Who Faces the Highest Job Loss Risk, How Long to Find New Employment, and Where Do the Laid-Off Go?

In-Depth Analysis of Layoffs in the Israeli High-Tech Sector

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Introduction

After two years of unprecedented job growth in the Israeli high-tech industry, during 2022 the trend halted, and the sector has since maintained a relatively stable number of employees (see Figure 1). During this period, we have witnessed significant waves of layoffs in companies that are reducing their workforce to cut costs or are shutting down. In this paper, we analyze the impact of these layoffs on employees and analyze the resulting redistribution of human capital among companies in the industry.

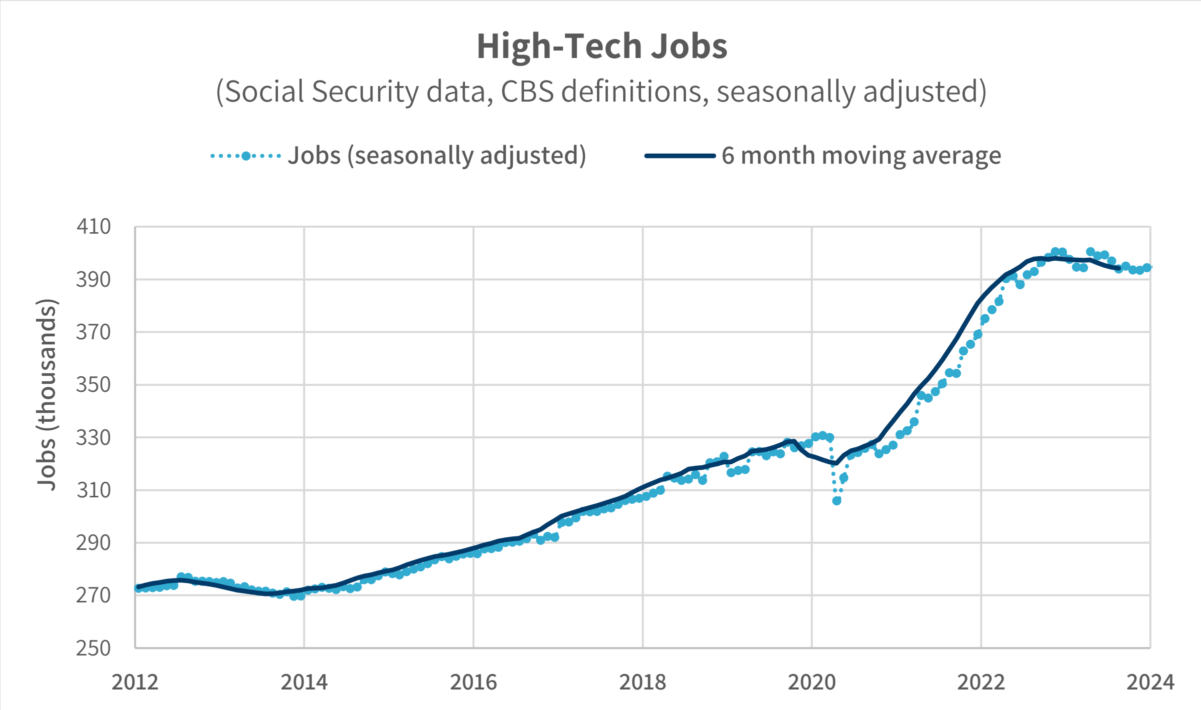

Figure 1

We aim to answer three main questions:

1. **Who was laid off?** That is, how various characteristics of employees affect their risk of losing their jobs.
2. **How long does it take for the laid-off employees to find new jobs?** Specifically, how do different characteristics of the employees influence this outcome.
3. **Where do the laid-off employees find new jobs?** Specifically, how many remain in high-tech, how many leave the sector, how many transition to roles in other fields, how many move from small companies to large ones, and vice versa.

Methodology and definitions

Databases

For the current research, we collected data on 168 "layoff events" that occurred in Israeli high-tech companies and R&D centers of multinational companies (MNCs) in Israel from March 2022 to May 2023. The information was gathered from media reports and a dedicated website (https://www.lastartup.co.il/layoffs) that tracks such events. We cross-referenced these companies with the Start-up Nation Finder database to collect additional information about them.

In the second stage, we identified profiles of Israeli users on the LinkedIn social network who worked in the aforementioned companies at the time of the layoff events[1]. In total, we identified 33,203 employees this way.

In the third stage, we used all available information on the employment history of the employees to estimate if they were laid off during the layoff event in the company they worked for. This allows us to calculate the time that elapsed between the layoff and the start of a new job (if any), as well as the details of the new job.

In the following analyses, we use employment and education details from the profile to examine how these factors influence various outcomes. Additionally, we use the year of completion of the bachelor's degree as a proxy for age and estimate gender based on the first name (cross-referenced with frequency data from the Central Bureau of Statistics).

Definitions

We distinguish between high-tech companies in the research according to three dimensions: ownership (local or multinational), number of employees, and the funding stage according to the definitions of Start-up Nation Finder.

We classify the positions into five job families: "Senior," "Technological" (all R&D and IT roles), "Product", "Business" (marketing, customer relations, sales, etc.), and "Operations" (human resources, accounting, legal consulting, administration, etc.). The classification is done by analyzing the text entered under “job description” in the employee's profile.

We classify the employee's education along the following dimensions:

- **Degree level**: Bachelor's, advanced degree, non-academic education.
- **Degree field**: Fields defined as "high-tech professions" (computer science, mathematics, electrical and electronics engineering, and similar degrees), other STEM fields (natural sciences, life sciences, other engineering fields, etc.), and other degrees.
- **Degree-granting institution**: Universities, colleges, others.

Additional details on the data collection process, descriptive statistics of the databases, and details on how the algorithm estimates who was laid off can be found in the appendix.

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[1] The profile database from LinkedIn was collected by Bright Initiative and made available to us for research purposes. We are grateful to Bright Initiative by Bright Data for their generosity.

1. Characteristics of the Laid-Off Employees

In this chapter, we try to understand which high-tech workers were at higher risk of layoffs in the past two years based on various characteristics such as education, position, job tenure, gender, and age. The question we ask is: For a worker in a company undergoing a layoff event, what is the likelihood of being laid-off given one's personal characteristics? To answer this, we build a database that contains, for each layoff event, all the employees who worked at the company during the event. For each employee, we estimate whether they were laid off during the event. We then estimate a logistic regression that accounts for different characteristics to assess how each characteristic influences the risk of being laid off during the event. A full explanation of the model and the complete regression results are provided in the appendix.

Job Families

As mentioned, we classify all positions in high-tech into five job families. The following table and Figure 2 display the layoff rate in each family:

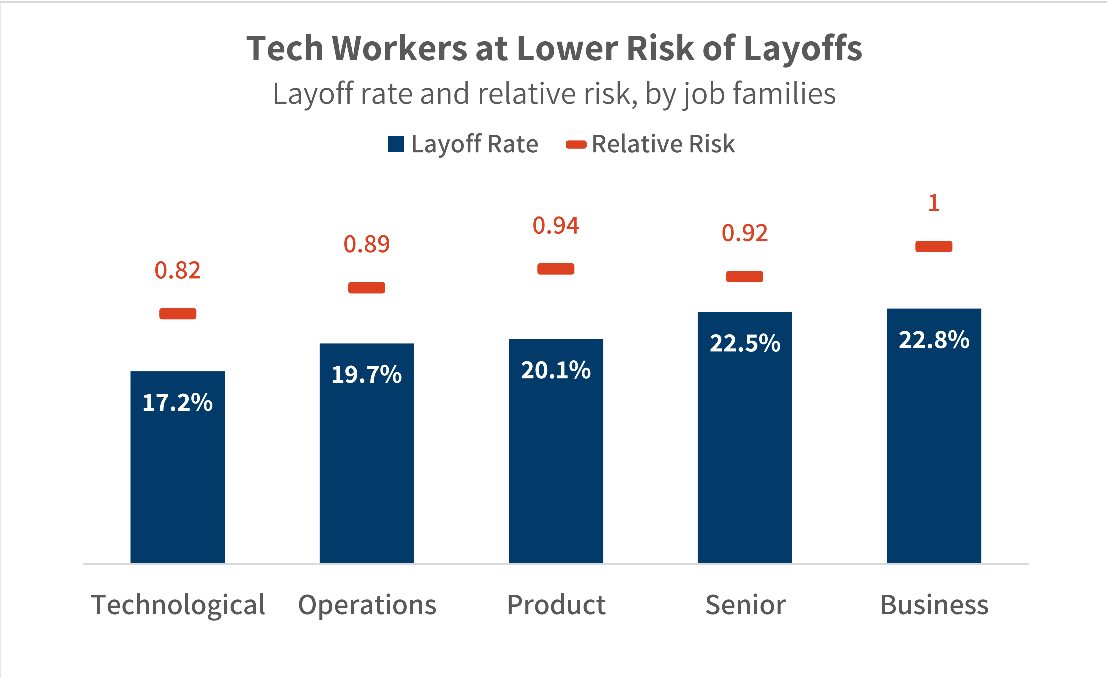

Figure 2

Job family	Sample share (%)	Layoff rate (%)	Relative risk
Technological	51.2	17.2	0.73-0.9
Operations	10.2	19.7	0.83-0.94
Product	10.0	20.1	0.9-0.97
Senior	2.9	22.5	0.88-0.96
Business	9.3	22.8	0.99-1

Table 1

The median employee's risk of being laid off is about 18.7%. Technological employees were laid off at a lower rate, and other departments had a higher rate. However, employees in different positions also differ on other characteristics, so the variation is layoff rates is not necessarily attributable to the position. For example, technological employees tend to be younger, and as we will see below, younger employees tend to be laid off at higher rates. Therefore, to isolate the impact of different factors, we calculate relative risks based on the regression.

Relative risk is a statistical quantity that answers the following question: suppose there are two workers whose characteristics are all identical except for one, how does this characteristic affect the risk of each of them being fired.

As can be seen in the diagram, working in a technological position reduces the risk of layoffs by the most significant rate: between 0.76 times 0.87 (in other words - given that the other characteristics are the same, the chance of a technological worker being fired is 13%-24% lower compared to a non-technological worker). This is probably due to the fact that these employees are the core of the activity of high-tech companies, and also that it is more difficult to replace them.

Probabilistic Models and "Relative Risk"

How do we determine how variables such as gender, education, tenure, etc., influence the likelihood of layoffs or other outcomes? It is, of course, possible to directly compare the outcome in different groups – for example, the layoff rate of those with a master's degree versus those with other education – but such a comparison does not account for the fact that those with a master's degree differ from others in additional characteristics (e.g., they are, on average, older, more senior, etc.). Ideally, we would want to take two workers who are identical in all characteristics except education (for example), and compare the likelihood of layoffs when one has a master's degree and the other has different education. Probabilistic models allow us to do something close to this: estimate the probability of layoffs (or another outcome) given the known characteristics of the individual.

For brevity, we report the results in terms of **relative risk**. Relative risk is defined as the ratio of the probabilities of an outcome (e.g., layoffs) in a specific group (e.g., master's degree holders) compared to the reference group (e.g., those without a degree). For example, if the probability of a master's degree holder being laid off is 6% and that of someone without a degree is 10%, then the relative risk for master's degree holders is 0.6.

Typically, the relative risk depends on the additional characteristics we hold constant. For example, the relative risk of layoffs among master's degree holders (compared to those without a degree) may differ between men and women, different tenures, etc. Therefore, in the tables in this paper, the relative risk is reported as a range. We calculate the relative risk for most possible values of the additional characteristics and report the resulting range.

Tenure and Age

The risk of layoffs decreases sharply with the employees' tenure in the company. In fact, this is the **factor found to have the greatest impact**. The risk drops by 4-12% for employees with over two years of tenure, and for those with 5 to 10 years of tenure the risk is up to two-thirds lower than for new employees.

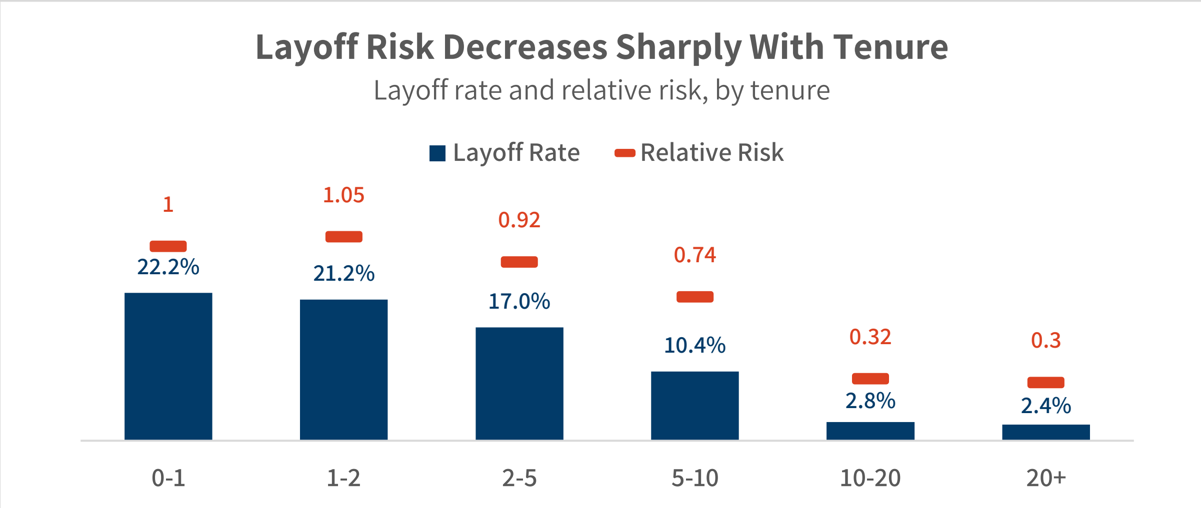

Figure 3

Tenure (years)	Sample share (%)	Layoff rate (%)	Relative risk
0-1	22.3	22.2	
1-2	26.8	21.2	1.02-1.07
2-5	27.5	17.0	0.88-0.96
5-10	13.8	10.4	0.64-0.84
10-20	7.1	2.8	0.2-0.44
20+	2.5	2.4	0.18-0.41

Table 2

There are two obvious explanations for why companies prefer to avoid laying off long-tenured employees: (1) More tenured employees have specific knowledge and experience that is hard to replace; (2) The desire to show loyalty to long-tenured employees to avoid harming morale, especially during downsizing. On the other hand, employee wages usually increase with tenure, so companies tend to balance the benefit of retaining tenured employees against their higher cost. As the data shows, in this episode the advantages of long-tenured workers outweighed the cost.

We do not have direct data on the employees' ages, but for most employees, we have education data, and we can use the year they started their bachelor's degree as a proxy for age. Here, too, we find a very strong preference for laying off younger employees (even after accounting for tenure), although this effect exists only up to an "age" of 5 years (since starting a bachelor's degree). This suggests that companies value the overall work experience of the employee (not necessarily firm specific) and perhaps also the desire to avoid what is perceived as a more severe impact on older employees (preferring to lay off employees in their twenties).

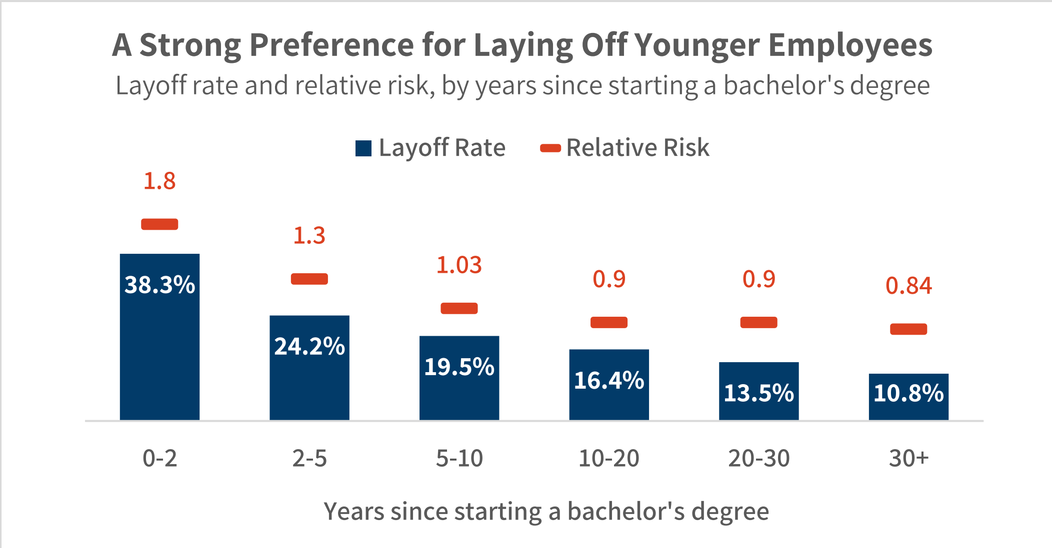

Figure 4

"Age" (years since start of bachelor's degree)	Sample share (%)	Layoff rate (%)	Relative risk
0-2	0.6	38.3	1.38-2.21
2-5	4.9	24.2	1.18-1.42
5-10	18.3	19.5	1.02-1.04
10-20	29.6	16.4	0.87-0.93
20-30	11.9	13.5	0.86-0.93
30+	2.9	10.8	0.79-0.88

Table 3

Gender

Among all employees in the firms in the study, about 63% are men - a typical percentage for the high-tech sector. The layoff rate among men is slightly higher than among women (17.2% compared to 15.9%). This result is somewhat surprising, especially considering that men are overrepresented in technological roles, and higher tenure and age groups - three characteristics that, as we have seen above, tend to reduce the risk of layoffs. That is, we see a clear tendency for companies to prefer not to lay off women that outweighs the differences in other characteristics: *ceteris paribus* men are 9% more likely to be laid-off (4%-14%).

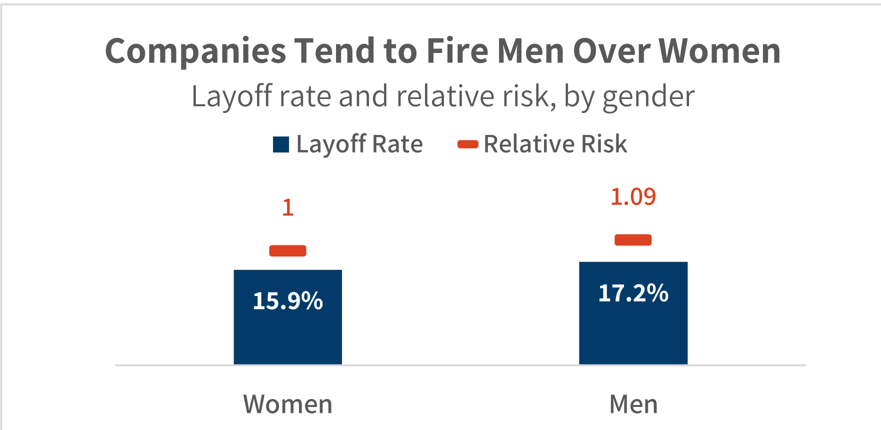

Figure 5

Gender	Sample share (%)	Layoff rate (%)	Relative risk
Women	37%	15.9	
Men	63%	17.2	1.04-1.14

Table 4

One might hypothesize that this stems from the fact that there is already underrepresentation of women in high-tech, and companies try to avoid exacerbating the gap. However, if this were correct, one would expect to find that the relative risk for men would be lower in companies where the share of women is higher, and this is not the case (it is actually the opposite, but not significant). An alternative hypothesis is that since high-tech is perceived as a male-dominated field, the women who do integrate into the industry are already highly skilled, and therefore, they are less likely to be laid off.

Education

As mentioned, we have education data for most employees. The main limitation of the data in this context is that when we do not have education data, we cannot know if the individual has no higher education or chose not to share it online. We examined the impact of three characteristics of the degree:

- **Degree level:** Bachelor's, advanced degree, non-academic education.
- **Degree field:** Fields defined as "high-tech professions" (computer science, mathematics, electrical and electronics engineering, and similar degrees), other STEM fields (natural sciences, life sciences, other engineering fields, etc.), and other degrees.
- **Degree-granting institution:** Universities, colleges, others.

We find that employees with non-academic education are at higher risk of layoffs. Beyond that, we did not find significant differences between bachelor's and advanced degrees, between different fields of study, or between colleges and universities. In other words, among employees who have already found a job in high-tech, there is a slight advantage for those with academic education, but the type of degree does not affect the risk of layoffs (although it does affect the likelihood of being hired).[2]

[2] See in this context our previous report on the relationship between education and employment in high-tech: https://rise-il.org/he/insight/education-and-employment-in-the-israeli-high-tech/

2. Duration of Time to Find a Job After Layoffs

Layoffs are never a pleasant experience, but there is a big difference between those that lead to a short spell of unemployment followed by a similar or better job at another company and those that lead to long-term unemployment or force the laid-off person to accept an inferior job offer. In this chapter, we analyze the duration it took for laid-off high-tech employees in the past two years to find a new job.

Theoretically, the relationship between an employee's characteristics and the duration of expected unemployment in the event of a layoff is not-monotonic. On the one hand, employees with higher education levels (and correspondingly higher productivity) have an advantage over others and will find jobs more easily, thus, the duration of unemployment is expected to be shorter. On the other hand, these employees have higher value for the match with the employer, so they will be more selective and prefer to spend more time searching. Additionally, they are generally wealthier, so they can afford to spend more time unemployed.

It is important to emphasize our data does not allow us to measure unemployment by the standard economic definitions. LinkedIn data does not distinguish between unemployed employees (seeking a job) and those who have temporarily (for studies, vacation) or permanently left the labor market. Also, it is likely that some employees in our sample started new jobs but did not update their profiles, so our results likely overestimate the length of the unemployment spell.

In our sample, we identified 6,009 employees who were laid off, and measured the duration until they started a new job (including employees who did not start a new job within the observation window). Using a simple survival model, we estimated the duration until finding a new job, as shown in Figure 6.

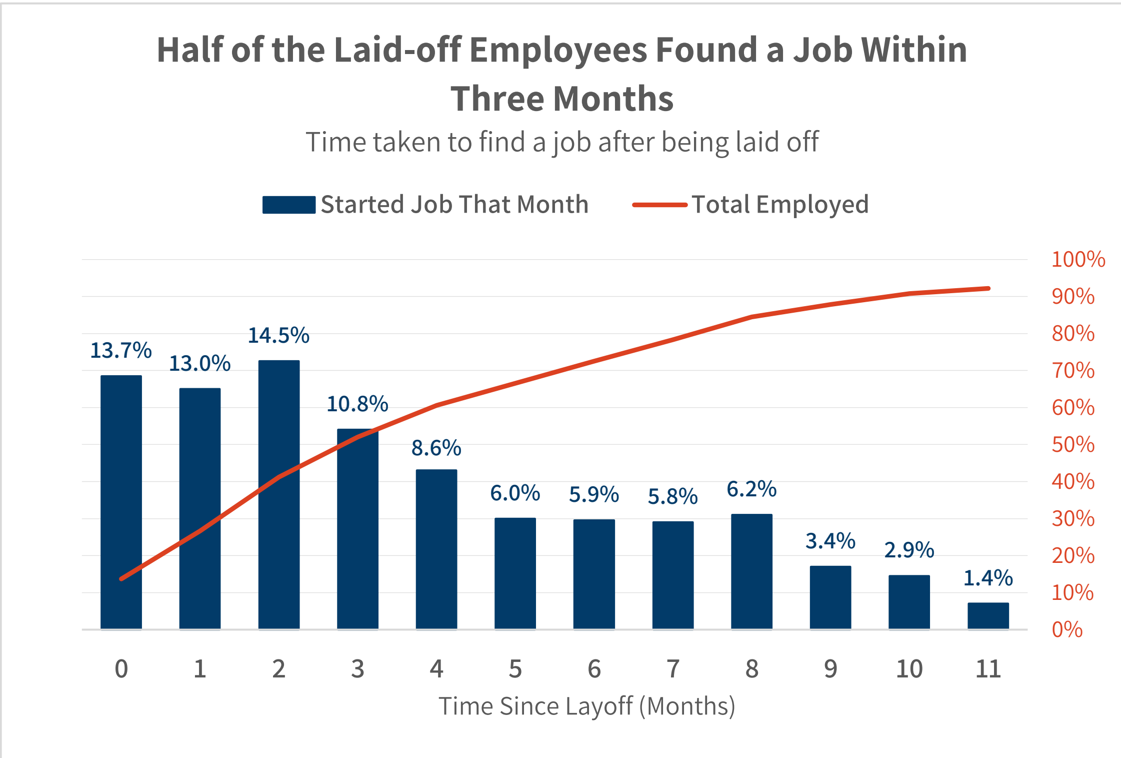

Figure 6

Month	Started a job that month	Total not started yet
0	13.7%	86.3%
1	13.0%	73.3%
2	14.5%	58.8%
3	10.8%	48.0%
4	8.6%	39.4%
5	6.0%	33.4%
6	5.9%	27.5%
7	5.8%	21.7%
8	6.2%	15.5%
9	3.4%	12.1%
10	2.9%	9.2%
11	1.4%	7.8%

Table 5

As shown in the figure/table, about 27% of employees start a new job in the same calendar month as the layoffs or the following month. **More than half of the laid-off employees found a job within three months of the layoff event.**

The table/figure indicates a relatively high percentage of employees who have not started a new job after periods of more than six months. As mentioned, many of them are probably out of the labor market or have not updated their profiles, since chronic unemployment is not common in this population.

As in the previous chapter, here too, we want to understand how the time to find a new job is influenced by various characteristics of the employee and the previous workplace. To do this, we use a Cox proportional hazard model that allows us to examine the impact of these factors on the probability of finding a job at any given time.

For brevity, we focus here on the median time to find a job. Technically, the calculation checks for each characteristic (e.g., age group) the model's prediction for the median time to find a job for an employee with that characteristic value and with average values for all other characteristics (the sample population of laid-off employees).

The full details of the estimation results are provided in the appendix.

Job Families

In the previous chapter, we saw that employees in technological roles are at the lowest risk of being laid off, and as shown in the table, they are also the ones who find a new job the fastest. This is another indication of the high demand for the skills of these employees. After technological employees, business and product employees find new jobs the fastest, with a small gap. In fact, only operations employees are at a significant disadvantage. Generally, it seems that the less specific the employees' skills are to high-tech, the longer the time to find a new job.

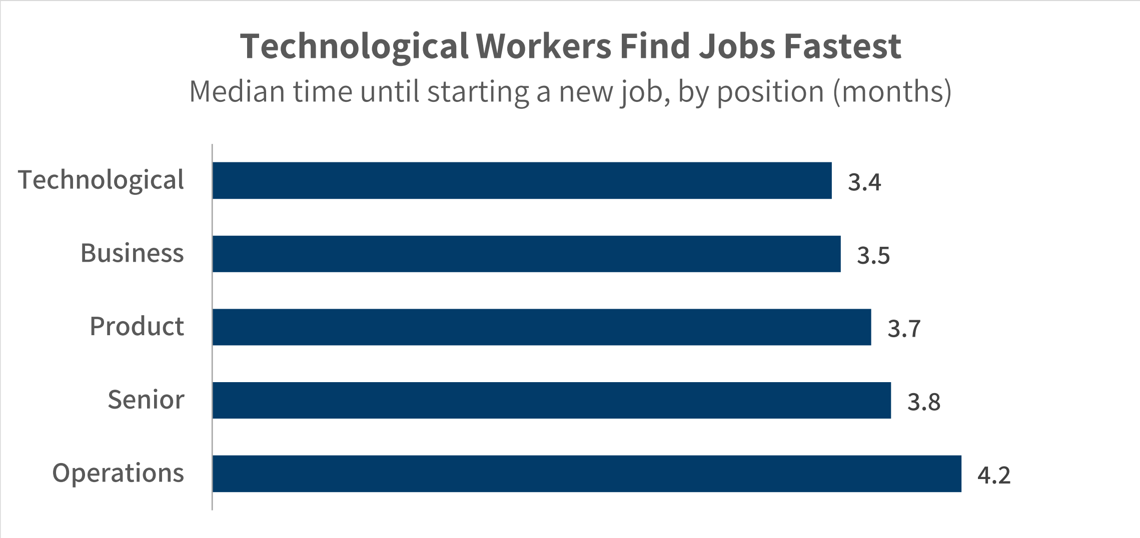

Figure 7

Role family	Sample rate (in %)	Median time to start a new job (months)
Technological	47	3.44
business	11	3.49
product	10	3.66
Senior	3.6	3.77
Operations	11	4.16

Table 6

Education

Considering the education level of the employee, we find that **employees with a bachelor's degree find jobs faster** than those without a degree and those with a higher degree. This result is consistent with the non-monotonicity explained at the beginning of this chapter: on the one hand, employees with higher education are more in demand; on the other hand, they tend to be more selective.

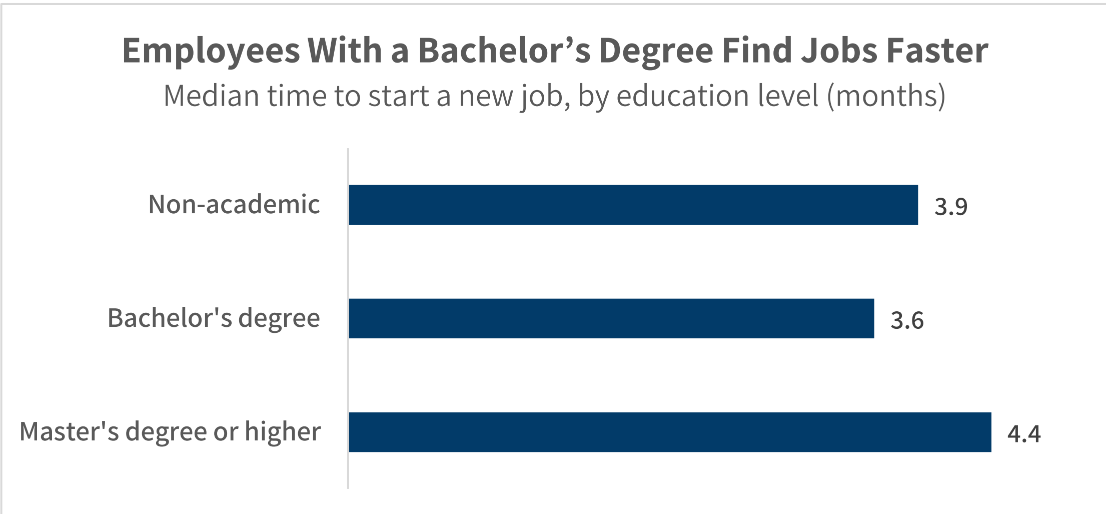

Figure 8

Education level	Sample share (%)	Median time to start a new job (months)
Non-academic	6	3.9
Bachelor's degree	52	3.6
Master's degree or higher	22	4.4

Table 7

A similar picture emerges when considering the degree granting institution. **College graduates find jobs faster** than those without academic education and faster than university graduates. This again reflects the same non-monotonicity.

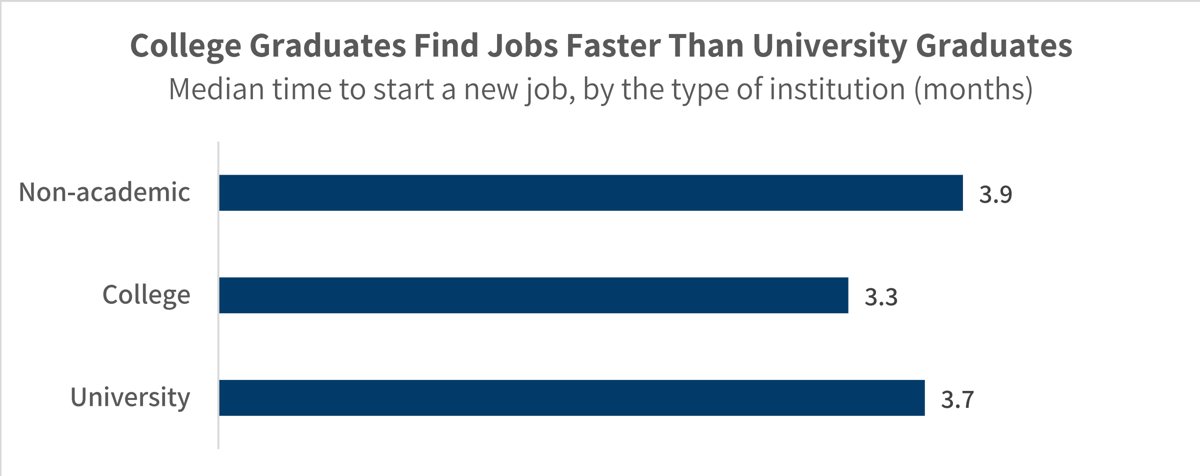

Figure 9

Educational institution	Sample share (%)	Median time to start a new job (months)
Non-academic	15	3.9
College	26	3.3
University	52	3.7

Table 8

We also examined the impact of the degree field and found no differences.

Recall that in the previous chapter, we found that an employee's education level does not significantly affect the risk of being laid off. This can be summarized as follows: from the employer's perspective, once an employee has been hired, their education is no longer relevant to the layoff decision, but for the next employer, education does matter

Tenure and age

In the previous chapter, we saw that age and tenure have a very strong impact on the risk of layoffs: employers tend to lay off younger and less tenured employees. This trend continues when examining the time to find a job. The gap is particularly noticeable for very young employees (0-2 years since starting a bachelor's degree), for whom the median time is 7.9 months, much higher than the other groups. For employees in the 2-5 year category, the time is slightly longer (3.8 months), and from 5 years and above, there are no significant differences. Contrary to the stigma regarding high-tech, it does not seem that older employees have difficulty finding a job.

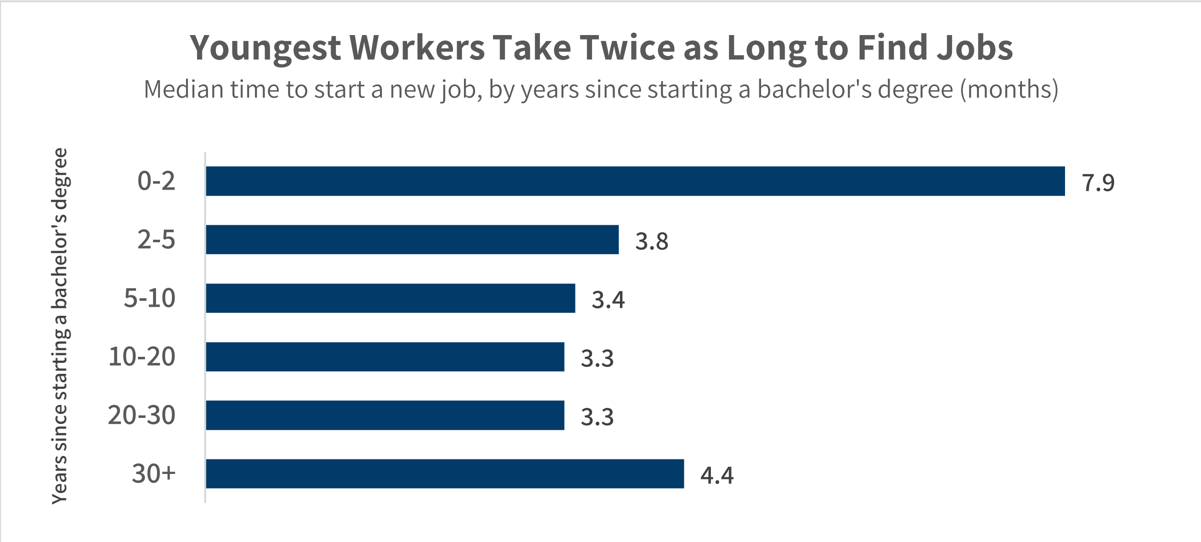

Figure 10

"Age" (years from start of bachelor's degree)	Sample share (%)	Median time to start a new job (months)
0-2	1	7.9
2-5	7	3.8
5-10	21	3.4
10-20	29	3.3
20-30	9	3.3
30+	2	4.4

Table 9

Tenure at the last job also has an impact but is more moderate and mainly affects tenure of up to 5 years. The time to find a job decreases from 4.25 for employees with up to one year of tenure to 3.6 for those with 1-2 years of tenure and down to 3.2 for those with 2-5 years of tenure. After that, the time increases again, but the differences in the more tenured groups are not significant.

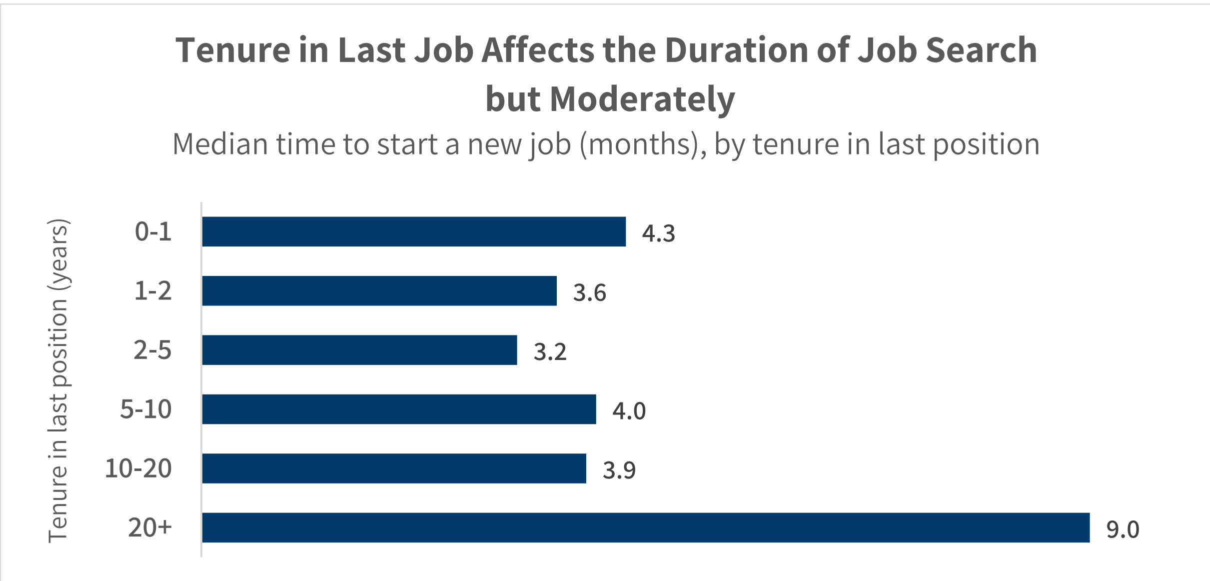

Figure 11

Tenure in last job (years)	Sample share (%)	Median time for a new job (months)
0-1	29	4.3
1-2	33	3.6
2-5	27	3.2
5-10	8	4.0
10-20	1.2	3.9
20+	0.3	9.0

Table 10

Overall, these results demonstrate the high value placed on experience in the high-tech sector. The difficulty young employees face in finding a job ("the junior problem") is relevant even for those who have already started working in the field but have not gained sufficient experience.

3. Characteristics of New Jobs After Layoffs

In this chapter, we will try to characterize the new jobs of about 4,300 employees in our database who found new jobs after being laid off. High-tech layoff events create a movement of employees out of the sector and redistribute human capital within the sector among companies. We try to characterize these transitions according to the type of companies (ownership, size, funding stage, etc.) and job roles within the companies.

Remaining in High-Tech

Among employees who found new jobs, about 84% remained in high-tech. By job families, **those most likely to stay in high-tech are employees in technological and product positions** (relative risk of about 1.3 compared to other roles). Overall, over 90% of employees in technological positions found new jobs in high-tech. Following them, in order, are business, senior, and operations roles.

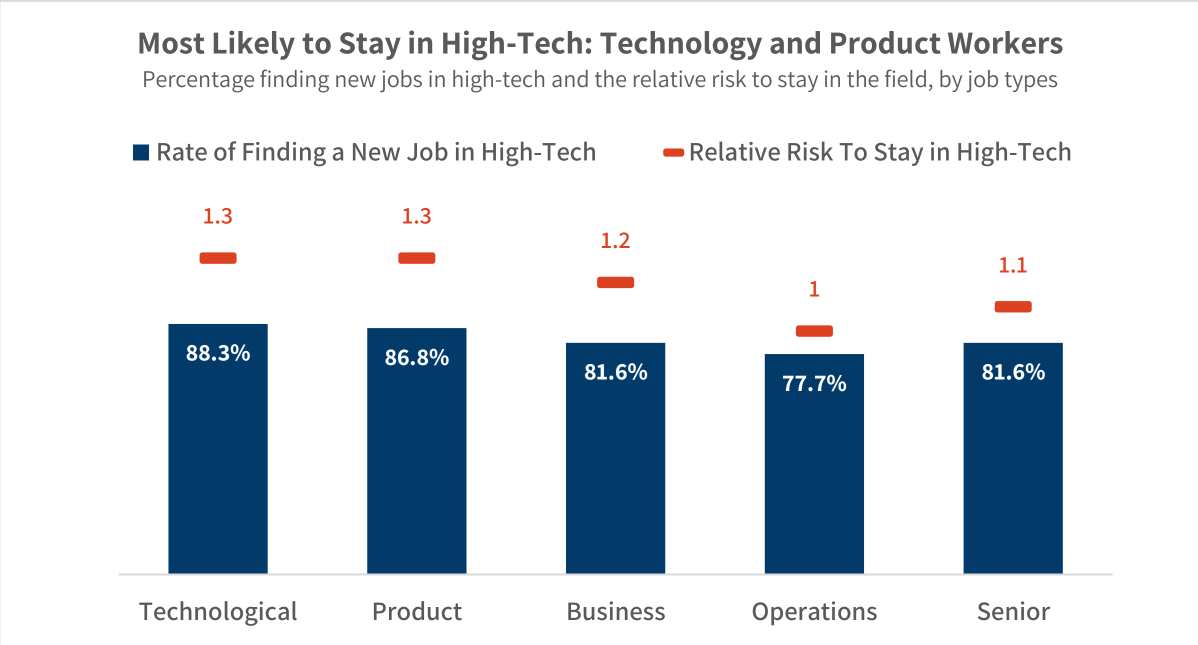

Figure 12

Job Family	New work in high-tech (%)	Relative risk of staying in high-tech
Everybody	84%	
Technological	88.3	1.0-1.6
Product	86.8	1.0-1.6
Business	81.6	1.0-1.3
Operations	77.7	1
Senior	81.6	1-1.2

Table 11

This hierarchy has a simple explanation: the more specific the skills required for the job are to high-tech, the higher the likelihood of staying in the sector. In particular, there is a clear difference between product (e.g., product managers) and business (marketing, sales, customer relations, etc.), where the skills of the latter are likely more general in terms of suitability for other sectors of the economy.

In terms of **education**, we do not find significant effect of education level or institution type. Employees with higher education have a slight advantage in staying in high-tech, but the gap is small (relative risk of 1.04).

However, we do find significant gaps by degree subject: the probability of employees with a degree in STEM fields, regardless of whether the degree is in a "high-tech profession" or another STEM field, to continue in high-tech is 1.25 times higher than for those with degrees in the humanities, social sciences, and others.

Age plays a central role in the likelihood of finding a new job in high-tech, but only for the youngest employees. Employees in the youngest age group (0-2 years since starting a bachelor's degree) have a relative risk of 0.58. Employees in the 2-5 year age group still continue in high-tech at a lower rate than older employees, and after that, the differences are insignificant. The gender differences are also negligible.

Transitions between types of companies: local vs. multinational

Approximately 7.6% of active high-tech companies in Israel (about 390 out of 5100) are R&D and production centers of multinational companies. These centers employ about 24% of high-tech employees in Israel. About 18 out of 168 layoff events (10.7%) occurred in multinational companies, meaning layoff events were more common in multinational companies, but these events occurred in relatively small companies with a relatively small number of laid-off employees. Ultimately, only 9% of the laid-off employees in our database worked in multinational companies.

Among employees laid off from multinational companies who found new jobs in high-tech, about 26% moved to another multinational company. This distribution is similar to the overall distribution among high-tech employees. In contrast, employees from local companies tend to stay in local companies: only about 14% of them moved to a multinational company.

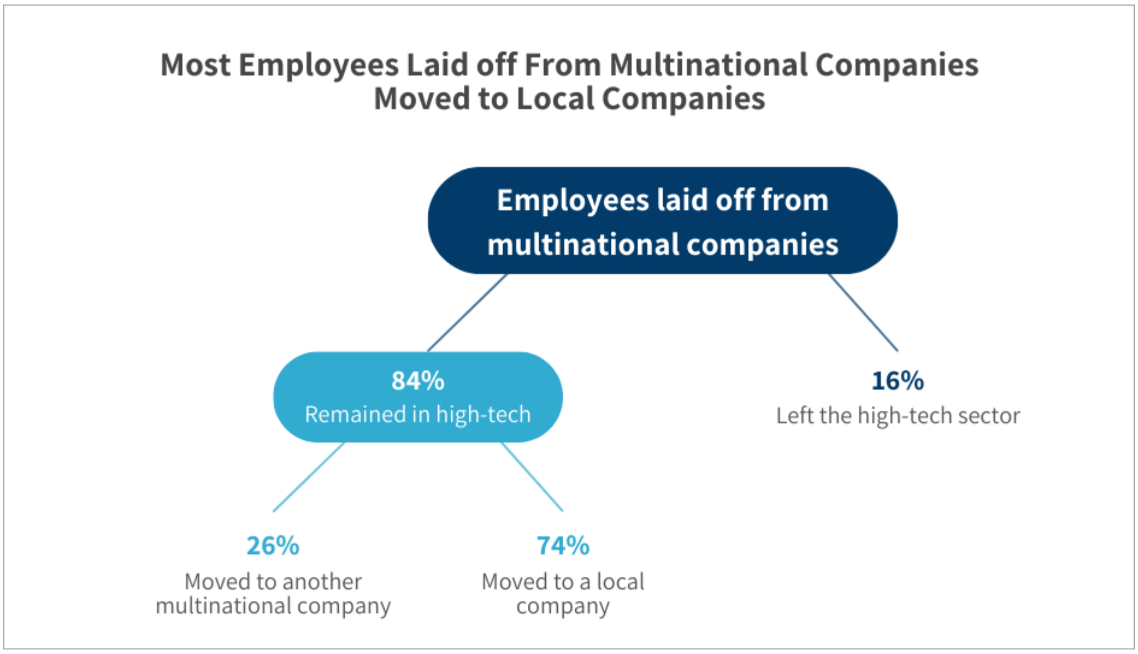

Figure 13

Share of employees from	New workplace		Company Ownership		Comparative risk
	Outside Hi-Tech	High Tech	Local	Multinational	Transition to multinational
Local company	15.9%	84.1%	86%	14%	
Multinational	15.8%	84.2%	74%	26%	1.54-1.97

Table 12

While there is a significant tendency for employees from multinational companies to remain in multinational companies, this tendency is not as strong among employees from local companies. The overall result is a net movement of employees from local companies to multinational companies: out of 100 laid-off employees, 9 originally worked in multinational companies and about 13 after layoffs and finding new jobs. This result is summarized in the following table:

	From high-tech by ownership		Outside high-tech
	Local	Multinational	
All high-tech employees	76%	24%	
Dismissed people who found work: original place of work	91%	9%	
Dismissed people who have found work: a new place of work	71.6%	12.5%	15.9%

Table 13

Transitions Between Company Sizes and Funding Stages

Next, we repeat the analysis by company size (number of employees). The table below presents the probability that an employee who left a company of a certain size (rows) will start a new job in a company of a certain size (columns):

Previous company size	Outside Hi-Tech	High Tech (by size)			
		1-50	51-200	201-500	501+
1-50	14%	16%	42%	9%	19%
51-200	17%	18%	28%	14%	23%
201-500	11%	19%	29%	14%	26%
501+	17%	14%	23%	13%	33%

Table 14

It can be seen that employees leaving large companies tend to stay in large companies more than those leaving small companies, and vice versa. However, this tendency is not very strong. Additionally, since many more employees are laid off from large companies, the overall result of high-tech layoff events is a net movement of human capital from large companies to smaller companies. About 45% of employees moved to companies in a lower size category, while only 21% moved to a company in a higher size category.

Overall transitions between companies are summarized in the following table:

	High Tech (by size)				Outside Hi-Tech
	1-50	51-200	201-500	501+	
All high-tech employees	17%	24%	18%	42%	
Dismissed people who found work: original place of work	4%	31%	12%	52%	
Dismissed people who have found work: a new place of work	16%	26%	13%	29%	**16%**

Table 15

Analysis by the company's funding stage shows a similar pattern (see Appendix C).

It can, therefore, be said that the layoffs have an element of "creative destruction", that is, employees leave large companies (which have probably grown too large), and move to smaller companies and at earlier stages.

Research Abstract

	Significant impact	Modest impact	Low Impact
Who is at lower risk of being fired?	▪ Veteran employees in the company versus new ones (**2-5 times lower risk**). ▪ Older workers versus young people.	▪ Employees in technological positions are less likely than others. ▪ Women less than men. ▪ Those with academic education.	Type of education (degree profession, institution of study, degree level)
Who finds a new job faster?	▪ Very young workers (up to two years after completing a bachelor's degree) **more than twice as slowly**. The rest in a fairly similar time period.	▪ Tech workers - a little faster, and operations workers more slowly. ▪ Holders of a bachelor's degree a little faster than those non-academics, and also those with graduate degrees. ▪ College graduates are a little faster than non-academics, and also university graduates. ▪ Employees with little seniority in the last position slower than others.	Degree subject
Who is more likely to stay in tech after being laid off?	▪ Employees in the fields of R&D and product. ▪ Older workers (over 5 years from completing a bachelor's degree). ▪ Employees laid off as part of cuts compared to employees at companies that shut down.	Holders of an academic degree in STEM subjects (regardless of the specific profession)	Characteristics of the previous company (local or multinational, company size, stage of recruitment)

The layoff phenomenon in the past two years has led to a redistribution of human capital in high-tech, resulting in:

- A moderate net movement from local companies to R&D centers of multinational companies.
- A significant movement of employees from large companies to small companies and from later-stage to early-stage companies.

Appendix A: Methodology and Descriptive Statistics

First, we collected data on 168 layoff events that occurred in Israeli high-tech companies and R&D centers of multinational companies in Israel. The information was gathered from media reports and the https://www.lastartup.co.il/layoffs website. The list includes 11 companies that laid off all employees and closed down, and 157 that conducted workforce reductions. The research covers layoff events that occurred from March 2022 to May 2023. For most events, we also found information on the number and/or percentage of laid-off employees. Table 1 includes descriptive statistics of the layoff events used in the research.

	N	Min	Median	Max	average
Date of event	168	6/3/2022	2/11/2022	4/5/2023	21/10/2022
Company size (employees) 1-50 51-200 201-500 501+	 18 71 22 57				
Ownership: Israeli Multinational	 148 18				
Companies that made cuts (N=157)					
Number laid off	147	6	37	370	60.6
As % of the workforce	137	2%	15%	70%	18.3%
Companies closed (N=11)					
Number of laid off	10	15	45	400	92

table 1 Detected dismissal events - descriptive statistics

In the second stage, we use a database of profiles of Israelis from the LinkedIn website to identify individuals who worked at the mentioned companies during the layoff events. In total, 33,203 employees were identified this way. The employee profile page allows us to know the employment and education history of the employees (to the extent that the individual decided to share the information publicly). The education and employment data are entered as free text, but we use algorithms we developed to classify education data into categories of institution type and degree type, and job roles into job families. We also estimate the gender of the individual based on their first name.

In the third stage, we try to estimate whether the employee was laid off during the layoff event. We must consider that LinkedIn users do not necessarily update their resumes on the site accurately regarding the end date of employment. Specifically, users often update the end date of the previous job as the start date of the new job to show continuous employment. Additionally, start and end dates for jobs on LinkedIn are provided in monthly resolution.

Our algorithm works as follows: Suppose we are looking at a layoff event in Company A that occurred in calendar month M. We set a time window from calendar month M-1 to M+m. We classify as laid off in the layoff event anyone who meets one of the following criteria:

1. The employee's profile shows an end date at A within the window;
2. The employee has no end date at A (shown as "Present") but has a start date at a new company within the window.

The basic algorithm tends to overestimate the number of laid-off employees because it includes people who resigned voluntarily or were laid off around the time of the layoff event but not necessarily as part of the event. Of course, the larger the window we choose (m), the greater this problem. On the other hand, the algorithm misses employees who were laid off but did not update their profiles.

To address potential biases, we check each analysis with different window sizes (m) and compare the results to alternative criteria (for example, counting as laid off only those who meet the first criterion above). Additionally, since there are 11 layoff events of companies that closed down, meaning events where we know for certain that all employees were laid off, we can use this group for comparison in some analyses.

Another complication is that some companies had more than one layoff event. In such a case, it is not always possible to determine for each laid-off employee in which event the layoffs occurred (for example, when an employee's profile shows a start date at a new job after the second layoff event). This problem can be addressed in several ways depending on the analysis: excluding these companies from the sample, artificially combining several layoff events into one large event, and more. Our approach is to test different methods and report if a significant difference is found between them.

Below are the descriptive statistics for the employee data:

N=33,203	Unknown (lesson)	Min	Median	Max	average
Tenure in position (years)		0.08	2.0	39.8	3.9
Age (years from bachelor's degree)	32.5%	1	12	39	13.5

Degree level	non-academic	4.7%
	bachelor	51%
	advanced	21.8%
Degree institution	non-academic	13.2%
	college	24.5%
	university	52.5%
Professional degree	High-tech profession	37.3%
	other STEM	8.1%
	other	21.7%
Recruitment phase	Seed	5.3%
	A round	2.1%
	B round	7.2%
	C+ round	36.6%

Position:	technological	51%
	product	9.9%
	business	9.3%
	operations	10.3%
	senior	2.9%
Gender	woman	24%
	man	38%
Company ownership	local	80.8%
	multinational	19.2%
Company Size	1-50	1.3%
	51-200	15.3%
	201-500	8.4%
	501+	75%

Relative Risk

In several places in this paper, we estimate logit models and report the results in the body of the article using "relative risk." For example, we calculate the relative risk of layoffs for employees with a master's degree compared to those without a degree, keeping other variables (age, gender, job role, etc.) constant. In these calculations, we chose to perform partial identification and report all possible values of relative risk when the constant variables take all possible values in the sample, except for those that occur with low probability (we chose to ignore values with a marginal probability of less than 10%).

Thus, we denote the variable we are examining as X and the values we compare as x_1 (treatment group) versus x_0 (reference group), and denote the other variables (held constant) as $Y = (Y^1 ... Y^n)$. Relative risk is defined as:

$$RR(x_1, x_0; y) = P[X = x_1, Y = y)]/P[X = x_0, Y = y)],$$

And we report the interval:

$$.\{RR(x_1, x_0; y) \big| \forall i, 0.1 < P\left[Y^i \leq y^i\right] < 0.9\}$$

Appendix B: Regression Results

Impact of Characteristics on the Likelihood of Being Laid Off (logit model)

Category	Value	Estimate	Std. Dev.	Relative Risk
Job Family (baseline: missing)	Business	-0.065	(-0.06)	0.94-0.98
	Operations	-0.188***	(-0.061)	0.83-0.96
	Product	-0.102*	(-0.06)	0.9-0.98
	Seniors	-0.189**	(-0.096)	0.83-0.96
	Tech	-0.291***	(-0.045)	0.75-0.93
Highest Degree (baseline: missing)	Non-Academic	0.212***	(-0.078)	1.05-1.23
	BA level	0.089	(-0.086)	1.02-1.09
	MA level or higher	0.127	(-0.092)	1.03-1.13
Institute (baseline: missing)	Other	0.25***	(-0.077)	1.06-1.28
	College	0.174**	(-0.077)	1.05-1.19
	University	0.165**	(-0.075)	1.04-1.18
Degree Field (baseline: missing)	Non-STEM	-0.03	(-0.048)	0.97-0.99
	Non-HT STEM	-0.15**	(-0.066)	0.86-0.96
	"High-tech" degree	-0.012	(-0.045)	0.99-1.00
Gender (baseline: Female)	Male	0.127***	(-0.04)	1.03-1.13
	Missing	0.04	(-0.046)	1.01-1.04
Years since BA (baseline: missing)	0-2	0.764***	(-0.173)	1.26-2.13
	2-5	0.312***	(-0.096)	1.12-1.36
	5-10	0.003	(-0.081)	1.00-1.00
	10-20	-0.151*	(-0.078)	0.86-0.94
	20-30	-0.136	(-0.088)	0.87-0.95
	30+	-0.245*	(-0.134)	0.78-0.9
Tenure at company (baseline: 0-1)	1-2	0.066*	(-0.04)	1.02-1.07
	2-5	-0.125***	(-0.042)	0.89-0.97
	5-10	-0.463***	(-0.06)	0.64-0.88
	10-20	-1.683***	(-0.131)	0.19-0.49
	20+	-1.895***	(-0.237)	0.16-0.43
Company Ownership	Local	0.691***	(-0.051)	1.22-1.98
Company Size (baseline: 11-50)	51-200	-0.464***	(-0.113)	0.64-0.88
	201-500	-0.801***	(-0.117)	0.46-0.78
	501+	-1.542***	(-0.111)	0.22-0.55
Observations	N	32854		
Adj. generalized R^2		0.078		

Impact of Characteristics on the Duration of Time to Find a Job (Cox Proportional Hazard Model)

Category	Value	Estimate	Std. Dev.	Effect on Median (months)
Job Family (baseline: missing)	Business	0.14**	(0.061)	-0.8
	Operations	0.028	(0.063)	-0.2
	Product	0.104*	(0.063)	-0.6
	Seniors	0.111	(0.097)	-0.7
	Tech	0.156***	(0.047)	-0.9
Highest Degree (baseline: missing)	Non-Academic	-0.165**	(0.08)	0.9
	BA level	-0.112	(0.09)	0.6
	MA level or higher	-0.223**	(0.098)	1.2
Institute (baseline: missing)	Other	0.086	(0.082)	-0.6
	College	0.202**	(0.081)	-1.2
	University	0.135*	(0.08)	-0.9
Degree Field (baseline: missing)		-0.005	(0.048)	0.03
	Non-STEM			
	Non-HT STEM	0.034	(0.067)	-0.2
	"High-tech" degree	0.032	(0.046)	-0.2
Gender (baseline: Female)	Male	0.048	(0.042)	-0.3
	Missing	0.076	(0.046)	-0.4
Years since BA (baseline: missing)	0-2	-0.425**	(0.172)	3.6
	2-5	0.05	(0.098)	-0.3
	5-10	0.116	(0.084)	-0.6
	10-20	0.139*	(0.082)	-0.8
	20-30	0.129	(0.094)	-0.7
	30+	-0.046	(0.152)	0.3
Tenure at company (baseline: 0-1)	1-2	0.128***	(0.04)	-0.8
	2-5	0.194***	(0.042)	-1.1
	5-10	0.031	(0.067)	-0.2
	10-20	0.044	(0.17)	-0.3
	20+	-0.495	(0.36)	4.8
Company Ownership	Multinational	-0.053	(0.058)	0.3
Company Size (baseline: 11-50)	51-200	-0.193**	(0.082)	1.0
	201-500	-0.205**	(0.09)	1.0
	501+	-0.137*	(0.082)	0.7
Firm shutdown	Yes	-0.326***	(0.082)	2.25
Observations	N	5764		
Log likelihood	log L	-4.47E+4		

Impact of Characteristics on the Likelihood of Finding a New Job in High-Tech After Layoffs (Logit Model)

Category	Value	Estimate	Std. Dev.	Relative Risk
Job Family (baseline: missing)	Tech	0.637***	(0.121)	1.02-1.61
	Product	0.618***	(0.17)	1.02-1.59
	Business	0.311**	(0.153)	1.01-1.27
	Operations	0.025	(0.149)	1-1.02
	Seniors	0.217	(0.243)	1.01-1.19
Highest Degree (baseline: missing)	Non-Academic	-0.267	(0.196)	0.81-0.99
	BA level	0	(0.233)	1-1
	MA level or higher	-0.151	(0.251)	0.89-1
Institute (baseline: missing)	Other	-0.464**	(0.225)	0.7-0.98
	College	-0.362	(0.23)	0.76-0.99
	University	-0.371*	(0.225)	0.76-0.99
Degree Field (baseline: missing)	Non-STEM	-0.315**	(0.124)	0.78-0.99
	Non-HT STEM	0.264	(0.196)	1.01-1.21
	"High-tech" degree	0.243*	(0.128)	1.01-1.19
Gender (baseline: Female)	Male	-0.21*	(0.115)	0.85-0.99
	Missing	0.019	(0.128)	1-1.02
Years since BA (baseline: missing)	0-2	-1.459***	(0.358)	0.38-0.88
	2-5	-0.119	(0.25)	0.94-1
	5-10	0.377*	(0.222)	1.01-1.18
	10-20	0.285	(0.213)	1.01-1.14
	20-30	0.216	(0.244)	1.01-1.1
	30+	-0.393	(0.355)	0.81-0.98
Tenure at company (baseline: 0-1)	1-2	0.246**	(0.107)	1.01-1.21
	2-5	0.34***	(0.116)	1.01-1.3
	5-10	0.222	(0.181)	1.01-1.19
	10+	0.137	(0.373)	1-1.11
Company Ownership	Local	0.118	(0.157)	1-1.1
Company Size (baseline: 11-50)	51-200	-0.324	(0.237)	0.78-0.99
	201-500	0.104	(0.266)	1-1.08
	501+	-0.418*	(0.239)	0.73-0.98
Firm shutdown?	Yes	-0.502**	(0.2)	0.66-0.98
Observations	N	4321		
Adj. generalized R^2		0.070		

Appendix C: Transitions between companies according to recruitment stages

We summarize the statistical results regarding employee transfers from companies according to funding stage.

Employee transitions according to the funding stage of the previous and next company.

Previous company stage	**Outside Hi-Tech**	**Hi-Tech (by funding stage)**				
		Seed/Pre-Seed	**A round**	**B round**	**C+ round**	**other**
Seed/Pre-Seed	32%	12%	8%	8%	25%	15%
A round	20%	11%	18%	11%	27%	15%
B round	20%	13%	13%	14%	26%	14%
C+ round	16%	10%	12%	12%	34%	15%

Also, the proportion of employees who have "gone up/down stages" are in the table below:

$\geq +2$	$+1$	0	-1	≤ -2	Step difference
7%	10%	41%	17%	25%	Employee share

In other words, most of the employees moved to companies at an earlier funding stage than the company from which they were laid off, and very few moved to a company at a more advanced stage.

Total net movement between companies (only for employees who remained in high-tech and for whom the funding stage of the before and after companies is known):

	From high-tech by recruitment stage:			
	Seed/Pre-Seed	**A round**	**B round**	**C+ round**
Original workplace	9.0%	7.5%	19.1%	64.3%
New workplace	16.1%	18.4%	17.1%	48.5%

As stated in the body of the report, this result is consistent with the concept of "creative destruction".