IMF Country Report No. 21/212

MALTA

SELECTED ISSUES

September 2021

This paper on Malta was prepared by a staff team of the International Monetary Fund as background documentation for the periodic consultation with the member country. It is based on the information available at the time it was completed on August 31, 2021.

Copies of this report are available to the public from

International Monetary Fund • Publication Services
PO Box 92780 • Washington, D.C. 20090
Telephone: (202) 623-7430 • Fax: (202) 623-7201
E-mail: publications@imf.org Web: http://www.imf.org
Price: $18.00 per printed copy

International Monetary Fund
Washington, D.C.

INTERNATIONAL MONETARY FUND

MALTA

SELECTED ISSUES

August 31, 2021

Approved By
European Department

Prepared by Michelle Tejada and Yifei Wang.

CONTENTS

NOWCASTING THE MALTESE ECONOMY _______ 3

A. Background _______ 3

B. Methodology and Data _______ 3

C. Model Performance _______ 5

D. Applying the Nowcasting Models and Conclusions _______ 7

References _______ 9

FIGURE

1. Backtesting Results of Selected Methods _______ 7
2. Real Time Nowcasts _______ 8

TABLES

1. A Short Introduction on ML Algorithms _______ 4
2. Backtesting Performance of Selected Methods _______ 6

APPENDIX

I. Data Description _______ 10

CORPORATE LIQUIDITY AND SOLVENCY DURING THE PANDEMIC AND POLICY RESPONSE _______ 12

A. Introduction _______ 12

B. Data and Methodology _______ 13

C. Liquidity and Solvency Gaps Estimates _______ 15

D. Conclusions and Policy Response Going Forward _______ 19

References _______ 21

FIGURES

1. Corporate Sector: Pre-COVID Selected Indicators ____ 13
2. Firms Distribution by Sector ____ 14
3. Corporate Sector: Distribution of Firms by Liquidity and Solvency Stance ____ 16
4. Corporate Sector: Liquidity and Solvency Gaps ____ 17
5. Distribution of Equity to Assets Ratio ____ 17
6. Corporate Sector: Liquidity and Solvency Gaps ____ 18
7. Type of Equity Instruments ____ 20

NOWCASTING THE MALTESE ECONOMY[1]

A. Background

1. The COVID-19 shock underscores the need to nowcast economic activity. Nowcasting is the prediction of the present, the very near future and the very recent past, which is a combination of two terms, *now* and *forecasting* (Giannone and others. 2008). Nowcasting is useful since key statistics on the present state of the economy (e.g., GDP) are available with a lag and at a low frequency. During times of heightened uncertainty and stress like the COVID-19 crisis, such a timely assessment becomes more urgent. To obtain an "early estimate" of the current economic situation before the official figures are released, we can exploit data published earlier and possibly at higher frequency.

2. Nowcasting employs a technique to synthesize information from a large set of distinct economic variables. The theoretical premise of nowcasting lies in the empirical findings that relevant data series co-move strongly so that their dynamics can be captured by few common factors (Stock and Watson 2016; Bańbura and others. 2013). In this light, nowcasting can be interpreted as the exercise of reading the flow of data releases in real time and forming assessment on the state of the economy. Ideally, nowcasting will replicate the way professional economists or policy makers formulate their judgments on the economy through continuous inflow of a large set of relevant economic indicators.

3. This paper uses nowcasting models to estimate GDP growth in Malta. Traditional regression-based econometric methods have some shortcomings, including collinearity, high dimensional problems, or ability to capture nonlinear relationships (Bolhuis and Rayner 2020). To address these shortcomings, we apply both standard dynamic factor models (DFM) and selected machine learning (ML) algorithms to a large dataset to nowcast current economic activity in Malta.[2] This chapter is organized as follows. Section B discusses the methodology and data, and Section C summarizes model performance. Section D applies our models to nowcast GDP in the second quarter of 2021 and concludes.

B. Methodology and Data

4. Both dynamic factor models and machine learning algorithms are used to filter information and infer real time GDP growth.

- **DFM:** DFM is a Kalman filter based econometric method which has been widely used as a standard method for nowcasting purposes. Compared to traditional regression-based econometric methods, DFM can provide a parsimonious yet robust solution to infer the low frequency variables from a rich data set of mixed-frequency unbalanced data, with no practical

[1] Prepared by Yifei Wang (EUR).

[2] See Dauphin, J-F., et al., "Nowcasting GDP: A Cross-country, Automated, Big Data approach, Combining DFM and Machine Learning Models," IMF working paper (forthcoming). The paper developed automated and integrated toolkit for nowcasting.

or computational limits on the number of variables (Stock and Watson 2016). However, the linearity in DFM may limit its ability to detect anomalies and nonlinearities. And the estimation of DFM could be time- and resource-intensive if the data set is large enough or not properly transformed.

- **ML Algorithms:** Recently there has been an emerging strand of literature using ML algorithms to nowcast economic activity (Tiffin and Fedelino 2016, Bolhuis and Rayner 2020, Richardson Mulder and Vehbi 2020, and Table 1). ML algorithms could be more effective in capturing the patterns in either structured or unstructured data, and are also good at learning about complex and nonlinear relationships from a large set of data while avoiding overfitting or over-extrapolation, making them particularly suited for models with a large number of regressors (Richardson Mulder and Vehbi 2020). However, ML algorithms require more balanced data sets and are often seen as black boxes, lacking solid economic foundations and sound interpretabilities (Woloszko 2020).

Table 1. Malta: A Short Introduction on ML Algorithms

Methods	Description
LASSO, Ridge, Elastic Net	LASSO, Ridge and Elastic net are essentially linear regression methods with different setting of regularization (a penalty imposed on the use of coefficients). Compared to traditional regression methods, these methods can avoid dimensionality and overfitting, but still face the challenge of linearity.
Support Vector Machine (SVM)	SVM is an algorithm that constructs hyperplanes to partition predictor combinations and make a point forecast for each of the sections, similar to kernel regression with regularization. SVM can overcome the drawbacks of linear regression models, which however would depend on proper selection of the kernel function or regularization parameters. Complicated kernel function or parameters on the other way may limit SVM's interpretability.
Random Forest (RF)	RF uses forecast combinations of multiple decision trees to construct an aggregate forecast. As a non-parametric algorithm, RF can also overcome the drawbacks of linear regression models. However, RF is not suitable for task of extrapolating data as the forecasts of RF are drawn from the historical range of the target variable, i.e. RF can hardly forecast unprecedented declines like the pandemic shock. Besides, the complex structure of RF also limits its interpretability.
Neural Networks (NN)	NN is a multi-layer non-linear method to map a series of inputs to a target output. Each layer is composed of artificial neurons (or nodes), which take inputs, produce a single output via certain function, then send it to other neurons in next layer. Eventually, a final set of nodes is mapped to the target output. Given the high flexibilities in both the choice of functions in each artificial neuron and the structure of the layers, we could have numerous variations of NN algorithms. As a sophisticated and flexible algorithm, NN has proven to be a very powerful tool for prediction without any drawbacks of the traditional regression methods. Such sophistication and flexibility, however, significantly limit the interpretability of predictions from NN.

5. A large dataset to capture the current economic condition of Malta's economy is constructed. Currently, the Central Bank of Malta (CBM) is using DFM to calculate the Business Condition Index based on an 8-variable mixed-frequency dataset. To incorporate more information on the state of the economy, we expand the CBM's dataset and include 48 variables in total (See Appendix 1 for the complete list and more detailed description). Note that for better model performance, the data should meet the following "3V" conditions:

- Volume: the dataset is big enough to cover a large chunk of the economy.
- Velocity: variables are also in mixed frequency, either daily, monthly, quarterly, or even in real time.[3]
- Variety: the dataset includes various variables to reflect different aspects of the economy, not limited to macro, financial or survey data, but also ultra-high-frequency variables like Google Trends and air pollution, as leading indicators for tourism sector and economic activity.

C. Model Performance

6. A pseudo out-of-sample nowcast strategy is taken to assess the performance of each method in real time. Given that our primary purpose of nowcasting is to infer GDP growth in real time with limited historical data vintages, we focus on the out-of-sample nowcasting accuracy (rather than in-sample fitness) and design a pseudo out-of-sample (backtesting) model assessment strategy[4]:

- First, create quarterly "as-if" vintages from 2012:Q4 to 2021:Q1 (the latest observation of GDP data). Our variable of interest here is the year-over-year growth of GDP (in percent).
- Each "as-if" vintage is named by a quarter, meaning that this vintage contains data as if they are available or released by that quarter, except for GDP. For example, 2020:Q3 vintage contains all variables by the end of September 2020, except for the GDP in 2020:Q3 (GDP is up to 2020:Q2).
- Re-estimate each model with the "as-if" vintages in expanding windows, and generate 1-step-ahead nowcasts at each quarter to get the time series of backtesting results for each method.
- A simple AR(1) model on GDP series is used as the benchmark.

7. The backtesting exercise shows that some models are promising. Based on the backtesting results, we use the root-mean-square-error (RMSE) to evaluate models. To distinguish the performance of different methods in different periods, we split the full backtesting sample into

[3] For convenience, variables with higher frequency will be aggregated to monthly frequency.

[4] A pseudo out-of-sample nowcast strategy has some drawback. Revisions to Malta's GDP data are frequent, sizeable, biased upwards, volatile and increase with the horizon (Grech 2018). As a result, the strategy might overestimate the forecast accuracy of nowcasting models. Moreover, instability in high frequency data may also undermine the validity of statistical relationships identified by the models.

three subsamples (Q4:2012-Q4:2015, Q1:2016-Q4:2019, and Q1:2020-Q1:2021) and calculate RMSEs for the full sample and each subsample respectively. As expected, not all models perform well in terms of RMSEs. Therefore, we select DFM and the three best ML algorithms based on full-sample RMSEs and compare these models with a benchmark AR(1) model (Table 2). We observe that:

- For the whole backtesting period and subperiods of 2016:Q1–2019:Q4 and 2020:Q1–2021:Q1, DFM outperforms all the other methods including the benchmark AR(1)[5].
- In fact, for some periods, DFM could yield quite accurate nowcasts. For example, in 2018:Q3 and Q4, the actual GDP growth rates are 6.5 percent and 5.7 percent respectively, meanwhile DFM nowcasts 6.5 percent and 5.8 percent respectively.
- AR(1) is more accurate during the first subperiod (2012:Q4–2015:Q4), likely due to the factor that this subperiod shows a clear upward trend in GDP growth, therefore an AR(1) with more weight (large coefficient) on the lagged variable is not an unreasonable guess.

Table 2. Malta: Backtesting Performance of Selected Methods
(RMSE, percentage points)

	Full sample	Sub sample		
Methods	**2012:Q4–2021:Q1**	**2012:Q4–2015:Q4**	**2016:Q1–2019:Q4**	**2020:Q1–2021:Q1**
DFM	2.8	2.6	2.1	4.9
ML Algorithms				
Lasso	3.9	2.7	3.3	7.2
SVM	3.9	3.0	3.1	7.5
Convolutional NN	3.7	2.8	2.6	7.6
Weighted Ave. of DFM and Lasso /1	2.8	2.4	2.2	4.7
AR(1)	3.5	2.0	2.3	8.0

1/ Average of Lasso and DFM weighted by inverse RMSEs in full sample of each method.

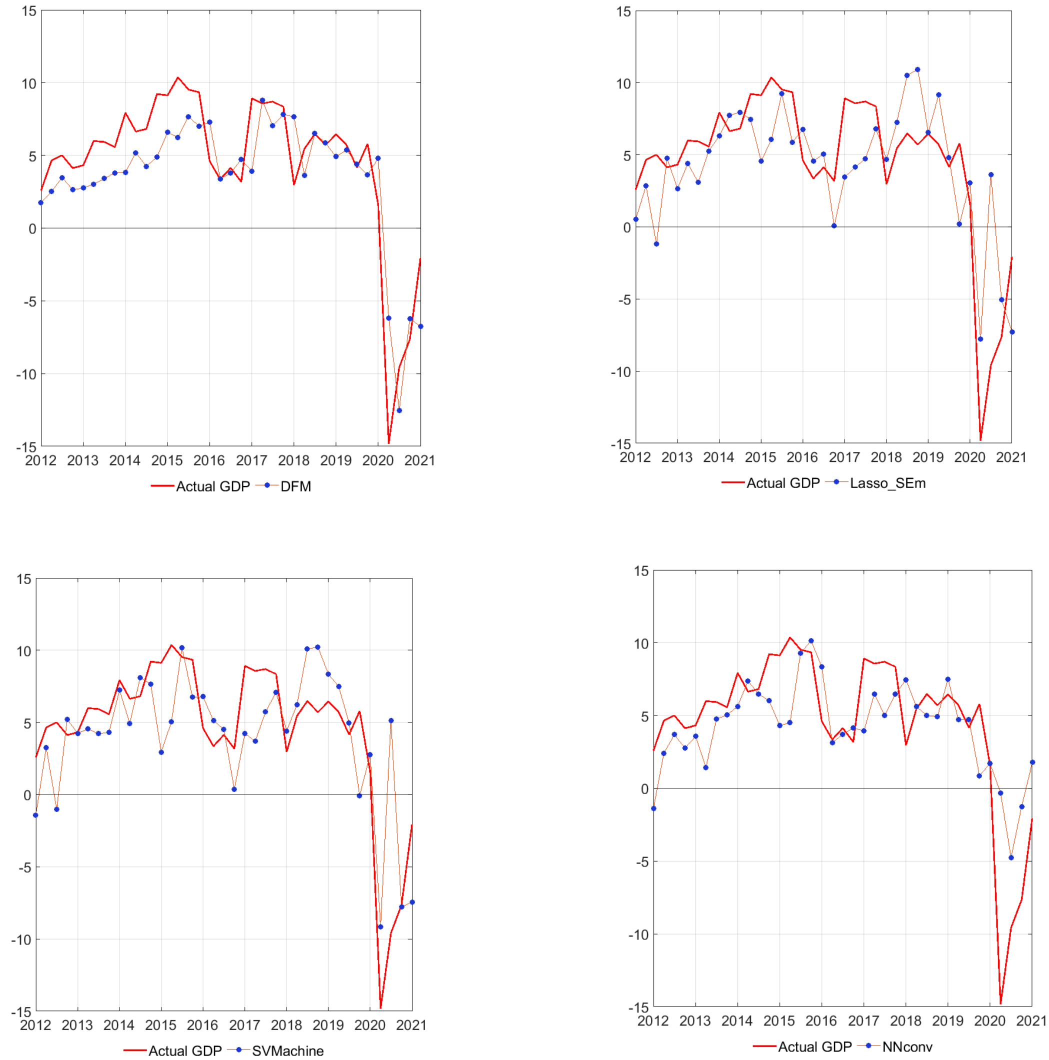
8. To get more accurate nowcasts, results of different models can be averaged. Despite the possible dominance of DFM, single statistics like RMSE could hide the tradeoff between accuracy and sensitivity for different methods. For example, Figure 1 (which plots the backtesting results against the historical outturn) shows that while DFM outperforms other methods in most periods, it is lagged by 1 quarter to catch the large GDP contraction and rebound in 2020. On the other hand, Lasso and SVM seem to be overreacting to the shocks in 2020. Such patterns imply potential gains from model averaging techniques over any individual model (Stock and Watson 2004). As a simple

[5] Diebold-Mariano tests show that models listed here have statistically the same accuracy as AR1 in full sample.

example, we calculate the weighted average of DFM and Lasso with their inverse RMSEs as weights (Table 2). The weighted average is more accurate than Lasso and DFM (though marginally) during 2020:Q1–2021:Q1.

Figure 1. Backtesting Results of Selected Methods

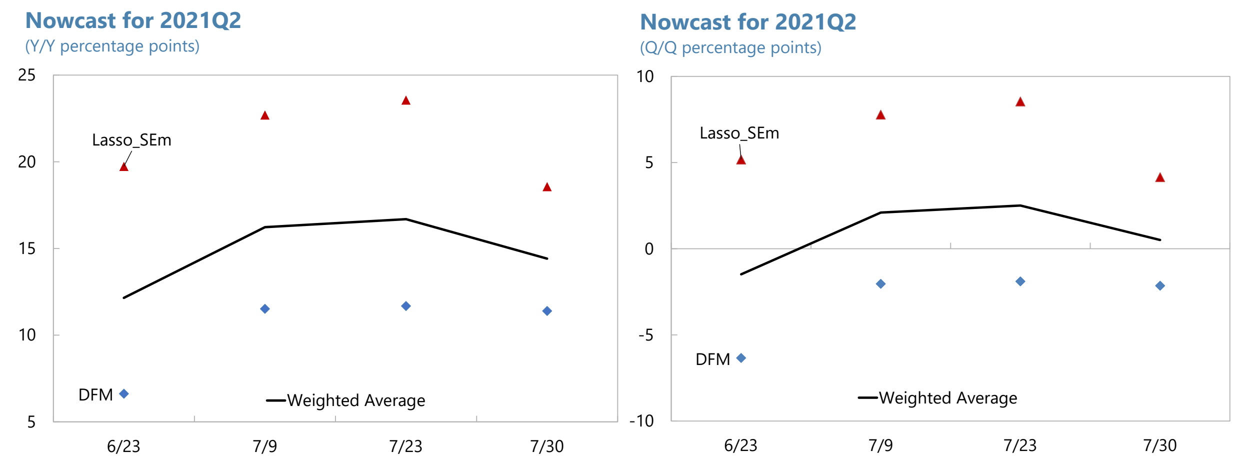
(all series are the percentage points of year-over-year growth)



D. Applying the Nowcasting Models and Conclusions

9. Our models are applied to nowcast Q2 GDP growth in 2021. Figure 2 summarizes the evolution of nowcasting results for Q2:2021 estimated at four different data points, June 23, July 9, July 23, and July 30. Despite the converging evolution of nowcasts from both Lasso and DFM methods, significant gap remains, probably due to the huge uncertainty in 2021:Q2. The weighted average suggests 14.4 percent y/y growth or 0.5 percent q/q growth for Q2 as of July 30. The large upwards revision in DFM between June 23 and July 9 nowcasts are mainly explained by the incoming data in the tourism sector, which show a strong recovery given the extremely low base in 2020.

Figure 2. Real Time Nowcasts



10. Interpreting ML algorithms remains a challenge. In the real world where data are released asynchronously, the toolkit developed by this paper can constantly provide updated assessments on current economic conditions. Understanding the drivers of the predictions made by ML algorithms is important to ensure the model is consistent with economic intuitions (Woloszko 2020). Despite attempts to provide interpretability techniques to ML algorithms, this remains a challenge and requires more efforts to improve the toolkit.

References

Dauphin, J-F., Dybczak, K., Maneely, M., Sanjani, M.T., Suphaphiphat, N., Wang, Y. and Zhang, H., forthcoming. "Nowcasting GDP: A Cross-Country, Automated, Big Data Approach, Combining DFM and Machine Learning Models." International Monetary Fund, Washington, DC.

Hastie, T., Tibshirani, R. and Wainwright, M., 2015. "Statistical Learning with Sparsity: The Lasso and Generalizations." CRC Press.

Giannone, D., Reichlin, L. and Small, D., 2008. "Nowcasting: The Real-Time Informational Content of Macroeconomic Data." *Journal of Monetary Economics*, 55(4), pp.665-676.

Stock, J.H. and Watson, M.W., 2016. "Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics." In *Handbook of Macroeconomics* (Vol. 2, pp. 415-525). Elsevier.

Stock, J.H. and Watson, M.W., 2004. "Combination Forecasts of Output Growth in a Seven-Country Data Set." *Journal of Forecasting,* 23(6), pp.405-430.

Bańbura, M., Giannone, D., Modugno, M. and Reichlin, L., 2013. "Now-Casting and the Real-Time Data Flow." In *Handbook of Economic Forecasting* (Vol. 2, pp. 195-237). Elsevier.

Richardson, A., van Florenstein Mulder, T. and Vehbi, T., 2021. "Nowcasting GDP Using Machine-Learning Algorithms: A Real-time Assessment." *International Journal of Forecasting*, 37(2), pp.941-948.

Bolhuis, M.A., Rayner, B., 2020. "Deus ex Machina? A Framework for Macro Forecasting with Machine Learning." IMF Working Paper No. 20/45, Washington, DC.

Tiffin, A.J., 2016. "Seeing in the Dark: A Machine-Learning Approach to Nowcasting in Lebanon." IMF Working Paper No. 16/56, Washington, DC.

Banbura, M., Giannone, D. and Reichlin, L., 2010. "Nowcasting."

Woloszko, N., 2020. "Tracking Activity in Real Time with Google Trends (No. 1634)." OECD Publishing.

Grech, O., 2018, "An Analysis of Revisions to Maltese GDP Data." Research Bulletin 2018.

Appendix I. Data Description

Series ID	Series Name	Frequency	Category
J181GDPT@EUNA	Malta: Gross Domestic Product (SWDA, Mil.Ch.15.EUR)	q	Real
J181PCT@EUNA	Malta: HH Consumption (SWDA, Mil.Ch.15.EUR)	q	Real
J181GCT@EUDATA	Malta: Public Consumption (SWDA, Mil.Ch.15.EUR)	q	Real
J181GCFT@EUDATA	Malta: Gross Capital Formation (SWDA, Mil.Ch.15.EUR)	q	Real
J181EXPT@EUNA	Malta: Exports (SWDA, Mil.Ch.15.EUR)	q	Real
J181IMPT@EUNA	Malta: Imports (SWDA, Mil.Ch.15.EUR)	q	Real
MTNIM@ALPMED	Malta: Imports (NSA, Mil.Euros)	m	Real
MTNIX@ALPMED	Malta: Exports (NSA, Mil.Euros)	m	Real
MTSTS@ALPMED	Malta: Industrial Turnover (SA, 2015=100)	q	Real
S181D47@EUDATA	Malta: Retail Trade Volume Excluding Autos & Motorcycles (SWDA,2015=100)	m	Real
MTSD@ALPMED	Malta: Industrial Production (SA, 2015=100)	m	Real
S181RGNZ@EUDATA	Malta: Services Trade [Value](SWDA, 2015=100)	q	Real
S181D46@EUDATA	Malta: Wholesale Trade, Except of Motor Veh & Cycles [Volume] (SWDA, 2015=100)	m	Labor
N181ERQT@EUDATA	Malta: Employment Rate: 15-64 Years (NSA, %)	q	Labor
N181URQT@EUDATA	Malta: LFS: Unemployment Rate: 15-64 Years (NSA, %)	q	Labor
S1816Z@EUDATA	Malta: Hours Worked: Industry Excluding Construction (SWDA, 2015=100)	m	Labor
S1816FQ@EUDATA	Malta: Hours Worked: Construction (SWDA, 2015=100)	q	Labor
S181QDE@EUDATA	Malta: Employees: Domestic Concept (SA)	q	Labor
S181R@EUDATA	Malta: Unemployment Rate (SA, %)	m	Labor
tax_revenue	Sum of VAT, income tax and customs	m	Fiscal
MTNCVS@ALPMED	Malta: Total Stock of Licensed Motor Vehicles (EOP,NSA,Units)	q	Financial
MTNCOJHR@ALPMED	Malta: OMFI Loans to HH & Individuals: For House Purchase (NSA, EOP, Mil.EUR)	m	Financial
term_premium	spread between 10yr and 3m treasury	m	Financial
S181HPRX@EUDATA	Malta: Building Permits Residential Buildings (SWDA, 2015=100)	q	Soft
E181R@EUDATA	Malta: Retail Trade: Confidence Indicator (SA, % Bal)	m	Soft
E181I@EUDATA	Malta: Industrial Confidence Indicator, Percent Balance (SA, %)	m	Soft

Series ID	Series Name	Frequency	Category
E181S@EUDATA	Malta: Services Confidence Indicator (SA, % Balance)	m	Soft
E181C@EUDATA	Malta: Consumer Confidence Indicator, Percent Balance (SA, %)	m	Soft
E181ES@EUDATA	Malta: Economic Sentiment Indicator (SA, Long-term Average=100)	m	Soft
E181IO@EUSRVYS	Malta: Industry: Volume of Order Books, Percent Balance (SA, %)	m	Soft
E181IEX@EUSRVYS	Malta: Industry: Volume of Export Order Books, Percent Balance (SA, %)	m	Soft
E181RBE@EUSRVYS	Malta: Retail Trade: Order Expectations (SA, % Bal)	m	Soft
E181SNO@EUSRVYS	Malta: Services: Expected Demand Over Next 3 Months (SA, % Balance)	m	Soft
E181TE@EUSRVYS	Malta: Construction: Employment Expectations: Next 3 Months (SA, % Bal)	m	Soft
Google	Google search for tourism-related keywords	m	Soft
NO2	Air Pollution	m	Soft
DESDZ@GERMANY	Germany: Industrial Production	m	External
DESDUM@GERMANY	Germany: Capacity Utilization: Manufacturing (SA, %)	q	External
DESVBC@GERMANY	Germany: Business Climate (SA, % Bal)	m	External
DESTOC@GERMANY	Germany: Manufacturing Orders (SWDA, 2015=100)	m	External
E997ES@EUDATA	EU27: Economic Sentiment Indicator (SA, Long-term Average=100)	m	External
IP@USECON	US: Industrial production index	m	External
S025OCO@EUDATA	EU: Manufacturing new orders	m	External
E025BC@EUDATA	EA: Business climate	m	External
MTNTK@ALPMED	Malta: Total Departing Tourists: Total Nights (NSA, Number)	m	Tourism
MTNTD@ALPMED	Malta: Total Departing Tourists (NSA, Number)	m	Tourism
N181TT@EUDATA	Malta: Tourism: Overnight Stays (NSA, Thous. Persons)	m	Tourism
MTNTE@ALPMED	Malta: Total Departing Tourists: Total Expendiutre (NSA, Thous.Euros)	m	Tourism

CORPORATE LIQUIDITY AND SOLVENCY DURING THE PANDEMIC AND POLICY RESPONSE[1]

This paper analyzes non-financial corporate (NFC) sector vulnerability in Malta focusing on firms' liquidity and solvency. The impact of the pandemic shock on firms' cash flows and equity positions is simulated, using firm-level data. The analysis suggests that the pandemic crisis eroded corporates liquidity and equity positions with varying impact across firms' size and sectors, depending on their pre-COVID financial health. The authorities' policy response has been effective in supporting firms' liquidity and equity positions. As the economic recovery gains strength, firms' balance sheets are expected to recover, but it could take time for several firms to restore their balance sheets. It is important to understand if additional support to corporates is needed for firms to thrive in the post-COVID economy. However, there are important trade-offs in choosing the right policy instruments, governance issues, and challenges in assessing firms' viability that should be taken into consideration.

A. Introduction

1. **Pre-COVID-19 pandemic crisis, Maltese NFCs had relatively strong balance sheets but with high leverage.** Pre-COVID, Maltese firms were benefiting from strong economic growth following the global financial crisis and reinvested their profits to expand their business. Between 2010–2019, the real gross value added of the NFC sector in Malta grew by 8.3 percent a year on average, compared to 2.8 percent in the EU, with Maltese firms' profitability and liquidity ratio higher than EU firms' in 2019. The leverage ratio of the Maltese NFCs, however, was quite high at over 2.0, compared to around 0.7 for the NFCs in the EU. Prior to the pandemic crisis, high leverage in the NFCs, especially for small and medium-sized enterprises (SMEs), was identified as one of the vulnerabilities in the Maltese economy and could weigh on corporate investment (IMF, 2017).

2. **The pandemic hit non-financial companies hard, as the economic environment deteriorated sharply.** The service sector was impacted the most, with real gross value added falling by 7.6 percent in 2020. The wholesale and retail sectors were the most affected by various social distance measures and low tourism arrivals. Gross operating surplus fell in almost all sectors, with the largest decline recorded in the transportation and storage sector and in the accommodation and food service sector. More recently, as the rollout of vaccines has proceeded and containment measures eased, the economy has been recovering, driven primarily by the information and technology sector.

3. **The Survey on Access to Finance shows that SMEs in Malta had a sharper deterioration in activity in 2020 than those in the EU.** On balance, 64 percent and 70 percent of Maltese SMEs reported a decline in turnover and profits, respectively, compared to 44 percent and 45 percent of SMEs across the EU. In Malta, turnover declined by 63 percent in 2020, compared to 40 percent

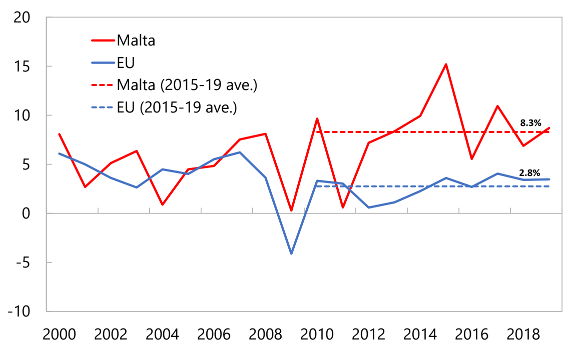
[1] Prepared by Michelle Tejada (EUR).

during the global financial crisis. The higher incidence of companies reporting lower turnover and profits in Malta may reflect the larger share of respondents in trade and services, which include the sectors hit hardest by the pandemic.

4. This paper analyzes the impact of the pandemic shock on firms' liquidity and equity position in Malta. Using firm-level data, the size of the liquidity and equity gaps is estimated under different scenarios. The rest of the paper is organized as follows: the description of the data and methodology used to undertake the analysis (Section B); the presentation of results, first focusing on estimates of liquidity and solvency pre-COVID and post-COVID without policy measures, and then on the impact of the policy package on firms' financial health (Section C); and the conclusions and policy response going forward (Section D).

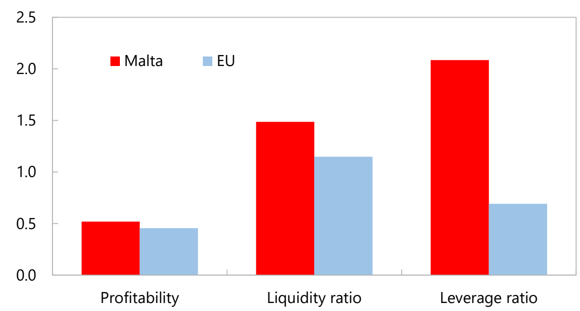
Figure 1. Corporate Sector: Pre-COVID Selected Indicators

Nonfinancial Corporates: Gross Value Added
(Year on year percent growth)



Sources: Eurostat and Haver Analytics

Nonfinancial Corporates Financial Indicators, 2019 1/
(Ratio)



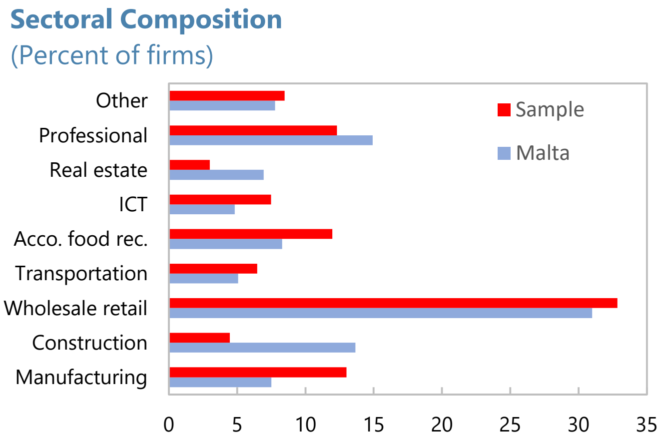
Sources: Eurostat and Haver Analytics.
1/ Data are based on national accounts. Profitability is calculated as gross operating surplus/gross value added; liquidity ratio, current assets / current liabilities; and leverage ratio, debt / equity.

B. Data and Methodology

5. Methodology. The analysis follows the methodology outlined in the *Regional Economic Outlook: Europe, October 2020* and simulates the uneven effect of the COVID-19-induced shock across economic activities in 2020, by taking into account differential impacts on sales across different sectors. The sector-specific shocks to sales are estimated to be consistent with gross value-added sectoral growth in 2020. The analysis uses firm-level data on balance sheets and income statements from the Orbis database. The simulation covers about 3,250 firms operating in Malta between 2017–19, taking the latest financial statements available for each firm. Although this represents a small proportion of registered companies, and micro firms may be particularly underrepresented, it represents almost 80 percent of the total operating revenue of corporates in Malta. Moreover, the distribution of firms by sector comparing registered enterprises and the sample suggests that the analysis provides an adequate representation of the Maltese corporate sector (see Figure 2).

Figure 2. Firms Distribution by Sector

(Percent of Firms)



Sources: European Commission, Orbis, and IMF staff calculations.
Note: excluding Air Malta and other outliers.

6. Scenario design. The financial position in 2019 (pre-COVID) is assumed to be equal to that of the last pre-COVID balance sheet available. Then, two alternative scenarios are examined: (i) post-COVID with no policy measures (focused on 2020 only); and (ii) post-COVID with policy measures. To support corporates during the crisis, the authorities implemented a large package of support measures amounting to 11.2 percent of GDP in 2020. For our simulation analysis, we selected the key measures which had a relatively large impact on corporates' financial positions, namely:

- Wage supplement scheme: assumes the provision of €800 per month and employee.
- Tax deferral scheme: applied to eligible taxes.
- Grants to business: assumes a one-time cash grant of €1,000 per firm.
- Loan moratoria program: applied to 50 percent of loans amount and interest payment amounts.
- Loan guarantee scheme: applied to the loan amount of €2 million for SMEs, and €5 million for large enterprises; but not larger than two times the wage bill.

7. Definition of firm illiquidity and insolvency. A company is considered illiquid if its liquid assets are insufficient to cover net cash outflows and debt repayments. The liquidity gap is calculated as the aggregate cash flow deficit as a share of GDP. A company is considered insolvent if the book value of debt exceeds the value of assets (i.e., if it has negative equity).[2] The equity gap is calculated as the equity shortfall as a share of GDP. A firm is considered in distress if it is illiquid, insolvent, or both illiquid and insolvent.

[2] The reliance on the book value of equity over other solvency indicators has the advantage of expanding the coverage of the analysis beyond the narrow group of listed firms.

8. The analysis relies on some assumptions to overcome data limitations.

- The same sectoral growth rate applies to all firms within each sector without consideration to size or comparative advantage of some firms.
- Firms' size is defined based on assets. Corporates with assets below €2 million are considered micro firms; those with assets between €2 million–€10 million, small firms; those with assets ranging between €20 million–€43 million, medium firms; and those with assets above €43 million, large firms. Data is weighted by turnover size to ensure representativeness.
- Firms with estimated liquidity or equity gap above €40 million are considered outliers and dropped from the sample (including Air Malta). Given the challenge to simulate individual firms' eligibility and/or desire to apply for each of the measures, the analysis assumes that all firms benefited from all policy measures (universal take-up of measures).
- The analysis assumes that 30 percent of corporates liabilities consist of intercompany or intracompany debt and is therefore excluded from the book equity calculations.[3]
- To estimate cash flows the analysis assumes an adjustment in material costs in proportion to the reduction in sales, but firms continue to pay other obligations, such as wages, fixed costs, interest expenses, and debt repayments. Moreover, it is assumed that the pandemic renders firms' inventories illiquid. Other variables included in the balance sheet are considered constant.
- The post-COVID book equity is calculated as the sum of pre-COVID book equity plus the post-COVID net increase in assets.
- The post-COVID scenario focuses only on 2020, and the analysis is not extended to 2021 given the degree of uncertainty about the economic recovery and the gradual unwinding of the policy measures throughout 2021.

C. Liquidity and Solvency Gaps Estimates

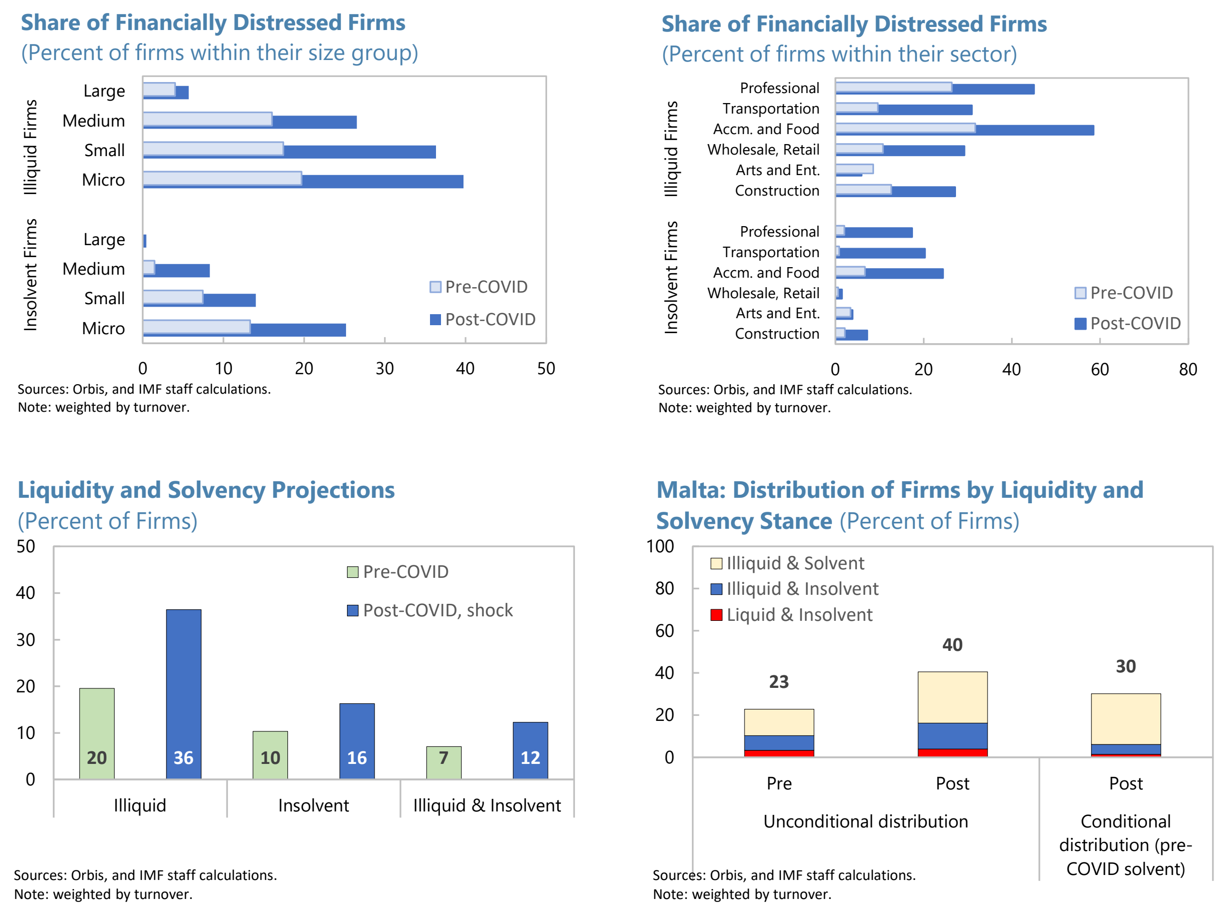
Pre-COVID and Post-COVID Without Policy Measures

9. The share of financially distressed firms rose sharply post-COVID, varying across size and sectors (see Figure 3). The size of the sectoral shock and pre-COVID liquidity and equity positions affect the likelihood of being in distress post-COVID. The smaller firms are more likely to be in distress, with 40 percent of micro firms estimated to be in distress post-COVID, compared to only 6 percent of large firms. This may reflect greater financial constraints in the form of lower access or costly access to borrowing for smaller firms, as they typically have lower financial buffers. Indeed, the Bank Lending Survey conducted by the Central Bank of Malta indicates that Maltese

[3] Intercompany lending has become the largest source of corporate funding in Malta. Following the decline in bank credit, intercompany loans between domestic corporates have grown considerably to represent approximately 30 percent of corporate non-equity liabilities in 2017, from 15 percent in 2007.

banks became more risk adverse in the years prior to the pandemic. Banks increased restrictions in the form of stricter conditions, such as those on collateral and tighter loan covenants, which are more difficult to fulfill by smaller firms. In addition, firms in contact-intensive sectors may be facing challenges, especially firms under financial pressures prior to the pandemic (i.e., retail). Moreover, although firms might have strategically adjusted their operations to the current state of the economy and policy measures are providing much-needed support, the most affected companies may be running down their equity, raising the risk of insolvency if the crisis is prolonged.

Figure 3. Corporate Sector: Distribution of Firms by Liquidity and Solvency Stance



Share of Financially Distressed Firms
(Percent of firms within their size group)

Sources: Orbis, and IMF staff calculations.
Note: weighted by turnover.

Share of Financially Distressed Firms
(Percent of firms within their sector)

Sources: Orbis, and IMF staff calculations.
Note: weighted by turnover.

Liquidity and Solvency Projections
(Percent of Firms)

Sources: Orbis, and IMF staff calculations.
Note: weighted by turnover.

Malta: Distribution of Firms by Liquidity and Solvency Stance (Percent of Firms)

Sources: Orbis, and IMF staff calculations.
Note: weighted by turnover.

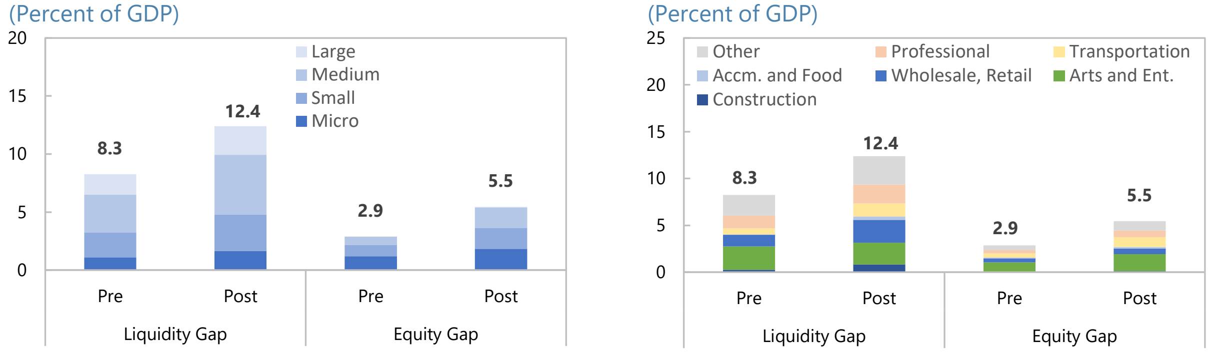
10. Simulation results suggest that firms' balance sheets have weakened during the crisis. A breakdown by liquidity and solvency positions shows that the share of illiquid firms could have risen from 20 to 36 percent; the share of insolvent firms from 10 to 16 percent; and the share of illiquid and insolvent firms from 7 to 12 percent. At the aggregate level, the share of financially distressed firms irrespective of their pre-COVID financial health (i.e., unconditional distribution) is estimated to have increased from 23 to 40 percent, with liquidity being the largest constraint. Moreover, the analysis suggests that 30 percent of firms that were solvent prior to the pandemic (i.e., conditional distribution) are estimated to have illiquidity or insolvency concerns.

11. An assessment of the liquidity and equity gaps shows the large deterioration in corporates' financial soundness at the aggregate level. The pandemic shock eroded corporates cash flows and capital, particularly of SMEs and those in contact-intensive sectors. The pre-COVID liquidity and the equity gaps increased in proportion to the size of sector-specific shocks and firms' pre-COVID vulnerabilities (see Figure 4). At the aggregate level, the liquidity gap is estimated to have increased from 8.3 to 12.4 percent of GDP, while the equity gap increased from 2.9 to 5.5 percent of GDP.

Figure 4. Corporate Sector: Liquidity and Solvency Gaps

Liquidity and Equity Gaps by Firms' Size (Percent of GDP)

Malta: Liquidity and Equity Gaps by Sector (Percent of GDP)

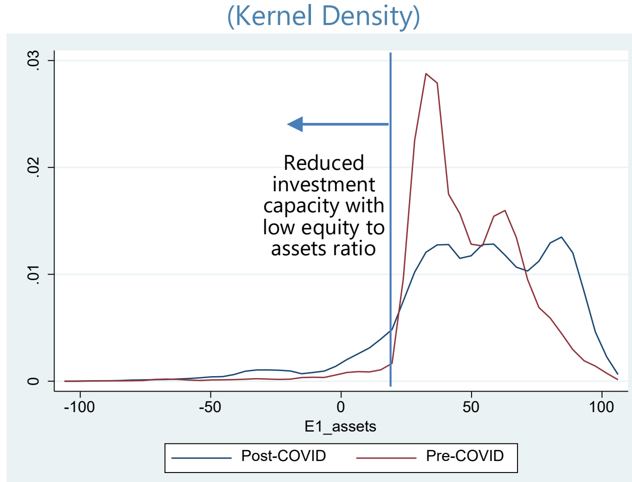


Sources: Orbis, and IMF staff calculations.
Note: excluding Air Malta and other outliers.

Sources: Orbis, and IMF Staff Calculations.
Note: excluding Air Malta and other outliers.

12. The post-COVID distribution of the equity to assets ratio shows a flattening of the curve as not all firms were affected equally by the crisis (see Figure 5). During the pandemic, a proportion of firms with low equity to assets ratio performed worse than pre-COVID, and a proportion with high equity to assets ratio seems to have improved their financial position. The increased share of under-capitalized firms could raise concern over post-pandemic recovery prospects, especially because these firms have a weakened capacity to invest and take business risks.

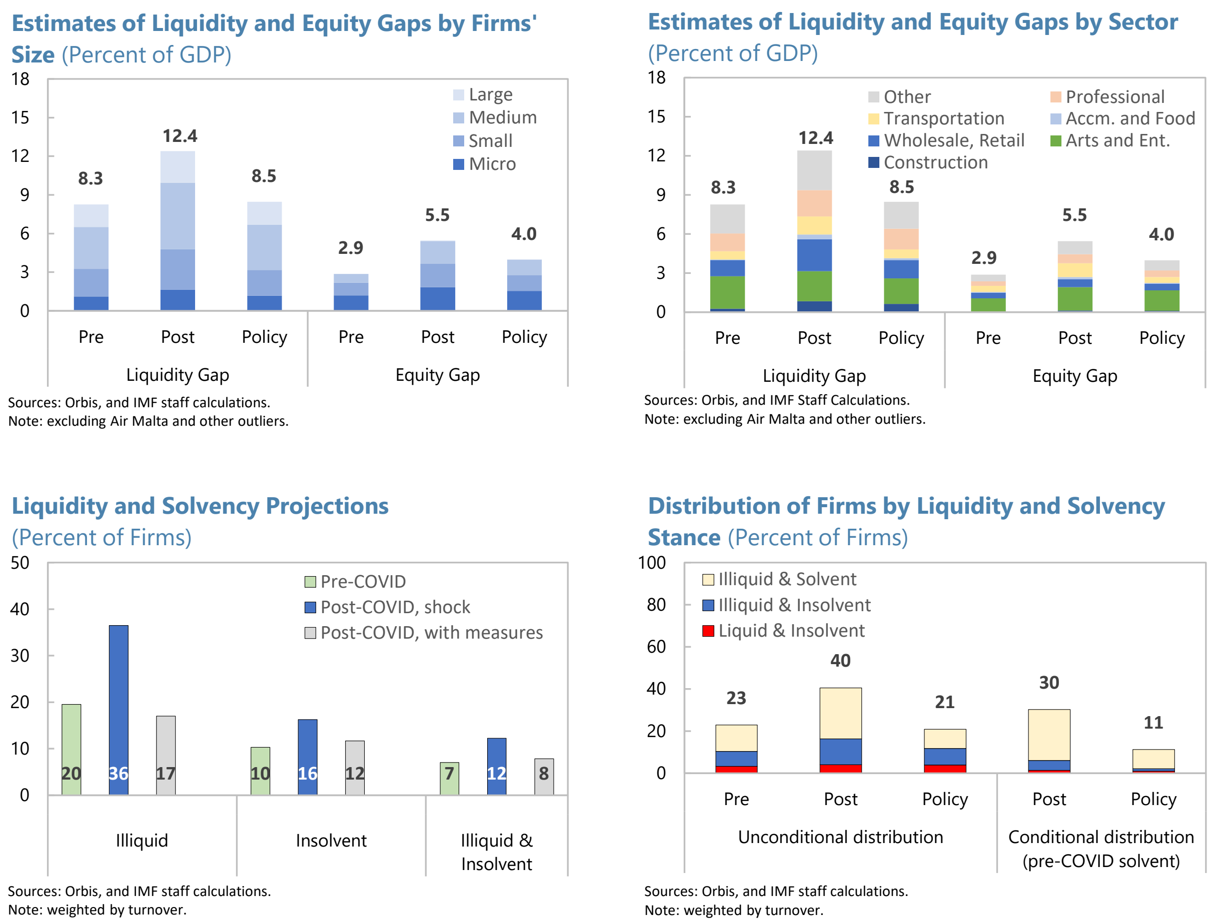
Figure 5. Distribution of Equity to Assets Ratio
(Kernel Density)



The Impact of the Policy Package

13. The authorities' policy measures helped to mitigate the impact of the pandemic. The simulation results suggest that the liquidity gap could have been reduced to about pre-pandemic levels with policy measures, while the equity gap could have declined to about 4 percent of GDP, above pre-COVID levels (see Figure 6). The equity gap of the SMEs subset increased by 1.9 percent of GDP, of which about 1.1 percent could be covered by existing policies. At the aggregate level, the wage supplement, the loan moratoria, and the loan guarantee schemes have contributed the most to reducing the deficits.[4] These results are expected as the support measures were aimed primarily at providing lifelines to households and businesses to weather the crisis in the form of liquidity support.

Figure 6. Corporate Sector: Liquidity and Solvency Gaps



14. However, several firms' balance sheets have been weakened, and a large portion is estimated to remain in financial distress. Despite the large policy package, at least 11 percent of

[4] The actual use of the loan moratoria and guarantees has been lower than shown in this exercise as the take-up of moratoria and guarantees' eligibility criteria partially limited firms' participation.

pre-COVID solvent firms are estimated to remain in financial distress, meaning that they are facing illiquidity, insolvency, or a combination of both (see Figure 6). This is in line with the results in Figure 5, which shows that the share of under-capitalized firms increased post-COVID.

15. The results should be interpreted with caution but suggest the importance of careful monitoring of corporate sector vulnerabilities. A large increase in bankruptcies did not materialize in 2020, as firms adjusted their operations and costs and the authorities provided extensive support measures. As economic activity resumes and the recovery strengthens in 2021, for the corporate sector as a whole, the liquidity gap may have almost closed, and the equity gap narrowed. The take-up of loan guarantees and moratoria has declined in recent months, suggesting that firms are in a better financial position than in 2020. Nonetheless, given the high degree of uncertainty pertaining to the economic outlook and the degree of corporate balance sheet damage, corporate sector vulnerabilities need to be carefully monitored.

D. Conclusions and Policy Response Going Forward

16. The pandemic eroded liquidity and equity positions of Maltese firms with varying impacts across firms' size and sectors, but the authorities' policy response mitigated the effect. The authorities' policy response has been swift and decisive, supporting firms. As the economic recovery gains strength, firms' liquidity and equity positions are expected to recover.

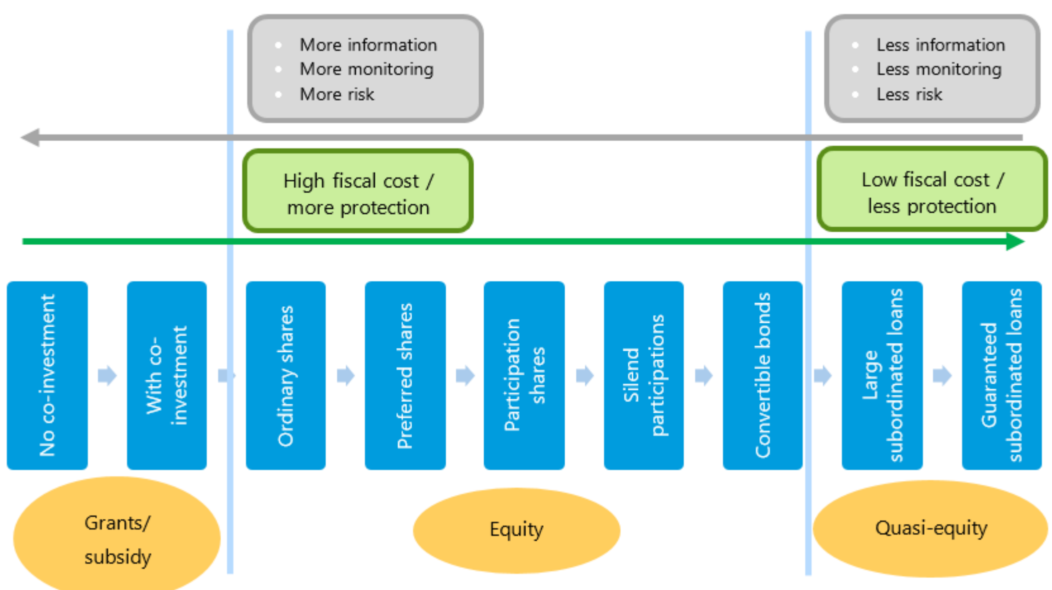
17. The pandemic, however, could have left some corporates with debt overhang and at risk of insolvency. This risk could be higher if the economic recovery falters. If downside risks were to materialize, an under-capitalized corporate sector could hold back growth by leading to a misallocation of capital and lower productivity. Recapitalization needs appear to be primarily concentrated in SMEs, and the private sector alone may be unlikely to provide enough equity capital to avoid an increase in bankruptcies as policy measures expire. Accordingly, the pandemic impact of the corporate sector should continue to be carefully monitored, and the authorities should consider whether additional measures to support firms are needed, including investment tax credits, subsidized loans, as well as solvency support to viable SMEs. Rehabilitating weakened balance sheets of viable enterprises will promote private investment, create jobs, and allow firms to be competitive in the post-COVID economy.

18. Beyond the COVID-19 policies discussed above, the authorities have rolled out other measures to support firms, but these are of a smaller scale and not directly intended to provide solvency support. Malta Development Bank has the Guarantee Facility for Loans to SMEs, the family business transfer facility, and the tailored facility for SMEs, aimed at helping firms increase their access to finance. Malta Enterprise offers investment aid and business development programs to support new businesses and the expansion of the existing ones, as well as other initiatives to support innovation and research. However, these may not be scalable to the level needed in the event of increased demand for solvency and investment support.

19. There are important trade-offs in choosing the right policy instruments. The objective should be to avoid excessive bankruptcies of viable firms while allowing for a market-based reallocation of resources, as well as to avoid the exit of strategic, systemically important, or innovative firms, or to avoid the disruption of critical services. The targeting mechanism should exclude firms that were in financial distress pre-COVID, those that can survive without government support, and those for which existing policies have been sufficient to stabilize their balance sheets. For solvency support measures, different firm's sizes will require different instruments depending on market access and other challenges. In addition, there is a trade-off between simple but imperfectly-targeted schemes and more complex targeting mechanisms. The instruments could range from grants and subsidies provided directly by the government to quasi-equity instruments in partnership with the private sector (see Figure 7).[5]

20. Other design challenges and governance issues should also be considered to ensure the success of new policy measures and to limit their cost. Assessing the viability of firms is a key challenge at the current juncture. Some insolvent firms could become viable if their business model would allow them to return to healthy profitability after the pandemic. Partnering with the private sector is important as it is better positioned to conduct viability assessments and help contain adverse selection and moral hazard issues. Furthermore, transparency and accountability are critical for the legitimacy of the program and to prevent and uncover misuse of funds. The timing of the intervention should balance the preference for early intervention with a more phased-in approach in view of the high uncertainty. Finally, securing a timely government exit is essential, as the measures should be temporary and include an option and incentive for early redemption or accelerated exit.

Figure 7. Type of Equity Instruments



Source: Corporate Living Project Group.

[5] For further discussion, see Chapter 3, "Corporate Liquidity and Solvency in Europe during the Coronavirus Disease Pandemic: The Role of Policies," in Regional Economic Outlook: Europe, October 2020.

References

Central Bank of Malta. 2021. "Access to Finance in 2020." In the *Annual Report 2020*. March 2021. Valletta, Malta.

Gourinchas, P-O., Kalemli-Ozcan, S., Penciakova, V., and Sander, N., 2020. *"COVID-19 and SME Failures."* IMF Working Paper No. 20/207, International Monetary Fund, Washington, DC.

International Monetary Fund (IMF). 2017. "The Non-Financial Corporate Sector in Malta: Balance Sheet Vulnerabilities and Impact on Innovation." *Malta: Selected Issues Paper* February 2017. Washington, DC.

_____. 2020. "Corporate Liquidity and Solvency in Europe during the Coronavirus Disease Pandemic: The Role of Policies." Chapter 3 in *Regional Economic Outlook: Europe: Whatever It Takes: Europe's Response to COVID-19."* October 2020. Washington, DC.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., and Yesiltas, S., 2015. *"How to Construct Nationally Representative Firm-Level Data from the Orbis Global Database: New Facts and Aggregate Implications."* NBER Working Paper 21558, National Bureau of Economic Research, Cambridge, MA.