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The Composition of Human Capital and the Wage Premium in the Israeli High-Tech Sector

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- The employment rate in Israel’s high-tech sector—11% of all employees—is notably high compared to OECD countries. Moreover, the skill gaps between high-tech workers and other employees are considerably larger than in most international comparisons.
- The wage gap between the high-tech sector and the rest of the economy has widened over the past decade and is among the highest in the OECD, even after accounting for differences in worker characteristics between sectors.
- The increase in the “high-tech premium”—that is, the wage differential between high-tech and other industries, net of differences in employee characteristics—is largely due to changes in the composition of firms and a shift in high-tech employment toward large firms with exceptionally high productivity and wages (“superstar firms”).

1. Introduction

The Israeli economy features a distinctive dual structure. The high-tech sector is characterized by rapid growth, high productivity by international comparison, and some of the highest wage levels in the economy. In 2024, approximately 11% of all employees in Israel were employed in high-tech, compared with 9% a decade earlier. This sector accounts for about 18% of GDP, roughly 60% of exports, and nearly one-third of total GDP growth in Israel since 2017.¹ Income tax payments from the high-tech sector account for around 24% of all direct tax revenues in Israel and more than one-third of income tax payments on wages (Chief Economist Division and Israel Innovation Authority, 2024).² In contrast, most of the business sector is characterized by relatively low productivity by international comparison (Bank of Israel, 2023). This duality has intensified in recent years as the high-tech sector has expanded. Between 2018 and 2024, employment in high-tech grew by 35%, compared with a 10% increase in the rest of the economy—more than double the growth rate of high-tech employment in the previous period (2012–2018), which stood at 16%.³

This study characterizes the composition of human capital in Israel’s high-tech sector in an international context, examines its evolution over time, and reviews the development and sources of wage disparities between the high-tech sector and the rest of the economy. The first part of the study focuses on an international comparison of the composition of the high-tech labor force, analyzing its development over time based on the Programme for the International Assessment of Adult Competencies (PIAAC) survey, which enables cross-country analysis of the characteristics of high-tech workers. In addition, this section examines wage differentials between the high-tech sector and the rest of the economy in Israel from an international perspective, finding that these gaps have widened since the previous decade.⁴

The second part of the study provides an in-depth exploration of the widening wage gap in Israel between employees of high-tech and non-high-tech firms in the business sector. This analysis is based on detailed Israeli data and examines the relative roles of worker and firm characteristics in wage

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¹ Calculations are based on authors’ analysis of data from the Central Bureau of Statistics.

² Other direct tax payments measured (besides income tax) include corporate tax and National Insurance contributions.

³ Authors’ calculations based on Labor Force Survey data.

⁴ For an overview of PIAAC findings regarding the general population in Israel, see Bachar and DeMalach (2024).



developments, using administrative data from the Israel Tax Authority that track all employees and firms in the economy between 2010 and 2022.

The PIAAC international skills survey was first conducted in Israel in 2014–2015, with a second wave carried out in 2022–2023 and published recently. Findings from the first wave highlighted the distinctiveness of human capital in the high-tech sector. The gap between the average skill level of high-tech employees and that of other workers in the economy was exceptionally large compared with other advanced economies. The relatively low skill levels among workers in other industries, combined with the stability of high-tech employment until 2017 despite high wages, raised concerns about a structural supply constraint on the sector's expansion (Brand, 2018).⁵ In practice, the sharp increase in high-tech employment between 2017 and 2022 was primarily due to growth in the share of workers employed in high-tech occupations requiring advanced technological skills (Hashai et al., 2022). Furthermore, Somkin (2020) documented an increase in the share of students in STEM fields and in the number of high school students pursuing advanced-level mathematics and science studies (five-unit level) between 2012 and 2016, concluding that this trend would enable high-tech employment to reach 12% by 2030—a target nearly achieved by 2022. These developments underscore the importance of understanding the sources of high-tech employment growth and the composition of its workforce and firms.

The analysis in this study covers developments up to 2022 based on Tax Authority data and up to 2023 based on PIAAC data, due to the lack of more recent information from these sources. Although high-tech employment growth has slowed since 2022—mainly due to a global decline in demand—we believe that the underlying structural patterns described in this study have not changed, as the share of high-tech employment and the wage gap between the high-tech sector and the rest of the economy have remained stable.⁶

2. International Comparison of Human Capital and Wages in High-Tech (Based on PIAAC Surveys)

Findings from the second wave of the PIAAC survey, conducted in Israel and OECD countries in 2022–2023, illustrate the exceptional nature of Israel's high-tech sector by international comparison. The share of high-tech employees in Israel stood at approximately 11% of total employment—two-and-a-half times the OECD average and the highest among the surveyed countries—representing an increase relative to the previous decade (Figure 1a). When classified by occupation, Israel also ranks exceptionally high, with about 16% of all employees working in high-tech occupations, a category that includes workers not necessarily employed in high-tech firms (Figure 1b).⁷ However, Israel is similar to

⁵ Another study found that a relatively high share of skilled workers in Israel are employed in occupations requiring higher education compared with other countries—evidence of high human capital utilization (Brand, 2019).

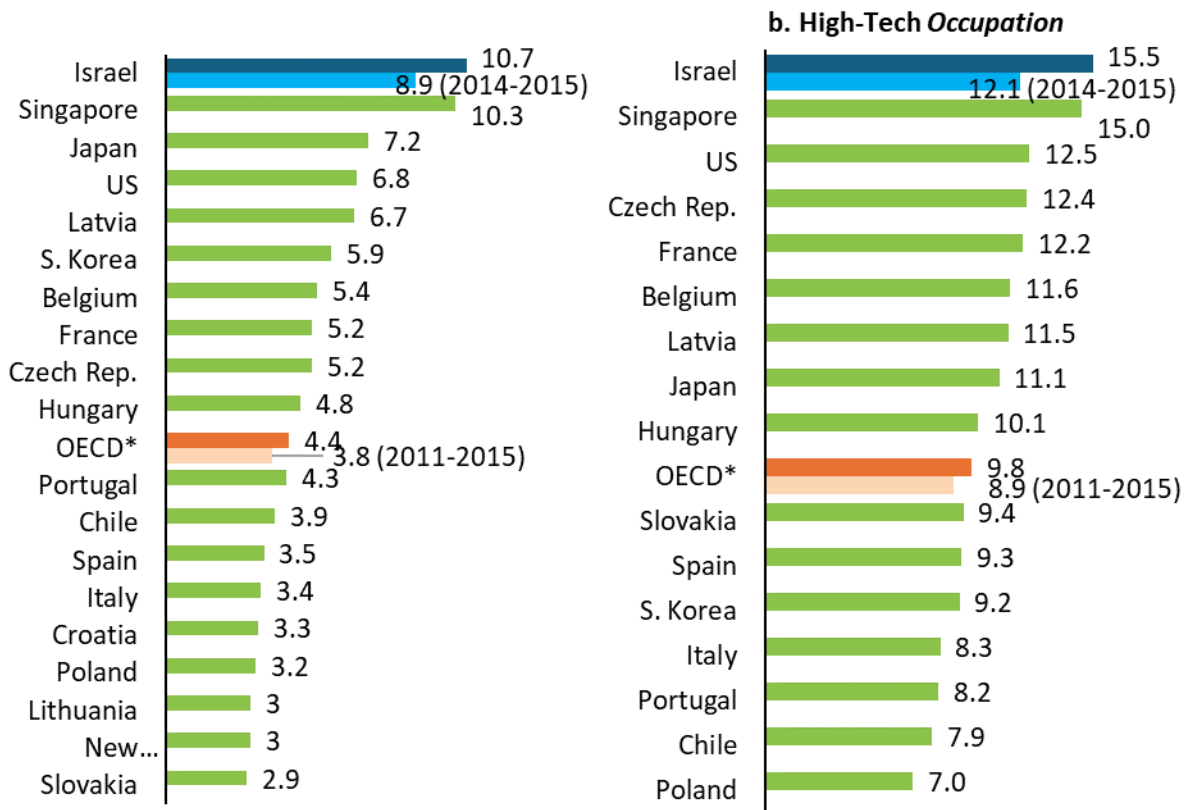
⁶ According to authors' analysis of CBS data, the share of employees in high-tech in 2024 was 11%, similar to 2022 and 2023, as was the ratio of average wages per employee post between high-tech and the rest of the business sector (a ratio of 2.6).

⁷ The "high-tech sector" is defined according to the international industrial classification ISIC Rev. 4, adopted by the Central Bureau of Statistics (CBS) in 2011 in its Standard Industrial Classification of Economic Activities in Israel. This classification includes two clusters: (a) *High-tech manufacturing*, comprising pharmaceuticals (21), computer, electronic, and optical products (26), and transport equipment (30); and (b) *High-tech services*, comprising computer programming, consultancy, and related services (62), information services (63), and scientific research and development (72). "High-tech occupations" are defined according to the international standard classification ISCO-08, adopted by the CBS in 2011, and include groups 21 (science and engineering professionals), 25 (information and communication technology professionals), 31 (science and engineering associate professionals), and 35 (ICT technicians).



the OECD average in the share of workers employed in high-tech occupations outside the high-tech sector—about 8% of all employees (see Figure A.1 in Appendix A).

Figure 1 | Rate of High-Tech Employees in Israel and in Selected Comparison Countries, 2022–2023



Notes: The OECD (orange lines) includes only countries for which there are data on high-tech workers in both waves of the survey. Among the countries appearing in the figure, Singapore, Czech Republic, Latvia, Hungary, New Zealand, and Lithuania do not fall into this category. Singapore is not part of the OECD, but is included in the comparison because it is a high-tech superpower. Footnote 7 provides a definition of high-tech sector and high-tech occupation.

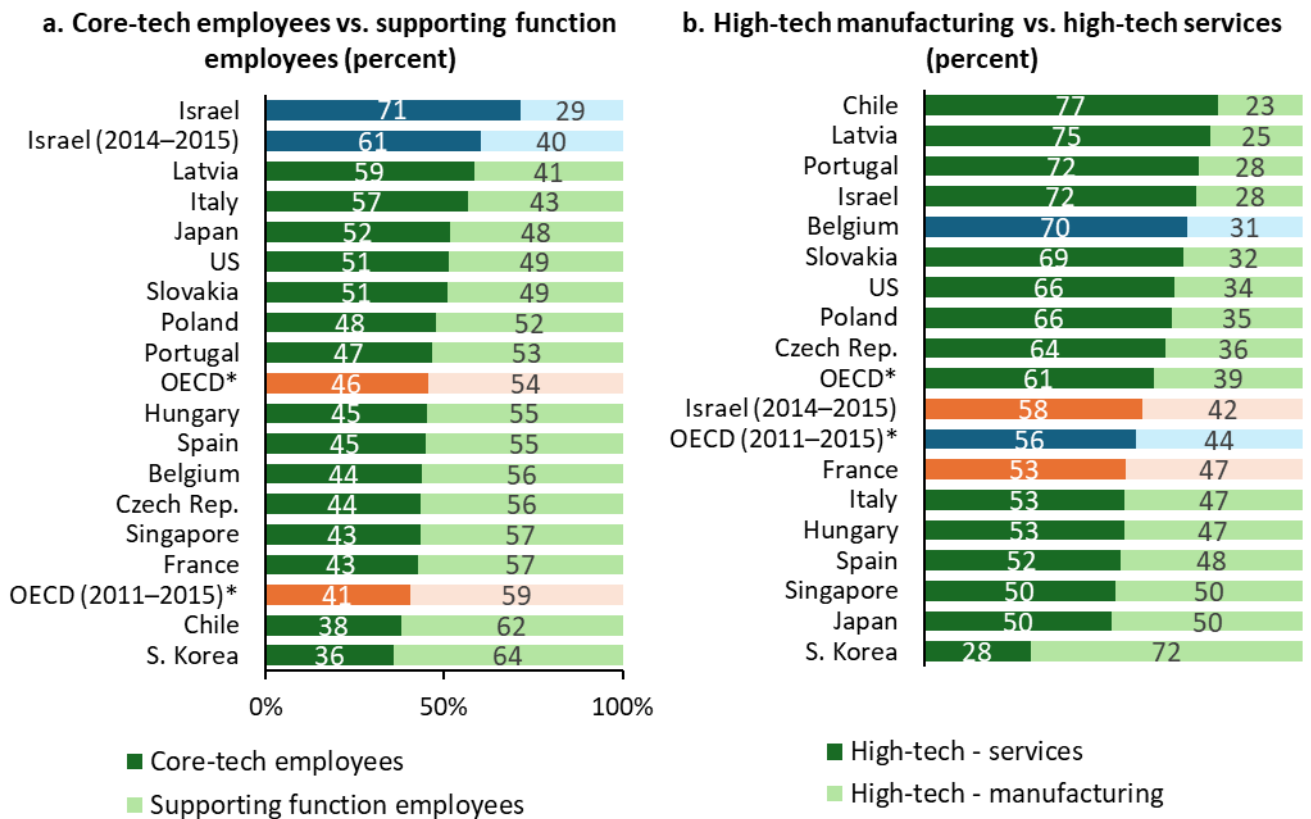
SOURCE: Based on PIAAC.

A key characteristic of Israel’s high-tech sector is the high concentration of employees in core technological occupations, such as software development and engineering, which together account for approximately 70% of total employment in the sector. This share is the highest among OECD countries, and has increased relative to the previous wave of the survey conducted in 2014–2015 (Figure 2a). In contrast, in many advanced economies, a larger proportion of high-tech employees work in supporting functions such as production, marketing, operations, and human resources.

Most of the increase in high-tech employment between the two survey waves stems from the expansion of high-tech services—fields such as software development, cybersecurity solutions, and research and development services—which now account for about 72% of total employment in the sector (compared with 58% in the previous survey). This has been accompanied by a moderate decline in the share of employees in high-tech manufacturing industries, which involve the physical production of high-technology goods such as semiconductors, communication equipment, and medical devices (Figure 2b).



Figure 2 | Composition of the High-Tech Sector by Workers' Occupation and by Industry, 2022–2023



Notes: The OECD (orange lines) includes only countries for which there are data on high-tech workers in both waves of the survey. Among the countries appearing in the figure, Singapore, Czech Republic, Latvia, Hungary, New Zealand, and Lithuania do not fall into this category. Singapore is not part of the OECD, but is included in the comparison because it is a high-tech superpower. Core function employees are those with a high-tech occupation, and supporting function employees are all other high-tech employees. Footnote 7 provides a definition of high-tech sector and high-tech occupation.

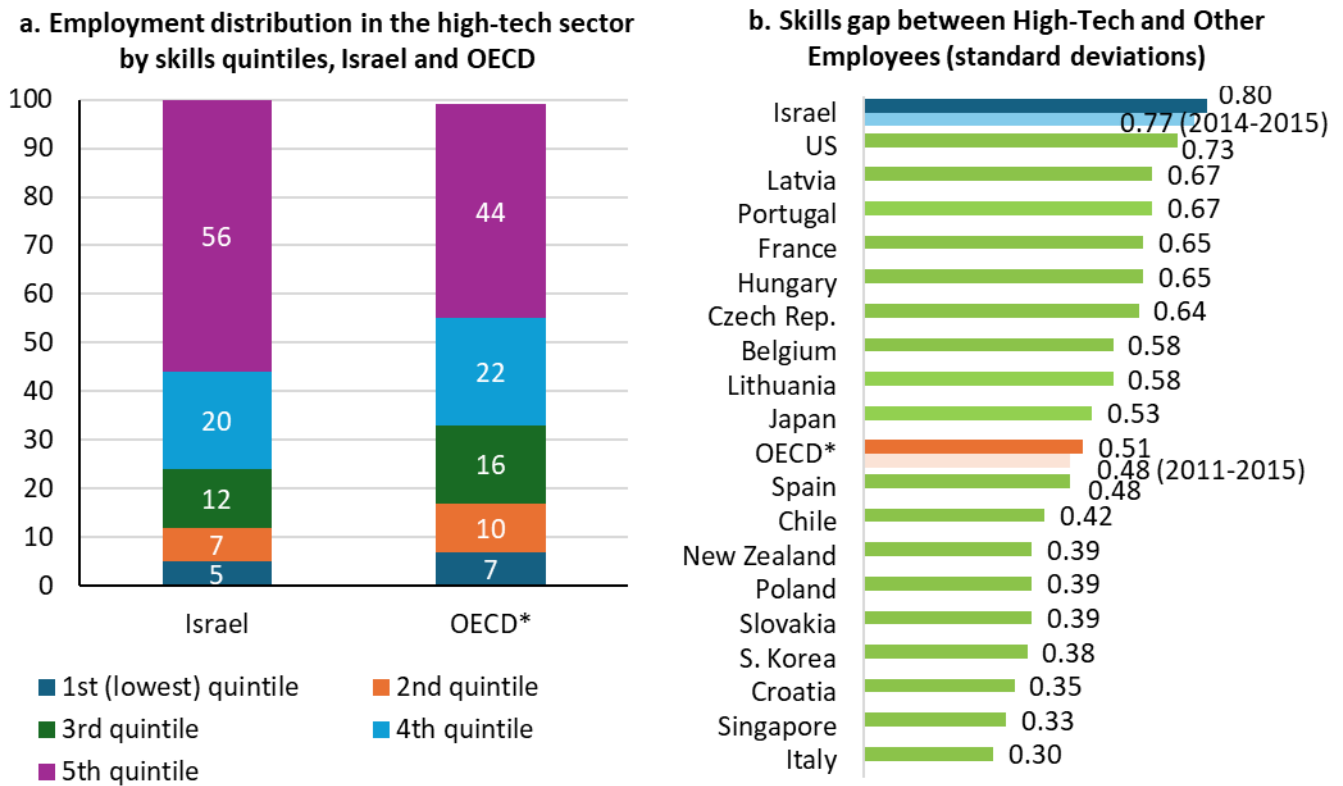
SOURCE: Based on PIAAC.

This trend aligns with the long-term increase in the share of core-tech employees (those in high-tech occupations) relative to supporting staff. Structurally, high-tech services include a smaller proportion of supporting roles, primarily because they require fewer low-skill tasks such as assembly-line work. For example, in OECD countries, high-tech manufacturing industries employ an average of 2.2 supporting function workers for every core-tech worker, whereas in high-tech services the ratio is only 0.6.

The relatively low share of supporting workers in Israel reflects the selective and homogeneous nature of the high-tech sector, which is also evident in the high average skill levels of its employees as measured by the literacy and numeracy components of the PIAAC survey. For instance, about 56% of high-tech employees in Israel fall within the top quintile of the combined skill distribution (a composite index of literacy and numeracy; see Appendix B for details).⁸ This share is significantly higher than the OECD average of approximately 44% (see Figure 3a and Figure A.2 in Appendix A).

⁸ Throughout this study, we use a composite index of literacy and numeracy skills, as detailed in Appendix B. However, the results remain very similar when the two domains are analyzed separately. The third PIAAC domain, “problem solving,” is not

Figure 3 | Skills in the High-Tech Sector Compared to the Other Industries, 2022–2023



Notes: The OECD (orange lines) includes only countries for which there are data on high-tech workers in both waves of the survey. Among the countries appearing in the figure, Singapore, Czech Republic, Latvia, Hungary, New Zealand, and Lithuania do not fall into this category. Singapore is not part of the OECD, but is included in the comparison because it is a high-tech superpower. Core function employees are those with a high-tech occupation, and supporting function employees are all other high-tech employees. Footnote 7 provides a definition of high-tech sector and high-tech occupation.

Another aspect of this pattern is evident from the opposite perspective. About 26% of all workers in the top skill quintile across the entire Israeli labor market are employed in high-tech industries—an increase from roughly 20% in the previous survey wave and an exceptionally high figure by OECD standards (Figure 4).

A further distinctive feature of Israel’s labor market is the distribution of skill levels across the labor market as a whole. The skill levels of high-tech employees in Israel are similar to those of their counterparts in other countries, but the skill levels of the rest of the adult population are considerably lower than the OECD average (Figure A.3 in Appendix A).⁹ Consequently, the skill gap between high-tech employees and other workers in Israel is the widest among all comparison countries (Figure 3b), amounting to approximately 0.8 standard deviations. The method used to calculate the standard deviations of individual-level skill is described in detail in Appendix 2. As a

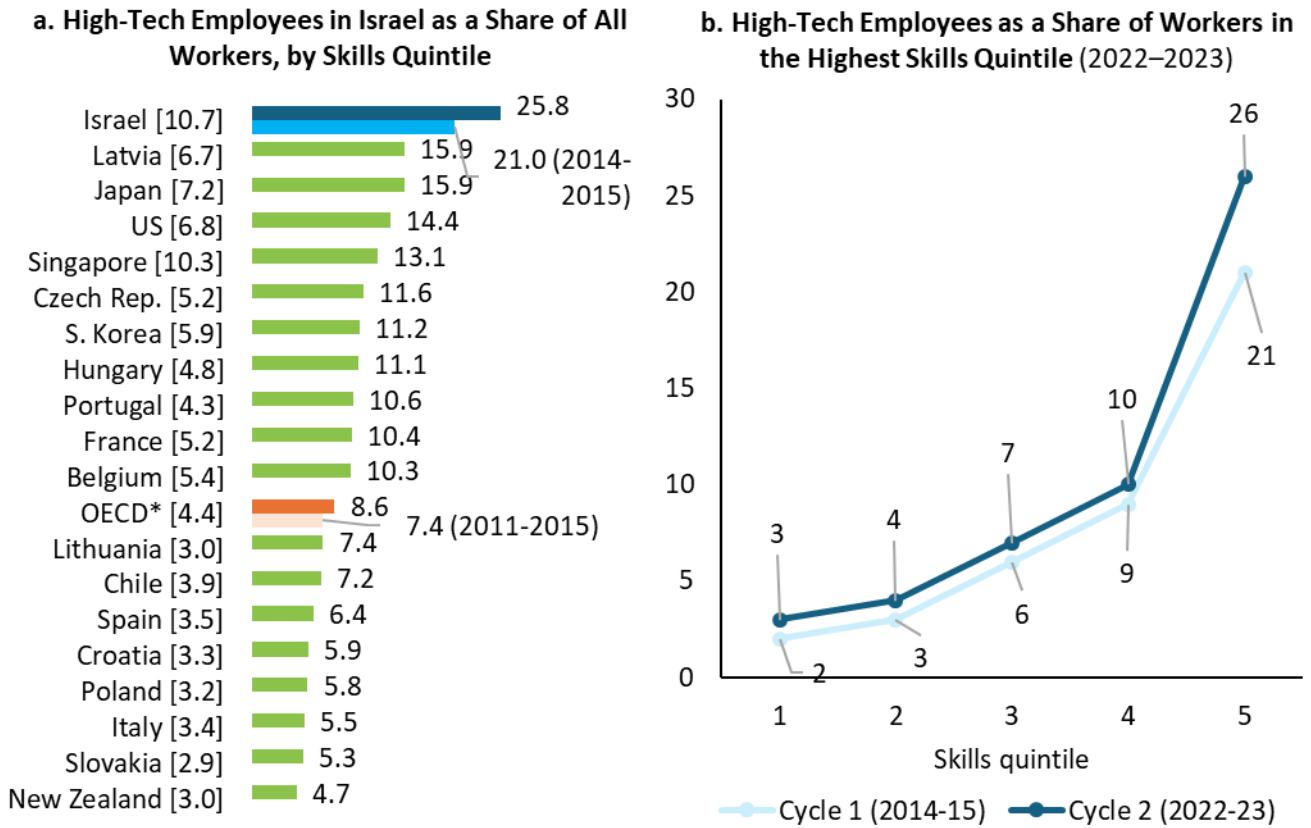
included in the present analysis because it underwent substantial changes between the two survey waves, preventing valid comparison over time. For further discussion, see Bachar and DeMalach (2025).

⁹ This is the case even though the occupational composition of Israel’s high-tech sector is more heavily weighted toward core occupations requiring higher skill levels, as shown in Figure 2a.



general benchmark, in OECD countries, an increase of one standard deviation in individual skill level is associated with an 18% increase in wages on average (Hanushek et al., 2015).

Figure 4 | High-Tech Employment by Employee Skills, Change Over Time and International Comparison



Notes: The square brackets next to the country names indicate the rate of high-tech employees in the country in general. OECD (orange lines) includes only countries for which there are data on high-tech workers in both waves of the survey. Among the countries appearing in the figure, Singapore, Czech Republic, Latvia, Hungary, New Zealand, and Lithuania do not fall into this category. Singapore is not part of the OECD, but is included in the comparison because it is a high-tech superpower. Core function employees are those with a high-tech occupation, and supporting function employees are all other high-tech employees. Footnote 7 provides a definition of high-tech sector and high-tech occupation.

SOURCE: Based on PIAAC.



The dual structure of Israel's labor market, as reflected in the skill disparities among employees, is also evident in the wage gaps between the high-tech sector and the rest of the economy. Figure 5 presents an international comparison based on detailed wage data from nine OECD countries, alongside a broader comparison using aggregated wage-decile data for sixteen countries.

These comparisons show that in Israel, the median wage of high-tech employees is 2.7 times higher than that of employees in other sectors. This ratio is significantly above the average ratio of 1.8 observed in the comparison countries, and represents an increase relative to the gap measured in Israel during the previous survey wave, which stood at 2.3 (see Figure 5a).

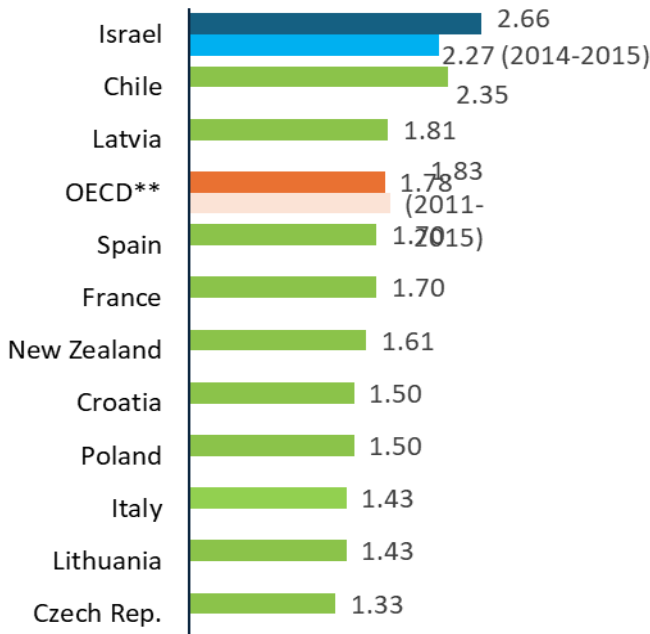
A similar picture emerges from the broader comparison by wage deciles, which includes a larger set of countries. The average wage decile for a high-tech employee is higher in Israel than in almost any other country in the sample, with the exception of New Zealand (Figure 5b).

While part of the wage gap between sectors can be attributed to differences in worker quality, a substantial wage differential remains even after controlling for skill level and age. Israel continues to stand out as the country with the largest wage gap between the high-tech sector and the rest of the economy (Figures 5c and 5d). Moreover, this gap has widened since the previous wave of the survey.

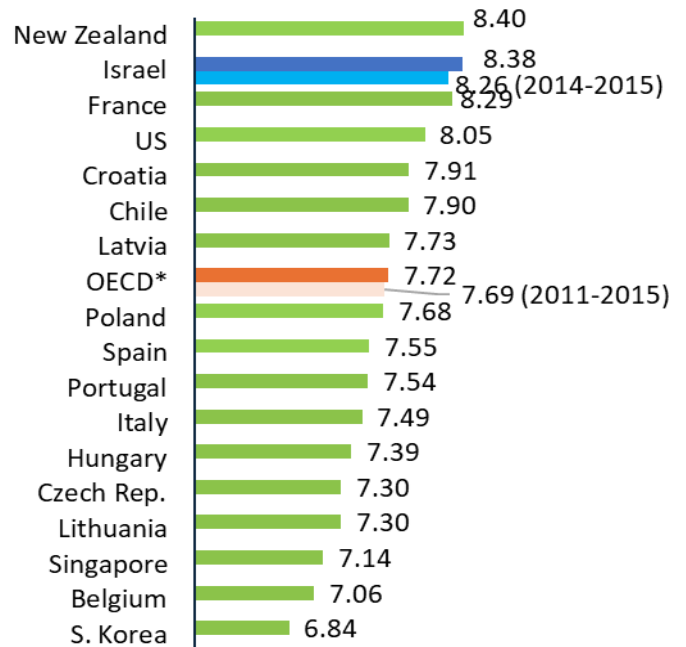


**Figure 5 | Wage Differences Between High-Tech and the Rest of the Economy
2022–2023**

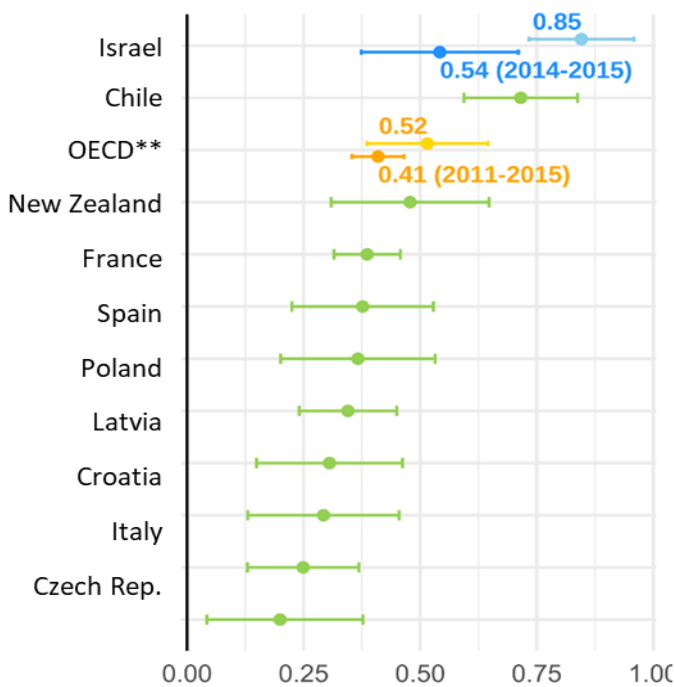
a. Ratio of Median Wage between High-Tech and Non-High-Tech Employees



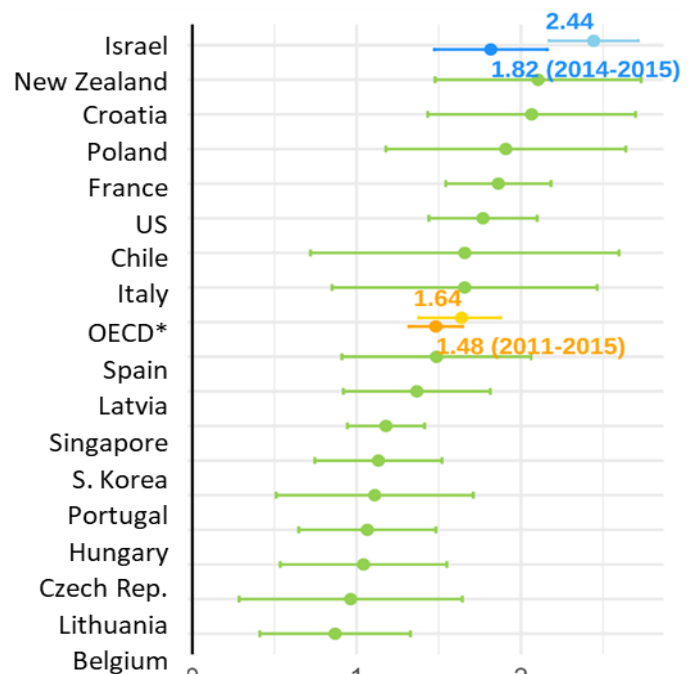
b. Average Wage Decile of High-Tech Employees



c. Estimated wage premium (log) of high-tech after controlling for worker FE



d. Estimated wage premium (gaps between wage deciles) of high-tech after controlling for worker FE



Notes: The wage premium presented in Figures 5c and 5d is after controlling in the regression for the employee's skill level and age. OECD* (orange lines) includes only countries for which there are data on high-tech workers in both waves of the survey. Among the countries appearing in the figure, Singapore, Czech Republic, Latvia, Hungary, New Zealand, and Lithuania do not fall into this category. OECD** (orange lines) includes countries for which there are detailed wage data on high-tech employees in both waves of the survey (all the countries appearing in the figure on the right). Singapore is not part of the OECD, but is included in the comparison because it is a high-tech superpower. Core function employees are those with a high-tech occupation, and supporting function employees are all other high-tech employees. Footnote 7 provides a definition of high-tech sector and high-tech occupation.

3. Development of the wage premium and the composition of high-tech firms in the past decade, based on Tax Authority data

A key finding of the PIAAC skills survey is that wage gaps between high-tech and non-high-tech employees are exceptionally large and have widened over time. This section provides a more detailed analysis of this finding for Israel and examines three main questions:

1. To what extent are wage differences explained by variations in worker characteristics, and to what extent do they reflect the “high-tech premium”—that is, the differential between the wage that the same worker would receive in a high-tech firm compared with other industries?
2. What factors account for the high-tech premium, and how have they evolved over time?
3. How does the high-tech premium vary among workers with different skill levels?

The analysis is based on a comprehensive dataset from the Israel Tax Authority covering the years 2010–2022, which enables tracking individual workers over time and identifying transitions between firms. This makes it possible to estimate each firm’s unique contribution to its employees’ wages while controlling for worker fixed effects, including unobservables. This approach allows for a more precise estimation of the high-tech premium than the initial estimate derived from the PIAAC survey data.

The analysis relies on the estimation method first introduced by Abowd, Kramarz, and Margolis (1999)—hereafter referred to as the AKM model.¹⁰ This methodology, described in detail in Appendix B, decomposes the logarithm of an individual’s wage into four components, as expressed in Equation (1).

$$\underbrace{\ln wage_{i,t}}_{\text{Log wage}} = \underbrace{\alpha_i + \beta' x_{i,t}}_{\text{Worker FE}} + \underbrace{\psi_j(i,t)}_{\text{Firm FE}} + \underbrace{\delta_t + \theta_t \times D_{i,t}^{HT}}_{\text{Year FE}} + \underbrace{\varepsilon_{i,t}}_{\text{Residual}} \quad (1)$$

where:

Worker Fixed Effect (α_i): The first component represents the worker’s individual “signature” (i) or earning potential, and captures characteristics that are time-invariant—both observable and unobservable—such as education and personal skills. These characteristics accompany the worker even when switching between firms. The model also controls for the worker’s age ($\beta' x_{i,t}$).¹¹

Firm Fixed Effect ($\psi_j(i,t)$): The second component represents the firm-specific and time-invariant wage component, identified in the model through worker mobility between firms. In other words, this component reflects the wage premium that a firm offers its employees beyond what can be attributed to their individual characteristics. The premium is influenced by a combination of the firm’s productivity, profitability, and the bargaining power of its employees.

Year Fixed Effects (δ_t): The third component captures wage changes common to all firms in the economy and not specific to any individual worker or firm. These include fluctuations arising from the

¹⁰ This method has been applied in several major studies in the economic literature, including Card et al. (2013); Barth et al. (2016); Goldschmidt and Schmieder (2017); Song et al. (2019); and Bassier et al. (2022). Recent studies have also implemented this approach in Israel, including San (2022); Buzaglo-Baris (2023); and Amior and San (2025).

¹¹ Following Card et al. (2013), we estimated the model in a specification that reduces collinearity between the age variable and the year fixed effects. The regression requires a sufficient number of worker transitions between firms to identify firm effects. Because this requirement may introduce a *limited mobility bias*, we apply the standard split-sample approach, detailed in Appendix B, in which firm effects are estimated using one part of the sample and then used to estimate worker effects in the remaining part. The AKM regression does not require a balanced panel, and changes in the firm effect over time reflect shifts in the composition of active firms—namely, firm entry and exit or changes in the relative employment shares of different firms.



business cycle or macroeconomic shocks. This component is estimated separately for the high-tech sector and for the rest of the economy in order to capture distinct wage growth trends across sectors ($\theta_t \times D_{i,t}^{HT}$) where $D_{i,t}^{HT} \in \{0,1\}$ denotes that the worker is employed in the high-tech sector.

Residual ($\varepsilon_{i,t}$): The residual represents the portion of an individual’s wage development that is not explained by the three preceding components.

Using this equation, we analyze the raw wage gaps between the high-tech sector and the rest of the economy, and assess the extent to which each of the components described above contributes to these differences. The purpose of the analysis is to determine how much of the increase in wage disparities is due to changes in the composition of the high-tech workforce, as opposed to changes in the “high-tech premium”—that is, the differential between the wage that the same worker would receive in a high-tech firm compared with other industries (components 2–4).¹²

The change in the high-tech premium since the beginning of the previous decade can be attributed to three elements:

- **Component 2** reflects changes over time in the composition and quality of firms;
- **Component 3** captures the general wage increase common to all high-tech firms that is not explained by changes in the composition of workers or firms;
- **Component 4**, the residual, represents additional worker-specific wage changes not captured by the other components.

The administrative data used in this analysis are drawn from the Israel Tax Authority (“SHAAM”) and include all employees and firms in the business sector between 2010 and 2022 (matched employer–employee data). High-tech firms were identified in the tax data through cross-referencing with external databases specializing in the analysis of Israeli high-tech firms—**IVC Research Center** and **Start-Up Nation Central (SNC)**.¹³

It is important to note that this definition of high-tech differs from the Central Bureau of Statistics (CBS) definition used in the PIAAC-based analysis. The CBS definition is based on the economic industry of the workplace, following international classification standards and self-reported information from survey respondents. Consequently, the high-tech data from these two sources are not identical. Nevertheless, both definitions capture similar underlying trends, as comparative analysis has shown a high degree of consistency in aggregate characteristics (Chief Economist Division and Israel Innovation Authority, 2024).¹⁴

¹² Formally, the high-tech premium is defined according to Equation (1) as:

$$\text{HTPrem}_t = \underbrace{\overline{\text{wage}}_{\text{HT},t} - \overline{\text{wage}}_{\text{NHT},t}}_{\text{total wage gap}} - \underbrace{(\overline{\alpha + \beta' x_{\text{HT},t}} - \overline{\alpha + \beta' x_{\text{NHT},t}})}_{\text{Contribution of worker characteristics}} \\ \text{High-tech wage premium}$$

¹³ SNC – Start-Up Nation Central; IVC – IVC Research Center. In addition to firms classified under these definitions, the analysis also includes other companies eligible for tax benefits under the *Encouragement of Capital Investments Law* through the technological track.

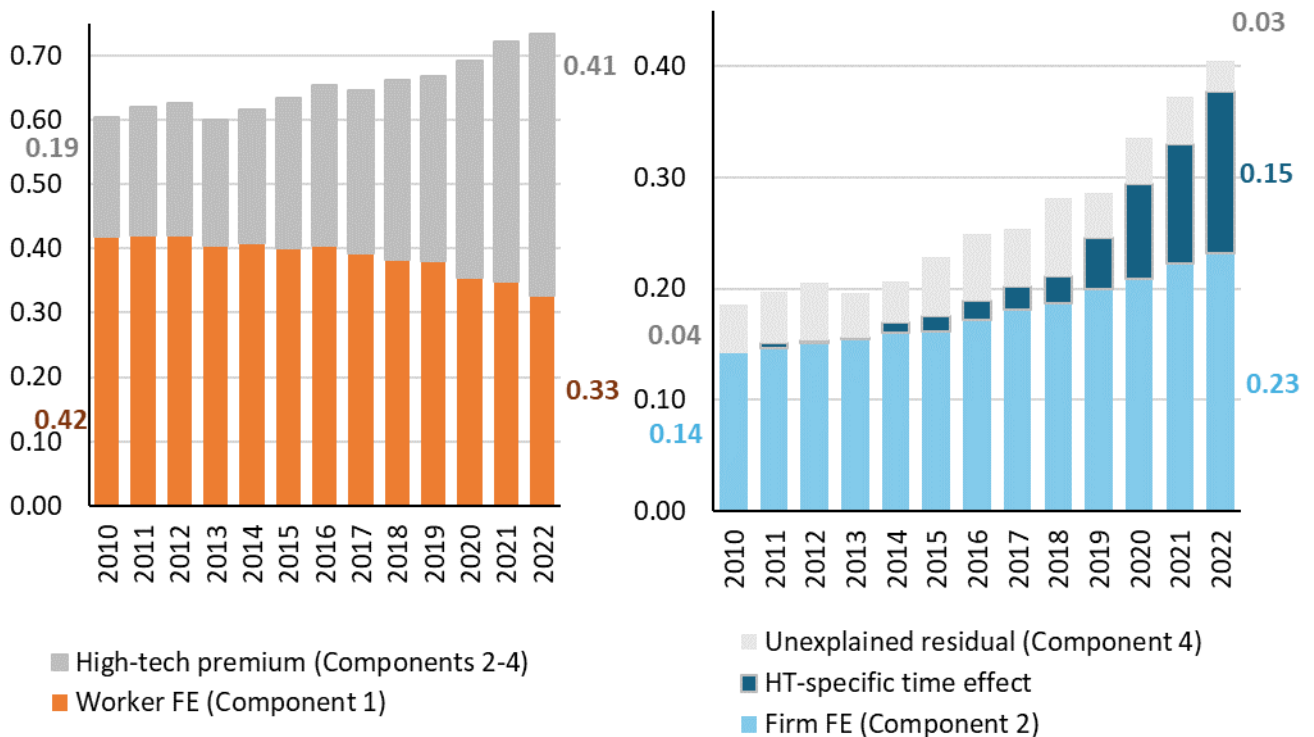
¹⁴ The Chief Economist Division and the Israel Innovation Authority (2024) found that the number of jobs in 2020 according to the external high-tech definitions was 255,000, compared with 285,000 according to the CBS definition for 2021. The average full-time monthly wage was NIS 27,000, and the average monthly income tax was approximately NIS 6,400 under both definitions.



Due to estimation constraints inherent in the AKM methodology, the analysis was limited to employees whose monthly income from their primary job exceeded the minimum wage. Full methodological details are provided in Appendix C.

The results are presented in Figure 6. The left graph presents the decomposition of the wage gap between high-tech employees and other workers in the economy, distinguishing between the portion explained by differences in worker composition (Component 1) and the portion attributed to the high-tech premium. The right graph focuses on the premium itself and presents the main factors explaining it: firm composition (Component 2), the general wage trend common to all high-tech firms (Component 3), and the unexplained residual (Component 4).

Figure 6 | Decomposition of Wage Gaps Between Employees of High-Tech and Non-High-Tech Firms, and Estimate of the High-Tech Wage Premium 2010–2022



Notes: The high-tech premium reflects the wage premium net of differences in Worker Fixed Effects. The composition of companies presents the Firm Fixed Effect. Wage changes that are common to all high-tech firms are presented using a differential Time Fixed Effect for high-tech and the rest of the economy, in addition to the unexplained remainder. For details on the components and the AKM estimation, see Equation (1) and the explanation attached to it, or a more detailed explanation in Appendix C.

SOURCE: Based on Israel Tax Authority (SHAAM) data.

The findings indicate that the increase in the relative share of employment in firms with exceptionally high productivity—reflected in the rise of the firm component (Component 2, Firm FE)—accounts for a large part of the widening wage gap between the high-tech sector and the rest of the economy. This phenomenon reflects a shift in the composition of firms between 2010 and 2022, driven by the reallocation of employment toward leading high-tech firms that offer particularly high wages.



Moreover, the relative wage increase in high-tech is also associated with the sector-wide component common to all high-tech firms (Component3)—for example, due to an overall rise in sectoral productivity or demand for high-tech outputs. There is no evidence that the growth in relative wages in high-tech over the past decade resulted from an improvement in worker quality within the sector compared with the rest of the economy, consistent with the PIAAC-based analysis (see Figure 3b above). Furthermore, the contribution of worker characteristics has gradually declined over time. This finding warrants further investigation beyond the scope of the present study.¹⁵

Figure 7 illustrates the growing importance of the firm component by showing the distribution of employment across firms by quality (Firm FE). It reveals that approximately 90% of the increase in high-tech employment between 2010 and 2022 occurred among the top 20% of high-tech firms—those in the highest quintile of the firm FE distribution. In contrast, the rest of the business sector exhibits the opposite trend, with employment shifting toward lower-quality firms.¹⁶

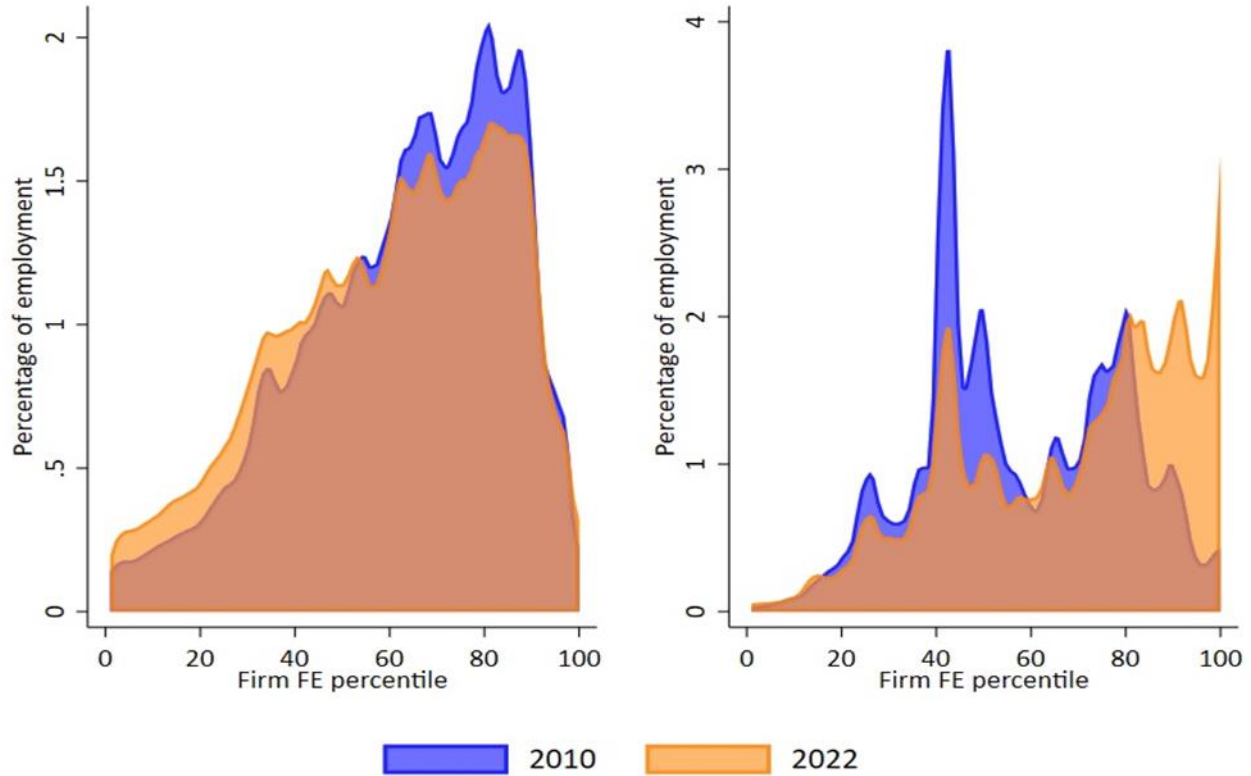
Table 1 shows that high-tech firms above the 80th percentile of the firm-quality distribution are characterized by large workforces, a high share of multinational firms, and exceptionally high wage levels compared with other high-tech firms. This finding aligns with a global trend of the growing dominance of “superstar firms”—firms that capture an increasing share of employment and economic activity while deepening wage disparities between themselves and other firms (*Autor et al., 2020*).

The shift of employment toward high-productivity firms identified as “superstar firms” has also been accompanied by another process—positive assortative matching—whereby firms offering the highest wages increasingly attract workers with the highest earning potential.

¹⁵ One possible explanation for the declining contribution of worker characteristics to wage disparities is a narrowing of skill gaps in the general population. However, we find no evidence supporting this based on the skill measures in the PIAAC survey. *Bental et al. (2025)* present a theoretical model suggesting that if skilled and unskilled workers are complementary production factors, an increase in skilled employment in the high-tech sector may lead to a decline in productivity in other sectors.

¹⁶ See Appendix C for further details on the distributional analysis of firm quality and employment shares.

Figure 7 | Distribution of Employment by Firm FE Percentile, High-Tech and Non-High-Tech Firms, 2010 and 2022



For details on the Firm FE component and the AKM estimation method, see Equation (1) and the explanation attached to it, or a more detailed explanation in Appendix C. The percentiles are calculated separately for each group.

SOURCE: Based on Israel Tax Authority (SHAAM) data.

This phenomenon is becoming more prominent in the Israeli high-tech sector as well, as illustrated in Figure 8. In recent years, the high-tech “superstar firms” have significantly expanded their workforce, primarily by hiring employees from the upper end of the earning potential spectrum. In contrast, most other high-tech firms have tended to employ a larger number of workers from the middle and lower ranges of earning potential—apparently due to supply constraints, which have been exacerbated by the growing attractiveness of the “superstar firms.”



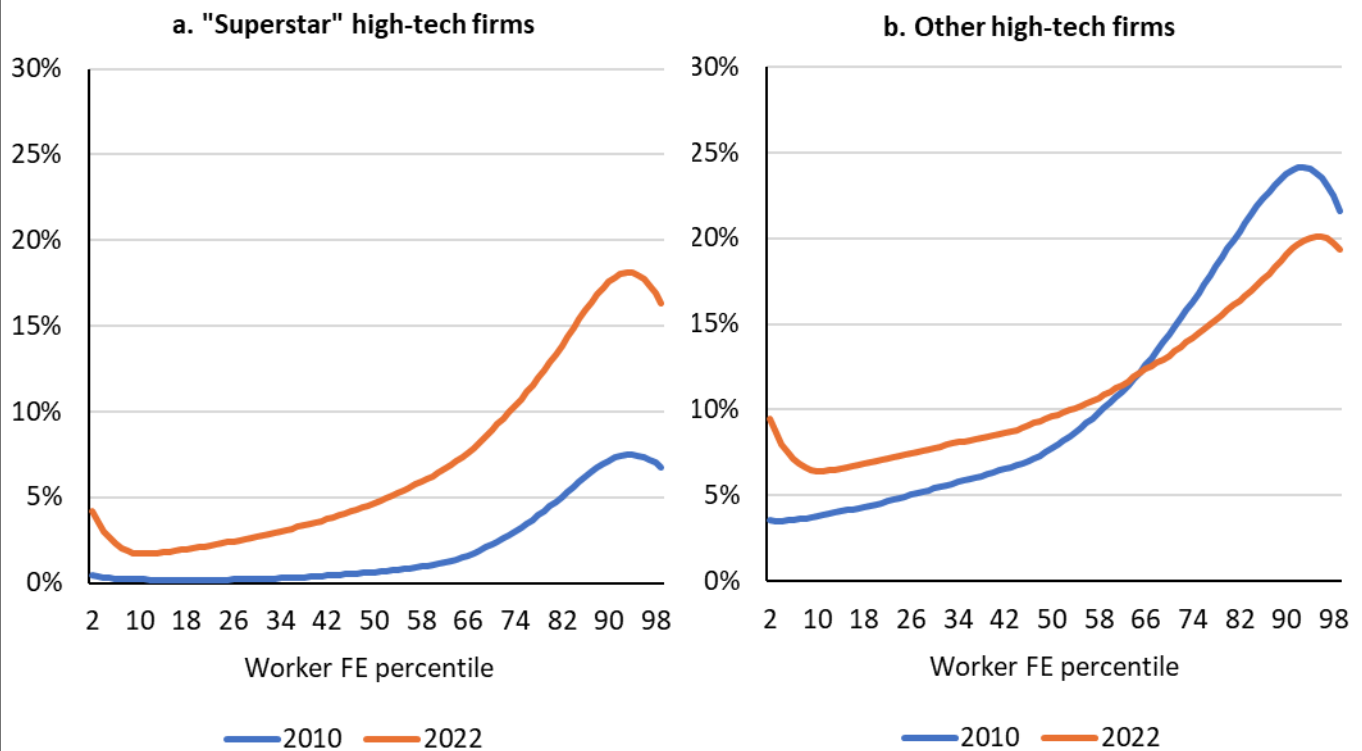
Table 1 | Characteristics of High-Tech Firms Above ("Superstar") and Below the 80th Percentile in the Distribution of Firm FE

	Superstar High-Tech Firms		Other High-Tech Firms	
	2010	2022	2010	2022
Employees as a share of all high-tech employees	18%	39%	82%	61%
Average wage (NIS per month)	33,480	38,326	20,206	23,178
Average number of employees in the firm	73	171	72	67
Percentage of employees in multinational firms	51%	39%	17%	20%
Median Worker FE	86	79	75	67

The superstar firms are defined as firms in the 80th or higher percentiles of the firm FE component among high-tech firms. For more details on the firm FE and Worker FE components according to the AKM estimation method - see Equation (1) and its accompanying explanation, or the more detailed explanation in Appendix C.

SOURCE: Based on Israel Tax Authority ("SHAAM").

Figure 8 | Share of Employment, by Worker FE Percentile
2010–2022

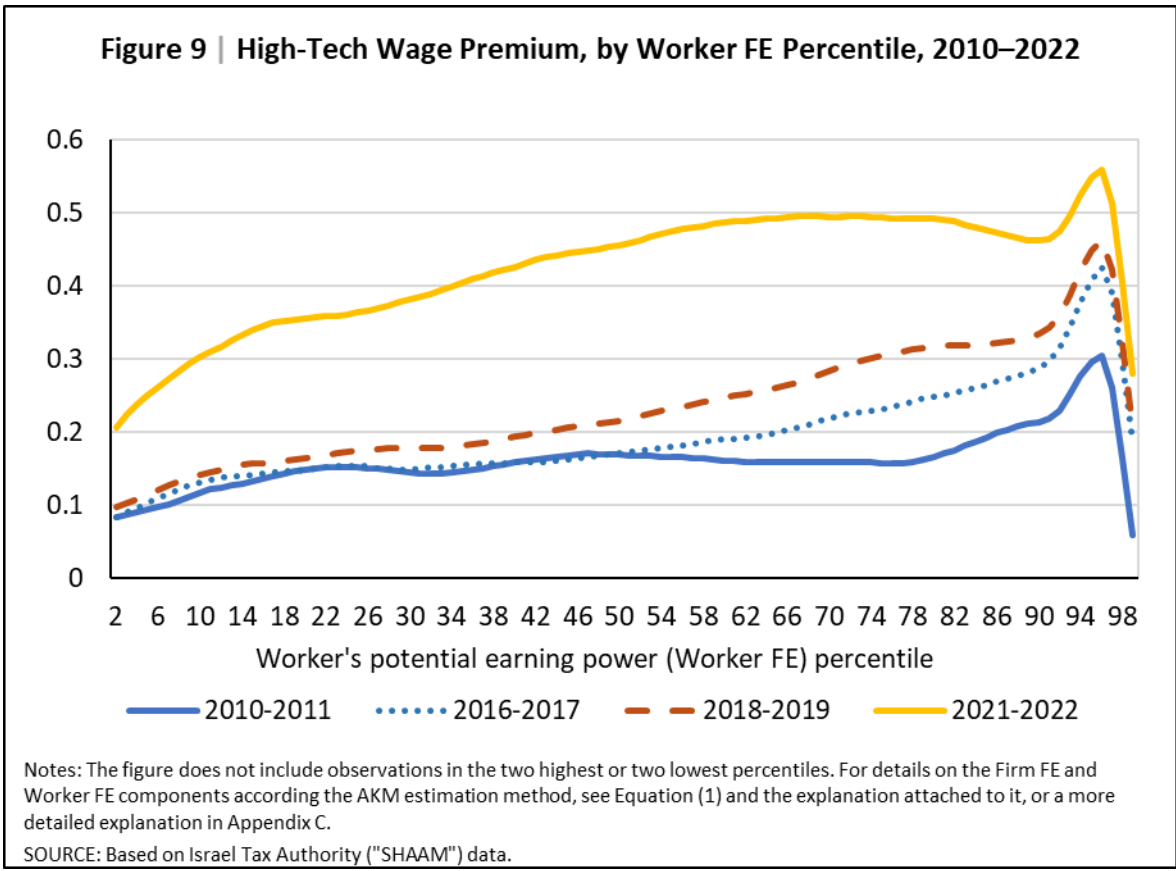


Notes: The Superstar firms are defined as the firms in the 80th or higher percentile of the firm effect from among high-tech companies. The graphs present the rate of workers employed in a high-tech company in each Worker FE percentile, divided among the Superstar firms and the other firms in the sector. For details on the Firm FE and Worker FE components according to the AKM estimation method, see Equation (1) and the explanation attached to it, or a more detailed explanation in Appendix C.

SOURCE: Based on Israel Tax Authority ("SHAAM") data.



Finally, we examine how the high-tech wage premium varies among employees ranked by percentiles of earning potential (Worker FE). The comparison presented in Figure 9 indicates a clear positive relationship between a worker’s level of earning potential and the size of the high-tech premium. In other words, the return on skills in the high-tech sector is higher than in the rest of the economy. This relationship strengthened substantially throughout the previous decade, with most of the increase in the premium observed among employees ranked in the upper percentiles of earning potential. However, during the high-tech boom of 2021–2022, there was a sharp rise in the premium, which also extended to workers with lower earning potential. The Figure also shows that the high-tech premium declines sharply at the far right end of the distribution. This phenomenon may reflect growing competition for these employees, which moderates the wage gaps between them and their counterparts employed outside the high-tech sector.





4. Conclusion

During the previous decade and up to 2022, wage gaps between the high-tech sector and other industries in the economy widened, and from 2017 onward, there was a significant acceleration in employment in the sector. The increase in productivity and employment in high-tech firms made a substantial contribution to economic growth during this period. Against this backdrop, this review examined trends in the high-tech sector using two complementary sources: the Skills Survey (PIAAC), which enables international comparison, and an administrative database based on employee–employer data from the Tax Authority, which allows for an in-depth analysis of Israeli data over time.

The international comparison highlights the uniqueness of Israel’s high-tech sector. A particularly high share of the skilled labor force is employed in it compared with other countries, and it stands out for its exceptionally high wage levels and for a gap of about one full standard deviation in skill levels between high-tech employees and other workers—the largest among the comparison countries. Over time, Israel’s high-tech sector has gradually concentrated on core professions, mainly in programming and engineering, while employment in technological manufacturing industries has declined and the technological services sector has expanded.

The analysis indicates that the success of Israel’s high-tech sector is closely linked to an innovation-supportive environment that combines skilled human capital with leading, high-productivity firms that pay a significant wage premium to their employees. This environment has evolved in Israel over the years as a result of a combination of factors, including a local entrepreneurial culture, high-quality technological training within military service, and openness to international markets. It has also been supported by a system of economic incentives and tax benefits under the Encouragement of Capital Investments Law, which helped firms operate, expand, and establish their activities in Israel.

To ensure balanced and inclusive growth, it is important that government support for the high-tech industry be considered in light of its potential impact on the development of additional growth engines in the economy. A broad government policy is required—one that focuses on increasing the supply of skilled labor at all stages of the education system, with an emphasis on English, mathematics, computer science, artificial intelligence (AI), and soft skills, as well as on training and pathways for continuous skill improvement throughout careers. Such a policy could support the continued growth of high-tech while also alleviating the shortage of skilled workers in other sectors of the economy. These policy measures should not be narrowly aimed at placing workers solely in the high-tech sector, since technological human capital and high skill levels can contribute to productivity across all industries.



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Appendix A – Figures

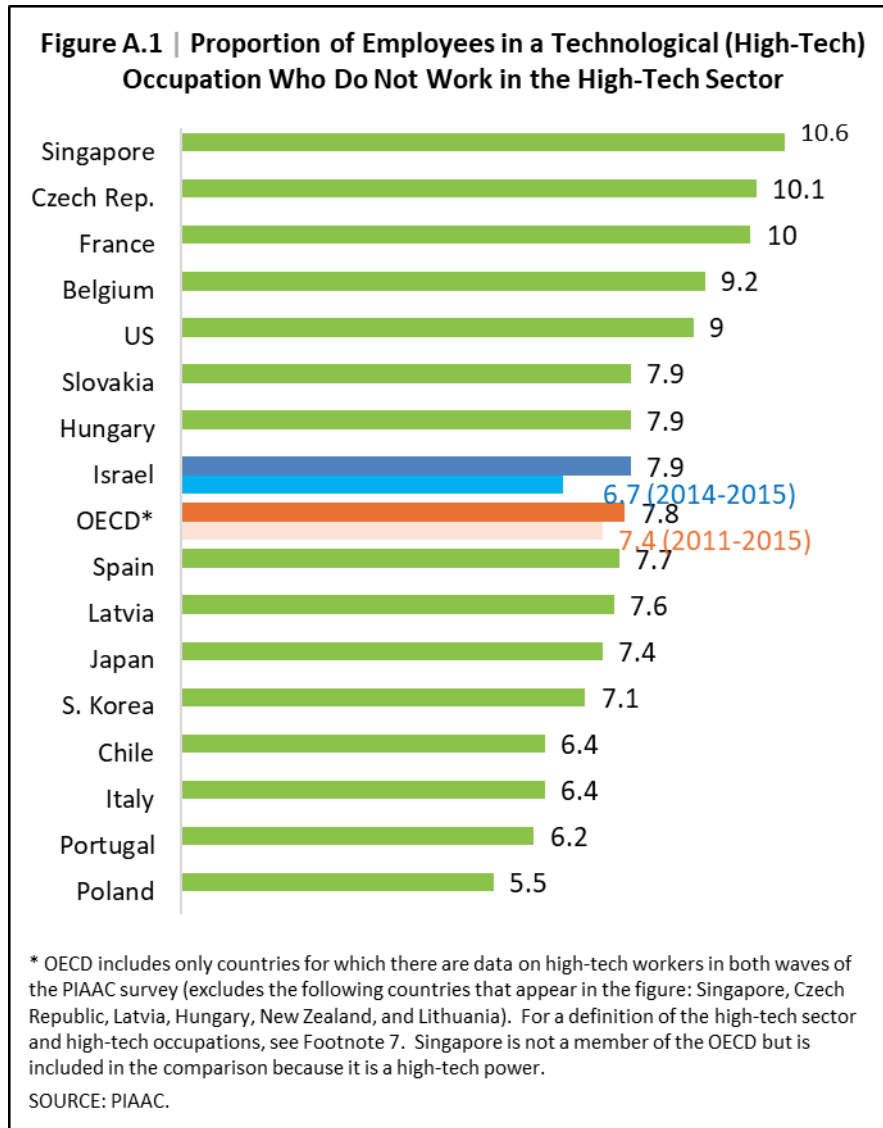
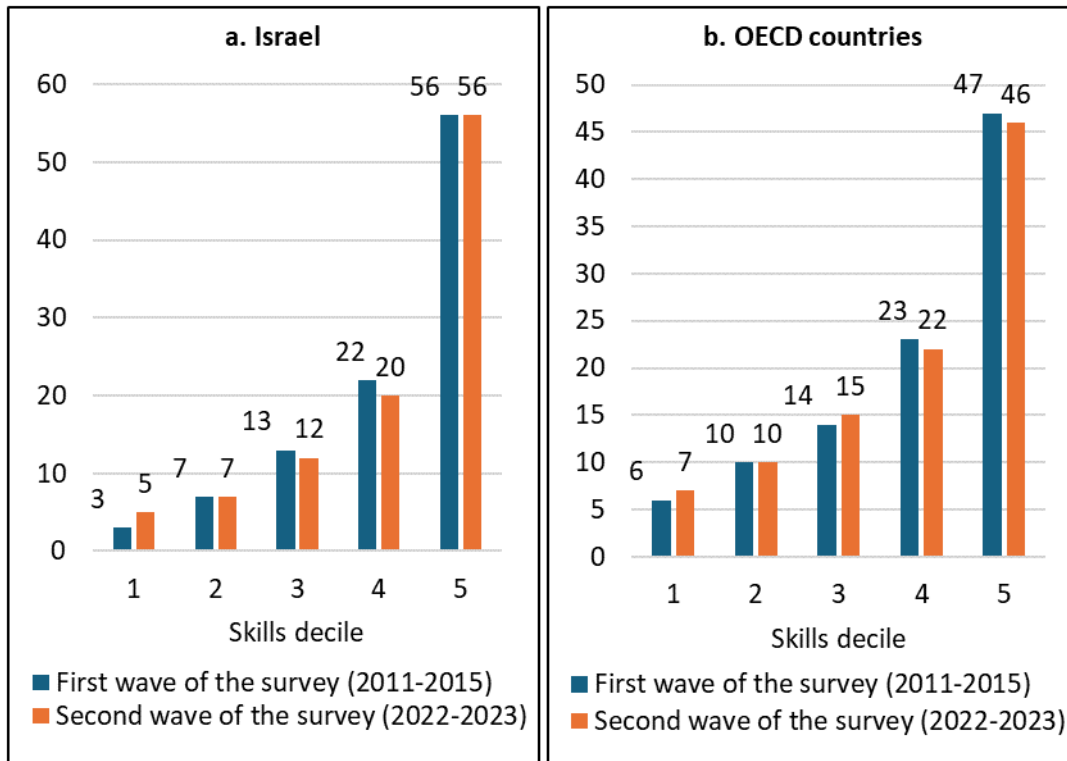


Figure A.2 | Composition of Skills in the High-Tech Sector in the Two PIAAC Survey Waves (percent)

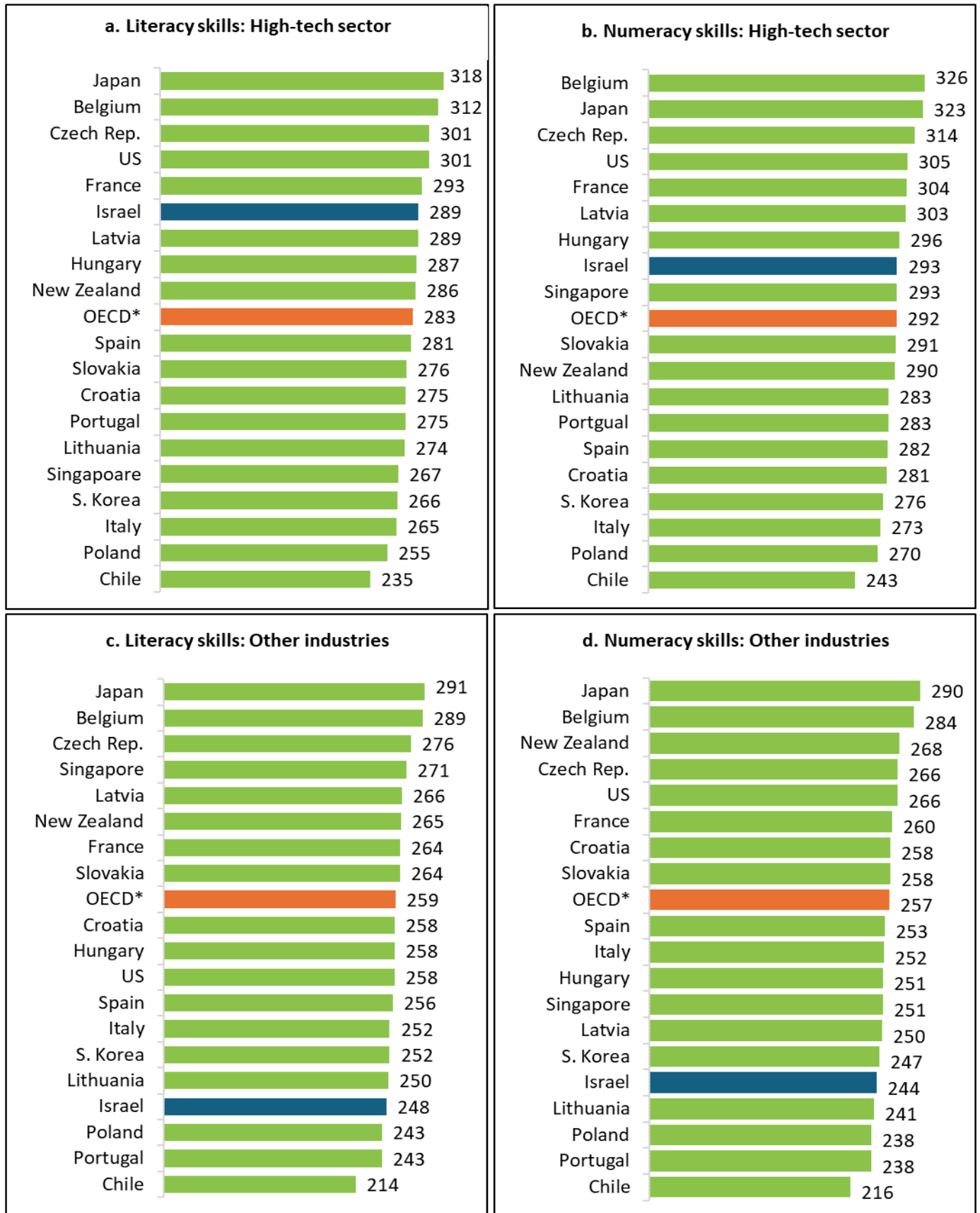


* The OECD comparison countries include only countries for which there are data on high-tech workers in both waves of the PIAAC survey (excludes the following countries that appear in the figure: Singapore, Czech Republic, Latvia, Hungary, New Zealand, and Lithuania). For a definition of the high-tech sector and high-tech occupations, see Footnote 7. Singapore is not a member of the OECD but is included in the comparison because it is a high-tech power.

SOURCE: PIAAC.



**Figure A.3 | International Comparison of Skill Levels of High-Tech Sector Employees
PIAAC Survey, 2022–2023**



* The OECD comparison countries include only countries for which there are data on high-tech workers in both waves of the PIAAC survey (excludes the following countries that appear in the figure: Singapore, Czech Republic, Latvia, Hungary, New Zealand, and Lithuania).
SOURCE: PIAAC.



Appendix B – Standard score and standard deviation in the PIAAC survey

The original test scores in the PIAAC survey range between 0 and 500 in each skill domain. In this paper, we chose to move from the original PIAAC scale to a standard score (Z-Score) scale, so that the differences in scores between individuals and groups would be presented in terms of the individual's standard deviation—a universal scale that is not dependent on the original scores scale. Furthermore, the Z-scores enable us to average out the scores in the different skill domains (literacy and numeracy) to a weighted combined score.

$$Z_{si} = \frac{X_{si} - \mu_s}{\sigma_s}$$

where:

- X_i is individual i 's score in skill domain s . (The score in skill domain s is calculated as the average of 10 "plausible values".)¹⁷
- μ_s is the average score in all OECD countries in the second wave of the PIAAC survey in skill domain s .
- σ_s is the average standard deviation of the OECD countries in skill domain s .

The skills index that we used in this work is the average Z-Score of literacy and numeracy.

$$Z_{combined} = \frac{Z_{literacy} + Z_{numeracy}}{2}$$

Table A.1 presents the raw data and the standards scores for Israel and the OECD.

Table A.1 Gap in Absolute Terms and in Standard Deviation in Scores in the Various Skill Domains Included in the Test, 2022		
	Literacy	Numeracy
Average score in the OECD	260	262
Standard deviation in the OECD	55	58

¹⁷ See [OECD \(2025\), Survey of Adult Skills 2023 Data Analysis Manual](#).

Appendix C – AKM data source and estimation method

According to the estimation framework of Abowd, Kramarz, and Margolis (1999), which was developed using long-term tracking of employee transitions between various firms, we can isolate the wage premium unique to each company. This approach enables us to control for employee fixed effects, and thereby distinguish between wages gaps due to differences in worker FE (including unobserved effects) and those reflecting the characteristics of the firm itself.

The AKM estimation framework is based on an equation in which the log wage (*lwage*) of employee *i* is expressed as follows:

$$(1) \underbrace{\overbrace{lwage_{i,t}}^{\log wage}}}_{(1)} = \underbrace{\alpha_i + \beta'x_{i,t}}_{(1)} + \underbrace{\psi_j(i,t)}_{(2)} + \underbrace{\delta_t + \theta_t \times D_{i,t}^{HT}}_{(Year FE)} + \underbrace{\varepsilon_{i,t}}_{(4)} + \underbrace{\quad}_{Residual}$$

(Worker FE) (Firm FE)

where: α_i is the fixed effect of employee *i*, which expresses an unobserved fixed ability, $\psi_j(i,t)$ is the fixed effect of firm *j* in which the employee is employed during that year, reflecting the unique wage premium for each firm, which is identified by the transition of employees between firms, *x* is a polynomial of the employee's age¹⁸, and δ_t is a vector of year fixed effects. We added an interaction between a dummy variable for employment in a high-tech firm and the year fixed effects ($\theta_t \times D$) to reflect trajectories in the high-tech sector that are common to all firms in the sector.

Estimating Equation (1) enables us to apply the wage gaps in high-tech firms to the non-high-tech firms (the wage premium on high-tech employment):

$$\underbrace{\overbrace{lwage_{HT,t} - lwage_{NHT,t}}^{\text{total wage gap}}}_{\text{High-tech wage premium}} - \underbrace{(\alpha + \beta'x_{HT,t} - \alpha + \beta'x_{NHT,t})}_{\text{Contribution of worker characteristics}} = \underbrace{\bar{\psi}_{HT,t} - \bar{\psi}_{NHT,t}}_{(2)} + \underbrace{\theta_t}_{(Year FE)}$$

(Firm FE)

To ensure the identification of the fixed effects, we employ the instrumental-variable method. The sample is randomly divided into two equally sized groups, with each worker's entire employment history retained within a single group. According to this approach, the wage equation is estimated separately for each group, and the estimated firm fixed effects from one group are used as an instrumental variable in the estimation for the other group.¹⁹ The interaction term $\theta_t \times D$ is introduced only in the second stage of the estimation. Robustness tests indicate that the estimated fixed effects are not sensitive to the inclusion of the interaction term.

¹⁸ In keeping with Card et al. (2013), we estimated $(age - 40)^2 + (age - 40)^3$ to avoid problems of collinearity between the age variable and the year fixed effects.

¹⁹ This method has been used by Amior and San (2025), Goldschmidt and Schmiieder (2017), and Bassier et al. (2022), among others.



As is common in this estimation framework, the model explains the vast majority of the variation in wages ($R^2 \approx 0.95$), with year dummy variables absorbing a substantial portion of the variation not explained by worker and firm characteristics.

The analysis is based on detailed administrative data on individual-level employee wages (Form 126). The dataset includes all wage earners whose income was reported to the tax authority during the relevant period, providing information on income level, year of employment, and basic demographic characteristics. Form 126 also contains reports on income from pensions, maternity benefits, and other sources. In this analysis, we rely solely on reports of wages and income from options under the “proceeds-based” (labor income) taxation track.²⁰

For the purpose of the analysis, the sample is restricted to the business sector only, including employees aged 25–64, while excluding defense-related firms and nonprofit organizations. In the AKM model estimation, each worker contributes one observation per year. Accordingly, and following standard practice, for each worker we select the job in which the average monthly wage was highest during that year. Estimates of worker and firm fixed effects can be computed only within “connected” sets of firms—namely, groups of firms among which worker mobility occurs over time. Consequently, the analysis focuses on the largest connected set, which includes over 90% of the observations.

Administrative data do not contain information on employment scope or hours worked. Therefore, to mitigate potential effects of part-time employment on observed wages, and in line with the literature, we exclude observations with wages below the statutory minimum wage. This restriction aims to reduce the influence of differences in employment intensity, and results are found to be insensitive to the choice of this threshold.²¹ Apart from these exclusions, the dataset covers nearly the entire population of wage earners and reporting firms in Israel over the study period.

²⁰ Income from options under the “capital-based” (capital gains) taxation track is typically processed through a trustee and therefore not fully reported in this form.

²¹ See discussion in Card et al. (2013) and Amior and San (2025).