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NETWORKS AND SPILLOVERS IN SOFTWARE IN ISRAELI HI-TECH

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Abstract

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Networks and Spillovers in Software in Israeli Hi-Tech

January 15, 2019

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A large literature has used patent data to measure knowledge spillovers across inventions but has not explicitly considered the collaboration networks formed by inventors as a mechanism for shaping these knowledge flows. Using a recently developed methodology, we examine the incidence and nature of knowledge flows mediated by the collaboration networks of inventors. We apply this methodology to three sectors in which programming skills are vital: (i) Information and Communication Technology/Information Security (ICT/IS) (ii) Financial Technology (Fin-Tech,) and (iii) Medical Technology (Med-Tech.) These are all areas of innovation in which Israel should have a comparative advantage.

We find the following: (I) the quality of the Israeli ICT/information security inventions is systematically linked to the structure of the collaborative network. In particular, we find positive and significant direct and indirect knowledge spillovers. (II) We find no evidence of such spillovers in either Fin-Tech or Med-Tech.

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1. Introduction

High-tech R&D is typically done by teams. Working in teams necessarily involves exchanging ideas and sharing information. Participants of such research teams carry this knowledge to other teams and other projects in which they are involved or become involved. Interestingly, though a great deal of research has focused on measuring knowledge spillovers in patents, over time and space, little previous research has tried to link knowledge spillovers in the networks formed by inventors' joint work to the quality of patents.

In this paper, we use data on the inventors that appear in patent documents to trace out and construct two-mode networks: (I) a Patent Network and (II) an Inventor Network. In the case of the patent network, the nodes are patents, and two patents are linked if there is a common inventor who works on both patents. In the case of the inventor network, the nodes of this network are the inventors themselves. There is a link between two inventors if they are co-inventors of the same patent.

Using the network data, we then employ a simple model to examine the existence and importance of collaborator network-mediated knowledge spillovers in three areas of innovation using patents granted in the United States to Israeli innovators:

(I) Information and Communication Technology/Information security (ICT/IS)
(2) Financial Technology (Fin-Tech)
(3) Medical Technology (Med-Tech)

These are all areas of innovation that require computer science expertise and programming skills, areas in which Israel should have a comparative advantage. In the analysis, we use data from the United States Patent and Trademark Office (USPTO.)

Using the theoretical model we present, we then regress patent invention quality, measured by the total number of forward citations, on network centrality measures within the patent network at the time when the patent application was submitted. We control for other characteristics of the patent.

We find that the quality of the Israeli ICT/information security inventions is systematically linked to the structure of the collaborative network. In particular, we find positive and significant direct and indirect knowledge spillovers. Further, the spillovers are stronger when we restrict ourselves to patents in the narrow IS/ICT network, that is patents that do not also fall into Med-Tech or Fin-Tech. We find no evidence of spillovers in either Fin-Tech or Med-Tech.

One possible explanation for our results is that the connected networks formed in Elite Israel Defense Force (IDF) units, such as the well-known Unit 8200, play an important role in seeding successful ICT/IS startups in Israel by creating a connected network of programmers. Unit 8200, a military intelligence unit focusing on signal intelligence and code decryption, is the largest unit in the Israel Defense Forces, comprising several thousand soldiers.[1] Once they leave the military, 8200 veterans use the network of 8200 veterans to found start-ups and develop ICT/IS technologies based in part on their experience and connections in the military.[2] Such effects are not likely present in the Med-tech and Fin-tech categories.

1.1 Literature Review

With the exception of Gandal, Kunievsky, and Branstetter (2018,) which we discuss below, no previous studies in the economics literature have examined the impact of inventors' collaboration network traced out by coinventions (that is, inventors appearing together previously on the same patent document) on knowledge flows and invention quality.

This omission in the innovation literature is striking given the significant attention placed on collaboration networks in economics. Recent studies have examined the relationship between network structure and behavior (e.g., Ballester, Calvó-Armengol, & Zenou, 2006; Calvo-Armengol & Jackson, 2004; Goyal, van der Leij and Moraga-Gonzalez, 2006; Jackson & Yariv, 2007; Karlan, Mobius, Rosenblat, & Szeidl, 2009) and the relationship between network structure and performance (Ahuja, 2000; Calvó-Armengol, Patacchini, & Zenou, 2009,

[1] See Idan Tendler, "From the Israeli Army Unit 8200 to Silicon Valley," 23 March 2015, available at https://techcrunch.com/2015/03/20/from-the-8200-to-silicon-valley/
[2] It is claimed that 70 percent of successful Israeli startups are led by 8200 graduates. See "from "High-tech elites to nurture Arab-Israeli startups,"17.4.2016, available at http://www.israel21c.org/high-tech-elites-to-nurture-arab-israeli-startups/.

Fershtman and Gandal (FG 2011), and Gandal and Stettner, 2016). Gandal, Kunievsky, and Branstetter (2018) were the first to apply the FG (2011) methodology to patents. They did the analysis for the case if ICT/IS patents; this paper extends their analysis for Med-tech and Fin-tech across different software fields. Our results suggest that spillovers are not universal across all "software" industries.

2. Theoretical Foundations for Network-Mediated Knowledge Spillovers

Network-mediated knowledge spillovers can be either direct or indirect. In the case of network-mediated spillovers between patented inventions, *direct* spillovers occur when two patented inventions have a common inventor who transfers knowledge from one patent to another. That is, an inventor takes the knowledge that he/she acquired while working on a previously patented invention and implements it in another invention. However, knowledge may also flow between invention teams even if they are not directly connected by a common inventor. The indirect route occurs whenever an inventor learns something from participating in one invention, takes the knowledge to a second invention and "shares" it with another inventor on that invention team, who, in turn, uses it when she works on a third invention. In such a scenario, knowledge flows from the first patent to the third patent, even though they do not have any inventors in common. Clearly, such indirect spillovers may be subject to decay depending on the distance (the number of the indirect links) between the patents.

Fershtman and Gandal (FG 2011) show theoretically that when there are project spillovers that decrease with decay, there should be a positive correlation between project success and project *closeness centrality*, which is defined as the inverse of the sum of all distances between the project and all other projects. Closeness centrality measures how far each project is from all the other projects in the network.

2.1 A Formal Model for Exploring Network-Mediated Knowledge Spillovers

As discussed, the academic literature has frequently used forward patent citations as a measure of invention quality. Following this convention, we assume that the quality (denoted S_i) of each patent "*i*" is closely related to its count of forward citations, i.e., the citations received from subsequently granted patents. As is typical, we exclude self-citations (both to assignees and to inventors.) We write:

$$(1)\ S_i = X_i\,\omega + \varepsilon_i$$

where X_i is a vector of observable patent characteristics, ω is a vector of parameters to be estimated, and ε_i is an error term.

We define two patents to be linked if they have an inventor in common. Similarly, we define two inventors to be connected if they work together on a patent.

We focus on national networks. A patent is defined to be from a country if all its inventors are residents of that country, i.e., all inventors have an address in that country on a given patent document.

We now present a simplified version of the FG (2011) model. The model assumes that each patent *i* may enjoy positive spillovers from patents that are directly connected and patents that are indirectly connected, but that these spillovers are subject to decay that increases as the distance between the patents - that is, the number of intervening connections - in the patent network increases. Formally when the distance between patent *i* and *j* is $d(i,j)$, we assume that the quality of each patent is $\gamma/\sum_j d(i,j)$ where γ is the magnitude of the spillover.[3]

Under this assumption, the quality of each patent *i* can be written

$$(1)\ (2) \qquad S_i = X_i\omega + \frac{\gamma}{\Sigma_j d(i,j)} + \varepsilon_i$$

Formally, closeness centrality is the inverse of the sum of all the (shortest) distances between a focal patent and all other patents multiplied by the number of other patents. Closeness centrality measures how far each patent is from all the other patents in a network and is calculated as:

[3] For two patents that are directly connected (that is, share an inventor in common), d(i,j) = 1. For two patents that are indirectly linked via a third patent, d(i,j) = 2.

$$(3) \qquad C_i \equiv \frac{(N-1)}{\sum_{j \in N} d(i,j)},$$

where N is the number of patents and $d(i,j)$ is the shortest distance between patents i and j, as measured by the network of coinventions traced out in patent documents. Patents that indirectly link to a large number of other patents have a higher closeness centrality measure than patents near or at the edge of a network. (See Freeman (1979), pp. 225-226.)

Using (3), the expression for closeness centrality, patent i's success can be rewritten as

$$(4) \qquad S_i = X_i\omega + \gamma \frac{C_i}{N-1} + \epsilon_i$$

Hence, for each patent (denoted "i"), we calculate the cited patent's closeness centrality. By construction, we only consider the possibility of *intra*national knowledge spillovers, because our networks are based on co-inventions between inventors who "meet" in Israel.[4] The closeness centrality measure is only defined within groups of patents that are actually connected to each other by common inventors. For that reason, following the usual practice in the network literature, we will focus our analysis on the largest single group of patents within Israel that are connected to a common network. This is referred to in the literature as the "giant component." The second largest component is typically significantly smaller.

If controlling for other factors, closeness centrality is significant in explaining the success of a patent, then there are both direct and indirect knowledge spillovers from directly and indirectly connected nodes, and the spillovers decay with distance between the patents.

We need to address the endogeneity issue associated with network formation. High quality patents will attract large numbers of citations from subsequently granted patents. This raises the possibility that the causal linkage between network density and invention quality runs in both directions, with higher quality patents growing a denser network around them after they are invented.

[4] This does not imply the assumed absence of international spillovers but rather the difficulty of tracking inventor networks across countries and our interest in measuring the impact of intranational networks, especially in Israel, on invention quality. To the extent that unmeasured international collaborations raise the quality of invention, our approach is likely to generate a downward-biased estimate of the impact of Israeli inventor networks on inventions quality.

To address this issue, we need to distinguish between the "ex-ante" network that was in effect when the application for the patent was filed, and the "ex-post" network that exists at the end of our data window. To do this, following Gandal, Kunievsky, and Branstetter (2018,) we create, for each patent, the network that exists at the time of the patent filing — meaning that there is a different network for each patent. Logically, this "ex ante" network is the network that could have plausibly raised the quality of the invention.

This methodology (using the "ex-ante" network) solves the endogeneity issue, unless agents (inventors) are forward-looking when forming links with other inventors. In the case of patents, inventors do not typically form links in a forward-looking manner: (I) Patents are generally held by one firm and (II) typically all inventors on a particular patent work at that firm. Virtually no inventor would choose to leave a firm just to apply for a patent with someone else at another firm.

3. Data and Empirical Analysis

In order to begin, we first define the relevant *i* patent classes for the three areas:

- **ICT/IS**: From detailed examination of United States Patent and Trademark Office (USPTO) patent class descriptions, we were able to determine the patent classes relevant for information security innovations, broadly defined. In particular, the USPTO defines patent classes that contain information security patents.[5] We use this definition. Thus, our data include patents outside of information security, but they are likely to encompass the full universe of relevant patents. If we only had used narrow Information Security patents, we would not have enough observations to conduct an econometric analysis. See Appendix A1.
- **Fin-Tech and Med-Tech:** USPTO documentation was not helpful here. We categorized Fin-Tech and Med-Tech (digital medicine) patents by utilizing the International Patent Classification (IPC) code classification system. Like ICT/IS, we use the IPC's broad definition for these classes. Similar, to ICT/IS these data include patents outside digital medicine (Med-Tech) or Fin-Tech, but they are likely to encompass the full universe of relevant patents. In order to identify Fin-Tech and

[5] See https://www.uspto.gov/web/patents/classification/uspc726/defs726.htm, accessed 1 December 2018.

digital medicine patents, we followed a multi-stage process. The first step utilizes the text in the IPC code definitions and considers any IPC codes that explicitly mention any relevant key words, such as “finance” or “payment” in the case of Fin-Tech or “health” or “medicine” in the case of digital medicine. The textual definitions of the IPC classes containing any of these key words were then examined to identify the most relevant. Finally, after narrowing down the set of classes, we examined the IPC classes of patents taken out by top firms in each category to ensure no important categories were missing. These patent classes appear in Appendix A2.

3.1 Descriptive Data

We first examine the data descriptively. We use data from the USPTO, which are patents issued in the US. Overall, there have been 1,145,089 patents issued up through application year 2014 in the areas of ICT/IS, Fin-Tech and Med-Tech. During the same period, there were 12,194 Israeli patents (or slightly more than 1% of all such patents.) These patents are Israeli in the sense that all innovators on the patent had an address in Israel at the time the patent was issued. Table 1 below shows that Israeli patents as a proportion of patents in these areas increased steadily over time.

Additionally, the Table shows that 71% of the Israeli patents in these fields were applied for in the 2005-2014 period. In the rest of the world, 57% of the patents in these categories were applied for in the 2005-2014 period. This illustrates the increased prominence of Israel in these fields. Despite this increase, the “narrative” is that the quality of the Israeli information software patents make them stand out.

Application Year	All patents	Israeli Patents	Percent Israeli
Before 2000	269,953	1,398	0.52
2000-2004	217,969	2,120	0.97
2005-2009	294,218	3,551	1.21
2010-2014	362,949	5,125	1.41
All (through 2014)	1,145,089	12,194	1.06

Table 1. ICT/IS + Fin-Tech + Med-Tech patents through application year 2014

Some patents fall into just one of the three categories, while other patents fall into multiple categories. In the case of Israel, 31% of the patents are Med-Tech only, 22% of the patents are

ICT/IS only, and 9% of the patents are Fin-Tech only. Thus 61% of the Israeli patents in these fields do not overlap into another field. (See Table 2.)

Overall, 68% of the patents in the "rest of the world" do not overlap into another field. See Table3. Thus, Israeli "software" patents are more interdisciplinary in some sense. Fully 18% of the Israeli patents fall into both Fin-Tech and Med-Tech fields, while 13% of all patents fall into both Fin-Tech and Med-Tech fields.

Application Year	% Med-Tech Only	% ICT/IS only	% Fin-Tech Only	Percent Mixed
Before 2000	0.41	0.29	0.02	0.28
2000-2004	0.30	0.29	0.03	0.38
2005-2009	0.28	0.26	0.07	0.39
2010-2014	0.31	0.11	0.16	0.42
All (through 2014)	0.31	0.21	0.09	0.39

Table 2. Israel: Distribution of ICT/IS + Fin-Tech + Med-Tech patents (through 2014)

Application Year	% Med-Tech Only	% ICT/IS only	% Fin-Tech Only	Percent Mixed
Before 2000	0.30	0.46	0.04	0.20
2000-2004	0.21	0.36	0.10	0.33
2005-2009	0.22	0.30	0.13	0.35
2010-2014	0.30	0.12	0.20	0.38
All (through 2014)	0.26	0.30	0.13	0.31

Table 3. World: Distribution of ICT/IS + Fin-Tech + Med-Tech patents (through 2014)

We then collected data from the USPTO on all of these patents. Our data include the number of forward citations, backward citations (citations made to previously granted patents), grant year, application year, location of inventor (hence we know whether the inventor(s) are Israeli), number of inventors, and the assignee (owner) of the patent.

For each patent in each of the three categories, we calculate its proximity to other patents in the network, where the links are through inventors. We then calculate the closeness centrality of these patents within the network, in a manner defined below.

Typically, over time networks are characterized by one giant component and many other smaller components. Closeness centrality is only defined for connected nodes. Because we construct the patent network (for each patent) at the time the patent was applied for, we need to have a large enough existing giant component of connected patents already in existence. Hence, we begin the empirical analysis with patents that were applied for in 2006 or later. (We have patent data through 2014.)

Since we have two networks (a patent network and an inventor network,) we can construct a giant component in two ways:

- Using the patent network (where two patents are linked if they have an inventor in common)
- Using the inventor network, where two inventors are linked in they work together on a patent. Since the analysis is done at the level of the patent, we then take the average closeness value of the inventors (from the inventor network) for each patent, using the patents that are in the giant component connected via the inventor network.
- Most, but not all patents are in both giant components. Hence, we will have two sets of descriptive statistics and two sets of regressions. Both sets of analysis are at the level of the patent. The results are qualitatively the same, regardless of how we do this. [6]

For these patents, all inventors had an address in Israel. We exclude patents with both Israeli inventors and inventors from other countries (primarily the US) from the main analysis, since we want to focus on the local network.

The variables used in the analysis are

[6] It is also possible to use the average closeness of the inventors from the inventor giant component – and do the analysis using the patent giant component. Additionally, we could take the maximum value of closeness of the relevant inventors on a patent, rather than the average. The results are qualitatively unhanged when using these alternative specifications.

- Number of Forward Citations “no self-citations” (that is forward citations excluding forward citations from the same inventor and same assignee
- Application Year[7]
- Number of Backward Citations received by the Patent
- Number of Inventors on the Patent
- Closeness Centrality

Descriptive Statistics appear below.

3.2 Summary Measures on Patents Using Inventor Giant Component

In the case of ICT/IS, descriptive statistics appear in Table 4a; Fin-Tech descriptive statistics appear in Table 4b, and Med-Tech descriptive statistics appear in Table 4c.

	# of Obs.	Mean	Std. Dev	Min	Max
Forward Citations – “No self cites”	874	1.45	5.76	0	64
Application Year	874	2009.78	1.83	2006	2014
# of inventors	874	2.78	1.49	1	11
Backward Citations	874	33.82	80.17	0	548
Closeness Centrality	874	0.00012	0.000074	0.000044	0.00064

Table 4a: Descriptive Statistics – Giant Component – IS/ICT - Inventor Giant Component

	# of Obs.	Mean	Std. Dev	Min	Max
Forward Citations – “No self cites”	766	0.093	0.89	0	17
Application Year	766	2012.23	1.66	2006	2014
# of inventors	766	3.07	1.59	1	11
Backward Citations	766	15.02	35.06	0	366
Closeness	766	0.00025	0.00058	0.000041	.0044

Table 4b: Descriptive Statistics – Giant Component Fin-Tech - Inventor Giant Component

	# of Obs.	Mean	Std. Dev	Min	Max
Forward Citations – “No self cites”	1,105	0.36	6.69	0	218

[7] We include dummy variables for application year in the regressions, but do not report the estimated coefficients.

Application Year	1,105	2011.98	1.95	2006	2014
# of inventors	1,105	2.70	1.43	1	11
Backward Citations	1,105	33.70	85.74	0	823
Closeness	1,105	0.00014	0.00026	0.0000010	0.0016

Table 4c: Descriptive Statistics – Giant Component Med-Tech - Inventor Giant Component

3.3 Summary Measures on Patents Using Patent Giant Component

In the case of ICT/IS, descriptive statistics appear in Table 5a; Fin-Tech descriptive statistics appear in Table 5b, and Med-Tech descriptive statistics appear in Table 5c.

	# of Obs.	Mean	Std. Dev	Min	Max
Forward Citations – "No self cites"	857	1.45	5.81	0	64
Application Year	857	2009.82	1.85	2007	2014
# of inventors	857	2.77	1.49	1	11
Backward Citations	857	34.28	80.89	0	548
Closeness Centrality	857	.00010	.000051	.000034	.00024

Table 5a Descriptive Statistics – Giant Component – IS/ICT - Using Patent Giant Component

	# of Obs.	Mean	Std. Dev	Min	Max
Forward Citations – "No self cites"	763	0.081	0.76	0	17
Application Year	763	2012.24	1.61	2008	2014
# of inventors	763	2.91	1.53	1	11
Backward Citations	763	16.30	37.66	0	366
Closeness	763	.00026	.00048	.000024	.0026

Table 5b: Descriptive Statistics – Giant Component Fin-Tech - Using Patent Giant Component

	# of Obs.	Mean	Std. Dev	Min	Max
Forward Citations – "No self cites"	1,153	0.41	6.56	0	218
Application Year	1,153	2011.67	2.08	2006	2014
# of inventors	1,153	2.73	1.48	1	11
Backward Citations	1,153	36.07	92.97	0	823

Closeness	1,153	.000193	.00033	.000020	.0022

Table 5c: Descriptive Statistics – Giant Component Med-Tech - Using Patent Giant Component

4. Estimation and Results

We now estimate equation (4) which we repeat below

$$(4)\ S_i = X_i\omega + \gamma \frac{C_i}{N-1} + \epsilon_i$$

Recall that S_i, the number of forward citations received by a given patent, is our measure of quality. We exclude self-citations and citations made by patents from the same assignee and the same inventor. We further assume that the number of forward citations received by patent i depends on a vector of observable factors, denoted X_i. C_i is the *closeness centrality* of patent *i* in the Israeli network and γ is the parameter associated closeness. We use the existing network for each patent (at the time the application was submitted.)

Citations are highly skewed; additionally, some of the independent variables (like the number of inventors) are also highly skewed. Hence, it makes sense to use logarithms and employ the log/log specification. The term "ln" before the variable means natural log. The dependent variable used in the regressions in Tables 6 and 7 is the natural log of forward citations excluding citations from the same inventor and assignee. Since some patents receive no forward citations, following a common practice in the patents literature, we will add one to the number of forward citations and take the natural log of this transformed variable.

Results Using Patent Component Giant Component:

Table 6 displays our results when we used the giant component formed by the Patent Network. Column 1 shows the results for the ICT/IS patents. The estimated coefficient on closeness (γ) is positive and significant at the 1% level, suggesting that there are both direct and indirect knowledge spillovers from ex-ante "connections" in the giant component. Recall that the coefficient on closeness (γ) captures both direct and indirect spillovers.[8]

[8] We include dummy variables for application year in all regressions, but do not report the coefficient estimates for these variables. "ln" before the variable means natural log.

In columns 2 and 3, we repeat the analysis in column 1 for Fin-Tech and Med-Tech. As Table 6 shows, we find no evidence of knowledge spillovers in Fin-Tech and Med-Tech.

The results in columns 1-3 are for the broadly defined categories. Hence, they include some overlapping patents. When we repeat the analysis for the narrowly defined networks, we find that in the case of ICT/IS, the estimated coefficient on closeness centrality is 0.32 for the narrow ICT/IS network vs. 0.22 for the case of the broad ICT/IS network. This suggests stronger spillovers in the narrowly defined networks for ICT/IS patents. In the case of narrowly defined Fin-Tech and Med-Tech sectors, there are no knowledge spillovers, which is what we found for the broadly defined networks.

	IS/ICT broadly defined	Fin-Tech broadly defined	Med-Tech broadly defined
Dependent Variable	ln(Forward_Citations)	ln(Forward_Citations)	ln(Forward_Citations)
	coefficient (std. error)	coefficient (std. error)	coefficient (std. error)
Independent Variables			
ln(# of Inventors)	-0.026 (0.040)	0.026 (0.014)*	0.030 (0.018)*
ln(Backward Cites)	0.11 (0.016)***	-0.0028 (0.0060)	0.0058 (0.0092)
ln(Closeness)	0.22 (0.089)***	0.0075 (0.0091)	0.040 (0.033)
Adjusted R^2	0.27	0.21	0.23
Observations	857	763	1,153

Table 6: Regression Analysis using Patent Giant Component[9]

Results Using Patent Inventor Component:

We then repeat the analysis for the giant component formed by the Inventor Network. Table 7 displays our results. Column 1 shows the results for the ICT/IS patents. Again, as in Table 6, the estimated coefficient on closeness (γ) is positive and significant (here at the 0.08 level,) suggesting that there are both direct and indirect knowledge spillovers from ex-ante “connections” in the giant component. In columns 2 and 3, we repeat the analysis in column 1 for Fin-Tech and Med-Tech. As Table 7 shows, we find no evidence of knowledge spillovers in Fin-Tech and Med-Tech.

[9] The dependent variable is the natural log of one plus the number of forward citations. While counting forward citations, we exclude citations made by the patent's inventors other patents, and citations made by other patents that are listed under the patent's assignee. Standard errors appear in the parentheses. (*=significant at 10% level, **=significant at 5% level, ***=significant at 1% level.)

When we repeat the analysis for the narrowly defined networks, we find that in the case of ICT/IS, the estimated coefficient on closeness centrality is 0.26 for the narrow ICT/IS network vs. 0.19 for the case of the broad ICT/IS network. This suggests stronger spillovers in the narrowly defined networks. In the case of narrowly defined Fin-Tech and Med-Tech sectors, there are no knowledge spillovers, which is what we found for the broadly defined networks.

	IS/ICT broadly defined	Fin-Tech broadly defined	Med-Tech broadly defined
Dependent Variable	ln(Forward_Citations)	ln(Forward_Citations)	ln(Forward_Citations)
	coefficient (std. error)	coefficient (std. error)	coefficient (std. error)
Independent Variables			
ln(# of Inventors)	-0.023 (0.040)	0.033 (0.014)**	0.030*(0.017)
ln(Backward Cites)	0.11 (0.016)***	-0.0038 (0.0061)	0.015 (0.0092)*
ln(Closeness)	0.19 (0.11)*	0.027 (0.045)	0.026 (0.016)
Adjusted R^2	0.26	0.23	0.25
Observations	874	766	1,105

Table 7: Regression Analysis using Inventor Giant Component

4. Brief Conclusions

This study seeks to advance the literature by using the pattern of inventor interaction traced out in patent documents to create measures of inventor networks; we go on to empirically measure the association between the location of a patent within this network and the quality of invention as measured by forward citations. We find that the quality of Israeli inventions is systematically related to the location of these patents within the Israeli invention network in the case of ICT/IS, but not for Fin-Tech and Med-Tech. This may in part may be due to the networks formed in the 8200 intelligence unit.

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Appendix A: Patent Classes

A1: Relevant Patent Classes for ICT/Information security:

326, Electronic Digital Logic Circuitry, subclass **8** for digital logic circuits acting to disable or prevent access to stored data or designated integrated circuit structure.

340, Communications: Electrical, subclasses **5.2** through **5.74,** for authorization control without significant data process features claimed, particularly subclasses 5.22-5.25 for programmable or code learning authorization control; and subclasses 5.8-5.86 for intelligence comparison for authentication.

365, Static Information Storage and Retrieval, subclass **185.04** for floating gate memory device having ability for securing data signal from being erased from memory cells.

380, Cryptography, subclasses **200** through **242**for video with data encryption; subclasses 243-246 for facsimile encryption; subclasses 247-250 for cellular telephone cryptographic authentication; subclass 251 for electronic game using cryptography; subclasses 255-276 for communication using cryptography; subclasses 277-47 for key management; and subclasses 287-53 for electrical signal modification with digital signal handling.

455, Telecommunications, subclass **410** for security or fraud prevention in a radiotelephone system.

704, Data Processing: Speech Signal Processing, Linguistics, Language Translation, and Audio Compression/Decompression, subclass **273** for an application of speech processing in a security system.

705, Data Processing: Financial, Business Practice, Management, or Cost/Price Determination, subclass **18** for security in an electronic cash register or point of sale terminal having password entry mode, and subclass 44 for authorization or authentication in a credit transaction or loan processing system.

708, Electrical Computers: Arithmetic Processing And Calculating, subclass **135** for electrical digital calculating computer with specialized input for security.

709, Electrical Computers and Digital Processing Systems: Multicomputer Data Transferring, subclass 225 for controlling which of plural computers may transfer data via a communications medium.

710, Electrical Computers and Digital Data Processing Systems: Input/Output, subclasses **36** through **51**for regulating access of peripherals to computers or vice-versa; subclasses 107-125 for regulating access of processors or memories to a bus; and subclasses 200-240 for general purpose access regulating and arbitration.

711, Electrical Computers and Digital Processing Systems: Memory, subclass **150** for regulating access to shared memories, subclasses 163-164 for preventing unauthorized memory access requests.

713, Electrical Computers and Digital Processing Systems: Support, subclasses **150** through **181**for multiple computer communication using cryptography; subclasses 182-186 for system access control based on user identification by cryptography; subclass 187 for computer program modification detection by cryptography; subclass 188 for computer virus detection by cryptography; and subclasses 189-194 for data processing protection using cryptography.

714, Error Detection/Correction and Fault Detection/Recovery, subclasses **1** through **57**for recovering from, locating, or detecting a system fault caused by malicious or unauthorized access (e.g., by virus, etc.).

726 Protection of data processing systems, apparatus, and methods as well as protection of information and services.

A2: Relevant Patent Classes for Fin-Tech and Med-Tech:

	Fin-Tech	Med-Tech
IPO Patent Classes	G06Q 20 G06Q 40 G06Q 30 G06F 3 G06F 12 G06F 17 G06F 21 H04L	A61B G01T G06F 3 G06F 11 G06F 17 G06F 19 G16H G0Q 50 G06T H04B H04L H04M H04Q H04W