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A mixed frequency approach to the forecasting of private consumption with ATM/POS data

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ABSTRACT

The recent worldwide development and widespread use of electronic payment systems has provided an opportunity to explore new sources of data for the monitoring of 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. We take advantage of the availability of such high frequency data by using mixed data sampling (MIDAS) regressions. A comparison of several MIDAS variants proposed in the literature is conducted, and both single- and multi-variable models are considered, together with different information sets within the quarter. Given the substantial use of ATM/POS technology in Portugal, it is important to assess the information content of this data for tracking private consumption. We find that ATM/POS data display a better forecast performance than typical indicators, which reinforces the potential usefulness of this novel type of data among policymakers and practitioners.

1. Introduction

The development of national statistical systems and the improvements made by statistical agencies in compiling and disseminating data to meet the needs of both policymakers and the general public have led to the availability of higher frequency indicators for monitoring changes in economic activity. Although key macroeconomic aggregates, such as GDP, are typically only available at a quarterly frequency, we currently have a relatively wide range of monthly indicators, covering a broad set of economic dimensions. The availability of data at a daily frequency has generally been limited to financial variables, such as stock prices and interest rates.

At the same time, a growing body of literature has focused on the use of higher frequency variables for nowcasting and forecasting the main quarterly macroeconomic variables. The mixed data sampling (MIDAS) regression models introduced by Ghysels, Santa-Clara, and Valkanov (2004) have received considerable attention in the literature. The work of, *inter alia*, Ghysels et al. (2004); Ghysels, Santa-Clara, and Valkanov (2005, 2006), and the growing empirical evidence of its usefulness, have led to a gain in the popularity of MIDAS for forecasting. There is a significant body of literature on the advantages of using MIDAS regressions to improve quarterly macroeconomic forecasts based on monthly and daily data. For instance, Clements and Galvão (2008); Clements and Galvão (2009), Kuzin, Marcellino, and Schumacher (2011), Marcellino and Schumacher (2010), and Schumacher and Breitung (2008) provide evidence of improvements in quarterly forecasts from

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using monthly data, and Andreou, Ghysels, and Kourtellos (2013), Ghysels and Wright (2009) and Monteforte and Moretti (2013), among others, show forecast improvements from the use of daily data. However, given the limited availability of high frequency economic data, MIDAS forecasting has generally been restricted to daily financial series.

Technological progress has encouraged the development and widespread use of electronic payment systems, providing possible new data sources for the monitoring of economic activity, especially data collected from automated teller machines (ATM) and points-of-sale (POS). Typically, electronically recorded data are very timely and free of measurement errors. Such data encompass cash withdrawals at ATM terminals and debit card payments that allow consumers to pay for their purchases by having funds transferred immediately from the cardholder's bank account. Studies relating to this type of data are limited. For instance, Galbraith and Tkacz (2013a) examine daily debit card data in Canada in order to assess the impacts of specific events like the September 11 terrorist attacks; Galbraith and Tkacz (2007) show that debit card payments data can help to lower Consensus forecast errors of 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; and Esteves (2009), using quarterly ATM/POS data for Portugal, presents supporting evidence of the usefulness of such 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 such data are available at a higher frequency than quarterly private consumption, we adopt a MIDAS regression approach, considering both monthly and daily ATM/POS data. To the best of our knowledge, this is the first paper to use the MIDAS approach to forecast using 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 used the MIDAS regression framework for forecasting purposes. In this respect, we consider several variants of MIDAS regressions, including the traditional MIDAS setting of Ghysels et al. (2004), the multiplicative MIDAS discussed by Chen and Ghysels (2011), the unrestricted MIDAS advocated by Foroni and Marcellino (2014), Foroni, Marcellino, and Schumacher (2015) and Marcellino and Schumacher (2010), the common factor MIDAS of Clements and Galvão (2008), and the unrestrictedly augmented (with an autoregressive component) MIDAS regressions, known as ADL-MIDAS, representations discussed by Andreou et al. (2013) and Duarte (2014).

This paper focuses on the Portuguese case because ATM/POS technology has a high dissemination rate in Portugal. Thus, information is compiled by a single entity, which allows us to obtain timely data for the purpose of real-time economic assessments and policy-making. Also, the Portuguese economy has experienced considerable turbulence in recent years, with the Great Recession and the subsequent European sovereign debt crisis, leading to a profound macroeconomic adjustment process. This period constitutes a challenging time for forecasting purposes.

In addition to ATM/POS data, several other predictors are also considered for forecasting quarterly private consumption, such as monthly retail sales and consumer confidence. These indicators are among the most commonly used, and allow us to put into perspective the added value of considering the ATM/POS data for forecasting purposes. For the sake of completeness, we also determine whether there is evidence of ATM/POS data playing such an informative role when using other popular models in the literature, such as bridge equations or factor models. Regarding bridge equations (see for example Schumacher, 2016, and references therein), we consider single predictor models. In the case of factor models, we follow the work of Dias, Pinheiro, and Rua (2015) and use the approach developed by Stock and Watson (2002a,b) on a large dataset for the Portuguese economy with and without ATM/POS series.

Overall, we find that the use of high frequency data improves the forecasting performance, with ATM/POS data offering the largest gains. We also find that augmenting MIDAS regressions with an autoregressive component improves the forecast results, while the unrestricted MIDAS framework delivers the best results.

The paper is organized as follows. Section 2 discusses why Portugal is a natural case study for assessing the information content of ATM/POS data. Section 3 briefly describes the MIDAS regression approaches that will be considered in the empirical application, while Section 4 presents the data. Section 5 discusses the forecasting exercise conducted and the corresponding empirical results. Finally, Section 6 provides conclusions.

2. Why is the Portuguese case special?

The Portuguese ATM and POS network (also known as the *Multibanco* network) dates back to 2 September, 1985, when the first ATM terminals were introduced in the main Portuguese cities of Lisbon and Oporto. Initially, only a limited set of operations were possible, including cash withdrawals and the checking of account balances. Thus, customers had access to banking services that previously had been available only at bank branches. This allowed customers to save time and banks to reduce costs (see also Humphrey, Willesson, Bergendahl, & Lindblom, 2006). Over time, the range of services available at ATM terminals increased considerably. Nowadays, ATM terminals can be used to pay for services, top-up mobile phones, pay for transports and tolls, transfer money to other accounts, etc. The Portuguese network is one of the leading cases worldwide in terms of both innovation and functionality. The growing availability of POS and ATM terminals across the country facilitates consumers' day to day lives and allows firms to benefit from a secure and efficient payment system, with natural positive spillovers for businesses.

The *Multibanco* network is run by a single entity, the SIBS Forward Payment Solutions, which simplifies the compilation of data and ensures that data are readily available and up to date. Cardholders can use the *Multibanco* network at any ATM or POS terminal throughout the country. Moreover, by Portuguese law, banks and merchants are forbidden to charge customers any kinds of fees for operations on ATM terminals or POS transactions. That is, all ATM withdrawals and payments in Portugal are free of charge. The legal and technological environment has led to a high success rate of the interbank *Multibanco* network among the Portuguese population (see also Evans & Abrantes-Metz, 2013). In 2013, there were 1540 ATM and 24,471 POS terminals located in the country for each million inhabitants. The amount of money that was circulated through the network by residents was equivalent to around 50% of GDP, and accounted for about 70% of private consumption expenditure.

Portugal has seen a more rapid progress in electronic payment technology than the United States (see Gerdes, Walton, Liu, & Parke, 2005; Humphrey, Pulley, & Vessala, 2000), and our interest in the Portuguese experience is further reinforced by an Europe-wide comparison.[1] In fact, Portugal ranks first in terms of the number of ATM terminals located in the country per million inhabitants (see Fig. 1(a)), with a number that is well above the euro area average (Fig. 1(b)). The number of ATM terminals in Portugal recently decreased as a result of the economic and financial crises. Fig. 2 shows how the European countries compare in terms of usage of ATMs. The graphs indicate that, in addition to their extensive availability, Portuguese residents' use of ATM terminals has been extensive, well above the euro area average. In terms of cash withdrawals from ATMs, Portugal follows immediately behind Ireland, another country in which ATM users are not charged usage fees.

Interestingly, Spain and Finland display contrasting behaviors in terms of these two indicators. In the Spanish case, we observe that, although Spain ranks third in terms of the number of ATM terminals per million inhabitants, it is among the bottom four in terms of usage per card issued in the country. This may be due to the fact that Spanish banks generally apply a fee whenever ATM withdrawals are made. These fees are significantly higher when the ATM withdrawals are made on third party owned/operated ATMs, including those owned/operated by other Spanish banks. In contrast, Finland has the third lowest 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.

Portugal is also a leading country in terms of the number of POS terminals located in the country per million inhabitants, with Finland and Denmark also standing out (see Fig. 3(a)). Interestingly, Portugal was below the euro area average until about 2005, but witnessed significant growth in the second half of the decade, far surpassing the euro area levels (Fig. 3(b)). Fig. 4 shows how Portugal evolved relative to both the euro area and the euro area countries in terms of POS usage per card issued.

The timely availability of ATM and POS transaction data and the importance of understanding their relevance in terms of private consumption make these series of potential interest for modeling and forecasting. This will be analyzed in detail in Section 4.

3. MIDAS modelling approaches

This section provides a brief overview of the MIDAS approaches that we consider in our forecasting exercise. The general MIDAS approach, introduced by Ghysels et al. (2004), allows the series y_t, sampled at some low frequency (for instance, quarterly or annually), to be regressed on data $x_t^{(m)}$, which is sampled at a higher frequency, such as daily or monthly (for interesting surveys, see e.g. Andreou et al., 2013; Foroni & Marcellino, 2014; Ghysels & Valkanov, 2012).

To illustrate the approach in a framework which is close to that in our empirical analysis, consider that we are interested in forecasting a quarterly time series y_t that is available only once between quarters $t-1$ and t, using a variable $x_t^{(m)}$ that is observed at a higher sampling frequency (m times) over the same period (e.g., $m = 90$ for daily or $m = 3$ for monthly data when the dependent variable is observed quarterly), based on the dynamic relationship between y_t and $x_t^{(m)}$. Traditionally, the problem of mixed-frequency data has been circumvented by converting the higher-frequency data to the sampling rate of the lower-frequency data. However, although several other solutions, such as the time-averaging model or the step-weighting model, have been put forward in the literature, these solutions can lead to considerable parameter proliferation. The advantage of the elegant MIDAS approach introduced by Ghysels et al. (2004) is that it controls for parameter proliferation, and also preserves the timing of information (Armesto, Engemann, & Owyang, 2010).

The simple MIDAS model (Ghysels, Sinko, & Valkanov, 2006) that we consider for h-step-ahead forecasts is

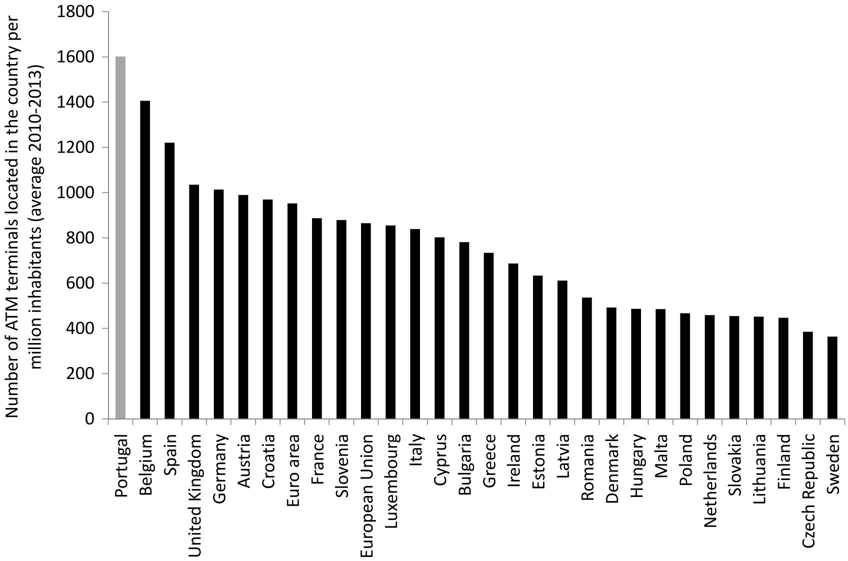
$$y_{t+h} = \beta_0 + \beta_1 B(L^{1/m}; \theta) x_t^{(m)} + \varepsilon_{t+h}, \tag{1}$$

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 parametrized as a function of a low-dimensional vector of hyperparameters θ. Thus, $B(k; \theta)$ is a weighting scheme that is used for aggregation and is assumed to be normalized to sum to one, and ε_{t+h} is a standard i.i.d. error term.

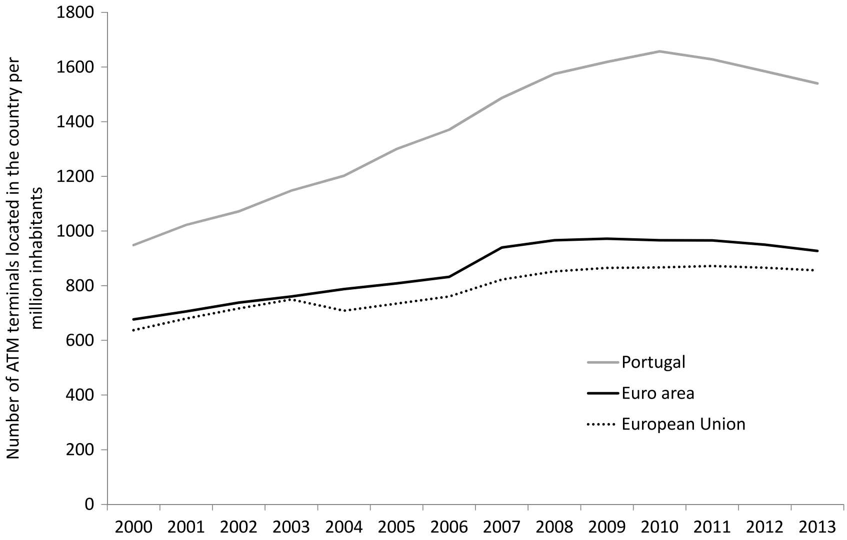
In the mixed-frequency framework in Eq. (1), the number of lags of $x_t^{(m)}$ is likely to be significant, which could lead to the substantial parameter proliferation that is observed in other methods if the associated parameters are left unrestricted. However, the MIDAS regression addresses this issue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

The parametrization 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 of which assume that the weights are determined by a finite one-sided polynomial with a vector of hyperparameters θ. One parametrization of $B(k; \theta)$ is the exponential Almon lag,

[1] The payment statistics data considered throughout Section 2 are provided by the European Central Bank (http://sdw.ecb.europa.eu).



(a) Country comparison.



(b) Evolution over time.

Fig. 1. Numbers of ATM terminals located in the country, per million inhabitants.

which is given as

$$B(k;\theta_1,\theta_2) := \frac{\exp(\theta_1 k + \theta_2 k^2)}{\sum_{i=0}^{K} \exp(\theta_1 i + \theta_2 i^2)}. \tag{2}$$

Although only two parameters are considered in Eq. (2), $\theta := [\theta_1, \theta_2]$, as per Ghysels et al. (2004), a functional form with more parameters could have been used instead; see e.g. Ghysels, Sinko et al. (2006).

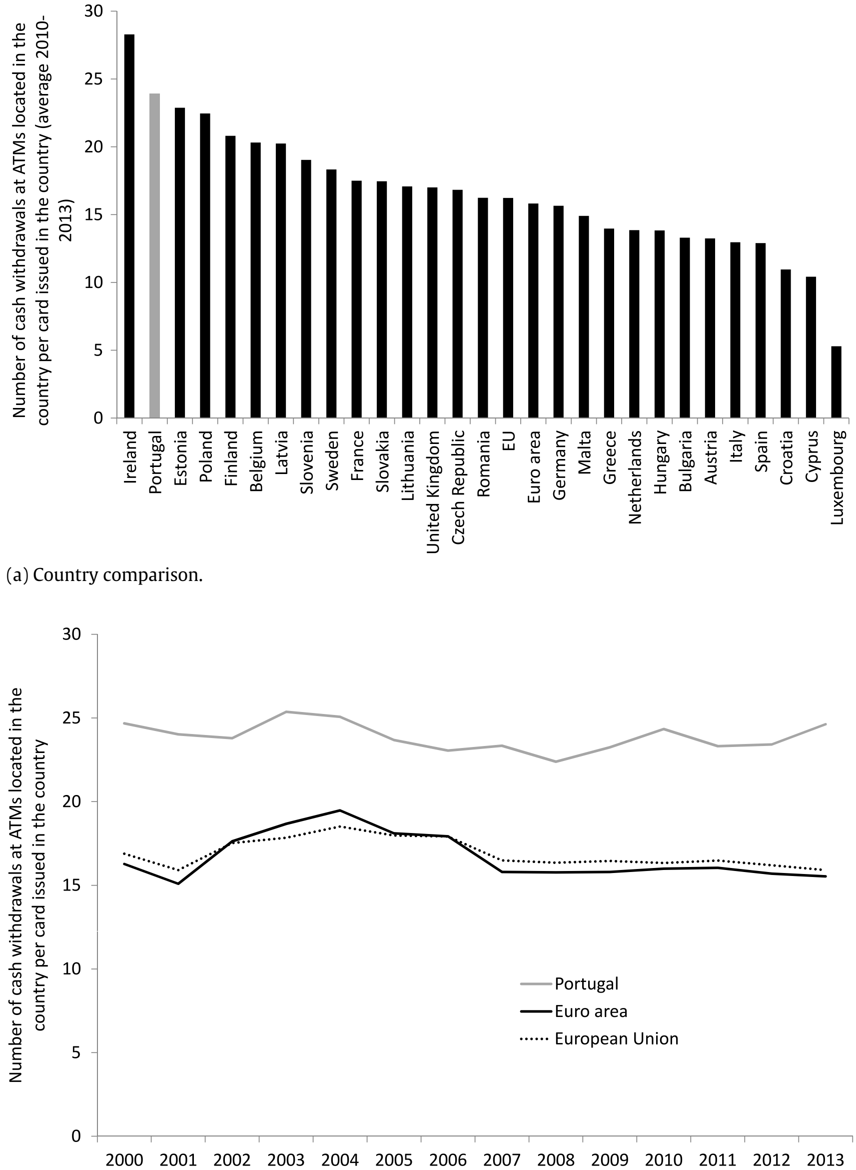
The other parametrization of $B(k;\theta)$ is the Beta polynomial,

$$B(k;\theta_1,\theta_2) := \frac{f\left(\frac{k}{K},\theta_1,\theta_2\right)}{\sum_{i=0}^{K} f\left(\frac{i}{K},\theta_1,\theta_2\right)}, \tag{3}$$

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, the resulting MIDAS regressions have to be estimated using nonlinear least squares in both cases.

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, the lag length selection is purely data-driven once the functional form has been specified.

In addition to the two aggregation polynomials just described in Eqs. (2) and (3), the traditional Almon lag polynomial can also be considered. This aggregation scheme assumes that J lag weights can be related to d linearly



(a) Country comparison.

(b) Evolution over time.

Fig. 2. Numbers of cash withdrawals at ATMs located in the country per card issued in the country.

estimable underlying parameters, with $d < J$, as follows:

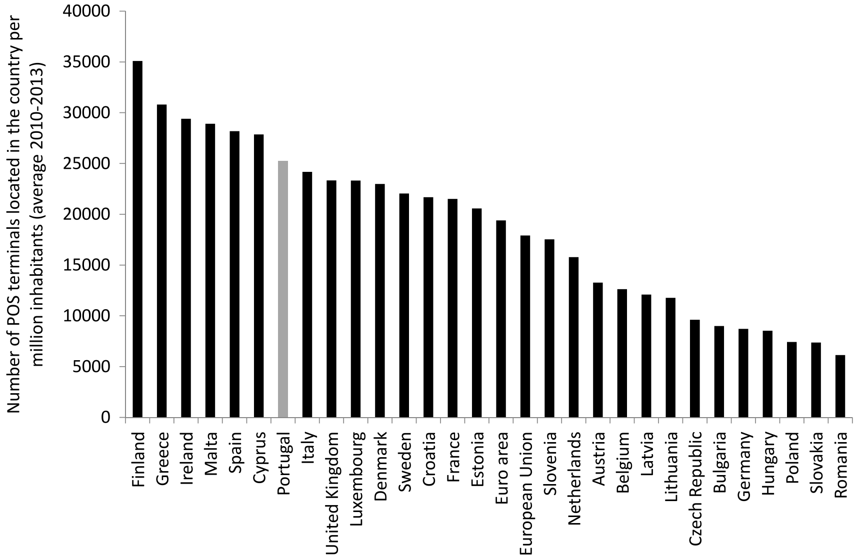
$$B(j; \theta) = \sum_{i=0}^{d} \theta_i j^i, \quad j = 1, \ldots, J, \tag{4}$$

where θ_i, $i = 0, \ldots, d$, denotes the hyperparameters. In our analysis (following the literature), it is assumed that $d = 2$. This weighting scheme also works when m is not fixed (e.g., when combining monthly and 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.

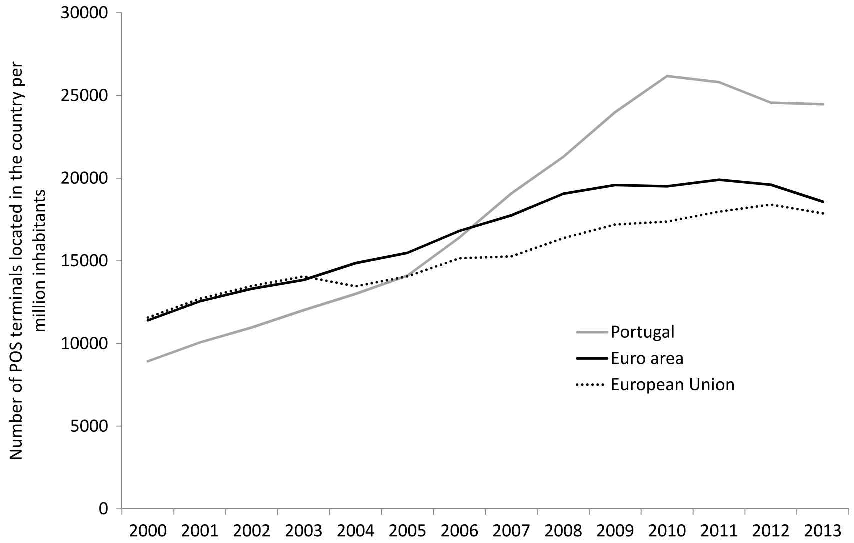
Another MIDAS approach that has been proposed in the literature and that we will be evaluating in our application is the multiplicative MIDAS (M-MIDAS). The M-MIDAS framework is closer to traditional aggregation schemes. Instead of aggregating all lags in the high frequency variable to a single aggregate, M-MIDAS regressions include m-aggregates of high-frequency data and their lags, i.e.,

$$y_{t+h} = \beta_0 + \sum_{i=0}^{p} \beta_i x_{t-i}^{mult} + u_{t+h}, \tag{5}$$

where $x_t^{mult} := \sum_{j=0}^{m-1} B(j; \theta) L^{j/m} x_t^{(m)}$. Eq. (5) resembles a standard distributed lag (DL) model, except that this approach considers parameter-driven regressors that mimic an aggregation scheme. Although this approach has several advantages (e.g., the weighting scheme corresponds to the structure of a steady state Kalman filter with mixed data



(a) Country comparison.



(b) Evolution over time.

Fig. 3. Numbers of POS terminals located in the country per million inhabitants.

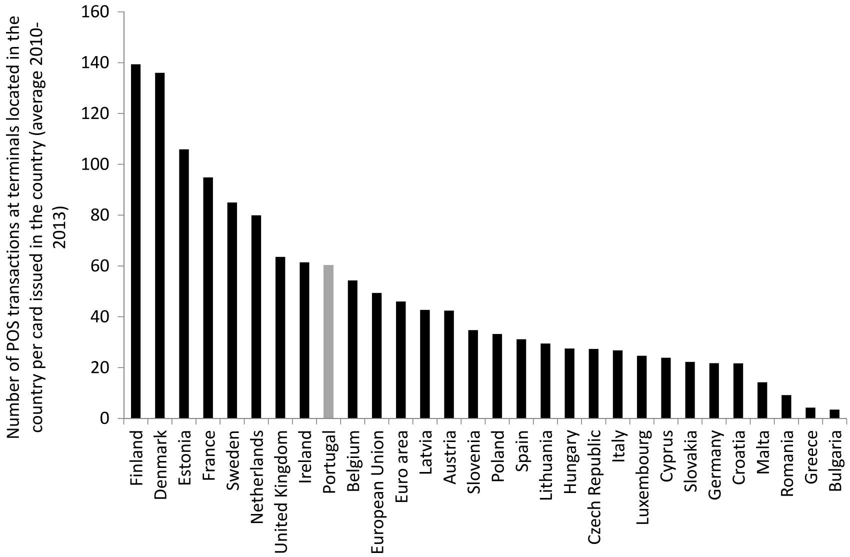
sampling, as indicated by Bai, Ghysels, and Wright (2013), and nests different aggregation schemes, see Chen & Ghysels, 2011), its major disadvantage is that it is not as parsimonious as the conventional MIDAS approach introduced in Eq. (1). Bai et al. (2013) also showed that the forecast performance of this approach does not differ much from that of the standard MIDAS in Eq. (1).

An additional MIDAS variant which does not resort to functionals of distributed lag polynomials, as indicated in Eqs. (2)–(4), and which proves quite useful for forecasting, was introduced recently by Foroni et al. (2015); see also Koenig, Dolmas, and Piger (2003). The authors refer to this approach as the unrestricted MIDAS (U-MIDAS) regression, and it has the comparative advantage that it can be estimated by OLS. The U-MIDAS regression is simply

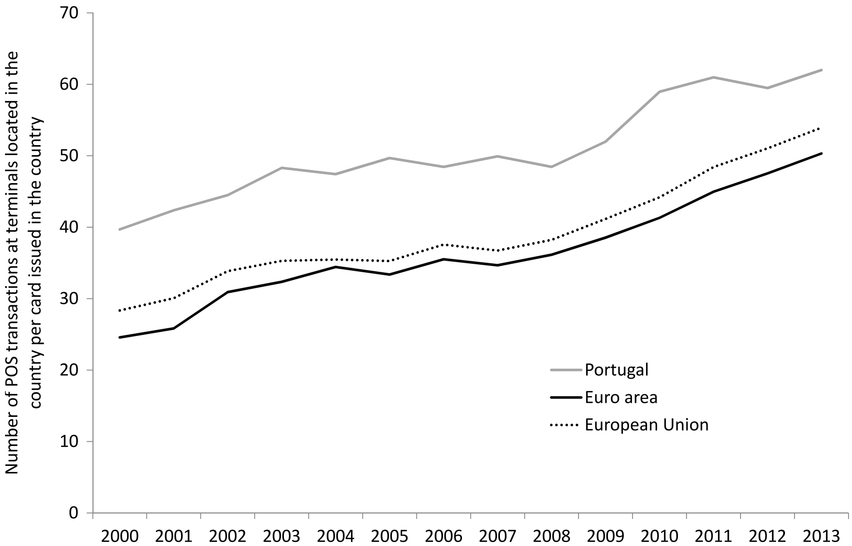
$$\begin{aligned} y_{t+h} &= \beta_0 + \sum_{k=0}^{K} \beta_{k+1} L^{k/m} x_t^{(m)} + u_{t+h} \\ &= \beta_0 + \beta_1 x_t^{(m)} + \beta_2 x_{t-1/m}^{(m)} + \cdots + \beta_{K+1} x_{t-K/m}^{(m)} \\ &\quad + u_{t+h}. \end{aligned} \tag{6}$$

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 for introducing autoregressive dynamics in MIDAS regressions



(a) Country comparison.



(b) Evolution over time.

Fig. 4. Numbers of POS transactions at terminals located in the country per card issued in the country.

that considered the dynamics in y_t as a common factor (Hendry & Mizon, 1978). This assumption rests on the hypothesis that y_t and $x_t^{(m)}$ share the same autoregressive dynamics, even though, as Hendry and Mizon (1978) pointed out, a common factor may not always be found. The MIDAS framework considered in this case is

$$y_t = \beta_0 + \beta_1 B(L^{1/m}; \theta)x_t^{(m)} + u_t \tag{7}$$

$$u_t = \gamma u_{t-1} + \varepsilon_t, \tag{8}$$

and replacing u_t in Eq. (7) results in

$$(1 - \gamma L)y_t = \beta_0(1 - \gamma) + \beta_1(1 - \gamma L) \times B(L^{1/m}; \theta)x_t^{(m)} + \varepsilon_t. \tag{9}$$

This model is known as the common factor MIDAS (CF-MIDAS) model.

Since, as was discussed by Duarte (2014), an autoregressive term can simply be added to the traditional MIDAS equation, our forecasting exercise will also consider all previous MIDAS frameworks augmented with an unrestricted autoregressive component, which will result in the general ADL-MIDAS representation suggested by Andreou et al. (2013), viz.,

$$y_t = \beta_0 + \beta' \mathcal{F}(L^{1/m})x_t^{(m)} + \sum_{k=1}^{p} \gamma_k y_{t-k} + u_t, \tag{10}$$

where $\mathcal{F}(L^{1/m})$ corresponds to the respective MIDAS component used in Eqs. (1), (5) and (6). For reference purposes in what follows, and for clarity in the identification of which versions of MIDAS we are referring to, we will denote the resulting models as MIDAS+AR, M-MIDAS+AR and U-MIDAS+AR, respectively.

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

4. Data

Since the focus of this paper is on assessing the information content of high-frequency ATM and POS network data for the forecasting of Portuguese quarterly private consumption, we consider both the daily and monthly frequencies. The available sample period runs from September 1, 2000, to December 31, 2014, comprising a total of 5235 daily observations and 172 monthly observations. The ATM/POS data considered consist of all ATM cash withdrawals and POS payments by residents, and are made available by Banco de Portugal. This type of data is available readily and can be used the day following that to which it refers.

As was mentioned earlier, ATM terminals allow cardholders to perform a wide range of operations beyond cash withdrawals, for which data are also collected. However, we restrict our analysis of operations on ATM machines to cash withdrawals only, for several reasons. First, as expected, the majority of the total amount corresponds to cash withdrawals. Second, there are several operations that can be conducted at ATM terminals, like deposits or tax and social security payments, that do not reflect consumption expenditures. Finally, for several operations, there can be a mismatch between the timing of the payment and the date on which the expenditure occurred. For instance, several kinds of payments can be made through a functionality that is available in the *Multibanco* network, in which the debtor arranges to pay for a certain good or service by inserting a specific reference number given by the creditor, with these bill payments typically being 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. Hence, the series considered includes both ATM cash withdrawals and POS payments, and accounts for more than 50% of private consumption. Note that this weight was around 35% at the beginning of the 2000s, increased noticeably until 2007 (up to around 50%), and increased only modestly thereafter (up to 56% in 2014).

As ATM/POS data are not seasonally adjusted, we proceed as follows. For monthly data, we use the seasonal adjustment procedure applied by Statistics Portugal (the Portuguese National Statistics Office) for the seasonal adjustment of monthly official statistics, namely the X-13 ARIMA with a calendar effects adjustment, working with the JDemetra+ software provided by Eurostat. Regarding the daily series, as the previous procedure cannot be applied to daily data, we begin by adjusting for calendar effects, including holidays and weekday effects (see for example Esteves & Rodrigues, 2010; Leamer, 2011), then seasonally adjust the data with the seasonal and trend decomposition using LOESS (STL) approach proposed by Cleveland, Cleveland, McRae, and Terpenning (1990). The nonparametric STL method has several interesting features, and, unlike the most extensively used procedures, can handle any data frequency, not only monthly and quarterly data. For recent applications of STL, see for example Bergmeir, Hyndman, and Benítez (2016) and Hyndman and Athanasopoulos (2014). Finally, the daily series is corrected for outliers by taking observations of the transformed series which have absolute deviations that exceed four times the interquartile range and replacing them with a centered average value.

Regarding private consumption, we consider the 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 either bank transfers or loans (see Carlsen & Storgaard, 2010; Esteves, 2009). Hence, one should not expect ATM/POS data to be able to capture this component of consumption, which currently accounts for less than 10% 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 for forecasting 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. In addition, we also use four factors computed from a large data set of monthly economic variables.

It is also important to mention that we use final data, that is, the latest available vintage for all series in a seasonally adjusted form. Hence, we do not consider data revisions caused by either changes in the raw data or the seasonal adjustment process. In this respect, one should mention that there is no real-time dataset available for retail sales, and its calculation has undergone several methodological changes over time. Consumer confidence, on the other hand, is not typically subject to revisions, as it results from opinion pools in response to several questions, and is seasonally adjusted using the Dainties method, which is known to mitigate revisions. In the case of ATM/POS, the raw data are not revised, and we find that the seasonal adjustment does not lead to major revisions regarding its evolution over time. Finally, revisions to quarterly private consumption in Portugal are usually relatively small (see Cardoso & Rua, 2011).

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

5. The nowcasting and forecasting exercise

5.1. Design of the exercise

We assess the relative performances of the above-mentioned models and predictors for forecasting private consumption growth by conducting the following out-of-sample forecasting exercise.

The out-of-sample forecast evaluation period runs from the beginning of 2008 through to the end of 2014, which corresponds to around half of the sample period.[2] It should be noted that Portugal was one of the economies that was hit hardest by the most recent economic and financial crisis. Hence, such an out-of-sample period constitutes a considerable challenge of the informational content of each predictor, as well as of each model's ability in a context of major macroeconomic stress.

Given the types of predictors at hand, we consider both their nowcasting performances and their one-quarter-ahead forecasting behaviors. In both cases, besides assuming the known private consumption growth in previous quarters, we also consider three possible information sets for the predictors within the quarter, namely, the case where only the first monthly observation of the current quarter for each predictor is available, the case where there are observations for the first two months, and the case in which information is available for all months of the quarter. This allows the information content of each predictor to be assessed, regardless of its timeliness.[3]

As was discussed in Section 3, we consider several types of MIDAS regressions, namely the traditional MIDAS (henceforth denoted simply by MIDAS), the multiplicative MIDAS (M-MIDAS), the unrestricted MIDAS (U-MIDAS), the MIDAS with common factor autoregressive dynamics (CF-MIDAS), and all of these cases allowing for unrestricted autoregressive dynamics (denoted MIDAS+AR, M-MIDAS+AR and U-MIDAS+AR, respectively). The model specification is selected based on the Bayesian information criteria (BIC), and, apart from U-MIDAS, the weighting function used in each MIDAS regression is the exponential Almon polynomial in Eq. (2) when monthly predictors are considered, and the traditional Almon lag polynomial in Eq. (4) for the case of daily predictors. The choice of the latter for daily data was due to its superior forecast performance relative to the results with the exponential Almon polynomial. Our analysis also considered the Beta polynomial in Eq. (3), but it did not improve the forecast performance. All in all, this corresponds to the computation of 78 cases for each forecasting horizon.

As in the related literature, we conduct a recursive exercise with an expanding window.[4] In particular, a recursive estimation process is implemented for each predictor and model, allowing the coefficients to change over time. Starting from the initial estimation period (from 2000 to 2007), a new observation is added to the sample in each round, and both the nowcast and the one-quarter-ahead forecast are computed. As is usual in this type of exercises, we consider an univariate autoregressive (AR) model with the lag order determined by the BIC as the benchmark.

The forecasting performance is assessed based on 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 that is lower than one denotes a forecasting gain by the MIDAS approach, whereas a value that is higher than one means that the univariate model outperforms the alternative model.

We assess the statistical significance of the forecasting gains using 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.

5.2. Empirical results

Table 1 presents the results for the exercise described above. Several findings emerge from an analysis of Table 1. Firstly, in terms of predictors, the so-called hard data (retail sales and ATM/POS) always outperform the soft data (the consumer confidence indicator). Only in the case of the CF-MIDAS with one month of available data does the consumer confidence index perform marginally better than the other predictors. This relative lack of predictive ability of the consumer confidence indicator over the last decade has also been found by Dreger and Kholodilin (2013) for both 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 the CF-MIDAS, for which the use of the first two months of retail sales slightly outperforms ATM/POS data. Regarding the frequency of ATM/POS data, the CF-MIDAS always does better with daily data than with monthly data, and the same is true in the case of the MIDAS+AR with only one month of available data. In all other cases, though, the monthly series improve on its daily counterpart. Although one would expect the use of higher frequency data to be more informative than its lower-frequency counterpart in principle, such does not seem to be the case here. This may reflect the fact that the daily ATM/POS series is very noisy, which makes it harder to extract the relevant signal for forecasting purposes. It may also reflect the difference between the seasonal adjustment procedure that we are forced to use in the case of daily ATM/POS data and 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 (for a thorough discussion, see e.g. Wallis, 1974, 1978). Despite all this, one should note that the use of ATM/POS daily data, namely through a MIDAS+AR regression, enhances the forecasting performance by around 25% vis-à-vis the univariate benchmark.

In terms of the different MIDAS regressions, one should highlight the fact that the MIDAS specifications that allow for the presence of autoregressive dynamics almost

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2 We assessed potential variations in forecast performances over time by also conducting a sub-sample analysis, and found the results to be qualitatively similar across sub-periods.

3 We have also re-run the exercise allowing for release lags. In particular, the quarterly private consumption is released with a lag of two months and retail sales with a lag of around one month, whereas both consumer confidence and ATM/POS data are available immediately after the end of the reference period. We find that the results remain qualitatively unchanged.

4 We also tried using a rolling window, but the results were qualitatively very similar to those reported here.

Table 1
Relative RMSFEs of MIDAS models vis-à-vis an autoregressive model.

	Forecasting horizon	Nowcast			One-quarter-ahead		
	Available data	One month	Two months	Full quarter	One month	Two months	Full quarter
MIDAS	Retail sales	0.867***	0.856***	0.848***	0.932**	0.873***	0.862***
		[0.001]	[0.003]	[0.001]	[0.016]	[0.000]	[0.001]
	Consumer confidence	1.023	1.027	1.026	0.971*	1.002	0.999
		[0.281]	[0.251]	[0.271]	[0.056]	[0.124]	[0.124]
	ATM monthly	0.842***	0.833***	0.808***	0.905***	0.906***	0.907***
		[0.000]	[0.000]	[0.000]	[0.005]	[0.007]	[0.010]
	ATM daily	0.917***	0.926***	0.937***	0.879***	0.875***	0.894***
		[0.006]	[0.010]	[0.009]	[0.001]	[0.000]	[0.001]
M-MIDAS	Retail sales	1.028	1.005*	0.846***	1.010	1.014	0.989
		[0.266]	[0.092]	[0.000]	[0.244]	[0.184]	[0.120]
	Consumer confidence	1.045	1.067	1.048	0.949**	0.977**	0.997
		[0.290]	[0.342]	[0.314]	[0.027]	[0.046]	[0.118]
	ATM monthly	0.809***	0.817***	0.846***	0.956**	0.963*	0.887***
		[0.001]	[0.000]	[0.000]	[0.040]	[0.059]	[0.003]
	ATM daily	0.994*	0.974***	1.031	1.025*	0.969**	0.984**
		[0.055]	[0.010]	[0.121]	[0.089]	[0.024]	[0.026]
U-MIDAS	Retail sales	0.870***	0.882***	0.853***	0.910***	0.884***	**0.819*****
		[0.001]	[0.002]	[0.001]	[0.008]	[0.001]	[0.000]
	Consumer confidence	1.058	1.059	1.081	1.039	1.080	1.003
		[0.427]	[0.458]	[0.628]	[0.125]	[0.105]	[0.112]
	ATM monthly	0.768***	0.764***	0.848***	0.876***	**0.847*****	0.905***
		[0.000]	[0.000]	[0.000]	[0.002]	[0.001]	[0.007]
CF-MIDAS	Retail sales	0.871***	0.841***	0.879***	0.919***	0.872***	0.897***
		[0.000]	[0.000]	[0.000]	[0.009]	[0.001]	[0.004]
	Consumer confidence	0.853***	0.876***	0.848***	0.948**	0.921**	0.953**
		[0.000]	[0.003]	[0.000]	[0.019]	[0.011]	[0.030]
	ATM monthly	0.885***	0.884***	0.884***	0.904***	0.903***	0.903***
		[0.003]	[0.003]	[0.003]	[0.005]	[0.009]	[0.007]
	ATM daily	0.867***	0.850***	0.815***	0.897***	0.921**	0.934***
		[0.000]	[0.001]	[0.000]	[0.002]	[0.011]	[0.009]
MIDAS+AR	Retail sales	0.780***	0.727***	0.775***	0.932**	0.958**	0.938***
		[0.000]	[0.000]	[0.000]	[0.024]	[0.024]	[0.010]
	Consumer confidence	0.839***	0.846***	0.859***	0.918***	0.961**	0.953**
		[0.000]	[0.000]	[0.000]	[0.010]	[0.043]	[0.021]
	ATM monthly	0.797***	0.667***	**0.676*****	**0.860*****	0.861***	0.862***
		[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
	ATM daily	0.744***	0.748***	0.770***	0.862***	0.897***	0.886***
		[0.000]	[0.000]	[0.000]	[0.000]	[0.003]	[0.002]
M-MIDAS+AR	Retail sales	0.869***	0.874***	0.850***	0.933**	0.943**	0.981**
		[0.001]	[0.000]	[0.000]	[0.026]	[0.024]	[0.037]
	Consumer confidence	0.870***	0.909***	0.919***	0.885***	0.927**	0.961**
		[0.000]	[0.003]	[0.003]	[0.006]	[0.012]	[0.031]
	ATM monthly	0.695***	0.692***	0.676***	0.959**	0.848***	0.883***
		[0.000]	[0.000]	[0.000]	[0.027]	[0.000]	[0.003]
	ATM daily	0.834***	0.834***	0.885***	0.998**	0.965**	0.998**
		[0.000]	[0.000]	[0.001]	[0.042]	[0.026]	[0.028]
U-MIDAS+AR	Retail sales	0.760***	0.763***	0.746***	0.871***	0.868***	0.826***
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	Consumer confidence	0.870***	0.884***	0.929***	0.932**	0.952**	0.959**
		[0.001]	[0.002]	[0.006]	[0.014]	[0.027]	[0.022]
	ATM monthly	**0.662*****	**0.647*****	0.698***	0.891***	0.874***	0.860***
		[0.000]	[0.000]	[0.000]	[0.002]	[0.001]	[0.001]

Note: The figures in bold correspond to the best performing models.
* Indicate statistical significance at the 10% significance level.
** Indicate statistical significance at the 5% significance level.
*** Indicate statistical significance at the 1% significance level.

always have lower RMSFEs for any given predictor and information set. In fact, the MIDAS specifications that also consider autoregressive terms improve on their non-autoregressive counterparts by an average of around 15%. This reflects the fact that non-durable private consumption typically embeds consumers' habit persistence, presenting a relatively smooth behavior. Of the MIDAS regressions with autoregressive dynamics, the MIDAS+AR and U-MIDAS+AR generally outperform the CF-MIDAS and M-MIDAS+AR for any predictor and information set within the quarter.

The model and predictor that deliver the lowest RMSFEs for nowcasting purposes when one or two months of data are available are the U-MIDAS+AR with monthly ATM/POS data. The forecasting gains are statistically significant, at around 35% vis-à-vis the univariate benchmark. When a full quarter of data is available, the MIDAS+AR with monthly ATM/POS is the best performing model, only slightly better than the U-MIDAS+AR, with a gain of more than 30%. Table 1 also presents the results for the one-quarter-ahead forecast exercise. As expected, and in line with the related literature, the forecasting power of this type of predictors decreases as the forecasting horizon increases. Despite being statistically significant, the forecasting gains for the one-quarter-ahead horizon are lower than those recorded in the nowcast exercise. The differences in terms of forecasting performances are also smaller. Nevertheless, the consumer confidence indicator still delivers higher RMSFEs than those obtained with hard data in most cases, albeit lower than the univariate benchmark. When only one month of data is available for the current quarter, MIDAS+AR with monthly ATM/POS is the best performing model, allowing for a statistically significant gain of 14% vis-à-vis the univariate model. For the case where two months of data for the quarter are available, the U-MIDAS with monthly ATM/POS is the preferred model, delivering a gain of more than 15%, whereas for the full quarter case, it is again the U-MIDAS, but using retail sales data, giving a gain of around 18%.

The above findings highlight the usefulness of ATM/POS data for nowcasting purposes in the context of single-variable models, and for one-quarter-ahead forecasting to a lesser extent. We also assess whether such a noteworthy informational content remains when one considers multiple predictors in MIDAS regressions. In particular, we focus on nowcasting, drawing on MIDAS models that allow for autoregressive dynamics, which were the models that delivered the better performances, as was discussed above.[5] Besides including the ATM/POS variable, we also consider the case where retail sales and consumer confidence are each added to the model one at a time, as well as the case where both are included simultaneously.

The results are reported in Table 2. Although MIDAS regressions with multiple indicators outperform the benchmark autoregressive model in most cases, the inclusion of information beyond that conveyed by ATM/POS data leads to an improvement in terms of nowcasting performances in only a few cases, and even in these 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 retail sales and consumer confidence, do not contain additional predictive power beyond that which is already present in ATM/POS data.

We reinforce the potential usefulness of the ATM/POS data by also assessing whether there is evidence of such an informative role when using other popular models in the literature, such as bridge equations or factor models. Regarding bridge equations (see for example Schumacher, 2016, and references therein), we begin by considering a bridge model for each of the indicators assessed so far, namely consumer confidence, retail sales and ATM/POS. In the case of factor models, we follow the work of Dias et al. (2015) and pursue the approach developed by Stock and Watson (2002a,b), using a large dataset[6] for the Portuguese economy to compute the factors (for more details, see Dias et al., 2015). We also assess the forecasting performances of the factor models when one excludes or includes the ATM/POS data in the dataset. As has been indicated, the performances of the above models are compared with that of the univariate autoregressive benchmark, and reported in Table 3.

Focusing on the single-indicator bridge equations, we find that the one with ATM/POS performs best. When considering the factor models, we find that using the dataset that includes ATM/POS delivers slightly better results than using the one that excludes it. In the context of a large dataset with more than 100 variables, one would not expect large quantitative differences in the performances of the factor model; however, qualitatively the results seem to support the usefulness of including the ATM/POS data in the dataset.

We support these conclusions further by also performing a forecasting exercise using each individual variable of the large dataset (a total of 126 variables) that is used to extract the factors for the factor model. Fig. 5 reports the empirical distribution density of the relative RMSFE of each model with respect to the AR benchmark. The first observation that we can make is that most models generally outperform the benchmark. Note that the large majority of relative RMSFEs are less than one, for both nowcasting and forecasting. Moreover, we also plot the relative RMSFEs for the ATM/POS data explicitly, and clearly observe its superior performance in both the nowcasting and forecasting exercises, relative to all of the other predictors used.

Hence, this evidence reinforces the usefulness of this novel type of data for nowcasting and forecasting private consumption.[7]

6. Conclusions

This paper addresses the use of a novel type of high frequency data collected from ATM and POS terminals for predicting quarterly private consumption. We take advantage of the high frequency nature of such data by pursuing a MIDAS approach. In this respect, we consider several variants of MIDAS regressions that have been proposed in the literature, namely the traditional MIDAS, the multiplicative MIDAS, the unrestricted MIDAS and the MIDAS with common factor autoregressive dynamics, as well as allowing for unrestricted autoregressive dynamics with all variants of MIDAS. Furthermore, we also allow for the use of different information sets within the quarter, and consider

[5] The remaining cases have also been addressed, but do not change the main findings qualitatively.

[6] The dataset comprises 126 series and includes both hard and soft data. It covers business and consumer surveys, retail sales, industrial production, turnover in industry and services, employment, hours worked and wage indices in industry and services, tourism nights spent in Portugal, car sales, cement sales, vacancies and registered unemployment, energy consumption, goods exports and imports, the effective exchange rate, the stock market index, and ATM/POS series (see Dias et al., 2015).

[7] ATM/POS data may also be useful for forecasting other macro variables, such as GDP. However, we find that it presents a superior performance when nowcasting private consumption.

Table 2
Relative RMSFEs of MIDAS models with multiple indicators vis-à-vis an autoregressive model.

Model	Forecasting horizon	Nowcast		
	Available 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]
MIDAS + AR	Retail sales + ATM/POS			
	Monthly	$\mathbf{0.781}^{***}$	0.804^{***}	0.757^{***}
		[0.000]	[0.000]	[0.000]
	Daily	0.797^{***}	$\mathbf{0.727}^{***}$	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-MIDAS + AR	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-MIDAS + AR	Retail sales + ATM/POS			
	Monthly	1.013^{***}	0.797^{***}	$\mathbf{0.699}^{***}$
		[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]

Note: The figures in bold correspond to the best performing models.
* Indicate statistical significance at the 10% significance level.
** Indicate statistical significance at the 5% significance level.
*** Indicate statistical significance at the 1% significance level.

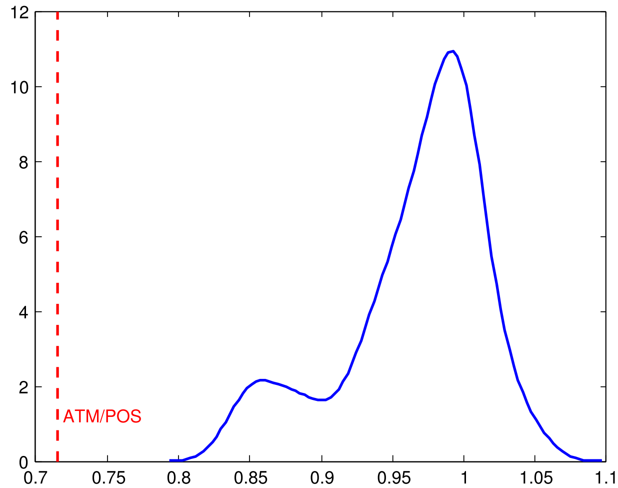
commonly-used variables for tracking private consumption, such as retail sales and consumer confidence.

Given the important role played by ATM/POS technology within the Portuguese payments system, it is clearly relevant to assess the informational content of such data for predicting private consumption. Moreover, since we focus on forecast performances over the last few years, which covers the recent economic and financial crisis, both models and variables are put to test in a period that is clearly challenging.

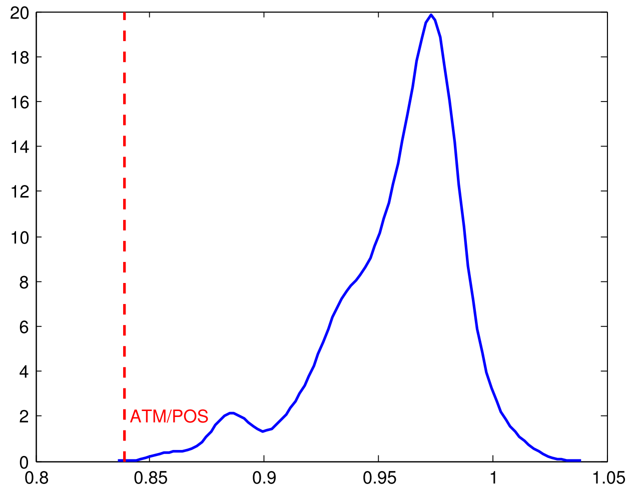
Table 3
Relative RMSFEs of bridge and factor models vis-à-vis an autoregressive model.

	Forecasting horizon	Nowcast	One-quarter-ahead
Bridge model			
	Consumer confidence	1.017	0.983
		[0.716]	[0.219]
	Retail sales	0.778***	0.888***
		[0.000]	[0.009]
	ATM/POS	0.715***	0.839***
		[0.000]	[0.001]
Factor model			
	Without ATM/POS	0.881***	0.892**
		[0.004]	[0.036]
	With ATM/POS	0.874***	0.887**
		[0.004]	[0.031]

** Indicate statistical significance at the 5% significance level.
*** Indicate statistical significance at the 1% significance level.



(a) Nowcasting.



(b) One quarter ahead.

Fig. 5. Empirical distribution density of the relative RMSFEs.

In terms of models, we find that using autoregressive dynamics in MIDAS regressions improves the forecasting performance. In terms of variables, hard data outperform soft data, while ATM/POS generally delivers better results among the hard data. The gains are noteworthy for nowcasting purposes (around 35%), and for one-quarter-ahead forecasting to a lesser extent (over 15%). Hence, our results suggest that high frequency data from ATM and POS terminals should be considered as potentially useful inputs for predicting macroeconomic developments, especially private consumption.

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