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International Trade and Foreign Direct Investment as Innovation Factors of the U.S. Economy

Abstract

The aim of this research is to asses the hypothesis that foreign direct investment (FDI) and international trade have had a positive impact on innovation in one of the most significant economies in the world, the United States (U.S.). To do so, the author used annual data from 1995 to 2010 to build a set of econometric models. In each model, 11 in total) the number of patent applications by U.S. residents is regressed on inward FDI stock, exports and imports of the economy as a collective, and in each of the 10 SITC groups separately.

Although the topic of FDI is widely covered in the literature, there are still disagreements when it comes to the impact of foreign direct investment on the host economy [McGrattan, 2011]. To partially address this gap, this research approaches the host economy not only as an aggregate, but also as a sum of its components (i.e., SITC groups), which to the knowledge of this author has not yet been done on the innovation-FDI-trade plane, especially for the U.S.

Unfortunately, the study suffers from the lack of available data. For example, the number of patents and other used variables is reported in the aggregate and not for each SITC groups (e.g., trade). As a result, our conclusions regarding exports and imports in a specific SITC category (and the total) impact innovation in the U.S. is reported in the aggregate.

General notions found in the literature are first shown and discussed. Second, the dynamics of innovation, trade and inward FDI stock in the U.S. are presented. Third, the main portion of the work, i.e. the econometric study, takes place, leading to several policy applications and conclusions.

Keywords: FDI, innovation, foreign trade
JEL: F21, O30

Topic Overview

International trade has existed since nations were conceived, and the concept of FDI as a valid contributor to economic development traces back to at least 2500 B.C. [Lipsey, 2001]. This study looks at the years 1995 to 2010 in the U.S., which is encompasses two rallies and two harmful recessions.

Branstetter [2004] has oserved that trade and FDI impact domestic innovation via spillovers, noting that "recent empirical work has examined the extent to which international trade fosters international 'spillovers' of technological information... with... FDI... as an alternative, potentially equally important channel for the mediation of such knowledge spillovers."

Vahter[2], consistent with other researchers [e.g., Nunnenkamp, 2002], states that "the larger is the technology gap of domestic firms the lower is the possibility of spillovers" [2010]. This becomes clear upon considering that that in order for the spillover to take place there needs to be some infrastructure already in place, i.e., "pre-conditions" [Nunnenkamp, 2002]. It is crucial to recognize that the U.S. is a special case, as a vast number of investors and traders coming from abroad are less developed economies. For example, as of 2011 (according to WIPO[3]) in the number of patents, or patents per GDP, the U.S. is surpassed only by China. Remembering that, it is important to understand that U.S. does not have a monopoly on innovation and can learn from countries generally less developed but having a core competency that the U.S. lacks.

In general[4], it is hard to understate the benefits (e.g., on economic growth) flowing from trade. Exports not only facilitate new markets, but may also lead to resource and process expansions. With imports come new competition, new goods and new practices that benefit domestic customers by adding consumption diversity and forcing domestic firms to become more competitive, be it on quality or on price. In short, "trade exposes domestic firms to the best practices of foreign firms and to the demands of discerning customers, encouraging greater efficiency" [Schneider, 2005] that is achieved via some form of innovation, be it through product, or process, or both.

The impact of trade on innovation can be divided according to the direction of trade. On the export side, Branstetter [2004] talks about "learning-by-exporting" by which domestic firms, via the channel of exports, interact with foreign economies that may be more advanced as a whole and highly specialized in the goods and services being traded. Regarding imports, Schneider states that "high-technology imports are relevant in explaining domestic innovation both in developed and developing countries" [2005] as, e.g., "imported manufactured goods can serve as channels of knowledge spillovers" [Branstetter, 2004].

Moving to FDI, Nunnenkamp states that it is "considered a powerful mechanism to transfer technology and know-how to host countries" [2002]. As for its impact, it is said that FDI "can benefit innovation activity in the host country via spillover channels such as reverse engineering, skilled labor turnovers, demonstration effects, and supplier-customer relationships" [Cheung, Lin, 2003].

Given these dynamics, two questions arise. One question is why, from an innovation point of view, do less developed economies invest in the U.S.? An answer is suggested in the results of Pottelsberghe de la Potterie and Lichtenberg, which describe the FDI as "tak[ing] on the characteristics of a 'Trojan horse'; [as] they are intended more to take advantage of the technology base of the host countries than to diffuse the technological advantage originating in the home country. This 'technology boomerang' feature emerged mainly during the eighties" [2000].

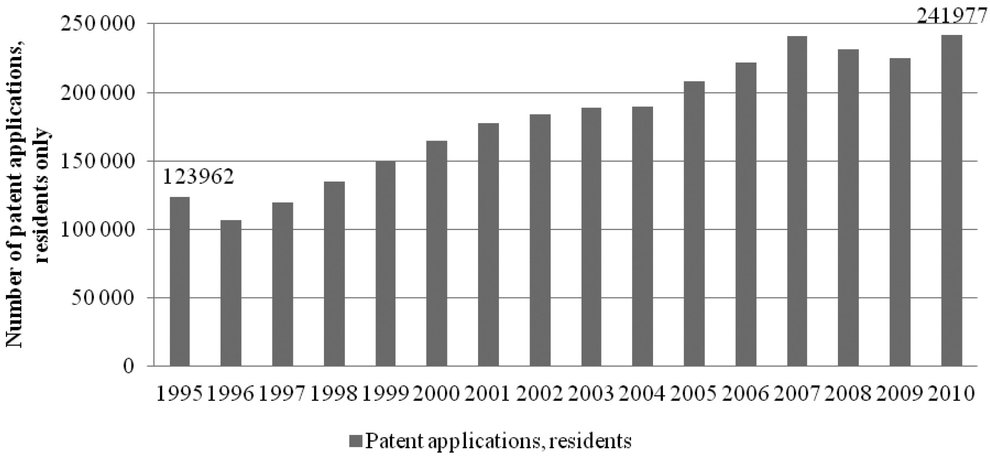
The second question is – if the U.S. as a host is more developed than the home economy, why should inward FDI have an impact on the home economy's innovation capacity? The work of Cheung and Lin suggest an answer; that is, the "positive effect of FDI on the number of domestic patent applications in China" [2003], a country that has a higher number of patents (and patents per GDP) than the U.S. This finding further supports the notion that generally better developed economies can still seek and obtain innovation benefits from less developed investors.

Innovation, International Trade, U.S. National Innovation System and Foreign Direct Investment in the U.S.

This section analyzes the recent trends in patent applications, U.S. foreign trade as well as FDI stock in the U.S.

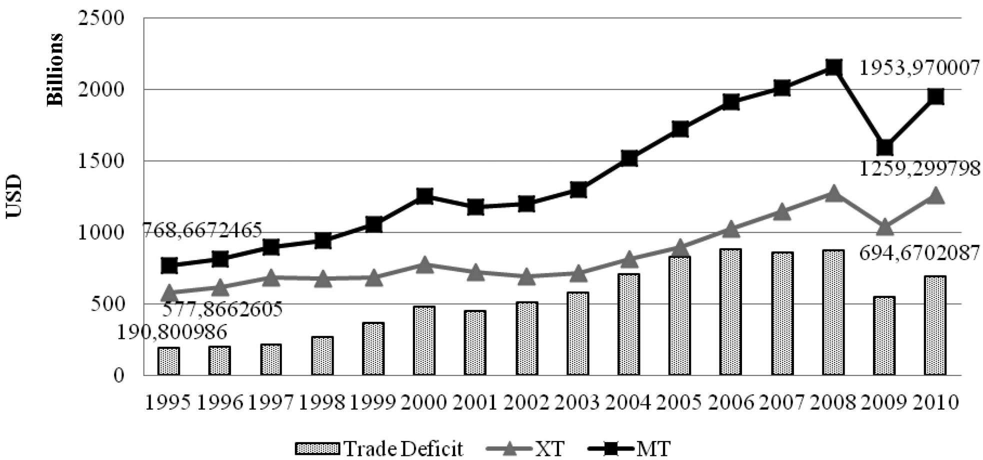
As appears in the graph above, the U.S. has enjoyed an increasing number of patent applications (Graph 1) with only three notable slowdowns over the examined years: in 1996, in 2004 (albeit slight), and a two-year dip from 2008 to 2009. Since the last slowdown coincides with the recent recession, it is unlikely that economic hardship is responsible for this or previous slowdowns. This is truer as the dot-com recession that took place at the turn of the millennium is not reflected in the series. Overall, the number of patent applications has increased from 123,962 (1995) to 241,977 (2005).

GRAPH 1. **U.S. Patent applications by residents (left-hand axis: number of patents)**



Source: Author's own presentation of data from the World Bank.

GRAPH 2. **U.S. exports, imports and trade deficit (left-hand axis: USD)**

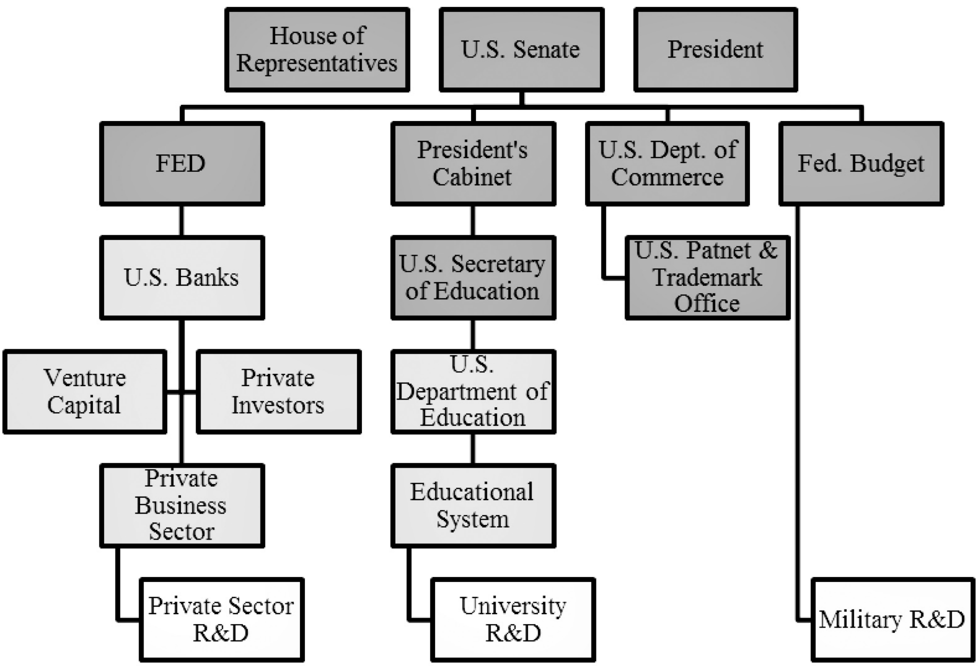


Source: Author's own presentation of data from UN Comtrade.

Both U.S. exports and imports (Graph 2) enjoyed an increase from 1995 (578 billion, $ 769 billion respectively) to 2010 ($ 1,259 billion, $ 1,954 billion). Both series saw a decline at the start of the 21st century, increasing thereafter to their maximum values in 2008 after which a one-year steep decline (attributed to significantly worsening economic conditions in the world) took place, which benefitted the U.S. economy by decreasing its trade deficit (2009).

Looking at exports by SITC classification, U.S. exports are heavily concentrated in the Machinery and Transport Equipment (X7) category, with the Beverages and Tobacco and Animal and Vegetable Oil and Fats (X1 and X4) groups being the least exported. All but the latter two show a significant increase starting around 2000. Generally, this growth was highest in the 2007–2008 period – Commodities and transaction not classified according to kind (X9) group being the exception as it enjoyed its highest growth rate starting in 2008. All export components saw an increase in 2010. Similar, if not identical, trends are seen when looking at U.S. imports according to SITC classification.

FIGURE 1. **U.S. National Innovation System**



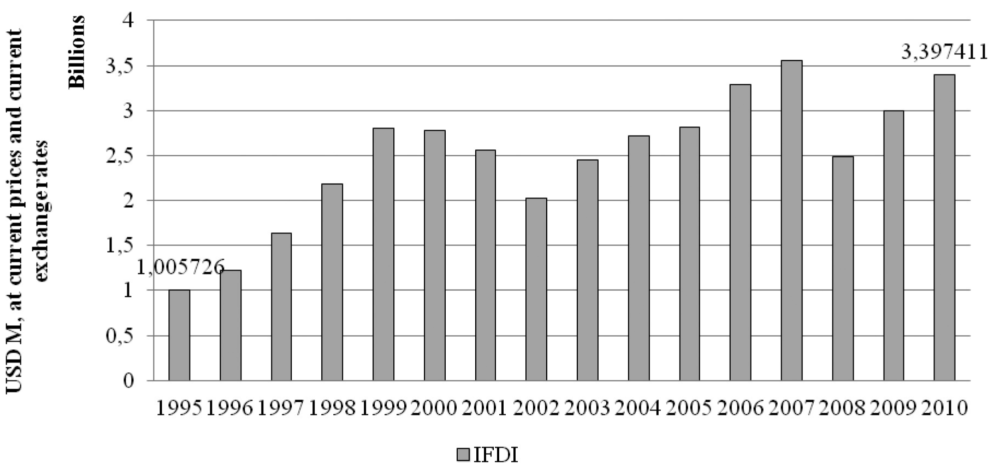
Source: Author's own graphic.

The U.S. National Innovation System (NIS, Figure 1) is considered to be one of the best in the world.[5] Though the main topic of this work, it is a vital component (via the "R&D expenditures" explanatory variable) of models used in later sections. In general, U.S. NIS can be divided into three components: one, the U.S. government, two, the intermediate, or the connecting component, and three, R&D. The first level consists of the main decision-makers (i.e., the House of Representatives, the U.S. Senate and the President) as well as other policymakers (e.g., the U.S. Federal Reserve). The intermediate (connecting) component of the system is comprised of cooperating agents, e.g., U.S. banking policy allows for budget planning by private businesses that work together with the education system. The last level of the system is where R&D activities take place.

Noteworthy is the fact that the U.S. NIS is presented here as trickle-down system whereas, in fact, communication is a two-way via feedback. In addition, to enhance clarity not all connections are shown. Part of a good NIS is a high level of cooperation and communication. Therefore, each of the elements shown is interconnected with all the rest.

It is important to note at this point that this work does not separate between businesses, universities, and think tank-derived patents as there is no data that would allow for such a distinction. Also, military R&D is excluded from this work because it is highly unlikely that inward foreign direct investments and trade have an impact on the level of innovation seen in the U.S. military – which is a highly internalized organization.

GRAPH 3. U.S. inward FDI stock (left-hand axis: U.S. Dollars, USD, at current prices and current exchange rates in millions, M)



Source: Author's own presentation of data from UNCTAD.

Inward FDI stock in the U.S. has been very volatile over the examined period. It reached peaks in 1999 ($ 2.8 million), 2007 ($ 3.55 million) and 2010 ($ 3.4 million) with dips in 2002 ($ 2.02 million) and 2008 ($ 2.5 million). The series is greatly impacted by the economic health of the U.S. (which determines its investment attractiveness) and of the world (which determines the ability of foreign economies to make investments).

Foreign Direct Investment, International Trade – SITC Models of Innovation in the U.S.

In this part of our analysis, an econometric study is conducted for 1995 to 2010 period. The aim of that study is to examine how international trade and inward FDI impact innovation in the U.S., in addition to two staple determinants of innovation – that is, R&D intensity and the stock of human capital, both of which are expected to be positively correlated with the dependent variable [Schneider, 2005].

A proxy for innovation is its output component; that is, the number of patent applications by resident [Narula, Wakelin, 1997].[6] Data was obtained from the World Bank's World Development Indicators database.

Two variables have been collected to represent the concept of human capital; namely, labor force (total, *LFT*)[7] and labor force participation rate (percentage of total population ages 15 plus, *LFP*)[8]. Data for both has been extracted from the World Bank's World Development Indicators database. After examining the two, a decision was made to use the labor force participation rate.[9] The decision is based on the fact that when it has been introduced into the models in place of the *LFT*, the adjusted R-squared has increased significantly.[10] This impact was unexpected as the Pearson correlation coefficient[11] for the labor force participation rate (–0.890) is smaller than the coefficient for the labor force expressed as a total (0.978); both coefficients are highly statistically significant (p-values < 0.000). R&D intensity is represented by research and development expenditure (percentage of GDP)[12], obtained from data from the World Development Indicators database. Data on inward FDI stock (U.S. Dollars, USD, at current prices and current exchange rates in millions, M)[13] comes from UNCTAD's UNCTADSTAT database[14].Finally, U.S. exports and imports are represented according to SITC classification[15] by their relative totals. Data for these trade variables has been collected from UN Comtrade[16] and is presented in USD.

TABLE 1. Hypotheses assigned to used independent variables

Independent Variable	Null Hypothesis	Alternative Hypothesis
Labor force participation rate	$H_0 : \beta_{LFP} = 0$	$H_0 : \beta_{LFP} \neq 0$
R&D expenditures	$H_0 : \beta_{RDSPEND} < 0$	$H_0 : \beta_{RDSPEND} > 0$
Inward FDI stock	$H_0 : \beta_{IFDI} < 0$	$H_0 : \beta_{IFDI} > 0$
Export	$H_0 : \beta_X < 0$	$H_0 : \beta_X > 0$
Import	$H_0 : \beta_M < 0$	$H_0 : \beta_M > 0$

Source: Author's own table.

Using the economic variables presented above, the structural equation for all the models has been created (Equation 1).

Equation 1

$$PATENT_t = \beta_0 + \beta_1 LFP_t + \beta_2 RDSPEND_t + \beta_3 IFDI_t + \beta_4 X_{n,t} + \beta_5 M_{n,t} + \varepsilon_t$$

Source: Author's own equation.

Here, *PATENT* is the dependent variable (i.e., the number of patent applications by residents), *LFP* represents the labor force participation rate, *RDSPEND* means R&D expenditures, *IFDI* stands for inward FDI stock in the U.S. and *X* and *M* represent export and import components, respectively, of U.S. trade with ε being the error term. Subscript t represents the year and subscript n is assigned to trade variables that represents the SITC classification (0, 1... 9, T – total). Coefficients of these time-series models are calculated with the Ordinary Least Squares method. Overall there are 11 models.

Each of the models is evaluated based on the statistical significance of each of its components (i.e. explanatory variables), value of R-squared and Prob.(F-statistic). In addition, every model is tested for the presence of autocorrelation in its residuals (via the Breusch--Godfrey Serial Correlation LM test with H_0: No Autocorrelation) and their normal distribution (via the Jarque-Bera statistic with H_0: Normal Distribution). In terms of the strictness of each test, the ideal level of significance is 5% with 10% also being acceptable.

Statistically, for each model (Appendix 1), all R-squared values are very high (min. value of 0.9273) and all Prob.(F-stat.) are equal to 0.000. Regarding the presence of the autocorrelation, the Prob.F. of the test has been greater than the required 0.05 value. The smallest value, 0.1005, is associated with the residuals of the SITC 3 model. The decision to fail to reject the null hypothesis of no autocorrelation in this case is supported by the value of Durbin-Watson statistic that is equal to 2.039 – which is very close to its ideal value of 2.00. In the SITC 0 model, the problem of autocorrelation has been detected (Prob.F. = 0.0663) and then mended (Prob.F. = 0.3849) by introduction of $PATENT_{t-1}$ as an explanatory variable (its p-value = 0.0022, further justifying the procedure). The coefficients in the models were then adjusted by dividing them by one minus the value of the coefficient of $PATENT_{t-1}$. Residuals for all the models have a normal distribution.

Unfortunately, some models exhibit signs of multicolinearity[17]; that is, high R-squared and high p-values of coefficients of the explanatory variables used. The model for the SITC 7 group is a prime example of that. The only solution for future research is to obtain more observations, i.e., extend the time frame or shift to e.g. quarterly data, which at this point is too short to add more explanatory variables.

Shifting the attention to individual explanatory factors, coefficients of labor force participation are negative for all models (which is in line with the Pearson correlation coefficient, –0.890, p-value < 0.000) and statistically insignificant for SITC 0, 1, 5, 7 and 8.

The negative sign is surprising. One possible reason for this is that two series – *LFP* and the number of patents – diverge with time, with the former decreasing. This is especially evident in the recent crisis.

The coefficient of spending on R&D is positive in all models and significant for SITC 3, 5 (at 10%), 6 and 8 only. An explanation for the lack of significance can be hypothesized as emanating from the "innovation intensity" in each group. E.g. SITC 1 (Food and live animals) vs. SITC 5 (Chemicals).

Coefficients for inward FDI stock are statistically significant only in SITC models 4 and 5 (at 10%), and positive for all but SITC 6 and 8. These results are not unexpected given the fact that the U.S. is a highly developed economy with immense innovation output, and therefore gains little, if anything, from investments coming from less developed countries. Against the validity of these results are those obtained by Keller and Yeaple in their 2009 publication, as quoted by Keller [2009]. There, the authors find "robust and statistically significant evidence for technology spillovers [that are expected to impact the innovation pattern] resulting from horizontal FDI... [and that they are]... concentrated in high-technology sectors" [Keller, 2009]. This difference is fully acceptable for two reasons. One, the quoted study was done on a firm-level; hence, the results on a macro level can differ as they incorporate the input of the entire economy. Two, the study was conducted over a distant (and much different) technology period from 1987 to 1996.

The international trade of the U.S. plays a very limited role as explanatory variables, by virtue of the very small magnitudes of their coefficients. In general, positive changes in exports impact the number of patents negatively, but are statistically significantly only for STIC 1, 3, 5 and 6. Regarding imports, an increase in the dollar value of goods to the U.S. do have a positive result is expected to have a positive (all models) and statistically significant (all but SITC 2, 4 and 7) impact. These results are in line with the literature on the topic, e.g., Keller and Yeaple [2003], who state that "[t]here is also some evidence from import-related spillovers, but it is weaker than for FDI."As a side note, it would be very interesting explore what import channels impact U.S. innovation, as it is highly unlikely that the U.S. imports goods from less developed countries for the purpose of reverse engineering.

Lastly, in the model that looks at total values of export and import activity of the U.S., all but the coefficient of inward FDI stock is statistically significant. Labor force participation and exports have coefficients with a negative sign.

Applications for Economic Policy, Especially Innovation and Trade Policies

An analysis of these results (keeping in mind their limitations), permit several recommendations. The first two are to invert the downward LFR trend and continue strong R&D funding. A Third recommendation is, from the innovation development point of view, to limit resources devoted to inward FDI promotion, as it is statistically insignificant, resembling (in that regard) the UK, where the magnitudes are "so modest that the costs of the UK's FDI promotion policy plausibly exceed the benefits" [Branstetter, 2004]. Lastly, imports are important in determining patent patterns and, as a result, policy makers should encourage imports especially from economies from which the U.S. can learn how to do things (i.e. products, tasks and processes) better.

Conclusions

This work analyzed the dynamics of U.S. international trade and the amount of inward FDI stock. It then, with the help of two other determinants of innovation, attempted to see how they collectively impact innovation in the U.S. From a trade perspective, the study has been conducted on the U.S. as an aggregate, and by disaggregating its trade according to the SITC classification.

The study suffers from some limitations, which are all derivatives of the lack of data. Still, this work serves as a starting point for further research and does permit several conclusions.

The concept that trade and FDI impact innovation has been present in the literature on both of those topics and their importance is rarely questioned – although same cannot be said for the magnitudes of those impacts. Usually, the idea is that the less advanced economy (host) learns from the more advanced one through such channels as technology or know-how transfers. This work reversed that order by examining what happens when one of the biggest and most innovative economies, the U.S., is the host.

The first conclusion is that as much as the number of patent application by residents does appear to be slightly impacted by the economic condition of the U.S. (e.g. the recent recession), still the series exhibits a very strong increasing trend. Economic downturns have a greater impact on trade and inward FDI stock, but still provide an overall benefit to the U.S. economy by decreasing its trade deficit.

Looking at SITC categories, aggregate levels of inward FDI generally do not play a statistically significant role in determining the aggregate level of innovation. When it comes to trade, U.S. exports impact the dependent variable negatively and are statistically significant in only half of SITC categories. U.S. imports have a positive and statistically significant impact in seven SITC categories. Similar inferences are drawn from an analysis of the aggregate model that looks at total values of U.S. exports and imports. These results show that foreign investments into the U.S. are geared to helping investors learn, not the host. Still, a positive sign of imports can be explained by the fact that as much as the U.S. as a collective is very innovative, it is not, and cannot be, a leader in each and every product or process. As a result, it is likely that the U.S. does engage in learning from imports from other, generally less developed, economies that have comparative advantages as compared to the U.S.

Overall, taking under consideration the statistically insignificant coefficients of the FDI and, more generally, U.S. exports – despite encouraging coefficients assigned to U.S. imports, the work fails to confirm the hypothesis that foreign direct investment and international trade have had a positive impact on U.S. innovation. This may be attributed to the fact that the inward FDI enjoyed by the U.S. generally comes from less-developed (innovative) economies, and as much as the U.S. may benefit by learning from those investments, it is hypothesized that such learning is on a small scale and is limited to case-specific instances.

Finally, this work identifies several areas for further study. Given that trade is at least somewhat connected to the level of innovation in the U.S., the first recommendation for additional study is to separate the main hypothesis stated in this work into its two components, FDI and trade, and see how those two, accompanied by other independent variables, impact the dependent variable separately. Secondly, there is the issue of LFT vs. LFP. Is there another explanation than the one given earlier in this work for the negative sign of the coefficient of the LFP variable? Perhaps a different way of introducing labor force into the model should be explored? The third potential area of further interest is the negative sign of the export coefficient. Fourth – to copy this study but use data, if available,[18] for each SITC category only (e.g., how inward FDI and trade in SITC 1 impact the number of patent applications in the SITC 1 or least build a model based on panel data). Also, it would be advantageous, data permitting, to separate business, university, and think tank contributions to the field of innovation in the U.S., and then repeat this study on each of these groups separately. This would allow the researcher(s) to test the hypothesis that the business sector is chiefly impacted by inward FDI and trade, while the latter two sectors experience very little (or no) impact. Lastly, a substitute for R&D spending and labor force-related variables with a longer series would allow for an aggregate approach to the topic (all other variables have data available from 1980).

Notes

[1] Mr. T. Napiórkowski is a recipient of the "Stypendia – dla nauki, dla rozwoju, dla Mazowsza" scholarship conducted by the Warsaw School of Economics and financed by the European Union (European Social Fund).

[2] The WHO performs an interesting review of the literature on spillovers [Vahter, 2010].

[3] http://www.wipo.int/export/sites/www/ipstats/en/wipi/pdf/941_2012_stat_tables.pdf

[4] Mostly for developing countries, but keeping in mind the previous paragraph can also be applied to the U.S.

[5] This by no means suggests that it is ideal, as there are many areas in which the system can be improved, such as, the delay in processing of patents from application to issuance, which is currently close to 35 months (White House: http://www.whitehouse.gov/innovation/strategy/executive-summary).

[6] Defined by the World Bank as a "worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office for exclusive rights for an invention – a product or process that provides a new way of doing something or offers a new technical solution to a problem. A patent provides protection for the invention to the owner or the patent for a limited period, generally 20 years." (http://data.worldbank.org/indicator/IP.PAT.RESD)

[7] Defined by the World Bank as "people ages 15 and older who meet the International Labour Organization definition of the economically active population: all people who supply labor for the production of goods and services during a specified period. It includes both the employed and the unemployed. While national practices vary in the treatment of such groups as the armed forces and seasonal or part-time workers, in general the labor force includes the armed forces, the unemployed, and first-time job-seekers, but excludes homemakers and other unpaid caregivers and workers in the informal sector." (http://data.worldbank.org/indicator/SL.TLF.TOTL.IN)

[8] Defined by the World Bank as: "the proportion of the population ages 15 and older that is economically active: all people who supply labor for the production of goods and services during a specific period." (http://data.worldbank.org/indicator/SL.TLF.CACT.ZS/countries/1W?display=graph)

[9] Although in the literature there is talk of labor force stock, it seems that the amount of stock active in the economy should be used. In particular, if an economy has a high LFT but low LFP (say 10%), then it is highly unlikely that this economy will be innovation intensive. Admittedly, an economy with high LFP cannot be said to be more innovative, but there is a higher chance of that happening.

[10] LFT generally has proven to worsen the explanatory power of the group of independent variables used by, for example, intensifying the problem of multicolinearity and rendering all other coefficients statistically insignificant. Results of models with LFT are presented in Appendix 2.

[11] The full table of correlation coefficients between the dependent variable and the examined independent variables is attached in Appendix 3.

[12] Defined by the World Bank as: "current and capital expenditures (both public and private) on creative work undertaken systematically to increase knowledge, including knowledge of humanity, culture, and society, and the use of knowledge for new applications. R&D covers basic research, applied research, and experimental development." (http://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?page=2)

[13] Unfortunately, data for the 1995 and 2010 period were not available at the time of data extraction. As a solution, it was subjectively assumed that the delta between years 1996 and 1997 is the same as the one between years 1995 and 1996 with a parallel assumption being made for deltas between years 2008 and 2009 and 2009 and 2010.

[14] This measure, admittedly, is not ideal as "[a] drawback of R&D as a measure of technology in that it ignores the stochastic nature of the process of innovation. The current flow of R&D expenditures is a noisy measure of technology improvements in that period" [Keller, 2009]. A different approach would be to use a lag of this variable. The problem with that approach is the extent of the lag, i.e., should R&D expenditures be lagged one period, two or more. This issue is itself a topic for a future study of the spending-to-innovation process.

[15] Source definition and logic on the variable: http://unctad.org/en/Pages/DIAE/Foreign--Direct-Investment-(FDI).aspx

[16] UNCTAD, UNCTADSTAT, http://unctadstat.unctad.org/TableViewer/tableView.aspx?ReportId=88

[17] 0 – Food and live animals, 1- Beverages and tobacco, 2 – Crude materials, inedible, except fuels, 3 – Mineral fuels, lubricants and related materials, 4 – Animal and vegetable oils and fats, 5 – Chemicals, 6 – Manufactured goods classified chiefly by material, 7 – Machinery and transport equipment, 8 – Miscellaneous manufactured articles, 9 – Commodities and transactions not classified according to kind.

[18] http://comtrade.un.org/db/

[19] Estimates are still BLUE (Best Linear Unbiased Estimator), but imprecise.

[20] This kind of data was unavailable to the author.

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World Bank

Appendices

Appendix 1 Results for 11 models (LFP) estimated with OLS

SITC	C	p-value	LFP	p-value	RDPSEND	p-value	IFIDI	p-value	X	p-value	M	p-value	R^2	Prob.(F-stat)	LM Prob. F(2, 8)	Prob. (Jarque--Bera)
0	−1,212,785.1	0.312	13,668.9	0.342	72,134.0	0.391	0.0166	0.442	−3.17E-6	0.079	6.31E-6	0.071	0.9862	0.00	0.3849	0.8081
1	167,366.4	0.672	−2,009.9	0.676	45,487.3	0.114	0.0063	0.292	−7.83E-6	0.023	6.12E-6	0.003	0.9773	0.00	0.3971	0.5534
2	1,589,144.0	0.013	−22,808.3	0.013	83,201.8	0.370	0.0176	0.148	−6.45E-7	0.503	2.64E-6	0.230	0.9314	0.00	0.1426	0.8082
3	1,175,222.0	0.003	−19,020.0	0.001	148,966.9	0.017	0.0099	0.125	−1.53E-6	0.009	2.65E-7	0.001	0.9749	0.00	0.1005	0.7074
4	1,423,454.0	0.017	−17,604.6	0.016	3,543.3	0.948	0.0251	0.015	−7.53E-6	0.499	1.09E+5	0.264	0.9273	0.00	0.3179	0.7988
5	439,132.3	0.237	−6,256.6	0.189	54,740.2	0.098	0.0096	0.076	−9.69E-7	0.008	1.38E-6	0.000	0.9804	0.00	0.3829	0.5615
6	726,262.9	0.035	−15,590.8	0.001	232,671.4	0.003	−0.0017	0.809	−2.46E-6	0.006	1.33E-6	0.001	0.9784	0.00	0.5339	0.7817
7	632,973.7	0.418	−8,812.9	0.350	34,686.9	0.366	0.0041	0.716	−1.10E-7	0.582	2.77E-7	0.181	0.9583	0.00	0.6896	0.7318
8	273,990.7	0.464	−6,265.3	0.143	101,132.3	0.033	−0.0011	0.875	−7.59E-7	0.125	7.64E-7	0.001	0.9782	0.00	0.5957	0.6187
9	1,466,778.0	0.003	−19,722.7	0.009	42,151.2	0.467	0.0078	0.302	−2.81E-7	0.379	1.56E-6	0.050	0.9827	0.00	0.3842	0.9296
T	591,845.7	0.107	−10,128.0	0.021	113,152.6	0.023	0.0066	0.286	−1.51E-7	0.018	1.16E-7	0.002	0.9759	0.00	0.3944	0.6950

Numbers in the SITC column refer to respective SITC classifications. *T* refers to the model in which total export and total import values were used.

Source: Author's own table with results obtained with OLS with the use of EViews software.

Appendix 2 Results for 11 models (LFT) estimated with OLS

SITC	C	p-value	LFT	p-value	RDPSEND	p-value	IFIDI	p-value	X	p-value	M	p-value	R^2	Prob. (F-stat)	LM Prob. F(2, 8)	Prob. (Jarque--Bera)
0	−473,990.0	0.108	0.004	0.100	−18,670.0	0.728	0.0010	0.922	−3.19E-7	0.761	1.31E-6	0.504	0.9618	0.00	0.5817	0.0622
1	447,504.1	0.241	−0.004	0.240	94,036.5	0.048	0.0094	0.139	−1.29E-5	0.016	1.03E-5	0.009	0.9800	0.00	0.2158	0.8424
2	−509,821.9	0.026	0.006	0.000	−67,692.9	0.258	0.0075	0.411	6.01E-7	0.238	−7.32E-7	0.592	0.9644	0.00	0.6883	0.7197
3	−616,124.3	0.014	0.005	0.007	−4,576.4	0.948	0.0033	0.711	−1.10E-7	0.847	6.20E-8	0.513	0.9608	0.00	0.6919	0.4978
4	−744,317.6	0.003	0.007	0.001	−34,852.4	0.416	0.0022	0.810	5.97E-6	0.513	3.80E-6	0.658	0.9592	0.00	0.6320	0.6021
5	61,069.7	0.836	−0.001	0.716	66,970.9	0.191	0.0097	0.166	−1.07E-6	0.059	1.73E-6	0.026	0.9768	0.00	0.2543	0.7530
6	−724,637.8	0.002	0.005	0.009	64,064.5	0.535	−0.0033	0.719	−6.74E-7	0.520	4.65E-7	0.361	0.9638	0.00	0.6966	0.4773
7	−45,345,935.0	0.007	0.004	0.015	8,350.1	0.770	−0.0051	0.437	−1.64E-7	0.080	2.46E-7	0.023	0.9754	0.00	0.5881	0.4923
8	−436,568.9	0.031	0.002	0.324	90,422.3	0.121	−0.0055	0.405	−7.19E-7	0.178	6.97E-7	0.025	0.9753	0.00	0.5356	0.2599
9	32,312.4	0.952	0.002	0.652	−84,216.0	0.190	−0.0059	0.495	4.84E-7	0.196	2.75e-6	0.166	0.9651	0.00	0.4390	0.3936
T	−528,022.4	0.009	0.003	0.091	66,403.7	0.327	−0.0003	0.968	−9.49E-8	0.228	7.94E-8	0.112	0.9689	0.00	0.4177	0.5039

Numbers in the SITC column refer to respective SITC classifications. *T* refers to the model in which total export and total import values were used.

Source: Author's own table with results obtained with OLS with the use of EViews software.

Appendix 3 Pearson correlation coefficients between the dependent variable (Patent applications, residents) and examined independent variables

		LFP	LFT	RDSPEND	IFDI	XT	MT				
Patent applications, residents	Pearson Correlation	−.890	.978	.686	.837	.890	.951				
	Sig. (2-tailed)	.000	.000	.003	.000	.000	.000				
		X0	X1	X2	X3	X4	X5	X6	X7	X8	X9
Patent applications, residents	Pearson Correlation	.758	−.837	.784	.779	.501	.907	.895	.791	.926	.609
	Sig. (2-tailed)	.001	.000	.000	.000	.048	.000	.000	.000	.000	.012
		M0	M1	M2	M3	M4	M5	M6	M7	M8	M9
Patent applications, residents	Pearson Correlation	.949	.972	.699	.895	.777	.966	.895	.948	.970	.959
	Sig. (2-tailed)	.000	.000	.003	.000	.000	.000	.000	.000	.000	.000

S o u r c e : Author's own presentation of calculation performed with SPSS 19 software.