Export and Productivity—Evidence from Israel

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פריון החברות היצואניות בישראל

ליאור גאלו

תקציר

אנו אומדים את הקשר שבין יצוא ופריון באמצעות סקרי תעשייה לשנים 1993 - 2003. אנו מוצאים שהפריון של פירמות יצואניות בישראל גבוה מזה של הלא יצואניות. עוד נמצא כי הפריון של הפירמות היצואניות גבוה מזה של הפירמות הלא יצואניות עוד לפני שהראשונות החלו לייצא - ממצא המצביע על כך שפריון גבוה משפיע על החלטת הפירמה לייצא. אנו מוצאים כי לאחר שהפירמות החלו לייצא הפריון שלהם גדל עוד יותר - ממצא המצביע על כך שיתכן והייצוא משפיע על הפריון. אנו עושים שימוש בשיטות הסטטיסטיות המקובלות בספרות על מנת לאמוד את הקשר הסיבתי שבין פריון וייצוא. כאשר אמדנו את הקשר תוך שימוש בשיטת ההתאמה קיבלנו כי הייצוא מגדיל את הפריון של פירמות יצואניות בכ - 12 אחוזים תוך 5 שנים. כאשר אמדנו את הקשר תוך שימוד בשיטת המומנטים שהוצעה על ידי בלנדל ובונד (1998) אין אנו מוצאים כל השפעה של הייצוא על הפריון.

Abstract

We estimate the relationship between exporting and productivity using data on Israeli manufacturing firms from the years 1996-2003. We find that the total factor productivity of exporting firms in Israel is higher than that of non-exporters. The export premium is higher before firms enter the export market, an indicator of a self-selection effect. We also find an additional premium for firms after they have entered the export market, which is suggestive of a learning by exporting effect. We then use econometric methods to estimate the causal link between export and productivity, and obtain varying results depending on the estimation method. Using a matched differences-in-differences methodology we find a significant positive learning effect. Growth in the productivity of exporting firms is approximately 12 percent 5 years after they enter the export market. When using the system GMM methodology proposed by Blundell and Bond (1998) however, we find a non-significant negative effect of exporting on productivity.

1 Introduction

The observation that exporters perform better than non-exporters has been documented and analyzed in numerous studies during the last 15 years, and is still a very popular research topic for economists. Evidence worldwide confirms that exporters are larger, more productive, pay higher wages, and are more likely to survive than domestic firms selling only to local markets.

The causal link that explains this positive correlation between export status and firm performance can, in principle go in either direction. For example, higher productivity firms may self-select into the export market; their productivity is higher than that of non-exporters even before they start exporting and this higher productivity is what turns exporting into a profitable activity. At the same time, firms in the export market can learn from experience and improve their productivity as they are exposed to foreign competitors and clients –the learning by exporting (LBE) effect. Obviously, both directions of causality can coexist simultaneously.

If LBE proves to be an important determinant of productivity, export promotion initiatives can then be used as policy instruments for increasing productivity, i.e., for generating export-led growth. While the self-selection perspective enjoys substantial empirical support, the evidence for LBE is weaker. Greenaway and Kneller (2008) review this issue, and report that the evidence for LBE depends on the econometric method used. Specifically, researchers who estimate the LBE effect using (matched) differences-in-differences (MDID) usually find support for the existence of an LBE effect, while researchers who use a general method of moments (GMM) estimation method usually do not.

This is the first study to examine the export-performance nexus with Israeli data. We use firm-level data for manufacturing firms from the period 1996-2003. The data were collected and assembled by the Central Bureau of Statistics (CBS). Consistent with the empirical literature, we find that the performance of exporters in Israel is superior to that of non-exporters. Israeli exporters are larger, more productive, and pay higher wages than non-exporters. We also find that the productivity of future exporters is higher than that of future non-exporters, thereby supporting the self-selection mechanism. Moreover, there is some evidence that the productivity growth of future exporters increases after they start exporting, which is supportive of the LBE effect.

In order to estimate the causal effect of exporting on productivity, we use the two econometric methods usually employed in the literature: MDID and GMM. The results from MDID suggest that exporting does indeed increase firm productivity. The LBE effect begins two years after the firm starts exporting and last for at least another 3 years. We find that 5 years after a firm begins to export, its productivity is growing approximately 12 percent faster than that of non-exporters. We then use Blundell and Bond's (1998) version of GMM (SYS-GMM), and obtain a non-significant (negative) effect of exporting on productivity. These results conform to Greenaway and Kneller (2008)'s previously mentioned observation. Interestingly, the GMM estimator originally proposed by Arellano and Bond (1991) (DIFF-GMM) gives a negative and significant effect of exporting on productivity, while Arellano and Bover's (1995) version of GMM (LEVEL-GMM) gives positive and significant effects. The reason for these contradictory results is currently under investigation.

The rest of the paper is organized as follows: In the second section, we provide a brief theoretical background of the relationship between exporting and productivity. In the third section, we describe the data, while a preliminary analysis of the productivity-export relationship is presented in Section 4. The fifth section estimates the causal link between export and productivity using MDID and three versions of GMM. The paper ends with a brief summary.

2 Theoretical Background

Exporters have been found to be more productive and to pay higher wages than non-exporters. The pioneering work of Clerides et al. (1998) and Bernard and Jensen (1999) suggested that the correlation between exporting and productivity reflects a selection of more productive firms into exporting. Potentially however, the causal link between export status and productivity or more generally, firm performance can go in either direction. Below we present some of the theoretical arguments underlying each direction of causality.

From Performance to Export

Melitz (2003) describes two conditions that imply a threshold level of productivity above which the firm decides to start exporting.[1] The first condition is a "zero cutoff profit" condition that compels exporting firms to exit the global market if their profits fall below a certain level. The second condition is a "free entry" condition stating that if the net present value of exporting is positive, (non-exporting) firms will enter the global market and start exporting. The net present value includes the non-recoverable (sunk) costs which firms must incur in order to enter the global market.[2] The intersection of these two conditions will create a productivity threshold. Firms with productivity above this threshold will self-select into the global market and will export, while firms with productivity below it will sell only to the local market. Self-selection of high productivity firms into the global market implies that exporters are larger and pay higher wages to their workers.

From Export to Performance

Firm performance could be affected by exporting. This is the LBE hypothesis referred to by Clerides, Lach and Tybout (1998) and by others. This hypothesis rests on three underlying premises. In his classical work on learning-by-doing, Arrow (1962) suggests that learning can only take place through the attempt to solve a problem, and therefore only occurs in the course of activity. Accordingly, firms may improve their productivity by participating in the export market and solving the logistical and technical problems associated with exporting. The second premise refers to the stronger competition faced by firms when they are active in the global market, which compels them to improve their performance faster than firms exposed only to local markets. The

[1] Melitz describes a productivity threshold for a firm's decision to produce and another threshold for the decision to export. Here, I ignore the first threshold and focus on the export threshold.

[2] These sunk costs may be considerable as they could include market research costs, transportation costs, costs related to establishing distribution channels, or costs related to modifying domestic products to foreign tastes.

third premise refers to the larger potential for knowledge spillover accruing to exporters simply because of the larger pool of players (firms and clients) which they face. These larger spillovers enable exporters to progress more rapidly than non-exporters facing a smaller pool of players.

There are attendant caveats to the underlying premises of the LBE hypothesis. First, regarding Arrow's learning-by-doing mechanism, experience gathered from export activity may improve the export performance of the firm but not necessarily its total performance. Specifically, if the technology employed in producing for the export market is the same as that used in producing for the local market, learning by producing for the export market should not be different than learning by producing for the local market.

Second, better performance in global markets due to the intense competition implies that firms active in the local market alone could actually improve their efficiency but prefer not to do so, which would contradict the profit-maximization hypothesis if the costs of improving efficiency are not excessively high. The third premise assumes that knowledge can spill over to exporters from other firms and from mutual clients around the world. Yet, knowledge spillover does not have to stop there. If knowledge spills over from firms around the world to exporters, it may also spill over from exporters to non-exporters. In this scenario, productivity growth between exporters and non-exporters will not differ to any significant extent. Knowledge can also spill over from foreign firms that sell in the local market (importers) to local firms, and such a mechanism will have the same effect on exporters and non-exporters. Even though exporters may face a larger pool of players and therefore gather more and better information on production processes, the technological improvements in information and communication technology during recent decades makes it difficult to maintain support for the case of asymmetric information regarding production improvements between exporters and non-exporters.

The self-selection hypothesis enjoys not only theoretical but also very strong empirical support, and therefore dominates contemporary economic literature.[3] The evidence

[3] Bernard and Wagner (1997), Clerides et al. (1998), Bernard and Jensen (1999), Aw et al. (2009), Isgut (2001), Fafchamps et al. (2002), Delgado et al. (2002), Arnold and Hussinger (2005), Alvarez and Lopez (2004).

on the LBE hypothesis however, is less clear. Nevertheless, several papers have found an LBE effect after allowing for self-selection.[4] The search for a causal link dates back to the papers of Clerides, Lach and Tybout (1998) and Bernard and Jensen (1999), who examined differences between exporters and non-exporters using firm-level data. These researchers found that exporters' performance was indeed superior to that of non-exporters. They examined performance before and after entry into global markets, and found clear evidence to show that better firms become exporters. The benefits from exporting however were more difficult to identify, especially in terms of productivity growth which was no better for exporters than for non-exporters.

Since then many economists have followed these pioneering papers and explored differences in performance between exporters and non-exporters. Strong evidence of self-selection was found, while the LBE effect was found only in certain countries and under special conditions. Wagner (2007) reviewed this issue and claimed that ten years of research into the relationship between exporting and productivity point to the conclusion, "exporters are more productive than non-exporters, and that more productive firms self-select into global markets, while exporting does not necessarily improve productivity." Greenaway and Kneller (2008) also review this issue and suggest that the empirical evidence of the LBE effect depends on the estimation method used. Specifically, researchers who tried to estimate the causal link using MDID found a significant LBE effect, while those using a GMM approach found no significant effect (or in some cases, found a negative LBE effect).

Overall, the LBE hypothesis suffers from unclear theoretical underpinnings and has weaker empirical support than the self-selection perspective. Nevertheless, it is an attractive hypothesis because it provides a clear rationale for export-promoting policies (export-led growth). Understanding the magnitudes of LBE can be useful to a policy maker interested in increasing growth by promoting export activity.

Another reason for the popularity of the LBE hypothesis is firms' revealed pref-

[4] Kraay (1999), Castellani (2002), Baldwin and Gu (2003), Van Biesebroeck (2005), Girma et al. (2004), Bigsten et al. (2004), Hahn (2004), Blalock and Gertler (2004), De Loecker (2004), Fernandes and Isgut (2005).

erences. Criscuolo, Haskel and Slaughter (2005) used subjective survey data collected from EU countries and found that management of firms operating globally claim that they learn more from sources such as suppliers and customers. The managers' subjective statements find objective reinforcement in that they devote more resources to assimilating knowledge from abroad. These recent papers illustrate firms' view that exporting can improve their performance.

3 The Data

The principal data in this paper come from annual manufacturing surveys in Israel for the period 1996-2003. These surveys were conducted by the CBS and consist of a sample from all manufacturing establishments in Israel (except those in the diamond industry). The CBS survey population covers establishments employing more then 5 persons comprise 94 percent of the manufacturing industry share in GDP and 99 percent of the manufacturing industry share in export. The data in this paper are a sample of 20 percent of the establishments in the survey population. The sample includes the entire population of Israeli manufacturing firms with 75 or more employees (comprising 10 percent of the survey population) and a sample of small firms with more than 5 and less than 75 employees (comprising 10 percent of the survey population). Small firms that exited the sample were replaced by firms with similar characteristics drawn from the population. The sample comprises 90 percent of the survey population's exports and 75 percent of the population's product. The manufacturing surveys provide most of the data necessary for estimating productivity at the firm level: *local sales, export, labor, investment* and *year of establishment*. These manufacturing data were merged with employer-employee administrative data on salaries paid to workers. In this paper, the main variable used from the latter source of data—as will be explained below—is the age of the firm.

Firms in the manufacturing surveys were not asked about their capital stock. To overcome this problem, Griliches and Regev (1995) constructed a capital services variable defined as the sum of the estimated depreciation and interest (at five percent) of the net stock of capital plus the rental cost of equipment and building,

$$k_{it} = \delta_{it} K_{it} + 0.05 \left(1 - \delta_{it}\right) K_{it} + R_{it}$$

where K_{it} is capital stock, δ_{it} is the depreciation rate and R_{it} is the rental cost.

It should be noted that the depreciation rate changes over time since Griliches and Regev (1992) defined the durability of buildings as 30 years, that of equipment as 15 years and that of automobiles as 8 years. The authors' data on capital stock were obtained from surveys of the gross capital stock conducted by the CBS. (For a full description of the creation of this variable see Regev [2006]). The capital stock of firms that did not participate in the survey was calculated in two steps. Firstly, a regression of capital services on wages and materials per employee was estimated using all the firms with computed capital services. Secondly, the coefficients of this regression were used to predict the capital services (using the wage and material data) for firms not appearing in the capital survey.

This capital services variable is available until 1999. We extended the methodology to the years after 1999 and to firms that entered the sample after 1999. We have data on the rental cost and on investment for every year after 1999, but do not have data on depreciation because this requires information on firms' investment over the last 30 years. We therefore estimated capital services as a linear function of past capital services and the rental cost of equipment and building plus investment,

$$\begin{aligned} \hat{k}_{it+1} &= \alpha \left(k_{it} - R_{it}\right) + R_{it+1} + \beta_{it} \Delta K_{it+1} \\ t &= 1999, ..., 2002 \end{aligned}$$

where α is an industry-specific parameter estimated using data until 1999, ΔK_{it+1} is the investment in year t and β_{it} is the durability that was calculated according to the definition of Griliches and Regev (1992).

Firms are entering and exiting the sample. When firms exit the sample, the CBS samples new firms to replace them with the result that the sample's share of the survey's population remains at approximately 20 percent. The final data set is an unbalanced panel of 2,688 firms and 14,638 observations over the period 1996-2003. The first column of Table 1 presents the distribution of firms over the years. The survey begins with 2,027 firms and contracts at an annual average rate of 3 percent, which is similar to the rate of contraction in the survey population.

The average annual rate of exit is 8.2 percent.[5] The two main reasons for exit are bankruptcy and censoring (firms that are still operating but stopped collaborating with the CBS), but we do not have information about the precise cause of exit.[6] A selective exit of firms from the sample can bias the estimated productivity if for example, those exiting are firms with lower productivity levels (Olley and Pakes, 1996).[7] We will follow a control function approach and include an estimated probability of exit into the production function specification to allow for the correlation between unobserved factors in the production function and the probability of exit.

The average annual rate of entry into the sample is 5.2 percent. Firms that entered the sample are those that were sampled in order to replace exiting firms (80 percent of the entering firms) or firms that grew beyond 75 workers. The entrants may be young firms that were established recently or firms that existed for some time, but were first sampled during the sample period.

It should be noted that the exit rate of firms from the sample is higher than the

[5] Cassiman and Golovko (2007) report exit rates of 10 percent for Spanish firms. De Loecker (2004) reports an exit rate of 3.5 percent in Slovenia. Since 2003 the CBS publishes formal data on the distribution of openings and closings of businesses by industry. The data were drawn from the administrative Business Register. According to this publication, the annual rate of business death in the manufacturing industry was 7.9 percent in 2003 and 7.7 percent in 2004.

[6] Other reasons for exit could be a change in the industry specification of the firm which is very rare, or a change in ownership which causes a change in the firm's identification number. Another reason for exit can be the merger of a subsidiary firm with the parent firm. We do however, have information about these causes. We find that omitting these firms from the sample or using dummy variables to allow for these cases does not change the main results of the estimation.

[7] Olley and Pakes (1996) found that moving from a balanced to an unbalanced panel data more than doubles the capital coefficient and decreases the labor coefficient by 20 percent in a production function estimation.

entry rate of firms into the sample, and the difference reflects a net exit of firms from the sample. This can be seen in the 3 percent annual contraction rate in the number of firms.

The entry and exit rates are informative of the dynamics around the productivity threshold for production. If entry and exit are correlated with firms' age, they could affect the average age of firms in the sample and, if age is correlated with productivity, that may create a selection problem. It is therefore important to allow for firms' age in estimating the determinants of productivity. However, age is missing for many firms. We can infer the age of the firm indirectly from employer-employee data. These provide information on the date when each employee began working in the firm. We will use the current year minus the most senior employee's starting date as a proxy for the firm's age. After constructing this variable we found that approximately 50 percent of the entering firms were young firms (firms that were established in the current year). Accordingly, half of entering firms are established firms that were sampled for the first time during the sample period. This also means that the share of young firms in the sample is approximately 2.5 percent, which is lower than the rate of new firms in the industry.[8] Numerous studies have found that the export premium for young firms is larger than that for older firms.[9] This difference could be explained by Arrow's motivation for the LBE effect. Since young firms are more likely than established firms to face new situations, their potential to learn from experience is greater. The small share of young firms in the sample may therefore lead to a downward bias in the estimated effect of exporting on productivity (the LBE effect) or an upward bias in the estimated variance of the effect.

The next four columns (4-7) of Table 1 present the share of exporters among the firms in the sample, the share of exporters in the group of firms that enter the sample, their share among firms that exit the sample, and their share among firms that stayed in the sample. Approximately 41 percent of the firms are exporters at the beginning of the

[8] According to the administrative Business Register the average annual rate of business birth in the manufacturing industry is about 5 percent.

[9] Delgado et al. (2002) for Spain, Baldwin and Gu (2003) for Canada, and Fernandes and Isgut (2004) for Colombia.

sample period, and this share increased to 47.6 percent in 2003.[10] The share of exporters among entering and exiting firms is lower than their share among firms remaining in the sample. The lower share of exporters among entrants may reflect the high share of young firms among entrants relative to the share of young firms in other groups. Melitz (2003) suggests that productivity is unknown to the firm before starting production. Firms explore their productivity in the local market before entering the global market which implies that there will be fewer exporting firms among the young firms.[11] Since the share of young firms among entrants is large, the share of exporters among them is smaller. The smaller share of exporters among firms exiting the sample is also broadly consistent with Melitz's (2003) model. Exporters are firms with higher productivity levels—above the production threshold—and this enables them to cope better with exogenous negative shocks. As a result, their probability of exiting production is lower than that of non-exporting firms.

The share of exporter firms entering and exiting is quite similar, but their share among the net-exiting firms is lower than their share among the staying firms. The share of exporters in the sample thereby increases over the years.

Columns 8 and 9 present the annual rate of firms that started exporting (but were producing for the local market in the previous year) and the rate of firms that stopped exporting (but continue selling to the local market). Approximately 5.2 percent of the exporting firms are new exporters, while 5.4 percent of the exporters cease selling to the global market every year. These transitions occur around the productivity threshold to export.

Table 2 presents the distribution of firms in 13 industries and the share of exporters by industry. The industries are ordered according to their knowledge intensity. Pharmaceuticals, computers and aircraft are considered high-tech industries, while food and textiles are considered low-tech industries. The share of exporters differs among in-

[10] De Loecker (2004) found similar share of exporters for Slovenia. Delgado, Farinas and Ruano (2002) found an even higher share of exporters for Spanish manufacturing firms but used a selective sample of exporters.

[11] However, 30 percent of the new entrants enter directly into the export market.

dustries. Exporters' share in the high-tech industries is relatively high because they are higher productivity firms. The annual rate of decrease in the number of firms also differs across industries. The number of firms in the computer and aircraft industries increases at an average annual rate of 1.8 percent, while the annual contraction rate of firms in the textile industry is 9 percent. The increase in the share of exporters in the sample therefore reflects an increase in the share of industries that are more export intensive (Figure 1).

4 Preliminary Analysis

In this section we present descriptive evidence on the relationship between performance indicators and export status. Table 3 presents summary statistics of a number of firm performance indicators by year and export status. The table is divided into three panels corresponding to all the firms in the sample, to exporters and to non-exporters. The figures in Table 3 are consistent with the findings in the literature. Exporters are bigger than non-exporters in the sense that they have more workers and higher levels of capital. Nevertheless, exporters' capital per worker is no different than that of non-exporters. Exporters' shipments are larger than that of non-exporters even when these are to local markets. Their value-added is on average 5 times that of non-exporters. Exporters also pay higher wages and their value added per worker is 8 percent higher than that of non-exporters. Overall, the findings with the Israeli data conform to the findings in the empirical literature.

We now examine more thoroughly the differences in productivity between exporters and non-exporters. The differences in other performance indicators (such as sales, labor, capital, and investment) are presented in Appendix A.

We follow Bernard and Jensen (1999) and examine the following regression,

$$\omega_{it} = \beta_0 + \beta_{exp} exp_{it} + \varepsilon_{it}, \quad (1)$$

where ω_{it} is the log of the firm's productivity and exp_{it} is a dummy variable for export status.

The export coefficient β_{exp} captures exporters' premium. This is a purely descriptive parameter and no causal interpretation should be given to it because export status is endogenous. We will address the causal relationship between export status and productivity later.

Tables 4 presents the estimates of β_{exp} from equation (1) using three indicators of productivity. The first two use log value added of the firm (VA) and log value added per worker or labor productivity (LP).[12] The third indicator of productivity is an estimate of total factor productivity (TFP) and was calculated using the Olley and Pakes (1996) approach which expresses unobserved productivity in terms of observed capital investment flows. The Olley-Pakes procedure is described in Appendix B. Standard errors are clustered at the firm level to allow for arbitrary heteroskedasticity and serial correlation. All regressions include dummy variables for years and for industries.

According to the results in Table 4, the value added of exporters is 1.5 times higher than the value added of non-exporters. It should be noted that this export premium is lower than that in Table 3 because here, we control for year and industry effects. LP and TFP of exporters are 32 and 42 percent higher than those of non-exporters, respectively.

In columns (4)-(6) we present the estimates of β_{exp} where we also control for the size of the firm (employment level in the first observed year) and the firm's age.[13] Firm's size should capture the effect of economies of scale, while age is included in order to allow for the convergence of productivity over the firm's lifespan that may cause correlation between productivity and age.[14] After controlling for size and age, the export premium declines sharply but exporters still perform better than non-exporters. Exporters' value added is 22 percent higher than that of non-exporters, while their labor productivity is 14 percent higher and their TFP is 10 percent higher. In appendix A we present these estimates separately for each industry.

Exporters are more productive than non-exporters in Israel, a result similar to

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[12] I use these two measures of productivity mainly for ease of comparison with other papers.

[13] Dummy variables for a subsidiary firm and for firms whose capital services I estimated were insignificant and therefore no included in the final regression.

[14] See Brouwer, Kok and Fris (2005) for a review.

that found in other papers. Bernard and Jensen (1995) report an export premium of 16.9-22.6 percent for LP and an export premium of 7.1-12.4 percent for TFP in the US. The estimates in Girma, Greenaway and Kneller (2003) for the UK are 9.7 percent for LP and 8.3 percent for TFP. De Loecker (2004) found an export premium of 29.6 percent for LP in Slovenia. Haller (2007) used micro-level panel data for 14 countries and a set of identically specified empirical models to investigate the relationship between exports and LP, and found that the exporter premium varies considerably (between 7 and 60 percent) across countries. In a meta-analysis of the results it was found that countries which are more open and have more effective government report a higher productivity premium.

We now follow Clerides et al. (1998) by classifying firms into different groups according to the timing of their export activity.[15] The groups are defined for firms that always export, firms that start exporting, firms that stopped exporting, firms that export randomly, and firms that never export. Productivity differences between these groups are of interest because they shed additional light on whether the data are consistent with theory, and make it possible to learn about the self-selection of firms into the export market.

Firms with productivity way above the export productivity threshold may always export. Even if they experience a negative productivity shock, their productivity level may still be high enough to continue exporting. We classify firms that always export throughout the sample period as *always* firms. On the other hand, there are firms with a very low productivity level that will *never* export; even when a positive shock hits their productivity level. Between these two polar cases are firms with productivity levels around the export productivity threshold. These firms will export if their productivity is higher than the threshold and vice versa.

The underlying assumption of this classification is that apart from stochastic shocks, firms maintain their initial productivity and therefore also maintain their initial export status. However this assumption is not valid because some firms change their

[15] Other papers also classified exporters according to the timing of export. For example, Girma et al. (2003, 2004), Delgado et al. (2002), Wagner (2008), Farinas and Martín-Marcos (2007).

export status permanently. If a non-exporting firm with low productivity experiences a large positive productivity shock, or if its productivity monotonically increases over time, it may start exporting and continue exporting permanently (that is, the firm will change its status from the never group to the always group). We classify these firms as *start* firms. If an exporting firm experiences a severe negative shock, or if its productivity monotonically decreases over time, it may stop exporting permanently (that is, the firm will change its status from the always group to the never group). We classify these firms as *stop*. The rest of the firms are classified as *random* firms since they start and stop exporting randomly. The productivity level of this group of firms should be close to the export threshold, and minor differences in productivity may therefore turn them into exporters or non-exporters.[16]

In short, the classification of firms according to the timing of their exporting activity is:

1. *always* — Firms that export throughout the sample.
2. *start* — Firms that did not export for at least two consecutive years, and then export until the end of the sample (for at least two years).
3. *stop* — Firms that exported for at least two consecutive years, and then did not export until the end of the sample (for at least two years).
4. *never* — Firms that did not export at all throughout the sample.
5. *rand* — The remaining firms are firms that enter and exit the global market randomly.

Figure 2 presents the share of each group in the sample. Approximately 82 percent of the firms remain in their initial export status (either exporting or non-exporting). This persistence in exporting status might make it difficult to explore the dynamics of

[16]Although firms in this group enter and exit the export market they are not classified as starters or stoppers since the evolution of their productivity is different. It is therefore important to distinguish the random firms from the other groups.

exporting in the sample. Only 2.3 percent of the firms started exporting and just 1.5 percent left the global market. The rest of the firms exit and enter the global market randomly.

We expand equation (1)to allow for a different export premium by export group,

$$\omega_{it} = \alpha + \sum_{g \in G} \varphi_g I_{i \in g} + \varepsilon_{it}, \qquad G = \{always,\ start,\ stop,\ rand\}, \tag{2}$$

where $I_{i \in g}$ receives the value 1 if firm i belongs to group g and 0 otherwise.

The main interest here is the estimation of the coefficients: $\varphi_{always}, \varphi_{start}, \varphi_{stop}, \varphi_{rand}$. The export premium from equation (1) is roughly a weighted average of these coefficients according to their weight in the sample.

Table 5 presents the estimates from equation (2). The never exporting firms are the baseline group. The results suggest that there are significant differences between the different types of exporters. The value added of firms that always export is 1.8 times higher than that of firms which never export (close to the estimate in Table 4). The LP and TFP of firms that always export are 38 and 50 percent higher than the productivity of those that never export.

As in Table 4, the export premium decreases after controlling for the firm's size and age. Nevertheless, even after controlling for these factors, the LP and the TFP of firms that always export are 17 and 12 percent higher than those of firms that never exported. The export premium of firms that start exporting (relative to never exporting) is 15.4 percent and 12.3 percent for LP and TFP respectively. The corresponding premiums for firms that export randomly are 8.4 percent and 4.9 percent. Firms that exit the export market have the lowest productivity among the exporters. Before controlling for size and age they have higher productivity than those that never export, but the difference in productivity is small. After controlling for size and age, the estimated productivity of firms that exit the export market is lower than that of firms that never export, but this difference is not statistically significant.

In order to examine if the differences between the different types of exporters are significant, we performed the following test,

$$H_0 : \varphi_{g_1} = \varphi_{g_2}, \qquad g_1, g_2 \in G = \{always,\ start,\ stop,\ rand\}$$

In Table 5.1 we present the p-values of these pairwise tests of similarity using the estimated coefficients in column (6). The TFP of firms that always export and the TFP of firms that start to export are significantly larger than that of firms that stopped exporting. The differences between the TFP of firms in the always and the start groups and the TFP of firms that export randomly are not significant. In addition, the differences between the productivity of firms in the random group and the productivity of firms in the stop group are not significant.

These results are broadly consistent with the theoretical framework whereby the most productive firms are those that always export, followed by firms that sometimes export and then by those firms that never export. It is difficult to place firms that switch their status in this hierarchy. The results here suggest that firms in the start group are similar in their productivity to firms in the always group, while the productivity of firms in the stop group is similar to that of firms in the never group and is significantly smaller than the productivity of firms in the always and the start groups.

We can also utilize the panel structure of the data to examine the change in export premium among firms that change their export status during the sample period. For this purpose, we subclassify the starting, stopping and randomly exporting firms into the following subgroups:

2.1 $start\_before$ — Firms in the start group before they started exporting.

2.2 $start\_after$ — Firms in the start group after they started exporting.

3.1 $stop\_before$ — Firms in the stop group before they stopped exporting.

3.2 $stop\_after$ — Firms in the stop group after they stopped exporting.

5.1 $rand\_export$ — Firms in the rand group in years when they export.

5.2 $rand\_not\_export$ — Firms in the rand group in years when they do not export.

We then re-estimate equation (2) using dummies for each of these groups as well as for the firms that always export (the never exporting firm are the baseline group). The export premium coefficients are also denoted by φ_g where now

$$g \in G = \left\{ \begin{array}{c} always,\ start\_before,\ start\_after, \\ stop\_before,\ stop\_after,\ rand\_export,\ rand\_not\_export \end{array} \right\}$$

This specification enables us to examine whether the export premium for the various groups is realized before or after firms switch their status. Bernard and Jensen (1999) suggest that the productivity-to-export causal link can be examined by checking whether the productivity of exporters is higher than that of non-exporters before they start exporting. Specifically, they examine whether future exporters that do not export in the current year have higher productivity than future non-exporters that also do not export in the current year. If the productivity of future exporters is indeed higher that of future non-exporters in the current year then the coefficient of $start\_before$ will be positive:$\varphi_{start\_before} > 0$.[17]

We present the estimation results in Table 6. Starters have higher productivity than those who never exported even before they started—an indication of the self-selection of more productive firms into the global market. The productivity premium of starters is roughly the same before (12.7 percent) and after (12.1 percent) they enter the export market. Those that export randomly do indeed export in years when their productivity is higher than the productivity of those that never exported (by 8.4 percent), and do not export in the other years. The productivity of firms that exit the export market is lower than the productivity of those that never exported, before and after they stopped exporting, but the difference is not significant.

In Table 6.1, we test for similarity in the export premium coefficients estimated in column 6 between the different groups. The results reveal the logical hierarchy in the

[17] Note that firms from the *rand* group could actually be classified as both future exporters and future non-exporters. The results in Table 5 emphasize that there are significant differences between the firms in the *start*, *rand* and *never* groups. It is therefore important that future non-exporters should be taken only from the group of firms that never export and that future exporters should be taken only from the group of starters defined under the strict definition.

export market. The export premium of firms in the always group is not different than that of firms in the start group before and after they started exporting. The p value decreases when we check the differences in the premium of firms in the always and start group and compare them with the productivity of the firms in the rand group in years that they export. However, the differences are still non-significant. The export premium of each one of these four groups of exporters (always, start before, start after and rand in years they export) is significantly higher than that of each one the other three groups (rand in non-export years, stop before and stop after).

An additional perspective on the productivity-exporting nexus can be obtained by estimating the effect of exporting status on the change in productivity. Specifically, we estimate the following equation:

$$\Delta\omega_{it} = \widetilde{\alpha} + \sum_{g \in G} \widetilde{\varphi}_g I_{i \in g} + u_{it} \tag{3}$$

Analyzing productivity growth makes the effect of unobserved time-invariant factors negligible. In estimating equation (3) we add the lagged-dependent variable ω_{it-2} as a regressor because it is important to allow for a possible negative correlation between the level of productivity and productivity growth if the firm's productivity converges to a steady state.[18]. It should be noted that this specification does not follow from equation (2). In the estimation of this equation, too, the group of firms never exporting is the baseline group.[19]

The results of this estimation are presented in Table 7. Firms that always export have higher productivity growth rates than those that never exported. In addition, new exporters increase their productivity growth after they start to export while the other groups maintain their growth rates.

If exporting does indeed increase productivity, then the productivity growth rates

[18] If the growth in productivity decreases with the level of productivity then omitting the productivity level from the regression may result in a downward biased estimator of the exporter premium since exporters have higher productivity levels.

[19] All the tests for differences in these coefficients between the different types of exporters were not-significant and therefore we do not present it.

of firms that export throughout the sample should be positive ($\widetilde{\varphi}_{always} > 0$), and this is the case, as shown in Table 7. Additionally, the productivity growth rate of firms that started to export should increase after they enter the export market ($\widetilde{\varphi}_{start\_after} > \widetilde{\varphi}_{start\_before}$). This was also seen in the data in Table 7. These results suggest, though not prove, the presence of LBE.

The results from this preliminary analysis indicate that exporters in Israel are indeed more productive than non-exporters, and that the most productive firms always export. These results conform to the extensive empirical literature on the subject. New exporters are more productive than firms that never export even before they enter the export market, which is suggestive of self-selection as predicted by theoretical models. There is also evidence that the productivity growth rates of new exporters increases significantly after they start exporting. This result is suggestive of the LBE effect.

In the next section we employ the econometric methods used in the literature to estimate the causal link between export status and productivity.

5 Learning By Exporting

With respect to the identification of the causal effect of exporting on productivity, the empirical literature uses two main estimation methods: MDID as in, for example, Girma, Greenaway and Kneller (2003), Arnold and Hussinger (2005), De Loecker (2004), Alvarez and Lopez (2005), and GMM as in for example, Clerides, Lach and Tybout (1998), Bernard and Jensen (1999), Baldwin and Gu (2003), and Van Biesebroeck (2005). Each method is based on different assumptions and uses different techniques to estimate the average effect of export (the treatment) on productivity (the outcome).

In this section we describe both econometric methods in detail and use them to estimate the export premium in Israel.

5.1 Matched Difference-in-Differences

MDID is an estimation method that combines a matching methodology with a difference-in-differences methodology. To evaluate the causal effect of exporting on productivity, the MDID method estimates the differences between the productivity growth of exporting firms and that of the same firms had they not exported (difference-in-differences). Since the latter scenario is not observed, it has to be estimated and this is done by using the productivity growth of a selected group of non-exporting firms which are as similar as possible to the exporting firms in terms of pre-exporting characteristics (matching).

Much of the following description of MDID is adapted from Blundell and Costa Dias (2008) to the case of exporting. We begin by defining the treatment effect that will be estimated and will then describe the motivation and assumptions of the matching and the differences-in-differences approaches separately. Finally, we will integrate these two methods into the matched difference-in-differences estimator.

The simplest model to be estimated using a single cross-section is:

$$\omega_i = \alpha_0 + \alpha_i export_i + u_i \tag{4}$$

where, as before, ω_i is the (log) productivity of firm i, u_i is an unobserved component of the firm's productivity, $export_i$ is a dummy variable representing the export status and α_i is the *firm-specific* effect of export on productivity in year t.

For this model, we can define three treatment effects of interest:

- The population average treatment effect (ATE),

$$\alpha^{ATE} = E(\alpha_i).$$

- The average treatment effect on firms that were assigned to treatment (ATT),

$$\alpha^{ATT} = E(\alpha_i | export_i = 1).$$

- The average treatment effect on firms that were not assigned to treatment (ATNT),

$$\alpha^{ATNT} = E(\alpha_i | export_i = 0).$$

Two issues must be considered when estimating one of the treatment effects: heterogeneous treatment effects and selection bias. If the effect of the treatment is homogenous for all firms, then all of the three effects will be identical because $\alpha_i = \alpha$ for *all* i.

However, if the treatment effect is heterogeneous across firms then the effects— ATE, ATT, ATNT—will differ and one must clarify which treatment effect is being estimated.

Estimating (4) by OLS amounts to estimate the following model

$$\begin{aligned} \omega_i &= \alpha_0 + \alpha^{ATE} export_i + export_i \left(\alpha_i - \alpha^{ATE}\right) + u_i \qquad (5) \\ &= \alpha_0 + \alpha^{ATE} export_i + e_i \\ \text{where } e_i &= export_i \left(\alpha_i - \alpha^{ATE}\right) + u_i \end{aligned}$$

Estimating α^{ATE} with simple OLS provides a consistent estimator if the composite error e_i is uncorrelated with exporting status. For this to be the case, we need u_i to be uncorrelated with $export_i$. When u_i and $export_i$ are correlated, we say there is selection on the untreated outcomes as firms with different untreated outcomes (due to differences in their $u's$) have varying likelihoods of becoming exporters (Blundell and Costa Dias, 2008). In this case, the relationship between ω_i and $export_i$ is not directly observable from the data since exporters and non-exporters are not comparable.

Accordingly, the first assumption for obtaining an unbiased estimator of the treatment effect known as the Independence Assumption (IA) requires export status to be independent of the unobserved component of productivity,

$$IA : u_i \perp export_i \qquad (6)$$

where $\perp$ means "stochastically independent".

Under homogenous treatment effect, this assumption suffices for consistency of OLS since $\alpha_i = \alpha^{ATT}$. However, when the effects are heterogeneous, the selection effect is expected to be more severe because the return on exporting may be larger for those firms that decide to export. In this case we say there is an additional selection on the expected gains (Blundell and Costa Dias, 2008). This selection arises due to the presumably positive relationship between α_i and $export_i$. For this not to occur, we assume:

$$\alpha_i \perp export_i \qquad (7)$$

Recall that for this simple model the OLS estimator of the slope equals the difference in mean productivity between exporters and non-exporters, $\widehat{\alpha}^{OLS} = \overline{\omega}^1 - \overline{\omega}^0$, where $\overline{\omega}^1$ and $\overline{\omega}^0$ are the sample productivity means for exporting and non-exporting firms, respectively. Since

$$E\left(\overline{\omega}^1\right) = E\left(\omega_i|export_i = 1\right) = \alpha_0 + \alpha^{ATE} + E(\alpha_i - \alpha^{ATE}|export_i = 1) + E(u_i|export_i = 1)$$

and

$$E\left(\overline{\omega}^0\right) = E\left(\omega_i|export_i = 0\right) = \alpha_0 + E(u_i|export_i = 0)$$

we have

$$E\left(\widehat{\alpha}^{OLS}\right) = \alpha^{ATE} + E(\alpha_i - \alpha^{ATE}|export_i = 1) + E(u_i|export_i = 1) - E(u_i|export_i = 0) \tag{8}$$

This equation is instructive because it shows what is estimated in the course of the running of an OLS regression. If the treatment effects are homogeneous and assumption IA is satisfied, then OLS consistently estimates the ATE. If however, there is heterogeneity in the effects, OLS consistently estimates $\alpha^{ATE} + E(\alpha_i - \alpha^{ATE}|export_i = 1) = E(\alpha_i|export_i = 1) = \alpha^{ATT}$, the treatment effect *on the treated.*

When the goal is to estimate the ATT, as it is in this paper, the crucial assumption is therefore IA. It is difficult however to justify this assumption in the current context because of the endogeneity caused by the selection of the most productive firms into exporting. The results from the preliminary analysis suggest that productivity affects the decision to export. This means that exporting status is correlated with productivity or in other words, firms with higher $u's$ are more likely to export. Accordingly, we would expect $E(u_i|export_i = 1) - E(u_i|export_i = 0)$ to be positive and OLS to overestimate the export premium.

In order to cope with this problem, we can use matched and DID estimation methods which make it possible to estimate the ATT under the following weaker assumptions.

Matching

Matched methods exploit the additional information in the data to facilitate the independence assumption (6). The objective is to find a valid comparable (control) group for the exporting firms among the non-exporting firms. Consider a vector of observables X_i that affect the decision to export. Two firms having the same $X's$ are then expected to make the same decision up to random variation. If given the observables X, the assignment to export is indeed random, then a valid control group for an exporter with characteristics X is a non-exporter with the same characteristics. Estimating the ATT then amounts to comparing the productivity of the exporting firms with the productivity of the non-exporting firms that belong to this control group.

Formally, to estimate the ATT consistently in this manner we require that independence between exporting status and u be valid only for firms having the same $X's$. In other words, we require a conditional independence assumption (CIA):

$$CIA : u_i \perp export_i | X_i \tag{9}$$

It should be noted however that if the covariates predict export participation exactly, then a counterfactual group cannot be built. For this reason, another assumption is required to ensure that the counterfactual groups can be created. This assumption is known as the common support assumption (CSA),

$$CSA : Prob\,(export_i = 1 | X_i) < 1 \tag{10}$$

If there are several dimensions in X_i, it may be impossible to find a match for each exporter in the sample. Rosenbaum and Rubin (1983,1984,1985) solved this "dimensionality problem" by showing that if the CIA is valid for X_i, then it is also valid for a function of X_i, namely the conditional probability of exporting $Prob\,(export_i = 1|X_i)$, which is known as the "propensity score". That is:

$$CIA : u_i \perp export_i | X_i \Longrightarrow u_i \perp export_i | Prob\,(export_i = 1 | X_i)$$

We can then match exporters to non-exporters firms based on the propensity score rather than on the multidimensional vector X_i. That is, for each exporting firm with a propensity score value equal to p, the control group is the set of non-exporting firms having the same, or "very close", value of the propensity score. Obviously, $Prob\,(export_i = 1|X_i)$

is usually unknown and has to be estimated.

The propensity to start exporting is used as an index for the distance in characteristics space between firms. The two most commonly methods used to select firms having similar propensity scores are nearest neighbor matching and kernel matching. The nearest neighbor matching assigns a weight of one to the closest—in term of the propensity score—non-exporting observation and zero to all others.[20] Kernel matching defines a neighborhood for each exporting firm and assigns a positive weight to all non-exporting observations in this neighborhood. This weight can be constant or can give more weight to firms with similar values of the propensity score of the exporting firm.

The kernel matching estimator is given by:

$$\begin{aligned} \widehat{\alpha}^K &= \frac{1}{N^T} \sum_{i \in T} \left[\omega_i - \sum_{j \in C} w_{ij} \omega_j \right] \\ w_{ij} &\equiv \frac{G\left(\frac{p_j - p_i}{h_n}\right)}{\sum\limits_{k \in C} G\left(\frac{p_k - p_i}{h_n}\right)} \end{aligned} \tag{11}$$

where T is the set of exporting (treated) firms and C the set of non-exporting (control) firms, p_j is the probability of exporting for firm j, $G(.)$ is a Gaussian kernel density function and h_n is a standard bandwidth parameter. The weight w_{ij} decreases with the difference between the propensity score of treated firm i and the propensity score of control firm j.

Blundell and Costa Dias (2008) argue that kernel matching produces more precise estimates than nearest neighbor matching because it uses more observations per exporting firm. Kernel matching is also simpler to calculate because the standard error of the estimated treatment effect has to be bootstrapped and as shown by Abadie and Imbens (2006), when using the nearest neighbor matching the bootstrap variance diverges from the actual variance.

Difference-in-Differences

[20] Or it can assign a weight of one to the $k-$closest non-treated observations and zero to all others.

Our firm level data has a panel structure and we therefore introduce a time dimension into the analysis. Having panel data will allow us to use differences in productivity over time—productivity growth—to estimate the treatment effects. The model is now:

$$\omega_{it} = \alpha_0 + \alpha_i export_{it} + u_{it}$$

with the obvious notation.

Before applying DID to the productivity-export model we need to pay particular attention to the characteristics of our panel data. DID is often used in the field of labor economics to estimate the effect of participation in job training programs on workers' employment and earnings (Heckman et al., 1997). In this case, none of the individuals is treated at the beginning of the sample period. The program begins at some point in time and some individuals receive the treatment while others do not. The earnings of treated and non-treated individuals are compared some time after the program ends.

In our firm level data, we observe firms exporting at the beginning of the sample period, for example those firms exporting throughout the sample. The structure of the data therefore differs from that in the job training application. In order to understand why this is a problem it should be noted that since productivity affects the decision to export, we must allow for this initial productivity effect if we wish to estimate the effect of exporting on subsequent productivity growth. Due to the fact that these firms were already exporting at the beginning of the examined period, it is not possible to control for the initial productivity effect. To overcome the problem, we follow De Loecker (2004) and others, and only use firms that were defined in the preliminary analysis in the start group (firms that did not export for at least two consecutive years, and then export until the end of the sample for at least two years)—the treated firms—and compare them with firms that never exported during the sample period—the non-treated firms. By doing this, we ensure that: a) none of the firms is treated at the beginning of the sample period; b) at a certain point in time some firms start to export while others never export; and c) exporting firms remain so until the end of the sample period.

Let t_0 be the time at which the firm starts to export, and t_{-1} and t_1, with $t_{-1} < t_0 < t_1$, be the times before and after the firm started exporting. For the sake of simplicity, we consider a two-period case where we observe the firms at t_{-1} and t_1, and will address the multiple-period case later.

First-differencing the productivity equation yields:

$$\omega_{it_1} - \omega_{it_{-1}} = \alpha_i export_{it_1} + u_{it_1} - u_{it_{-1}} \tag{12}$$

since $export_{it_{-1}} = 0$ for all firms by the sample design.

Estimating (12) by OLS amounts to estimating:

$$\omega_{it_1} - \omega_{it_{-1}} = \alpha^{ATE} export_{it_1} + \left[export_{it_1}\left(\alpha_i - \alpha^{ATE}\right) + (u_{it_1} - u_{it-1})\right] \tag{13}$$

Under first-differences, the independence assumption required for consistency of OLS is then

$$DID - IA : \left(u_{it_1} - u_{it_{-1}}\right) \perp export_{it_1} \tag{14}$$

This assumption is weaker than IA. It should be remembered that the endogeneity of exporting is due to productivity affecting the decision to export. Assume that u_{it} has an error component structure, $u_{it} = \eta_i + v_{it}$ and it is only the time invariant part which affects the decision to export. We then find that while u_{it_1} and exporting are correlated, $u_{it_1} - u_{it_{-1}} = v_{it_1} - v_{it_{-1}}$ and exporting are not if v_{it} is strictly exogenous.

The OLS estimator of α^{ATE} in (13) is the difference in mean productivity growth between exporters and non-exporters, $\widehat{\alpha}^{OLS} = \overline{\omega_{t_1} - \omega_{t_{-1}}}^1 - \overline{\omega_{t_1} - \omega_{t_{-1}}}^0$, where $\overline{\omega_{t_1} - \omega_{t_{-1}}}^1$ ($\overline{\omega_{t_1} - \omega_{t_{-1}}}^0$) is average productivity growth among exporters (non-exporters). This estimator is known as the difference-in-difference estimator, since it is calculated as the change in productivity across time (the first difference), between exporting and non-exporting firms (the second difference). Since

$$\begin{aligned} E\left(\overline{\omega_{t_1} - \omega_{t_{-1}}}^1\right) &= E\left(\omega_{it_1} - \omega_{it_{-1}} | export_{it_1} = 1\right) \\ &= \alpha^{ATE} + E(\alpha_i - \alpha^{ATE} | export_{it_1} = 1) + E(u_{it_1} - u_{it-1} | export_{it_1} = 1) \end{aligned}$$

and

$$E\left(\overline{\omega_{t_1} - \omega_{t_{-1}}}^0\right) = E\left(\omega_{it_1} - \omega_{it_{-1}} | export_{it_1} = 0\right) = E(u_{it_1} - u_{it-1} | export_{it_1} = 0)$$

we have

$$\begin{aligned} E\left(\widehat{\alpha}^{OLS}\right) &= \alpha^{ATE} + E(\alpha_i - \alpha^{ATE}|export_{it_1} = 1) \\ +E(u_{it_1} - u_{it-1}|export_{it_1} &= 1) - E(u_{it_1} - u_{it-1}|export_{it_1} = 0) \end{aligned}$$

One way to view the mechanism of DID is as follows: a within-firm differencing eliminates the time-invariant firm effects from the error term, while between-firm differencing eliminates common unobserved factors in the error term (such as aggregate shocks). Under the independence assumption DID-IA, OLS (13) consistently estimates the ATT effect,

$$E\left(\widehat{\alpha}^{OLS}\right) = \alpha^{ATE} + E(\alpha_i - \alpha^{ATE}|export_{it_1} = 1) = E(\alpha_i|export_{it_1} = 1) = \alpha^{ATT}$$

Matched Difference-in -Differences

Heckman, Ichimura and Todd (1997) suggest combining matching with DID as a way of weakening the assumptions needed for consistency relative to the case when both methods are used separately. They propose using:

$$\widehat{\alpha}^{MDID} = \frac{1}{N^T} \sum_{i \in T} \left[\left(\omega_{it_1} - \omega_{it_{-1}i}\right) - \sum_{j \in C} w_{ij} \left(\omega_{jt_1} - \omega_{jt_{-1}}\right) \right] \tag{15}$$

where the weights w_{ij} defined in (11) are based on the value of the propensity score for treated firm i.

As in the simple matching estimator, we compare the productivity growth of an exporter with the weighted average productivity growth of a control group comprised of non-exporters. We therefore only need to ask for $u_{it_1} - u_{it_{-1}}$ to be uncorrelated with exporting status $export_{it_1}$ for firms in the control group. This is a weaker requirement than (14). Formally, we require a DID conditional independence assumption on the propensity score,

$$DID - CIA : \left(u_{it_1} - u_{it_{-1}}\right) \perp \left(export_{it_1}\right) | P\left(export_{it_1} = 1 | X_{it_{-1}}\right) \tag{16}$$

Note that the probability of exporting is a function of pre-exporting characteristics.

Condition (16) and a common support assumption (CSA) ensure that $\widehat{\alpha}^{MDID}$ is consistent for α^{ATT}.

The first step in estimating the ATT effect using MDID is to match each treated firm with other firms according to the probability of exporting. We estimate the probability of starting to export separately for each year and each industry. This probability is estimated using a probit model:

$$\begin{aligned} \widehat{P}_{it} &= Prob\left(export_{it} = 1 | export_{it-1} = 0, X_{it-1}, t\right) \qquad (17) \\ t &= 1998, ..., 2002 \\ X_{it} &= \{\omega_{it}, a_{it}, inv_{it}, k_{it}, private_{it}\} \end{aligned}$$

where *inv* is the investment of the firm, a is the firm's age, k is its capital and *private* is a dummy variable of a private firm. Note that the firm's characteristics are measured at time $t-1$ when the firm is not exporting.

As mentioned in the preliminary analysis, in order to be defined as a starter, a firm must have been observed as not exporting for at least two years and then observed exporting until the end of the sample. Under this definition, firms can start exporting during the years 1998–2002. We estimate the probability of starting to export separately in each one of these years conditional on firm's characteristics during the pre-exporting period. Accordingly, we have 5 estimated probabilities of starting to export for each firm. Using these propensity scores, we calculate the weights of each non-exporting firm using a Gaussian kernel, as in equation (11). Note that firms in the control group of one exporting firm can also be part of the control group of another exporting firm.

After matching each exporting firm to a set of non-exporting firms, we use the Becker and Ichino (2004) algorithm to test equality in the mean of the covariates (X) determining the propensity score between treated and non-treated firms. If the matching works, there should be no significant differences in X. This is done by dividing the sample into 5 intervals according to the estimated propensity to start exporting. The algorithm then tests if there are differences in the mean of the propensity covariates between treated firms and their control group within each interval. If the means differ, the interval is further divided into two intervals and the means are examined again. This process continues until the equality of means cannot be rejected. Otherwise, the test fails and a new specification of the covariates must be considered (usually higher moments of the covariates).[21]

In labor economics there are usually only two periods—before and after treatment—and this creates a very well defined sequence of events. Treated individuals are matched with individuals in the control group according to their characteristics before the treatment, and the changes in outcome before and after the treatment of the two groups are compared. If the treatment does indeed affect the outcome, then its entire effect can be observed in the second period.

Within the present context, conditions are different. Firstly, the timing of the treatment varies between firms and secondly, the export premium may evolve for several years after the commencement of export. As Arrow (1962) suggests, the learning associated with repetition of essentially the same problem is subject to sharply diminishing returns. The export premium is therefore not necessarily constant over time.

Below we propose a procedure that addresses these timing issues while assuming that the export premium is constant. We will then address the possibility that the export premium changes over time. An example might clarify what this procedure does. We estimate the ATT as the difference between the productivity growth of firm A and the average productivity growth of a counterfactual group. Assume that firm A started exporting in year t_1 and that we wish to estimate the export premium in year $t_2 > t_1 > t_0$, $\omega_{At_2} - \omega_{At_0}$. The average productivity growth of the counterfactual group C_{t_1} in year t_2 is $\sum_{j \in C_{t_1}} w_{Ajt_1} \left(\omega_{jt_2} - \omega_{jt_0}\right)$ and the estimated ATT at t_2 is

$$\widehat{\alpha}_A^{MDID} = (\omega_{At_2} - \omega_{At_0}) - \sum_{j \in C_{t_1}} w_{Ajt_1} \left(\omega_{jt_2} - \omega_{jt_0}\right)$$

Note that the weights of each firm in the control group were calculated using the differences in probability to start exporting of firm j and firm A in the year that firm A

[21] For further explanations see Becker and Ichino (2004) and De Loecker (2003).

started exporting, that is, $w_{Ajt_1} \equiv \frac{G\left(\frac{p_{jt_1}-p_{At_1}}{h_n}\right)}{\sum\limits_{j\in C_{t_1}} G\left(\frac{p_{jt_1}-p_{At_1}}{h_n}\right)}$.

If a number of firms started exporting at t_1, $A_1, ..., A_{N_{t_1}}$, then the estimated ATT at t_2 is the average of the treatment effects in year $t_2 : \widehat{\alpha}_{t_2}^{MDID} = \frac{1}{N_{t_1}} \sum\limits_{i\in T_{t_1}} \widehat{\alpha}_i^{MDID}$, where T_{t_1} is the set of treated firms in year t_1, i.e., $T_{t_1} = \left\{A_1, ..., A_{N_{t_1}}\right\}$.

Assume now that in year $t_3 \neq t_1$ another group of firms started exporting, $B_1, ..., B_{N_{t_3}}$ and we want to estimate their export premium in year $t_4 > t_3$. The firms' ATT will be estimated in the same way as for those that started exporting in t_1, and the weighted ATT will be calculated using the number of treated firms in each group,

$$\begin{aligned} \widehat{\alpha}^{MDID} &= \frac{N_{t_1}}{N_{t_1}+N_{t_3}} \frac{1}{N_{t_1}} \sum_{i\in T_{t_1}} \widehat{\alpha}_i^{MDID} + \frac{N_{t_3}}{N_{t_1}+N_{t_3}} \frac{1}{N_{t_3}} \sum_{i\in T_{t_3}} \widehat{\alpha}_i^{MDID} \\ &= \frac{1}{N_{t_1}+N_{t_3}} \sum_{i\in T_{t_1}, T_{t_3}} \widehat{\alpha}_i^{MDID} \end{aligned}$$

Accordingly, the estimated ATT is simply an average of the estimated ATT's across groups of firms that started exporting in different years.

In order to cope with the possibility that the export premium changes over time, we will estimate the export premium using longer time horizons. We define a new time index that captures time since the commencement of export. Let $s = t - \tau$, where τ is the first year in which the firm exports. In this way, s denotes the number of years the firm has been exporting. For example, $s = 0$ during the first year of exporting, while $s = -1$ is one year before starting to export. By estimating the ATT for each s, we can examine how it changes with time since the commencement of export.

The MDID estimator of the export premium s years after (or before) starting to export is

$$\widehat{\alpha}_s^{MDID} = \frac{1}{N_{T_s}} \sum_{i \in T_s} \left\{ \left(\omega_{is} - \omega_{i\tau-1}\right) - \sum_{j \in C_{T_s}} w_{ij\tau} \left(\omega_{js} - \omega_{j\tau-1}\right) \right\} \tag{18}$$

$$w_{ij\tau} \equiv \frac{G\left(\frac{p_{j\tau}-p_{i\tau}}{h_n}\right)}{\sum_{k \in C_\tau} G\left(\frac{p_{k\tau}-p_{i\tau}}{h_n}\right)} \tag{19}$$

where T_s is the set of exporting (treated) firms, and C_s is the set of firms in the control (non-treated) group, s years after they started to export or after they were matched to a firm that started to export. Additionally, N_{t_s} is the number of firms in the treated group, $p_{j\tau}$ is the probability of firm j starting to export in year τ, $G(.)$ is a Gaussian kernel density function, and h_n is a standard bandwidth parameter.

Table 8 presents MDID estimates of three different ATT's: the ATT for the productivity level, the ATT for the year-to-year productivity growth and the ATT for the change in productivity since the pre-exporting year,

$$\widehat{\alpha}_{s,LEV}^{MDID} = \frac{1}{N_{T_s}} \sum_{i \in T_s} \left\{ \omega_{is}^T - \sum_{j \in C_s} w_{ij\tau} \omega_{js}^C \right\}$$

for the level effect

$$\widehat{\alpha}_{s,YTY}^{MDID} = \frac{1}{N_{T_s}} \sum_{i \in T_s} \left\{ \left(\omega_{is}^T - \omega_{is-1}^T\right) - \sum_{j \in C_s} w_{ij\tau} \left(\omega_{js}^C - \omega_{js-1}^C\right) \right\}$$

for the year-to-year growth

$$\widehat{\alpha}_{s,YT(\tau-1)}^{MDID} = \frac{1}{N_{T_s}} \sum_{i \in T_s} \left\{ \left(\omega_{is}^T - \omega_{i\tau-1}^T\right) - \sum_{j \in C_s} w_{ij\tau} \left(\omega_{js}^C - \omega_{j\tau-1}^C\right) \right\}$$

for the change from pre-exporting year

Bootstrap standard errors are presented in parentheses.

In the first row of Table 8 we present the estimated differences in the level of productivity between the treated and the control group. It should be remembered that in the preliminary analysis, we showed that firms that start to export have higher productivity levels than those of non-exporters even before they start exporting. Now, however, we observe that the productivity level of the exporting firms in the year before they started exporting ($s = -1$) is not significantly different from the productivity level of the control group. This result is driven by our construction of the sample. We used lagged productivity as one of the covariates in estimating the propensity score in the equation (17). Hence the lagged productivity between the treated and control groups before starting to export should not differ to any significant extent. In fact, Becker and Ichino's algorithm confirms that the average productivity of the control group is close to the average productivity of the treated group in the year when they started exporting. Nevertheless, it should be noted that 6 years before they start to export, the productivity level of future exporters is 4.7 percent lower than the productivity of future non-exporters. The productivity level of exporters increases over time more than that of non-exporters, and two years after they start exporting the gap becomes significantly positive. The export premium 5 years after they start exporting reaches 13.7 percent. These results reveal that future exporters start with lower productivity before they start exporting and reach higher levels of productivity after they start exporting.

In the second row we present the differences in year-to-year productivity growth between the treated and the control group. In the years before they started exporting, the productivity growth rates of future exporters are not significantly different from those of future non-exporters. The productivity growth rates are statistically similar in the first year of exporting as well. The productivity growth rate of exporters becomes significantly larger than that of non-exporters in the third, fourth and fifth year (3.1, 4.3, and 4.8 respectively) after they start exporting. These results suggest that the productivity growth rates of exporters appear to increase for several years and then stabilize at approximately 4.5 percent more than those of non exporters. In the last year, the export premium to productivity growth ratio is not significant. However, this may result from the small number of treated firms in the estimation.

The last estimation presented in Table 8 is for the cumulative productivity gain. We estimate the productivity change between the pre export year ($\tau - 1$) and s years after starting to export. By definition, this is equal to zero in the pre-export year ($s = -1$), is equal to the year-to-year estimation in the first year the firm exports ($s = 0$), and equals minus the annual export premium between years $\tau - 2$ and $\tau - 1$. We observe that the export premium is not significantly positive in the first two years of exporting, but becomes significant in the third year and increases over time. Exporters increase their productivity by approximately 12 percent after they gain a foothold in the global market and it takes them 4 to 5 years to reach their maximum productivity.

5.2 General Method of Moments

GMM is commonly used in the economic literature to evaluate the causal link between export and productivity (see Greenaway and Kneller (2007) for a survey). In this section we will summarize three versions of GMM used in the literature, and will present estimates of the causal link between export and productivity according to each one of them.

A major advantage of this method is that productivity does not need to be estimated, as is the case when using MDID. If we assume that the residual from the regression of value added on capital and labor is all due to productivity, then the correlation between export and this residual estimates the effect of exporting on productivity.

In the traditional context of estimating production functions, GMM uses the panel structure of the data to account for the endogeneity of inputs. We also use this framework to account for the endogeneity of the export decision. More precisely, under certain assumptions one can use past values of the variables as an instrument for the current values. In this context, two versions of GMM were suggested. The first version suggested by Arellano and Bover (1995) uses past differences of the endogenous variable as instruments for the current levels of the endogenous variable, and the covariance between them is the moment used for estimation. This version of GMM is denoted LEVEL-GMM. In the second version, suggested by Arellano and Bond (1991), past levels of the endogenous variable are used as an instrument for current differences of the endogenous variable. This version is termed DIFF-GMM. The correlation between past levels and current differences are the moments used for estimation. The third version of GMM is denoted by SYS-GMM and was proposed by Blundell and Bond (1998, 2000). This version takes the moments from the two previous versions and uses them as a system of equations for estimating the parameters. The applied literature usually uses the DIFF or SYS estimators Arellano and Bond's version, or the Blundell and Bond's combination of the two versions.

We now describe the application of these estimators to estimating the export-productivity relationship. Following Blundell and Bond's (1998, 2000) specification, we assume that the production function has the Cobb-Douglas form

$$
\begin{aligned}
y_{it} &= \beta_l l_{it} + \beta_k k_{it} + \beta_a a_{it} + \gamma_t + (\eta_i + \omega_{it} + m_{it})\,, \qquad (20)\\
\omega_{it} &= \rho\omega_{it-1} + \beta_{exp} exp_{it-1} + e_{it}
\end{aligned}
$$

where y_{it} is log value-added of firm i in time t, l_{it} is log labor, k_{it} is log capital, a_{it} is age, γ_t is a year effect, η_i is a time-invariant, firm-specific unobserved effect, ω_{it} is productivity, and m_{it} is a serially uncorrelated measurement error.[22]

Note that the productivity shock is serially correlated in an autoregressive fashion and can be affected by export status in the previous year (exp_{it-1}) as suggested by the LBE hypothesis. e_{it} is assumed to be serially uncorrelated.

Although we estimate the coefficients from both equations, the main interest here lies on the export coefficient β_{exp} which represents the LBE effect. The problem in estimating the export premium to productivity is that productivity is not observed, and estimating it from the first equation gives a biased estimator when employment and capital are correlated with the firm-specific effect (η_i) and with productivity shocks (ω_{it}).

Quasi-differentiating equation (20) eliminates the productivity shock from the equation and yields the following dynamic specification

$$
y_{it} = \rho y_{it-1} + \beta_l l^*_{it} + \beta_k k^*_{it} + \beta_a a^*_{it} + \gamma^*_t + \beta_{exp} exp_{it-1} + \eta^*_i + \varpi_{it}, \qquad (21)
$$

$$
\begin{aligned}
\varpi_{it} &\equiv (e_{it} + m^*_{it})\\
x^*_{it} &\equiv x_{it} - \rho x_{it-1} \text{ for } x = l, k, a, \gamma, \eta, m
\end{aligned}
$$

We will refer to this equation as the level equation. As noted by Blundell and Bond (1998), if one is willing to assume that there are no measurement errors, then $\varpi_{it} = e_{it}$

[22] Blundell and Bond (1998) suggest adding measurement errors.

and ϖ_{it} will be serially uncorrelated. Otherwise, ϖ_{it} evolves according to an $MA\,(1)$ process because $m_{it}^{*} = m_{it} - \rho m_{it-1}$. Note that $\eta_i^{*} = (1-\rho)\eta_i$.

Arellano and Bover (1995) used lagged first differences as an instrument to estimate the level equation (LEVEL-GMM). Lagged differences will be valid instruments for the level variables if they are not correlated with the errors. To observe this, define $x_{it} \equiv (y_{it-1}, k_{it}, l_{it}, exp_{it-1})$; lagged differences will be valid instrument for the levels when $E\left(\Delta x_{it-s}\left(\eta_i^{*} + \varpi_{it}\right)\right) = 0$ for $s = 1$ if there are no measurement errors, and $s = 2$ otherwise (Blundell and Bond ,1998).

Arellano and Bond's (1991) version of GMM takes first differences to eliminate unobserved firm-specific effects (η_i) and uses lagged levels as a means of adjusting for simultaneity in the first differenced equation (DIFF-GMM),

$$\Delta y_{it} = \rho \Delta y_{it-1} + \beta_l \Delta l_{it}^{*} + \beta_k \Delta k_{it}^{*} + \beta_k \Delta a_{it}^{*} + \Delta \beta_{exp} exp_{it-1} + \Delta \gamma_t^{*} + \Delta \varpi_{it} \qquad (22)$$

We will refer to this equation as the differences equation. In this case Δx_{it}^{*} are instrumented using lagged levels of the variables x_{it-s}. The use of past levels as instruments to contemporaneous differences is valid under the assumption that past levels variables are not correlated with the errors' first-differences, that is when $E\left(x_{it-s}\Delta\varpi_{it}\right) = 0$ for $s \geq 2$ if there are no measurement errors, and $s \geq 3$ otherwise (Blundell and Bond, 1998). Note that if the coefficient of the lagged dependent variable equals one (i.e., $\rho = 1$) then the quasi-differences (k_{it}^{*} and l_{it}^{*}) will behave like a random walk, and using lagged levels as instruments for the first differences would give poor results. It is therefore important to check that $\rho < 1$.

Using each one of these methods separately will provide poor estimation results when only a weak correlation exists between the instruments and the endogenous variables (the problem of weak instruments). Blundell and Bond (1998) show that weak instruments could cause large finite sample biases in this framework. These authors also show that these biases can be dramatically reduced by incorporating more information from both moments' conditions. They suggest that the moments from both versions be used simultaneously as one system to estimate the unknown parameters. This gives rise to the third version of GMM, the system estimator (SYS-GMM).

In order to test the specification of the model we present Hansen's test (1982) for overidentifying restrictions and Arellano and Bond's test (1991) for serial correlation of the residuals. The Hansen statistics test whether the moments' expectations are close to zero as assumed by the model. If the moments' expectations are not close to zero, the instruments are invalid. Arellano and Bond (1991) proposed a serial correlation test based on the residual of the differences equation. To understand the logic of their test, note that the error term is defined as the sum of the unpredictable part of the productivity shock (e_{it}) and the quasi differential of the measurements errors $\varpi_{it} \equiv e_{it} + m_{it} - \rho m_{it-1}$. The error term will be serially uncorrelated if there are no measurement errors. In this case, its first differences $\Delta\varpi_{it} = \Delta e_{it}$ will be serially correlated of order 1. For example, the covariance between the first differences in time t and time $t-1$ is due to the common element e_{t-1}.[23] However, under the assumption of no measurement errors, any higher order should be serially uncorrelated.

If one allows for measurement errors, there should be serial correlation of first and second order. To observe this, note that the covariance between the first differences in time t and time $t-2$ is due to the common element m_{it-2}.[24] Accordingly, we should reject the lack of serial correlation even if e is serially uncorrelated. Under the assumptions of the model however, the correlation between the differenced errors at t and at $t-3$ is zero and we therefore test for this in the row labeled AR3. The error term in the level equation $(\eta_i^* + e_{it} + m_{it}^*)$ is autocorrelated because it contains a fixed effect (Rodman (2006)).

Table 9 reports the results from estimating the level equation (21) and the differences equation (22). At the bottom of the table we present Hansen's test for overidentification, and the Arellano Bond test for first, second and third order autoregressive

[23] To see this note that the covariance is defined as:
$cov\,(\Delta\varpi_{it}, \Delta\varpi_{it-1}) = cov\,(e_{it} - e_{it-1}, e_{it-1} - e_{it-2})$.

[24] To see this note that the covariance is defined as:
$cov\,(\Delta\varpi_{it}, \Delta\varpi_{it-2}) = cov\left(\Delta e_{it} + \Delta m_{it}^*, \Delta e_{it-2} + \Delta m_{it-2}^*\right)$.
where $\Delta m_{it}^* = m_{it} - \rho m_{it-1} - m_{it-1} + \rho m_{it-2}$
and $\Delta m_{it-2}^* = m_{it-2} - \rho m_{it-3} - m_{it-3} + \rho m_{it-4}$

errors.

Columns (1) and (2) present OLS estimates of the level equation (21) with and without lagged export status. According to this estimation, the labor coefficient is 0.8 and the capital coefficient is 0.24. The lagged dependent coefficient is 0.67 and we reject the hypothesis that it equals 1. The export coefficient is 0.03, meaning that the export premium to productivity according to this equation is approximately 3 percent. The regressors are endogenous if they are correlated with the firms' fixed effects and OLS estimates are therefore likely to be upward biased.

In columns (3)-(4) we address this endogeneity problem by estimating the coefficients using the within-firm variance. The labor and capital coefficients from this estimation remained unchanged. However, the lagged dependent variable's coefficient decreased to 0.1 and the export coefficient became negative but not significantly different from zero. The fixed-effect estimation does not completely eliminate the dynamic panel bias (Nickell 1981, Bond 2002). The problem is that the dependent lagged variable will be negatively correlated with the error term and as a result, its coefficient will be downward biased.[25] Accordingly, OLS gives an upward-biased and the fixed effect estimator gives a downward-biased estimate of the lagged dependent variable's coefficient. These two estimators provide an approximate interval within which the true coefficient value lies and as Bond (2002) notes, this provides a useful check on the results from theoretically superior estimators.

In columns (5) and (6) we present the estimates based on Arellano and Bover's (1995) version of GMM that uses lagged first differences as instruments in the levels equations. According to this estimation, the export premium to productivity is 6.6 percent and is significantly different from zero.

In columns (7) and (8) we present estimates of the difference equation (22). We estimate this equation using Arellano and Bond's (1991) GMM, which employs lagged levels as instruments in the first-differenced equations. Export premium to productivity

[25] To see this note that under the fixed-effect estimation the lagged dependent variable transform into $\widetilde{y}_{i,t-1} = y_{i,t-1} - \frac{1}{T-1}(y_{i2} + ... + y_{iT})$ while the error becomes $\widetilde{\varpi}_{it} = \varpi_{it} - \frac{1}{T-1}(\varpi_{i2} + ... + \varpi_{iT})$.
The problem is that $y_{i,t-1}$ in $\widetilde{y}_{i,t-1}$ is negatively correlated with the $-\frac{1}{T-1}\varpi_{it-1}$ term in $\widetilde{\varpi}_{it}$.

here is negative. According to this estimation, export decreases productivity by 16 percent and is significantly different from zero.

Finally, in columns (9)-(10) we show the results from SYS-GMM estimation. This method uses lagged levels as instruments in the first-differenced equations combined with lagged first differences as instruments in the levels equations. Generally speaking, the estimated coefficients from the SYS-GMM lie between the estimated coefficients from LEVEL-GMM estimation and DIFF-GMM estimation. Since the export premium from DIFF-GMM is negative and the export premium from LEVEL-GMM is positive, their joint estimation is not significantly different from zero.

At the bottom of Table 9 we present autocorrelation tests. The first order differences are autocorrelated and as expected, the AR1 coefficient is negative and significantly different from zero for all equations. The second order differences are also significantly different from zero which indicates that one cannot assume that there are no measurements errors. In addition, the Hansen test for overidentifying restrictions is significantly different from zero in the differences equation (and therefore in the SYS estimation as well), meaning that the moments' expectations are not close to zero.

In Table 9.1 we re-estimate the equations allowing for measurement errors. This amounts to using second order lags (or higher) in the level equations and third order lags in the differences equation as instruments. Once we take higher order differences, the moments' expectation in the differenced equation is closer to zero as can be seen in the Hansen test which now is not significant. The export coefficient in the level equations remains positive, but its significance decreases to some extent (its p-value is 0.099).

To conclude, the estimated learning by exporting effect depends on the estimation method used, as noted by Greenaway and Kneller (2008). To the best of our knowledge, there is no explanation in the literature for these seemingly contradictory results.

6 Concluding Remarks

This paper joins the copious existing literature exploring the causal link between export status and firm performance. This is done for the first time for Israeli firms during the years 1996– 2003. We begin by exploring the data, and find that exporters' performance is superior to that of non-exporters. This is consistent with the literature. We analyze the performance differences between exporters and non-exporters and find that exporters are indeed more productive than non-exporters. We classify exporters into groups and sub-groups and find that there are significant differences among the exporting firms. The most productive firms are those that always export and those that start to export, followed by firms that export randomly, and after them firms that exit the global market and those that never export. We further subclassify these groups and find that within each group, firms have different characteristics depending on the timing of their export activity. We find that firms which started exporting have higher productivity even before they started—which is suggestive of self-selection of highly productive firms into the export market. However, the firm productivity growth increases after they enter the export market, which is suggestive of an LBE process.

We address the endogeneity of inputs and export status by using matched difference-in-difference (MDID) and GMM estimators in order to identify a causal link between export status and productivity. The results from the MDID technique provide some evidence for the LBE effect: Firms that entered the export market increased their productivity by 12 percent in the 5 years following their entry. When using GMM however, we do not find a significant effect of exporting on productivity. This intriguing result is also present in the empirical literature. Greenaway and Kneller (2008) survey the issue and report that researchers who estimate the LBE effect using MDID usually find support for the existence of a LBE effect, while researchers who use a GMM estimation method usually do not. We present estimation of the LBE effect using two versions of GMM: DIFF-GMM and LEVEL-GMM. The DIFF-GMM, originally proposed by Arellano and Bond (1991) gives a negative and significant effect of exporting on productivity, while the LEVEL-GMM, proposed by Arellano and Bover's (1995) gives positive and significant effects. An explanation for these contradictory results is currently under study.

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Appendix A : The export premium to firm characteristics (other than TFP)

Table A1 : Characteristics of Firms in the Sample

	Employment	Average wage	Capital	Capital per worker	Investment	Investment per capital	Shipment
				Panel A			
Export	1.163***	0.272***	1.449***	0.286***	1.763***	0.67***	1.584***
Observations	(0.044)	(0.018)	(0.062)	(0.042)	(0.072)	(0.046)	(0.057)
R-squared	0.28	0.28	0.23	0.09	0.26	0.15	0.31
				Panel B			
Export	0.073***	0.117***	0.28***	0.206***	0.46***	0.397***	0.306***
Observations	(0.015)	(0.019)	(0.050)	(0.047)	(0.055)	(0.051)	(0.037)
R-squared	0.91	0.38	0.53	0.09	0.56	0.18	0.78

The dependent variable is in logs and the independent variable is a dummy variable for export.
All the regressions include dummy variables for years and economic branch.
Panel B also include the size of the firm measured as labor in the first observed year and the age of the firm.
Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A2 : Characteristics of Firms in the Sample

	Employment	Average wage	Capital	Capital per worker	Investment	Investment per capital	Shipment
				Panel A			
Always	1.401***	0.312***	1.733***	0.332***	2.13**	0.798***	1.899***
	(0.054)	(0.022)	(0.075)	(0.050)	(0.870)	(0.056)	(0.070)
Start Before	0.529***	0.117*	0.79***	0.261*	1.141***	0.68***	0.727***
	(0.146)	(0.064)	(0.238)	(0.147)	(0.241)	(0.152)	(0.210)
Start After	0.835***	0.204***	1.048***	0.213	1.631***	0.869***	1.187***
	(0.130)	(0.054)	(0.210)	(0.142)	(0.207)	(0.138)	(0.157)
Stop Before	0.91***	0.076	0.884***	-0.026	1.109***	0.242	1.022***
	(0.159)	(0.076)	(0.207)	(0.145)	(0.281)	(0.195)	(0.198)
Stop After	0.495***	0.018	0.522**	0.027	0.419	-0.051	0.578***
	(0.167)	(0.089)	(0.249)	(0.170)	(0.328)	(0.244)	(0.221)
Rand Not export	0.512***	0.098***	0.539***	0.027	0.874***	0.355***	0.725***
	(0.075)	(0.031)	(0.111)	(0.070)	(0.128)	(0.080)	(0.103)
Rand Export	0.885***	0.255***	1.11***	0.225***	1.42***	0.605***	1.284***
	(0.076)	(0.036)	(0.115)	(0.080)	(0.122)	(0.076)	(0.102)
Observations	13863	13863	13863	13863	13863	13863	13863
R-squared	0.31	0.28	0.24	0.1	0.28	0.16	0.33
				Panel B			
Always	0.087***	0.129***	0.331***	0.244***	0.557***	0.48***	0.369***
	(0.019)	(0.024)	(0.062)	(0.058)	(0.069)	(0.064)	(0.047)
Start Before	0.1***	0.058	0.334**	0.234	0.671***	0.586***	0.228***
	(0.032)	(0.053)	(0.143)	(0.144)	(0.161)	(0.147)	(0.088)
Start After	0.173**	0.131**	0.323**	0.151	0.865***	0.712***	0.399***
	(0.074)	(0.056)	(0.160)	(0.147)	(0.182)	(0.144)	(0.101)
Stop Before	0.017	-0.065	-0.086	-0.103	0.057	0.028	-0.36***
	(0.052)	(0.070)	(0.173)	(0.157)	(0.196)	(0.187)	(0.131)
Stop After	-0.096	0.085	-0.131	-0.034	-0.234	-0.182	-0.133
	(0.085)	(0.078)	(0.200)	(0.160)	(0.265)	(0.238)	(0.169)
Rand Not export	0.018	0.034	0.02	0.002	0.255***	0.236***	0.154***
	(0.024)	(0.028)	(0.078)	(0.070)	(0.087)	(0.077)	(0.057)
Rand Export	0.035	0.133***	0.2**	0.165***	0.427***	0.407***	0.289***
	(0.026)	(0.034)	(0.084)	(0.018)	(0.083)	(0.074)	(0.062)
Observations	13863	13863	13863	13863	13863	13863	13863
R-squared	0.91	0.83	0.53	0.1	0.56	0.19	0.78

The dependent variable is in logs and the independent variable is a dummy variable for export.

All the regressions include dummy variables for years and economic branch.

Panel B also include the size of the firm measured as labor in the first observed year and the age of the firm.

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A3 : Export Premiume to Productivity in different industries

	VA (1)	LP (2)	TFP (3)	VA (4)	LP (5)	TFP (6)
Pharmacy	0.875**	0.296	0.345*	0.628	0.285	0.305
	(0.40)	(0.19)	(0.19)	(0.46)	(0.19)	(0.20)
Observations	187	187	187	187	187	187
R-squared	0.05	0.11	0.09	0.55	0.28	0.31
Comp and Aircraft	1.990***	0.789***	0.508***	1.420***	0.674***	0.453***
	(0.19)	(0.07)	(0.06)	(0.18)	(0.07)	(0.07)
Observations	1367	1367	1367	1367	1367	1367
R-squared	0.23	0.22	0.11	0.42	0.25	0.13
Machinery	1.376***	0.255***	0.113	1.127***	0.210**	0.081
	(0.28)	(0.09)	(0.08)	(0.27)	(0.09)	(0.08)
Observations	602	602	602	602	602	602
R-squared	0.2	0.1	0.04	0.33	0.14	0.06
Chemicals	1.267***	0.162	0.576***	1.432***	0.17	0.652***
	(0.30)	(0.16)	(0.18)	(0.25)	(0.16)	(0.17)
Observations	640	640	640	640	640	640
R-squared	0.15	0.05	0.1	0.4	0.15	0.3
Electric no High	1.404***	0.233***	0.093	1.162***	0.180**	0.068
	(0.20)	(0.08)	(0.07)	(0.19)	(0.08)	(0.07)
Observations	850	850	850	850	850	850
R-squared	0.23	0.07	0.02	0.4	0.12	0.04
Non Metallic Minerals	1.409***	0.153	0.221**	1.184***	0.150*	0.190**
	(0.21)	(0.10)	(0.09)	(0.20)	(0.09)	(0.09)
Observations	1581	1581	1581	1581	1581	1581

The dependent variable is in logs and the independent variable is a dummy variable for export.
All the regressions include dummy variables for years and economic branch.
Columns 4, 5 and 6 also include the size of the firm measured as labor in the first observed year and the age of the firm.
Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A3 (cont) : Export Premiume to Productivity in different industries

	VA	LP	TFP	VA	LP	TFP
R-squared	0.11	0.02	0.02	0.37	0.26	0.19
Plastic and Rubber	1.619***	0.389***	0.695***	1.296***	0.276***	0.531***
	(0.18)	(0.08)	(0.10)	(0.16)	(0.07)	(0.08)
Observations	995	995	995	995	995	995
R-squared	0.27	0.11	0.17	0.45	0.21	0.32
Mnuf Basic Metal	1.652***	0.183***	0.469***	1.244***	0.086	0.318***
	(0.14)	(0.06)	(0.06)	(0.14)	(0.06)	(0.06)
Observations	1438	1438	1438	1438	1438	1438
R-squared	0.32	0.06	0.15	0.46	0.12	0.25
Jewelry, Furniture and N.E.C.	1.081***	0.275***	0.467***	0.800***	0.222**	0.349***
	(0.22)	(0.10)	(0.12)	(0.22)	(0.10)	(0.11)
Observations	567	567	567	567	567	567
R-squared	0.16	0.11	0.11	0.28	0.15	0.2
Paper	1.920***	0.16	0.445***	1.720***	0.131	0.385***
	(0.28)	(0.17)	(0.13)	(0.34)	(0.17)	(0.13)
Observations	279	279	279	279	279	279
R-squared	0.23	0.08	0.1	0.29	0.09	0.14
Wood and Stone	1.108***	0.179***	0.304***	0.756***	0.091	0.182***
	(0.17)	(0.06)	(0.07)	(0.15)	(0.06)	(0.07)
Observations	1831	1831	1831	1831	1831	1831
R-squared	0.1	0.05	0.06	0.32	0.17	0.21
Food	1.345***	0.400***	0.392***	0.775***	0.247***	0.225***
	(0.15)	(0.06)	(0.06)	(0.15)	(0.07)	(0.06)
Observations	1831	1831	1831	1831	1831	1831
R-squared	0.16	0.13	0.1	0.4	0.22	0.22
Textile	1.789***	0.386***	0.297***	1.568***	0.308***	0.240***
	(0.14)	(0.07)	(0.06)	(0.14)	(0.07)	(0.06)
Observations	1616	1616	1616	1616	1616	1616
R-squared	0.33	0.15	0.07	0.39	0.19	0.1

The dependent variable is in logs and the independent variable is a dummy variable for export.
All the regressions include dummy variables for years and economic branch.
Columns 4, 5 and 6 also include the size of the firm measured as labor in the first observed year and the age of the firm.
Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix B: Olley and Pakes's (1996) method for estimating TFP

Total Factor Productivity (TFP) measures a firm's efficiency. For example, if two firms produce the same product with the same quantities of inputs, then the more efficient firm will be able to produce more of the same product compared with the less efficient firm.[26] Unlike the firm's labor and capital that are well defined and can be observed and quantified, the firm's TFP is not observed by the econometrician and needs to be estimated. Assuming a Cobb-Douglas production function the estimation equation is:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_a a_{it} + \omega_{it} + \varepsilon_{it} \tag{A1}$$

where y_{it} is firm's i log output at time t, and the input variables l and k are log labor and log capital, respectively. a_{it} is the firm's age, ω_{it} is the firm's log productivity, and ε_{it} is an i.i.d. error term.

When β_l, β_k and β_a are known, then a measure of TFP can be calculated as the residual output after accounting for the contributions of labor, capital and age,

$$y_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_a a_{it} = \omega_{it} + \varepsilon_{it}.$$

In the usual case when β_l, β_k and β_a are not known, they have to be estimated using data on output and inputs. If the firm's productivity ω_{it} (unobserved to the econometrician) is correlated with labor and capital, then the estimated coefficients will be biased and the residual will not be a consistent estimate of TFP.[27] An additional endogeneity problem arises due to the possibility of sample selection. If firms exit when their productivity level falls below a certain threshold, then the sample of firms will be a sample of the most productive firms. When productivity affects the demand for inputs, this selection creates a selection bias in the OLS estimator. Olley and Pakes (1996) suggest an estimating procedure that deals with these problems. We briefly describe

[26] Or it can produce the same quantity with lower levels of inputs.

[27] Note that ε_{it} is assumed to be uncorrelated with l, k, a and TFP and the endogeneity is due to the possible correlation between l, k, a and the unobserved TFP.

their approach—which is an algorithm with three steps—and its underlying assumptions.

Olley and Pakes (1996) model a firm's (log) capital as a function of the last period's capital and investment:

$$k_{it+1} = k_{it}(1-\delta) + i_{it} \tag{A2}$$

where δ is the depreciation rate.

The firm's profit maximization yields an investment rule as a function of productivity, capital, and age:

$$i_{it} = i_{it}(\omega_{it}, k_{it}, a_{it}) \tag{A3}$$

where the function can be specific to each firm and time period.

If investment is strictly increasing in productivity as shown by Pakes (1994) then this function can be inverted and the productivity can be expressed as a function of investment, capital and age ,

$$\omega_{it} = h(i_{it}, k_{it}, a_{it}) \tag{A4}$$

In order to estimate a firm's productivity Olley and Pakes (1996) made the following assumptions. Labor is assumed to be the only variable factor, and the firm's choice of labor is affected by the current value of its productivity. Capital is assumed to be affected only by the distribution of productivity in the previous year. To observe the implication of these assumptions we write current productivity as the expectation of current productivity given last period's productivity and the firm's remaining in the sample in the current period, $E(\omega_{it}|\omega_{it-1}, \chi_{it} = 1)$, and an innovation part ξ_{it},

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}, \chi_{it} = 1) + \xi_{it} \tag{A5}$$

where χ_{it} equals 0 if firm i exited in the sample year t and equals 1 when the firm is in the sample.

The investment decision, and therefore capital, is assumed to be correlated with $E(\omega_{it}|\omega_{it-1}, \chi_{it} = 1)$ since this is the productivity expected by the firm in time $t-1$ for the next year. Perhaps more importantly however, capital is assumed to be independent from the innovation part of productivity ξ_{it}.

Given these assumptions, the inputs' coefficients can be estimated in three steps. The first step estimates the labor coefficient, the second step estimates the probability that the firm will decide to exit the market, and the third step estimates the capital and age coefficients. Using these coefficients, productivity can be calculated as the residual of output from labor, capital and age.

Step 1

The first step provides an estimator of the labor coefficient β_l. By replacing the productivity in (A1) with (A4), we obtain:

$$y_{it} = \beta_l l_{it} + \phi\left(i_{it}, k_{it}, a_{it}\right) + \varepsilon_{it} \tag{A6}$$

where

$$\phi\left(i_t, k_t, a_{it}\right) \equiv \beta_k k_t + \beta_a a_{it} + h\left(i_t, k_t, a_{it}\right) \tag{A7}$$

This can be estimated by OLS if the error term ε_{it} is indeed uncorrelated with the inputs. Because the exact function $\phi\left(i_t, k_t, a_{it}\right)$ is unknown, it is approximated by a fourth-order-polynomial in investment, capital and age with a full set of interactions. Note that since labor is assumed to be the only variable factor, the firm's decision regarding it can be affected by the current value of productivity. Note also that this step does not allow separation of the effect of capital and age on the investment decision from their effect on output. Accordingly, the coefficients of capital and age will be estimated later.

Define $\widehat{V}_{it} \equiv y_{it} - \widehat{\beta}_l l_{it}$, and $\widehat{\phi}_{it} = \widehat{V}_{it} - \widehat{\varepsilon}_{it}$ to be an unknown function of productivity, capital and age. [28]

Step 2

[28] In the third step we would try to clear this function from capital and age: $\left(\widehat{h}\left(i_t, k_t, a_{it}\right) = \widehat{\phi}_{it} - \widehat{\beta}_k k_{it} - \widehat{\beta}_a a_{it}\right)$.

The firm's profit maximization yields an exit rule conditional on lagged productivity,

$$P_{it} = P\left(\chi_{it+1} = 1|\omega_{it}\right) = P\left(\chi_{it+1} = 1|h\left(i_{it}, k_{it}, a_{it}\right)\right) \tag{A8}$$

P_{it} can be estimated by probit using a fourth-order-polynomial in investment, capital and age with a full set of interactions.

Step 3

The last step in the algorithm is to estimate β_k and β_a. This is done by estimating the following equation:

$$\begin{aligned} & E\left(V_{it+1}|k_{it+1}, a_{it+1}, \chi_{it+1} = 1\right) \qquad \text{(A9)} \\ = \; & \beta_k k_{it+1} + \beta_a a_{it+1} + E\left(\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1\right) + \xi_{it+1} + \varepsilon_{it+1} \end{aligned}$$

As mentioned above, capital and age are assumed to be correlated with the predicted part of productivity $E\left(\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1\right)$ but independent of the innovation ξ_{it+1}. Hence, we must control for the predicted part of productivity in order to provide a consistent estimator of the capital and age coefficients. However, productivity in the previous year as well as the exact functional form of $E\left(\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1\right)$ are unknown. In order to deal with this issue, we use (A4) and (A7) to write $\omega_{it} = \phi\left(i_t, k_t, a_{it}\right) - \beta_k k_t - \beta_a a_{it}$. Using the estimate of $\phi\left(i_t, k_t, a_{it}\right)$ obtained in the first step and the predicted probability of staying in the sample obtained in the second step, we can estimate $E\left(\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1\right)$ by

$$\widehat{E}\left(\omega_{it+1}|\omega_{it}, \chi_{it+1} = 1\right) = g_{it+1}\left(\widehat{\phi}_{it} - \beta_k k_t - \beta_a a_{it}, \widehat{P}_{it+1}\right) \tag{A10}$$

As can be seen in (A9) and (A10) the coefficients of capital and age affect current output and are also required to eliminate the effect of capital and age form $\widehat{\phi}_{it}$ to obtain the productivity term $\widehat{h}_{it}\left(\beta_k, \beta_a\right)$. Estimating this complex structure can be done by non-linear least squares of the following equation:

Table B : Production Function Coefficients

Industry	ISIC	OP Capital	OP Labor	OLS Capital	OLS Labor	FE Capital	FE Labor
Pharmacy	245	0.25	0.71	0.37	0.53	0.42	0.86
Comp and aircraft	32,33,34	0.31	0.54	0.29	0.91	0.34	0.80
Machinery	29,30	0.15	0.77	0.17	0.72	0.21	0.87
Chemicals	23,24 excl 24	0.27	0.34	0.29	0.72	0.47	0.53
Electric no high	31	0.29	0.72	0.26	0.70	0.32	0.87
Non metallic mineral	26	0.23	0.70	0.21	0.95	0.32	0.84
Plastic and rubber	25	0.37	0.48	0.34	0.76	0.40	0.68
Mnuf basic metal	27,28	0.20	0.58	0.20	0.75	0.30	0.76
Jewelry, furniture and nec	36,38,39	0.23	0.58	0.25	0.96	0.31	0.81
Paper	21,22	0.20	0.74	0.15	0.96	0.25	0.91
Wood and stone	20	0.18	0.65	0.20	0.83	0.27	0.82
Food	14,15,16	0.29	0.53	0.26	0.76	0.41	0.69
Textile	17,18,19	0.27	0.54	0.27	0.81	0.37	0.72

$$\widehat{V}_{it+1} = c + \beta_k k_{t+1} + \beta_a a_{it+1} + g_{it+1}\left(\widehat{\phi}_{it} - \beta_k k_t - \beta_a a_{it}, \widehat{P}_{it+1}\right) + \xi_{it+1} + \varepsilon_{it+1} \quad \text{(A11)}$$

Since g is unknown, it is approximated by a fourth-order-polynomial

$$V_{it+1} = c + \beta_k k_{t+1} + \beta_a a_{it+1} + \sum_{j=0}^{4-m} \sum_{m=0}^{4} \beta_{mj} \left(\widehat{\phi}_{it} - \beta_k k_t - \beta_a a_{it}\right)^m \widehat{P}_{it}^j + \xi_{it+1} + \varepsilon_{it+1} \quad \text{(A12)}$$

Table B presents the results of estimating TFP in each industry. All coefficients are significant at the 5 percent level or less.

Table 1: Firms Dynamics in the Sample

	Firms' Dynamics			Exporters' Share				Export Dynamics	
	All	Enter	Exit	All	Enter	Exit	Stay	Start	Stop
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1996	2,027		8.3	40.9		32.1			
1997	1,991	6.6	8.0	40.7	27.3	24.4	41.7	6.1	8.5
1998	1,933	5.3	8.1	42.2	34.3	28.0	42.6	4.8	5.6
1999	1,878	5.4	9.8	41.5	28.4	33.2	42.2	3.7	7.5
2000	1,794	5.6	7.5	42.4	27.0	31.1	43.3	4.4	3.8
2001	1,735	4.4	8.1	44.4	32.9	32.9	44.9	6.3	4.6
2002	1,666	4.3	7.8	46.0	38.0	39.2	46.3	5.2	4.1
2003	1,614	4.8		47.6	37.2		48.2	6.2	3.6
Average	1,830	5.2	8.2	43.2	32.2	31.6	44.2	5.2	5.4

Firms' Dynamics - transition of firms in the sample.

Exporters' Share - the share of exporters in each one of the groups.

Export Dynamics - started exporting but were producing in the local market in the previous year and stopped exporting but continue selling to the local market.

Table 2: Distribution of Firms by Industry

	ISIC	1996	1997	1998	1999	2000	2001	2002	2003	Share of exporters	Annual Average contraction rate
Pharmacy	245	25	25	25	25	26	26	25	24	85.1	-0.5
Comp and aircraft	32,33,34	172	178	183	186	189	199	201	194	72.8	1.8
Machinery	29,30	89	86	81	82	75	72	70	67	44.9	-3.9
Chemicals	23,24 excl 245	90	86	89	87	82	78	76	75	73.8	-2.5
Electric no high	31	118	119	117	117	110	105	100	91	48.3	-3.6
Non metallic mineral	26	231	227	225	219	207	195	183	172	15.3	-4.1
Plastic and rubber	25	140	140	137	130	132	130	129	127	65.7	-1.4
Mnuf basic metal	27,28	199	208	198	188	181	180	179	181	32.4	-1.3
Jewelry, furniture and n.e.c.	36,38,39	86	83	84	79	70	70	68	67	67.5	-3.4
Paper	21,22	44	41	38	36	33	31	33	32	11.1	-4.3
Wood and stone	20	287	272	258	250	238	224	208	208	20.2	-4.5
Food	14,15,16	264	263	251	245	240	235	226	229	40.6	-2.0
Textile	17,18,19	282	263	247	234	211	190	168	147	44.3	-8.8

Table 4 : Export Premium to Productivity

	VA (1)	LP (2)	TFP (3)	VA (4)	LP (5)	TFP (6)
Export	1.489***	0.323***	0.427***	0.217***	0.144***	0.099***
	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
Observations	13672	13672	13672	13672	13672	13672
R-squared	0.3	0.19	0.41	0.8	0.27	0.58

The dependent variable is in logs and the independent variable is a dummy variable for export.

All the regressions include dummy variables for years and economic branch.

Columns 4, 5 and 6 also include the size of the firm measured as labor in the first observed year and the age of the firm.

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Characteristics of Firms in the Sample

Characteristics	Measure	1996	1997	1998	1999	2000	2001	2002	2003
					All Firms				
Employment	(Number of workers)	117	118	120	122	115	113	116	116
Average wage	(monthly NIS)	6265	7118	7887	8523	9097	9308	9564	9811
Capital services	(Yearly thous.NIS)	48	56	63	85	58	81	104	76
Capital per worker	(Ratio)	0.33	0.37	0.41	0.47	0.47	0.51	0.58	0.66
Investment	(Yearly thous.NIS)	4389	4758	4677	6582	4833	4614	4008	3802
Investment per capital	(Ratio)	22.6	22.7	22.6	31.7	26.6	27.8	23.6	22.2
Shipment	(Yearly thous.NIS)	52097	58578	65580	74446	69750	68593	76518	78942
Value added	(Yearly thous.NIS)	18607	21975	25550	29152	26561	24225	27115	27548
Value added per worker	(Ratio)	4.45	4.59	4.72	4.79	4.85	4.86	4.87	4.92
Export shipment	(Yearly thous.NIS)	18036	22238	27346	32190	33296	32283	36189	36693
					Exporters				
Employment	(Number of workers)	203	202	202	208	193	182	182	176
Average wage	(monthly NIS)	7201	8168	9206	9919	10942	11073	11220	11649
Capital services	(Yearly thous.NIS)	90	105	116	165	106	150	192	127
Capital per worker	(Ratio)	0.37	0.43	0.49	0.56	0.50	0.55	0.65	0.75
Investment	(Yearly thous.NIS)	8741	9618	9100	13359	9382	8679	6702	6715
Investment per capital	(Ratio)	30.4	31.7	31.3	46.5	38.2	42.5	33.1	30.5
Shipment	(Yearly thous.NIS)	95856	106235	118339	137083	127240	121932	130101	132271
Value added	(Yearly thous.NIS)	34984	41610	47978	55213	49361	43024	47170	46955
Value added per worker	(Ratio)	4.60	4.77	4.95	5.00	5.08	5.05	5.07	5.13
Export shipment	(Yearly thous.NIS)	43484	53766	63855	75618	76972	71367	76950	74343
					Non - Exporters				
Employment	(Number of workers)	57	59	59	58	57	56	58	57
Average wage	(monthly NIS)	5601	6376	6899	7488	7691	7851	8094	8020
Capital services	(thous.NIS)	19	21	23	25	22	24	26	25
Capital per worker	(Ratio)	0.31	0.33	0.36	0.41	0.44	0.48	0.52	0.57
Investment	(Yearly thous.NIS)	1305	1331	1316	1559	1365	1256	1616	964
Investment per capital	(Ratio)	17.1	16.4	16.1	20.8	17.7	15.7	15.1	14.0
Shipment	(Yearly thous.NIS)	21083	24964	26061	28016	25922	24536	28946	26968
Value added	(Yearly thous.NIS)	7000	8125	8751	9834	9179	8697	9309	8635
Value added per worker	(Ratio)	4.35	4.46	4.55	4.63	4.67	4.71	4.69	4.71
Export shipment	(Yearly thous.NIS)	0	0	0	0	0	0	0	0

Table 5 : Export Premium of Different groups of exporters

	VA (1)	LP (2)	TFP (3)	VA (4)	LP (5)	TFP (6)
Always	1.781***	0.379***	0.508***	0.258***	0.170***	0.116***
	(0.07)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)
Start	0.938***	0.253***	0.296***	0.288***	0.154***	0.123***
	(0.17)	(0.07)	(0.06)	(0.08)	(0.06)	(0.05)
Rand	0.878***	0.189***	0.247***	0.112**	0.084**	0.049*
	(0.09)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
Stop	0.795***	0.056	0.149*	-0.11	-0.09	-0.096
	(0.20)	(0.09)	(0.09)	(0.13)	(0.09)	(0.07)
Observations	13672	13672	13672	13672	13672	13672
R-squared	0.32	0.2	0.42	0.8	0.27	0.58

The dependent variable is in logs and the independent variable is a dummy variable for the export group.
All the regressions include dummy variables for years and economic branch.

Columns 4, 5 and 6 also include the size of the firm measured as labor in the first observed year and the age of the firm.

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5.1 : Test for Differences Between Different Types of Exporters

	Always	Start	Rand
Start	0.89		
Rand	0.19	0.14	
Stop	0.00	0.01	0.54

P values from tests of differences in the coefficients.

The coefficients that were tested are from the estimation of TFP on exporters groups with control for the firm's size and age.

Table 6 : Productivity Differences between Subgroups of Exporters

	VA (1)	LP (2)	TFP (3)	VA (4)	LP (5)	TFP (6)
Always	1.787***	0.380***	0.510***	0.262***	0.172***	0.118***
	(0.07)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)
Start Before	0.766***	0.234***	0.255***	0.267***	0.166**	0.127**
	(0.20)	(0.08)	(0.07)	(0.08)	(0.07)	(0.05)
Start After	1.119***	0.276***	0.340***	0.312***	0.145**	0.121**
	(0.17)	(0.07)	(0.06)	(0.10)	(0.07)	(0.05)
Rand Export	1.167***	0.280***	0.341***	0.176***	0.141***	0.084**
	(0.10)	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)
Rand Not export	0.644***	0.116***	0.170***	0.063	0.04	0.023
	(0.10)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
Stop Before	0.973***	0.06	0.198**	-0.092	-0.103	-0.086
	(0.19)	(0.08)	(0.08)	(0.12)	(0.09)	(0.07)
Stop After	0.627***	0.054	0.104	-0.123	-0.074	-0.104
	(0.23)	(0.13)	(0.11)	(0.16)	(0.12)	(0.10)
Observations	13672	13672	13672	13672	13672	13672
R-squared	0.33	0.2	0.42	0.8	0.27	0.58

The dependent variable is in logs and the independent variable is a dummy variable for export subgroup.
All the regressions include dummy variables for years and economic branch.
Columns 4, 5 and 6 also include the size of the firm measured as labor in the first observed year and the age of the firm.
Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6.1 : Test for Differences Between Different Sub-Types of Exporters

	Always	Start Before	Start After	Rand Export	Rand Not export	Stop Before
Start Before	0.87					
Start After	0.96	0.91				
Rand Export	0.35	0.48	0.54			
Rand Not export	0.00	0.07	0.08	0.07		
Stop Before	0.00	0.01	0.02	0.03	0.13	
Stop After	0.02	0.03	0.03	0.06	0.19	0.82

P values from tests of differences in the coefficients.

The coefficients that were tested are from the estimation of TFP on exporters groups with control for the firm's size and age.

Table 7 : Productivity Growth Differences Between Subgroups of Exporters

	VA (1)	LP (2)	TFP (3)	VA (4)	LP (5)	TFP (6)
Always	0.029**	0.027***	0.034***	0.027**	0.006	0.016**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Start Before	0.066**	0.002	0.024	0.066**	0.001	0.023
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Start After	0.057***	0.064***	0.041**	0.057***	0.054***	0.033**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Rand Export	-0.002	0.009	0.008	-0.001	-0.004	-0.002
	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Rand Not export	0.04	0.089**	0.026	0.04	0.069	0.009
	(0.05)	(0.05)	(0.03)	(0.05)	(0.04)	(0.03)
Stop Before	0.02	0.025**	0.021**	0.019	0.017	0.014
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Stop After	0.003	0.012	0.014	0.001	-0.001	0.002
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Observations	9179	9179	9179	9179	9179	9179
R-squared	0.02	0.01	0.02	0.02	0.02	0.02

The dependent variable is in diff-logs and the independent variable is a dummy variable for export subgroups.

All the regressions include dummy variables for years and economic branch and productivity in t-2.

Columns 4, 5 and 6 also include the size of the firm measured as labor in the first observed year and the age of the firm.

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8 : ATT Estimation Using Matched Control Group

Start to Export Time Line	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5
Level	-0.047**	-0.058	-0.029***	-0.021	-0.015	0.019	0.009	0.067	0.061***	0.119***	0.142***	0.137***
	(0.023)	(0.041)	(0.010)	(0.017)	(0.034)	(0.029)	(0.029)	(0.056)	(0.022)	(0.041)	(0.028)	(0.015)
Year to year growth	0.006	0.011	0.0135**	0.005	0.012	0.021	0.024	0.027	0.0315***	0.0435**	0.048***	0.045
	(0.011)	(0.016)	(0.006)	(0.008)	(0.047)	(0.032)	(0.021)	(0.018)	(0.012)	(0.022)	(0.012)	(0.045)
Change from pre-export year	-0.067***	-0.077	-0.049***	-0.040	-0.012	0	0.024	0.048	0.042**	0.100	0.122***	0.118***
	(0.014)	(0.051)	(0.016)	(0.033)	(0.047)	.	(0.021)	(0.063)	(0.019)	(0.061)	(0.025)	(0.018)

Bootstrapped standard errors in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

$$\widehat{\alpha}_{s,LEV}^{MDID} = \frac{1}{N}\sum_{i\in T_t}\left\{\omega_{is}^T - \sum_{j\in C} w_{ij\tau}\omega_{js}^C\right\} \text{ for the level effect}$$

$$\widehat{\alpha}_{s,YTY}^{MDID} = \frac{1}{N}\sum_{i\in T_t}\left\{\left(\omega_{is}^T - \omega_{is-1}^T\right) - \sum_{j\in C} w_{ij\tau}\left(\omega_{js}^C - \omega_{js-1}^C\right)\right\} \text{ for the year-to-year growth}$$

$$\widehat{\alpha}_{s,YT(\tau-1)}^{MDID} = \frac{1}{N}\sum_{i\in T_t}\left\{\left(\omega_{is}^T - \omega_{i\tau-1}^T\right) - \sum_{j\in C} w_{ij\tau}\left(\omega_{js}^C - \omega_{j\tau-1}^C\right)\right\} \text{ for the change from pre-exporting year}$$

where s is the "Start to Export Time Line" and τ is the first year the firm export ($\tau = \{t; s = 0\}$).

Table 9 : Export Premium Estimation Using GMM

	OLS		FE		LEVEL - GMM		DIF - GMM		SYS - GMM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged VA	0.675***	0.673***	0.104***	0.104***	0.672***	0.695***	0.364***	0.355***	0.425***	0.432***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.09)	(0.09)	(0.07)	(0.07)	(0.05)	(0.05)
Labor	0.803***	0.803***	0.795***	0.794***	0.609***	0.650***	0.786***	0.782***	0.809***	0.823***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.17)	(0.17)	(0.11)	(0.11)	(0.04)	(0.04)
Lagged Labor	-0.559***	-0.562***	-0.089***	-0.088***	-0.380**	-0.446***	-0.232***	-0.219***	-0.282***	-0.294***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.17)	(0.16)	(0.06)	(0.06)	(0.04)	(0.04)
Capital	0.244***	0.244***	0.229***	0.229***	0.321***	0.307***	0.174***	0.174***	0.217***	0.218***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)
Lagged Capital	-0.118***	-0.118***	-0.001	-0.001	-0.146***	-0.147***	-0.075***	-0.072***	-0.065***	-0.066***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Firm's Age	0.001***	0.001***	0.010***	0.011***	1.537***	1.434***	-0.002	-0.001	2.667***	2.566***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.44)	(0.41)	(0.00)	(0.00)	(0.21)	(0.21)
Lagged Firm's Age	0	0	0	0	-1.539***	-1.435***	0	0	-2.670***	-2.568***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.44)	(0.41)	(0.00)	(0.00)	(0.21)	(0.20)
Lagged export		0.030***		-0.011		0.066**		-0.163***		-0.004
		(0.01)		(0.02)		(0.03)		(0.05)		(0.03)
Observations	11316	11316	11316	11316	11316	11316	11316	11316	11316	11316
Hansen's test					0.450	0.110	0.000	0.000	0.000	0.000
AR1					-4.40	-4.39	-5.74	-5.76	-5.17	-5.27
P-value AR1					0.00	0.00	0.00	0.00	0.00	0.00
AR2					2.24	2.27	2.22	2.08	2.20	2.24
P-value AR2					0.03	0.02	0.03	0.04	0.03	0.03
AR3					-0.21	-0.29	-0.56	-0.32	-0.22	-0.04
P-value AR3					0.83	0.78	0.58	0.75	0.83	0.97

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9.1 : Export Premium Estimation Using GMM and Allowing for Measurements Errors

	LEVEL - GMM		DIF - GMM		SYS - GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged VA	0.568***	0.622***	0.398***	0.358***	0.470***	0.512***
	(0.12)	(0.11)	(0.12)	(0.11)	(0.08)	(0.08)
Labor	0.710***	0.665***	1.225***	1.259***	1.206***	1.213***
	(0.23)	(0.22)	(0.21)	(0.21)	(0.17)	(0.17)
Lagged Labor	-0.35	-0.358	-0.852***	-0.759***	-0.677***	-0.722***
	(0.24)	(0.22)	(0.25)	(0.24)	(0.20)	(0.20)
Capital	0.284***	0.280***	0.07	0.075	0.198***	0.206***
	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)	(0.03)
Lagged Capital	-0.135***	-0.145***	-0.145***	-0.135***	-0.107***	-0.121***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Firm's Age	2.061***	1.814***	-0.002	0.003	2.414***	2.208***
	(0.54)	(0.48)	(0.01)	(0.01)	(0.34)	(0.35)
Lagged Firm's Age	-2.065***	-1.817***	0	0	-2.416***	-2.209***
	(0.54)	(0.48)	(0.00)	(0.00)	(0.34)	(0.35)
Lagged export		0.063*		-0.610***		-0.01
		(0.04)		(0.23)		(0.07)
Observations	11316	11316	11316	11316	11316	11316
Hansen's test	0.36	0.33	0.10	0.14	0.23	0.29
AR1	-4.99	-5.13	-5.64	-5.67	-6.21	-6.26
P-value AR1	0.00	0.00	0.00	0.00	0.00	0.00
AR2	2.65	2.76	2.22	2.08	2.36	2.51
P-value AR2	0.01	0.01	0.03	0.04	0.02	0.01
AR3	-0.33	-0.38	-0.56	-0.32	-0.22	-0.04
P-value AR3	0.74	0.71	0.58	0.75	0.83	0.97

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

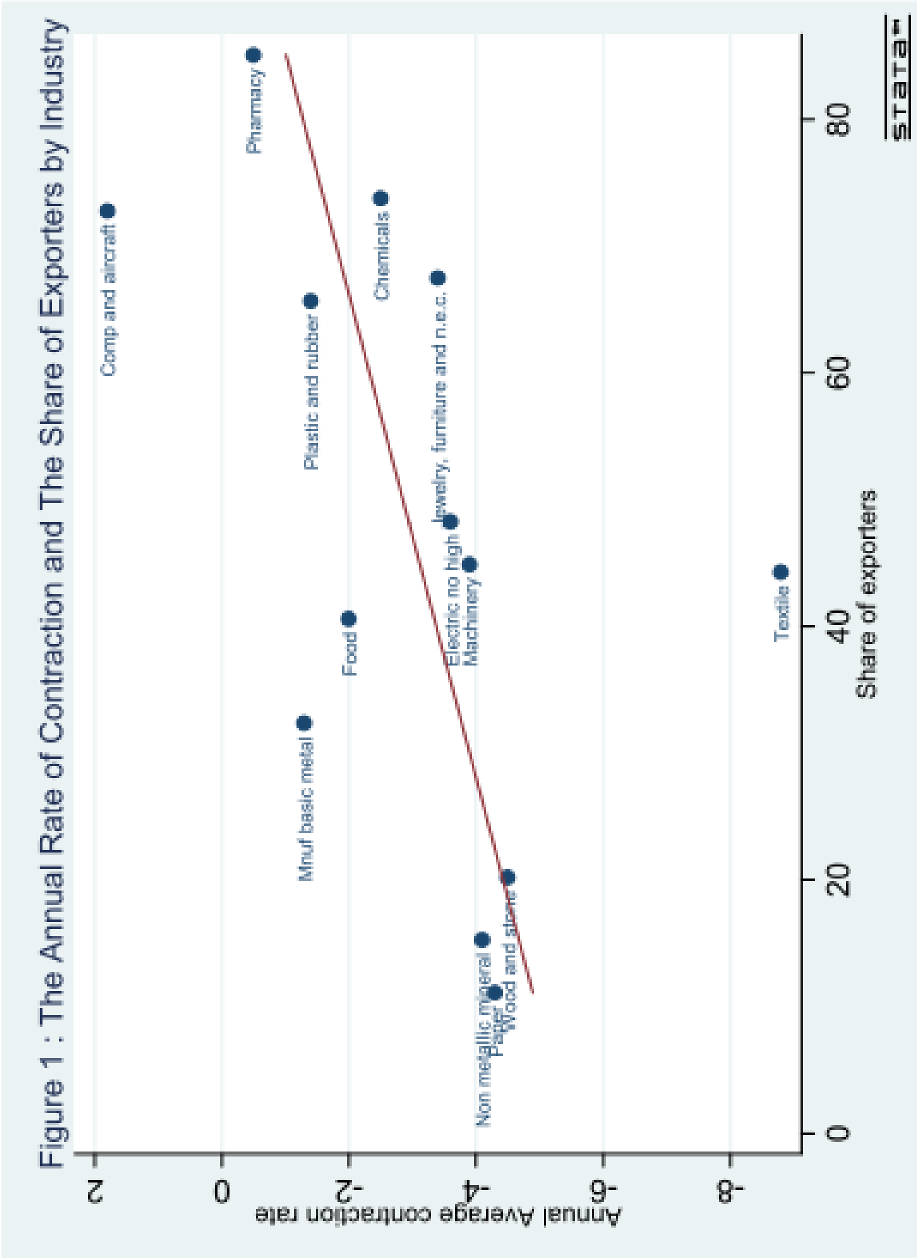

Figure 1 : The Annual Rate of Contraction and The Share of Exporters by Industry

Figure 2 : Firm Distribution By Export Status