plots the quarter over quarter percentage changes of consumption and of the debit card values and numbers, suggests that debit card transaction data track well changes in consumption. Therefore,

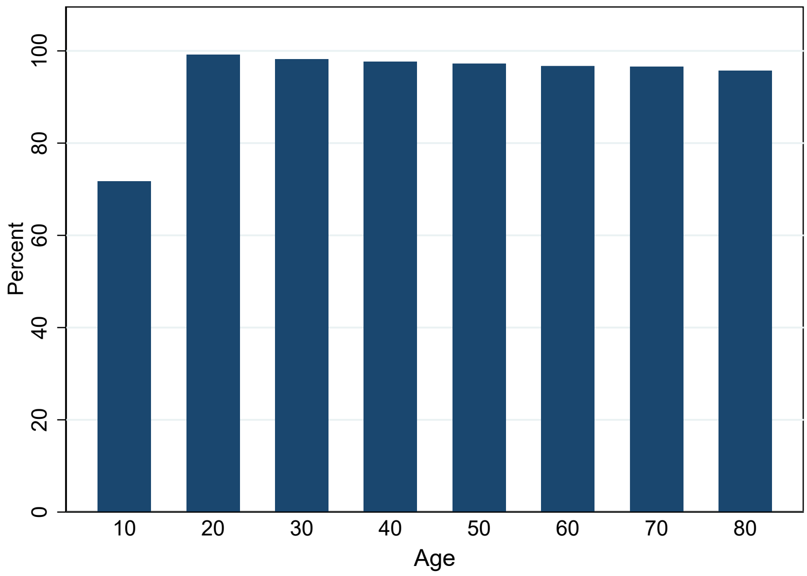
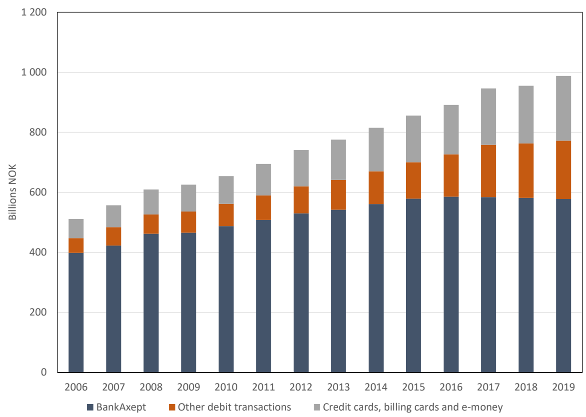
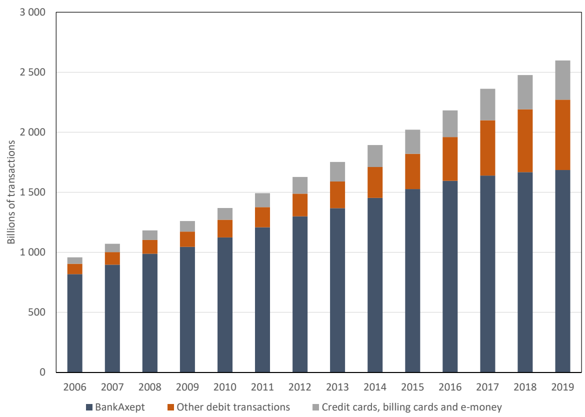


Figure 2: Percentage of population by age group that has completed at least one transaction using a BankAxept card in 2018. The horizontal axis reports the first year included in the age bracket.

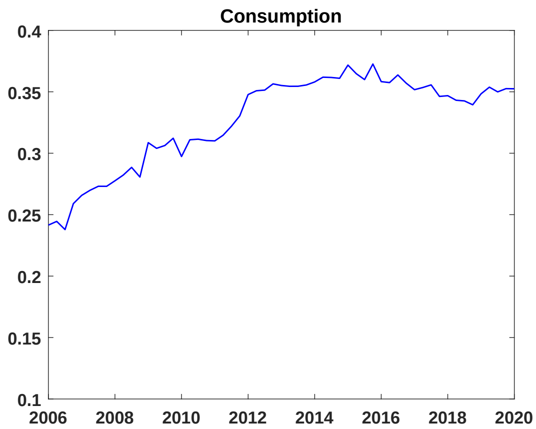


(a) Value of Transactions

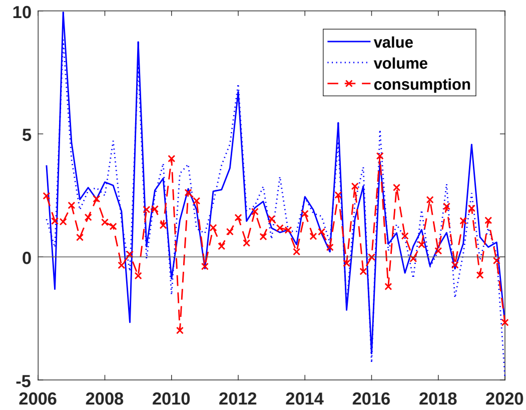


(b) Volume of Transactions

Figure 3: Card Usage Across Categories



(a) Share



(b) Quarterly Growth Rates

Figure 4: Consumption and Debit Card Data

at a first visual inspection using these electronic payments data to nowcast consumer behaviour seem promising.

The coverage of debit card data for different consumption components is quite heterogeneous. Figure 5 shows for the main consumption components the value of debit card transactions compared to the values of personal consumption from the National Accounts. BankAxept data cover well food and beverages, clothing and footwear and furnishing, but they are less successful in capturing housing, water and heating, recreation and culture and restaurants and hotels. The latter is due to the fact that the BankAxept data does not include transactions by foreigners. Overall, our data covers goods consumption well, while consumption of services is captured less precisely. Household consumption is made for 49% of services consumption and 47% of good consumption. The remaining 4% is given by the difference between direct purchase abroad by Norwegian resident households and direct purchase by non-residents.

The data is available at the daily frequency only from January 2019. Therefore, given the limited time span of observations at the daily frequency, we focus on data aggregated at the weekly, i.e. the sum of the value of all transactions within a week.

Our main target variable is the quarterly Norwegian total household consumption, at current prices. The quarter over quarter growth rate of Norwegian household consumption has been relatively stable since 1990, averaging at 1.2% per quarter. As shown in panel (b) of figure 4, during the financial crisis consumption growth dropped for three consecutive quarters in 2009, following a decrease in economic activity at the time. The first quarter of 2020 has seen a severe drop in consumption, with the quarter over quarter growth rate plummeting to -2.7% for the seasonally adjusted series and to an astonishing -10.2% for the unadjusted series. For both series the decline is as severe as the drop registered during the financial crisis.

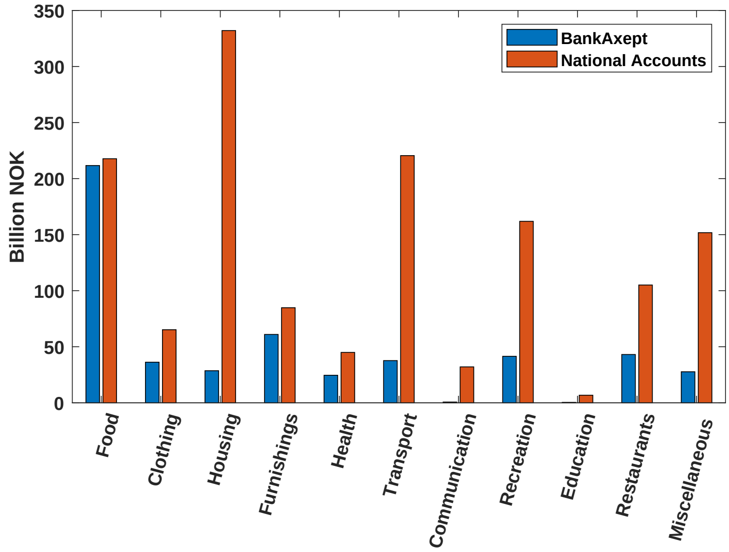


Figure 5: Value of BankAxept Data and Consumption from National Accounts for several subcategories (Million NOK): 'Food' refers to Food, beverages and tobacco, 'Clothing' to Clothing and footwear, 'Housing' to Housing, water and heating, 'Furnishing' to Furnishings and household equipment, 'Recreation' to Recreation and culture, 'Restaurants' to Restaurants and hotels and 'Miscellaneous' to Miscellaneous goods and services. Values refer to the year 2019.

2.2 Other data

In addition to the debit card data, we consider several alternative predictors for consumption, capturing sales, financial conditions, uncertainty and labor market conditions. Specifically we include a retail sales index, car sales volumes, the purchase manager index, the benchmark index at the Oslo stock exchange, a financial news index based on textual data for Norway (Larsen and Thorsrud, 2019; Thorsrud, 2020), a macro uncertainty index based on textual data for Norway (Larsen, 2017)[10], and the unemployment rate. These variables are available at a high frequency, early in the quarter of reference and, except for the retail sales index are not subject to revisions.

2.3 Models Specification

In the first part of our analysis, we compare the forecasting accuracy of different models and predictors to nowcast consumption over the sample 2011Q4-2020Q1. This section describes the details of our baseline evaluation exercise.

As a benchmark model we consider a simple Autoregressive (AR) model, which has proven to be a competitive benchmark:

$$y_t = \alpha + \sum_{p=1}^{P} \beta_p y_{t-p} + \varepsilon_t \tag{1}$$

where y_t is the quarter on quarter growth rate of consumption at the quarterly frequency, P the

[10] Ozturk and Sheng (2018) provide an alternative uncertainty index for Norway. Using individual survey data from the Consensus Forecasts they develop monthly measures of global and country-specific macroeconomic uncertainty for 45 countries.

number of lags and ε_t are normally distributed errors.

Second, we consider models that include exogenous regressors. The predictors considered in our study are available at a higher frequency than the target variable y_t. Traditionally, the issue of mixed frequency data has been addressed by converting the higher-frequency data to the sampling rate of the lower frequency data in the autoregressive distributed lag (ARDL) models, where a single predictor is added as extra regressor in (1):

$$y_t = \alpha + \sum_{p=1}^{P} \beta_p y_{t-p} + \sum_{k=0}^{K} \beta_k x_{n,t-k} + \varepsilon_t \tag{2}$$

where $x_{n,t}$ is the exogenous predictor n temporally aggregated at the quarterly frequency and ε_t are normally distributed errors.[11]

Clearly, the quarterly autoregressive distributed lag model above does not make use of the high frequency information available during the quarter of interest. To explicitly account for high frequency regressors, we use a mixed-data sampling (MIDAS) approach. The MIDAS model controls for parameter proliferation and is particularly suitable for our analysis given the size of our evaluation sample.

The general MIDAS model can be written as:

$$y_t = \alpha + \beta B\left(L^{1/m}; \theta\right) x_{n,t}^{(m)} + \varepsilon_t \tag{3}$$

where $x_{n,t}^{(m)}$ is variable n observed at the high frequency (e.g. $m = 3$ for monthly data and $m = 13$ for weekly data when the dependent variable is quarterly), $B\left(L^{1/m}; \theta\right) = \sum_{k=0}^{K} B(k; \theta) L^{k/m}$, $L^{1/m}$ is a lag operator such that $L^{k/m} x_{n,t}^{(m)} = x_{n,t-k/m}^{(m)}$ and the lag coefficient in $B(k; \theta)$ associated to the lag operator $L^{k/m}$ is parameterized as a function of a low-dimensional vector of parameters θ. As for the previous models we assume ε_t are normally distributed errors. MIDAS models differ according to the aggregation weighting scheme $B(k; \theta)$. In this paper we use the Almon lag polynomial, which has the advantage to retain linearity of the model in (3) with respect to the parameter vector θ. This aggregation scheme assumes that the lag weights are a linear function of M estimable nuisance parameters: $B(k; \theta) = \sum_{i=0}^{M} \theta_i k^i$. Following the literature, in our baseline specification we set $M = 2$ and we use the past three months of data to obtain the nowcast. Also, the predictors are the quarter over quarter log-difference for the variables in growth rates.

This MIDAS model is very flexible and is easily modified to include weekly rather than monthly debit predictors. In this case, we just need to set $m = 13$, which correspond to number of weeks in a quarter, while we can keep the size of the parameter vector θ fixed to $M = 2$. Therefore, we are always using the past 13 weeks of data to nowcast. The regressors are the quarter over quarter log-difference of the variables in growth rates, e.g. the growth from week one in the first quarter of 2013 to week one in the second quarter of 2013.

[11] For completeness, we report results for these models in the Appendix. Because of the relatively small number of observations available, we consider only one extra predictor for each specification and the lag length is fixed to one in all the models considered: $P = 1$, $K = 1$. Including only one regressor and fixing the lag structure allows us to retain parsimony and to evaluate the performance of each single predictor.

3 Real time nowcasting with debit card data

In this section we first evaluate the out-of-sample nowcasting performance of the debit card transaction data over the whole evaluation sample while in the next section we focus on the first quarter of 2020 and show how debit card data provided an early signal of the sharp decline in consumption.

3.1 The design of the empirical analysis

In Norway, official quarterly statistics are released six or seven weeks after the end of the reference quarter. We are interested in an estimate of the current quarter or the past quarter before the first release from the statistical agency. For the models using monthly predictors, we evaluate the forecast performance of the models for three points in time, corresponding to the release of month 1, month 2 and month 3 information for the various predictors. For most predictors the month 1 data are available during the first week of month 2, prior to the release of national accounts for the pervious quarter, while month 2 and 3 data are available during the first week of month 3 and the first week after the end of the quarter, respectively. In both the latter cases, the national accounts for the pervious quarter has been released. For example, when nowcasting 2011Q4 we produce a first nowcast during the first week of November 2011, when the consumption figures for 2011Q3 are not yet available and we only observe the first month of the monthly indicators, a second nowcast during the first week of December 2011 after the release of national accounts for 2011Q3 and two months of monthly indicators, and finally a last nowcast during the first week of January 2012, when we have the full quarter information for the monthly indicators but not yet the release for 2011Q4. Note, however, that we give an informational advantage to the retail sale index, as this the variable is normally released towards the end of the month with a one month lag. In our evaluation, we "pretend" that the retail sale index is released at the same time as the other predictors, i.e., during the first week of the month.

For the MIDAS model using weekly data we obtain a nowcast for each week in the quarter, starting from the second week, when data for the first week has just been released. The last nowcast is produced when the data for the thirteenth week has been released. Note that weekly data include transactions from Monday through Sunday.

Nowcasts are obtained from models (1) through (3) in a recursive fashion with a rolling window estimation scheme. [12] Because of the relatively short size of the sample, we set the lag length of the autoregressive component to one. Table 2 describes the transformation of the predictors, as well as their highest available frequency and the release lag. The predictors are transformed as follows: BankAxept data, car sales, the retail sales index and stock prices are in quarter over quarter growth rates, while the uncertainty index, the financial news index, the PMI and the unemployment rate are in levels. As the debit card data are available starting in January 2006, the first estimation sample spans 2006Q1 to 2011Q3. Then, the evaluation sample runs from 2011Q4 to 2020Q1, for a total of 34 observations. The exercise is done using real time

[12] We find the rolling estimation scheme preferable to the expanding window one given the increasing share of the value of debit card transactions over consumption. For robustness we report the results of the evaluation exercise using the expanding window in the appendix.

Table 1: Description of the data

Name	Transf	Timing	Publishing lag
BankAxept	Δln	Every Monday	1 day
Stock Prices	Δln	Daily	1 day
Unemployment	*Level*	1st wd of month	1-3 days
Uncertainty	*Level*	Every Thursday	4 days
Car Sales	Δln	3-6th of month	3 to 6 days
Financial News	*Level*	1-3rd of month	1 month
PMI	*Level*	3-6th of month	1 month
Retail Sales	Δln	25-30th of month	1 month

Table 2: Variable names are reported in Column 1. Column 2 reports the transformation that is used for each of the explanatory variables in various MIDAS regressions. Finally, Column 3 and Column 4 indicate the official dates of the publication and the lag with which the data are reported, respectively.

data for consumption and nowcasts are evaluated against the first data release. Following the literature, we evaluate point forecast accuracy by comparing root mean squared forecast errors (RMSFE), while for density forecasts we compute log-scores.

3.2 Results: Out-of-sample nowcasting evaluation

The results for point forecast accuracy are reported in Table 3, which shows the relative root mean squared error of the alternative models versus the AR model at the different forecast origins described. A value smaller than one indicates that the alternative model performs better than the benchmark. The significance level for the equal predictive ability test by Diebold and Mariano (1995) are indicated by stars.[13] Note that the denominator is different as we move forward in time: up to week seven the AR nowcasts refer to the AR model where we do not know the value of the previous quarter consumption, because the national account statistics have not been released yet. For weeks eight to thirteen, the AR nowcasts make use of the knowledge of the past quarter consumption. Also, for data sampled weekly, i.e. BankAxept data, stock prices and uncertainty index, the nowcast is produced for each week in the quarter. For example, the row "week 1" reports the nowcast produced when the first week of data is available. For monthly sampled regressors, the nowcast is produced after the end of each month in the reference quarter, e.g. the row "week 5" reports the nowcast produced after the first month of data is released.

The table highlights that the AR is indeed a competitive benchmark, as for most models the relative RMSFE is larger than one and the difference in performance is statistically significant at all forecast origins considered. After the first month of data the relative RMSFE ranges from 1.046 for the car sales to 1.168 for the PMI predictor. The relative performance deteriorates over the quarter so that after the full quarter information is available, i.e. after three months for monthly data or after thirteen weeks for weekly data, the relative RMSFE ranges from 1.047

[13]The issue of real-time data complicates any assessment of whether the resulting differences in forecast accuracy between models are significant, see Clark and McCracken (2009). Monte Carlo evidence in Clark and McCracken (2015) indicates that, with nested models, the Diebold Mariano test compared against normal critical values can be viewed as a somewhat conservative (in the sense of tending to have size modestly below nominal size) test for equal accuracy in the finite sample.

for car sales up to 1.476 for the uncertainty index. The monthly MIDAS models including the unemployment rate improves over the benchmark, although only early in the quarter, when the previous quarter consumption figures are not available. In contrast, gains for the BankAxept predictors, both volume and value, as well as for retails sales are sizable, statistically and economically significant and increasing over the quarter. After the first month of data the BankAxept value, unemployment rate and retail sales exhibit similar relative RMSFE, around 0.84 while the BankAxept volume improves even further with respect to the benchmark, showing gains up to 26%. After nine weeks or two months of data retails sales improves by 50% over the AR, while gains for the BankAxept models are still large, around 30%, but more modest. Finally, after the whole information for the quarter becomes available, i.e. at week thirteen for weekly data or after three months for monthly data, BankAxept value and retails sales provide gains of up to 55% while BankAxept volume of up to 45%.

Note that we are giving a notable advantage to the retail sales series for two reasons: first, although the series is revised, we are using as predictor the latest vintage available to date.[14] Second, and more importantly, we are assuming that the retail sales data are available without delays at the end of the reference period, while they are released with one month lag. This implies that the retail sales for the last month of the quarter are released just two weeks before the release of the national accounts data, while BankAxept data are released the day after the end of the reference month, i.e., 6-7 weeks prior to the release of the national accounts. These considerations are important for the assessment of the relative performance of the indicators: while comparable in terms of forecast accuracy, the BankAxept data are a much more timely indicator, as they are available about four weeks earlier, and they are not revised. Moreover, they are available at the weekly frequency. Overall, BankAxept data, both value and volume, are accurate predictors of consumption, providing large and statistically significant gains over a very competitive benchmark and alternative indicators. Also, gains improve over the quarter.

Table 4 shows the results for the density forecasts for the monthly and weekly frequency predictors. The same considerations as for point forecast accuracy hold for density forecasts. Consumption growth is a very good predictor of future consumption. For most MIDAS models the information included in the extra predictors does not help to improve over the AR model. The relative performance of the models deteriorates over the quarter. Similar to the case of point nowcasts, the best models in terms of density nowcasting performance are the ones that include the Bank-Axept data, either value or volume, and the retail sales index for monthly indicators.

[14] Unfortunately, real time data for the retail sale index in Norway is not available.

Week	BA-Val	BA-Vol	Stock Prices	Uncertainty	Car Sales	Retail Sales	Financial News	Unemp. Rate	PMI
		Weekly models					**Monthly models**		
1	0.951	1.137*	1.175**	1.132***					
2	1.066	0.998	1.146**	1.127***					
3	1.057	0.862**	1.139***	1.112***					
4	0.964	0.801**	1.147***	1.128***					
5	0.858**	0.738***	1.151***	1.165***	1.046	0.843***	1.153***	0.839***	1.168***
6	0.829***	0.806***	1.163***	1.156***					
7	0.788***	0.794***	1.192***	1.189***					
8	0.794**	0.799**	1.389***	1.338***					
9	0.700***	0.690***	1.394***	1.346***	1.020	0.494***	1.404***	1.021	1.400***
10	0.619***	0.618***	1.400***	1.412***					
11	0.507***	0.474***	1.405***	1.466***					
12	0.356***	0.368***	1.432***	1.439***					
13	0.456***	0.558***	1.471***	1.476***	1.047	0.438***	1.353***	1.186	1.385***

Table 3: RMSFE relative to the AR model. The RMSFE for the AR model is 3.98 for week 1 through 7, when the previous quarter figures for consumption have not been released yet, and equals 3.47 for weeks 8 through 13 after the release of the previous quarter value. Entries smaller than one indicate the alternative model is more accurate than the AR. The differentials in the squared forecast errors are corrected for heteroskedasticity and autocorrelation using Newey and West (1987). '*', '*** and '***' indicate significance levels for the Diebold and Mariano (1995) test at the 10, 5 and 1 percent respectively. For weekly available data nowcasts are produced for each week in the quarter. For monthly predictors nowcasts are produced at three forecast origin: at week 5, when one month of information for the current quarter is available, at week 9 with two months of data for the reference quarter, at week 13 immediately after the end of the reference quarter, when all monthly information is available. Note that Retail Sales is available about one month after the end of the reference month.

Week	BA-Val	BA-Vol	Stock Prices	Uncertainty	Car Sales	Retail Sales	Financial News	Unemp. Rate	PMI
		Weekly models					**Monthly models**		
1	-2.815	-2.939*	-2.977**	-2.942***					
2	-2.892	-2.791	-2.956***	-2.937***					
3	-2.863	-2.626***	-2.961***	-2.926***					
4	-2.756	-2.539***	-2.980***	-2.943***					
5	-2.626***	-2.445***	-2.990***	-2.973***	-2.930**	-2.605**	-2.959***	-2.684	-2.951
6	-2.596***	-2.569***	-3.007***	-2.963***					
7	-2.565**	-2.599*	-3.586***	-3.476***					
8	-2.410**	-2.418**	-3.591***	-3.362***					
9	-2.262***	-2.245***	-3.575***	-3.477***	-2.934	-1.932***	-3.789***	-2.761	-3.721***
10	-2.215**	-2.235**	-3.569***	-3.588***					
11	-2.530	-2.228**	-3.584***	-3.740***					
12	-2.087*	-1.991***	-3.729***	-3.673***					
13	-1.966***	-2.089***	-3.933***	-3.779**	-3.031	-2.162***	-4.168***	-2.844*	-3.749***

Table 4: Log Scores, averages over the evaluation sample. '*', '*** and '***' indicate significance levels for the Amisano and Giacomini (2007) test at the 10, 5 and 1 percent respectively. The average log score for the AR model is -2.822 for week 1 through 7, when the previous quarter figures for consumption have not been released yet, and equals -2.688 for weeks 8 through 13 after the release of the previous quarter value.

3.3 Distinguishing between goods consumption and consumption of services

Figure 5 in Section 2.1 showed that the BankAxept data covered goods consumption well, while consumption of services was captured less precisely. To investigate further what are the source of the improvements for the BankAxept data over the benchmark, we split the BankAxept predictors in two subcategories, goods and services. We then repeat the forecast evaluation exercise for total household consumption as described above. Results are reported in table 5. The results reveal that the value and volume of goods are more accurate predictors of household consumption than the value and volume of services. In fact the value of services provide limited gains over the benchmark AR model, while the volume of services does not outperform the benchmark.

Week	Value Goods	Value Services	Volume Goods	Volume Services
1	0.891*	0.978	1.131*	1.103*
2	1.034	1.029	1.034	1.030
3	1.040	1.052*	0.879**	1.004
4	0.932	1.082***	0.776***	1.011
5	0.818***	1.101***	0.689***	1.038
6	0.803***	1.061	0.756***	1.097
7	0.772***	0.967	0.755***	1.134*
8	0.781***	0.983	0.771***	1.241**
9	0.681***	0.898*	0.659***	1.205*
10	0.605***	0.867**	0.597***	1.188*
11	0.531***	0.631***	0.505***	0.864
12	0.393***	0.859	0.343***	1.199
13	0.466***	0.955	0.487***	1.096

Table 5: RMSFE relative to the AR model for total household consumption. Target variable: qoq growth rate of total household consumption. RMSFE for the AR model: 3.98 for week 1 through 7 and 3.47 for weeks 8 through 13. Entries smaller than one indicate the alternative model is more accurate than the AR. The forecast errors are corrected for heteroskedasticity and autocorrelation using Newey and West (1987). '*', '*** and '***' indicate significance levels for the Diebold and Mariano (1995) test at the 10, 5 and 1 percent respectively

To explore further the distinction of subcomponents of the debit card data (goods vs services), we investigate the ability of the two subcomponents to nowcast goods consumption and services consumption in the national accounts. The relative RMSFE for this experiment are shown in Table 6. Unsurprisingly, the value and volume of BankAxept data for goods transactions are accurate predictors of goods consumptions, with gains over the benchmark model that reach 80% at week 12. The value of services outperforms the AR model but gains are limited and mostly not statistically significant. Interestingly, the value of goods is as accurate as the value of services in nowcasting services consumption. Moreover, starting from week 8 the volume of goods exhibits a lower RMSFE than the volume of services. Overall, the results from this exercise and from Table 5 suggest that while the value of debit card data for goods delivers an accurate nowcast for total consumption as well as for both goods and services consumption, the value of debit card data for services is a reliable indicator only of consumption of services.

Week	Goods Consumption				Services Consumption			
	Value Goods	Value Services	Volume Goods	Volume Services	Value Goods	Value Services	Volume Goods	Volume Services
1	0.576***	0.735***	0.976	1.075*	1.309***	1.436***	1.344*	1.289***
2	0.799***	0.816***	0.976	1.038	1.274**	1.392***	1.179	1.135*
3	0.916**	0.859**	0.905***	1.029	1.105	1.353***	1.035	1.098
4	0.896***	0.921*	0.842***	1.024	0.964	1.296***	0.962	1.094
5	0.832***	0.976	0.780***	1.032	0.908	1.207**	0.955	1.128
6	0.810***	0.977	0.827***	1.061**	0.898	1.112	0.937	1.200
7	0.793***	0.918***	0.816***	1.122***	0.862	1.022	0.943	1.239
8	0.777**	0.891***	0.784***	1.170***	0.635***	0.694***	0.695***	0.862
9	0.696***	0.806***	0.675***	1.129**	0.678***	0.733***	0.736***	0.915
10	0.585***	0.759***	0.571***	1.115**	0.745***	0.781**	0.785**	0.927
11	0.392***	0.566***	0.373***	0.874	0.844***	0.819*	0.876*	0.884
12	0.197***	0.846	0.210***	1.158	0.716***	0.696***	0.754***	0.735***
13	0.366***	0.959	0.516***	1.122**	0.671***	0.652***	0.721***	0.803*

Table 6: RMSFE relative to the AR model for goods consumption (left 4 columns) and services consumption (right 4 columns). Target variable: qoq growth rate of goods or services consumption. RMSFE for the goods consumption AR model: 8.904 for week 1 through 7 and 8.294 for weeks 8 through 13. RMSFE for the services consumption AR model: 1.606 for week 1 through 7 and 2.309 for weeks 8 through 13. Entries smaller than one indicate the alternative model is more accurate than the AR. The forecast errors are corrected for heteroskedasticity and autocorrelation using Newey West (1987). '*', '*** and '***' indicate significance levels for the DM test at the 10, 5 and 1 percent respectively

3.4 Robustness

We perform two robustness checks: first, with respect to the use of final vintage data; second, with respect to results being driven by outliers.

The choice of benchmark vintage is a key issue in any application using real-time vintage data (see Croushore (2006) for a survey of forecasting with real-time macroeconomic data). To make sure that our results are not driven by the use of first release data, we also evaluate the nowcast against the final data vintage. Results are reported in Table 7 in the Appendix. This experiment confirms the findings of our baseline analysis: the AR model is a hard benchmark to beat. From week 5 the BankAxept data, both value and volume are significantly more accurate than the benchmark. Towards the end of the quarter, the gains with respect to the benchmark exceed 40%.

Given the relatively short size of the evaluation sample, one might wonder whether the superior performance of the BankAxept data is driven by a few observations. To ease this concern, we plot the time series of the squared forecast errors for the BankAxept data and the AR model in Figure 10 in the Appendix for three forecast origins: after week 4, week 8 and week 12. The figure shows that the models including BankAxept data perform better than the AR throughout the evaluation sample, indicating that our results are not driven by a few extreme observations.

4 Real Time Nowcasting During the COVID-19 Pandemic

In this section we illustrate the performance of our models for the nowcasting of the first quarter of 2020, characterized by increased uncertainty due to the coronavirus pandemic.

Norway implemented drastic restrictions as a response to the coronavirus outbreak on March 12th, two weeks after its first registered coronavirus case, including closing kindergartens, schools, many shops and establishments. Initially, the restrictions were put in place for two weeks and subsequently extended for three additional weeks. The lock-down was gradually lifted from late April, with kindergartens, primary schools and most establishments allowed to reopen, but distancing and other infection prevention measures still negatively affecting profitability.

As a result of the corona crisis, registered unemployment rose sharply in March. During the month more than 238,000 new unemployment benefit applications were registered. Consequently, the seasonally adjusted unemployment rate increased substantially at the end of the month to 10.7 percent, up from 2.7 percent in February. Stock prices plummeted by almost 25 percent and the uncertainty index almost doubled from February to March. At the same time the value of debit card transactions fell by 14 percent with respect to March 2019 and by 10 percent with respect to the previous month, while the volume of transactions dropped by 25 percent with respect to March 2019 and by 21 percent with respect to February 2020. In contrast, retail sales have fallen by only 6 percent in year over year terms, and have even increased by 3.7 percent with respect to February 2020. Consumption dropped by 10.2 percent in quarter-over-quarter terms and by 6% in year-over-year terms. The decline was driven mainly by a fall in goods consumption, which plummeted by 16.2% in quarter over quarter terms, while services consumption declined by 2%.

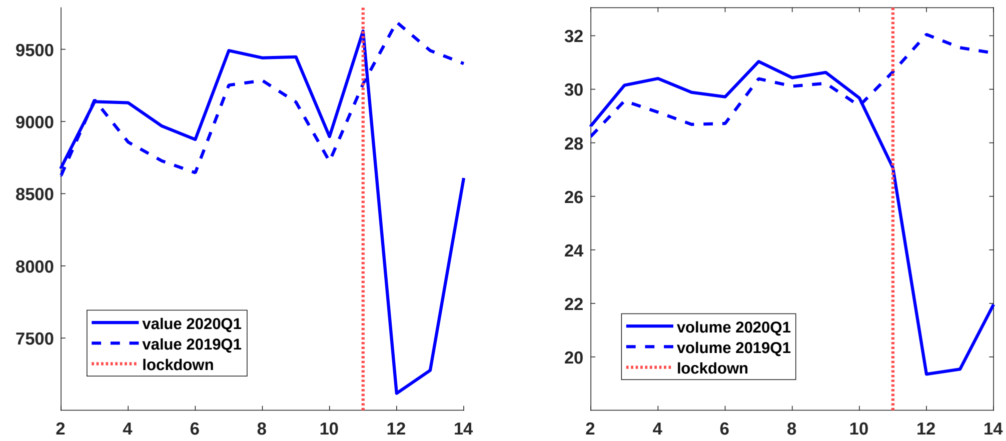


Figure 6: Weekly Debit Card Data 2020Q1: Value and Volume

Figure 6 shows the time series of the weekly debit card data during the first quarter of 2020 compared with the same weeks in the first quarter of 2019 and figure 7 reports the evolution of the data for two sub-categories: goods and services. The figures document several interesting facts. First the volume of transactions dropped one week earlier than the value of payments and by a larger proportion. In fact the volume of transactions declined the week before the lockdown was implemented. This suggests that households were making fewer purchases even before the lockdown but the amount per transaction was larger. Second, both the value and volume of services started to plummet the week before the lockdown, as households were limiting social interactions in restaurants, bars and other establishments, reached the minimum the week after the beginning of the lockdown and did not recover in the sample considered. Finally, the value of goods increased dramatically during week eleven, when the lockdown was implemented and household stocked food items, declined sharply on week twelve and finally recovered starting on week thirteen with the increase in value more pronounced than the increase in the volume.

We now evaluate the weekly performance of the BankAxept indicators during the first quarter of 2020 and the first week of the second quarter of 2020. The point forecast for 2020Q1 obtained for the AR model, the MIDAS models using retail sales and the BankAxept data are shown in Figure 8. [15] The AR model predicts a slightly negative growth rate of consumption early on in the quarter and the nowcast drops to -3.6% after the quarterly figure of consumption for the previous quarter has been released. The nowcast from the retail sales MIDAS model is available from week 5 and initially almost coincides with the nowcast from the AR model. From week 9 to 12 the retail sales nowcast drops to the value obtained from the AR model. Finally, at the end of the quarter, after all three months of retail sales data are released, the nowcast falls further to -6%. The nowcast obtained from the weekly MIDAS models using BankAxept data is initially positive but declines gradually throughout the quarter. In particular from week 11 onwards the nowcast falls below the ones from the retail sales and AR model and the highest drop is seen in

[15] In the figure we do not report the point forecasts from the MIDAS models including the other predictors, given the poor performance compared to the benchmark in the evaluation exercise of the previous section. The nowcast for 2020Q1 are quite inaccurate and range from 2% to -2% at the end of the quarter, after all monthly information becomes available.

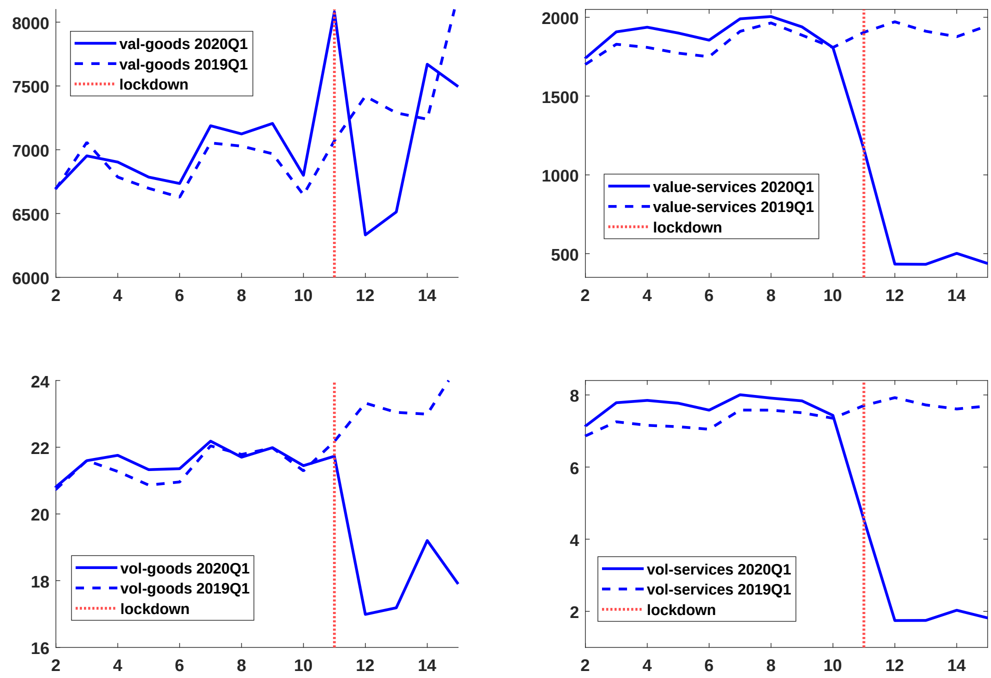


Figure 7: Weekly Debit Card Data 2020Q1 by Sub-Cathegories: Goods (left panels) and Services (right panels)

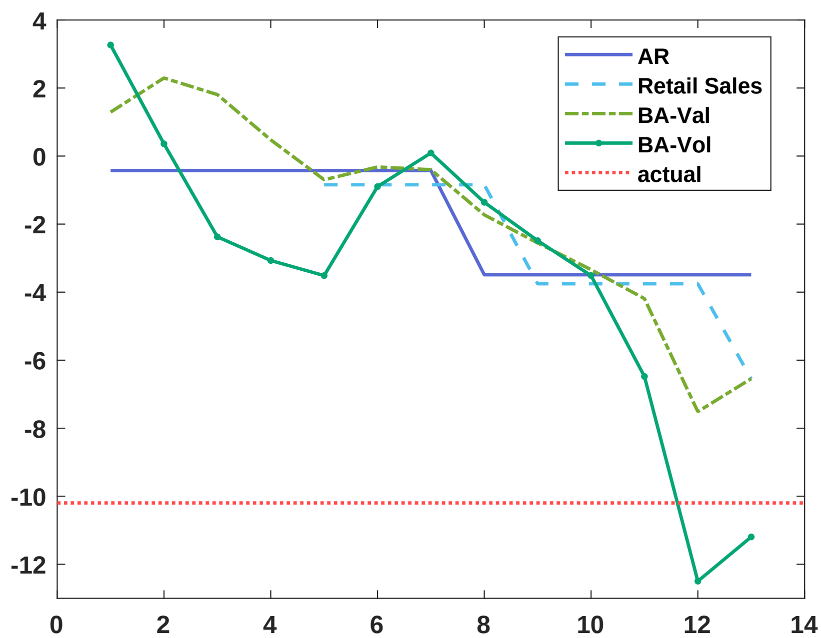


Figure 8: Nowcasting 2020Q1 household consumption: weekly point forecasts

week twelve for both value and volume. The prediction from the BankAxept volume model is lower than for the BankAxept value, reflecting a larger drop in the volume than in the value of transactions. On week 13 the nowcast for the BankAxept volume is -10.7%, which is remarkably close to the actual value of -10.2%.

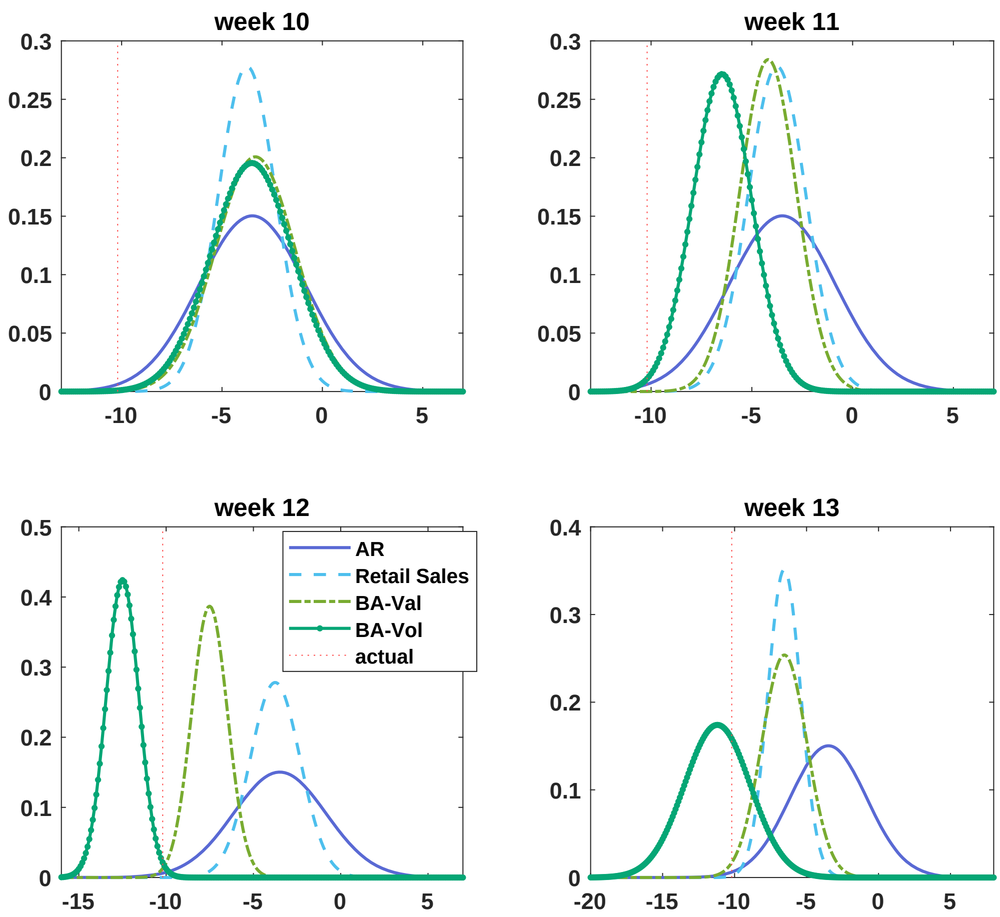


Figure 9: Nowcasting 2020Q1 household consumption: weekly density forecasts for the BanAxept MIDAS model and the AR model starting on week 10, which is the week preceding the lockdown.

Next, we show the density forecast for the BankAxept, the retail sales and the AR model for selected weeks in Figure 9. In week ten, the week before the lockdown measures were implemented, the models have a remarkably similar point forecast but the AR density is more dispersed and therefore assigns a larger probability of a -10.5 percent fall in consumption. The density for the retail sales model is quite concentrated around the point forecast and assigns a negligible probability of observing a fall larger than 9%. The densities for the BankAxpet models, both value and volume are almost identical and their variance lies in between the one of the AR and the retail sales model. During the following week the densities for the weekly MIDAS models shift to the left, and the change is larger for the model with the volume of transactions. The densities become more concentrated around the mean. In week twelve we observe a further shift to the left for both BankAxept models and a further reduction in the variance. Finally, on week thirteen both the densities shift slightly to the right and become less concentrated around the point forecast. While clearly, the BankAxept volume model provides the more accurate nowcast, the BankAxept value is the second best performing model and assigns a higher probability than the AR or retail sales model of observing the actual realization for 2020Q1 consumption growth.

Although the evaluation exercise on the overall sample seemed to highlight a similar forecast accuracy of the retail sales and BankAxept data, the illustration of the 2020Q1 nowcast has proven that BankAxept data might be a more reliable and timely indicator during periods of large adverse shocks. Overall, our analysis shows that BankAxept data are a valuable indicator of household spending, not only in the longer evaluation sample but also in the highly uncertain environment generated by the pandemic.

5 Conclusion

In this paper we showed that debit card data are an accurate and reliable predictor of household consumption not only on average but also during periods of high uncertainty brought by large exogenous and unanticipated shocks. This data is available without delays and sampling errors and at a higher frequency than other commonly used indicators such as retail sales.

We documented sizable gains for point and density forecast over commonly used benchmark models to nowcast consumption and report that the improvements are statistically significant starting early in the quarter, when about one month of debit card data is available.

While this paper focus on the case of Norway, we expect debit card transactions data to also be useful for real time monitoring of consumption in other countries, particularly for countries where card payments account for a high share of consumption expenditures.

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6 Appendix

Week	BA-Val	BA-Vol	Stock Prices	Uncertainty	Car Sales	Retail Sales	Financial News	Unemp. Rate	PMI
		Weekly models					**Monthly models**		
Week 1	0.902*	1.111*	1.114**	1.121***					
Week 2	1.019	0.997	1.123***	1.098***					
Week 3	1.028	0.876*	1.119***	1.099***					
Week 4	0.962	0.834**	1.129***	1.107**					
Week 5	0.877**	0.782***	1.131***	1.138***	0.984	0.812***	1.103***	0.780***	1.123***
Week 6	0.857**	0.852**	1.143***	1.139***					
Week 7	0.834**	0.854**	1.162***	1.176***					
Week 8	0.857**	0.865*	1.344***	1.296***					
Week 9	0.775***	0.753***	1.350***	1.323***	0.943	0.646***	1.337***	0.977	1.348***
Week 10	0.688***	0.664***	1.356***	1.369***					
Week 11	0.579***	0.528***	1.362***	1.405***					
Week 12	0.558***	0.557***	1.388***	1.358***					
Week 13	0.622***	0.685***	1.428***	1.395**	1.006	0.556***	1.288***	1.195*	1.358***

Table 7: RMSFE relative to AR model, final release. The RMSFE for the AR model is 4.25 up to week 7 and 3.77 from week 8 onwards after the release of the previous quarter value. Entries smaller than one indicate the alternative model is more accurate than the AR. Differential in squared forecast errors are corrected for heteroskedasticity and autocorrelation using Newey and West (1987). '*', '*** and '***' indicate significance levels for the Diebold and Mariano (1995) test at the 10, 5 and 1 percent respectively. Predictors in growth rates are computed as qoq.

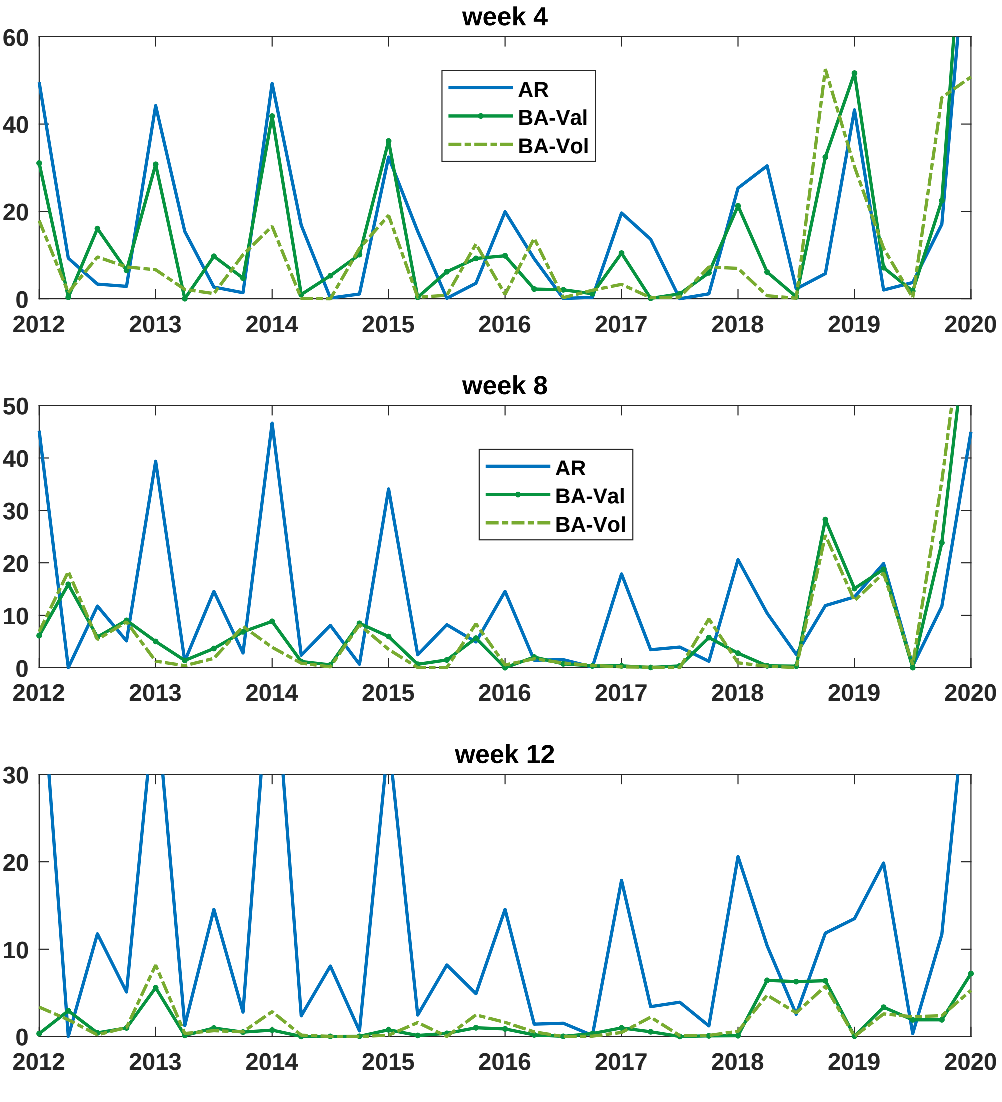

Figure 10: Time series squared forecast errors for selected models and weeks. Target variable is qoq growth of consumption.