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Generative Artificial Intelligence and Foundational Skills of Israeli Workers

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Generative Artificial Intelligence and Foundational Skills of Israeli Workers

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Introduction

Generative artificial intelligence (AI) technology is being adopted across the Israeli economy at a lightening pace. More than one-third of businesses in Israel use the technology (Roash et al., 2026), and it is already beginning to have a discernible impact on the demand for (human) workers in occupations where technology is capable of performing a substantial share of the tasks (Debowy et al., 2026b). These developments have been accompanied by an active public debate, with some predicting the end of knowledge work—or even of work altogether (Arlosoroff, 2026)—or, at the very least, anticipating a fundamental change in the skills required in the labor market (Manela, 2025). This chapter examines whether demand for foundational cognitive skills, such as reading literacy and numeracy, is likely to decline as AI is integrated into different occupations and workers are reallocated to other fields.

Our analysis is based on data from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), conducted in Israel in 2022–2023, which assessed three foundational cognitive skills: literacy, numeracy, and adaptive problem solving. The findings indicate that workers in occupations where AI is expected to substitute for human labor ("AI-exposed occupations")

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possess higher levels of foundational skills than other workers (and accordingly earn higher wages), but no significant difference was found in the returns to foundational skills between AI-exposed occupations and other occupations. In other words, the contribution of foundational skills to wages in AI-exposed occupations is similar to their contribution in other occupations, including those far removed from the knowledge economy. As noted, the importance of foundational skills is so similar across occupations that, statistically, no difference is observed between them. Nevertheless, even if the estimated difference were interpreted as a forecast of a decline in demand for foundational skills, that decline would be expected to be offset by the increase in labor productivity.

Contrary to claims that AI technology is ushering society into a "post-literate" era, in which these skills are largely unnecessary (Harrington, 2025; O'Conner, 2024), our findings indicate that the importance of foundational cognitive skills in the labor market is likely to increase as AI tools become more widely integrated into the workplace. Given Israel's poor standing relative to other developed countries with respect to these skills (Behar & Demalach, 2024), our findings underscore the need for broad-based investment in high-quality education, higher education, and vocational training, and especially as we enter into the age of artificial intelligence.

Background: Basic skills and wages

Workers' wages are determined to a large extent by their productivity in the workplace, which in turn derives from their level of proficiency in performing the tasks required in their jobs. In general, the skills most important for workers' wages tend to be occupation-specific skills that are relevant to their particular field of work—for example, programming, driving a tractor-trailer truck, or teaching in early childhood education. These occupation-specific skills, however, are based on more general foundational skills, which tend to explain workers' earning capacity across a broad range of different occupations. Historically, the effect of foundational skills on wages was measured primarily indirectly—through experience, education, or prior school-age test scores, such as Bagrut or Meitzav scores—but over the past decade, more direct measurement of certain foundational skills has become possible through the OECD's Programme for the International Assessment of Adult Competencies (PIAAC).

The survey, most recently conducted in 2022–2023, collected estimates of foundational skills among a representative sample of the country's adult population, particularly in the areas of literacy, numeracy, and adaptive problem solving, together with background information on the respondents. It should be noted that the average proficiency level of adults in Israel is low by international comparison, with the country ranking between 25th and 27th out of 31 countries in these three domains. Proficiency levels are particularly low among Arab adults and, to a lesser extent, among Haredi adults. Even among non-Haredi Jews, average proficiency is no higher than the OECD-country average, despite Israel being one of the most highly educated countries in the survey in terms of formal educational attainment.

The low level of foundational skills among adults in Israel is especially concerning given the strong association between these skills and various labor market outcomes, most notably individual wages. In many countries, individuals' estimated proficiency levels are consistently correlated with their wages (Hanushek et al., 2015), and an increase of one standard deviation in foundational skills is associated with wages that are approximately 18% higher on average across high-income countries. This issue has also been examined in Israel, where foundational skills—particularly numeracy—were found to contribute more to wages than the international average,[1] with their effect evident mainly among private-sector rather than public-sector employees (Bank of Israel, 2016). An analysis of data from the latest survey cycle, on which this paper is based, shows that an increase of one standard deviation in foundational skills is associated with wages that are 26%–31% higher (Table 1) among workers ages 25–65. Overall, differences in foundational skills explain approximately one-tenth of wage differences between workers.

1 The fact that the returns to foundational skills in Israel are high relative to other countries, while proficiency levels are low, is consistent with the hypothesis of diminishing marginal returns to foundational skills.

Table 1. Percentage increase in wages associated with a one standard deviation increase in foundational skills, employed individuals ages 25–65, 2022–2023

Foundational skills	Literacy	Numeracy	Adaptive problem solving	Composite index
Coefficient	0.29***	0.29***	0.26***	0.31***
(Standard error)	(0.060)	(0.061)	(0.062)	(0.064)
R^2	0.10	0.09	0.08	0.10

Significance levels: *p < 0.10; **p < 0.05; ***p < 0.01.

Notes: Standard errors are shown in parentheses. The reported coefficients are based on a simple regression without control variables. The results for the "composite index" are based on two methods that yielded identical estimates, to the reported decimal place: principal component analysis (PCA) of the first principal component common to the three foundational skills, and factor analysis of the first factor common to all three. See the Appendix for further details.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

The relationship presented above between foundational skills and wages is not necessarily driven by their direct application in the workplace, but rather by their importance for acquiring more occupation-specific skills that are relevant both to occupational choice and to developing expertise within an occupation. Accordingly, foundational skills are not only associated with wages at a given point in time; they also allow individuals flexibility to change occupations, because they make it easier to acquire new occupation-specific skills (Semtner et al., 2025).

In addition to their effect on individual earning capacity, foundational skills tend to be associated with other positive aspects of people's lives, including public trust and a sense of influence over government policy, better self-reported health, and greater overall life satisfaction (Schleicher & Scarpetta, 2024; Vera-Toscano et al., 2017). These findings underscore the value of private and public investment in foundational skills beyond the direct economic motivation reflected in wages.

Generative artificial intelligence and foundational skills

The current generation of generative artificial intelligence technologies, including large language models (LLMs) and reinforcement learning systems, is explicitly designed to emulate the types of foundational skills measured in the OECD's Programme for the International Assessment of Adult Competencies (PIAAC).[2] Accordingly, occupations at particularly high risk of AI substituting for human workers (hereafter, "AI-exposed occupations"; for a complete list, see Appendix Box A1)[3] tend to be those in which foundational skills are especially important. On average, workers employed in these occupations in Israel exhibit higher levels of foundational skills than workers in other occupations (Table 2). It is important to emphasize, however, that this pattern is not uniform across all occupations. For example, while workers in technology occupations (an AI-exposed group) rank highest in the economy in terms of both wages and skill levels, clerical workers (another AI-exposed group of similar overall size) exhibit skill levels comparable to the average in occupations that are not exposed to AI, while earning wages that are approximately 20% lower.

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2 It is likely that the AI tools currently being integrated into the labor market would receive perfect scores in all three foundational skill domains assessed by the survey if they were tested today. Somewhat less advanced AI tools were evaluated using tests from the previous cycle of the Survey of Adult Skills and achieved nearly perfect results (OECD, 2023).

3 In this paper, the term "AI-exposed occupations" is equivalent to "full exposure" according to the automation measure developed by Eloundou et al. (2024). For further details on the exposure measures and the definition of AI-exposed occupations, see "Data and definitions" in the Appendix.

Table 2. Basic skills and wages by exposure to artificial intelligence, employed individuals ages 25–65, 2022–2023

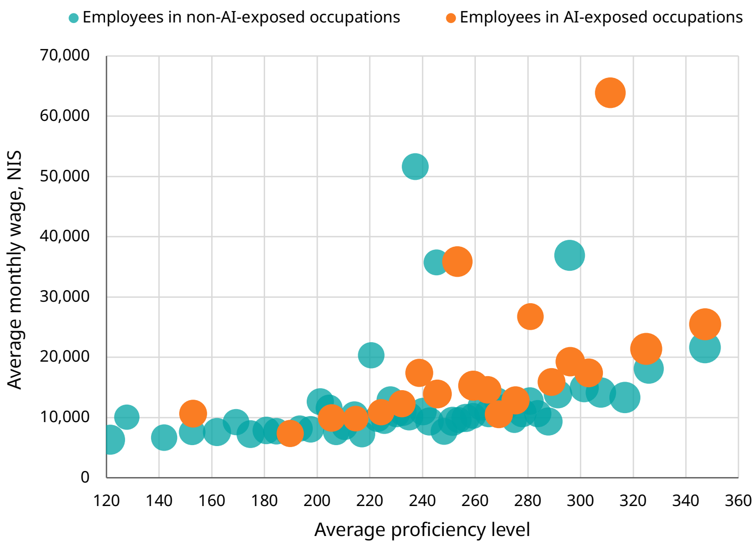
	Average score in foundational skills					Average wage (NIS, current prices)	
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Monthly	Hourly
AI-exposed occupations	270	270	256	265	265	13,600	85
	(49)	(50)	(41)	(47)	(47)	(9,500)	(70)
All other occupations	243	248	236	242	243	9,600	65
	(56)	(55)	(48)	(51)	(51)	(7,300)	(65)

Notes: Standard deviations are shown in parentheses. The data exclude individuals with monthly wages above NIS 50,000 (32 individuals, divided equally between the groups); the full data, including these individuals, are reported in Appendix Table A1. The PCA composite score is based on the first principal component common to the three foundational skills, while the FA composite score is based on the first factor common to all three. See the Appendix for further details.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

A more detailed breakdown reveals the association between workers' foundational skill levels and their wages. Figure 1 presents average wages among workers with similar proficiency levels, distinguishing between those employed in AI-exposed occupations and those who are not. Two insights emerge from the figure. First, the overall association between proficiency and wages is positive but weak, and tends to be stronger, though less consistent, at above-average proficiency levels. Second, no substantial difference is evident in the association between proficiency and wages when AI-exposed occupations are considered as a group and compared with all other occupations. Overall, the total association—both between and within occupations—is similar across the two groups.

Figure 1. Average skills level and average monthly wage, by exposure to artificial intelligence and skill level, employed individuals ages 25–65, 2022–2023



Note: Each bubble represents a group of approximately 50 workers in the sample, defined by their proficiency level. Bubble size represents the group's share of the total workforce in the population (because the sample is nearly representative, the bubbles are very similar in size). Average proficiency is measured using a composite score based on the first principal component common to the three foundational skills (principal component analysis, PCA). See the Appendix for further details.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

A broad view of the descriptive data makes it difficult to determine whether differences in foundational skills between workers in AI-exposed occupations and those in other occupations have a significant effect on earning capacity. It is possible, however, that the descriptive picture conceals systematic differences in the returns to foundational skills that are obscured by other factors. We now turn to a more in-depth estimation of the returns to skills and the potential for AI to reduce them.

Will the replacement of workers by AI reduce the returns to skills?

In principle, the replacement of workers by AI could reduce the contribution of skills to wages, thereby lowering workers' earnings—particularly those of the most highly skilled workers—even if all displaced workers are optimally reallocated to alternative employment. Specifically, if foundational skills are more important in occupations where AI replaces workers than in other occupations, then the average importance of foundational skills will decline as these occupations become automated. In economic terms, such a scenario represents a structural decline in the demand for foundational skills. The objective of this study is to assess how plausible such a decline is in light of the available data.

Our first objective is to examine whether any difference exists between AI-exposed occupations and other occupations with respect to the demand for foundational skills. To do so, we use our data to estimate the wage elasticities with respect to foundational skills for the two groups of workers and apply standard statistical tests to determine whether the hypothesis of no difference between them can be rejected. We conduct a series of tests based on alternative measures of foundational skills and different identification strategies for estimating the elasticity, which captures the causal effect of skills on wages. A full description of the economic model, the statistical methods, and the results is provided in the Appendix. Table 3 presents ten estimates of the difference between the wage elasticity in AI-exposed occupations and the wage elasticity in all other occupations. Two overarching findings emerge from the table. First, all estimated differences are positive, implying that foundational skills are better compensated on average in AI-exposed occupations. Second, none of these differences is statistically significant, meaning that none of the skill measures predict significantly greater compensation. We first discuss the second finding—the uniformly insignificant difference in wage elasticities—and then turn to the first.

Table 3. Difference in the wage elasticity with respect to foundational skills between AI-exposed occupations and other occupations, by estimation method and proficiency measure, 2022–2023

Skills index / Estimation method	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Direct estimation (MLE)	0.43 (0.29)	0.15 (0.30)	0.47 (0.34)	0.37 (0.28)	0.38 (0.28)
Instrumental variables	0.80 (0.57)	1.27 (0.77)	1.17 (0.75)	0.90 (0.58)	0.87 (0.57)

Significance levels: *p < 0.10; **p < 0.05; ***p < 0.01.

Notes: Each cell presents the estimated difference between the elasticities, with the standard error shown in parentheses below. The estimates are based on regressions that include control variables such as gender, age, and experience, together with a Heckman correction (Heckman, 1976) for employment. The instrumental variables method uses parental education as the instrument and parental income when the individual was age 14 as an additional control variable. The elasticity estimates themselves, together with the full regression results and the results of χ^2 tests for the significance of the difference between the elasticities, are presented in columns (1.1)–(5.1) of Appendix Table A2 for the MLE estimates and columns (1.1)–(5.1) of Appendix Table A3 for the IV estimates.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Across all estimated models, no meaningful difference was found in the wage elasticity with respect to foundational skills between AI-exposed occupations and other occupations, and the hypothesis that the elasticities are equal cannot be rejected. In other words, occupations vulnerable to substitution by AI do not rely unusually heavily on foundational skills, nor do they constitute an irreplaceable channel for the monetization of those skills in the labor market. Moreover, none of the models found a significant wage difference between the two groups beyond that explained by differences in skills and other observable characteristics. Statistically, the hypothesis that both the wage elasticity and the skill-independent component of wages are identical across the two groups of workers cannot be rejected.[4] This latter finding implies not only that there is no difference between AI-exposed occupations and other occupations in the returns to foundational skills, but also that there is no additional difference between them once other observable factors are taken into account. For example, the higher wages earned by workers in technology occupations are explained primarily by their higher skill levels, together with other observable characteristics: the model predicts that if these workers were employed in other occupations, their wages would remain broadly similar.

In our interpretation, the similarity in the wage elasticities with respect to foundational skills between AI-exposed occupations and other occupations suggests that a structural decline in the demand for foundational skills is unlikely, even if demand for certain occupations were to disappear entirely. On the contrary, insofar as AI technology reduces costs and increases overall productivity, the demand for foundational skills is likely to increase (we return to this point below).

Despite these findings, attention should be paid to the estimated difference between the elasticities, which is consistently positive across the tests presented in Table 3. Setting aside the issue of statistical significance, this finding suggests that the wage elasticity with respect to foundational skills may indeed be higher in AI-exposed occupations than in other occupations, and that a relative decline in employment in AI-exposed occupations could lead to a modest structural decline in the demand for foundational skills. Figure 2 presents the predicted decline in the value of foundational skills associated with a decline in demand for AI-exposed occupations, based on the various estimates. This decline can be interpreted as the expected reduction in wages if the adoption of AI technology made no contribution whatsoever to productivity.

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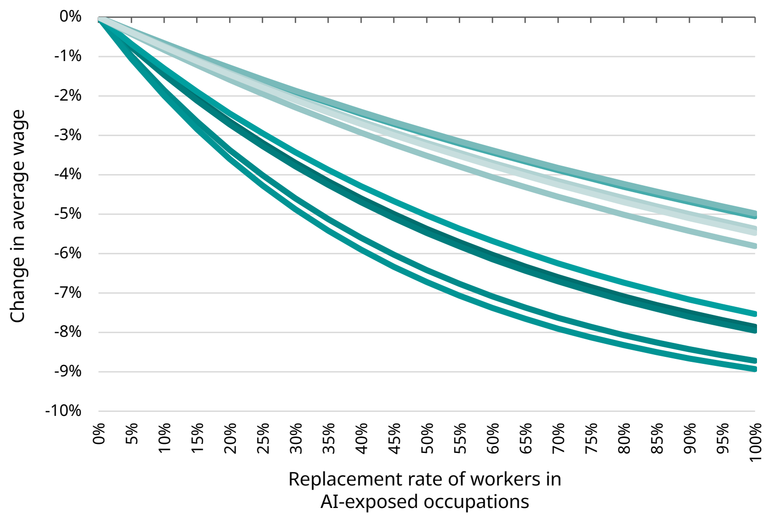
4 In each model, a χ^2 test was conducted to evaluate a joint hypothesis consisting of two components: (a) the wage elasticity with respect to foundational skills is identical in AI-exposed occupations and all other occupations; and (b) the dummy variable for AI-exposed occupations is not statistically significant. The resulting test statistic and corresponding p-value are reported in the bottom rows of Appendix Table A3 (MLE estimates) and Appendix Table A5 (IV estimates). The null hypothesis cannot be rejected in any of the models.

Figure 2. Expected change in average wages by the share of workers in AI-exposed occupations replaced, under the assumption that AI-driven replacement has no effect on productivity, based on alternative estimates



Notes: The figure presents ten curves derived from the ten estimates reported in Table 3. For details of the calculations, see "The Skills and Wages Model" in the Appendix.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

As Figure 2 shows, in a scenario in which most workers in AI-exposed occupations are replaced by AI, the direct effect of the resulting decline in demand for foundational skills is expected to reduce wages by approximately 5%–9%. Under scenarios in which one-quarter or fewer of these workers are replaced (as projected by Acemoglu [2025] and Svanberg et al. [2024]), the decline amounts to only a few percentage points. In practice, however, the replacement of workers in AI-exposed occupations by AI is expected to be accompanied by higher labor productivity in other occupations, owing to the cost savings generated by the adoption of the technology,[5] as well as by the creation of new tasks that will enable the more profitable monetization of foundational skills.

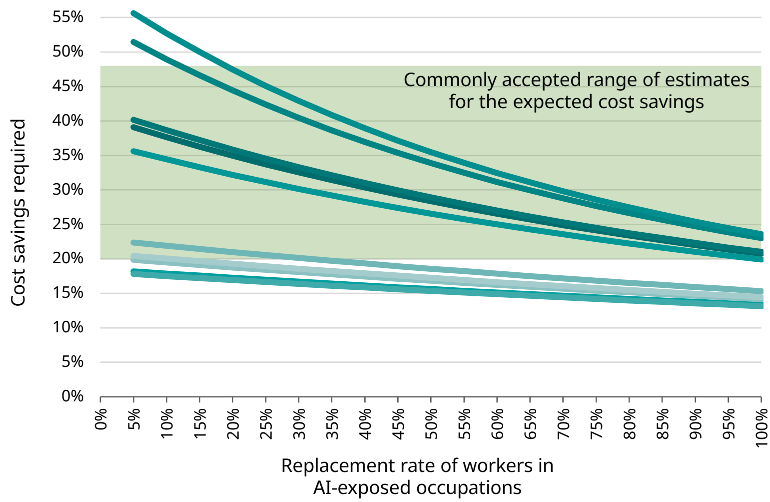
5 Theoretically, the cost savings could be very small, but they cannot be zero, since in that case there would be no incentive to adopt the technology in the first place.

Global estimates of AI-related cost savings range from 20% to 48% (Chui et al., 2023), corresponding to a productivity increase of approximately 3.5%–9% in the case of Israel (under a full-replacement scenario).[6] This range suggests that wage levels—and thus the absolute demand for foundational skills—could increase even under a full-replacement scenario, although average wages might not rise if the most pessimistic cost-saving scenarios were to materialize. As for the emergence of new tasks and occupations, it is not yet possible to produce reliable estimates of AI's impact in this regard. Estimates from earlier waves of automation suggest that the creation of new tasks offset roughly one-third of the wage losses caused by automation, and we incorporate this figure into our calculations.[7]

6 The total labor cost of workers in AI-exposed occupations amounts to approximately 17% of value added in the economy (Debowy et al., 2026a). Given the range of estimated cost savings, the potential savings amount to 3%–8% of value added, corresponding to an increase in output of approximately 3.5%–9%.

7 Acemoglu et al. (2025) show that, in the context of technological change in the United States between 1980 and 2016, the effect of newly created tasks on wage changes was approximately one-third the magnitude of the effect of automation, with the two effects equal in magnitude but opposite in sign (automation reduced wages, whereas new tasks increased them). The source for these estimates is Panel C of Table 1 in their paper.

Figure 3. AI-induced cost savings required to prevent a decline in wages, based on alternative estimates



Notes: The figure presents ten curves derived from the ten estimates reported in Table 3. For details of the calculations, see "The Skills and Wages Model" in the Appendix.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Figure 3 presents ten curves corresponding to those in Figure 2, showing the minimum level of AI-induced cost savings required for the resulting increase in overall productivity to fully offset the decline in the demand elasticity for foundational skills and thereby prevent wages from falling. The curves are shown against the range of estimated cost savings reported in a variety of studies and practical applications. The required level of cost savings appears to fall within—or below—this estimated range for each of our estimates (except in scenarios where the actual extent of worker replacement is very small and the resulting wage effect is negligible), and lies near the lower end of the range even under high rates of worker replacement. In other words, the productivity gains generated by the adoption of AI are expected to be sufficient to offset any decline in the demand for foundational skills. Thus, even if the demand elasticity with respect to these skills declines, total demand will increase. Under such a scenario, the relative return to investing in foundational skills would decline, but the absolute return (measured in real monetary terms) would increase.

Overall, the evidence suggests that it is highly unlikely that replacing human workers with AI in occupations where such substitution is feasible will reduce the returns to foundational skills in the labor market. The statistical tests indicate that these returns are similar—if not identical—between AI-exposed occupations and all other occupations, allowing workers to monetize their skills for comparable wages at any given skill level. Moreover, even if we focus on the average difference in the wage elasticities with respect to foundational skills across occupational groups, its magnitude suggests that any decline in the demand elasticity for foundational skills would be small and that the productivity gains resulting from the adoption of AI would more than offset this decline, thereby increasing the returns to foundational skills.

Conclusion

This chapter has examined the importance of foundational skills as a key component of the human capital of workers in Israel. Their importance extends beyond employment and wages to other aspects of well-being, including self-reported health and overall life satisfaction. We focused on the foundational skills measured in the 2022–2023 OECD Programme for the International Assessment of Adult Competencies (PIAAC)—literacy, numeracy, and adaptive problem solving—and showed that they have a substantial effect on wages across the labor market, including in blue-collar occupations. Although the generative AI tools currently being adopted are designed to perform tasks that rely on these foundational skills, our findings indicate that this reliance is not unique to AI-exposed occupations. These skills are no less important in occupations where the risk of AI substitution is low than in occupations where that risk is high.

Our quantitative analysis further shows that even if changes in the occupational composition of the economy resulting from AI adoption slightly reduce the demand elasticity with respect to foundational skills, the resulting increase in labor productivity due to cost savings is expected to more than offset this effect, raising demand above its original level and thereby increasing the real returns to private and public investment in foundational skills. Indeed, technological change is likely to increase productivity and wage responsiveness beyond the estimates presented here, owing to structural changes in the labor market and the emergence of new jobs and occupations (Autor et al., 2026). The returns to foundational skills are therefore likely to increase rather than decline.

It should be emphasized, however, that our findings concern long-run equilibrium rather than short-run adjustment. For example, although workers currently employed in technology occupations may, in the long run, be able to earn comparable wages in other occupations, this does not imply that a programmer forced to retrain for a new occupation will maintain the same wage continuously throughout the transition. Occupation-specific skills, such as programming, may well experience a substantial decline in demand. The foundational skills on which these occupation-specific skills are built, however, will remain relevant across most occupations in the economy and will facilitate workers' movement between them. It is also important to reiterate that generative AI technology is advancing at an extraordinarily rapid pace, and considerable uncertainty remains regarding the capabilities of different AI tools in the workplace. Accordingly, the classification of occupations as vulnerable to AI substitution is inherently somewhat speculative, although the exposure measures used in this study have demonstrated meaningful predictive power in recent years with respect to labor demand (Debowy et al., 2026b; Massenkoff & McCrory, 2026).

Another issue not addressed in this chapter is the effect of AI adoption on the level of foundational skills themselves. A number of studies have raised the possibility that the use of AI to perform workplace tasks may lead to the erosion or depreciation of workers' skills ("deskilling").[8] In principle, this phenomenon is relevant to the vast majority of workers, not only to those whose jobs may eventually be replaced by AI. Indeed, even workers in occupations for which AI has no direct workplace application could be affected if similar deskilling occurs through the use of AI tools in education, training, or leisure activities. We are unable to examine this issue here, but if AI does in fact erode foundational skills, it is likely to have adverse consequences for Israeli workers.

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8 For a review of this phenomenon in the context of healthcare workers, see Natali et al. (2025); for technology workers, see Le (2025).

In conclusion, the AI era does not eliminate the need for foundational cognitive skills; at least at present, their economic importance is likely to increase rather than diminish. Israel's education system, higher education institutions, and vocational training programs should therefore place even greater emphasis on developing these skills as AI becomes more deeply integrated into the Israeli economy. This imperative is especially compelling in light of the current relatively low level of foundational skills in Israel's workforce compared with other high-income countries—a finding that is particularly striking given that Israel is one of the world's most highly educated countries in terms of formal educational attainment and has an exceptionally high share of workers employed in professional and academic occupations (Behar & Demalach, 2024). Government institutions—and in particular the Ministries of Education and Labor—should invest in the high-quality development of these foundational skills, alongside others not measured in PIAAC, such as soft skills and physical skills, in order to strengthen the true human capital of Israel's workforce and enable workers to thrive in this new era of generative artificial intelligence.

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Manela, M . (2025, February 21). So AI won't replace you — these are the skills you need now in high-tech. *Calcalist*.

Appendix

Data and definitions

The main database used in this paper consists of the results of the second cycle of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), conducted in Israel in 2022–2023, with a focus on individuals ages 25–65. The survey was administered to a representative sample of the country's population and included a background questionnaire and an assessment of three foundational skills: literacy, numeracy, and adaptive problem solving.

Because the measurement method relies on a relatively short assessment in each domain, there are limits to the precision with which an individual's score on each assessment reflects their true proficiency level. To address this measurement issue, the survey does not report a single score for each assessment, but rather a distribution of possible "true" scores derived from the individual's performance on the different parts of the assessment. Given the individual's observed performance, this distribution reflects the probability that their "true" proficiency level corresponds to each possible score. For example, for an individual with a raw score of 250, there is a high probability that their "true" proficiency level lies between 240 and 260, but there is also a nonzero probability that it lies between 260 and 280—for example, if the individual was having a "bad day" when taking the assessment—or between 220 and 240—for example, if the individual was lucky. The distribution of an individual's possible proficiency levels in each domain is represented by "plausible values": ten possible "true" scores for each skill, randomly drawn from the proficiency distribution estimated on the basis of the individual's performance. Accordingly, every proficiency score reported in this paper—and every statistic related to that score, such as a regression coefficient—is the average result of ten separate calculations, each based on a different plausible score for that skill for every individual in the sample. It should be noted that the variation among the possible scores for each individual is considerably smaller than the variation between individuals, and the results obtained from the different calculations are therefore generally almost identical. Moreover, scores in the three foundational skills are very highly correlated, and the three skills can readily be treated as a single measure of foundational proficiency. We therefore also use two composite measures calculated using different methods: one based on principal component analysis (PCA) and one based on factor analysis (FA).[9] Both measures are calculated one thousand times using the possible combinations of scores in the three skills for each individual, and each captures approximately 99% of the information contained in the three skills, on average.

The survey data also include the background questionnaire, which contains information on education, gender, population group, age, parental education, work experience, and other characteristics; these data are matched with administrative income data. Individuals are also identified by occupation, which we use to classify their exposure to AI. Appendix Table A1 presents descriptive statistics for the sample as a whole and separately for workers in AI-exposed occupations and all other occupations. The income data exhibit extremely high variation because of the presence of workers with exceptionally high monthly wages, reaching six- and even seven-digit amounts.[10] Data excluding these individuals are presented in Table 2 in the main text; excluding them also has no effect on the estimation results.

9 The measure used in the calculations is the first principal component or the first factor, with no need to analyze additional components or factors. Because of the high degree of shared variation among the measures, principal component analysis tends to yield results very similar to those obtained from factor analysis. In the calculations presented in the main text, we standardize this variable so that its mean and standard deviation match those of the other proficiency scores.

10 This group consists of 32 individuals, approximately one-third of whom are managers and about one-quarter of whom work in technology occupations. Each individual’s monthly wage is calculated as total annual income divided by the total number of months worked during that year. As a result, compensation from one-time events, such as exits, is reflected in the monthly wage.

Table A1. Descriptive statistics, employed individuals ages 25–65, 2022–2023

	Average score in foundational skills						Average wage (NIS, current prices)	
	Observations	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Monthly	Hourly
Full sample	4,592	244 (58)	246 (57)	236 (50)	241 (63)	241 (63)	9,400 (54,250)	60 (310)
All employed individuals	2,946	251 (56)	255 (54)	242 (47)	242 (52)	242 (52)	14,700 (67,500)	95 (390)
AI-exposed occupations	931	270 (49)	269 (49)	256 (42)	261 (46)	261 (45)	19,600 (58,600)	120 (310)
All other occupations	2,015	243 (56)	249 (55)	236 (47)	234 (53)	234 (53)	12,800 (70,800)	85 (417)

Note: For each variable, the mean is reported, with the standard deviation shown in parentheses below.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

To define AI-exposed occupations, we rely on the automation measure developed by Eloundou et al. (2024), which focuses on the substitution of human labor by AI, although, because of measurement difficulties, it may also capture the augmentation and complementarity of workers. The original measure was assigned to occupations in the US O*NET classification, which we convert to the ISCO classification used in Israel, thereby obtaining an AI-exposure score for each of approximately 300 occupations. We matched these exposure scores to the Survey of Adult Skills data and classified workers as "AI-exposed" if they received an automation score of 0.5 or higher. The list of exposed occupations, at the four-digit classification level, appears in Appendix Box A1. Approximately 30% of workers in the sample were employed in these occupations during the survey period and accounted for about 40% of total labor income.[11]

11 Labor Force Survey data from the Israeli Central Bureau of Statistics (CBS) covering the period of the Survey of Adult Skills (September 2022 to July 2023) indicate a similar share of workers employed in these occupations: 32%.

Box A1. AI-exposed occupations (ISCO-08 four-digit classification)

Financial managers (1211); human resource managers (1212); policy and planning managers (1213); advertising and public relations managers (1222); sports, recreation and cultural center managers (1431); services managers not elsewhere classified (1439); mathematicians, actuaries and statisticians (2120); graphic and multimedia designers (2166); information and communications technology trainers (2356); accountants (2411); financial and investment advisers (2412); financial analysts (2413); internal auditors (2414); management and organization analysts (2421); policy administration professionals (2422); personnel and careers professionals (2423); training and staff development professionals (2424); advertising and marketing professionals (2431); public relations professionals (2432); technical and medical sales professionals (excluding ICT) (2433); software developers (2512); web and multimedia developers (2513); applications programmers (2514); software and applications developers not elsewhere classified (2519); database designers and administrators (2521); systems administrators (2522); computer network professionals (2523); database and network professionals not elsewhere classified (2529); authors and related writers (2641); journalists (2642); translators, interpreters and other linguists (2643); radio, television and other announcers (2656); draughtspersons (3118); process control technicians not elsewhere classified (3139); air traffic controllers (3154); pharmaceutical technicians and assistants (3213); medical records and health information technicians (3252); securities and finance dealers and brokers (3311); credit and loan officers (3312); accounting associate professionals and bookkeepers (3313); statistical, mathematical and related associate professionals (3314); valuers and loss assessors (3315); insurance representatives (3321); commercial sales representatives (3322); buyers (3323); trade brokers (3324); importers (3325); exporters (3326); clearing and forwarding agents (3331); business services agents not elsewhere classified (3339); legal secretaries (3342); administrative and executive secretaries (3343); medical secretaries (3344); government tax and excise officials (3352); government social benefits officials (3353); government licensing officials (3354); government regulatory associate professionals not elsewhere classified (3359); information and communications technology operations technicians (3511); information and communications technology user support technicians (3512); computer network and systems technicians (3513); web technicians (3514); general office clerks (4110); general secretaries (4120); typists and word-processing operators (4131); data entry clerks (4132); bank tellers and related clerks (4211); pawnbrokers and moneylenders (4213); debt collectors and related workers (4214); money exchange clerks (4215); travel consultants and clerks (4221); contact center information clerks (4222); telephone switchboard operators (4223); hotel receptionists (4224); client information workers (4225); receptionists (general) (4226); survey and market research interviewers (4227); client information workers not elsewhere classified (4229); accounting and bookkeeping clerks (4311); statistical, finance and insurance clerks (4312); payroll clerks (4313); production clerks (4322); transport clerks (4323); library clerks (4411); coding, proof-reading and related clerks (4413); scribes and related workers (4414); personnel clerks (4416); clerical support workers not elsewhere classified (4419); cashiers and ticket clerks (5230); contact centre salespersons (5244); sales workers not elsewhere classified (5249); pre-press technicians (7321).

Note: The list includes occupations (at the four-digit ISCO classification level) classified as fully AI-exposed occupations.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: Eloundou et al. (2024)

The skills and wage model: A theoretical framework

The model provides a simple framework for analyzing the implications of changes in the level of foundational skills for average wages in the economy. We assume that worker output is an isoelastic function of the level of foundational skills:

$$(1) \quad Y = \omega \cdot S^{\alpha}$$

where Y denotes output, S denotes foundational skills, α is the elasticity of output with respect to the skill level, and ω captures factors that do not depend directly on the skill level, including other foundational skills or advanced skills that are uncorrelated with foundational skills, skill-complementary capital, demand for final output Y, and total factor productivity. For simplicity, we refer to ω below as "total productivity."[12] Individual wages are determined in relation to marginal product, which is derived from the skill level:

$$(2) \quad W = \omega \cdot \alpha \cdot S^{\alpha-1}$$

where W denotes the wage level, and all other variables are defined as in Equation (1).

Equation (2) makes it possible to calculate the change in the wage level in the economy resulting from changes in the elasticity α (due to changes in the occupational composition), conditional on estimates of its baseline value and the corresponding changes (or lack thereof) in total productivity, ω, resulting from the diffusion of artificial intelligence. Let α_0 denote the current elasticity (based on the labor market in 2022–2023) and α_1 the elasticity after the change. Assuming that the overall stock of skills remains unchanged between the two periods, the percentage change in the wage level is given by:[13]

$$(3) \quad \Delta^{\%} W = \frac{W_1}{W_0} - 1 = \frac{\omega_1}{\omega_0} \cdot \frac{\alpha_1}{\alpha_0} \cdot S^{\alpha_1 - \alpha_0} - 1$$

12 We emphasize that this formulation is also relevant to more complex models. In particular, we do not rule out the possibility that the level of skills has an indirect effect on the production process as a whole, such that $\omega = f(\cdot, S, \alpha)$ and $\alpha = g(\cdot, S, \omega)$.

13 The full version of the equation, which allows the stock of skills to differ between periods 0 and 1, is:

$$\Delta^{\%} W = \frac{W_1}{W_0} - 1 = \frac{\omega_1}{\omega_0} \cdot \frac{\alpha_1}{\alpha_0} \cdot \frac{S_1^{\alpha_1 - 1}}{S_0^{\alpha_0 - 1}} - 1$$

The results of Equation (3) do not depend on the baseline level of total productivity. Therefore, ω_0 can be normalized to 1, provided that ω_1 is adjusted to reflect the expected percentage change. The results of the equation do, however, depend directly on the baseline level of the wage elasticity with respect to skills (and not only on the relative change in this parameter). Accordingly, a baseline estimate of this elasticity is required to apply the model. For details on the estimation of this parameter using data from the 2022–2023 Survey of Adult Skills, see "Wage elasticity with respect to foundational skills" below.

The skills and wage model: Results

As a starting point, we calculate the change in wages under the assumption that productivity remains unchanged ($\omega_0=\omega_1$) for different rates of actual worker replacement in AI-exposed occupations, (x), which determines the change from α_0 to α_1 according to the following equation:

$$(4)\quad \begin{Bmatrix} \alpha_0 = \hat{\alpha}_0 \\ \alpha_1 = x\hat{\alpha}_1 + (1-x)\hat{\alpha}_0 \end{Bmatrix}$$

where the ten alternative values for $\hat{\alpha}_0$ are taken from the estimated coefficients for the wage elasticity with respect to foundational skills for the economy as a whole (plus 1; the values are reported in columns (1.1)–(5.1) of Appendix Tables A2 and A4), and the corresponding values for $\hat{\alpha}_1$ are taken from the estimated coefficients for the wage elasticity with respect to foundational skills among workers in non-AI-exposed occupations only (plus 1; the values are reported in columns (1.1)–(5.1) of Appendix Tables A3 and A5). Figure 2 presents the change in wages ($\Delta^{\%}W$ from Equation (3)) as a function of the replacement rate (x from Equation (4)) for the ten alternative estimates of the wage elasticities.

As noted above, these calculations are based on the scenario in which worker replacement is not accompanied by any increase in labor productivity in the rest of the economy, however small—an assumption that is, to say the least, highly implausible. Nevertheless, they make it possible to calculate the minimum increase in productivity required to prevent a decline in wages. Since this paper focuses on worker replacement by artificial intelligence, rather than on other channels through which AI may affect the economy, it is appropriate to calibrate the productivity increase with reference to this channel. We therefore define the increase in total productivity as a function of the cost savings generated by the output of the replaced workers. Let ω_1^* denote the minimum increase in total productivity required to prevent a decline in wages.[14] The required cost savings depend inversely on the results presented in Figure 2 ($\widehat{\Delta\%W}$ see Footnote 14), on the share of the wages of replaced workers in total costs, C_x (calibrated at 0.17 based on Debowy et al., 2026a), on the increase in productivity resulting from additional investment and the creation of new jobs (Δk and μ, respectively), and on the actual replacement rate, x. The required cost-saving rate, π^*, is given by:[15]

$$(5) \quad \pi^* = \left(1 - \frac{1}{\omega_1^*}\right)\frac{\mu}{C_x \cdot x \cdot \Delta k} = \frac{-\Delta\%\widehat{W(x)}}{x} \cdot \frac{\mu}{C_x \cdot \Delta k}$$

Figure 3 presents ten curves for the required cost-saving rate, π^*, at different actual replacement rates, x, corresponding to the ten curves shown in Figure 2 ($\widehat{\Delta\%W}$ as a function of x). The shaded area shows a broad range of estimates for the actual cost-saving rate, π, drawn from various sources,[16] although there is currently no consensus regarding the appropriate range.

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14 Formally, the required rate of change in total productivity, ω_1^*, is calculated by setting the change in wages in Equation (3) equal to zero:

$$\omega_1^* = \frac{1}{\Delta\%\widehat{W(x)} + 1}$$

where $\Delta\%\widehat{W(x)}$ (presented in Figure 2) is the change in wages at each replacement rate (x) under the assumption that total productivity remains unchanged.

15 In practice, we assume that the increase in labor productivity exceeds the cost savings because the cost savings induce additional investment in capital (see Acemoglu, 2025). We approximate the full relationship between cost savings, π, and productivity growth, ω, as follows:

$$\pi \cdot C_x \cdot x \cdot \Delta k = \left(1 - \frac{1}{\omega_1^*}\right) \cdot \mu$$

where Δk = 1.47, based on Debowy et al. (2026a). The parameter μ represents the offset resulting from the creation of new jobs and is calibrated at 0.66, as explained in the main text.

16 See Acemoglu, 2025; Shui et al., 2023; Svanberg et al., 2024.

Wage elasticity with respect to foundational skills

In principle, the parameters cannot be identified without bias through a simple estimation of Equation (2), owing to the simultaneity of S, α, and ω. We therefore conduct several alternative exercises in an attempt to identify the elasticity α using data from the Survey of Adult Skills.

The first and simplest exercise estimates the wage elasticity with respect to foundational skills while controlling for additional variables. The estimated equation is:

$$(6) \quad lnw_i = \eta + \beta \cdot lns_i + \gamma \cdot X_i + \varepsilon_i$$

where X_i is a vector of control variables—including education, experience, gender, and age—for individual i, and ε_i is an independent error term. The identifying assumption underlying this approach is that, conditional on the control variables X, the skill level S is independent of unobserved factors, such that the estimated coefficient β provides an unbiased estimate of the elasticity parameter α-1.

Even under this assumption, the estimates may still be subject to selection bias because we do not observe the potential wages of individuals who were not employed at the time of the survey. We address this issue using the Heckman correction (Heckman, 1976) by estimating Equation (6) in a two-step framework. In the first step, the probability of employment is estimated, and in the second step the wage elasticity is estimated while controlling for the probability of employment. As an exclusion restriction in the employment equation, we use the annual unemployment trend in the economy during the most recent year in which each individual entered or exited the labor force. This variable captures the effect of the business cycle on an individual's employment history and, through that channel, on their current employment status.[17] The estimation results are reported in Appendix Tables A2 (all workers) and A3 (AI-exposed and non-AI-exposed occupations separately).

17 For individuals who have never been employed (17% of the sample), we use the unemployment trend in the year in which they completed their most recent degree or certification.

Equation (6) may nevertheless yield biased estimates, particularly if the control variables do not adequately account for the simultaneous correlation between S and W. As an alternative, we employ an instrumental variables (IV) approach to estimate the elasticity parameter as the causal effect of skill level on wages. Specifically, we replace the two-step model described above with a three-step estimation procedure. First, skill level is predicted using the instrumental variable and the control variables. Next, the probability of employment is estimated within the Heckman correction framework using the predicted skill level. Finally, the wage equation is estimated using the predicted skill level while including the Heckman correction term. For brevity, the procedure is summarized in the following equations (the second step is omitted for clarity):

$$(7.1)\quad lns_i = \vartheta + \theta \cdot IV_i + \varphi \cdot X_i + \epsilon_i$$

$$(7.2)\quad lnw_i = \eta + \beta \cdot \widehat{lns}_i + \gamma \cdot X_i + \varepsilon_i$$

where IV_i is the instrumental variable, and all other variables are defined as in Equation (6). For the estimated coefficient β to provide an unbiased estimate of the elasticity parameter α-1, the instrument must, on the one hand, be relevant for predicting skill levels and, on the other hand, affect wages only through its effect on skills.

The instrumental variable we use is the educational attainment of the individual's parents (when the individual was age 14), interacted with the individual's gender and age. Our interpretation is that parental education affects the individual's educational attainment, which in turn affects their level of foundational skills. The main concern with this interpretation is that parental education (and the individual's own education) may also be correlated with wages through indirect channels. For example, parents with greater skills or stronger social networks may be more highly educated, and these skills or networks may be transmitted to their children independently of education, thereby affecting both their skill levels and educational attainment. To mitigate this concern, we include parental income (when the individual was age 14, adjusted to 2022–2023 prices) as a control variable in all stages of the estimation. This variable serves as a proxy for parental skill levels.[18] Our identifying assumption is therefore that, conditional on parental income, parental education is an exogenous determinant of the individual's skill level and is unrelated to any other unobserved characteristics that affect wages.

In practice, parental education is reported only in broad categories (high school completion and tertiary education for each parent). As a result, individuals can be classified into only nine parental education groups, with approximately two-thirds belonging to the "diagonal" groups in which both parents have the same level of education. To maximize the variation in the sample, our instrument is defined as the interaction between the parental education category and the individual's gender and age (which are included as control variables in any case). The estimation results are reported in Appendix Tables A4 (all workers) and A5 (AI-exposed and non-AI-exposed occupations separately), while the first-stage estimates are reported in Appendix Table A6.

18 In practice, parental income is observed for approximately one-third of the individuals in the sample. For the remaining individuals, we impute parental income using average parental income by the mother's and father's occupations. Based on the availability of these variables, together with the parental education variables, we estimate the instrumental variables regression for approximately 70% of individuals in the full sample.

Table A2. MLE regression results (with Heckman correction) for estimating the wage elasticity with respect to foundational skills

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Log of skill level	0.695***	0.597***	0.770***	0.651***	0.652***	0.652***	0.152	-0.059	0.097	0.110
	(0.17)	(0.15)	(0.17)	(0.15)	(0.15)	(0.15)	(0.11)	(0.15)	(0.12)	(0.13)
Education										
High school	0.255***	0.288***	0.269***	0.264***	0.262***	0.262***	0.256	0.274*	0.259	0.258
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.14)	(0.14)	(0.14)	(0.14)
Non-academic higher education	0.248***	0.265***	0.279***	0.248***	0.246***	0.246***	0.170	0.202	0.180	0.178
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.15)	(0.15)	(0.15)	(0.15)
BA	0.579***	0.626***	0.610***	0.580***	0.577***	0.577***	0.484*	0.536**	0.496*	0.492*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.20)	(0.20)	(0.20)	(0.20)
Advanced degree	0.758***	0.814***	0.788***	0.759***	0.756***	0.756***	0.593*	0.660**	0.611**	0.606**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.24)	(0.23)	(0.23)	(0.23)
Man x age	0.048**	0.043**	0.046**	0.047**	0.047**	0.047**	0.077***	0.075***	0.077***	0.077***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Woman x age	0.030	0.027	0.029	0.030	0.030	0.030	0.056**	0.054**	0.056**	0.056**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Table continues

Table A2 (continued). MLE regression results (with Heckman correction) for estimating the wage elasticity with respect to foundational skills

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Man x age squared	-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.00)	(0.00)	(0.00)	(0.00)
Woman x age squared	-0.0005*	-0.0005*	-0.0005*	-0.0005*	-0.0005*	-0.0005*	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.00)	(0.00)	(0.00)	(0.00)
Experience	0.030**	0.036**	0.029**	0.030**	0.030**	0.030**	0.088***	0.089***	0.088***	0.088***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)		(0.02)	(0.02)
Experience squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001*	-0.001*	-0.001*	-0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Instrumental variable: unemployment trend							-0.076**	-0.073**	-0.075**	-0.075**
							(0.03)	(0.03)	(0.03)	(0.03)
λ	-0.113**	-0.079**	-0.141	-0.122*	-0.120*	-0.120*				
	(0.046)	(0.039)	(0.115)	(0.069)	(0.062)	(0.062)				
Intercept	3.992***	4.560***	3.611***	6.927***	6.928***	6.928***	-1.258	-0.089	-0.562	-0.580
	(0.83)	(0.81)	(0.89)	(0.37)	(0.37)	(0.37)	(0.73)	(0.82)	(0.63)	(0.63)

Table continues

Table A2 (continued). MLE regression results (with Heckman correction) for estimating the wage elasticity with respect to foundational skills

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Observations	2,946	2,946	2,946	2,946	2,946	2,946				
χ^2 all variables	470	442	434	455	458	458				
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				

Significance levels: *p < 0.10; **p < 0.05; ***p < 0.01.

Notes: The table presents estimates of the wage elasticity with respect to different measures of foundational skills. The five left-hand columns (1.2–5.2) present the first stage of the model, in which the probability of employment is estimated. The five right-hand columns present the corresponding second stage, in which the wage elasticity with respect to foundational skills is estimated while controlling for unobserved factors that affect the individual's employment. Each cell reports the estimate, with the standard error shown in parentheses below. In all regressions, standard errors are clustered at the occupational level.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Table A3. MLE regression results (with Heckman correction) for estimating the wage elasticity with respect to foundational skills, by AI exposure of occupation

	Wage equation - dependent variable: Log monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Log of exposure level: not exposed	0.494***	0.472***	0.566***	0.479***	0.477***	0.477**	0.393***	0.292	0.563***	0.585***
	(0.10)	(0.11)	(0.13)	(0.10)	(0.10)	(0.15)	(0.10)	(0.15)	(0.12)	(0.12)
Log of skill level: exposed	0.924***	0.622*	1.040***	0.852**	0.858***	0.298	0.216	0.115	-0.115	-0.095
	(0.27)	(0.28)	(0.31)	(0.26)	(0.26)	(0.17)	(0.13)	(0.17)	(0.21)	(0.21)
Exposed	-2.097	-0.523	-2.313	-0.237	-0.250	0.310*	0.317*	0.332*	0.311*	0.309*
	(1.51)	(1.59)	(1.80)	(0.33)	(0.32)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)
Education										
High school	0.234***	0.251***	0.241***	0.238***	0.237***	0.232	0.232	0.268	0.222	0.218
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Non-academic higher education	0.240***	0.235***	0.259***	0.234***	0.234***	0.589***	0.606***	0.650***	0.593***	0.586***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.17)	(0.17)	(0.18)	(0.17)	(0.17)
BA	0.565***	0.589***	0.583***	0.559***	0.559***	0.643**	0.660**	0.711***	0.658***	0.650**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Advanced degree	0.769***	0.797***	0.783***	0.760***	0.760***	0.055*	0.053*	0.053*	0.059**	0.059**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Table continues

Table A3 (continued). MLE regression results (with Heckman correction) for estimating the wage elasticity with respect to foundational skills, by AI exposure of occupation

	Wage equation - dependent variable: Log monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Man x age	0.049**	0.046**	0.049**	0.049**	0.049**	0.035	0.034	0.033	0.038	0.038
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Woman x age	0.031	0.030	0.032	0.033	0.032	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Man x age squared	-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Woman x age squared	-0.0005*	-0.0005*	-0.0005*	-0.0005*	-0.0005*	0.099***	0.101***	0.101***	0.098***	0.097***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Experience	0.031**	0.034***	0.030**	0.031**	0.031**	-0.001**	-0.001**	-0.001**	-0.001*	-0.001*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.032	-0.032	-0.029	-0.037	-0.037
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Instrumental variable: unemployment trend						-2.116*	-1.641**	-1.091*	-0.342*	-0.370*
						(0.94)	(0.62)	(0.68)	(0.18)	(0.18)

Table continues

Table A3 (continued). MLE regression results (with Heckman correction) for estimating the wage elasticity with respect to foundational skills, by AI exposure of occupation

	Wage equation - dependent variable: Log monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	**(2.1)**	**(3.1)**	**(4.1)**	**(5.1)**	**(1.2)**	**(2.2)**	**(3.2)**	**(4.2)**	**(5.2)**
	Literacy	**Numeracy**	**Adaptive problem solving**	**PCA composite score**	**FA composite score**	**Literacy**	**Numeracy**	**Adaptive problem solving**	**PCA composite score**	**FA composite score**
λ	-0.077**	-0.079**	-0.11	-0.093**	-0.088*					
	(0.034)	(0.030)	(0.073)	(0.046)	(0.047)					
Intercept	4.774***	4.911***	4.385***	6.826***	6.833***	0.477**	0.393***	0.292	0.563***	0.585***
	(0.74)	(0.77)	(0.88)	(0.42)	(0.42)	(0.15)	(0.10)	(0.15)	(0.12)	(0.12)
χ^2 all variables	2,946	2,946	2,946	2,946	2,946					
(p value)	794	785	706	741	754					
χ^2 significance of the difference between elasticity of those exposed and those not	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(p value)	2.22	0.25	1.93	1.81	1.91					
χ^2 significance of the difference between those exposed and those not (elasticity and intercept)	(0.14)	(0.61)	(0.17)	(0.18)	(0.17)					

Table continues

Table A3 (continued). MLE regression results (with Heckman correction) for estimating the wage elasticity with respect to foundational skills, by AI exposure of occupation

	Wage equation - dependent variable: Log monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
(p value)	3.84	4.24	4.52	4.15	4.08					
	(0.15)	(0.12)	(0.11)	(0.13)	(0.13)					

Significance levels: *p < 0.10; **p < 0.05; ***p < 0.01.

Notes: The table presents estimates of the wage elasticity with respect to different measures of foundational skills. The five left-hand columns (1.2–5.2) present the first stage of the model, in which the probability of employment is estimated. The five right-hand columns present the corresponding second stage, in which the wage elasticity with respect to foundational skills is estimated while controlling for unobserved factors that affect the individual's employment. Each cell reports the estimate, with the standard error shown in parentheses below. In all regressions, standard errors are clustered at the occupational level.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Figure A4. Two-stage least squares (2SLS) regression results for estimating the wage elasticity with respect to foundational skills

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Log of skill level	1.888***	2.191***	2.532***	1.840***	1.812***	1.466**	1.609**	1.697**	1.352**	1.343**
	(0.36)	(0.44)	(0.48)	(0.35)	(0.35)	(0.48)	(0.55)	(0.62)	(0.46)	(0.46)
Parental income when subject was 14	0.058	0.074	0.048	0.061	0.061	-0.034	-0.016	-0.024	-0.026	-0.027
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Man x age	0.100***	0.095***	0.095***	0.098***	0.098***	-0.034	-0.016	-0.024	-0.026	-0.027
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Woman x age	0.078**	0.078**	0.077**	0.079**	0.079**	0.066**	0.061**	0.059**	0.063**	0.064**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Man x age squared	-0.0006***	-0.0007***	-0.0007***	-0.0007***	-0.0007***	0.038	0.036	0.034	0.037	0.037
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Woman x age squared	-0.0005**	-0.0006**	-0.0006**	-0.0006**	-0.0006**	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience	0.018	0.021	0.018	0.018	0.018	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table continues

Figure A4 (continued). Two-stage least squares (2SLS) regression results for estimating the wage elasticity with respect to foundational skills

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Experience squared	0.000	-0.000	0.000	-0.000	-0.000	0.095***	0.098***	0.098***	0.096***	0.096***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Instrumental variable: unemployment trend						-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
						(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
λ	-0.151**	-0.150**	-0.159	-0.152*	-0.152*					
	(0.059)	(0.065)	(0.122)	(0.086)	(0.087)					
Intercept	-3.862	-5.681*	-7.166**	3.987***	4.034***	-0.063	-0.063	-0.064*	-0.063	-0.063
	(2.09)	(2.52)	(2.69)	(0.87)	(0.87)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	2,736	2,736	2,736	2,736	2,736					
χ^2 all variables	169	166	177	171	171					
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
F-statistic of endogeneity	10.3	14.4	10.6	10.3	10.1					
(p value)	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)					

Table continues

Figure A4 (continued). Two-stage least squares (2SLS) regression results for estimating the wage elasticity with respect to foundational skills

Significance levels: *p < 0.10; **p < 0.05; ***p < 0.01.

Notes: The table presents estimates of the wage elasticity with respect to different measures of foundational skills. The five left-hand columns (1.2–5.2) present the first stage of the model, in which the probability of employment is estimated. The five right-hand columns present the corresponding second stage, in which the wage elasticity with respect to foundational skills is estimated while controlling for unobserved factors that affect the individual's employment. Each cell reports the estimate, with the standard error shown in parentheses below. In all regressions, standard errors are clustered at the occupational level. The F-statistic for endogeneity is based on the Wooldridge (1995) test for the endogeneity of the instrumental variables.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Table A5. Two-stage least squares (2SLS) regression results for estimating the wage elasticity with respect to foundational skills, by AI exposure of occupation

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Log of skill level: not exposed	1.681***	1.691***	1.911***	1.490***	1.491***	1.807**	1.908*	1.889*	1.704**	1.715**
	(0.30)	(0.33)	(0.35)	(0.27)	(0.27)	(0.67)	(0.78)	(0.83)	(0.62)	(0.62)
Log of skill level: exposed	2.478***	2.965***	3.088***	2.390***	2.365***	1.523*	1.624*	1.603	0.560	0.568
	(0.48)	(0.69)	(0.66)	(0.51)	(0.50)	(0.69)	(0.80)	(0.85)	(0.72)	(0.72)
Exposed	-4.063	-6.705	-6.121	-0.911	-0.872	-9.847*	-12.627	-11.841	-3.060**	-3.022**
	(2.43)	(3.91)	(3.60)	(0.65)	(0.63)	(4.47)	(6.45)	(6.11)	(1.18)	(1.15)
Parental income when subject was 14	0.053	0.067	0.043	0.055	0.055	-0.007	-0.011	-0.013	-0.011	-0.011
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Man x age	0.090**	0.085**	0.085**	0.088**	0.088**	-0.045***	-0.044***	-0.044***	-0.044***	-0.044***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Woman x age	0.068*	0.067*	0.066*	0.068*	0.068*	-0.049***	-0.048***	-0.048***	-0.048***	-0.048***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Man x age squared	-0.0008***	-0.0008***	-0.0008***	-0.0008***	-0.0008***	-0.063	-0.063	-0.064*	-0.063	-0.063
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)

Table continues

Table A5 (continued). Two-stage least squares (2SLS) regression results for estimating the wage elasticity with respect to foundational skills, by AI exposure of occupation

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
Woman x age squared	-0.0006**	-0.0007**	-0.0007**	-0.0007**	-0.0007**	-7.613*	-8.549*	-8.851*	-1.462	-1.436
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(2.99)	(3.36)	(3.72)	(1.14)	(1.13)
Experience	0.029	0.031	0.029	0.028	0.028	0.114***	0.113***	0.113***	0.113***	0.113***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Experience squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Instrumental variable: unemployment trend						-0.094*	-0.095*	-0.095*	-0.095*	-0.095*
						(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
λ	-0.072**	-0.075**	-0.077	-0.067*	-0.067*					
	(0.036)	(0.036)	(0.095)	(0.038)	(0.038)					
Intercept	-2.863	-4.562*	-5.957**	4.363***	4.406***	-2.856	-4.525	-4.523	0.646	0.671
	(1.63)	(2.01)	(2.19)	(0.77)	(0.77)	(3.38)	(3.99)	(4.10)	(1.20)	(1.19)
Observations	2,736	2,736	2,736	2,736	2,736					
$\chi 2$ all variables	223	215	224	211	211					

Table continues

Table A5 (continued). Two-stage least squares (2SLS) regression results for estimating the wage elasticity with respect to foundational skills, by AI exposure of occupation

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
F-statistic for endogeneity	2.9	3.1	2.2	2.1	2.2					
(p value)	(0.069)	(0.059)	(0.012)	(0.138)	(0.128)					
χ^2 significance of difference in elasticity between those exposed and those not	3.19	3.12	3.11	3.21	3.23					
(p value)	(0.17)	(0.17)	(0.12)	(0.13)	(0.13)					
χ^2 significance of the difference between those exposed and not (elasticity and intercept)	4.00	3.93	3.68	3.85	3.87					
(p value)	(0.14)	(0.14)	(0.16)	(0.15)	(0.14)					

Table continues

Table A5 (continued). Two-stage least squares (2SLS) regression results for estimating the wage elasticity with respect to foundational skills, by AI exposure of occupation

Significance levels: *p < 0.10; **p < 0.05; ***p < 0.01.

Notes: The table presents estimates of the wage elasticity with respect to different measures of foundational skills, following a preliminary stage in which foundational skills are predicted based on parental education. The five left-hand columns (1.2–5.2) present the second stage of the model, in which the probability of employment is estimated. The five right-hand columns present the corresponding third stage, in which the wage elasticity with respect to foundational skills is estimated while controlling for unobserved factors that affect the individual's employment. Each cell reports the estimate, with the standard error shown in parentheses below. In all regressions, standard errors are clustered at the occupational level. The F-statistic for endogeneity is based on the Wooldridge (1995) test for the endogeneity of the instrumental variables.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Figure A6. First-stage results (predicting foundational skill level)

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite sccore
Exposed						1.347	1.173	0.888	0.941	0.905
						(0.90)	(0.96)	(0.57)	(0.61)	(0.58)
Parental income when subject was 14	0.041**	0.028*	0.031**	0.039**	0.040**	0.041**	0.029*	0.030**	0.039**	0.041**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Man x age	-0.024***	-0.018***	-0.016**	-0.024***	-0.024***	-0.024***	-0.018***	-0.016**	-0.024***	-0.024***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Woman x age	-0.018**	-0.016**	-0.013*	-0.019**	-0.019**	-0.019**	-0.016**	-0.012*	-0.020**	-0.019**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Man x age squared	0.00001*	0.00001*	0.00001*	0.00001*	0.00001*	0.00001*	0.00001*	0.00001*	0.00001*	0.00001*
	(0.000006)	(0.000006)	(0.000007)	(0.000005)	(0.000005)	(0.000006)	(0.000006)	(0.000007)	(0.000005)	(0.000005)
Woman x age squared	0.00001	0.00001	0.00001	0.00001	0.000004	0.00001	0.00001	0.00001	0.00001	0.000004
	(0.000009)	(0.00001)	(0.00001)	(0.00001))	(0.00001)	(0.000009)	(0.00001)	(0.00001)	(0.00001))	(0.00001)
Experience	0.014***	0.011***	0.010***	0.014***	0.014***	0.014***	0.011***	0.010***	0.014***	0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience squared	-0.00015**	-0.00014*	-0.000014	-0.00015*	-0.00014*	-0.00015**	-0.00014*	-0.000014	-0.00015*	-0.00014*
	(0.00007)	(0.00007)	(0.00008)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00008)	(0.00007)	(0.00007)

Table continues

Figure A6 (continued). First-stage results (predicting foundational skill level)

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite sccore
Age x man x mother did not complete high school, father completed high school	0.004***	0.004***	0.003***	0.004***	0.004***	0.004***	0.004***	0.003***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x man x mother did not complete high school, father has higher education	0.006***	0.004***	0.004***	0.006***	0.006***	0.006***	0.004***	0.004***	0.006***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x man x mother completed high school, father did not complete high school	0.002	0.001	0.002	0.002	0.002	0.002	0.001	0.002	0.002	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x man x mother and father completed high school	0.004***	0.003***	0.003***	0.004***	0.004***	0.004***	0.003***	0.003***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x man x mother completed high school, father has higher education	0.005***	0.004**	0.004***	0.005***	0.005***	0.005***	0.004**	0.004***	0.005***	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x man x mother has higher education, father did not complete high school	0.001	0.002	0.000	0.001	0.001	0.001	0.002	0.000	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x man x mother has higher education, father completed high school	0.006***	0.006***	0.005***	0.007***	0.007***	0.006***	0.006***	0.005***	0.007***	0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table continues

Figure A6 (continued). First-stage results (predicting foundational skill level)

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite sccore
Age x woman x mother and father have higher education	0.007***	0.006***	0.006***	0.008***	0.008***	0.007***	0.006***	0.006***	0.008***	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x woman x mother did not complete high school, father completed high school	0.002***	0.002***	0.002*	0.003***	0.003***	0.002***	0.002***	0.002*	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x woman x mother did not complete high school, father has higher education	0.003***	0.002**	0.002**	0.003**	0.003**	0.003***	0.002**	0.002**	0.003**	0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x woman x mother completed high school, father did not complete high school	0.000	-0.000	0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x woman x mother and father completed high school	0.002**	0.001*	0.001	0.001*	0.002*	0.002**	0.001*	0.001	0.001*	0.002*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x woman x mother completed high school, father has higher education	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x woman x mother has higher education, father did not complete high school	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table continues

Figure A6 (continued). First-stage results (predicting foundational skill level)

	Wage equation - dependent variable: Log of monthly wage					Employment equation - dependent variable: Working or not working				
	(1.1)	(2.1)	(3.1)	(4.1)	(5.1)	(1.2)	(2.2)	(3.2)	(4.2)	(5.2)
	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite score	Literacy	Numeracy	Adaptive problem solving	PCA composite score	FA composite sccore
Age x woman x mother has higher education, father completed high school	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age x woman x mother and father have higher education	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	5.369***	5.462***	5.357***	1.267***	1.256***	5.411***	5.397***	5.108***	1.340***	1.277***
	(0.15)	(0.16)	(0.13)	(0.17)	(0.17)	(0.16)	(0.17)	(0.14)	(0.16)	(0.15)
Observations	1,761	1,761	1,761	1,761	1,761	1,761	1,761	1,761	1,761	1,761
F all variables	191	270	141	266	272	193	274	142	259	268
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.31	0.19	0.24	0.27	0.27	0.31	0.20	0.25	0.27	0.27

Table continues

Figure A6 (continued). First-stage results (predicting foundational skill level)

Significance levels: *p < 0.10; **p < 0.05; ***p < 0.01.

Notes: The table presents the first-stage results of the two-stage least squares (2SLS) model. The five right-hand columns present the first stage for the model without distinguishing between AI-exposed and non-AI-exposed occupations; the results of the subsequent stages are reported in Table 4. The five left-hand columns present the first stage for the model that distinguishes between AI-exposed and non-AI-exposed occupations; the results of the subsequent stages are reported in Table 5. Each cell reports the estimate, with the standard error shown in parentheses below. In all regressions, standard errors are clustered at the occupational level.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS