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Ana Beatriz Galvão and Rory Macqueen

ESCoE Discussion Paper 2023-10

June 2023

ISSN 2515-4664

DISCUSSION PAPER

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Published by:
Economic Statistics Centre of Excellence
King's College London
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# Nowcasting UK consumption and investment with monthly output components and real-time indicators

Ana Beatriz Galvão and Rory MacQueen[1]

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The first ONS estimates of UK Investment and Consumption growth are revised to incorporate data that was not previously available. We draw on a large set of traditional and alternative economic indicators to nowcast investment and aggregate consumption growth. We compare the nowcast performance of mixed frequency models with the ONS first estimates for both macroeconomic variables. When predicting the latest estimate, the nowcasting models cannot improve over the ONS' first estimate. Nonetheless, some classes of predictors can assist in improving early estimates under some circumstances. In particular, monthly sectoral growth data and real-time data on vacancies would offer potential timely insights into both consumption and investment movements during volatile periods such as 2020-2021.

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This research has been funded by the Office for National Statistics as part of the research programme of the Economic Statistics Centre of Excellence (ESCoE)

[1] We are grateful to the ONS for funding this research via the Economic Statistics Centre for Excellence. We thank Paul Mizen for useful comments. Comments and suggestions to Ana Galvão at ana.galvao@wbs.ac.uk.

## 1 – Introduction

Aggregate Investment, or Gross Fixed Capital Formation, is the GDP component regarded by economic theory and empirical evidence as the main driver of business cycles. Investment is frequently the most volatile component of GDP. The standard deviation of the UK quarterly investment growth is 3.7% for the 1998Q1 to 2021Q4 sample period. Even if the last two years are removed, the standard deviation is still 2.75%, which is large compared to mean quarterly investment growth of 0.5%.

The main contribution of this paper is to exploit a large set of traditional and alternative economic indicators to nowcast investment and aggregate consumption growth. By comparing nowcasts of investment and consumption, we aim to understand better the role of investment's high variability on the results, as consumption is considerably smoother.

All the indicators considered are sampled monthly, and we use a state-of-art mixed-frequency regression model to link quarterly investment growth and consumption to these indicators. Among the monthly indicators, we consider components of GDP computed using the output approach, VAT-based activity estimates, ONS real-time indicators, and traditional leading indicators.

The ONS revises the first and the Quarterly National Accounts (QNA) estimates of investment growth and consumption as the availability of the survey data required for their computation improves. In the following section, we compute the standard deviation of the data revisions to investment and consumption. The value for investment growth is 2.2% -- four times larger than consumption growth (0.55%), a less volatile GDP component.

As nowcasting models provide an alternative prediction for these estimates, a key research question is whether they can improve over the first ONS estimate when the target is the revised values of consumption and investment growth. We design our forecasting exercise such that the nowcasting model uses all information on the indicators that would be available before the ONS's first release, which is published 40 days after the end of the reference quarter. Our empirical results indicate that nowcast models do not perform better than the ONS first estimate when the target is investment and consumption growth as recorded in the latest available vintage (2022Q1). We show, however, that nowcast models that exploit the information of monthly GVA data and real-time indicators do better than a simple autoregressive model. They are particularly good in nowcasting the bounce-back from the effect of the Covid restrictions during the 2020-2021 period.

Section 3 describes the nowcasting methods employed in this paper. It also includes our methodology to incorporate the short time series of the real-time indicators in the forecasting exercise. The design of the forecasting exercise is described in section 4, and section 5 presents the empirical results, which are summarised in section 6.

## 2 – Analysis of Consumption and Investment Data Revisions

Figure 1 shows four estimates of UK quarterly aggregate investment growth, computed as $y_t = 100\left(\left({Y_t}/{Y_{t-1}}\right) - 1\right)$ where $Y_t$ is the value in pounds in volume terms. First, we show the estimate of investment growth published in the middle month of the quarter following the reference quarter (in May for Q1, for example). Then we show the Quarterly National Accounts estimate, usually published by the end of the next quarter (June for Q1). Then we include two revised estimates: the values published 16 quarters (4 years) after the reference quarter and the values in the latest vintage (2022Q1). In the nowcasting exercise in section 5, we evaluate forecasting performance using the latest vintage, as then we can evaluate forecasts for the 2020-2021 period. To measure the characteristics of investment and consumption growth revisions, we prefer to keep the number of potential rounds of revisions fixed, so we use instead the release observed four years after the reference quarter.

An inspection of Figure 1 suggests that, for quarters in the years 2002 and 2011, the improved availability of survey data led the ONS to revise investment growth upwards, offering a more buoyant investment activity than previously thought. On average, revisions led to higher investment growth. This arises from the fact that businesses that have undertaken a large amount of investment take longer to complete the necessary paperwork to report this to the ONS; consequently, early estimates are biased downwards because of overly sampling firms with low investment expenditure. The ONS has added adjustments to account for this issue in the observations from 2013 onwards.

The effect of data revisions is described in detail in Table 1, where we show a set of statistics. Data revisions are computed as $y_t^{t+16} - y_t^{t+j}$ where $y_t^{t+16}$ is the estimate available

16 quarters after the reference quarter. As j<16, $y_t^{t+j}$ is an earlier estimate, with j=1,...,15. As there are two estimates in the first quarter after the reference quarter, we consider revisions to the first and the QNA estimates. The statistics displayed in Table 1 are the revision's mean and standard deviation for the different maturities.

Early released estimates of investment growth tend to underestimate the revised values of investment growth. The positive mean revisions are statistically not different from zero for all maturities of consumption and investment revisions, except the first investment estimate, which has a mean revision of 0.55%, as the period includes observations before 2013, when the ONS adjustment was implemented. Note that the standard deviation of the investment revision is around 2% for maturities up two years after the first estimate (*j=10*). This suggests significant annual revisions to investment in the two years following the first estimate. The mean revision declines fast and is only sizeable until the first yearly revision (usually in September).

In contrast, the mean revision to consumption growth is typically zero. Still, the standard deviation only declines in size after two rounds of annual revision (from 0.5 to 0.2), as in the case of investment.

In summary, early estimates of consumption and investment growth are subject to sizeable data revisions as the ONS improves the quality of the estimates. These revisions suggest that to design a realistic nowcasting exercise, one must use only data available at the time the forecast would have been made, that is, real-time data. We consider real-time data of consumption and investment when computing nowcasts in section 5.

## 3 – Forecasting Methods and Real-time Indicators

### 3 .1 – Nowcasting Model

We mainly use monthly indicators to predict quarterly consumption and investment growth, so we employ a Bayesian mixed-data sampling approach. Let $y_t$ be the quarterly GDP component of interest (either consumption or investment growth) sampled quarterly ($t = 1,2, \dots, T$). Now assume a predictor $x_t$ available at a higher frequency (monthly or weekly), that is, at a frequency $m$ times higher than $y$, such that, $t = 1/m, 2/m, \dots, 1, 1 + (1/m), 1 + (2/m), \dots, 2, \dots., T$. In the case of monthly data, $m = 3$, and we observe $x_t$ for $t =$

$1/3, 2/3, 1, 4/3, 5/3, 2, 7/3, \ldots, T$. The Unrestricted Mixed Data Sampling (UMIDAS) regression to use $x_t$ to forecast $y_t$ is:

$$y_t = \alpha_{L,0} + \sum_{i=1}^{py} \alpha_{L,i}\, y_{t-i} + \sum_{j=0}^{px-1} \beta_{L,j+1}\, x^{(m)}_{t-(\frac{L+j}{m})} + \varepsilon_{t,L}, \qquad (1)$$

where py is the maximum number of quarterly lags for the target variable y, and px is the maximum number of the predictor's high frequency (monthly) lags. $L$ is the number of high-frequency monthly lead periods. For example, if all data on $x_t$ is available before the publication of $y_t$, we set $L = 0$. As the last month of the quarter of some monthly predictors may not be available before the publication of the quarterly target, $L$ may be set to 1.

As we consider many lags of the indicator variable x, say px=12, we use Bayesian methods to estimate the UMIDAS regression to dampen the effect of parameter uncertainty on nowcasts. We follow the suggestions of Carriero, Clark and Marcellino (2018) and use the normal/inverse gamma conjugate priors' strategy, where we assume the prior mean for betas is zero, leading to a shrinkage-like estimator.

Our empirical exercise considers a large set of monthly predictors and combines forecasts of single indicator models using equal weights (or averaging). This strategy is recommended by Carreiro, Galvão and Kapetanios (2019) after reviewing a set of approaches to deal with many indicators.

**3.2 – Real-Time Indicators.**

To help decision-making, the ONS published several real-time indicators in the last few years to help gauge trends and changes in the UK economy. Many time series are available weekly but cover a short history (3 to 4 years). Historical data is needed to estimate the parameters of forecasting models described earlier. We propose a strategy that allows us to use the information of real-time indicators for forecasting during the 2020-2021 period.

Our strategy matches a weekly real-time indicator with an ONS monthly indicator, inspired by traditional interpolation approaches. We extended the traditional approach by using a mixed-frequency regression to link the monthly predictor $x_t$ with the weekly real-time indicator $z_t$. Assume now t is monthly, and that we observe the weekly indicator as t=1/4,2/4,3/4,1,5/4,6/4,7/4,2,…, the linking regression is:

$$x_t = \beta_0 + \sum_{i=1}^{4} \beta_i\, z_{t-(\frac{i}{4})} + \epsilon_t,$$

where the sample period $t = \tau + 1, \ldots, T$ such that time series data is available for both $x_t$ and $z_t$. If we know the coefficients of the linking regression, we can create a time series $\widetilde{x_t}$ such that it is equal to $x_t$ for t=1,…, $c$, but for t= $\tau + 1, \ldots T$, $\widetilde{x_t} = \widehat{x_t}$, where $\widehat{x_t}$ is the predicted value using the linking regression. Using $\widetilde{x_t}$ in the nowcasting model, we can exploit the information of the real-time indicator $z_t$ while being able to estimate the parameter of the model over historical data. The central assumption required is that both the traditional monthly and real-time indicators measure the same economic concept and are highly correlated.

Looking at the real-time indicator currently available, we find two matches. The first one links the time series of the number of online ads (for all industries) with the monthly time series of vacancies (total services). The second links retail sales (current values, NSA) with aggregate card spending. Figure 2 shows the augmented series, $\widetilde{x_t}$, in both cases. We also include the sales series augmented with card spending after removing the impact of prices (using CPI goods) and seasonal adjustment. Note that an advantage of this method is that we can apply seasonal adjustment to a series with few seasons (as is the case with card spending data) by assuming the pattern is in line with another time series (retail sales). We use the augmented time series in our forecasting exercise in the next section to consider the performance of models that include these two weekly real-time indicators.

## 4 – Forecasting Exercise Design

In addition to verifying whether a nowcast model can provide a better estimate of investment and consumption growth at the time of the ONS first release, the forecasting exercise in this paper is designed to understand the contribution of four classes of predictors when nowcasting GDP components.

First, we consider the monthly components of GDP computed via the output approach, that is, the 20 sectoral components of gross value added (GVA). They are: (i) Mining, (ii) Agriculture, (iii) Manufacturing, (iv) Electricity, (v) Water, (vi) Construction, (vii) Retail, (viii) Transport, (ix) Hospitality, (x) Communication, (xi) Finance, (xii) Property, (xiii) Professional, (xiv) Administrative, (xv) Public, (xvi) Education, (xvii) Health, (xviii) Arts, (xvix) Other Services, (xx) Household. Time series for these are available dating back to 1998Q1; they are transformed to growth rates by comparing this month's value with the one three months ago, that is, $x_t = 100((X_t/X_{t-3}) - 1)$, where $X_t$ is the original value in volume terms.

Second, we consider a set of traditional monthly survey indicators (drawing on Galvão and Lopresto, 2020): ONS Retail Sales (Great Britain) and GfK's Consumer Confidence indicator for consumption; CBI Retail Orders, OECD Business Confidence indicator and OECD consumer confidence indicator for investment. They are available over the same period as GVA components. We apply the same data transformation as GVA data, except for the consumer confidence and retail order indicators, where we use the 3-month difference instead of growth rates.

Third, we use the monthly diffusion indices based on HMRC VAT data, published by the ONS since 2020. These include turnover, expenditure and new reporter indices for each industry sector included in the GVA listed above, plus aggregated production and services, flash (early), and revised estimates: in total, 107 indices. They are available from 2013Q1, and they are transformed by summing the monthly change of each of the three months in a quarter.

Fourth, we consider two real-time indicators: online adverts and card spending. To obtain nowcasts using these indicators, we use them as part of the augmentation of vacancies and retail sales series as described in detail in the previous section. They are transformed to 3-month growth rates.

As there are many indicators in each class of predictors and we want to understand how successful each class is for nowcasting consumption and investment growth, we combine forecasts from single predictors UMIDAS nowcasting models by using equal weights as suggested by Carriero, Galvão and Kapetanios (2019), principally because our sample sizes are too short to effectively use past forecasting performance to set the weights. When evaluating results, we also consider whether any individual indicator performs better than the combined forecast obtained for each of the four classes of indicators. Compared with the best forecast, the advantage of the combined forecast is that indicators' predictive power may change over time. So even if a nowcasting model with a specific predictor is ex-post over a particular period of time the most accurate, it may be that, in future, a model with another predictor does better. Forecasting combination is also a way to hedge against instability.

We evaluate the forecasting performance of the nowcasts using two sub-periods: 2010Q1-2019Q4 (the "pre-Covid" period) and 2020Q1-2021Q4 (the "Covid" period). Due to the unavailability of data in the first of these, we can only evaluate the forecasting performance of nowcasts exploiting VAT information and real-time indicators during the shorter period, in which only eight observations are available.

As discussed in section 2, we use data available in real-time on consumption and investment growth. Forecasting errors are computed using the values in the 2022Q1 vintage of these two economic measures. Nowcasts are computed using real-time vintages of consumption and investment growth as suggested by Clements and Galvão (2013). This means that we regress $y_t^{t+1}$ on $y_{t-1}^{t+1}$ (if py=1, for t=py+1,…,T) where t+1 indicates a release published in the first quarter after the reference quarter. Our benchmark results are based on the first release, issued in the second month of t+1, but we also consider the case that the QNA estimate, published at the end of the t+1 quarter, is available.

Real-time data on the indicators are not available, although the monthly components of GVA are subject to revision. As we need first to link the real-time indicators to a monthly statistic before including them in the model, they will also not be available in real-time. For the future, however, one can keep the estimates in the linking equation fixed so that the approach can be applied in real time.

## 5 – An Analysis of Empirical Results

Our baseline empirical results are in Tables 2 and 3. They show how nowcasts using a combination of predictors of each class of indicators perform in comparison with an autoregressive model and the ONS initial estimate (that is, we consider $y_t^{t+1}$ as a "forecaster" of $y_t^{22Q1}$). Tables 2 and 3 use the first (middle-quarter) estimate of consumption and investment growth. Tables 4 and 5 check the robustness of this assumption and consider the QNA estimate (end of the quarter) of these variables instead. The baseline case is that L=0 in equation (1), but we also consider L=1 for monthly GVA indicators.

Two measures of forecasting performance are presented in the Tables. Tables 2 and 4 measure accuracy using the root mean squared forecast error (RMSFE). The RMSFE measures how far the forecast is from the actual value. The Tables also show the RMSFE of the MIDAS models with the class of indicators against the autoregressive model. Values for the Relative RMSFE smaller than 1 suggest that the MIDAS model performs better than the benchmark. Tables 3 and 5 show the biases, which are computed as the average difference between the value in the 2022Q1 vintage and the nowcast. The bias can be positive or negative, and a larger absolute value of the bias is worse. For the ONS first estimate, the bias is equivalent to the average of the data revision to the 2022Q1 vintage (Table 3). Similar interpretation can be made for the ONS QNA estimates in Table 5. Figures 3 to 5 show how the RMSFE changes across classes of indicators (GVA components and VAT).

***Investment Growth***

For forecasting investment growth in the pre-Covid period, we find in Table 2 that monthly sectoral GVA components have similar predictive power to traditional survey indicators, and neither adds much in terms of accuracy to the autoregressive model. Instead, in the Covid period (Table 2B), the predictive power of the traditional survey indicators deteriorates along with the autoregressive model – unsurprising, given the large economic fluctuations at the start of the pandemic. However, the sectoral monthly GVA indices, the VAT, and real-time indicators (vacancies data, in particular) can significantly improve on the autoregressive benchmark over the Covid period as they lead to RMSFEs smaller than the benchmark, as indicated in Table 2B. The sector GVA and VAT-based forecasts exhibit a smaller sized bias relative to the latest estimate than the first estimate for that period (Table 3B).

Amongst the monthly GVA series (assuming $L = 0$), the RMSFEs of individual sector UMIDAS investment forecasts ranged between 2.36 percentage points (Administrative Services) to 2.57pp (Hospitality) during the pre-Covid period (Figure 3A) and between 5.24pp (Manufacturing) and 25.53pp (Hospitality) during the Covid period (Figure 3B). These minima are below the minimum RMSFE for reported (including combined) forecasts in Table 3 (4% smaller for the pre-Covid and 24% for the Covid periods). Amongst the VAT indices during the Covid period, the lowest RMSFE was for the turnover index for 'Other services' (6.88pp), and the highest was the number of new VAT reporters in Electricity & Gas: see Figure 5.

***Consumption Growth***

For forecasting consumption growth during the pre-Covid evaluation period, we find that the autoregressive model and all other models have a smaller sized bias relative to the latest estimate than the first estimate. This result ceases to hold during the Covid period. Note, however, that the average bias is small in all cases.

As with investment, the nowcast errors for all indicators' classes are similar in accuracy during the pre-Covid period. Consumption nowcasts also deteriorate during the Covid period, with again the sectoral GVA indices and vacancies data having the smallest forecast errors, but (as for investment) all outperform the simple autoregressive model.

As indicated in Figure 4, the sector GVA models' RMSFEs lie between 0.79pp (Other Services) and 0.87pp (Hospitality) before the Covid period, and between 7.57pp (Education) and (Hospitality) during the Covid period for forecasting consumption growth. Amongst the VAT indices during the Covid period (Figure 5), the lowest RMSFE was for 'VAT new reporters: Construction' (9.31pp) and the highest RMSFE was for 'VAT new reporters: Agriculture, forestry and fishing' (14.10pp).

***Quarterly National Accounts estimate***

Tables 4 and 5 repeat the empirical exercise in Tables 2 and 3, but assuming that the real-time data for consumption and investment is from the Quarterly National Accounts (QNA) release. As expected, the RMSFEs for the second estimate are smaller than the first. In most cases, there is little difference in terms of the relative RMSFEs relative to the results in Tables 2 and 3. The principal exception is for investment during the Covid period, for which the second estimates were notably more accurate than the first (RMSFEs of 1.52 and 2.86, respectively), as a result of which the improvement yielded by the UMIDAS monthly elements were proportionately smaller over and above the accuracy of the early ONS estimate.

The finding that UMIDAS forecasts have a smaller, albeit not significantly smaller, bias for consumption in regular times than the ONS first estimate remains true when using the QNA estimate in real time.

***Removing AR term***

Tables 6A and 6B repeat, respectively, Tables 2B and 3B but with the autoregressive term removed (i.e. with py=0). The results for the Covid period only are shown here because the forecasting contribution of the AR term turned sharply negative during this period, most notably in 2020Q3, when a large fall in both consumption and investment during the first national lockdown was followed by a large rise.

The exclusion of the AR term significantly improves the accuracy of the MIDAS model over the Covid period. When forecasting investment growth, gains to the AR model benchmark are between 39% and 47%, and when forecasting consumption growth, they are between 73% and 79%. The best model for both variables is the one that combines the information of the 20 GVA components over two months of the quarter being targeted.

## 6 – Summary and Conclusions

For neither consumption nor investment was the UMIDAS model able to beat the ONS' first estimate when it comes to predicting the latest estimate. Nonetheless, there are suggestions that including some predictors in a UMIDAS framework may assist in improving early estimates under some circumstances. Monthly sectoral growth data and real-time data on vacancies would offer potential timely insights into both consumption and investment movements during volatile periods such as 2020-2021.

Figures 6 and 7 display the nowcasts evaluated earlier. The majority of nowcasts are around the unconditional mean. This suggests that predictors have limited information to predict such noisy time series, and that an agnostic nowcast may, on average, perform better.

During the Covid period, there is a clear divergence between the models whose predictors seem to be able to overcome the unhelpful autoregressive term. For investment in 2020Q3, for example, the real-time indicators and sectoral GVA indices pick up on the 'bounceback' while the autoregressive model, survey and VAT indices appear not to. For consumption, this is true to a lesser extent of the sectoral GVA forecasts in 2020Q3 and the real-time indicators in 2021Q2.

Looking at the individual elements in the sectoral GVA and VAT indices combined forecasts, it seems possible that services sectors, which may be broadly correlated with other sectors and, therefore, the rest of the economy – administration and 'other services', provide more information about macroeconomic fluctuations than others.

Future research in this area ought to investigate the optimal use or combinations of sector GVA and VAT diffusion index forecasts: particularly during volatile economic periods. It might be that by putting greater weight on sectors which are known to predict the macroeconomy more accurately, forecast accuracy can be improved. The relative strength of individual sectors' forecasts to the combination alternatives increases during the Covid period may partly reflect the sectoral nature of the Covid shock.

## 7- References

Carriero, A., Clark, T. and Marcellino, M. (2015). Real-Time Nowcasting with a Bayesian Mixed Frequency Model with Stochastic Volatility. *Journal of the Royal Statistical Society, Series A*, 2015 (October).

Carriero, A., Galvão, A. and Kapetanios, G. (2019). A comprehensive evaluation of macroeconomic forecasting methods. *International Journal of Forecasting*. 35: 1226-1239.

Clements, M. P. and Galvão, A. B. (2008). Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the United States, *Journal of Business and Economic Statistics*. 26: 546-554.

Clements, M. P. and Galvão, A. B. (2013). Real-time Forecasting of Inflation and Output Growth with Autoregressive Models in the Presence of Data Revisions. *Journal of Applied Econometrics*. 28: 458-477

Galvão, A., and Lopresto, M. (2020).Real-time Probabilistic Nowcasts of UK Quarterly GDP Growth using a Mixed-Frequency Bottom-up Approach. *National Institute Economic Review*, 254, R1-R11. doi:10.1017/nie.2020.37

Table 1: Characteristics of Revisions to UK Investment (Gross Fixed Capital Formation) and Consumption (Household Consumption) in volume terms. The revised value is observed 16 quarters after the reference quarter. Using real-time vintages from 1998Q3 to 2022Q1 with revisions for reference quarters from 1998Q2 to 2018Q1 (80 quarters).

| | Investment Revisions | | Consumption Revisions | |
|---|---|---|---|---|
| Initial Release: | mean | standard dev | mean | standard dev |
| 1( 1st, M2) | **0.55** | 2.22 | -0.01 | 0.56 |
| 1 (QNA) | 0.26 | 2.12 | 0.01 | 0.55 |
| 2 | 0.13 | 2.32 | 0.00 | 0.51 |
| 3 | 0.21 | 2.39 | 0.01 | 0.52 |
| 4 | 0.28 | 2.20 | 0.01 | 0.51 |
| 5 | 0.02 | 2.24 | -0.04 | 0.52 |
| 6 | 0.09 | 2.19 | -0.02 | 0.48 |
| 7 | -0.01 | 1.90 | 0.00 | 0.48 |
| 8 | 0.07 | 2.05 | 0.00 | 0.46 |
| 9 | 0.08 | 2.03 | -0.03 | 0.43 |
| 10 | 0.15 | 1.96 | -0.02 | 0.41 |
| 11 | 0.12 | 1.87 | -0.02 | 0.40 |
| 12 | 0.07 | 1.75 | -0.02 | 0.37 |
| 13 | 0.18 | 1.26 | 0.00 | 0.29 |
| 14 | 0.00 | 1.03 | -0.02 | 0.17 |
| 15 | 0.04 | 0.60 | 0.00 | 0.12 |

Note: The mean revisions is statistically equal to zero using standard t-test for all maturities except for the first release (1st or M2).

Figure 1: UK Aggregate Investment (Gross Fixed Capital Formation) Growth Estimates

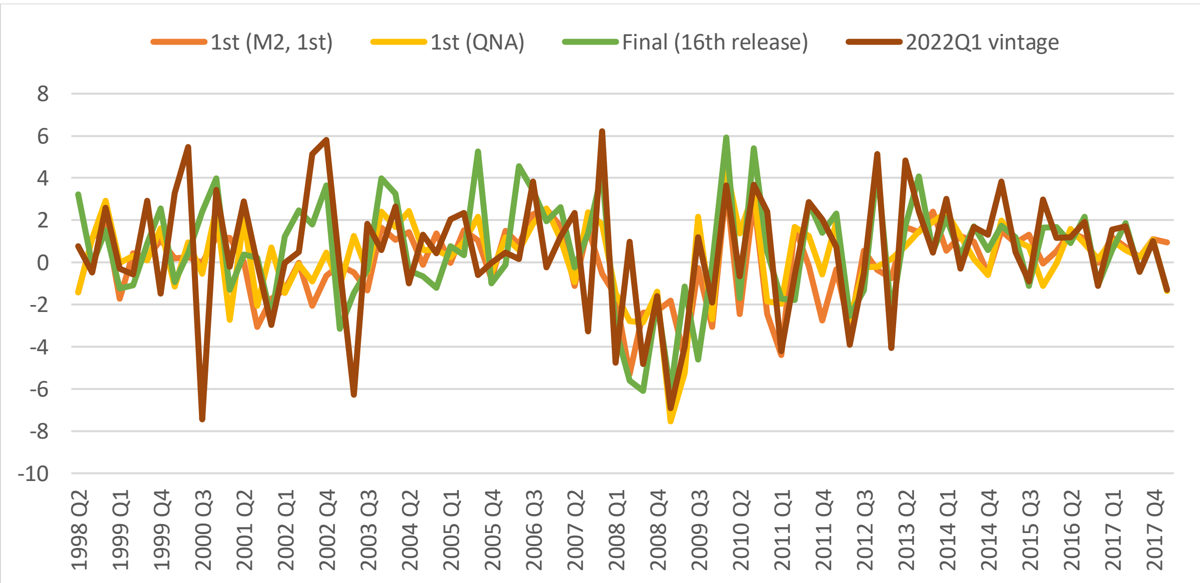
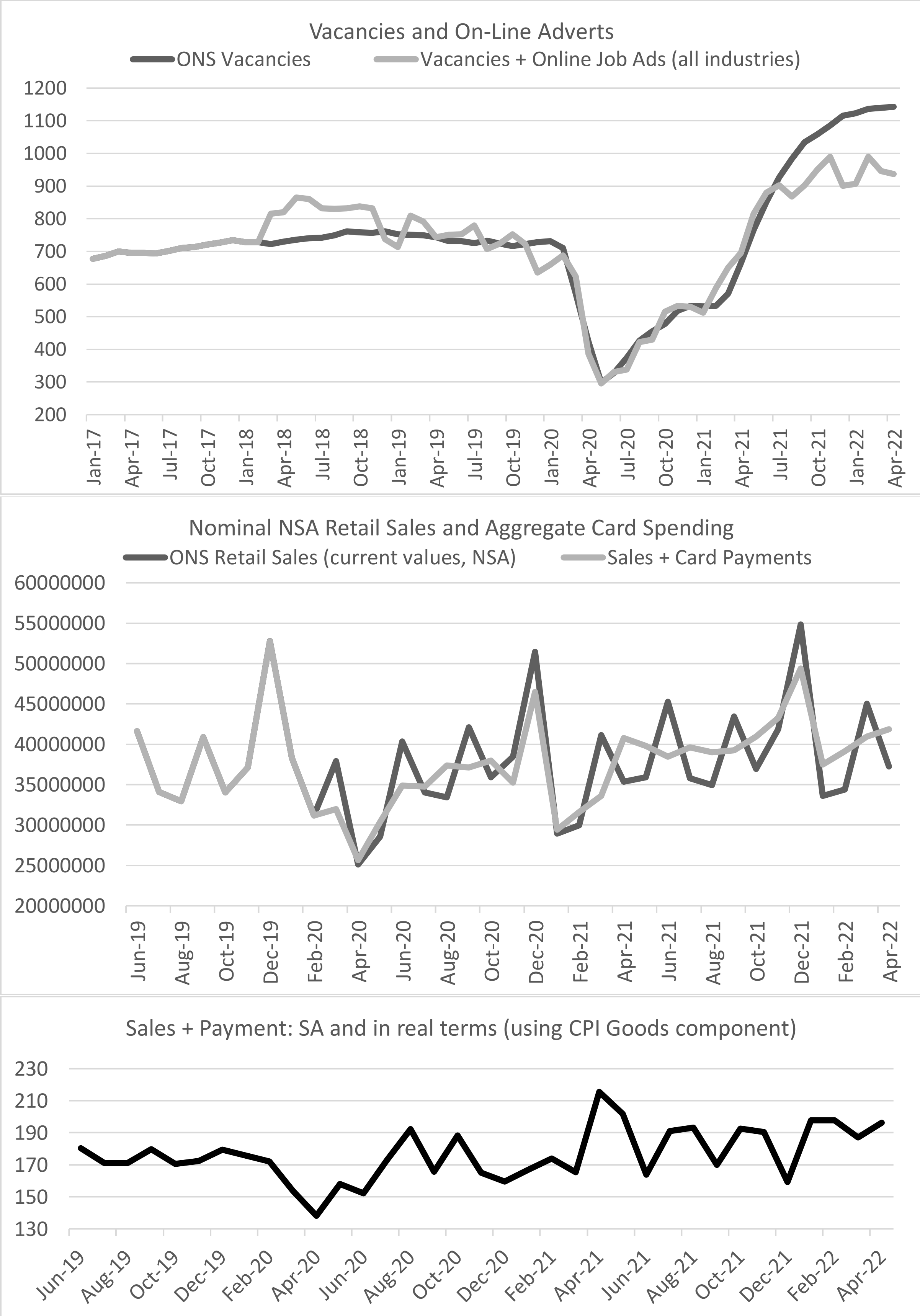


Figure 2: Monthly Series augmented with Weekly Real-Time Indicators.




Note: Data Augmentation starts in May 2018 for vacancies + online adverts time series, and from March 2020 for the sales + payment data.

Table 2: Evaluating Forecasts of Consumption and Investment over two out-of-sample periods: Accuracy measured by RMSFE. Forecasts computed using first estimates.

*Table 2A: Pre-Covid period (2010Q1-2019Q4)*

| | 2010Q1-2019Q4 | | Diebold-Mariano test p-stats | | Relative RMSFEs (AR only = 1) | |
|---|---|---|---|---|---|---|
| | Consumption | Investment | Consumption | Investment | Consumption | Investment |
| ONS first estimate | 0.69 | 2.04 | | | | |
| AR only | 0.81 | 2.44 | | | | |
| Monthly GVA (3mths) | 0.81 | 2.44 | 0.92 | 1.00 | 1.00 | 1.00 |
| Monthly GVA (2mths) | 0.81 | 2.44 | 0.66 | 0.94 | 1.00 | 1.00 |
| Survey indicators | 0.80 | 2.40 | 0.14 | 0.33 | 0.98 | 0.99 |

*Table 2B: Covid period (2020Q1-2021Q4)*

| | 2020Q1-2021Q4 | | Diebold-Mariano test p-stats | | Relative RMSFEs (AR only = 1) | |
|---|---|---|---|---|---|---|
| | Consumption | Investment | Consumption | Investment | Consumption | Investment |
| ONS first estimate | 1.45 | 2.86 | | | | |
| AR only | 35.65 | 11.30 | | | | |
| Vacancies | 9.16 | 6.18 | 0.31 | 0.30 | 0.26 | 0.55 |
| Card spending | 13.56 | 8.76 | 0.31 | 0.35 | 0.38 | 0.78 |
| Monthly GVA (3mths) | 11.74 | 6.89 | 0.31 | 0.26 | 0.33 | 0.61 |
| Monthly GVA (2mths) | 9.60 | 6.08 | 0.31 | 0.26 | 0.27 | 0.54 |
| Survey indicators | 12.62 | 10.04 | 0.31 | 0.25 | 0.35 | 0.89 |
| VAT | 11.96 | 9.06 | 0.31 | 0.29 | 0.34 | 0.80 |

*Note: Root mean squared forecast error (ratio to AR-only RMSFE in brackets) with Diebold-Mariano test p-statistics against null hypothesis of no forecasting accuracy difference from AR-only*

Table 3: Evaluating Forecasts of Consumption and Investment over two out-of-sample periods: Accuracy measured by Forecast Error Bias.

*Table 3A: Pre-Covid period*

| | 2010Q1-2019Q4 | |
|---|---|---|
| | Consumption | Investment |
| ONS first estimate | 0.10 | 0.53 |
| AR only | 0.03 | 0.94 |
| Monthly GVA (3mths) | 0.03 | 0.93 |
| Monthly GVA (2mths) | 0.02 | 0.94 |
| Survey indicators | 0.03 | 0.92 |

*Table 3B: Covid period*

| | 2020Q1-2021Q4 | |
|---|---|---|
| | Consumption | Investment |
| ONS first estimate | 0.54 | 1.32 |
| AR only | 11.93 | 2.16 |
| Vacancies | -2.17 | -3.81 |
| Card spending | 2.59 | -1.36 |
| Monthly GVA (3mths) | 1.65 | -0.79 |
| Monthly GVA (2mths) | 0.64 | -1.64 |
| Survey indicators | 2.34 | 0.85 |
| VAT | 1.87 | 0.25 |

Note: The bias is computed as the difference between the actual (value from the latest release) and the nowcast model combination indicated (or the ONS first estimate for the first row). The values are the average over the out-of-sample period indicated on the table heading. The bias can be positive or negative, and a larger absolute value of the bias is worse.

Table 4: Evaluating Forecasts of Consumption and Investment over two out-of-sample periods: Accuracy measured by RMSFE. Forecasts computed using QNA estimates.

*Table 4A: Pre-Covid period*

| | 2010Q1-2019Q4 | | | | | |
|---|---|---|---|---|---|---|
| | Consumption | Investment | | | | |
| ONS QNA | 0.66 | 1.95 | Diebold-Mariano test p-stats | | Relative RMSFEs (AR only = 1) | |
| AR only | 0.81 | 2.27 | Consumption | Investment | Consumption | Investment |
| Monthly GVA (3mths) | 0.81 | 2.27 | 0.56 | 0.91 | 1.00 | 1.00 |
| Monthly GVA (2mths) | 0.81 | 2.26 | 0.94 | 0.27 | 1.00 | 0.99 |
| Survey indicators | 0.80 | 2.28 | 0.17 | 0.75 | 0.99 | 1.00 |

Table 4B: Covid period

| | 2010Q1-2019Q4 | | | | | |
|---|---|---|---|---|---|---|
| | Consumption | Investment | | | | |
| ONS QNA | 0.66 | 1.95 | Diebold-Mariano test p-stats | | Relative RMSFEs (AR only = 1) | |
| AR only | 0.81 | 2.27 | Consumption | Investment | Consumption | Investment |
| Monthly GVA (3mths) | 0.81 | 2.27 | 0.56 | 0.91 | 1.00 | 1.00 |
| Monthly GVA (2mths) | 0.81 | 2.26 | 0.94 | 0.27 | 1.00 | 0.99 |
| Survey indicators | 0.80 | 2.28 | 0.17 | 0.75 | 0.99 | 1.00 |

*Note: Root mean squared forecast error (ratio to AR-only RMSFE in brackets) with Diebold-Mariano test p-statistics against null hypothesis of no forecasting accuracy difference from AR-only*

Table 5: Evaluating Forecasts of Consumption and Investment over two out-of-sample periods: Accuracy measured by Forecast Error Bias. Forecasts computed using QNA estimates.

Table 5A: Pre-Covid period

| | 2010Q1-2019Q4 | |
|---|---|---|
| | Consumption | Investment |
| ONS QNA | 0.10 | 0.32 |
| AR only | 0.05 | 0.59 |
| Monthly GVA (3mths) | 0.05 | 0.58 |
| Monthly GVA (2mths) | 0.05 | 0.58 |
| Survey indicators | 0.05 | 0.59 |

Table 5B: Covid period

| | 2020Q1-2021Q4 | |
|---|---|---|
| | Consumption | Investment |
| ONS QNA | 0.79 | 0.30 |
| AR only | 11.62 | 1.92 |
| Vacancies | -2.34 | -3.39 |
| Card spending | 2.40 | 0.04 |
| Monthly GVA (3mths) | 1.50 | -0.58 |
| Monthly GVA (2mths) | 0.50 | -1.23 |
| Survey indicators | 2.19 | 0.62 |
| VAT | 2.70 | 1.65 |

Note: See note to Table 3.

Table 6: Evaluating Forecasts of Consumption and Investment over Covid period without AR terms in the MIDAS Models:. Forecasts computed using first estimates.

Table 6A: Accuracy measured by RMSFE

| | 2020Q1-2021Q4 | | Diebold-Mariano test p-stats | | Relative RMSFEs (AR only = 1) | |
|---|---|---|---|---|---|---|
| | Consumption | Investment | Consumption | Investment | Consumption | Investment |
| ONS first estimate | 1.45 | 2.86 | | | | |
| AR only | 35.65 | 11.30 | | | | |
| Vacancies | 8.17 | 6.05 | 0.31 | 0.30 | 0.23 | 0.53 |
| Card spending | 8.46 | 7.80 | 0.31 | 0.34 | 0.24 | 0.69 |
| Monthly GVA (3mths) | 8.13 | 6.31 | 0.31 | 0.26 | 0.23 | 0.56 |
| Monthly GVA (2mths) | 7.56 | 5.94 | 0.31 | 0.26 | 0.21 | 0.53 |
| Survey indicators | 8.60 | 8.40 | 0.31 | 0.28 | 0.24 | 0.74 |
| VAT | 9.79 | 7.98 | 0.32 | 0.28 | 0.27 | 0.71 |

Table 6B: Accuracy measured by Forecast Error Bias.

| | 2020Q1-2021Q4 | |
|---|---|---|
| | Consumption | Investment |
| ONS first estimate | 0.54 | 1.32 |
| AR only | 11.93 | 2.16 |
| Vacancies | -3.72 | -3.77 |
| Card spending | -0.76 | -0.50 |
| Monthly GVA (3mths) | -1.57 | -1.57 |
| Monthly GVA (2mths) | -2.17 | -2.24 |
| Survey indicators | -0.89 | -0.63 |
| VAT | -0.71 | -0.98 |

Figure 3: Forecasting Investment Growth: Box plot of RMSFEs for individual monthly sectoral GVA models

Figure 3A: Pre-Covid period

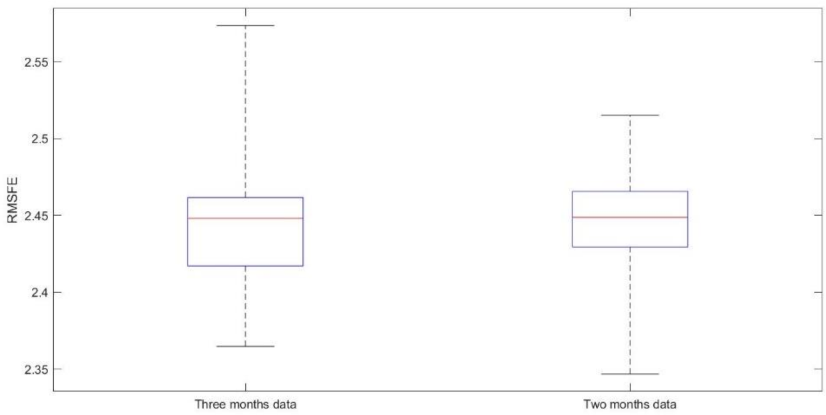



Figure 3B: Covid Period.

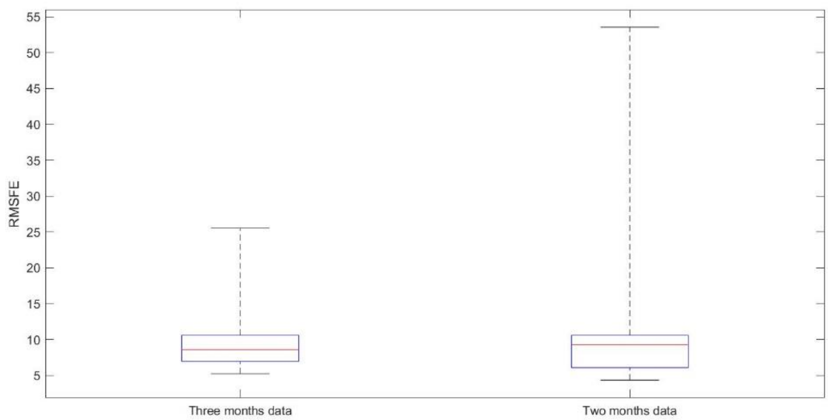


Figure 4: Forecasting Consumption Growth: Box plot of RMSFEs for individual monthly sectoral GVA models

Figure 4A: Pre-Covid Period

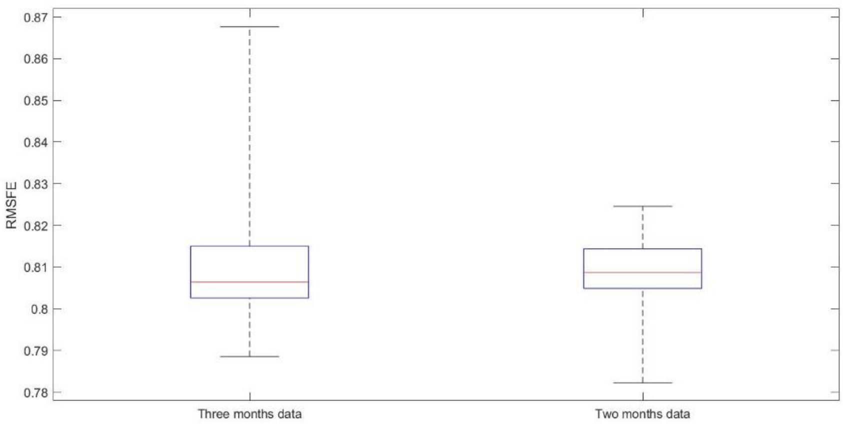



Figure 4B: Covid Period

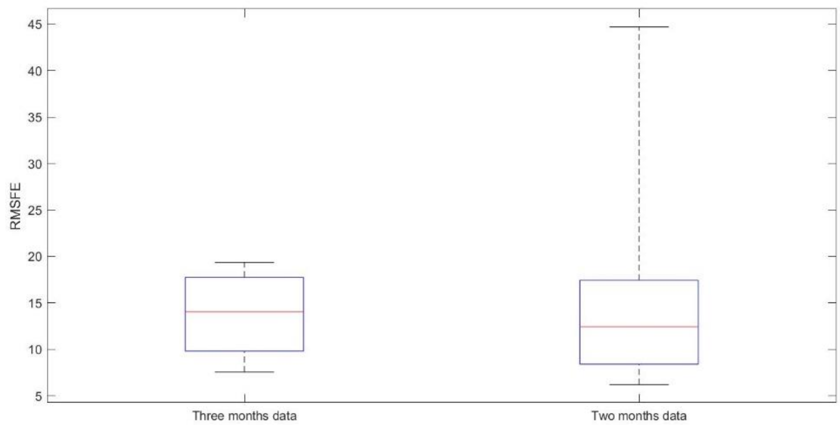


Figure 5: Forecasting Consumption and Investment Growth using VAT indices during the Covid Period.

Figure 5A: Investment

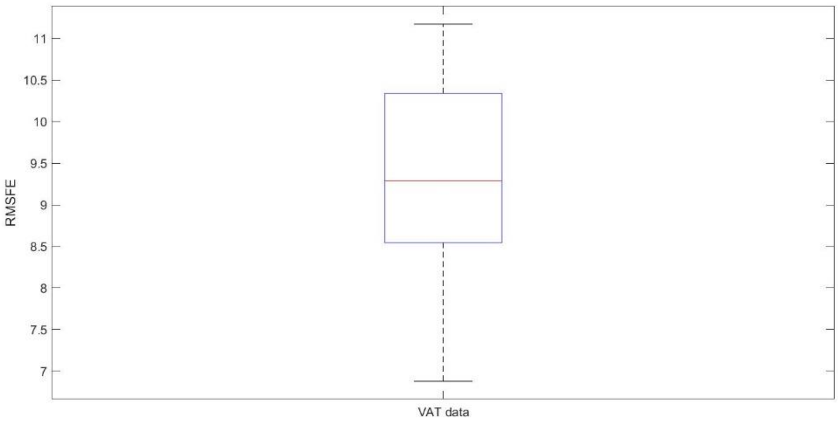



Figure 5B: Consumption

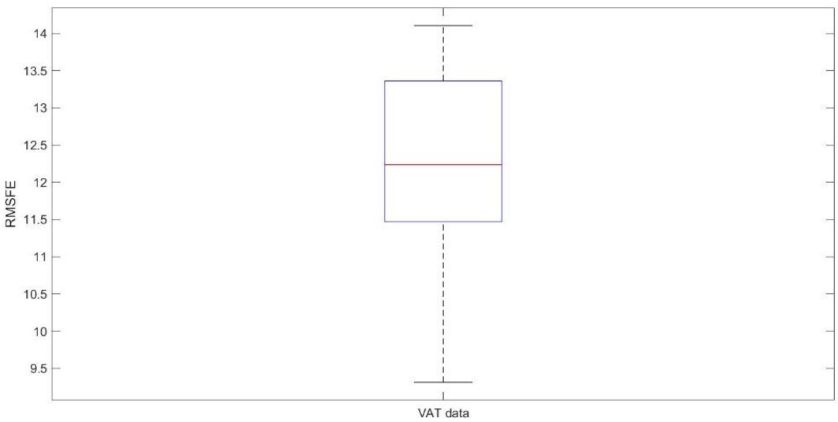


Figure 6: Investment Forecasts

Figure 6A: 2010Q1-2019Q4.

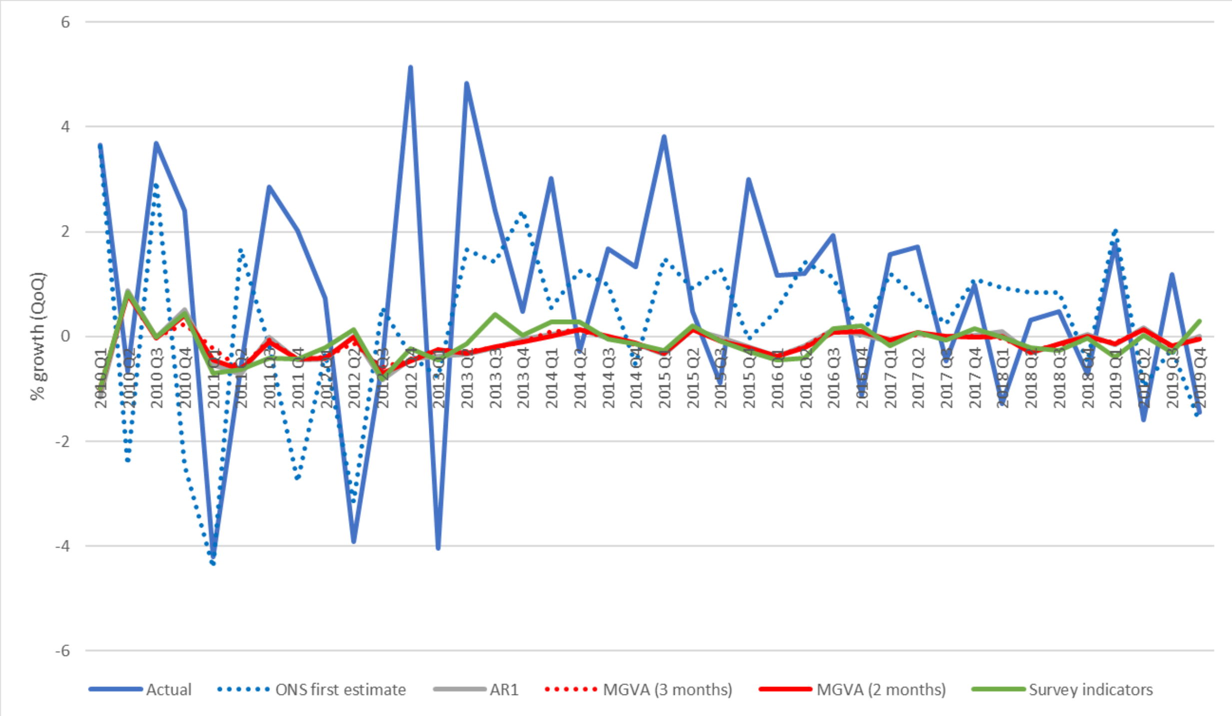



Figure 6B: 2020Q1-2021Q4

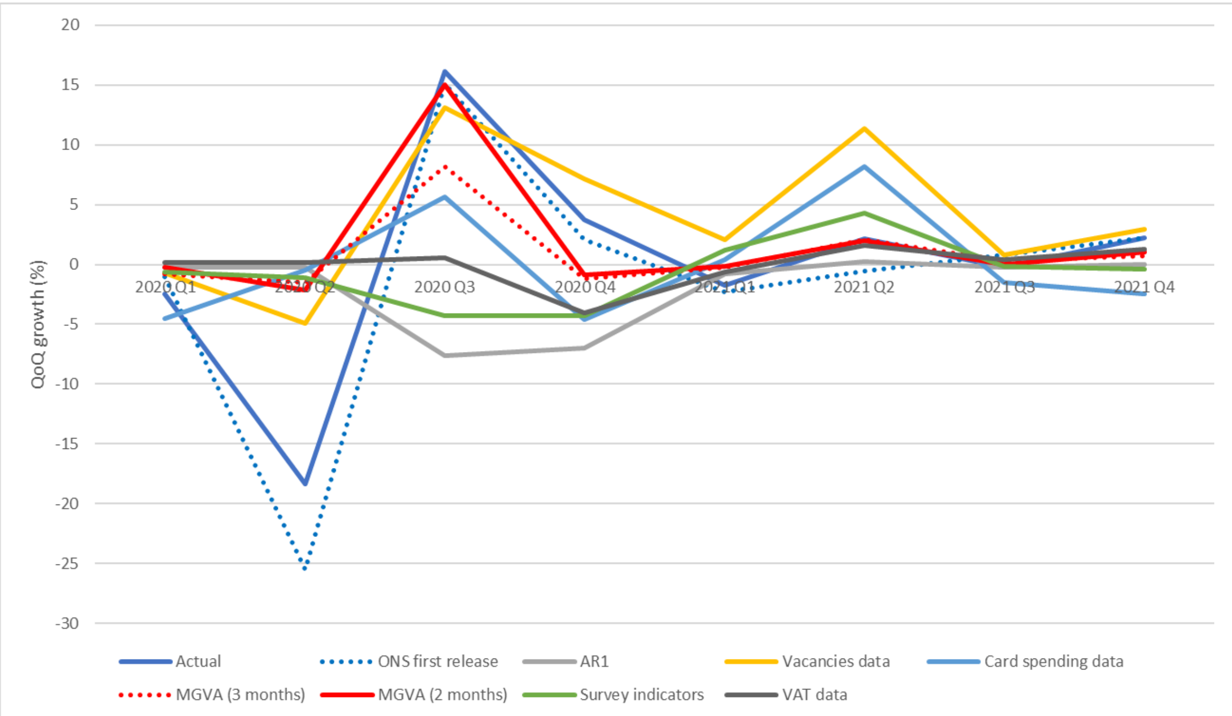


Figure 7: Consumption forecasts

Figure 7A: 2010Q1-2019Q4

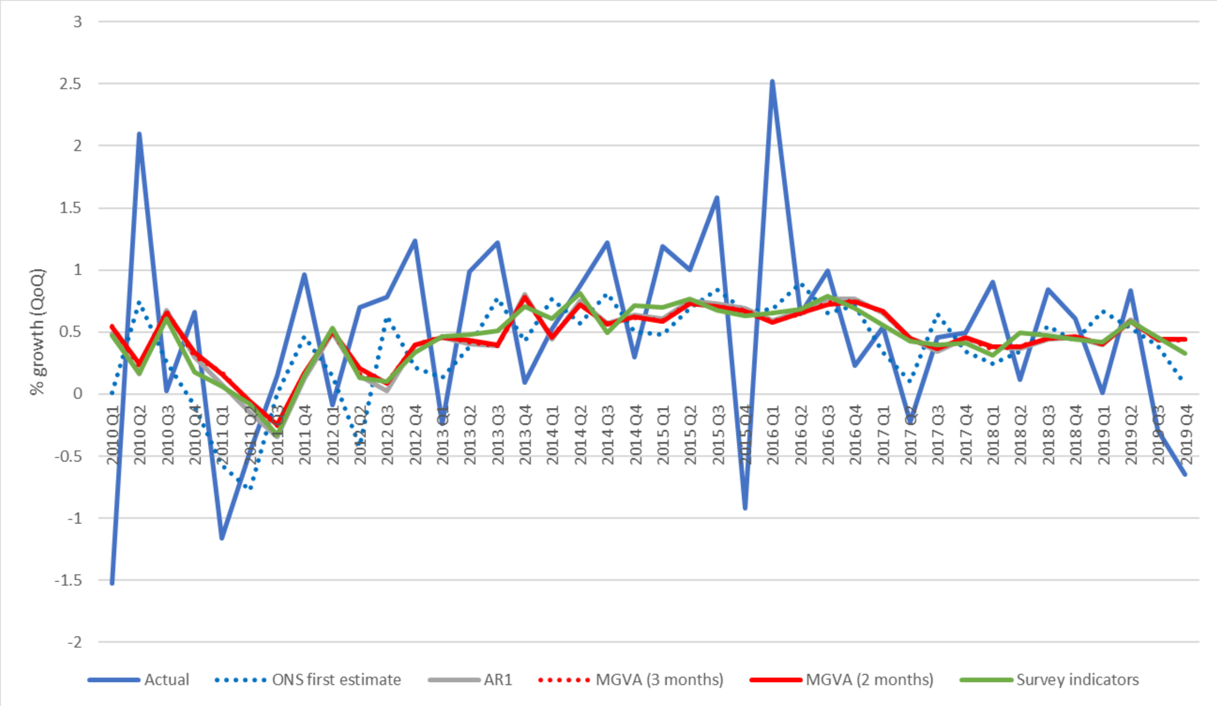



Figure 7B: 2020Q1-2021Q4