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Please address correspondence to
Banco de Portugal, Economics and Research Department
Av. Almirante Reis 71, 1150-012 Lisboa, Portugal
T +351 213 130 000 | estudos@bportugal.pt

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A Mixed Frequency Approach to Forecast Private Consumption with ATM/POS Data

Cláudia Duarte
Banco de Portugal

Paulo M. M. Rodrigues
Banco de Portugal
NOVA School of Business and Economics

António Rua
Banco de Portugal
NOVA School of Business and Economics

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Abstract
The recent worldwide development and widespread use of electronic payment systems opened the opportunity to explore new data sources for monitoring macroeconomic activity. In this paper, we analyse the usefulness of data collected from Automated Teller Machines (ATM) and Points-Of-Sale (POS) for nowcasting and forecasting quarterly private consumption. To take advantage of the high frequency availability of such data, we use Mixed Data Sampling (MIDAS) regressions. A comparison of several MIDAS variants proposed in the literature is conducted, both single- and multiple variable models are considered, as well as different information sets within the quarter. Given the high penetration of ATM/POS technology in Portugal, it becomes a natural case study to assess its information content for tracking private consumption behaviour. We find that ATM/POS data displays better forecast performance than typical indicators, reinforcing the potential usefulness of this novel type of data among policymakers and practitioners.

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E-mail: cfduarte@bportugal.pt; pmrodrigues@bportugal.pt; antonio.rua@bportugal.pt

1. Introduction

The development of national statistical systems along with the improvements operated by statistical agencies in the compilation and dissemination of data pushed by policymakers and the public in general, has led to an increasingly availability of higher frequency indicators for monitoring economic activity. Although key macroeconomic aggregates, such as GDP, are typically only available at a quarterly frequency there is by now a relatively wide range of monthly indicators covering a broad set of economic dimensions. Regarding data availability at a daily frequency it has been mostly limited to financial variables, such as stock prices and interest rates.

In parallel, a growing body of literature has focused on how to take on board higher frequency variables to nowcast and forecast main quarterly macroeconomic variables. In this respect, a noteworthy strand of literature has been developing, the so-called Mixed Data Sampling (MIDAS) regression models. The work of, *inter alia*, Ghysels *et al.* (2004, 2005, 2006a) and the growing empirical evidence of its usefulness, have lead MIDAS to gain popularity for forecasting purposes. There is by now a significant body of literature documenting the advantages of using MIDAS regressions for improving quarterly macroeconomic forecasts with monthly and daily data. For instance, Clements and Galvão (2008, 2009), Kuzin *et al.* (2011), Marcellino and Schumacher (2010), and Schumacher and Breitung (2008) provide evidence of improvements of quarterly forecasts using monthly data and Andreou *et al.* (2013), Ghysels and Wright (2009) and Monteforte and Moretti (2013), among others, forecast improvements resulting from the use of daily data. However, regarding the latter, forecasting with MIDAS using daily data has been mainly restricted to financial data, given the limited availability of high frequency data in economics.

The technological progress has boosted the development and widespread use of electronic payment systems opening a window to consider new data sources for the monitoring of economic activity, in particular through data collected from Automated Teller Machines (ATM) and Points-Of-Sale (POS). Typically, electronically recorded data is very timely and free of measurement errors. It encompasses cash withdrawals at ATM terminals and debit card payments, which allows consumers to pay for their purchases by having funds transferred immediately from the cardholder's bank account. There are still only a few papers using this type of data. For instance, Galbraith and Tkacz (2013a) examine daily debit card data in Canada to assess the impact of specific events like the September 11 terrorist attacks; Galbraith and Tkacz (2007) show that debit card payments data can help in lowering Consensus forecast errors for GDP and private consumption growth in Canada; and Galbraith and Tkacz (2013b) find that monthly electronic payments data can improve Canadian GDP nowcasting. For Denmark, Carlsen and Storgaard (2010) find that monthly electronic payments by card (Dankort) provide a useful indicator for nowcasting retail sales. Esteves (2009), using quarterly ATM/POS data for Portugal, presents supporting evidence of the usefulness of such type of data for nowcasting quarterly private consumption.

The aim of this paper is to forecast private consumption using high-frequency electronically recorded data from ATM and POS terminals. As this type of data is available at a higher frequency than quarterly private consumption, we pursue a MIDAS regression approach, considering both monthly and daily ATM/POS data. As far as we are aware, this is the first paper that uses the MIDAS approach to forecast with non-financial daily data. This reflects the fact that it is unusual to have non-financial data available at such a high frequency. Furthermore, the previous literature on payments data has not considered so far the use of the MIDAS regression approach for forecasting purposes. In this respect, we consider several variants of MIDAS regressions, including the traditional MIDAS setting, the multiplicative MIDAS discussed by Chen and Ghysels (2011), the unrestricted MIDAS (Marcellino and Schumacher (2010), Foroni and Marcellino (2014) and Foroni *et al.* (2015)), the common factor MIDAS by Clements and Galvão (2008), as well as unrestrictedly augmented (with an autoregressive component) MIDAS regressions, as discussed in Duarte (2014).

The focus is on the Portuguese case which is *per se* an interesting case. In fact, in Portugal, ATM/POS technology has a very high penetration rate with the advantage of data being compiled by a single entity which allows it be timely and useful for real time economic assessments and policy making. This makes Portugal a natural case study. Moreover, since the Portuguese economy has experienced a turbulent evolution over the last years with the Great Recession and the subsequent European sovereign debt crisis which has led to a profound macroeconomic adjustment process, it constitutes a very challenging period by any standards for forecasting purposes.

Besides ATM/POS data, we also consider several other typical predictors, such as monthly retail sales and consumers confidence, to forecast quarterly private consumption. These indicators are among the most popular ones for the current purpose and allows us to put the value added of considering the ATM/POS data for forecasting purposes into perspective. We find that using high frequency data improves the forecasting performance and that the ATM/POS data enables the largest gains. We also find that augmenting MIDAS regressions with an autoregressive component improves the forecast results while the unrestricted MIDAS framework seems to deliver, in overall terms, the best results.

The paper is organized as follows. In section 2, we motivate the Portuguese case as a natural case study to assess the information content of ATM/POS data. In section 3, we briefly describe the MIDAS regression approaches that will be considered in the empirical application, while in section 4, we present the data. In section 5, we discuss the forecasting exercise conducted and the corresponding empirical results. Finally, section 6 concludes.

2. Why is the Portuguese case a special one?

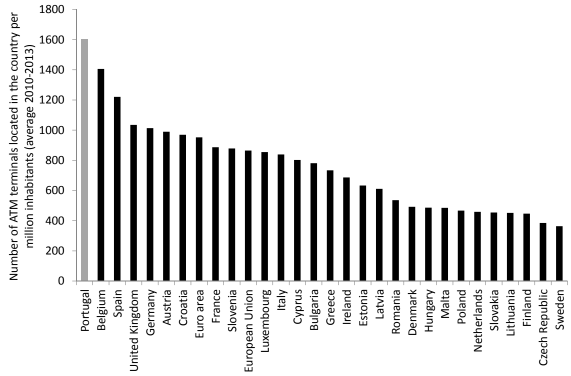
The roots of the development of the Portuguese ATM and POS network (also known as *Multibanco* network) go back to 2 September 1985, when the first ATM terminals were introduced in the main Portuguese cities, namely Lisbon and Oporto. At that time, it was only possible to perform a small set of operations, such as cash withdrawals or bank account balance consulting. In this way, banks could allow customers to have access to banking services which were previously available only at branches' desks. Hence, allowing customers to save time and banks to reduce costs. Over time, the range of services available at ATM terminals has increased considerably. Nowadays ATM terminals can be used, among other things, to pay for services, to top-up mobile phones, to pay for transports and tolls, and to transfer money to other bank accounts. The Portuguese network is one of the leading cases in terms of innovation and functionality. The growing availability of POS and ATM terminals across the country facilitates the consumer's day by day life and allows firms to benefit from a secure and efficient payments system with natural positive spillovers for business.

The *Multibanco* network is run by a single entity, the SIBS Forward Payment Solutions, which simplifies the compilation of data and enhances timeliness. Furthermore, since any card holder can use the *Multibanco* network through a large number of ATM and POS terminals available throughout the country, it assures nationwide coverage. Moreover, banks and merchants are, by Portuguese law, forbidden to charge customers any kind of fees for operations on ATM terminals and POS transactions. That is, all ATM withdrawals and payments in Portugal are free. Such a legal and technological environment has led to a very high penetration rate of the interbank *Multibanco* network among the Portuguese population. In 2013, there were 1540 ATM and 24471 POS terminals located in the country per million inhabitants and the amount of money that circulated through the network by residents accounted for around 50 per cent of GDP and 70 per cent of private consumption expenditure.

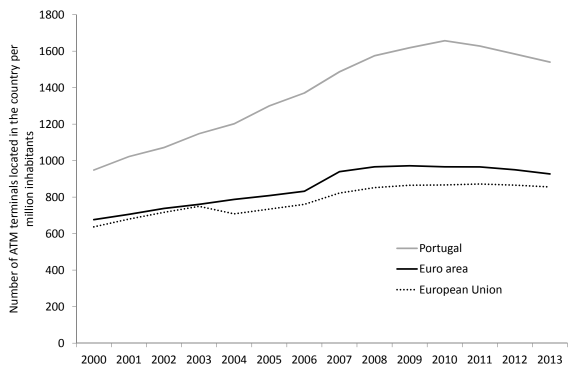
The interest in the Portuguese experience is reinforced by the comparison at the European-wide level.[1] In fact, Portugal ranks first in terms of the number of ATM terminals located in the country per million inhabitants (see Figure 1 (a)) and the availability of such terminals has been increasing over time continuing well above euro area average (Figure 1 (b)). Only in the most recent period was there a slight decrease of the number of ATM terminals reflecting the economic and financial crisis that Portugal underwent over the last few years which led banks to close some branches. Besides its extensive availability, Portuguese residents also have been using the ATM terminals intensively and well above

1. In this respect, one should mention that in the case of the United States the adoption of the electronic payments technology has been slower than elsewhere (see Humphrey *et al.* (2000) and Gerdes *et al.* (2005)).

euro area average (see Figures 2(a) and 2(b)). According to the number of cash withdrawals at ATMs located in the country per card issued in the country, Portugal only falls behind Ireland, where ATM usage fees are also forbidden.



(A) Country comparison

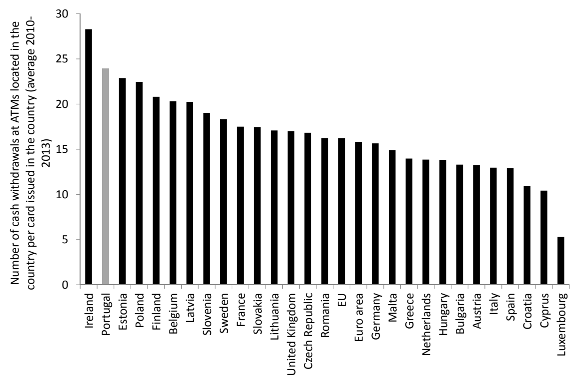


(B) Evolution over time

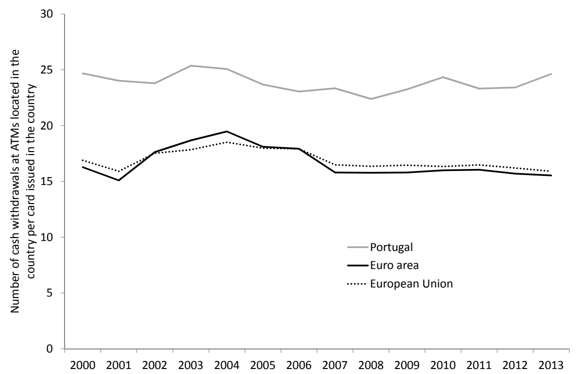
FIGURE 1: Number of ATM terminals located in the country per million inhabitants

In this respect, it is also interesting to refer to the Spanish and Finnish cases for its contrasting behavior in terms of the above indicators. In the case of Spain, although it ranks third in terms of number of ATM terminals per million inhabitants, it is among the bottom four in terms of usage per card issued in the country. Note that one of the reasons of this reduced usage may be the fact that a card issued by a Spanish bank usually incurs in a relatively moderate fee to be applied to ATM withdrawals when the transaction is conducted on an

ATM operated and owned by the customers own bank, and that significantly higher fees are typically applied when third party owner/operated ATMs are used, including those owned/operated by other Spanish banks. In contrast, Finland is among the bottom three in terms of the number of ATMs per million inhabitants but ranks fifth in terms of usage. In the Finnish case, cash withdrawals are free for any owner of a Finnish bank card in the largest ATM network operating in the country.



(A) Country comparison

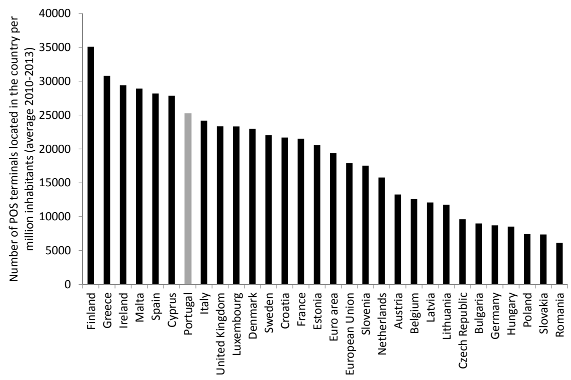


(B) Evolution over time

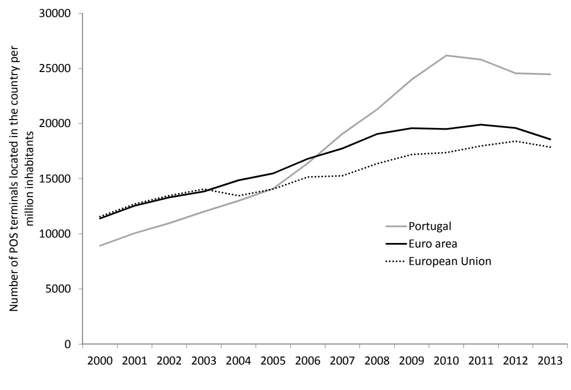
Figure 2: Number of cash withdrawals at ATMs located in the country per card issued in the country

Regarding POS, Portugal is also top ranked in terms of the number of POS terminals located in the country per million inhabitants with Finland and

Denmark standing out (see Figure 3 (a)). One should note that Portugal was below euro area average in the first half of 2000's but it observed a significant growth in the second half of the decade overcoming euro area levels (Figure 3 (b)). In terms of POS usage in Portugal, the number of POS transactions at terminals located in the country per card issued in the country has been increasing over time, attaining levels well above the euro area (Figures 4 (a) and 4 (b)).

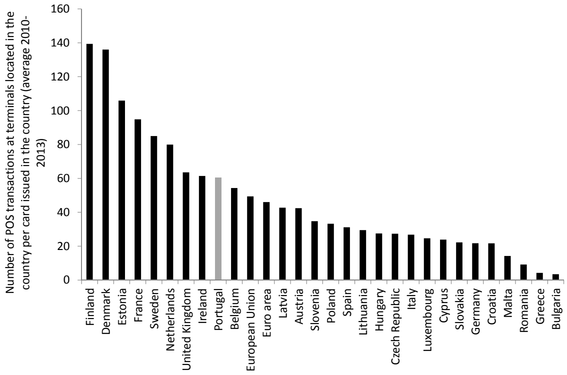


(A) Country comparison

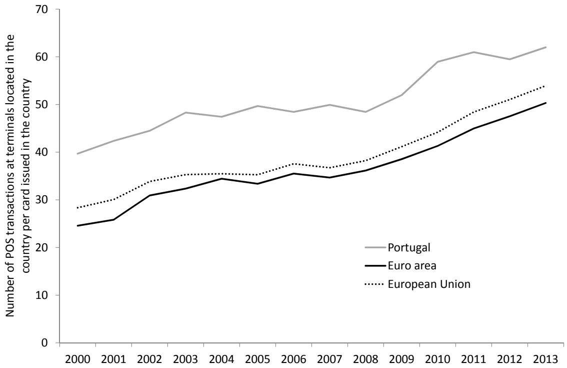


(B) Evolution over time

FIGURE 3: Number of POS terminals located in the country per million inhabitants



(A) Country comparison



(B) Evolution over time

FIGURE 4: Number of POS transactions at terminals located in the country per card issued in the country

The timely availability of ATM and POS transactions data and its relevance in understanding private consumption make these series of potential interest for modelling and forecasting this variable. This will be analysed in detail in Section 4.

3. MIDAS modelling approaches

In this section, we provide a brief overview of the Mixed-Data Sampling (MIDAS) approaches that we will use in our forecasting exercise. The general MIDAS approach introduced by Ghysels *et al.* (2004), allows series y_t sampled at some low-frequency (e.g. quarterly or annually), to be regressed on data $x_t^{(m)}$, which is sampled at higher-frequencies, such as daily or monthly, (for interesting surveys, see e.g., Andreou *et al.* (2013), Ghysels and Valkanov (2012) and Foroni and Marcellino (2014).

For illustration of the approach in a framework close to the one we have in our empirical analysis, consider that we are interested in forecasting a quarterly time series, denoted by y_t, using a variable $x_t^{(m)}$ observed m times in the same period (e.g. daily or monthly) and that we want to forecast y_t, which is available only once between $t-1$ and t, based on the dynamic relation between y_t and $x_t^{(m)}$. Traditionally, the solution to circumvent the problem of mixed-frequency data was to convert the higher-frequency data to match the sampling rate of the lower-frequency data. However, although several solutions, such as the time-averaging model or the step-weighting model, have been put forward these solutions can originate considerable parameter proliferation. The advantage of the elegant solution introduced by Ghysels *et al.* (2004), i.e., the MIDAS approach, is that it controls for parameter proliferation and also preserves the timing of information (Armesto *et al.* (2010)).

The simple MIDAS model (Ghysels *et al.* (2006b)) is,

$$y_{t+h} = \beta_0 + \beta_1 B(L^{1/m};\theta)x_t^{(m)} + \varepsilon_{t+h} \tag{1}$$

where $B(L^{1/m};\theta) = \sum_{k=0}^{K} B(k;\theta)L^{k/m}$, $L^{1/m}$ is a lag operator such that $L^{k/m}x_t^{(m)} = x_{t-k/m}^{(m)}$, and the lag coefficient in $B(k;\theta)$ of the corresponding lag operator $L^{k/m}$ is parametrised as a function of a small-dimensional vector of hyper parameters θ. Thus, $B(k;\theta)$ is a weighting scheme used for aggregation, which is assumed to be normalised to sum to 1, and ε_{t+h} is a standard i.i.d. error term.

In the mixed-frequency framework in (1) the number of lags of $x_t^{(m)}$ is likely to be significant and if the associated parameters are left unrestricted this could lead to substantial parameter proliferation as observed in other methods. However, this issue is addressed in the MIDAS regression through the known function $B(L^{1/m};\theta)$ of a few hyper parameters summarised in the vector θ.

The parametrisation of the lagged coefficients of $B(k;\theta)$ in a parsimonious fashion is one of the key features of MIDAS. Typically, two alternative functional specifications for the weighting scheme are used, both assuming that the weights are determined by a finite one-sided polynomial with hyperparameters θ, where θ is a $K \times 1$ vector. One parametrisation of $B(k;\theta)$

is the exponential Almon lag, which is given as,

$$B(k;\theta_1,\theta_2) := \frac{e^{(\theta_1 k+\theta_2 k^2)}}{\sum_{k=1}^{K} e^{(\theta_1 k+\theta_2 k^2)}}. \tag{2}$$

Although in (2) only two parameters were considered, θ :=[θ_1, θ_2], as in Ghysels *et al.* (2004), a functional form with more parameters could have been used; see e.g. Ghysels *et al.* (2006b).

The other parametrisation of $B(k;\theta)$ is the Beta type polynomial given as,

$$B(k;\theta_1,\theta_2) := \frac{f(\frac{k}{K},\theta_1,\theta_2)}{\sum_{i=1}^{K} f(\frac{k}{K},\theta_1,\theta_2)} \tag{3}$$

where $f(q,\theta_1,\theta_2) := (q^{\theta_1-1}(1-q)^{\theta_2-1}\Gamma(\theta_1+\theta_2))/(\Gamma(\theta_1)\Gamma(\theta_2))$ and $\Gamma(\theta) := \int_0^\infty e^{-k}k^{\theta-1}dk$. Given that exponential Almon and Beta polynomials have nonlinear functional specifications, in both cases the MIDAS regressions have to be estimated using nonlinear least squares.

Note that although only two parameters are considered in the weights functions, these specifications are flexible enough to generate various shapes. Moreover, since the parameters are estimated from the data, once the functional form is specified the lag length selection is purely data driven.

Another MIDAS approach proposed in the literature and which we will also evaluate in our application is the multiplicative MIDAS (M-MIDAS). The multiplicative MIDAS framework is closer to traditional aggregation schemes. However, instead of aggregating all lags in the high frequency variable to a single aggregate, the multiplicative MIDAS regressions include m-aggregates of high-frequency data and their lags,

$$y_{t+h} = \beta_0 + \sum_{i=1}^{p} \beta_i x_{t-i}^{mult} + u_{t+h} \tag{4}$$

where $x_t^{mult} := \sum_{j=0}^{m-1} B(j;\theta)L^{j/m}x_t^{(m)}$. Equation (4) resembles a standard autoregressive distributed lag (ADL) model except that this approach considers parameter-driven regressors that mimic an aggregation scheme. Although this approach presents several advantages (e.g., the weighting scheme corresponds to the structure of a steady state Kalman filter with mixed data sampling (as indicated in Bai *et al.* (2013)) and nests different aggregation schemes (see Chen and Ghysels (2011))), its major disadvantage however is that it is not as parsimonious as the conventional MIDAS approach introduced in (1). It is also shown in Bai *et al.* (2013) that the forecast performance of this approach comparatively to the standard MIDAS in (1) does not differ much.

An additional MIDAS variant which does not resort to functionals of distributed lag polynomials as indicated in (2) and (3) and which proves quite useful for forecasting was recently introduced by Foroni *et al.* (2015); see also Koenig *et al.* (2003). The authors refer to this approach as the unrestricted

MIDAS (U-MIDAS) regression, which has the comparative advantage that it can be estimated by OLS. The U-MIDAS regression is simply,

$$
\begin{aligned}
y_{t+h} &= \beta_0 + \sum_{k=0}^{K} \beta_{k+1} L^{k/m} x_t^{(m)} + u_{t+h} & (5)\\
&= \beta_0 + \beta_1 x_t^{(m)} + \beta_2 x_{t-1/m}^{(m)} + \ldots + \beta_{K+1} x_{t-K/m}^{(m)} + u_{t+h}. & (6)
\end{aligned}
$$

A further relevant extension that needs to be considered, particularly in a forecasting context, refers to the use of autoregressive structures in the MIDAS framework, as autoregressive models typically provide competitive forecasts.

Clements and Galvão (2008) suggested an approach of introducing autoregressive dynamics in MIDAS regressions, which considered the dynamics on y_t as a common factor (Hendry and Mizon (1978)). This assumption rests on the hypothesis that y_t and $x_t^{(m)}$ share the same autoregressive dynamics, though, as Hendry and Mizon (1978) pointed out, a common factor may not always be found. The MIDAS framework considered in this case is,

$$
\begin{aligned}
&y_t = \beta_0 + \beta_1 B(L^{1/m};\theta) x_t^{(m)} + u_t\\
&u_t = \gamma u_{t-1} + \varepsilon_t
\end{aligned}
\qquad (7)
$$

and replacing u_t in (7) it follows that

$$
(1-\gamma L) y_t = \beta_0(1-\gamma) + \beta_1 (1-\gamma L) B(L^{1/m};\theta) x_t^{(m)} + \varepsilon_t. \qquad (8)
$$

The model in (8) is known as the common factor MIDAS ($CF - MIDAS$) model.

As discussed in Duarte (2014), an autoregressive term can simply be added to the traditional MIDAS equation. Thus, finally, in our forecasting exercise we will also consider all previous MIDAS frameworks augmented with an unrestricted autoregressive component which we will denote by AR-MIDAS, M-AR-MIDAS, U-AR-MIDAS i.e.,

$$
y_t = \beta_0 + \beta' \mathcal{F}(L^{1/m}) x_t^{(m)} + \sum_{k=1}^{p} \gamma_k y_{t-k} + u_t \qquad (9)
$$

where $\mathcal{F}(L^{1/m})$ corresponds to the respective MIDAS component used in (1), (4) and (6).

For details on the econometrics of the MIDAS regressions discussed above see, for instance, Ghysels *et al.* (2006b), Andreou *et al.* (2013), Bai *et al.* (2013), Kvedaras and Rackauskas (2010) and Rodriguez and Puggioni (2010).

4. Data

As the focus is on assessing the information content of taking on board high-frequency data regarding ATM and POS network usage for forecasting Portuguese quarterly private consumption, we consider both daily and monthly frequencies. The available sample period runs from the beginning of September 2000 up to the end of December 2014, comprising 5235 daily and 172 monthly observations. The ATM/POS data considered comprises all ATM cash withdrawals and POS payments by residents and is made available by Banco de Portugal.

As mentioned earlier, the ATM terminals allow cardholders to perform a wide range of operations beyond cash withdrawals, for which data is also collected. We restrict the analysis to cash withdrawals for several reasons. Firstly, as expected, the bulk of the amount corresponds to cash withdrawals. Secondly, there are operations that can be conducted at ATM terminals, like deposits or tax and social security payments, which do not reflect consumption expenditures. Finally, in several operations, there can be a mismatch between the timing of the payment and the date at which the expenditure occurred. For instance, several payments can be made through a functionality available in the *Multibanco* network, in which the debtor in order to pay for a certain good or service inserts a specific reference number given by the creditor. Typically, bill payments are performed after the acquisition of a certain good or service. In fact, we find that including other ATM information beyond that conveyed by cash withdrawals tends to lag the information content of the series.

As ATM/POS data is not seasonally adjusted, we proceed in the following way. For monthly data, we use the same seasonal adjustment procedure used by Statistics Portugal (the Portuguese National Statistics Office) for seasonally adjusting monthly official statistics, namely the X-13 ARIMA with calendar effects adjustment resorting to JDemetra+ software provided by Eurostat. Regarding the daily data, as the previous procedure cannot be applied to daily frequency data, we first adjust the series for calendar effects, including holidays and weekday effects (see, for example, Leamer (2011) and Esteves and Rodrigues (2010)), and then seasonally adjust it with STL, the seasonal-trend decomposition procedure based on Loess smoothing (see Cleveland and Devlin (1988)), proposed by Cleveland *et al.* (1990). The nonparametric STL method has several interesting features and unlike the most extensively used procedures, STL can handle any data frequency, not only monthly and quarterly data. See for example, Hyndman and Athanasopoulos (2014) and Bergmeir *et al.* (2015) for recent applications of STL. Finally, the series is outlier corrected.

Regarding private consumption, we consider nominal quarterly private consumption excluding durables taken from the Quarterly National Accounts released by Statistics Portugal. We exclude durables consumption, which includes vehicles, as this type of expenditure is usually paid for by resorting to bank transfers or loans (see Esteves (2009) and Carlsen and Storgaard

(2010)). Hence, one should not expect ATM/POS data to be able to capture this component of consumption which currently accounts for less than ten per cent of private consumption in Portugal.

Furthermore, besides ATM/POS data, we also consider the retail sales index, as well as the consumer confidence indicator, as potentially useful indicators to forecast private consumption in the short-run. Both indicators are available at a monthly frequency. The nominal retail sales index excluding durables is provided by Statistics Portugal whereas the consumer confidence indicator is released by the European Commission.

It is also important to mention that we consider final data, that is, the latest available vintage for all series. In this respect, one should note that both consumer confidence and ATM/POS data are typically not subject to revisions and that revisions to private consumption are usually relatively small in Portugal (see Cardoso and Rua (2011)). Concerning retail sales, a real-time dataset is not available and it has underwent several methodological changes over time.

As usual, all variables have been taken in logarithms, excluding the confidence indicator, and in first differences.

5. The nowcast and forecast exercise

5.1. Design of the exercise

To assess the relative performance of the above mentioned models and predictors to forecast private consumption growth, we conduct the following out-of-sample forecasting exercise.

The out-of-sample forecast evaluation period runs from the beginning of 2008 up to the end of 2014, which corresponds to around half of the sample period. One should note that Portugal was one of the hardest hit economies as from the latest economic and financial crisis. Hence, such an out-of-sample period constitutes a challenge by all means putting to test the informational content of each predictor, as well as each model ability in a context of major macroeconomic stress.

Given the type of predictors at hand, we focus on the nowcasting performance but we also assess the one-quarter ahead forecasting case. In both cases, we consider three possible information sets for the predictors within the quarter, namely, the case where only the first month of the current quarter is available, the case where there is data for the first two months and the case in which all months of the quarter are available.[2]

2. As a robustness analysis, we also re-run the exercise allowing for release lags. In particular, retail sales present a release lag of around one month whereas both consumer confidence and ATM/POS data are available immediately after the end of the reference

As discussed in section 3, we consider several types of MIDAS regressions namely the traditional one (denoted henceforth as MIDAS), the multiplicative MIDAS (M-MIDAS), the unrestricted MIDAS (U-MIDAS), the MIDAS with common factor autoregressive dynamics (CF-MIDAS) and the former cases allowing for unrestricted autoregressive dynamics (denoted as AR-MIDAS, M-AR-MIDAS and U-AR-MIDAS, respectively). The model specification is selected based on the Bayesian information criteria (BIC) and, apart from U-MIDAS, the weighting function used in the MIDAS regressions is the exponential Almon polynomial.[3] All in all, this means 78 cases for each forecasting horizon.

As in related literature, we conduct a recursive exercise with an expanding window. In particular, for each predictor and model, a recursive estimation process is implemented allowing the coefficients to change over time. Starting from the initial estimation period, up to the end of 2007, in each round a new observation is added to the sample. In each round of this recursive estimation process, both the nowcast and the one-quarter ahead forecast are computed. As usual in this type of exercises, we consider as a benchmark a univariate autoregressive model with the lag order determined by BIC.

The forecasting performance is assessed through the Root Mean Squared Forecast Error (RMSFE). In particular, we present the relative RMSFE for each MIDAS model and for each predictor vis-à-vis the univariate benchmark. A ratio lower than one denotes a forecasting gain by the MIDAS approach whereas a value higher than one means that the univariate model outperforms the alternative model.

To assess the statistical significance of the forecasting gains, we use the equal forecast accuracy test proposed by Clark and McCracken (2005). As this test has a non-standard limiting distribution, the critical values are obtained by a bootstrap procedure.

period. We find that the main qualitative results remain broadly unchanged. All the results are available from the authors upon request.

3. In our empirical analysis we also considered the Beta polynomial, however it did not improve the forecast performance. In the case of MIDAS regressions with daily data we use the traditional Almon lag polynomial. This aggregation scheme assumes that J lag weights can be related to d linearly estimable underlying parameters, with $d < J$, as follows:

$$B(j;\theta) = \sum_{i=0}^{d} \theta_i j^i, \quad j = 1, \ldots, J$$

where θ_i, $i = 0, \ldots, d$, denotes the hyperparameters. In the following analysis it is assumed that $d = 2$. This weighting scheme also works in the cases where m is not fixed (e.g., combining monthly with weekly or daily data). In these cases, instead of having one set of weights, we have a different set of weights for each low-frequency period of the sample.

5.2. Empirical results

In Table 1 we present the results for the nowcasting case. Several findings emerge from the analysis of Table 1. Firstly, in terms of predictors, the so-called hard data (retail sales and ATM/POS) always outperform soft data (the consumer confidence indicator). Only in the case of the CF-MIDAS with one month of data available does the consumer confidence index perform marginally better than the other predictors. This relative lack of predictive ability by the consumer confidence indicators over the last decade has also been found by Dreger and Kholodilin (2013) for the euro area and individual EU countries.

Regarding hard data, the use of ATM/POS data always delivers the best forecasting performance for any given MIDAS variant and information set within the quarter. The only exception is again in the case of CF-MIDAS, in which the use of the first two months of retail sales slightly outperform ATM/POS data. Regarding the frequency of ATM/POS data, the CF-MIDAS model with daily data always does better than with monthly series and in the case of the AR-MIDAS this is also true with only one month of data available. In all the other cases, the monthly series improve on the daily counterpart. Although, in principle, one would expect the use of higher frequency data to be more informative than the corresponding lower frequency counterpart, it does not seem to be the case here. This may reflect the fact that the ATM/POS daily series is very noisy making it harder to extract the relevant signal for forecasting purposes. It may also reflect the difference in the seasonal adjustment procedure which we are forced to use in the case of ATM/POS daily data from the one applied to the monthly series, which mimics the procedure used by Statistics Portugal. In fact, the use of a different seasonal adjustment method may distort the link between the predictand and the predictor (see, e.g., Wallis (1974, 1978) for a thorough discussion). Despite all, one should note that the use of ATM/POS daily data, namely through an AR-MIDAS regression enhances the forecasting performance by around 25 per cent vis-à-vis the univariate benchmark.

In terms of the different MIDAS regressions, one should highlight that the MIDAS specifications that allow for autoregressive dynamics present almost always lower RMSFE for any given predictor and information set. In fact, the MIDAS specifications that take on board autoregressive terms improve on the non-autoregressive counterparts by around 15 per cent, on average. This reflects the fact that non-durable private consumption typically embeds consumers' habit persistence and presents a relatively smooth behaviour. Among the MIDAS regressions with autoregressive dynamics, in general, the AR-MIDAS and U-AR-MIDAS outperform the CF-MIDAS and M-AR-MIDAS for any predictor and information set within the quarter.

	Forecasting horizon	Nowcast		
	Available monthly data	One month	Two months	Full quarter
MIDAS				
	Retail sales	0.867	0.856	0.848
		[0.001]	[0.003]	[0.001]
	Consumer confidence	1.023	1.027	1.026
		[0.281]	[0.251]	[0.271]
	ATM/POS			
	Monthly	0.842	0.833	0.808
		[0.000]	[0.000]	[0.000]
	Daily	0.917	0.926	0.937
		[0.006]	[0.010]	[0.009]
M-MIDAS				
	Retail sales	1.028	1.005	0.846
		[0.266]	[0.092]	[0.000]
	Consumer confidence	1.045	1.067	1.048
		[0.290]	[0.342]	[0.314]
	ATM/POS			
	Monthly	0.809	0.817	0.846
		[0.001]	[0.000]	[0.000]
	Daily	0.994	0.974	1.031
		[0.055]	[0.010]	[0.121]
U-MIDAS				
	Retail sales	0.870	0.882	0.853
		[0.001]	[0.002]	[0.001]
	Consumer confidence	1.058	1.059	1.081
		[0.427]	[0.458]	[0.628]
	ATM/POS			
	Monthly	0.768	0.764	0.848
		[0.000]	[0.000]	[0.000]
CF-MIDAS				
	Retail sales	0.871	0.841	0.879
		[0.000]	[0.000]	[0.000]
	Consumer confidence	0.853	0.876	0.848
		[0.000]	[0.003]	[0.000]
	ATM/POS			
	Monthly	0.885	0.884	0.884
		[0.003]	[0.003]	[0.003]
	Daily	0.867	0.850	0.815
		[0.000]	[0.001]	[0.000]
AR-MIDAS				
	Retail sales	0.780	0.727	0.775
		[0.000]	[0.000]	[0.000]
	Consumer confidence	0.839	0.846	0.859
		[0.000]	[0.000]	[0.000]
	ATM/POS			
	Monthly	0.797	0.667	0.676
		[0.000]	[0.000]	[0.000]
	Daily	0.744	0.748	0.770
		[0.000]	[0.000]	[0.000]
M-AR-MIDAS				
	Retail sales	0.869	0.874	0.850
		[0.001]	[0.000]	[0.000]
	Consumer confidence	0.870	0.909	0.919
		[0.000]	[0.003]	[0.003]
	ATM/POS			
	Monthly	0.695	0.692	0.676
		[0.000]	[0.000]	[0.000]
	Daily	0.834	0.834	0.885
		[0.000]	[0.000]	[0.001]
U-AR-MIDAS				
	Retail sales	0.760	0.763	0.746
		[0.000]	[0.000]	[0.000]
	Consumer confidence	0.870	0.884	0.929
		[0.001]	[0.002]	[0.006]
	ATM/POS			
	Monthly	0.662	0.647	0.698
		[0.000]	[0.000]	[0.000]

TABLE 1. Relative RMSFE vis-à-vis an autoregressive model for nowcasting

	Forecasting horizon	One-quarter ahead		
	Available monthly data	One month	Two months	Full quarter
MIDAS				
	Retail sales	0.932	0.873	0.862
		[0.016]	[0.000]	[0.001]
	Consumer confidence	0.971	1.002	0.999
		[0.056]	[0.124]	[0.124]
	ATM/POS			
	Monthly	0.905	0.906	0.907
		[0.005]	[0.007]	[0.010]
	Daily	0.879	0.875	0.894
		[0.001]	[0.000]	[0.001]
M-MIDAS				
	Retail sales	1.010	1.014	0.989
		[0.244]	[0.184]	[0.120]
	Consumer confidence	0.949	0.977	0.997
		[0.027]	[0.046]	[0.118]
	ATM/POS			
	Monthly	0.956	0.963	0.887
		[0.040]	[0.059]	[0.003]
	Daily	1.025	0.969	0.984
		[0.089]	[0.024]	[0.026]
U-MIDAS				
	Retail sales	0.910	0.884	0.819
		[0.008]	[0.001]	[0.000]
	Consumer confidence	1.039	1.080	1.003
		[0.125]	[0.105]	[0.112]
	ATM/POS			
	Monthly	0.876	0.847	0.905
		[0.002]	[0.001]	[0.007]
CF-MIDAS				
	Retail sales	0.919	0.872	0.897
		[0.009]	[0.001]	[0.004]
	Consumer confidence	0.948	0.921	0.953
		[0.019]	[0.011]	[0.030]
	ATM/POS			
	Monthly	0.904	0.903	0.903
		[0.005]	[0.009]	[0.007]
	Daily	0.897	0.921	0.934
		[0.002]	[0.011]	[0.009]
AR-MIDAS				
	Retail sales	0.932	0.958	0.938
		[0.024]	[0.024]	[0.010]
	Consumer confidence	0.918	0.961	0.953
		[0.010]	[0.043]	[0.021]
	ATM/POS			
	Monthly	0.860	0.861	0.862
		[0.001]	[0.000]	[0.000]
	Daily	0.862	0.897	0.886
		[0.000]	[0.003]	[0.002]
M-AR-MIDAS				
	Retail sales	0.933	0.943	0.981
		[0.026]	[0.024]	[0.037]
	Consumer confidence	0.885	0.927	0.961
		[0.006]	[0.012]	[0.031]
	ATM/POS			
	Monthly	0.959	0.848	0.883
		[0.027]	[0.000]	[0.003]
	Daily	0.998	0.965	0.998
		[0.042]	[0.026]	[0.028]
U-AR-MIDAS				
	Retail sales	0.871	0.868	0.826
		[0.000]	[0.000]	[0.000]
	Consumer confidence	0.932	0.952	0.959
		[0.014]	[0.027]	[0.022]
	ATM/POS			
	Monthly	0.891	0.874	0.860
		[0.002]	[0.001]	[0.001]

TABLE 2. Relative RMSFE vis-à-vis an autoregressive model for one-quarter ahead

The model and predictor that delivers the lowest RMSFE for nowcasting purposes is the U-AR-MIDAS with monthly ATM/POS data when one or two months of data are available. The forecasting gains are statistically significant and attain around 35 per cent vis-à-vis the univariate benchmark. When the full quarter of data is available, the AR-MIDAS with monthly ATM/POS is the best performing model, only slightly better than the U-AR-MIDAS, with a gain of more than 30 per cent. Table 2 presents the results for the one-quarter ahead forecast exercise. As expected, and in line with related literature, as the forecasting horizon increases the forecasting power of this type of predictors decreases. Despite being statistically significant, the forecasting gains for the one-quarter ahead horizon are substantially lower than those recorded in the nowcast exercise.

Now, the differences in terms of the forecasting performance are also much smaller. Nevertheless, the consumer confidence indicator still delivers, in most cases, a RMSFE higher than those obtained with hard data albeit lower than the univariate benchmark. When only one month of data is available for the current quarter, AR-MIDAS with monthly ATM/POS is the best performing model allowing for a statistically significant gain of 14 per cent vis-à-vis the univariate model. For the case where two months of the quarter are available, the U-MIDAS with monthly ATM/POS is the preferred model delivering a gain of more than 15 per cent whereas for the full quarter case, it is again the U-MIDAS but using retail sales data which allows for a gain of around 18 per cent.

The above findings highlight the usefulness of ATM/POS data for nowcasting purposes and to a lesser extent for one-quarter ahead forecasting in a context of single-variable models. We also assess if such noteworthy informational content still holds when one considers multiple predictors in MIDAS regressions. In particular, we focus on nowcasting drawing on MIDAS models that allow taking on board autoregressive dynamics, which deliver a better performance as discussed above.[4] Besides including the ATM/POS variable, we consider the case where retail sales and consumer confidence are added to the model each one at a time as well as the case where both are included simultaneously.

4. One should mention that the remaining cases have also been addressed but do not change qualitatively the main findings. All results are available from the authors upon request.

Model	Forecasting horizon	Nowcast		
	Available monthly data	One month	Two months	Full quarter
	Predictors			
CF-MIDAS				
	Retail sales + ATM/POS			
	Monthly	0.995	0.920	0.792
		[0.031]	[0.000]	[0.000]
	Daily	0.937	0.865	0.932
		[0.000]	[0.000]	[0.000]
	Consumer confidence + ATM/POS			
	Monthly	0.897	0.891	0.880
		[0.002]	[0.002]	[0.000]
	Daily	0.919	0.885	0.950
		[0.000]	[0.000]	[0.000]
	Retail sales + Consumer confidence + ATM/POS			
	Monthly	0.873	0.841	0.976
		[0.000]	[0.000]	[0.007]
	Daily	0.948	0.888	1.034
		[0.010]	[0.000]	[0.045]
AR-MIDAS				
	Retail sales + ATM/POS			
	Monthly	0.781	0.804	0.757
		[0.000]	[0.000]	[0.000]
	Daily	0.797	0.727	0.877
		[0.000]	[0.000]	[0.000]
	Consumer confidence + ATM/POS			
	Monthly	0.901	0.901	0.901
		[0.002]	[0.002]	[0.003]
	Daily	0.895	0.876	0.982
		[0.000]	[0.002]	[0.011]
	Retail sales + Consumer confidence + ATM/POS			
	Monthly	0.805	0.848	0.782
		[0.000]	[0.000]	[0.000]
	Daily	0.825	0.783	0.874
		[0.000]	[0.000]	[0.000]
M-AR-MIDAS				
	Retail sales + ATM/POS			
	Monthly	0.987	0.912	0.860
		[0.048]	[0.002]	[0.000]
	Daily	0.937	0.966	0.922
		[0.003]	[0.000]	[0.000]
	Consumer confidence + ATM/POS			
	Monthly	0.851	0.851	0.851
		[0.000]	[0.000]	[0.000]
	Daily	0.964	1.011	1.069
		[0.010]	[0.032]	[0.087]
	Retail sales + Consumer confidence + ATM/POS			
	Monthly	1.181	1.090	1.026
		[0.243]	[0.082]	[0.033]
	Daily	0.917	0.946	1.000
		[0.000]	[0.003]	[0.027]
U-AR-MIDAS				
	Retail sales + ATM/POS			
	Monthly	1.013	0.797	0.699
		[0.004]	[0.000]	[0.000]
	Consumer confidence + ATM/POS			
	Monthly	0.898	0.921	1.099
		[0.007]	[0.006]	[0.077]
	Retail sales + Consumer confidence + ATM/POS			
	Monthly	1.031	0.895	0.744
		[0.030]	[0.001]	[0.000]

Table 3. Relative RMSFE with multiple indicators vis-à-vis an autoregressive model

The results are reported in Table 3. Although in most cases MIDAS regressions with multiple indicators outperform the benchmark autoregressive model, only in a few cases does including information beyond that conveyed by ATM/POS data leads to an improvement in terms of the nowcasting performance. However, even in those cases, the improvement is not enough to outperform the best performing single-variable model with ATM/POS data. This suggests that typical indicators, such as the retail sales and the consumer confidence, do not carry additional predictive power beyond that already present in ATM/POS data. Hence, this evidence reinforces the usefulness of this novel type of data for nowcasting and forecasting private consumption.

6. Conclusions

In this paper, we address the use of a novel type of high frequency data collected from ATM and POS terminals for predicting quarterly private consumption. To take advantage of the high frequency nature of such data we pursue a MIDAS approach. In this respect, we consider several variants of MIDAS regressions proposed in the literature, namely the traditional MIDAS, the multiplicative MIDAS, the unrestricted MIDAS, the MIDAS with common factor autoregressive dynamics and the other cases allowing for unrestricted autoregressive dynamics. Furthermore, we also allow for different information sets within the quarter and consider commonly used variables for tracking private consumption such as retail sales and consumers confidence.

Given the striking role of ATM/POS technology in the Portuguese payments system, it constitutes a natural case study to assess the informational content of such data for predicting private consumption. Moreover, since we are focusing on the forecasting performance over the last years which covers the recent economic and financial crisis, both models and variables are put to test in a clearly challenging period by all standards.

We find that, in terms of models, taking on board autoregressive dynamics in MIDAS regressions improves forecasting performance. In terms of variables, hard data outperforms soft data whereas among the hard data, in general, ATM/POS delivers better results. The gains are noteworthy for nowcasting purposes and to a lesser extent for one-quarter ahead forecasting. Hence, the results obtained herein suggest that high frequency data from ATM and POS terminals should be considered as potentially useful input for predicting macroeconomic developments.

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