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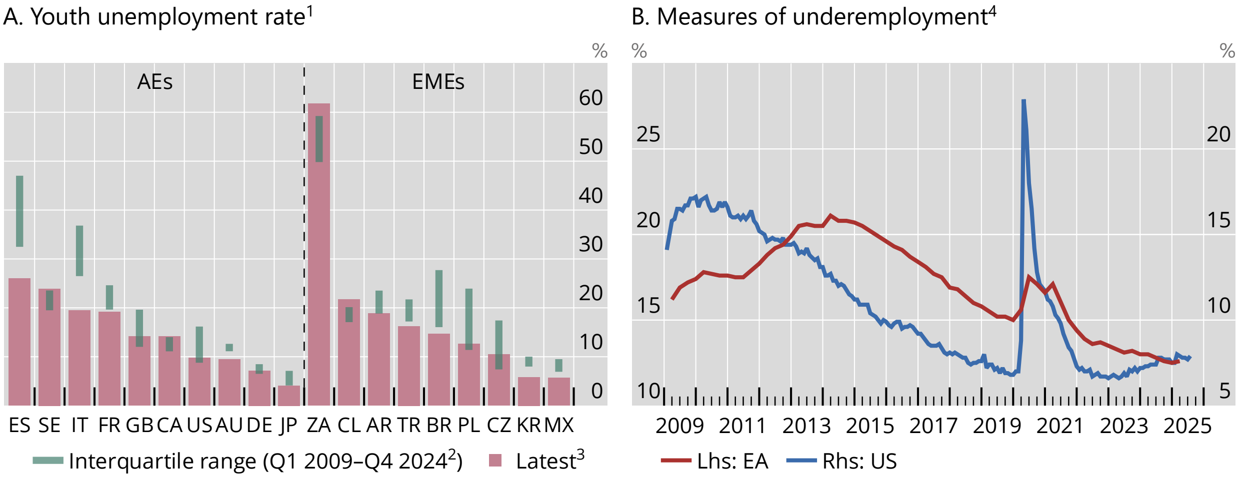
Online annex for BIS Bulletin no 112: "Labour markets at a crossroads: softening trends amid elevated uncertainty"

Annex A: Additional information

This annex presents additional charts referenced in the main text. They provide complementary evidence on labour market developments across advanced and emerging market economies. The charts cover alternative measures of unemployment, sectoral employment growth, informal employment, Beveridge curves, labour force participation, survey indicators, labour hoarding, employment protection, the impact of ageing, sectoral shifts and wage dynamics across jurisdictions.

Alternative measures for unemployment — Graph A.1



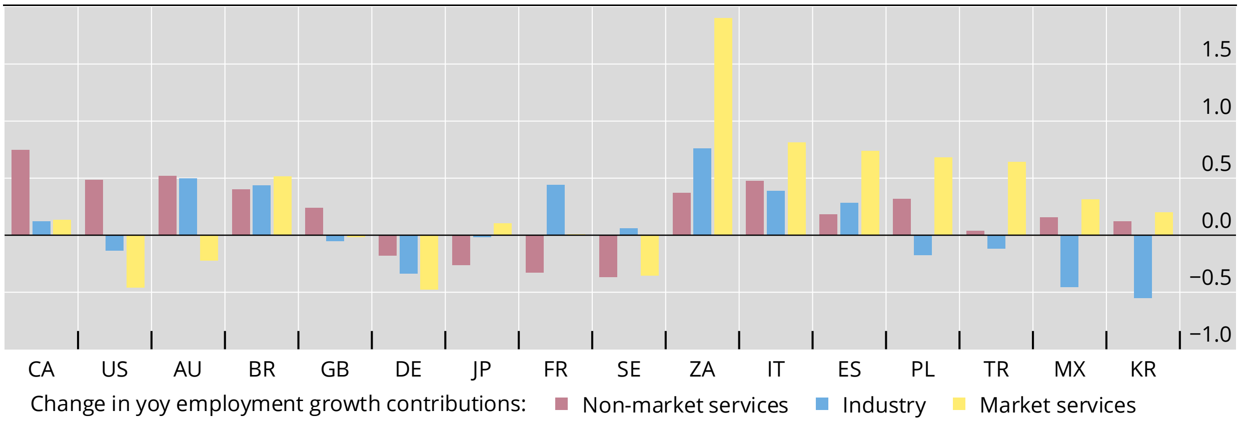
[1] Aged 15–24. Seasonally adjusted series. [2] For AR, Q1 2009–Q3 2024; for BR, Q1 2012–Q4 2024; for CL, Q1 2010–Q4 2024. [3] For AU, CA, JP, KR, TR and US, Q2 2025; for AR, Q3 2024; for other countries, Q1 2025. [4] For US: total unemployed, plus all people marginally attached to the labour force, plus total employed part-time for economic reasons, as a percentage of the civilian labour force. For EA: unemployed, underemployed part-time workers, people seeking a job but not immediately available to work and people available to work but not seeking, as a percentage of extended labour force (employed, unemployed and those available but not seeking, and those seeking but not available).

Sources: International Labour Organization; LSEG Datastream; Macrobond; BIS.

Changes in employment growth by sector[1]

In percentage points

Graph A.2



[1] Change in average year-on-year (yoy) employment growth contributions between Q1 2023–latest and Q1 2013–Q4 2022. Latest = Q1 2025 or Q4 2024. Industry = manufacturing, construction, mining and utilities; market services = trade, transportation, accommodation and food, and business and administrative services; non-market services = public administration, education, healthcare, social, leisure and other services. Agriculture and unclassified sectors are not shown.

Sources: International Labour Organization; national data; BIS.

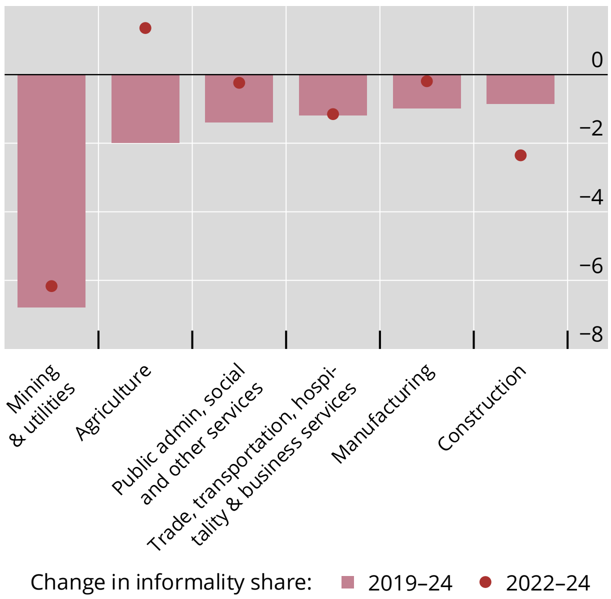
Informal employment is receding in several EMEs

In percentage points

Graph A.3

A. Total economy informal employment shares

B. Sectoral informal employment shares[1]

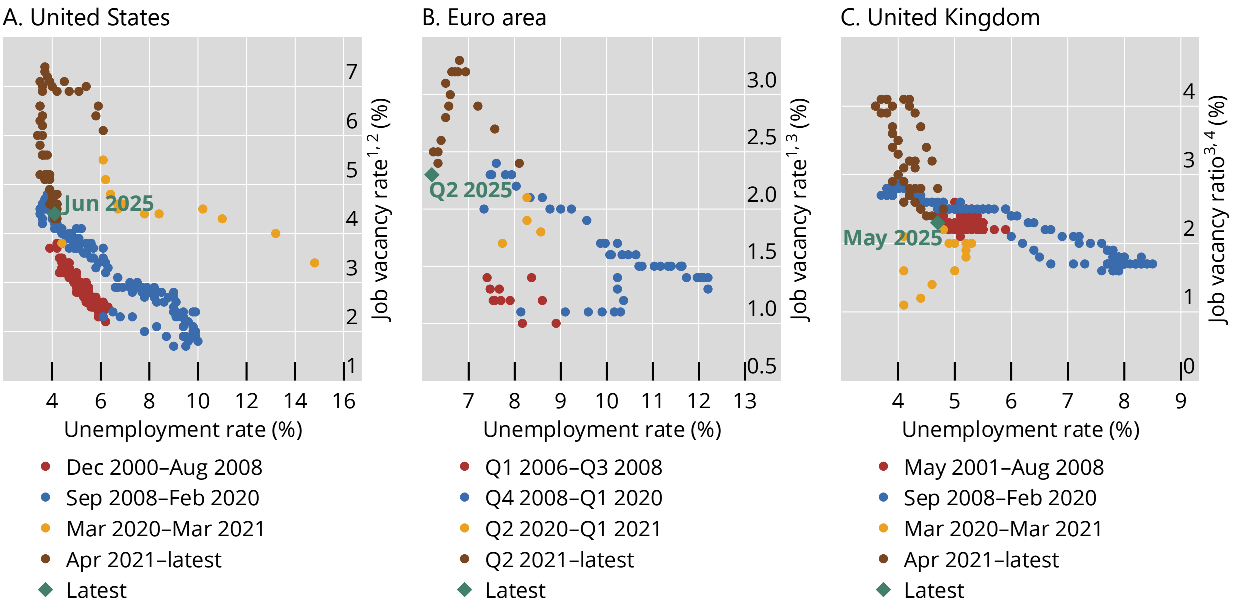


[1] Median across AR, BR, CL, CO, IN, MX, PE, TR and ZA.

Sources: International Labour Organization; BIS.

Beveridge curves

Graph A.4



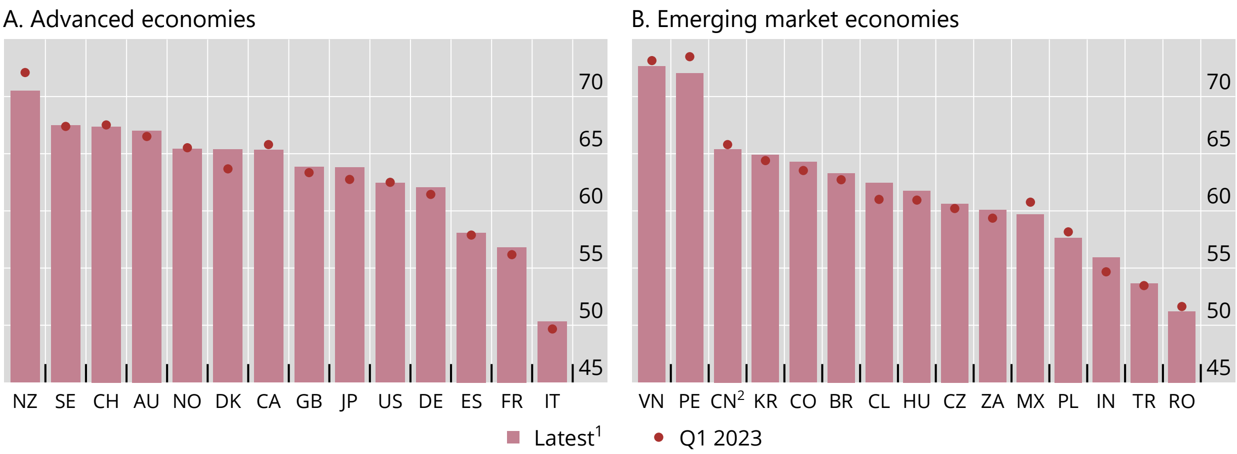
[1] Job vacancy rate computed as number of job vacancies / (number of occupied posts + number of job vacancies)*100. [2] Total non-farm. [3] Industry, construction and services (except activities of households as employers and of extraterritorial organisations and bodies). [4] Job vacancy ratio computed as three-month rolling average ratio of vacancies per 100 employee jobs.

Sources: OECD; LSEG Datastream; BIS.

Labour force participation

As a percentage of working age population

Graph A.5



[1] Q1 2025, except for AU, CA, GB, JP, KR, NZ, TR, US and ZA (Q2 2025); IN and VN (Q4 2024). [2] Annual data (2022 and 2024).

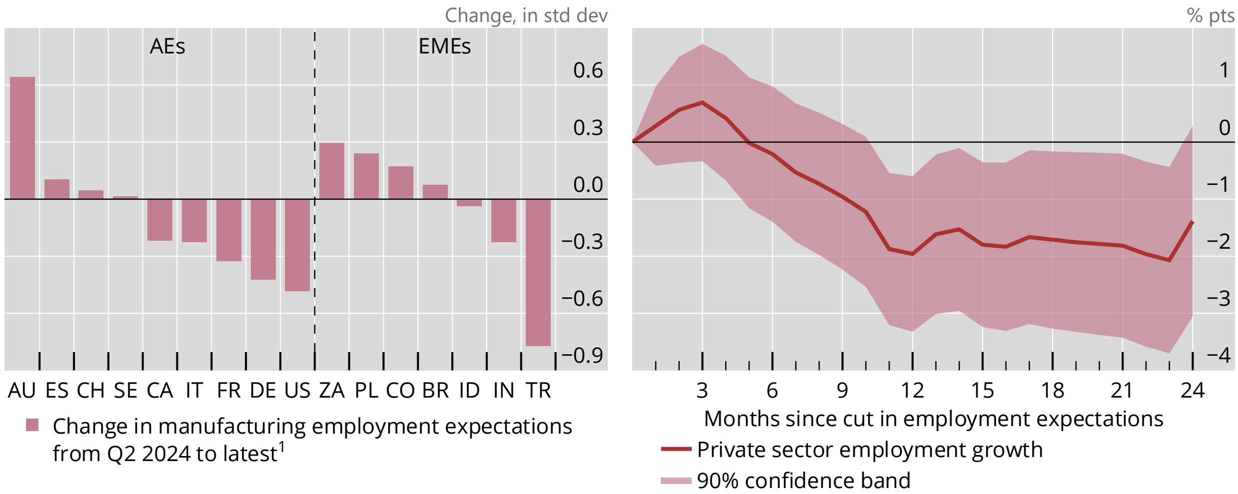
Sources: International Labour Organization; LSEG Datastream; national data; BIS.

Bridging the gap between survey signals and outcomes takes some time

Graph A.6

A. In many AEs, the soft data point to weaker labour markets

B. In the US, the pass-through from soft to hard data takes about 10 months[2]



[1] Survey-based measure of expected changes in manufacturing sector employment in the near future; varying definitions by country. Measured as changes in standard deviations from historical averages between Q2 2024 and Q2 2025, except for CO, ID and IN (Q1 2025). [2] Impact of a 1 percentage point cut to one-year-ahead employment expectations growth. Estimation controls for current private sector employment growth, and firm one-year-ahead revenue expectations growth.

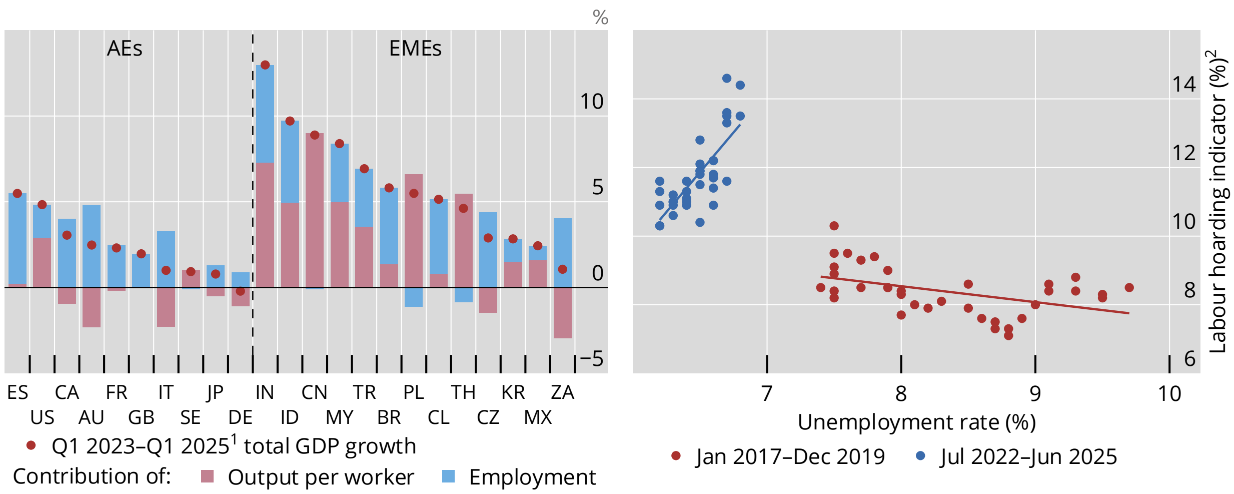
Sources: Federal Reserve Bank of Atlanta, *Survey of Business Uncertainty*; OECD; BIS.

Labour hoarding weighs on productivity, but keeps unemployment low

Graph A.7

A. Recent drivers of GDP growth

B. Strong labour hoarding in the euro area

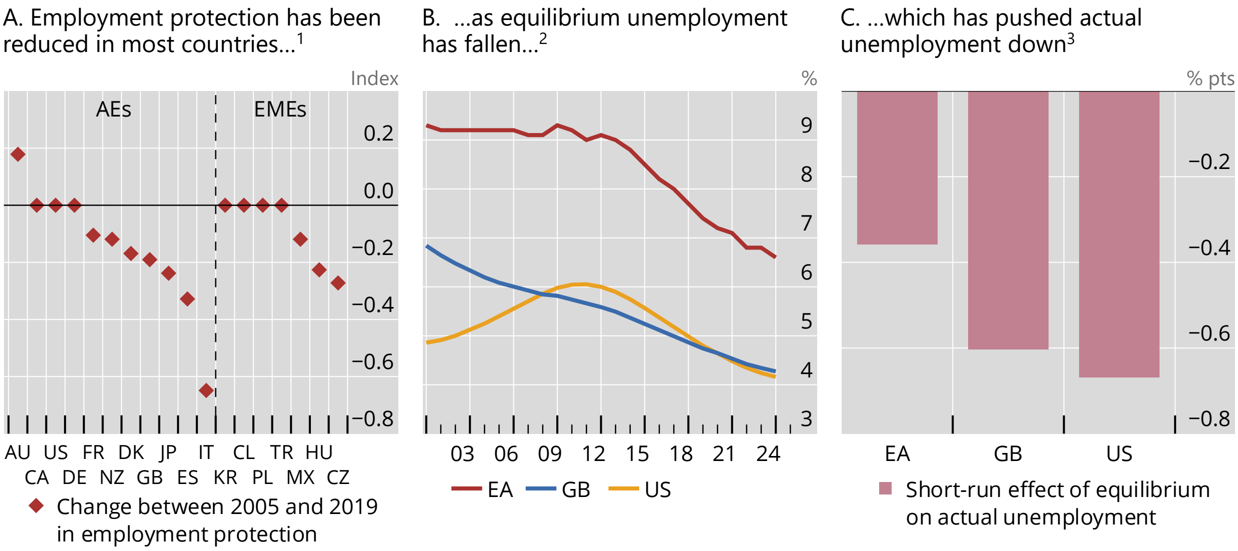


[1] For CN and IN, up to Q4 2024. [2] Labour hoarding indicator is defined as the share of firms expecting lower output but stable or higher employment over the next three months.

Sources: International Labour Organization; LSEG Datastream; Macrobond; national data; BIS.

Employment protection: equilibrium and actual unemployment

Graph A.8

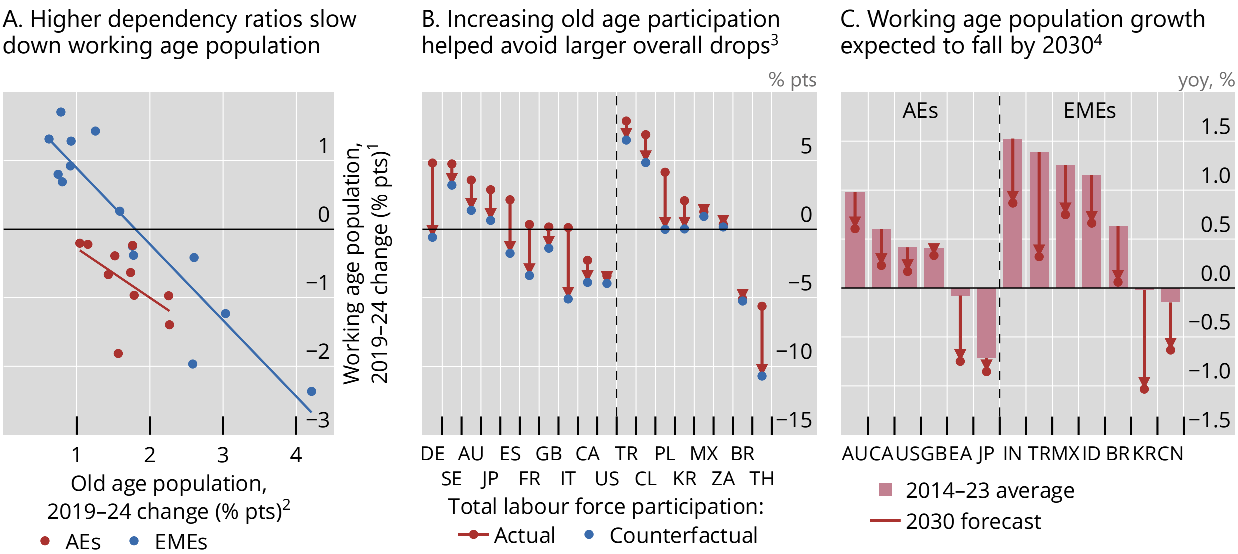


[1] Employment protection index evaluates regulations on dismissal of workers based on statutory laws, collective bargaining agreements and case law. Scale from zero (least protection) to six (maximum protection). Change between 2005 and 2019, except for CL (2008–19). [2] Non-accelerating wage rate of unemployment (NAWRU). [3] One-year-ahead impact of a one standard deviation decrease in NAWRU on unemployment rate. GB estimates based on non-accelerating inflation rate of unemployment (NAIRU).

Sources: European Commission, *AMECO database*; OECD; LSEG Datastream; BIS.

Impact of ageing on the labour force

Graph A.9



[1] Share of population aged 15–64. [2] Share of population aged 65 and above. [3] Labour force participation rates change between 2004 and 2024. Counterfactual assumes that the participation rates of the 55–64 age cohort remained at 2004 levels. [4] Working age population defined as those aged 15 to 64. Forecasts use data from the UN Population Division, medium fertility variant.

Sources: International Labour Organization; United Nations; World Bank; Macrobond; BIS.

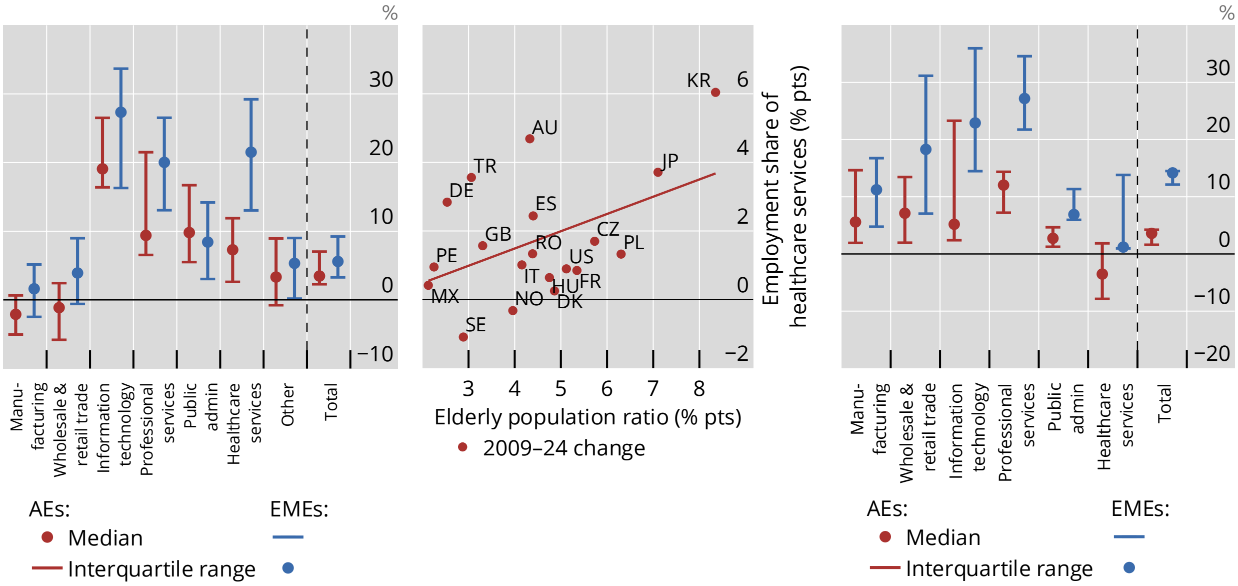
Ageing and sectoral shifts: health services on the rise

Graph A.10

A. 2019–24 employment growth by industry[1]

B. Correlation between old age dependency ratio and health services employment share

C. Labour productivity growth by industry, 2017–22



[1] Based on data for 12 AEs and 16 EMEs.

Sources: OECD; BIS.

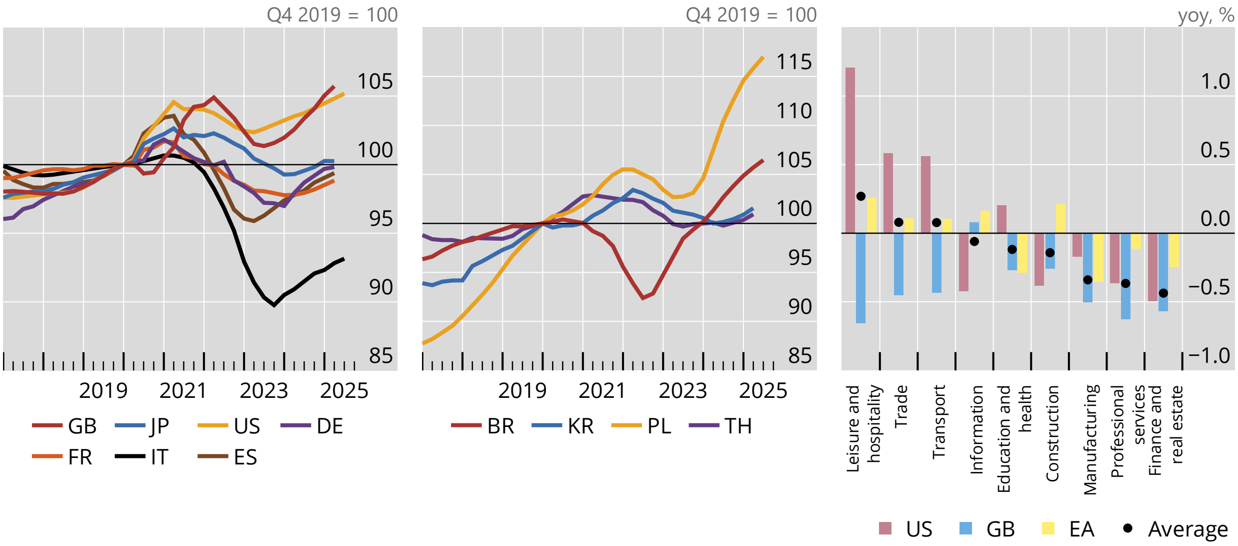
Real wages still below or close to 2019 levels in several jurisdictions

Graph A.11

A. Real wages in AEs[1, 2]

B. Real wages in EMEs[1, 2]

C. Relative wage growth since 2019[2, 3]



[1] Real wages are computed by deflating nominal wages with headline CPI. [2] Definitions and sectoral coverage differ among economies. Four-quarter moving averages. [3] Average year-on-year industry wage growth between Q4 2019 and Q4 2024 relative to the total economy.

Sources: Federal Reserve Bank of St Louis, *FRED*; International Labour Organization; OECD; LSEG Datastream; national data; BIS.

Annex B: Labour market flows, monetary policy and inflation

Labour market flows between employment, unemployment and inactivity can be summarised by the conditional probabilities that workers switch from a given state to another between two periods. The transition matrix – which gathers all conditional probabilities – then summarises the dynamics of the labour market, and determines how the distribution of workers between employment, unemployment and inactivity evolves over time.

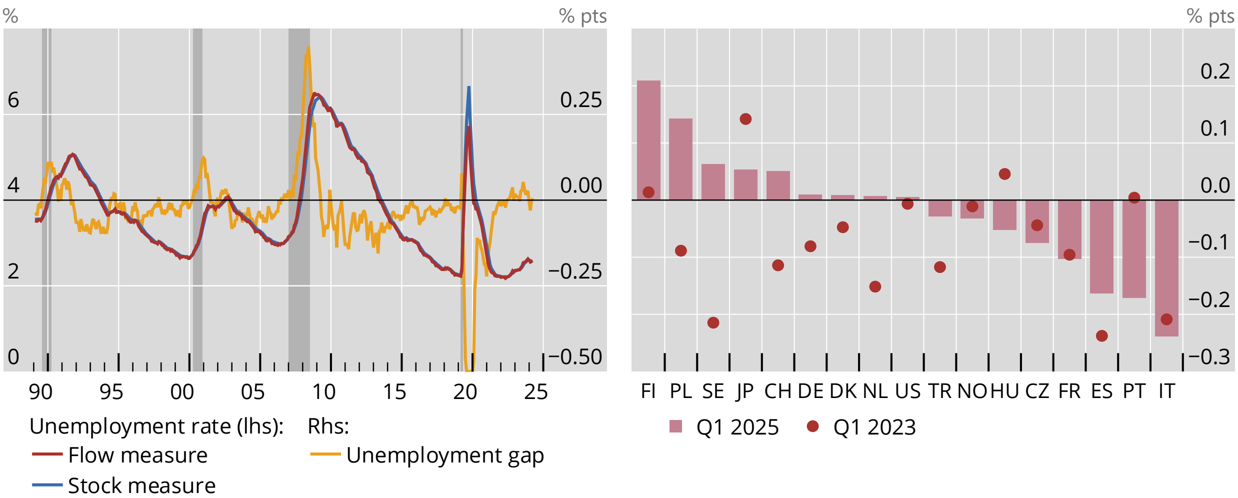
The transition matrix also provides information on the steady-state distribution of the labour market, ie the distribution that would prevail given the transition probabilities observed at a point in time. Formally, if M_t denotes the (three-by-three) transition matrix between $t-1$ and t, and $m_t = (e_t, u_t, i_t)'$ the labour market distribution at time t between employment (e), unemployment (u) and inactivity (i), then the law of motion of the labour market distribution is simply $m_t = M_t m_{t-1}$, while the ergodic steady-state distribution $m_t^* = (e_t^*, u_t^*, i_t^*)'$ satisfies $m_t^* = M_t m_t^*$.

The steady-state distribution m_t^* is useful for two reasons. First, by comparing it with the actual distribution m_t, one can get a sense of the *direction* of the labour market. For example, let us consider the unemployment gap, ie the difference between steady-state and actual unemployment $u_t^* - u_t$. Then, a positive reading, ie steady-state unemployment u_t^* above actual unemployment u_t, is associated with higher subsequent unemployment u_{t+h} as actual unemployment tends to catch up with (higher) flow-based unemployment u_t^*. The second reason is that one can evaluate how *quickly* the gap between steady-state and subsequent unemployment $u_t^* - u_{t+h}$ gets closed.

Labour market flows and the flow/stock unemployment gap[1] Graph B.1

A. US flow/stock unemployment gap turns positive[1, 2]

B. Flow/stock unemployment gap on the rise in several countries[2]



[1] Based on monthly data from the US Bureau of Labor Statistics Current Population Survey. All variables plotted as six-month backward-looking moving averages. Unemployment gap measure truncated at –0.5 to ensure visibility. The shaded areas denote NBER recession periods. [2] Unemployment gap is the difference between flow- and stock-based unemployment. Flow-based unemployment is the steady state unemployment rate conditional on the matrix of labour market transition probabilities as derived from observed flows between employment, unemployment and inactivity. Flow- and stock-based unemployment expressed as fractions of working age population. Computations based on quarterly transitions, except for US and JP, where monthly transitions have been converted into quarterly.

Sources: Kharroubi and Koechlin (2025); BIS.

Data on labour market flows from the US Bureau of Labour Statistics Current Population Survey show the unemployment gap $u_t^* - u_t$ turned deeply negative very early after the beginning of the Covid-19 pandemic and remained so far into 2022 (Graph B.1), reflecting the tightness in the US labour market then.

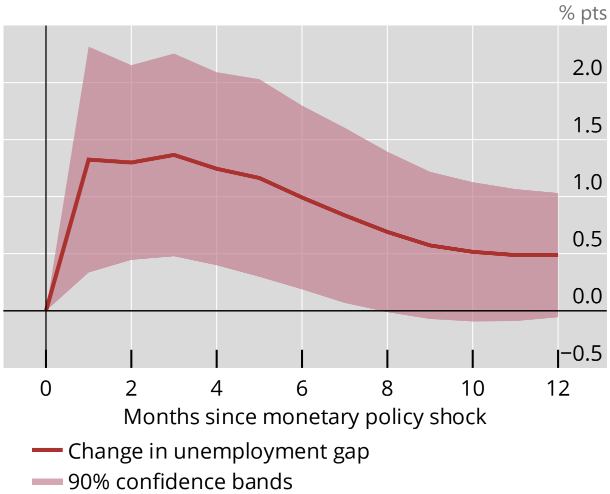
However, more recently the unemployment gap has turned positive, albeit by a small margin compared with historical precedents. Applying this methodology more broadly shows a great variety of situations with many countries, especially in southern Europe, still running large and significant negative unemployment gaps.

Turning to the properties of the flow/stock unemployment gap, we highlight two below. First, the unemployment gap measure responds as expected to monetary policy (Graph B.2). A tightening shock typically raises steady-state unemployment above actual unemployment, with the impact dying out after about eight to nine months. Because flow-based variables adjust faster than stock-based ones, tight monetary policy typically cuts flow into employment and raises flows into unemployment, thereby raising steady-state unemployment above actual unemployment.

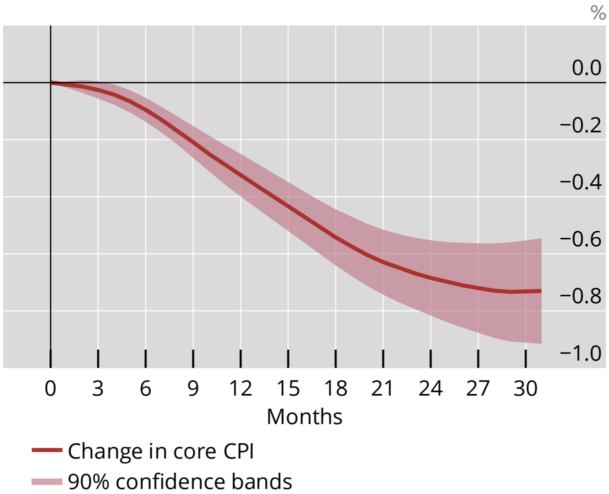
Second, an increase in the flow/stock unemployment gap is associated with lower price pressures, the negative impact stabilising after about 24 months. Again, as would be expected, a positive unemployment gap, insofar as it reflects higher subsequent unemployment, is naturally associated with lower inflation down the road.

Monetary policy shocks, the flow/stock unemployment gap and inflation[1] Graph B.2

A. Tight monetary policy opens the unemployment gap[1]



B. Higher unemployment gap cuts price pressures[2]



[1] The red line plots the estimated percentage change in the flow/stock unemployment gap resulting from a 100 basis point tightening monetary policy shock, conditional on past values of the flow/stock unemployment gap. Red dashed lines represent the 90% confidence interval. [2] The red line plots the estimated percentage change in core CPI resulting from a standardised increase in the unemployment gap, controlling for standard determinants of inflation.

Sources: Kharroubi and Koechlin (2025); BIS.

Annex C: Advances in technology and the labour market

A structural trend with potentially far-reaching implications for labour markets is the rapid diffusion of new technologies. Over recent decades, advances in information and communication technologies (ICT) and robotics have reshaped production processes across a wide range of sectors. More recently, the rapid emergence of generative artificial intelligence (gen AI) has introduced a new set of capabilities that have the potential to affect both labour demand and productivity in fundamental ways.

On the one hand, gen AI holds promise for substantial productivity gains, especially by automating components of non-routine cognitive tasks. Most studies reveal consistent productivity gains ranging from 10 to 55%, with particularly strong effects in technical, customer support and creative tasks such as coding.[1] A consistent pattern across these studies is AI's equalising effect on workplace performance between employees with different levels of experience. For example, in software development and coding, research has found that junior developers experienced productivity increases of 21–67%, while senior developers saw more modest gains of 7–26%.

These effects point to two broad forces at work: the complementarity of gen AI with tasks that benefit from human input, and its substitution for routine tasks that can be fully or partially automated. The overall effect on employment is therefore likely to be heterogeneous across occupations.[2] Sectors that could experience an increase in employment include information technology, product development and professional services, where gen AI is primarily used to augment human capabilities and support innovation. By contrast, more negative effects on employment are expected in service operations, supply chain management and administrative support, where automation is higher due to the predominance of routine-intensive tasks (Artificial Intelligence Index Report (2025)).

For these reasons, the estimates of the effect of AI adoption on aggregate employment are ambiguous, with outcomes that depend on institutional and technological conditions at the country level.[3] On the one hand, some studies using occupation-level variation in European countries and those using firm-level variation in East Asian countries suggest a positive impact of AI adoption on employment.[4] On the other hand, studies focusing on regional variation in the United States suggest a negative impact on employment.[5]

Projections indicate that by 2030, up to 60% of existing occupations could undergo significant task reallocation, with the net effect on employment depending on timely reskilling, upskilling and supportive labour policies.[6] Rather than triggering mass unemployment, gen AI may instead shift demand towards AI-literate, adaptable workers, underlining the growing importance of lifelong learning and digital competencies. However, some studies that model the progression of gen AI towards more general forms

1 See Brynjolfsson et al (2023), Dell'Acqua et al (2023), Noy and Zhang (2023), Gambacorta et al (2024), Hoffmann et al (2025) and Peng et al (2024). These studies employ diverse methodologies, including natural or quasi experiments, randomised controlled trials and large-scale surveys, to measure AI's impact across different organisational contexts.

2 As analysed in Felten et al (2021), gen AI will have an impact mostly on white-collar occupations that require advanced degrees, such as genetic counsellors, financial examiners and actuaries. The lowest impact will be on occupations that predominantly require a high degree of physical effort and include, for example, dancers, fitness trainers or iron and rebar workers.

3 Cerutti et al (2025) examine how AI's effects vary across countries depending on their exposure to AI, preparedness (eg digital infrastructure, human capital, regulatory frameworks) and access to technology. It uses a multi-sector general equilibrium model to show that AI could exacerbate income inequalities, benefiting AEs more than low-income countries.

4 See Albanesi et al (2025) and Guarascio and Reljić (2025) for studies on European countries, Park and Shin (2025) for research on Korean firms, and Yang (2022) for studies on Taiwanese firms. Necula et al (2024), using survey data for Romania, find varied expectations for AI's impact on workforce size: 43% of organisations anticipate reductions, 30% expect little change, 15% project increases and 12% remain uncertain about the long-term implications.

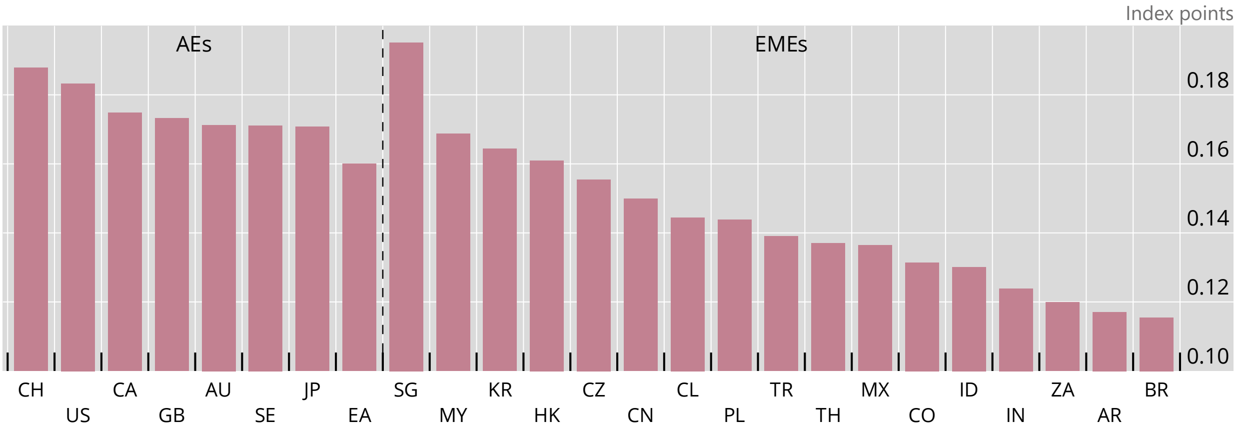
5 See Huang (2024) and Bonfiglioli et al (2025). Hui et al (2024) indicate that the use of large language models, such as ChatGPT, has substituted tasks previously performed by freelancers.

6 See McKinsey (2023) and Hatzius et al (2023) for quantitative estimates.

of intelligence caution that future AI agents could further reduce workforce needs, particularly in knowledge-intensive industries.[7] These may produce heterogeneous effects because there are large disparities across countries not only in AI-related hardware capital (eg cloud computing and data centres) but also in labour market policies, including reskilling and upskilling programmes tailored to gen AI disruptions, wage insurance or mobility support for displaced workers, and incentives for firms to retrain rather than replace their workforce (Graph C.1).

AI preparedness: AI capital and labour market policies[1]

Graph C.1



[1] Assesses the level of AI preparedness in the field of human capital and labour market policies, based on a rich set of macro-structural indicators. Contribution to the overall AI preparedness index which is standardised between zero and one. 2023 data.

Sources: IMF (2024); BIS.

The effects of an AI-driven productivity shock on employment could vary substantially across countries. A BIS study simulates the impact of a sustained increase in productivity due to AI in 70 countries (23 AEs and 47 emerging market and developing economies), each with different sectoral compositions and levels of preparedness for generative AI (Cornelli et al 2025). The simulation assumes an increase in total factor productivity of 0.5% per year over a decade. This magnitude is calibrated based on recent estimates for the United States and adjusted for each country according to its sectoral structure (which differs from that of the United States) and its AI readiness. Preliminary results suggest that the long-run (steady-state) effects on labour demand are highly heterogeneous across countries due to a different sectorial composition. Employment in sectors such as construction and healthcare benefits from stronger demand effects and more limited scope for labour substitution. By contrast, sectors such as mining and agriculture could face larger disruptions, particularly where AI is applied to robotics and automation technologies that directly replace labour.

Overall, the labour market impact of gen AI and related technologies will depend on the interplay between productivity gains, the pace of task reallocation, and the capacity of workers and firms to adapt. Early evidence points to substantial opportunities for complementarity between human skills and AI, particularly in innovation-intensive sectors, alongside clear risks of displacement in routine-intensive activities. Cross-country differences in AI-related hardware capital, sectoral composition and the scope and design of labour market policies will shape outcomes. Ensuring that the benefits of these technologies are widely shared will require proactive investment in skills, targeted support and retraining for affected workers, and policy frameworks that encourage innovation while mitigating adjustment costs.

[7] As discussed in Bell et al (2025), a more radical "agent" scenario considers the deployment of autonomous AI systems that perform entire tasks or roles independently, potentially displacing significant portions of the workforce. See also Korinek and Juelfs (2022) and Chen et al (2025).

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