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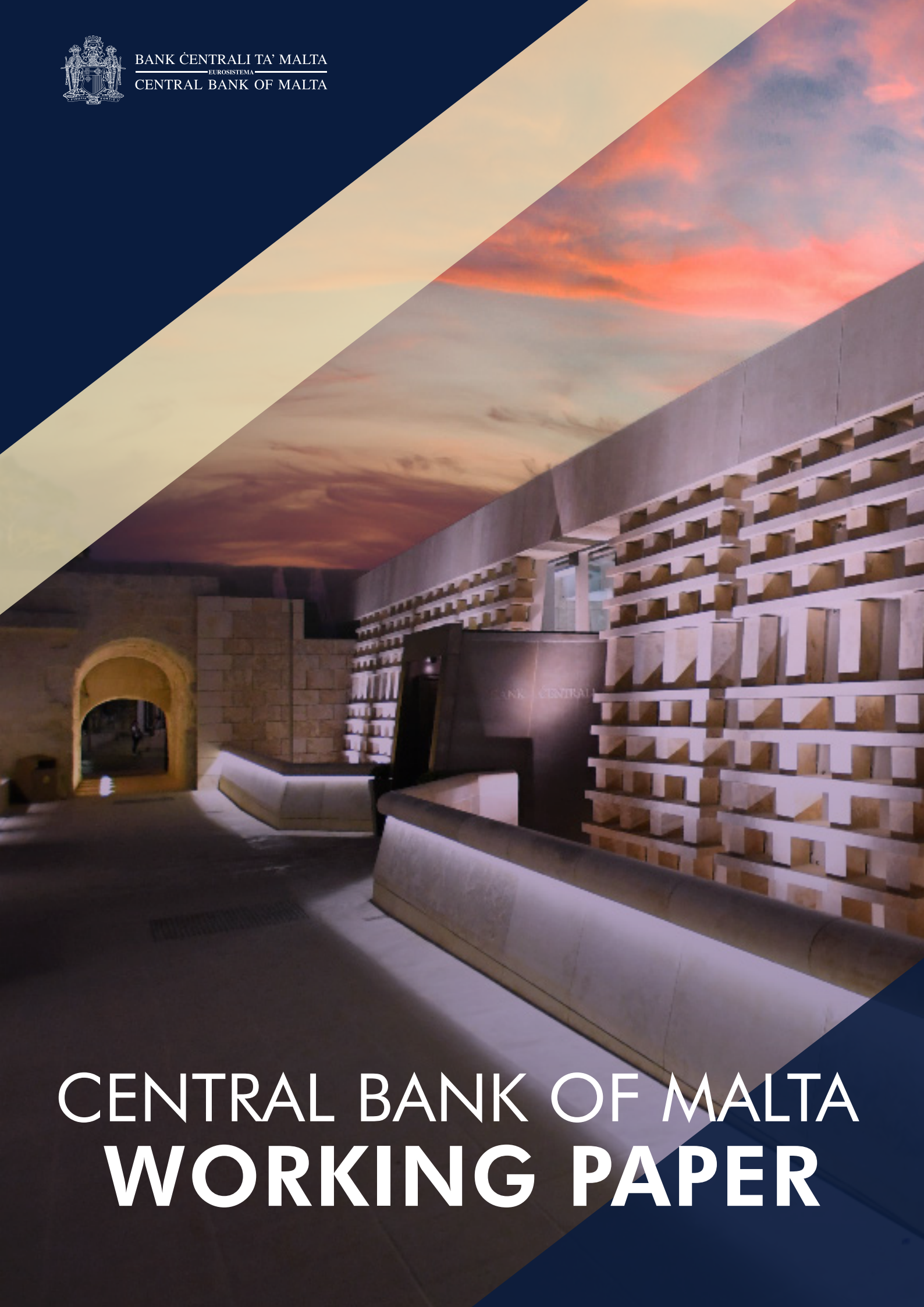

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Real-time Consideration of Systematic Patterns in Maltese GDP Data and Revisions*

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WP/03/2024

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Abstract

Economic policies are generally formulated on the basis of data available in real time, which might subsequently be revised. Implicitly, the possibility of data revisions creates an element of uncertainty around the very same data driving policy decisions. Given that such uncertainty could be mitigated if data revisions were predictable, this paper sets out to identify any systematic patterns in the Maltese 'Real GDP' data and underlying revisions which could in turn prove useful when making economic assessments in real time. These patterns are identified through the application of VAR econometric techniques applied in previous economic literature to model Malta's first-release output data alongside the revisions made within a maximum of two years from the date of first release. Systematic patterns in Maltese data are recorded, and in turn used to anticipate in real time the revisions that might be made upon the publication of future vintages. The analyses conducted in this paper show that the real-time consideration of these forecasts has the potential to improve the precision with which past, contemporaneous and (forecasted) future Maltese output data could be interpreted in real time. The uncertainty surrounding these forecasts is also aptly demonstrated through the use of simulation techniques, density functions, and event probability forecasts.

JEL Classification: C32; C53; D84; E37

Keywords: Real GDP; real-time; revisions; forecasts; uncertainty; Malta

Contents

1 Introduction

One of the main predicaments facing policymakers is that timely policy making relies heavily on the use of real-time data which might subsequently be revised. Such revisions may not be negligible but could indeed be pronounced to the extent that policy recommendations made in real time might not subsist under the revised data (Orphanides, 2001; Gerberding et al., 2004; Grigoli et al., 2015). Mankiw and Shapiro (1986) distinguish between two components of data revisions: "noise" and "news". The former originates from a perspective in which initial estimates are viewed as the true estimate measured with some error ("noise") that is corrected by subsequent data revisions. The other perspective views initial estimates as the best possible forecast of the true measure using all the data available at the time. These estimates would then be revised to reflect new data ("news") that eventually become available. As such data revisions hinder the ability of policymakers to make optimal judgments of the true economic performance in real time, literature has devoted considerable effort to better understand the statistical properties of data revisions, including their size and direction of any underlying bias (e.g. Van Walbeek (2006); Aruoba (2008); Rusnák (2013)). Others have also focused on the predictability of the revisions, with Faust et al. (2005) finding a predictable element in the data revisions of Italy, Japan, and the U.K.

Applied to a study of real-time estimates of the output gap, Clements and Galvão (2012) find that the reliability of such estimates could be enhanced by modelling data revisions through a "vintage-based" Vector Autoregressive (VAR) framework. Their work is in part inspired by that of Garratt et al. (2008) who jointly model the revision process of the 'output' series alongside the (growth in) first-release estimates of GDP within a VAR framework. Under this approach, any detectable patterns in the revisions are used to predict future revisions and thereby forecast post-revision output levels in real time. These and other similar analyses have been greatly facilitated by the construction of real-time macroeconomic datasets. Such datasets, which collate past data observed at each time period into a single dataset, are nowadays available for numerous countries, including the U.S. (Croushore and Stark, 2001), the U.K. (Castle and Ellis, 2002), Australia (Lee et al., 2012), and the Euro area bloc (Giannone et al., 2012). The wide breadth of information contained in these datasets has been exploited in numerous ways, such as to analyse the robustness of empirical findings to different data vintages (Croushore and Stark, 2003; Croushore and Evans, 2006), to identify business cycle turning points in real time (Chauvet and Piger, 2002), for *ex-post* policy evaluation (Gerberding et al., 2004), and in forecasting exercises

(Stark and Croushore, 2002; Koenig et al., 2003; Golinelli and Parigi, 2008).

This paper uses a recently-constructed, publicly-available real-time macroeconomic database for Malta to identify any patterns in Maltese 'Real GDP' data and the underlying revisions made within a maximum of two years from the date of first release. In the spirit of Garratt et al. (2008), this paper shows how the informative content of these patterns could be used in real time to obtain forecasts of the "true" Real GDP levels for past, contemporaneous and future periods, taking into account the expectations of future revisions formed on the basis of patterns observed from historical revisions. The advantages of considering these forecasts in real time are confirmed through a series of exercises which quantify the extent to which the anticipation of future revisions reduces the differences between the real-time data and that published in the latest vintage available - the latter assumed to contain the "true" data. Besides being particularly relevant for Malta, where revisions to GDP data have been found to be "sizeable" (Grech, 2018), these analyses are also highly innovative to the Maltese context and could be particularly useful to policymakers when interpreting economic data and taking decisions in real time. Moreover, as interest in wider real-time issues in Malta has also been largely lacking (with the exception of very few studies such as Ellul (2016)), this paper should also demonstrate the useful role that the real-time macroeconomic database recently constructed for Malta by Grech (2018) could have in advancing macroeconomic research on the island.

This study proceeds as follows. Section 2 describes the Maltese real-time macroeconomic database used throughout this work, before the methodology is described in detail in Section 3. The paper's analyses are found in Section 4, with the main conclusions, caveats, ideas for further research, and policy implications discussed in Section 5.

2 Maltese GDP Data

This paper makes use of a Maltese real-time macroeconomic database first compiled by the Central Bank of Malta in 2018 (Grech, 2018).[1] The database is made up of quarterly vintages of Maltese National Accounts data releases and incorporates 14 different series, comprising GDP and its principal components, all measured both in *real* and *nominal* values. The first vintage available is dated 2002Q1 and at the commencement date of this work the database included all successive quarterly vintages of data through to 2023Q1.[2] The quarterly data that makes

[1]The database compiled by the CBM is publicly available and can be accessed here: `https://www.centralbankmalta.org/site/excel/economics/real-time-macroeconomic-database.xlsx?revcount=4238&revcount=2873`.

[2]The cut-off point for this work is the 2023Q1 data vintage, although the database has since been extended with the publication of new vintages.

up each vintage are provided by Malta's National Statistics Office (NSO). Each vintage comprises historical data generally stretching back to 2000Q1, although for vintages prior to 2011 the sample size is generally shorter due to data unavailability. Each vintage t contains data points up to period $t-1$, reflecting a one-quarter delay in the release of Maltese GDP data. Table 1 provides a snippet of the real-time database in the case of the 'Real GDP' series, which is the one used throughout this work. The respective 2002Q1-2023Q1 vintages are represented in separate columns, whereas each row pertains to a particular data point. Constructed in this way, each row in the real-time database contains information about the way Real GDP data for the respective quarter has changed with the publication of new data vintages. The last data point in each column contains the first-release estimate of Real GDP for the respective quarter.[3]

Table 1: An Excerpt from the Maltese Real-Time Database: **Real GDP** (€000s)

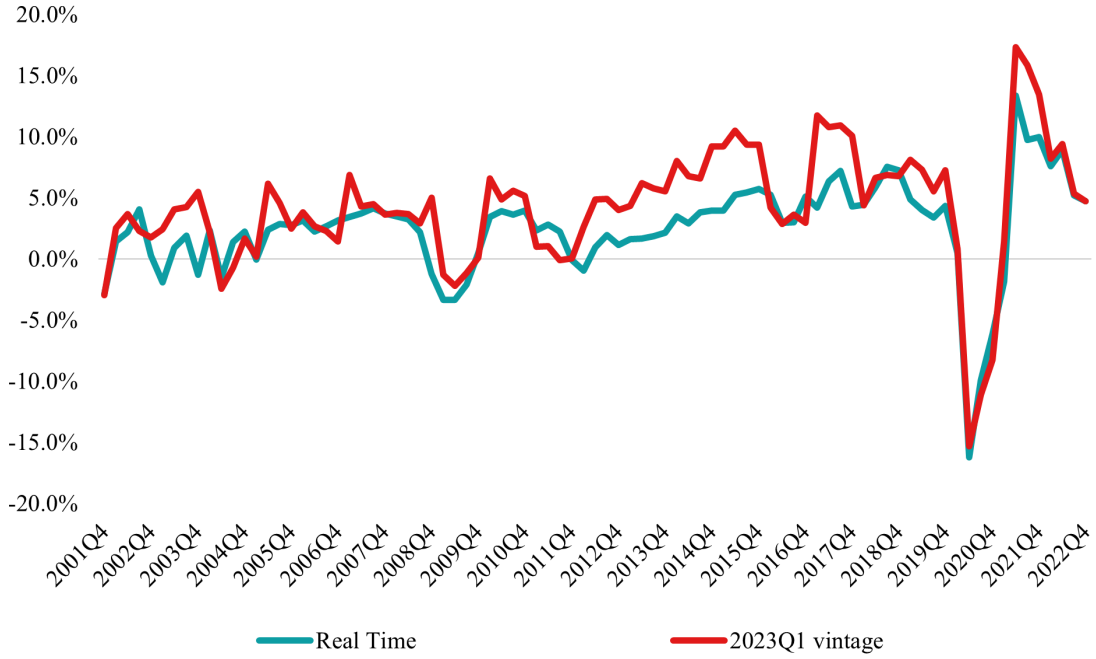
	Vintage								
	2002Q1	2002Q2	2002Q3	2002Q4	...	2022Q2	2022Q3	2022Q4	2023Q1
2000Q1	779,175	781,039	776,613	785,465	⋮	1,377,934	1,377,934	1,377,934	1,377,934
2000Q2	815,980	817,377	813,650	823,899	⋮	1,532,472	1,532,472	1,532,472	1,532,472
2000Q3	839,739	844,864	839,506	849,522	⋮	1,589,434	1,589,434	1,589,434	1,589,434
2000Q4	860,005	861,402	853,017	863,732	⋮	1,543,734	1,543,734	1,543,734	1,543,734
⋮					⋮	⋮	⋮	⋮	⋮
2022Q1						3,304,311	3,314,301	3,409,607	3,410,258
2022Q2							3,468,250	3,522,963	3,530,816
2022Q3								3,654,443	3,663,559
2022Q4									3,610,745

Source: CBM database using NSO data.
Note: The figures shown in this table are taken directly from the dataset constructed and maintained by the CBM, without any modifications described in the text.

One of the primary advantages of a real-time macroeconomic database is that it allows for an analysis of data revisions across different vintages. For instance, Figure 1 compares the annual growth rate in Malta's Real GDP as measured in real time (i.e. based on the first-release figure for the respective quarter) and from the vintage dated 2023Q1 (i.e. the last vintage considered in this work). While both series generally move in the same direction, significant discrepancies between the two are apparent. In fact, over the whole sample period, the difference between

[3]The GDP figures recorded in the dataset are not readily adjusted for seasonality, although some recent vintages comprising seasonally-adjusted data are separately available. For other vintages comprising seasonally-unadjusted data, this paper makes use of the X-13 seasonal adjustment tool to generate a complete seasonally-adjusted real-time dataset. The plausibility of this seasonal adjustment strategy is confirmed by comparing the X-13-generated seasonally-adjusted data to that made available by the NSO over vintages for which seasonally-adjusted data is readily available, achieving highly satisfactory results. More detail about the seasonal adjustment process can be obtained from the author upon request.

Figure 1: Annual Real GDP Growth Rate calculated in Real Time and from last (2023Q1) vintage available



Source: Author's calculations from the CBM database using NSO data.
Note: Calculations are based on the figures recorded in the dataset constructed and maintained by the CBM, without any modifications described in the text.

the first-release growth figure and the corresponding figure obtained from the 2023Q1 vintage averaged 2.2 percentage points (p.p.) in absolute terms. In some quarters, differences are even more pronounced. For example, whereas the 2017Q1 annual growth rate was first recorded at 4.2% in the 2017Q2 vintage, subsequent revisions to Real GDP data saw this being revised upwards to the 11.7% figure published in the latest 2023Q1 vintage.

Differences between real-time and final data are not solely due to routine revisions but may also be affected by other, "major" revisions. These may be of two types: either major *ad-hoc* revisions undertaken to ensure consistency with methodological or definitional changes, or periodical *benchmark* revisions made to regularly update GDP estimates (National Statistics Office, 2020). These large-scale revisions are typically announced by the statistical office in advance and are generally effected to the whole sample period covered by the specific vintage to ensure historical consistency with the new definitions and/or methodologies in place. On the other hand, routine revisions are typically effected either to reflect new information that would have come to light since previous releases or to correct any previous errors. Among the most significant benchmark revisions implemented during the years considered in this work, Real GDP previously measured on the basis of the 1995 European System of National Accounts (ESA-95)

started being measured according to ESA 2010 as of the 2014Q4 vintage. At the same time, measurement of Real GDP changed from one based on *constant base-year prices* to *chain linking* (Pace Ross et al., 2014; Grech, 2018). Another, and to date the latest, benchmark revision conducted by the NSO is reflected in the GDP data published in the 2020Q3 vintage, with revisions effected to all past Real GDP data from 2000Q1 onwards (National Statistics Office, 2020). Other somewhat pronounced revisions are also observed in the 2007Q2 and 2012Q4 vintages, although such revisions were not as significant as those undertaken in the 2014Q4 and 2020Q3 vintages.

Effected to the whole sample period covered by the specific vintage, benchmark revisions are discernible from a discrete shift in the GDP data found within the vintage characterised by the benchmark revision, relative to the previous vintage (i.e. the vintage just prior to the implementation of the benchmark revision). As a result, large-scale revisions somewhat limit the comparability of the raw data across vintages, with a particularly detrimental effect on revision analyses. While the 2014Q3 vintage was also available with data measured in line with ESA 2010 principles, and was therefore consistent with later vintages, the discrete shift in the GDP series resulting from the 2020Q3 benchmark revision is treated in line with a rescaling procedure discussed by Lee et al. (2012). In their work, they assume that the magnitude of a benchmark revision could be well-captured by an additive and multiplicative component. As such, whenever a benchmark revision is observed to have taken place, the (logarithm) Real GDP series following the benchmark revision is regressed against the series immediately preceding the benchmark revision, and an intercept. The estimated intercept and slope coefficient are then applied to the pre-revision series to ensure its consistent measurement with the post-revision series. Given the interest of this paper in revision analyses, the GDP series covered by earlier vintages are then modified to be measured consistently with later vintages by ensuring that the size of revisions between successive vintages remains identical (in % terms) to that found in the original seasonally-adjusted data.[4] Applied to all past Maltese vintages in succession, this process yields a seasonally adjusted dataset free of benchmark revisions to Real GDP data, with all vintages comprising data measured consistently with the latest vintage available. Any remaining revisions are interpreted solely as routine revisions.

[4]In practice, the data in the 2020Q3 vintage is regressed against that found in the 2020Q2 vintage, and an intercept. The additive and multiplicative factors are then applied to the 2020Q2 data vintage. The 2020Q1 vintage is then modified to be measured consistently with the following vintages in such a way that the revisions between the 2020Q1 and 2020Q2 vintages remain identical (in % terms) to those found in the original, seasonally adjusted data.

3 Methodology

The substantial revisions to Maltese Real GDP data that are illustrated in Section 2 and in the work of Grech (2018) highlight the potential for real-time economic assessments to benefit from internalising any information that can be extracted from historical data vintages. This follows from the observation that if at any point in time, say, future revisions to Real GDP data could be forecasted on the basis of some historical patterns in the revisions, the policymaker could, in real time, consider the forecasts of the post-revision GDP levels instead of the data still undergoing routine revisions. By the same argument, data-based GDP forecasts of future periods need not be based only on the data as published in one particular vintage but may also consider the revisions that might be made in the subsequent vintages following the initial release of data. By considering the forecasts of the post-revision levels in real time, this approach could be particularly helpful in making economic assessments that are less prone to revisions, while at the same time ensure that these are based on a wider breadth of information available to the policymaker.

In what follows, this paper seeks to demonstrate how real-time assessments of Maltese GDP data could be ameliorated by considering any data revisions that might subsequently be made in the publication of future vintages. By means of notation, the (logarithm) output level, y, for period $t-j$ as published in the vintage t is denoted by ${}_{t}y_{t-j}$, where $j > 0$ in reflection of the one-quarter delay in the publication of Maltese GDP data. The period-t vintage is denoted by Y_t and includes a time-series of output levels for a sample period ending at $t-1$, i.e. $Y_t = \{{}_{t}y_1, ..., {}_{t}y_{t-3}, {}_{t}y_{t-2}, {}_{t}y_{t-1}\}$. All the information available in period t is captured by an information set Ω_t, which includes the whole collection of vintages available for period t and earlier, i.e. $\Omega_t = \{Y_1, ..., Y_{t-2}, Y_{t-1}, Y_t\}$. A tabular illustration of these notations within the context of a real-time database is provided in Table 2.

To identify the presence of *systematic* patterns in Maltese Real GDP data, this paper adopts the framework introduced by Garratt et al. (2008, 2009) (henceforth also referred to as GLMS), and later by Lee et al. (2012).[5] This exercise involves the joint modelling of the growth in first-release output levels and the relevant revisions that at any point in time t, the researcher knows that the statistical office had made in earlier vintages. Specified in this way, such framework could identify any systematic patterns in the historical data published by the statistical office. As

[5]Following GLMS, the term 'systematic' will be used to refer to revisions which contain some pattern or informational content. This does not exclude the possibility of revisions to earlier periods, but these will be assumed to be "random" or "non-meaningful".

Table 2: An Illustration of the Real-Time Database

		Vintage							
	$\dots$	Y_{t-3}	Y_{t-2}	Y_{t-1}	Y_t	Y_{t+1}	Y_{t+2}	Y_{t+3}	$\dots$
$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$t-7$	$\ddots$	${}_{t-3}y_{t-7}$	${}_{t-2}y_{t-7}$	${}_{t-1}y_{t-7}$	${}_{t}y_{t-7}$	${}_{t+1}y_{t-7}$	${}_{t+2}y_{t-7}$	${}_{t+3}y_{t-7}$	$\cdots$
$t-6$	$\ddots$	${}_{t-3}y_{t-6}$	${}_{t-2}y_{t-6}$	${}_{t-1}y_{t-6}$	${}_{t}y_{t-6}$	${}_{t+1}y_{t-6}$	${}_{t+2}y_{t-6}$	${}_{t+3}y_{t-6}$	$\cdots$
$t-5$	$\ddots$	${}_{t-3}y_{t-5}$	${}_{t-2}y_{t-5}$	${}_{t-1}y_{t-5}$	${}_{t}y_{t-5}$	${}_{t+1}y_{t-5}$	${}_{t+2}y_{t-5}$	${}_{t+3}y_{t-5}$	$\cdots$
$t-4$		${}_{t-3}y_{t-4}$	${}_{t-2}y_{t-4}$	${}_{t-1}y_{t-4}$	${}_{t}y_{t-4}$	${}_{t+1}y_{t-4}$	${}_{t+2}y_{t-4}$	${}_{t+3}y_{t-4}$	$\cdots$
$t-3$			${}_{t-2}y_{t-3}$	${}_{t-1}y_{t-3}$	${}_{t}y_{t-3}$	${}_{t+1}y_{t-3}$	${}_{t+2}y_{t-3}$	${}_{t+3}y_{t-3}$	$\cdots$
$t-2$				${}_{t-1}y_{t-2}$	${}_{t}y_{t-2}$	${}_{t+1}y_{t-2}$	${}_{t+2}y_{t-2}$	${}_{t+3}y_{t-2}$	$\cdots$
$t-1$					${}_{t}y_{t-1}$	${}_{t+1}y_{t-1}$	${}_{t+2}y_{t-1}$	${}_{t+3}y_{t-1}$	$\cdots$
t						${}_{t+1}y_{t}$	${}_{t+2}y_{t}$	${}_{t+3}y_{t}$	$\cdots$
$t+1$							${}_{t+2}y_{t+1}$	${}_{t+3}y_{t+1}$	$\cdots$
$t+2$								${}_{t+3}y_{t+2}$	$\cdots$
$\vdots$									$\ddots$
Information set		Ω_{t-3}	Ω_{t-2}	Ω_{t-1}	Ω_t	Ω_{t+1}	Ω_{t+2}	Ω_{t+3}	

an example of the mechanics of the GLMS approach, assume that in every vintage published, the NSO makes systematic revisions to the output data for the q most recent periods. Specifically, vintage t sees the first release of the GDP figure for the $t-1$ quarter, denoted by ${}_{t}y_{t-1}$, while the published output data still undergoing routine revisions, namely ${}_{t}y_{t-2}$, ${}_{t}y_{t-3}$,...,${}_{t}y_{t-q-1}$ are revised from the previous vintage. Output levels for the earlier periods ${}_{t}y_{t-q-2}$, ${}_{t}y_{t-q-3}$, ${}_{t}y_{t-q-4}$... are assumed to remain reliable from previous data vintages. Under the plausible assumptions that actual output data is $I(1)$ and the revisions are stationary, this information can be modelled by the following VAR(p) framework, which models the growth in first-release output levels alongside the first q revisions considered to contain some informative content:[6]

$$\mathbf{x_t} = \mathbf{a} - \sum_{\mathbf{i=1}}^{\mathbf{p}} \mathbf{B_i x_{t-i}} + \mathbf{e_t} \tag{1}$$

for $t = \{1, 2, ..., T\}$ and where $\mathbf{x_t}$ captures all the information on growth in first-release Maltese output levels (${}_{t}y_{t-1} - {}_{t-1}y_{t-2}$) and the q revisions made by the statistical authority when publishing vintage t (i.e. ${}_{t}y_{t-2} - {}_{t-1}y_{t-2}, ..., {}_{t}y_{t-q-1} - {}_{t-1}y_{t-q-1}$). Represented in matrix form as in (2), this framework models the historical information about the growth in first-release output levels available in Ω_t (row 1) alongside the information about the q systematic revisions made

[6]Unit root tests confirm that: (1) first-release Maltese output levels are first-difference stationary, and (2) data revisions are stationary. Results are not presented for brevity reasons but will be made available by the author upon request.

to past output data at each time t in rows 2 to $(q+1)$.

$$\begin{bmatrix} {}_{t}y_{t-1} - {}_{t-1}y_{t-2} \\ {}_{t}y_{t-2} - {}_{t-1}y_{t-2} \\ {}_{t}y_{t-3} - {}_{t-1}y_{t-3} \\ {}_{t}y_{t-4} - {}_{t-1}y_{t-4} \\ \vdots \\ {}_{t}y_{t-q-1} - {}_{t-1}y_{t-q-1} \end{bmatrix} = a - B_1 \begin{bmatrix} {}_{t-1}y_{t-2} - {}_{t-2}y_{t-3} \\ {}_{t-1}y_{t-3} - {}_{t-2}y_{t-3} \\ {}_{t-1}y_{t-4} - {}_{t-2}y_{t-4} \\ {}_{t-1}y_{t-5} - {}_{t-2}y_{t-5} \\ \vdots \\ {}_{t-1}y_{t-q-2} - {}_{t-2}y_{t-q-2} \end{bmatrix} - ... - B_p \begin{bmatrix} {}_{t-p}y_{t-p-1} - {}_{t-p-1}y_{t-p-2} \\ {}_{t-p}y_{t-p-2} - {}_{t-p-1}y_{t-p-2} \\ {}_{t-p}y_{t-p-3} - {}_{t-p-1}y_{t-p-3} \\ {}_{t-p}y_{t-p-4} - {}_{t-p-1}y_{t-p-4} \\ \vdots \\ {}_{t-p}y_{t-p-q-1} - {}_{t-p-1}y_{t-p-q-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \xi_{1t} \\ \xi_{2t} \\ \xi_{3t} \\ \vdots \\ \xi_{qt} \end{bmatrix} \tag{2}$$

If this model suggests that historical publications of first-release Real GDP data and revisions contain a predictable element, this information could be used to forecast the growth in first-release estimates and the revisions that might be made in the upcoming vintages, assuming that such patterns persist over the forecast horizon. In turn, these forecasts could easily be employed to generate the forecasts of how Real GDP levels might look like once they have been routinely revised by the NSO. To continue with the general example outlined above, if the first q revisions to GDP data made by the NSO historically contain some identifiable patterns, real-time economic judgements could potentially be ameliorated by replacing the published data ${}_{t}y_{t-1}$, ${}_{t}y_{t-2}$,..., ${}_{t}y_{t-q}$ with forecasts of their respective level following the q^{th} revision. As an example, suppose that Real GDP estimates are revised three times following the initial release (i.e. $q = 3$.) Therefore, in vintage t, ${}_{t}y_{t-1}$ is replaced by $\widehat{{}_{t+3}y_{t-1}}|\Omega_t$, ${}_{t}y_{t-2}$ is replaced by $\widehat{{}_{t+2}y_{t-2}}|\Omega_t$ and ${}_{t}y_{t-3}$ is replaced by $\widehat{{}_{t+1}y_{t-3}}|\Omega_t$. The value ${}_{t}y_{t-4}$ is not replaced by its post-revision forecast as it would have undergone the 3^{rd} revision in vintage t.[7] Vintage t would now be comprised of the post-revision output levels from the earliest period in the sample up to $t-q-1$ and forecasts of post-revision levels for the period $t-q$ forwards. The same framework could also be extended to obtain forecasts of the post-revision Real GDP levels for future periods beyond the final data point covered by the vintage.

4 Exploiting Patterns in Real GDP Data and Revisions

The GLMS framework outlined in equation (1) is now used to identify and subsequently exploit any patterns that exist in the Maltese Real GDP data, particularly in the underlying revisions.

[7] This argument is illustrated in more detail in Appendix A.

The usefulness of this framework to the Maltese context is determined by the degree to which it helps improve real-time assessments of past, contemporaneous and (forecasted) future Real GDP data made on the basis of the vintages dated 2011Q2-2022Q4.[8] In turn, these improvements will be judged by the extent to which the application of this modelling framework approximates the data available in real time within the respective vintages to the levels published by the NSO in the 2023Q1 vintage. The decision to consider the 2023Q1 vintage as a "benchmark" rests on the reasonable assumption that the data published in this vintage are, at the time of writing, the best estimates of the "true" Real GDP data. Because the first vintage in the real-time macroeconomic database is the 2002Q1 vintage and the first information about growth in first release and data revisions is thus derived from the 2002Q2 vintage, considering the 2011Q2 vintage as the starting point of the analyses ensures that any patterns in the first-release GDP growth and revisions data are identified on a minimum of 37 data points (when based on Ω_{2011Q2}). This number rises progressively as the model is estimated recursively on all subsequent information sets Ω_t; $t = \{2011Q3, 2011Q4, ...2022Q4\}$, reaching a total of 83 data points when based on Ω_{2022Q4}. Hence, the model is recursively estimated 47 times, each time using the information contained within each information set on historical growth in first-release output and data revisions to obtain forecasts of the post-q^{th} revision output levels for past, contemporaneous and future periods. On the other hand, the terminal point is taken to be the 2022Q4 (rather than the 2023Q1) vintage so as to be able to compare the forecasts of the post-q^{th} revision based on Ω_{2022Q4} to the Real GDP levels actually published in the 2023Q1 vintage.

4.1 Identifying systematic patterns in Maltese Real GDP data

The use of the GLMS framework to identify systematic patterns in Real GDP data necessitates a decision about the VAR order p and the revision horizon q, where the latter should ideally reflect the actual number of revisions which contain a systematic pattern. Starting with the arguments surrounding the choice of q, Grech (2018) finds the revision process in Malta to be rather lengthy. Combined with the fact that the Maltese real-time database is in turn relatively short and suffers from some missing data, this makes it practically impossible to incorporate all the revisions into the framework.[9] Therefore this paper starts with an exercise seeking to determine the benefits of this framework when considering any patterns in the (maximum) first

[8] In view of the likelihood of policymakers to be most interested in the Real GDP data for the most recent period, analyses start from the 2011Q2 vintage so as to be able to analyse the contemporaneous Real GDP data from 2011Q1 onwards.

[9] As an example of the missing data which would be necessary, the 2004Q2 vintage provides data for a sample period beginning in 2003Q1. This implies that this vintage contains information only about four revisions.

four revisions (i.e. $q = 4$) only, implicitly assuming that later revisions contain no systematic patterns. This notwithstanding, given that the first four revisions might not adequately capture the whole revision process, it is not entirely certain that the model with four revisions is necessarily preferable to models with a shorter revision horizon, thereby introducing an element of uncertainty as to which model specification should be considered. As a result, this paper follows Garratt et al. (2009) and estimates different specifications of the model at each recursion. The respective specifications differ in the number of revisions assumed to contain systematic patterns and their respective estimation is an effective way to deal with the presence of model uncertainty. The respective specifications estimated at each recursion are denoted by M_t^q, where $q = \{1, ..., 4\}$, and where M_t^1 represents a specification in which only the first revision is considered to contain systematic patterns and M_t^4 considers four revisions to the first-release GDP data. Each of the four specifications is estimated at each recursion on the basis of the information available in Ω_t and are respectively used to generate the forecasts of output levels following the q^{th} revision. Turning to the choice regarding lag length, each model is stipulated to be of maximum order 4 (i.e. $p = 4$). Such choices of p and q imply that each equation of the most complex model, M_t^4, includes a maximum of $[1 + (4 \times 5)] = 21$ parameters.[10] The risk of over-parameterisation is reduced by excluding lags from a particular specification which at that specific recursive estimation of the model do not carry any statistically significant coefficients in any of the equations of the model. This notwithstanding, the final choice regarding lag length always ensures that the VAR model satisfies the stability condition and there is no serial correlation in the residuals.[11]

Insights about the presence of any systematic patterns in Maltese Real GDP data can be inferred from the econometric results of the respective 47 recursions over which each specification is estimated. Table B.1 in Appendix B presents the results derived from the last recursion of the M_t^4 specification, estimated using all the relevant information available in Ω_{2022Q4}. The findings illustrate the presence of important informative content ingrained within the first four revisions to Maltese Real GDP data, as evidenced by the statistical significance of some of the explanatory variables in the regressions explaining the respective revisions (columns 2-5). Similar systematic patterns in the data are detected in all the other recursive estimations of the M_t^4 model and in all recursive estimations of $M_t^1 - M_t^3$, convincingly demonstrating the presence of important

[10] It is also recognised that the Great Recession and, for recent recursions, COVID-19, will have had large effects on the first-release growth data and (potentially) the revisions data. As a result, the respective equations in the VAR at each recursion include also dummy variables representing these events. Moreover, each equation includes a dummy variable for 2016Q4 to capture a relatively major revision effected in this vintage to the sample period 2014Q1 onwards.

[11] At each recursion and for each specification, the VAR model satisfies the stability condition (all roots lie inside the unit circle), while tests are also conducted to ensure no presence of serial correlation (LM test). Satisfactory results are obtained throughout, which are not presented for conciseness but will be made available by the author upon request.

information content that could be extracted from the historical revisions to Maltese Real GDP data.[12] At the same time, results also demonstrate the complexity of the revision process in Malta, with the third and fourth lags of the third and fourth revisions still showing significantly, for example. As a result, considering only the first four revisions to the initial release of data is unlikely to adequately capture the revision process.

In an attempt to incorporate information content from a larger number of revisions, while concurrently maintaining model parsimony despite data limitations, the GLMS framework outlined in equation (1) is adjusted so as to model the growth in first-release Maltese output levels $({}_{t}y_{t-1} - {}_{t-1}y_{t-2})$ alongside a weighted average of the first 8 revisions to Maltese Real GDP data made by the NSO at each time t (i.e. $\sum_{q=2}^{q=9} W_{q-1}({}_{t}y_{t-q} - {}_{t-1}y_{t-q})$). That is, at every vintage t, a weighted average of the revisions made to the most recent eight GDP figures in the vintage is constructed, with each of the eight revisions assigned a weight $W \in \{0, 1\}$ based on the historical average magnitude of the respective revision.[13] While this model - denoted by $\bar{M}_t^8$ - is unlikely to yield forecasts of individual revisions as accurate as the original framework explained in equation (1), it has the advantage that, in the presence of data constraints, can straightforwardly consider more revisions without adding a large number of variables to the VAR. Similar to the other four M_t^q specifications, this model is estimated recursively on the Maltese data available in each information set Ω_t; $t = \{2011Q2, 2011Q3, ...2022Q4\}$ to identify patterns in the (weighted average of the) first eight revisions. Because the sample period covered by some vintages prior to 2005Q2 is not lengthy enough to capture the 8^{th} revision, this specification is estimated on a minimum of 25 data points (when based on Ω_{2011Q2}), rising progressively to 71 when moving recursively through the dataset up to Ω_{2022Q4}.[14]

Table 3 presents the results derived from estimating specification $\bar{M}_t^8$ on the basis of all the information available in Ω_{2022Q4}. Similar to results from the estimation of $M_t^1 - M_t^4$, statistically significant patterns in revisions to Real GDP data (column 2) are also detected when considering this modification of the GLMS framework. In fact, results presented in Table 3 show that the average revision made in vintage t to the Real GDP level of the eight most recent quarters is negatively related to the average revision made in earlier vintages. By way of example, the magnitude of this average revision as made in each vintage t falls by 0.490 units following a 1

[12] Results for the other recursive estimations can be obtained from the author upon request.

[13] As an example of this approach in practice, suppose that upon the publication of the 2023Q1 vintage, it is calculated that over all the previous vintages, each of the first eight revisions to GDP levels averaged 2% in absolute terms. Then, in this scenario, a weighted average of the first eight revisions made in the 2023Q1 vintage is constructed, with each of these revisions weighted equally by 0.125 in this case. Further information about this process and the weight assigned to each revision made in each vintage is provided in Appendix C.

[14] A similar exercise was conducted assuming equal weights for each of the eight revisions made in each vintage. All results presented henceforth remain qualitatively similar.

Table 3: VAR Model of First-Release Real GDP Growth and Weighted Average of Eight Data Revisions: 2006Q2-2022Q4

	Dependent Variable	
	${}_{t}y_{t-1} - {}_{t-1}y_{t-2}$	$\sum_{q=2}^{q=9} W_{q-1}({}_{t}y_{t-q} - {}_{t-1}y_{t-q})$
Intercept	0.010^{***}	0.006^{***}
	(0.003)	(0.001)
${}_{t-1}y_{t-2} - {}_{t-2}y_{t-3}$	0.341^{***}	0.184^{***}
	(0.133)	(0.067)
${}_{t-2}y_{t-3} - {}_{t-3}y_{t-4}$	-0.051	0.055
	(0.087)	(0.044)
${}_{t-3}y_{t-4} - {}_{t-4}y_{t-5}$	0.123	0.148^{***}
	(0.082)	(0.041)
${}_{t-4}y_{t-5} - {}_{t-5}y_{t-6}$	0.132	0.034
	(0.086)	(0.043)
$\sum_{q=2}^{q=9} W_{q-1}({}_{t-1}y_{t-q-1} - {}_{t-2}y_{t-q-1})$	-0.409^{*}	-0.490^{***}
	(0.245)	(0.123)
$\sum_{q=2}^{q=9} W_{q-1}({}_{t-2}y_{t-q-2} - {}_{t-3}y_{t-q-2})$	-0.216	-0.417^{***}
	(0.235)	(0.119)
$\sum_{q=2}^{q=9} W_{q-1}({}_{t-3}y_{t-q-3} - {}_{t-4}y_{t-q-3})$	-0.037	-0.326^{***}
	(0.228)	(0.115)
$\sum_{q=2}^{q=9} W_{q-1}({}_{t-4}y_{t-q-4} - {}_{t-5}y_{t-q-4})$	-0.169	-0.292^{***}
	(0.222)	(0.112)
Observations	67	67
R^2	0.765	0.599
Recession Dummy	✓	
2016Q4 Vintage Dummy	✓	✓
COVID-19 Dummies	✓	✓
	Post-estimation tests	
SC	0.805	
VAR Stability	✓	

Source: Author's calculations.
Notes: * significant at 10% level ** significant at 5% level *** significant at 1% level. Standard errors are shown in brackets. Post-estimation tests refer to the p-values calculated from tests of serial correlation (SC) and confirmation that the VAR satisfies the stability condition. All equations include a dummy variable for the 2016Q4 vintage and two dummies pertaining to the economic downturn and upturn associated with the COVID-19 pandemic, while the equation explaining the growth in first-release GDP data includes a dummy variable covering the Great Recession period as described in the text. This dummy proved statistically insignificant in the equations explaining the weighted-average revision and was thus omitted.

unit increase in the size of the revisions made in vintage $t-1$.[15] This coefficient declines as the number of lags increases, suggesting that the average revision made in vintage t is mostly affected by the revisions made in vintage $t-1$, and least affected by the revisions made in the $t-4$ vintage. Results also indicate that the average revision made in vintage t is positively related to the growth in first-release data published in vintages $t-1$ and $t-3$. These systematic patterns in the data revisions lend further credence to the potential benefits of using this modelling approach to improve the economic assessments made in real time.

4.2 The use of systematic patterns in Maltese Real GDP data

Having detected systematic patterns in the revisions to Maltese Real GDP data, we now proceed to examine the benefits from considering this additional information in real time. As a first exercise, this paper examines the extent to which consideration of potential future revisions could help in better interpreting the first-release Real GDP estimates published in the vintages

[15]This does not mean that GDP levels are revised downwards but solely that the *size* of the revision declines.

dated 2011Q2-2022Q4, corresponding to the period 2011Q1-2022Q3. In other words, this exercise seeks to determine the extent to which the initial estimates of Real GDP levels for the period 2011Q1-2022Q3 could be better interpreted in real time by anticipating and considering the revisions expected to be made in vintages to be published in the future. The benefits of using the forecasts generated by models $M_t^1 - \bar{M}_t^8$ in real time are assessed by the extent to which the mean absolute revision (MAR) and root mean squared error (RMSE) statistics between the initial release and the GDP level published in the $T = 2023Q1$ vintage improve when using these forecasts in real time instead of the initial release value. The general expressions denoting the calculation of the MAR and RMSE are provided in equations (3) and (4). The relevance of the respective model specifications is also judged by the proportion of quarters in which the anticipated sign of the revision to initial releases concurs with the actual sign of the revision between the actual initial data release and the data recorded in the 2023Q1 vintage. As already stated, this analysis primarily considers the initial Real GDP estimates for the period 2011Q1-2022Q3, but is also conducted over the 2011Q1-2017Q4 period (i.e. 2011Q2-2018Q1 vintages) to only cover quarters for which Real GDP data had already been fully revised in the 2023Q1 vintage.

Mean Absolute Revision (MAR) between ${}_T y_{t-1}$ and $\widehat{{}_{t+q}y_{t-1}}|\Omega_t$ for model M_t^q:

$$MAR_{\widehat{t+q},T} = \frac{1}{T}\sum_{t=1}^{T}|{}_T y_{t-1} - \widehat{{}_{t+q}y_{t-1}}|\Omega_t| \tag{3}$$

Root Mean Squared Error (RMSE) for model M_t^q:

$$RMSE_{\widehat{t+q},T} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}({}_T y_{t-1} - \widehat{{}_{t+q}y_{t-1}}|\Omega_t)^2} \tag{4}$$

Results presented in Table 4 show that without considering any patterns in revisions, initial Real GDP releases for 2011Q1-2022Q3 would have on average been revised by 6.1% in absolute terms.[16] The magnitude of this revision declines when considering patterns in data revisions. In fact, under models M_t^1-M_t^4, the average size of the revision (in absolute terms) to initial Real GDP levels drops by $2.6\% - 13.4\%$ depending on the specification considered, with an inverse relationship generally observed between the MAR and the number of revisions considered. A particularly pronounced improvement is recorded when considering revisions made within the first two years from the date of first release. In fact, considering the forecasts of the post-8^{th}

[16]Recall that these statistics are based on a dataset free of benchmark revisions to Real GDP data as described in Section 2.

Table 4: Real-time prediction of first-release Real GDP levels data ($_t y_{t-1}$) following the revision process

***Actual GDP level*: 2023Q1 vintage (V)**

	2011Q2-2022Q4 V			2011Q2-2018Q1 V		
	MAR (%)	RMSE	% agreement on revision sign	MAR (%)	RMSE	% agreement on revision sign
$_T y_{t-1} - {}_t y_{t-1}$	6.086	0.067		7.746	0.081	
M_t^1: $(_T y_{t-1} - \widehat{{}_{t+1} y_{t-1}} \mid \Omega_t)$	5.930 [−2.7%]	0.067 [+0.1%]	74.5	7.577 [−2.1%]	0.080 [−1.1%]	71.4
M_t^2: $(_T y_{t-1} - \widehat{{}_{t+2} y_{t-1}} \mid \Omega_t)$	5.900 [−2.6%]	0.068 [+1.0%]	72.3	7.310 [−4.9%]	0.078 [−3.8%]	71.4
M_t^3: $(_T y_{t-1} - \widehat{{}_{t+3} y_{t-1}} \mid \Omega_t)$	5.551 [−8.5%]	0.065 [−3.6%]	74.5	6.790 [−11.9%]	0.073 [−9.4%]	75.0
M_t^4: $(_T y_{t-1} - \widehat{{}_{t+4} y_{t-1}} \mid \Omega_t)$	5.312 [−13.4%]	0.063 [−6.5%]	78.7	6.820 [−11.7%]	0.074 [−8.9%]	78.6
$\bar{M}_t^8$: $(_T y_{t-1} - \widehat{{}_{t+8} y_{t-1}} \mid \Omega_t)$	3.519 [−41.4%]	0.043 [−36.1%]	95.7	4.684 [−38.4%]	0.053 [−34.5%]	96.4

Source: Author's calculations.
Notes: MAR represents the mean of absolute revisions; whereas RMSE denotes the root mean squared error. The actual revisions recorded from the dataset described in Section 2 are calculated as the difference between the actual GDP level published in the latest vintage available ($_T y_{t-1}$) and $_t y_{t-1}$, where $T = 2023Q1$. For model M_t^q, revisions are calculated as the difference between $_T y_{t-1}$ and $\widehat{{}_{t+q} y_{t-1}} \mid \Omega_t$, in each case considering the q revisions expected to be made in later vintages. The % agreement on revision sign represents the share of quarters in which the real-time prediction of the direction of the revision by model M_t^q matches the actual revision sign calculated between the initial release and the corresponding 2023Q1 vintage level from the dataset. Figures in square brackets underneath the MAR and RMSE statistics show the % improvement in the respective measure, relative to that recorded for the published data.

revision generated by model $\bar{M}_t^8$ instead of the initial release sees the eventual size of revision drop by around 2.5 p.p. in absolute terms, representing an improvement of 41.4% in the MAR. With the exception of the models considering just one or two revisions (and for the full sample only), consideration of the revision process in real time also has a positive effect on the RMSE, with model $\bar{M}_t^8$ again bringing about the most pronounced improvement (36.1%) in this criterion over the whole period. These encouraging results, which hold also when the forecasts are judged against the fully-revised GDP data for the 2011Q1-2017Q4 period only, are largely driven by the decent ability of the respective models to correctly predict the sign of the revision in real time. In fact the individual models, all of which are fairly simple in the sense of considering only few revisions, are able to correctly predict the sign of subsequent revisions in real time in at least 70% of the quarters considered. Again, model $\bar{M}_t^8$ appears to be the best individual model to predict the revision's sign, correctly doing so in more than 95% of the quarters considered. The good performance of model $\bar{M}_t^8$ in relation to the other individual models is well in line with *a priori* expectations given the longer revision horizon that it considers, and suggests further that the respective specifications of models $M_t^1 - M_t^4$ potentially fail to capture important information contained within later revisions. Nonetheless, these results begin to suggest that

the consideration of patterns in the revisions could greatly improve the ability to make better economic judgements in real time, particularly when considering revisions made over longer horizons.

Having confirmed that the real-time consideration of the first eight data revisions could elicit a significantly better understanding of the "true" Real GDP value of first-release estimates (i.e. period ${}_{t}y_{t-1}$), the preferred individual specification $\bar{M}_t^8$ is next used to check for any improvements in the real-time assessments of Real GDP data for historical periods which have already undergone some, but not all, revisions.[17] Starting with data that in vintage t would have already been revised once, i.e. ${}_{t}y_{t-2}$, model $\bar{M}_t^8$ is used to determine any improvements in the understanding of the true GDP level for period $t-2$ from using the forecast $\widehat{{}_{t+7}y_{t-2}}|\Omega_t$ in place of ${}_{t}y_{t-2}$. A similar exercise is conducted on data that in the publication of vintage t would have undergone a maximum of one year worth of revisions, namely ${}_{t}y_{t-3}$, ${}_{t}y_{t-4}$, and ${}_{t}y_{t-5}$. Results are presented in Table 5 and show that considering a horizon of eight revisions, even if these revisions are straightforwardly included in the model as a weighted average, also helps improve significantly the understanding of the "true" Real GDP levels for historical periods in real time. As an example, for Real GDP data that would have undergone the first revision in vintage t, model $\bar{M}_t^8$ is found to yield forecasts of the "true" Real GDP level for period $t-2$ that reduce the size of subsequent revisions by more than 40% in the full sample and by 38% in the fully-revised data covered by the 2011Q2-2018Q1 vintages. Similar inferences could be made when observing the improvements in the RMSE and, again, these results are largely driven by the ability of model $\bar{M}_t^8$ to correctly anticipate the sign of future revisions in real time. Qualitatively similar results in terms of MAR and RMSE are attained when using model $\bar{M}_t^8$ to forecast the post-revision values of ${}_{t}y_{t-3}$, ${}_{t}y_{t-4}$, and ${}_{t}y_{t-5}$. However, it is also noted that the extent of improvement declines as the number of revisions already made increases. In fact, the least pronounced improvement derived from estimating model $\bar{M}_t^8$ is observed when trying to predict the post-revision Real GDP level of ${}_{t}y_{t-5}$ (although the improvement still approaches 30%). This trend reflects the likelihood that Real GDP levels which at any point in time have already undergone a set number of revisions, are likely to be closer to their "true" level than values that have undergone fewer revisions or have even just been published. This necessarily implies that the relevance of applying the GLMS framework to forecast future revisions in real time should be greater for the more recent periods.

Besides their interest in having more accurate information about historical and contempo-

[17] This exercise is also conducted using models $M_t^1 - M_t^4$ but, similar to results in Table 4, these specifications yield improvements that are much less pronounced than those brought about by model $\bar{M}_t^8$.

Table 5: Real-time prediction of historical Real GDP levels data following the revision process

A. Prediction of Real GDP data already revised once ($_{t}y_{t-2}$)

	2011Q2-2022Q4 V			2011Q2-2018Q1 V		
	MAR (%)	RMSE	% agreement on revision sign	MAR (%)	RMSE	% agreement on revision sign
$_{T}y_{t-2} - {}_{t}y_{t-2}$	5.573	0.061		6.921	0.073	
$\bar{M}_t^8$: $({}_{T}y_{t-2} - \widehat{{}_{t+7}y_{t-2}}\|\Omega_t)$	3.201 [−41.9%]	0.040 [−35.0%]	95.7	4.292 [−37.8%]	0.048 [−33.6%]	92.9

B. Prediction of Real GDP data already revised twice ($_{t}y_{t-3}$)

	2011Q2-2022Q4 V			2011Q2-2018Q1 V		
	MAR (%)	RMSE	% agreement on revision sign	MAR (%)	RMSE	% agreement on revision sign
$_{T}y_{t-3} - {}_{t}y_{t-3}$	4.996	0.056		6.263	0.067	
$\bar{M}_t^8$: $({}_{T}y_{t-3} - \widehat{{}_{t+6}y_{t-3}}\|\Omega_t)$	3.050 [−37.6%]	0.038 [−31.5%]	93.6	3.967 [−34.5%]	0.046 [−30.8%]	96.4

C. Prediction of Real GDP data already revised three times ($_{t}y_{t-4}$)

	2011Q2-2022Q4 V			2011Q2-2018Q1 V		
	MAR (%)	RMSE	% agreement on revision sign	MAR (%)	RMSE	% agreement on revision sign
$_{T}y_{t-4} - {}_{t}y_{t-4}$	4.538	0.051		5.599	0.060	
$\bar{M}_t^8$: $({}_{T}y_{t-4} - \widehat{{}_{t+5}y_{t-4}}\|\Omega_t)$	2.872 [−35.8%]	0.037 [−28.1%]	91.5	3.640 [−33.6%]	0.043 [−28.4%]	92.9

D. Prediction of Real GDP data already revised four times ($_{t}y_{t-5}$)

	2011Q2-2022Q4 V			2011Q2-2018Q1 V		
	MAR (%)	RMSE	% agreement on revision sign	MAR (%)	RMSE	% agreement on revision sign
$_{T}y_{t-5} - {}_{t}y_{t-5}$	4.100	0.048		5.207	0.057	
$\bar{M}_t^8$: $({}_{T}y_{t-5} - \widehat{{}_{t+4}y_{t-5}}\|\Omega_t)$	2.856 [−29.0%]	0.036 [−23.7%]	91.5	3.659 [−28.7%]	0.043 [−23.3%]	89.3

Source: Author's calculations.
Notes: MAR represents the mean of absolute revisions, whereas RMSE denotes the root mean squared error. The % agreement on revision sign represent the share of quarters in which the real-time prediction of the sign of the GDP data revision by model $\bar{M}_t^8$ matches the sign of the actual revision observed from the database. Figures in square brackets underneath the MAR and RMSE statistics show the % improvement in the respective measure, relative to that recorded for the published data.

raneous Real GDP data, policymakers might also be interested in forecasting future Real GDP data. Data-based forecasts of Real GDP for future periods could easily be obtained through some autoregressive (AR) process applied to the most recent data vintage published, without considering the ways in which some data points contained within the vintage might subsequently be revised. In modelling the growth in first-release data alongside data revisions, the GLMS framework could also be used to obtain forecasts of Real GDP levels for future periods that inherently consider the anticipated revisions that might eventually be made to the initial estimates. To determine the advantages of the GLMS framework in this respect, models $M_t^1 - \bar{M}_t^8$ are estimated to obtain the one-step ahead forecast of the Real GDP level for the period spanning 2011Q2-2022Q4, recursively based on the information set $\Omega_t; t = \{2011Q2, ..., 2022Q4\}$. The usefulness of employing the GLMS framework for this purpose is judged by the way these forecasts compare to the actual Real GDP levels published in the 2023Q1 vintage, relative to the forecasts generated in real time via an AR process.[18] Results presented in Table 6 yield evidence that, relative to forecasts generated via a simple AR process, the real-time consideration of subsequent data revisions generates one-step ahead forecasts that better approximate the actual Real GDP levels, while at the same time be subject to smaller revisions. Model $\bar{M}_t^8$ is again deemed to be the preferable specification, reducing the size of subsequent revisions by more than 30% and improving the RMSFE by more than 25%, relative to the forecasts generated by the AR process. The improvements under both these indicators are even more pronounced when considering the (fully revised) 2011Q2-2017Q4 sample period, further supporting the relevance of considering anticipated revisions to make better assessments of Maltese Real GDP data in real time.

The analyses conducted thus far deal with Real GDP *levels* and consistently provide evidence that $\bar{M}_t^8$, being a model which considers revisions taking place within the first two years from the date of first release, is able to generate better forecasts of post-revision output levels, relative to the other individual models that consider shorter revision horizons. One other advantage of considering a model which assumes a rather lengthy revision process is that such models could potentially also be used to make better judgments regarding the "true" year-on-year growth rate of Real GDP data in real time. For instance, because model $\bar{M}_t^8$ considers all the Real GDP data between ${}_ty_{t-8}$ to ${}_ty_{t-1}$ to still be undergoing routine revisions, it can straightforwardly be used to (indirectly) generate forecasts of the "true" annual growth rates in real time. As an

[18]The AR process is originally applied to the 'output growth' series $({}_ty_{t-1} - {}_ty_{t-2})$ in view of the $I(1)$ nature of the Real GDP series. With the exception of the 2017Q3-2020Q2 vintages, where an AR(8) is necessary to ensure serially uncorrelated errors, forecasts based on all other vintages are generated through an AR process of order 4. Tests for serial correlation are conducted via the Breusch-Godfrey (B-G) LM test and for all vintages, the null hypothesis of "no serial correlation" under the B-G test could not be rejected.

Table 6: Real-time prediction of one-step-ahead forecasts of Real GDP levels

***Actual GDP level*: 2023Q1 vintage**

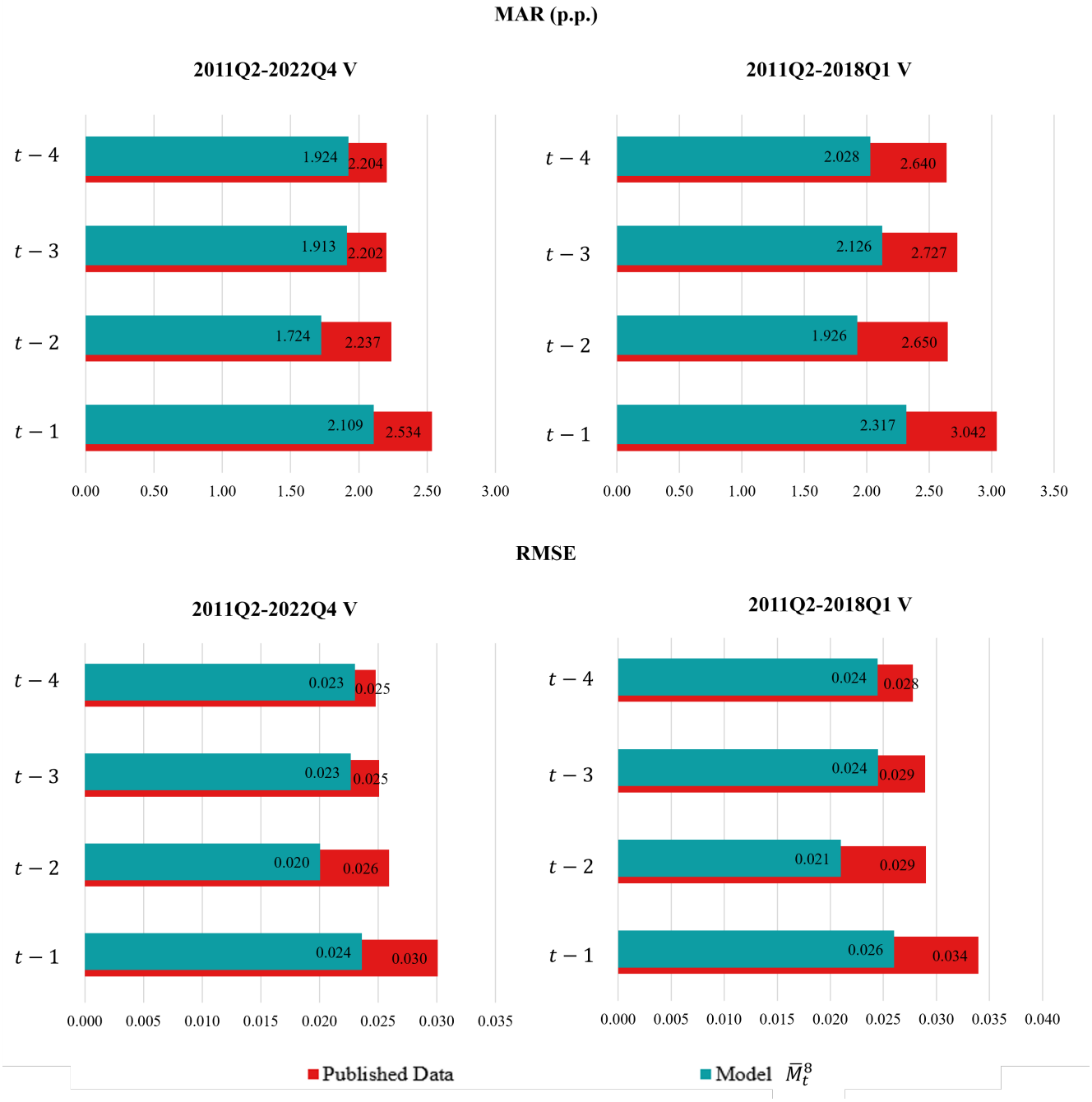
	2011Q2-2022Q4 V		**2011Q2-2017Q4 V**	
	MAR (%)	RMSFE	MAR (%)	RMSFE
Autoregressive process $({}_T y_t - \widehat{{}_{t+1} y_t} \vert Y_t)$	7.474	0.081	8.813	0.091
M_t^1: $({}_T y_t - \widehat{{}_{t+2} y_t} \vert \Omega_t)$	7.143 [−4.0%]	0.080 [−0.8%]	8.256 [−5.7%]	0.087 [−5.0%]
M_t^2: $({}_T y_t - \widehat{{}_{t+3} y_t} \vert \Omega_t)$	6.984 [−5.6%]	0.080 [−1.6%]	7.738 [−11.5%]	0.082 [−10.2%]
M_t^3: $({}_T y_t - \widehat{{}_{t+4} y_t} \vert \Omega_t)$	6.761 [−8.5%]	0.077 [−4.4%]	7.386 [−15.6%]	0.079 [−13.2%]
M_t^4: $({}_T y_t - \widehat{{}_{t+5} y_t} \vert \Omega_t)$	6.789 [−8.7%]	0.078 [−3.1%]	7.690 [−12.5%]	0.083 [−9.0%]
$\bar{M}_t^8$: $({}_T y_t - \widehat{{}_{t+9} y_t} \vert \Omega_t)$	4.969 [−30.2%]	0.059 [−26.5%]	5.317 [−38.4%]	0.060 [−34.6%]

Source: Author's calculations.
Notes: MAR represents the mean of absolute revisions, whereas RMSFE denotes the root mean squared forecast error. For the forecasts generated by an autoregressive process, revisions are calculated as the difference between the actual GDP level ${}_T y_t$ and $\widehat{{}_{t+1} y_t} \vert Y_t$, where $T = 2023Q1$. For model M_t^q, revisions are calculated as the difference between ${}_T y_t$ and $\widehat{{}_{t+q+1} y_t} \vert \Omega_t$, where $T = 2023Q1$. Figures in square brackets underneath the MAR and RMSE statistics show the % improvement in the respective measure, relative to that recorded for forecasts generated by the autoregressive process.

example, a forecast of the annual growth rate for period $t-1$ could be obtained by calculating $(\widehat{{}_{t+8} y_{t-1}} \vert \Omega_t - \widehat{{}_{t+4} y_{t-5}} \vert \Omega_t)$, where these forecasts are obtained from the estimation of model $\bar{M}_t^8$ using all the information found within Ω_t. Figure 2 shows the results from an exercise in which model $\bar{M}_t^8$ is applied to each Ω_t in order to forecast the year-on-year growth rates for periods $t-1$ to $t-4$ in real time, once forecasts of subsequent revisions are considered. The suitability of these forecasts is judged by the extent to which their consideration is able to approximate the annual growth rates published in real time to the "true" year-on-year growth rates recorded in the 2023Q1 data vintage. Results show that even when considering the first eight revisions as a weighted arithmetic average, the exploitation of inherent patterns in historical data is able to generate substantial improvements in measuring the "true" year-on-year growth rate for periods $t-1$ to $t-4$ in real time. As an example, considering the fully-revised data covered by the 2011Q2-2018Q1 vintages, it is observed that annual growth rates have on average been revised from their initial estimates (period $t-1$) by a magnitude of 3.04 p.p. in absolute terms. The consideration of historical data patterns in real time would have reduced the size of these revisions by around 0.7 p.p. to 2.32 p.p. Broadly similar improvements are also observed in terms of the year-on-year growth rates for the periods $t-2$ to $t-4$. Moreover, the observed improvements in the RMSE further imply that the real-time consideration of systematic patterns in the revisions is capable of measuring the annual growth rates in real time with greater precision. Although these results are rather encouraging, the size of outstanding revisions remains fairly substantial,

as indeed was the case when the *levels* were considered. To understand the reasons behind these persistent differences, it has to be recognised that the GLMS framework applied in this paper is only able to capture *systematic* components in historical data and is therefore unable to predict the "random" component of revisions that changes over time. Consequently, it is practically impossible to predict future revisions in their entirety in real time. Having said that, it is also plausible that there may be further revisions beyond those effected within the first two years of initial release that have not been considered due to data constraints, but which should ideally be taken into account. In this respect, the findings of Grech (2018) suggest that this is very likely to be the case. This notwithstanding, this exercise begins to demonstrate practical ways in which the uncertainty associated with real-time analyses could be mitigated by anticipating and considering future revisions in real time.

Figure 2: Comparison between the annual Real GDP growth rate calculated from the 2023Q1 vintage to that published in real-time and that estimated in real time by model $\bar{M}_t^8$



Source: Author's calculations.
Note: MAR represents the mean of absolute revisions, whereas RMSE denotes the root mean squared error. Values shown in this figure represent the respective MAR and RMSE of the real-time annual growth rates derived from the respective source (i.e. from published real-time data and model $\bar{M}_t^8$), relative to the annual growth rates derived from the 2023Q1 vintage.

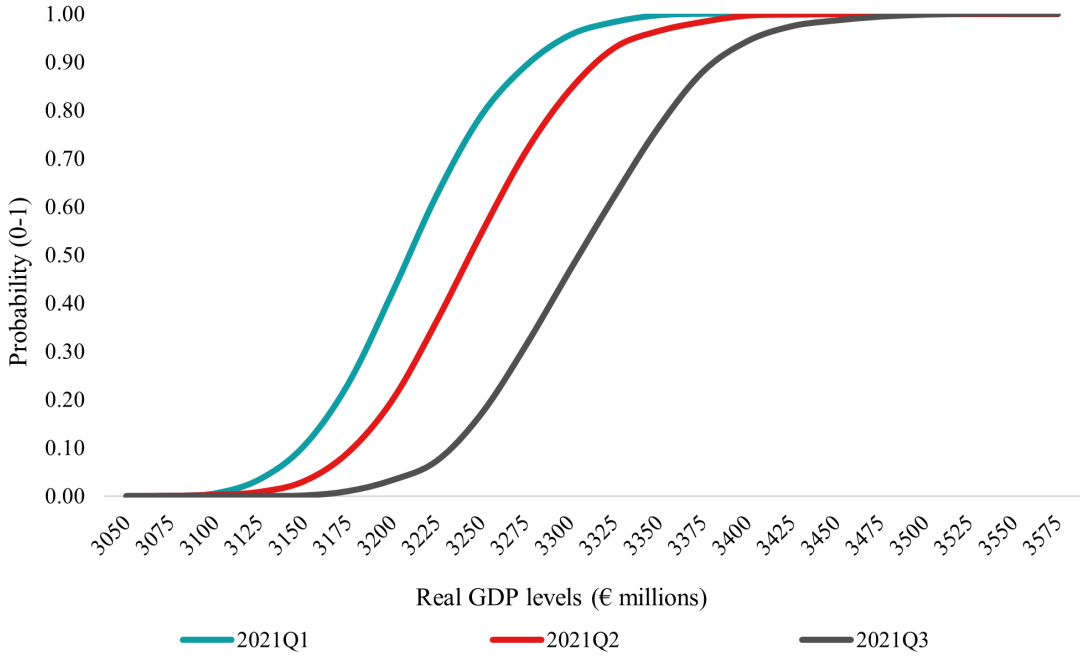
4.3 Representing the uncertainty surrounding real-time GDP estimates

The application of the GLMS framework to forecast output levels following q revisions in real time relies heavily on the use of forecasts, which implicitly generates a degree of uncertainty around the point estimate of the forecast itself. In this light, analyses of the point forecasts could be usefully complemented by an illustration of the uncertainty that characterises them. Insights about this uncertainty can be inferred from probability density functions (PDFs) constructed using simulation techniques. This exercise involves the use of the model stipulated in equation (1), which at recursion t is estimated on the basis of the vintages $\{x_1, x_2, ..., x_t\}'$, to generate S simulations of $\{\overset{s}{\widehat{x_{t+1}}}, \overset{s}{\widehat{x_{t+2}}}, ..., \overset{s}{\widehat{x_{t+m+q+1}}}\}$, for $s = \{1, 2, ..., S\}$, and where $(t+m)$ denotes the end of the forecast horizon, and q denotes the number of revisions. In total, this process, which assumes that the estimated model remains valid over the forecast horizon, generates S forecasts of the future first-release growth figures and the q revisions as attainable from S simulations of the data published in vintages $(t+1)$ to $(t+m+q+1)$. These are then used to construct S simulations of the post-revision output series in the t-vintage, $\{{}_t y_1, {}_t y_2, ..., {}_t y_{t-q-1}, \overset{s}{\widehat{{}_{t+1} y_{t-q}}}, \overset{s}{\widehat{{}_{t+2} y_{t-q+1}}}, ..., \overset{s}{\widehat{{}_{t+m+q+1} y_{t+m}}}\}$. The resulting distribution of the S period-t Real GDP level estimates obtained from these stochastic simulations form the PDF for the period-t estimate of the Real GDP level.[19] This simulation exercise can be conducted recursively by estimating the framework presented in equation (1) on the basis of each information set $\Omega_t; t = \{2011Q2, 2011Q3, ..., 2023Q1\}$.

As an example of the uncertainty that characterises the real-time point forecasts of Real GDP for Malta following the application of the GLMS framework, Figure 3 presents the cumulative density functions (CDFs) of the "true" Real GDP levels for 2021Q1-2021Q3 as forecasted from the information set available in 2021Q4 (i.e. Ω_{2021Q4}) on the basis of the $\bar{M}_t^8$ model. The respective CDFs yield important insights for policymakers. For example, in this particular case, the over-time shift of the CDFs to the right suggests that even when considering forecasts of future revisions, Real GDP levels would have been assessed to be on an upward trend between 2021Q1 and 2021Q3, at least when based on the information available as at 2021Q4. Moreover, the (slightly) flatter slope of the 2021Q3 CDF, relative to that for 2021Q1 and 2021Q2, reflects a higher degree of uncertainty surrounding the forecast for this quarter, relative to the other two quarters. This is in line with *a priori* expectations given that the 2021Q3 Real GDP

[19] The simulations in this work total 1,000 and take into account coefficient uncertainty. Innovations are generated from a (parametric) normal distribution, rather than from bootstrap methods, following the discussion in Garratt et al. (2001) and due to the relatively restricted sample size in this work.

Figure 3: Cumulative Density Functions on the basis of information set Ω_{2021Q4}

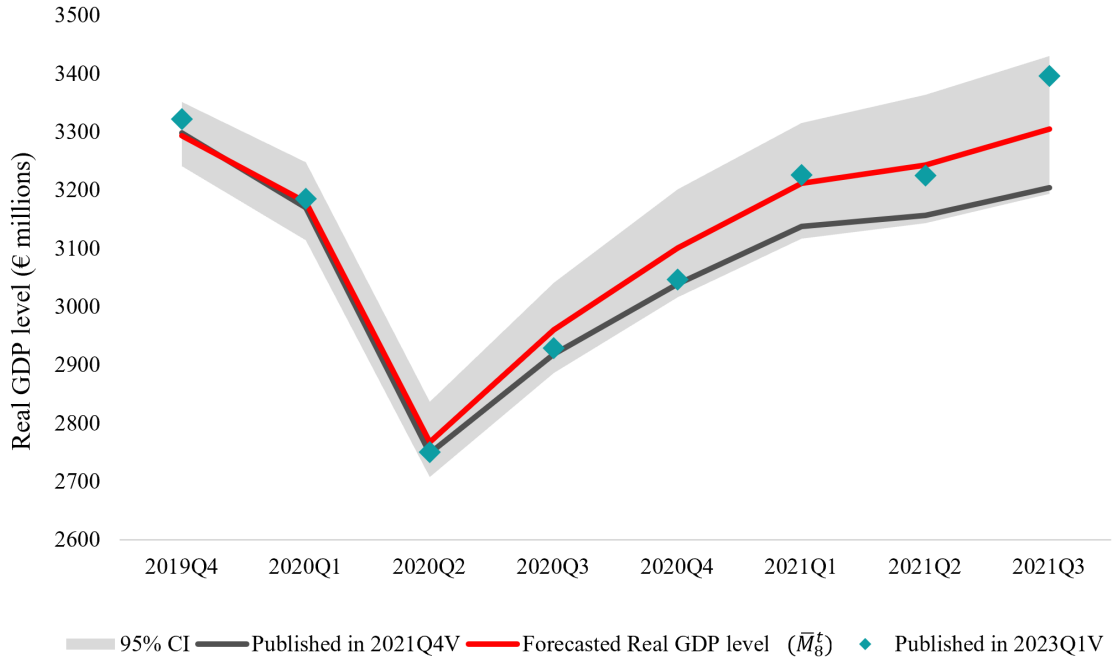


Source: Author's calculations.
Note: The respective cumulative density functions (CDFs) are calculated from 1,000 simulations of future data vintages based on the model specification $\bar{M}_t^8$, performed on the basis of the information set Ω_{2021Q4}, as described in the text.

was released for the first time in the 2021Q4 vintage, whereas that for 2021Q1 and 2021Q2 had already undergone some revisions. The CDF for 2021Q1 suggests that, based on Ω_{2021Q4}, the "true" Real GDP level for this quarter would be expected to fall in the range [3057,3362] (€millions) once forecasts of revisions to be made in future vintages are factored in, with the most likely figure hovering around €3,211mln. Indeed, while the Real GDP figure for this quarter was actually published by the NSO in the 2021Q4 vintage as €3,138mln, it was subsequently revised to €3,226mln by the time of publication of the 2023Q1 vintage. Similarly, the range of possible values for the 2021Q2 Real GDP based on Ω_{2021Q4} is estimated to be [3074,3426] (€millions), with €3,243mln being the most likely level. The value published in the 2021Q4 vintage reads €3,156mln and this has since been revised upwards by NSO to €3,225mln in the 2023Q1 vintage. Turning to the "true" Real GDP level for 2021Q3, this would have been expected to take a value in the range [3141,3506] (€millions) on the basis of Ω_{2021Q4}, with the most likely value being €3,306mln. The actual figure published at the time stood at €3,204mln and has since been revised to €3,395mln. This example, which could be replicated for all other information sets Ω_t, highlights clearly the level of uncertainty which characterises real-time economic assessments in Malta and the relevance of CDFs to illustrate the confidence with which policymakers could form judgements and expectations in real time.

Beyond the use of CDFs, the uncertainty surrounding point forecasts could also be represented by the (traditional) use of confidence intervals. Figure 4 depicts the uncertainty around the forecasts of 2019Q4-2021Q3 output levels based on the application of model $\bar{M}_t^8$ to the information set Ω_{2021Q4}. The first point of note is that, similar to the pattern observed from the CDFs presented in Figure 3, forecasts of the "true" output levels for historical periods are characterised by less uncertainty than more recent periods.[20] Moreover, while the respective point forecasts are sufficient for policymakers to expect, in this example, the GDP figures published in the 2021Q4 vintage to be subsequently revised upwards, the use of confidence intervals provides highly relevant information about the confidence with which this assessment can be made. For example, it is evident from Figure 4 that the output levels for 2020Q2-2021Q3 as published in the 2021Q4 vintage lie close to the lower limit of the 95% confidence interval. This implies that, following the publication of the 2021Q4 vintage, policymakers could form real-time expectations of subsequent upward revisions to output data with a very high degree of confidence. Indeed, the data published in the 2023Q1 vintage shows that revisions have truly been in an upward direction, and the actual output levels published in the most recent vintage fall within the 95% confidence bands calculated based on the information available in 2021Q4.

Figure 4: Real-time understanding of Real GDP levels on the basis of Ω_{2021Q4}

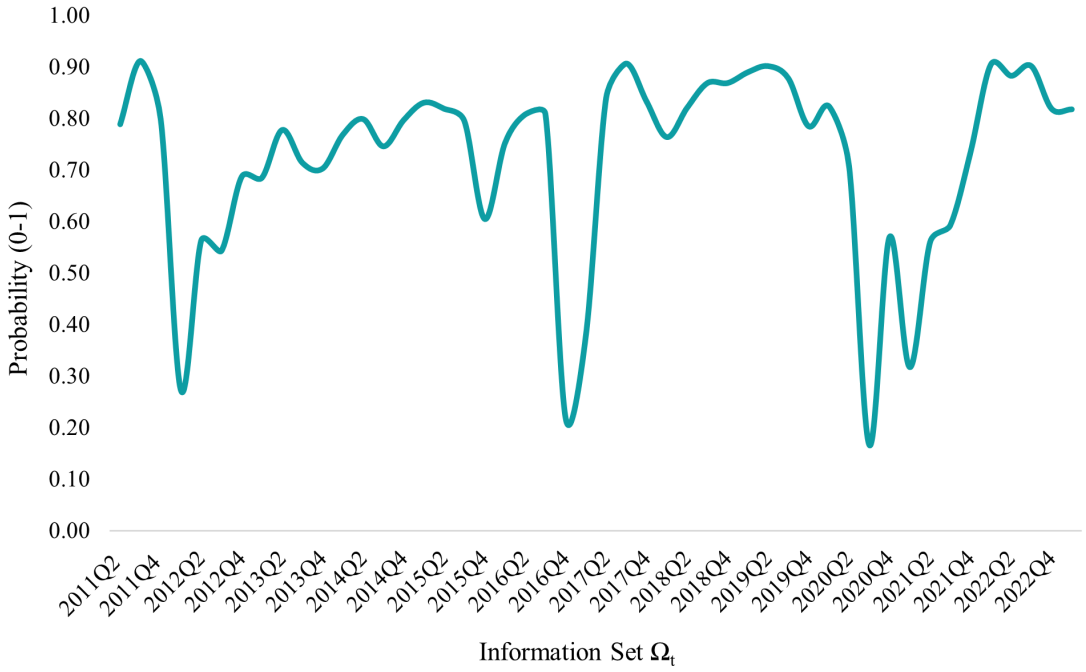


Source: Author's calculations.
Note: The shaded area represents the 95% confidence interval around the forecasted Real GDP levels.

[20] This is represented by a widening 95% confidence interval when moving from 2019Q4 to 2021Q3.

The use of simulation techniques is also highly useful for policymakers interested in the probability that any event of interest occurs. This can be straightforwardly determined by observing the share of times the particular event is observed to happen among the S simulations. As an example, suppose that at time t, a policymaker is interested in the probability that the first-release estimate published in the most recent vintage (i.e. ${}_{t}y_{t-1}$) would be subsequently revised upwards by at least 2% over the upcoming vintages. Using simulation techniques and assuming 1,000 simulations made on the basis of the information set Ω_t, this probability can be easily determined by observing the share of these simulations in which this event happens. Using the specification $\bar{M}_t^8$ to denote forecasts of future vintages, this probability can be denoted by $prob\Big[\widehat{{}_{t+8}y_{t-1}}|\Omega_t > (1.02 * {}_{t}y_{t-1})\Big] = \frac{1}{1000}\sum_{s=1}^{1000} I\Big(\overset{(s)}{\widehat{{}_{t+8}y_{t-1}}}|\Omega_t > (1.02 * {}_{t}y_{t-1})\Big)$, where $I(.)$ is an indicator function taking a value of 1 if the event is observed to happen in simulation s and 0 otherwise. Figure 5 shows the probability with which the policymaker would, in real time, expect a revision of such magnitude to be made to the ${}_{t}y_{t-1}$ figure over subsequent revisions. This analysis is based on the $\bar{M}_t^8$ model applied to the data available in real time from the respective information sets $\Omega_{2011Q2}, ..., \Omega_{2023Q1}$. The respective simulations show that assessments could be made with relatively high degrees of certainty in many of the periods considered. In fact, the probability of the event in question (i.e. upward revision of at least 2%) happening averaged 72% over the period considered. Moreover, the policymaker would expect this event to happen with at least 80% certainty in around 40% of the quarters considered. However, other periods are characterised by higher levels of uncertainty, and Figure 5 thereby provides additional informative content which is not attainable from analyses limited to point estimates.

Figure 5: Real-time probability of ${}_t y_{t-1}$ being subsequently revised upwards by at least 2%



Source: Author's calculations.
Note: The respective probabilities are calculated from 1,000 simulations of future data vintages based on the model specification $\bar{M}_t^8$, as described in the text.

5 Concluding Remarks

National Accounts data are often subject to a number of revisions, generally effected either to incorporate new information that would have come to light since previous releases or to correct errors in the original data. Such revisions - which are not limited to National Accounts data for Malta only - raise the possibility that economic inference made on the basis of the data available in real time might change substantively as the underlying data is revised. Based on the premise that real-time economic analyses could benefit from internalising any information that could be extracted from the historical publications of data, this paper set out to identify any systematic patterns found within historical data vintages and the inherent revisions. This is done via the application of modelling techniques previously introduced in the economic literature to model Malta's first-release output data alongside the revisions made within a maximum of two years from the date of first-release. Systematic patterns in the data are recorded and used to forecast in real time Real GDP levels for past, contemporaneous and future periods that take into account forecasts of the revisions expected to be made in subsequent vintages. The consideration of

the generated forecasts is consistently found to improve the real-time understanding of Real GDP levels and year-on-year growth rates, compared to a situation where such forecasts are not utilised. This notwithstanding, the forecasts are implicitly surrounded by a degree of uncertainty, and this paper's use of simulation techniques and cumulative density functions highlights clearly the relevance of this information to complement point-estimate analyses.

The findings of this paper, along with its caveats and the relative lack of research about real-time issues in Malta, create interesting fora in which this study could be extended. Firstly, while this study sought to identify patterns in output *levels*, a similar study could be applied directly to *growth rates* and revisions in the growth rates in the spirit of Clements and Galvão (2012). It is also acknowledged that the relatively limited span of data vintages covered by the Maltese real-time database currently constrains the number of revisions that could be considered to exhibit systematic patterns. In light of evidence about the lengthy process of Maltese data revisions documented in Grech (2018), it is very plausible that the model specifications estimated in this work omit other important data revisions. This could explain why, despite the evident benefits that considering forecasts of future revisions could have in real-time analyses, some substantial differences from the actual levels published in the most recent vintage remain. Subject to the continuous updating of the Maltese real-time macroeconomic database with the publication of new data vintages, future research could therefore integrate a larger number of revisions into the modelling framework considered in this work, which in turn could further improve the real-time understanding of Real GDP data. These improvements could also be possible if the methods considered in this work are applied to also look for patterns in the sub-components of GDP.

Going forward, the search for patterns in the data could also be conducted on a rolling set of data vintages rather than on all the vintages covered by the real-time macroeconomic database. This strategy would likely reduce the risk of basing the identification of data patterns on dated vintages which might have exhibited patterns no longer seen in more recent vintages. One application of the GLMS framework that is given much attention in the literature but has not yet been addressed in the Maltese context pertains to real-time analyses of the output gap. Future research could therefore study the potential for improvements in the reliability of real-time Maltese output gap estimates derived from a better understanding of the real-time data. On a final note, we are not aware that the Maltese real-time macroeconomic database developed by the CBM has been used in economic research since it was introduced by Grech (2018). In this light, studies which analyse other issues such as the evaluation of forecasts based on different vintages, among other research possibilities, could contribute greatly to Maltese

macroeconomic research while at the same time exploit more fully the research potential of the country's real-time macroeconomic database.

As these are only few of the possibilities for future research, it is evident that the field of research about real-time issues in the Maltese context is ripe with potential for further studies. Although this paper's primary focus revolved around a discussion of relevant ways in which real-time analyses could be ameliorated, the analyses carried out throughout also strikingly highlight the extent to which conclusions made in real time may be subject to change as new data and information become available. The susceptibility of real-time data to change should therefore be a key consideration in policy making, policy evaluation and economic research in general.

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A The Use of Data Revisions

This appendix illustrates the way that, in the spirit of the framework of Garratt et al. (2008), data revisions are used to obtain forecasts of output levels following the q^{th} revision made by the statistical authority. For ease of illustration, it is assumed that output levels are revised three times from their initial estimate (i.e. $q = 3$) and remain reliable after the third revision. The "reliable" output levels in each data vintage are marked in bold in Table A.1. The figures not marked in bold represent output levels that are expected to be further revised in the publication of future data vintages.

Table A.1: An Illustration of Data Revisions in a Real-Time Database

		Vintage							
	$\dots$	Y_{t-3}	Y_{t-2}	Y_{t-1}	Y_t	Y_{t+1}	Y_{t+2}	Y_{t+3}	$\dots$
$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$t-7$	$\ddots$	$\mathbf{t-3y_{t-7}}$	$\mathbf{t-2y_{t-7}}$	$\mathbf{t-1y_{t-7}}$	$\mathbf{ty_{t-7}}$	$\mathbf{t+1y_{t-7}}$	$\mathbf{t+2y_{t-7}}$	$\mathbf{t+3y_{t-7}}$	$\cdots$
$t-6$	$\ddots$	${}_{t-3}y_{t-6}$	$\mathbf{t-2y_{t-6}}$	$\mathbf{t-1y_{t-6}}$	$\mathbf{ty_{t-6}}$	$\mathbf{t+1y_{t-6}}$	$\mathbf{t+2y_{t-6}}$	$\mathbf{t+3y_{t-6}}$	$\cdots$
$t-5$	$\ddots$	${}_{t-3}y_{t-5}$	${}_{t-2}y_{t-5}$	$\mathbf{t-1y_{t-5}}$	$\mathbf{ty_{t-5}}$	$\mathbf{t+1y_{t-5}}$	$\mathbf{t+2y_{t-5}}$	$\mathbf{t+3y_{t-5}}$	$\cdots$
$t-4$		${}_{t-3}y_{t-4}$	${}_{t-2}y_{t-4}$	${}_{t-1}y_{t-4}$	$\mathbf{ty_{t-4}}$	$\mathbf{t+1y_{t-4}}$	$\mathbf{t+2y_{t-4}}$	$\mathbf{t+3y_{t-4}}$	$\cdots$
$t-3$			${}_{t-2}y_{t-3}$	${}_{t-1}y_{t-3}$	${}_{t}y_{t-3}$	$\mathbf{t+1y_{t-3}}$	$\mathbf{t+2y_{t-3}}$	$\mathbf{t+3y_{t-3}}$	$\cdots$
$t-2$				${}_{t-1}y_{t-2}$	${}_{t}y_{t-2}$	${}_{t+1}y_{t-2}$	$\mathbf{t+2y_{t-2}}$	$\mathbf{t+3y_{t-2}}$	$\cdots$
$t-1$					${}_{t}y_{t-1}$	${}_{t+1}y_{t-1}$	${}_{t+2}y_{t-1}$	$\mathbf{t+3y_{t-1}}$	$\cdots$
t						${}_{t+1}y_{t}$	${}_{t+2}y_{t}$	${}_{t+3}y_{t}$	$\cdots$
$t+1$							${}_{t+2}y_{t+1}$	${}_{t+3}y_{t+1}$	$\cdots$
$t+2$								${}_{t+3}y_{t+2}$	$\cdots$
$\vdots$									$\ddots$
Information set		Ω_{t-3}	Ω_{t-2}	Ω_{t-1}	Ω_t	Ω_{t+1}	Ω_{t+2}	Ω_{t+3}	

Suppose that the data vintage t has just been published, and therefore the latest information set available is Ω_t. Assuming that the statistical authority makes three systematic revisions, it is known that ${}_{t}y_{t-3}$, ${}_{t}y_{t-2}$, and ${}_{t}y_{t-1}$ are still in the process of routine revisions (non-bold in Table A.1).[21] More specifically, the figure ${}_{t}y_{t-3}$ is still subject to the third revision, ${}_{t}y_{t-2}$ is still subject to the second and third revision, and ${}_{t}y_{t-1}$ is still subject to all three revisions. Forecasts of their post-revision levels could be denoted by $\widehat{{}_{t+1}y_{t-3}}$, $\widehat{{}_{t+2}y_{t-2}}$, and $\widehat{{}_{t+3}y_{t-1}}$, respectively. Following the modelling approach of Garratt et al. (2008), these forecasts are generated by estimating a VAR model of the first release data alongside the three revisions using all such data available

[21] In vintage t, ${}_{t}y_{t-4}$ would have been revised for the third time since the first release figure ${}_{t-3}y_{t-4}$.

in information set Ω_t (i.e. as inferred from data vintages Y_t, Y_{t-1}, Y_{t-2}...). This estimation allows for the construction of forecasts of the first release, first revision, second revision, and third revision figures that are expected to be made by the statistical authority when publishing vintages $t+1$, $t+2$, $t+3$, etc. Once these forecasts are obtained, ${}_t y_{t-3}$ could be replaced by $E[\widehat{{}_{t+1}y_{t-3}}|\Omega_t]$, the latter obtained by adding the forecasted third revision to be made in the $t+1$ vintage to the ${}_t y_{t-3}$ figure published in vintage t. Following an analogous argument, ${}_t y_{t-2}$ would be replaced by $E[\widehat{{}_{t+2}y_{t-2}}|\Omega_t]$, the latter obtained by adding the forecasted second revision to be made in vintage $t+1$ and the forecasted third revision to be made in the $t+2$ vintage to the ${}_t y_{t-2}$ figure published in vintage t. Finally, ${}_t y_{t-1}$ could also be replaced by $E[\widehat{{}_{t+3}y_{t-1}}|\Omega_t]$, taking into account the three revisions that will be made in the meantime. This could be easily done by taking ${}_t y_{t-1}$ as published in vintage t and adding the forecasted first revision to be made in the $t+1$ vintage, the second revision to be made in the $t+2$ vintage, and the third revision forecasted to be made in vintage $t+3$.

The same approach could also be used to augment the data vintage t by forecasts of future output levels as they are expected to be recorded after three revisions, namely $E[\widehat{{}_{t+4}y_t}|\Omega_t]$, $E[\widehat{{}_{t+5}y_{t+1}}|\Omega_t]$, $E[\widehat{{}_{t+6}y_{t+2}}|\Omega_t]$, etc. As an example, $E[\widehat{{}_{t+4}y_t}|\Omega_t]$ is obtained by first adding the forecasted growth in first-release output to be published in vintage $t+1$ to the ${}_t y_{t-1}$ figure. The resultant figure, which represents $E[\widehat{{}_{t+1}y_t}|\Omega_t]$ is then modified by adding the forecasted first revision to be made in the $t+2$ vintage, the second revision to be made in the $t+3$ vintage, and the third revision forecasted to be made in vintage $t+4$, eventually yielding $E[\widehat{{}_{t+4}y_t}|\Omega_t]$.

B VAR Framework: An Estimation

Table B.1: VAR Model of First-Release Real GDP Growth and Four Data Revisions: 2003Q2-2022Q4

	Dependent Variable				
	${}_{t}y_{t-1} - {}_{t-1}y_{t-2}$	${}_{t}y_{t-2} - {}_{t-1}y_{t-2}$	${}_{t}y_{t-3} - {}_{t-1}y_{t-3}$	${}_{t}y_{t-4} - {}_{t-1}y_{t-4}$	${}_{t}y_{t-5} - {}_{t-1}y_{t-5}$
Intercept	0.008***	0.004**	0.004**	0.003*	0.004**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
${}_{t-1}y_{t-2} - {}_{t-2}y_{t-3}$	0.193	0.029	0.241**	0.200**	0.114
	(0.144)	(0.099)	(0.100)	(0.085)	(0.087)
${}_{t-2}y_{t-3} - {}_{t-3}y_{t-4}$	−0.155	−0.026	−0.029	0.012	0.081
	(0.109)	(0.075)	(0.076)	(0.064)	(0.066)
${}_{t-3}y_{t-4} - {}_{t-4}y_{t-5}$	0.211*	0.207***	0.231***	0.123*	0.141**
	(0.107)	(0.074)	(0.075)	(0.063)	(0.065)
${}_{t-4}y_{t-5} - {}_{t-5}y_{t-6}$	0.072	−0.002	0.071	0.091	0.070
	(0.099)	(0.068)	(0.069)	(0.058)	(0.060)
${}_{t-1}y_{t-3} - {}_{t-2}y_{t-3}$	0.160	0.192	−0.330**	0.006	0.061
	(0.193)	(0.134)	(0.135)	(0.114)	(0.117)
${}_{t-2}y_{t-4} - {}_{t-3}y_{t-4}$	0.025	0.254	0.294*	−0.081	0.174
	(0.237)	(0.163)	(0.165)	(0.139)	(0.143)
${}_{t-3}y_{t-5} - {}_{t-4}y_{t-5}$	−0.152	−0.454**	−0.384**	−0.241	−0.345**
	(0.269)	(0.185)	(0.187)	(0.158)	(0.162)
${}_{t-4}y_{t-6} - {}_{t-5}y_{t-6}$	0.038	0.072	0.085	0.301**	0.179
	(0.241)	(0.165)	(0.167)	(0.141)	(0.145)
${}_{t-1}y_{t-4} - {}_{t-2}y_{t-4}$	0.390	0.467*	0.156	−0.213	0.092
	(0.377)	(0.258)	(0.260)	(0.220)	(0.226)
${}_{t-2}y_{t-5} - {}_{t-3}y_{t-5}$	−0.259	−0.546**	−0.574**	−0.216	−0.292
	(0.373)	(0.257)	(0.259)	(0.219)	(0.225)
${}_{t-3}y_{t-6} - {}_{t-4}y_{t-6}$	0.032	0.073	−0.297	0.126	0.127
	(0.360)	(0.246)	(0.249)	(0.211)	(0.216)
${}_{t-4}y_{t-7} - {}_{t-5}y_{t-7}$	0.272	0.179	−0.079	−0.060	−0.103
	(0.252)	(0.174)	(0.175)	(0.149)	(0.152)
${}_{t-1}y_{t-5} - {}_{t-2}y_{t-5}$	−0.304	−0.366	0.145	0.218	−0.269
	(0.450)	(0.307)	(0.310)	(0.262)	(0.269)
${}_{t-2}y_{t-6} - {}_{t-3}y_{t-6}$	−0.033	−0.054	−0.060	0.042	−0.601**
	(0.450)	(0.311)	(0.313)	(0.266)	(0.272)
${}_{t-3}y_{t-7} - {}_{t-4}y_{t-7}$	−0.334	−0.087	−0.068	−0.261	−0.244
	(0.452)	(0.312)	(0.315)	(0.267)	(0.273)
${}_{t-4}y_{t-8} - {}_{t-5}y_{t-8}$	−0.227	−0.113	−0.240	−0.518*	−0.506*
	(0.447)	(0.308)	(0.311)	(0.263)	(0.270)
${}_{t-1}y_{t-6} - {}_{t-2}y_{t-6}$	−0.380	−0.417*	−0.303	−0.420**	−0.322
	(0.349)	(0.241)	(0.243)	(0.206)	(0.211)
${}_{t-2}y_{t-7} - {}_{t-3}y_{t-7}$	0.138	0.081	0.024	−0.091	0.232
	(0.338)	(0.233)	(0.235)	(0.199)	(0.204)
${}_{t-3}y_{t-8} - {}_{t-4}y_{t-8}$	0.541*	0.330	0.448**	0.162	0.209
	(0.306)	(0.212)	(0.213)	(0.181)	(0.185)
${}_{t-4}y_{t-9} - {}_{t-5}y_{t-9}$	−0.040	−0.164	0.071	0.090	0.219
	(0.297)	(0.205)	(0.207)	(0.175)	(0.180)
Observations	79	79	79	79	79
R^2	0.763	0.618	0.605	0.603	0.620
Recession Dummy	✓				
2016Q4 Vintage Dummy	✓	✓	✓	✓	✓
COVID-19 Dummies	✓	✓	✓	✓	✓
			Post-estimation tests		
SC			0.779		
VAR Stability			✓		

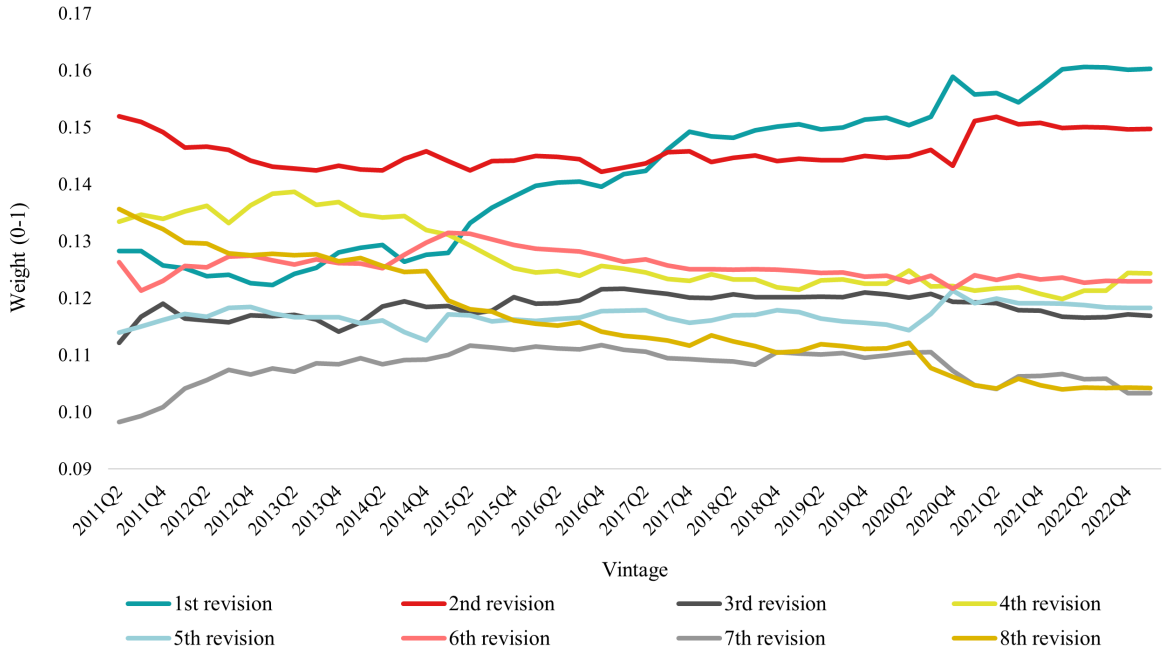
Source: Author's calculations.

Notes: * significant at 10% level ** significant at 5% level *** significant at 1% level. Standard errors are shown in brackets. Post-estimation tests refer to the p-values calculated from tests of serial correlation (SC) and confirmation that the VAR satisfies the stability condition. All equations include a dummy variable for the 2016Q4 vintage and two dummies pertaining to the economic downturn and upturn associated with the COVID-19 pandemic, while the equation explaining the growth in first-release GDP data includes a dummy variable covering the Great Recession period as described in the text. This dummy proved statistically insignificant in the equations explaining revisions and was thus omitted.

C Weighting Process of Data Revisions - Model $\bar{M}_t^8$

As described in the text, the revisions made in each vintage t to the Real GDP data covering the period $t-8$ to $t-2$ are each assigned a weight (between 0 and 1) in order to construct a weighted average of the revisions made by the NSO in each vintage. Using all the data available within the information set Ω_t, model $\bar{M}_t^8$ is then specified in a way to model the growth in first-release GDP data alongside the resulting weighted average of revisions. At every vintage t, the weight assigned to each of the eight revisions is based on the historical average magnitude of the respective revision measured in absolute terms. In other words, when vintage t is published, the information set Ω_t is used to calculate the average of all historical first, second, third,..., up to the eighth (absolute) revisions made by the NSO. Weights are then assigned to the respective eight revisions made in vintage t based upon the respective historical size of each of the eight revisions. These weights are then updated when new information becomes available upon the publication of vintage $t+1$, and subsequently updated further with every future publication of data vintages.

Figure C.1: Weight assigned to each revision by vintage



Source: Author's calculations.

Figure C.1 shows the weight assigned to each of the eight revisions made by the NSO in each vintage t, calculated as described above. Based on all the historical information available to date, it appears that the first two data revisions have generally been more pronounced than

later revisions and are therefore currently being assigned a higher weight. On the other hand, the seventh and eighth revisions are currently assigned the smallest weight by virtue of being the smallest in absolute size. This notwithstanding, all eight revisions are generally assigned broadly similar weights, with the latest set of weights varying between 0.10 and 0.16. This is reflective of the fact that the first eight revisions made to initial data releases are all typically sizeable.