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SLOVAK REPUBLIC

SELECTED ISSUES

March 2025

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European Department

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CONSUMPTION ANALYSIS BASED ON DISTRIBUTIONAL NATIONAL ACCOUNTS[1]

We construct a distributional national accounts dataset for Slovakia, which contains distributional information fully consistent with the national accounts. An analysis using the data finds that to maintain robust consumption growth amid downward pressure from unfavorable demographic dynamics, an increase in consumption per person, primarily driven by income, will be necessary. This underscores the importance of policy measures to raise income growth, such as increasing productivity and encouraging labor force participation, especially among the elderly. The analysis also shows that inequality, as well as the gender gap, has declined owing to a labor shift towards high-skill jobs and fewer unemployed household heads. To maintain these favorable trends, policies to encourage a shift towards higher skilled jobs and labor force participation, such as strengthening active labor market policies and addressing skill mismatches, will be important.

A. Introduction

1. The aim of this paper is to gain distributional insights into household consumption in line with the national accounts by constructing a distributional national accounts dataset. National accounts (NA) provide comprehensive information about economic activities, including GDP, consumption, income, and wealth. However, NA can only describe the behavior of aggregated households and lacks insights into household heterogeneity. On the other hand, microdata such as household surveys contain various household characteristics but are not necessarily consistent with NA data. The distributional national accounts (DNA) combine the advantages of both NA and microdata, enabling us to conduct distributional analysis of household consumption as well as income and wealth in a manner fully consistent with NA. This means that DNA totals (the sum of individual households) are fully aligned with NA data.

2. There is increasing interest in DNA datasets. Research to construct DNA has been undertaken by various bodies. Eurostat (2024) released experimental DNA data for household consumption and income, including data for Slovakia. The ECB also publishes household distributional wealth data called the Distributional Wealth Accounts (DWA) that are consistent with the aggregates of Quarterly Sector Accounts (QSA).[2] However, the Eurostat experimental data is missing several important elements important for conducting macroeconomic analysis, such as real values of the variables in the dataset and a breakdown among categories of households. To address this gap, this paper estimated the DNA of household consumption, income, and wealth in Slovakia by employing microdata from the Household Budget Survey (HBS) and the Household Finance and

[1] Prepared by Shinya Kotera (EUR).

[2] See Blatnik et al. (2024) for a detailed analysis of DWA. QSA data are constructed by the ECB following international standards for NA and provide comprehensive wealth information for all resident institutional sectors.

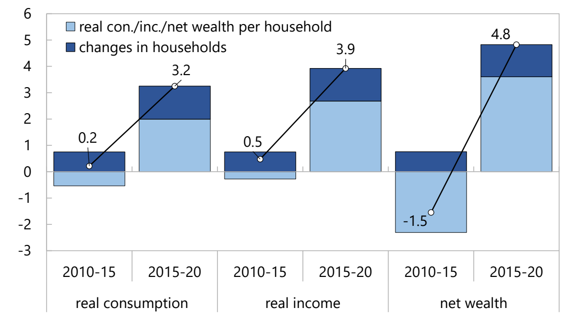
Consumption Survey (HFCS). Given the availability of microdata, DNA data are estimated for 2010, 2015, and 2020. Technical details regarding construction of the DNA can be found in the Appendix.

B. Demographic Analysis Using DNA

3. This paper uses the DNA dataset for Slovakia to analyze the impact of demographic change on consumption. NA data show that Slovakia's real consumption stagnated during 2010-15 (with only a 0.2 percent compounded annual growth rate), but consumption, as well as income and wealth, grew steadily during 2015-20 (with a 3.2 percent compounded annual growth rate) (Figure 1). Using the DNA data, these growth rates can be decomposed into the following four elements (contributions).

Figure 1: Consumption, Income, and Wealth Growth

(Compound Annual Growth Rate, in percent, percentage points)



Note: All deflated by Household Consumption Deflator

Sources: Eurostat and IMF staff estimation.

- **Composition**: Contributions due to changes in household share (structure). For example, aggregate consumption will be lower if the share of household categories with lower consumption levels increases. The DNA data allows us to differentiate households according to household type and age of the household head.[3]
- **Number of households**: Contributions due to changes in the total number of households. Aggregate consumption levels will be higher if a country has more households.
- **Household size**: Contributions due to changes in the number of persons per household. The level of household consumption will be higher if the average household has more persons.[4]
- **Real consumption (income/wealth) per person**: Contributions due to changes in real consumption (income/wealth) per person (equivalence scale).

In other words, the DNA data allow us to evaluate how total consumption changed as a result of changes to these four factors changes while keeping all other factors fixed.

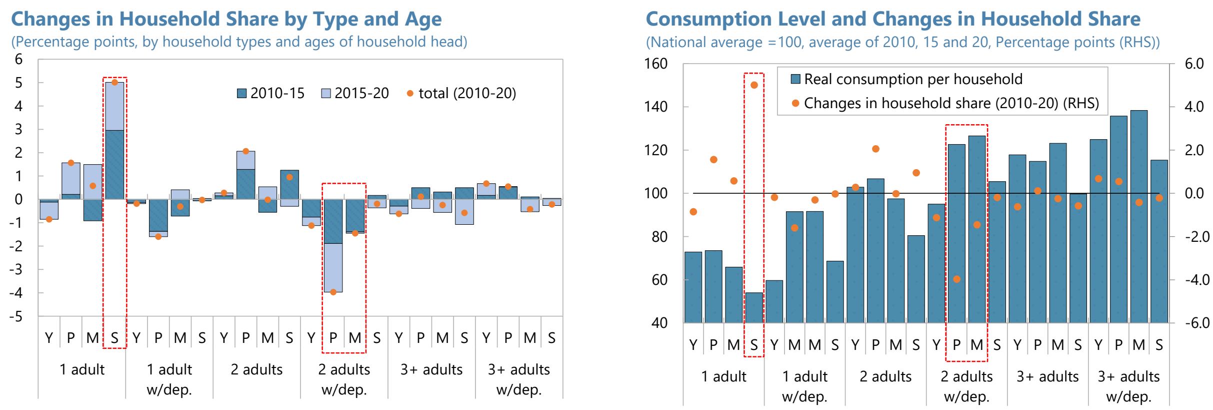
4. Household composition changes due to aging exerted downward pressure on consumption growth. Figure 2 (left) illustrates the changes in household shares with respect to household type and age of the household head from 2010 to 2020. The chart indicates that over this time period the share of single adult households (aged 60+) increased the most (by 5 percentage points (ppt)), while that of two adults with dependent children (aged 30-59) decreased the most (by

[3] Household type contains the following six categories: one adult, one adult with dependent children, two adults, two adults with dependent children, three or more adults, and three or more adults with dependent children. The age of the household head contains the following four categories: aged less than 30, aged 30-44, aged 45-59, and aged 60 and over. In this paper, the household head refers to the household's reference person in the HBS to simplify the argument, although they are not necessarily the same. Generally, the reference person in the HBS is the adult with the highest income.

[4] The household size here refers to equivalent size (modified OECD scale). The modified OECD scale attributes a weight to all household members: a weight of 1 to the first adult, a weight of 0.5 to each additional adult, and a weight of 0.3 to each child. The equivalent size is the sum of the weights of all the members.

5.4 ppt). Figure 2 (right) compares the changes in household share and the consumption level per household (note that the orange dots, representing changes in household share, are the same across both the right and left charts). Figure 2 (right) suggest that changes in household share and the consumption level per household are negatively correlated.[5] For example, the share of single adults (aged 60+) has increased, and the consumption level among this group is the lowest among all household categories. Similarly, the share of two adults with dependent children (aged 30-59) has decreased, and the consumption level among this category of households is relatively higher. This implies that the changes in household composition contributed negatively to consumption growth between 2010-20 and will continue to do so unless this trend changes.[6]

Figure 2. Household Share and Consumption Level (by Household Type and Age)



Note: w/dep. = with dependent children. Age of household head = Y: less than 30, P: 30-44, M: 45-59, S:60 and over
Sources: HBS and IMF staff estimation.

5. Consumption in Slovakia benefited from an increase in the total number of households, although this is no longer the case after 2022. Until 2022, the total number of households in Slovakia had been increasing, along with the population (Figure 3, left).[7] Other things equal, simply having more households helps raise aggregate consumption growth. However, the number of households started to decline in 2022, consistent with the decline in the overall population, implying that this demographic factor now contributes negatively to total consumption growth.

6. The average household size has been shrinking over the past decade. Figure 3 (right) shows the changes in household size (equivalent scale) from 2010 to 2020. The figure indicates that the average household size has been shrinking for all household types, except for households with 3 or more adults with dependent children (aged less than 44). On average, the number of persons per

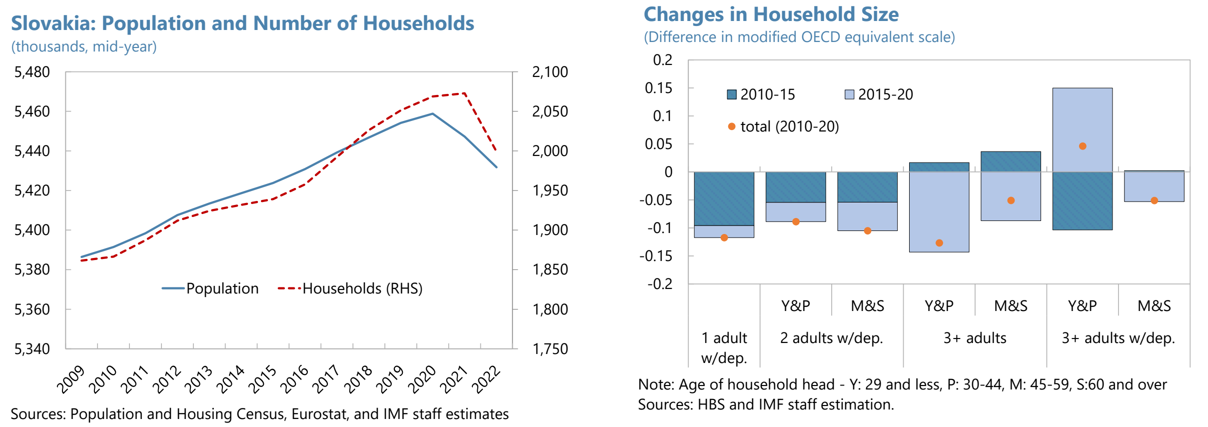
[5] They have a correlation of -0.4.

[6] Similar trends (negative correlation) can also be observed between the changes in household share and the level of real income (or net wealth), implying that changes in household composition also put downward pressure on the growth of real income and net wealth.

[7] The number of households is estimated based on the Population and Housing Census and EU-LFS (labor force survey). See appendix.

household decreased from 2.9 in 2010 to 2.6 in 2020. Other things equal, this decline in the household size will reduce the level of consumption per household and aggregate consumption.

Figure 3. Number of Households and Household Size



7. **An increase in consumption per person will be needed to offset the negative impact of demographic change moving forward.** Based on the estimated DNA, the contributions of the aforementioned four elements are calculated (Figure 4). Note that the total annual growth rates in Figure 4 (from DNA) are the same as in Figure 1 (from NA). The DNA data indicate that both composition and household size have put downward pressure on real consumption growth (-0.3 ppt and -0.2 ppt, respectively), while the number of households contributed positively (0.9 ppt). If trends related to the composition and size of the average household continue, current and future annual consumption growth rate will, other things equal, be around 0.5 ppt (the sum of average contributions from composition and household size) lower than would otherwise have been the case. The anticipated decline in the number of households moving forward implies that the overall impact of demographic change on aggregate consumption will likely be even higher. Similar analysis can be applied to real income and net wealth, where demographic changes could reduce annual growth by at least 0.6 ppt and 0.4 ppt, respectively.[8] To mitigate the negative impact from demographic change and achieve robust consumption growth, an increase in consumption per person, which is the last of the four elements discussed above, will be required.

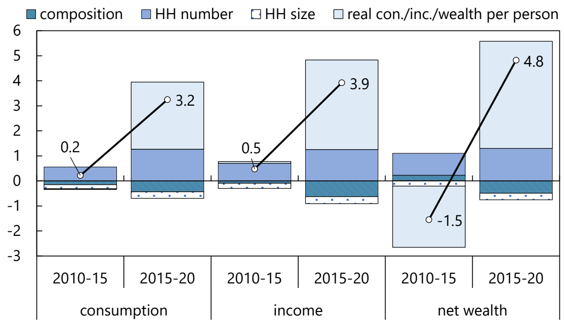
8. **Raising consumption per person requires higher income growth.** DNA data indicate that real consumption per person was almost constant (zero growth) during 2010-15 but grew strongly during 2015-20 (Figure 4). To examine the drivers behind these movements a simple regression analysis is conducted which attempts to explain real consumption by real income and net wealth. Figure 5 presents the results of this analysis: the left figure shows the compounded annual growth rate of real consumption, real income, and net wealth for 2010-15, and the right figure for 2015-20. This simple regression analysis suggests that while both real income and net wealth growth contributed to real consumption growth, income growth tends to play a more important role. This

[8] Demographic change could also impact savings rate. From 2010 to 2020, the composition effect contributed negatively (on average, -0.1 ppt annually) to the change in gross savings rate.

implies that policy measures to increase income growth per person are particularly important for sustaining consumption growth moving forward.

Figure 4. Decomposition Analysis

Decomposition: Consumption, Income, and Wealth Growth
(Compound Annual Growth Rate, in percent, percentage points)



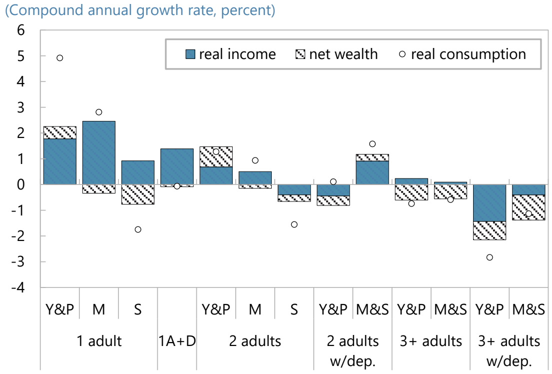
Note: All deflated by Household Consumption Deflator
Sources: Eurostat, HBS, NFCS, and IMF staff estimation.

Decomposition of Consumption, Income and Wealth Growth
(compounded annual growth rate, percent, percentage points)

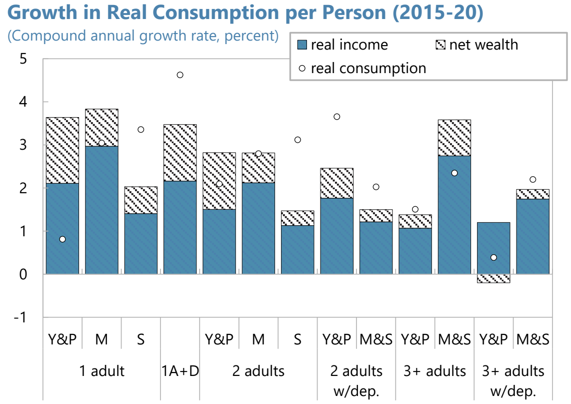
	real consumption			real income			net wealth		
	2010-15	2015-20	avg	2010-15	2015-20	avg	2010-15	2015-20	avg
total	0.2	3.2	1.7	0.5	3.9	2.2	-1.5	4.8	1.6
composition	-0.1	-0.4	-0.3	-0.1	-0.6	-0.4	0.2	-0.5	-0.1
HH number	0.6	1.3	0.9	0.7	1.3	1.0	0.9	1.3	1.1
HH size	-0.2	-0.3	-0.2	-0.2	-0.3	-0.2	-0.2	-0.3	-0.2
per person	0.0	2.7	1.3	0.1	3.6	1.8	-2.4	4.3	0.9
Composition + HH size	-0.3	-0.7	-0.5	-0.3	-0.9	-0.6	0.0	-0.8	-0.4

Figure 5. Drivers of Real Consumption per Person

Growth in Real Consumption per Person (2010-15)
(Compound annual growth rate, percent)



Growth in Real Consumption per Person (2015-20)
(Compound annual growth rate, percent)



Note 1: w/dep. = with dependent children. 1A+D = 1 adult with dependent children.
Note 2: The charts show the fitted values for a simple regression analysis by setting real consumption per person growth as the dependent variable and growth in real income per person and net wealth per person as independent variables. Some of the household categories with smaller sample sizes are aggregated to achieve more stable numbers.
Sources: Eurostat, HBS, NFCS, and IMF staff estimation.

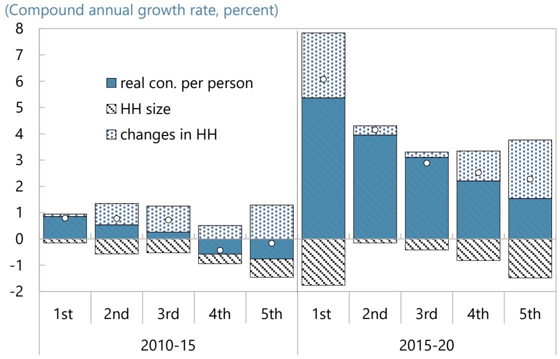
C. Inequality Analysis using DNA

9. The second part of this paper uses the DNA dataset to analyze changes in inequality. Inequality measures, such as the Gini coefficient, are generally estimated using income or consumption per person from microdata, but these measures do not necessarily align with the NA numbers. By employing the DNA, which adjusts microdata to be fully consistent with the NA, inequality can also be measured in line with the NA.

10. The DNA dataset suggests that consumption and income inequality in Slovakia has declined. Figure 6 indicates the real consumption growth (left figure) and real income growth (right figure) by income quintile over 2010-15 and 2015-20.[9] For both periods, annual growth rates of real consumption tend to be higher for households in lower quintiles, as these households experienced higher income growth than those in the higher income quintiles. From 2010 to 2020, this helped reduce the Gini coefficient (measured by income) from 0.3 to 0.26 and the coefficient (measured by consumption) from 0.28 to 0.23, implying that inequality has declined.

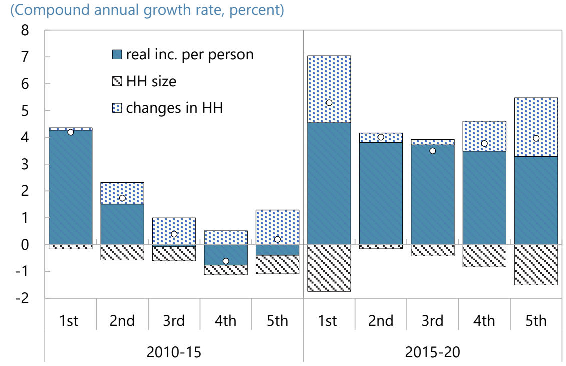
Figure 6. Consumption and Income Growth by Income Quintile

Real Consumption Growth by Income Quintile
(Compound annual growth rate, percent)



Sources: Eurostat, HBS, and IMF staff estimation.

Real Income Growth by Income Quintile
(Compound annual growth rate, percent)



Sources: Eurostat, HBS, and IMF staff estimation.

11. The decline in inequality can be attributed to a shift towards high skilled jobs and lower unemployment. Figure 7 (left) shows the changes in household share by labor status of the household head from 2010 to 2020. The figure shows that over this period there was a decrease in the share of unemployed households (by 5.2 ppt) and an increase in the share of households with employment in high skill jobs (by 12 ppt). Figure 7 (right) compares the changes in household share by labor status and the real income level per person. Note that the orange dots, representing the changes in household share, are the same across the right and left figures. Figure 7 (right) demonstrates that there is a positive correlation between the changes in household share that occurred between 2010 and 2020 and the level of real income.[10] For example, the share of households with high skill jobs has increased, and the level of income per person among this category of households are the highest, while the opposite holds for unemployed households. This suggests that the labor shift towards high-skill jobs and away from unemployment contributed to lowering income inequality.

12. The DNA data suggests that the gender gap (especially in income) has declined, as relatively more females have moved toward higher skilled jobs. Figure 8 (left) presents the results of a regression analysis estimating the percentage difference in income and consumption between male- and female-headed households. The analysis suggests that there is a statistically significant difference between male- and female-headed households, especially in terms of income, even after controlling for household type, age, and size. However, the chart also suggests that the income difference between genders has narrowed over the years. One possible reason for this

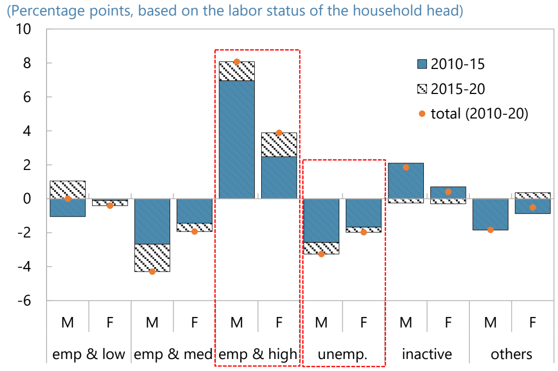
[9] Quintiles based on equivalized income.

[10] They have a correlation of 0.6.

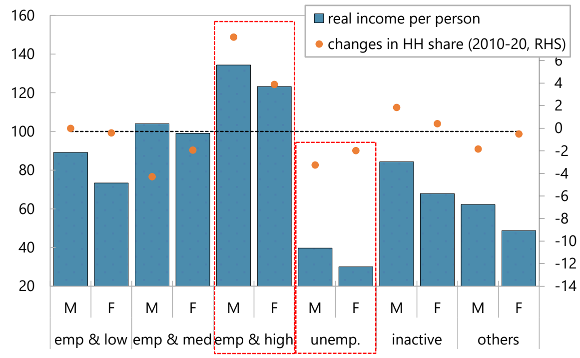
narrowing is a shift in the occupation of female workers. Figure 8 (right) shows the changes in household share by the household head's gender and occupation. The figure suggests that more female heads of households are moving toward higher skilled jobs. For example, the increase in the share of managers and professionals is higher for female heads compared with male heads.

Figure 7. Household Share and Income Level (by Labor Status)

Changes in Households Share by Labor Status
(Percentage points, based on the labor status of the household head)



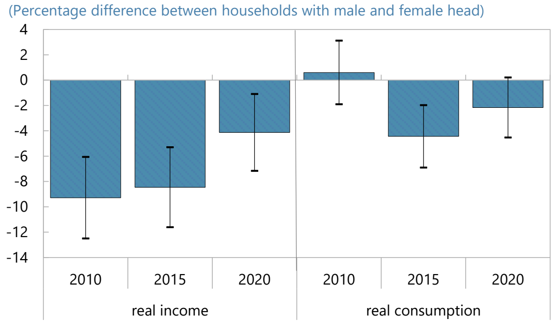
Real Income and Changes in Households Share
(National average =100, average of 2010, 15 and 20, Percentage points (RHS))



Note 1: Gender of household head = M: male, F: female.
Note 2: Labor status of household head = emp & low: low skill job, emp & med: medium skill job, emp & high: high skill job. Skill classification is based on the defintion by the ILO, which is ISCO major groups 1–3: high skill, major groups 4–8: medium skill, and major group 9: Low skill.
Sources: Eurostat, HBS and IMF staff estimation.

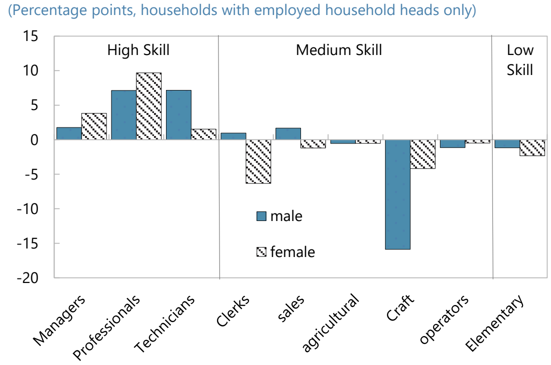
Figure 8. Gender Gap

Gender Gap (adjusted)
(Percentage difference between households with male and female head)



Note: The error bars indicate the 95 percent confidence interval. The gap is controlled for household type, age of household head, and household size.
Sources: Eurostat, HBS and IMF staff estimation.

Changes in Households Share by Occupation (2010-20)
(Percentage points, households with employed household heads only)



Sources: HBS and IMF staff estimation.

D. Conclusions and Policy Considerations

13. Efforts to improve the quality and usability of DNA data should continue. Despite its comprehensiveness, the interpretation of NA data can be challenging due to its lack of distributional insights. As seen in this note, DNA data have the potential to help uncover hidden dynamics behind NA. The new G20 Data Gaps Initiative (IMF, 2023) also includes specific recommendations for household distributional results. To enhance the quality and usability of DNA data, the authorities need to recognize the importance of distributional insights and invest resources for further data improvements. For example, increasing the frequency of micro datasets and improving micro-macro linkages to reduce discrepancies between the micro and macro results would be beneficial.[11]

14. In Slovakia, measures to increase income are essential to achieve robust consumption growth amid the challenges from demographic changes. Unfavorable population dynamics characterized by changing household composition, a decreasing total number of households, and shrinking household size will exert downward pressure on consumption growth. To mitigate these negative trends and maintain robust aggregate consumption growth, an increase in consumption per person, primarily driven by income, will be necessary. This underscores the importance of policy measures to raise income growth, such as increasing productivity and encouraging labor force participation.[12] In particular, the old-age labor force participation rate in Slovakia has room to increase, given that the current rate remains one of the lowest in Europe.

15. Policies that encourage higher skilled jobs and labor force participation are important to maintain the favorable trend in inequality. Inequality measured by both income and consumption has declined from 2010 to 2020 due to a shift towards high skill jobs and decline in unemployed household heads. While the gender gap (especially in terms of income) still exists, it has narrowed as relatively more females moved toward higher skilled jobs. To sustain these positive trends, the authorities should continue to encourage labor force participation among females, and enhance the education system and options for reskilling and upskilling, including strengthening active labor market policies and addressing skill mismatches.

[11] See OECD (2024) for more discussion about this.

[12] See "A Micro-Meso-Macro view of labor productivity growth in the Slovak Republic" in this Selected Issue Paper for more discussion about productivity.

Appendix I. Methodology of Estimating the Distributional National Accounts

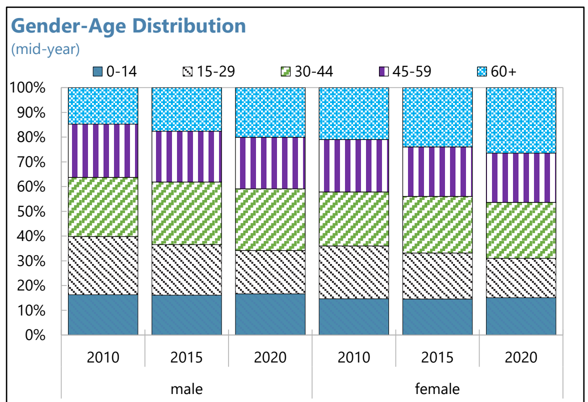
The basic strategy of estimating DNA can be found in OECD (2024), Eurostat (2024), ECB (2024), and Coli et al. (2022), although ad-hoc adjustments are made to serve this paper's purposes. Given that consumption is our primary variable of interest, HBS is treated as our main dataset. Note that the HBS microdata for Slovakia is available for 2010, 2015, and 2020.[1]

Weight Adjustment

- Eurostat experimental data adjusted NA data proportionally to deduct consumption/income from the NA that corresponds to the population not covered in EU-SILC (statistics on income and living conditions) and HBS. However, given this paper's aim is to explain trends fully consistent with NA, this analysis adjusted the sample weight of HBS as follows.

- First, the total number of households is estimated. Although the EU-LFS (labor force survey) provides estimates of the number of households, the data series has breaks in 2011 and 2021. Hence, the paper calculated the number of persons per household based on the Population and Housing Census 2011 and 2021 from the Statistical Office of the Slovak Republic (SOSR). The numbers of persons per household for other years (other than 2011 and 2021) are extended based on the growth rate from EU-LFS.[2] Using the total population (break adjusted) from Eurostat, the total number of households can be calculated as the total population divided by the number of persons per household. Since both population and number of households are as of 1st January in each year, the average is taken to calculate the mid-year estimates. The estimated results can be found in Figure 3.

- Next, based on the estimated number of households and population distributions, the weight of HBS is adjusted. The right chart shows the population distribution of gender-age groups for 2010, 2015, and 2020 from Eurostat. The original HBS weight is adjusted by employing entropy reweighting to be consistent with these population distributions.3 Finally, the weight scale is adjusted to match with the total number of households.



Sources: Eurostat and IMF staff calculation.

[1] The fieldwork period for the HBS 2020 wave in Slovakia is 2019-2021.

[2] Since extending the 2011 census data by using the growth rates of EU-LFS does not reach the 2021 census level, the growth rates of EU-LFS are adjusted by minimizing the sum of squared residuals between the growth rates (from EU-LFS) and adjusted growth rates, subject to the constraint in two census years (2011 and 2021).

[3] Stata packaged prepared by Hainmueller and Xu (2013) is used.

Matching HBS and HFCS

- Based on the discussion by Balestra and Oehler (2023), HBS microdata from 2010, 2015, and 2020 are matched with HFCS microdata from 2010, 2014, and 2021, respectively. In this analysis, HBS is the recipient dataset and HFCS is the donor dataset (providing wealth data to HBS). The integration of the two datasets is conducted through statistical matching. In this paper, this is performed using K-nearest neighbor (KNN) matching based on the 13 common variables between HBS and HFCS.[4]

- As distance is a critical factor for the KNN algorithm, three datasets with different distances are prepared: one emphasizes household structure, another emphasizes income and consumption, and the third is somewhere in between.[5] Using these three datasets, households between HBS and HFCS are matched three times. A simple average of the wealth data from these three results is used as the outcome of this matching exercise.

Gap adjustment

Consumption adjustment

- Following Eurostat (2024) and Coli et al. (2022), a proportional allocation method is used for gap allocation. This method distributes the entire micro-macro gap proportionally across households. The coefficients used for upscaling or downscaling the microdata are calculated as the weighted sum of the microdata divided by the corresponding NA item. In our exercise, the coefficients are calculated to match the main 12 ECOICOP (European Classification of Individual Consumption according to Purpose) divisions and four durability categories (durable, semi-durable, non-durable, and services) from NA.

Income adjustment

- Given the limited availability of income information from HBS, the variable for net income from HBS — defined as total income from all sources, including non-monetary components, minus income taxes — is used. This variable is adjusted to match the gross disposable income from NA. The gap between microdata and NA is adjusted based on the ascending gap shares by decile (consistent with the Eurostat (2024) method). The method assumes under-coverage or under-reporting of higher income households and allocates the higher gap shares to higher income decile groups. Then, each household within the respective

[4] These variables are age, education, labor status, household size, number of children, number of elderly members, number of household members in employment, household type, income ventiles, food consumption ventiles, utility consumption ventiles, food and utility consumption ventiles, and goods and services consumption ventiles. Due to data availability, for the 2010 KNN matching only, the categories of household type differ from those in other matching years, and the goods and services consumption ventiles is missing.

[5] Following three datasets are prepared. 1) greater distances for age and household type, 2) greater distances for income and food and utility ventiles and less distances for number of children and elderly members, and 3) distances that are around the average between 1 and 2 datasets.

decile is adjusted by an equal amount. In our exercise, the gap share per decile is slightly adjusted (see the table below) so that the estimated Gini coefficient using HBS data is close to the Gini coefficient from Eurostat experimental data, which is estimated from EU-SILC.

M3.1 Ascending gap shares by decile	decile	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
	gap share,%	0	0	4	6	8	12	14	16	18	22
	adjusted	0	2	4	6	8	12	14	16	18	20
	Each household within the respective decile has been adjusted by an equal amount rather than proportionally to their initial relative contribution.										

Wealth adjustment

- Following the study by Ahnert et al. (2020), the following HFCS items are matched with NA financial assets/liabilities (see table below). For fixed assets, the sum of AN.112 (Buildings other than dwellings and other structures) and AN.211 (Land) from NA is matched with HFCS codes HB0900 and HB280$x.

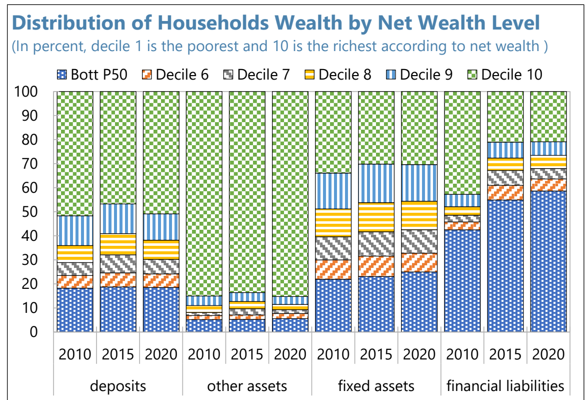
ESA 2010 code	NA instrument name	HFCS variable(s)	HFCS variable label and/or codes
F.22	Transferable deposits	HD1110	Sight accounts
F.29	Other deposits	HD1210	Savings accounts
F.3	Debt securities	HD1420	Bonds
F.4	Loans	HD1710	Amount owed to household
F.511	Listed shares	HD1510	Publicly traded shares
F.521	Money market fund (MMF) shares or units	HD1320c	Investments in mutual funds c
F.522	Non-MMF investment fund shares/units	HD1320a+HD1320b+HD1320d+HD1320e+HD1320f	Investments in mutual funds a, b, d, e, f
F.62	Life insurance and annuity entitlements	DA2109 = sum of (PF0920) over household members	Voluntary pension/whole life insurance
F.4	Loans	DL1000	Total outstanding balance of household's liabilities

- The net wealth in this paper is defined as "deposits + other assets (debt securities + listed shares + investment fund shares + life insurance) + fixed assets (dwellings + land) – financial liabilities (mortgage + non-mortgage)." As our focus is on consumption analysis, this paper excludes business wealth (financial and non-financial business wealth) to simplify the estimation process, which is approximately 10 percent of total assets based on DWA by ECB.

- As discussed by ECB (2024), the HFCS/QSA coverage ratios of deposits are large in many countries, including Slovakia (about 35 percent), implying the under-reporting of deposit numbers. Based on the suggestions by ECB (2024), some of the possible outliers of deposit numbers in HFCS (extremely small levels of deposits given the income level) are corrected.[6]

- The gap allocations between macro and micro data are conducted based on the following four items: deposits, other assets, fixed assets, and financial liabilities. A proportional allocation (see consumption adjustment) is used with information from DWA to fill the gap.

[6] Deposit numbers are corrected to 10 percent of households' monthly income if their annual gross incomes are above €10,000 and their reported deposit numbers are less than 10 percent of the monthly income. Deposit numbers are corrected to 5 percent of households' monthly income if their annual gross income is above €5,000 but below €10,000, they do not have any financial liabilities, and their reported deposit numbers are less than 5 percent of the monthly income.



Sources: ECB and IMF staff calculations.

The DWA data provide the share of household wealth items by the level of households' net wealth (the bottom 50 percentiles and deciles 6-10 of the, or six household groups in total), as illustrated by the chart below. Although the net wealth of DWA includes business wealth, the differences are assumed to be marginal. Based on this share data from DWA, the corresponding NA items (deposits, other assets, fixed assets, and financial liabilities) are divided into six groups (bottom 50 percentile and deciles 6-10). Similarly, the matched household microdata (HBS-HFCS microdata) are also divided into the six groups based on the net wealth concept. Then, the proportional allocation is applied to the corresponding four wealth items and six net wealth groups between NA and HBS-HFCS microdata.

Deflator adjustment

- The deflator for each household is constructed based on the Harmonized Index of Consumer Prices (HICP). At the time of writing, given that the latest deflator of NA is set to 2020 = 100, all HICP deflators are converted to 2020 = 100 (instead of 2015 = 100). Then, the weighted average of the HICP deflator for each household is constructed at the ECOICOP level 3 in 2010 and level 4 in 2015 and 2020. For imputed rent, the deflator from NA is used, as HICP does not cover this price index. Additionally, some items that HICP does not cover (e.g., narcotics, games of chance, life insurance, etc.) are disregarded, given their potentially small impacts on the total index. The weighted average of the constructed HICP-based deflator for all households and the total deflator from NA is compared, and a proportional allocation is applied (the HICP-based deflator is adjusted) to match the two numbers.

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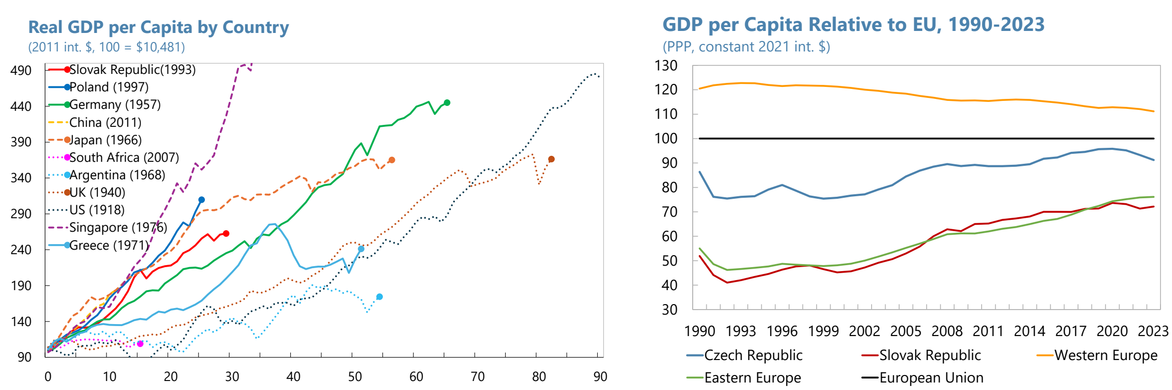
A MICRO-MESO-MACRO VIEW OF LABOR PRODUCTIVITY GROWTH IN THE SLOVAK REPUBLIC[1]

After the great financial crisis, the pace of labor productivity growth in Slovakia slowed markedly, but in recent years there are signs of a recovery. We link this potential recovery to macroeconomic, industry-level, and firm-level factors, including reduced labor hoarding compared to the EU, a healthy birthrate of rapidly growing young firms, and a resurgence of productivity growth in both established frontier firms and laggards in manufacturing as well as services. To boost productivity growth over the medium-term, policies should encourage investment in physical, human, and intangible capital to drive renewed TFP growth and continued capital deepening, which will also help Slovakia transition to higher value-added segments of value chains. At the industry level, policies should promote sectoral diversification and economic resilience, for example by expanding vocational education and training with a focus on competencies that are in high demand such as digital skills, and by streamlining procedures for skilled migrant workers in professions with shortages. Finally, micro evidence points to the need for stronger support for innovation. Potential avenues include a further deepening of capital markets, e.g., by nurturing the domestic venture capital ecosystem, stimulating the uptake of existing R&D tax incentives, and more technical assistance to promising firms in emerging sectors.

A. A Macro Perspective

Figure 1. Income per Capita and Convergence to Western Europe, 1990-2023



Sources: Feinstein (1972), Maddison (1995), Bolt and Van Zanden (2024), and IMF staff calculations.

Sources: World Bank World Development Indicators, and IMF staff calculations.

1. **Slovakia is part of a select group of countries that leapfrogged their development by growing faster than Western pioneers.** Historical data shows that early industrializers like the US and UK, who had to advance the technology frontier themselves, grew more slowly than later developers in Western Europe. Even faster growth was achieved by East Asian and Eastern European latecomers, including Slovakia, Singapore, Poland, and China, who could rapidly adopt frontier technologies. Slovakia maintained this accelerated growth until the 2007-2008 global financial crisis

[1] Prepared by Christian Bogmans (RES).

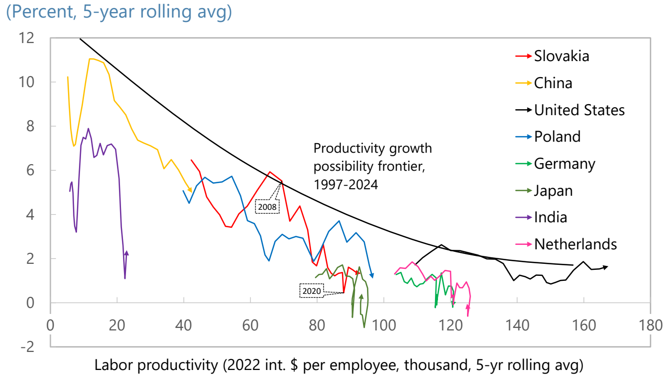
(GFC), after which its growth rates moderated to levels more typical of Western European development (Figure 1, left).

2. Slovakia continues to catch up to Western Europe and improve living standards, though at a markedly slower pace. Between 1993-2008, Slovakia's real GDP per capita (in PPP terms) grew on average by 5.1 percent annually, enabling swift convergence with Western European income levels at a pace of 1.7 percentage points per year. However, slower growth in the post-GFC period has given way to a slower rate of convergence, with the catch-up rate declining to roughly 1 percentage points per year between 2019-2023. At the current pace Slovakia needs at least another generation to close the gap. In 2023, Slovakia's real GDP per capita stood at 67 percent of the Western European average and at 74 percent of the EU average.[2] In terms of income growth Slovakia has been surpassed by several of its peers in recent years, Poland in particular, thus explaining the fact that convergence to the EU average has stalled (Figure 1, right). After the GFC, real GDP per capita (in PPP terms) continued to grow in absolute terms, with annual growth averaging 2.9 (1.3) percent between 2009-2019 (2020-2023).

3. A sharp decline in labor productivity (LP) growth underlies Slovakia's slower income convergence. The relationship between LP growth and LP levels across countries at different development stages shows a clear negative trend, with high performers like China and the United States tracing out the 'LP growth possibility frontier' (Figure 2). As Slovakia aims to reach a higher stage of development, a pressing question then emerges: How does its LP growth decline compare to historical patterns seen in other countries at similar stages of economic development? While Slovakia touched the LP growth frontier during its 2002-2007 'Tatra tiger' period, it has since fallen substantially below it, though recent data shows some recovery signs (Figure 2). While over the medium-term higher LP growth appears feasible given the distance to the frontier, the experiences of Japan (with similar income levels and demographics) and Germany (a key trading partner) suggest a recovery in LP growth is far from inevitable.

Figure 2. Labor Productivity Growth by Country, 1997-2024

(Percent, 5-year rolling avg)



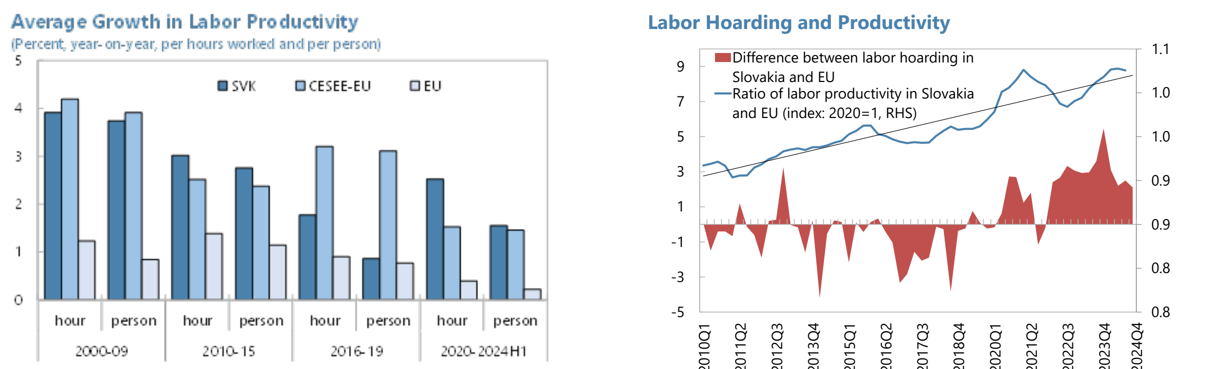
Sources: The Conference Board Total Economy Database; and IMF staff calculations.

4. Labor productivity growth in Slovakia has picked up in recent years, which can be partially attributed to labor hoarding. Growth of LP per hour worked and per employee slowed

[2] Using World Bank data, income levels of Western Europe and Eastern Europe are here defined as the GDP weighted average of GDP per capita (in 2011 int. $) of the following countries, that is, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Liechtenstein, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom for Western Europe, and Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Moldova, Montenegro, North Macedonia, Poland, Romania, Serbia, Slovakia, and Slovenia for Emerging Europe.

from an average of 3.9 and 3.7 percent respectively in the 2000s to 1.8 and 0.9 percent between 2016-19. However, since 2019, average labor productivity per hour worked has increased to 2.3 percent and to 1.4 percent per employee, outpacing the EU average and other CESEE-EU countries (Figure 3, left). According to the National Bank of Slovakia (NBS), the strong productivity growth in Slovakia in recent years in part reflects a combination of relatively fast GDP growth and tight labor markets, implying reduced labor hoarding.[3] While labor hoarding in the EU is estimated to have increased, it has been declining in Slovakia due to a less pronounced drop in domestic demand (Figure 3, right). A lack of labor hoarding suggests Slovakia is already utilizing its labor efficiently. In addition to this cyclical macroeconomic factor, the next sections will explore industry-level and firm-level factors to explain LP growth trends in Slovakia.

Figure 3. Labor Hoarding and Aggregate Labor Productivity Growth in Slovakia



Note: CESEE-EU: Central, Eastern and Southeastern Europe, EU member states
Sources: Haver Analytics and IMF staff calculations.

Sources: Haver Analytics and European Commission.

B. A Meso Perspective

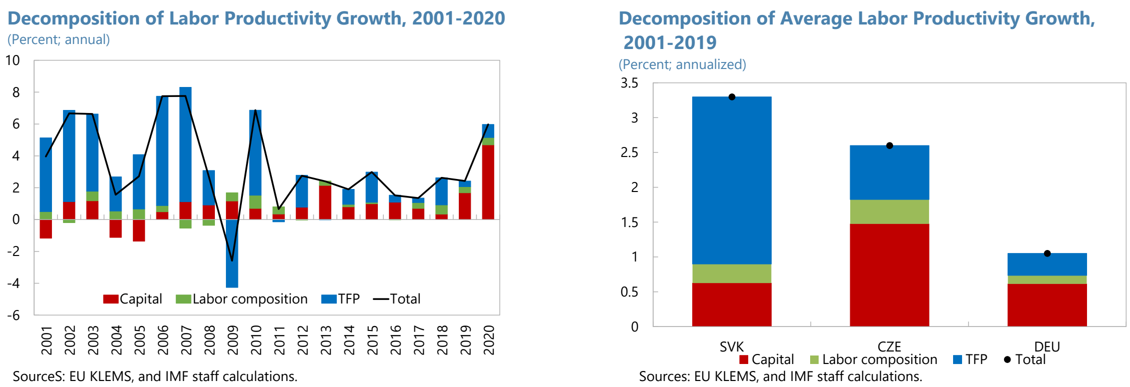
5. Slovakia's LP gains were historically mainly driven by Total Factor Productivity (TFP) growth, but over time capital deepening has become more important as TFP growth weakened. Growth in LP comes from three main sources: capital deepening, TFP growth, and labor composition improvements.[4] Between 2001 to 2019, TFP and capital contributed on average 2.4 percentage points and 0.6 percentage points respectively to LP growth in Slovakia. TFP's contribution was significantly larger than in the Czech Republic (0.8 percentage points) and Germany (0.3 percentage points), while capital's contribution was smaller than in the Czech Republic (1.5 percentage points) but equal to Germany's (0.6 percentage points) (Figure 4, right). The slowdown in Slovakia's LP

[3] National Bank of Slovakia (2022). Structural Challenges.

[4] Capital deepening occurs when workers have better or more capital to work with. This includes the accumulation of physical capital such as factories and machines, but also ICT capital like computes, and intangible capital such as software, data, and brands. TFP growth, i.e., efficiency improvements not captured by measured inputs of capital and labor, happens when firms adopt recent technologies, when they improve management practices, and when other firms learn from then. Finally, the composition of labor improves if the workforce shifts towards more educated and/or more experienced workers.

growth after the GFC is linked primarily to a slowdown in TFP growth, from 3.8 percentage points between 2001 and 2010 to 0.8 percentage points between 2011 and 2020, while capital deepening increased from 0.3 percentage points to 1.35 percentage points. This shift from TFP-led to TFP-and-capital-led growth reflects two factors. First, the exhaustion of easy efficiency gains from the transition to a market economy (reflecting low initial TFP levels even compared to Czech Republic) - gains that had come through better resource allocation, exit of inefficient state enterprises, and knowledge spillovers from multinational enterprises associated with relatively small capital investments. Second, EU accession (2004) and euro adoption (2009) not only boosted public investment financed with EU funds, but they also reduced investment risk and enhanced market access, thereby leading to a deeper integration of Slovakia into European manufacturing networks, with new capital investments focused on expanding production capacity within established value chains. Slovakia's growth process has consequently become more similar to Czech Republic in recent years in that capital accumulation has become a more important driver of LP growth.

Figure 4. Decomposition of Labor Productivity Growth

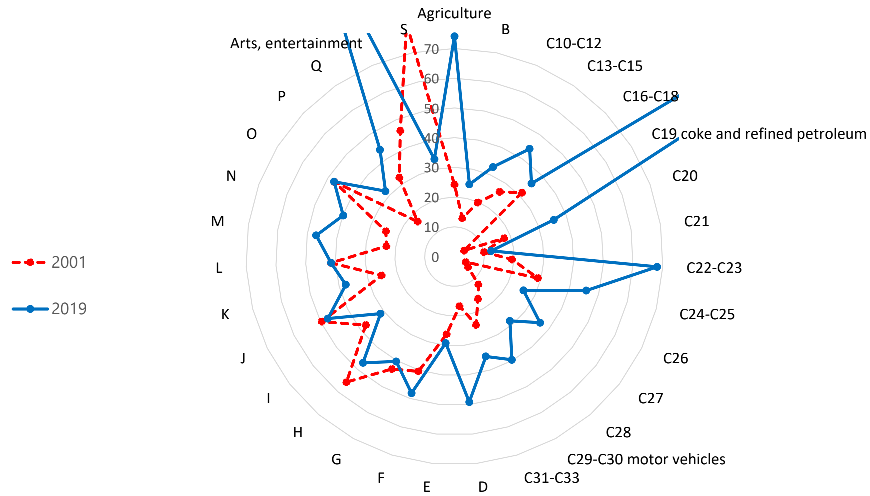


6. In recent decades, Slovakia has moved closer to the LP frontier, but the degree of catch-up varies across sectors. Between 2001 and 2020, LP caught up by 26 percentage points on average across 31 sub-sectors, reaching on average 54 percent of the EU11 frontier. The degree of catch-up, however, has been uneven across sectors, with labor productivity catching up the most in agriculture and certain manufacturing sectors (Figure 5, right half of the circle). Stagnation (and in a few cases regression) has been more common in certain service sectors (G-S). In "Arts, recreation, and entertainment" and "Coke and refined petroleum products", labor productivity exceeds the EU11 frontier. Slovakia's sectoral labor productivity distribution shows high dispersion, with a coefficient of variation (standard deviation divided by mean) of 1.19 in 2020, after excluding the outlier sector C19 ("Coke and refined petroleum products"). This high ratio indicates substantial variation across sectors and a right-skewed sectoral productivity distribution.

Figure 5. Sectoral Labor Productivity is Catching-up to The EU Frontier Albeit Unevenly

Slovakia Labor Productivity by Sector

(Percent of EU11 frontier)



Sources: EU KLEMS; and IMF staff calculations.

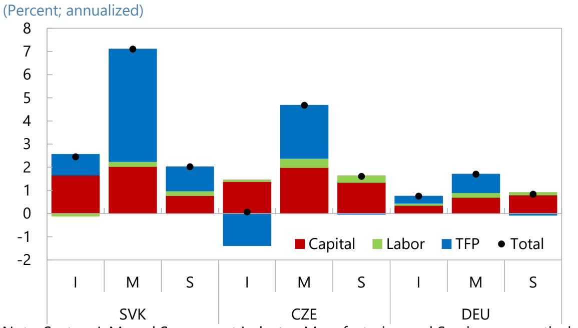
Notes: labor productivity defined as value added per employee at the 2-digit industry level.

Frontier is defined as the weighted average productivity of 11 EU countries (AT, BE, CZ, DE, DK, ES, FI, FR, IT, NL, SE), except for sectors C20 and C21 where, due to lack of data, it is defined as the 90th percentile among the EU6 (BE, DE, FR, IT, NL, LUX).

Figure 6. Labor Productivity Growth by Sector Aggregates, 2001-2020 and 2015-2019

Labor Productivity Growth by Sector for Selected Countries, 2001-2020

(Percent; annualized)

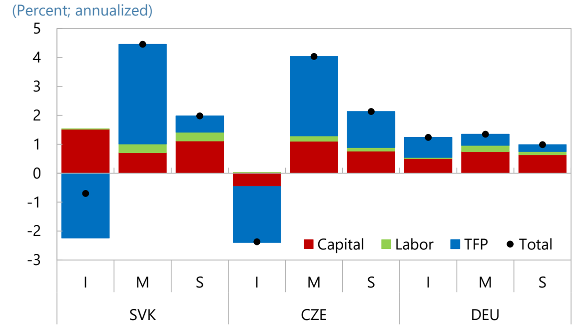


Note: Sectors I, M, and S represent Industry, Manufacturing and Services, respectively.

Sources: EU KLEMS, and IMF staff calculations.

Labor Productivity Growth by Sector for Selected Countries, 2015-2019

(Percent; annualized)



Note: Sectors I, M, and S represent Industry, Manufacturing and Services, respectively.

Sources: EU KLEMS, and IMF staff calculations.

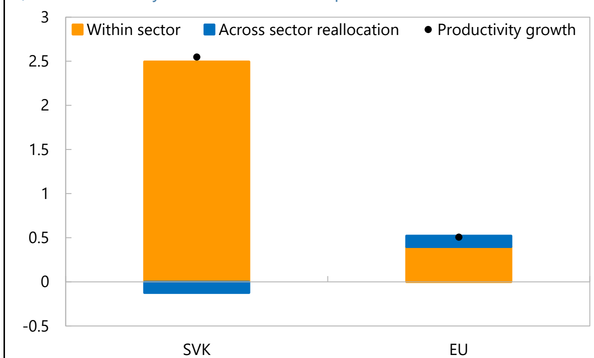
7. **From 2015 to 2019, Slovakia's LP growth was driven primarily by services, as labor productivity in both agriculture and industry contracted and labor productivity growth in manufacturing slowed sharply.** Between 2001 and 2020, the country's convergence toward the EU frontier was led by TFP growth in manufacturing and services, while industry (i.e., construction, mining, utilities) relied mainly on capital deepening (Figure 6, left). During 2015-2019, capital deepening was stronger in services compared to Germany and the Czech Republic, but weaker in manufacturing (Figure 6, right). This same period saw significant productivity challenges: agriculture and industry experienced declining productivity (-3.7 percent and -0.7 percent annually,

respectively), while manufacturing productivity growth slowed amid weak global industrial activity in 2016 and 2019. Only the service sector maintained robust productivity growth.

8. Recent labor productivity growth in Slovakia has been driven primarily by sectors becoming more productive rather than structural change. Aggregate productivity growth can occur through two channels: sectors becoming more productive, or labor shifting toward more productive sectors. A shift-share analysis following McMillan and Rodrik (2011) reveals that while all sectors showed productivity gains between 2019H1 and 2024H1—particularly manufacturing and services—some labor shifted toward less productive sectors. However, the positive within-sector productivity improvements significantly outweighed these negative reallocation effects (Figure 7). Three potential mechanisms could explain these within-sector gains: existing firms becoming more productive, market entry of productive new firms, or worker reallocation from low to high-productivity firms. Some recent research suggests limited resource transfer between firms of varying productivity (Institute for Economic Analysis-IHA, 2023) casting doubt on the importance of the third mechanism. The next section examines whether the first two mechanisms have contributed to productivity developments, analyzing differences between firm types, and comparing current trends to historical patterns.

Figure 7. Productivity Growth Decomposition

(Shift-share analysis, 2019H1-2024H1; percent annualized



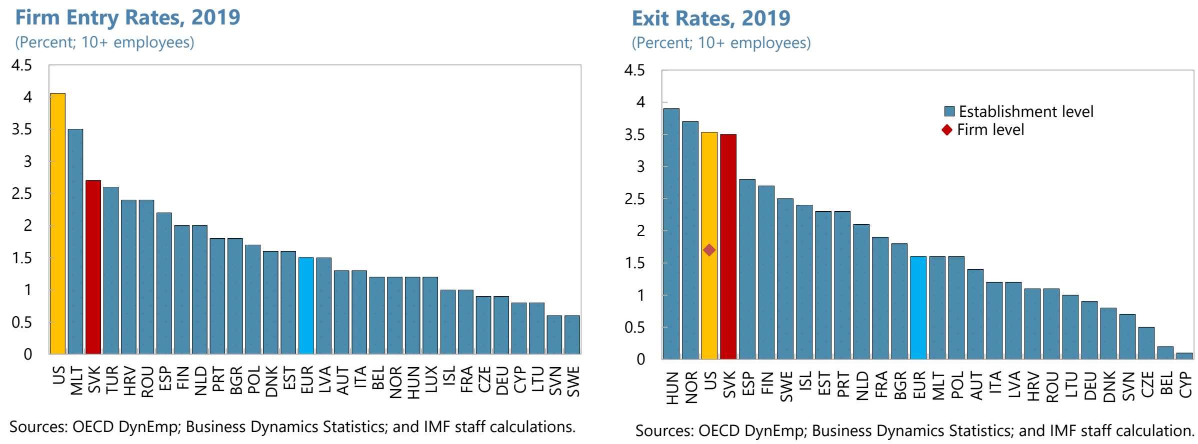
Sources: Haver Analytics, and IMF staff calculations.

C. A Micro Perspective

9. Firm entry and exit rates in the Slovak economy are relatively high, suggesting business dynamism is not constraining productivity growth. Slovakia's firm turnover exceeds the European average, with exit rates approaching US levels - typically considered the benchmark for economic dynamism (Figure 8). While Slovakia recorded negative net firm entry in 2019, bankruptcy data indicates this was an outlier. However, high business turnover alone does not guarantee productivity growth. The key challenge for Slovakia is not firm creation, but rather scaling up promising young firms ('gazelles') that can drive economy-wide productivity gains.

10. Slovakia has been successful in generating and growing 'gazelles'. Gazelles are young firms under 10 years old that achieve three consecutive years of 20 percent+ sales growth and reach at least 100 employees. The birthrate of these high-growth firms in Slovakia is broadly in line with that of most CEE peers in per-capita terms, though Poland and Hungary have shown stronger recent momentum (Figure 9, left). In addition, Slovak gazelles demonstrate strong productivity performance. They match EU averages in sales growth relative to large non-gazelle firms (Figure 9, middle), and recent cohorts show high sales-to-asset ratios compared to their larger, established counterparts (Figure 9, right).

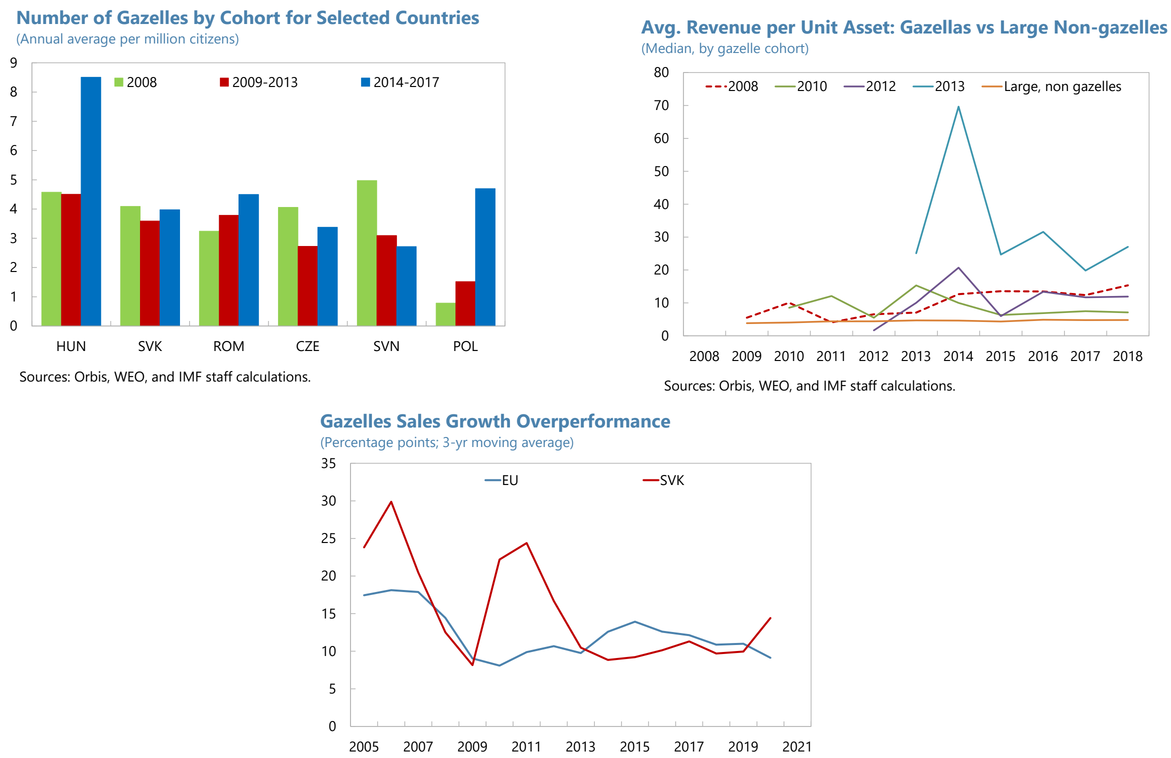
Figure 8. Firm Entry and Exit in The Slovakian Economy, 2019



Sources: OECD DynEmp; Business Dynamics Statistics; and IMF staff calculations.

Sources: OECD DynEmp; Business Dynamics Statistics; and IMF staff calculation.

Figure 9. Birthrate of Gazelles in Slovakia and Their Performance Relative to Peers



Sources: Orbis, WEO, and IMF staff calculations.

Sources: Orbis, WEO, and IMF staff calculations.

Sources: Orbis, and IMF staff calculations.

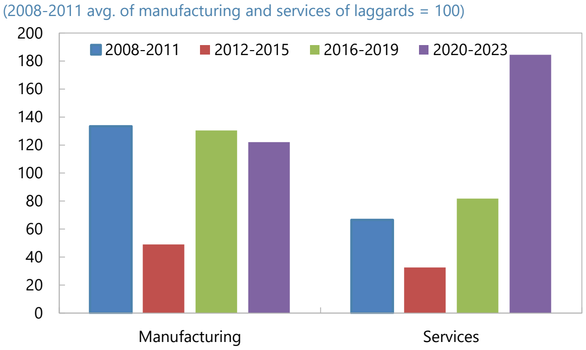
11. An analysis of labor productivity growth in Slovakia between 2008-2023 shows substantial variation across different periods and firm type. Laggard firms, representing the bottom 50 percent of firms by labor productivity, achieved higher productivity growth compared to frontier firms (top 5 percent) across both manufacturing and services sectors, indicating a pattern of convergence. The evolution of productivity growth followed a distinctive U-shaped pattern over four distinct periods, with a significant downturn during 2012-2015 after the global financial crisis, when both frontier and laggard firms experienced depressed productivity growth across all sectors.

12. **Firm-level analysis reveals a broad-based recovery in LP growth in Slovakia in recent years, a result that aligns with observations from industry and macroeconomic data.** While Slovakia's frontier firms experienced stagnation between 2008-2018 (manufacturing) and 2008-2015 (services), mirroring the broader EU experience, they notably diverged from the EU average by achieving sustained productivity growth across all sectors during 2020-2023, a pattern also observed among laggard firms. This recent performance suggests a broader productivity revival in the Slovak economy, distinct from general EU trends. These firm-level results regarding LP growth align with results observed in industry and national accounts data, particularly the subdued or negative productivity growth observed in certain sectors during 2015-2019, and the signs of a robust recovery in aggregate labor productivity growth during 2020-2023.

Figure 10. Labor Productivity Growth in Manufacturing and Services by Firm Type

Average Annual Labour Productivity Growth of Laggard Firms, Different Periods

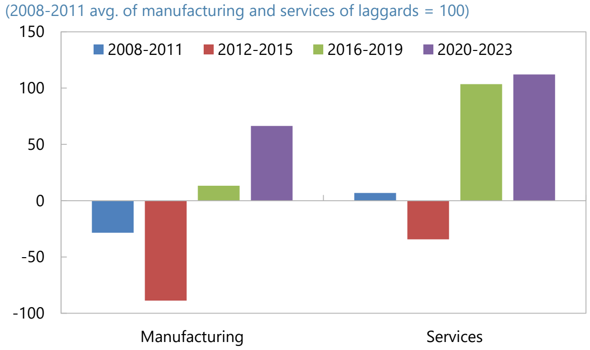
(2008-2011 avg. of manufacturing and services of laggards = 100)



Source: Orbis; EU KLEMS; and IMF staff calculations.

Average Annual Labour Productivity Growth of Frontier Firms, 2008-2023

(2008-2011 avg. of manufacturing and services of laggards = 100)



Source: Orbis; EU KLEMS; and IMF staff calculations.

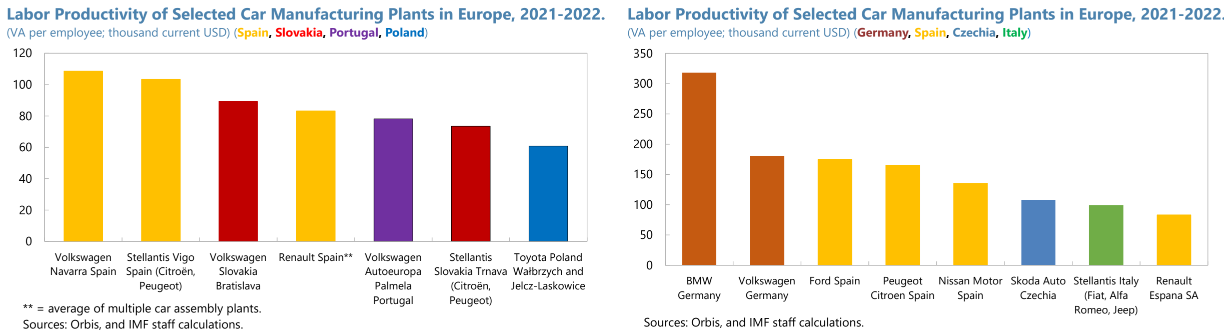
Note: labor productivity (LP) defined as value added per employee. Laggard firms defined as bottom 50 percent of LP at beginning of each period at Nace2 sub-sector level. Sub-sector growth rates aggregated to sector (manufacturing, services) using EU KLEMS employment shares for Nace2 industries.

13. **Slovakia's automotive sector shows substantial variation in productivity depending on how it is measured.** Starting in the 1990s, a stream of investments by foreign multinationals has turned Slovakia into the EU’s largest car producer in per-capita terms. The country is currently home to three automotive groups with operational assembly plants (Kia, Stellantis, Volkswagen) and should be home to a fourth (Volvo cars) by 2026. Firm-level analysis reveals that productivity in the automotive sector varies depending on whether we look at the whole sector, individual firms, or their position within the corporate structure.

- Labor productivity metrics from 2022 Orbis firm data highlight clear differences across the industry: while the Volkswagen Bratislava plant achieved labor productivity of US$89,000, the sector's average labor productivity stood at $68,000, reflecting the influence of smaller, less productive domestic component suppliers.

- Slovakia's car assembly plants demonstrate productivity levels comparable to their counterparts in Portugal, Poland, and Spain (Figure 11, top). While these plants are more productive than the average Slovak firm in other sectors, they lag parent companies like Volkswagen Germany and subsidiaries such as Ford Spain (Figure 11, bottom).[5]

Figure 11. Labor Productivity at Selected Car Manufacturing Plants, and Car Parent Companies or Subsidiaries in Europe



- The lower productivity of Slovak automotive plants compared to their parent companies and foreign subsidiaries reflects both their position in value chains and differences in capital returns. This gap can be attributed to two key factors: first, parent companies and subsidiaries typically engage in higher value-added activities along the value chain, including R&D, car design, and sales and distribution; second, they benefit from higher returns on intangible capital, particularly brand value, as exemplified by BMW Germany's exceptionally high productivity levels (Figure 11, bottom).

D. Policy Recommendations

14. Sustaining and boosting productivity growth in Slovakia is essential to generate the economic surplus needed to achieve higher living standards, address the fiscal challenges of an aging population, and finance the energy transition. While Slovakia's position offers opportunities for rapid catch-up growth, sustainable productivity improvements and the transition to an innovation-driven economy will require a comprehensive long-term strategy that strengthens its innovation ecosystem, reforms higher education, further improves its investment climate, and deepens capital markets.

15. At the macroeconomic level, government policies should prioritize investment in physical, human, and intangible capital to drive both renewed TFP growth and continued capital deepening. To achieve this, the government must maintain a favorable investment climate

[5] Note that these cross-country productivity comparisons should be interpreted with caution, as multinationals often utilize transfer pricing to shift profits (costs) to low-tax (high-tax) jurisdictions, which could artificially inflate or deflate measured labor productivity in different locations.

that sustains and redirects FDI to high-growth potential sectors like electric vehicles and other cleantech goods and services, while also enhancing their capacity to utilize EU funds effectively. At the same time, reforming the education sector (such as through the 2024 introduction of performance contracts in higher education) will help accumulate human capital, boost study efficiency, reduce skill mismatches, and limit net brain drain. Better educational outcomes will also support the transition to higher-value segments of value chains.

16. Given Slovakia's dependence on the automotive sector and recent weakness in industrial and agricultural productivity growth, policies should promote sectoral diversification and economic resilience. This will require targeted reskilling of the existing workforce and upskilling of new entrants to the labor market through expanded vocational training and education with a focus on competencies that are in high demand including digital and AI-related skills. To address immediate labor market shortages, Slovakia could simplify its immigration procedures for skilled workers through a one-stop shop system. Additionally, the government should identify and support promising firms in emerging sectors for example by means of technical assistance (as provided by the Ministry of Economy), preferably with the potential to create spillovers to the broader Slovak economy. These measures would help address the observed secular productivity slowdown in traditional sectors while building new centers of excellence beyond ICE-focused automotive manufacturing.

17. Finally, firm-level evidence points to the need for stronger support of innovation and technology adoption. To help Slovakian firms catch up to domestic and global productivity frontiers, they will need to increase spending on applied and business R&D. Several potential avenues exist. First, in the short-run policymakers can encourage the uptake of existing R&D tax incentives by reducing administrative barriers, especially for small firms. Second, recent progress in developing retail bond markets is encouraging, but further deepening of domestic capital markets remains crucial. In this context, Slovakia could strengthen its startup financing environment through two key initiatives: nurturing Bratislava's venture capital ecosystem and supporting the EU capital markets union. The latter would facilitate cross-border capital flows, particularly equity and venture capital financing that startups need to grow. Third and last, in the long-run a strengthening of ties between the innovation ecosystems in Bratislava and other culturally and/or geographically proximate cities in Central Europe, such as Prague, would help create a more integrated innovation region that benefits from larger scale, deeper networks, and enhanced knowledge flows between research institutions and entrepreneurs, thereby fostering a "culture of growth" (Mokyr, 2016). These initiatives would serve multiple objectives: enable stalling frontier firms to catch up to the global frontier, help laggards and micro-firms with their convergence to domestic frontier firms, and support gazelles in their rapid expansion to drive aggregate productivity growth (IMF, 2024).

Appendix I. Data

A. Labor Productivity Growth in Frontier and Laggard Firms

Data Cleaning

The analysis of productivity growth in frontier firms and laggards is based on Bureau van Dijk's Orbis database. The Orbis data is cleaned following closely the steps described by Kalemli-Ozcan and others (2015), and Díez et al (2021):

- Basic cleaning steps taken include the removal of duplicates, dropping zero-revenues firms, keeping only 12-month reporting periods, and removal of firms from the financial and public sectors (NACE codes 11 and 15).

- Variable cleaning consisted of dropping observations with negative values in operating variables, financial expenses, and selected balance sheet items, dropping observations with any missing values in comprehensive balance sheet structure (current/fixed assets, current/non-current liabilities, shareholders' funds and all their components).

- Outlier removal based on: cost ratio (0.01 < total cost/ (material + labor costs) < 1); revenue/asset ratio (0.015 < ratio < 12); liability checks (0.9 < total liabilities ratio < 1.1); growth thresholds of employment, revenues, and assets by firm size, that is, -90 percent to 2000 percent for firms with less than 10 employees, -90 percent to 1000 percent for firms with 11-20 employees, -90 percent to 600 percent for firms with 21-50 employees, -90 percent to 400 percent for firms with 51-100 employees, and -90 percent to 200 percent for firms with more than 100 employees. After duplicate removal, cleaning, and outlier removal I end up with 95,997 firm-year observations for the period 2007-2023.

Analysis

I measure labor productivity (LP) as added value (in current EUR) per employee, and subsequently calculate its growth rate in percentages. Firms are organized into 2-digit NACE sectors. I use the sectoral categorization based on NACE REV. 2 from EU KLEMS (see Bontadini et al. 2023), which combines 13 manufacturing subsectors within section C with 18 1-digit sectors (A, B, D, E, F,... R, S) for a total of 31 sectors. I then take the following steps:

- Firms are classified into three productivity groups within each NACE sector, namely the bottom 50 percent, the middle (50-95th percentile), and the top 5 percent (frontier firms). Classifications are made at the start of each period (2007, 2011, 2015, 2019).

- For sample selection, only firms are kept that are present in the base year of each of the 4 distinct periods: 2007-2011, 2011-2015, 2015-2019, 2019-2023.

- I then aggregate the firm-year LP growth observations into sector LP growth estimates by using each firm's share in sectoral value added as its weight.

- Next, the sectoral LP growth figures are then aggregated into four main sector aggregates (agriculture A, industry I, manufacturing M, services S) by using sectoral VA shares from EU KLEMS as weights. The use of these weights disciplines the calculation of aggregate LP growth as (firms from) certain sectors may be over- or underrepresented in the Orbis data. Before the aggregation I removed outliers if the sectoral growth rate > 75 percent or <-75 percent and replaced them with sector averages. Sector A corresponds to NACE code A; sector I corresponds to NACE codes B, D, E, and F; sector M corresponds to 13 subsectors within NACE code C; sector S corresponds to the remaining 1-digt NACE codes, namely G, H, I, J, K, L, M, N, O, P, Q, R, and S.

The final output consists of labor productivity estimates by industry (A, I , M, S) for different firm types (laggard, middle, frontier) for 4 different time periods.

B. Labor Productivity in The Automotive Industry

To analyze labor productivity in the automotive industry, I also rely on Bureau van Dijk's Orbis database. As before, labor productivity (LP) is measured as added value (in current EUR) per employee.

- For Figure 11 top I compare labor productivity in Slovakia’s car assembly plants with other assembly plants in Poland, Portugal, and Spain. Selection of these plants is based on data availability and information retrieved via Google search to ensure the firm is an assembly plant or an average of multiple assembly plants. Observations are for 2022. If that year is not available for a particular plant, I take 2021. I make an exception for Stellantis Slovakia and take the observation for 2021 to make a fairer comparison with Volkswagen Palmela in Portugal for which only 2021 data is available.

- For Figure 11 bottom I compare labor productivity across car company subsidiaries or parent companies in Germany, Spain, Italy, and Czech Republic. Selection is again driven by data availability. Google search is again used to ensure that the firm is either a subsidiary or a parent company. Observations are for 2022. If that year is not available for a particular plant, I take 2021.

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AI EXPOSURE AND PREPAREDNESS IN SLOVAKIA'S LABOR MARKET[1]

This analysis uses measures of exposure and complementarity to Artificial Intelligence (AI) on employment data from Slovakia to examine the potential implications of AI on the labor market. Around half the workers in Slovakia have high exposure to AI, with significant variations across sectors. While 27 percent of jobs also exhibit high complementarity, 24 percent are at risk of displacement especially in certain service sectors such as finance and information and communications. Women in particular have higher exposure to AI, and face both greater opportunities and greater risks of job displacement from AI. Slovakia has relatively low AI preparedness and digital skills compared to its peers. Policies to support a digital ecosystem, enhance human capital and manage labor market transitions, as well as a supportive regulatory framework would allow Slovakia to maximize the opportunities and mitigate the negative impacts from AI.

A. Introduction

1. **Artificial Intelligence (AI) holds the potential to significantly impact economies globally, with profound shifts particularly in the labor market**. AI has the potential to enhance productivity and boost growth – it could generate a positive productivity shock, which broadens the productive capabilities of economies, and facilitate shifts between labor and capital. The advent of generative AI (GenAI) in particular, with its cognitive capabilities, has broadened AI's potential applications. In some economic sectors and jobs, AI could augment worker productivity and boost labor demand; conversely, other sectors could see large job displacements if AI reduces the need for human input. However, given the rapid evolution of the AI landscape, its vast and flexible applications in numerous domains, and society still grappling with the acceptability of its use, the impact of AI on economies and societies remain highly unpredictable.

2. **The impact of AI is likely to vary significantly across countries, depending on the level of development and economic structure.** Advanced economies (AE) are likely to reap greater benefits and experience more of the negative effects of AI on the labor force compared to emerging markets and developing economies (EMDEs), primarily due to their workforce being more oriented towards cognitive-intensive jobs. This could exacerbate economic disparities across countries. While AI-induced job displacement poses risks for higher-wage earners, potential AI complementarity is also correlated with income, which could affect income and wealth inequalities within countries.

3. **This analysis studies the potential impact of AI on the labor market in Slovakia.** It aims to link the findings from the academic literature onto the specific circumstances of the Slovak labor market, looking at the impact on various population groups and economic sectors.

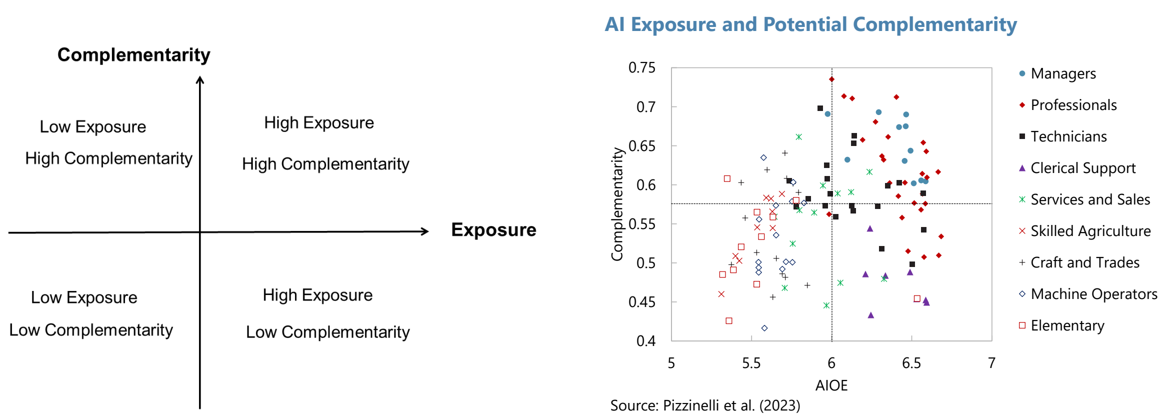
[1] Prepared by Shinya Kotera and Yen Mooi (EUR).

B. Conceptual Framework

4. The analysis uses a conceptual framework that measures various jobs' exposure to, and complementarity with, AI. It uses the occupational classification proposed by Cazzaniga et al (2024), which is in turn based on the work of Felten et al (2021) and Pizzinelli et al (2023). Exposure is defined as the degree of overlap between AI applications and required human abilities in each occupation (Felten et al, 2021), also known as the standard measure of AI occupational exposure (AIOE). Pizzinelli et al (2023) augment this measure with an index of potential AI complementarity, by considering information on the social, ethical, and physical context of occupations, as well as required skill levels. This enables the framework to account for the potential of AI as a labor complement or substitute, where complementarity reflects the degree of shielding from AI-driven job displacement. Paired with AI exposure, this framework can thus give an indication of the amount of jobs at risk of being made redundant by AI.

5. Using this framework, occupations can be categorized according to their exposure to, and complementarity with, AI. We categorize jobs into four groups in the exposure/complementarity quadrant: high exposure/high complementarity (HE/HC), high exposure/low complementarity (HE/LC), low exposure/high complementarity (LE/HC) and low exposure/low complementarity (LE/LC). These categories are determined based on whether the exposure and complementarity to AI of occupations fall above or below the respective median values (Figure 1). HE/HC occupations are those that stand to benefit the most from AI, including because there is significant potential for AI support and limited scope for unsupervised use (for example due to ethical or societal concerns). These are primarily cognitive jobs with a high degree of responsibility and personal interactions (e.g., surgeons, judges). Meanwhile, HE/LC occupations are well-positioned for AI integration but with a greater likelihood of AI replacing human tasks (e.g., telemarketers) – and hence most vulnerable to displacement from widespread AI adoption.

Figure 1. AI Exposure and Complementarity



C. Labor Market Implications for Slovakia

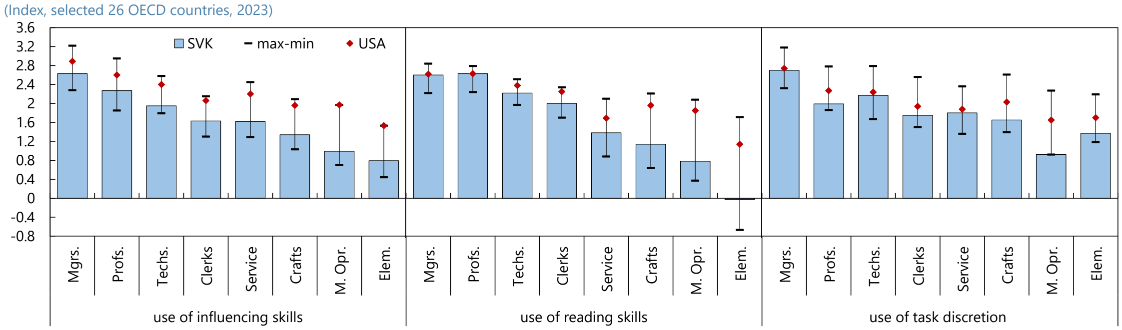
6. The conceptual framework is applied to the Slovak labor market to assess AI exposure and complementarity. Using the data by occupational classifications mentioned above, AI exposure and complementarity was estimated for Slovakia by applying the employment data (ISCO 3-level digit) provided by the Statistical Office of the Slovak Republic (SOSR). The employment data are 2023 yearly averages obtained from the quarterly labor force survey and include self-employed individuals. This allows for a more granular look at the potential impact of AI on the distribution of occupations in Slovakia.

7. Several caveats apply. Importantly, the level of complementarity and exposure estimated is based on US data, and applying the classification framework assumes that tasks performed within similar occupations are homogeneous around the world, thus ignoring likely cross-country variations. For example, jobs with higher complementarity require higher cognitive skills, but the PIAAC (Program for the International Assessment of Adult Competencies) data suggests that Slovak workers tend to use such skills less often than US workers, suggesting that the results in our analysis might overestimate the share of high exposure and high complementarity jobs in Slovakia (Figure 2). The large gap in the use of cognitive skill by clerks and service workers between the US and Slovakia also suggests such workers could face higher risks of displacement from AI in Slovakia compared to their US counterparts. The main analysis in this paper relies on the assumption of homogeneity of tasks to simplify international comparisons. However, we also show adjusted results for Slovakia based on the PIAAC data (see Box 1). Another important caveat is that that the analysis is static, assuming that sector sizes and tasks in each occupation remain unchanged even after the introduction of AI.

Figure 2. Use of Skills at Work

Use of Skills at Work by Occupation

(Index, selected 26 OECD countries, 2023)



Note: influencing skills ranges from 1 to 5, reading ranges from -3 to 7, and task discretion ranges from -1 to 5

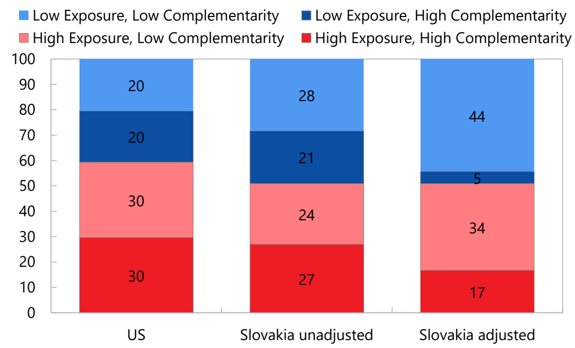
Sources: OECD and IMF staff calculation.

Box 1. Adjusting for Skill Differences Between Slovakia and the US

This box adjusts the complementarity index used in this paper using PIACC data to better reflect the differences in skill usage between the US and Slovakia. The analysis in this paper assumes that the tasks performed in the US are homogeneous around the world by using the same occupation classification. However, as shown in Figure 2, the skills used at work can differ globally, even within the same occupation category. To address this issue as much as possible, the data for complementarity is adjusted based on the PIAAC data (2nd Cycle) for the US and Slovakia.[1]

The adjusted data implies that Slovakia could face higher risks of AI displacement compared with the US. Comparing the data before and after the adjustment, the share of HE/HC jobs in Slovakia — occupations which are likely to benefit the most from the introduction of AI—decreases from 27 to 17 percent. On the other hand, the share of HE/LC jobs increases to 34 percent from 24 percent in the unadjusted data. This suggests that job disruptions from AI in Slovakia could be larger than suggested by the unadjusted index.

Employment Share by AI Exposure and Complementarity
(Percent)



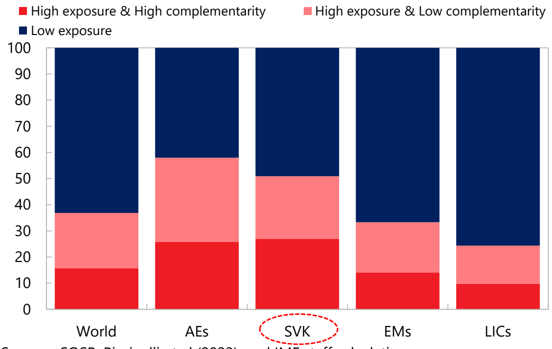
Sources: SOSR, PIAAC, Pizzinelli et al (2023), and IMF staff calculations

[1] The complementarity estimated by Pizzinelli et al. (2023) using O*NET consists of six components. Based on the percentage difference in the average skill usage between US and Slovak workers, each of the six components is adjusted at the level 2 of ISCO. However, if the sample size of a certain category is less than 30, the data for ISCO level 1 is used instead. The PIAAC variables used for the adjustment are as follows: 1) Communication: F2_Q01b, F2_Q02a , F2_Q05a , H2_Q03c, 2) Responsibility: H2_Q03b, H2_Q03d, H2_Q14a, 3) Physical Conditions: H2_Q07a, H2_Q07b, 4) Criticality: H2_Q05a, H2_Q05b, H2_Q06b, 5) Routine: TASKDISCC2_T1, 6) Skills: D2_Q12a , D2_Q12d. See OECD (2024) for detailed data and codebooks.

8. **The share of employment with high AI exposure in Slovakia is slightly lower than in other advanced economies (AEs)** (Figure 3). Around half the labor force in Slovakia is highly exposed to AI, with 27 percent of jobs characterized by high complementarity (HE/HC) and 24 percent at risk of AI-related displacement (HE/LC). In general, AEs have a larger share of high-exposure occupations (57 percent) than emerging market economies (EMs, 33 percent) and low-income countries (LICs, 24 percent). Slovakia's share of HE/HC occupations is similar to the average AE (27 percent of employment in SVK and 26 percent in AE), while the share of HE/LC high exposure/low complementarity occupations is slight lower (24 percent in SVK and 32 percent in AE). Compared to other EU countries, the share of HE/HC occupations is lower, and the share of high HE/LC occupations slightly higher.

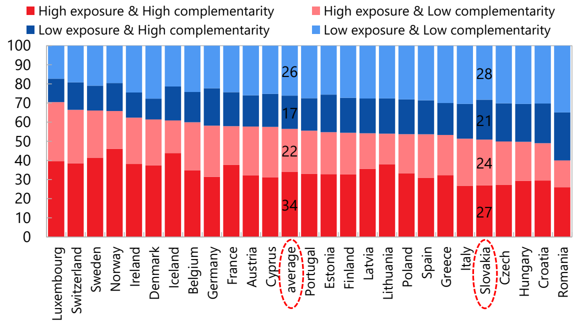
Figure 3. Employment Shares by AI Exposure and Complementarity: Country Groups and Selected European Countries

Employment Share by AI Exposure and Complementarity
(Percent)



Sources: SOSR, Pizzinelli et al (2023), and IMF staff calculations.

Employment Share by AI Exposure and Complementarity
(Percent, Selected European Countries, data for 2022 except Slovakia (2023))



Note: Countries where ISCO-3 digit information is available.
Sources: SOSR, Eurostat, Pizzinelli et al (2023), and IMF staff calculations.

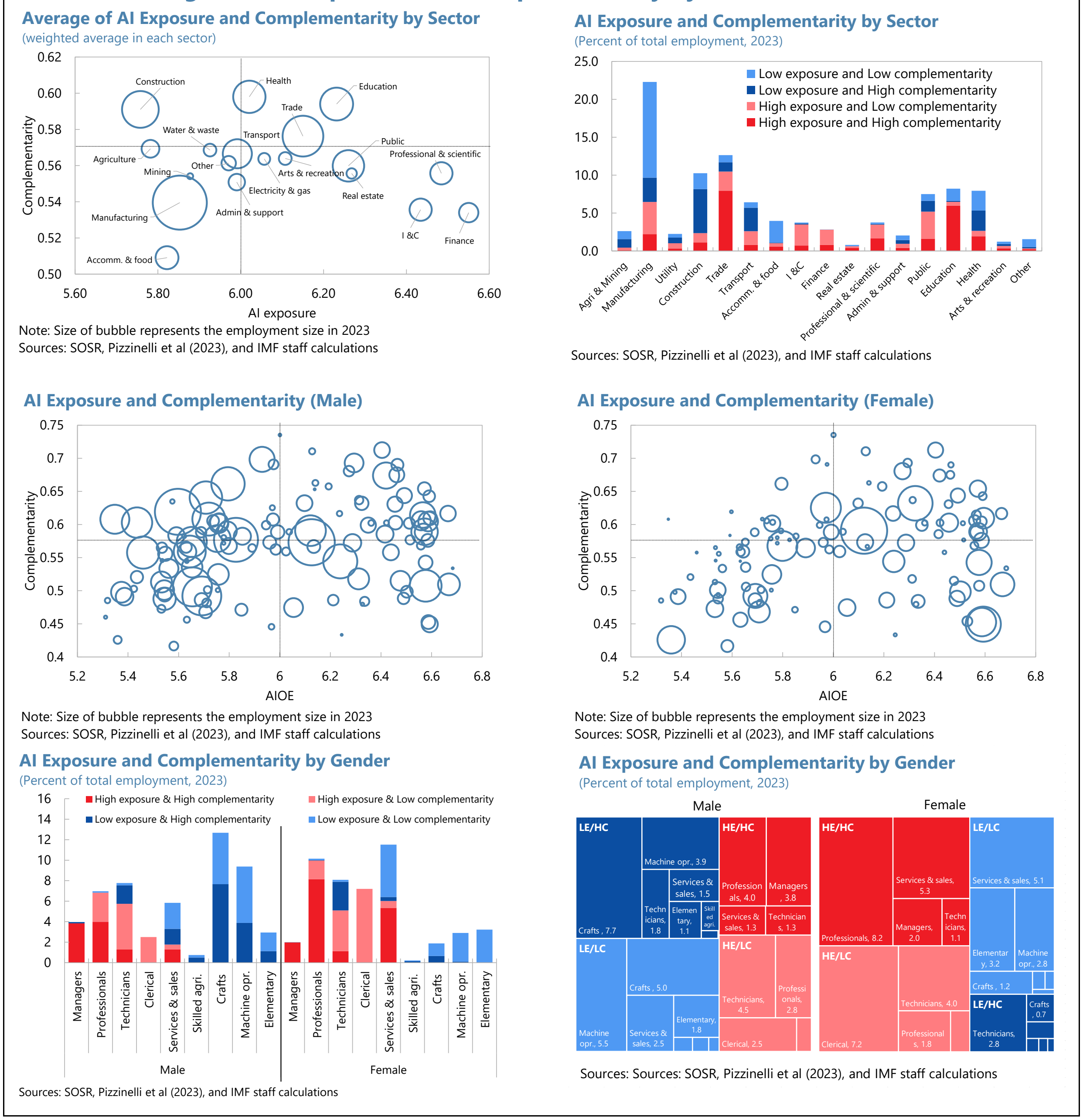
9. Service sector jobs in Slovakia stand to gain the most from widespread AI adoption, but workers in these jobs are also at the highest risk of displacement (Figure 4)**.**

- HE/HC: A large share of the jobs in the education, wholesale and retail, real estate, and professional sectors exhibit high exposure and high complementarity to AI. These jobs are well-positioned to take advantage of productivity gains from AI and emerging AI growth opportunities.

- HE/LC: A significant proportion of finance, information and communication, and public sector jobs exhibit high exposure and low complementarity. In Slovakia, about two-thirds of jobs in finance (e.g. financial professionals), and information and communication (e.g., software and application developers and analysts) exhibit high AI exposure and low complementarity, making them more susceptible to risks from AI-related labor market shifts. Public sector occupations also fall into this category, with around half of the jobs in this sector (e.g., general office clerks) at risk.

10. Jobs in the manufacturing sector, which accounts for the highest share of employment in Slovakia, are relatively less exposed to AI. Around 70 percent of manufacturing employment has low AI exposure. Only 20 percent of manufacturing jobs (e.g., physical and engineering science technicians, clerical support in manufacturing) have high exposure and low complementarity to AI and thus at greater risk of job displacement. Applying the analysis to the automotive sector specifically, the results are very similar, although the small sample of data available makes it less reliable. However, these jobs might face the threat of replacement by robots or automation instead of AI, due to the nature of their manual tasks, although this is beyond the scope of this paper.

Figure 4. AI Exposure and Complementarity by Sector and Gender



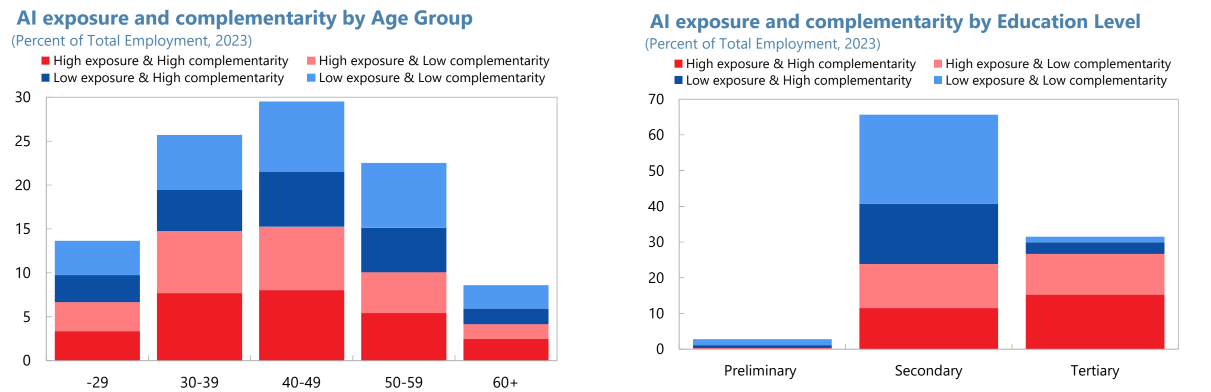
11. Female workers are more exposed to AI than male workers in Slovakia. 64 percent of female workers in Slovakia have high exposure to AI, while for men, the share is 39 percent.[2] In Slovakia, more women are employed in high-exposure occupations such as clerical, services and sales, and professional occupations, while there is a higher share of men in low-exposure jobs such as crafts and machinery operation occupations (Figure 4). This is similar to the finding in Cazzaniga et al (2024) where in most countries, more women tend to be employed in high-exposure jobs

[2] Females comprise 47 percent of total employment in Slovakia and males are 53 percent.

relative to men. By complementarity, women with HE/HC jobs make up 35 percent of total female employment, relative to 20 percent of men in Slovakia. Conversely, almost 30 percent of females are in the HE/LC category compared to 20 percent of men, which reflects the higher share of women in certain jobs (especially clerical jobs). This can be interpreted to mean that women face both higher risks and higher opportunities, consistent with the finding in Cazzaniga et al (2024) for most countries.

12. The degree of exposure and complementarity to AI is broadly similar across age groups, and higher for more educated workers (Figure 5)**.** The distribution of jobs according to AI exposure and complementarity is relatively equal across age groups in Slovakia. In terms of education level, more educated workers have jobs with high AI exposure, and many of those jobs are in occupations with high AI complementarity. This is similar to the finding for other countries (Cazzaniga et al, 2024).

Figure 5. AI Exposure and Complementarity by Age and Education



Sources: SOSR, Pizzinelli et al. (2023), and IMF staff calculation.

Sources: SOSR, Pizzinelli et al. (2023), and IMF staff calculation.

D. AI Preparedness and Digital Skills

13. The level of AI preparedness in Slovakia is below the average of EU countries (Figure 6)**.** The AI preparedness index (AIPI) developed by Cazzaniga et al (2024) looks at four key dimensions relevant for smooth AI adoption: (i) digital infrastructure; (ii) innovation and economic integration; (iii) human capital and labor market policies; and (iv) regulation and ethics.[3] While there is high uncertainty around the institutional requirements for an economy-wide integration of AI, the AIPI can point toward areas for improvement. The AIPI for Slovakia is 0.6, lower than the average EU country (0.7) and the average AE (0.7). Although performing better than EMs, Slovakia scores at the

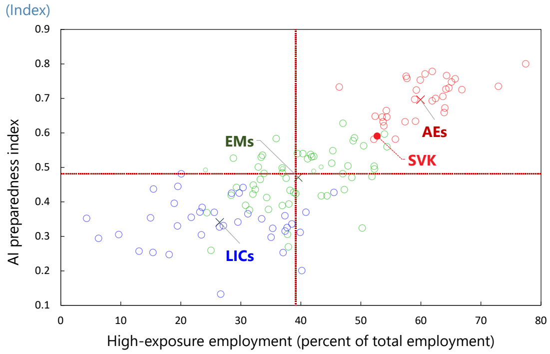
[3] The index is composed of a set of indicators expected to be important for smooth AI adoption, including sustained human capital investment, inclusive expertise in STEM (science, technology, engineering and mathematics), labor and capital mobility, and adaptability of legal frameworks to digital business models. The indicators are normalized to a 0-1 scale and averaged, with the AIPI a simple average of the four dimensions.

low end of the AE grouping (Figure 6). In particular, Slovakia lags in *regulation and ethics*, and *innovation and economic integration* relative to the average EU and AE country.[4]

Figure 6. AI Preparedness

AI Preparedness and Exposure

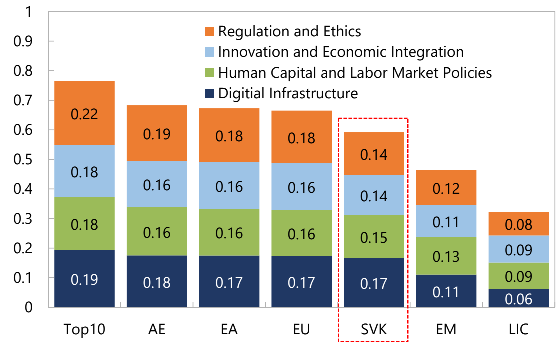
(Index)



Sources: Cazzaniga and others (2024) and IMF staff calculations.

AI Preparedness Index by Factors

(Index)

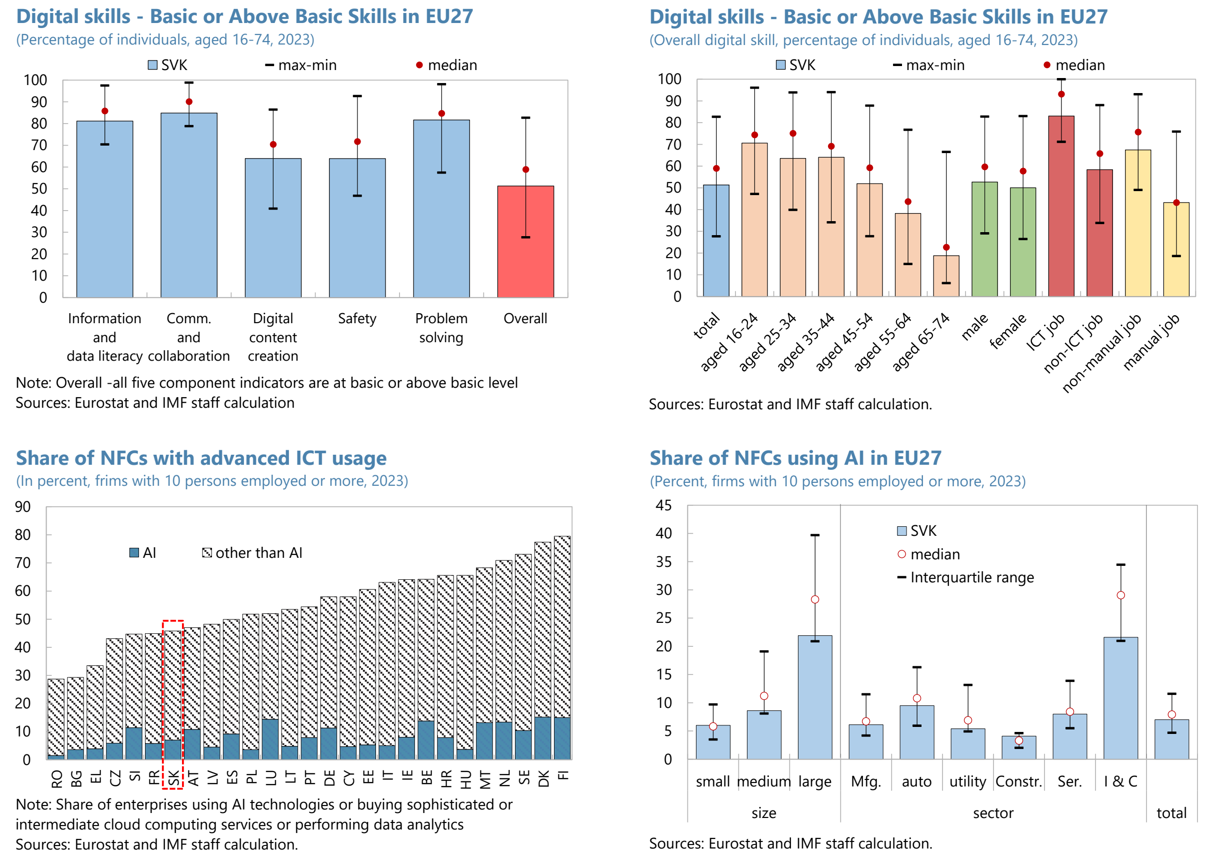


Sources: Cazzaniga and others (2024) and IMF staff calculations.

14. Digital skills and the use of information, communication, and technology (ICT) in Slovakia is also generally lower than the EU median (Figure 7). Basic or above basic digital skills in Slovakia are below the EU median across all types of digital skills, as well as across all age groups and gender. In terms of occupations, digital skills of manual jobs are at the EU median, while other jobs are below. In addition, Slovak firms are below the EU median in terms of advanced ICT usage. While small firms are on par with the median in terms of AI usage, medium and large Slovak firms lag behind. By sector, the information and communications firms are below the EU median on AI usage.

[4] These two indicators (*innovation and economic integration*, and *regulation and ethics*) can be considered "second-generation" elements likely to maximize the economic impact of AI. *Digital infrastructure* and *human capital and labor market policies* can be considered "foundational" elements, more relevant for AI adoption. (Cazzaniga et al, 2024)

Figure 7. Digital Skills and ICT/AI usage



E. Conclusions and Policy Considerations

15. While the impact of AI on economies and the implications on society are challenging to predict, it has the potential to have large impacts on the labor market. The high uncertainty about its socioeconomic implications can be linked to its rapid development and fast-evolving landscape, and also its nature as a general-purpose technology, akin to electricity and the internet. AI could cause potential disruptions in the labor market, bringing gains via a productivity boost to some workers, and also risks by displacing jobs in certain industries.

16. A substantial share of the labor force in Slovakia will be impacted by AI, particularly female workers. Around half of all Slovak workers are highly exposed to AI, including almost a quarter of whom are at risk of job displacement from widespread AI adoption. The rest of the highly exposed workers – 27 percent in Slovakia – have jobs with high complementarity to AI and are thus likely to benefit from widespread AI adoption. In terms of sectors, some services could face higher risks of AI displacement, e.g., finance, information and communication, and professional and scientific sectors. Female workers in Slovakia in particular have a higher degree of exposure to AI. They stand to reap the potential benefits of AI adoption but are also more at risk from AI-related job displacement.

17. Policymakers can take action to ensure readiness to AI adoption, to harness the benefits and manage the risks of labor market displacement.

- Support the development of a **digital ecosystem** that is conducive to AI adoption. Greater R&D spending in relevant areas can foster technological advancements and enable the smooth integration of AI through the economy. The use of AI and advanced ICT is relatively low amongst Slovak firms relative to EU peers, and improving the digital ecosystem could help in increasing the adoption of AI and digital skills.

- **Human capital and labor market policies** to ensure a skilled labor force and to manage AI-induced job transitions:
  - Enhance human capital through education and training. Policies could be taken to ensure that the education system is able to prepare the workforce for AI and digital literacy, and is agile to help workers adapt to new technologies.
  - Policies must promote an equitable and ethical integration of AI and ensure social cohesion. This could include supporting business in integrating AI responsibly.
  - Support workers through transitions – reskilling or upskilling. Policies should facilitate the reallocation of labor while providing support for workers that are affected by AI-induced transitions.

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