# IMPACT OF FOREIGN LICENSING ON FIRM-LEVEL INNOVATION IN DEVELOPING COUNTRIES

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Budapest, 13 June 2016

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# Abstract

Technology transfer is a key determinant for firm level innovation. In the literature, although foreign licensing has been described as an important channel for technology transfer, no empirical evidence is provided. Using a firm-level survey across 39 countries, this thesis examines the impact of foreign licensing on firm-level innovation. I find that foreign licensing has a strongly positive effect on firm level innovation in developing countries. Genetic matching was used to further validate my results, which remained strongly positive. The findings also suggest both national and firm level factors are important to have greater impact from foreign licensing.

# Table of Contents

# List of Tables and Figures



List of Figures

# Introduction

Prior to the 1980s, technological imitation was thought to be an important driver of economic growth in developing countries, but in the 1990s the evidence and academic literature began to suggest that that innovation was more important than imitation (Fagerberg and Verspagen, 2007). Indeed, in the last few decades, many influential economics articles have identified innovation as a key driver of economic growth (Furman et al, 2002, Segerstrom 1991 etc.), and today, policymakers from developing countries often devise policies to spur innovation in an attempt to grow their economies. One of the primary ways that developing countries gain innovation capabilities is via international technology transfer, defined as an intentional interaction between two or more actors to exchange technological knowledge and rights (Autio and Laamanen, 1995; Saggi 2002). International technology transfer can happen through several channels, the most important of which include foreign direct investment, joint venture, international trade or direct licensing (Hoekman and Javorcik, 2006).

While foreign licensing is an expensive, knowledge-intensive, and time consuming process, it has been becoming increasingly popular (Radosevic, 1997). A typical case would be a firm that buys a foreign license that enables it to launch new products in local or regional markets. While launching a new or customized product, the firm internalizes the associated knowledge, and in this way technology gets transferred to developing countries.

Although there is extensive literature on international technology transfer and its different channels, foreign licensing has received relatively little attention (Yang and Maskus, 2001) and there is a lack of empirical evidence on the impact of foreign licensing. Most of the literature is based on different case studies, which make important contributions about particular cases but do not necessarily readily generalize to other contexts. This thesis uses a using a large, global, firm-level data set to fill this gap in the literature, producing evidence of impact of foreign licensing on technology transfer, showing that this impact is heterogeneous in different regions, and theorizing about the source of this heterogeneity and its policy implications.

In this thesis, since I am focusing on developing countries, and these countries possess relatively little technical knowledge at the domestic level, I have chosen to focus on international technology transfer. In the literature, the channels of technology transfer have been explored from both sides – both licensor or seller and licensee or buyer, and a key question has often been: how do firms decide between licensing and a starting joint venture (Saggi, 2002)? In this thesis, I examine this problem from a host country's point of view – from the licensee's point of view – because this is the point of view of developing countries.

I find that foreign licensing is a more important driver for technology transfer than firm ownership. I also find that the impact of licensing on innovation exhibits considerable heterogeneity. Licensing has a higher impact on innovation in East Asian, European and Central Asian firms than the African firms, which lends support to the notion of national "absorptive capacity".

The thesis proceeds as follows: Chapter 1 reviews the relevant literature on international technology transfer and foreign licensing, and also develops four hypotheses on the impact of foreign licensing and its heterogeneity. Chapter 2 describes the data and provides summary statistics. Chapter 3 produces the results using both probit regression and genetic matching and analyzes findings, which show the link between foreign licensing and innovation; this chapter also deals with robustness checks. Finally, I conclude and consider some policy implications.

# Chapter 1: Literature Review

## Introduction

This chapter reviews the relevant literature on international technology transfer for developing countries and related topics. In Section 2.1, by reviewing some prominent studies on international technology transfer literature I define technology and technology transfer for this thesis and discuss why technology transfer is important for developing countries. Section 2.2 discusses different channels of technology transfer and summarizes the relevant literature on these channels. After explaining different channels of technology transfer, in section 2.3 I discuss the heterogeneity of impact of foreign licensing on different countries. In this section I summarize the four frameworks and constructs from the literature which try to explain the heterogeneity of the different levels of impact in different countries. These four constructs are national innovation system, national innovation capacity, national absorptive capacity, and firm level absorptive capacity. This section concludes that both firm-level characteristics and national level factors matter to explain heterogeneity in firm level innovation. In section 2.4 based on the literature review, I develop four major hypotheses with regards to firm level innovation and foreign licensing.

## 2.1 International Technology Transfer

There is a debate within the academic literature about whether the word technology is best defined as "information" or "knowledge" (Radosevic, 1999), or both. In this thesis, technology signifies both "disembodied and codified information" as well as "very locally specific and embodied knowledge" (Radosevic, 1999: 17). For this thesis, my perspective of technology is consistent with the view that technology is both information and knowledge.

Technology transfer[1] can be defined as “the movement of know-how, technical knowledge, or technology from one organizational setting to another” (Roessner as quoted in Bozeman 2000: 629).

Technology transfer is not like transferring conventional goods; it is a complicated process, which is both knowledge intensive, time consuming and expensive (Mowery and Oxley, 1995). This process has both tangible and intangible aspects to it. For instance, in the case of foreign licensing, it is not only the “blueprints” and the licensing agreement. There is an intangible component or tacit knowledge with the blueprint, which cannot be codified into a written document.

Some technologies are easier to transfer, and some are harder. For instance, physical equipment is often easier to transfer than tacit knowledge, because transferring the latter often requires significant time and often involves close partnerships and effective communication between firms (Cavusgil et al 2003).

### 2.2 Major Channels of Technology Transfer

The major channels of technology transfer are FDI, joint ventures, foreign licensing, imports and exports, cooperative alliances, subcontracting, transfer of people and development assistance. There are also unconventional channels for technology transfer, such as reverse engineering and brain gain (Radosevic, 1999: 17). Despite the differences among these diverse channels, they are interconnected in several ways (Saggi, 2002), which makes it difficult to assess the importance of any single channel. Mowery and Oxley (1995) argued that FDI and licensing are complementary to each other for technology transfer. In this chapter I will briefly describe three major conventional channels of technology transfer.

[1] In this thesis, when I use technology transfer, I use it as international technology transfer.

### 2.2.1 Foreign Direct Investment

Foreign Direct Investment or FDI has always been one of the major channels for technology transfer (Cheng et al, 2005). FDI consists of capital, assets, technology, management skills and access to markets (Radosevic, 1999). Scholars have noted that technology and talents have become an increasingly important part of FDI than investment (Cheng et al 2005). Saggi (2002) discusses how FDI can help to transfer technology and relevant knowledge. First, local talent is introduced to the new technology, then they get trained, and finally the technology is transferred to another firm. In this way, locals absorb the new knowledge. Furthermore, multinational firms sometimes transfer knowledge to their buyers or suppliers and open the door for imitation or reverse engineering by others when they demonstrating new process or products.

Although FDI is widely considered to be an important channel for technology transfer Hanson (2001) argues that there is no strong evidence that FDI has a positive spillover for host countries. This is even more so in the case of developing countries. Multinational countries are mostly attracted to countries with higher productivity or specific industries with higher productivity. There is not enough evidence that FDI has increased domestic firm productivity by spillover effect for developing countries. One explanation for this could be that foreign firms are not innovating in developing countries where industries are not productive enough. Almeida and Fernandes (2008) found that majority foreign ownership inhibits technology transfer because firms are less inclined on innovative activities. Therefore, developing countries with industries that want to innovate should look at somewhere else for technology transfer.

A major issue with respect to FDI is that the benefits of FDI's impact depend on the characteristics of the host countries. There is evidence that FDI's impact depends on a country's human capital and infrastructure (Yamin and Sinkovics, 2009). Good infrastructure cannot be created within a short span of time; it often requires years of investment. To reap the benefits of

FDI, developing countries need to make a substantial investment in their human capital and infrastructure.

Impacts of FDI on host countries also depend on firms' ownership structure. Several studies have examined firms' ownership on firms' propensity to innovate (Alvarez and Robertson, 2004) or technology adoption (Damijan et al 2005). One major limitation of these studies is that they either focus on a single country or on very few countries. Almeida and Fernandez  (2008) did a cross-country comparison and Julio Rafflo et al (2008) used six countries including European and Latin American countries. Rafflo et al (2008) found that firm ownership has a heterogeneous effect on innovation, whereas Almeida and Fernandes (2008) found that majority ownership plays a significant negative role in innovation. These results are significant because if a developing country wants to benefit from FDI, it needs to understand what kind of ownership helps a country get ahead in innovation.

### 2.2.2 International Joint Venture

International Joint Ventures are also an important channel for technology transfer. Multinational firms are sometimes unable to start a wholly-owned subsidiary for regulatory reasons, or due to information asymmetry (Saggi, 1999).  To minimize risk or to test the market, multinational firms start with an international joint venture with local firms. While doing so they may deliberately or accidentally transfer technologies to the host country. In this case this transfer process also depends on absorptive capacity[2]  (Lane, Salk, and Lyles 2001).

### 2.2.3 Foreign Licensing

Another channel for technology transfer is foreign licensing, but it received less attention than other channels (Yang and Maskus, 2001). Multinational companies might find it easier or

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[2] Absorptive capacity will be explained in next section

more cost effective to license the technology to another company in another country (Saggi, 1999; 2002). In this case, there are many restrictions that are applied to the buyer firms; for instance the buyer firm can sell the products or services in only specific market or countries. An example would be: a Japanese firm that would sell a license to a South African firm if only that South African sells the products within the country. Despite all of its limitations, licensing is an important source for technology transfer.

The exchange of foreign licenses depends on several factors. For licensing, if the buyer country's intellectual property rights (IPR) are not strong enough, a licensor might not feel safe to sell the license. From copying to industrial espionage there are many reasons that a licensor might not want to sell their licenses. In some cases they could sell old licenses (Almeida and Fernandes, 2008). If that is the case, then a buyer firm will find it hard to innovate with old technology, which could limit the potential of technology transfer.

The academic literature suggests that firms from developed countries may be incentivized to transfer older, less valuable technology to a host country (Mansfield et al, 1979; Mansfield and Romeo, 1980; Coughlin, 1983). There are several reasons for this. First, it could be a way to save them from future competition (Glass and Saggi, 1998). Second, there is a significant cost to transfer technology and this cost declines with the age of technology (Teece, 1976). Third, the local partner might not protect the licensor's reputation or IPR. To summarize, transferring technologies depends on a lot of factors, from IPR to the cost of transfer.

National institutions play an important role for all the channels of technology transfer. For instance, Yang and Maskus (2001) argued that stronger IPR help to reduce the cost of transferring foreign license. By strengthening IPR a host country can reduce transaction cost and then invest the associated transaction cost on innovation. This should lead to higher innovation and again a higher level of technology transfer. Yang and Maskus (2001) also argue that stronger IPR would encourage additional license transfer. Recent literature has also found evidence of host countries' IPR' effect on technological transfers from multinational parents to local firms (Branstetter et al 2005).

### 2.3 Heterogeneity in Firm-level Innovation

Although knowledge is a non-rival good and is often theorized to freely travel through borders, there is significant heterogeneity in knowledge-based innovation activities around the world (Saggi, 2002). Scholars have attempted to explain this phenomenon using different concepts, the most important of which include the National Innovation System, the National Innovation Capacity and absorptive capacity – all of these frameworks or perspectives have been proposed to explain the heterogeneity in innovation output. At first, I will briefly discuss all of these frameworks and will conclude with the argument that both firm-level and national factors are needed to explain the heterogeneity of foreign licensing's impacts.

#### 2.3.1 National Innovation System

The National Innovation System is one of the major frameworks to explain the different levels of success in innovation (Mowery, 1994). National Innovation System (henceforth NIS) or National System of Innovation has been roughly defined as the ecosystem of public and private institutions in a country that directly or indirectly affect R&D and the translation of that R&D into commercial products (Mowery, 1994; Nelson 1993). Research has shown that institutions play a significant role in firms' decisions (Furman et al, 2002; Filippetti and Archibugi, 2011). For instance, in the US, during the Second World War government funding was increased substantially, which spurred university based innovation. Also legal institutions in a country affect how firms or universities conduct research and diffuse that research to other entities. For example, a strong Intellectual Property right system encourages firms to innovate more because firms know that their rights will be protected. The NIS concept indicates that firms' decisions to innovate, to learn and also to share the acquired knowledge are influenced by labor markets, local industries and financial structures (Filippetti and Archibugi, 2011).

### 2.3.2 National Innovation Capacity

Another popular concept is the National Innovation Capacity (henceforth NIC). NIC has been used since the 90s. Furman et al (2002) defines the NIC as "the ability of a country to produce and commercialize a flow of new-to-the-world technologies over the long term "(2002:1). Although NIC is similar to NIS and also has its root in the concept of NIS, NIC also goes beyond the "array of institutions" and macro-level policies of the NISs. Furman et al (2002) divided the determinants of NIC into three major categories: the first category is the same as NIS, which is general institutions, infrastructure, and macro level policies; the second category is the environment and industry clusters firm are in; and the third category is the linkages between the first two categories. According to Furman, NIC depends on the interplay of these three factors. The major difference between NIC and NIS is that NIC focuses on the determinants of NIS.

For NIC, the first factor is institutional and common infrastructure (Furman et al 2002). This includes the pool of engineers and research scientists in a given economy; IPR; the number of patents, the number of research universities, government funding and financial structures. Both the NIS and the NIC are closely interrelated; a country needs to have basic infrastructure and supporting institutions to innovate.

The second factor for NIC is firms and firms' environment and the industry cluster (Furman et al 2002). The local environment can either help or inhibit a firm's propensity to innovate. In an industry cluster, firms could benefit from knowledge spillover and competition. Moreover, regulations and policies also affect firm performance. For instance, Thomas (1994) detailed the two different trajectories of local British and French pharmaceutical firms even though they had the similar basic infrastructure. Thomas argued that the different trajectories of these firms were the results of different regulatory policies. While British pharmaceuticals enjoyed a global success due to local positive competition, French firms failed to take advantage of their local industry.

The third factor for NIC is the quality and strength of linkages between the first two factors (Furman et al 2002). Linkages between common infrastructure and local industry clusters shape the rate at which local firms innovate and commercialize products. Universities and trade associations can act as linkages to facilitate the translation procedure from knowledge to innovation.

### 2.3.3 Absorptive Capacity

Another framework to explain the national difference in translating technical knowledge into innovation is absorptive capacity. In the literature absorptive capacity's origin can be found in the 1960s where the focus was not on innovation but on international development. At that time, JH Adler referred to absorptive capacity as "the total amount of capital, or the amount of foreign capital, or the amount of foreign aid (capital plus technical assistance) that a developing country can use productively" (1965: iii). Since then absorptive capacity has been used in various contexts. For instance, it has been used at the national level (Mowery and Oxley, 1995) as well as at the firm level (Zahra and George, 2002; Cohen and Levinthal, 1990). Unfortunately, there is no universally acceptable definition of absorptive capacity at either firm level or at the national level. Different scholars defined absorptive capacity in different ways and used different indicators for that. For example, Castellacci and Natera (2013) defined it as the set of factors that helps developing countries in the technological catch up process. An et al (2008) defined absorptive capacity as the ability of local firms to deploy the transferred technologies from foreign entities. An et al (2008) used the percentage of students in the tertiary education system as the proxy for absorptive capacity and Kamal Saggi (2002) referred to it as the "stock of human capital" in a country. In addition to human capital Castellacci and Natera (2013) used international trade, infrastructures, social cohesion, inequality, the quality of institutions and governance system to quantify absorptive capacity. Absorptive capacity has been used in both national and firm level. In the later sections, I will differentiate between these two constructs by terming them as "national absorptive capacity" (as termed in Mowery and Oxley (1995)) and "firm-level absorptive capacity" (Giuliani and Bell, 2005; Schildt et al, 2012) respectively. Firm level absorptive capacity is more common in the management field, as firms are usually the unit of analysis.

NIS, NIC and national level absorptive capacity have considerable overlaps. Among the three concepts, different scholars used their preferred concepts to explain country level innovation capabilities and some have used more than one concept. For instance, Castellacci and Natera (2013) used the co-evolution of both national innovation capability and absorptive capacity to investigate the dynamics of innovation systems. In the next section I will explain the firm-level absorptive capacity.



### 2.3.4 Firm-level Absorptive Capacity

While the construct of absorptive capacity has been used at the national level, it is even more popular at the firm level. Since Cohen and Levinthal (1990) introduced the topic in the management field, it has become one of the major constructs to explain firm-level performance heterogeneity. Cohen and Levinthal (1990) defined firm-level absorptive capacity as the abilities of a firm to understand new external knowledge, internalize it, and then apply that to produce new products. This construct was later re-conceptualized by Zahra and George (2002), by dividing the construct into two subsets: potential absorptive capacity and realized absorptive capacity.

Zahra and George (2002)'s conceptualized version of the absorptive capacity is the most widely used version of firm-level absorptive capacity. According to Zahra and George (2002) absorptive capacity has two subsets. The first subset is concerned with knowledge acquisition and assimilation capabilities, which they term potential absorptive capacity. The second subset is termed as realized absorptive capacity, which is concerned with knowledge transformation and exploitation. If exposed to diverse external knowledge, firms can increase their absorptive capacity (Zahra and George, 2002). This suggests that there is a feedback loop between firm-level absorptive capacity and external knowledge. Table 1 summarizes all the major constructs for explaining the national innovation level.

**Table 1: A comparison of four major frameworks**



| Name of the framework/constructs | Dimensions and determinants | Level | Studies |
|---|---|---|---|
| NIS | • Ecosystem of private and public institutions<br>• Transformation of R&D into commercial products<br>• Legal, financial institutes play an important role | National | (Nelson, 1993) |

| | | | |
|---|---|---|---|
| | • Local industries are important | | |
| NIC | • Ecosystem and interplay of national and institutions<br>• Institutions and infrastructure<br>• Local environment and industry cluster<br>• Linkages between national and local institutions | National | (Furman et al, 2002) |
| National absorptive capacity | • Human Capital<br>• Number of trained engineers<br>• Trained R&D workers as percentage of total population<br>• R&D Spending | National level | (Mowery and Oxley, 1995) |
| Firm level absorptive capacity | • Organizational routine and processes to gain dynamic capabilities<br>• Knowledge acquisition<br>• Assimilation<br>• Transformation<br>• Exploitation | Firm level | (Zahra and George, 2002) |

Industrial clusters also influence firm level absorptive capacity. Within an industrial cluster localized knowledge spillover is an important factor for firm-level innovation where absorptive capacity plays a significant role (Giuliani and Bell, 2005). Giuliani and Bell (2005) argue that firms with higher absorptive capacity can acquire higher level of external knowledge. Knowledge acquisition is an important step in Zahra and Geroge's (2002) reconceptualized absorptive capacity.

For different channels of technology transfer different levels of absorptive capacity is needed (Mowery and Oxley, 1995). Although the construct "absorptive capacity" suggests that R&D is an important factor, Teece (1986) demonstrated that for a technology's commercial viabilities, R&D is not enough. He argued that benefitting from technology requires many other skills: e.g., skills in production and distribution. Teece's (1986) argument suggests that innovation goes beyond R&D and needs other skills, which also depends on local and national factors.

Scholars have suggested that one way to improve absorptive capacity is to invest in human capital and relevant technological infrastructures. Srholec (2011) argued that developing countries should spend more on human capital instead of looking at the percentage of GDP on R&D. For absorptive capacity, Abramovitz (1986) also emphasized that education-dependent social capabilities are important. Srholec (2011) suggested that it would be futile for developing countries to try to develop by attempting to mimic the development of innovation capabilities enjoyed within developed countries.

In this section I explained the major channels of technology transfer to differentiate their processes and also to highlight each channel's limitation. I also discussed four major constructs to explain the heterogeneity of country level absorption capability. Based on the above discussion it is clear that there is a considerable overlap among the four concepts, and that each of the concepts focuses on different national institutions, local talents and infrastructures. It is also evident from these different frameworks that firms' innovation capabilities depend not only on the firms but also on external factors, such as local environment and national systems. Building on this literature in the next section I will develop hypotheses.

## 2.4 Hypotheses

Building on that discussion and existing literature in the previous sections, I will develop four major hypotheses around firm-level innovation and foreign licensing.

As discussed in the previous sections, foreign licensing is an important channel for technology transfer. Therefore, I hypothesize that:

**Hypothesis 1: The impact of foreign licensing on innovation is positive and significant for firm-level innovation.**

Using foreign technology requires a certain level of knowledge, which can come from trainings or highly skilled professionals. Foreign-owned firms or international joint ventures have access to proprietary knowledge that they can share. Foreign-owned firms also can send their labor force to other countries for further trainings or give the trainings themselves. This transfer of knowledge helps foreign-owned firms absorb the new technologies from foreign licenses. On the other hand, domestic firms often do not have access to these resources. Moreover, international trainings are expensive, and building alliances is often challenging. Therefore, it is harder for domestic firms to utilize foreign licenses to their maximum capacity. Blomström and Sjöholm (1999) have argued that foreign-owned firms have higher labor productivity than domestic firms.

Thus, I hypothesize that:

**Hypothesis 2: The impact of foreign licensing on innovation will tend to be lower for domestic firms than for foreign-owned firms.**

As discussed previously, a firm's ability to utilize licenses depends on its human capital, national institutions, local market competitions and domestic market. As East Asian countries have stronger institutions and a higher human capital level, I expect that they will tend to receive higher impact compared to African countries from foreign licensing. For instance, both Vietnam and the Philippines have higher primary completion rate than Zambia and Egypt (World Bank, 2013).

**Hypothesis 3: The impact of foreign licensing on innovation will tend to be higher for East Asian countries than for African countries.**

The literature on absorptive capacity suggests R&D will increase a firm's ability to adopt, adapt, and innovate (Cohen and Levinthal, 1990). Other scholars also agree with the complementary relationship of R&D and foreign licenses. R&D is not only about innovation, it is also a way to learn and absorb new knowledge (Cohen and Levinthal, 1989). Hu et al (2005) argued that the effects of technology transfer are largely contingent on in-house R&D. They argued that in-house R&D increases the absorbing capabilities of acquired technologies. Fan (2006) also suggested that domestic R&D should be a priority to build innovation capability that should be supplemented by other alliances. Almeida and Fernandes (2008) argued that foreign firms are not interested in innovating in developing countries, which suggests that R&D in foreign companies are not as helpful as domestic firms.

Based on this literature I hypothesize that:

**Hypothesis 4: Domestic firms' R&D tends to be more helpful for innovation than foreign-owned firms' R&D.**

In this section based on the literature review I developed four hypotheses concerning firm level innovation and foreign licensing. I also hypothesized about the heterogeneity of the impact of foreign licensing. In chapter two I will provide empirical support to my hypotheses based on a unique dataset, which will be described in the next chapter.

# Chapter 2: Data and Methodology

This thesis analyzes a uniquely rich firm-level data set spanning 39 different countries. First, I discuss the data set: its advantages, relevance and limitations. Afterwards, I provide summary statistics of the data set, describe some of its properties, and introduce my dependent and independent variables.

**Data: The World Bank's Investment Climate Survey Data**

This data set provides information on a rich set of indicators from more than 11000 firms across 39 countries from 2002-2005. In each country the survey was carefully designed to ensure industry-specific representativeness of the sample. There are several advantages to using this data set. First, a common questionnaire was used across all the countries that measures innovation in the same way. Second, this is an extremely rich data set with a lot of variables, makes it easier to statistically control for important firm-level characteristics. Available indicators are firm age and size, management education level, R&D spending of the firms and GDP per capita of that country. Industries are auto and auto components, beverages, chemicals, electronics, food, garments, leather, metals and machinery, non-metallic and plastic materials, paper, textiles, and wood and furniture.

This World Bank data set makes it possible to utilize a definition of innovation that is appropriate for developing countries, which includes both new processes and products introduced in a different market by the licensee. These new products are not necessarily original, but they may be new in specific markets. This broader definition of innovation allows me to account for the incremental and catching up innovation in emerging economies[3].

One potential shortcoming of the World Bank dataset is that its measurement of technological innovation is to some extent subjective. In the survey questionnaire, the question posed was “Have you introduced any new product within last three years”. If the answer was yes, then the value of the variable innovation is 1. This answer could vary from country to country. For instance, an Egyptian representative of a firm might show a different understanding of what is meant by a new product than a Brazilian representative. This subjective interpretation of the survey question can introduce some measurement error into my estimates. But even so, despite its possible limitations, this rich data set is widely used in the literature (Almeida and Fernandes, 2008; Srholec 2011).

**Descriptive statistics**

A simple overview of the data set is given in Table 2. This table provides more information on the sample, mean and standard deviation for key variables. There are 11387 observations. Almost 50% of the firms answered that they have introduced new products. Although the high level of innovation is surprising, this definition of innovation is context dependent, because (as mentioned above), the product might not be new to the market but it could be new to that specific firm or in specific area. Also, roughly half of the firms are involved with some level of R&D. Among all the firms 90% of them are domestic, the rest are partially owned by foreign entities or governments. The average age of the firms is 13 years.



[3] While R&D spending is an important measure at the country level and firm level, R&D does not always translate into innovation (Srholec, 2011), and therefore, R&D spending is not a good way to measure innovation. Patents are more applicable for innovation at the frontier while top firms or research institutes work to introduce new patents by pushing the current boundaries of innovation. That is why patents as a measurement of innovation is also not applicable for developing countries.

**Table 2: Descriptive Statistics**

| Variable | Observations | Min | Max | Mean |
|---|---|---|---|---|
| Innovation | 11381 | 0 | 1 | 0.5171778 |
| License | 11381 | 0 | 1 | 0.08162727 |
| Size | 11381 | 0.6931472 | 9.854665 | 3.738512 |
| Partially Public owned | 11381 | 0 | 1 | 0.062824 |
| Training | 11381 | 0 | 1 | 0.4781654 |
| Percentages of Educated Workforce | 11381 | 0 | 1 | 0.2091826 |
| R&D | 11381 | 0 | 1 | 0.4999561 |
| Exporter | 11381 | 0 | 1 | 0.3793164 |
| Importer | 11381 | 0 | 1 | 0.5312363 |
| Majority Foreign Owned | 11381 | 0 | 1 | 0.1051753 |
| Minority Foreign Owned | 11381 | 0 | 1 | 0.02187857 |
| Domestic | 11381 | 0 | 1 | 0.8729461 |
| Age | 11381 | 0 | 5.26269 | 2.557305 |

I have also added a table on the correlations between the most important characteristics. From table 3 it is clear that there is little correlation between firm innovation and licensing: only 15% of the firms identified as “innovative” have obtained a license. Yet, from Table 2 we can see that roughly 50% of the firms say that they have introduced a new product in the market. It shows that firm-level innovation and licensing are not that strongly correlated.

**Table 3: Correlation table, which shows the correlation between Innovation and other covariates**

| | Innovation | License | Size | Public | Training | R&D | Age | Exporter |
|---|---|---|---|---|---|---|---|---|
| Innovation | | | | | | | | |
| License | 0.15*** | | | | | | | |
| Size | 0.19*** | 0.14*** | | | | | | |
| Public | 0.00 | 0.04*** | 0.28*** | | | | | |
| Training | 0.23*** | 0.12*** | 0.35*** | 0.09*** | | | | |
| R&D | 0.12*** | 0.10*** | 0.29*** | 0.17*** | 0.19*** | | | |
| Age | 0.02* | 0.01 | 0.21*** | 0.12*** | 0.09*** | -0.02* | | |
| Exporter | 0.13*** | 0.08*** | 0.46*** | 0.08*** | 0.23*** | 0.18*** | 0.10*** | |
| Importer | 0.16*** | 0.10*** | 0.32*** | 0.06*** | 0.21*** | 0.17*** | 0.08*** | 0.33*** |

From the data it is evident that innovation varies country by country. The top three countries with the highest level of innovation are Brazil (77%), South Africa (75%) and Armenia (72%). The lowest percentage of innovation is recorded in Egypt, which has only 13% record of success. The highest numbers of firms in the sample are from Brazil. There are 1626 Brazilian firms, and 1110 Vietnamese (the second largest country in the sample) firms in the sample.

**Table 4: List of countries from the data set**

| Continents | Countries |
|---|---|
| Africa | Egypt, Madagascar, South Africa, Zambia |
| Europe and Central Asia | Albania, Armenia, Belarus, Bosnia & Herzegovina, Bulgaria, Croatia, Czech, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Tajikistan, Turkey, Ukraine, Uzbekistan |
| East Asia | Philippines, Vietnam |
| Latin America | Brazil, Chile, Ecuador, El Salvador, Guatemala, Honduras, Nicaragua |

The following figure shows country wise innovative firms.

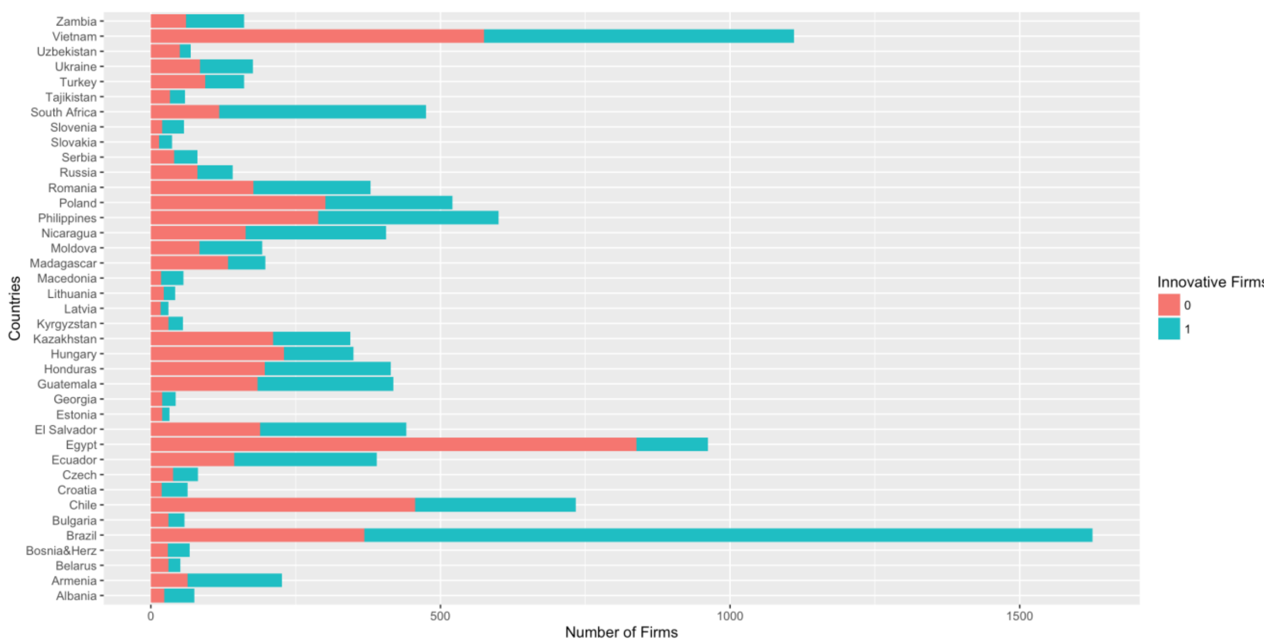


**Figure 1: Country wise innovation, blue green indicates the innovative firms**

## Methodology

Firm level innovation has been measured using various econometric methodologies, from OLS regressions to multilevel modeling (Srholec, 2011). As the treatment is a binary variable, to estimate the effect I am using a probit model. Other scholars (Almeida and Fernandes, 2008) have used probit model in the innovation context. Due to the cross-sectional nature of the data I was unable to use other methods such as fixed effects.

Multilevel modeling is also not applicable in this case for two reasons. First, the intraclass cluster is small here. From table 4, we can see that only less than 8% of the variation is due to clusters, and the literature suggests that multilevel models are recommended when the intraclass cluster value is higher. Second, the literature also warns against running multilevel models when sample sizes are less than 50 (Maas and Hox 2005). In my data set, for the country level, I have only 39 countries.

**Table 5: Results from a null mixed model**

| Parameter | Estimate | Standard Error |
|---|---|---|
| Level 2 Variance | 0.0179 | 0.1338 |
| Level 1 Variance | 0.2189 | 0.4679 |
| Intra-class correlation | .0755 | |

As multilevel modeling is not applicable for this particular case and fixed effects are also not useful, my analysis begins with a relatively simple and conventional approach for data in this form: probit regression.

In the next section, I will describe my dependent and independent variables. After that I will describe the probit model. I will also briefly discuss matching and genetic matching, which are widely used for causal inference in observational studies.

**Dependent variable**

Innovation is the dependent variable; if a firm has introduced any new product within the last three years then the result is 1, and otherwise it is coded as zero. This definition of innovation captures the "catching up" condition of developing countries because at this stage they are not working at the frontier of innovation rather they are playing the catch-up game with the Global North or more advanced countries. In this pursuit they are licensing technology and introducing products in their chosen markets that might be new to their market, but not to the world. While doing so they are gaining new capabilities in new technical domains.

It is much harder to differentiate between the impacts of licensing from FDI in the case of productivity. To circumvent this problem, I am using "propensity to innovate" in developing countries as my dependent variable. Looking at the impact of domestic firms allows me to find the treatment effect of licensing which can be independent of the FDI impact. Of course there could be a spillover effect from local industries from a specific FDI but with the current data set there is no way to control for that. I am also comparing domestic firms and foreign-owned firms, which clarifies that foreign licensing is an important source of innovation for domestic firms even without foreign ownership.

**Independent variables**

In this section I will introduce all the major independent variables.

*License or Foreign License:* is the treatment variable, which is a binary variable. If a firm has obtained a new license from a foreign entity within last three years then the value is 1, otherwise it is 0.

*Majority foreign ownership* is a binary variable. If a firm is mostly owned by a foreign entity (more than 50% of the share) then the value is 1; otherwise the value is 0. I constructed this from the raw data.

*Minority Foreign ownership* is another binary variable. If less than 50% of firm ownership belongs to foreign entities then this value is 1. These two dummy variables on firm ownerships are important because foreign firms have access to both advanced knowledge and skilled people to rely on.

*Domestic* is another dummy variable; value 1 indicates that either the firm is a fully-owned by government or a local company. Value 0 indicates that either the firm's majority or minority shares are owned by foreign entities.

*Age* is the difference between firms' establishment and survey year. The author took a natural log after calculating the age from the raw data. While on the one hand older firms have an advantage of accumulated knowledge and wider resources to innovate, on the other hand younger firms are more nimble, less bureaucratic and might innovate more.

*Size* is a continuous variable of the size of the firm. This too is a natural log of the actual size data. Shan et al (1994) found that larger startups have better innovation outcomes. Therefore, it is important to control for size.

*Industry* is a categorical variable. The survey covers 14 industries, from manufacturing to garments, textiles to beverages (the list will be found in the appendix section). The classification was taken from the survey.

*R&D:* this is also a binary variable. The value 1 indicates that the firm engages or put resources in research and development and 0, if otherwise. It is important to control for R&D because the absorptive capacity concept says that R&D helps to gain the knowledge and skills to use the licenses. Also it should be kept in mind that in the context of developing countries R&D does not equal innovation.

*Workforce education:* This is a dummy variable; the value is 1 if the managers have postgraduate education and 0 otherwise. This was directly taken from the survey, null values were discarded.

*Management training:* Another dummy variable. This variable indicates that the management has received any training by firm. It is important to control for management training and workforce education level because human capital is an important factor in firm-level productivity (Pack 2006).

*Partial Public Ownership:* A dummy variable, which is true when the firm is partially owned by a government entity. The value would be zero if it the firm is not owned by a government entity.

**The Probit Model**

To test the hypotheses I am using this equation:

$$Innovation* = \alpha License + \beta X_{ij_c} + I_j + I_c + \epsilon_{ij_c} \tag{1}$$

Where, Innovation=1 if Innovation*>0

Innovation = 0 if Innovation* <=0

Here, “Innovation” is a binary variable, “license” is also a binary variable and $X_{ijc}$ is a vector of firm level characteristics, $I_c$ denotes country level fixed effects and $I_j$ denotes industry level fixed effects, and E is the error term.

I use several versions of this model and include country dummies and industry dummies to control for the differences between countries and industries. Afterward, I apply a different approach--genetic matching--and demonstrate that either way the results are substantively the same. Now I will briefly discuss matching methods and genetic matching.

**Matching For Causal inference in observational studies**

Matching methods are very popular for causal inference in observational studies in the social sciences from economics, epidemiology to political science (Ho et al. 2007; Stuart, 2010; King and Nielsen, 2015). In observational setting, estimating causal effects is difficult because of the risks posed by observed and unobserved confounders. But causal estimates can be achieved by imitating randomized experiments using comparable treated and control groups based on distribution of covariates. These treated and control groups can be obtained from observational data using matching methods combined with analyses that test the sensitivity of results to the presence of unobserved confounders.

Ever since Rubin (1973) proposed matching to reduce bias in the observational studies, many matching methods (Stuart, 2010) have been introduced to reduce bias and model dependency in observational or quasi-observational studies[4]. There are many ways to do

[4] For a survey of existing literature please refer to (Stuart 2010)

matching, including nearest neighbor matching, optimal matching, matching with replacement or without replacement and propensity score matching.

How best to match is an ongoing debate in the matching literature. Almost everyone agrees that achieving balance is an important criterion to judge the balanced data (Sekhon, 2008; Diamond and Sekhon, 2013; King and Nielsen, 2015). Journal editors and scholars recommend using matching methods for causal inference including propensity score matching (Bettis et al. 2014; Reeb et al 2012).

**Genetic matching: A covariate balance optimizing matching method**

Genetic matching is a popular matching method. This matching uses a genetic algorithm to optimize the covariate balance between the treated units and the control units (Diamond and Sekhon, 2013). Covariate balance means that the treated units and the control units have the same joint distribution of the covariates. Genetic algorithm iteratively checks and improves covariate balance for the two groups. This method uses both t-tests and Kolmogorov-Smirnov tests to check balance between the two groups.

Balance is an important criterion for matching methods. Achieving covariate balance means finding similar treated and control units. Stuart (2010) recommends avoiding matching methods that produce highly imbalanced sample and use alternative methods that can produce well-balanced sample. If the distribution of treated and control units are different then reliable estimates cannot be provided. In this case genetic matching performs well, it not only provides matched data set but also the balance results.

Genetic matching method has been shown to be better than many other available matching methods in terms of achieving balance among covariates. (Radice et al. 2012; Diamond and Sekhon, 2013). On the other hand, propensity score matching has been found to be counterproductive on several occasions, where instead of achieving balance propensity score increases imbalance (King and Nielsen, 2015; Franco and Macdonald, 2015). Successful matching requires both reduced imbalance between the treated and control units and also the sample size should be large enough. Genetic matching allows me to achieve highest balance and I also get a large enough sample.

# Chapter 3: Results and Analysis

**Findings**

The previous chapter introduced a rich and large data set on firm-level innovation. This chapter uses that data set to test the hypotheses that were put forward in chapter two. In the following sections I present the results of the probit models in which my dependent variable is firm-level innovation. I used various models to test all the hypotheses I developed in the last chapter. In order to examine my first hypothesis I run three probit models, primarily to examine the relationship between foreign licensing and innovation on the whole dataset. Then I divide the data set into two groups, domestic firms and foreign owned firms, to test hypothesis two. After that I divide the original data set into four groups to test hypothesis three. Results from each of these analysis is shown in tables 6, 7 and 8 respectively. Additionally, I use genetic matching and run regressions on the matched data set for causal inference, which reaffirms my probit model results.

To examine my first hypothesis, which states that foreign licensing has significant positive impact on firm-level innovation I use probit models. The probit models in table 6 show the strong positive correlation between foreign license and firm-level innovation[5]. With each model I add more covariates to show that the results are still significant. In models four and five, I control for industry level and country level fixed effects by including a dummy variable. All the models show that the results are statistically significant at p-value $<0.01$ levels. My final model is model five, which controls for all the major variables. The results are still significant with this model. From model five, it can be interpreted that all other things being equal, firms that use a

[5] Table 6, 7 and 8 show marginal effects while tables (13,14,15 and 16) in Appendices show original coefficients.

foreign license are 23% more likely to innovate more. Model five includes all the important firm level characteristics as well as controls for country level and industry level effects. This result gives strong support to the first hypothesis.

**Table 6: Marginal effects from probit models, results demonstrate that foreign licensing is significant even after controlling for all major variables.**

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Foreign License | 0.26 *** | 0.24*** | 0.22*** | 0.22*** | 0.23*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Majority Foreign Ownership | -0.04*** | -0.09*** | -0.10** | -0.11** | -0.08** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Minority Foreign Ownership | -0.01 | -0.02 | -0.2 | -0.02 | 0.02 |
| | (0.03) | (0.03) | (0.10) | (0.03) | (0.04) |
| Exporter | 0.09** | 0.03** | 0.02* | 0.02 | 0.03 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Importer | -0.13** | -0.1** | -0.08** | 0.08* | 0.07 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Age (ln) | | -0.01** | -0.02* | -0.01 | -0.01 |
| | | (0.01) | (0.01) | (0.01) | (0.01) |
| Size (ln) | | 0.06** | 0.05* | 0.04 | 0.05 |
| | | (0.00) | (0.00) | (0.00) | (0.00) |
| Partial Public Ownership | | -0.14 | -0.14 | -0.13 | -0.07 |
| | | (0.02) | (0.05) | (0.02) | (0.02) |
| Management Training | | | 0.17 | 0.17 | 0.11 |
| | | | (0.01) | (0.01) | (0.01) |
| Percentage of Educated Workforce | | | 0.10 | 0.11 | 0.11 |
| | | | (0.02) | (0.02) | (0.03) |
| R&D | | | 0.05 | 0.05 | 0.05 |
| | | | (0.01) | (0.01) | (0.01) |
| Industry Dummy | No | No | No | Yes | Yes |
| Country Dummy | No | No | No | No | Yes |
| N | 11387 | 11387 | 11387 | 11387 | 11387 |

Notes: *p<0.1; **P<0.05, ***P<0.01

Table 6 also shows that foreign licensing is a more important determinant than ownership of the firms. For instance, majority ownership is an important factor when all the factors are considered and this ownership has a negative relationship with innovation as demonstrated by Almeida and Fernandes (2008). Although, this relationship is significant for innovation, ownership is less important than foreign licensing when we consider the estimates. Additional analysis shows that ownership does not matter *all* the time.

Another way to see the treatment effect of the foreign licensing is to look at the confidence interval of the marginal effects. Figure 2 shows a confidence interval for marginal effects, which is similar to that of table 1 results.

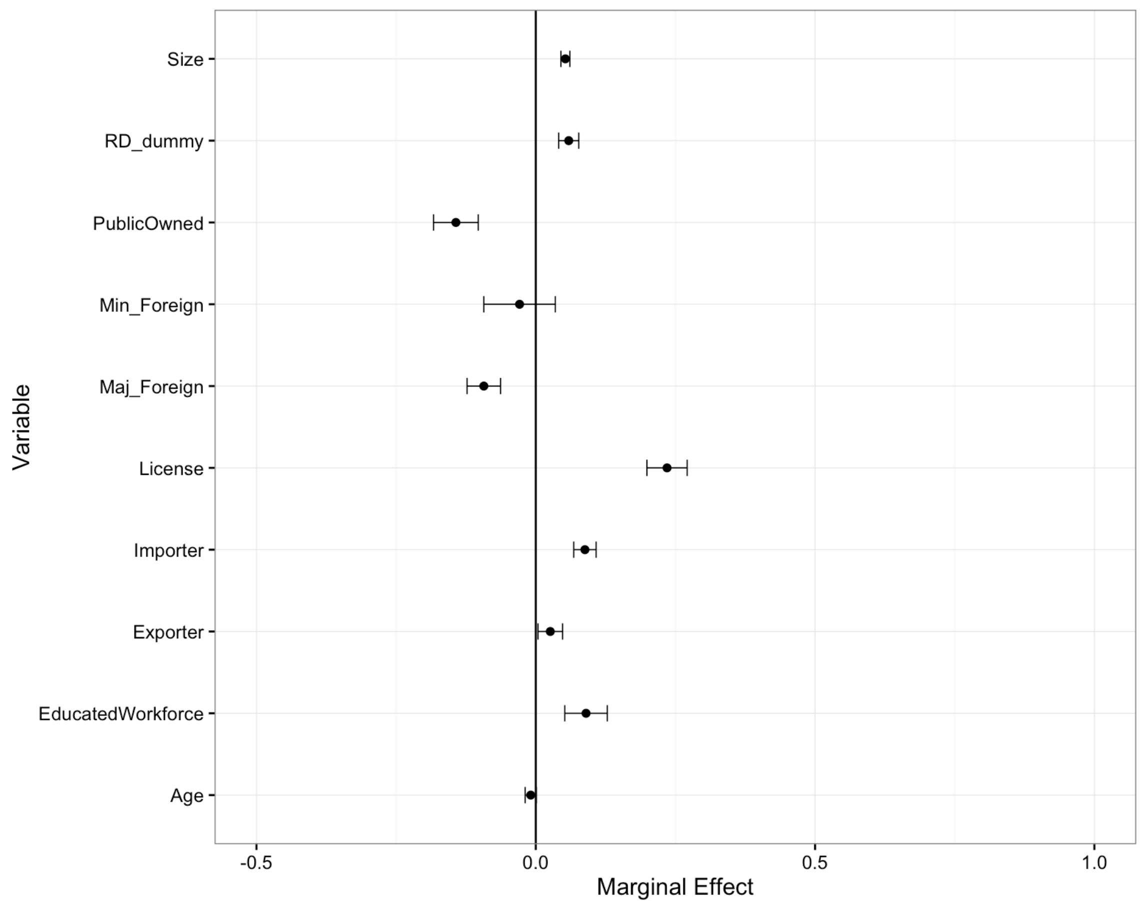


**Figure 2: Marginal Effects from regressions, which shows the confidence interval of the marginal effects for Licensing on innovation.**

To examine hypothesis two, which states that domestic firms will have less impact from foreign licensing, I divided the original data into two groups – domestic firms and foreign-owned firms. Table 7 shows the results of two probit models. In both models, foreign licensing is the most important factor for firm-level innovation. In one group, I include all the domestic firms, and in another, I includie all the foreign firms (both majority and minority foreign owned). The results indicate that, everything else being equal, foreign owned firms have 25% higher probability in propensity to innovate. In case of domestic firms, this propensity to innovate is 23%. This lends support to hypothesis two that domestic firms will be less innovative compared to foreign-owned ones.

**Table 7: Marginal effects from probit models on both domestic and foreign owned firms, results show that foreign-owned firms have higher impact**

| | Domestic Firms | Foreign Owned Firms |
|---|---|---|
| Foreign License | 0.23 *** | 0.25*** |
| | (0.02) | (0.03) |
| Exporter | 0.03* | 0.04 |
| | (0.01) | (0.04) |
| Importer | 0.07* | 0.03 |
| | (0.01) | (0.04) |
| Age (ln) | -0.02 | 0.02 |
| | (0.01) | (0.02) |
| Size (ln) | 0.05* | 0.05** |
| | (0.01) | (0.01) |
| Partial Public Ownership | -0.06 | -0.05 |
| | (0.03) | (0.02) |
| Management Training | 0.11 | 0.07 |
| | (0.01) | (0.03) |
| Percentage of Educated Workforce | 0.11 | 0.06 |
| | (0.03) | (0.06) |
| R&D | 0.05 | 0.00 |
| | (0.01) | (0.03) |
| Industry Dummy | Yes | Yes |
| Country Dummy | Yes | Yes |
| N | 9941 | 1446 |

Notes: $^*p<0.1$; $^{**}P<0.05$, $^{***}P<0.01$

Another significant observation from table 7 is that from the first model I get the impact of foreign licensing only on domestic firms. This estimate is an even more accurate estimate of the impact of foreign licensing on firm level innovation because, for domestic firms, there is even less scope to acquire foreign technology compared to foreign owned firms or join ventures. Thus impact on domestic firm gives a stronger support to hypothesis one.

**Table 8: Marginal effects from probit models on four continents. The results indicate the heterogeneity in the impact of foreign licensing on firm-level innovation**

| | East Asia | ECA | Africa | Latin America |
|---|---|---|---|---|
| Foreign License | 0.30 *** | 0.26*** | 0.16** | 0.16*** |
| | (0.04) | (0.03) | (0.08) | (0.03) |
| Majority Foreign Ownership | -0.06 | -0.08* | 0.00* | -0.12** |
| | (0.04) | (0.03) | (0.04) | (0.03) |
| Minority Foreign Ownership | 0.08 | -0.03 | 0.13 | -0.03 |
| | (0.07) | (0.06) | (0.09) | (0.07) |
| Exporter | 0.02 | 0.04 | 0.04 | 0.02 |
| | (0.03) | (0.02) | (0.03) | (0.02) |
| Importer | 0.07* | 0.09 | 0.09 | 0.05 |
| | (0.03) | (0.02) | (0.04 | (0.05)) |
| Age (ln) | 0.02 | -0.04 | -0.01 | -0.01 |
| | (0.02) | (0.01) | (0.01) | (0.01) |
| Size (ln) | 0.06* | 0.06* | 0.04 | 0.02 |
| | (0.01) | (0.01) | (0.02) | (0.01) |
| Partial Public Ownership | 0.11 | -0.08 | -0.21 | 0.01 |
| | (0.05) | (0.04) | (0.09) | (0.09) |
| Management Training | 0.08 | 0.10 | 0.09 | 0.13 |
| | (0.03) | (0.02) | (0.04) | (0.02) |
| Percentage of Educated Workforce | 0.11 | 0.12 | 0.18 | 0.05 |
| | (0.05) | (0.05) | (0.11) | (0.04) |
| R&D | -0.03 | -0.03 | 0.10 | 0.10 |
| | (0.04) | (0.02) | (0.04) | (0.02) |
| Industry Dummy | Yes | Yes | Yes | Yes |
| Country Dummy | Yes | Yes | Yes | Yes |
| N | 1710 | 3445 | 1796 | 4434 |

Notes: *p<0.1; **P<0.05, ***P<0.01

To test hypothesis three, I split the original data set into four groups. In each group I include firms from a different continent. To divide the firms into different continents, I followed the World Bank group's original classification. The four continents are East Asia, Europe and Central Asia, Africa and Latin America. The probit models in table 8 showcase the heterogeneity in the impact of foreign licensing on firm level innovation in each continent. This result supports hypothesis three. It can be seen that foreign licensing is significant for all four continents. The significance level is higher in three continents -- East Asia, Europe and Central Asia, and Latin

America at p-value <0.01. In the case of Africa, the significance level is 95%. Another interesting point is that majority foreign ownership is not significant for all the continents. This lends support to hypothesis one, which states foreign licensing is an even *more* important factor than majority ownership.

Hypothesis three states that East Asian firms would have higher impact than African firms. The results from table 8 also indicate that East Asian firms have much higher probability to innovate than African or Latin American firms. If a firm uses foreign licenses, then an East Asian firm is 30% more likely to innovate if everything else stays the same. The same propensity to innovate for Africa is only 16%, and for Latin America, it is 16%. Europe and Central Asia sits in the middle of the group with 26% probability to innovate if the firm has foreign licensing. These results support the hypothesis that firm-level innovation depends on national absorptive capacity.

To test hypothesis four, I use interaction terms in domestic and foreign-owned firms. Hypothesis four states that R&D is more helpful for domestic firms compared to foreign-owned firms. The results show that if everything else stays the same, domestic firms have higher propensity to innovate compared to foreign-owned firms. This lends support to hypothesis four about the importance of domestic firms' R&D.

**Table 9: Marginal effects from probit models. Domestic firms get more benefits from R&D than Foreign-owned firms from foreign licensing.**

| | Domestic Firms | Foreign Owned firms |
|---|---|---|
| Foreign License | 0.22*** | 0.29*** |
| | (0.03) | (0.03) |
| Majority Foreign Ownership | | -0.06* |
| | | (0.03) |
| Exporter | 0.03 | 0.04 |
| | (0.01) | (0.04) |
| Importer | 0.07* | 0.03 |
| | (0.01) | (0.04) |
| Age (ln) | -0.02 | 0.02 |
| | (0.01) | (0.02) |
| Size (ln) | 0.04* | 0.05 |
| | (0.01) | (0.01) |
| Partial Public Ownership | -0.06 | -0.07 |
| | (0.03) | (0.07) |
| Management Training | 0.11 | 0.07 |
| | (0.01) | (0.03) |
| Percentage of Educated Workforce | 0.11 | 0.06 |
| | (0.03) | (0.06) |
| R&D | 0.05 | 0.01 |
| | (0.01) | (0.03) |
| License * R&D | 0.03 | -0.10 |
| | (0.05) | (0.09) |
| Industry Dummy | Yes | Yes |
| Country Dummy | Yes | Yes |
| N | 9941 | 1446 |

Notes: *p<0.1; **P<0.05, ***P<0.01



The interaction terms of table 9 also give further support to the results. A common problem in using a single set of survey is common method variance. To counter this problem, I included interaction terms. Chang et al (2010) suggested this solution to counter the common method variance problem. The results from two models, which are using interaction terms, also show that foreign licensing is an important source for firm-level innovation.

**Genetic matching results**

Genetic matching allows me to prove the robustness of my results. I use genetic matching to find a matched data set with a treatment and a control group and then I run a regression on the matched data set. Table 10 shows regression results on genetic matched data set. I controlled for all the major covariates to get the treatment effect for foreign license, which is shown in the table 10. The average treatment effect on the treated (ATT) is 0.24, which is consistent with my probit model results where the result was 0.23 (from table 6, model five). This treatment effect is significant at $p<0.01$ level. Genetic matched results[6] produced a good balance with the smallest p-value of 0.21. This p-value comes from KS-tests and paired t-tests from the variables being matched (Diamond and Sekhon, 2013). Results from genetic matching give strong support to hypothesis one, which states that foreign license has positive significant effect on firm-level innovation.

**Table 10: Results from genetic matched data set. This result reaffirms the relationship between foreign licensing and firm-level innovation**

| | Value |
|---|---|
| Treatment Effect (ATT) | 0.24 |
| Confidence Interval (95%) | [0.196, 0.275] |
| Standard Error | 0.02 |
| Significance level | 99% |
| The smallest p-value (KS and paired t-tests for covariate balance) | 0.15 |
| Covariates Matched on | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership |
| Covariates Balance Achieved on | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership, R&D, Management Training |

In hypothesis two, I stated that foreign-owned firms would have higher impact from foreign licensing than domestic firms. To test this using genetic matching, I divided the data into

6 I used a caliper matching here with a value of 0.02. For full methodology, please see Diamond and Sekhon (2013).

two groups: domestic and foreign-owned firms. I ran genetic matching and on the matched data, I ran regression, which estimated ATT for these two groups. From table 11 it shows that domestic firms have higher impact (0.21) compared to foreign-owned firms. This goes against hypothesis two and probit model results.

**Table 11: Results from genetic matched data set. This result shows the domestic firms have higher impact from foreign licensing on innovation**

| | Domestic firms | Foreign-owned firms |
|---|---|---|
| Treatment Effect (ATT) | 0.21 | 0.19 |
| Confidence Interval (95%) | [0.15, 0.25] | [0.11,0.27] |
| Standard Error | 0.02 | 0.04 |
| Significance level | 99% | 99% |
| The smallest p-value (KS and paired t-tests for covariate balance) | 0.09 | 0.07 |
| Covariates Matched on | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership |
| Covariates Balance Achieved on | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership, R&D, Management Training | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership, R&D, Management Training |

To test hypothesis three to explore the heterogeneity of the impacts of foreign licensing, I again divide the data set into four groups, then use genetic matching and finally run regressions on the matched data set. The results are shown in table 12. East Asian firms have higher impact (0.29) than the average treatment effect (0.24, showed in table 10) and African firms have a lower level of impact (0.22). East Asian firms have 7% more probability to innovate if everything else stays the same compared to African firms and the result is significant at p-value < 0.01. But the treatment effect for Africa is significant at p-value <0.10. This gives strong support to hypothesis three which states East Asian firms will have higher impact compared to African firms.

**Table 12: Results from genetic matched data set. This result reaffirms heterogeneity of the impacts of foreign licensing on firm-level innovation**

| | East Asia | Africa |
|---|---|---|
| Treatment Effect (ATT) | 0.29 | .22 |
| Confidence Interval (95%) | [0.21, 0.36] | [0.05,0.36] |
| Standard Error | 0.02 | 0.08 |
| Significance level | 99% | 90% |
| The smallest p-value (KS and paired t-tests for covariate balance) | 0.32 | 0.31 |
| Covariates Matched on | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership |
| Covariates Balance Achieved on | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership, R&D, Management Training | Majority Foreign Ownership, Exporter, Importer, Size, Public Ownership, R&D, Management Training |

I did not include results in table 12 for two continents because genetic matching did not achieve covariate balance both for Latin America, and Europe and Central Asia, which means that estimates for these two continents are less reliable. Nonetheless, my genetic matching results show that the impact of licensing is significant for both East Asia and Africa, although the impact level is different.

From the analysis it is clear that, licensing has significant positive impact even after controlling for all the important firm level characteristics, and industry and country dummies. All of the probit and genetic matching results support the hypotheses except for hypothesis two, which has different results in probit models and in genetic matching.

## Limitations

This research has two major limitations. First, the direction of causality is an important limitation. While foreign licenses help a firm to be more innovative, it is also true that innovative firms tend to license more. But licensing is an expensive and time-consuming process. A company would buy a foreign license if it were confident about commercializing a new product or service. I also used genetic matching, which compared firms that are buying licenses with the firms that are not. This powerful matching method estimate is of a more robust and reliable nature. Second, the questionnaire for survey result was to some extent subjective. This subjectivity could introduce some errors in the result. To counter this problem I also showed some results from two interaction terms in both domestic and foreign owned firms in table 9. Results from interaction terms suggest that foreign licensing is indeed an important determinant for firm-level innovation.

# Conclusion

This thesis sought to examine the impact of foreign licensing on firm level innovation. Previous studies on the topic (such as Yang and Maskus, 2001) highlighted the importance of foreign licensing but did not give any empirical evidence at the firm level. Using a rich and large data set from the World Bank Enterprise Survey, I provide empirical evidence that foreign licensing is an important source of technology transfer. To show causality in the relationship, the study further employs genetic matching on the data set. The robust finding is that foreign licensing is important for innovation and there is significant heterogeneity at the country level of the impact of foreign licensing. These findings are statistically significant.

Two limitations are worth reiterating. First, the data is a cross-country one, not a panel data. The absence of a temporal component made analysis difficult. Second, although the survey data is rich, as previously discussed the interpretation of the survey questionnaire may vary from country to country and firm to firm. Nevertheless, using a novel matching method allowed me to compare similar firms to similar firms.

I also discussed the potential explanations for the heterogeneity of different levels of impact on different countries using two frameworks: firm-level and national level absorptive capacity. I argued that firm level innovation depends on both firms and national factors.

The findings show that although FDI is given higher priority by policy makers, licensing foreign technologies is also a significant channel for firm-level innovation in developing countries. It was found that the impact of foreign licensing depends on countries' national absorptive capacity as well as firm-level absorptive capacity.

The significance of this study lies in the policy recommendations that can be drawn from its empirical findings. Policymakers from the Global South should focus on increasing the absorptive capacity at the national level to increase firm-level innovation. To do that, policymakers need to invest in human capital and strengthen local institutions. Firm managers should focus on increasing the firm-level absorptive capacity by doing more local R&D and training managers.

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# Appendices

**Table 13: Results from probit models, results demonstrate that foreign licensing is significant even after controlling for all the major variables.**

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Innovation | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Foreign License | 0.702*** | 0.656*** | 0.589*** | 0.589*** | 0.623*** |
| | (0.048) | (0.048) | (0.049) | (0.049) | (0.051) |
| Majority Foreign Ownership | -0.109*** | -0.236*** | -0.257*** | -0.257*** | -0.194*** |
| | (0.041) | (0.043) | (0.043) | (0.043) | (0.045) |
| Minority Foreign Ownership | 0.033 | -0.060 | -0.050 | -0.050 | 0.049 |
| | (0.084) | (0.085) | (0.086) | (0.086) | (0.088) |
| Exporter | 0.222*** | 0.079*** | 0.046 | 0.046 | 0.075** |
| | (0.027) | (0.029) | (0.029) | (0.029) | (0.031) |
| Importer | 0.317*** | 0.262*** | 0.204*** | 0.204*** | 0.171*** |
| | (0.026) | (0.026) | (0.027) | (0.027) | (0.028) |
| Age (ln) | | -0.030** | -0.032** | -0.032** | -0.031* |
| | | (0.014) | (0.014) | (0.014) | (0.016) |
| Size (ln) | | 0.147*** | 0.105*** | 0.105*** | 0.114*** |
| | | (0.010) | (0.011) | (0.011) | (0.012) |
| Partial Public Ownership | | -0.347*** | -0.378*** | -0.376*** | -0.163*** |
| | | (0.053) | (0.053) | (0.053) | (0.059) |
| Manager Training | | | 0.431*** | 0.431*** | 0.280*** |
| | | | (0.026) | (0.026) | (0.029) |
| Percentage of Educated Workforce | | | 0.245*** | 0.246*** | 0.278*** |
| | | | (0.051) | (0.051) | (0.062) |
| R&D Dummy | | | 0.124*** | 0.125*** | 0.112*** |
| | | | (0.026) | (0.026) | (0.029) |
| Constant | -0.250*** | -0.597*** | -0.703*** | -0.692*** | -0.316* |
| | (0.018) | (0.044) | (0.047) | (0.053) | (0.166) |
| Industry dummy | No | No | No | Yes | Yes |
| Country dummy | No | No | No | No | Yes |
| Observations | 11,387 | 11,387 | 11,387 | 11,387 | 11,387 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 | | |

**Table 14: Probit model results which include interaction terms, foreign licensing is still significant and positive**

**Regression Results**

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Innovation | | | |
| | Domestic Firms | | Foreign-Owned Firms | |
| | (1) | (2) | (3) | (4) |
| Foreign License | 0.620*** | 0.584*** | 0.697*** | 0.838*** |
| | (0.058) | (0.095) | (0.110) | (0.184) |
| Exporter | 0.079** | 0.079** | 0.099 | 0.094 |
| | (0.033) | (0.033) | (0.090) | (0.090) |
| Importer | 0.176*** | 0.176*** | 0.065 | 0.064 |
| | (0.030) | (0.030) | (0.099) | (0.099) |
| Age (ln) | -0.037** | -0.037** | 0.049 | 0.048 |
| | (0.017) | (0.017) | (0.043) | (0.043) |
| Size (ln) | 0.108*** | 0.108*** | 0.121*** | 0.121*** |
| | (0.013) | (0.013) | (0.030) | (0.030) |
| Partial Public Ownership | -0.152** | -0.152** | -0.131 | -0.132 |
| | (0.063) | (0.063) | (0.178) | (0.178) |
| Manager Training | 0.288*** | 0.288*** | 0.219*** | 0.215*** |
| | (0.031) | (0.031) | (0.083) | (0.083) |
| Percentage of Educated Workforce | 0.277*** | 0.277*** | 0.193 | 0.191 |
| | (0.068) | (0.068) | (0.155) | (0.155) |
| R&D Dummy | 0.129*** | 0.126*** | 0.012 | 0.039 |
| | (0.031) | (0.032) | (0.081) | (0.085) |
| license2:RD_dummy | | 0.057 | | -0.220 |
| | | (0.118) | | (0.227) |
| Constant | -0.243 | -0.242 | -0.797** | -0.814** |
| | (0.185) | (0.185) | (0.387) | (0.389) |
| Industry dummy | Yes | Yes | Yes | Yes |
| Country dummy | Yes | Yes | Yes | Yes |
| Observations | 9,941 | 9,941 | 1,446 | 1,446 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 15: Results from probit models, results demonstrate that licensing has higher impact on foreign owned firms than domestic firm**

**Regression Results**

| | *Dependent variable:* | |
|---|---|---|
| | Innovation | |
| | Domestic Firms | Foreign-Owned Firms |
| | (1) | (2) |
| Foreign License | 0.620*** | 0.697*** |
| | (0.058) | (0.110) |
| Exporter | 0.079** | 0.099 |
| | (0.033) | (0.090) |
| Importer | 0.176*** | 0.065 |
| | (0.030) | (0.099) |
| Age (ln) | -0.037** | 0.049 |
| | (0.017) | (0.043) |
| Size (ln) | 0.108*** | 0.121*** |
| | (0.013) | (0.030) |
| Partial Public Ownership | -0.152** | -0.131 |
| | (0.063) | (0.178) |
| Manager Training | 0.288*** | 0.219*** |
| | (0.031) | (0.083) |
| Percentage of Educated Workforce | 0.277*** | 0.193 |
| | (0.068) | (0.155) |
| R&D Dummy | 0.129*** | 0.012 |
| | (0.031) | (0.081) |
| Constant | -0.243 | -0.797** |
| | (0.185) | (0.387) |
| Industry dummy | Yes | Yes |
| Country dummy | Yes | Yes |
| Observations | 9,941 | 1,446 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 16: Results from probit models, results demonstrate that licensing has different effects on four continents.**

**Regression Results**

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Innovation | | | |
| | East Asia | ECA | Africa | Latin America |
| | (1) | (2) | (3) | (4) |
| Foreign License | 0.816*** | 0.681*** | 0.417** | 0.464*** |
| | (0.116) | (0.075) | (0.191) | (0.100) |
| Majority Foreign Ownership | -0.109 | -0.199** | -0.032 | -0.291*** |
| | (0.110) | (0.078) | (0.118) | (0.077) |
| Minority Foreign Ownership | 0.227 | -0.071 | 0.308 | -0.092 |
| | (0.185) | (0.148) | (0.235) | (0.175) |
| Exporter | 0.076 | 0.093* | 0.102 | 0.072 |
| | (0.077) | (0.056) | (0.085) | (0.050) |
| Importer | 0.166** | 0.187*** | 0.265*** | 0.119*** |
| | (0.073) | (0.051) | (0.084) | (0.044) |
| Age (ln) | 0.059 | -0.093*** | -0.005 | -0.039 |
| | (0.039) | (0.034) | (0.038) | (0.024) |
| Size (ln) | 0.168*** | 0.163*** | 0.126*** | 0.050** |
| | (0.029) | (0.020) | (0.035) | (0.021) |
| Partial Public Ownership | -0.220** | -0.205** | -0.785*** | 0.028 |
| | (0.097) | (0.095) | (0.256) | (0.232) |
| Manager Training | 0.211*** | 0.263*** | 0.261*** | 0.327*** |
| | (0.074) | (0.050) | (0.088) | (0.045) |
| Percentage of Educated Workforce | 0.302** | 0.352*** | 0.533* | 0.117 |
| | (0.122) | (0.112) | (0.273) | (0.101) |
| R&D Dummy | -0.058 | -0.083* | 0.287*** | 0.262*** |
| | (0.097) | (0.050) | (0.078) | (0.044) |
| Constant | -1.264*** | -0.288 | -1.834*** | 0.230** |
| | (0.165) | (0.187) | (0.171) | (0.100) |
| Industry dummy | Yes | Yes | Yes | Yes |
| Country dummy | Yes | Yes | Yes | Yes |
| Observations | 1,712 | 3,445 | 1,796 | 4,434 |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |