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A quantitative occupational forecasting model for Lebanon

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Abstract

The project Collaborative network for career building, training and e-learning is being funded by the ERASMUS+ Programme: Capacity Building in the Field of Higher Education. The project is intended to support Lebanese Higher Education Institutes in their digital transition, by linking their skill supply to future jobs. This part of the project introduces a quantitative occupational forecasting model which anticipates future trends of the supply and demand for labour. The methodology is based on research of the European Training Foundation (ETF), European Centre for the Development of Vocational Training (Cedefop) and the International Labour Office (ILO).

We consider three concepts in modelling: (1) a basic quantitative occupational forecasting model in Excel spreadsheet format, (2) univariate time series methods and (3) using forecasts provided by IHS, ILO and UN. All three methodologies suggest an increase of employment in the forecasting horizon. However, there are diverging results regarding the future development of the labour force. In the first model the labour force is expected to remain unchanged. The second model forecasts an increase in the labour force and the third model forecasts a decline. Therefore, each of the models points to different challenges in the labor market.

The basic model consists of three parts: labour demand, labour supply and the equilibrium condition. The variables cover the major aggregates of the labour market. The data set of the model has only one observed point in time and one forecast. The model results show that a lift in employment impacts occupations with medium and high skills. It would therefore particularly lead to a higher demand for persons with a doctoral degree. However, such a rise in the labour demand cannot be met by labour supply.

Looking at developments from 1991 to 2009 the labour market improved gradually, when the unemployment rate fell from 8.5 to 6.4 percent. From 2010 onwards unemployment increased rapidly reaching 14.5 percent in 2021.

Univariate time series methods show how developments of the past will continue in the coming years. We applied such methods forecasting aggregate employment and the labour force. We based our model selection process on the differenced data sets. ARIMA(1,0,0) models have been selected on basis of unit root and information criteria. The model results suggest that in the coming years, the situation on the labour market will continue to deteriorate, because labour supply will grow faster than labour demand. Hence, if the growth pattern of the past continues, unemployment is expected to widen in the years to come.

Another approach in forecasting aggregate employment and labour force is to apply forecasts of IHS, ILO and UN. The forecasting results suggest that the gap between employment and labour force, which has widened in recent years, will close at the end of the forecast horizon. This is because employment is expanding, and the labour supply is falling slightly. The consequence of such a development is a shortage of labour at the end of the forecasting horizon. The problematic that arises for one economy is that, on the one hand, fewer jobs need to be created, but on the other hand, fewer workers must produce more output to keep the economy going.

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1 Introduction

The project **Collaborative network for career building, training and e-learning** is being funded by the ERASMUS+ Programme: Capacity Building in the Field of Higher Education. The project is intended to support Lebanese Higher Education Institutes in their digital transition, by linking their skill supply to future jobs. The main objective is to improve the employability of students and graduates, especially in sectors and jobs affected by the digital revolution.

Like in many other countries the Lebanese labour market is hit by a matching problem. Hence, this part of the project introduces a quantitative occupational forecasting model to anticipate future trends of the supply and demand for labour. The outcome of this study will show the current mismatch in the Lebanese labour market, particularly in the field of higher education. It will also point to future trends in occupations needed and the supply of qualified graduates. This study will support Higher Education Institutions in their policy decisions and allow students and graduates to optimize their careers. It's to be expected that the new findings will have a positive impact on the labour market as imbalances might decrease.

Goals to achieve:

- A quantitative forecasting model for the Lebanese labour market,
- showing past and future trends in labour supply and demand,
- identifying imbalances on the labour market.
- It will allow simulation analyses.
- Hence, it will contribute to a better understanding of labour market needs and skills matching.
- Quantitative results can inform qualitative research and vice versa.
- Policy makers will learn how to identify, to understand, to cope with, to control imbalances.
- Anticipation and matching approaches that help to develop a skilled workforce with the right mix of skills in response to labour market needs, particularly in the field of higher education and digitalisation.
- These approaches will help to reduce unemployment, particularly among young people, leading to a better life for individuals by improving employability, social mobility and inclusion.

When setting up a quantitative forecasting model, first, one has to decide on the methodology. Hence, the section “Methodology” of this study is devoted to this issue. Here we address forecasting techniques and the model design.

However, quantitative forecasting also requires a fixed sequence of steps. The initial step is the collection of data. Then the relevant indicators are visualized, validated and processed. We describe this workflow in the section "Data".

In the "Models" section three concepts in model development are introduced. All models forecast employment and labour supply and they provide information about future imbalances in the labour market. The first model is set up in Excel spreadsheet format. In the second model, univariate time series methods are applied. The third concept is to use forecasts from IHS, ILO and UN for labour market analyses.

The forecast results are analysed and discussed. The new findings are highlighted for further communication.

2 Methodology

The European Training Foundation (ETF), European Centre for the Development of Vocational Training (Cedefop) and the International Labour Office (ILO) are the major sources in labour market analyses. ETF et al. (2016) distinguish between skill foresights and forecasts and propose systems at a national level. While foresights are qualitative and a visionary tool that requires less formalised inputs, forecasts are based on quantitative modelling of labour market relations. This section will focus on quantitative methodologies, which are suitable to forecast labour market imbalances on a national level. It will explain the forecasting techniques and also the model design.

2.1 Forecasting techniques

The books of Clements & Hendry (2000) and Franses, et al. (2014) are the theoretical background for model building. They claim that there is not a single time series model that can be used to describe specific developments and that is also reasonably precise in out-of-sample forecasting. In fact, there are several models to describe each of these features, and all these models can be used to generate out-of-sample forecasts. Such techniques could be:

- an extrapolation of past trends,
- or more complex time series methods,
- introducing behavioural content.

The quantitative model will be built in R. This is an open-source software which provides a comprehensive set of the necessary tools. It is an integrated suite of software facilities for data manipulation, calculation and graphical display. R is very much a vehicle for newly developing methods of interactive data analysis. It has developed rapidly and has been extended by a large collection of packages.

2.2 Model design

El Achkar (2010) and later ETF et al. (2016) developed a road map to occupational forecasting. It is a methodology for modelling labour demand, labour supply and labour market imbalances. A basic occupational forecasting model, which can then be expanded or modified as needed, is summarized in Figure 1.

Figure 1: Basic occupational forecasting model

Labour demand

Output by activity
↓
Employment by activity
↓
Occupations by activity
↓
Educational distribution by occupation
↓
Replacement and expansion demand
↓
Occupational demand

Labour supply

Population
↓
Number of labour force participants
↓

Number of graduates by educational level

↓

Occupational supply

Equilibrium condition

Occupational demand = Occupational supply

↓

Identifying imbalances

↓

Determining occupational outlook

↓

Feedback on national income and education policy

2.3 Estimating labour demand

Output by activity The first step involves determining the output (gross domestic product) by industrial activity and estimating the dependencies among industries by taking into account the changing structure of the economy. Growth projections of the gross domestic product (GDP) may be derived from national or international sources. We recommend considering a survey of forecasts.

Employment by activity The second step involves the determination of employment by activity. The explanatory variables are the output by industrial activity obtained in the previous step. Also, the information on the supply of labour and the changing structure of the economy have to be considered.

Occupations by activity The occupational level is determined by changes in employment between industries and by changes in employment between occupations within an industry. Technological progress may lead to such changes. El Achkar (2010) proposes a simple calculation method using a (historical) industry/occupation matrix to obtain occupation coefficients or shares of occupations in industry employment, which could then be extrapolated into the future. The projected employment for each occupation is then summed across industries to obtain future employment level by occupation.

Educational distribution by occupation Models that explicitly account for the distribution by education level often use fixed coefficients, that is, assume that past trends will simply continue in the future. Trends can therefore be obtained from historical data and used to project future education (skills) demand.

Replacement demand It refers to the number of workers required to replace the workers leaving an occupation. This includes retirement, family care or other reasons for temporary leaving the workforce, and emigration.[1] Replacement demand often provides a very large share of the job openings in an economy. It easily surpasses the share of job openings based on **expansion demand** like changes in the employment structure, such as growing occupations or growing demand.

Occupational demand Net labour demand by occupation is calculated as expansion demand plus replacement demand.

2.4 Estimating labour supply

Education models are often developed as separate models, outside the occupational forecasting model. Forecasts of future demographic trends of one country are typically provided by international organisations.

Population and labour force participation Projections for demographic developments may be obtained from external sources. Trends can also be calculated from historical data and projected forward using an extrapolation technique. The trends are then applied to the corresponding demographic groups to obtain the projected labour force for these groups.

Number of graduates by educational level Educational institutions may provide historical data on the number of graduates by field of education. In addition, historical data on graduations by level of schooling can be used to determine graduation rate trends. When forecasting the number of graduates by field of education, the future demographic trends are the explanatory variables in the model. If graduation trends were estimated, these rates can be applied to obtain the corresponding estimates of the labour force by educational level.

Occupational supply The occupational labour supply may be estimated by using historical trends of the occupational shares in the labour force, or by using an education to occupation matrix.

[1] Projections of replacement demand require three main inputs: A forecast of demographic development within a country; a forecast of (changes in) participation, preferably by gender and age groups; an estimate of the outflow by occupation/education category, gender and age group.

2.5 Equilibrium condition

For simplicity, labour supply and labour demand are generally modelled separately; there is no interaction between the two, except macroeconomic or global interactions. The demand and supply estimates, namely the projected employment level and projected labour force, have to be combined to develop an indicator of labour market imbalances. However, such projected imbalances do not account for the responses of firms and workers to changing occupational outlooks. The implementation of feedback loops is, therefore, subject for further research.

A frequently used option is a qualitative evaluation and interpretation of quantitative forecasting results. They may be discussed within a group of (external) experts from employer associations, sector councils, and government agencies. This feedback will be included in the final interpretation of the quantitative results.

3 Data

This section contains an overview on indicators covering the Lebanese labour market, which allows a comparison of labour demand and supply to identify imbalances. Labour market statistics should allow us to analyse past developments and to forecast the future. The focus is on persons with tertiary education. However, in order to do this the relevant data set has to be compiled.

First, we emphasize the relevant sources of statistics. Second, we explain the international classification scheme, which applies to the sub-grouping of indicators. Thirdly, we visualize the available data set.

If the data, relevant to the project, does not appear in existing statistics, the conduction of an own survey may be considered.

3.1 Sources

In forecasting the key element is the availability of data (ILO, 2015). Various data sources are available to identify key past and current trends. In most countries, a central statistical agency collects and publishes data and indicators of which the main contributing parts are household surveys, social surveys, the national accounts, education statistics, demographic indicators, enterprise surveys and other administrative data sources. Each data source has its own strengths and limitations and provides insight into different labour market aspects. Ideally, a number of different data and indicators need to be considered in the analysis to gain a detailed and objective picture.

We consider the following data sets for the Lebanese labour market, which serve as input to quantitative forecasting:

- Lebanon Central Administration of Statistics (CAS)
    - National Account Statistics
    - Other economic indicators
- International Labour Organisation, Department of Statistics (ILOSTAT)
    - Demographic trends
    - Employment by industrial sector
    - Occupations
    - Education (limited availability!)
    - Imbalances (limited availability!)
- International Monetary Fund (IMF)
    - World economic developments and outlook
- Labour market surveys conducted by our project partners

3.2 Classifications

Classifications of industrial activities, occupations and education are important in running quantitative forecasting models. These classifications allow combining different data sources and set the level to which forecasts can generally be made. The international classification scheme for industrial activities, occupations and education is explained and listed in the section "Classifications" of the appendix. If existing classifications do not reflect the level of detail to which a forecast is to be done, alternative classifications would need to be determined.

To make industrial activities comparable across sources we put some of the groupings of ISIC classifications together:

- We aggregated the group "transportation and storage" (H) and "information and communication" (J) to the new group "transportation, information and communication" (HJ).
- We also aggregated the "real estate activities" (L), "professional, scientific and technical activities" (M) and "administrative and support service activities" (N) to the new group "real estate, professional, scientific and technical activities" (LMN).
- Furthermore, we aggregated "arts, entertainment and recreation" (R), "other service activities" (S), "activities of households as employers, undifferentiated goods- and services producing activities of households for own use" (T), "activities of extraterritorial organizations and bodies" (U) and "not elsewhere classified" (X) to (RSTU).

3.3 Visualisation

The visualisation of statistics plays a crucial role in model building and forecasting. It is a process of representing data graphically to identify trends and patterns that would otherwise be unclear or difficult to discern. Hence, data visualisation serves to bring clarity for analyses and communication.

Our data set consists of the gross domestic product (GDP), employment, labour supply and imbalances. The data sources are the IMF, CAS and ILO. All observations have a yearly frequency.

It is important to note that ILO provides two sets of data. One is the ILO modelled estimates and projections database (ILOEST, 2021), which provides an extensive set of estimated time series from 1990 to date, and for major aggregates short-term projections are available. The second source is the Labour Force and Household Living Conditions Survey 2018/2019 for Lebanon, downloadable from the ILO labour force statistics database (ILOLFS, 2022). The two data sets are not comparable because of differing definitions of the content.

The data, disaggregated by level of education is available only for the year 2019. This causes problems in econometric modelling and time series analyses. For the development of a quantitative occupational forecasting-model with the focus on education we would need time series from 1990 to date.

3.3.1 Gross domestic product

Figure 2 shows the economic growth rates for Lebanon (LBN), USA, EU, and MENA (Middle East and North African countries). We consider observations starting from 1995 to date. Hence, the strong economic upswing after the Lebanon War in the early 1990s will not be shown. Figure 2 suggests that the economic development in Lebanon is not synchronised with business cycles of the USA, the EU and MENA. It rather points to a negative relationship. Furthermore, the volatility of Lebanese time series is much higher particularly in comparison with USA and EU.

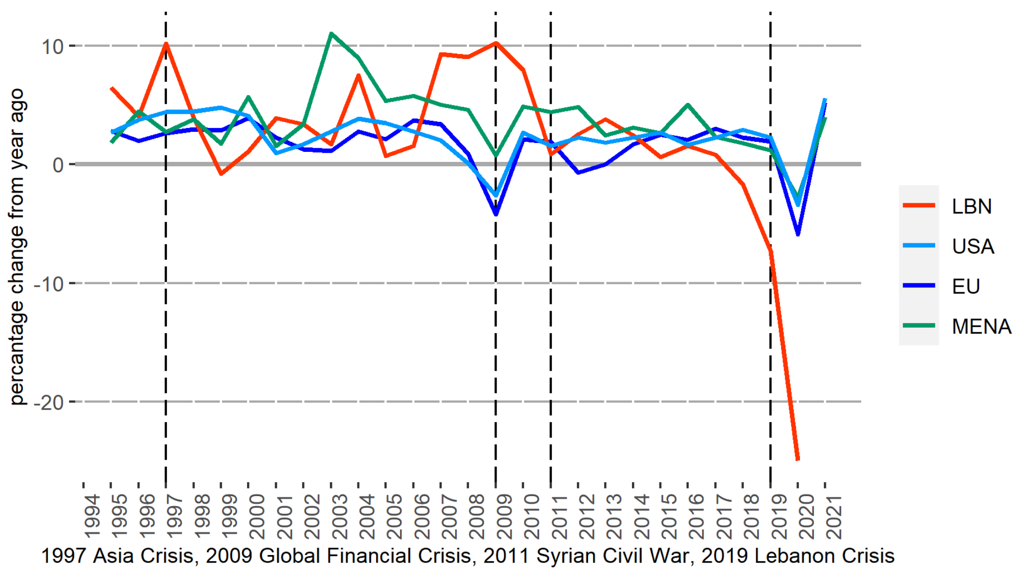
The industrial sector is of great importance for economic development of one country. There is clear evidence, that countries with a successful industrial sector generate more economic growth compared to others. The National Accounts Statistics provided by CAS are used to give an overview of the importance of each sector in the Lebanese economy. Economic activities are disaggregated by the rules of the International Standard Industrial Classification of All Economic Activities, Revision 4 (ISIC-4).

Figure 3 shows the distribution of GDP across economic sectors in Lebanon from 2004 to 2020 There is evidence that, up to 2019, no major structural changes have occurred.

Service industries are the main drivers of economic activity in Lebanon. By far the largest contribution to GDP comes from real estate, professional, scientific and technical activities (LMN). This sector accounts for more than a fifth of economic output. From 2010 onwards its importance even increased. The second largest sector is the wholesale and retail trade, automotive repair industry (G). However, the sector's share in GDP has been falling since 2012. The group of financial and insurance activities (K) containing the banking sector has always acted as the backbone of the economy. The share of the entire sector (K) in the country's total economic output has increased during the observation period.

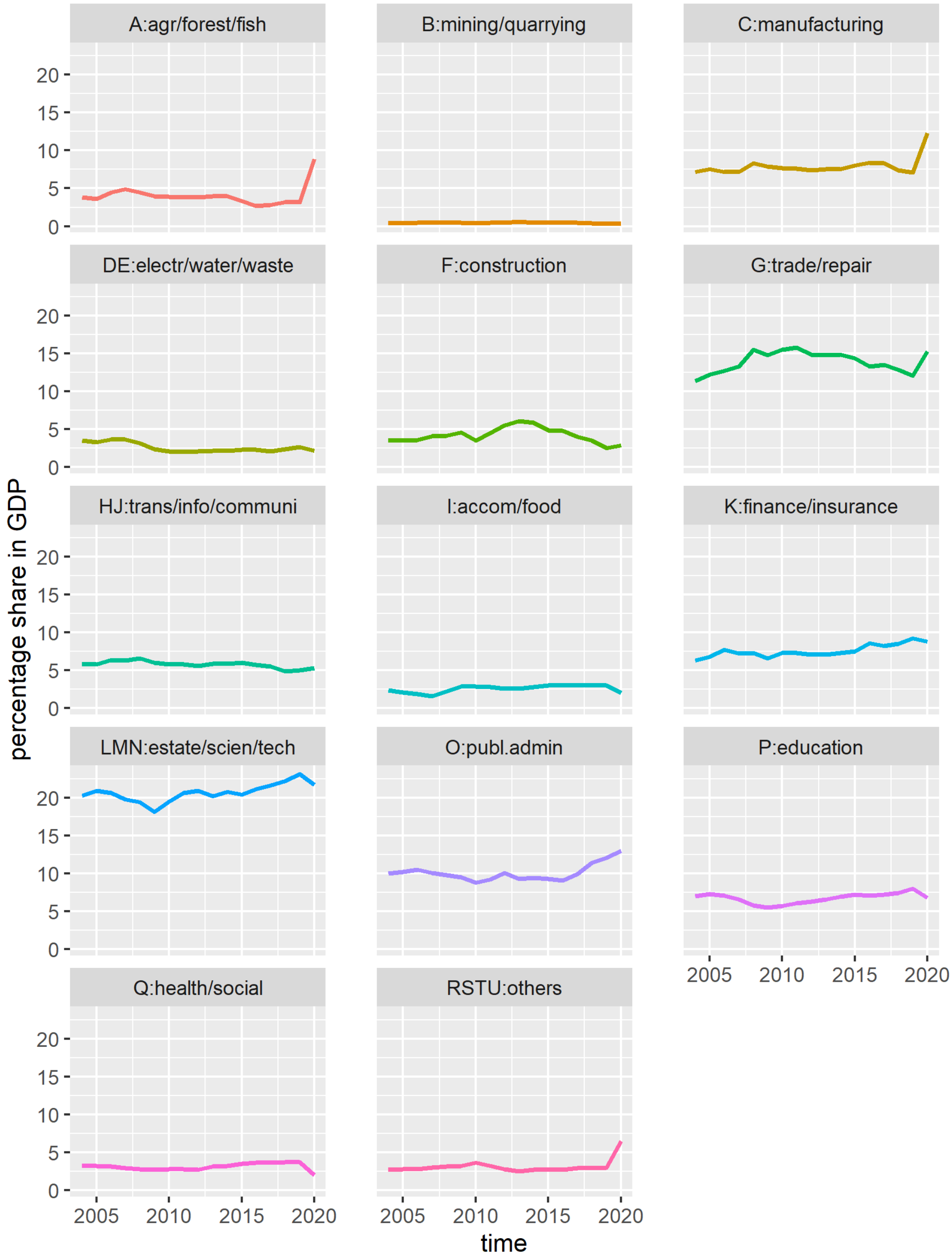
Table 1 lists the distributions of all economic activities of the economy of the year 2019. The sector with the biggest share in GDP is the real estate, professional, scientific and technical activities (LMN) sector accounting for 23.2 percent of total output. Followed by wholesale and retail trade, automotive repair services (G) sector as well as public administration and defence, compulsory social security services (O) sector with a share of 12.1 percent each. The sector of financial and insurance activities (K) has a share of 9.2 percent in the country's total economic output.

Figure 2: Economic growth comparison, 1995 to 2021



Source: IHS based on IMF, March 2022.

Figure 3: Lebanon GDP by activity, 2004 to 2020



Source: IHS based on CAS, 2022.

Table 1: Lebanon GDP by activity, 2019

percentage share in total GDP

ISIC classification	2019
A: Agriculture, forestry and fishing	3.2
B: Mining and quarrying	0.3
C: Manufacturing	7.1
DE: Electricity, water and waste	2.7
F: Construction	2.5
G: Wholesale and retail trade, automotive repair	12.1
HJ: Transportation, information and communication	5.0
I: Accommodation and food service activities	3.0
K: Financial and insurance activities	9.2
LMN: Real estate, professional, scientific and technical activities	23.1
O: Public administration and defense, compulsory social security	12.1
P: Education	8.0
Q: Human health and social work activities	3.7
RSTU: Entertainment, household services, others	3.0

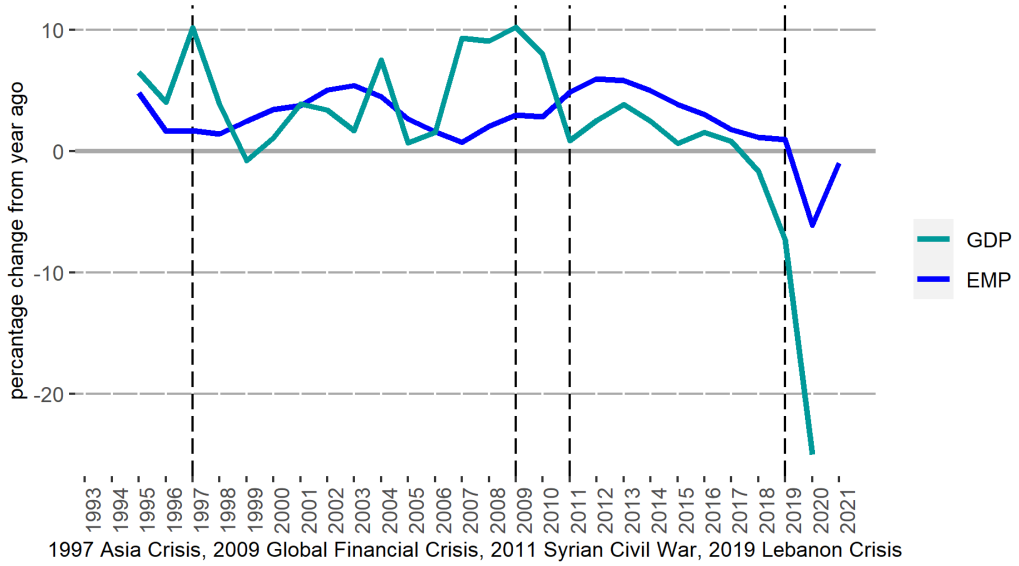
Source: IHS based on CAS, 2022. Note: Values do not add up to 100 because taxes and subsidies are not included.

3.3.2 Labour demand

Demand for labour is a concept that describes the amount of demand for labour that an economy or firm is willing to employ at a given point in time. In the following analysis the employed comprise all persons of working age who, during a specified brief period, were in one of the following categories: a) paid employment (whether at work or with a job but on leave); or b) self-employment (whether at work or with an enterprise but not at work).

When producing goods and services, businesses require labour and capital as inputs to their production process and vice versa. Employment is typically a lagging indicator of economic activity. In general, economic theory as well as plausibility support the existence of such a clear relationship. However, in Lebanon this is not true for the entire observation period. Only from 2011 onwards, such a relationship might exist. In addition, employment has grown faster than GDP, leading to a decline in productivity in these years (Figure 4).

Figure 4: Lebanon GDP and employment growth, 1995 to 2021



Source: IHS based on IMF, March 2022 and ILO modelled estimates and projections, November 2021.

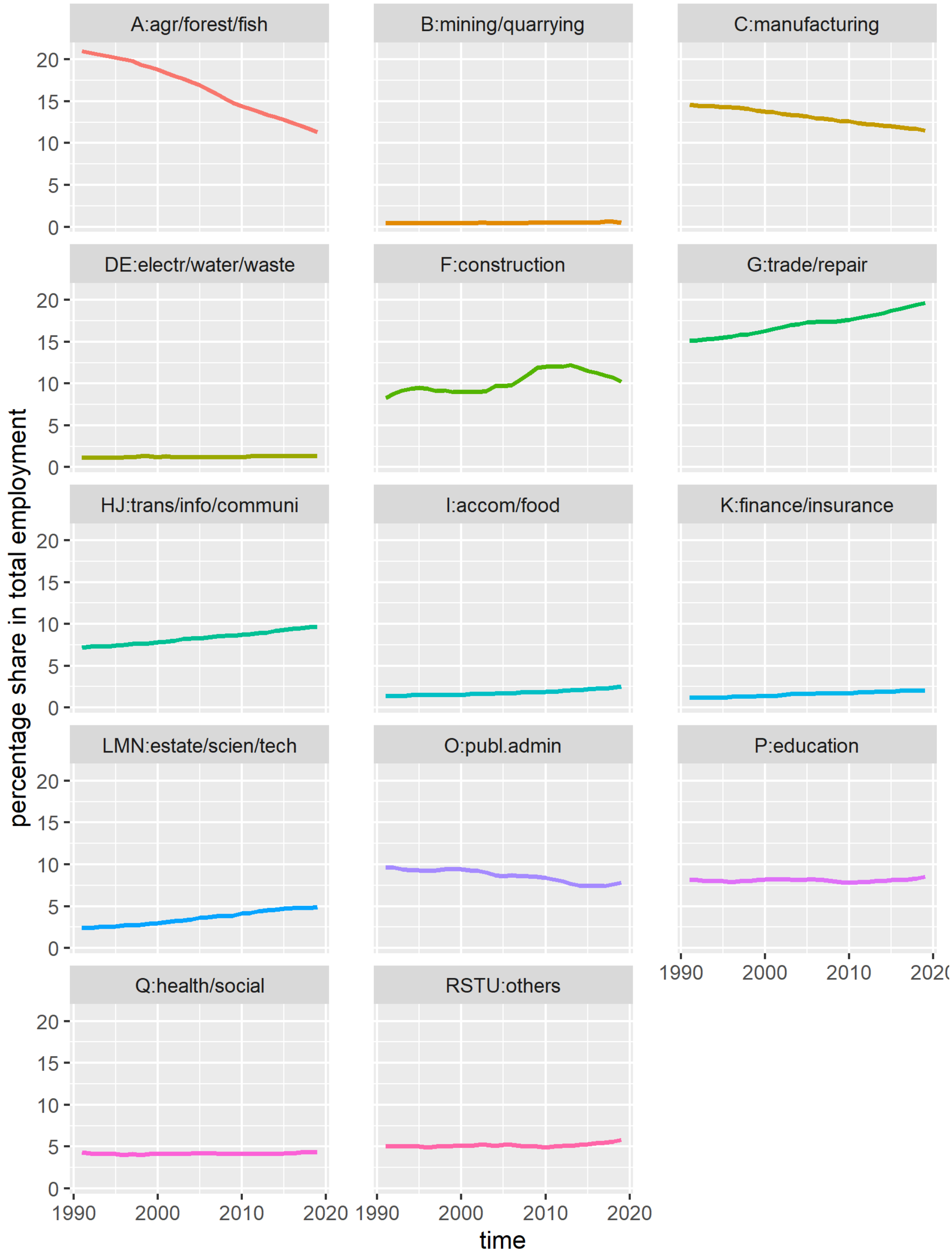
Employment by economic activity

The aggregate employment data is disaggregated by economic activity, which refers to the main activity of the establishment in which a person worked during the reference period. The economic activity has been disaggregated by the rules of the International Standard Industrial Classification of All Economic Activities, Revision 4 (ISIC-4).

Figure 5 shows the employed persons by activity as share in total employment. During the entire observation period, only slight fluctuations occurred. Exceptions are the employment shares in agriculture and manufacturing, which fell in favour of trade services.

In 2019 most persons had been employed in trade services (20 percent) and manufacturing as well as agriculture (11 percent). Table 2 lists the employment shares of all economic activities.

Figure 5: Lebanon Employment by activity, 1995 to 2019



Source: IHS based on ILO modelled estimates and projections, November 2021.

Table 2: Lebanon Employment by activity, 2019

percentage share in total employment

ISIC classification	2019
A: Agriculture, forestry and fishing	11.3
B: Mining and quarrying	0.5
C: Manufacturing	11.5
DE: Electricity, water and waste	1.3
F: Construction	10.2
G: Wholesale and retail trade, automotive repair	19.6
HJ: Transportation, information and communication	9.7
I: Accommodation and food service activities	2.5
K: Financial and insurance activities	2.0
LMN: Real estate, professional, scientific and technical activities	4.9
O: Public administration and defence, compulsory social security	7.8
P: Education	8.5
Q: Human health and social work activities	4.4
RSTU: Entertainment, household services, others	5.8

Source: IHS based on ILO modelled estimates and projections, November 2021.

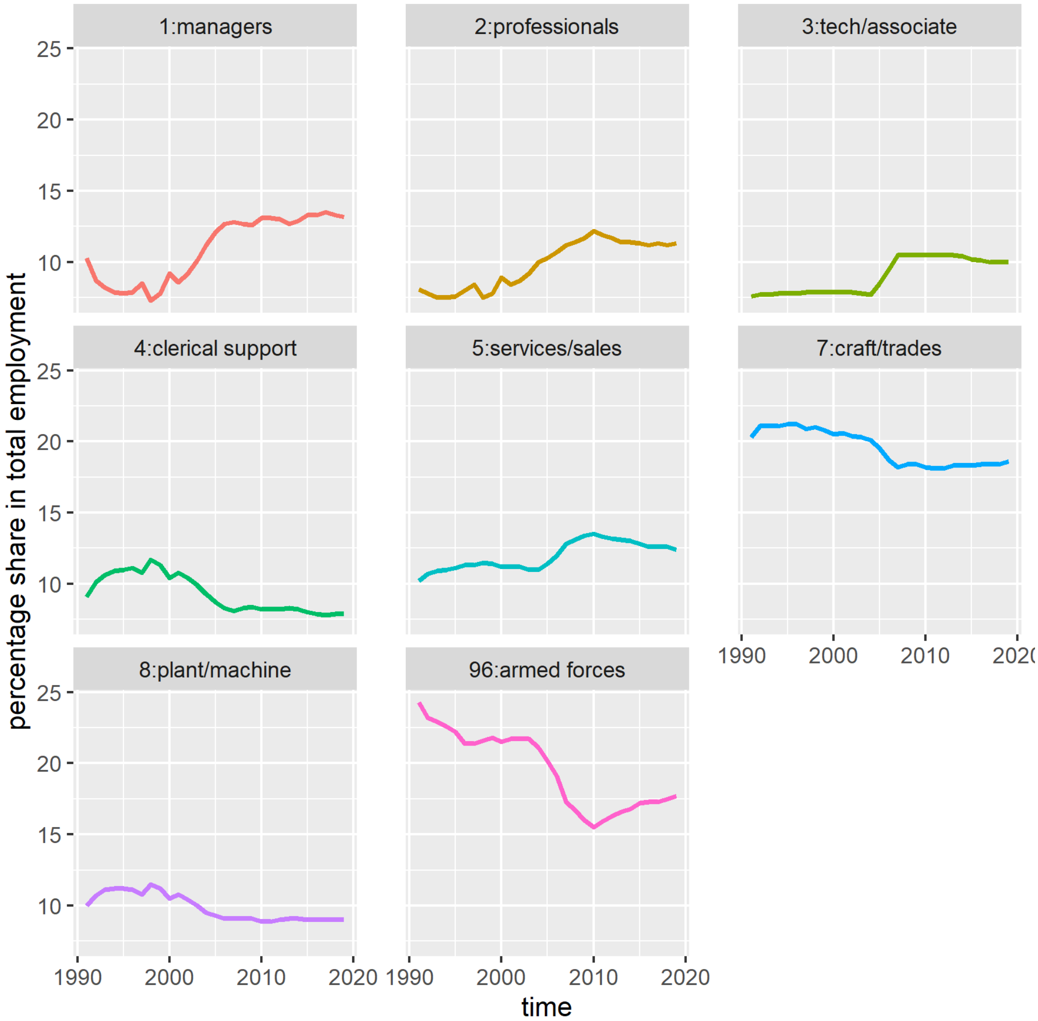
Employment by occupations

Employment data are disaggregated by occupation according to the latest version of the International Standard Classification of Occupations (ISCO-08).

The development of occupations of the employed persons, as percentage share in total employment, is shown in Figure 6. The focus of the underlying research project is on occupations which require a higher education degree, consisting of managers, professionals and technicians and associate professionals. The share of these occupations shows an increasing trend over time.

In the year 2019, the share of managers in total employment amounted to 13 percent, of professionals 11 percent and of technicians and associate professionals 10 percent. Table 3 lists the share of employment by occupations in total employment.

Figure 6: Lebanon employment by occupations, 1995 to 2019



Source: IHS based on ILO modelled estimates and projections, November 2021.
Note: For the occupations group 6: Skilled agricultural, forestry and fishery workers no ILOSTAT modelled estimates are available.

Table 3: Lebanon employment by occupations, 2019

percentage share in total employment

ISCO classification	2019
1: Managers	13.2
2: Professionals	11.3
3: Technicians and associate professionals	10.0
4: Clerical support workers	7.9
5: Services and sales workers	12.4
7: Craft and related trades workers	18.6
8: Plant and machine operators and assemblers	9.0
96: Armed forces occupations	17.7

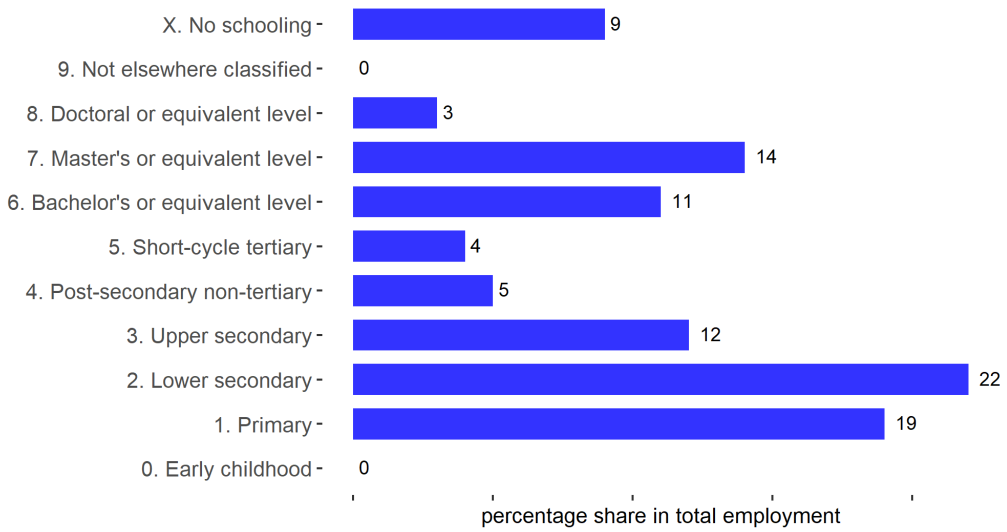
Source: IHS based on ILO modelled estimates and projections, November 2021.

Employment by education

The disaggregation of employment by level of education, refers to the highest level of education completed, classified according to the International Standard Classification of Education (ISCED).

Figure 7 shows the distribution of employment by educational level. Persons with higher education, including those with a doctorate, master’s or bachelor's degree, as well as graduates of short-cycle tertiary courses form the largest group of employees. Their share accounts for 32 percent of total employment. The second largest group are those employees obtaining a secondary school diploma with a share of 22 percent.

Figure 7: Lebanon employment by educational level, 2019



Source: IHS based on ILO labour force statistics, February 2022.

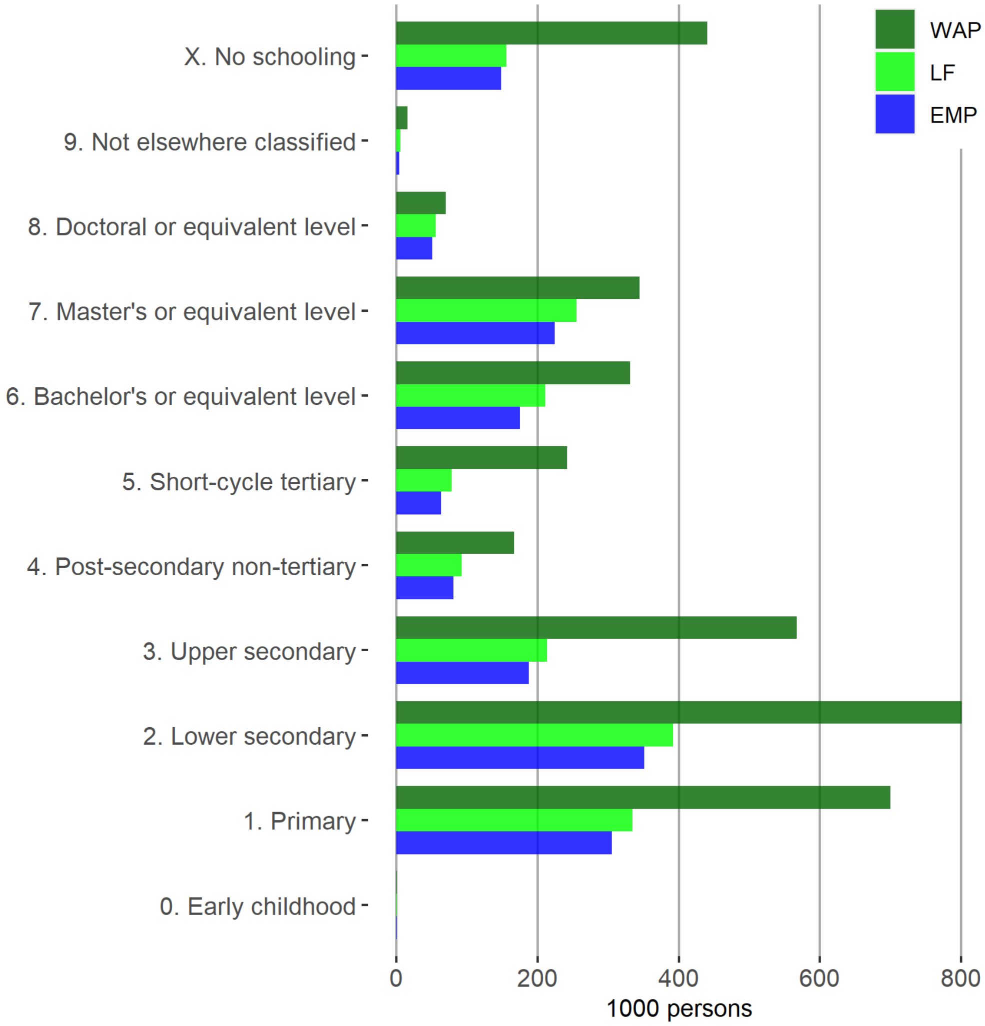
3.3.3 Labour supply

The working age population is commonly defined as persons aged 15 years and older. The labour force comprises all persons of working age who furnish the supply of labour for the production of goods and services during a specified time-reference period. It refers to the sum of all persons of working age who are employed and those who are unemployed. In Lebanon the economically active persons, the labour force is constituting only 49 percent of the overall population aged 15 years and above. This is a very low labour participation rate compared to industrialized countries.

Labour supply by level of education

The disaggregation of labour supply by level of education, refers to the highest level of education completed, classified according to the International Standard Classification of Education (ISCED). Figure 8 shows the working age population (WAP), labour force (LF) compared to employment (EMP) by educational level. The data suggests that persons obtaining a doctoral or a master's degree have at 80 and 74 percent respectively the highest participation rate in the labour market. In contrast, the labour market participation is very low for persons with a secondary educational level. The discrepancy between the labour force and employment will be discussed later.

Figure 8: Lebanon labour supply and demand by education level, 2019

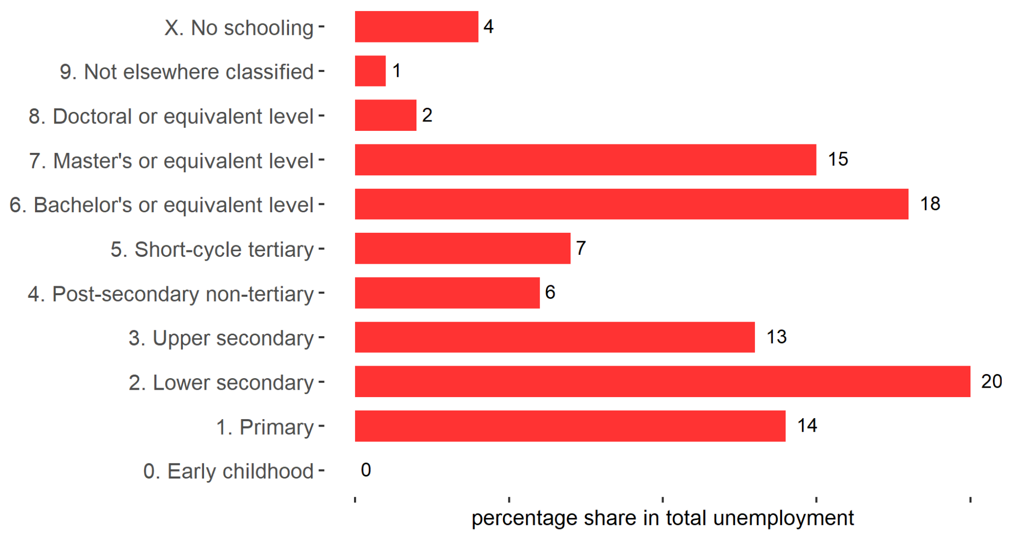


Source: IHS based on ILO labour force statistics, February 2022.

3.3.4 Imbalances

Unemployment is a major indicator for labour market imbalances. It is the discrepancy between the labour force and employed persons. In 2019, 11.3 percent of the labour force has been unemployed. Figure 9 shows that unemployment is the highest among persons with master's or bachelor's educational level. This group has a share of 33 percent in total unemployment. The second largest group hit by unemployment are persons obtaining a lower secondary educational level. They account for 20 percent in total unemployment. Very low unemployment is observable at persons obtaining a doctoral degree or at persons with a post-secondary non-tertiary or a short-cycle tertiary educational level.

Figure 9: Lebanon unemployment by education, 2019



Source: IHS based on ILO labour force statistics, February 2022.

3.3.5 Matching

There is no comprehensive information on the reasons why persons are unemployed. But there is evidence, that the Lebanese labour market is characterised by a mismatch between qualifications and the skills required in open positions. In the literature, this discrepancy derives from the lack of current labour market information, insufficient career guidance, and the prevalence of recruiting and retaining practices that are somewhat outdated.

Besides the mismatch between job seekers and open position, there exists also a mismatch across employed persons. In the ideal case, one person's qualification matches with the skills required. But employees may also be over or under skilled in their jobs. Figure 10 shows the mismatch of employed persons, distinguishing between statistic[1] and the normative[2] approach.

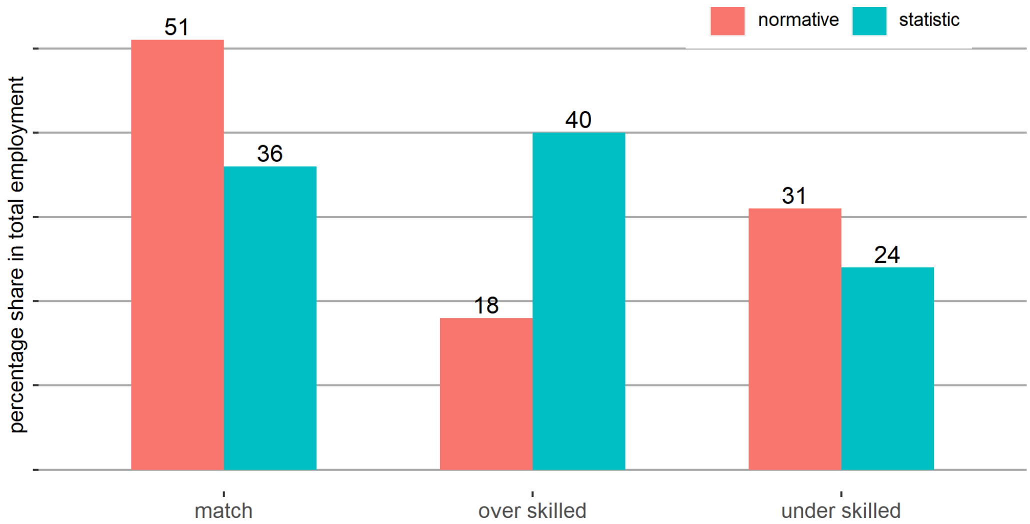
[1] Statistic approach (ILO definition): The expected level of education for workers in each occupation is determined not based on a standard (as is done in the normative approach), but on what is actually happening in the labour market. That is, the most common educational level for workers in each occupation (the mode) is identified and workers with that level are considered well matched. Workers with a lesser educational level than the most common educational level in their occupation (less than the mode) are under-educated and vice-versa.

[2] The normative approach (ILO definition) is a standard level of education required in each occupation, and all workers who do not have that standard level are considered mismatched.

Considering the statistic approach, only 36 percent of the employees obtain a job where their qualifications meet the required skills. 40 percent of the employees think they are over skilled, and 24 percent think they are under skilled.

Considering the normative approach, 51 percent of the employees obtain a job where their qualifications meet the required skills. 18 percent of the employees are over skilled, and 31 percent are under skilled.

Figure 10: Lebanon labour market matching, 2019



Source: IHS based on ILO education and skills mismatch indicators (SKILLS), February 2022

3.3.6 Conclusions

The visualisation of statistics plays a crucial role in model building and forecasting. Data visualisation serves to bring clarity for analyses and communication. Our data set for Lebanon consists of the gross domestic product (GDP), employment, labour supply and imbalances. The data sources are the IMF, CAS and ILO.

The economic development in Lebanon is not synchronised with business cycles of the USA, the EU and MENA. It rather looks like a negative relationship. In Lebanon service industries are the main drivers of economic activity. By far the largest contribution to GDP comes from real estate, professional, scientific and technical activities.

Employment is typically a lagging indicator of economic activity. In general, economic theory as well as plausibility support the existence of such a clear relationship. However, in Lebanon this is not true for the entire observation period. Only from 2011 onwards, such a relationship might exist. In addition, employment has grown faster than GDP, leading to a decline in productivity in these years. During the entire observation period, employment structures remained more or less unchanged. Exceptions are the employment shares in agriculture and manufacturing, which fell in favour of trade services. And the share of occupations with a higher education degree, shows an increasing trend over time.

Only 49 percent of the overall population aged 15 years and above participate actively in the labour market, which is a very low rate compared to industrialized countries. While a high level of labour participation can be observed among people with higher educational qualifications, the labour participation rate among those with secondary school qualifications is very low. In 2019, 11.3 percent of the labour force has been unemployed. Unemployment is the highest among persons with master’s or bachelor’s educational level. The second largest group hit by unemployment are persons obtaining a lower secondary educational level.

Besides the mismatch between job seekers and open position, there exists also a mismatch across employed persons. Considering the statistic approach, only 36 percent of the employees think to obtain a job where their qualifications meet the required skills. 40 percent of the employees think they are over skilled, and 24 percent think they are under skilled.

4 Models

4.1 Basic concept

This is an introduction to a basic quantitative occupational forecasting model for Lebanon. The concept has been described earlier in the "Methodology" section. The data source is the LFHLC (2020) downloaded from ILOLFS (2022). The model consists of three parts: labour demand, labour supply and the equilibrium condition. Due to simplicity reasons and availability the data set of the model has only one observed point in time and one forecast. The variables cover the major aggregates of the labour market. Subgroups of employment by economic activity and the demand and supply of labour by age groups are not yet considered. The model is set up in an Excel spreadsheet format.

The observed data point of the model is the year 2019 and the forecast is for the year 2024. The variables for labour demand are employment by occupations and employment by level of education. The labour force by educational level forms the supply side of the labour market. Unemployment by educational level shows the imbalances of the labour market. For a detailed description of the data set see the section "Statistics for Lebanon" in the appendix.

In our base scenario we assume that all variables, numbers as well as distributions, of demand and supply remain unchanged in 2024 compared to 2019. In our growth scenario employment increases by 2.8 percent on a yearly average. However, structures of the labour market do not change. This view is supported by developments of the past.

The explanation for our growth assumption is that the severe economic downturn in 2019 and 2020 will be followed by a strong recovery. Therefore, one might expect that an increase in employment will have a positive impact on the labour market.

The responses to such an employment shock are quantified by our model. This is shown in Table 4 to Table 7, supplemented with an analysis of the observed situation and expected developments. The determinants of labour demand are employment by occupations as well as employment by level of education as shown in Table 4 and Table 5. The supply side of the labour market is covered by the labour force by level of education (Table 6). The imbalances are shown in Table 7.

Table 4: Total employment by occupations and skills, 2019 and 2024

NB = 1000 persons, DT = percentage share in total, F = forecast

		2019 NB	2019 DT	2024F NB	2024F DT
occupations	1:managers	109	7	125	7
	2:professionals	251	16	289	16
	3:tech/associate	79	5	91	5
	4:clerical support	69	4	80	4
	5:services/sales	322	20	371	20
	6:agr/forest/fish	38	2	44	2
	7:craft/trades	264	17	303	17
	8:plant/machine	141	9	162	9
	9:elementary	242	15	278	15
	96:armed forces	75	5	86	5
	99:total	1590	100	**1829**	100
skills	1:high	439	28	505	28
	2:medium	834	52	959	52
	3:low	242	15	278	15
	4:not classified	75	5	86	5
	5:total	1590	100	1829	100

Source: IHS model calculations based on ILOLFS (2022).

Employment by occupations (Table 4). In 2019, 1.6 million persons have been employed. The majority of jobs are in low-productivity sectors. The relatively high employment share of medium skilled persons can be explained by the outflow of relatively well-educated and skilled Lebanese, such that those remaining comprise a relatively less-educated domestic workforce. However, this development encourages the expansion of economic activities with low productivity with a negative impact on economic growth in the long run (ILO, 2016). The economic structure also determines the demand for occupations and skills. Therefore, more than half of the employees (52 percent) have medium skills. They are employed as services and sales workers, as craft and related trades workers and as plant and machine operators and assemblers. Overall, 28 percent of employment is situated in the occupational groups that by definition require high skills. This group comprises managers, professionals, technicians and associate professionals. The share of high skilled occupations expanded significantly between 2000 and 2010. In the following years their share remained more or less unchanged.

Table 5: Total employment by level of education, 2019 and 2024

NB = 1000 persons, DT = percentage share in total, F = forecast

		2019 NB	2019 DT	2024F NB	2024F DT
education	0. Early childhood	0	0	0	0
	1. Primary	305	19	351	19
	2. Lower secondary	351	22	404	22
	3. Upper secondary	188	12	216	12
	4. Post-secondary non-tertiary	80	5	92	5
	5. Short-cycle tertiary	63	4	73	4
	6. Bachelor's or equivalent level	175	11	201	11
	7. Master's or equivalent level	224	14	258	14
	8. Doctoral or equivalent level	51	3	59	3
	9. Not elsewhere classified	4	0	5	0
	X. No schooling	148	9	171	9
	Z. Total	1590	100	1829	100
aggregates	0. Less than basic	148	9	171	9
	1. Basic	657	41	755	41
	2. Intermediate	268	17	308	17
	3. Advanced	513	32	590	32
	X. Level not stated	4	0	5	0
	Z. Total	1590	100	1829	100.

Source: IHS model calculations based on ILOLFS (2022).

Employment by education In Table 5 the 1.6 million employees are broken down according to their level of education. It shows that 41 percent of employees obtain a basic school education. This includes elementary and lower secondary education. It suggests that the majority of persons with occupations requiring medium skills, as shown in Table 5, obtain an elementary or a lower secondary education. Only 12 percent of employed persons with medium skills obtain an upper secondary education. The second largest group of employees have an advanced educational level. Advanced education contains short-cycle tertiary education and bachelor's, master's or doctoral or equivalent degrees. Employees with an advanced educational level typically obtain occupations requiring high skills as shown in Table 5.

An increase of employment by 2.8 percent on a yearly average would, particularly, lead to a lift in the demand for persons with a basic and an advanced educational level. For 2024 we assume that the structure of the employment by educational level remains unchanged compared to 2019.

Table 6: Labour force by level of education, 2019 and 2024

NB = 1000 persons, DT = percentage share in total, F = forecast

		2019 NB	2019 DT	2024F NB	2024F DT
education	0. Early childhood	0	0	0	0
	1. Primary	335	19	335	19
	2. Lower secondary	392	22	392	22
	3. Upper secondary	213	12	213	12
	4. Post-secondary non-tertiary	92	5	92	5
	5. Short-cycle tertiary	78	4	78	4
	6. Bachelor's or equivalent level	211	12	211	12
	7. Master's or equivalent level	255	14	255	14
	8. Doctoral or equivalent level	56	3	56	3
	9. Not elsewhere classified	6	0	6	0
	X. No schooling	156	9	156	9
	Z. Total	1794	100	1794	100
aggregates	0. Less than basic	156	9	156	9
	1. Basic	727	41	727	41
	2. Intermediate	306	17	306	17
	3. Advanced	600	33	600	33
	X. Not classified	6	0	6	0
	Z. Total	1794	100	1794	100

Source: IHS model calculations based on ILOLFS (2022).

Labour force by education (Table 6). In 2019 the labour force amounted to 1.8 million persons. The majority of workers (22 percent) have only secondary education and 28 percent have primary education or no education at all. The labour force with a medium-level technical expertise is extremely scarce. The share with an upper secondary or a post-secondary non-tertiary level of education amounts to only 17 percent. In contrast, the share of university degree holders is with 33 percent relatively high. In Jaoude (2015) this discrepancy is being explained by the fact that vocational and technical education has a low social value in society while university degrees have a high social value and status. Therefore, the labour market is facing increasing numbers of university degree holders who graduate each year in specialisations that do not match the needs of the economic activities. For this reason, a high number of skilled graduates migrate for job opportunities outside Lebanon.

In our growth scenario we assume for the year 2024 that the labor supply and its structure will not change compared to 2019. However, a stable supply of labor combined with rising labor demand suggests an improvement of labour market conditions.

Table 7: Unemployment by level of education, 2019 and 2024

NB = 1000 persons, RT = unemployment rate, F = forecast

		2019 NB	2019 RT	2024F NB	2024F RT
education	0. Early childhood	0	6	0	-8
	1. Primary	29	9	-17	-5
	2. Lower secondary	41	10	-12	-3
	3. Upper secondary	26	12	-2	-1
	4. Post-secondary non-tertiary	12	13	0	0
	5. Short-cycle tertiary	15	19	6	7
	6. Bachelor's or equivalent level	36	17	10	5
	7. Master's or equivalent level	31	12	-3	-1
	8. Doctoral or equivalent level	5	8	-3	-5
	9. Not elsewhere classified	1	24	1	13
	X. No schooling	8	5	-15	-9
	Z. Total	204	11	-35	-2
aggregates	0. Less than basic	8	5	-15	-9
	1. Basic	70	10	-29	-4
	2. Intermediate	38	12	-2	-1
	3. Advanced	87	14	10	2
	X. Not classified	1	24	1	13
	Z. Total	204	11	-35	-2

Source: IHS model calculations based on ILOLFS (2022).

Equilibrium condition Unemployment by level of education is shown in Table 7. All values are calculated by our model. The values of the first and third column are the differences between labour force (Table 6) and employment by level of education (Table 5). The second and fourth column of Table 7 contain the relating unemployment rates.

In 2019 the aggregate unemployment rate amounted to 11 percent. This corresponds to 204 thousand persons being unemployed. Persons with an advanced educational level have the highest risk of getting unemployed. The highest unemployment rate is observed among persons with a short-cycle tertiary level (19 percent) followed by persons with a bachelor's or equivalent level (17 percent) and master's or equivalent level (12 percent). This highlights the mismatch of labour supply and demand among academics. In contrast, the unemployment rate of persons with a doctoral or equivalent level is at 8 percent, well below the overall average.

An increase in employment of yearly 2.8 percent together with a labour force remaining at the level of 2019 would lead to a shortage of labour in 2024. Table 7 shows that the aggregate unemployment rate will be minus 2 percent, indicating a lack of 35 thousand persons on the labour market. Particularly the demand for persons with a doctoral degree will exceed the supply. There will also be a lack of persons with a primary or lower secondary educational level.

4.1.1 Conclusions

We set up a basic occupational model in Excel spreadsheet format. The data source for the model is the LFHCS (2020). The determinants of the model are employment broken down according to occupations and education. The labour force is broken down to education. Imbalances are calculated by our model. The observed data set is the year 2019 and the forecast is for the 2024.

In our base scenario we assume that the determinants will not change in 2024. In our growth scenario we assume that employment will increase by a yearly average of 2.8 percent, however, leaving the structures unchanged compared to 2019.

The model results show that a lift in employment impacts occupations with medium and high skills. It would particularly lead to a higher demand for persons with a doctoral degree. However, such a rise in the labour demand cannot be met by the labour supply.

4.2 Forecasting with univariate time series models

In this section we introduce univariate methods for forecasting employment and labour force in Lebanon. Univariate time series models are generally not based on any underlying economic behaviour. They relate a target variable to its past values and to possibly serially correlated random errors. A well-specified model is capable of summarising the dynamic pattern in the data. It provides a characterisation of what one expects for the future, conditional on the present and the past. The mainstream models in this regard are autoregressive and moving average models, and combinations of both.

The workflow of forecasting consists of: (1) providing the data set; (2) visualization of the data and of basic time series characteristics, such as autocorrelation functions; (3) specifying the quantitative models; (4) generating estimates and forecasts; (5) evaluation of the outcome. The transformation of the observed data set, the estimation of models and the forecasting is done in R using tidyverse, fable and fabletools packages.

The data source is ILO modelled estimates and forecasts, November 2022. It is important to note that this data set is being compiled with different concepts compared to the LFHLC (2020) statistics we applied earlier in the "Basic concept" section.

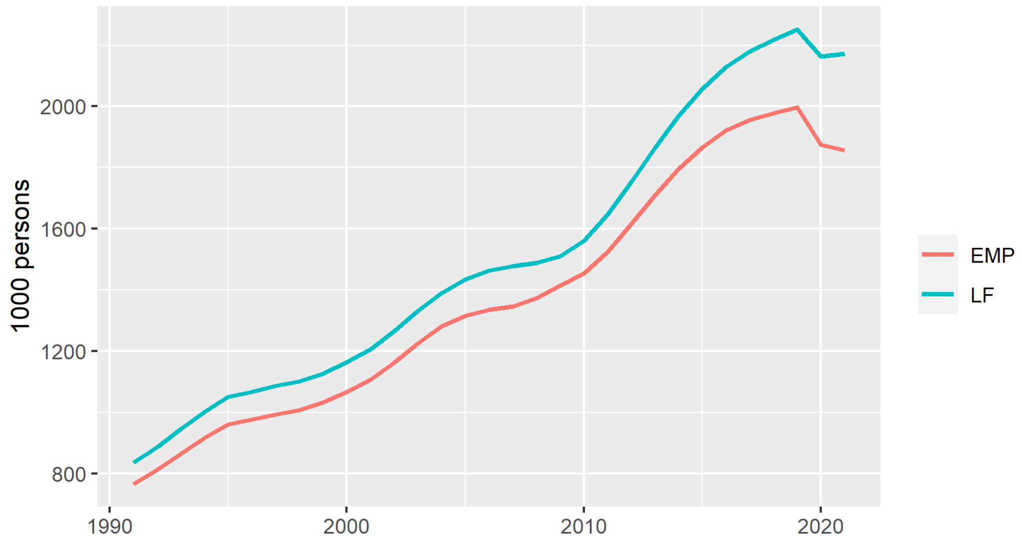
According to the ILOSTAT definition, the employed (EMP) comprise all persons of working age who, during a specified brief period, were in one of the following categories: (a) paid employment (whether at work or with a job but on leave); (b) self-employment (whether at work or with an enterprise but not at work). ILOSTAT points out that the imputed observations are not based on national data, are subject to high uncertainty and should not be used for country comparisons or rankings.

The labour force (LF) comprises all persons of working age who furnish the supply of labour for the production of goods and services during a specified time-reference period. It refers to the sum of all persons of working age who are employed and those who are unemployed. ILOSTAT points out that the series is harmonized to account for differences in national data and scope of coverage, collection, and tabulation methodologies as well as for other country-specific factors.

Figure 11 suggests that employment and the labour force show an upward moving trend pattern from 1991 to 2019. This development stopped in 2020. Due to the economic crisis in Lebanon and the covid pandemic the economic activities have fallen sharply and consequently also employment dropped. In 2021, the downturn has slowed. The development of the labour force follows that of employment, but the gap between these two series has been widening over time.

Forecasting requires correct handling of non-stationarity in a time series. One way that often succeeds in making non-stationary, particularly trending, time series stationary is to compute first differences between consecutive observations in logs.

Figure 11: Employment and labour force, 1991 to 2021



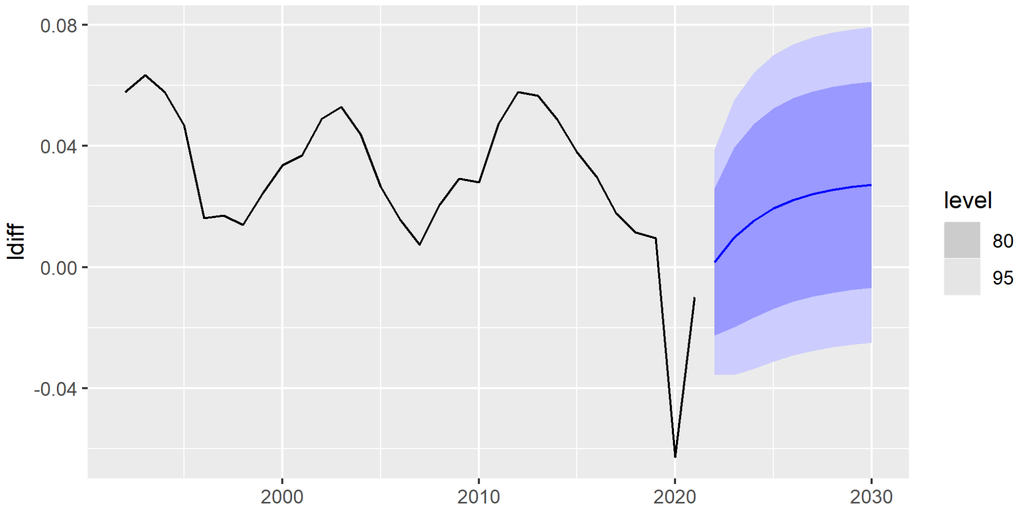
Source: IHS based on ILO modelled estimates and projections, November 2021.

We based our model selection process on such a differenced data set. Univariate time series models use only the previous values in the time series to predict future values. The description of autocorrelations in the data is a widely used approach in time series forecasting. Autoregressive integrated moving average models (ARIMA) are very often used for this purpose. The selection process of models with the best fit has been based on unit root tests and information criteria. We selected ARIMA(1,0,0) models to forecast employment and the labour force.

4.2.1 Employment

Figure 12 shows the growth rates of employment from 1992 to 2021 and the forecast from 2022 to 2030. The forecast has been generated with the ARIMA(1,0,0) model consisting of a point forecast and the relating confidence interval. After the severe downturn of 2020, the development in employment reached the lower turning point in 2021. Employment will resume growth in 2022 and it is expected to accelerate in the following years. However, the expansion of employment will remain below the average yearly growth of 3 percent of the past thirty years. The wide confidence interval points to the high uncertainty of the forecast.

Figure 12: Forecasting employment with an ARIMA(1,0,0) model

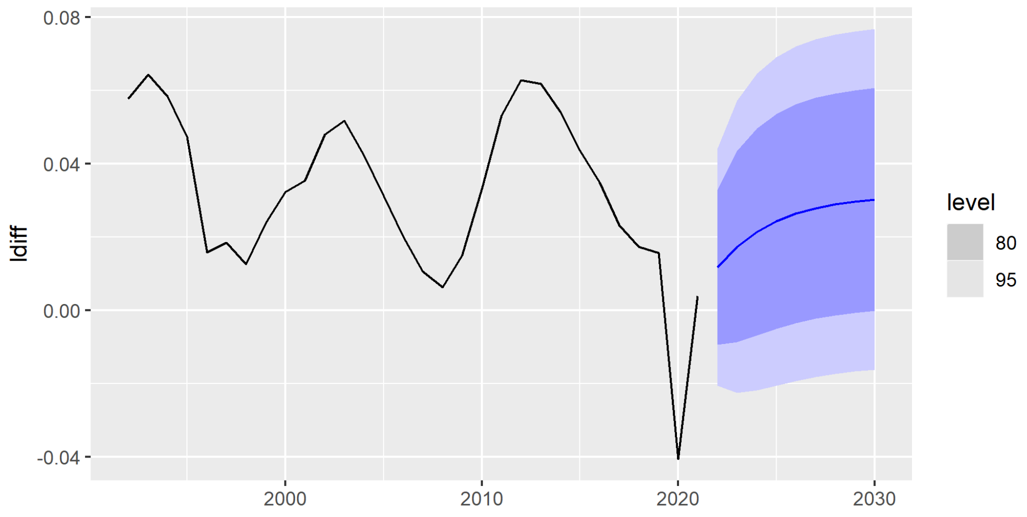


Source: ILO modelled estimates and projections, November 2021; IHS calculations and forecasts.

4.2.2 Labour force

When forecasting the labour force, we as well selected an ARIMA(1,0,0) model which is capable to produce a stable forecast. Figure 13 shows the forecasting results of the model with point forecasts and the relating confidence interval. After the considerable decline in 2020 labour force resumed growth in 2021. The point forecast suggests that the expansion of the labour force will continue in the forecasting horizon, however, below the yearly average growth rate of 3.2 percent of the past thirty years. The wide confidence interval points to the high uncertainty of the forecast.

Figure 13: Forecasting labour force with an ARIMA(1,0,0) model



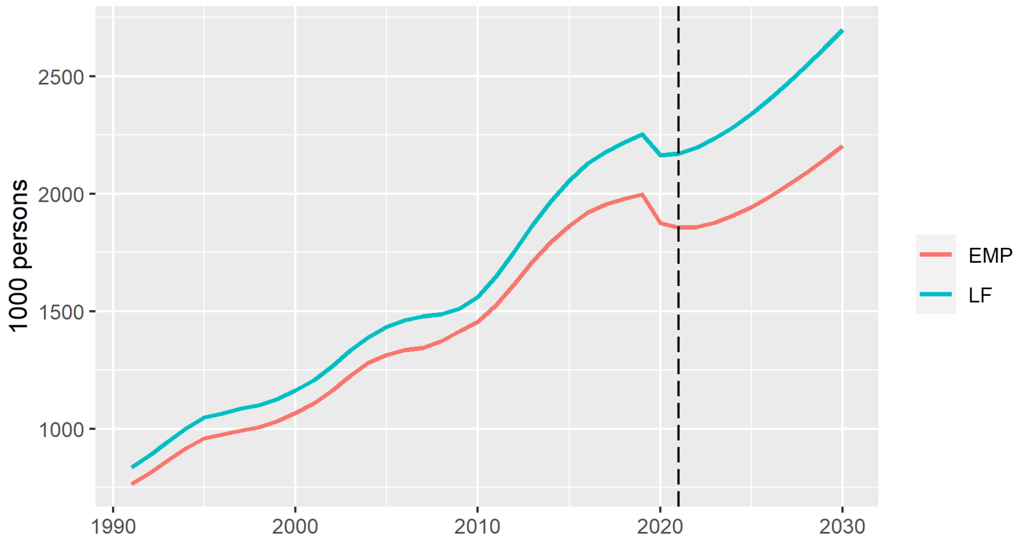
Source: ILO modelled estimates and projections, November 2021; IHS calculations and forecasts.

4.2.3 Imbalances

The forecasts of the two ARIMA models have been used to obtain employment and labour force data in levels from 2022 to 2030. Comparing employment with labour force points to imbalances in the labour market. Figure 14 shows the developments from 1991 to 2021 and the forecast from 2022 to 2030. There is evidence that the gap between labour demand and labour supply will continue to widen, which implies that imbalances will increase in the years to come.

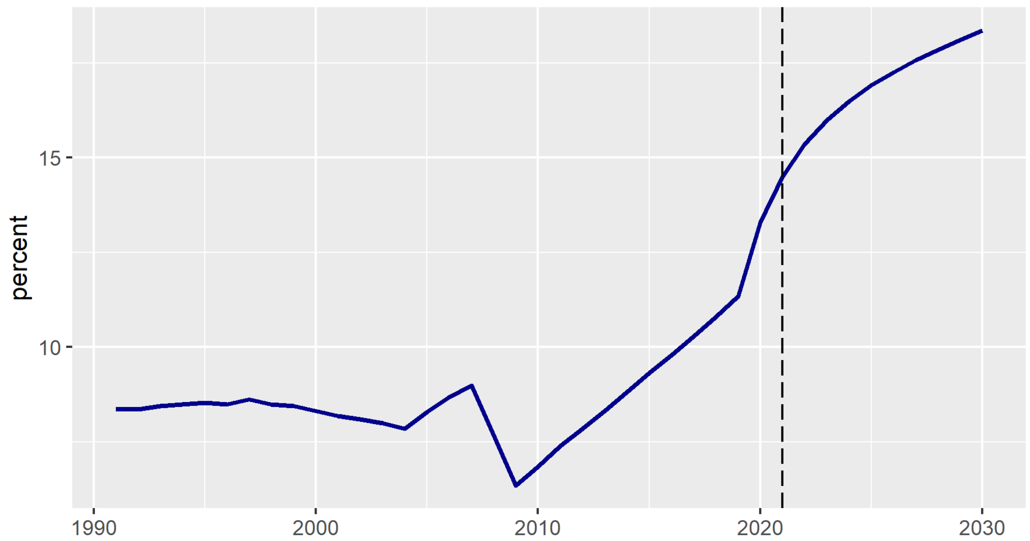
Figure 15 shows the development of the unemployment rate over time. From 1991 to 2009 the labour market improved gradually, when the unemployment rate fell from 8.5 to 6.4 percent. From 2010 onwards unemployment increased rapidly reaching 14.5 percent in 2021. If the development of the past few years continues, the unemployment rate will continue to rise.

Figure 14: Employment and labour force, observations and forecast



Source: ILO modelled estimates and projections, November 2021; IHS calculations and forecasts.

Figure 15: Unemployment rate, observations and forecast



Source: ILO modelled estimates and forecasts, November 2021; IHS calculations and forecasts.

4.2.4 Conclusions

We introduced univariate methods forecasting employment and labour force in Lebanon. The observations start in 1991 and end in 2021. The forecasting horizon ranges from 2022 to 2030. We based our model selection process on the differenced data sets.

ARIMA(1,0,0) models have been selected on basis of unit root and information criteria. The growth forecasts of the models have been used to obtain employment and labour force data in levels from 2022 to 2030.

From 1991 to 2009 the labour market improved gradually, when the unemployment rate fell from 8.5 to 6.4 percent. From 2010 onwards unemployment increased rapidly reaching 14.5 percent in 2021. In the coming years, the situation on the labour market will continue to deteriorate, because labour supply will grow faster than labour demand. Hence, if the growth pattern of the past continues, imbalances in the labour market will widen in the years to come.

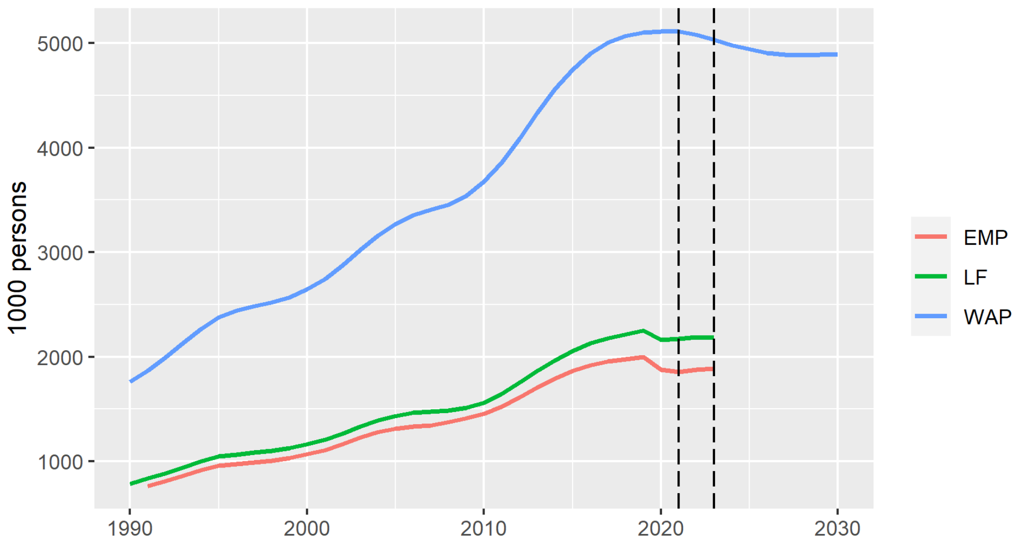
4.3 Applying forecasts from IHS, ILO and UN

Like in the section on “Forecasting with univariate time series models”, we attempt to forecast aggregate employment and labour force. However, this time – besides our own univariate time series forecasts – we also consider information provided by other forecasters, namely ILO and the United Nations (UN).

In the “ILO modelled estimates and projections” database, ILO provides short-time forecasts for major aggregates of the labour market. Total population estimates and projections are produced by the UN and are published in the "World Population Prospects: The 2019 Revision" (UN 2019). This is the official source for future demographic trends of one country. Besides other possibilities, the data set can be downloaded from the “ILO modelled estimates and projections” database.

Figure 16 shows the combined data set of ILO and the UN. It contains the development of working age population (WAP), the labour force (LF) and employment (EMP). The definition of the labour force and employment are already given in the “Forecasting with univariate time series models” section. The working age population (WAP) comprises persons of age 15+ who were living in the country during the reference period, regardless of residency status or citizenship.

Figure 16: Employment, labour force and working age population, 1990 to 2030

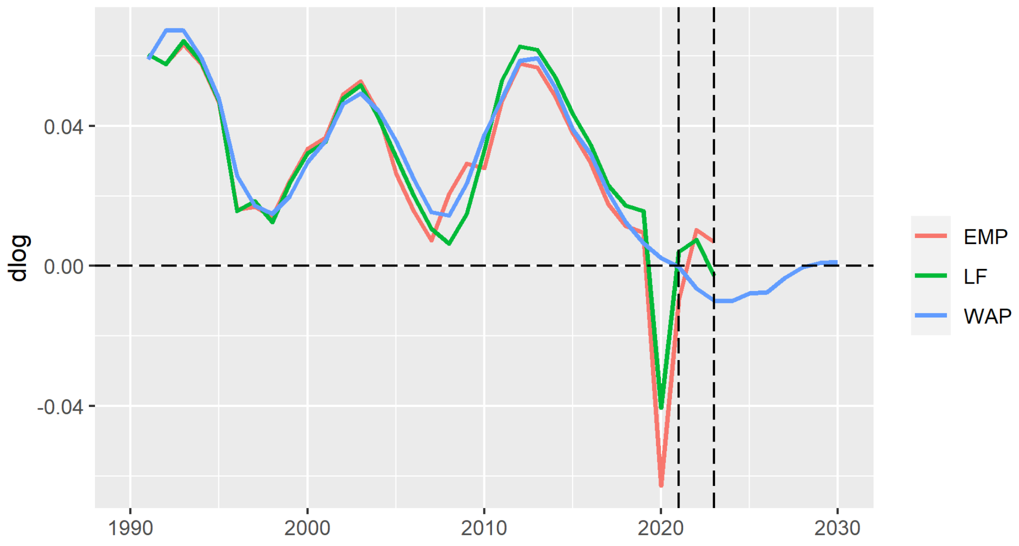


Source: IHS based on ILO modelled estimates and projections, November 2021.

For the years 2022 and 2023 ILO provides forecasts for employment and the labour force. From 2024 to 2030 we consider the official working age population prospects of the UN, which gives an indication for the future development of the labour force.

The calculated growth rates of the data set in Figure 17 show a synchronous growth pattern from 1990 to 2019. Hence, one could conjecture that this development will continue in the forecast period. It is therefore obvious to use growth rates of the working age population to forecast labour force, particularly from 2024 to 2030. However, we do not infer the demand for labour from the future development of the working age population. According to our own forecast we expect an expansion of employment in the years to come.

Figure 17: Growth of employment, labour force and working age population, 1991 to 2030



Source: ILO modelled estimates and projections, November 2021; IHS calculations.

4.3.1 Employment

The employment forecast consists of the ILO forecast for the years 2022 and 2023 and the IHS forecast for the years 2024 to 2030. The IHS forecast has been generated with an ARIMA(1,0,0) model as described in the "Forecasting with univariate time series models" section. The model is based on observations from 1992 to 2021.

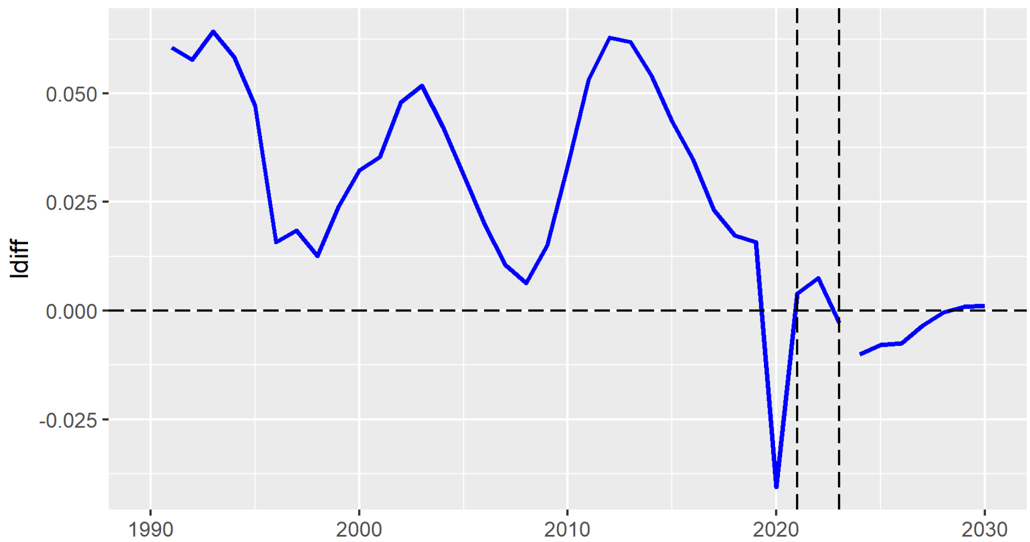
For the years 2022 and 2023 ILO foresees a slight increase in employment. In the IHS forecast from 2024 to 2030, this expansion is expected to accelerate. However, the growth of employment will remain below the average annual growth of 3 percent of the past thirty years.

4.3.2 Labour force

The labour force forecast consists of the ILO forecast for the years 2022 and 2023 and the development of the working age population of the UN for the years 2024 to 2030.

For the years 2022 and 2023 ILO foresees a slight increasing in labour force. The forecast, based on the development of the working age population, suggests a decline from 2024 to 2028 and a gradual rise in the following two years, as shown in Figure 18.

Figure 18: Labour force with ILO and UN forecasts



Source: ILO modelled estimates and projections, November 2021; IHS calculations.

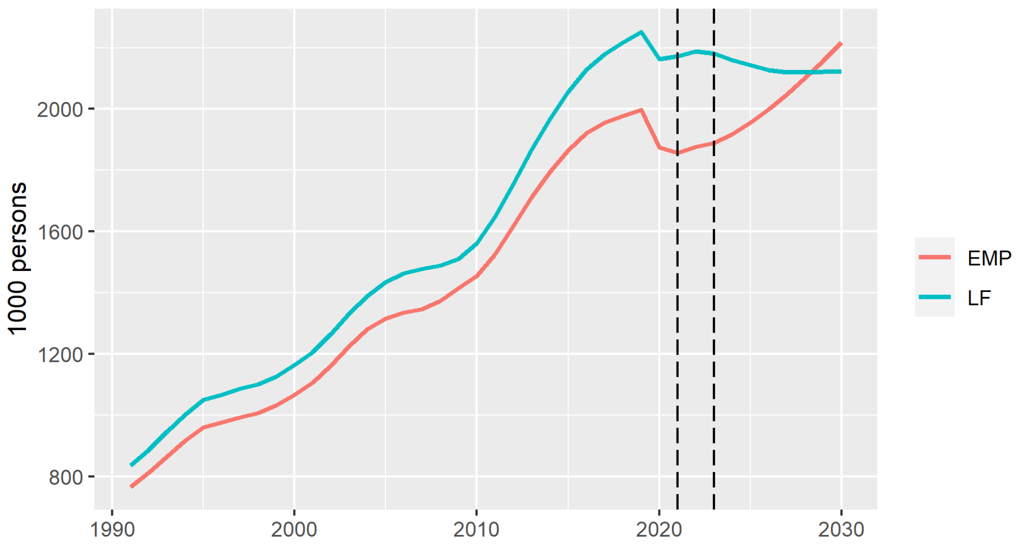
4.3.3 Imbalances

The development of employment and the labour force indicates imbalances in the labour market, but these imbalances have very different characteristics compared to the outcome of the section on "Forecasting with univariate time series models".

Figure 19 shows the observed developments from 1991 to 2021 and the forecast from 2022 to 2030. The gap between employment and the labour force, which has widened in recent years, will close in the forecast period. This is because employment will continue expanding and the labour force will be falling slightly. The consequence of such a development is a shortage of labour from 2029 onwards. The problematic that arises for one economy in such a situation is that on the one hand, fewer jobs need to be created, but on the other hand, fewer workers must produce more output to keep the economy going.

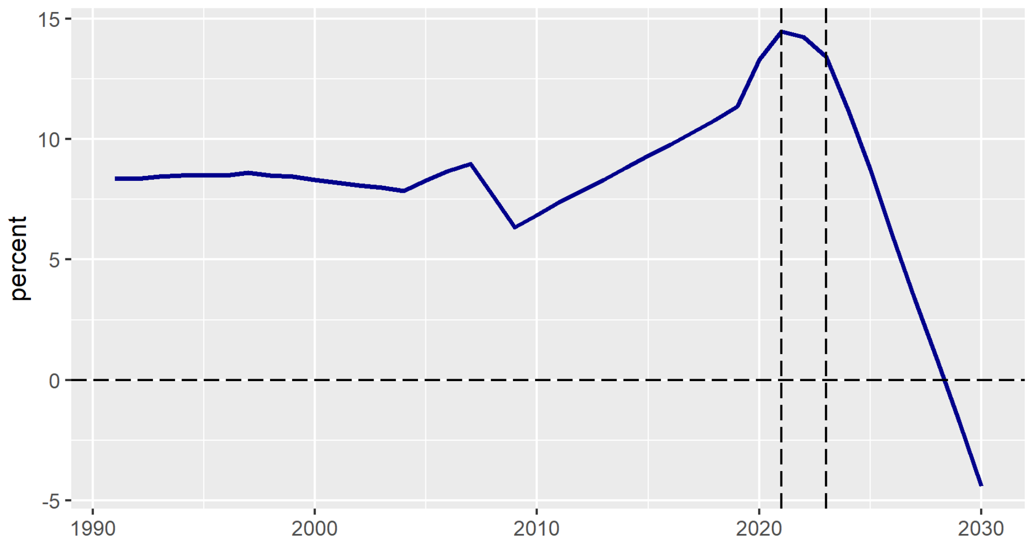
Figure 20 shows the development of the unemployment rate over time. From 1991 to 2009 the labour market improved gradually, when unemployment rate fell from 8.5 to 6.4 percent. From 2010 onwards unemployment increased rapidly reaching a peak of 14.5 percent in 2021. However, the upward moving trend of the past decade will be reversed to a downward moving trend in the forecast period. The unemployment rate will decrease from 14.2 percent in 2022 to 0.8 percent in 2028.

Figure 19: Employment and labour force, observations and forecast of IHS, ILO and UN



Source: ILO modelled estimates and projections, November 2021; IHS calculations and forecasts.

Figure 20: Unemployment rate, observations and forecast



Source: ILO modelled estimates and projections, November 2021; IHS calculations.

4.3.4 Conclusions

Like in the section on "Forecasting with univariate time series models" we attempt to forecast aggregate employment and labour force. However, this time – besides our own univariate time series forecasts – we also consider information provided by other forecasters, namely ILO and UN.

The employment forecast consists of the ILO forecast for the years 2022 and 2023 and the IHS forecast for the years 2024 to 2030, which has been generated with an ARIMA(1,0,0) model. The labour force forecast consists of the ILO forecast for the years 2022 and 2023, and for the years 2024 to 2030 we apply the development of the official UN forecast of the working age population.

The forecasting results suggest that the gap between employment and labour force, which has widened in recent years, will close in the forecast period. This is because employment is expanding, and the labour supply is falling slightly. The consequence of such a development is a shortage of labour at the end of the forecasting horizon. The problematic that arises for one economy is that, on the one hand, fewer jobs need to be created, but on the other hand, fewer workers must produce more output to keep the economy going.

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6 Appendices

6.1 Classifications

Classifications of industrial sectors, occupations and qualifications are important in running quantitative forecasting models. These classifications allow combining different data sources and set the level to which forecasts can generally be made. If existing classifications do not reflect the level of detail to which a forecast is to be done, alternative classifications would need to be determined.

6.1.1 Industrial activity (ISIC)

The International Standard Industrial Classification of all Economic Activities (ISIC) is the international reference classification of productive economic activities. Its main purpose is to provide a set of activity categories that can be utilized for the production of statistics according to such activities.

The major aims are:

- fostering international comparability of data,
- providing guidance for the development of national classifications
- and for promoting the development of sound national statistical systems.

The major groups of the ISIC classification are listed in Table A 1.

Table A 1: Major groups of ISIC Rev. 4.

Codes	Group names
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade, repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication

Codes	Group names
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organizations and bodies
X	Not elsewhere classified

Source: https://ilostat.ilo.org/resources/concepts-and-definitions/classification-economic-activities/

6.1.2 Occupations (ISCO)

The International Standard Classification of Occupations (ISCO) is a tool for organizing jobs into a clearly defined set of groups according to the tasks and duties undertaken in the job. Its main aims are to provide:

- a basis for the international reporting, comparison and exchange of statistical and administrative data about occupations;
- a model for the development of national and regional classifications of occupations; and
- a system that can be used directly in countries that have not developed their own national classifications.

The major groups of the ISCO classification are listed in Table A 2.

Table A 2: Major groups of ISCO-08

Codes	Group names
1	Managers
2	Professionals

Codes	Group names
3	Technicians and associate professionals
4	Clerical support workers
5	Services and sales workers
6	Skilled agricultural, forestry and fishery workers
7	Craft and related trades workers
8	Plant and machine operators and assemblers
9	Elementary occupations
x	Armed forces occupations

Source: https://www.ilo.org/public/english/bureau/stat/isco/

6.1.3 Education (ISCED)

Qualifications are the formal outcome of an assessment and validation process which is obtained when a competent body determines that an individual has achieved learning outcomes to given standards. The International Standard Classification of Education (ISCED) links every single qualification to several standard classification codes.

In labour market research, correlates of fields of education as well as mismatch between fields of education and occupation or industry are important topics.

The major groups of the ISCED classification are listed in Table A 3.

Table A 3: Major groups of ISCED-2011-Level

Codes	Group names
X	No schooling
0	Early childhood education
1	Primary education
2	Lower secondary education
3	Upper secondary education
4	Post-secondary non-tertiary education
5	Short-cycle tertiary education
6	Bachelor's or equivalent level
7	Master's or equivalent level

Codes	Group names
8	Doctoral or equivalent level
9	Not elsewhere classified

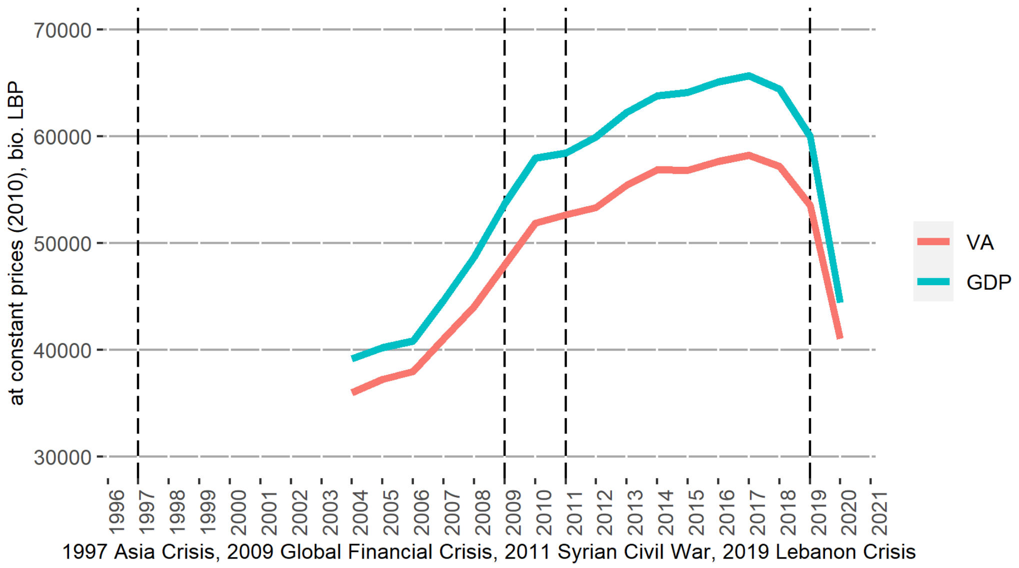
Source: https://www.surveycodings.org/education/classification-educational-qualifications/

6.2 Statistics for Lebanon

6.2.1 Gross domestic product

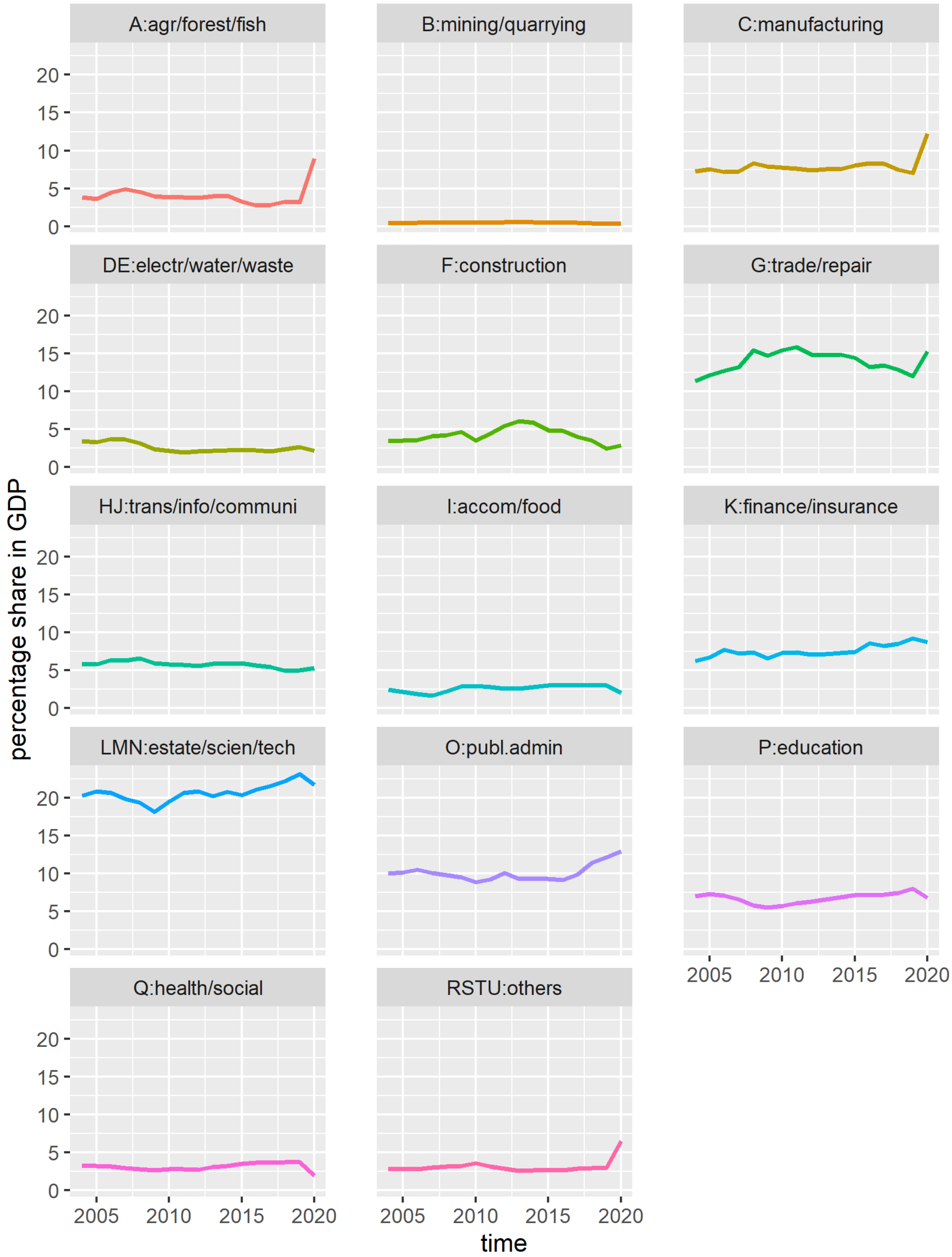
Gross domestic product The Central Administration of Statistics (CAS) Lebanon released the National Accounts estimates for the year 2019 with a revision of previous years estimates. The methodology used is based on the System of National Accounts (SNA) 2008. The economic activity is disaggregated by the rules of the International Standard Industrial Classification of All Economic Activities, Revision 4 (ISIC-4).

Figure A 1: Gross domestic product (GDP) and value added (VA), 2004 to 2020



Source: IHS based on CAS (2022).

Figure A 2: Value added by economic activity, 2004 to 2020



Source: IHS based on CAS (2022).

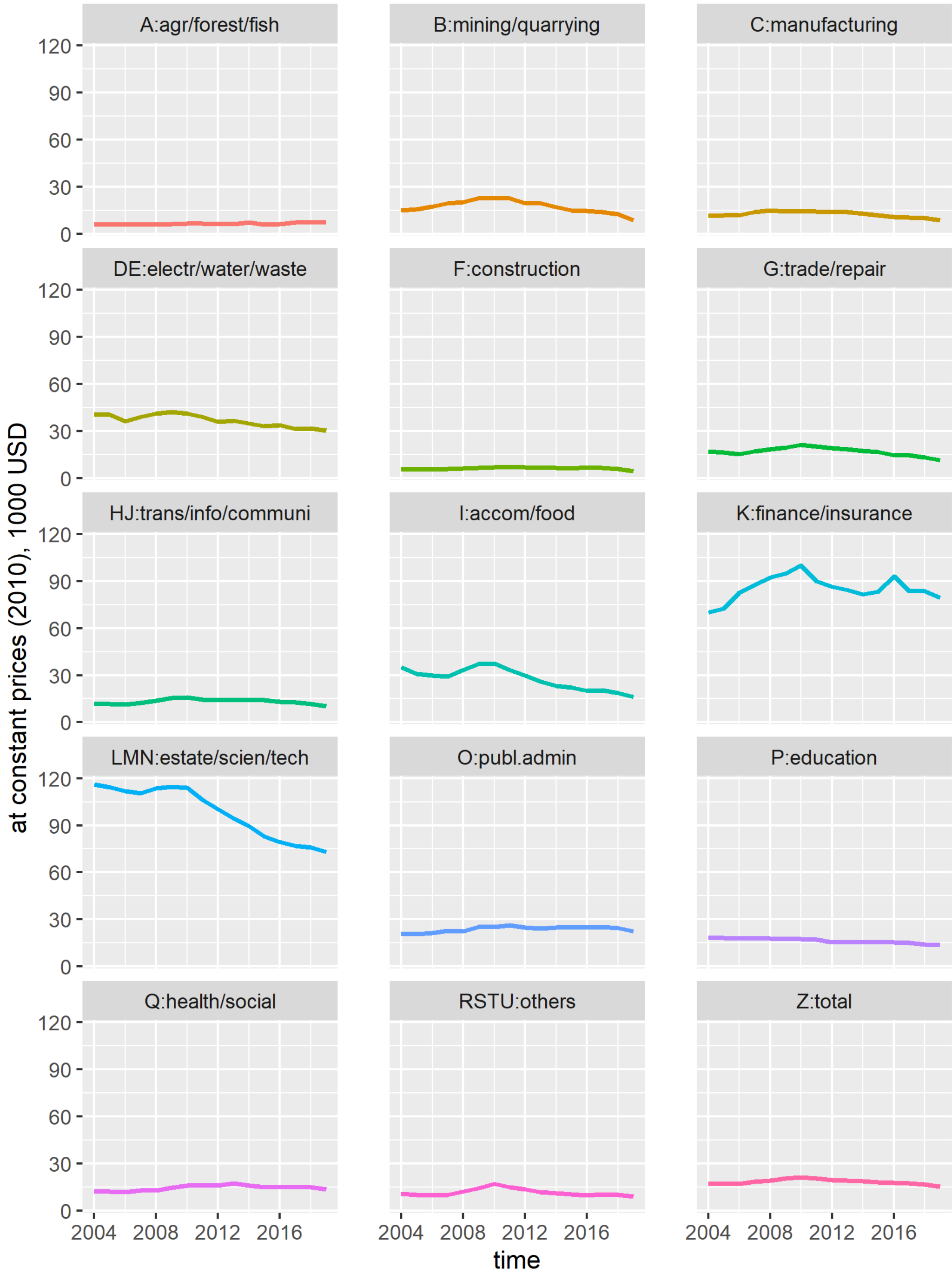
Table A 4: Gross domestic product by economic activity, at constant prices (2010), 2004 to 2019

	billion LBP			distribution in percent		
activity	2004	2010	2019	2004	2010	2019
GDP	39165	57954	59983	100.0	100.0	100.0
SUB	-1591	-1850	-2318	-1.9	-3.2	-3.0
TAX	4753	7916	8704	14.4	13.7	8.0
VAUE ADDED	35995	51888	53533	87.5	89.5	95.0
A:agr/forest/fish	2222	2238	2813	3.8	3.9	3.2
B:mining/quarrying	136	260	160	0.4	0.4	0.3
C:manufacturing	3153	4475	3375	7.2	7.7	7.1
DE:electr/water/waste	982	1240	1385	3.5	2.1	2.7
F:construction	1073	2028	1521	3.5	3.5	2.5
G:trade/repair	6005	8957	7747	11.4	15.5	12.1
HJ:trans/info/communi	2030	3361	3408	5.8	5.8	5.0
I:accom/food	1221	1709	1393	2.4	2.9	3.0
K:finance/insurance	2337	4213	5556	6.3	7.3	9.2
LMN:estate/scien/tech	8273	11297	12171	20.3	19.5	23.1
O:publ.admin	3749	5124	6035	10.0	8.8	12.1
P:education	3170	3324	4006	7.0	5.7	8.0
Q:health/social	1057	1595	2042	3.2	2.8	3.7
RSTU:others	1167	2067	1832	2.7	3.6	3.0

Source: IHS based on CAS (2022).

Employee productivity Employee productivity is the amount of real gross domestic product (GDP) produced by one person employed. National currency values have been converted to constant USD.

Figure A 3: Employee productivity by economic activity, 2004 to 2020



Source: IHS based on CAS (2022) and ILO modelled estimates and projections, Nov. 2021.

Table A 5: Employee productivity by economic activity, 2004 to 2019, at constant prices (1000 USD)

activity	2004	2010	2019
A:agr/forest/fish	6.2	6.4	7.2
B:mining/quarrying	14.9	22.8	8.7
C:manufacturing	11.4	14.8	8.5
DE:electr/water/waste	40.3	41.1	30.4
F:construction	5.3	7.0	4.3
G:trade/repair	16.9	21.1	11.5
HJ:trans/info/communi	11.8	16.0	10.3
I:accom/food	35.2	37.7	16.2
K:finance/insurance	70.0	99.9	79.4
LMN:estate/scien/tech	115.9	114.1	73.0
O:publ.admin	20.7	25.4	22.5
P:education	18.7	17.6	13.7
Q:health/social	12.2	16.1	13.6
RSTU:others	10.9	17.3	9.2
Z:total	17.3	21.5	15.6

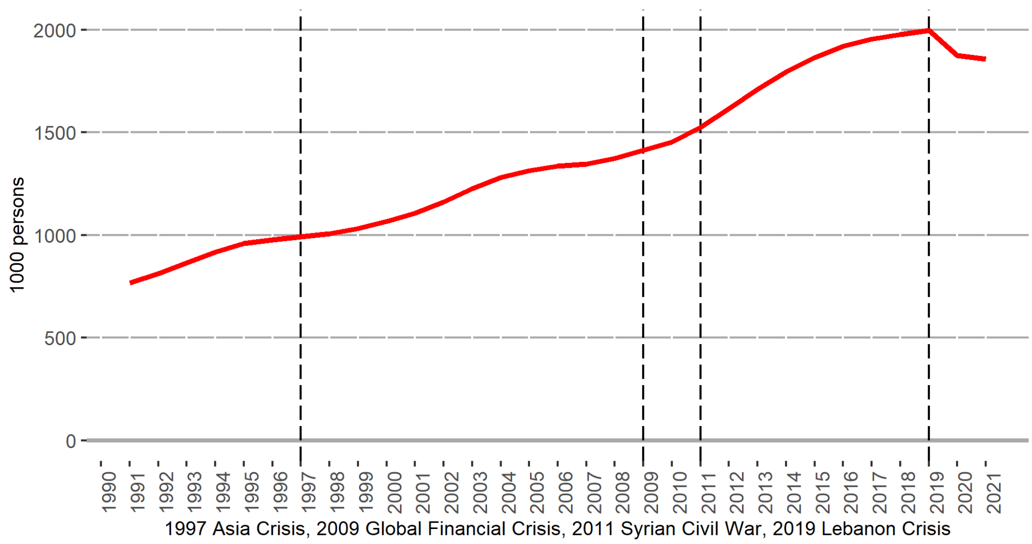
Source: IHS based on CAS (2022) and ILO modelled estimates and projections, Nov. 2021.

6.2.2 Labour demand

Regarding labour supply, there are two sources of data. First, the ILO modelled estimates and projections database (ILOEST, 2021), which provides estimated time series from 1990 to 2021 and projections for the years 2023 and 2024 for major aggregates. The second source is the Labour Force and Household Living Conditions Survey 2018-2019 Lebanon, downloadable from the ILO labour force statistics database (ILOLFS, 2022). Time series from the ILO modelled estimates and projections database may differ from the ILO labour force statistics database.

The employed comprise all persons of working age who, during a specified brief period, were in one of the following categories: a) paid employment (whether at work or with a job but on leave); or b) self-employment (whether at work or with an enterprise but not at work). The series is part of the ILO modelled estimates and is harmonized to account for differences in national data and scope of coverage, collection and tabulation methodologies as well as for other country-specific factors.

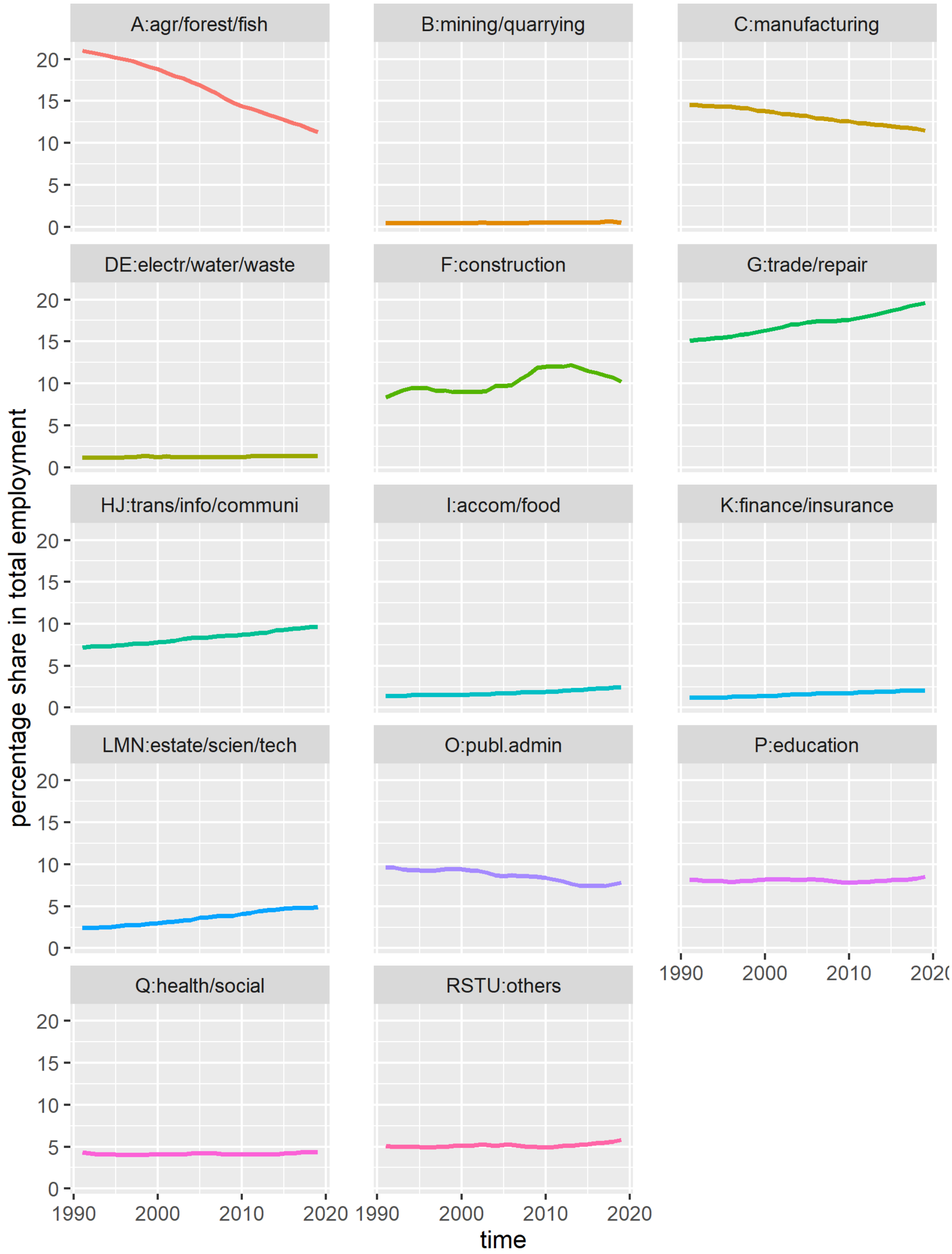
Figure A 4: Employment, 1991 to 2021



Source: IHS based on ILO modelled estimates and projections, November 2021.

Employment by economic activity Data is disaggregated by economic activity, which refers to the main activity of the establishment in which a person worked during the reference period. The economic activity is disaggregated by the rules of the International Standard Industrial Classification of All Economic Activities, Revision 4 (ISIC-4).

Figure A 5: Employment by economic activity, 1991 to 2019



Source: IHS based on ILO modelled estimates and projections, November 2021.

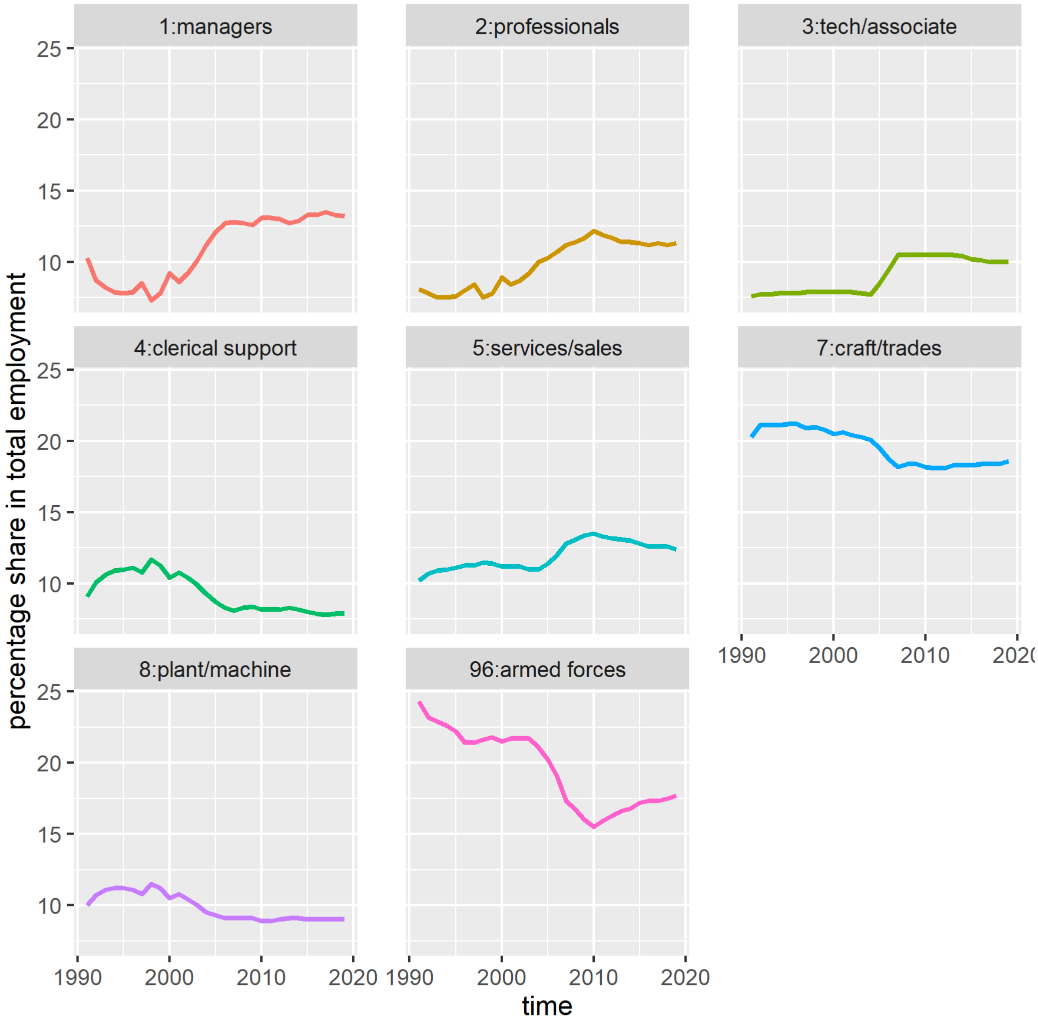
Table A 6: Employment by economic activity, 1991 to 2019 (1000 persons)

activity	1991	2000	2010	2019
A:agr/forest/fish	158	211	231	258
B:mining/quarrying	3	5	8	12
C:manufacturing	109	155	201	262
DE:electr/water/waste	9	14	20	30
F:construction	62	101	192	232
G:trade/repair	114	182	281	446
HJ:trans/info/communi	55	88	139	220
I:accom/food	11	17	30	57
K:finance/insurance	9	16	28	46
LMN:estate/scien/tech	18	33	66	110
O:publ.admin	73	105	134	178
P:education	61	92	126	194
Q:health/social	32	46	66	99
RSTU:others	38	57	79	132
Z:total	752	1122	1601	2277

Source: IHS based on ILO modelled estimates and projections, November 2021.

Employment by occupation Employment data is disaggregated by occupation according to the latest version of the International Standard Classification of Occupations (ISCO-08).

Figure A 6: Employment distribution by occupation, 1991 to 2019



Source: IHS based on ILO modelled estimates and projections, Nov. 2021.
Note: For the occupations group 6: Skilled agricultural, forestry and fishery workers no ILO modelled estimates are available.

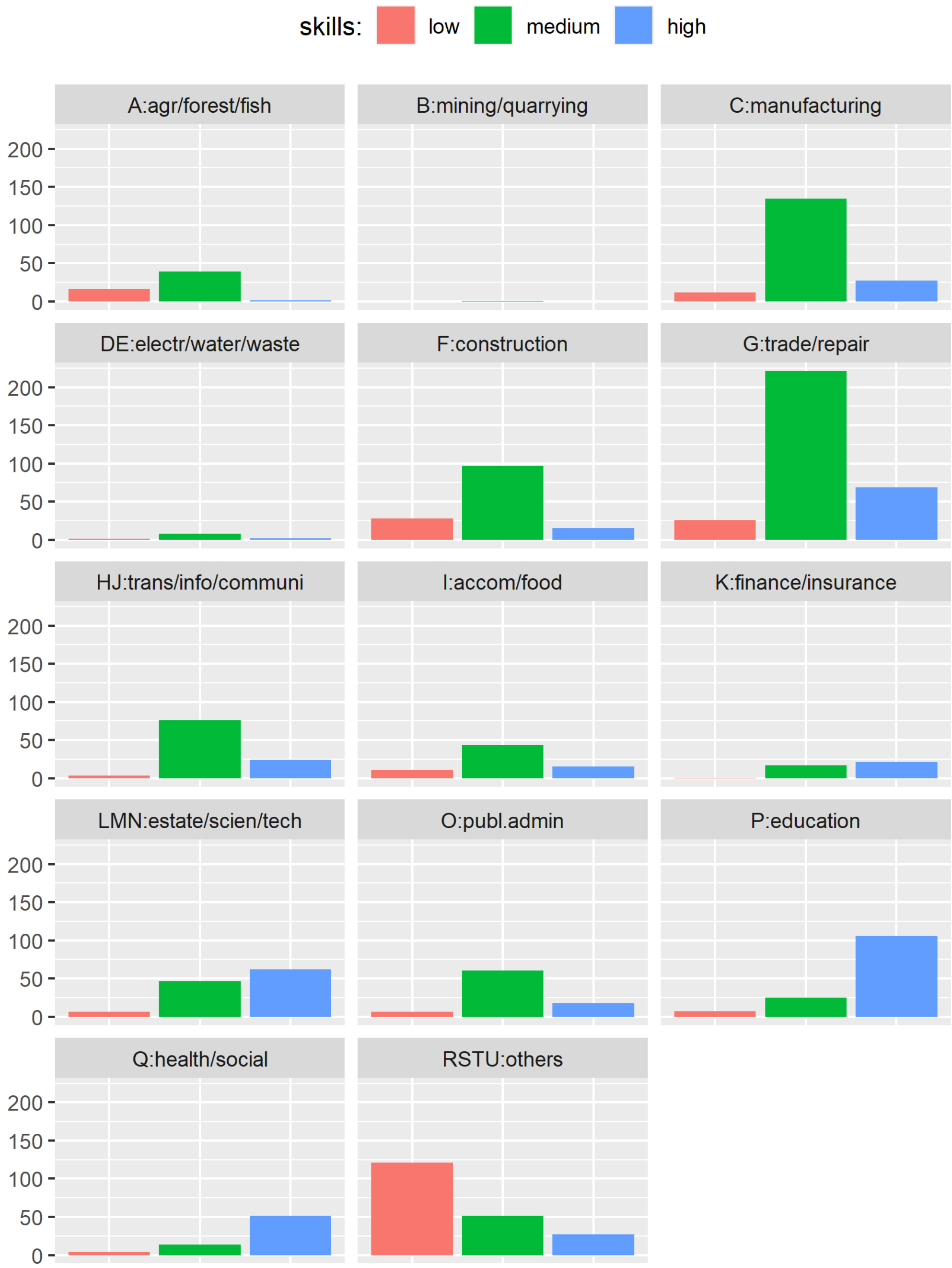
Table A 7: Employment by occupation, 1991 to 2019 (1000 persons)

occupations	1991	2000	2010	2019
1:managers	78	103	209	300
2:professionals	61	99	195	257
3:tech/associate	57	89	168	227
4:clerical support	68	117	131	179
5:services/sales	77	126	215	283
7:craft/trades	153	230	291	422
8:plant/machine	75	117	143	205
96:armed forces	183	241	249	403
99:total	752	1122	1601	2277

Source: IHS based on ILO modelled estimates and projections, Nov. 2021.
Note: For the occupations group 6: Skilled agricultural, forestry and fishery workers no ILOSTAT modelled estimates are available.

Employment by skills and economic activity Employment is disaggregated by economic activity and skills, according to the latest versions of the International Standard Industrial Classification of All Economic Activities (ISIC) and International Standard Classification of Occupations (ISCO), respectively.

Figure A 7: Employment by skills and economic activity, 2019 (1000 persons)



Source: IHS based on ILO labour force statistics, February 2022.

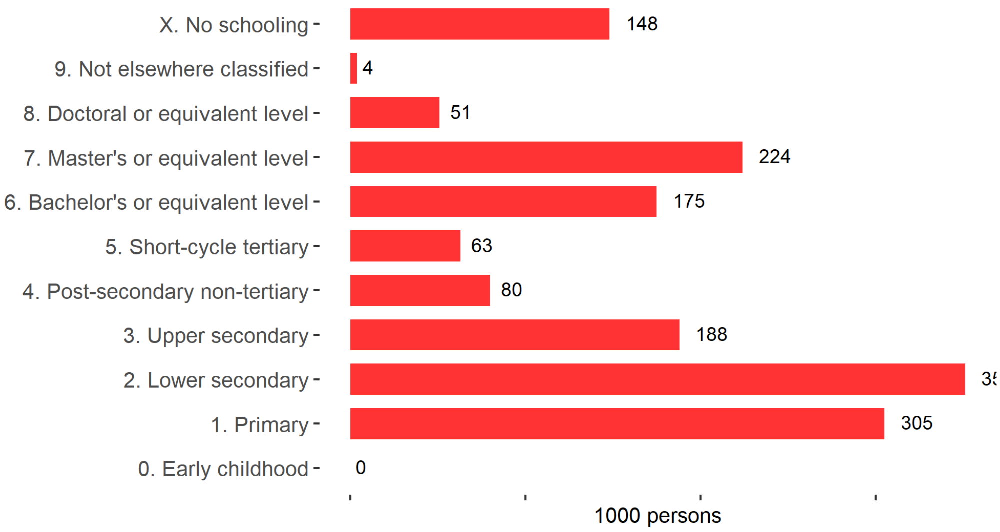
Table A 8: Employment by skills and economic activity, 2019 (1000 persons)

activity/skills	low	medium	high	total
A:agr/forest/fish	16	39	2	57
B:mining/quarrying	…	0	0	0
C:manufacturing	11	135	27	173
DE:electr/water/waste	1	8	2	12
F:construction	28	97	16	141
G:trade/repair	25	221	69	315
HJ:trans/info/communi	3	76	24	104
I:accom/food	11	43	15	69
K:finance/insurance	1	17	21	39
LMN:estate/scien/tech	6	47	62	115
O:publ.admin	6	61	17	84
P:education	7	25	106	137
Q:health/social	4	14	51	70
RSTU:others	121	52	27	200
Z:total	242	834	439	1515

Source: IHS based on ILO labour force statistics, February 2022.
Note: 75 thousand persons are not classified.

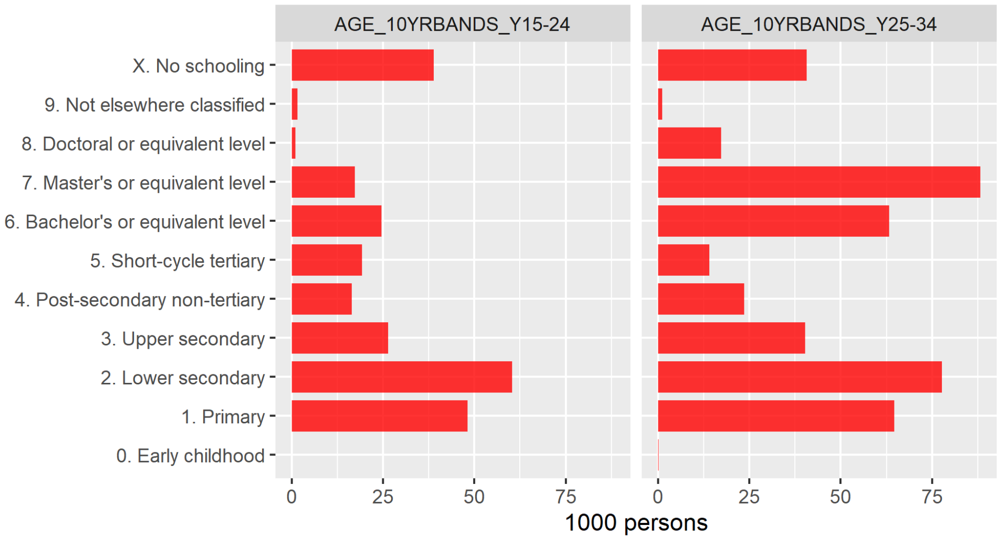
Employment by level of education refers to the highest level of education completed, classified according to the International Standard Classification of Education (ISCED).

Figure A 8: Employment by level of education, 2019



Source: IHS based on ILO labour force statistics, February 2022.

Figure A 9: Employment by level of education of age 15 to 34, 2019



Source: IHS based on ILO labour force statistics, February 2022.

Table A 9: Employment by level of education, 2019 (1000 Persons)

age	education	2019
TOTAL	0. Early childhood	0
	1. Primary	305
	2. Lower secondary	351
	3. Upper secondary	188
	4. Post-secondary non-tertiary	80
	5. Short-cycle tertiary	63
	6. Bachelor's or equivalent level	175
	7. Master's or equivalent level	224
	8. Doctoral or equivalent level	51
	9. Not elsewhere classified	4
	X. No schooling	148
	Total	1590
Y15-24	1. Primary	48
	2. Lower secondary	60
	3. Upper secondary	26
	4. Post-secondary non-tertiary	16
	5. Short-cycle tertiary	19
	6. Bachelor's or equivalent level	25
	7. Master's or equivalent level	17
	8. Doctoral or equivalent level	1
	9. Not elsewhere classified	2
	X. No schooling	39

age	education	2019
	Total	254
Y25-34	0. Early childhood	0
	1. Primary	65
	2. Lower secondary	78
	3. Upper secondary	40
	4. Post-secondary non-tertiary	24
	5. Short-cycle tertiary	14
	6. Bachelor's or equivalent level	63
	7. Master's or equivalent level	88
	8. Doctoral or equivalent level	17
	9. Not elsewhere classified	1
	X. No schooling	41
	Total	431

Source: IHS based on ILO labour force statistics, February 2022.

6.2.3 Labour supply

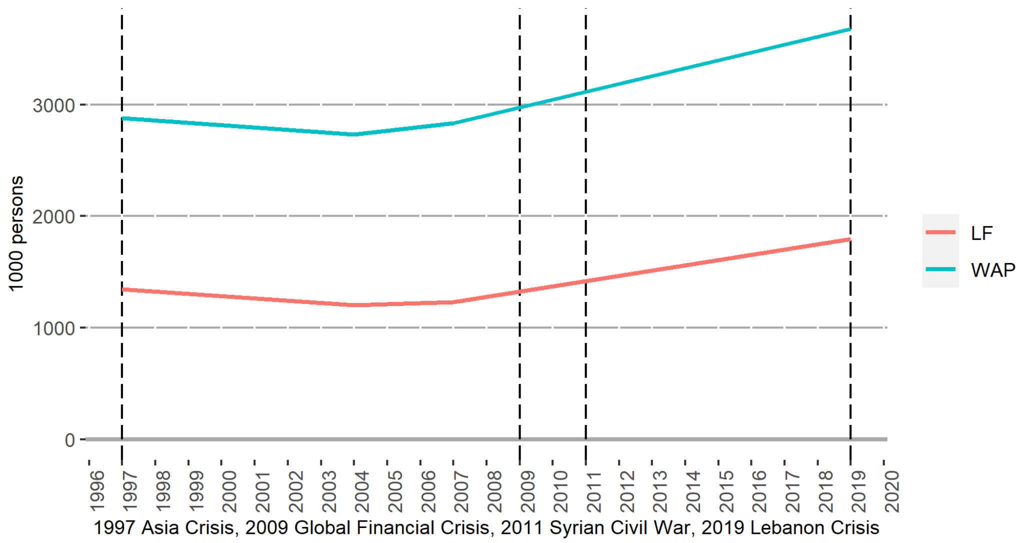
Regarding labour supply, there are two sources of data. First, the ILO modelled estimates and projections database, which provides estimated time series from 1990 to 2021 and projections for the years 2023 and 2024 for major aggregates. The second source is the Labour Force and Household Living Conditions Survey 2018-2019 Lebanon, downloadable from the ILO labour force statistics database. Time series from the ILO modelled estimates and projections database may differ from the ILO labour force statistics database.

The working age population (WAP) is commonly defined as persons aged 15 years and older. Data are disaggregated by level of education, which refers to the highest level of education completed, classified according to the International Standard Classification of Education (ISCED).

The labour force (LF) comprises all persons of working age who furnish the supply of labour for the production of goods and services during a specified time-reference period. It refers to the sum of all persons of working age who are employed and those who are unemployed. Data are disaggregated by level of education, which refers to the highest level of education completed, classified according to the International Standard Classification of Education (ISCED).

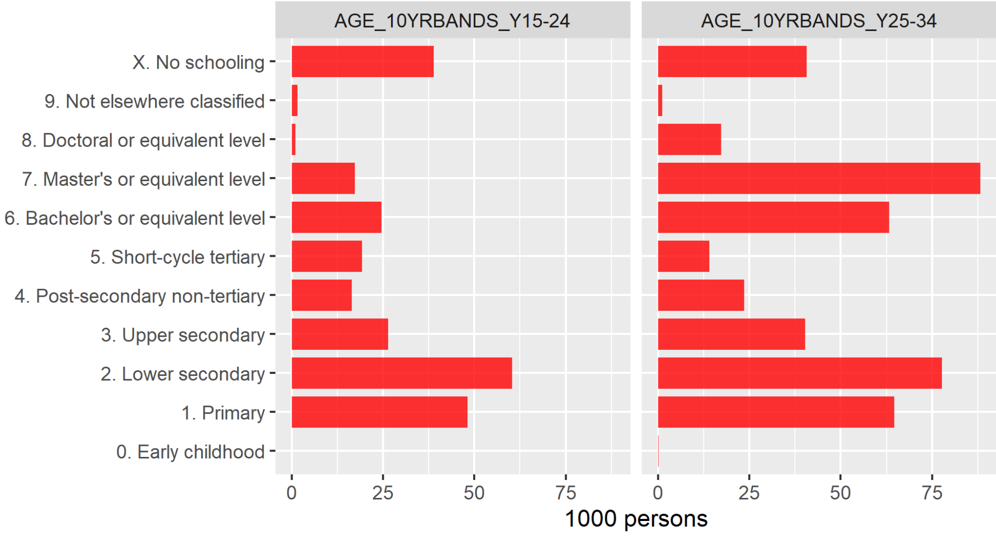
The participation rate (PR) is the number of people working or actively seeking work as a percent of the working age population. The formula for PR is the sum of all workers who are employed or actively seeking employment divided by the total working-age population (WAP).

Figure A 10: Working age population (WAP) and labour force (LF), 1991 to 2019



Source: IHS based on ILO labour force statistics, February 2022.

Figure A 11: Working age population (WAP) and labour force (LF) of age 15 to 34, 1990 to 2019



Source: IHS based on ILO labour force statistics, February 2022.

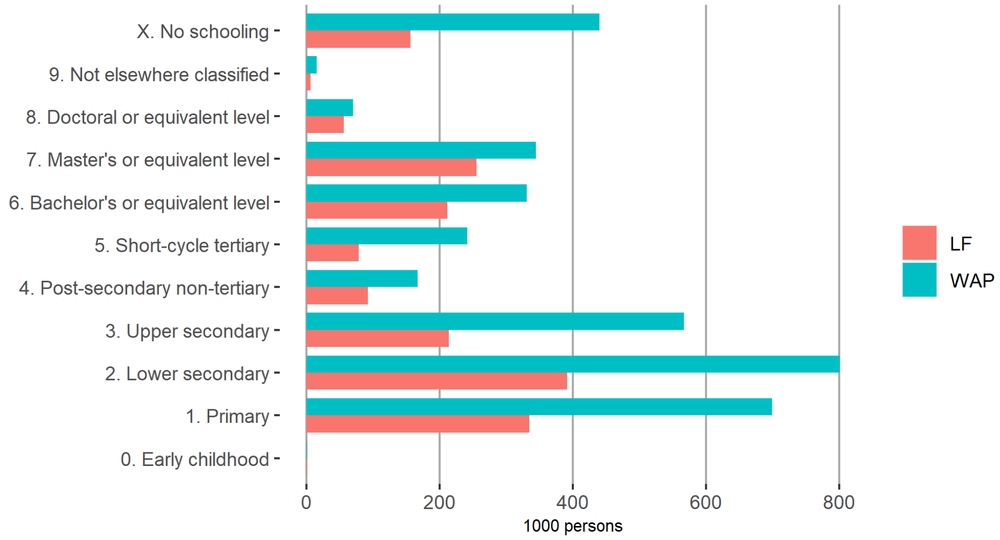
Table A 10: Working age population WAP), labour force (LF) and participation rate (PR), 1997 to 2019 (1000 persons)

indicator	age	1997	2004	2007	2019
WAP	TOTAL	2878	2732	2831	3677
	Y15-19	440	373	364	405
	Y20-24	397	373	368	441
	Y25-29	361	298	306	377
	Y30-34	319	276	277	322
LF	TOTAL	1347	1203	1229	1794
	Y15-19	95	62	59	81
	Y20-24	175	168	166	250
	Y25-29	227	183	199	268
	Y30-34	194	166	176	225
PR	TOTAL	47	44	43	49
	Y15-19	22	17	16	20
	Y20-24	44	45	45	57
	Y25-29	63	61	65	71
	Y30-34	61	60	63	70

Source: IHS based on ILO labour force statistics, February 2022.

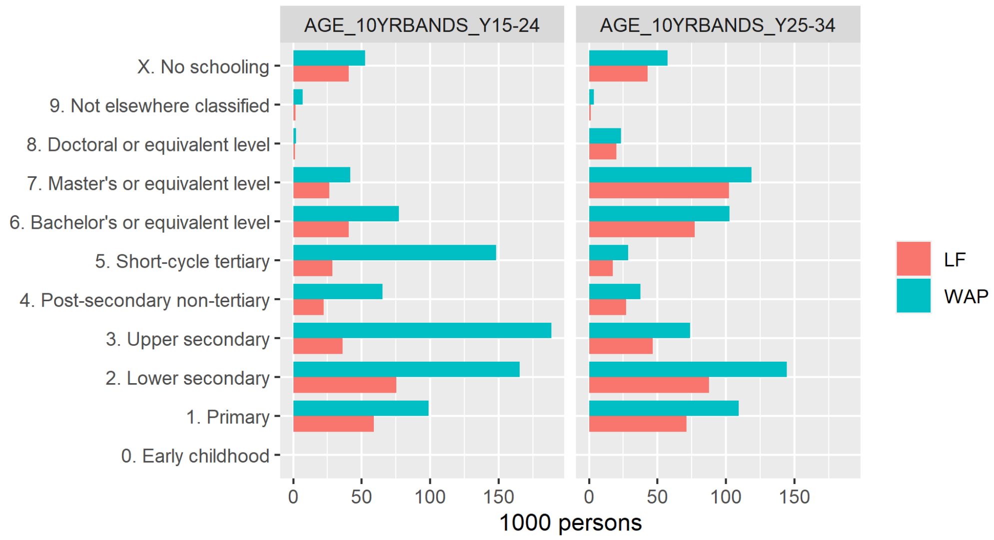
Education The disaggregation by level of education, refers to the highest level of education completed, classified according to the International Standard Classification of Education (ISCED).

Figure A 12: Working age population (WAP) and labour force (LF) by level of education, 2019



Source: IHS based on ILO labour force statistics, February 2022.

Figure A 13: Working age population (WAP) and labour force (LF) by level of education of age 15 to 34, 2019



Source: IHS based on ILO labour force statistics, February 2022.

Table A 11: Working age population (WAP), labour force (LF) and participation rate (PR) by level of education of age 15+ and 15 to 34, 2019 (1000 persons)

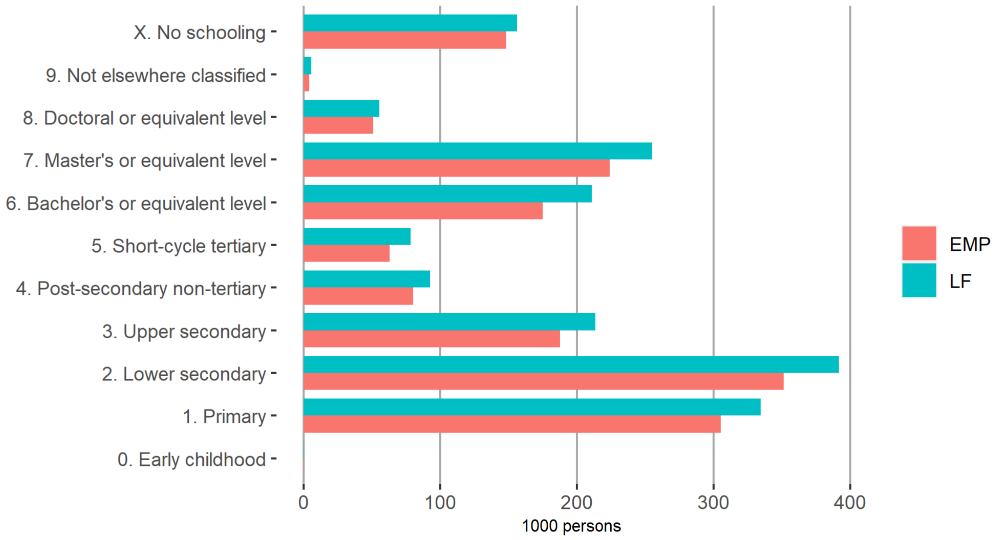
age	education	WAP	LF	PR
Y15+	0. Early childhood	0.8	0.5	57.1
	1. Primary	699.5	334.5	47.8
	2. Lower secondary	800.4	391.7	48.9
	3. Upper secondary	566.9	213.3	37.6
	4. Post-secondary non-tertiary	166.5	92.4	55.5
	5. Short-cycle tertiary	241.5	78.3	32.4
	6. Bachelor's or equivalent level	331.0	211.0	63.8
	7. Master's or equivalent level	344.7	255.0	74.0
	8. Doctoral or equivalent level	69.9	55.7	79.6
	9. Not elsewhere classified	15.5	5.6	36.2
	X. No schooling	440.3	156.0	35.4
	Z. Total	3677.1	1794.0	48.8
Y15-24	0. Early childhood	0.0	NA	NA
	1. Primary	98.8	58.7	59.4
	2. Lower secondary	165.1	75.3	45.6
	3. Upper secondary	188.5	36.1	19.2
	4. Post-secondary non-tertiary	65.3	22.2	34.0
	5. Short-cycle tertiary	148.2	28.7	19.3
	6. Bachelor's or equivalent level	77.3	40.5	52.4
	7. Master's or equivalent level	41.5	26.3	63.4
	8. Doctoral or equivalent level	1.9	1.4	77.1
	9. Not elsewhere classified	6.7	1.8	26.9

age	education	WAP	LF	PR
	X. No schooling	52.5	40.4	76.9
	Z. Total	846.0	331.4	39.2
Y25-34	0. Early childhood	0.1	0.1	70.6
	1. Primary	109.2	71.0	65.0
	2. Lower secondary	144.5	87.6	60.6
	3. Upper secondary	73.9	46.4	62.8
	4. Post-secondary non-tertiary	37.4	27.1	72.6
	5. Short-cycle tertiary	28.4	17.4	61.3
	6. Bachelor's or equivalent level	102.4	77.0	75.3
	7. Master's or equivalent level	118.7	102.1	86.0
	8. Doctoral or equivalent level	23.5	19.9	84.7
	9. Not elsewhere classified	3.5	1.4	41.2
	X. No schooling	57.3	42.9	74.8
	Z. Total	698.9	493.0	70.5

Source: IHS based on ILO labour force statistics, February 2022.

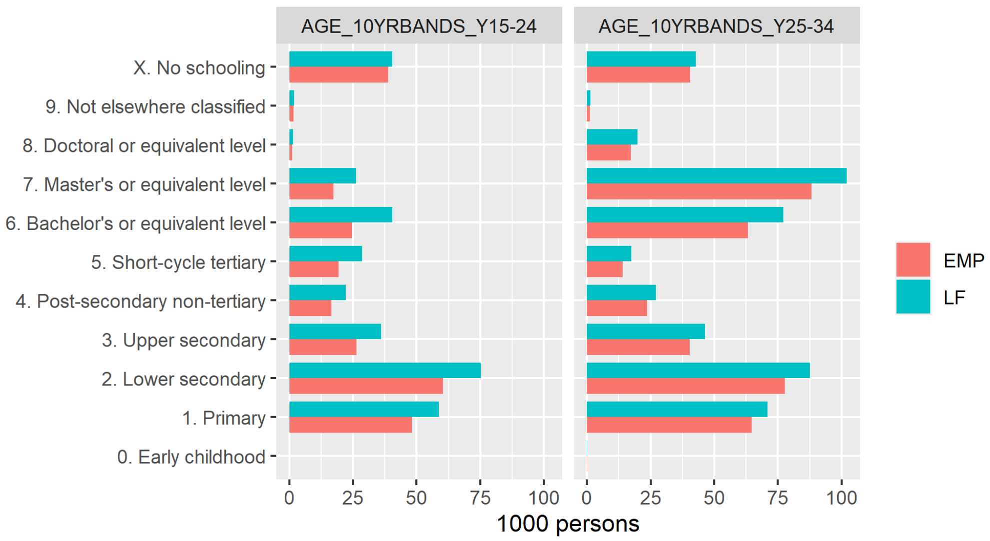
6.2.4 Imbalances

Figure A 14: Comparison of labour force (LF) and employment (EMP) by level of education, 2019



Source: IHS based on ILO labour force statistics, February 2022.

Figure A 15: Comparison of labour force (LF) and employment (EMP) by level of education of age 15 to 34, 2019



Source: IHS based on ILO labour force statistics, February 2022.

Table A 12: Labour force (LF), employment (EMP), unemployment (UNE) and unemployment rate (UNR) by level of education (1000 Persons and %)

age	education	LF	EMP	UNE	UNR
Y15+	0. Early childhood	0.5	0.4	0.0	0.0
	1. Primary	334.5	305.3	29.2	8.7
	2. Lower secondary	391.7	351.1	40.6	10.4
	3. Upper secondary	213.3	187.6	25.7	12.0
	4. Post-secondary non-tertiary	92.4	80.3	12.1	13.1
	5. Short-cycle tertiary	78.3	63.1	15.2	19.4
	6. Bachelor's or equivalent level	211.0	174.8	36.2	17.2
	7. Master's or equivalent level	255.0	224.1	30.9	12.1
	8. Doctoral or equivalent level	55.7	51.0	4.6	8.3
	9. Not elsewhere classified	5.6	4.3	1.3	23.2
	X. No schooling	156	148.3	7.7	4.9
	Z. Total	1794.0	1590.4	203.6	11.3
Y15-24	1. Primary	58.7	48.1	10.6	18.1
	2. Lower secondary	75.3	60.3	15.0	19.9
	3. Upper secondary	36.1	26.4	9.7	26.8
	4. Post-secondary non-tertiary	22.2	16.5	5.7	25.7
	5. Short-cycle tertiary	28.7	19.3	9.4	32.8
	6. Bachelor's or equivalent level	40.5	24.6	15.8	39.0
	7. Master's or equivalent level	26.3	17.3	8.9	33.9
	8. Doctoral or equivalent level	1.4	1.0	0.5	34.5
	9. Not elsewhere classified	1.8	1.6	0.2	11.0

age	education	LF	EMP	UNE	UNR
	X. No schooling	40.4	38.9	1.5	3.7
	Z. Total	331.4	254.1	77.4	23.4
Y25-34	0. Early childhood	0.1	0.1	0.0	0.0
	1. Primary	71.0	64.7	6.3	8.9
	2. Lower secondary	87.6	77.7	9.9	11.3
	3. Upper secondary	46.4	40.3	6.2	13.3
	4. Post-secondary non-tertiary	27.1	23.6	3.5	12.9
	5. Short-cycle tertiary	17.4	14.1	3.3	19.0
	6. Bachelor's or equivalent level	77	63.3	13.8	17.9
	7. Master's or equivalent level	102.1	88.3	13.8	13.5
	8. Doctoral or equivalent level	19.9	17.3	2.6	13.1
	9. Not elsewhere classified	1.4	1.1	0.3	21.0
	X. No schooling	42.9	40.7	2.2	5.1
	Z. Total	493.0	431.1	61.9	12.6

Source: IHS based on ILO labour force statistics, February 2022.