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Working Paper

Timing the Maltese business cycle: A historical perspective

CBM Working Papers, No. WP/01/2021

Provided in Cooperation with:

Central Bank of Malta, Valletta

Suggested Citation: Ellul, Reuben (2021) : Timing the Maltese business cycle: A historical perspective, CBM Working Papers, No. WP/01/2021, Central Bank of Malta, Valletta

This Version is available at:

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Timing the Maltese business cycle: A historical perspective

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Working Paper
WP/01/2021

February 2021

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Abstract

Despite data limitations, formal methods can still be applied to identify business cycle turning points and hence date appropriately the Maltese business cycle. An extension of the official quarterly GDP time series to the 1970s allows for a historical view on dating the business cycle, leading to the identification of tentative set of recessionary episodes. In line with the business cycle literature, which suggests that multiple data ought to be considered when timing the business cycle, unemployment rate data are also considered. Findings with respect to developments in the labour market are also discussed. The study also highlights pitfalls in the timing of recessions in Malta, relating to problems in the estimation of national accounts, as well as the number of observations of the GDP time-series. This study represents a first step towards maintaining a chronology of Maltese business cycles by collating a dataset, analysing it and focusing on the statistical aspects of business cycles.

Keywords: Malta, business cycle, recessions

JEL: C24, C25, E32.

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1. Introduction

Short-term forecasting and medium-term projections are often used by policymakers to assess the likely future path of an economy. Often, such projections couch the current estimated position of the economy with respect to some long-term business cycle position. Generally, business cycle analysis separates periods of expansion from periods of contraction (Schumpeter, 1954), with more modern methods going so far as to add more than two states to describe the different positions of the economy. Policymakers may choose different policies depending on the estimated economic position within the business cycle.

In many cases, dating of the business cycle is carried out by national committees. A lot of research refers to work carried out in the United States (US) by the Business Cycle Dating Committee within the National Bureau of Economic Research (NBER). Their views regarding the business cycle are the official dating reference for the US economy. No official or exhaustive dating for the Maltese business cycle has been carried out.² Malta is a very small open economy with specialised exports in a number of particular niches, such as tourism, the semiconductor industry and, more recently, online gaming. It is not clear whether the overall Maltese economy is synchronised with the cycles of its European neighbours,³ or whether any synchronisation has been affected by changes in Malta's political economy, or membership of the Monetary Union.

This study has three broad contributions. First, Maltese business cycle turning points are identified for the Maltese economy for the period 2000Q1 to 2019Q4, using official data from the National Statistics Office (NSO). Secondly, this analysis is extended using unofficial quarterly estimates for Maltese gross domestic product (GDP) from 1972 onward. Finally, two classes of Markov models are used on historic unemployment data, to assess whether the timing of the business cycle translates into similar cycles in the labour market.

² Although Ellul (2016) uses a modified Bry-Boschan algorithm to date the business cycle, in order to benchmark a business conditions index.

³ For an analysis of the synchronisation of sectoral confidence estimates of the Maltese economy with other EU economies, see Grech and Ellul (2020).

The idea behind these contributions is to use the most simple and established methods to assess the timing of the Maltese business cycle, and to do so in a manner which may be fully replicable by other analysts with the minimum effort necessary.

This working paper also highlights that while the methods and “rules” discussed in the economic literature do serve a purpose, these should not be looked at as directives which codify the timing of business cycles, but as evidence in favour of – or against – the timing of periods. It should be noted that the NBER does not accept the ‘two consecutive quarters of negative GDP growth’ definition used by many economists and other institutions in dating recessions. This is because analysis on business cycle should, ideally, use more economic data than GDP, particularly data at higher frequency than quarters. Moreover, the NBER assess declines in activity rather than GDP, as well as assessing indicators relating to incomes.

Ideally, assessments on turning points and timing of the business cycle ought to be carried out once estimates for economic statistics have been finalised. In Malta, as discussed by Grech (2018), “revisions to initial overall real GDP growth rates are sizeable, biased upwards, volatile and increase with the horizon”. This serves as a further cautionary evidence against the solitary use of GDP to time the business cycle.

In terms of findings, using the official NSO GDP time series,⁴ and applying the most common tool in the timing of business cycles, namely the Bry-Boschan algorithm, there is evidence for recessionary episodes between 2001Q1 and 2001Q2, 2004Q1 and 2004Q2, 2011Q1 and 2011Q2, and from 2019Q4 onward. When extending the GDP time series in a benchmarking exercise going back to 1972, there is evidence for recessionary episodes between 1973Q2 and 1973Q3, 1982Q3 and 1983Q2, 2001Q1 and 2001Q2, 2004Q1 and 2004Q2, 2011Q1 and 2011Q2 and from 2020Q1 onward. Interestingly, the timing of the last recession is different in the two datasets – this may be due to the sharp drop in GDP in 2020Q2 which affects the timing earlier in the official time-series. This episode, linked with the COVID-19 Pandemic and ensuing mitigation efforts, is excluded from this study as its effects are still ongoing and significantly much larger than any other recession so far. Finally, in the latest National

⁴ This covers the years from 2000, onward.

Accounts vintage, the recession following the 2008/9 crisis disappears from the data, and is not captured at all by the Bry-Boschan algorithm.

Applying a Markov switching model to the latest official time-series finds that there are no longer consecutive periods where the recession probability is higher than 50.0%, but that there are four sharp peaks with short intense periods where the recession probability is high. These appear to coincide with the 2001 recession, the 2004 episode, the 2009Q1 recessionary episode and another one in 2011.⁵ In the extended timeline recessionary episodes are found between 1973Q2 and 1973Q4, and between 2001Q1 and 2001Q2.⁶ This latter method also finds single quarters with evidence for a recession, but which are not followed up by a similar recessionary quarter.⁷ Such “single quarter recessions”, or rather shocks with a short duration, are found in 1976Q4, 1978Q3, 1982Q4, 2000Q3, and 2009Q1. All the four approaches used consider 2009Q1 to be a recessionary episode, three methods provide some evidence for a further episode in 2004, but evidence is sparser for other dates.⁸

The study then looks at the labour market and finds distinct phases in the development of the labour market in Malta, which may be used to explain and analyse the different natures of the recessionary episodes discussed in the first section of this study. This approach is augmented with a further methodology which can compute monthly recession probabilities on the bases of unemployment rate data. Monthly recession estimates are computed from July 1966 onward, with evidence for at least six consecutive months of negative conditions in the economy confirmed between September 1972 and July 1973, April and December 1990, January and June 1992, March 1996 and November 1996, and between October 2001 and April 2002. Other shorter periods (less than six months) occur around the Great Recession of 2008/9, in 1977, and in other periods. Unemployment data is seen to be a timely additional source of information, which is useful in gauging the likely state of the Maltese

⁵ The 2001 Recession episodes may not be fully captured in this method because the autoregressive nature of the method drops some observations at the start of the official timeline.

⁶ Again, as the method used here casts data in autoregressive form, some observations are lost at the start of the time-series, such that quarters before 1973Q2 do not appear in the extended timeline.

⁷ These will be termed “orphan” quarters in this study.

⁸ See Appendix A for a table presenting the findings.

economy, with a number of caveats linked with underlying differences between the labour market and other sectors of the economy.

All in all, the study concludes that while the dating of the business cycle in Malta is fraught with problems relating to data quality, a scientific and impartial method of dating recessions in Malta is still possible and informative. In particular, such a dating process should be based on multiple methods, using both official and extended GDP data, and finally, should be supplemented with further indicators – in particular data related to the labour market.

Finally, this working paper was first completed before the publication of GDP estimates for 2020Q1, and thus did not consider the impact of the COVID-19 epidemic on the Maltese economy. Although updated to include the latest 2020Q3 vintage, in the spirit of the findings of the paper and the literature, it is thought best to leave an analysis of the recessionary episode in 2020 for a future date.

2. Literature review

Timing the business cycle properly is a very important matter in economic analysis. Proper economic policymaking, as well as a host of decisions by many other economic agents, depend on a good assessment of present and future economic conditions. In order for this assessment to be carried out in full, a historic analysis of the macroeconomic cycle would also be useful. Obviously, it is not a strict requirement to know where the economy was along the cycle thirty years ago in order to assess where it will be in the next ten years. However, looking at business cycles over a longer time period allows us to have a broader perspective of the relative magnitude of shocks and events. The importance of such historical analysis, therefore, ought not to be downplayed.

The importance of business cycle dating is reflected in the amount of emphasis other countries place in setting up committees and official dating rules to analyse their respective business cycles. While at times the financial press stresses that two consecutive quarters of negative growth coincide with a recession, many committees say that recessions tend to be dated in quarters recording negative quarter on quarter declines in GDP growth, but that GDP growth is not the only variable looked at when making this determination.⁹ For example, both business cycle dating committees for the euro area and the US highlight how a plurality of data are used for business cycle dating, more than the blunt use of two consecutive declines in GDP growth. The NBER's Business Cycle Dating Committee goes so far as to say that it "does not accept the two-quarter definition."¹⁰ In fact, the first traceable use of the 'two consecutive quarters' rule of thumb is found in an opinion article published in the *New*

⁹ As an example, see the [Euro Area Business Cycle Dating Committee \(EABCDC\)](#) within the Centre for Economic Policy Research and for the US, the [Business Cycle Dating Committee](#) within the National Bureau for Economic Research.

¹⁰ The NBER states that the Business Cycle Dating Committee does not accept the two-quarter definition: "*The committee's procedure for identifying turning points differs from the two-quarter rule in a number of ways. First, we do not identify economic activity solely with real GDP and real GDI (gross disposable income), but use a range of other indicators as well. Second, we place considerable emphasis on monthly indicators in arriving at a monthly chronology. Third, we consider the depth of the decline in economic activity. Recall that our definition includes the phrase, 'a significant decline in activity.' Fourth, in examining the behavior of domestic production, we consider not only the conventional product-side GDP estimates, but also the conceptually equivalent income-side GDI estimates. The differences between these two sets of estimates were particularly evident in the recessions of 2001 and 2007–2009.*" See above link for further explanations.

York Times in 1974, by Julius Shiskin - then the Commissioner of the Bureau of Labor Statistics.¹¹ This informal rule of thumb was presented as one of multiple ways of gauging the state of the business cycle, and was over time adopted by the financial press as the definition for recessions (Kose and Terrones, 2015). Other countries however, generally do look at two consecutive quarters of declining GDP growth as officially constituting a recession, such as the United Kingdom.¹²

The vagueness relating to the methodology used to date the business cycle is also evident in the way recessions and expansions are defined by the NBER, with the chronology used comprising

“[...] alternating dates of peaks and troughs in economic activity. A recession is a period between a peak and a trough, and an expansion is a period between a trough and a peak. During a recession, a significant decline in economic activity spreads across the economy and can last from a few months to more than a year. Similarly, during an expansion, economic activity rises substantially, spreads across the economy, and usually lasts for several years.”

These definitions appear to involve judgment, and are vague. A non-parametric algorithm was introduced by Bry and Boschan (1971), which came closest to rendering the NBER definition into a replicable tool. The algorithm uses a set of filters to identify local maxima and minima in the level (or log-levels) of the series.

A local minimum is seen to be a trough, and the following local maximum will be a peak. The period between the trough and the peak is defined to be an expansion, and that from a peak to a trough is defined as a recession. This algorithm served as a useful basis for a number of refinements carried out in various studies.¹³

An alternative method to date the business cycle is the Markov-switching (MS) approach. Following Hamilton (1989), this approach models business cycles as the result of a Markov process - switching between two discrete states, namely

¹¹ Shiskin, J., (December 1, 1974), [The Changing Business Cycle](#), The New York Times.

¹² In the 2010 Budget document for the United Kingdom, the “commonly accepted definition of a recession in the UK is two or more consecutive quarters (a period of three months) of contraction in national GDP.” (HM Treasury, 2010)

¹³ These are discussed in more technical detail in the Methodology section.

expansions and contractions. This approach assumes business cycles are unobserved stochastic processes. In practice, this means that the modeller's view with respect to particular dates are not a strict prior requirement. More recent approaches have expanded the method to include duration dependence parameters in the model.¹⁴

No serious attempt at dating the historical Maltese business cycle has been carried out. Ellul (2016) uses a modified Bry-Boschan algorithm to assess and benchmark estimates of a business conditions index (BCI).¹⁵ Grech (2015) constructs an annual macroeconomic database of the Maltese economy, with data going back to before Malta's independence; while there is a broad discussion on Maltese economic development, business cycle dating is not discussed in detail, due to the limitations of the annual dataset.¹⁶

Unfortunately, lack of data is a limiting issue, especially with respect to the length of high frequency time series published by the NSO. Official quarterly GDP estimates are published from 2000 onward in chain-linked volumes, and from 1995 onward in nominal terms. This means that, effectively, there are only around 80 observations of chain-linked GDP volumes in Malta upon which to time the development of the business cycle. If one were to assume an average business cycle duration of five years (Cotis and Coppel, 2005), this would mean that potentially the data would limit the analysis to, at most, five full cycles over around twenty years. If one were to consider that the evolution of the business cycle in Malta were slower, or that the normal evolution may have been affected by shocks, the analysis would be further limited in its scope.

¹⁴ See Durland and McCurdy (1994) and Kim and Nelson (1998).

¹⁵ An analysis on the robustness of the Central Bank of Malta's Business Conditions Index and its ability to capture real-time turning points in the Maltese economy was carried out using the Bry-Boschan (1971) technique, dating the business cycle from the year 2000 onward.

¹⁶ The annual macro-economic database is used as an important source for the construction of an extended quarterly time-series in this study.

3. Methodology

Turning point analysis

As noted in the literature applying turning point analysis, simple rule-based methods identify turning points in univariate time series at time t as local peaks (Pagan, 2013). After taking logarithms¹⁷ of the target variable Y_t , a turning point will be one where $\{y_{t-1} < y_t > y_{t+1}\}$, that is, $\{\delta y_{t-1} > 0, \delta y_{t+1} < 0\}$ ¹⁸. Most turning point algorithms follow this intuition. In general, algorithms also incorporate smoothing mechanisms with fixed-time windows in which the data is smoothed, before applying the turning point rule found above.¹⁹ In practice, this is done by following a definition that peaks happens at time t if $\{y_{t-k}, \dots, y_{t-k+1} < y_t > y_{t+1}, \dots, y_{t+k}\}$ (and a trough would involve $\{y_{t-k}, \dots, y_{t-k+1} > y_t < y_{t+1}, \dots, y_{t+k}\}$). The symmetric window parameter k is set by the user, and should be linked with the underlying data frequency being used. Typical values for k are, for example, $k = 2$ for quarterly data, $k = 5$ for monthly data and $k = 1$ for yearly data.

Frequency also raises another issue, namely having consecutive periods with peaks or troughs in a row. Ideally, theory would suggest troughs and peaks should alternate. In that case, the algorithm would need to select and drop one of these consecutive observations. Once that happens, the user may also have some views on expected minimum durations of the business cycle timing, namely ensuring that the observed downturns are long enough to be considered so,²⁰ and so on. This will in turn lead to the dropping of peaks and troughs, which in turn will require the algorithm to again ensure that the two features alternate, until the algorithm's iterations come to a stable definition of the business cycle.

¹⁷ The eventually chosen turning points will be invariant to monotonic transformations, such that those deriving from Y_t will be identical to those identified in logarithms, $y_t = \log(Y_t)$.

¹⁸ See Wecker, (1979).

¹⁹ In practice, this implies $\{y_{t-k}, \dots, y_{t-1} < y_t > y_{t+1}, \dots, y_{t+k}\}$.

²⁰ A two-quarter minimum requirement for expansions and contractions is often used in empirical analyses, following the rules used by the NBER in dating phases. Further parametrisations include a minimum phase parameter and a minimum cycle parameter. A complete cycle length (that is, contraction and expansion duration together) of five quarters is also common. If the fall in the series is very large, a threshold parameter – usually set at a 25.0% drop – is included to allow for a short-duration.

Once the turning points are defined, the time series is split into phases of expansions (i.e., the periods between troughs and peaks) and contractions (i.e., the period between peaks and troughs). In turn, these dates will provide analysts with information regarding the duration, amplitude and cumulative movements between periods.

These procedures imply notoriously complex optimisation algorithms, with a number of issues – in particular its performance with simulated data (Pagan, 2013). While the original methods behind turning-point analysis were discussed in Bry and Boschan (1971), these methods were improved upon by Harding and Pagan (2002), and reached its current (and perhaps most widespread use) with the James Engels modification. While the original method developed by Bry and Boschan (1971) referred to monthly data (the ‘BB’), this was altered by Engel (2005),²¹ Harding and Pagan (2002), and Watson (1994) to better consider quarterly data (that is, ‘BBQ’), and introduced more modern methods relating to filtering and state analysis.

The final result of these complex algorithms, however, is a simple phase output which summarises the business cycle characteristics discussed above, as represented by a binary random variable $S(t)$, with the ‘states’ of the economy taking the value 1 in expansions and 0 during contractions.

Markov switching models

Another way of looking at business cycle timing is by using Markov switching models, first introduced in Hamilton (1989). This is known as a regime switching model and is a non-linear time-series model.²² This approach models behaviour under different regimes, which in turn allows the model to describe more accurately the complex patterns under dynamic conditions. The model class has an unobservable state variable, which follows a first-order Markov chain.²³ This means that the state process will prevail for a random length of time, and it will then be replaced by some other structure once, and if, a switch occurs. These techniques have proven to be a very

²¹ The Engel approach is sometimes referred to as the Modified-BBQ, or MBBQ.

²² Linear models tend to be very popular in time-series econometrics. While they are very useful, they may not be able to incorporate a number of features found in some data – in particular, volatility clustering, amplitude dependence and asymmetry. GDP growth rates tend to fluctuate around a higher level during an expansion and be more persistent. However, during contractions, they may stay at a lower level, and be less persistent. Having a uniform model to capture these different behaviours may not be ideal, or even possible.

²³ One of the interesting properties of these chains is that the current value of the state variable depends on its immediate prior value.

popular way to model and analyse time series.²⁴ A simple autoregressive model AR(4) is constructed, with the process mean switching between two states. One state will refer to expansions, the other refers to recessions. This can be written as:

$$y_t = \mu_{s_t} + \phi_1(y_{t-1} - \mu_{s_{t-1}}) + \phi_2(y_{t-2} - \mu_{s_{t-2}}) + \phi_3(y_{t-3} - \mu_{s_{t-3}}) + \phi_4(y_{t-4} - \mu_{s_{t-4}}) + \varepsilon_t$$

In every period, the regime may transition between two states $[i, j]$ – according to the following transition probability matrix:

$$P(S_t = s_t | S_{t-1} = s_{t-1}) = \begin{bmatrix} P_{0,0} & P_{1,0} \\ P_{0,1} & P_{1,1} \end{bmatrix}$$

where $p_{i,j}$ is the probability of transitioning from regime i to regime j . Once the above structure is specified, the model is fit via maximum likelihood estimation methods.²⁵ One of the main drawbacks of these methods is the inclusion of lags in an autoregressive structure. This means that some of the initial observations are lost, due to these lags. This means that this method will be unable to show the recessionary episodes towards the beginning of the sample. This may be the case for the official time series, with an episode in 2001 marked by the Bry-Boschan technique. The timing of this episodes in the data is unfortunate in the Maltese case.

Hidden Markov models

A first-order hidden Markov model (HMM) assumes that the state variable it is interested in depends only on the state existing in the previous time step, but that such state is hidden, that is, an unobservable variable. Instead, only some random variable generated under a particular state is observed – without knowing what state that was. This approach is particularly useful if states exhibit great persistence, meaning that they are likely to endure for long periods of time. In this regard, they are particularly useful with labour market data such as unemployment rates.

Let U_t be the observed variable at time t , (e.g. change in unemployment rates). The distribution of U_t will depend on the state at time t , which state - S_t - has three possible

²⁴ See Hamilton (1988, 1989), Engel and Hamilton (1990), Lam (1990), Garcia and Perron (1996), Goodwin (1993), Kim and Nelson (1998).

²⁵ Good starting parameters are based on a number of steps of the expectation maximisation algorithm, with the quasi-Newton (BFGS) applied to find the maximum.

values – job gain state (0), job loss state (1) and normal state (2). For simplicity, it is assumed that the observations can be modelled by a Gaussian distribution.

A three-state HMM can be defined as $f(U_t|S_t = i) \sim N(\mu_i, \sigma_i^2)$, $f(U_t|S_t = j) \sim N(\mu_j, \sigma_j^2)$ and $f(U_t|S_t = k) \sim N(\mu_k, \sigma_k^2)$. The state at time t , S_t will depend on the state at the previous time step, S_{t-1} . Letting \mathbf{P} be a state transition matrix, where each element $p_{i,j,k}$ represents the probability of transitioning from state i at time t to states j or k at time $t + 1$, and \mathbf{P} is an $n \times n$ matrix where n is the number of states ($n = 3$).

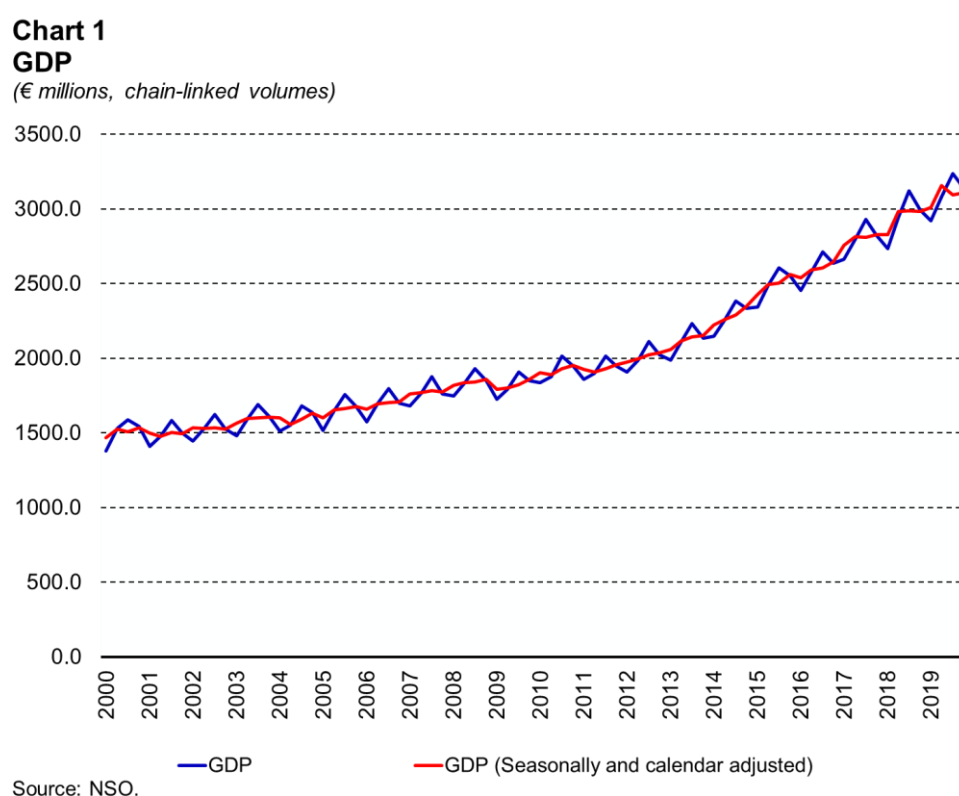
In all Markov models, hidden or otherwise, the unconditional probability of being in each state, π , can be modelled as $\Pi = \pi\mathbf{P}$, where Π is a $1 \times n$ vector where each element π_i represents an unconditional probability of being in state i , that is, $\Pi_i = P(S_t = i)$.²⁶ As there is no prior information on which condition one should first set the observations for the labour market, the initial probability of being in each state is assumed to be the stationary distribution.

When fitting a three-state Gaussian HMM, the following vector of parameters has to be estimated: $\theta = [\mu_0, \sigma_0, \mu_1, \sigma_1, \mu_2, \sigma_2, p_{00}, p_{11}, p_{22}]$

²⁶ Π is also called the HMM's stationary distribution, and may be calculated as described above.

4. Data

With a population of over 500,000,²⁷ and a gross domestic product (GDP) standing at around €12.4 billion²⁸ at end-2019, Malta is the smallest economy in the European Union in terms of both GDP level and population size. This study first attempts to look at the timing of the business cycle as found in official data. Official GDP estimates for Malta are available in chain-linked volumes from 2000Q1 onward. The series is highly seasonal, although official seasonally and calendar adjusted data are also available (see Chart 1).²⁹



The level of GDP appears to be relatively stable prior to 2014, with a level decrease in 2009. Following 2014, however, the trend in GDP accentuates dramatically. By end-2019, seasonally adjusted GDP surges to double the level seen in 2000. While looking at the GDP series in levels is instructive in terms of seasonality and the recognition of trends, the series is not as informative when it comes to the exact timing of the

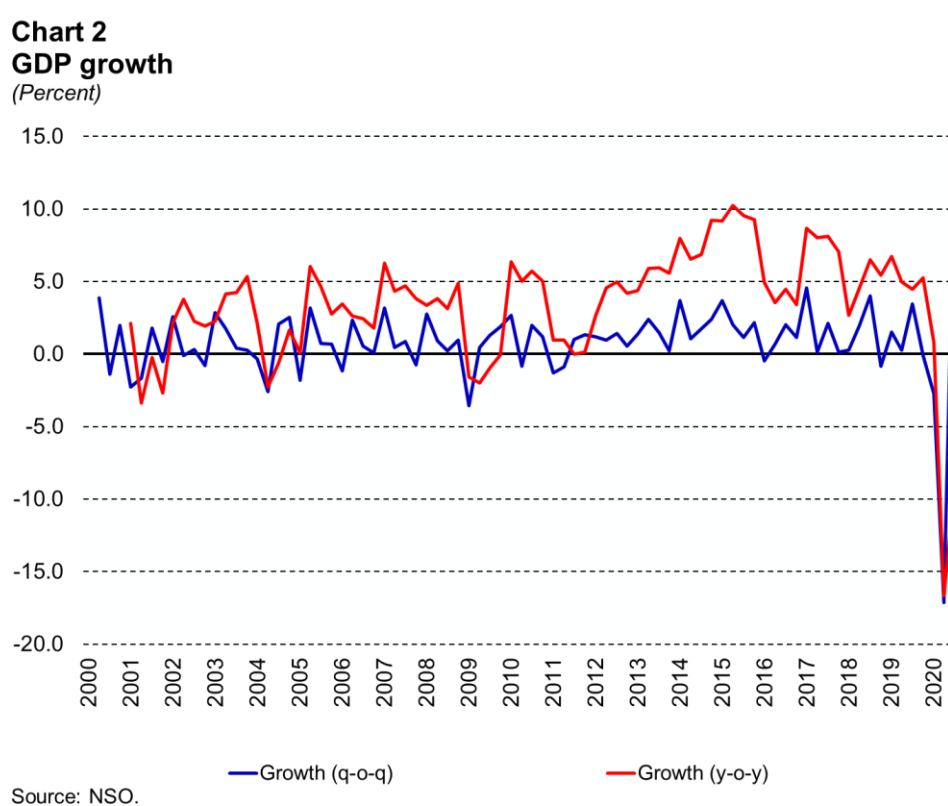
²⁷ Total population in Malta and Gozo stood at 514,564 at end-2019, as per NSO release No. 114/2020. This figure excludes tourist levels.

²⁸ Measured in chain-linked volumes as at end-2019 in NSO release No. 194/2020.

²⁹ Only data up to 2019Q4 are shown in this Chart.

business cycle. A look at growth rates allows a more comprehensive analysis, as these are the basis for most of the business cycle dating techniques in use today.

When looking at time-series, there are alternate ways with which to measure growth. Two of the most popular methods are year-on-year and quarter-on-quarter methods. The former compares growth in a quarter of a particular year with the same quarter of the previous year. The latter calculates growth in a quarter on the basis of the previous quarter. Most of the literature for business cycle dating tends to prefer quarter-on-quarter measures, possibly due to the phenomenon of lagging turning points in year-on-year growth rates (Musso, 2003).



In Malta, GDP growth rates are marked by significant volatility, even if the COVID-19 pandemic has had outsized effects on this variable (see Chart 2). In general, strong positive quarter-on-quarter growth rates tend to be followed by negative ones, reflecting the noise found in Maltese time-series data. Excluding post-2019 data, average quarter-on-quarter growth stands at 1.0% per quarter, with a standard deviation of 1.6. Year-on-year growth rates have an average of 3.9%, and a standard deviation of 3.0.

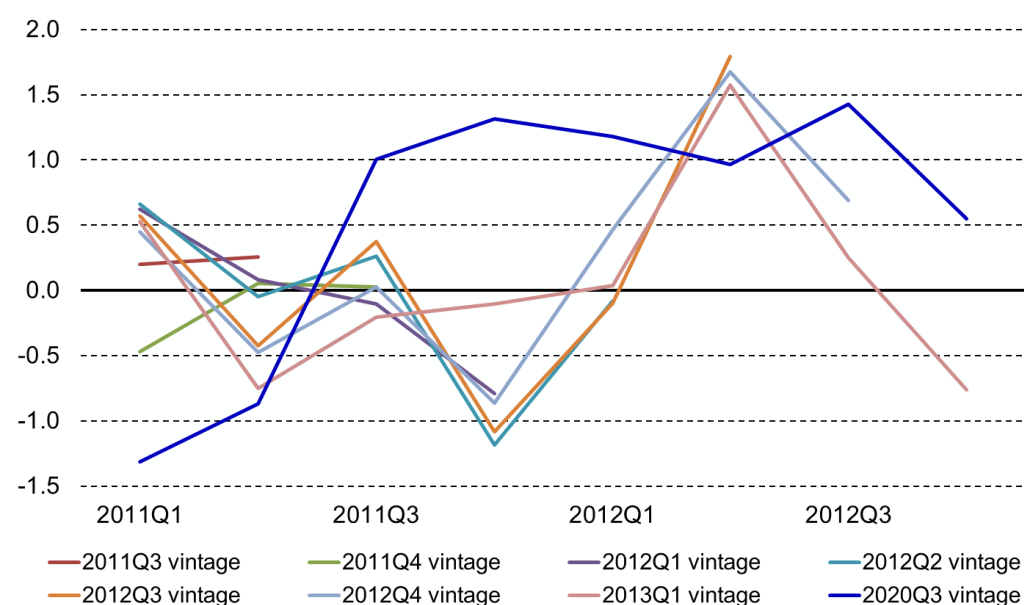
Both growth rate measures have marked declines in 2008/9 which can – for now – be hypothesised to be a turning point around the Great Recession, and strong growth rates following 2013. Some evidence of other declines appears around 2001 and 2004. However, this type of analysis is rather speculative in nature, as it is based on a mere visual inspection of growth rates, rather than the scientific analysis of time-series data. Of note, however, is the lagging of a hypothesised turning point around end-2008 and beginning 2009, between the quarter-on-quarter and the year-on-year measure – as discussed above.

Revisions and business cycle dating

Before carrying out a proper business cycle analysis, it is important to understand the revision properties of Maltese GDP data. These are discussed at length in Grech (2018). Chart 3 shows seasonally adjusted quarter-on-quarter growth from seven successive vintages of national account releases,³⁰ as well as that from the latest release considered in this study (2020Q3), for the years 2011 to 2012.

Chart 3A
Successive vintages of GDP growth

(Percent)



Source: Author's calculations.

³⁰ Obtained from Grech (2018).

Apart from the obvious differences in estimated growth between the latest vintage and the data published between 2012 and 2013, the differences between intermediate estimates of growth are also apparent. Unfortunately, not only does the magnitude of the growth rates differ between successive vintages, but at times the sign of the growth rate changes too.

Table 1 depicts a simple logical test for seven successive vintages of seasonally adjusted national accounts and the latest available one over the period 2011Q3 to 2012Q3 as a simple check whether at time t there are two successive quarters of growth estimates in the seasonally adjusted series – in line with the strict definition of recessions assumed by many financial analysts.

It becomes immediately evident that if one follows such a definition, given the peculiarities of Maltese national account estimates, recessions would be far more frequent, and these would appear and disappear over time, depending on the figures in the latest available national accounts vintage.³¹ Thus, for example, while two periods of negative quarter-on-quarter growth were apparent in 2011Q3-4 in the 2012Q1 vintage, this ‘recession’ was revised in the successive vintage to occur between 2011Q4-2012Q1 in the successive two vintages. In the last vintage for 2012, no recession is apparent anywhere along the five quarters being analysed, however in the first estimate for 2012Q3 (i.e. the 2013Q1 vintage), there are two successive periods of negative quarter-on-quarter growth between 2011Q3 and 2011Q4. By the latest currently available vintage, that is, 2020Q3, this period’s recession has moved back to 2011Q2. This volatility may also affect the algorithms used to derive seasonally adjusted GDP.

³¹ In no way should this work, or any parts thereof, be seen to question the work and effort carried out by the NSO. On the contrary, this study attempts to highlight the proud and long spanning history of statistical data collection, and the keeping of National Accounts in Malta. The author is aware that the limitations of the data highlighted above are but a reflection of the statistical constraints imposed by the quality of data inputs in Malta.

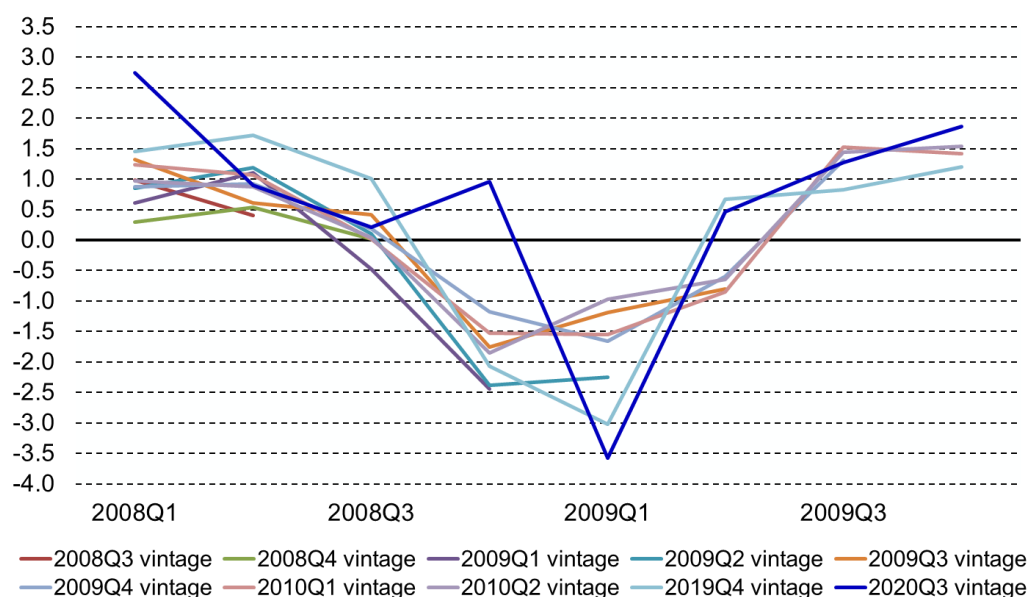
Table 1: Strict recession definition

	2011Q3 vintage	2011Q4 vintage	2012Q1 vintage	2012Q2 vintage	2012Q3 vintage	2012Q4 vintage	2013Q1 vintage	2020Q3 vintage
2011Q2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
2011Q3	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
2011Q4		FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE
2012Q1			FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
2012Q2				FALSE	FALSE	FALSE	FALSE	FALSE
2012Q3					FALSE	FALSE	FALSE	FALSE

Source: Author's calculations.

Likewise, the 2008/9 period is of particular interest, given the expected timing of the Great Recession. Chart 3B shows quarter-on-quarter growth rates for these two years over different vintages of GDP growth, over multiple years, as well as in the latest vintage. There is a clear difference between the latest vintage (2020Q3), and previous ones. While the 2019Q4 vintage already had an earlier switch back to growth in 2009Q2, the latest set of GDP figures show a shift to positive growth in 2008Q4.

Chart 3B
Successive vintages of GDP growth
(Percent)



Source: Author's calculations.

Of course, such comparisons are not strictly fair given the introduction of new European System of Accounts methodologies between the 2013Q1 vintage and the latest available one. However, statistical methods were consistent between the

2011Q3 vintage and the 2013Q1 vintages in Chart 3A, as well as in the vintages immediately during and following the recession in Chart 3B. A first look at the data also shows that vintages published close to the same time period are rather similar, subsequent revisions tend to be much larger and more fundamental.

What this suggests is that policymakers, economists and analysts should be very wary when discussing the timing of recessions in Malta, particularly so because of the tendency for national accounts estimates to be heavily revised, as better data is made available to statisticians with considerable lags. Additionally, there are also methodological changes. For example, in the 2020Q2 vintage, the national accounts were benchmarked by the NSO, affecting significantly the timing and historic pattern of growth from 2000 onward.

Moreover, strict adherence to rules of thumb which ignore the characteristics of Maltese data, such as ‘two periods of negative quarter-on-quarter growth,’ ignores the element of volatility in Maltese data. It has also to be noted that with successive revisions, economic history tends to change, sometimes dramatically. Using the ‘two periods of negative growth’ rule of thumb, and looking at the latest set of national accounts, it appears that the Great Recession – which in previous vintages was dated 2008Q4-2009Q1, disappears as a recession as the growth estimate for 2008Q4 was shifted to positive territory in the 2020Q2 vintage.

An interesting avenue for further research may be the application of Bayesian averaging methods to different GDP vintages to account for the effect of revisions to the data.

Finally, statistical maxima and minima, outliers and overall series volatility should be considered when dating business cycles, especially as shifts in such variables between releases will naturally tend to affect the timing of the business cycle. Many of these issues in business cycle dating are handled automatically by the Bry-Boschan algorithm.

Benchmarking quarterly data from the 1970s to the 1990s

The oldest official national accounts data-point available for Malta refers to 2000Q1. Grech (2018) has some quarterly observations before this point in ‘real’ terms from some early vintages of published NSO data.

Using a combination of sources, namely archive databases published by the Central Bank of Malta, published releases and old archived websites,³² a nominal quarterly series was collated and checked as far back as 1972.³³ The first step to create a viable quarterly series consistent with the current vintage of GDP estimates is to use deflators to convert the nominal figures. Annual deflators, found in Grech (2015) were used, interpolated over the whole year. The resulting quarterly series is then adjusted by forcing the resulting annual growth rates to match those published in Grech (2015). The resulting quarterly GDP series goes back to 1972Q1 (see Chart 4). While this approximation leads to a workable estimate for quarterly GDP, the problem is that there is a lot of volatility in some years. In particular, the years 1995 to 1998 have a series of successive spikes due to changes in the indirect taxation regimes. These spikes are spread out, and adjusted without affecting the annual growth rate – again ensuring that the annual growth rate follows Grech (2015).³⁴ The resulting growth rates are rather stable, especially in comparison with the official GDP figures from the early 2000s (see Chart 5).³⁵

These estimates are imperfect. They are based on nominal quarterly GDP series, deflated by implicit annual deflators. The historic growth rates are not chain-linked and

³² The author holds the work carried out by archive.org in high regard, particularly the archives relating to the Maltese government website and that of the Malta National Statistical Office, and its predecessors.

³³ See [CBM website database](#).

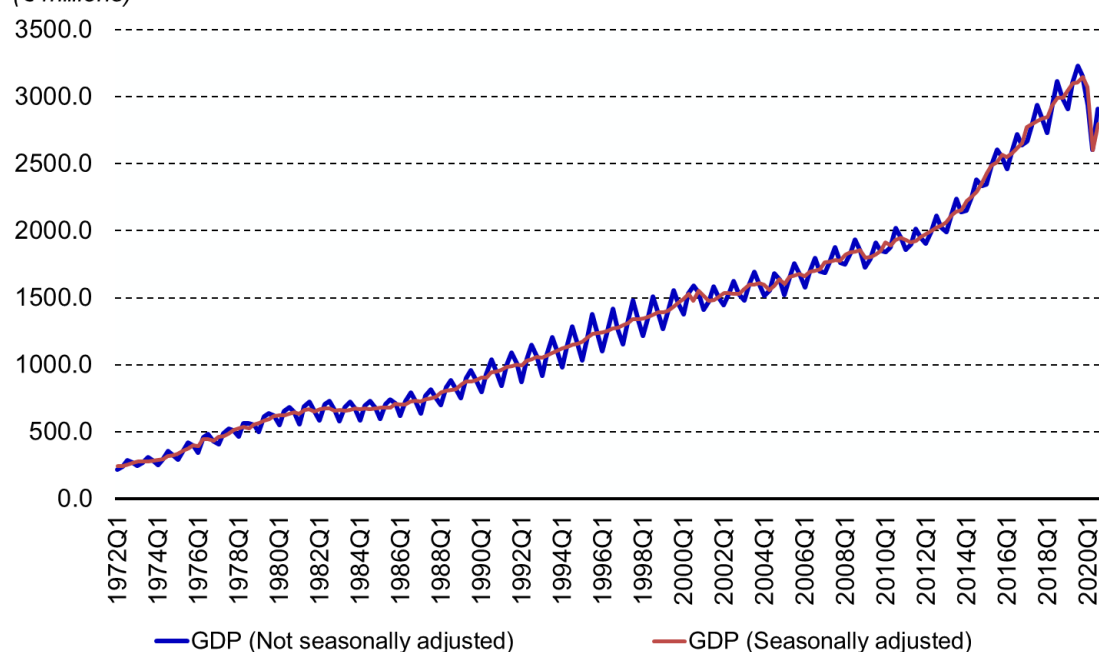
³⁴ Between 1995 and 1999, a number of changes were carried out to the indirect (excise) tax regime levied on the Maltese economy. These changes, dealing with the introduction of Value Added Tax (VAT) and Customs and Excise Tax (CET) are documented in successive Ministry for Finance Budget Speeches and Economic Surveys between 1995 and 1999. VAT was first levied in Malta in January 1995, it was then scrapped and replaced by CET in July 1997 and re-introduced in January 1999. An IMF study summarises the performance of VAT and its proposed replacement (IMF, 1997). These changes resulted in some distortion in many nominal and real historic time-series series of the Maltese economy throughout these years. The volatility is present in published national accounts figures. In short, this leads to a number of positive and negative spikes in the path of GDP growth during these years which may be linked with these price effects. In order to avoid having these events distorting the estimates for the business cycle, the path for GDP growth was smoothened out, in effect changing the distribution of the estimated quarterly GDP levels, and retaining the annual sum constant. While intrusive, this approach is deemed to be justified by the volatility of the GDP series in these years. Unfortunately this means that data quality falls significantly in the 1990s, making a meaningful – and scientific – analysis of the path for GDP problematic in this period. Using an unemployment rate based indicator (introduced in subsequent sections of this working paper) there is evidence for recessions in the 1990s, in particular in the mid-1990s, however the estimates for GDP are not complete enough to discuss these with confidence in GDP data.

³⁵ The historic year-on-year time series, until 2019Q4, has 188 observations, a mean annual growth rate of 5.6%, a standard deviation of 4.6 and a kurtosis of 2.9. The historic quarter-on-quarter time series has 191 observations, an average quarterly growth rate of 1.4%, a standard deviation of 2.0 and a kurtosis of 6.1.

are based on old systems of national accounts. Moreover, between 1995 and 1998 the volatility created by indirect tax regime changes had to be adjusted. These figures should be looked, at best, as flawed estimates of missing GDP data – an improvement over the interpolation of annual data in that they are based on an original nominal quarterly series, and a further contribution toward the economic history of the Maltese economy. Finally, these estimates should by no means be thought of as final, but as a first step towards establishing a higher frequency data source for economic analysis and research in Malta.

Chart 4
Benchmarked historic GDP

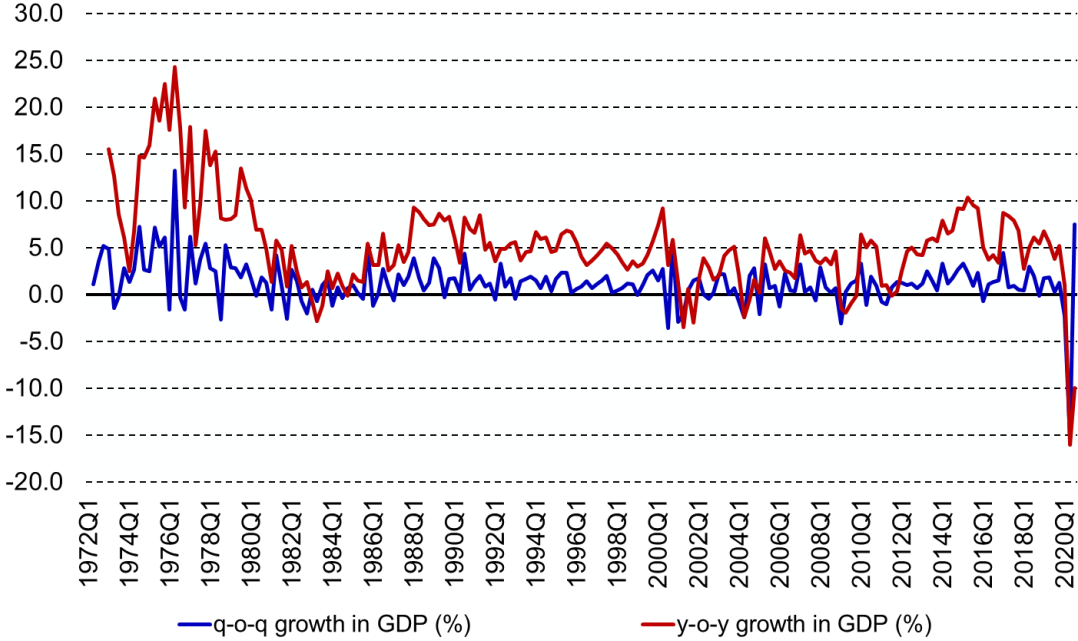
(€ millions)



Source: Author's estimates.

Chart 5
Benchmarked historic GDP growth rates

(Percent)



Source: Author's estimates.

5. Results³⁶

Bry-Boschan technique

Bry-Boschan technique and the official quarterly GDP time series

The application of the BBQ algorithm to official seasonally adjusted national accounts data identifies a number of turning points in Maltese data.³⁷ These refer to troughs or recessions occurring between 2001Q1 and 2001Q2, between 2004Q1 and 2004Q2, between 2011Q1 and 2011Q2 (see Chart 6).³⁸ The main issue in terms of important dates in timing the business cycle, is the Great Recession. While in all previous vintages of National accounts this was a serious and negative period in terms of economic growth, usually timed at around 2008Q4 and 2009Q1, in the latest set of national accounts this episode's negative impact mellowed significantly.³⁹ The use of standard BBQ methodologies do not find evidence for a two quarter recession in this period. This is a highly puzzling development.

Historically, the 2001 episode can be identified with the effects of the bursting of the dot-com bubble, and its impact on one of Malta's main exports of goods, namely semiconductors. The year was also marked by shocks related to tourism following the 9/11 event. The 2004 episode can be linked with the impact of Malta's EU entry on several sectors in the manufacturing industry. The 2011Q1-Q2 episode possibly reflects global trade developments, in particular a slowdown in exports following the sharp recovery seen in 2010, and the emergence of sovereign debt concerns in some euro area countries.

³⁶ Where turning points are shaded, they refer to likely recession episodes as identified by the method being discussed in the current sub-section.

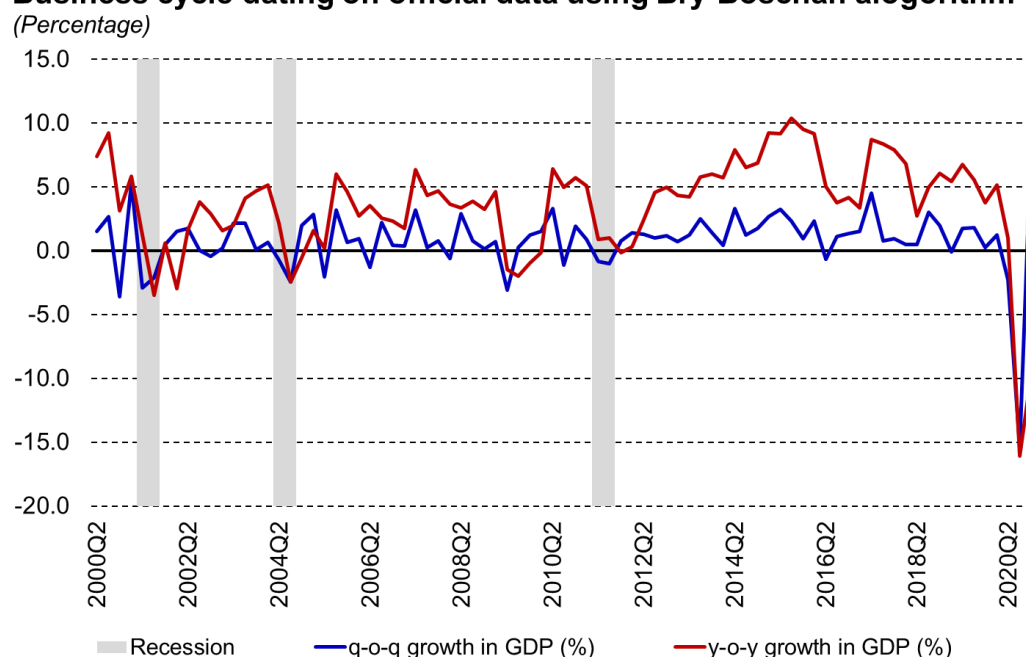
³⁷ A full set of dates which time recessions in Malta can be found in Table A1 in the Appendix.

³⁸ In a previous National Accounts vintage (2019Q4), the identified recessions were 2001Q1 and 2001Q4, 2004Q1 and 2004Q2, 2008Q4 and 2009Q1, and 2011Q1 and 2011Q2. The latest vintage, following a benchmark exercise, led to a shortening of the first recession which now ends in 2001Q2, and the disappearance of the 2008/9 recession, which now only occurs in 2009Q1.

³⁹ Using seasonally adjusted chain-linked quarterly figures, the quarter on quarter growth rate in GDP in 2008Q4 and 2009Q1 (2019Q4 vintage) were -2.1% and -3.0%, respectively. In the 2020Q2 vintage, the quarter on quarter growth rates were revised to 1.0% and -3.6% respectively. Effectively, this erases the Great Recession from Maltese National Accounts.

Two of these episodes (2001, 2004) were already identified in Ellul (2016).⁴⁰ The latest set of seasonally adjusted national accounts data also leads to the identification of a third recessionary episode in 2011. As seen in Table 1, however, the exact timing of a recession in this period, if there is one at all, is highly problematic due to instability across national accounts data vintages due to revisions.

Chart 6
Business cycle dating on official data using Bry-Boschan algorithm



A fourth recessionary episode is also found in by the algorithm, beginning in 2019Q4. This finding may be affected by the exceptional nature of the estimates for 2020Q1 and 2020Q2, which are causing the filtered data to identify the start of the recession linked with the COVID-19 Pandemic to shift to an earlier quarter. Care and attention should be made when using these methods to date the business cycle, particularly towards the end-point of a series. Supplementary data and other indicators ought to be looked at to assess the likelihood of such estimates. This is especially the case for

⁴⁰ Ellul (2016) discusses how in “...2001, adverse external shocks hit the electronics industry and tourism – two important economic activities for Malta. The first was a slowdown of the global semiconductors industry in the aftermath of the bursting of the US technology bubble in 2000. Moreover, geopolitical tensions in the Middle East and their impact on world travel, depressed the local tourist industry. In 2004, Malta’s accession into the European Union led to substantial restructuring in a number of specific sectors - particularly the local shipyards and the textile industry. The global crisis episode in late 2008 and early 2009, however, resulted in a severe shock to the local economy - with many sectors of the economy being affected simultaneously.”

exceptional periods such as the first half of 2020. This episode is excluded from the analysis, and the quarters referring to it are left unshaded.

The average duration of contractions is two quarters, while the average duration of expansions is just under twenty-three quarters. The average amplitude of contractions is -3.0%, while that of expansions 27.0%. The amplitude (percentage change) measure describes how the average decline in real GDP in recessions is significantly lower than the average rise during periods of expansions. This betrays the upward trending nature of GDP in Malta, and the strong growth rates reported in national accounts.

Two caveats ought to be kept in mind with these findings. The first relates to seasonal adjustment. Revisions to recent data may affect the seasonal patterns and trends throughout the whole series, such that more recent official seasonally adjusted data may lead to different growth rates some years prior to the revisions in underlying seasonally unadjusted data. Likewise, further work and research ought to be recommended on the proper seasonal adjustment of Maltese national accounts data, as improper seasonal adjustment may be affecting the quarter-on-quarter path for GDP. Secondly, the episode identified in 2001 is really two separate shocks – one to semiconductor exports, and the second to tourism, which coincided in the same year. Its closeness to the start of the algorithm's analysis period⁴¹ will also be problematic once the GDP time-series is extended backward.

Bry-Boschan technique and the extended quarterly GDP time series

The application of the BBQ algorithm to historic seasonally adjusted national accounts data does not change the story from the official time-series data. In this longer historic perspective, troughs or recessions are seen to occur between 1973Q2-Q3, 1982Q3 and 1983Q2, 2001Q1-Q2, 2004Q1-Q2, between 2011Q1-Q2 and from 2020Q1 onward (see Chart 7).

The recession in the early 1970s can be linked with a period of successive economic shocks which hit much of the Western world, such as the 1973 oil crisis and the collapse of the Bretton Woods system, which led to a long period of economic

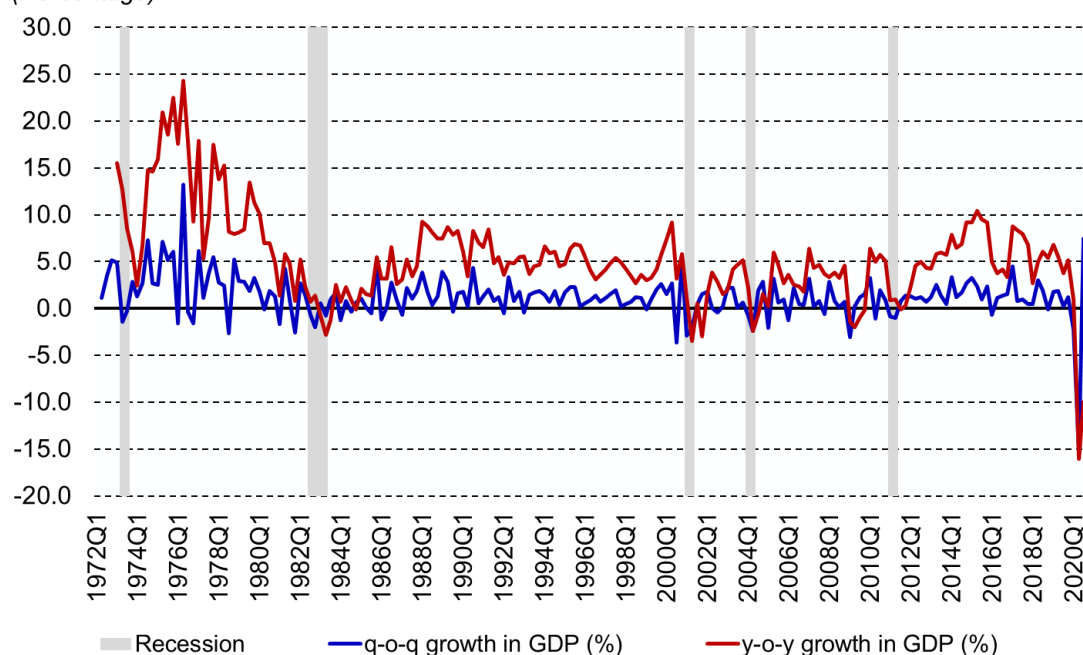
⁴¹ The first quarter-on-quarter growth data-point is 2000Q2.

stagnation that put an end to the overall Post–World War II economic expansion episode. The episodes identified in the 1970s are also confirmed in the narrations found in the historic Quarterly Reviews published by the Central Bank of Malta.⁴² Grech (2015) discusses how economic growth picked up its pace by the late 1970s, before a sharp slowdown began in the early 1980s following a second oil price shock. The early 1980s was a period of low growth, with several shocks and negative growth rates in GDP. The 1980s recession, and its impacts on total factor productivity, female participation and other macroeconomic variables are also explained at length in Grech (2015).

Interestingly, all recessions in the official time series are confirmed by the historic time series – confirming that the extension with estimated historic data did not affect the timing of these recessions. The minor exception refers to the late 2019 recession, which disappears in the historic timeline – and reappears in the first half of 2020. This can be attributed to changes due to the exceptional nature of data in the wake of the COVID-19 Pandemic: The quarters for this latest episode are left unshaded due to this uncertainty.

⁴² This is especially the case for the results found in the unemployment rate based indicator presented in the next section. The author would like to thank Bank staff at the Central Bank of Malta Library for their continued effort in digitising historic publications.

Chart 7
Business cycle dating on historic estimates
(Percentage)



Source: Author's estimates.

The average duration of contractions in this extended time-series is slightly higher than two quarters, with the average duration of expansions standing at around nine years. The average amplitude of contractions is -2.9%, that of expansions 51.0%.⁴³ Again, this confirms the long-run growth path of GDP in Malta, which has historically been typified by long years of upward trending growth, broken by short periods of recessions.

Markov switching models

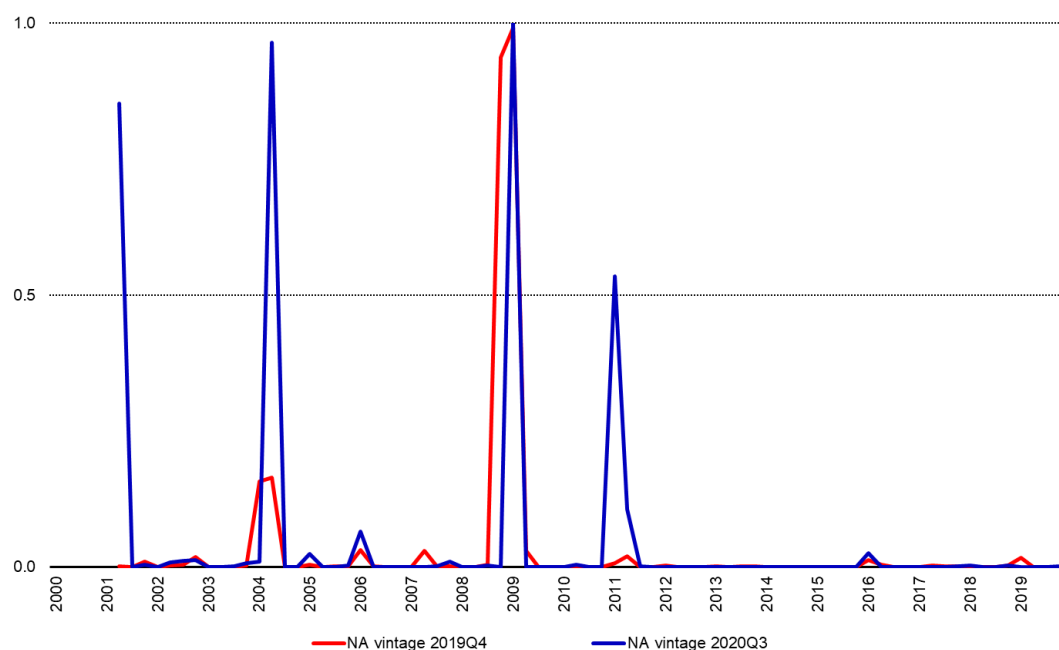
The results from estimating a Markov state-switching model on the two time-series can be seen in Charts 8 and 9.⁴⁴ Both the estimates of the official and the extended time-series agree that 2009Q1 is associated with a recession. As noted earlier, in previous vintages, this particular recession was dated to start in 2008Q4 and end in 2009Q1. The probabilities in both cases and both quarters are higher than 0.94. This

⁴³ The BBQ algorithm defines peaks and troughs. A peak will be the turning point when an expansionary phase transitions into a contractionary phase. A trough will be the turning point when the contraction transitions again into an expansionary phase. These definitions will allow users to discuss the duration of episodes, being the number of quarters between a peak and a trough, and the amplitude, which is the height of the differences between a peak and a trough.

⁴⁴ See Appendix B for the full regression outputs, including standard errors. While the regime parameters in both cases are statistically significant, the regime switching parameters cannot be identified.

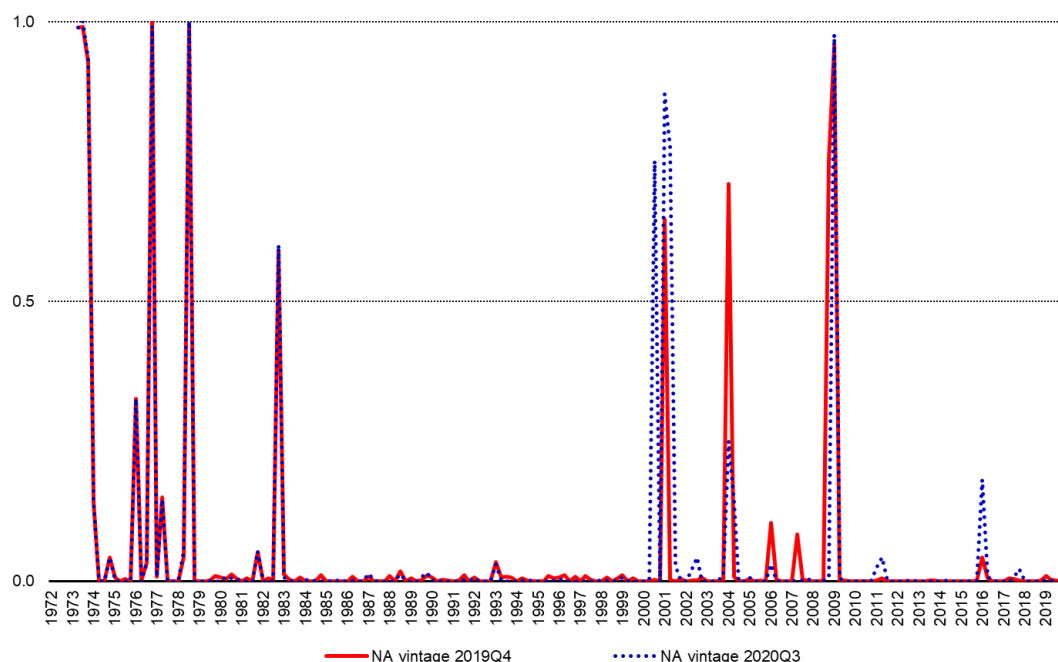
is a confirmation of the findings of the Bry-Boschan technique which up until the 2019Q4 vintage found a recession in 2008Q4 and 2009Q1. The results are confirmed across all methodologies, although the length of the recession episode now falls below the two-quarter cut-off. Moreover, findings are consistent within vintages – while minor differences can be attributed to the methods. In fact, the main component of the revisions appears to derive from changes in the official GDP data, rather than the methods.

Chart 8
Smoothened probability of recession



Source: Author's calculations.

Chart 9
Smoothed probability of recession



Source: Author's calculations.

For the earlier episodes, however, the official GDP time-series is much less informative, due to its length. The extended time-series is more informative, and has some evidence for the start of the 2001 recessionary episodes in 2001Q1.⁴⁵ The dates largely coincide with the dates in the previous Bry-Boschan technique – although the duration is much shorter. In fact, contractions have a duration of just over one quarter in the extended GDP time-series, while expansions are seen to have a duration of just over 23 quarters.⁴⁶ In the extended timeline, recessions – that is – two consecutive quarters where the probability of being in a recession is higher than 0.50, are found in 1973Q2-Q4 and 2001Q1-Q2. Other short periods where this probability surges above 0.50 are 1976Q4, 1978Q3, 1982Q4 and 2009Q1.

The results are again a confirmation of the shortcomings found in Maltese GDP time-series.⁴⁷ As discussed above, its disposition to revisions, and its relative short-time

⁴⁵ With a probability of 0.87.

⁴⁶ In the official time series, contractions have an expected duration of around 1.0 quarter, while expansions have an expected duration of 19.3 quarters.

⁴⁷ An interesting avenue for further research here would be looking at how latest available information sets would trigger a change in classification from a recession to a non-recession period, or vice-versa, following Chauvet and Hamilton (2005). This is touched upon here with an analysis of the difference in business cycle dating between the 2019Q4 and the 2020Q3 National Accounts vintages.

span means that discussions on the exact timing of recessions within the context of wider business cycle analysis is at times problematic. However, there is evidence for some particular dates where the methods discussed in this study do agree.

Hidden Markov models

The literature on business cycle analysis, as well as practical methods described by business cycle analysts suggest that data other than GDP series ought to be looked to arrive at a well-rounded view on the economic narrative when dating a particular time period. These data would include industrial production, sales and turnover, hours worked, and labour market data.⁴⁸

Unfortunately, there is a relatively limited amount of time-series at higher frequencies going so far back in Malta's economic history. In order to investigate business cycle dating beyond GDP, this part of the analysis shifts the attention to the labour market, and uses the unemployment rate dataset going back to the 1960s which was first introduced in Ellul (2018), and constructs a hidden Markov model.

These models are useful to describe developments in labour market variables.⁴⁹ If one assumes the existence of periods of strong job gains and losses (such as job-rich recoveries, etc.), one could infer that periods with a decrease in unemployment will be linked with those job gains even if one does not know the causes of the anomalies in employment in those years. Even if these anomalies are known, such as the timing of a recession, other more predictive – but unknown – regime-shifting events in the labour market may be operating.

Labour market developments

A first-order Hidden Markov Model (HMM) with three states is estimated on changes in the unemployment rate, following the literature, in order to assess the timing of periods marked with strong job gains, strong job losses and 'stable' unemployment.

There are some benefits in modelling unemployment rate changes as an HMM, instead of for example, a simple autoregressive model. Very often, correlation in changes in unemployment rates may not be too high, even if there may be long periods

⁴⁸ An interesting avenue for further research would be the use of monetary data, particularly that with respect to deposits, as ways with which to better inform business cycle dating in Malta.

⁴⁹ See, for example, Shibata (2019) and Hall and Kudlyak (2019).

of time with successive decreases (or increases) in unemployment. In fact, in some cases such changes are treated as random walk processes. Moreover, the literature on the persistence of unemployment suggest that there may be more complex factors at play than what is captured in simple autoregressive models.⁵⁰

Results

The three hidden states are associated with increasing, stable and decreasing unemployment. One can expect that each mean of the three states will be positive, close to zero and negative, respectively. This is confirmed by the estimates (see Table 2).

Table 2: States and statistics for the Hidden Markov model

State	State description	Mean	Variance
$S_U = 0$	Decreasing U	-0.0381	0.0007
$S_U = 1$	Stable U	-0.0005	0.0002
$S_U = 2$	Increasing U	0.0394	0.0007

Log-likelihood of Gaussian HMM: 1546.4228

As seen in the estimates above, three clear periods are identified with a period where the unemployment rate is close to its mean (Stable U), one when it is decreasing and one when it is increasing. While simplistic, this first attempt at analysing the labour market in terms of Hidden Markov models leads to a number of interesting findings. The results of the HMM estimations are presented in Charts 10 and 11, below. By plotting the estimated states with the logarithmic differences in unemployment, one is able to assess the timing of events in the labour market. Most notably, periods with strong job gains (decreasing unemployment) and strong job losses (increasing unemployment) occur in close succession pre-1985, before subsiding over time. Unemployment rates are known to exhibit persistence characteristics. One way to gauge this is to look at the transition probability matrix estimated from the Hidden Markov model:

$$\begin{bmatrix} P_{00} & P_{01} & P_{02} \\ P_{10} & P_{11} & P_{12} \\ P_{20} & P_{21} & P_{22} \end{bmatrix} = \begin{bmatrix} 0.8573 & 0.0875 & 0.0550 \\ 0.0447 & 0.9355 & 0.0198 \\ 0.0584 & 0.1078 & 0.8337 \end{bmatrix}$$

⁵⁰ The seminal contribution of Barro (1988) on unemployment persistence, based on Hall (1979).

When in a decreasing unemployment state, that is, when unemployment is on a downward trend, there is an 85.7% chance of transitioning to a decreasing unemployment state in the next period, while in an increasing unemployment state, this chance is 83.4%. The prevalent state remains “stable” unemployment, with a persistence of 93.6% given being in a stable unemployment rate period. A problem with this approach is the assumption that a “stable” state exists, and that it coincides to some long-term average unemployment rate. Finally, while scale is a factor affecting these estimates, the scale of the decrease in unemployment seen post-2013 still appears to be significant, if not unique.

More broadly, six stylised facts can be drawn from the resulting periods identified by the algorithm:

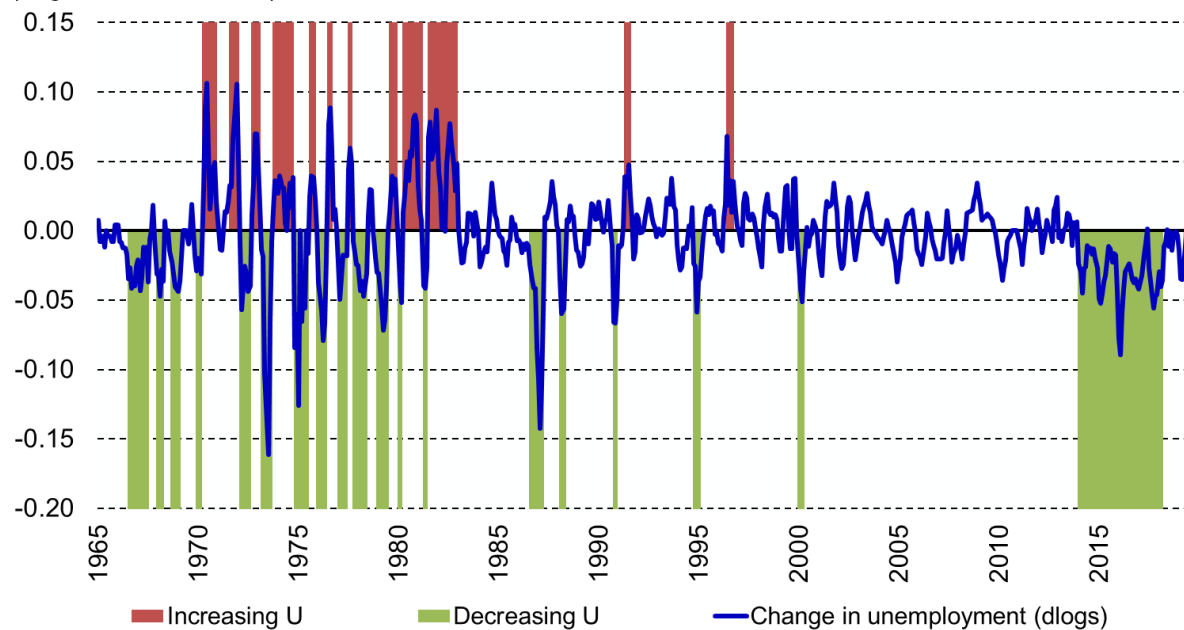
- Pre-1970, the Maltese employment market was benign, with a marked decrease in unemployment rates - albeit from a high rate. This may reflect elements of outward migration and the beginning of economic development in Malta as a way to offset the run-down in British armed forces expenditures.
- From the 1970s to mid-1980s, unemployment returns severe cyclical and alternating fluctuations, with systematic job losses being offset by job gains in successive periods. By the mid-1980s, this cyclical loss-gain pattern slows down.
- The 1990s retain these cyclical and alternating fluctuations, although at a much slower pace.
- A “great moderation” in terms of job losses and gains appears in the 2000s. The labour market appears to have reached some sort of equilibrium in these years. This period marked the Maltese economy with structural change, slowing traditional manufacturing industries and a surge in services – as well as a surge in female participation and the introduction of flexible working practices.
- Interestingly, within the wider context of historic unemployment rate changes in Malta, the 2008/9 recession does not appear to have made any significant effect on unemployment in Malta, while it does appear as a significant recessionary period in the previous analyses. This matches Micallef (2013) who finds evidence for increased labour hoarding in this period, with the unemployment rate only rising

modestly to 6.9% in 2009 from 6.0% in 2008.⁵¹ Of course, this conclusion may differ if one uses hours worked data, with the latter being a better indicator of the business cycle.

- Finally, post-2013 there appears to be an unprecedented period of job gains, probably due to several labour market reforms, and reforms to the unemployment system.

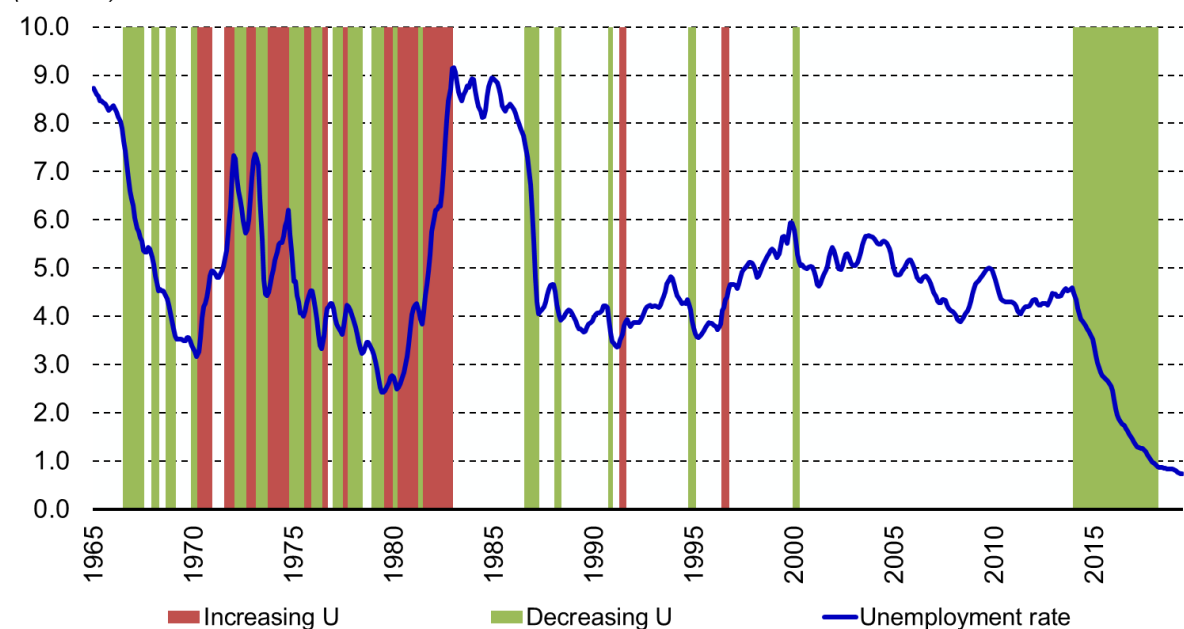
⁵¹ The shortcomings of this approach are addressed in the next section, which constructs a composite hidden Markov model of the unemployment rate to account for both the annual change in unemployment (momentum) as well as changes over a shorter six month period (acceleration). This will lead to the 2008/9 episode showing up as a recessionary episode.

Chart 10
Labour market states
(Logarithm differences)



Source: Author's calculations.

Chart 11
Unemployment rate and labour market states
(Percent)



Source: Author's calculations.

Estimating monthly recession probabilities using a composite HMM

In the previous section, the usefulness of HMMs was applied to understanding trends in the labour market to infer developments in the wider economy. While interesting, the shortcomings relating to assuming the existence of “some average rate of unemployment” means that it might be misleading at times. Another approach to assess the business cycle from the labour market follows from Lihn (2019). This uses a composite HMM to calculate recession probability using unemployment rate data, however it considers significantly richer dynamics. The model assumes that positive momentum in unemployment kicks off a recession, with the momentum accelerating during the recession. Eventually, its rapid deceleration marks the recession’s end. This approach incorporates the views in Hamilton (2005), who looks into how short-run failures to credit and employment markets coincide with the business cycle, specifically looking into the stickiness of unemployment.⁵²

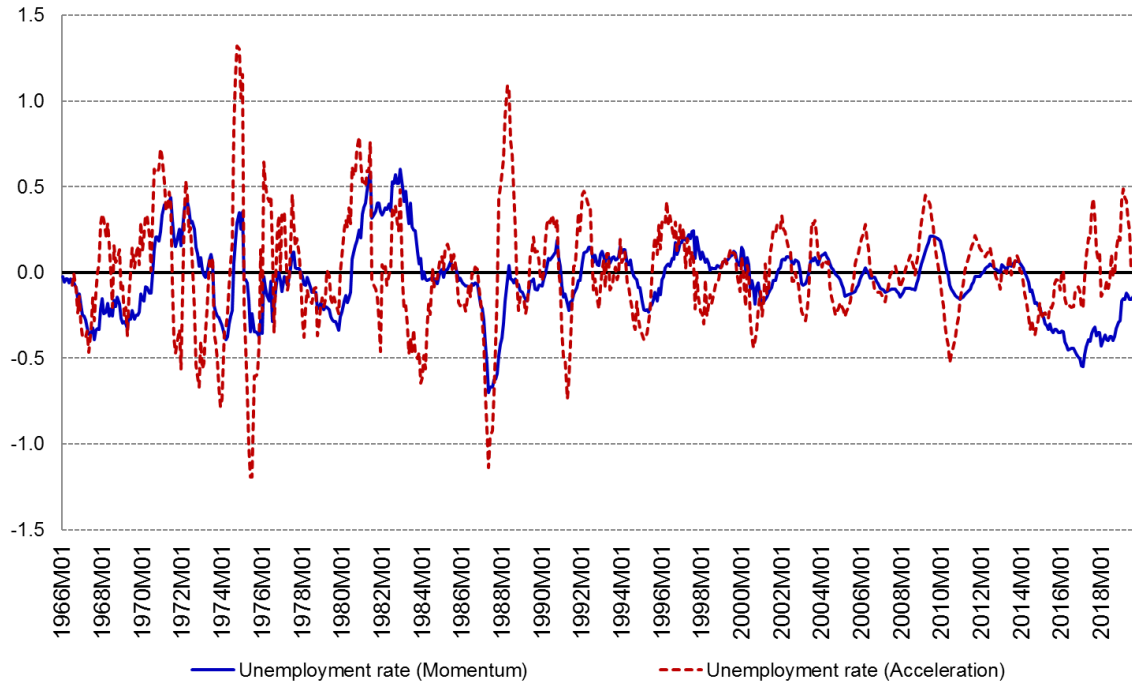
There are two sub-models within this approach, the unemployment one-year momentum model $U_{1y}(t)$,⁵³ and the unemployment 6-month acceleration model, $A_{6m}(t)$, with the variables defined following the literature (see Chart 12).⁵⁴ The product of the two is used to compute the recession probabilities.

⁵² That is, how unemployment rates rise quicker than they fall.

⁵³ Defined as $U_{1y}(t) \equiv \log(UNRATE_t) - \log(UNRATE_{t-1})$

⁵⁴ Defined as $A_{6m}(t) \equiv 2 U_{1y}(t) - U_{1y}(t-0.5)$

Chart 12
Log changes in unemployment rate



$U_{1y}(t)$ is treated as a two-state HMM, the first state is a recession or “bad” state and the second state is a “normal” state. The economy rests in this normal state for most of the time, in which the unemployment rate is decreasing, the job market improving and there is an overall “negative momentum” on the unemployment rate. The “bad” state is linked with a large positive momentum, with the economy losing jobs at a rapid pace. This two-regime scenario follows the regime-switching behaviour described in Bae et al. (2014), and Mulvey and Liu (2016).

In the acceleration sub-model, $A_{6m}(t)$ is defined as the unemployment acceleration, that is, the 6-month rate of change of $U_{1y}(t)$. This model considers three states, the accelerating state, the middle state, and the decelerating state. The accelerating state is often linked with a recession. Monthly recession probabilities are then computed as the probability estimate for the “bad” state in the momentum model and the probability in the accelerating state of the acceleration model.⁵⁵

⁵⁵ That is, the recession probability $P_{Rec}(t) \equiv P(t; S_u = 1) \times P(t; S_A = 1)$

The momentum model is decomposed into two states, where lambda is the state density, mu is the mean and sigma the standard deviation of the normal distribution (see Table 3). One state has a positive mean, the other has a negative mean, as expected.

Table 3: Summary of Momentum Model

	State 1	State 2
Lambda (λ)	0.2446	0.7554
Mu (μ)	0.0452	-0.0172
Sigma (σ)	0.5079	0.2300

Log-likelihood at estimate: -156.5065

The acceleration model is decomposed into three states (see Table 4). The first state has a negative mean, the second state's mean is almost zero while the third state's mean is positive. This is a construct of the accelerating nature of the input variable. One also notices that the negative mean's standard deviation is the largest of the three.

Table 4: Summary of Acceleration Model

	State 1	State 2	State 3
Lambda (λ)	0.3769	0.5439	0.0792
Mu (μ)	-0.2023	0.0030	0.3812
Sigma (σ)	0.1777	0.1127	0.1024

Log-likelihood at estimate: 107.6752

The momentum states are described in Table 5. The first state, the "bad" period has a larger positive mean than the normal state. Its standard deviation is larger, as is the kurtosis, which is close to a normal distribution. The normal state has a small negative mean, in line with the view that a normal economy reduces unemployment, and a small standard deviation. It is platykurtic, meaning that the distribution produces fewer and less extreme outliers than a normal distribution (a flatter normal distribution).

Table 5: λ distribution parameters of two states in the Momentum model

$S_U : U_{1y}(t)$ State	State	Mean (μ)	Volatility (SD)	Kurtosis
$S_U = 1$	Bad	0.0500	0.4467	2.7751
$S_U = 2$	Normal	-0.0599	0.1339	2.1998

Likewise, the states of the acceleration model are described in Table 6. The accelerating state has the largest mean, and the middle state a negative one. The kurtosis for both states is slightly lower than in a normal distribution. The negative acceleration data appears to be captured by both the middle and the decelerating states. The latter state is also the furthest away from a normal distribution.

Table 6: λ distribution parameters of three states in the Acceleration model

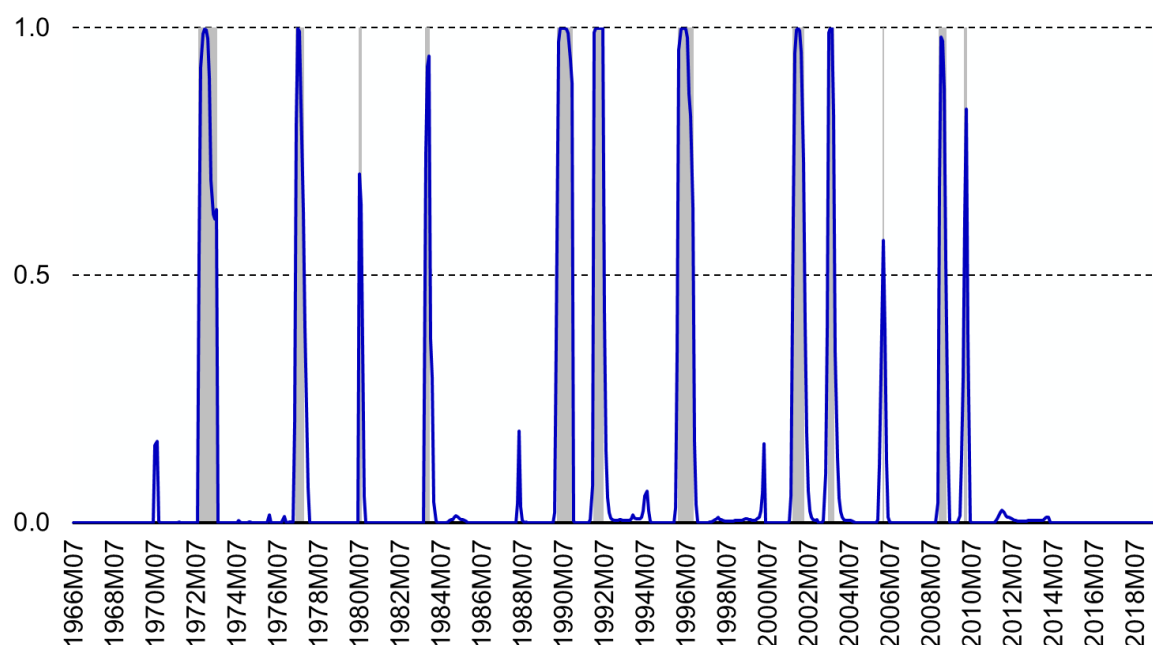
$S_U : U_{1y}(t)$ State	State	Mean (μ)	Volatility (SD)	Kurtosis
$S_U = 1$	Accelerating	0.0624	0.0445	2.6874
$S_U = 2$	Middle	-0.1018	0.0573	2.5956
$S_U = 3$	Decelerating	-0.0319	0.3144	1.9936

In order to calibrate the beginning and end date probability of being in a recession, a 50.0% cut-off rate is given to the recession probability $P_{Rec}(t)$, see Chart 13. The grey lines indicate the months in which the probability of being in a recession exceeds this 50.0% threshold, while the blue lines are the raw probabilities computed from the two HMM state models.

By limiting the recession to those episodes where the probability was higher than 50.0%, and with a duration longer than six months, following Chauvet and Hamilton (2005), the episodes are limited to five. These are September 1972 to July 1973, April 1990 to December 1990, January 1992 to June 1992, March 1996 to November 1996, and October 2001 to April 2002. Although spilling over two quarters, the 2008/9 recession fails to be classified in this manner as its length is limited to five months from December 2008 to April 2009. However, its high estimated probability indicates that it still was a period consistent with an economic recession. Differences in timing between this measure and the others proposed above may be due to asymmetric impacts between the labour market and the rest of the economy, and phenomena particular to employment - such as labour hoarding. A striking finding is that from May 2010 onward, this indicator reports the longest uninterrupted stretch of time where the

labour market showed no indication of a recession in the wider economy (117 months to end-2019).⁵⁶

Chart 13
Monthly recession probability



Source: Author's calculations.

The merits of this method, namely its higher frequency and quality of the data available, make it a viable supplement to the GDP based measures discussed above. Discrepancies between the two with respect to the timing and severity of recessions may be attributed to underlying methodological differences, but also to the different impacts a recession may have on the labour market with respect to the wider economy. Moreover, there may be supply-side shocks which emerge or affect an economy, improving output more than employment or even, possibly, adversely affecting employment while boosting output.

Thus, while in general, a GDP-based measure and an unemployment-based measure tend to be complementary, if not fully synchronised, this may not always be necessarily the case.

⁵⁶ See Table A2 in Appendix A for a full month by month calendar of likely recessions states based on the hidden composite Markov model.

Conclusions

In the US, the NBER has identified the chronology of business cycles for decades. In recent years, the EABCDC has carried out similar analysis in the euro area. Unfortunately, the dating of the Maltese business cycle has not garnered much attention so far. Even if there are a few tangential references, either in narrative form or in actual dating, researchers have not focused in identifying the chronology of the Maltese business cycle.

This study was the first focused attempt to identify the periods of expansion and contraction in the Maltese economy, over the past decades. The approach used both an official quarterly NSO time-series going back to 2000, and an extended benchmarked GDP series going back to 1972, using two main methods. A supplementary method using an unemployment rate time-series to time the business cycle is also presented.

The study was able to pinpoint a reasonable dating of the Maltese business cycle using quarter-on-quarter GDP growth rates. Using the official NSO GDP time series, and applying the Bry-Boschan algorithm, there is evidence for recessionary episodes between 2001Q1 and 2001Q4, 2004Q1 and 2004Q2, and 2011Q1 and 2011Q2.

After extending the GDP time series in a benchmarking exercise going back to 1972, there is evidence for recessionary episodes between 1973Q2 and 1973Q3, 1982Q3 and 1982Q4, 2004Q1 and 2004Q2, and 2011Q1 and 2011Q2. Revisions to recent GDP vintages have effectively erased the Great Recession of 2008Q4-2009Q1 from Maltese economic history. Finally, as this paper uses data available until 2020Q3, there is an element of uncertainty in the data for the exact timing of a recession in 2020.

The uncertainty relating to some recessionary episodes may imply a limitation such that there may be other statistical factors at play in some quarters. Applying a Markov switching model to the official time-series finds four sharp peaks consistent with high recession probabilities in early 2001, 2004Q1-Q2, 2008Q4-2009Q1 and 2011Q1-Q2. In the extended timeline recessionary episodes are found between 1973Q2 and 1973Q4, and 2008Q4 and 2009Q1. This latter method also finds single quarters with evidence for a recession, but which are not followed up by a similar recessionary

quarter. These “single quarter recessions”, or rather short-lived shocks, are found in 1976Q4, 1978Q3, 1982Q4, 2001Q1, and 2004Q1. All the four approaches used consider 2008Q4 – 2009Q1 to be a recessionary episode, three methods provide some evidence for a further episode in 2004, but evidence is sparser for other dates.

Historical developments in Malta’s labour markets were also analysed, and a number of stylised facts were drawn from a Hidden Markov model. The study looked at the labour market and finds distinct phases in the development of the labour market in Malta, which may be used to explain and analyse the different natures of the recessionary episodes discussed in the first section of this study. This approach is augmented with a further methodology which can compute monthly recession probabilities on the bases of unemployment rate data.

Monthly recession estimates are computed from July 1966 onward, with evidence for at least six consecutive months of negative conditions in the economy confirmed between September 1972 and July 1973, April and December 1990, January and June 1992, March 1996 and November 1996, and between October 2001 and April 2002. Other shorter periods (less than six months) occur around the Great Recession of 2008/9, in 1977, and in other periods.

Unemployment data is seen to be a timely additional source of information, which is useful in gauging the likely state of the Maltese economy, with a number of caveats linked with underlying differences between the labour market and other sectors of the economy, as well as supply-side shocks which can lead to a divergence between the signals behind changes in GDP and in unemployment.

Reliance on multiple sources, rather than looking only at GDP growth, is key when dating business cycles, and unemployment rate data appears to have qualities which are – in some cases - more useful than GDP to time the business cycle in a stable manner. Alternative indicators, in the form of long-term time series such as monetary data and other data related to variables such as household deposits, may also be an interesting data source to be pursued. An interesting avenue for further research may be the application of Bayesian averaging methods to different GDP vintages to account for the effect of revisions to the data.

Despite the limitations highlighted above, the contractions registered in the 2000s and the high economic growth rates registered by the Maltese economy imply that Malta

gained considerable momentum in the later part of the 2010s, achieving higher levels of economic convergence to its European peers in recent decades. This is an encouraging element for medium term ahead, allowing the immediate implementation of targeted economic policies to counter the extraordinary economic environment triggered by the COVID-19 pandemic, in an economy which is not too overburdened by debt.

Appendix A – Timing the Maltese business cycle

Table A1
Quarterly recession states based on GDP data

	BBQ Official time- series	BBQ Extended time-series	Markov switching model Official time- series ¹	Markov switching model Extended time- series ¹
1972Q1	NA	0	NA	NA
1972Q2	NA	0	NA	NA
1972Q3	NA	0	NA	NA
1972Q4	NA	0	NA	NA
1973Q1	NA	0	NA	NA
1973Q2	NA	1	NA	1
1973Q3	NA	1	NA	1
1973Q4	NA	0	NA	1
1974Q1	NA	0	NA	0
1974Q2	NA	0	NA	0
1974Q3	NA	0	NA	0
1974Q4	NA	0	NA	0
1975Q1	NA	0	NA	0
1975Q2	NA	0	NA	0
1975Q3	NA	0	NA	0
1975Q4	NA	0	NA	0
1976Q1	NA	0	NA	0
1976Q2	NA	0	NA	0
1976Q3	NA	0	NA	0
1976Q4	NA	0	NA	(1)
1977Q1	NA	0	NA	0
1977Q2	NA	0	NA	0
1977Q3	NA	0	NA	0
1977Q4	NA	0	NA	0
1978Q1	NA	0	NA	0
1978Q2	NA	0	NA	0
1978Q3	NA	0	NA	(1)
1978Q4	NA	0	NA	0
1979Q1	NA	0	NA	0
1979Q2	NA	0	NA	0
1979Q3	NA	0	NA	0
1979Q4	NA	0	NA	0
1980Q1	NA	0	NA	0
1980Q2	NA	0	NA	0
1980Q3	NA	0	NA	0
1980Q4	NA	0	NA	0
...

Table A1
Quarterly recession states based on GDP data (cont).

	BBQ Official time- series	BBQ Extended time-series	Markov switching model Official time- series ¹	Markov switching model Extended time- series ¹
...
1981Q1	NA	0	NA	0
1981Q2	NA	0	NA	0
1981Q3	NA	0	NA	0
1981Q4	NA	0	NA	0
1982Q1	NA	0	NA	0
1982Q2	NA	0	NA	0
1982Q3	NA	1	NA	0
1982Q4	NA	1	NA	(1)
1983Q1	NA	1	NA	0
1983Q2	NA	1	NA	0
1983Q3	NA	0	NA	0
1983Q4	NA	0	NA	0
1984Q1	NA	0	NA	0
1984Q2	NA	0	NA	0
1984Q3	NA	0	NA	0
1984Q4	NA	0	NA	0
1985Q1	NA	0	NA	0
1985Q2	NA	0	NA	0
1985Q3	NA	0	NA	0
1985Q4	NA	0	NA	0
1986Q1	NA	0	NA	0
1986Q2	NA	0	NA	0
1986Q3	NA	0	NA	0
1986Q4	NA	0	NA	0
1987Q1	NA	0	NA	0
1987Q2	NA	0	NA	0
1987Q3	NA	0	NA	0
1987Q4	NA	0	NA	0
1988Q1	NA	0	NA	0
1988Q2	NA	0	NA	0
1988Q3	NA	0	NA	0
1988Q4	NA	0	NA	0
1989Q1	NA	0	NA	0
1989Q2	NA	0	NA	0
1989Q3	NA	0	NA	0
1989Q4	NA	0	NA	0
...

Table A1
Quarterly recession states based on GDP data (cont).

	BBQ Official time- series	BBQ Extended time-series	Markov switching model Official time- series ¹	Markov switching model Extended time- series ¹
...
1990Q1	NA	0	NA	0
1990Q2	NA	0	NA	0
1990Q3	NA	0	NA	0
1990Q4	NA	0	NA	0
1991Q1	NA	0	NA	0
1991Q2	NA	0	NA	0
1991Q3	NA	0	NA	0
1991Q4	NA	0	NA	0
1992Q1	NA	0	NA	0
1992Q2	NA	0	NA	0
1992Q3	NA	0	NA	0
1992Q4	NA	0	NA	0
1993Q1	NA	0	NA	0
1993Q2	NA	0	NA	0
1993Q3	NA	0	NA	0
1993Q4	NA	0	NA	0
1994Q1	NA	0	NA	0
1994Q2	NA	0	NA	0
1994Q3	NA	0	NA	0
1994Q4	NA	0	NA	0
1995Q1	NA	0	NA	0
1995Q2	NA	0	NA	0
1995Q3	NA	0	NA	0
1995Q4	NA	0	NA	0
1996Q1	NA	0	NA	0
1996Q2	NA	0	NA	0
1996Q3	NA	0	NA	0
1996Q4	NA	0	NA	0
1997Q1	NA	0	NA	0
1997Q2	NA	0	NA	0
1997Q3	NA	0	NA	0
1997Q4	NA	0	NA	0
1998Q1	NA	0	NA	0
1998Q2	NA	0	NA	0
1998Q3	NA	0	NA	0
1998Q4	NA	0	NA	0
...

Table A1
Quarterly recession states based on GDP data (cont).

	BBQ Official time- series	BBQ Extended time-series	Markov switching model Official time- series ¹	Markov switching model Extended time- series ¹

1999Q1	NA	0	NA	0
1999Q2	NA	0	NA	0
1999Q3	NA	0	NA	0
1999Q4	NA	0	NA	0
2000Q1	0	0	NA	0
2000Q2	0	0	NA	0
2000Q3	0	0	NA	(1)
2000Q4	0	0	NA	0
2001Q1	1	1	NA	1
2001Q2	1	1	(1)	1
2001Q3	0	0	0	0
2001Q4	0	0	0	0
2002Q1	0	0	0	0
2002Q2	0	0	0	0
2002Q3	0	0	0	0
2002Q4	0	0	0	0
2003Q1	0	0	0	0
2003Q2	0	0	0	0
2003Q3	0	0	0	0
2003Q4	0	0	0	0
2004Q1	1	1	0	0
2004Q2	1	1	(1)	0
2004Q3	0	0	0	0
2004Q4	0	0	0	0
2005Q1	0	0	0	0
2005Q2	0	0	0	0
2005Q3	0	0	0	0
2005Q4	0	0	0	0
2006Q1	0	0	0	0
2006Q2	0	0	0	0
2006Q3	0	0	0	0
2006Q4	0	0	0	0
2007Q1	0	0	0	0
2007Q2	0	0	0	0
2007Q3	0	0	0	0
2007Q4	0	0	0	0

Table A1
Quarterly recession states based on GDP data (cont).

	BBQ Official time- series	BBQ Extended time-series	Markov switching model Official time- series ¹	Markov switching model Extended time- series ¹
2008Q1	0	0	0	0
2008Q2	0	0	0	0
2008Q3	0	0	0	0
2008Q4	0	0	0	0
2009Q1	0	0	(1)	(1)
2009Q2	0	0	0	0
2009Q3	0	0	0	0
2009Q4	0	0	0	0
2010Q1	0	0	0	0
2010Q2	0	0	0	0
2010Q3	0	0	0	0
2010Q4	0	0	0	0
2011Q1	1	1	(1)	0
2011Q2	1	1	0	0
2011Q3	0	0	0	0
2011Q4	0	0	0	0
2012Q1	0	0	0	0
2012Q2	0	0	0	0
2012Q3	0	0	0	0
2012Q4	0	0	0	0
2013Q1	0	0	0	0
2013Q2	0	0	0	0
2013Q3	0	0	0	0
2013Q4	0	0	0	0
2014Q1	0	0	0	0
2014Q2	0	0	0	0
2014Q3	0	0	0	0
2014Q4	0	0	0	0
2015Q1	0	0	0	0
2015Q2	0	0	0	0
2015Q3	0	0	0	0
2015Q4	0	0	0	0
2016Q1	0	0	0	0
2016Q2	0	0	0	0
2016Q3	0	0	0	0
2016Q4	0	0	0	0
...

Table A1
Quarterly recession states based on GDP data (cont).

	BBQ Official time- series	BBQ Extended time-series	Markov switching model Official time- series ¹	Markov switching model Extended time- series ¹

2017Q1	0	0	0	0
2017Q2	0	0	0	0
2017Q3	0	0	0	0
2017Q4	0	0	0	0
2018Q1	0	0	0	0
2018Q2	0	0	0	0
2018Q3	0	0	0	0
2018Q4	0	0	0	0
2019Q1	0	0	0	0
2019Q2	0	0	0	0
2019Q3	0	0	0	0
2019Q4	0	0	0	0

¹ Identified with a filtered probability of being in a recession exceeding 50% for at least two consecutive quarters.
(In brackets, single "orphan" quarters with probabilities higher than 50%).

Unemployment based business cycle dating

Table A2

Monthly recession states based on a composite hidden Markov model¹

Jan 1966	-	Jan 1969	0	Jan 1972	0	Jan 1975	0	Jan 1978	0	Jan 1981	0
Feb 1966	-	Feb 1969	0	Feb 1972	0	Feb 1975	0	Feb 1978	0	Feb 1981	0
Mar 1966	-	Mar 1969	0	Mar 1972	0	Mar 1975	0	Mar 1978	0	Mar 1981	0
Apr 1966	-	Apr 1969	0	Apr 1972	0	Apr 1975	0	Apr 1978	0	Apr 1981	0
May 1966	-	May 1969	0	May 1972	0	May 1975	0	May 1978	0	May 1981	0
Jun 1966	-	Jun 1969	0	Jun 1972	0	Jun 1975	0	Jun 1978	0	Jun 1981	0
Jul 1966	0	Jul 1969	0	Jul 1972	0	Jul 1975	0	Jul 1978	0	Jul 1981	0
Aug 1966	0	Aug 1969	0	Aug 1972	0	Aug 1975	0	Aug 1978	0	Aug 1981	0
Sep 1966	0	Sep 1969	0	Sep 1972	1	Sep 1975	0	Sep 1978	0	Sep 1981	0
Oct 1966	0	Oct 1969	0	Oct 1972	1	Oct 1975	0	Oct 1978	0	Oct 1981	0
Nov 1966	0	Nov 1969	0	Nov 1972	1	Nov 1975	0	Nov 1978	0	Nov 1981	0
Dec 1966	0	Dec 1969	0	Dec 1972	1	Dec 1975	0	Dec 1978	0	Dec 1981	0
Jan 1967	0	Jan 1970	0	Jan 1973	1	Jan 1976	0	Jan 1979	0	Jan 1982	0
Feb 1967	0	Feb 1970	0	Feb 1973	1	Feb 1976	0	Feb 1979	0	Feb 1982	0
Mar 1967	0	Mar 1970	0	Mar 1973	1	Mar 1976	0	Mar 1979	0	Mar 1982	0
Apr 1967	0	Apr 1970	0	Apr 1973	1	Apr 1976	0	Apr 1979	0	Apr 1982	0
May 1967	0	May 1970	0	May 1973	1	May 1976	0	May 1979	0	May 1982	0
Jun 1967	0	Jun 1970	0	Jun 1973	1	Jun 1976	0	Jun 1979	0	Jun 1982	0
Jul 1967	0	Jul 1970	0	Jul 1973	1	Jul 1976	0	Jul 1979	0	Jul 1982	0
Aug 1967	0	Aug 1970	0	Aug 1973	0	Aug 1976	0	Aug 1979	0	Aug 1982	0
Sep 1967	0	Sep 1970	0	Sep 1973	0	Sep 1976	0	Sep 1979	0	Sep 1982	0
Oct 1967	0	Oct 1970	0	Oct 1973	0	Oct 1976	0	Oct 1979	0	Oct 1982	0
Nov 1967	0	Nov 1970	0	Nov 1973	0	Nov 1976	0	Nov 1979	0	Nov 1982	0
Dec 1967	0	Dec 1970	0	Dec 1973	0	Dec 1976	0	Dec 1979	0	Dec 1982	0
Jan 1968	0	Jan 1971	0	Jan 1974	0	Jan 1977	0	Jan 1980	0	Jan 1983	0
Feb 1968	0	Feb 1971	0	Feb 1974	0	Feb 1977	0	Feb 1980	0	Feb 1983	0
Mar 1968	0	Mar 1971	0	Mar 1974	0	Mar 1977	0	Mar 1980	0	Mar 1983	0
Apr 1968	0	Apr 1971	0	Apr 1974	0	Apr 1977	0	Apr 1980	0	Apr 1983	0
May 1968	0	May 1971	0	May 1974	0	May 1977	0	May 1980	0	May 1983	0
Jun 1968	0	Jun 1971	0	Jun 1974	0	Jun 1977	(1)	Jun 1980	0	Jun 1983	0
Jul 1968	0	Jul 1971	0	Jul 1974	0	Jul 1977	(1)	Jul 1980	(1)	Jul 1983	0
Aug 1968	0	Aug 1971	0	Aug 1974	0	Aug 1977	(1)	Aug 1980	(1)	Aug 1983	0
Sep 1968	0	Sep 1971	0	Sep 1974	0	Sep 1977	(1)	Sep 1980	0	Sep 1983	0
Oct 1968	0	Oct 1971	0	Oct 1974	0	Oct 1977	(1)	Oct 1980	0	Oct 1983	(1)
Nov 1968	0	Nov 1971	0	Nov 1974	0	Nov 1977	0	Nov 1980	0	Nov 1983	(1)
Dec 1968	0	Dec 1971	0	Dec 1974	0	Dec 1977	0	Dec 1980	0	Dec 1983	(1)

Table A2

Monthly recession states based on a composite hidden Markov model (cont.)

Jan 1984	0	Jan 1987	0	Jan 1990	0	Jan 1993	0	Jan 1996	0	Jan 1999	0
Feb 1984	0	Feb 1987	0	Feb 1990	0	Feb 1993	0	Feb 1996	0	Feb 1999	0
Mar 1984	0	Mar 1987	0	Mar 1990	0	Mar 1993	0	Mar 1996	1	Mar 1999	0
Apr 1984	0	Apr 1987	0	Apr 1990	1	Apr 1993	0	Apr 1996	1	Apr 1999	0
May 1984	0	May 1987	0	May 1990	1	May 1993	0	May 1996	1	May 1999	0
Jun 1984	0	Jun 1987	0	Jun 1990	1	Jun 1993	0	Jun 1996	1	Jun 1999	0
Jul 1984	0	Jul 1987	0	Jul 1990	1	Jul 1993	0	Jul 1996	1	Jul 1999	0
Aug 1984	0	Aug 1987	0	Aug 1990	1	Aug 1993	0	Aug 1996	1	Aug 1999	0
Sep 1984	0	Sep 1987	0	Sep 1990	1	Sep 1993	0	Sep 1996	1	Sep 1999	0
Oct 1984	0	Oct 1987	0	Oct 1990	1	Oct 1993	0	Oct 1996	1	Oct 1999	0
Nov 1984	0	Nov 1987	0	Nov 1990	1	Nov 1993	0	Nov 1996	1	Nov 1999	0
Dec 1984	0	Dec 1987	0	Dec 1990	1	Dec 1993	0	Dec 1996	0	Dec 1999	0
Jan 1985	0	Jan 1988	0	Jan 1991	0	Jan 1994	0	Jan 1997	0	Jan 2000	0
Feb 1985	0	Feb 1988	0	Feb 1991	0	Feb 1994	0	Feb 1997	0	Feb 2000	0
Mar 1985	0	Mar 1988	0	Mar 1991	0	Mar 1994	0	Mar 1997	0	Mar 2000	0
Apr 1985	0	Apr 1988	0	Apr 1991	0	Apr 1994	0	Apr 1997	0	Apr 2000	0
May 1985	0	May 1988	0	May 1991	0	May 1994	0	May 1997	0	May 2000	0
Jun 1985	0	Jun 1988	0	Jun 1991	0	Jun 1994	0	Jun 1997	0	Jun 2000	0
Jul 1985	0	Jul 1988	0	Jul 1991	0	Jul 1994	0	Jul 1997	0	Jul 2000	0
Aug 1985	0	Aug 1988	0	Aug 1991	0	Aug 1994	0	Aug 1997	0	Aug 2000	0
Sep 1985	0	Sep 1988	0	Sep 1991	0	Sep 1994	0	Sep 1997	0	Sep 2000	0
Oct 1985	0	Oct 1988	0	Oct 1991	0	Oct 1994	0	Oct 1997	0	Oct 2000	0
Nov 1985	0	Nov 1988	0	Nov 1991	0	Nov 1994	0	Nov 1997	0	Nov 2000	0
Dec 1985	0	Dec 1988	0	Dec 1991	0	Dec 1994	0	Dec 1997	0	Dec 2000	0
Jan 1986	0	Jan 1989	0	Jan 1992	1	Jan 1995	0	Jan 1998	0	Jan 2001	0
Feb 1986	0	Feb 1989	0	Feb 1992	1	Feb 1995	0	Feb 1998	0	Feb 2001	0
Mar 1986	0	Mar 1989	0	Mar 1992	1	Mar 1995	0	Mar 1998	0	Mar 2001	0
Apr 1986	0	Apr 1989	0	Apr 1992	1	Apr 1995	0	Apr 1998	0	Apr 2001	0
May 1986	0	May 1989	0	May 1992	1	May 1995	0	May 1998	0	May 2001	0
Jun 1986	0	Jun 1989	0	Jun 1992	1	Jun 1995	0	Jun 1998	0	Jun 2001	0
Jul 1986	0	Jul 1989	0	Jul 1992	0	Jul 1995	0	Jul 1998	0	Jul 2001	0
Aug 1986	0	Aug 1989	0	Aug 1992	0	Aug 1995	0	Aug 1998	0	Aug 2001	0
Sep 1986	0	Sep 1989	0	Sep 1992	0	Sep 1995	0	Sep 1998	0	Sep 2001	0
Oct 1986	0	Oct 1989	0	Oct 1992	0	Oct 1995	0	Oct 1998	0	Oct 2001	1
Nov 1986	0	Nov 1989	0	Nov 1992	0	Nov 1995	0	Nov 1998	0	Nov 2001	1
Dec 1986	0	Dec 1989	0	Dec 1992	0	Dec 1995	0	Dec 1998	0	Dec 2001	1

Table A2

Monthly recession states based on a composite hidden Markov model (cont.)

Jan 2002	1	Jan 2005	0	Jan 2008	0	Jan 2011	0	Jan 2014	0	Jan 2017	0
Feb 2002	1	Feb 2005	0	Feb 2008	0	Feb 2011	0	Feb 2014	0	Feb 2017	0
Mar 2002	1	Mar 2005	0	Mar 2008	0	Mar 2011	0	Mar 2014	0	Mar 2017	0
Apr 2002	1	Apr 2005	0	Apr 2008	0	Apr 2011	0	Apr 2014	0	Apr 2017	0
May 2002	0	May 2005	0	May 2008	0	May 2011	0	May 2014	0	May 2017	0
Jun 2002	0	Jun 2005	0	Jun 2008	0	Jun 2011	0	Jun 2014	0	Jun 2017	0
Jul 2002	0	Jul 2005	0	Jul 2008	0	Jul 2011	0	Jul 2014	0	Jul 2017	0
Aug 2002	0	Aug 2005	0	Aug 2008	0	Aug 2011	0	Aug 2014	0	Aug 2017	0
Sep 2002	0	Sep 2005	0	Sep 2008	0	Sep 2011	0	Sep 2014	0	Sep 2017	0
Oct 2002	0	Oct 2005	0	Oct 2008	0	Oct 2011	0	Oct 2014	0	Oct 2017	0
Nov 2002	0	Nov 2005	0	Nov 2008	0	Nov 2011	0	Nov 2014	0	Nov 2017	0
Dec 2002	0	Dec 2005	0	Dec 2008	(1)	Dec 2011	0	Dec 2014	0	Dec 2017	0
Jan 2003	0	Jan 2006	0	Jan 2009	(1)	Jan 2012	0	Jan 2015	0	Jan 2018	0
Feb 2003	0	Feb 2006	0	Feb 2009	(1)	Feb 2012	0	Feb 2015	0	Feb 2018	0
Mar 2003	0	Mar 2006	(1)	Mar 2009	(1)	Mar 2012	0	Mar 2015	0	Mar 2018	0
Apr 2003	0	Apr 2006	0	Apr 2009	(1)	Apr 2012	0	Apr 2015	0	Apr 2018	0
May 2003	0	May 2006	0	May 2009	0	May 2012	0	May 2015	0	May 2018	0
Jun 2003	0	Jun 2006	0	Jun 2009	0	Jun 2012	0	Jun 2015	0	Jun 2018	0
Jul 2003	(1)	Jul 2006	0	Jul 2009	0	Jul 2012	0	Jul 2015	0	Jul 2018	0
Aug 2003	(1)	Aug 2006	0	Aug 2009	0	Aug 2012	0	Aug 2015	0	Aug 2018	0
Sep 2003	(1)	Sep 2006	0	Sep 2009	0	Sep 2012	0	Sep 2015	0	Sep 2018	0
Oct 2003	(1)	Oct 2006	0	Oct 2009	0	Oct 2012	0	Oct 2015	0	Oct 2018	0
Nov 2003	0	Nov 2006	0	Nov 2009	0	Nov 2012	0	Nov 2015	0	Nov 2018	0
Dec 2003	0	Dec 2006	0	Dec 2009	0	Dec 2012	0	Dec 2015	0	Dec 2018	0
Jan 2004	0	Jan 2007	0	Jan 2010	0	Jan 2013	0	Jan 2016	0	Jan 2019	0
Feb 2004	0	Feb 2007	0	Feb 2010	0	Feb 2013	0	Feb 2016	0	Feb 2019	0
Mar 2004	0	Mar 2007	0	Mar 2010	(1)	Mar 2013	0	Mar 2016	0	Mar 2019	0
Apr 2004	0	Apr 2007	0	Apr 2010	(1)	Apr 2013	0	Apr 2016	0	Apr 2019	0
May 2004	0	May 2007	0	May 2010	0	May 2013	0	May 2016	0	May 2019	0
Jun 2004	0	Jun 2007	0	Jun 2010	0	Jun 2013	0	Jun 2016	0	Jun 2019	0
Jul 2004	0	Jul 2007	0	Jul 2010	0	Jul 2013	0	Jul 2016	0	Jul 2019	0
Aug 2004	0	Aug 2007	0	Aug 2010	0	Aug 2013	0	Aug 2016	0	Aug 2019	0
Sep 2004	0	Sep 2007	0	Sep 2010	0	Sep 2013	0	Sep 2016	0	Sep 2019	0
Oct 2004	0	Oct 2007	0	Oct 2010	0	Oct 2013	0	Oct 2016	0	Oct 2019	0
Nov 2004	0	Nov 2007	0	Nov 2010	0	Nov 2013	0	Nov 2016	0	Nov 2019	0
Dec 2004	0	Dec 2007	0	Dec 2010	0	Dec 2013	0	Dec 2016	0	Dec 2019	0

Identified with a filtered probability of being in a recession exceeding 50% for at least six successive months and thus shaded. (In brackets, single "orphan" months with probabilities higher than 50%).

Appendix B – Markov Autoregression output

Output for the official time-series

Optimization terminated successfully.

Current function value: -2.856040

Iterations: 26

Function evaluations: 32

Gradient evaluations: 32

Markov Switching Model Results

Dep. Variable:	OFFICIAL	No. Observations:	75
Model:	Markov-Autoregression	Log Likelihood	214.203
		AIC	-410.406
		BIC	-389.549
Sample:	06-30-2000 - 12-31-2019	HQIC	-402.078

Covariance Type: approx

Regime 0 parameters

	coef	std err	z	P> z	[0.025 0.975]
const	-0.0229	0.011	-2.164	0.030	-0.044 -0.002

Regime 1 parameters

	coef	std err	z	P> z	[0.025 0.975]
const	0.0112	0.002	5.333	0.000	0.007 0.015

Non-switching parameters

	coef	std err	z	P> z	[0.025 0.975]
sigma2	0.0002	2.81e-05	5.804	0.000	0.000 0.000
ar.L1	-0.1549	0.119	-1.303	0.193	-0.388 0.078
ar.L2	0.1196	0.115	1.036	0.300	-0.107 0.346
ar.L3	0.1815	0.116	1.561	0.118	-0.046 0.409
ar.L4	0.1300	0.111	1.174	0.240	-0.087 0.347

Regime transition parameters

	coef	std err	z	P> z	[0.025 0.975]
p[0->0]	0.4187	0.344	1.217	0.224	-0.256 1.093
p[1->0]	0.0190	0.021	0.901	0.367	-0.022 0.060

Warnings:

[1] Covariance matrix calculated using numerical (complex-step) differentiation.

Output for the extended time-series

Optimization terminated successfully.

Current function value: -2.928187

Iterations: 27

Function evaluations: 34

Gradient evaluations: 34

Markov Switching Model Results

Dep. Variable: EXTENDED

No. Observations: 147

Model: Markov-Autoregression

Log Likelihood 430.444

AIC -842.887

BIC -815.973

Sample: 06-30-1982 - 12-31-2019

HQIC -831.952

Covariance Type: approx

Regime 0 parameters

	coef	std err	z	P> z	[0.025 0.975]
const	-0.0198	0.008	-2.559	0.011	-0.035 -0.005

Regime 1 parameters

	coef	std err	z	P> z	[0.025 0.975]
const	0.0119	0.001	9.247	0.000	0.009 0.014

Non-switching parameters

	coef	std err	z	P> z	[0.025 0.975]
sigma2	0.0001	1.89e-05	7.451	0.000	0.000 0.000
ar.L1	-0.2044	0.088	-2.336	0.020	-0.376 -0.033
ar.L2	0.0659	0.082	0.806	0.420	-0.094 0.226
ar.L3	0.2140	0.086	2.490	0.013	0.046 0.382
ar.L4	0.1257	0.082	1.525	0.127	-0.036 0.287

Regime transition parameters

	coef	std err	z	P> z	[0.025 0.975]
p[0->0]	0.2644	0.246	1.076	0.282	-0.217 0.746
p[1->0]	0.0228	0.017	1.315	0.189	-0.011 0.057

Warnings:

[1] Covariance matrix calculated using numerical (complex-step) differentiation.

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