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Forecasting unemployment rates in Malta: A labour market flows approach

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Abstract

This study extends the flow approach to forecasting unemployment, as carried out by Barnichon and Nekarda (2013) and Barnichon and Garda (2016), to the Maltese labour market using a wider number of estimating techniques. The flow approach results in significant improvements in forecast accuracy over an autoregressive (AR) process. Particular improvements to forecasting accuracy are returned over shorter time horizons. When including flows, forecast improvements over both an AR process and non-flow forecasts are found when applying VECM methods. Bayesian and OLS VARs also show strong improvements over an AR, with or without the inclusion of flows. For Maltese data, the use of flows computed using aggregate data in these two latter methodologies does not bring about a significant improvement over the forecasts which exclude them.

JEL classification: E24, E27, J64.

Keywords: forecasting; unemployment rate; flows; Malta;

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1. Introduction

In most applications, unemployment rate forecasts are based on observed empirical relationships - like Okun's law - or simple time-series projections using ARMA models. Evidence likewise suggests that the inclusion of information on labour market flows and stocks leads to marked improvements in short-term forecasts of unemployment rates in the United States (Barnichon and Nekarda, 2013) and was extended to a number of OECD countries (Barnichon and Garda, 2016).

Labour market statistics are very useful in gauging the state of the economy. They can be used in a wide array of studies. Labour can be looked at as a production input factor in macroeconomic studies, in competitiveness analyses as well as in productivity studies. These statistics can also be used to assess a wide range of behavioural and socio-economic factors linked with individual labour market situations. These include factors like migrant workers, labour market duality, employment as a source of disposable income, and unemployment as a risk to poverty or social exclusion.

Unemployment and employment data are both short-term indicators as well as structural statistics. The latter property occurs because these two variables describe the balance between labour demand and supply. In that sense, employment status data summarises the structure of labour markets and economic systems. On the other hand, as short-term indicators, these data-sets follow developments in the business cycle. However, both employment and unemployment are a lagging indicator, such that there are limits to their usefulness.

The use of labour market flow data should help to better understand the dynamics between employment and unemployment levels. They are valuable because they qualify the changes in employment status, that is, between unemployment and employment. In that way, they allow policymakers to make informed decisions.

This paper builds on these studies, and extends the analysis by including forecasts-by-flows (FBF) in a number of different VAR and VECM approaches and applies these methods to Malta. Flows are calculated from aggregate labour force survey (LFS) data, which are publicly available and timely. Differences may be expected from the use of micro data, although the flow rates resulting from this methodology are remarkably similar to published studies based on micro data. These differences may reflect aggregation bias. Better timeliness and flexibility in using published and aggregated LFS data may be an advantage in a forecasting environment.

Unlike the previous literature, which uses relatively simple VAR methods, this study uses various Bayesian methodologies included in the BEAR toolbox (Dieppe, Legrand and van Roye, 2016), as well as VECM methods, to construct labour market flow forecasts.

The study estimates labour market flows - job finding and separation rates - based on long-term unemployment data within the context of a two-state labour market model for Malta. These are then included in a VAR and a VECM framework to forecast the unemployment rate. In the Maltese case, the forecast accuracy does not always improve in specifications which include flow rates.

This may be due to the structural changes the Maltese labour market has undergone over the past years, which are unaccounted for in the simple two-state labour market model considered in this study. However, when accounting for cointegrating relationships in a VECM environment, the FBF approach results in significant forecast improvement over both an AR benchmark, and the direct forecasting of unemployment, without the flows. The main conclusion is that the inclusion of these flows in VAR models do not yield a significant forecasting improvements compared to the VAR model without the flows, but they return a significant improvement over a simple AR process. The FBF approach is seen as a useful cross-check for other, simpler, forecasts of unemployment.

2. Literature Review

Labour markets differ substantially across countries. Search models, following Diamond (1982) and Mortensen and Pissarides (1994), are used to explain this cross-country heterogeneity. A key input in these models are estimates of job-finding and separation rates.¹

The ‘true’ job-finding rate is defined as the ratio of the flow from some other activity into employment to the number of people seeking jobs. The problem with such an aggregate definition is that the denominator includes flows from employment to employment (change in jobs), and from outside the labour force (inactivity) to employment. These are difficult to measure without access to Labour Force Survey (LFS) micro-data. Empirical studies tend to define that proportion of unemployed individuals flowing out of unemployment as the aggregate job-finding rate (f), and the fraction of workers leaving employment as the aggregate separation rate (s). This implies having a simple two-state model, where a worker can either be employed or unemployed, and excludes all forms of changes in state from or to inactivity.

The main contribution from this study is the use of published data for long-term unemployed workers as a substitute for LFS micro-data. The analysis is carried out following Shimer (2007), and uses further extensions proposed by Barnichon and Garda (2016), Elsby et al. (2013), Fujita and Ramey (2009) and Petrongolo and Pissarides (2008).

¹A distinction ought to be made between the creation of vacancies and worker flows. Vacancies, which can be viewed as job flows, are created by employers. These reflect job destruction and creation processes. Worker flows, on the other hand, are linked to factors which influence workers, making them move between different labour market states. This study focuses on the latter.

Constructing the flow rates

Due to data quality issues, flow rates for Malta are either unavailable or exhibit erratic behaviour. Thus, this study also computes flow rate probabilities for Malta, based on a simple two-state model. The strand of literature discussing transition rates between statuses is based on computing flow rates from micro or macro data.

A significant proportion of labour market literature attempts to explain the causes behind the actual unemployment level. Empirical results are mixed, due to differences in the chosen methodologies, or estimating assumptions. Some researchers hold that the important role belongs to inflows into unemployment, such as Elsby, et al. (2009). Others believe that the outflows are decisive, Shimer (2007).²

The general consensus, based upon research by Darby et al. (1985, 1986), Blanchard and Diamond (1990), and Davis and Haltiwanger (1990, 1992), intimates that recessions are periods characterised primarily by high exit rates from employment, that is, higher separation rates. This view is summarised by Darby et al. (1986) as “The Ins and Outs of Unemployment: The Ins Win,” where the ‘Ins’ refers to the inflow separation rate. Shimer (2012), on the other hand, holds that ninety percent of the fluctuations in the US unemployment rate since 1987 were a consequence of movements in the job-finding probability. Hall (2005) also agrees, noting that recessions do not begin with a surge in separation rates, but unemployment rises because jobs are hard to find (i.e. *a decrease in the job-finding rate ‘f’*). These latter two studies were disputed by a body of literature which highlighted the importance of cyclical surges in the separation rate to explain increases in unemployment. Large amounts of empirical evidence were compiled to sustain these arguments.³

Elsby et al. (2009) use the log change decomposition for systematic analysis of the contri-

²Revised in Shimer (2012).

³For a brief discussion of the evidence in favour of both arguments, see Elsby et al. (2009).

butions of the flow hazard rates to cyclical unemployment, with the decomposition being subsequently adapted by Fujita and Ramey (2009). Both studies underline the importance of cyclically induced unemployment inflows. More recently, the literature has developed in an analysis of the usefulness of separation and outflow rates to improve the performance of labour market forecasts, such as Barnichon and Garda (2016).

Cross-country heterogeneity

Many papers provide sets of comparable estimates of average job-finding and separation rates, for a number of countries. These are used in cross-country calibrations of search models of unemployment. One such study, by Hobijn and Sahin (2009), estimates job-finding and separation rates in the Organisation for Economic Co-operation and Development (OECD) countries.

Their estimates, carried out over different time-periods, apply the Generalised Method of Moments to the implications of the steady-state of a search model of the labour market for the aggregate unemployment duration distribution, as well as the aggregate job tenure distribution. Their findings are reproduced in Table 1.

It is apparent that the rates in the literature vary substantially across countries, and within the same countries over time. As seen in Table 1, the US job-finding rate appears by far the highest in the cohort. Hobijn and Sahin (2009) noted how this was 20 times higher than the rate estimated for Italy and more than 8 times higher than that in other continental Western European economies, like Belgium, France, Germany, the Netherlands, Spain, and Portugal.

The same heterogeneity exists, although to a lesser extent, in separation rates. While the results in Table 1 do shed light on this heterogeneity, their age may have decreased their usefulness for current analysis. In fact, most of this analysis ends in 2004.

Table 1: Estimation results for job-finding and separation rates

	Finding rate (%) (f)	Separation rate (%) (s)
Australia	17.05	1.75
Austria	15.61	n.a.
Belgium	3.45	0.92
Canada	28.90	1.78
Czech Republic	8.06	0.94
Denmark	9.64	1.87
Finland	13.36	1.38
France	6.69	1.14
Germany	6.98	1.06
Greece	5.28	0.70
Hungary	6.41	0.99
Iceland	30.47	1.85
Ireland	3.98	1.39
Italy	2.58	0.69
Japan	19.07	n.a.
Luxembourg	8.51	0.82
Netherlands	4.68	0.99
New Zealand	21.71	n.a.
Norway	30.52	1.34
Poland	7.20	0.99
Portugal	3.88	0.96
Slovak Republic	5.65	n.a.
Spain	3.98	2.03
Sweden	25.17	0.87
Switzerland	13.35	1.19
United Kingdom	11.27	1.53
United States	56.30	1.06

Source: Hobijn and Sahin (2009)

Table 2: More recent results for job-finding and separation rates

	Finding rate (%) (<i>f</i>)	Separation rate (%) (<i>s</i>)
Australia	22.27	1.67
Canada	25.83	2.35
France	7.77	0.76
Germany	6.98	1.06
Greece	6.01	0.51
Ireland	5.80	0.58
Italy	4.14	0.45
Japan	19.26	0.60
New Zealand	27.90	1.67
Norway	38.32	1.57
Portugal	6.47	0.40
Spain	6.19	1.02
Sweden	28.94	1.27
United Kingdom	13.33	1.01
United States	57.51	3.55

Source: Elsby et al. (2013)

Barnichon and Garda (2016) report transition rates with more recent data, based on Elsby et al. (2013), for a subset of these OECD countries. The starting year varies between 1968 (for the US) and 1986 (for New Zealand and Portugal). For all countries, the data ends in 2009. The results are presented in Table 2. It is apparent that the differences over time between the same countries are minor. Separation rates are, again in most cases, slightly lower than in Hobijn and Sahin (2009).

In parallel, Elsby et al. (2013) also note how there appears to be a clear separation which divides OECD economies in two groups. The first are economies with flexible labour markets. Here, Anglo-Saxon and Nordic economies tend to display high exit rates from unemployment, with monthly hazard rates exceeding 20.0%. Continental European economies, on the other hand, appear to be less flexible and have exit rates which are less than 10.0%.

Forecasting unemployment

Inflows and outflows in and out of unemployment help answer questions on why unemployment does not drop immediately after an economic recovery, or why it drops to historically low levels. For example, unemployment may be sluggish because substantial outflows of workers from unemployment to employment (*People finding a job*) are offset by inflows into unemployment from inactivity. In that case, this may be classified as a *recovery* in the labour market in spite of the stagnation in unemployment. This would be because large numbers of inactive individuals have taken up the search for unemployment, and may thus be counted as unemployed. In that case, discouraged workers who had dropped from the labour force have re-joined the labour-force. If, on the other hand, there are only minimal outflows from unemployment, the flow statistics would show that a recovery has not yet appeared in the labour market.

Information from labour force flows is then incorporated - via the idea of some conditional *steady-state* of unemployment - in a forecasting framework. This steady-state is seen to be that rate of unemployment that would eventually prevail were the flows out of and into unemployment to remain at their current rates (Barnichon and Nekarda, 2013).

This approach also assumes that the steady-state to which the actual unemployment rate is converging changes over time. Time-series models can be used to forecast the underlying labour flows. These forecasts are then used in the model's law of motion, which map those flows to the labour market stocks. These are then used to create the unemployment forecasts over the required time horizons.

The approach tends to outperform other unemployment rate forecasts; it allows the framework to better capture the dynamics of unemployment, by relating the unemployment stock to the flows. This is especially important if the contributions of different flows change throughout the cycle (Barnichon, 2012).

Barnichon and Garda (2016) extend the flow approach discussed in Barnichon and Nekarda (2013) to euro area economies. They find that the use of flows dramatically improves the forecast accuracy over professional forecasts for all countries - with substantial improvements appearing at year-ahead time horizons for European countries. The flow approach appears to be highly useful in periods of economic uncertainty around turning points and economic recessions.

While the literature on using flow rates to construct unemployment forecasts is in its infancy, other methods have long investigated the best methods to forecast unemployment in a number of countries. Most methods used to forecast unemployment are based on time-series econometric methods. The most researched unemployment rates in the literature are those of the United Kingdom or the United States. Montgomery et al., (1998) used rolling-forecasts for US quarterly unemployment rates. They show that non-linear models such as threshold autoregressive process (TAR) and Markov-switching methods perform better than benchmark linear models in terms of forecasting errors during decelerations and accelerations in the unemployment rates, but not during other periods. TAR models also approximate better the long-run structure of unemployment time-series, while ARIMA models represent better its short-term developments.

The use of higher frequency monthly data, instead of quarterly observations, appears to result in significant forecast gains. This is especially the case for short-term forecasts. For larger US data sets, the inclusion of monthly unemployment rates in Stock and Watson (1999) proved that linear forecasts have better accuracy than non-linear forecasts. Skalin and Teräsvirta (2002) show how logistic smooth transition autoregressive (LSTAR) models tend to model well asymmetries found in a number of OECD unemployment rate series.

Dynamic asymmetries in US unemployment rates are analysed in Koop and Potter (1999), who found strong empirical evidence for a two-regime threshold autoregressive model. They also discuss how unemployment rates appear to rise suddenly, and fall gradually. This ap-

pears to be an argument towards ‘sticky’ unemployment. Teräsvirta et al. (2005) note how LSTAR models are better than neural network or linear models when looking at unemployment rates in the G7 group of countries. While linearity is not rejected for some macroeconomic variables, unemployment rates behave most systematically in a non-linear fashion. Non-linear specifications are seen to outperform selected linear models for a shorter time spans.

Marcellino (2002), looking at structural models, showed how when forecasting unemployment rates in OECD countries the time-varying AR model was amongst the top performing methods. Proietti (2003) discussed how linear models with higher persistence will perform better than non-linear models.

3. Data

The Maltese labour market

With a total population of less than half a million, and a working age population of just under three-hundred thousand, one would expect Malta to offer limited employment prospects for workers, and constrained ways to fill vacancies for firms.⁴ However, a dynamic economic structure, which shifted strongly towards services, led to an unprecedented increase in demand for labour. This increase has not only accommodated secular demographic trends (Grech, 2015a) but also attracted migrant worker flows from European Union (EU) countries. Taken together, this dynamism helped the economy withstand the global crisis of 2008-9.

In fact, as noted by Micallef (2017), the Maltese economy recovered strongly after 2009, with the labour market keeping up with the rapid evolution of the economy since EU membership. This remarkable labour market resilience ought to be seen in the context of important labour market reforms undertaken in recent years. These have included the provision of free child-care, tax incentives for females returning to employment, on-the-job training schemes, the tapering of social benefits and the curtailing of abuse by those registering for unemployment. These have all played an important role in raising the Maltese economy's potential output growth rate, as discussed in Micallef (2015), and Micallef and Ellul (2017).

Grech (2015b) finds how following EU accession, foreign migrant worker flows picked up considerably in Malta, with most workers coming from EU countries. In fact, this study discusses how the number of EU nationals working in Malta trebled since 2004. In the absence of immigration, the working age population would have shrunk by 1.0%, instead

⁴For an in-depth assessment of historical trends in the Maltese labour market, particularly the effects of ageing and increased female participation, see Grech, A.G., (2015), 'The evolution of the Maltese economy since independence,' WP/05/2015 - Central Bank of Malta Working paper series.

of rising by 3.0%. These flows have eased pressures in the local economy, with evidence apparently indicating that the rising demand for labour by Maltese industries is too strong to be serviced by the supply of Maltese workers. This in a period where the supply expanded rather strongly due to a surge in female participation.

The increase in the labour supply was also complemented by a period of wage moderation (Micallef, 2013). Following the 2008-9 recession, nominal wage growth averaged 2.0% annually, roughly in line with the euro area and lower than the historical average wage growth of around 4.0% prior to the crisis. Wage moderation was especially pronounced in 2010 and 2011. Estimates by Grech et al. (2013) show how wage moderation sustained demand for private sector employment in Malta.

Micallef (2013) discusses how labour utilisation in Malta dropped in 2009, bringing it back to its long-term trend. Since the end of 2011, however, there were indications of an increasing degree of labour hoarding as labour productivity fell further below its long-term trend. Conceptually, it would be in a firm's interest to cut costs by cutting working hours, and hoard labour, especially if trained workers are in short-supply. The firm would not lose its training investment, and avoid future hiring and training costs for new workers. Micallef also notes how structural unemployment in Malta may be the result of a mismatch between the skills offered by the unemployed and those required by the country's growing services industries.

In recent years, employment has expanded at a comparatively strong average annual rate of around 3.0% in labour force survey data. This was relatively robust from a longer term historical perspective. This increase in the number of jobs mostly reflected a surge in full-time employment. The labour force expanded by around 2.0% in recent years. As a result, the activity rate (age group 20 - 64) rose to 69.6% in annual terms for 2016, just below the national target of 70.0% as found in the Europe 2020 targets. Female activity rates continue to return very strong gains, on the back of a secular trend increase in female participation.

Both the activity and the employment rates have reached the highest levels recorded since the first time the survey was conducted in Malta. Apart from buoyant economic conditions, additions in activity and employment rates partly reflect the continuation of active labour market policies. These were aimed at increasing employment among the more challenged job seekers, as well as encouraging inactive persons to join the labour market.

Shifting to unemployment, survey data shows that the number of unemployed continue to decline. This reflects growing demand for labour. The number of job seekers continues to be low, with the unemployment rate standing at around 4.0% in recent quarters. In 2017, the number of unemployed based on administrative data from Jobsplus data fell by almost one-third over that prevailing in 2016. Apart from the growing demand for labour, the decrease in the number of registered unemployed reflected the extension of previously introduced measures aimed at facilitating the transition from inactivity to activity and improving the employability of specific target groups. These schemes include the Tapering of Benefits Scheme, the Access to Employment (A2E) Scheme, the Youth Guarantee Scheme and the Mature Workers Scheme. The drop in the number of unemployed was broad-based across age groups, with the greatest decrease was registered among those aged 45 and over. The duration of unemployment also decreased, with the most significant decline recorded among those who had been registering for less than 21 weeks, although unemployment among other groups also declined significantly from already low levels.

A look at the data shows that most of the high frequency macroeconomic time-series for the Maltese economy begin in the early 2000s, with very few series being available before the year 2000.⁵ This feature is not limited to Malta alone. Efforts to harmonise European statistical practices led to inconsistent starting dates for coverage in most EU countries. Thus, for example, before early 2000s the LFS was conducted annually in spring, rather

⁵For a databank with annual historic macroeconomic time-series, in some cases going as back as the 1950's, see Grech, A.G., (2015a), 'The evolution of the Maltese economy since independence,' WP/05/2015 - Central Bank of Malta Working paper series.

than quarterly. The move from an annual survey to a continuous, quarterly survey began between 1998 and 2004, depending on the Member State.⁶

In Malta, the LFS was conducted annually twice in the year 2000 and 2001. It then shifted to a quarterly survey from 2002Q1, onward. This short length rather limits the study as it does not cover the economic transition in Malta during the 1980s-1990s. In fact, the use of seasonal adjustment and volatility in Maltese data further limited the results of this study to the period from 2001Q2 to 2017Q3. Finally, as the long-term unemployed series derived from a quarterly survey, a choice was made to use a quarterly frequency throughout the study, to avoid further frequency distortions.

On a positive note, other sources of high frequency data for Malta still exist - even if these are not directly comparable with LFS data.⁷ One such measure is the unemployment rate derived from administrative records (see Figure 1).⁸ The ‘churning flows’ described in labour economics literature are evident in this long term time-series. As the Maltese economy passed through successive periods of structural changes, economic booms and recessions, unemployment rates contracted and rose with it. The unemployment rate calculated on the basis of administrative records tracks well but differs substantially from the one reported in the LFS, (see Figure 2).

⁶See: ‘EU labour force survey - development and history,’ http://ec.europa.eu/eurostat/statistics-explained/index.php/EU_labour_force_survey_-_development_and_history

⁷For an in depth discussion on comparability, adjustment strategies and other technical considerations, see Grech, A.G., (2003), ‘Assessing Employment in Malta,’ WP/01/2003 - Central Bank of Malta Working paper series.

⁸The data were seasonally adjusted. Monthly observations were interpolated from quarterly figures for the period 2003 - 2012.

Fig. 1. Unemployment rate (%), monthly administrative records data (1965 - 2016). Source: Central Bank of Malta, NSO.

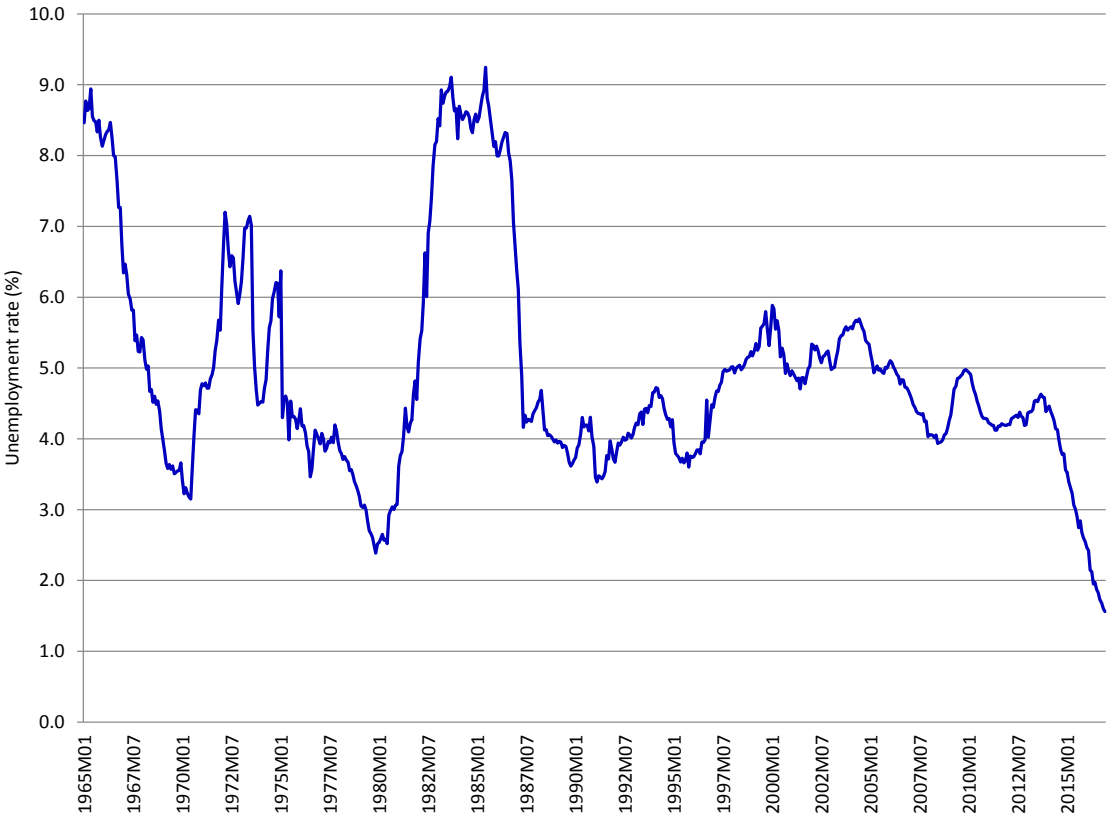
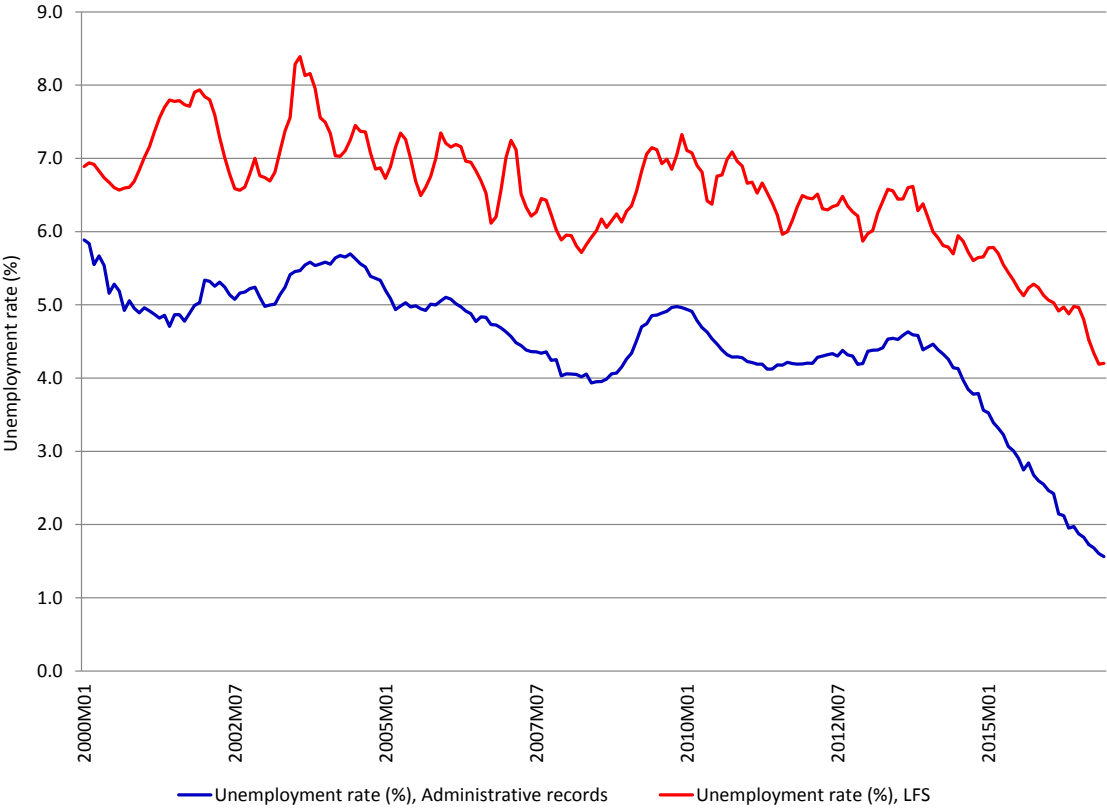


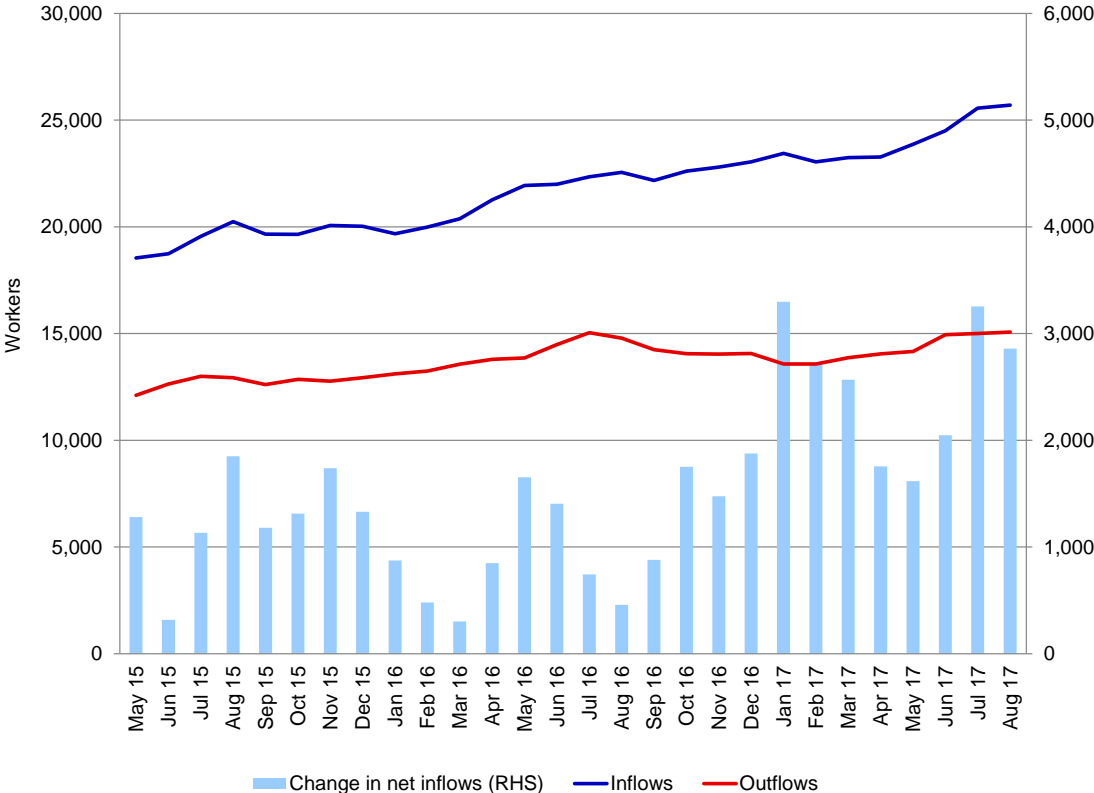
Fig. 2. Unemployment rate (%), monthly administrative records data and LFS (2000 - 2016).
 Source: Central Bank of Malta, NSO.



Administrative flow data

Annual inflow and outflow data are computed on the basis of administrative data obtained from Jobsplus. Inflows are defined as the sum of foreigners coming to work to Malta, retirees who have returned to work, unemployed who have found productive work (both as employees and self-employed), part-timers shifting to full-time employment, school-leavers, those who are returning to the labour market, and others. Outflows are defined as those shifting from full-time employed into registered unemployment, from self-employment into registered unemployment, from full-time into part-time primary employment, those who retire as they reached pensionable age, those who take up early retirement, those made redundant, the deceased, foreigners who exit gainful employment, and others.

Fig. 3. Annual flows, monthly administrative records data. Source: Jobsplus.

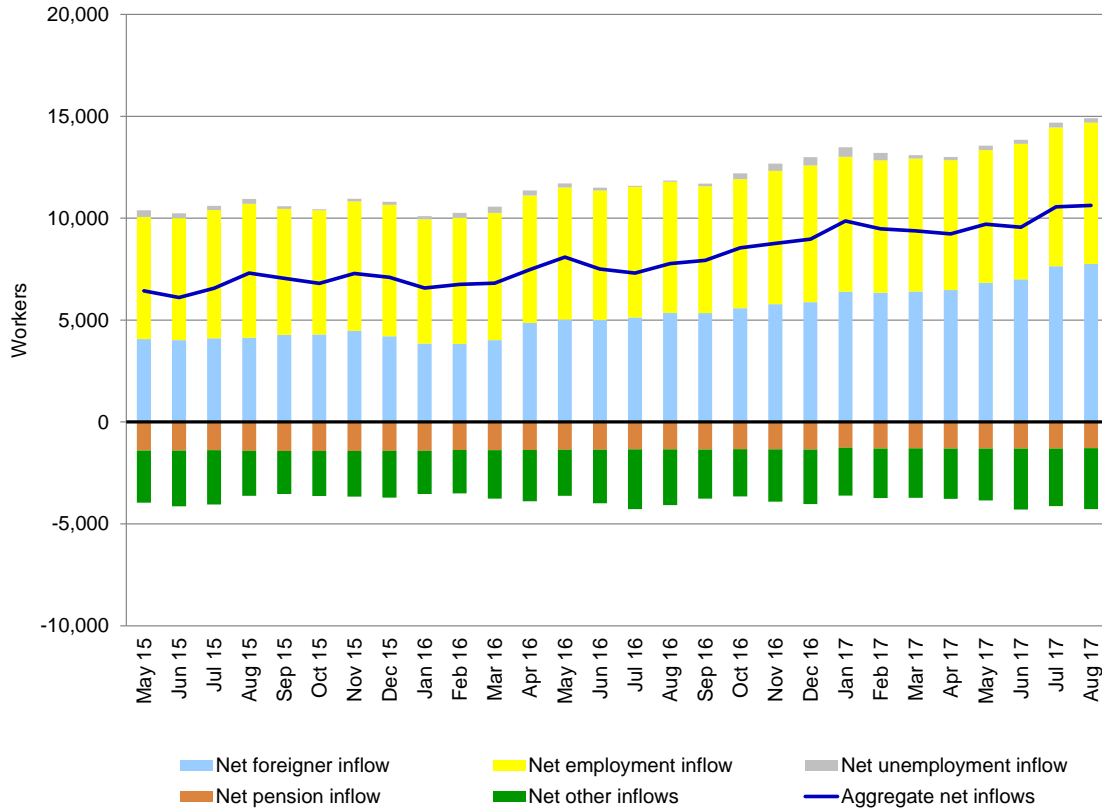


Over recent months, the flows in the Maltese labour market have been characterised by a surge in labour market inflows (see Figure 3). Outflows from the labour market have increased, however these have not kept up with the surge in inflows. A look at net annual inflows reveals that the increase in net inflows in the Maltese labour market is mostly linked with net foreigner inflows towards Malta, as well as net employment inflows (see Figure 4). Most other net inflow components remained stable over the recent past.

Net contribution components are aggregated on the basis of inflow and outflow data obtained from Jobsplus. For the sake of clarity, the categories are defined as follows: Net foreigner inflow is the sum of EU and third country nationals entering the gainfully occupied population (GOP) less the sum of those exiting the GOP. The net employment inflow is defined as part-time primary employment flowing into full-time employment and school leavers flowing into the GOP less the sum of full-time into part-time primary employment outflows. Net pension inflows are defined as inflows of those previously retired and returned to the GOP, less the sum of those retired as pensionable age was reached or who have taken up early retirement. Net unemployment inflows are the sum of inflows of registered unemployed flowing into full-time employment (employees) and registered unemployed into self-employment, less the sum of outflows from the full-time employed flowing into registered unemployed, the self-employed flowing into registered unemployed, and those made redundant. Net other inflows are a residual category.

A priori, from these administrative data, one would expect the job finding rate to have increased substantially over this period, while the separation rate should either be stable or on a downward path. Moreover, these flows indicate a period of strong structural change in the Maltese labour market.

Fig. 4. Annual flows, monthly administrative records data. Source: Jobsplus.



EUROSTAT experimental data

EUROSTAT has recently published a number of experimental statistics related to labour market flows.⁹ These derive from the longitudinal component of the EU-LFS dataset, and thus identify the flows between labour market statuses in consecutive quarters.

Initial quarter-on-quarter flow estimates are calculated as a 3-by-3 labour status transition matrix, by sex and for individual countries. All computations are restricted to workers aged 15-74. For all quarters from 2010Q1 onward, the longitudinal flow samples are defined as the overlap of the sample with the sample of the following quarter for the age group 15-74.

The coverage of the flows for Malta is rather sparse with many missing values, while the

⁹See: EUROSTAT, “Labour market transitions - LFS longitudinal data,” (*lfsi_long*) http://ec.europa.eu/eurostat/cache/metadata/en/lfsi_long_esms.htm

rounding to the nearest thousand may lead to, at times, inconsistent inference (see Table 3). From the limited coverage, it appears that there are seasonal patterns in the transition flows. The flows between employment and inactivity (E - I) and the flows from inactivity to employment (I - E) partly offset each other over the course of a year. At face value, this might betray seasonal labour supply patterns and the effect of labour demand from seasonal industries - such as tourism.

The transition probabilities computed from these flows in the Maltese labour market are even thinner, with the rates rounded as percentage of aggregate employment or unemployment stocks. The figures, where available, remain unchanged at for example 1.0% of employment for most of the available time horizon.

It is apparent from these statistics that flows and probabilities to be used in this way have to be computed in some other fashion.

Table 3: Flows in employment status, (thousands of persons).

Flows in a three-state system between employment (E), unemployment (U), and inactivity (I).

	2014Q1	2014Q2	2014Q3	2014Q4	2015Q1	2015Q2	2015Q3	2015Q4	2016Q1	2016Q2	2016Q3	2016Q4	2017Q1	2017Q2	2017Q3
Transition E - E	174	177	179	178	182	181	183	183	183	184	190	189	191	191	194
Transition E - U	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Transition E - I	4	-	1	5	0	1	-	5	-	1	-	4	2	1	2
Transition U - E	-	-	-	2	-	-	-	-	2	3	-	2	-	-	-
Transition U - U	10	9	9	9	10	7	8	8	8	7	8	7	7	6	6
Transition U - I	-	-	-	-	-	-	-	-	-	-	-	1	1	-	-
Transition I - E	3	-	-	2	-	-	4	-	1	6	3	2	2	4	5
Transition I - U	-	-	-	2	-	-	-	-	2	3	-	2	-	-	-
Transition I - I	135	137	133	133	138	136	132	132	136	133	132	131	135	134	130

Source: EUROSTAT.

4. Methodology

Calculating the flows

Comparability issues between LFS and administrative data, and the lack of micro-data linkable to individual participation choices and unemployment duration has limited this study. The analysis focuses on the post-2002 economic environment, modelled as a two-state model, and using aggregate unemployment duration decisions in lieu of individual data (see Figure 5).

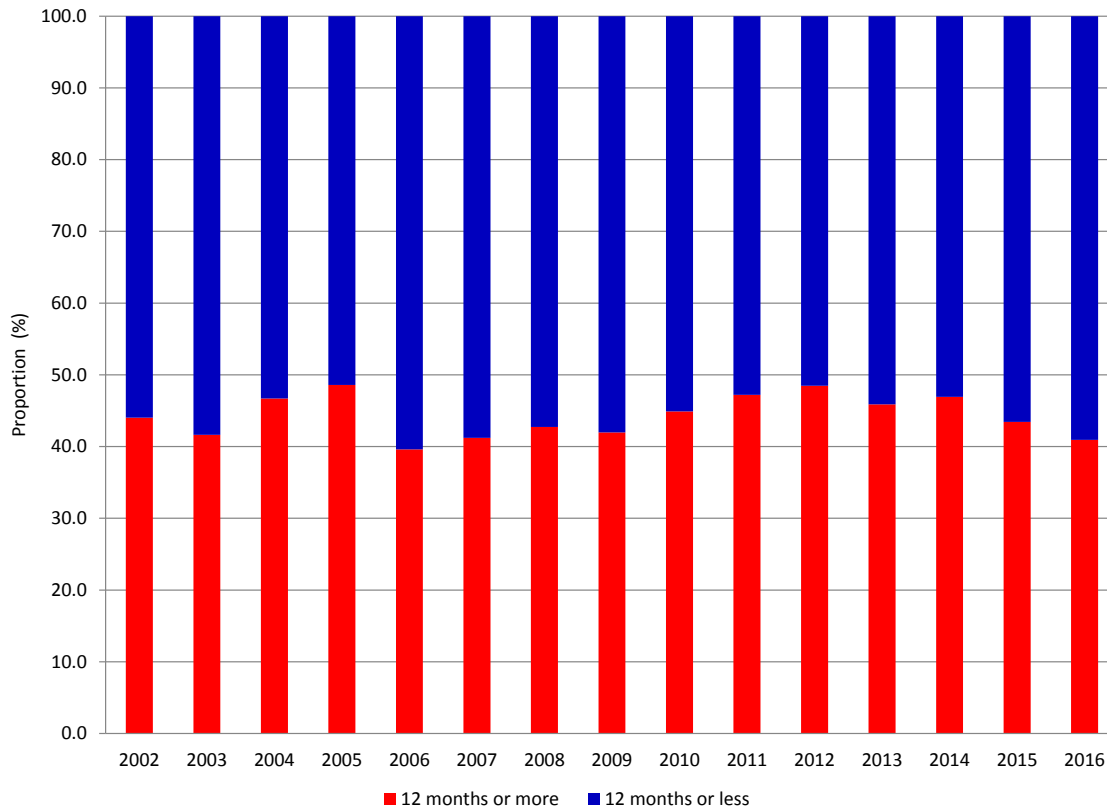
As a proportion of total unemployed, those who were unemployed for 12 months or more surged in 2005, following the structural changes undergone by the Maltese economy in the run-up to EU accession. This was sharply corrected in the following year, but long-term unemployment continued to creep until it peaked again in 2012. Thereafter, the share of the long-term unemployed decreased - almost reaching a historic low.

The flow rates are calculated following established methods. Shimer (2007) and Hall (2005) pioneered the use of the evolution of the number unemployed over time in the following approach:

$$\frac{du}{dt} = s_t(l_t - u_t) - f_t u_t = -(s_t + f_t)(u_t - u_t^*) \quad (1)$$

where l_t and u_t are the labour force and unemployment stocks and u_t^* is steady-state unemployment. The variables s_t and f_t are the unemployment inflow and outflow hazard rates. Equation (1) states that the change in the unemployment rate derives from workers who were employed in the previous period, and separated from work, less those who were unemployed who have found a job. Equation (1) accurately describes the evolution of unemployment only if one assumes that all the inflows into unemployment originate from employment.

Fig. 5. Proportion of long-term unemployment (12 months or more) in total unemployment. Source: EUROSTAT.



Thus, this model implicitly assumes the existence of two states. Unemployment originating from non-participation in the labour force is therefore excluded. This approach is limited in the sense that state switching from inactivity to unemployment is an important element in determining unemployment levels. However, in that this study faces a number of data constraints given the unavailability of LFS micro-data, this more standard two-state framework is seen to provide a useful, simple benchmark for Maltese data. This notwithstanding, the Maltese economy has experienced a number of structural changes over the past decades. Female participation rose from 35.8% in 2000 to 55.6% in 2016. Moreover, foreign worker numbers surged from relatively low levels in the early 2000s (Grech, 2015b) to more than 23,500 foreign full-timers and more than 4,800 foreign part-time workers in late 2015.¹⁰

¹⁰PQ 26653, LEG. XII, Sitting No. 417.

Conceptually, these two trends may result in problems when measuring flow rates into and out of unemployment in this simple framework. This results from the fact that the simple two-state labour market model considered in this study ignores flows from and into inactivity. This may result in the ‘intercept’ of the labour market separation rate, which is the residual in this simple methodology, to be underestimated.¹¹ However, as this study deals with forecasting unemployment rates, such a drawback may not be important if the inclusion of the resulting flow rates lead to measurable improvements in forecast accuracy. Moreover, problems in the determining the ‘true’ rates may be further overcome by exploiting the fact that the f_t and s_t rates are both highly cyclical, and may thus be cointegrated. The inclusion of this cointegrating relationship in the forecast framework might thus bypass data quality concerns.

As discussed above, the analysis is interested in the two flow rates, namely s_t and f_t . Moreover, the evolution of the actual unemployment rate, which we denote \tilde{u}_t , will be closely approximated by the steady-state unemployment rate, u_t^* :

$$\tilde{u}_t \equiv \frac{u_t}{l_t} \approx \frac{u_t^*}{l_t} = \frac{s_t}{s_t + f_t} \quad (2)$$

Finally, in order to be able to calculate the respective contributions of the separation and outflow rates, one can look at the contribution to variations in the unemployment rate itself. Thus, taking first differences in the steady-state unemployment rate of Equation (2), and re-arranging, the changes in the unemployment rate can be further decomposed as:

$$\Delta u_{t+1} = (1 - u_{t+1})u_t \frac{\Delta s_{t+1}}{s_t} - u_{t+1}(1 - u_t) \frac{\Delta f_{t+1}}{f_t} \quad (3)$$

¹¹Given the outflow rate f and the stock of unemployed persons U , the rate s incorporates all other movements in unemployment not included within the outflow rate. Theoretically, this may result in problems in periods where the participation margin is important, or when labour force growth is high.

or, further simplified as:

$$\Delta u_{t+1} = \Delta u_{t+1}^s + \Delta u_{t+1}^f \quad (4)$$

Equation (4) states that, in this simple framework, one may decompose changes in unemployment between the changes in the separation and the job-finding rates. Following the literature, and in particular Barnichon and Garda (2016), a simple stock-flow model for unemployment is defined. Persons can either be unemployed or employed. This abstraction from other states simplifies the data requirements.

The unemployment rate at instant $t + \tau$ is denoted by $u_{t+\tau}$. Time t indexes the period (e.g. a quarter) and τ is a continuous time measure within the period. Between time t and $t + 1$, unemployed persons find a job following a Poisson process with a constant arrival rate of f_{t+1} , and employed persons lose a job following a Poisson process with constant arrival rate of s_{t+1} .

In this case, the unemployment rate will evolve as:

$$\frac{du_{t+\tau}}{d\tau} = s_{t+1}(1 - u_{t+\tau}) - f_{t+1}(u_{t+\tau}) \quad (5)$$

and the changes in unemployment resulting from the differences between the inflows into unemployment (s) and outflows from unemployment (f). Solving the equation above results in:

$$u_{t+\tau} = \beta_{t+1}(\tau)u_{t+1}^* + [1 - \beta_{t+1}(\tau)]u_t \quad (6)$$

where the steady-state unemployment rate is defined as:

$$u_{t+1}^* \equiv \frac{s_{t+1}}{(f_{t+1} + s_{t+1})} \quad (7)$$

and

$$\beta_{t+1}(\tau) \equiv 1 - e^{-\tau(f_{t+1} + s_{t+1})} \quad (8)$$

is the rate of convergence to that steady-state. The model will depend on constructing historic labour market flows, and constructing forecasts for them.

Even this comparatively simple framework with just two states was only computable by using unemployment duration data found on the European Central Bank’s Statistical Data warehouse.¹² This series provides the percentage of total workers who have been unemployed for over twelve months. An extrapolation on this series provides those workers who have been unemployed over the short-term, used in Equation (9) below.

Continuous-time transition rates are computed from the seasonally adjusted series, assuming that these are constant during the quarter.¹³ Following Shimer (2012) and Barnichon (2012), let t denote the quarter and the continuous-time transition rate from unemployment to employment is f_t and that from employment to unemployment is s_t . Using information on the number of persons unemployed, u_{t+1} , and of those unemployed for less than 12 months, u_{t+1}^d , one can infer job-finding and job separation hazard rates. The unemployment inflow rate, s_t , is then obtained by solving Equation (10) recursively forwards over $[t, t + 1]$, and then finding the values for s_{t+1} .¹⁴

¹²These are the aggregated version of LFS micro-data for duration. Some of these data are available on EUROSTAT, such as the long-term unemployed (12 months or more) series, ‘*lfs_upgal*.’

¹³Missing quarters in 2001 and 2002 are interpolated from NAs, using IRIS toolbox in MATLAB.

¹⁴Elsby et al. (2013) re-scale the separation rate parameter by multiplying it by the expected value of u_t ,

Labour market flow rates are constructed using quarterly aggregated LFS data. In line with the literature, all data are seasonally adjusted. Unemployment duration data from SDW are combined in ‘duration bins’ with shares of workers unemployed for given amounts of time being calculated. Following Shimer (2012), Fujita and Ramey (2012), Barnichon and Nekarda (2013), Elsby et al. (2013), and Barnichon and Garda (2016), the probability F that an unemployed person finds a job within d months is calculated as:

$$F_{t+1} = 1 - \frac{(U_{t+1} - U_{t+1}^d)}{U_t} \quad (9)$$

with the outflow rate f then calculated as $f_{t+1} = -\ln(1 - F_{t+1})/d$, being the monthly hazard rate linked with the probability that an unemployed person at time t finds a job within the following d months. The inflow rate s_t is then obtained by solving Equation (5) forwards, and finding the value s_{t+1} which solves:

$$u_{t+1} = \frac{[1 - e^{-(f_{t+1} + s_{t+1})}]s_{t+1}}{(f_{t+1} + s_{t+1})}(U_t + E_t) + e^{-(f_{t+1} + s_{t+1})}U_t \quad (10)$$

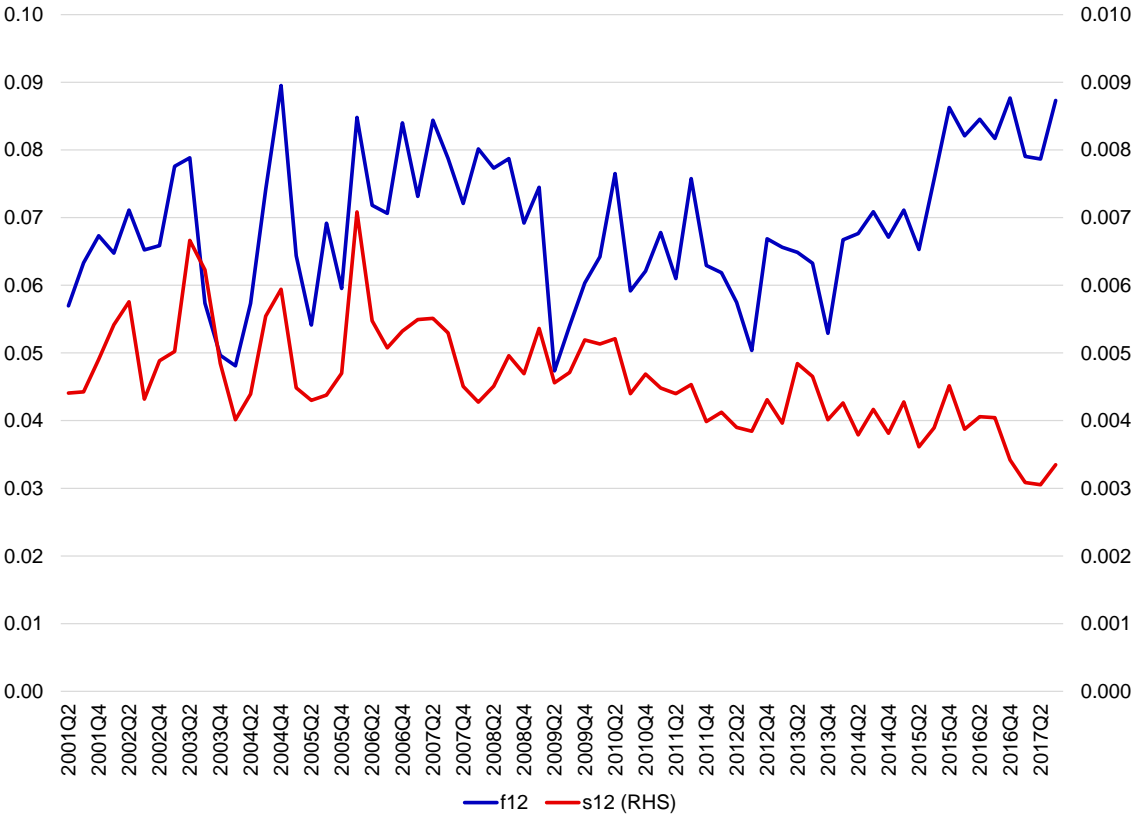
where $(U_t + E_t)$ is the labour force. In this simple model, given that the outflow rate f and the stock of unemployed persons are determined separately and exogenous respectively, the separation rate s will incorporate all movements in unemployment not included within the outflow rate. For different empirical purposes, flow rates are calculated at 1 month, 12 month and 24 month unemployment duration. For the purposes of forecasting, we focus on the flow rates calculated on the basis of 12 months’ unemployment duration. The job-finding rate and the separation rate at 12 months’ duration are defined f_{12} and s_{12} , respectively.

A striking result of this calculation is the increase in job-finding probabilities from 2014 onward, and the trend decline in separation rate (see Figure 6). This surge in outflow

$E(u)$.

prospects may be linked with various active labour market policies which have been put in place to aid job-finding. These have included a number of targeted training schemes explicitly designed to make target groups more employable, and a national apprentice scheme. The estimates show that the average job-finding probability in Malta, for the period 2001Q2 to 2017Q3 stood at 6.9%, while the average separation probability stood at 0.46%.

Fig. 6. Labour market flow rates.



This may result from active labour market initiatives, as well as efforts to reduce the reliance of the long-term unemployed on unemployment benefits, the tapering of social benefits and the curtailing of abuse and fraud, which may have reduced undeclared work and encouraged people to enter the formal economy.¹⁵

The active labour market policies and a clampdown on benefit fraud may have affected the unemployment duration composition, and the analysis has to be carried out with caution. Changes in the duration composition of an unemployment pool will influence the pace of changes in unemployment. The literature suggests that the long-term unemployed are less likely to search effectively for jobs. Those unemployed for longer spells face lower job-finding rates. This is termed ‘negative duration dependence.’ Elsby and Smith (2010), discuss how job seekers with less than one month’s unemployment duration in the UK find jobs at an average rate of over 15.0% per month, compared to less than 5.0% for workers with a duration above twelve months.

The improvement in the duration composition of the Maltese unemployment pool may be short-lived unless it is coupled with continued re-training of unemployed workers and vigilance by the authorities. In fact, these estimates of separation and job-finding rates may prove to be useful indicators for policymakers. For example, if job-finding rates were to drop to mid-2000s levels, the long-term unemployment share may return to levels seen in the aftermath of the 2004 recession. The concern, then, would be that the Maltese labour market would once more converge to a higher (and perhaps persistent) unemployment equilibrium.

¹⁵Recent inspections found around 3,500 illegal workers, while 1,105 workers were struck off the unemployment register for benefit abuse. See ‘Economic development has to be balanced by skilled workforce,’ Times of Malta, (July 4, 2017).

Comparison of flow rates with existing estimates

In its annual review on labour market and wage developments in Europe, the European Commission (EC) computes job finding and separation rates for EU countries (EC, 2017), following Elsby et al. (2009), for the period 2002Q4 to 2016Q4. Job finding rates are presented as a quarterly series, and smoothed with a moving-average procedure.¹⁶

The finding rate estimates in this study follow closely the figures computed by the EC, when expressed as a four-quarter moving average (see Figure 7). Differences may result from different estimating periods, the optimisation procedures implemented and input data precision levels.¹⁷ The estimated separation rate is not as close as the EC estimate pre-2006, and moves closer to it thereafter (see Figure 8). This might again result from differences in the estimation procedure, or underlying data differences in vintages or definitions. All in all, the flow rates in this study appear to be comparable with the EC's estimates for Malta.

Both measures indicate that job finding rates for job-seekers with spells of unemployment shorter than 12 months have started to recover from early 2013 onward. This recovery meant that, by mid-2016, job finding rates exceeded the pre-crisis level, and, as a consequence, the average unemployment duration continued to drop. The decline in the unemployment rates observed from 2013 onward was linked to reductions in the job separation rates and increases in job finding rates. Thus, both the separation and the finding rates have improved, especially for people with short unemployment durations. Rates at which jobs losses occur have persistently fallen, which may indicate job hoarding by firms. Job finding prospects have risen consistently for the past four years.

¹⁶Average of four-quarters: reference quarter and previous three quarters.

¹⁷The author acknowledges and is grateful for the data shared by the economists at Unit.A.3. - Country reform - DG Employment, social affairs & inclusion, within the European Commission.

Fig. 7. Job finding rate (%) comparison

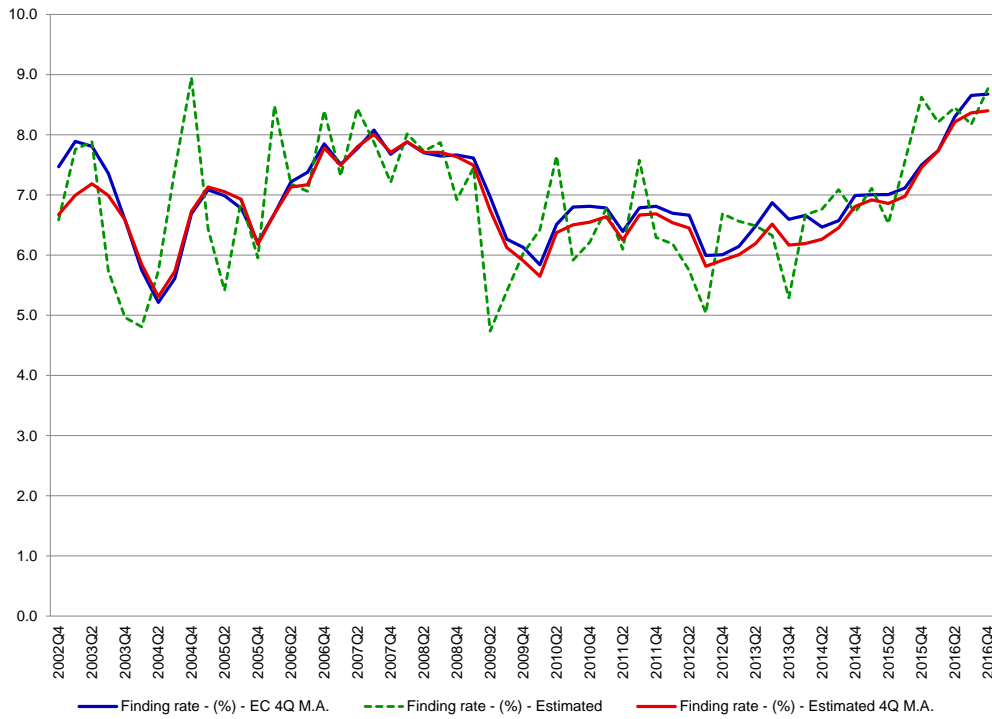
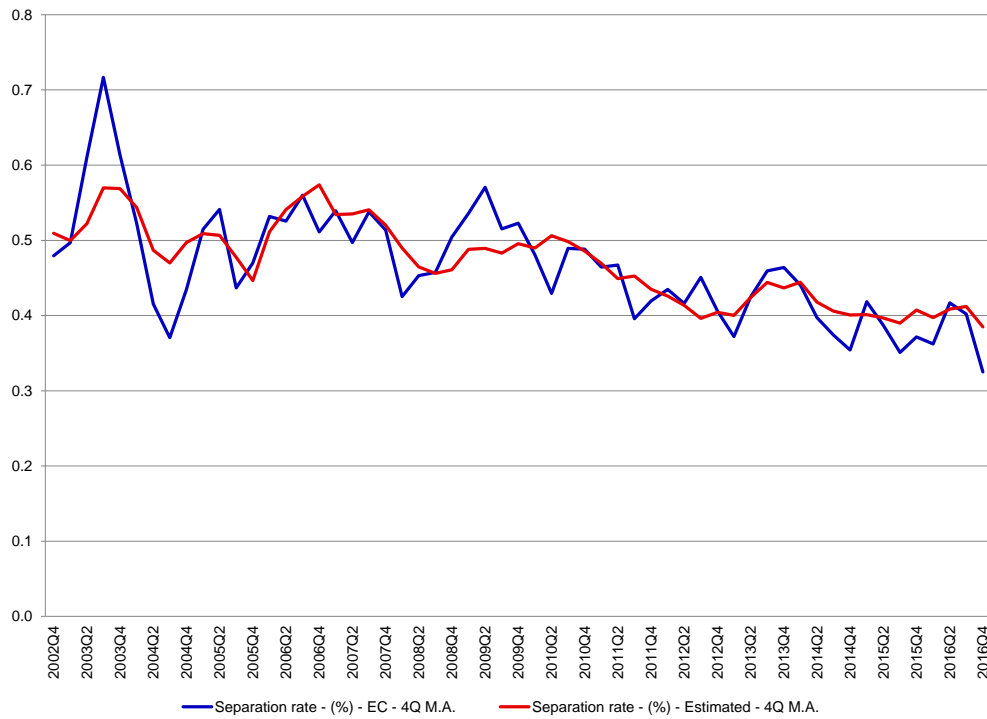


Fig. 8. Job separation rate (%) comparison



Forecasting approach

In order to arrive to flow based unemployment rate forecasts, labour market flow rates have to be forecasted. These are then used to arrive to a solution for Equation (2). A simple approach would be assuming the flow rates to be constant over the rest of the projection horizon. However, the flow rates are seen to change over time, sometimes dramatically. This underscores the need for their accurate forecasting. To generate these forecasts, a number of alternate VAR and VECM methodologies are explored. An illustrative example for Malta used in this study, is based on log-level data on labour market flows, GDP, vacancies and unemployment rates:¹⁸

$$y_t = (\ln s_t, \ln f_t, \ln u_t, \ln v_t, \ln gdp_t)' \quad (11)$$

The VARs are estimated over a rolling-time window of ten-years. Various specifications are implemented - both in log-levels and in differences - each time including or excluding variables or trends. Different VAR orders are also used. Each specification is repeated over the seven different methodologies considered in the study. These methodologies are five VAR approaches, namely simple OLS, simple BVAR, a BVAR with dummy-initial-observations, a BVAR with sum-of-coefficients and a BVAR with both dummy-initial-observations and sum-of-coefficients. Additionally, two VECMs are also estimated, subject to two different types of constraints. These are used to obtain identification by placing constraints on the parameters of cointegrating vectors; the study implements the Johansen and the constrained Johansen approach. For the sake of simplicity, this study reports the simplest variant, as shown in Equation (11).

VARs are very flexible time-series models which capture complex dynamic relationships

¹⁸Other, non-flow macroeconomic data included in the model are GDP and vacancies. Quarterly GDP data are seasonally adjusted. Vacancy data were unavailable; data from the EC's monthly surveys on hiring expectations are used instead.

between macroeconomic variables. However, they may suffer from unstable inference and inaccurate out-of-sample performance due to their dense parametrisation. A solution to this issue is to use informative priors, following Giannone, Lenza and Primiceri (2012) in order to shrink the richly parametrised and unrestricted model towards a more parsimonious and naïve benchmark. This reduces estimation uncertainty. Essentially, a hierarchical modelling approach is used for the prior structure. The appropriate prior shrinkage is selected automatically to get an optimal trade-off between in-sample fit and model complexity. This is particularly useful in this setting because of the sparse literature on prior selection for labour market models. Finally, this approach has been shown to over-perform flat priors even for small models, where optimal shrinkage is low but not zero.¹⁹

¹⁹The hyperparameter grid-search table and a short-discussion on changes carried out on an intermediate version of the BEAR toolbox are found in *Appendix: Technical Details*.

5. Results

This section summarises the main results of the study. At first glance, there are a number of policy implications from the use of flow rates - even beyond their use in forecasting. Policymakers ought to continue on their efforts to increase the matching efficiency of the Maltese labour market, and further improve training schemes and other active labour market policies. These are particularly crucial in view of Malta's ageing population, slowing demographic dividend from decelerating female participation in the labour market, and the expected path of the labour market's contribution to supply-side growth (Micallef and Ellul, 2017).²⁰ Adequate re-training should be provided to unemployed workers, especially those who find it difficult to thrive in fast-growing 'new' industries. Policies which drive labour market flexibility and the gradual weaning-off of able workers from social benefits should continue to be implemented.

The falling job separation rate may be an indicator of labour market tightness and hoarding - although migrant workers appear to have provided enough human capital for various industries to thrive, without compromising job prospects for Maltese workers. This foreign component, however, is by definition more footloose and depends on Malta's connectivity to and continued sectoral links with the European mainland.

The forecasting approach analyses two different issues, that is, the exercise's approach in terms of the model employed (AR(1) versus the VAR-VECM), and the variables employed (models including flows, models excluding flows).²¹ RMSE results for the forecasting part

²⁰This study shows that a broad measure of productivity, i.e. 'total factor productivity,' recovered strongly in recent years to levels last seen in the 1990s. The labour component's projected contribution over the medium term, however, is seen to decelerate to nil. This partly derives from unfavourable demographic conjuncture embedded in EUROPOP2013 estimates.

²¹This duality and the contributions to the improvements in forecasting accuracy may be further decomposed into model improvements and gains from using the flows. The improvements derived from the model employed for forecasting are presented in Table 4, the VAR lines. As an intermediate step, the analysis may be extended further by forecasting the flows themselves with an AR(1) - termed AR(1)-flow - and use these to construct an unemployment prediction. Differences between AR(1) and AR(1)-flows would provide the pure improvement in the forecast from the informational content of the flows. Further comparisons

of the study are included in Table 4. Significantly improved forecasts over the benchmark AR(1) model are found for both the VAR forecasts-by-flows approach and the direct forecast of unemployment. Moreover, the forecasts are also compared with the results from the forecasts-by-flows VECM.

With respect to the AR benchmark, the forecasts-by-flows method tends to result in worse forecasting performance than the direct approach for most specifications. A notable exception are the VECM forecasts. Substantial improvements in forecasting accuracy of Maltese unemployment rates are noted in this approach. The VECM methodologies specify cointegrating relationships, exploiting the fact that f_t and s_t are both highly cyclical. The two VECM specifications, the Johansen and the constrained Johansen, both use the flows and they both outperform significantly all other methodologies in the first few quarters ahead forecasts.

Eight step-ahead forecasts for the VECM Johansen approach are plotted in Figure 9. From 2014 onward, the VECM approach manages to forecast correctly the downward trend in unemployment rates. This occurs in a period where the labour market was experiencing strong structural changes with drastic declines in headline unemployment rates. This made this methodology the best performing one in the battery of approaches.

Over a longer time horizon, other competing BVAR-based specifications which both include and exclude flows outperform the VECM approach.²² The differing outcomes of the flow-based forecasts at different periods ahead may be used to advocate for further refinements of the framework, based on forecast averaging or forecast combinations of the competing methodologies.²³

may then be made between the AR(1)-flow and the VAR/VECM specifications.

²²It is indeed surprising that the VECM models outperform the other models at shorter horizons, and then proceed to do worse at longer horizons. A priori, VECM models would be expected to be better than other models in the long-run. This may indicate that the cointegration relationship is not stable, such that the further in time one goes, the higher the probability of using a misspecified cointegrating relationship for forecasting.

²³Indeed, the study may be further extended to combine forecasts from different models. As no model is

Two methodologies which stand out markedly are the OLS VAR and the BVAR Dummy-initial-observations VAR approach. Both specifications exclude labour market flows, and both result in sustained forecast improvements over the AR(1) benchmark right up to the eighth step ahead. Finally, these results derive from the same model specification, as shown in Equation (11) above. More exhaustive specification selection may yield to better results. An avenue for further research may be the inclusion of other variables, such as registered unemployment claims, in the VAR/VECM models.

The two shortcomings identified above, namely, data quality constraining the use of a simple two-state model and the structural changes of the Maltese economy may reduce the usefulness of this approach. These shortcomings may be overcome by using new data sources, such information from Google searches. These have been proven to be useful to forecast turning points in D'Amuri and Marcucci (2017).

preferred for any horizon, a forecast combination approach may have the potential to outperform single models. This exercise performs well in the original work by Barnichon and Nekarda (2013).

Fig. 9. Forecasts for the unemployment rate (%) using VECM Johansen approach.

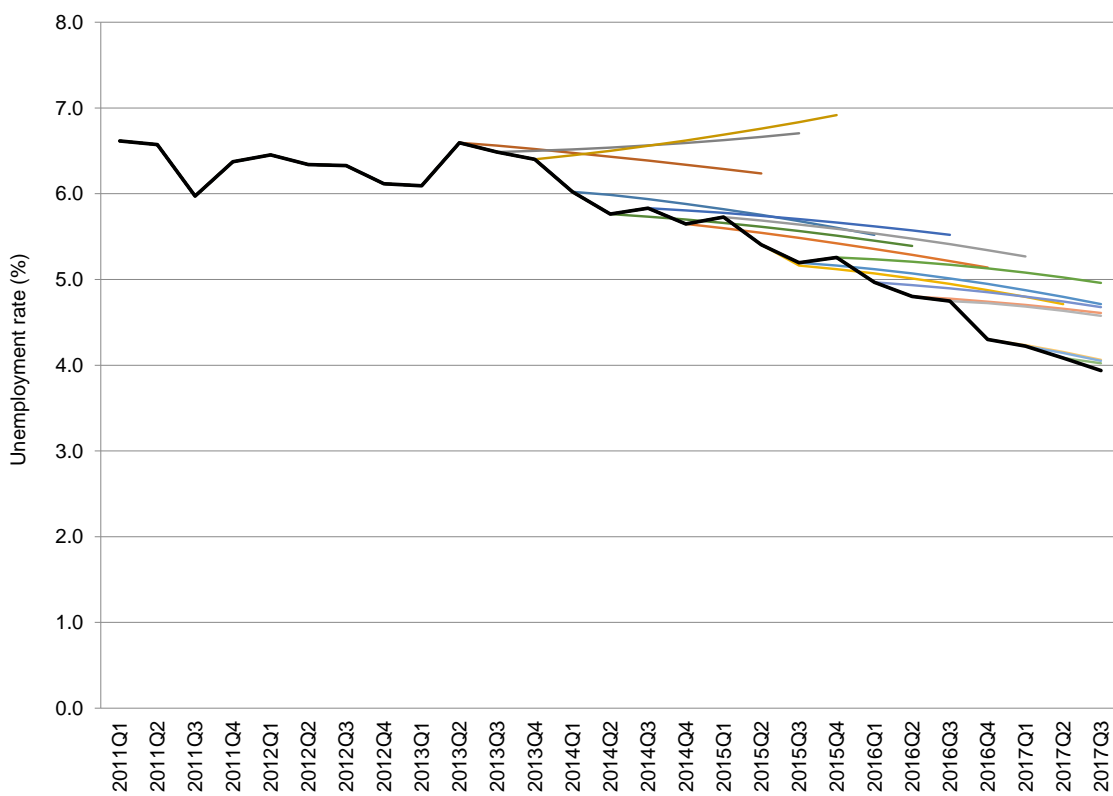


Table 4: RMSEs for eight steps ahead forecasts, different specifications.

RMSEs		t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8
AR(1) process		0.3357	0.4367	0.5247	0.6164	0.6873	0.7614	0.8359	0.8836
Relative RMSEs									
OLS VAR	VAR	0.7948	0.6697	0.6472	0.6350	0.7173	0.8048	0.8784	0.9528
	FBF	0.7570	0.7799	0.8565	0.8777	0.9578	1.0526	1.1318	1.2313
BVAR	VAR	0.6923	0.7403	0.8517	0.9099	1.0205	1.1075	1.1827	1.2741
	FBF	0.7579	0.7993	0.8898	0.9300	1.0232	1.1246	1.2129	1.3218
BVAR Dummy-initial	VAR	0.6619	0.6384	0.5519	0.5391	0.6428	0.6844	0.7499	0.8027
	FBF	0.7549	0.7954	0.8633	0.8867	0.9683	1.0517	1.1348	1.2233
BVAR Sum-of-coefficients	VAR	0.6881	0.6972	0.7709	0.7976	0.8666	0.9538	1.0461	1.1563
	FBF	0.7665	0.8087	0.8927	0.9146	0.9802	1.0787	1.1583	1.2600
BVAR Dummy-initial and Sum-of-coefficients	VAR	0.7409	0.8161	0.9072	0.9473	1.0451	1.1489	1.2404	1.3516
	FBF	0.7790	0.8357	0.9316	0.9613	1.0415	1.1497	1.2415	1.3560
VECM Johansen	FBF	0.6011	0.7402	0.8353	0.9253	0.9294	0.9939	1.0743	1.1268
VECM Constrained Johansen	FBF	0.6224	0.7711	0.8924	0.9815	1.0027	1.0893	1.1789	1.3007

6. Conclusions

This study has applied the novel approach discussed by Barnichon and Garda (2016) to Malta. The Maltese labour market has experienced deep structural change over the past decade, with ever rising female participation rates and migrant workers supporting economic growth.

The paper finds that models which use flows, as well as models which do not, yield very large forecast improvements over an AR(1) benchmark. Improvements occur right up to a year-ahead for most specifications, and up to eight quarters ahead for others. While there are improvements when using flows, these are not as strong as in other countries. The structural change discussed above may be influencing this result. Finally, there is no clear ‘winning’ methodology which prevails over all the others.

This methodology may serve as a useful cross-check for other, model-based unemployment rate forecasts. All in all, this approach appears to be a good starting point for further refinements and extensions. The small data requirements and the timeliness of aggregate flow data make this approach a promising contribution to forecasting unemployment in Malta.

This study also served as a basic introduction of the concept of labour market flows in Malta using publicly available data from the National Statistics Office’s Labour Force Survey. Access to individual micro-data would allow the matching of multiple labour market statuses in consecutive periods, and would be superior to the relatively simple method discussed in this paper. However, with this *caveat* in mind, this paper provides simple estimate of the transition rates, as well as analysing their contribution to the dynamics of unemployment. Comparisons, however, have to be made with caution as this study excludes the impact of flows into and out of the labour force. Taken together, this analysis is seen to provide a set of useful tools and indicators for policymakers.

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8. Appendix: Technical details

Estimation

The Bayesian Estimation, Analysis and Regression toolbox (BEAR) is an extensive (Bayesian Panel) VAR toolbox, used for forecasting and economic policy analysis.

The toolbox interface is written in a MATLAB based environment. While the original version of the toolbox is written to be easily understood by non-technical users, for the purposes of this study the codes behind the toolbox had to be altered. In particular, in order to be able to have rolling-window estimations, a main forecasting code was written to call the BEAR toolbox as the process progresses over the length of the time series.

Other minor changes were made to an intermediate version of the code, which was shared by the BEAR team. These mostly related to technical details, such as - amongst others - the way BEAR handled testing for positive semi-definite matrices, due to floating point computation precision in MATLAB.

The model is estimated separately for the seven methodologies. For the VAR estimates, unemployment forecasts are both constructed on the basis of the two-state labour market model - as well as direct outputs from the VAR.

For each hyperparameter in the model, a minimum value, a maximum value, and a step size are specified for the grid search. A finer grid results in more accurate estimates, but requires more time to be covered. For hyperparameters not involved into the model (for instance, the λ_7 when the dummy initial observation application is not running), the values are retained each time the model is run. The code ignores these figures unless it needs them for estimation. The grid-search table is included below.

	Minimum value	Maximum value	Step size
Autoregressive coefficient	0.5	1.0	0.1
Overall tightness (λ_1)	0.05	0.2	0.01
Cross-variable weighting (λ_2)	0.1	1.0	0.1
Lag decay (λ_3)	1.0	2.0	0.2
Exogenous variable tightness (λ_4)	100	1000	100
Sum-of-coefficient tightness (λ_6)	0.1	1.0	0.1
Dummy initial observation tightness (λ_7)	0.01	0.1	0.01

Data and model specification

The variables used in the forecasting model are the job-finding and separation rates, that is, f_{12} and s_{12} , the unemployment rate, gross domestic product and vacancies.

The labour market flow rates are computed on the basis of LFS data, as discussed in the *Methodology* section. Quarterly LFS unemployment rates are also used.

Chain-linked gross domestic product (GDP) data are also included in the VAR; vacancy figures for Malta are unavailable. In line with the literature, data from the EC's monthly surveys on hiring expectations are used instead.

For the VAR and VECM methods, these variables were included in addition to the labour market flows and the unemployment rates due to their behaviour as leading indicators of the labour market. The inclusion of further variables is restricted by data availability. The model may be further extended by including headcount unemployment insurance claims from administrative data. The VAR/VECM specification used were the logarithmic levels of f_{12} and s_{12} , the unemployment rate, GDP and vacancies. One lag is included, and the period of estimation stands between 2003Q1 and 2017Q3.