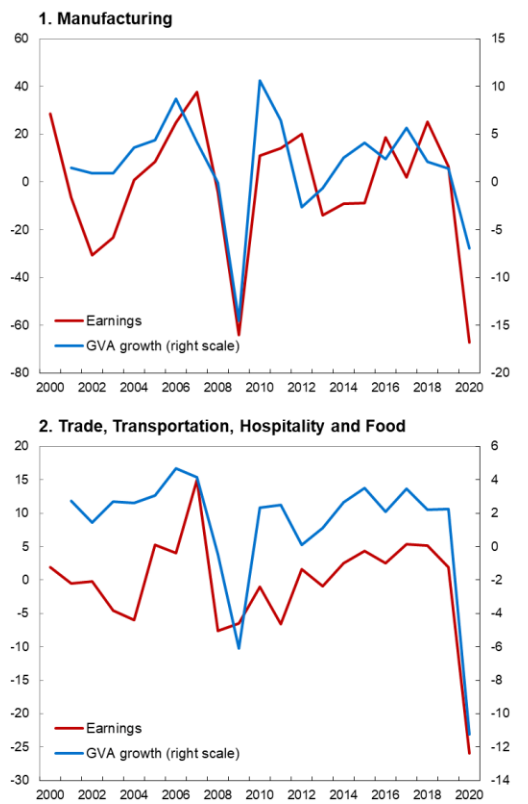
Online Annex 3.1. Expected Earnings and Sectoral GVA Growth Projection

This annex describes the methodology used to assess expected earnings and forecast gross value added (GVA) growth at the sectoral level.[1]

Data Description

Expected earnings are taken from the Institutional Brokers Estimate System (IBES) database, which provides institutional brokers' forecasts of earnings for listed firms from the current year to five years in the future. Sector-level expected earnings are computed by aggregating all available European firms in IBES (more than 9,000 in total), using market capital weighted medians (to avoid outliers). Sectoral GVA is annualized from quarterly GVA (as for most countries, only the 2020 quarterly outturns are available) from Eurostat and national statistical agencies. To ensure a sufficiently large sample of firms and maintain representativeness at the sectoral level, we forecast sectoral earnings for Advanced Europe and Emerging Market Europe as two country groups.[2]

Annex Figure 3.1.1. Historical Correlation Between Earnings and GVA Growth
(Euro; percentage points in right scale)



Sources: Eurostat; Haver Analytical; Refinitiv Eikon; IBES; and IMF staff calculations.
Note: Earnings are detrended using HP filtering. Panel 1 shows manufacturing sector, and Panel 2 shows trade, transportation, accommodation and food service sector. The sample covers firms from Advanced European countries.

To account for pre-pandemic differences in earnings, annualized expected earnings growth is presented relative to the reported 2019 level (as shown in Figure 3.4). Hard-hit sectors, such as accommodation and food services, reported negative earnings in 2020.

Empirical Strategy

Previous studies find that earnings of firms have a good predictive power for macroeconomic variables such as output and inflation (for instance, see de Bondt, 2009). As exemplified by manufacturing and contact-intensive sectors, the constructed sectoral earnings (HP filter detrended) are closely correlated with GVA growth (Annex Figure 3.1.1).

To pin down the relationship between GVA and firm earnings at the sectoral level, GVA growth is regressed on earnings for each of the 11 sectors, s, in the sample.

$$Growth_{st} = \alpha_s + \beta_s Earnings_{st} + \epsilon_{st}$$

[1] See Miguet, Salas and Zhou (forthcoming) for full analysis.

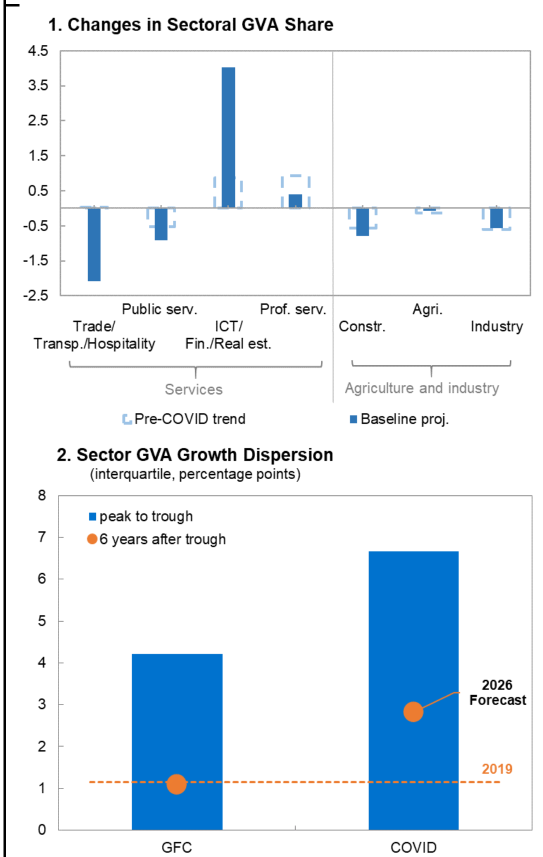
[2] Countries with relatively large number of listed firms—namely, CHE, DEU, ESP, FRA, GBR, ITA, NOR, POL, ROU, RUS, SWE, and TUR, are also estimated individually.

Using the estimated historical relationship, we project the medium-term path of GVA growth based on the five-year IBES earnings forecasts (for a similar approach, see Gormsen and Koijen, 2020).

Multi-Speed Sectoral Recovery

The divergence in sectoral earnings prospects (Figure 3.4) suggests a multi-speed recovery across sectors. Contact-intensive sectors, such as trade/transport/hospitality are expected to lag in the recovery, losing GVA share (Annex Figure 3.1.2, Panel 1). Meanwhile, less-contact intensive sectors are likely to go back on the pre-COVID-19 track. Some sectors such as ICT—which benefit from the pandemic-triggered technology advancement—are expected to gain significant share, especially when compared to their pre-COVID trend. Over the medium-term, the dispersion in growth rates across sectors may remain notably above the pre-COVID level based on the analysis (Annex Figure 3.1.2, Panel 2).

Annex Figure 3.1.2. Diverging Recovery Across Sectors
(Percentage points, 2026 relative to 2019)



Sources: Refinitiv Eikon; IBES; IMF, *World Economic Outlook*; and IMF staff calculations.
Note: Panel 1 shows weighted averages of European countries. Pre-COVID trend is calculated from changes during 2004-2019. Panel 2 shows GVA growth rates, annualized relative to pre-crisis level.

These findings withstand several robustness checks: in particular, using option-implied expected rate of return one-year ahead instead of IBES earnings forecasts (following Pagano, Wagner and Zechner, 2020), and using nominal GVA forecasts from Fitch Analysis.

References

De Bondt, G.J., 2009. “Predictive content of the stock market for output revisited.” *Applied Economics Letters*, 16(13), pp.1289-1294.

Gormsen, N.J. and R.S. Koijen. 2020. “Coronavirus: Impact on stock prices and growth expectations.” *The Review of Asset Pricing Studies*, 10(4), pp.574-597.

Miguet, F., J. Salas, and J. Zhou. Forthcoming. “Expected Earnings and Sectoral Growth.” IMF Working Paper.

Pagano, M., C. Wagner, and J. Zechner. 2020. “Disaster resilience and asset prices.” CEPR Working Paper.

Online Annex 3.2. Sectoral Employment Projections

This annex describes (i) the methodology used to understand how sectoral employment could evolve in response to the expected divergence in gross value-added growth across sectors; and (ii) how alternative scenarios for assessing labor reallocation needs are constructed.

Data Description

Quarterly sectoral GVA and employment (employed persons) data are obtained from Eurostat and national statistical agencies. These data are available for 10 Nomenclature of Economic Activities (NACE) sectors, namely agriculture (A); mining, utility, and energy (B, D, E); manufacturing (C); construction (F); trade, transportation, food and accommodation (G, H, I); information and communication (J); finance and insurance (K); real estate (L); professionals and administrative supports (M, N); public services (O, P, Q); and arts, entertainment and other services (R, S, T, U).[3] In terms of skill levels, sectors are grouped into low-, medium-, and high-skilled based on their skill distribution of occupations.[4]

Empirical Strategy: Sectoral Analysis of Okun's Law[5]

Estimating Okun's law-type relationship (Okun, 1962) at the sectoral level can shed light on the cross-sector heterogeneity in employment responses to output fluctuations. Factors behind different employment dynamics across sectors include differences in the production function, skill composition, institutional factors, and policy support (Goto and Bürgi, 2021).

As employment and output could depend on their past values, a dynamic empirical specification (Chapter 3 of the April 2010 *World Economic Outlook*) of the Okun's relationship is estimated at a country-sector level for the 20-year period prior to the COVID-19 crisis:[6]

$$\log \widetilde{Empl}_{qsc} = \alpha_{sc} + \sum_{j=q-2}^{q} \beta_{jsc} \log \widetilde{GVA}_{jsc} + \sum_{j=q-2}^{q-1} \gamma_{jsc} \log \widetilde{Empl}_{jsc} + \eta_{qsc}$$

where $Empl_{qsc}$ is employment in quarter q, in sector s, and country c; and GVA_{qsc} is gross value added. $\log \tilde{X}$ denotes the cyclical component of the HP-filtered logarithm of X.

Under this dynamic specification, the sectoral relationship between output and employment is reflected in the following dynamic coefficient:

$$\beta_{sc}^{dyn} = \frac{\sum_{j=q-2}^{q} \beta_{jsc}}{1 - \sum_{j=q-2}^{q-1} \gamma_{jsc}}$$

While there are some differences in sectoral employment responses across countries, results are broadly robust in terms of cross-sector relativity. Long-term employment elasticities are high in manufacturing and construction activities, as well as trade and

[3] The countries included in the analysis are AUT, BEL, BGR, CHE, CYP, CZE, DEU, DNK, EST, ESP, FIN, FRA, GBR, IRL, HRV, HUN, ITA, LTU, LVA, LUX, MLT, NLD, NOR, POL, PRT, SWE, SVK, SVN, and ROU.

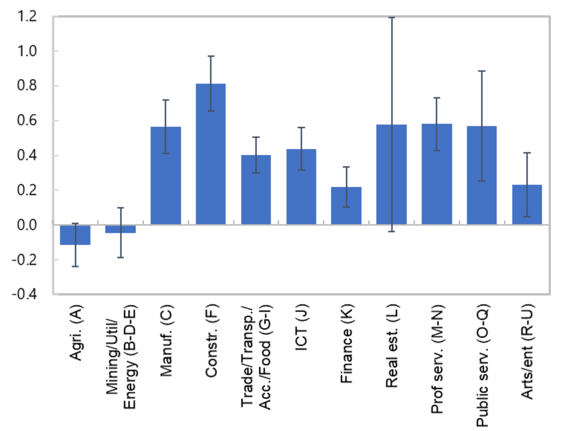
[4] Skill levels are determined according to the following classification of occupations in the International Standard Classification of Occupations (ISCO): managers and professionals (ISCO 1 and 2) are shown as high skill; laborers/elementary (ISCO 9) as low skill; and other skilled workers (ISCO 3–8, 10) as medium skill.

[5] For further details on the methodology and sectoral Okun's results, see Ando and others (forthcoming).

[6] As the unprecedented policy support during the pandemic could have temporarily changed labor market dynamics, the period of analysis is restricted to the years prior to the COVID-19 crisis, namely 1999-2019.

other hospitality-related services (Annex Figure 3.2.1).[7]

Annex Figure 3.2.1. Dynamic Sectoral Okun's Coefficients



Sources: Ando and others (forthcoming).
Note: Pooled regressions covering all European countries in the sample. Error bars represent a 90-percent confidence interval.

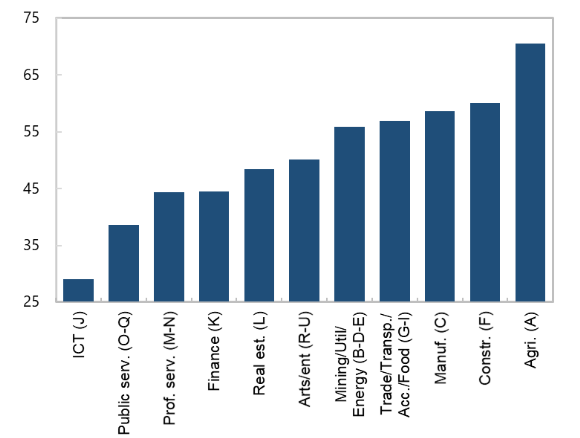
Alternative Scenarios for Assessing Labor Reallocation Needs

Given high uncertainty around baseline sectoral GVA projections, two sensitivity analyses are conducted.

First, sectoral demand shocks could be larger than envisaged in the baseline, owing to permanent changes in consumer and worker preferences away from in-person towards at-home or online activities (Ice and others, 2021). In this alternative scenario, additional changes in final demand are mapped to sectoral GVA through country-specific input-output tables, and additional resulting changes in sectoral employment are then calculated.

Second, the COVID-19 crisis could recast output-employment relationship through the potential acceleration of automation (McKinsey, 2021). To consider this potential change, assumptions are made on how occupations could be computerized and their associated probabilities (Frey and Osborne, 2017). Subsequently, the share of jobs in each of the sectors to be replaced by robots and/or computers are computed based on occupation-specific probabilities of being computerized and the occupational composition by sector (Annex Figure 3.2.2).

Annex Figure 3.2.2. Probability of Being Computerized
(Percent)



Sources: O*NET; Eurostat; Frey and Osborne (2017); and IMF staff calculations.

References

Ando, S., R. Balakrishnan, E. Cohn-Bech, B. Gruss, J. Hallaert, C. Jin, L.F. Jirasavetakul, K. Kirabaeva, N. Klein, A. Lariau, L.Q. Liu, D. Malacrino, H. Qu, and A. Solovyeva. Forthcoming. "Labor Market Fallout of the COVID-19 Crisis and Associated Policy Options." IMF Departmental Paper, International Monetary Fund, Washington DC.

Frey, C.B., and M.A. Osborne. 2017. "The Future of Employment: How Susceptible Are Jobs to Computerisation." *Technological Forecasting and Social Change*, 114, pp.254-280.

[7] Results are robust to several specification changes, including using first difference and percentage change.

Goto, E. and C. Bürgi. 2021. “Sectoral Okun’s Law and Cross-Country Cyclical Differences.” *Economic Modelling*, 94, pp.91-103.

International Monetary Fund. 2010. *World Economic Outlook—Chapter 3: Unemployment Dynamics During Recessions and Recoveries: Okun’s Law and Beyond*. Washington DC, April.

Lindsey I., M. J. Rieley, and S. Rinde. 2021. “Employment projections in a pandemic environment.” *Monthly Labor Review*, U.S. Bureau of Labor Statistics, February.

McKinsey Global Institute. 2021. *The Future of Work after COVID-19*. February.

Okun, A. 1962. “Potential GNP: Its Measurement and Significance.” *Proceeding of the Business and Economic Statistics Section*. American Statistical Association, pp.98-103.

Online Annex 3.3. Labor Market Dynamics and Reallocation

This annex describes the methodology used to assess labor market dynamics associated with reallocation.

Data Description and Reallocation Index

Consistent with the literature (e.g., David, 2020), reallocation is measured by the dispersion in sectoral stock returns. The advantage of stock return dispersion is that stock prices are available in real time, forward-looking and are less affected by short-term fluctuations than alternative measures of reallocation (Loungani and others, 1990).

Sector stock returns are based on FTSE indices for around 40 sectors (Industry Classification Benchmark (ICB) classification), across 22 countries in Europe.[8] Dispersion is proxied by the standard deviation of return rates across sectors, weighted by market capitalization at daily frequency and then collapsed to quarterly frequency (excluding outliers).

Real wage is measured by compensation per employee, deflated by CPI inflation.

Empirical Strategy

The analysis has two steps.

- Step 1: As labor market dynamics and reallocation are both affected by business cycles, we first purge the change in labor market dynamics that can be explained by standard macro relationships. For employment, Okun's Law is used; and for wage, Phillips Curve is used. The regression is estimated country-by-country.

$$\Delta \ln E_{it} \sim \text{GDP growth, 2 lags of } (\Delta \ln E_{it}, \text{GDP growth})$$

$$\Delta \ln W_{it} \sim \text{unempl. gap, 2 lags of } \Delta \ln W_{it}, \text{unempl. gap}$$

- Step 2: The residualized employment and wage growth—which represent the part that remains to be explained by factors other than standard macro variables—is regressed on the reallocation index in a panel regression with country fixed effects, for a horizon up to 20 quarters.

$$\epsilon_{it+h} = \alpha_i + \beta_h \times Reallocation_{it} + \delta_{it+h},$$
$$h = 0,1,\ldots,\ 20$$

Besides the baseline results shown in Figure 3.6, several sets of robustness regressions are estimated: 1) different number of lags in step 1, 2) allowing the coefficients in the Okun and Philipps curve to differ across normal and recession years; 3) purging movements in stock returns from the portion that can be explained by the Capital Asset Price Model (CAPM) before calculating sectoral dispersion to control for differences in the response of various sectors to aggregate shocks; 4) controlling for global uncertainty; 5) excluding COVID-19 crisis quarters. None of these change the results qualitatively.

References

David, J.M., 2020. *Will the Covid-19 Pandemic Lead to Job Reallocation and Persistent Unemployment?. Chicago Fed Letter*, pp.1-6.

Loungani, P., M. Rush, and W. Tave. 1990. "Stock market dispersion and unemployment." *Journal of Monetary Economics*, 25(3), pp.367-388.

[8] The countries included in the analysis are AUT, BEL, CHE, CZE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, HUN, IRL, ISR, ITA, NLD, NOR, POL, PRT, RUS, SWE, and TUR, and the sample period starts from 1995Q1 or earliest quarter available for each country.

Online Annex 3.4. Reallocation-Enhancing Policies in Response to the COVID-19 Crisis

Most countries in Europe have already started to or are planning to implement policies that would facilitate the reallocation of workers in the aftermath of the COVID-19 crisis and prepare the workforce to adapt better in a rapidly changing technological environment. While it is too early to evaluate the design and effectiveness of these policies, this annex presents some key trends and highlights some initiatives, based on a survey of reallocation-enhancing policy measures in European countries.

European countries are resorting to a wide range of measures to facilitate the structural transformation that may be triggered by the COVID-19 crisis, as well as the transition to a greener and smarter economy, as outlined in Recovery and Resilience Plans and other policy announcements.

As the recovery strengthens, policies are slowly shifting away from providing lifelines to households and firms, towards facilitating the reallocation of resources and easing adjustment costs. These include: i) hiring subsidies and wage-loss insurance, ii) incentives to invest, iii) ALMP: training and reskilling, iv) ALMP: education, v) ALMP: job search, vi) other policies (e.g., labor and product market reforms, insolvency regimes).

Among those, hiring subsidies are among the more popular tools, so far implemented by 35 of the 50 European countries, in some cases targeting vulnerable groups (e.g., youth workers in France and the U.K.) and/or vulnerable sectors.

Investment incentives have been also put in place, focusing mainly on green technology, digitalization, healthcare, and R&D. For instance, the Climate Fund in Switzerland, and the "Future Package" in Germany aim to foster green growth and accelerate digitalization.

Within ALMPs, emphasis has been put on reskilling workers with a view towards future needs. Examples include enhancing digital preparedness and technologies in training (Czech Republic, Italy), identifying future occupations (Turkey), skill and training needs (Slovenia), and expanding training programs to support the digital and green transition (Spain). Broader education curriculum reforms (Slovak Republic) aim to create a more adaptable workforce with the knowledge and skills to meet the evolving needs of businesses and the public sector.

Job search support in Slovenia and Italy comprise career planning services, improving employment centers' information systems, and strengthening coordination between regional and national systems.

In addition to strengthening ALMP and education policies, several countries intend to pursue other policies to enhance factor reallocation. Insolvency reforms to facilitate early restructuring and ease access to judicial reorganization are taking place in a number of countries, including Belgium, Estonia, France, Hungary, Latvia, Malta, the Slovak Republic, and Spain.

The proper implementation of these initiatives, careful monitoring and evaluation could yield important lessons for policymakers to continue supporting reallocation and strengthen the recovery.