Human Capital Spillovers in the Workplace: Labor Diversity and Productivity

Navon, Guy

Bank of Israel, Hebrew University of Jerusalem, Economics Depratment

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Guy Navon*

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* Research Department, Bank of Israel. http://www.boi.org.il
Guy Navon – Phone: 972-2-655-2650; Email: guy.navon@boi.org.il

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חטיבת המחקר, בנק ישראל ת״ד 780 ירושלים 91007
Research Department, Bank of Israel, POB 780, 91007 Jerusalem, Israel

Abstract

The paper studies the relationship between human capital spillovers and productivity using a unique longitudinal matched employer–employee dataset of Israeli manufacturing plants that contains individual records on all plant employees. I focus on the within-plant diversity of employees' higher-education diplomas (university degrees). The variance decomposition shows that most knowledge diversity takes place within the industries. Using a semi-parametric approach, the study finds that hiring workers who are diversified in their specific knowledge is beneficial for plants' productivity—the knowledge-diversity elasticity is about 0.2–0.25 and is robust—and that the benefit of knowledge diversity increase with the size of the plant. This suggests that for each allocation of labor in the production process it is beneficial for plants to diversify their skilled labor. The findings also suggest that the conventional way of estimating plant-level production function using Ordinary Least Squares or Fixed-Effects method is biased upward due to simultaneity of the inputs and the unobserved productivity shock.

גלישת הון אנושי במקום העבודה:
גיוון כוח העבודה ופריון

גיא נבון

תקציר

המחקר בוחן את השפעת גיוון הידע על גלישה של הון אנושי בתוך הפירמה ועל פריון העבודה באמצעות בסיס נתוני עובד-מעביד ייחודי של מפעלי תעשייה בישראל בשנים 2000-2003. פירוק מכונן של השונות למרכיביה מראה כי רוב גיוון הידע מתרחש בתוך ענפי התעשייה. נמצא שיש יתרון מובהק לגיוון כוח העבודה: העסקת עובדים בעלי ידע ספציפי מגוון (לפי התואר האקדמי) מועילה לפריון המפעל. מאמידת פונקציית הייצור ברמת המפעל, באמצעות הפרוצדורות של Olley and Pakes (1996) וזו של Levinsohn and Petrin (2003), נמצא שגמישות גיוון הידע-התוך מפעלי היא 0.2 – 0.25 לערך ויציבה – וכי התועלת של גיוון הידע גדלה עם גודל המפעל. מכאן עולה כי עבור כל הקצאה של עובדים בתהליך הייצור כדאי למפעל לגוון את כוח העבודה המיומן שלו. מהמחקר עולה עוד כי הדרך המקובלת לאמידת פונקציית היצור ברמת המפעל בשיטת הריבועים הפחותים (OLS) או בשיטת ההשפעות הקבועות (Fixed-Effects) מוטים כלפי מעלה עקב בעיית אנדוגניות של התשומות.

1. Introduction

The empirical literature provides extensive evidence that plants differ in the composition of skills and the productivity of their workers (Abowd et al., 1999; Dunne et al., 2002; Foster et al., 2008; Hellerstein et al., 1999; and Haltiwanger, et al., 2007). Despite this, our understanding of how the outcomes of plants are related to the composition of their workers is not very satisfactory (Moretti, 2002, 2004a, 2004b; Mas and Moretti, 2008).

This chapter examines human-capital spillovers in the workplace, namely the impact of human-capital diversity on labor productivity. In particular, I investigate one aspect of labor composition: the diversity of knowledge within the plant and human-capital spillovers. Using a unique longitudinally matched employer–employee dataset of Israeli manufacturing plants, I analyze the relationship between labor productivity and the intra-plant diversity of knowledge (also known in the literature as 'within-plant' diversity).

Knowledge diversity can play an essential role in human-capital spillovers at work. The idea is quite similar to Kremer’s (1993) O-ring theory of knowledge transmission by workers within a firm. Such a transmission of knowledge, however, depends on the workers’ complementarities. In general, if workers can draw on previous knowledge or information they have acquired, they may transmit these to the plant, thereby enhancing labor productivity. In the extreme case, if each worker is in possession of a distinct knowledge, it can be transmitted among themselves and, consequently, raise the firm’s labor productivity. At the other extreme where all workers are identical (posses the same knowledge), there cannot be a spillover because workers cannot learn anything new from their colleagues.

Although labor diversity may enhance firms’ productivity, it is likely to be associated with higher costs (e.g., communication costs). Hence, variations in diversity among firms may reflect variations in costs or in the productivity effect of the diversity.

According to Lazear (1999), diverse workers can generate productivity gains if three factors are present. First, they must have different skills, abilities, or information, thereby allowing the plant to gain from their complementarities. Second, their diverse skills, abilities, or information must be mutually relevant. Obviously, little complementarity will ensue if one worker’s skill is not relevant to another worker's production. Third, to enhance productivity, workers must be able to communicate in order to perform the relevant collaborative tasks and engage in knowledge transmission. i.e., they must speak the same "professional" language.[1] An increase in communication costs, however, may offset the gains achieved by the diversification of knowledge. Lazear's argument implies that for plants to maximize their productivity they should be diverse in terms of skills but homogeneous in other respects, such as demographics, in order to minimize the costs of communication or what Lazear calls "cross-cultural dealing."

While the theory underlying the role of human-capital heterogeneity in firms' performance is well developed, empirical evidence is still scanty due to the lack of matched employer–employee data. To address this problem, I use a unique longitudinally matched employer–employee dataset of Israeli manufacturing plants with at least five employees. The dataset covers the years 2000–2003 and includes detailed information on all wage-earners in each plant. In addition to copious information on plants and workers, the data provides university records on workers' higher-education diplomas. This data gives us a unique opportunity to study human-capital heterogeneity within and between plants and its role in the production function.

The correct way to measure human-capital diversity is greatly disputed. The most common proxies for human capital are the educational level and the experience of workers within the plant. Alternatively, some new studies use earnings as the proxy, assuming perfect competition and payment of workers at the full value of their marginal productivity. Wages, however, also depend on the firm's compensation policies, e.g., rent sharing, and the bargaining power of employees (Navon and Tojerow, 2006). Another way of measuring disparity in workers' human capital is the individual fixed effect obtained as a latent variable from individual wage regressions (Abowd, Kramarz, and Margolis, 1999). The latent variable is calculated not only on the basis of observable employee characteristics but also on employee unobservable characteristics — informal ability— and plant fixed effects. The main disadvantage of this method is that the latent variable may include factors other than skills.

This chapter measures human-capital diversity by gauging the diversity of knowledge among skilled workers in the plant in terms of the academic disciplines

[1] For this to occur and for human-capital spillover to take place, workers must have a shared activity.

(hereinafter: disciplines) in which they earned university degrees. This measure of human-capital diversity is important with respect to spillovers because the teamwork approach is widely encouraged, especially in R&D firms—hence the question of whether diverse skilled labor, in the sense of distinct knowledge, increases plants' productivity.

Following Davis and Haltiwanger (1991), Kremer and Maskin (1996), and Dunne et al. (2002), this study examines the relationship between productivity and human-capital heterogeneity at the plant level. First, I conducted a variance-decomposition analysis and found that most diversity of knowledge takes place within an industry. Second, I estimated a plant-level production function using a semi-parametric dynamic approach, as proposed by Olley and Pakes (1996) and later by Levinsohn and Petrin (2003).[2] The production-function estimates show that within-plant knowledge diversity has a positive and significant impact on productivity. By distinguishing between workers with university degrees and those without degrees, I found that hiring workers who have diversified specific knowledge (disciplines) is beneficial for the plants' productivity.

Although empirical data on the diversity of knowledge is insufficient, recent international evidence based on matched employer–employee data shows that skill heterogeneity does have a strong positive influence on productivity. In particular, Lazear and Shaw (2007), summarizing the findings from nine countries on wage dispersion within firms, conclude that better performance is achieved when people with complementary skills are matched with each other within the firm. These findings suggest that the positive relationship between human-capital diversity and productivity may be applicable beyond a specific aspect of heterogeneity, and could be generalized to situations in which workers complement each other, i.e., when one worker's skills enhance those of another in the workplace that they share.

The rest of this chapter is organized as follows: Section 2 describes the data and presents the diversity index, Section 3 decomposes the variance of workers' skills among and within firms, Section 4 examines the relationship between within-firm skill dispersion and productivity by estimating a production function that allows for heterogeneity of knowledge, and Section 5 presents the conclusions.

[2] In Chapter 2 of the thesis I presented the Olley and Pakes (1996) and the Levinsohn and Petrin (2003) method in general and implemented the first stage only. In this chapter I implement the entire method using a 3-stage semi-parametric estimation.

2. The Theoretical Framework

The aim of the theoretical model is to quantify both the gains from and the costs of collaboration among diversely skilled workers within a plant. The model defines two types of workers in the economy: skilled (L_s) and unskilled (L_{us}). The skilled workers are diversified in the sense that they hold different academic degrees, represented by diversity index D. The plants also differ in the costs of diversity.

Assuming a Cobb-Douglas production function, the plant produces its value added (Y) by using capital (K) and labor (L_s and L_{us}) as inputs, while the skilled labor is associated with knowledge-diversity. In this sense diversity is endogenous in the model, since it is assumed to be a function of the skilled workers. Following Berry (1971) and McVey (1972), I use the Herfindahl index as an index of knowledge diversity. The Herfindahl index takes into account the number of skilled employees in a plant (n) and their distribution across various academic disciplines:[3] the index decreases as both the number of disciplines and the disparity of knowledge decreases, and it is bounded by 0 and 1. The Herfindahl index may be written as:

(1) $$D(l_s^1,...,l_s^n) = 1 - \sum_{i=1}^{n} \frac{l_s^i}{L_s}$$

The firm maximizes its profits with respect to K, L_{us}, and $l_s^1,...,l_s^n$ subject to its technology and diversity constraints:

(2) $$\begin{aligned} &\Pi = PY - WL - c(D) - rK \\ &s.t. \qquad \mathrm{Y} = AK^{1-\beta}(D^{\gamma} L_s)^{\beta} \\ &\qquad\qquad D = D(l_s^1,...,l_s^n) \\ &\qquad\qquad l_s^1 + l_s^2 + ... + l_s^n = L_s \end{aligned}$$

where $c(D)$ is the communication cost of having diversified labor—the cost of cross-cultural dealing—which increases with D (i.e., $C'(D)>0$). I also assume that all skilled workers are identical in their productivity and hence in wages.

There is no analytical solution to equation (2) with respect to $k, L_{us}, l_s^1,...,l_s^n$; however it can easily be shown that in equilibrium plants choose a different diversity of knowledge according to β, γ, c, P, W .

[3] Tables A-1 and A-2 in the appendix, show how the Herfindahl diversity index of knowledge interacts with the number of academic disciplines (n) and the number of skilled workers (Ls) in the plant.

Since all skilled workers are assumed to be identical in productivity, behavior and wages, plants can reach optimum diversity using different allocations of skilled workers. However, it can be assumed that diversity is associated with geographic costs or communication costs. In this case there would be a single optimum in which the plant will hire minorities, although they raise labor costs, as long as they increase total productivity.

3. The Data

The data used in this chapter is a unique, matched worker–establishment longitudinal panel. The panel was constructed by the Israel Central Bureau of Statistics (hereinafter: CBS) and combines three large scale databases: (1) the CBS Manufacturing and Crafts Survey, which is conducted annually and provides information at the establishment level on production, materials, labor, investment, and other plant-level characteristics; (2) Israel Tax Authority records for 2000–2003, which provide information on all wage-earners in plants, including age, gender, marital status, number of months worked each year, and wages; and (3) a record of all university graduates, including information on degrees, disciplines, and year of graduation.

The sample of manufacturing plants was established in 2000.[4] Plants may exit the sample due to closures, mergers and acquisitions, or administrative errors. Due to a confidentiality constraint that the CBS must honor in the release of matched employer–employee data, the matched employer–employee sample was truncated and includes only plants with less than 1,000 employees.

The unit of investigation in this chapter is the plant,[5] defined as an economic unit that engages in manufacturing activity. As a rule, a plant is located at one site and engages in a single economic activity. Departments of a plant that are located in different geographic locations or belong to different manufacturing industries are

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[4] The sample for the Manufacturing and Crafts Survey is replaced from every 5-10 years in order to update the sample with the changes in the manufacturing sector. The last update was in 2000.

[5] This is in contrast to the previous two chapters, in which I used individual records to estimate wage equations.

considered separate economic units insofar as they keep separate books of account.[6] Multi-product and multi-plant firms are divided by their economic activities on the basis of this classification, which was performed by the CBS.

To estimate a plant-level production function, one needs a way of measuring capital. I adopted the capital-services measure proposed by Griliches and Regev (1995) and calculated by Haim Regev of the CBS (Regev, 2006). The concept measured is capital flow rather than capital stock. Flow is measured by converting owned fixed-capital stock into an estimate of implicit rental costs, and adding rental costs for rented/leased assets. Fortunately, the Manufacturing and Crafts Survey presents data on yearly capital rental payments. Annual capital services for each establishment were calculated on the basis of the cost of equipment and the building rental, and the estimated depreciation and interest on net capital stock.[7] Initial capital services for the year 2000 were calculated on the basis of historical data for 1995–1999.

3.1. Description of the Data

The matched employer-employee panel (hereinafter: EEP) includes 3,150 spells of plant–year observations for the years 2000–2003 in 834 plants with five or more employees. The dataset also includes 380,000 observations on all wage-earners in the plants. Due to lack of data on capital services in 98 plants, I restricted the sample to 736 manufacturing plants. Of these, 546 (74 percent) appear in the data for four years—the entire period—and another 84 (11 percent) appear for three years. Twenty-four plants (3 percent of the entire sample) entered the Manufacturing and Crafts Survey during the sample period and 196 plants (26 percent of the entire sample) exited the survey during this time. The final sample contains 309,570 observations on all wage earners in the plants.

Table 1 reports the characteristics of the workers for the entire sample and for the skilled workers only. The average gross monthly income in constant 2000 prices is

[6] Considerations relating to the method of recording plant activity in books of account are determined by the tax laws and not by the CBS. In practice, a plant that has its administrative offices in a different location (for marketing, sales, or other purpose) usually records both activities in its books of account. Furthermore, in measuring human-capital heterogeneity I omitted workers who completed degrees in disciplines that are irrelevant to the production process.

[7] Regev (2006) estimates this at 5 percent.

NIS 8,948 and the average worker is about 39 years old. Almost 30 percent of observations in the sample pertain to females. I divided the workers into two categories: skilled and unskilled. Skilled workers are defined as workers who appear in the records[8] of Israeli universities, while unskilled workers are those who do not appear. According to the university records, about 8 percent of manufacturing employees hold an Israeli academic degree. The skilled workers in the sample, as defined above, are younger and more likely to be female than the unskilled workers.

Table 1: Workers' Characteristics

	Sample		***Thereof:* skilled workers** [a]	
	Mean	**S.D.**	**Mean**	**S.D.**
Monthly wage (NIS, year 2000)	8,948	10,581	16,867	18,361
Age	39.2	12.1	32.4	6.1
Proportion of males	70.9		66.4	
Proportion with higher education	8.2			
Thereof:				
Engineering			37.5	
Exact sciences			13.1	
Natural sciences			9.9	
Full-time workers (percent)	97.8		97.7	
No. of observations	**309,570**		**25,270**	

a. Employees holding an Israeli university degree.

The most common academic disciplines studied are engineering (38 percent of skilled workers), business administration (22 percent), and the exact sciences (13 percent) (Table 2). The exact-sciences discipline encompasses three major sub-disciplines: mathematics, statistics, and computer sciences. The popularity of computer-science degrees among skilled labor in the sample is high—about 8 percent—while almost no skilled workers in the sample hold degrees in statistics. The natural-sciences discipline encompasses five major sub-disciplines that are evenly distributed, although degrees in geography, geology, oceanography, and space studies are not popular among skilled workers. The engineering discipline also encompasses five major sub-disciplines: civil engineering (0.7 percent of skilled workers), mechanical

[8] The records of the universities include data on graduates of the seven universities in Israel that award bachelors, masters, and doctoral degrees, as well as occupational certification. The records do not include data on graduates of the Open University of Israel, colleges, and universities abroad.

engineering (7.5 percent), electronic engineering (12.8 percent), chemical engineering (4.1 percent), and industrial and management engineering (12.4 percent). In those few plants that are fully diversified (and employ more than five engineers), industrial and management engineers are always present.

The diversity of degrees in the sample is narrow: 80 percent of skilled workers hold bachelors degrees and 17 percent have masters degrees. This finding strongly resembles previous findings about the skill composition of Israel's manufacturing sector (Navon, 2006).

Table 2: Distribution of Disciplines Studied

Discipline	Observations	Percent
Humanities and general studies	**2,036**	**8.1**
Medical studies	**436**	**1.7**
Social sciences:	**7,484**	**29.6**
Business administration	5,673	22.4
Economics	1,452	5.7
Law	359	1.4
Exact sciences:	**3,321**	**13.1**
Computer sciences	2,041	8.1
Mathematics	1,055	4.2
Statistics	225	0.9
Natural sciences:	**2,510**	**9.9**
Chemistry	735	2.9
Physics	645	2.6
Biology	629	2.5
Agriculture	342	1.4
Geography, geology, oceanography, and space	159	0.6
Engineering:	**9,483**	**37.5**
Electronic engineering	3,238	12.8
Industrial and management engineering	3,155	12.5
Mechanical engineering	1,874	7.4
Chemical engineering	1,040	4.1
Civil engineering	176	0.7
Total:	**25,270**	**100**

Since the study focuses on the diversity of skilled workers across various study disciplines, I define a "technological" discipline as any academic discipline in the exact sciences, the natural sciences, and engineering. By doing this, I omit all holders of degrees in the humanities and the social sciences on the assumption that these disciplines are not applicable to the production process. My definition also omits graduates in business administration—even though they may influence production decisions more than anyone else—because there are no data on their positions in the plants and their previous degrees. In the sample, more than 61 percent of skilled workers have a technological degree: 38 percent in engineering, 13 percent in the exact sciences, and 10 percent in the natural sciences.

Table 3: Distribution of Skilled Labor by Industry (Percent)

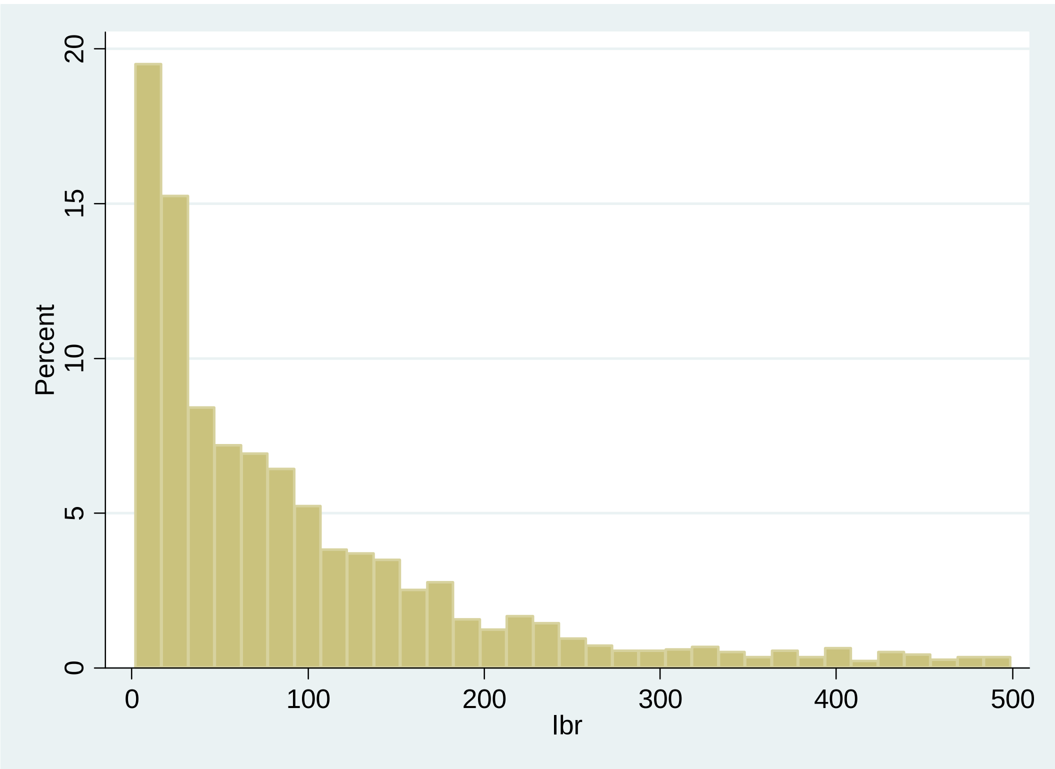
#	Two-digit industry (Division)	Engineering	Natural sciences	Exact sciences	Business administration	All others
23–24	Chemicals and refined petroleum	13.7	46.3	1.9	16.7	24.0
25	Plastic and rubber products	2.3	0.6	0.6	3.3	3.6
26	Non-metallic mineral products	1.6	0.4	0.7	5.0	5.1
27	Basic metal	0.9	0.7	0.2	2.1	1.5
28	Metal products	4.7	1.1	0.9	6.1	7.6
29	Machinery and equipment	7.5	6.7	6.4	5.8	5.7
31	Electric motors and electric distribution apparatus	5.1	2.0	3.2	5.2	4.6
32	Electronic components	10.3	5.7	6.0	6.5	6.5
33	Electronic communication equipment	21.1	9.8	46.2	22.2	16.5
34	Industrial equipment for control and supervision	28.5	25.8	32.2	21.2	18.7
35	Transport equipment incl. medical and scientific equipment	2.9	0.4	1.2	2.0	1.6
36	Furniture	0.7	0.1	0.0	1.0	1.4
38	Jewelry, goldsmiths' and silversmiths' articles	0.4	0.0	0.1	2.2	1.4
39	Manufacturing n.e.c.	0.4	0.5	0.3	0.8	1.8
B	**Total Manufacturing**	**100**	**100**	**100**	**100**	**100**

The distribution of skilled workers across industries is not uniform: skilled labor is more likely to be found in the 24 and 32–34 two-digit industries, the most technology-intensive manufacturing industries (Table 3).

Table 4 presents a condensed statistical picture of plant characteristics for the entire sample and for a sub-sample of plants that employ at least three skilled workers. In the entire sample, the average plant employs about 120 workers, of whom almost 8 percent have Israeli academic degrees. Reflecting the aforementioned CBS confidentiality constraint, the smallest plant in the sample employs only five workers and the largest 974.[9] Some 64 percent of the plant-year observations were of plants with less than 100 employees (Figure 1, Table 3). The yearly attrition rate in the sample is about 8 percent, resembling the CBS reports from the annual Register of Businesses.

Table 4 also presents condensed statistics on plants that employ at least three skilled workers who hold academic degrees in a technological discipline. These are the most interesting plants with respect to spillovers of knowledge among workers. Although these plants account for only 45 percent of the sample, they are dramatically different from the average plant: their wage bill and capital stock is almost as twice the average and their share of skilled workers—10.3 percent—far surpasses that in the population at large (Table 3).

Figure 1: Distribution of Plants by number of employees



[9] This is due to the definitions used in the Manufacturing and Crafts Survey and the CBS' restrictions on the sample.

Table 4: Plants' Characteristics

	Sample		*Thereof:* at least three skilled workers	
			Mean	S.D.
Value added	21.72	51.21	40.67	70.9
Capital stock	25.13	110.73	49.14	160.3
Wage bill	14.66	28.74	27.13	36.6
Employees	119.5	161.9	203.1	203.3
Unskilled	109.8	144.4	182.2	180.2
Skilled	9.7	33.3	20.9	47.8
Distribution of plants by number of employees (percent)				
0–10	13.9		3.1	
11–25	19.6		7.6	
26–50	16.9		11.6	
51–100	21.5		25.1	
100–200	15.9		27.7	
200+	12.2		24.9	
No. of observations	**2,582**		**1,167**	

3.2. Diversity

Calculated across all thirteen technological disciplines as defined, the average Herfindahl index for knowledge diversity is 0.37 and its range is 0–0.87.[10] About 17 percent of the plants are not diversified at all, i.e., their skilled workers have technological degrees in only one discipline. Using two different specifications—the ten and the six most common disciplines—we obtain similar results with hardly any loss of observations.

The definition of the diversity index may be sensitive to the number of groups – the technological disciplines. For that I compare the diversity index for the thirteen technological disciplines with five other definitions. The Herfindahl index for the thirteen technological disciplines may be calculated for 1,170 plant-year spells (45 percent of the sample). Restricting the index by using only the ten most common disciplines elicit similar results as the benchmark index, however, it reduces the available data to 1,130 observations, respectively. The diversity index that use only

[10] According to the Herfindahl index, the widest diversity that a plant can attain using the thirteen technological disciplines and assuming an even distribution, is 0.92.

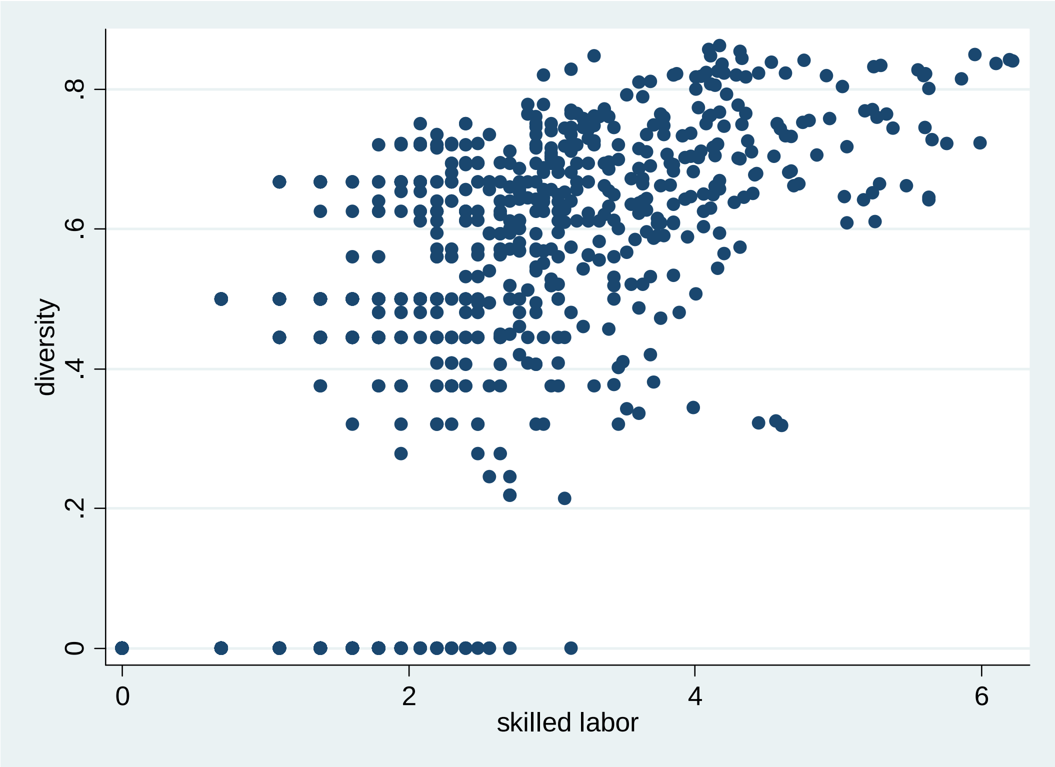
the six most common disciplines reduce the sample by another 15 percent and it obtains a different distribution (Table 5). As one may expect, the diversity index of that uses engineering graduates only is the most diversified.

Table 5: Diversity Indices

Diversity index	Mean	S.D.	Min	Max	*Thereof:* zero diversity (percent)
13 disciplines (herf_13)	0.37	0.31	0	0.87	17.1
10 disciplines (herf_10)	0.36	0.30	0	0.86	16.9
6 disciplines(herf_6)	0.27	0.28	0	0.80	18.2
Exact sciences	0.21	0.24	0	0.67	7.7
Natural sciences	0.23	0.27	0	0.75	9.2
Engineering	0.37	0.36	0	1.00	16.0

An important issue is the relationship between diversity and plant size, particularly in terms of skilled workers. One might expect the Herfindahl diversity indices of small plants to be close to zero and anticipate a positive correlation between skilled labor and diversity. Figure 2 illustrates the relationship between size and diversity: as expected, there is a positive correlation between size (number of employees) and diversity. However, it is weak at 0.54 overall (Figure 2) and is much lower among diversified plants (those that have positive diversity), at 0.29. This surprising result may be explained by noting that small plants tend to focus on a single product whereas large plants turn out several products and may use different technologies. Since the Herfindahl diversity index uses only 6–13 academic disciplines, diversity is bounded.

Figure 2: Distribution of the Diversity Index by Plant Size



4. Analysis of Variance

As we see in Table 5, the total diversity of knowledge in the sample is very volatile. The standard error is about 0.30—almost as large as the mean. The relatively extreme variation of the diversity index suggests a potential problem, namely, that the diversity of knowledge in the sample may originate in differences in technologies used in the different industries rather than in differences among plants within an industry.

To determine the source of the variation in the diversity index, I performed a variance decomposition exercise for knowledge diversity using a nested ANOVA. The total diversity of knowledge in the labor force may be decomposed into three components: between industries, among plants within an industry, and within the plants—due to yearly change in labor force diversity. The nested ANOVA, decomposing the variance of the knowledge-diversity index among these three components, leads to the conclusion that most of the variation originates within an industry, while only 20 percent stems from variation among industries (Table 6). Moreover, 18 percent of the total variation can be traced to variation within plants.

The large within-industry variation in knowledge diversity is robust. Conducting the variance decomposition severalty each year reveals a similar result as the nested ANOVA: 75 to 82 percent of the total variation originates from within an industry.

These findings somewhat contradict those of Davis and Haltiwanger (1991), Kremer and Maskin (1996), and Dunne et al. (2000), who found a significant upward trend of segregation among plants and determined that within-plant variation accounts for 40–50 percent of the total. The difference may be explained by the short time duration of my sample.

Although only a small portion of the total variation in knowledge diversity stems from variation among industries, the production-function estimates use dummy variables for the two-digit industries to control for differences in technologies.

Table 6: ANOVA of Knowledge-Diversity [a]

Source	**Partial SS**	**Df**	**MS**	**F-statistics**
Year=2000 (Obs. = 338)				
Between industries	8.4	13	0.6	7.9*
Within industry	26.3	324	0.1	
Year=2001 (Obs. = 298)				
Between industries	6.7	13	0.5	7.1*
Within industry	20.6	284	0.1	
Year=2002 (Obs. = 269)				
Between industries	5.3	13	0.4	5.4*
Within industry	19.4	255	0.1	
Year=2003 (Obs. = 262)				
Between industries	4.7	13	0.4	4.4*
Within industry	20.5	248	0.1	
Years 2000-2003 (Obs. = 1129)				
Between industries	18.1	13	1.4	7.7*
Within industry	65.0	366	0.2	8.4*
Within plants (residual)	15.9	749	0.0	

a. Analysis of variance using nested ANOVA. Plants assumed to be nested in industries.
In all regressions, the dependent variable is the diversity index of the ten most common technological disciplines (Herf_10).
* = significance at 1% level.

5. The Empirical Model

In this section I present the method used to estimate the plant production function. Following the theoretical model mentioned above, the plant produces its value added (*Y*) using a Cobb-Douglas production function and by using capital (K) labor (L_s and L_{us}) as inputs. The skilled workers are diversified in their knowledge with a diversity function (*D*). By transforming the production function into a logarithm, we allow the econometric model to correspond to a linear estimation. Henceforth, lower-case letters will represent logs (equation 1):

$$y_{it} = \alpha_{it} + \beta_k k_{it} + \beta_{us} l_{it}^{us} + \beta_s l_{it}^{s} + \gamma D_{it} + u_{it} \tag{3}$$

Estimating Equation (3) by the ordinary-least-squares (OLS) method raises two conceptual concerns: the assumption of labor homogeneity expressed in the typical denotation in variable *l* of total plant employees or hours worked, and the problem of simultaneity of inputs and unobserved productivity in the error term.

5.1. Simultaneity

The simultaneity problem arises because at least part of the error term in the regression includes plant productivity. Since productivity is observed by firm managers, the firm can change its inputs decisions. In particular, it allows firms to adjust the labor and diversity inputs. However, labor productivity may not correlate with capital stock, which is quasi-fixed. Usually, this will result in a downward bias of the capital coefficient and, possibly, an upward bias of the labor coefficients.

The simultaneity problem is sometimes referred to as an omitted-variable bias (OVB), because the endogeneity of inputs and the error term originate in the omission of the unobserved productivity term from the regression.

The problem of simultaneity bias in production function has been understood in the literature at least since Marschak and Andrews (1944), although satisfying solutions to this problem were not presented until 1995, when Olley and Pakes suggested an estimation algorithm that takes into account the relationship between productivity on the one hand and both input demand and survival on the other. They separated the error term from the production function (u_{it}) and reduced it to two components: a true unobserved shock to production, η_{it}, and a productivity component, ω_{it}, which is known to the firm manager and is therefore taken into account in periodic decisions on inputs. Neither component is observed by the econometrician. ω_{it} may reflect technological or managerial differences among plants. Since the firm manager knows about these differences before making input decisions, these decisions probably depend on ω_{it}. As a result, capital, labor, and the level of labor diversity are endogenous in the production function. The production function may be written as follows:

(4)
$$y_{it}=\alpha_{it}+\beta_k k_{it}+\beta_{us} l_{it}^{us}+\beta_s l_{it}^{s}+\gamma D_{it}+\omega_{it}+\eta_{it}$$

Estimating Equation (4) using least squares results in a bias in the coefficients of *l*, *D* and *k* due to the positive correlation between plant productivity and inputs.

The current state-of-the-art solution to the OVB problem was introduced by Olley and Pakes (1996, hereinafter: OP) as an alternative to the fixed-effect regression. OP developed a consistent semi-parametric estimator that solves the simultaneity problem by using the plant's investment decision as a proxy for unobserved productivity shocks, under the assumption of imperfect competition (Erickson and Pakes, 1995). In the OP model, the unobserved productivity term is derived, in the context of a dynamic model, as a function of investment and capital stock and is calculated as a semi-parametric function of these two variables. Once this is done, Equation (2) may be estimated for observations in which investment is non-zero.

While OP forfeit 8 percent of their observations by restricting observations to those with non-zero investment, other datasets (such as the current one) may lose a much larger fraction of observations and, in some cases, the majority of observations, for this reason. The OP procedure establishes a simple link between the estimation strategy and economic theory, mainly because intermediates are not typically state variables.

In the Chilean manufacturing dataset used by Levinsohn and Petrin (2003 (hereinafter: LP), over 50 percent of the observations have zero investment. To overcome this limitation, LP suggested using intermediates instead of investment in the estimation of plant productivity. Since many intermediates are almost always non-zero, this circumvents the data-truncation problem generated by zero-investment spells. Insofar as adjustment costs are large, intermediate inputs may confer another benefit: if it is cheaper to adjust intermediate input, it may respond better to the productivity component than to investment.

Under moderating assumptions about plant productivity and technology, LP show that the demand function increases monotonically in ω_{it}. As a result, a higher value of ω_{it} today will induce a higher investment today even if it comes too late to affect current capital stock. This allows the intermediate demand function to be inverted, so that ω_{it} may be written as a function of k_{it} and m_{it}:

(5) $$\omega_{it} = \omega_{it}(k_{it}, m_{it})$$

Following OP, LP assume that productivity is governed by a first-order Markov process:

(6) $$\omega_t = \mathrm{E}[\omega_t \mid \omega_{t-1}] + \xi_t$$

where ξ_t is uncorrelated with k_{it} (but is correlated with l_{it}). Under the LP assumptions, one can write the production function as:

(7) $$y_{it} = \beta_{us} l_{it}^{us} + \beta_s l_{it}^{s} + \gamma D_{it} + \phi_{it}(k_{it}, m_{it}) + \eta_{it}$$

and

(8) $$\phi_{it}(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + \omega_{it}(k_{it}, m_{it})$$

By substituting a third-degree polynomial function to approximate k_{it} and m_{it} instead of $\phi_{it}(k_{it}, m_{it})$, one may consistently estimate the parameters of the value-added equation using OLS. Equation (5) elicits an estimate of $\hat{\beta}_{us}, \hat{\beta}_s, \hat{\gamma}$ and an estimate of $\hat{\phi}_{it}$.

The second stage of the LP routine identifies the $\hat{\beta}_k$ coefficient. This is done by computing the estimated value of $\hat{\phi}_{it}$ by using the difference between the value added and the vector of the corresponding values above ($y - \hat{\beta}_{us} l_{us} - \hat{\beta}_s l_s - \hat{\gamma}\hat{\beta}_s D$). For any prediction of $\beta^*{}_k$, one may compute a prediction for the productivity term for all periods t using: $\hat{\omega}_{it} = \hat{\phi}_{it} - \beta^*{}_k k_{it}$.

Using these values, a consistent non-parametric approximation of $\mathrm{E}[\omega_t \mid \omega_{t-1}]$ may be calculated using a third-degree polynomial regression of the productivity term and the productivity in period *t-1*. This elicits a consistent estimate of $\hat{\beta}_k$.

It is important to note that if we are interested in estimating the coefficients of labor and diversity, it is not necessary to perform the entire OP or LP routines. However, since there are many zero-investment spells in the data used in this study and since I'm interesting in comparing the results to previous results for Israel, I perform the entire OP procedure and produce an unbiased estimator for capital as well as for labor and diversity.

The LP model is more complex to program than the OP procedure. However, a user-friendly Stata program called *levpet*, which applies production-function estimations using the LP technique, is available (Levinsohn, Petrin, and Poi, 2003).

5.2. Estimation Results

This section presents the results of the econometric analysis. In all estimations, the dependent variable is value added at the plant level. Discrete-year dummies and two-digit industry fixed effects are also used.

Table 7, reporting the preliminary results of the plant-level production function on the basis of 736 plants, confirms previous studies about the Israeli manufacturing sector (Bergman, Fuss and Regev, 1991 and 1999; Bergman and Marom, 1999 and 2005; and Lach, 1999). The first two columns report the results of the OLS method, while the remainder of the panel reports the LP and the OP semi-parametric dynamic programming approach that controls for the simultaneity problem. As expected, the OP regression omits more than 34 percent of the sample (1,648 observations in Column 5) as against a minor loss of observations using the LP method (2,340 observations in Column 3). Moreover, adding the diversity index as a state variable in the regression, the difference between LP and OP in the number of observations is greater (Columns 4 and 6). The knowledge-diversity index used in all regressions is the Herfindahl index for the ten most common technological disciplines.

The estimation found that knowledge-diversity has a positive effect on plant productivity. Using OLS, the elasticity of knowledge-diversity is 0.35 (Column 1). However, the use of the diversity index reduces the sample size because only 51 percent of plants in the sample have a diversity index. As mentioned above, the challenge to the econometric analysis is that the inputs in plant-level estimations are choice variables that may correlate with unobservable productivity shocks. Solving the simultaneity problem lowers elasticity to 0.31 and 0.2 when the LP method and the OP method, respectively, are used. As expected, the use of both methods, LP and OP, reduces the coefficients of labor and capital.

Table 7: Estimation Output

	OLS		**LP**		**OP**	
Variable	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Ln(labor)	0.88**	0.84**	0.69**	0.76**	0.43**	0.44**
	(0.03)	(0.03)	(0.04)	(0.06)	0.06	0.06
Ln(capital)	0.20**	0.19**	0.19**	0.14**	0.13**	0.11*
	(0.02)	(0.03)	(0.04)	(0.03)	(0.01)	(0.04)
Diversity	..	0.35**	..	0.31*	..	0.20*
		(0.09)		(0.12)		(0.09)
R^2	0.75	0.77	—	—	—	—
Observations (N)	1,087	1,087	2,340	1,060	1,648	673

Notes: The dependent variable in all estimations is log value added at the plant level. Diversity is measured using the Herfindahl index for the ten most common technological disciplines. All regressions include discrete-year dummies for 2001–2003, 13 two-digit industry dummies, and interactions between the year dummies and the two-digit industry dummies. Estimated standard errors are shown in parentheses.
* Denotes significance at the 5% level. ** Denotes significance at the 1% level.

An important criticism of the previous regressions is that they assume the homogeneity of labor and ignore the relationship between the proportion of skilled workers and knowledge diversity. Table 8 reports the estimation results in a way that differentiates between skilled and unskilled labor. The estimation finds a positive impact of knowledge diversity on labor productivity. Moreover, the elasticity of diversity is robust at about 0.2 in all three estimation techniques.

Table 8: Skilled and Unskilled Labor

P	OLS		LP		OP	
Variable	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Ln(skilled)	0.20**	0.17**	0.19**	0.13**	0.09**	0.03
	(0.02)	(0.04)	(0.04)	(0.04)	(0.02)	(0.03)
Ln(unskilled)	0.72**	0.71**	0.53**	0.65**	0.52**	0.61**
	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Ln(capital)	0.13**	0.19**	0.17**	0.14**	0.24**	0.13*
	(0.02)	(0.02)	(0.05)	(0.03)	(0.01)	(0.02)
Diversity	..	0.19	..	0.19*	..	0.21*
		(0.12)		(0.09)		(0.10)
R^2	0.76	0.77	-	-	-	-
Observations	1,087	1,087	1,502	1,060	1,498	1,057

Notes: The dependent variable in all estimations is log value added at the plant level. Diversity is measured using the Herfindahl index for the ten most common technological disciplines. All regressions include discrete-year dummies for 2001–2003, 13 two-digit industry dummies, and interactions between the year dummies and the two-digit industry dummies. Estimated standard errors are shown in parentheses.
* Denotes significance at the 5% level. ** Denotes significance at the 1% level.

The interpretation of the knowledge-diversity elasticity is not straightforward. Although diversity is measured not by the number of workers but as a percentage, it depends on the size of the plant and the number of complementary disciplines that its workers studied (See Diagrams A1, A2, A3 in the appendix). On the one hand, a plant can increase diversity by one percentage point by changing the number of skilled workers, changing the number of disciplines, or even changing both together; but, on the other, each change may result in different costs that are unique for the plant.[11] For example, assume that two plants employ only exact-science workers.[12] One plant has two workers (say, a mathematician and a statistician) and the other employs twenty workers (ten of whom are mathematicians and another ten are statisticians). Both have a 0.5 diversity index. Thus, replacing one statistician with a mathematician at the smaller plant will lower the diversity index to zero, thereby reducing labor productivity by 10 percent (0.5*0.2). Similarly, the diversity index of the larger plant will decrease by 0.005 and its productivity will decrease by only 0.1 percent. In

[11] The unique costs of knowledge diversity can arise from relative wages or simply from the geographic location of the plant.

[12] I assume for this comparison that both plants are identical in all aspects except for labor and capital, i.e., both produce the same product and use the same technology.

contrast, replacing one statistician with a different exact-science worker who is not a mathematician will not change labor productivity at the first plant but will boost productivity at the second plant by 0.9 percent (See Diagram A4 in the appendix).

Finally, I examine how the elasticity of knowledge diversity changes in response to changes in the specifications of the model. Since the diversity of knowledge correlates with the number of skilled workers (size), I estimated the model used in Table 8 on a panel of 289 plants that employ 100–1000 workers. The plants in this truncated panel are easily comparable; they are large enough to employ a skill-diversified labor force. The results again illustrate a positive and significant relationship between knowledge diversity and productivity. The outcomes of all three methods used (OLS, LP, and LP) result in the same elasticity of diversity - 0.25 (Table A-1 in the appendix).

Another issue of concern is that about 17 percent of the plant-year spells are of non-diversified plants, i.e., that employ only one specific type of skilled labor. One may argue that these plants use a different production function, i.e., that they specialize and behave differently from positively diversified plants. To examine this issue, I estimated the model used in Table 8 for plants that have strictly positive diversity indices. Here, the elasticity of knowledge diversity was much greater than in the previous findings: 0.6 – 0.67 (Table A-2 in the appendix).

6. Concluding Remarks

This study analyzed the effect of knowledge diversity on within-plant human-capital spillovers by using a unique longitudinal matched employer–employee dataset of Israeli manufacturing plants. The analysis was motivated by the strong encouragement that has been given to the teamwork approach, especially in high-tech firms, which raises the question of whether diversely skilled labor, in the sense of distinct knowledge, increases productivity.

Initially, I conducted a variance-decomposition exercise, which showed that most knowledge diversity takes place between and not within plants. Within-plant variation accounts for only 18 percent of the total.

Secondly, I found that hiring workers who possess diversified specific knowledge (a university degree) is beneficial for the plants' productivity. I estimated a Cobb-Douglas production function using a semi-parametric dynamic programming approach, as proposed by Olley and Pakes (1996) and later by Levinsohn and Petrin (2003). The plant-level production-function estimates show that knowledge diversity within the plant has a positive and robust impact on productivity: the elasticity is about 0.2. Furthermore, the benefit of knowledge diversification corresponds [is proportional] to the size of the plant (skilled labor), and ranges as high as 0.25 for plants that have at least 100 workers. The study does not offer a straightforward way of interpreting the estimation results, since the results depend on the costs of diversity within the plant. However, the study does suggest that plants would find it beneficial to diversify their skilled labor.

References

[1] Abowd, J. M., and Kramarz, F. (2006). "Human Capital and Worker Productivity: Direct Evidence from Linked Employer–Employee Data," mimeo, INSEE.

[2] Abowd, J. M., Creecy, R., and Kramarz, F. (2002). "Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data," United States Census Bureau working paper.

[3] Abowd, J.M., Kramarz, F., and Margolis, D.N. (1999). "High-Wage Workers and High-Wage Firms," *Econometrica* 67(2), 251–333.

[4] Abowd, J.M., Kramarz, F., and Roux, S. (2005). "Wages, Mobility and Firm Performance: an Analysis Using Matched Employee and Employer Data from France," *Economic Journal,* forthcoming.

[5] Acemoglu, D., and Angrist, J. (2000). "How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws," *NBER Macroeconomics Annual, Vol. 15,* pp. 9–59.

[6] Ackerberg, D., Caves, K., and Frazer, G. (2005), "Structural Identification of Production Functions," mimeo, UCLA.

[7] Battu H., Belfield, C.R., and Sloane, P.J. (2003). "Human Capital Spillovers within the Workplace: Evidence for Great Britain," *Oxford Bulletin of Economics and Statistics, Vol. 65(5),* pp. 575–594.

[8] Bergman, A. (1995). "The Production and Cost Structure of Israeli Industry: Evidence from Individual Firm Data," *Journal of Econometrics, Vol. 65(1),* pp. 45–81.

[9] Bergman, A., Fuss, M., and Regev, H. (1991). "High Tech and Productivity: Evidence from Israeli Industrial Firms," *European Economic Review, Vol. 35(6),* pp. 1191–1221.

[10] Bergman, A., Fuss, M., and Regev, H. (1999). "The Effects of Capital Subsidization on Israeli Industry," *Bank of Israel Economic Review, Vol. 72,* pp. 77–103.

[11] Bergman, A., and Marom, A. (1999). "Productivity Factors in Israel's Manufacturing Industry," *Bank of Israel Economic Review, Vol. 72,* pp. 51–77.

[12] ——————————— (2005). “The Contribution of Human Capital to Growth and Productivity in Israel's Business Sector, 1970 to 1999,” Bank of Israel Research Department, Discussion Paper 05.14.

[13] Blundell, R. and Bond S. (1998). “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models,” *Journal of Econometrics 87(1),* pp. 115–143.

[14] ——————————— (2000). “GMM Estimation with Persistent Panel Data: an Application to Production Functions,” *Econometric Reviews, Vol. 19(3),* pp. 321–340.

[15] Bresnahan, T., Brynjolfsson, E., and Hitt, L. (2002). “Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence,” *Quarterly Journal of Economics, Vol. 117(1),* pp. 339–376.

[16] Caroli, E., and Van Reenen, J. (2001). “Skill-Biased Organizational Change? Evidence From a Panel of British and French Establishments’, *Quarterly Journal of Economics* 116(4), 1449–1492.

[17] Cingano, F., and Schivardi, F. (2004). “Identifying the Sources of Local Productivity Growth,” *Journal of the European Economic Association, Vol. 2,* 720–742.

[18] Davis, S., and Haltiwanger, J. (1991). “Wage Dispersion between and within U.S. Manufacturing Plants, 1963–86,” Brookings Papers on Economic Activity, *Microeconomics*, pp. 115–180.

[19] Doms M., Dunne, T. , and Troske, K.R. (1997). “Workers, Wages, and Technology,” *The Quarterly Journal of Economics, Vol. 112(1),* pp. 253–290.

[20] Dunne, T., Foster, L., Haltiwanger, J., and Troske, K. (2002). “Wage and Productivity Dispersion in U.S. Manufacturing: the Role of Computer Investment,” IZA Discussion Paper 563.

[21] Eckhout, J., and B. Jovanovic (2002). “Knowledge Spillovers and Inequality,” *The American Economic Review, Vol. 92(5),* pp. 1290–1307.

[22] Foster, L., Haltiwanger, J. and Syverson, C. (2008). “Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?,” *American Economic Review*, Vol. 98(1), pp. 394-425.

[23] Garicano, L., and Rossi-Hansberg, E. (2004). “Inequality and the Organization of Knowledge,” *American Economic Review, Vol. 94(2),* pp. 197–202.

[24] Garicano, L., and Rossi-Hansberg, E. (2006). “Organization and Inequality in a Knowledge Economy,” *Quarterly Journal of Economics, Vol. 121(4),* pp. 1383–1435.

[25] Gollop, F., and Monahan, J. (1991). “A Generalized Index of Diversification: Trends in US Manufacturing,” *Review of Economics and Statistics, Vol. 73,* pp. 318–330.

[26] Grilliches, Z., and Mairesse, J. (1995). “Production Functions: the Search for Identification,” NBER Working Paper 5067.

[27] Grilliches, Z., and Regev, H. (1995) “Firm Productivity in Israeli industry: 1979–1988,” *Journal of Econometrics, Vol. 65(1),* pp. 175–203.

[28] Haltiwanger J., Lane, J., and Spletzer, J. (1999). “Productivity Differences across Employers: the Roles of Employer Size, Age, and Human Capital,” *American Economic Review, Vol. 89(2),* pp. 94–98.

[29] ———————————————— (2007). “Wages, Productivity and the Dynamic Interaction of Businesses and Workers,” *Labour Economics, Vol. 14(3),* pp. 575–602.

[30] Haskel, J., Hawkes, D., and Pereira, S. (2005). “Skills, Human Capital and the Plant Productivity Gap: UK Evidence from Matched Plant, Worker and Workforce Data,” CEPR Discussion Paper 5334.

[31] Hellerstein, J., and Neumark, D. (2004). “Production Function and Wage Equation Estimation with Heterogeneous Labor: Evidence from a New Matched Employer–Employee Data Set,” NBER Working Paper 10325.

[32] Hellerstein J., Neumark, D., and Troske, K. (1999). “Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations,” *Journal of Labor Economics, Vol. 17(3),* pp. 409–446.

[33] Jaffe A., Trajtenberg, M. and Henderson, R. (1993). “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations,” *Quarterly Journal of Economics,* Vol. 103(3), pp. 577-598.

[34] Jovanovic, B., and Rob, R. (1989). “The Growth and Diffusion of Knowledge,” *Review of Economics Studies, Vol. 56(4),* pp. 569–582.

[35] Kremer, M., and Maskin, E. (1996). “Wage Inequality and Segregation by Skill,” NBER Working Chapter 5718.

[36] Katz, L., and Murphy, K. (1992). “Change in Relative Wages 1963–1987: Supply and Demand Factors,” *Quarterly Journal of Economics*, *Vol. 107(1),* pp. 35–78.

[37] Kremer, M. (1993). “The O-Ring Theory of Economic Development,” *Quarterly Journal of Economics*, *Vol. 108(3),* pp. 551–575.

[38] Kremer, M., and Maskin, E. (1996). “Wage, Inequality and Segregation by Skill,” NBER Working Paper 5718.

[39] Krusell, P, O. L. R.-R. J. and Violante, G. (2000). “Capital-Skill Complementarity and Inequality: a Macroeconomic Analysis,” *Econometrica 68,* 1029–1053.

[40] Lach, S. (1999). “Labor Productivity in Israel Manufacturing Sector, 1990–1994,” *Bank of Israel Review*, *Vol. 72,* pp. 23–49.

[41] Lazear, E. (1999). “Personnel Economics: Past Lessons and Future Directions,” *Journal of Labor Economics*, *Vol. 17(2),* pp. 199–236.

[42] Lazear, E., and Shaw, K. (2007). “Personnel Economics: the Economist's View of Human Resources,” *Journal of Economics Perspectives*, forthcoming.

[43] Levinsohn, J. and Petrin, A. (2003). “Estimating Production Functions Using Inputs to Control for Unobservables,” *Review of Economic Studies*, *Vol. 70(2),* pp. 317–341.

[44] Levinsohn, J., Petrin, A., and Poi, B.P. (2003). “Production Function Estimation in Stata using Inputs to Control for Unobservables,” *Stata Journal* 4(2), 113-123.

[45] Marschak, J., and Andrews, W. Jr. (1944). “Random Simultaneous Equations and the Theory of Production,” *Econometrica*, *Vol. 12(3/4),* pp. 143–205.

[46] Mas, A., and Moretti, E. (2008). “Peers at Work,” *American Economic Review,* forthcoming.

[47] Milgrom, P., and Roberts, J. (1990). “The Economics of Modern Manufacturing: Technology, Strategy, and Organization,” *American Economic Review*, *Vol. 80(3),* pp. 511––528.

[48] Moretti, E. (2002). “Human Capital Spillovers in Manufacturing: Evidence from Plant-Level Production Functions,” *Economic Studies, Vol. 02–27,* US Census.

[49] ———— (2004a). “Workers' Education, Spillovers and Productivity: Evidence from Plant-Level Production Functions,” *American Economic Review, Vol. 94(3),* pp. 656–690.

[50] ———— (2004b). “Estimating the Social Return to Higher-Education: Evidence from Longitudinal and Repeated Cross-Sectional Data,” NBER Working Paper 9108.

[51] Navon, Guy, and Tojerow, I. (2006). “The Effects of Rent-Sharing on the Gender Wage Gap in the Israeli Manufacturing Sector,” IZA Discussion Paper 2361.

[52] Navon, Guy (2006). “Human Capital Heterogeneity: University Choice and Wages,” mimeo, The Hebrew University of Jerusalem.

[53] Olley, S., and Pakes, A. (1996). “The Dynamics of Productivity in the Telecommunications Equipment Industry,” *Econometrica*, Vol. 64(6), pp. 1263–1297.

[54] Regev, Haim (2006). “The Griliches-Regev Longitudinal Panel of Israeli Manufacturing Firms, 1955–1999,” mimeo.

[55] Van Biesebroeck, J. (2003). “Wages Equal Productivity: Fact or Fiction?” NBER Working Paper 10174.

[56] Zucker L., Darby, M., and Armstrong, J. (1999). “Intellectual Capital and the Firm: the Technology of Geographically Localized Knowledge Spillovers,” NBER Working Paper 4946.

Appendix

Diagram A-1: Maximum diversity in the number of academic disciplines within the plant

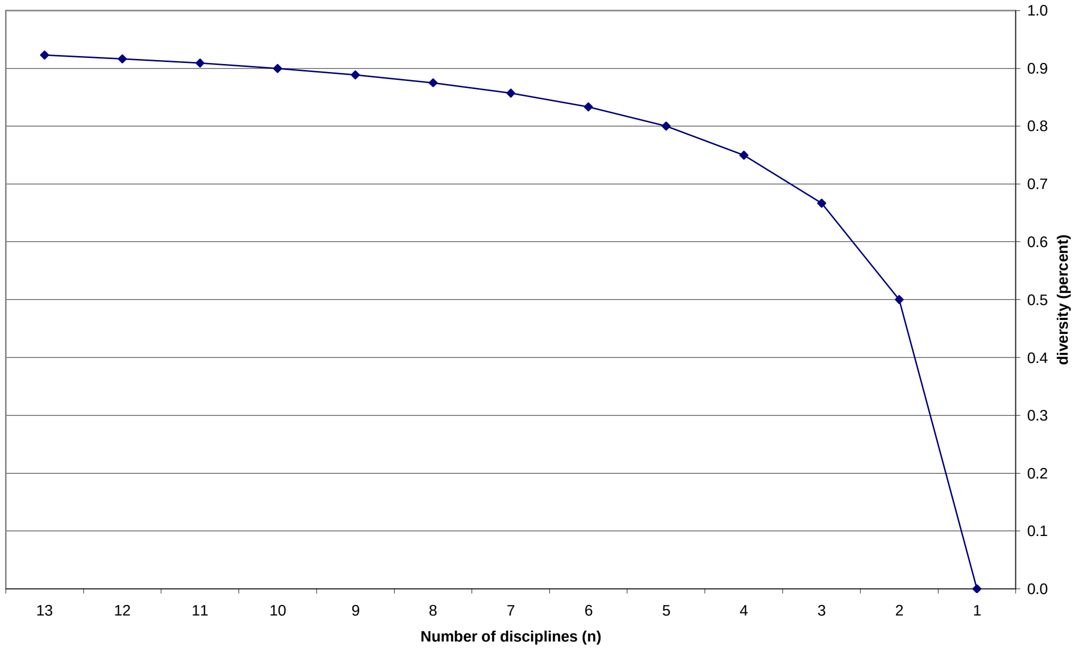


Diagram A-2: Maximum Diversity and the number of skilled workers (Ls)

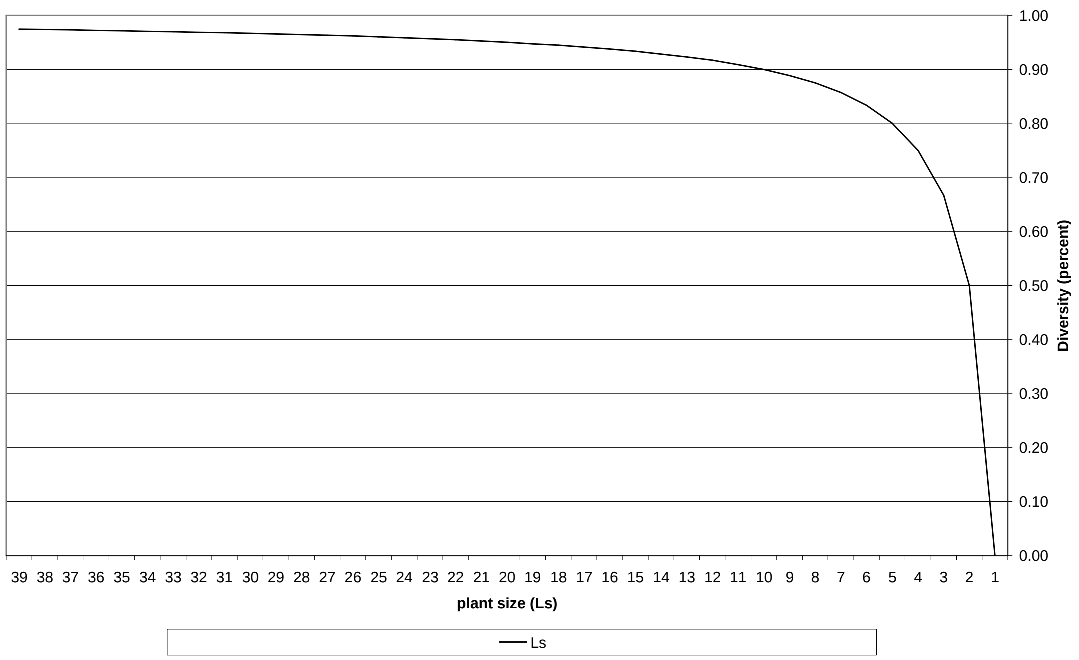


Diagram A3: The impact of divierisifng knowledge on plant diversity

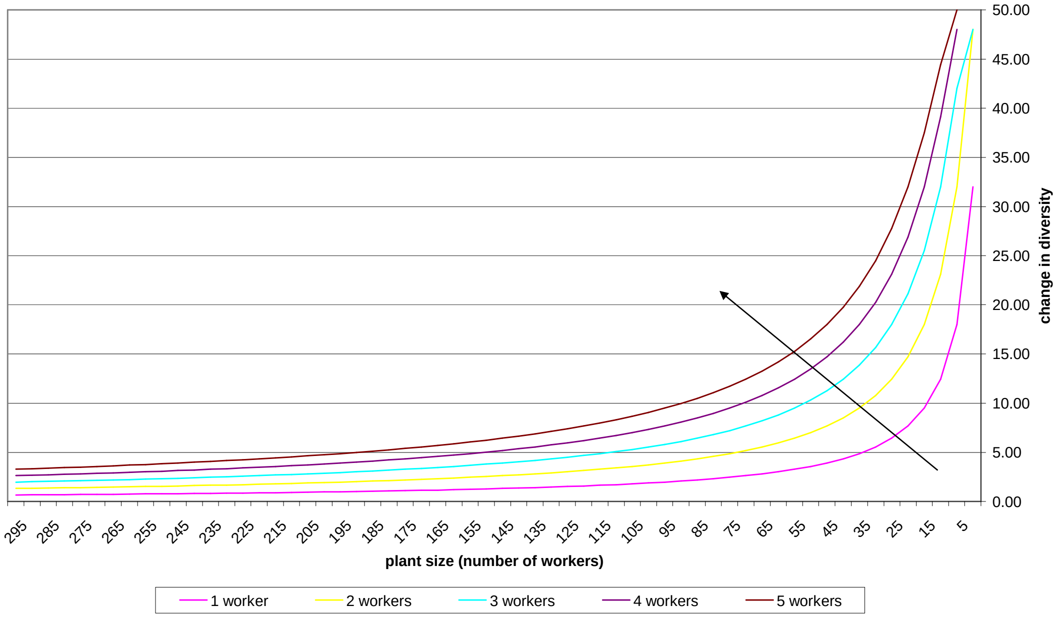


Table A-1: Large Plants (100–1000 Employees)

	OLS		LP		OP	
Variable	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Ln(skilled)	0.22**	0.18**	0.19**	0.14**	0.16**	0.13**
	(0.03)	(0.04)	(0.03)	(0.04)	(0.05	(0.05)
Ln(unskilled)	0.48**	0.59**	0.42**	0.52**	0.30**	0.35**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07	(0.07)
Ln(capital)	0.23**	0.19**	0.16**	0.15**	0.20**	0.12**
	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)
Diversity	..	0.25*	..	0.25*	..	0.25*
		(0.12)		(0.12)		(0.11)
R^2	0.63	0.64	—	—	—	—
Observations	1,089	852	1,077	842	1,073	839

Notes: The dependent variable in all estimations is log value added at the plant level. Diversity is measured using the Herfindahl index for the ten most common technological disciplines. All regressions include discrete-year dummies for 2001–2003, 13 two-digit industry dummies, and interactions between the year dummies and the two-digit industry dummies. Estimated standard errors are shown in parentheses.
* Denotes significance at the 5% level. ** Denotes significance at the 1% level.

Table A-2: Diversified Plants only (0<Herfindahl<1)

	OLS		LP		OP	
Variable	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Ln(skilled)	0.20**	0.17**	0.16**	0.13**	0.23**	0.16**
	(0.03)	(0.04)	(0.05)	(0.04)	(0.03)	(0.03)
Ln(unskilled)	0.66**	0.65**	0.57**	0.56**	0.54**	0.54**
	(0.04)	(0.04)	(0.07)	(0.07)	(0.04)	(0.04)
Ln(capital)	0.21**	0.21**	0.20**	0.21**	0.15**	0.22**
	(0.02)	(0.02)	(0.04)	(0.05)	(0.02)	(0.02)
Diversity	..	0.60*	..	0.67	..	0.65*
		(0.26)		(0.35)		(0.25)
R^2	0.65	0.66	—	—	—	—
Observations	652	652	652	652	652	652

Notes: The dependent variable in all estimations is log value added at the plant level. Diversity is measured using the Herfindahl index for the ten most common technological disciplines. All regressions include discrete-year dummies for 2001–2003, 13 two-digit industry dummies, and interactions between the year dummies and the two-digit industry dummies. Estimated standard errors are shown in parentheses.
* Denotes significance at the 5% level, ** Denotes significance at the 1% level.