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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Using debit card payments data for nowcasting Dutch household consumption*

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Abstract

In this paper we analyse whether the use of debit card payments data improves the accuracy of one-quarter ahead forecasts and nowcasts (current-quarter forecasts) of Dutch private household consumption. Since debit card payments data are timely available, they may be a valuable indicator of economic activity. We study a variety of models with payments data and find that a combination of models provides the most accurate nowcast. The best combined model reduces the root mean squared prediction error (RMSPE) by 18% relative to the macroeconomic policy model (DELFI) that is used by the Dutch central bank (DNB). Based on these results for the Netherlands, we conclude that debit card payments data are useful in modelling household consumption.

Keywords: Nowcasting, debit card payments, household consumption, Midas.
JEL classifications: C53, E27.

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1 Introduction

To make well-grounded monetary and macroeconomic policy decisions, central bankers and other policy makers require adequate information about the current state of a country's economy. Quarterly growth rates of gross domestic product (GDP) and private household consumption are two important measures that reflect the broad economic stance of a country, but are generally released with a considerable delay. In this paper we try to assess whether alternative economic indicators that are released at higher frequencies, are informative for Dutch consumer expenditures. Total volume and value of electronic payments are potential useful indicators of household consumption.

As consumption expenditures are an important input for various policy decisions, its current assessment and short term forecasts need to be as accurate as possible. If these forecasts deviate too much from realised values, real time decisions may be incorrect, causing potential inefficiencies and additional cost. Therefore, policy makers and forecasters are interested in alternative indicators that could lower forecast errors.

In this paper we evaluate the value added of electronic payments data for estimating household consumption patterns. Our research focuses on the Netherlands, a country for which the use of payments data to forecast consumption is promising given the high share of consumption expenditures that is paid electronically. Debit card transactions account for almost 30% of the total value of all consumption expenditures by Dutch households.[1] Point-of-Sale (POS) debit card payments data are collected by the Dutch Payment Association (DPA, Betaalvereniging Nederland) and are available on a monthly basis.

To investigate the usefulness of debit card payments data, we will apply these data to nowcast household consumption. Including payments data in existing models allows us to determine their value added, by comparing similar models with and without this addition to the information set. Nowcasting is defined as the prediction of the present, the very near future and the very recent past (Bańbura et al., 2013). Forecasting the present or past may sound odd, but in practice this technique is applicable in many cases. Many official statistics, such as GDP and in our case household consumption, often take 6 to 12 weeks before they are released. However, other economic indicators that are (highly) correlated with these official statistics may be available almost directly after the reporting period ends. By modelling the relationship between these "fast" indicators and "slow" statistics, researchers get an idea of their actual value even before these statistics are officially released. Hence, nowcasting can be a useful technique in macroeconomics.

[1] Throughout this paper we consider real and seasonally adjusted figures.

2 Literature review

Similar research to ours has been done by Esteves (2011), who conducted research on the consumption of non-durable goods in Portugal, using both data on cash withdrawals from Automated Teller Machines (ATMs) and POS data. In general, the year-on-year (y-o-y) growth rate of ATM/POS data has a high correlation ($\rho = 0.83$) with the y-o-y growth rate of non-durable goods consumption. A model including ATM/POS data only performs significantly better in pseudo-out-of-sample forecasts than most benchmark models, when the evaluation is based on the root mean squared prediction error (RMSPE) of these forecasts. Benchmark models include a standard autoregressive (AR) model, a carry-over model, a model based on consumer confidence, one using electricity consumption and one using retail sales. The model with payments data outperforms all other models, except for a model that uses retail sales as an indicator. When all of these measures are included in one model, the removal of ATM/POS data or the retail sales index causes the largest increase in RMSPE. Ultimately, the results using ATM/POS data are similar to using the retail sales index, but with ATM/POS data having the major advantage of becoming available earlier.

A key question is how payments data perform in comparison to more sophisticated variables related to household consumption, such as disposable income and unemployment, which are only available on a quarterly frequency. A possible solution, without losing the timely availability of the payments data, is proposed in a recent publication by Duarte et al. (2017). They implement a more advanced approach for now- and forecasting private consumption in Portugal. A variety of Mixed Data Sampling (MIDAS) regressions is used to incorporate data of varying frequencies in a single model. While now- and forecasting consumption on a quarterly basis, they use both monthly and daily payments data as explanatory variables. Their research shows that, in the Portugese case, in general the monthly payments data is more informative than the daily information. Also, the model using ATM/POS data generally provides a better out-of-sample forecast than a benchmark AR-model. The usefulness of the data is largest for nowcast purposes and to a lesser extent for one-quarter ahead forecasting.[2] Regarding the nowcast performance of models, only in a few cases adding some explanatory variables such as retail sales and consumer confidence provides an increase in forecast accuracy when the ATM/POS data is already included.

Galbraith and Tkacz (2015, 2017) make similar use of payments data in nowcasting Canadian GDP and retail sales. Multiple nowcasts are produced, one for every month in the quarter, and even some after the quarter has ended but before a new quarterly GDP forecast is released. They research debit card transactions, credit card payments and cheque transactions. Their analysis shows that including payments data, especially debit card transactions, improves the accuracy of nowcasts, in the sense that these data

[2] Nowcasting is forecasting intra-period, which in our case means that a forecast of household consumption in a certain quarter is constructed using monthly payments data up to and within this quarter.

reduce the RMSPE of nowcasts as compared to a benchmark model. This benchmark model uses all regressors except for the payments data, i.e. lagged GDP growth, change in unemployment rate, and price level. Although the payments data appears to be particularly useful in the first two months of a quarter, the marginal contribution of debit card information seems to disappear after the GDP value of the previous quarter has been observed in the third month of the current quarter and is included in the regression. For retail sales they find that debit card data are a good indicator as well.

Another paper about electronic payment indicators as a measure of economic activity is written by Gill et al. (2012), who examine the usefulness of a variety of indicators. They find that both wholesale payments data and retail payments data contain useful information about economic activity that is not available from official statistics or surveys. Apparently, these data are a better indicator of household demand than broader measures of economic activity, such as GDP and Gross National Expenditure (GNE). A possible explanation is the fact that the majority of debit card transactions is conducted by individuals rather than businesses.

In his research, Minish (2007) compares Electronic Card Transaction (ECT) data for New Zealand to Retail Trade Survey (RTS) data, a commonly used indicator of economic activity. He finds that generally these two indicators move in the same direction, and month-on-month ECT movements thus provide a good indicator of the level of the RTS data. The major advantage of ECT data over RTS data is the timely availability of ECT data, being available three weeks earlier than RTS data. ECT data also appear to be more volatile, and contain a steeper upwards trend due to the continuing increase in use of electronic payment methods. This is a problem we potentially need to deal with as well.

Overall, the existing literature on this topic concludes that electronic payments data may be useful indicators of economic activity. Especially regarding household consumption and retail sales, there is a strong relationship with payments data. This reflects that debit cards and other electronic payment instruments account for a significant share in the total volume and value of consumer payments. The timely availability of payments data is often mentioned as an advantage when compared to indicators that are currently used in modelling macroeconomic variables. In this paper, we investigate whether debit card payments data are useful for nowcasting and forecasting household consumption in the Netherlands. Rather than only comparing the data to other indicators in terms of predictive ability, we also study the macroeconomic policy model that is used by the Dutch central bank (DNB, De Nederlandsche Bank) for forecasting purposes. This offers a good benchmark, as the forecasts constructed using this model are published and used as input for monetary policy. Moreover, using the MIDAS modelling technique, we are able to take full advantage of the timely availability and high frequency of the payments data. Hereby, we can also assess the improvement of nowcasts when data becomes available during a quarter.

3 Data

Our main data source is a dataset of the total volume and value of debit card payments, available on a monthly basis from January 1995 until July 2016.[3] Since these data are recorded electronically and include all debit card payments made in the Netherlands, they are free of sampling bias and virtually free of non-sampling error. These properties combined with monthly data availability for more than twenty years, make them well suitable for modelling purposes. Indicators of economic activity, such as private consumption, are often based on survey or diary data, in which a representative sample of consumers report their expenses in a detailed manner. However, this type of data remains vulnerable to sampling error, unlike fully covered payments data.[4]

The debit card was introduced in the Netherlands in the mid-80s to create a uniform electronic retail payment system across all Dutch banks. Over the last twenty years, debit card usage has grown rapidly. While just over 250 million debit card payments in 1995, averaging roughly 17 transactions per person, more than 3.2 billion transactions were recorded in 2015, amounting to an average of almost 190 transactions per person.[5] Correspondingly, the total value of these payments increased from €15.7 billion in 1995 to €79.4 billion in 2015. After correcting for inflation, this implies the amount spent per inhabitant rose from just over €1000 to more than €4600. In Figure 1 the volume and value of debit card transactions on a quarterly basis are displayed, joint with the value of household consumption.[6] Since 2010, almost one third of the value of all consumption expenditures by households has been paid for by debit card. Figure 2 depicts the y-o-y growth rates of these same quantities on a monthly basis. The first years after the introduction of debit cards were very volatile regarding the growth rates of volume and value of transactions, likely due to the rapid uptake of this payment instrument.

The traditional point-of-sale payment method, cash, is the natural "victim" of the rise of debit card usage. However, after the strong growth in the first years after the introduction of the debit card, the substitution of cash by debit cards is now taking place at a slower pace. Possible reasons for this phenomenon are examined by Van der Cruijsen et al. (2017), who claim that a substantial share of consumers is "in love with the debit card" but still "married to cash". They find that persistent habits

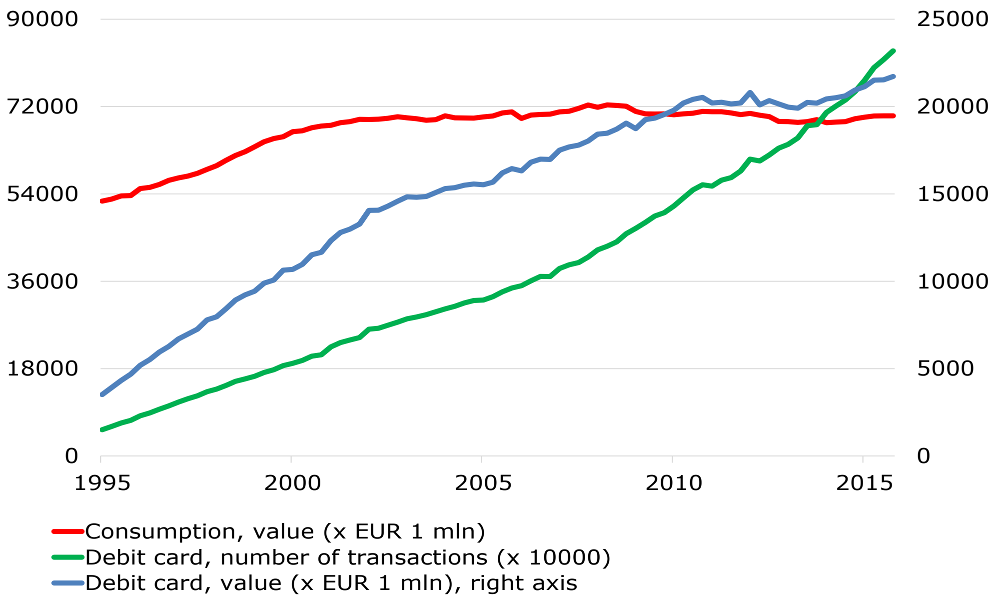
[3] As also stated by Galbraith and Tkacz (2015), in theory we could have daily data on debit card payments, since all transactions are recorded electronically. However, Duarte et al. (2017) find that this does not lead to a reduction of RMSPE, possibly because daily data are very noisy. For an application of using daily payments data, see Galbraith and Tkacz (2013).

[4] See Schuh (2017) for an anlaysis of measuring consumer expenditures using payment diaries.

[5] Source: Statistics Netherlands (CBS), http://www.cbs.nl, consulted on 14-9-2016 for number of Dutch inhabitants.

[6] The original dataset for the number of transactions contained an aberrant observation in December 2001; the amount of transactions was significantly higher. A possible explanation is the introduction of the Euro in January 2002, which introduced uncertainty for next month's cash balances. To avoid "left over" cash in guilders, the number of debit card payments increased in the run-up. This observation was replaced by a forecast based on preceding observations.

Figure 1: Quarterly debit card transactions and household consumption



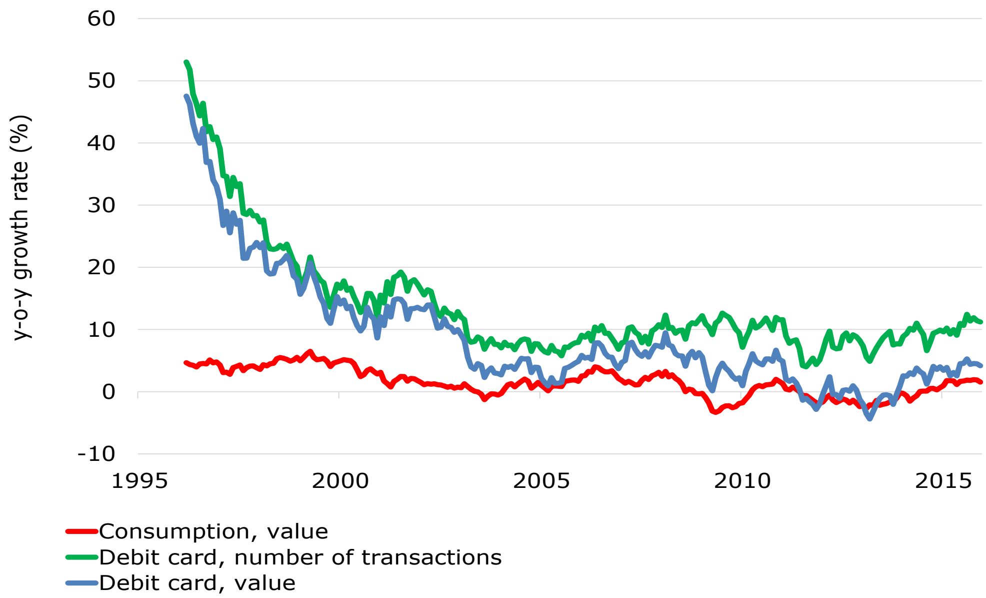
Note: The figure shows real and seasonally adjusted figures. Source: DNB, CBS, DPA.

are an important explanation for this effect. Van der Cruijsen and Van der Horst (2016) confirm that habits are a key driver of payment behaviour, but that other socio-psychological factors such as social norms and emotions play a role as well.

Other reasons for paying with cash regard having better insight into expenses and using cash as a disciplining device. Hernandez et al. (2017) find that households with lower incomes prefer cash as a budgeting tool. DNB/DPA (2016) shows that elderly people have a relatively strong cash habit and that the level of education is positively correlated with debit card usage. It also reports that in 2015 a milestone was reached; it was the first year in which Dutch consumers used the debit card more often than cash. Cash is mainly used for small purchases; it accounts for 70% of purchases under €5, but only for 18% of purchases over €100. This is also illustrated by the fact that in the same year, cash payments made up 49.5% of all payments, but only 29.7% of the total value of all payments.

The debit card currently fulfils a prominent role in Dutch society. One of the first POS locations where people could pay by debit card were petrol-service stations, followed by supermarkets, which caused the real influx in the use of debit cards. Since then, many other retail sectors have adapted the system, and today Dutch consumers can pay by debit card in the majority of the retail industry sectors. Nowadays supermarkets are the largest retail sector regarding highest volume and value of debit card transactions. Many supermarkets have special debit-card-only cash registers, which stimulates the use of debit cards and enhances the speed of serving the customers.

Figure 2: Quarterly debit card transactions and household consumption, y-o-y growth rates



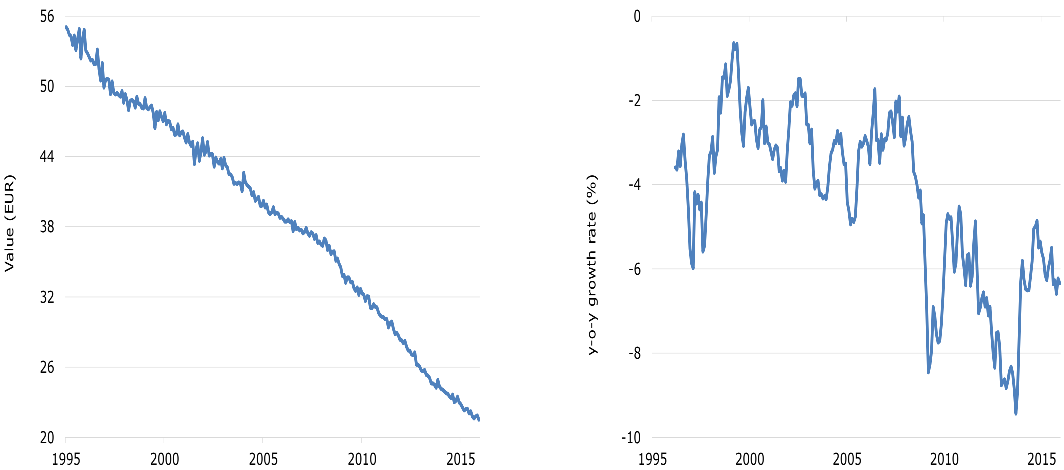
Note: The figure shows real and seasonally adjusted figures; 3-month moving averages. Source: DNB, CBS, DPA.

Over the last 20 years, given the rapid uptake of card usage, there has been a clear downward shift in the average value of debit card transactions. Figure 3 shows the development of the average transaction value and its y-o-y growth. Changing economic conditions due to the financial crisis could have caused the sudden drop in yearly growth rate just after 2008. Public campaigns may have also contributed to increased debit card use for smaller payments. In particular, in 2009, a public campaign "Small amount? Debit card allowed!" was launched in an attempt to motivate consumers to use debit card for small transaction amounts. Jonker et al. (2015) study the impact of public campaigns in favour of using the debit card. They find that, overall, these campaigns had a significant positive impact on debit card usage.

Another major factor that convinced people to pay by debit card for small amounts, was the reduction of surcharges by merchants. Previously, consumers had to pay a fee (surcharge) for paying small amounts by debit card, often for payments under €10 or €15. In 2006, the share of card accepting merchants that surcharged customers for paying by debit card was around 22%, it decreased to 2% in 2011 (Hoofdbedrijfschap Detailhandel, 2012). This was the result of an agreement between banks and merchants to reduce surcharging. Bolt et al. (2010) study the impact of removing these surcharges at the POS. They find an increase in the share of debit card payments with corresponding cost savings for society. This is also supported by evidence for Denmark where a similar surcharge was introduced instead. Carlsen and Storgaard (2010) find that this led to a significant decrease in debit card usage.

The major increase in debit card usage can be illustrated by the average value of a debit card payment, which was €61 in 1995, but by 2015 had decreased to €25 after accounting for price level changes. In 2014, contactless payments were introduced in the Netherlands, which might even further accelerate the downwards trend of the average transaction amount. This new way of paying by debit card, by simply tapping or waving your debit card at a payment terminal, should convince people to switch from cash to debit card for small transaction amounts. Paying contactless is quick and gives less hassle with small change; for payments under €25 no PIN-code is needed. Dutch consumers seem to have adapted this technology quickly, as in September 2016 more than one fifth of all debit card payments were contactless payments.

Figure 3: Monthly average debit card transaction value (left) and y-o-y growth rate (right)



Note: The figure shows real and seasonally adjusted figures; 3-month moving averages for growth rates. Source: DPA.

Since debit card payments account for an increasing share of all payments, they could be a useful indicator of household consumption, considering that most of the recorded payments are carried out by consumers. Our debit card payments data have been seasonally adjusted such that the major season-dependent fluctuations are smoothed.[7] We primarily study y-o-y growth rates and differenced natural logarithms to further reduce the influence of seasonal patterns. In addition to debit card payments data, we have some other measures available that are more frequently used as indicators of economic activity. We can utilise these to compare the predictive ability of the payments data. In particular, the monthly indicators we consider, are an indicator

[7]The X-12 multiplicative method is applied for seasonal correction.

of consumer confidence, the value of retail sales, and the share prices represented by the Amsterdam All Share Index (AAX Index).[8] In Appendix A, in Table A.1, an indication of the release dates of these and other statistics is given.

The last series we discuss is household consumption, a key variable in this paper. Two different time series are available. The first is released on a quarterly basis and includes the real value of household consumption in Euro's, available from 1977 up to and including 2015. The second series is monthly available from January 1995 until December 2015, and denotes the real volume index of monthly household consumption.[9] As shown in Figure 1, Dutch household consumption has substantially risen from the 1990's onwards. Since the start of the current millennium however, the real value of total consumption has been more or less stable. Over the last 15 years, Dutch households consumed for a total value of approximately €280 billion per year on average. During the financial crisis, consumption growth leveled off, in line with a general decrease in economic activity at the time.

Regarding the relationship between consumption and total value of debit card payments, a clear shift has occurred; in January 1995 the share of debit card payments in total consumption was a mere 8%, which increased to around 15% in 2000, to almost 30% in 2015. Hence, our payments data will likely be more representative for consumption expenditures in recent years rather than 15 to 20 years ago.

4 Methods

In this section, we discuss several techniques and models.

4.1 Nowcasting and forecasting

As mentioned in the introduction, our aim is to nowcast and forecast consumption; we predict the recent past, present and near future. We are mostly interested in the month or quarter that is pending or just finished. Nowcasting is generally used for intra-period forecasting, meaning that information about the current period is already available, which is then used for forecasting. In terms of the payments data, this means that for nowcasting in quarterly models we either have the data of the first, first two or all three months of a quarter to our disposal.

Two different forecast methods will be examined. Assume the original estimation sample runs up to and including observation T. The first method is the so-called

[8] Statistics Netherlands calculates the difference between the percentage of optimists and the percentage of pessimists for five survey questions. These are averaged to obtained the indicator of consumer confidence.

[9] While the quarterly statistic regards national household consumption, the monthly statistic represents domestic household consumption. The difference is that national consumption includes Dutch households that are currently not residents of the Netherlands, whereas domestic consumption includes consumption expenditures by households in the Netherlands only. However, the statistics are very similar, since the number of non-residents is relatively small.

“moving window”, which always uses the same number of observations. In this approach, in every step, a new model is estimated based on the n observations preceding $t + 1$. For example, in the first step the estimation sample will be $[T - n + 1, T]$, while in the second step it will be $[T - n + 2, T + 1]$, meaning the first observation is discarded and the estimation sample moves through time. In the other method, the “expanding window” forecast, all historical information is incorporated. Here, all observations preceding t+1 will be used when estimating the parameters of the model. In every step, after observation $t+1$ becomes available, the model will be re-estimated using all observations including the realised value at $t + 1$. This way, the estimation sample in the second step will be $[T-n+1, T+1]$. In case the distant past is relevant for what will happen in the future, the expanding window approach may be useful, as all historical information is incorporated in the model. If only the more recent past is relevant, a moving window could be taken into consideration, since the model will be based on more recent observations and contains less distorting information of the distant past. To determine which case is relevant for our research, we implement both methods and compare the results.

For all modelling exercises, the complete sample will cover the period up to and including December 2015, while the starting dates differ between the models.[10] Two different forecast samples will be considered for the forecast, the first starting in January 2008 and the second in January 2012. As we are also applying quarterly models, this simply translates to the first quarters of 2008 and 2012, respectively. Hence, the first sample includes the (aftermath of the) financial crisis of 2008, while the latter does not. This allows us to examine how the model performs when economic shocks hit. For our analysis, we are interested in one-period out-of-sample forecasts.

4.2 Models

To assess the usefulness of debit card payments data, we will apply these data to various regressions with various frequencies. The major issue when using a monthly frequency is the availability of data, since many economic variables, disposable income for example, are measured on a quarterly basis. Therefore, we also construct a model with payments data aggregated to a quarterly frequency. Moreover, different frequencies are combined as well, which allows us to use our monthly and quarterly variables in a single model.

4.2.1 Indicator models

Constructing models in which we compare the debit card payment data to other indicators will be the primary step in investigating whether the payments data is useful in forecasting household consumption. First, we will perform a simple linear regression

[10] Since quarterly consumption data are prone to substantial revisions, we only consider the data up to December 2015.

of monthly consumption on its lags and a variety of indicators. By comparing the forecasts of the models including the payments data to models including other monthly indicators as explanatory variables and models without any additional variables, we may assess the value added of payments data. We consider a sample period starting in January 1998, and the constructed forecasts will be one-month ahead forecasts.

The baseline model is

$$\bar{\Delta}^{12} C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12} C_{t-i} I_i + \epsilon_t. \tag{1}$$

Here, C_t represents household consumption in month t and $\bar{\Delta}^{12}$ is the notation we introduce for annual growth rates.[11] I_i is the indicator function taking value 1 if the i^{th} lag of C_t is included in the model and 0 otherwise, q lags are considered. ϵ_t is the usual error term.

Then, for each indicator j, an extra term will be added to this equation one at a time, such that the new equation is

$$\bar{\Delta}^{12} C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12} C_{t-i} I_i + \beta_j \bar{\Delta}^{12} IC_{j,t} + \epsilon_t, \qquad j = 1, .., 4 \tag{2}$$

where $IC_{j,t}$ is the value of indicator j in month t. These indicators are P_t, which denotes (a variation) of the debit card data in month t, RS_t, the value index of retail sales in month t, CC_t, the indicator of consumer confidence in month t, and AAX_t, the average value of the AAX-index in month t. The three variations of the debit card data that we use, are either the total volume (i.e. number of transactions), value or average value of debit card payments, but will be specified in Section 5.1.

The complete model including all indicators is

$$\bar{\Delta}^{12} C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12} C_{t-i} I_i + \beta_1 \bar{\Delta}^{12} P_t + \beta_2 \bar{\Delta}^{12} RS_t + \beta_3 CC_t + \beta_4 \bar{\Delta}^{12} AAX_t + \epsilon_t. \tag{3}$$

In total, for this forecasting exercise we consider ten different models, which are all examined for the two different forecast samples and two different forecast methods, as mentioned in Section 4.1. The various models we study are based on equation (1)-(3). Their exact specifications are given in Table 1.

4.2.2 DELFI-based models

Since official quarterly statistics on household consumption are released only 6-12 weeks after the end of a quarter, it is important to have an accurate nowcast of this

[11] For the remainder of this paper, $\bar{\Delta}^i$ denotes an i-month natural logarithm difference (for e.g. $i = 12$ this means that for a variable x_t, $\bar{\Delta}^{12} x_t$ is $log(x_t/x_{t-12})$), while Δ^i denotes a simple i-month difference. When i is omitted, we are dealing with a one-month difference or growth rate.

Table 1: Specification of various indicators models

No.	Model specification
1.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \epsilon_t$
2.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_1\bar{\Delta}^{12}P_t + \epsilon_t$
3.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_2\bar{\Delta}^{12}RS_t + \epsilon_t$
4.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_3 CC_t + \epsilon_t$
5.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_4\bar{\Delta}^{12}AAX_t + \epsilon_t$
6.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_1\bar{\Delta}^{12}P_t + \beta_2\bar{\Delta}^{12}RS_t + \beta_3 CC_t + \beta_4\bar{\Delta}^{12}AAX_t + \epsilon_t$
7.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_2\bar{\Delta}^{12}RS_t + \beta_3 CC_t + \beta_4\bar{\Delta}^{12}AAX_t + \epsilon_t$
8.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_1\bar{\Delta}^{12}P_t + \beta_3 CC_t + \beta_4\bar{\Delta}^{12}AAX_t + \epsilon_t$
9.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_1\bar{\Delta}^{12}P_t + \beta_2\bar{\Delta}^{12}RS_t + \beta_4\bar{\Delta}^{12}AAX_t + \epsilon_t$
10.	$\bar{\Delta}^{12}C_t = \beta_0 + \sum_{i=1}^{q} \gamma_i \bar{\Delta}^{12}C_{t-i}I_i + \beta_1\bar{\Delta}^{12}P_t + \beta_2\bar{\Delta}^{12}RS_t + \beta_3 CC_t + \epsilon_t$

consumption statistic, even before the realised value is released. Although modelling the three separate monthly statistics could give an idea of the value for the whole quarter, the monthly statistic only includes the index and its mutation. Hence, it is not possible to simply add up three consecutive months and obtain the quarterly measure. Therefore, we will also examine models based on a quarterly frequency. By aggregating the monthly total value and number of debit card transactions, we obtain quarterly data, which we can then use in such a framework.

DNB uses its own macroeconomic model, dubbed DELFI, for forecasting the Dutch economy.[12] Broadly, the dynamic economic relations between consumption, investments, government expenditures, and imports and exports determine total output. The model forecasts are published bi-annually and used as input for monetary policy making. DELFI contains a long run consumption-relation, which includes fundamental factors that influence consumption, such as households' gross housing wealth and disposable income. In an error correction framework, the lagged deviations from the long-run relation feeds back into the short-run relation. We are interested in the short-run relation, since we want to carry out one-quarter ahead forecasts of consumption. For estimating the model, the effective sample period starts in the second quarter of 1984. The DELFI model equation of the short term relation is

$$\begin{aligned}\bar{\Delta}C_t = {} & \beta_0 + \beta_1 EC_{t-1} + \beta_2\bar{\Delta}Ydis_t + \beta_3[\Delta U_{t-1} + \Delta U_{t-2} + \Delta U_{t-3} + \Delta U_{t-4}]/4 + \\ & \beta_4\bar{\Delta}(PS_{t-2}/PC_{t-2}/100) + \beta_5\bar{\Delta}(PH_t/PC_t/100) + \beta_6\Delta^6 CC_{t-1} + \\ & \beta_7 D_{93,t} + \beta_8 D_{06,t} + \beta_9[(\bar{\Delta}(1 - LTV_{t-1}))(1 - D_{LTV,t-1})] + \epsilon_t. \end{aligned} \tag{4}$$

The dependent variable is the first differenced natural logarithm of seasonally adjusted quarterly consumption. Of the following variables, some are used in a moving-average framework. EC is an error-correction term as discussed before, while $Ydis$ denotes

[12]For extensive details on this model, see http://www.dnb.nl/en/onderzoek-2/econometric-models-of-dnb/delfi-a-model-of-the-dutch-economy/index.jsp.

disposable income. U is the unemployment rate, PS is a weighted average of the MSCI (Morgan Stanley Capital International) world share index and AAX Index, as an indicator of share prices. PC is the deflator of private consumption, PH is the index of house prices, and CC denotes consumer confidence. D_{93} and D_{06} are two dummy variables, included to prevent a decrease in model quality due to two outliers in the first quarters of 1993 and 2006, respectively.[13] LTV is an abbreviation of loan-to-value, as an indicator of the relation between the value of mortgage loans and housing wealth. The dummy variable belonging to LTV, D_{LTV}, takes value one if $\Delta log(1 - LTV)$ is larger than zero, and takes value zero otherwise. Hence, the term with LTV is only incorporated in the model if current quarter's LTV-ratio is higher than last month's.

Three alternative DELFI-based models will be considered. The first of these will be model (4), over the complete sample period. The second model is the same as (4), but given that the payments data are only available from 1995 onwards, we have to adjust the starting period to the first quarter of 1995. As we have to shorten the sample period by more than ten years, this may affect the quality of the forecasts in a negative way. The third model is similar to the model starting in 1995, but now includes the payments data. Again, the same two different forecast samples and forecast methods as previously discussed, are considered.

4.2.3 MIDAS models

Next, we apply the MIDAS approach as introduced by Ghysels et al. (2004). This approach has the key advantage of allowing the dependent variable to have a lower frequency than the explanatory variables.[14] Therefore, the timing of the higher-frequency explanatory variables can be preserved (Armesto et al., 2010). This is useful here, as the official household consumption statistics are available on a quarterly basis, while the original payments data are sampled on a monthly frequency. Duarte et al. (2017) have also looked into the combination of high-frequency payments data and quarterly statistics using a MIDAS modelling approach.

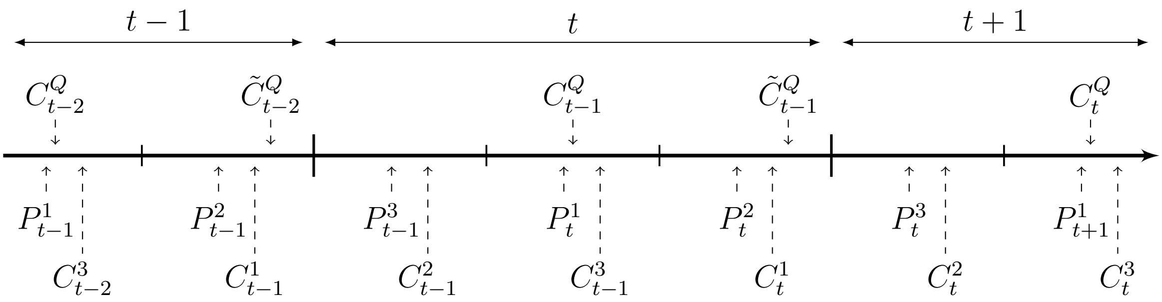
In nowcasting and forecasting using MIDAS-models, it is particularly important which data is available at what moment in the quarter, since we use intra-period data of a higher frequency. We analyse whether the accuracy of the nowcasts improves when additional data is used that becomes available before, during, or after the quarter. We are interested in forecasting from the moment just before the quarter starts until the moment of the release of the first vintage of the quarterly household consumption statistic by Statistics Netherlands, approximately six weeks after a quarter ends.

Figure 4 shows a timeline of data releases just before, during and after quarter t. For example, half way quarter t, three pieces of new information become available. First, the payment data (i.e. volume and value of debit card transactions) of the first

[13] D_{93} takes value one for the first quarter of 1993 and D_{06} takes value one for the first quarter of 2006 and for all other quarters their value is zero.

[14] Note that in the previous section, aggregating the data to a quarterly frequency was necessary in order to utilise DELFI.

Figure 4: Timeline of data releases



Note: $t-1$, t and $t+1$ denote three subsequent quarters; subscript t denotes the reporting period; superscript m, $m = 1, 2, 3$, represents the month of the reporting period. Quarterly consumption releases are denoted by C^Q_t (first vintage, released after 6 weeks) and $\tilde{C}^Q_t$ (second vintage, released after 12 weeks). P^m_t denotes monthly payment data (released after 2 weeks) and C^m_t the monthly consumption index (released after 6 weeks).

month of quarter t, denoted by P^1_t, become available, second, the first vintage (i.e. the "flash" forecast) of quarterly consumption of the previous quarter $t-1$, denoted by C^Q_{t-1} is released, and third, the consumption index of the third month of the previous quarter $t-1$, denoted by C^3_{t-1}, arrives. See Table A.1 in Appendix A for more detailed information regarding the timing and publication lags of data releases.

The forecasts are computed according to a simple MIDAS model, which is given by the following general formula proposed by Ghysels et al. (2007)

$$y^L_t = \beta_0 + \beta_1 B(L^{1/m}; \theta) x^H_t + \epsilon_t \tag{5}$$

where $B(L^{1/m}; \theta) = \sum_{k=0}^{K} B(k; \theta) L^{k/m}$ and $L^{k/m}$ is a lag operator such that $L^{k/m} x^H_t = x^H_{t-k/m}$, and the lag coefficients in $B(k; \theta)$ of the corresponding lag operator $L^{k/m}$ are parametrised by a function of a small-dimensional vector of parameters θ. In our application $m = 3$ (3 months in a quarter), and we define the low frequency RHS y^L_t as the quarterly growth rate of consumption. The high frequency LHS variables x^H_t are based on monthly payments and monthly consumption index data. For the functional form of the hyperparameters we choose a data-driven Almon polynomial weighting scheme, which is also referred to as polynomial distributed lag (or PDL) weighting. We apply a polynomial of degree two. This way, the model is parsimoniously specified and at the same time flexible enough to include higher frequency information. We include the first three lags, $K = 3$, of the high-frequency variables, so that we allow the model to incorporate all monthly information of the previous quarter.[15]

The forecast exercise will be carried out as follows. Nine different cases will be analysed, representing different points in time of monthly data releases before, during

[15] For more details on the econometrics of MIDAS modelling, we refer to e.g. Ghysels et al. (2007) and Andreou et al. (2013).

and after the quarter. The first nowcast is constructed just before the quarter starts, then the payments data of the first month becomes available allowing a second nowcast, and so on for the other data releases. The nowcasting process ends when the first vintage of the quarterly consumption statistic becomes available. The sample period starts in 1995 and again we consider the four cases mentioned in Section 4.1.

4.2.4 Combined forecasts

Finally, we combine the forecasts of our two previous models, the DELFI and MIDAS model. Historically, weighted forecasts have proven to provide competitive forecasts that are hard to outperform by forecasts constructed using a single model, see e.g. Clemen (1989) and Makridakis and Hibon (2000). Since both the consumption equation of DELFI and the MIDAS model have the same dependent variable, we are able to take a combination of the forecasts of these two models in an attempt to make even more accurate forecasts. Weighting is done by taking a simple average of the two, which works reasonably well relative to more complex methods (Clemen, 1989).

The different cases we distinguish are again linked to the particular timing of data releases. Note that in order to combine two forecasts, we need to assure that the monthly data for the MIDAS model is available. This way we can determine whether the forecasting accuracy improves during a quarter. The first forecast of quarter $t+1$ is made when the second vintage of the quarterly consumption statistic of t is available, just before quarter $t+1$ ends, while the last one is made before the release of the first vintage of the statistics of quarter $t+1$. All forecasts made in between, represent the point in time of data releases. The downside of combining these two models is that not all data used in DELFI are available at the moment of forecasting, which means that real-time forecasts would differ from these forecasts. However, the main purpose of combining these models is to determine whether the MIDAS model adds any value to the DELFI model.

5 Results

In this section we compare the forecasting performance of a variety of models by means of the RMSPEs of one step ahead, out-of-sample forecasts.[16] To test for significance of the results, we apply Diebold-Mariano (DM) tests for predictive accuracy (Diebold and Mariano, 1995), where a 5% significance level is used unless stated otherwise (see Appendix B).

5.1 Indicator models

Figure 5 suggests that the value of debit card payments is a better indicator of household consumption than the number of payments. A possible explanation is that the

[16] All results were obtained by using EViews 9.5.

substitution effect between cash and debit cards had more impact on the volume than value, consistent with the findings of Gill et al. (2012). As shown in Figure 5, the total value of debit card payments has the highest correlation with household consumption (both y-o-y growth rates), and follows a similar pattern since around 2000.

Therefore, we will use the total value of debit cards as indicator in in our forecasting evaluation. The correlations in Table 2 show that the growth of the total value of debit card transactions and retail sales are highly correlated with growth of household consumption. Hence, we expect these two variables to increase forecast accuracy in our exercises. Instead, the AAX-index shows a relatively low correlation with consumption and with the other indicators (except for consumer confidence). While the AAX-index may not be a good indicator of consumption by itself, it may perform well in combination with other indicators pickup some "left over" economic movements. It is also worth noting that debit card data show a lower correlation with retail sales than with consumption. This seems somewhat counterintuitive given that debit cards are more used for payment in the retail sector than in other businesses.

Table 2: Correlations between monthly household consumption and monthly indicators

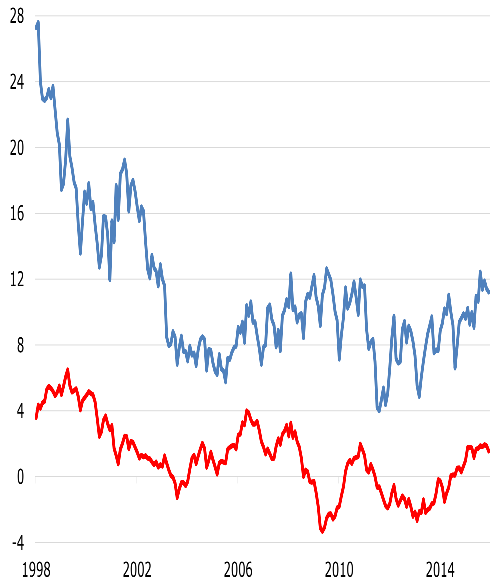
	Debit card data	Retail sales	Consumer confidence	AAX-index
Consumption	0.821	0.823	0.123	0.351
Debit card data		0.656	-0.102	0.083
Retail sales			0.235	0.243
Consumer confidence				0.734

Note: Growth figures, correlation coefficients computed using data from January 1998 till December 2015; see Table 1 for exact specification. Source: DNB, CBS, DPA.

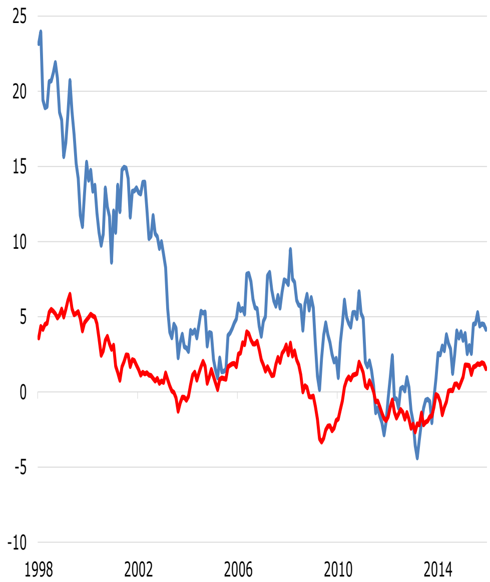
In order to evaluate the actual performance of the debit card data as an indicator of monthly household consumption, household consumption is regressed on different sets of indicators. We apply a simple AR(3) model (i.e., $q = 3$ in Table 1). Table 3 shows the average RMSPEs of the forecasts for various models.

From Table 3 we conclude that in most cases, the indicators improve the forecast accuracy when added to the simple AR(3) model. The debit card data and retail sales data account for the lowest RSMPE's when added as a single indicator. While the performance of the model with only debit card data included is on average slightly worse than the performance of the model with only retail sales data, policymakers may prefer the prior model due to the timely availability of debit card data. When all indicators are included in a single model, the highest forecast accuracy is attained. Removing the AAX-index from the model leads to the second largest increase in RMSPE, which could be partly explained by its ability to capture economic patterns that are not captured by the other indicators. Debit card data and retail sales data again perform similarly in this situation. Rolling or expanding windows make not much difference for the results.

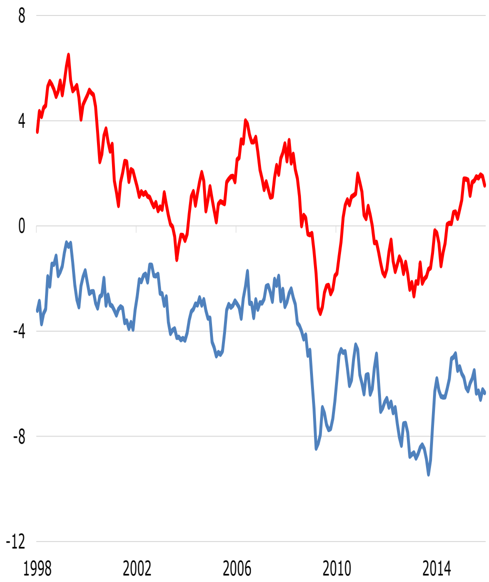
Figure 5: Y-o-y growth rates (%) of consumption (red) and debit card transactions (blue)



(a) Number, $\rho = 0.70$



(b) Total value, $\rho = 0.82$



(c) Average value, $\rho = 0.72$

Note: The figure shows real and seasonally adjusted figures; ρ denotes the correlation coefficient; 3-month moving averages. Source: DNB, CBS, DPA.

Table 3: RMSPEs of predictions using the monthly indicator model

		Moving window		Expanding window	
		2008-2015	2012-2015	2008-2015	2012-2015
1.	Autoregressive AR(3)	1.445	1.272	1.439	1.272
2.	Incl. Debit card data	1.146	1.095	1.141	1.107
3.	Incl. Retail sales	0.942	1.031	1.018	1.094
4.	Incl. Consumer confidence	1.427	1.282	1.410	1.283
5.	Incl. AAX-index	1.383	1.281	1.365	1.281
6.	All indicators	0.758	0.872	0.761	0.871
7.	Excl. Debit card data	0.856	0.908	0.902	0.957
8.	Excl. Retail sales	1.049	1.027	1.053	1.057
9.	Excl. Consumer confidence	0.807	0.955	0.819	0.954
10.	Excl. AAX-index	0.900	1.028	0.933	1.028

Note: The first five models contain an AR(3)-component and a single indicator, model (6) includes all indicators, and models 7-10 are obtained by removing a single indicator from the fully specified model. The exact specifications are given in Table 1. RMSPEs are calculated relative to the level of the monthly consumption index.

5.2 DELFI-based models

Regarding DELFI-based models we distinguish three cases. First we consider the original model that is estimated from 1984. Second, we adjust the start of the sample period to 1996, and third we add our payments data to model (4) using the following specification:

$$[\bar{\Delta}P_{t-1} + \bar{\Delta}P_{t-2} + \bar{\Delta}P_{t-3} + \bar{\Delta}P_{t-4}]/4 \tag{6}$$

where P_i is the total real value of debit card payments in quarter i.

Table 4: RMSPEs using DELFI-based models

	Moving window		Expanding window	
	2008-2015	2012-2015	2008-2015	2012-2015
Original DELFI (1984Q2)	393.96	453.51	387.20	448.64
Shortened DELFI (1996Q2)	368.36	413.46	402.72	427.02
Incl. Debit card data	366.58	414.46	397.99	419.92

Note: The original DELFI model equation for household consumption uses data from 1984q2. The third model is obtained by including payments data in the "shortened" DELFI model that starts from 1996q2; the specification of (6) is added as a transformed variable to the consumption equation in DELFI. RMSPEs are calculated relative to the level of quarterly household consumption.

Table 4 shows that, on average, the best results are obtained when using the model including debit card data. These models beat the original DELFI models in three out of four cases. More specifically, the moving window estimation for the out-of-sample period from 2008 onwards including the payments data provides the lowest RMSPE overall. Apparently, recent observations are more relevant for predicting short term values of consumption.[17] Although the model with debit card data with a rolling window provides the lowest overall forecast error, it is not significantly better than the shortened DELFI model (see Appendix B, Table B.1).

5.3 MIDAS models

So far we considered simple one-period ahead forecasts and assessed the quality of these forecasts. In this section, we construct a number of forecasts within a quarter mixing quarterly and monthly data.

To be concrete, following equation (5), we define the quarterly RHS $y_t^L = \bar{\Delta} C_t^Q$ and define the LHS monthly variables $x_{1t}^H = \bar{\Delta}^{12} P_t^m$ and $x_{2t}^H = \bar{\Delta}^3 C_t^m$. Note that we use y-o-y growth rates to further smooth the monthly payments data removing any left-over monthly seasonal fluctuations. We apply an Almon lag weighting scheme with a polynomial of the second degree, and choose $K = 3$ as the fixed number of high frequency lags to include in the regressions.

The availability of data at specific moments in time is illustrated in Figure 4 and a more detailed indication of release dates can be found in Appendix A, Table A.1.

Table 5: RMSPEs using MIDAS models

Approximate forecast date	Most recent releases	Moving window 2008-2015	Moving window 2012-2015	Expanding window 2008-2015	Expanding window 2012-2015
20^{th} day of $t-1\|3$	P_{t-1}^2 & C_{t-1}^1	425.93	401.98	429.11	393.72
15^{th} day of $t\|1$	P_{t-1}^3 & C_{t-1}^1	426.21	417.20	419.58	398.99
20^{th} day of $t\|1$	P_{t-1}^3 & C_{t-1}^2	416.16	424.46	415.96	413.17
15^{th} day of $t\|2$	P_t^1 & C_{t-1}^2	410.29	403.54	409.99	388.20
20^{th} day of $t\|2$	P_t^1 & C_{t-1}^3	396.67	403.28	397.24	402.27
15^{th} day of $t\|3$	P_t^2 & C_{t-1}^3	391.77	412.83	391.10	409.80
20^{th} day of $t\|3$	P_t^2 & C_t^1	364.36	391.77	363.43	381.67
15^{th} day of $t+1\|1$	P_t^3 & C_t^1	352.53	395.15	349.00	384.22
20^{th} day of $t+1\|1$	P_t^3 & C_t^2	351.79	332.46	349.54	323.15

Note: The first column denotes the date when a new forecast is made, the second column shows the most recent data releases available at the forecast date; $t|k$, $k = 1, 2, 3$, denotes the k-th month of quarter t. RMSPEs are calculated relative to the level of quarterly household consumption.

In Table 5 and Table 6, we consider different timing structures for making forecasts. The left column shows the date of a new forecast when a new release becomes available, ordered chronologically according to the release date. For instance, in Table 5, the

[17] As a robustness check, we replaced contemporaneous regressors in equation (4) by their one-period lagged values to make one step ahead forecasts; this did not qualitatively change the results.

Table 6: RMSPEs using MIDAS models, including only payments data

Forecast date	Most recent release	Moving window 2008-2015	Moving window 2012-2015	Expanding window 2008-2015	Expanding window 2012-2015
15^{th} day of $t-1\|3$	P^2_{t-1}	421.76	412.13	423.87	399.42
15^{th} day of $t\|1$	P^3_{t-1}	415.32	421.38	416.12	406.36
15^{th} day of $t\|2$	P^1_t	415.41	392.11	418.40	373.93
15^{th} day of $t\|3$	P^2_t	396.76	402.43	408.01	387.33
15^{th} day of $t+1\|1$	P^3_t	383.30	397.33	382.12	381.39

Note: The first column denotes the date when a new forecast is made, the second column shows the most recent data releases available at the forecast date; $t|k$, $k = 1, 2, 3$, denotes the k-th month of quarter t. RMSPEs are calculated relative to the level of quarterly household consumption.

third row tells us that a new forecast of quarterly household consumption C_t can be made on the 20th day of the first month in quarter t when the monthly consumption index C^2_{t-1} is released, 6 weeks after the closing of the second month of the previous quarter $t-1$. This new forecast will also use the latest payment data P^3_{t-1} available that arrived 15 days after the closing of the third month of the previous quarter $t-1$. While in Table 5 both monthly payments and consumption data are incorporated, Table 6 shows the results when only payments data are included. This way, we can compare the models and assess whether including monthly consumption data contributes to improved forecast accuracy.

Generally, looking at these tables, the further down in the table, the lower is the RMSPE. This implies an increased forecast accuracy when new data releases become available; if a more recent monthly release of P^k_t or C^k_t is used, the RMSPE is lower most of the time. Hence, payments data that are released during a quarter add substantial value to the information set. The lowest overall prediction error is attained when using the expanding window method for the prediction sample from 2012 onwards. When using the payments data only, the minimum is attained using the same approach. Not surprisingly, both minimum values correspond to models using all available data releases.

The accuracy of the predictions is similar to using the original DELFI model. When including monthly consumption statistics, for the shorter forecast periods, the MIDAS models perform better. However, for the longer forecast samples, the two models provide statistically equally accurate forecasts (See Appendix B, Table B.2). As well, the MIDAS models that only include payments data, perform similarly as the original DELFI model (See Appendix B, Table B.3).

5.4 Combined forecasts

In the previous section, we found that the DELFI model with debit card data performed best, while the MIDAS model was a close runner-up even though it only included monthly payments and consumption data as explanatory variables. The predictions in this section are acquired by averaging the forecasts of the original DELFI model (from 1984 onwards) and the various MIDAS models. This way, we might be able to construct even more accurate forecasts.

Table 7: RMSPEs combining the DELFI and MIDAS model

	Moving window		Expanding window	
	2008-2015	2012-2015	2008-2015	2012-2015
P_t^2	338.38	359.27	348.44	349.09
P_t^3	334.74	358.13	337.38	347.93
P_t^2 & C_t^1	325.74	364.24	331.40	357.80
P_t^3 & C_t^1	324.29	368.69	327.19	361.90
P_t^3 & C_t^2	321.85	335.56	324.90	331.72

Note: The first column denotes the most recent data releases used in the MIDAS model. RMSPEs are calculated relative to the level of quarterly household consumption.

Table 7 shows the results of the combined forecasts, which are considered from the moment the second vintage of quarterly consumption of the previous quarter is released, until the first vintage of this statistic of the current quarter becomes available. Indeed, the combined model performs better than the two separate models, and provides especially good nowcasts for the forecast sample starting in 2008. The minimum value of the RMSPE's in this table is 321.85 for the moving window approach from 2008 onwards, including the most recent values of monthly payments and consumption data. This model beats the original DELFI model by 18% in terms of RMSPE gain. On average, across all four forecasting procedures, the combined model reduces the RMSPE by more than 20% relative to the corresponding original DELFI model. As well, the combined models represented in the last row of Table 7, which include all data releases, significantly outperform their counterparts of the original DELFI model (see Appendix B, Table B.4).

6 Conclusion

Our analysis shows that timely available payments data contain useful information as an indicator for household consumption. The usage of payments data in now- and forecasting houesehold consumption may increase the effectiveness of policy decisions made by central bankers and other policymakers. Using data for the Netherlands, we conclude that using debit card payments data lowers nowcast errors when predicting household consumption. The best combined model reduces the RMSPE by 18% compared to the original macroeconomic policy model - DELFI - as used by DNB. Also, payments data perform reasonably well in simple indicator models relative to other monthly indicators of economic activity, which have longer release times. The parsimonious MIDAS model, which only includes monthly payments and consumption data, provides more accurate forecasts than DELFI. The forecast accuracy of the MIDAS models improves as new information during a quarter is released. The combined forecasts of DELFI and the MIDAS models outperform the forecasts of individual models, particularly the original DELFI model. This may also provide a valid reason to incorporate payments data in (quarterly) macroeconomic forecasting models.

There are several directions for future research. In our analysis we used the most recent available data. However, due to data revisions, most data series differ from the values that were first released. It is likely that forecasts based on the most recent data are more accurate than forecasts based on first releases. In particular the MIDAS model is vulnerable to this issue, given the frequent revisions of monthly consumption data. It is important to know to what extent our findings still hold when first releases are used. Also, other modelling approaches such as state space modelling, may be worthwhile to study in the context of release dates and mixed frequencies of available data.

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Appendix A: Data releases

Table A.1: Indication of publication dates of statistics (reporting period t)

Data	Frequency	(Approx.) publishing date	Publication lag	Source
Consumer confidence	Monthly	20^{th} day of month t	0	CBS
AAX-index average	Monthly	1^{st} day of month $t+1$	1 day	DNB
Debit card transactions	Monthly	14^{th} day of month $t+1$	2 weeks	DPA
Retail sales	Monthly	14^{th} day of month $t+2$	6 weeks	CBS
Hh consumption (index)	Monthly	20^{th} day of month $t+2$	6/7 weeks	CBS
Hh consumption (value, 1st vintage)	Quarterly	15^{th} day of 2^{nd} month of quarter $t+1$	6 weeks	CBS
Hh consumption (value, 2nd vintage)	Quarterly	23^{rd} day of 3^{rd} month of quarter $t+1$	12 weeks	CBS

Note: Hh = Household.

Appendix B: Diebold-Mariano Test Results

Table B.1: DM-test for forecast accuracy of DELFI models with and without payments data

H_0: Both forecasts are equally accurate

	Moving window		Expanding window	
	2008-2015	2012-2015	2008-2015	2012-2015
DM-statistic	0.068	0.211	-1.760	-1.060

Note: *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels for two-tailed probabilities, respectively.

Table B.2: DM-test for forecast accuracy of original DELFI models vs MIDAS including payments and consumption data

H_0: Both forecasts are equally accurate

	Moving window		Expanding window	
	2008-2015	2012-2015	2008-2015	2012-2015
DM-statistic	1.190	1.799*	1.409	1.997*

Note: DM-test results for equal forecast accuracy of original DELFI models vs MIDAS models incorporating data up to and including P_t^3 & C_t^2 (RMSPEs as shown in Table 4, row 1 and Table 5, row 9, respectively); *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels for two-tailed probabilities, respectively.

Table B.3: DM-test for forecast accuracy of original DELFI models vs MIDAS models including payments data only

H_0: Both forecasts are equally accurate

	Moving window		Expanding window	
	2008-2015	2012-2015	2008-2015	2012-2015
DM-statistic	0.394	0.806	0.587	1.007

Note: DM-test results for equal forecast accuracy of original DELFI models vs MIDAS models incorporating data up to and including P_t^3 (RMSPEs as shown in Table 4, row 1 and Table 6, row 5, respectively); *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels for two-tailed probabilities, respectively.

Table B.4: DM-test for forecast accuracy of combined models vs DELFI models including payments data

H_0: Both forecasts are equally accurate				
	Moving window		Expanding window	
	2008-2015	2012-2015	2008-2015	2012-2015
DM-statistic	2.177**	2.835***	3.240***	2.784***

Note: DM-test results for equal forecast accuracy of original DELFI models vs MIDAS models incorporating data up to and including P_t^3 & C_t^2 (RMSPEs as shown in Table 4, row 4 and Table 7, row 5, respectively); *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels for one-tailed probabilities, respectively.

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