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Create or Buy?

- Internal vs. External Source of Innovation and Firm Productivity

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1. Introduction

Innovation outsourcing is a rapidly increasing trend.[1] Technological convergence, declining transaction costs of acquiring external R&D inputs, and shortening product cycle times have driven firms to utilize external sources of knowledge (Narula 2004).

Despite rapidly growing innovation outsourcing, there is little systematic research and analysis of the effects of innovation outsourcing, specifically, whether the outsourced innovation produces a different effect than in-house innovation on firms' productivity. The existing research on innovation outsourcing focuses largely on its impact on firms' innovation performance, such as the number of new products or registered patents, rather than on firms' overall performance, such as final output and productivity. A firm invests in innovation primarily to enhance its final output and productivity; however, up to now little has been known about the wider effects of innovation outsourcing beyond its direct effect upon a firm's innovation performance.

Also, research on representative firms in developing countries is particularly rare. Existing research focuses mainly on a few developed economies and on selected industries, such as high-technology industries, even though these may not be the most innovative industries in developing countries. Also, research using innovation survey data was usually conducted for those firms that are more likely to invest in innovation or had responded in the affirmative for innovation outputs — which might lead to biased estimates of the effect of innovation for more general firms.

Although innovation has been widely recognized as a determinant of productivity, the role of innovation in improving productivity might vary according to a country's relative position in technology advancement.[2] Specifically, countries close to the technology frontier will grow faster by investing in innovation, while the follower group of countries will benefit more by adopting existing technology from the frontier (Aghion 2004; Aghion, et al. 2013). Therefore, depending on their level of technology advancement, the growth rate of the economy will depend not only on innovation but also on the ability to adopt or diffuse technology throughout the economy (Griffith et al. 2004).

In this regard, it is questionable whether innovation policy should vary according to the level of a country's technological advancement. Frontier countries might benefit more

1. For instance, the business process outsourcing (BPO) market has grown to be worth $309 billion in 2012, worldwide, and the overall volume is estimated to be growing at a rate of approximately 25 percent annually (Lacity and Willcocks 2013).
2. In Schumpeterian growth theory, innovation is a driver of economic growth and resource allocation from less innovative firms to more innovative ones. Entrepreneurs create innovation with the expectation of being rewarded with (monopoly) rents if their innovation is successful. However, these rents are decreased when other firms imitate those innovations, and eventually disappear when new innovations occur that compete with the current technologies and thereby drive them out of the market (creative destruction) (Aghion 2004).

from policies that promote firms' internal innovation (create); while follower countries would gain more from policies favouring efficient adoption of existing technologies through innovation outsourcing (buy).

Particularly in a developing country like Tunisia, where firms are constrained by limited resources and skill levels, it is important to understand which source of innovation is more efficient improves final output. However, the effect of innovation outsourcing on firm productivity is under researched, even in developed economies, and to my knowledge, has never been examined in Tunisia.

This paper fills this gap in knowledge on innovation outsourcing's effect on productivity from more general industries in developing countries, by examining representative firms in manufacturing sector in Tunisia. In this paper, I analyse the determinants of a firm's decision to invest in different sources of innovation, and the effects of these different sources on a firm's final output, via productivity. Specifically, I answer the following questions: are there any differences in determinants of a firm's decision to create and to buy? Are the effects on productivity different between create and buy; and if so, which source of innovation is more effective in increasing final output, via productivity?

The rest of the chapter is organized as follows: Section 2 provides literature review and an analytical framework. Section 3 describes the data set and the key variables used, including measurement of innovation variables. Section 4 provides the empirical strategy, and potential concerns and suggested solutions related to the empirical strategy. Section 5 presents the results, and section 6 provides the conclusion.

2. Literature and Analytical Framework

Empirical research tends to find positive effect of innovation on firms' productivity. Those empirical results are generally consistent with the earlier literature in that innovation inputs positively influences on firm productivity via increased innovation outputs (Crepon, Duguet, and Mairesse 1998)[3].

While innovation's positive effect on productivity are empirically supported in many developed economies, evidence is still rare in developing countries, where innovation's effect on productivity might be different from developed countries. Specifically, in developing countries, the cost of innovation might be higher because of greater distance from the technology frontier, and incentives to innovate might be lower because of

[3] More recent literature documents that different innovation inputs lead to different types of innovation outputs, depending on the specific characteristics of a firm. For instance, R&D and IT investment lead to product innovation in high-technology industries and process innovations for exporters (Brynjolfsson and Hitt 2003: Inklaar and Timmer 2008). Also, the type of innovation seems to matter for productivity. Hall (2011) surveyed empirical work on the relation between innovation and productivity and found that product innovation positively impacts output and productivity, but that the impact of process innovation is ambiguous.

lower expected rents of small domestic markets, and weak institutions, such as patent law or intellectual properties law, to protect against imitation by competitors.

In fact, firms in developing countries might be better off improving their ability to acquire existing external knowledge (buy), instead of trying to innovate within the firms (create) because innovation is costly, risky, and path-dependent. For these reasons innovation is highly concentrated in a few developed countries and among a small number of firms, while external sources of technology account for a large part of productivity growth in developing countries (Fu et al. 2010).

However, tapping existing knowledge is not easy either. The adaptation of knowledge requires well-directed technological efforts (Lall 1992) as well as sufficient human and financial resources and absorptive capacity (Cohen and Levinthal 1990) — essentially the same prerequisites as for internal innovation. Thus, internal innovation could play a role of absorptive capacity, thus enhance the ability of firms to imitate external innovation (Griffith et al. 2004).

Therefore, it is unclear whether create or buy contributes more for productivity increase, thus output increase, in developing countries. Also, it might be better to use a combination of both sources of innovation, instead of only one source, in developing countries. Understanding the effect of different sources of innovation will provide practical information to firms and policy makers.

However, research on the effect of different sources of innovation on firm productivity, instead of innovation outcome, with representative firms in more general industries in developing countries is extremely rare. Moreover, most previous studies have focused only on a few developed economies and high-technology industries, even though those industries are not necessarily the most innovative, especially in developing countries. Further, among those a few studies on developing countries, most of them were conducted only for those firms that responded in the affirmative to innovation outputs, which might produce biased results.

Different sources of innovation and their effects on productivity

I review previous literature on innovation outsourcing and provide views on why different sources of innovation might have different effects on firm productivity.

Despite the rapid acceleration of innovation outsourcing and increasing research that follow this trend, research so far has not systematically explored whether internal and external innovation produce different effects on the final output and firm productivity, and what makes for the differences. While innovation outsourcing has been widely studied in a number of different fields, such as industrial organization and management, the findings are fragmented, and there is no systematic framework to analyse the make or buy decision on innovation outsourcing separately from decisions on general outsourcing, even though innovation outsourcing might be very different from general outsourcing.

One advantage of innovation outsourcing, which also applies to general outsourcing, is short-term cost saving. For instance, outsourcing can reduce production cost because of economies of scale or lower wages of outsourcing providers. However, there is a certain cost associated with searching for providers for outsourced activities. Thus, literature in the field of management and industrial organization has tried to provide an analytical framework for firms' make-or-buy decisions, using a profit maximization model and its extension. Profit-maximizing firms decide whether or not to outsource by measuring the trade-off between operating a larger organization with less specialization or conducting a costly search with contracting incompleteness (Grossman and Helpman 2003, 2005).

There are several disadvantages in innovation outsourcing as there are in general outsourcing. Outsourcing is a trade-off situation and presents a dilemma because it may damage the capacity for producing new products, and thus the innovation capability of firms (Bengtsson and Berggren 2008). The outcome of outsourcing is moderated by the strategy for internal and external integration. The integration needs and mechanisms are themselves affected by the complexity of products and manufacturing processes (see, for example, Chesbrough and Teece 2002; Ulrich and Ellison 2005). In fact, despite strong arguments for the advantages of outsourcing, previous studies show few positive or else contradictory effects of outsourcing on performance (Bengtsson et al. 2009[4]).

In addition to the above mentioned advantages and disadvantages that innovation outsourcing shares with general outsourcing, it also has certain differentiating characteristics, such as a diverse motif and risks, which influence the particular way it affects productivity.

Unlike general outsourcing, in most cases innovation outsourcing activities are identified for strategic reasons, which is likely to produce a different effect on firm output. Firms choose outsource innovation in areas they do not have in-house ability and use innovation outsourcing as an instrument to acquire external knowledge, which is subsequently integrated into a firm's own knowledge base, and to access suppliers' competencies. Therefore, innovation outsourcing could potentially improve a company's capacity to stay current and innovate by interacting with "more advanced knowledge sources." Also, firms may need to outsource innovation to gain the capacity to produce unique products or improve quality. In fact, product innovation is conducted mainly for these strategic reasons and firms may also benefit from having ability to offer a variety of diversified products they otherwise do not have the capacity to produce. More firms now outsource globally to tap into the richer external source of knowledge,

4. Related literature is cogently summarized in Bengtsson, et al. 2009.

probably because rents from acquired new products or processes may significantly outweigh costs of innovation outsourcing (Quinn 1999; Chesbrough 2003; Fifarek et al. 2008).

However, unlike other general outsourcing, there is a risk of information leakage from firms that receive innovation outsourcing services therefore, firms' innovation outsourcing are less than optimal level, when information leakage cannot be monitored (Lai, Riezman, and Wang 2009[5]). According to a survey conducted by the Shared Services and Business Process Outsourcing Association in 2003, lack of control and loss of internal knowledge are the main concerns when considering whether or not to outsource innovation. Further, given that the provider typically has more knowledge than the buyer, and the buyer sometimes does not have full control of the innovation process, outsourcing could weaken firms' integrative capabilities. Buyers often question their capacity to deal with the experts and become overly dependent on the provider. Thus, buyers are legitimately concerned about losing the skills that they outsource (Quinn 1999).

Moreover, benefits of engaging in open innovation materialize mostly in the long term and it takes time before innovation investment actually contributes to the final outcome. Innovation outsourcing helps establish firms reputation, builds relationships, or signals talents to a wide group of innovators (and potential employers), which all take time. Further, innovation involves uncertainty in an essential way, and the institutional structure supporting innovation varies greatly from sector to sector (Nelson and Winter 1977). Overall, innovation outsourcing requires the attention of top management as it could face internal resistance from existing employees who are accustomed to the traditional way of working. Therefore, recommendations for outsourcing innovation are unlikely to come from below. In fact, lower- to intermediate-level managers tend to be hostile to innovation outsourcing, as they fear loss of jobs, prestige, or power. Lastly, innovation outsourcing incurs transaction costs for searching, contracting and controlling, and exposes firms to certain short-term risk, including introduction delay caused by internal bureaucracies (Quinn 1999; Lacity and Willcocks 2013).

Meanwhile, innovation outsourcing's effect on productivity can also be varied by the firm's level of technological advancement and its ability to innovate or imitate. As explained by the Schumpeterian Growth Theory, if the "follower" group of countries will benefit more by adopting existing technology from the frontier, while countries close to the technology frontier will grow faster by investing in innovation, it might be more efficient for developing countries, like Tunisia, to acquire technology created externally (buy) as long as it is easy to adopt. However, if technology is difficult to transfer and

5. Lai, Riezman, and Wang (2009) provides an analytical framework related to the cost-saving aspects of innovation outsourcing using a principal-agent framework to analyse whether a production firm under monopolistic competition should outsource R&D or do it in-house, as well as which type of contracts between fixed or revenue sharing is optimum.

adopt firms must have the ability to learn the external source of innovation (absorptive capacity), which because of lower levels of initial technology might not exist at firms in developing countries; in these cases innovation outsourcing might not be efficient.

Thus, given the diverse motif of conducting innovation outsourcing and its complex characteristics, it is unclear whether innovation outsourcing would have a positive effect on firm productivity in developing countries like Tunisia, and whether internal or external innovation is more efficient in increasing firms' productivity.

Meanwhile, there is scarce empirical evidence for the effects of innovation outsourcing on firms' productivity. The advantages and disadvantages of innovation outsourcing cited above are identified largely in case studies of a few selected firms from managerial science literature. Although it is insightful, their findings are not readily generalized to other contexts. Also, as previously mentioned, the evidence from developing countries is particularly rare, but the effect of innovation outsourcing on productivity increase could be different between developed and developing countries. Moreover, to my knowledge, there are few theoretical explanations about what makes a firm innovate internally or externally, and whether different sources of innovations produce different effects on firms' productivity and final outputs.

Are there any benefits of creating and buying jointly?

The finding that a firm needs to acquire absorptive capacity to benefit from an external source of innovation stimulated numerous investigations into a possible complementary effect of internal and external sources of innovation, given that internal innovation plays a role in the absorptive capacity of adapting external innovation. However, there are mixed evidence of the complementarity effect between internal and external sources of innovation.

Earlier literature found that in-house innovation plays a role in absorptive capacity, which helps a firm to assimilate and integrate external innovation into its own production, thus, prerequisite to deriving benefit from innovation outsourcing (Cohen and Levinthal 1990; Griffith et al. 2004; Spithoven et al.2011). Firms using both internal and external sources of innovation have better innovation performance than those using only one source of innovation (Cassiman and Veugelers 2006). Conditional on a significant level of internal R&D, a firm can achieve higher productivity gains by combining external and internal R&D; however, there are decreasing returns to scale at high levels of internal and external R&D (Lokshin et al. 2008).

However, a number of empirical studies report absence of a complementary effect or even a negative (supplementary) effect of using both sources of innovation. For instance, several studies document that internal and external innovation can substitute for each other, especially when resources are limited (Fikkert 1993; Basant and Fikkert 1996; Blonigen and Taylor 2000). This might be explained by that given a limited budget, an increase in either of the two options tends to reduce spending on the other. If the effect on innovation investment on productivity is not linear or requires a certain amount of investment (threshold) to produce a positive effect on final outcome, splitting resources between two types of innovation would actually have a lower effect than consolidating resources on just one.

While it is difficult to generalize, evidence of complementary effects seems to be more common in studies on developed countries, and evidence of complementary effects seems to be mostly from studies on developing countries. For instance, complementary effects were documented in the studies conducted on firms in Germany, Italy, the United Kingdom, Belgium, France, and Denmark; while those that document supplementary effects were conducted on firms in Andean-group countries, India, and China.[6]

In addition, other studies find that the complementary or substitution effects could be changed depending on the ratio of the sources of innovation used, the internal innovation status of the firm, and the external environment. Specifically, in environments in which learning is less demanding, a firm's in-house R&D has little impact on absorptive capacity. In the extreme case in which external knowledge can be assimilated without any specialized expertise, a firm's internal R&D would have no effect on its absorptive capacity (Cohen and Levinthal 1990). Also, open innovation moderates the internal and especially longer-term incentives to innovate. R&D outsourcing and innovation performance have an inverse U-shaped relationship, which is positively moderated by the extent to which firms engage in internal R&D and by the breadth of formal R&D collaborations. Both serve as instruments to increase the effectiveness of R&D outsourcing (Fu et al. 2010).

3. Data

The data used in this study come from the annual enterprise survey, L'Enquête Nationale sur les Activités Économiques, which is conducted by the Tunisian Institute of National Statistics (L'Institut National de la Statistique, INS).

The data are collected for the period 1997 to 2009, with about 2,300 firms surveyed each year, including some 1,500 firms in the manufacturing sector. The survey coverage is extensive, as about 30 percent of firms with six or more employees in each sector, excluding agriculture, are included in the sample. In each year, a sampling method was applied, taking into account stratifications by industry and company size in terms of actual employees. I have confirmed that the sample includes representative Tunisian enterprises by comparing key firm characteristics of INS data with the aggregated

6. The empirical evidence on supplementary effects includes Mytelka (1987) on Andean-group countries, Fikkert (1993) on Indian manufacturing firms, and Basant and Fikkert (1996) on Indian firm-level panel data. Also, a recent study by Hou and Mohnen (2013) found the complementary effect on Chinese manufacturing for only medium-size firms, but found a supplementary effect for firms, overall. However, there are more evidences of complementary and supplementary effects beyond of this literature review.

information of firms listed by the Investment Promotion Agency (Agence de Promotion de l'Industrie, API).

The drawback of the INS data is that the survey provides a repeated cross-section, which accurately represents the Tunisian economy, but makes it difficult to apply econometric techniques for the panel data. However, approximately 300 (*N*) firms are repeatedly selected for 13 consecutive years (*T*), and most of the firms appear for at least 2 of the 13 years; therefore, the whole set of data is a rather weakly balanced panel, which allows me to use econometric techniques for the panel data.

The advantage of the INS data is that they provide rich information on firm characteristics (firm creation year, export status, ownership), balance sheets (revenue, labor, capital, expenditure on intermediate goods), and production (goods category, exports, and ownership status), as well as other information included in standard firm-level surveys. Also, the INS data uniquely provide variables to identify internal and external innovation, which will be further described in the next subsection.

Since 2008, the INS has abridged questionnaires to reduce time and cost and to simplify the survey procedure. Consequently, questions related to internal and external innovation have been deleted. Therefore, I omitted observations for 2008 and 2009 and kept only those in manufacturing, with NACE codes between 15 and 36. I also omitted observations with missing information in labor, capital, material, and internal and external sources of innovation. Therefore, the total number of observations has been reduced to 16,471 for the period 1997 to 2007. A firm repeatedly selected on average around four times during this period, which makes this data set similar to unbalanced panel of observing around 4,100 firms over a four-year period (the higher N, the small *T*), which is still a large enough sample to test the questions posed in this paper.

Innovation variables

The concept of innovation is broadly treated in economics and managerial science literature, and typically understood as introducing new production processes, new products, new management methods, and new organization of production activities. These concepts have been measured with various proxies, depending on available data.

In most innovation surveys, such as the Community Innovation Survey (CIS), innovation has been measured as a process, products, and organizational activities that are new-to-market or new-to-firm.[7] However, innovation surveys are relatively new and have been

7. There are several limitations to the CIS, although it provides direct measures of innovation. First, the definition of an innovative firm is somewhat ambiguous. It asks firms if they have undertaken activities new to market or new to firm to measure innovation, and if the firm answers in the affirmative, it is treated as an innovator. Based on the new product/process measures in the survey, Cyprus and Portugal have been the most innovative countries in Europe for the past few years — which might raise concerns

conducted in a relatively small number of samples, and mostly in developed countries. In Tunisia, an innovation survey similar to CIS was conducted in 2005, targeting a specific group of firms that was most likely to innovate, causing a sample selection bias.[8] Also, the survey was conducted only once in Tunisia, which makes it harder to understand the time trend of innovation effects or to apply the panel technique to remove potential effects related to time trend.

With general firm-level surveys, researchers have used different proxies for innovation. Most studies have used capitalized R&D as a proxy for innovation input. Fewer studies have used patents as a proxy for intermediate innovation output. The INS data provide detailed information about expenses on innovation activities, such as conducting R&D, receiving consulting services, and purchasing royalties. Hence, I will use the expenses related to innovation activities as proxies for innovation inputs.

While the concept of innovation could include a wide range of activities, I follow a more conservative approach and construct an innovation variable using cost items that are directly related to technical innovation, such as the cost of conducting R&D, cost of receiving technical consulting services, and cost of purchasing royalties. Specifically, I consider cost of conducting R&D as internal innovation (create), and purchasing royalties and receiving technical consulting services as external innovation (buy). Then, I create a total innovation (all) variable by calculating the total cost of these three activities. Therefore, my innovation variable is limited to innovation inputs on technical innovation. This narrow definition of innovation has been widely used in previous literature, and importantly, allows me to compare the effects of similar innovation activities between internal and external sources of innovation.

These innovation proxies have commonly been used as innovation input variables in previous literature. Specifically, R&D and royalties are most widely used proxies for

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about this survey's accuracy. Second, the surveys usually do not give information on multifactor productivity, although they sometimes provide data on labor productivity. They also do not have information on organizational innovation or detail expenditures on various kinds of innovation investments.

8. The first innovation survey of Tunisian firms was carried out in 2005 by the Ministry of Scientific Research, Technology and Competency Development. The survey asked firms about various aspects of innovation for the period 2002 to 2004, modeling the CIS survey. The survey was given to 739 firms, which were likely to have innovative and/or R&D activity. Their criteria of sample include manufacturing firms with high technology intensity and/or strong value addition, with more than 10 employees firms registered in the Agency for Investment Promotion (API) and the Institutes of National Statistics (INS). Among these, 586 firms took the survey. Among those, 322 firms responded in the affirmative to innovation. The survey included questions about product and process innovation. Firms were asked if they have introduced a new product or process during the three years preceding the survey. The firms taking the survey were predominantly in textiles (19 percent of respondents), food and agro-processing (17 percent), electrical and equipment (17 percent), and IT (4 percent). Like the CIS, this survey included subjective questions and qualitative variables that are difficult to interpret. Also, the sample was restricted to certain type of firms.

innovation. Receiving technical consulting services has also been recognized as innovation outsourcing in several studies, since if technology is uncodified, merely purchasing existing technology is insufficient to adopt the technology, and also requires consulting services[9] (Quinn 1999; Bloom and Van Reenen 2007, 2010).

Table 1.1 provides the mean value and number of observations of internal and external innovation variables by year and by different sources of innovation from 1997 to 2007.

Table 1.1 Innovation Variables, 1997 to 2007

Data		Create (Internal innovation)			Buy (External innovation)			All (Total innovation)		
Year	Number of firms	Mean log amount (TD)	Number of firms	Ratio (%)	Mean log amount (TD)	Number of firms	Ratio (%)	Mean log amount (TD)	Number of firms	Ratio (%)
1997	1,580	2.09	407	26	5.11	882	56	5.60	924	58
1998	1,574	2.95	573	36	5.73	1,010	64	6.47	1,093	69
1999	1,503	2.99	557	37	5.94	984	62	6.56	1,043	66
2000	1,777	2.80	632	36	5.63	1,101	70	6.25	1,170	74
2001	1,810	2.86	644	36	5.64	1,106	70	6.28	1,179	75
2002	1,427	3.06	525	37	5.69	852	54	6.38	907	57
2003	1,199	3.06	433	36	5.71	712	45	6.38	752	48
2004	1,352	3.49	572	42	6.26	879	56	6.96	926	59
2005	1,368	3.19	521	38	6.13	872	55	6.86	918	58
2006	1,501	2.88	518	35	5.77	932	59	6.60	993	63
2007	1,382	2.73	458	33	5.59	823	52	6.34	861	54
Mean	*1,498*	*2.92*	*531*	*36*	*5.75*	*923*	*58*	*6.43*	*979*	*62*

Note: TD=Tunisian dinar.

Approximately 62 percent of Tunisian firms engaged in either internal or external innovation on average, between 1997 and 2007. During the period, about 36 percent of firms engaged in internal innovation, and about 58 percent in external innovation. Among those firms that invested in external innovation, most paid for consulting services, and only a few for royalties. This ratio of firms that engage in innovation is relatively large and similar to the ratios in developed economies.[10]

Table A.1 in appendix I provides innovation variables by two-digit industry level. There is large heterogeneity in the amount of innovation investment across industries, and even within manufacturing. Comparing innovators' share in entire firms (innovator's ratio) across the two-digit industry level, I found that innovators' ratios are not high in so-called "high-tech" industries, such as pharmaceutical or automobile industries, which

9. Also, recent literature finds that receiving consulting services enhance firms' productivity (Bloom and Van Reenen 2007, 2010; Bloom et al. 2012).

10. European Commission-Eurostat reveals that innovation existed in 51 percent of manufacturing firms and in 40 percent of services firms in the period 1994–96 in Europe (Pianta 2005). In the CIS survey, about 62 percent of firms claimed to innovate in 1993 in Belgium (Cassiman and Veugelers 2006).

are typically considered innovative. In fact, a large number of previous studies on innovation focused largely on these sectors. Meanwhile, those industries that are generally considered less technologically sophisticated, such as tobacco, furniture, apparel, and printing, have some of the highest innovators' ratios, together with refined petroleum, chemicals and their related products (like rubber and plastic products), which are typically capital intensive and also Tunisia's main export items. This finding contradicts most of the previous studies, which consider high-tech industries to be technological leaders and innovation-intensive, even in developing countries.

The low level of innovators' share in high-tech industries might be explained by the fact that Tunisian firms might not invest in innovation activities in sectors where the technology gap with the more technologically advanced countries is large. Another possible explanation could be that those sectors are not necessarily tech-intensive in developing countries, such as Tunisia. In fact, I visited firms that are in high-tech industries, such as automobile and aerospace, and found that they produce only certain parts of automobiles or airplanes, such as seats and plastic materials for the interior space, which might require a relatively low level of technology in the integrated global value chain. This suggests that two-digit industry level groups might be too aggregated, and the position of these firms in the relevant supply chain is more important. In other words, the more relevant factor is not industry level group but product or process level group. Therefore, firms in developing countries like Tunisia that belong to high-tech industries do not necessarily produce innovation-intensive products.[11]

Interestingly, there is no distinguishing feature between internal and external innovation across the two-digit industry level. In the sectors where more firms invest in internal innovation, more firms also invest in external innovation. However, the different characteristics of firms that invest in different sources of innovation will be further analyzed in the next subsection.

Other variables

To test whether key factors that determine firms' innovation are different between internal and external innovation, I identified major determinants of innovation investment from previous literature. The explanatory variables in X include a vector of variables that could influence a firm's decision to invest in innovation.

Export: Previous literature has found that exporting can influence firms' innovation investment decisions. Exporting firms tend to invest more in innovation. Process and product innovation would increase export market entry. Interaction between R&D and

11. In Tunisia, the FDI is mostly driven by short-term, cost-saving benefits. This is in contrast to some other emerging markets, such as China and India, where FDI is driven by long-term benefits and strategic reasons. Therefore, foreign firms in the latter cases invest in innovation by establishing local R&D centers and collaborate with the local universities, for instance.

exports could further influence productivity, and the decision to export is often accompanied by large R&D investment (Porter 1990; Grossman and Helpman 2003; Krugman 1991; Griffith, Redding, and Van Reenen 2004; Aw, Roberts, and Xu 2011; Bernard, Redding, and Schott 2011).

FDI: Similarly, FDI might be another factor that could influence firms' investment in innovation. Foreign investors' knowledge and know-how are transferred to domestic partners, competitors, suppliers, and customers, which might also influence their decision to invest in innovation. However, inward FDI may produce a negative effect on innovation of local firms if the FDI firms substitute local innovation efforts with foreign ones. In fact, recent studies provide mixed results of FDI's effect on local firms' innovation (Fu, Helmers, and Zhang 2012; Fu 2011).

Firm age: Previous literature finds that younger firms are more likely to innovate (Huergo and Jaumandreu 2004; Balasubramanian and Lee 2008).

Firm size (number of employees): Larger firms are more likely to invest in R&D. Specifically, large firms invest more in process R&D, while small firms invest more in product R&D (Acs and Audretsch 1991; Cohen and Klepper 1996).

Skill (Average wage): Ability of labor, measured by average wage, is positively correlated with a firm's innovation, and influences firm productivity (Van Reenen 1996; Abowd et al. 2005; Fox and Smeets 2011).

Number of technicians (technical staff ratio): Having more technicians could positively influence firms' innovation investment decisions since technical staff might be more directly involved in the process of how innovation is handled and of how innovation inputs are used in the production of final outputs.

Competition: Market competition influences firms' innovation investment. Previous studies reveal that firm entry spurs innovation in sectors close to the technology frontier, but discourages it in laggard sectors (Aghion et al. 2005; Aghion and Griffith 2008).

Details of the definition of the variables are presented in table 1.2.

Table 1.2 Summary Statistics of the Variables

	Variable	Definition	Obs.	Mean	S.D.	Min.	Max.
Dummy variables {Z}	Int only	Firms invest only in internal innovation	16,471	0.04	0.19	0	1
	Ext only	Firms invest only in external technology acquisition	16,471	0.30	0.46	0	1
	Innover	Firms invest in internal innovation	16,471	0.35	0.48	0	1
	Externer	Firms invest in external	16,471	0.62	0.49	0	1

		innovation					
	Both	Firms invest in both sources of innovation at the same time	16,471	0.32	0.47	0	1
	All	Firms invest in any sources of innovation	16,471	0.65	0.48	0	1
Innovation investment {U}	ln_n_innov	Log investment amount of any sources of innovation	16,471	6.00	4.65	0	16.37
	ln_n_inter	Log investment amount of internal innovation	16,471	2.93	4.21	0	16.25
	ln_n_exter	Log investment amount of external innovation	16,471	5.48	4.55	0	16.21
Inputs for production function	ln_revenue_d	Log amount of sales revenue, depreciated	16,457	13.91	1.65	6.17	21.50
	ln_labor	Log number of employees	16,471	3.98	1.23	0	8.48
	ln_capital_d	Log amount of capital assets beginning of the year, depreciated	16,015	13.42	1.83	4.61	20.57
	ln_interm_d	Log amount of intermediary inputs (materials), depreciated	16,167	12.73	2.23	1.60	20.19
Factors that influences innovation	Tech staff	Technical staff share among total employees	16,394	0.74	0.25	0	1
	ln_avewage	Log average wage	15,369	8.39	0.68	2.28	12.47
	Firm age	Years since firm's creation	14,279	27.06	13.45	6	200
	Dominance	Market share	16,457	0.01	0.06	0	1
	Export_stat	Export status dummy	16,471	0.51	0.50	0	1
	FDI_stat	FDI status dummy	16,471	0.27	0.44	0	1

The mean of the log investment amount of any sources of innovation, log investment amount of internal innovation, and log investment amount of external innovation are 6.00, 2.93, and 5.48, respectively, which is equivalent to TD 192,396[12] (US$101,725 or 3.4 percent of revenue), TD 45,883 (US$24,260 or 0.8 percent of revenue), and TD 146,513 (US$74,465 or 2.6 percent of revenue), respectively. For Tunisian manufacturing firm, the average sales revenue is TD 5,670,918 (US$2,998,365), the average wage is TD 4,225 per year (US$2,234) and average number of workers is 111. All the values are in real terms, depreciated by the price index provided by the INS.

4. Empirical Strategy

In this section, I provide empirical strategies to answer key questions posed in this paper, discuss potential concerns related to these econometric strategies, and provide solutions.

The questions I would like to answer are summarized here: First, what are the determinants of whether a firm will innovate at all, and further to this, whether they

[12] Tunisian Dinar (TD)

create, buy, or do both? Second, conditional on the response to question one, what determines the intensity of innovation? Third, how do the different types of innovations impact firm productivity?

These are difficult questions as there are three fundamental issues to address. First, there are deep endogeneity problems between innovation and productivity. Second, the innovation data are censored. Lastly, there is a debate about whether to measure the impact of technology on output or directly on (a derived measure of) total factor productivity (TFP).

Therefore, in this section, I provide both an empirical model to answer the questions posed above and also suggest solutions to address these three cross-cutting econometric problems.

Determinants of create or buy

To understand whether the factors that influence firms' innovation investment are different between firms that create and firms that buy, I analyze the determinants of firms' innovation for both create and buy, using a Probit model as seen in equation (1).

Denote firms by $i = 1,\ldots.,$ *N*, industries by $j = 1, \ldots,$ *J*, and years by $t = 1, \ldots,$ *T*. The dependent variable is dummy variable of whether there is investment in any innovation (all), internal innovation (innover), and external innovation (externer), respectively. To test whether there is any difference between those firms that invest in only one source of innovation and firms that invest in both sources of innovation, I have also created dummies of different exclusive categories — firms that have only internal innovation (int only), firms that have only external technology acquisition (ext only), and firms that invest in both internal and external sources of innovation (both).

Probit $Z'_{ijt} = \gamma X_{ijt} + v_{ijt}$, ($Z'_{ijt} = 1$, if $Z_{ijt} > 0$. Otherwise, $Z'_{ijt} = 0$) (1)

$Z_{ijt} = \{ int\ only_{ijt}, internal_{ijt}, ext\ only_{ijt}, external_{ijt}, both_{ijt}, all_{ijt} \}$
$X_{ijt} = \{\text{firm size}_{ijt}, technical\ staff\ ratio_{ijt}, ln\ Average\ Wage_{ijt}, firm\ age_{ijt}, export\ status_{ijt}, FDI\ status_{ijt}, Dominance_{ijt} \}$

- Firm size $_{ijt}$: Log number of employees is used as a proxy of size of firm *i* in sector *j* and time *t,* in log form.
- $Technical\ staff\ ratio_{ijt}$: The number of technicians/number of total employees. Since technical staff is a relatively small number compared to total labor, there is no strong correlation between labor and the ratio variables, which allows the joint use of technical staff ratio and labor variables as the right-hand–side (RHS) .
- $ln\ Average\ Wage_{ijt}$: Log average wage of a firm *i* in sector *j* and time *t,* which is used as proxy of workers' skill.
- $Firm\ age_{ijt}$: The number of years since a firm *i* was created.

- $Export\ status_{ijt}$: Dummy variable that shows whether a firm exports or not.
- $FDI\ status_{ijt}$: Dummy variable that shows whether a firm has any foreign ownership.
- $Dominance_{ijt}$: A proxy for competition, and measured as firms' share in the market. The indicator of dominance is constructed as $\text{dominance}_{ijt} = \frac{revenue_{ijt}}{\sum_{z=1}^{N} revenue_{izt}}$, where $revenue_{ijt}$ is the revenue of firm *i* at industry *j* and time *t. N* is the number of firms at industry *j* and time *t.*

$v_{ijt} = \alpha_t + \alpha_j + \delta_{ijt}$

- α_t : Time dummies (1997–2007)
- α_j : Industry dummies (NACE 15–36)
- δ_{ijt}: Idiosyncratic error, which varies across individual firms

I then use innovation intensity (investment amount) at my left-hand side (LHS) for the abovementioned six categories of firms — rather than using dummies — to capture information based on intensity, using firm fixed effect (FE) methods. The RHS variable remains the same.

$$\ln Z_{ijt} = \beta_1 X_{ijt} + \alpha_t + \alpha_j + \varepsilon'_{ijt} \quad (2)$$

Meanwhile, if a firm, which would have invested in innovation, decides not to under a certain threshold ($z = 0$), the observed innovation value Z_{ijt} is censored around zero. To address this issue, I consider using an econometric technique for the censored dependent variable, such as Tobit. I will further discuss the potential censoring problem and solution in the next subsection.

Does innovation affect final output?

To identify the effect of innovation on productivity, I adopt a production function approach that describes the relationship between factor inputs and output. Specifically, I use the standard Cobb-Douglas production function, where output is a function of the inputs the firm employs, such as labor, capital, and material, as well as its productivity. One advantage of using the production function is that it provides not only the coefficient for the variable of interest but also the coefficients of other factor inputs, which allow comparison of the relative size of the coefficient for variable of interest. Also, it reduces the problem of having to correct for other sources of firm heterogeneity that influence both innovation and overall performance, by including (controlling) key factor inputs as regressors.

I consider innovation investment as a factor input and add the identified innovation variables in the production function. In this functional form, the innovation is treated as an input, such as labor, capital, and material. The residual is now unobservable, which takes out the effect of innovation inputs.
All variables are quantity terms (number of labor) or proxy of quantity terms that are measured by value terms divided by price index, as in previous literature.[13] For the LHS, I use gross output, measured by sales revenue deflated with the output deflators constructed from the INS's Producer Price Index (PPI). Since there are no separate deflators for material and innovation, I use these output deflators for material and innovation inputs. For the capital input, I have constructed the deflators from the Gross Fixed Capital Formation (GFCF) of the National Account.

The empirical specification and description of variables can be written as follows:

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln I_{ijt} + \beta_5 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (3)$$

- Y_{ijt} : The real output of firm *i* operating in sector *j* at time *t,* which is calculated by the sales revenue deflated by subindustry-level deflators from the PPI obtained from INS.
- K_{ijt} : The value of fixed assets at the beginning of the year, deflated by GFCF, from the National Account.
- L_{ijt} : Number of labor.
- M_{ijt}: The value of physical material inputs, which is used directly for production, deflated by deflators based on input-output table.
- I_{ijt} : Sum of the innovation investment (all), which is cost of R&D, cost of consulting service, and cost of royalty payment, of firm *i* in sector *j* at time *t,* deflated by PPI deflators. The subindustry of the PPI index was used as its output subindustry.
- Θ_{ijt}: A vector of control variables that are the dummies of export and FDI status.
- α_t : Time dummies (1997–2007).
- α_j : Industry dummies (NACE 15–36).

To answer the main research question: Which source of innovation contributes more to productivity, I divide the innovation variables into internal and external innovation as seen in equation (4), and I simply compare coefficient of β_4 and β_5 in equation (4).

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln \text{Internal } I_{ijt} + \beta_5 \ln \text{External } I_{ijt} + \beta_6 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (4)$$

To test whether the effect on productivity is different between those firms that invest in one source of innovation and firms that invest in both sources, I add the interaction term between internal and external innovation as seen in equation (5). This is because

13. Industry-level price indexes are usually applied to deflate firm-level sales and input expenditures in production function estimates.

the β_4 in equation (4) actually includes not only those firms investing in internal innovation but also those that invest in both sources of innovation. By adding the interaction term, the distinct effects of different categories of firms can be separated. In equation (5), β_4 provides the potential effect of investing only in internal innovation; the overall effect on internal innovation is $\beta_4 + \beta_6$. The same holds for β_5 and $\beta_5 + \beta_6$ for the firms that invest only in external innovation and the overall effect on external innovation.

In previous literature, the interaction term has been used to measure whether there is any complementarity in using both sources of innovation at the same time (Cassiman and Veugelers 2006). Therefore, the coefficient of β_6 in equation (5) can also provide information about whether there is any synergy of using both sources of innovation.

$$\ln \mathrm{Y_{ijt}} = \beta_1 \ln \mathrm{K_{ijt}} + \beta_2 \ln \mathrm{L_{ijt}} + \beta_3 \ln \mathrm{M_{ijt}} + \beta_4 \ln \text{Internal } \mathrm{I_{ijt}} + \beta_5 \ln \text{External } \mathrm{I_{ijt}} + \beta_6 \ln \text{Internal } \mathrm{I_{ijt}} \times \ln \text{External } \mathrm{I_{ijt}} + \beta_7 \Theta_{ijt} + \alpha_\mathrm{t} + \alpha_j + \varepsilon_{ijt} \quad (5)$$

There are three major problems with the above econometric specifications: first, if the innovation decision is endogenous, and thereby correlated with the error term; second, if the innovation variables are censored, and third, if the effect on final output is an indirect measure of the effect on firm's productivity.

Simultaneity between innovation investment and productivity

Simultaneity bias (or endogenous input selection): If a firm's knowledge of its productivity influences its decisions to invest in innovation and the amount to invest, the estimated coefficient of innovation might be biased. Specifically, in the above specification, if more productive firms invest in innovation, the estimated coefficient of innovation might be biased upward since the innovation investment might be correlated with unobserved productivity shocks. Therefore, the above functional form using ordinary least squares (OLS) fails to convincingly isolate the causal effect of innovation on firm productivity.

To control for simultaneity between productivity and innovation, I applied the generalized method of moments (GMM) in the above specification. GMM gets rid of the simultaneity issue by using the previous year of own observations of the dependent variable and the endogenous variable (here, innovation investment) as its own instrument, removing them from the regression equation (using the differenced equation with lagged levels as instruments) or removing them from the instruments (using differences as the instrument in a levels regression). The INS dataset has a relatively short time dimension (T = 11, max, from 1997 to 2007, but most have less than 11 years of observations) and a larger firm dimension (N = 16,471, unbalanced), which is an advantage of using GMM.

In addition to innovation variables, I consider material as an endogenous variable, as in previous literature (Ackerberg et al. 2006). Firms can quickly adjust their material inputs based on their knowledge of productivity and final output, while it takes more time to adjust labor and capital inputs. Therefore, I use lagged values of the dependent variable, innovation variables, and material as its own instrument, by removing them from the regression equation (using the differenced equation with lagged levels as instruments) and from the instruments (using differences as instruments in the levels regression).

Due to gaps on previous year innovation in the weakly balanced INS data, using a dynamic equation significantly reduces the number of innovative firms that can be tested. A dynamic model that has lag dependent variable and/or lag factor inputs as additional regressors requires further lags of those additional regressors when they are instrumented. Therefore, I use a non-dynamic (the static model) equation, which is a long-run description, since it might take some time for inputs, such as innovation investment, to influence the output. To understand the short-run effects, my estimation required an assumption that the current year innovation investment of a firm reflects the previous innovation investment. This might be a valid assumption given that the overall number of innovative firms and the amount of innovation investment has been stable over the year during the data period.

In addition to using GMM, I also considered other econometrics techniques, which are widely used in previous literature, to deal with simultaneity issues in firm-level analysis; these include Olley and Pakes (OP) (1996) and Levinsohn and Petrin (LP) (2003)'s semi-parametric estimator. However, critical assumptions of OP methods on monotonicity of investment in productivity might not hold when introducing an innovation status variable (Van Biesebroeck 2003; De Loecker 2007, 2013). Also, the INS data are weakly balanced; thus, there is no information about those firms that enter into and exit from the market, which is important in controlling the selection bias in OP methods. Meanwhile, the current method of LP (such as the levpet command in Stata) is developed for one proxy variable (material) and one endogenous variable (capital) when using revenue as the dependent variable, and does not allow the addition of innovation as another endogenous variable; (it is possible, however, to manually code this method to have an additional endogenous variable). For these reasons, OP and the current method of LP are not the most suitable methods for analysing innovation effects for INS data; thus, I used GMM instead of these two semi-parametric methods.

As mentioned above, the OLS estimate would be biased upward, and the fixed effects (FE) estimate of coefficients would be biased downward.[14] However, those estimation results are still useful since they provide an upper and lower range of the estimated results, using GMM. Also, the current LP estimation, without considering the simultaneity issue of innovation variables, is still closer to true estimation than OLS and

14. The explanation on how FE provides an estimate with a downward bias is described well in Van Beeren 2012.

FE, since it disregards simultaneity issues of other factors inputs, such as capita, in estimating the production function. However, it does not remove the simultaneity issue in my interest variable, innovation. Therefore, I will report the results from OLS, FE, and the current LP methods to ensure my estimated results using GMM are within the credible range.

In case the innovation variables are censored

If there are costs to searching out innovation activities, and innovation activities require a certain scope to be materialized, firms would invest in innovation activities only when their investment amount is above a certain threshold. Thus, there are a number of firms that are reported as not investing in innovation, but they would have invested without these threshold constraints. Therefore, the innovation variable might be censored at zero, and in fact, about 40 percent of firms reported zero innovation investment.

Therefore, I consider firms' decisions about innovation as two step: first, whether to invest at all in innovation, if so whether to invest in internal or external innovation (or both), and second, how much to invest. I used the Type II Tobit model (selection in censored data) with three-stage equations. The first equation of the model explains the propensity to invest in innovation overall (all), invest in internal source of innovation (internal), and in external innovation (external). Those firms that reported having positive innovation investment are defined as innovator, creator, and buyer. The second equation explains the investment amount in each source of innovation activity (if a firm invests). Therefore, the first two equations estimate the predicted investment amount for those firms that could have invested if the cost of searching were zero or if there is no minimum requirement to invest in innovation (no threshold). Then, in the third stage, I used the predicted value of the innovation investment amount, instead of the observed innovation amount, in the main regressions. The empirical model is therefore as follows:

First stage: Decision equation (Probit model)

$$Z^*_{ijt} = \gamma X_{ijt} + v_{ijt,} \text{ and } z_{ijt} = 1 \text{ if, } z^*_{ijt} > 0, \ z_{ijt} = 0 \text{ if } z^*_{ijt} =< 0 \tag{6}$$

The first stage is shown in equation (6), which is the propensity of the decision to invest in innovation, and then, which source (create or buy) of innovation. I used the Probit model to understand the determinants of firms' innovation decisions in each source. As mentioned above, X is the vector of factors that could influence the probability of firms investing in innovation, where Z is a vector of dummy variables for investing in each type of innovation:

X_{ijt} ={ firm size $_{ijt}$, $technical\ staff\ ratio_{ijt}$, $ln\ Average\ Wage_{ijt}$, $firm\ age_{ijt}$, $export\ status_{ijt}$, $FDI\ status_{ijt}$, $Dominance_{ijt}$ },

Z_{ijt} = {invest in any source of innovation (all), invest in internal innovation (innover), and invest in external innovation (externer)}.

Second stage: Predict innovation investment amount, considering censoring issue (Tobit model)

$$U^*_{ijt} = \gamma' Q_{ijt} + \sigma\lambda_{ijt} + \mu_{ijt}, \text{ and } U_{ijt} = U^*_{ijt} \text{ if } z_{ijt} = 1, U_{ijt} = 0 \text{ if } z_{ijt} = 0 \quad (7)$$

$v_{ijt} = \alpha_t + \alpha_j + \varepsilon_{ijt}$, $\mu_{ijt} = \alpha'_t + + \alpha'_j + \varepsilon'_{ijt}$, t=1, ..., T, j= 1, ...J and I = 1, ... N
and $\varepsilon_{ijt} = \rho_1\varepsilon_{ijt-1} + \tau_{ijt}$, $\varepsilon_{ijt} = \rho_2\varepsilon'_{ijt-1} + \tau'_{ijt}$, $\tau_{ijt} \sim N(0, \sigma^2_{\tau})$, $\tau'_{ijt} \sim N(0, \sigma^2_{\tau'})$

Equation (7) is for the second stage, which is to predict the innovation investment amount, considering potential censoring issue, using the Tobit model. Here, *U* is the vector of log amount of innovation investment. *Q* is vectors of explanatory variables for innovation investment decision and innovation amount equations, which is essentially the same vector as *X.* Using the same vector of variable does not raise any identification issues in the Tobit model (Crepon, Duguet, and Mairesse 1998).

U_{ijt} = {log total innovation amount (all), log internal innovation amount (create), log external innovation (buy)}.

$Q_{ijt} = \text{firm size}_{ijt}$, $technical\ staff\ ratio_{ijt}$, $ln\ average\ wage_{ijt}$, $firm\ age_{ijt}$, $export\ status_{ijt}$, $FDI\ status_{ijt}$, $dominance_{ijt}$ }

σ is the standard deviation, and λ is the inverse Mills ratio. The components α_t and α'_t are time dummies; α_j *and* α'_j are industry dummies; and ε_{ijt} is an idiosyncratic error, which varies across individual firms. Hence the model allows unobserved heterogeneity, first order state dependence, and serial correlation in the error components.

When a firm, which would have invested in innovation, decides not to, under a certain threshold (z = 0), the observed innovation value i is zero. The significance of the presence of these potential censoring effects is indicated by the Rho statistics in the generalized Tobit model, which reflects the correlation between the error terms of the two equations (μ and υ).

I then used the predicted innovation investment amount ($U^{\wedge}_{ijt}$), which is measured in the second stage, and plugged them into the main specifications, which are equations (3) to (5). Now, equations (3) to (5) become equations (8) to (10).

In the third stage, I plugged in the predicted innovation investment amount ($U^{\wedge}_{ijt}$) into the main equations:

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \ln All^{\wedge}_{ijt} + \beta_5 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (8)$$

$$\ln \mathrm{Y_{ijt}} = \beta_1 \ln \mathrm{K_{ijt}} + \beta_2 \ln \mathrm{L_{ijt}} + \beta_3 \ln \mathrm{M_{ijt}} + \beta_4 \ln \mathit{Internal}^{\wedge}{}_{\mathrm{ijt}} + \beta_5 \ln \mathit{External}^{\wedge}{}_{\mathrm{ijt}} + \beta_5 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (9)$$

$$\ln \mathrm{Y_{ijt}} = \beta_1 \ln \mathrm{K_{ijt}} + \beta_2 \ln \mathrm{L_{ijt}} + \beta_3 \ln \mathrm{M_{ijt}} + \beta_4 \ln \mathit{Internal}^{\wedge}{}_{\mathrm{ijt}} + \beta_5 \ln \mathit{External}^{\wedge}{}_{\mathrm{ijt}} + \beta_6 \ln \mathit{Internal}^{\wedge}{}_{\mathrm{ijt}} \times \ln \mathit{External}^{\wedge}{}_{\mathrm{ijt}} + \beta_7 \Theta_{ijt} + \alpha_\mathrm{t} + \alpha_\mathrm{j} + \varepsilon_{ijt} \quad (10)$$

Meanwhile, it should be noted that the use of the Tobit model for potentially censored regressor is different from the selection bias of sample. If the analysis is made only for firms with innovation inputs or outputs, this could lead to a sample *selection bias* since the characteristics of innovative firms might be different from those firms that are not. To deal with this selection bias, previous literature also used a selection model with a two-stage estimation procedure, which is a similar econometric strategy to the above specification, such as Probit and Tobit specifications for the interval data on outputs to measure the probability of investment in innovation and plug in the estimated probability into the production function (Loskin, 2008, Crepon, Duguet and Mairesse 1998). Unlike the innovation surveys or samples of only innovators, my data include representative Tunisian firms, both innovators and non-innovators. Therefore, sample *selection bias* is not an issue with the INS data.

Having Total Factor Productivity (TFP) as a dependent variable

There might be questions about why I analyze the effects of different sources of innovation on final output, *Y,* instead of on productivity itself. In fact, some literature has used TFP as the dependent variable to measure the effect of innovation-related activities on productivity. That literature typically conducted these analyses with two steps: first, measuring TFP as residual of the standard production function, and second, testing innovation's effect on the measured TFP (for example, Brynjolfsson and Hitt 2003). This is a direct way to measure innovation's effect on productivity.

However, the product function with *Y* as a dependent variable is essentially the same as with TFP as a dependent variable. In a standard product function, the residual (ϵ_{ijt}) consists of productivity, A_{ijt}, the Hicksian neutral efficiency level of firm (average TFP), and ϵ', standard i.i.d. error term, capturing unanticipated shocks to production and measurement error.

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \Theta_{ijt} + \alpha_t + \alpha_j + \epsilon_{ijt} \quad (11)$$

$$\epsilon_{ijt} = \mathrm{A_{ijt}}, + \epsilon'_{ijt}$$

In equation (6), adding innovation — typically considered a key driver of productivity — as an input of the product function makes the innovation as a part of TFP ($\mathrm{A_{ijt}}$).

$$\mathrm{A_{ijt}} = f'(I_{ijt}) \quad (12)$$

Therefore, using specification (12) is essentially making equation (11) into equation (13), which is my specification.

$$\ln Y_{ijt} = \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \beta_4 \Theta_{ijt} + \alpha_t + \alpha_j + f'(I_{ijt}) + \epsilon'_{ijt} \quad (13)$$

In my view, measuring an innovation input's effect on output might be a better approach than measuring its effect on productivity for several reasons. First, measuring the innovation effect on TFP requires the assumption that innovation investment, such as investment in R&D or in IT equipment, doesn't affect the output directly but indirectly through productivity, which might be unlikely. Also, having innovation as an input in the projection function could automatically control other input intensity in production. Moreover, the coefficient of innovation could also provide the relative importance of innovation by allowing a comparison of the elasticity of innovation input to that of other key input variables. Lastly, the production function approach has been widely used; therefore, the limitations related to the econometric issues are well understood, and a number of solutions based on the latest econometric techniques have been suggested. In fact, most literature has used Y as the dependent variable and innovation as inputs in the production function to analyse the innovation effect on productivity.

Therefore, I will measure the effects of the innovation inputs on final output, which is an indirect measure of productivity, as a main specification. In addition, as a robustness check, I will undertake the abovementioned two-stage approach, and measure TFP as a residual of product function, and then use TFP as LHS variable, and test my results for consistency.

First, I measure TFP as the residual of a Cobb-Douglas production function, which has an output that is a function of the inputs the firm employs — the same equation of basic specifications as equation (3), but without an innovation term in the RHS.

The empirical specification of estimation TFP can be written as follows:

$$\ln Y_{ijt} = A_{ijt} + \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \beta_3 \ln M_{ijt} + \delta_t + \delta_i + \xi_{ijt} \quad (14)$$

- Y_{ijt} : The real output of firm i operating in sector j at time t, which is calculated by the sales revenue deflated by subindustry-level deflators from the Producer Price Index.
- K_{ijt} : The value of fixed assets at the beginning of the year, deflated by GFCF, from the National Account.
- L_{ijt} : Number of employees.
- M_{ijt}: The value of material inputs adjusted for changes in material inventories, deflated by deflators based on input-output tables.
- A_{ijt}: The Hicks neutral efficiency level of firm (TFP of firm) measured as the residual of the model/stochastic error term.
- δ_t : Time dummies for 1997–2007.

- δ_i: Firm fixed effect.
- ξ_{ijt}: Standard i.i.d. error term capturing unanticipated shocks to production and measurement error.

I use the generalized method of moments (GMM) in TFP estimation for consistency, by controlling simultaneous input selection issues when input is correlated with error term (A_{ijt}). The INS dataset has a relatively short time dimension (T = 11 max, after omitting information after 2008, but most firms have less than 11 years of observations) and a larger firm dimension (more than 16,000 manufacturing firm observations, although many are repeated several times), which is an advantage of using GMM.

With INS data, for each of the NACE two-digit industries in manufacturing (NACE 15–36), I obtained TFP estimation, with non-dynamic system GMM with 2 and 3 lags for instruments. One drawback of using a weakly balanced INS data set is that the dynamic model will significantly reduce the number of observations; therefore, I used the non-dynamic GMM model. Specifically, I treated all factor inputs — labor, capital, and material — as endogenous; so, factor inputs are instrumented by their own lag and differenced. Therefore, previous year information has already been used as an instrument. A dynamic model that has lag-dependent variables and lag factor inputs as additional regressors, requires one additional lag in instruments, which significantly reduces the number. Therefore, I used a non-dynamic equation. Likewise, further lags in instruments significantly reduce the number of observations; so, I used 2 and 3 lags in instruments. After omitting those observations that were missing values in key variables, such as revenue and employment, the number of observations fell significantly; I obtained approximately 15,800 TFP out of about 16,471 firm observations.

Second, I used this estimated TFP as a dependent variable, $A_{\mathrm{ijt}} = f'(I_{ijt})$, as described as below.

$$\ln A_{ijt} = \beta_1 \ln All_{ijt} + \beta_5 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \tag{15}$$

$$\ln A_{\mathrm{ijt}} = \beta_1 \ln Internal_{\mathrm{ijt}} + \beta_2 \ln External_{\mathrm{ijt}} + \beta_3 \Theta_{ijt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \tag{16}$$

$$\ln A_{\mathrm{ijt}} = \beta_1 \ln Internal_{\mathrm{ijt}} + \beta_2 \ln External_{\mathrm{ijt}} + \beta_3 \ln Internal_{\mathrm{ijt}} \times \ln External_{\mathrm{ijt}} + \beta_4 \Theta_{ijt} + \alpha_{\mathrm{t}} + \alpha_{\mathrm{j}} + \varepsilon_{ijt} \tag{17}$$

5. Results

Determinants of innovation investment

Table 1.3 presents estimation results of the determinants of firms' innovation for both create and buy, using the Probit model as seen in equation (1), with firm fixed effect. I provide the results of the Probit estimation using pooled regression in table B.1, appendix II.

Table 1.3 Determinants of Innovation Decision, Panel Firm Fixed Effects

Dep. Var. $\{Z_{ijt}\}$	(1) Internal Only	**(2) Internal All**	(3) External Only	**(4) External All**	(5) Both	**(6) All**
Firm size	-0.007	**0.015**	0.021	**0.043****	0.022	**0.036***
	(0.269)	**(0.328)**	(0.146)	**(0.005)**	(0.138)	**(0.015)**
Tech staff ratio	0.003	**-0.003**	0.049*	**0.043**	-0.006	**0.046**
	(0.741)	**(0.914)**	(0.023)	**(0.076)**	(0.796)	**(0.058)**
Ln (ave wage)	-0.009	**0.006**	0.026	**0.041****	0.015	**0.032***
	(0.179)	**(0.689)**	(0.091)	**(0.009)**	(0.289)	**(0.037)**
Export status	0.004	**0.021**	0.037*	**0.055****	0.017	**0.058*****
	(0.605)	**(0.189)**	(0.012)	**(0.001)**	(0.281)	**(0.000)**
FDI_stat	0.001	**0.005**	-0.026	**-0.022**	0.004	**-0.021**
	(0.898)	**(0.781)**	(0.167)	**(0.284)**	(0.818)	**(0.299)**
Firm age	-0.000	**0.001**	-0.001	**0.000**	0.001	**0.000**
	(0.665)	**(0.275)**	(0.290)	**(0.874)**	(0.233)	**(0.963)**
Dominance	-0.002	**0.289**	-0.258	**0.033**	0.291	**0.031**
	(0.943)	**(0.408)**	(0.385)	**(0.915)**	(0.401)	**(0.920)**
# of obs.	13,257	**13,257**	13,257	**13,257**	13,257	**13,257**
# of dep.=1 (among16,471)	613	**5,840**	4,926	**10,153**	5,227	**10,766**
# of dep.=1 (among13,257)	534	**5,225**	4,222	**8,913**	4,691	**9,447**
# of group	3,332	**3,332**	3,332	**3,332**	3,332	**3,332**
R^2, within	0.002	**0.005**	0.006	**0.010**	0.006	**0.011**
Rho	0.458	**0.647**	0.610	**0.601**	0.659	**0.598**

Note: Firm fixed-effects (within) regression; *t* statistics in parentheses, standard error are clustered and robust; year and industry dummies are included but not reported. Rho reports fraction of variance due to u_i. Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

Table 1.3 shows how each determinant is associated with each source of innovation decision, while controlling firm-specific, time-invariant unobserved bias (firm fixed effects [FE]).

Columns (2) and (4) show the factors that influence the probability of firms engaging in internal and external sources of innovation, respectively. Column (6) shows probability of investment in any source of innovation (all). I added columns (1), (3), and (5) to see whether there are any differences between those firms investing in only one source of innovation and those investing in both sources at the same time.

The determinants of firm's decision to invest in innovation are different between internal and external innovation. Tests for the difference of coefficients are conducted, and the null hypothesis that coefficients of the regressions from different columns are systematically the same is rejected by 1 percent significant level between columns (1) and (3), and between columns (2) and (4).

Overall, the number dependant variable that has value of 1 are 10,766 in the entire data set, but this number is reduced to 9,447 in the estimation of column (6) due to the missing values of regressors. Therefore, the above estimation includes 9,447 firms that invested in any sources of innovation. Among them, 4,691 invested in both sources of innovation. Approximately 8,913 firms invested in external innovation, and of those, 4,222 invested exclusively in external sources of innovation. A total of 5,225, firms invested in internal innovation, but only 534 invested in only internal sources of innovation.

All the coefficients of columns (1) and (2) are statistically insignificant, which implies that there is no systemic factors that encourage firms' investment in internal innovation. In addition, those firms that invest in only one type of innovation shows less systemic patterns that encourage firms' investment decision, comparing to those firms that invest in both sources of innovation. Specifically, most of coefficient in column (1), (3) and (5) are insignificant, except for the positive and significant coefficients of technical ratio and export status for those firms that invest in only external sources of innovation as shown in column (3).

Meanwhile, the estimation results in columns (4), and (6) show that being large, paying higher wages, and participating in exports are positive determinants of firms' investment in either external sources of innovation or any type of innovation. Interestingly, FDI is associated with less likelihood of investment in innovation, has a negative coefficient, however, the coefficient is statistically insignificant. Also, technical ratio, dominance, and firm age are not statistically significant determinants of all innovation and external innovation decisions.

Table 1.4 provides the above specification with the firm fixed effect, but with dependent variables of actual investment amounts in different sources of innovation, as seen in equation (2). The advantage of using the innovation amount as a dependent variable rather than using a dummy variable for innovation is that the results reflect the information on innovation intensity (investment amount to innovation) with firm FE. Table B.2 in appendix II provides the estimation results of the same specification as table 1.4 but using random effects rather than firm fixed effects. Hausman test results (table B.3) reveal that fixed effect is more appropriate to use in the above model.

Table 1.4 Determinants of Innovation Intensity, Panel Firm Fixed Effects

Dep. Var. { U_{ijt} }	(1) ln_Internal Only	**(2) ln_Internal All**	(3) ln_External Only	**(4) ln_External All**	(5) ln Both	**(6) ln_All**
Firm size	-0.041	**0.210***	0.274*	**0.564*****	0.291*	**0.523*****
	(0.391)	**(0.048)**	(0.011)	**(0.000)**	(0.016)	**(0.000)**
Tech staff ratio	0.064	**0.052**	0.438*	**0.308**	-0.101	**0.401***
	(0.437)	**(0.776)**	(0.019)	**(0.117)**	(0.627)	**(0.046)**
Ln (ave wage)	-0.069	**0.182**	0.320**	**0.574*****	0.240	**0.491*****
	(0.174)	**(0.106)**	(0.005)	**(0.000)**	(0.060)	**(0.000)**
Export status	0.047	**0.196**	0.354**	**0.533*****	0.198	**0.599*****
	(0.408)	**(0.122)**	(0.006)	**(0.000)**	(0.169)	**(0.000)**
FDI_stat	-0.014	**0.018**	-0.245	**-0.137**	0.096	**-0.163**
	(0.852)	**(0.912)**	(0.148)	**(0.441)**	(0.611)	**(0.368)**
Firm age	-0.001	**0.009**	-0.004	**0.004**	0.010	**0.005**
	(0.660)	**(0.225)**	(0.624)	**(0.576)**	(0.243)	**(0.566)**
Dominance	0.018	**5.747****	-1.145	**2.207**	4.613*	**3.486**
	(0.984)	**(0.004)**	(0.577)	**(0.308)**	(0.044)	**(0.114)**
# of obs.	13,257	**13,257**	13,257	**13,257**	13,257	**13,257**
# of group	3,332	**3,332**	3,332	**3,332**	3,332	**3,332**
R^2, within	0.002	**0.004**	0.006	**0.011**	0.062	**0.011**
Rho	0.429	**0.583**	0.585	**0.569**	0.632	**0.560**
F test (u_i = 0)	1.95	**3.39**	2.83	**3.49**	3.37	**3.48**
Prob > *F*	0.000	**0.000**	0.000	**0.000**	0.000	**0.000**

Note: Firm fixed-effects (within) regression. The dependent variable is the log investment amount of different sources of innovation as noted in each column. *t* statistics in parentheses, standard error are clustered and robust; year and industry dummies are included but not reported. Rho reports fraction of variance due to u_i. Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent.

Although the direction and statistical significance of coefficients of table 1.4 are similar to those in table 1.3, the estimation results of table 1.4 are slightly different from those of table 1.3, which explains that the decision related to innovation (whether to innovate or not) and decisions related to innovation intensity (how much to innovate) are not exactly the same.

Like as in table 1.3, for firms that invest only in internal sources of innovation, widely recognized determinants of investing in innovation do not influence its decision of how much it will invest. In column (1), all coefficients are statistically insignificant, implying that none of the abovementioned factors would increase the innovation investment amount for those firms that invest in internal innovation only.

Meanwhile, different from the results in table 1.3, firms that are larger and have a bigger market share (dominance) will have a larger amount of overall internal innovation, as seen in column (2). In fact, dominance has a very large effect on internal innovation investment amount, since 1 percent increase of market share is associated with 574.7 percent increase of internal innovation investment amount. The other determinants, including technical staff ratio, FDI status, and firm age, will not augment firms' internal innovation amount.

For firms that invest only in external sources of innovation, firm size, average wage and export status have positive and significant effects on external innovation amount, as seen in column (4). Meanwhile, technical staff ratio also become positive and statistically insignificant for the firms that invest in external innovation only and that invest in any sources of innovation, as seen in column (3) and (6) .

The above results of tables 1.3 and 1.4 are largely consistent with the findings of previous studies, although a few are in contrast to previous findings.

Firm size, measured by log number of labor, matters for the decision to invest in both source of innovation and innovation intensity, except for firms that invest in only one source of innovation. This finding is consistent with previous literature that finds firm size to be one of the determinants of innovation (Souitaris 2002), and there is an advantage of the biggest firms undertaking innovative activities (González and Jaumandreu 1998).

Worker's skill, measured by log average wage, also has a positive coefficient for both sources of innovation decisions, except for firms that invest in only one source of innovation. Also, skill has positive effects on innovation intensity of external sources. The magnitude of the coefficient for skill is larger than the coefficient for firm size in table 1.3. This might suggest that quality of labor, rather than quantity of labor, is more important in the decision to invest in innovation. This might be explained by the fact that those firms with higher wages might be more likely to invest in innovation, more as a means to save labor. While the coefficients of firm size and skill are similar in both internal and external innovation in the Probit model, both coefficients are larger for internal innovation than external innovation in the fixed effect model. Larger firms with more skilled employees would more likely invest in internal innovation.

Participating in exports also has a positive effect on both sources of innovation and innovation intensity (except for internal innovation intensity). The coefficient for export is larger for the external innovation decision than for the internal innovation decision. The coefficient of export on external innovation intensity is significant while the coefficient on internal innovation intensity is insignificant. Exporters might need more advanced technology, which might not exist in-house, or they may have better exposure to external markets or other firms, which might help them to buy external innovation.

Again, test for the difference of coefficients is conducted, and the null hypothesis that coefficients of the regressions from the mentioned columns are systematically the same is rejected by 1 percent significant level between columns (1) and (3), and between columns (2) and (4), which confirms that the determinants of invest in innovation are different between internal and external sources of innovation.

Table A.2 in appendix I provides more details on firms' innovation investment by level of their export status: full exporters, which export all of their production; partial exporters, which export some of their production but sell the remaining production in domestic market; and non-exporters. Partial exporters invest the most in innovation, followed by full exporters, and lastly, non-exporters. Full exporters and partial exporters invest much more in external innovation than in internal innovation.

Table A.3 in appendix I shows the innovator's ratio by FDI status. Interestingly, firms with joint ownership between foreign owner and domestic owner (partial FDI) invest more in innovation than fully domestic firms (no FDI), while those firms that are fully owned by foreign owner (full FDI) invest in innovation much less.

The low level of innovation investment of full FDI firms might be explained by the specific characteristics of foreign investment in Tunisia. FDI in Tunisia is mainly provided by a few European countries, such as France and Italy, and is concentrated heavily in the export processing zones (EPZs), known as the offshore regime, where foreign firms receive a tax incentive to export products back to Europe. The main purpose of their investment in Tunisia is cost saving, from both cheaper labor and tax incentives in natural resource–related industries, or from outsourcing a relatively simple part of the process, like textiles, in the production value chain. In fact, research on EPZs in developing countries found that foreign firms operating in EPZs mostly engaged in process trade based on cheap unskilled or semi-skilled labor available in the host country and did not generate linkages with the local economy. This situation might explain the lesser likelihood of innovation investment for FDI firms.

Also, the negative effects of FDI on technological upgrading in the domestic firms have been documented in previous literature. The strong competition from foreign subsidiaries may reduce local firms' R&D efforts (OECD 2002). Foreign subsidiaries may remain as enclaves in developing countries with lack of effective linkages with the local economies. However, these negative effects are more relevant for competitor firms or other firms in the domestic markets, rather than those firms that receive FDI. Therefore, there are many preconditions, such as a firm's absorptive capacity and business environment, for an effective technology transfer process to occur through FDI.

The above findings are also consistent with previous literature investigating determinants of innovation in Tunisia. Surveys on selected industries such as ICT and pharmaceutical sectors confirmed that innovation efforts are lacking in those so-called high technology industries (Harbi, Amamou, and Anderson 2009, 2012; Yacoub 2013). Also, a study using the innovation survey confirms that firm size has a positive effect (Ayadi et al. 2009)[15]. Moreover, labor quality has a positive effect on innovation, whereas FDI has a negative impact on innovation in Tunisia (Gabsi, Mhenni, and Koouba, 2008; Karray and Kriaa 2008), which is consistent with my results.

Which source of innovation are more efficient way to increase productivity?

Table 1.5 presents the main results of the paper with estimation results of equations (3), (4), and (5), using GMM with lag 2 and 3.

Table 1.5 Innovate Internally or Externally? Using GMM

Dep. Var.	(1)	(2)	(3)
ln revenue	Total innov	Internal vs. external	Synergies
ln_labor	0.355***	0.357***	0.362***
	(0.000)	(0.000)	(0.000)
ln_capital_d	0.005	0.001	0.017
	(0.899)	(0.988)	(0.674)
ln_intermed_d	0.640***	0.639***	0.642***
	(0.000)	(0.000)	(0.000)
ln_n_innovation inv	0.027**		
	(0.003)		
ln_n_internal ino		0.013	0.046
		(0.189)	(0.274)
ln_n_external ino		0.021*	0.030*
		(0.048)	(0.045)

[15] The innovation survey used a small sample, which was highly likely to innovate, and therefore, cannot provide information for general firms in Tunisia. Also, those studies using the innovation survey analyze the determinants of innovation output, not innovation efforts. Therefore, I cannot directly compare my results with those studies, however, they still provide valuable information to cross-check the characteristics of Tunisian firm behaviour related to innovation.

Interaction term			-0.006
			(0.207)
export_stat	0.244***	0.242***	0.241***
	(0.000)	(0.000)	(0.000)
FDI_stat	0.275***	0.275***	0.280***
	(0.000)	(0.000)	(0.000)
# of obs.	15,735	15,735	15,735
# of groups	4,255	4,255	4,255
sum of coefficient	1.105	1.106	1.02
AR2 (p-value)	0.001	0.001	0.002
Hansen (p-value)	0.000	0.000	0.000

Note: Year and industry dummies were included but not reported. Standard errors are clustered and robust (White's correction for heteroskedasticity).; p-values in parentheses. Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

The instrument set for the differenced equation consists of the log of revenue, the log of innovation investment (for all, internal and external innovation), the log of material input, in levels, in periods *t*-2 and *t*-3 (among which missing values are treated as 0, and the instruments for each period are collapsed), the log of labor and capital inputs, export and FDI status, and year and industry dummies, differenced. The instrument set for the levels equation consists of the log of revenue, the log of innovation investment (for all, internal and external innovation), the log of material, labor, and capital inputs; export and FDI status as a constant; and year and industry dummies.

The test results require a careful interpretation of GMM results. Test results for the AR2 are close to zero, rejecting the null hypothesis that the differenced residuals in period t and t-2 are uncorrelated — therefore, autocorrelation in these levels might be a concern in this system GMM measurement. The Sargan/Hansen test of overidentifying restrictions for GMM estimators also rejects the null hypothesis that instruments are exogenous. This might have been caused by the fact that the instrument is exactly identified. The difference-in-Sargan/Hansen test fails to reject similar results that these additional instruments are valid.

The coefficient of intermediary inputs is quite large, around 0.64 in columns (1) to (3), implying that Tunisian firms engage predominantly in relatively low value added activities. While the coefficient of labor is significant and around 0.36 in columns (1) to (3), the coefficient of capital is close to zero and statistically insignificant. A very small coefficient for capital is not unusual in previous research on firm-level TFP analysis in developing countries (for instance, see Van Beveren, 2012). The coefficient of factor inputs reflects both input and scale elasticities related to output. Control variables, participating in exporting activity (export) and having foreign ownership (FDI), have positive and significant effects on final output. Interestingly, the positive effect of FDI on output is in contrast to its effects on innovation decisions and innovation intensity. FDI would not increase either a firm's decision to innovate or the intensity of its innovation investment, but would still increase its final output.

I used the generalized method of moments (GMM) in TFP estimation to provide consistent estimation by controlling simultaneous input selection issues when input is correlated with error term (A_{ijt}). For instance, when there is exogenous price shock, if material is considered more easily adjustable than labor and capital, then material is more strongly correlated with the error term. Therefore, material is biased upward and labor and capital are biased downward. Instruments can be used to nullify this bias; however, in general it is hard to find such instruments. Therefore researchers use GMM, with lagged variables of output and inputs as instruments, which are already in the firm-level data. GMM thus provides a consistent estimate by removing the simultaneity issue that is caused by the endogenous input choice in TFP estimation.

Overall, results show that overall innovation (all) has a positive and statistically significant effect on output productivity, controlling simultaneity issues between innovation and final output. In particular, external innovation has a positive and statistically significant effect on output productivity. Meanwhile, the coefficient of internal innovation is statistically insignificant at the 5 percent level, which is surprising and contrasts with previous literature that finds a positive effect of internal innovation on productivity (Griffith et al et al. 2004). In addition, a complementary effect between internal and external innovation is not shown for Tunisian manufacturing firms.

Specifically, column (1) shows that overall innovation (all) has a positive and statistically significant effect on output productivity, controlling simultaneity issues between innovation and final output. The coefficient of innovation (all) variable is 0.027, implying that 1 percent increase of innovation investment would be associated with 2.7 percent increase of final output, controlling other inputs and export/FDI status, and the simultaneity issue that could be raised when firms with greater output invest more in innovation.

Column (2) shows the effect of each source of innovation separately, on output productivity. External innovation has a positive and statistically significant effect on output productivity, despite pros and cons of innovation outsourcing and their complex characteristics. In fact, the coefficient of external innovation is 0.021, so external innovation contributes the most to the overall innovation's effect on output productivity seen in column (1). This finding is particularly important since there has been little empirical evidence that quantifies the effect of innovation outsourcing on firms' output productivity, particularly in developing countries.

The insignificant coefficient of internal innovation might be explained by a number of factors. First, if innovation investment requires a certain threshold amount to successfully enhance firms' productivity, the current internal innovation has not yet been reached the threshold. Second, Tunisian firms' outsourced innovation might be relatively simple, so it does not require a high absorptive capacity, which can be measured by the internal innovation investment. Otherwise, internal innovation efforts might not be good proxies of absorptive capacity in Tunisia. As found in a previous study, if technology is difficult to transfer, firms must have a certain prerequisite capacity to learn and adopt the external source of innovation (absorptive capacity). Lastly, internal innovation is not used efficiently within the firms. In fact, the previous study found that Tunisia's relatively large spending on R&D has not increased innovation outcomes, at the national level, due to the inefficient innovation environment (World Bank 2010[16]). In any case, it has been more efficient for Tunisian manufacturing firms to simply acquire technology created externally to enhance their output productivity during the period of data coverage.

The results are consistent with the previous study on Tunisia. Using the innovation survey, Ayadi et al. (2009) concluded that Tunisian firms must benefit from external knowledge sources to exhibit significant innovation propensities for either product or process innovation. The internal innovation, specifically investment in R&D, plays a limited role in having a positive effect on product innovation but no effect on process innovation. Harbi, Amamou, and Anderson (2009) conducted surveys on 60 Tunisian ICT firms and found that internal innovation, specifically R&D, is negatively associated with firms' success. Later, Harbi, Amamou, and Anderson (2012) conducted surveys on 92 small Tunisian ICT companies and found that although some innovation cultural values were positively related to performance, others appeared counterproductive. Specifically, successful companies favoured managing and controlling employees, with a strong emphasis on cost control, rather than on creating a supportive and enabling environment.

Column (3) provides estimation results when the interaction terms of both sources of innovation are added. The coefficient of external innovation becomes larger than in column (2), showing that external innovation's effect on output productivity is larger for those firms that invest in only external sources of innovation than for firms that invest in both internal and external sources of innovation. The coefficient of internal innovation remains statistically insignificant.

Meanwhile, the coefficient of the interaction term is close to zero and statistically insignificant, implying that there is no synergy in using both sources of innovation

[16] Tunisia spent an estimated 1.25 percent of its GDP on R&D in 2009 and the number of researcher per million people, both of them are typical proxies showing innovation inputs and which are above regional average. However, innovation outcomes are disappointing in Tunisia, with limited the international patent application and utilization of the results of research by firms, both are below the regional average, WB (2010).

simultaneously. This result further supports the argument that internal innovation does not play a role in absorptive capacity in Tunisia, in contrast to earlier studies that argue it does by adapting external innovation; therefore, there is a complementary effect between internal and external sources of innovation.

Results from table 1.5 might suggest that in a developing country like Tunisia where firms face resource constraints and have limited internal skills and capability to innovate, it is better to invest more only in external innovation rather than dividing the resources between the two sources of innovation.

These results contradict some previous studies that find complementary effects of using both sources of innovation. For instance, Lokshin, et al. (2008) found the complementary effect in Dutch manufacturing firms, and Cassiman and Veugelers (2006) found it in Belgian manufacturing firms. My results are in contrast to those studies, probably because of sample selection bias. For instance, Lokshin, et al. (2008) conducted his studies only on 304 Dutch manufacturing firms that answered that they were innovating. More importantly, there might be differences in the way innovation works in developing and in developed countries. Specifically, firms in developing countries, such as Tunisia, have a lower level of innovation investment to start with. At the early stages of technology and productivity levels, much more investment is required; therefore, there is an increasing rate of return. But after a certain threshold, firms would reach the level close to the technology frontier, which might cause a diminishing rate of return and explain the complementarity of using both sources of innovation. If Tunisian firms face resource constraint, and their available investment amount is below the threshold, it is better for them to invest in one source of innovation, especially the one that contributes more to output productivity — external innovation.

In fact, complementary effects are identified mostly in developed economies. In the case of developing countries, the complementary effect was found only conditionally or only when certain characteristics hold. For instance, Hou and Mohnen (2013) documented complementary effect only for firms with 100 to 300 employees, however, for more general firms, they found a significant degree of substitutability between both sources of innovation in achieving a higher level of labor productivity in Chinese manufacturing firms.[17]

17. For instance, Lokshin et al., (2008) used a similar specification of the above regression on manufacturing firms and, found that the coefficients of the interaction term of both sources of innovation were positive and statistically significant. He concluded that it is more efficient to divide the resources into both sources of innovation, and explained that a decreasing rate of return on innovation is one of the reasons for synergies between two sources of innovation. He added quadric terms of each source of innovation in its specification, which allows decreasing or increasing returns to scale in internal and external innovation, and shows the existence of a decreasing rate of return. He argued that the scope of economies is accompanied by decreasing returns to scale at high levels of internal and external R&D. The analysis indicates that productivity grows by increasing the share of external R&D in total R&D.

The findings of table 1.5 might suggest that Tunisian firms with limited budgets for innovation would gain more by buying innovation, rather than creating in-house, and there are no synergies of using both sources of innovation at the same time.

While research on the effect of innovation outsourcing on firm productivity on more general industries with representative firms in developing countries is extremely rare, previous literature provides explanations on why no complementary or even a negative (supplementary) effect has been observed.

Internal and external innovation substitute for each other, especially when resources are limited (Basant and Fikkert 1996; Blonigen and Taylor 2000). Given a limited budget, an increase in either of the two options tends to reduce the spending incurred on the other option. If the effect on innovation investment on productivity is not linear or requires a certain amount of investment (threshold) to make a positive effect on the final outcome, splitting two types of innovation would actually have a lower effect than consolidating only one type of innovation. While it is difficult to generalize, existing evidence from studies shows that complementary effects tend to be more obvious in developed countries; whereas substitution tends to be more common in the analysis of developing countries.

In addition, other studies argue that the complementary or substitution effects could be changed depending on the ratio of different sources of innovation, the initial firm's internal innovation condition, and its external environment. In an environment where learning is less demanding, a firm's in-house R&D has little impact on absorptive capacity. In the extreme case in which external knowledge can be assimilated without any specialized expertise, a firm's internal R&D would have no effect on its absorptive capacity (Cohen and Levinthal 1990). Open innovation moderates the internal and especially the longer-term incentives to innovate. R&D outsourcing and innovation performance have an inverse U-shaped relationship, which is positively moderated by the extent to which firms engage in internal R&D and by the breadth of formal R&D collaborations. Both serve as instruments to increase the effectiveness of R&D outsourcing (Fu 2010).

Table 1.6 provides estimation results from other econometric methods, such as ordinary least squares (OLS), fixed effects (FE), and Levinsohn and Petrin (LP), to estimate equations (3) to (5). The estimation results of table 1.6 confirm that table 1.5 GMM estimation results are in the credible range.

Table 1.6 Innovation Impact on Output, OLS, FE, and LP

Dep. Var.	OLS			FE			Levinsohn and Petrin (LP)		
ln revenue	(1) Total innov	(2) Int.vs. ext.	(3) Synergy	(4) Total innov	(5) Int.vs. ext.	(6) Synergy	(7) Total innov	(8) Int.vs. ext.	(9) Synergy
ln_labor	0.393***	0.392***	0.391***	0.206***	0.205***	0.206***	0.352***	0.352***	0.351***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln_capital_d	0.198***	0.197***	0.196***	0.196***	0.196***	0.196***	0.320	0.272	0.207
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.058)	(0.061)	(0.174)
ln_intermed_d	0.397***	0.396***	0.396***	0.307***	0.307***	0.307***	0.359*	0.402***	0.491***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.001)	(0.000)
ln_n_innovationi	0.015***			0.005***			0.014***		
	(0.000)			(0.000)			(0.000)		
ln_n_internalino		0.007***	0.002		0.005***	0.000		0.007***	0.004
		(0.000)	(0.558)		(0.000)	(0.953)		(0.000)	(0.193)
ln_n_externalino		0.012***	0.010***		0.003**	0.002		0.011***	0.010***
		(0.000)	(0.000)		(0.001)	(0.098)		(0.000)	(0.000)
Interaction term			0.001**			0.001*			0.000
(ln_int × in_ext)			(0.007)			(0.011)			(0.180)
export_stat	0.198***	0.198***	0.197***	0.055***	0.055***	0.055***	0.178***	0.177***	0.177***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FDI_stat	0.253***	0.253***	0.252***	-0.032	-0.033	-0.033	0.207***	0.207***	0.206***
	(0.000)	(0.000)	(0.000)	(0.089)	(0.083)	(0.079)	(0.000)	(0.000)	(0.000)
N	15,735	15,735	15,735	15,735	15,735	15,735	15,735	15,735	15,735
Sum of coeffi	1.004	1.004	0.996	0.715	0.717	0.711	1.045	1.043	1.064

Note: Year and industry dummies were included but not reported. Standard errors are clustered and robust (White's correction for heteroskedasticity); *p*-values in parentheses: Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

As mentioned before, the estimation results using OLS and FE techniques can provide an upper and lower range to compare the estimation results of GMM in table 1.6, which aim to remove the simultaneity effects of innovation and final output.

The LP method, which uses the previous year's intermediate input (material) as a proxy for productivity shock and as an instrument to capital to remove the simultaneous effect of factor inputs and productivity, is currently developed for one proxy variable (material) and one endogenous variable (capital) when using revenue as the dependent variable, and does not allow the addition of other endogenous variables, such as innovation investment. Therefore, it still does not remove the simultaneous effect between innovation investment and final output; however, the estimation results using the LP technique are still closer to a true estimation than either OLS or FE, since it gets rid of simultaneity issues of other factor inputs, such as capital, in estimating the production function.

As expected, the coefficients of labor get larger when using OLS and smaller when using FE, compared to those in table 1.6. The coefficient of labor using LP is quite similar to the coefficients using GMM in table 1.6. The coefficients of capital are positive and statistically significant when using OLS and FE, but become insignificant when using LP when the simultaneous effect of factor inputs and final output are removed, which is consistent with the above results using GMM. This might imply that capital investment in Tunisia is highly correlated with the output; therefore, there could be an upward bias in the capital coefficient in OLS and FE estimation. In contrast, the coefficients of intermediate inputs get larger when using LP, which is also consistent with GMM estimation, although the coefficients of intermediary inputs with GMM get even larger, which might result from different assumptions of endogenous variables and different estimation methods in LP and GMM. Overall, the factor inputs coefficients using OLS, FE, and LP confirm that estimation results using GMM are in the credible range. The control variables, export and FDI, have significant and positive effects on final output, except for the coefficient of FDI, which is insignificant when using FE; these results are also consistent with table 1.5.

The coefficients of the overall innovation investment (ln_n_innovationi) are statistically significant and are 0.015 using OLS, 0.005 using FE, and 0.014 using LP. These coefficients are smaller than 0.027, the result in column (1) in table 1.5, implying that the innovations' effect on final output (via productivity) is actually larger when the simultaneous effect between innovation investment and final output (via productivity) is considered. As seen in columns (2), (5), and (8), both internal and external innovation have positive and significant effects on final output. The magnitude of the coefficient of external innovation is larger when using OLS and LP, but smaller when using FE. The results are different from the results in column (2) in table 1.5, where internal innovation does not significantly impact final effect, while external innovation does. However, when adding the interaction terms between the internal and external innovation investment amount, the coefficients of internal innovation become insignificant when using OLS, FE, and LP, as seen in columns (3), (6), and (9), which is consistent with the results of column (3) in table 1.5. Significantly, the coefficients of the interaction term are in columns (3) and (5), but the magnitude is very small (close to zero), and this coefficient becomes insignificant in column (9) when using LP, which is consistent with the results of table 1.5.

The above results using OLS and FE support that the main results using GMM are in the credible range. Also, the results using typical LP are consistent with the GMM results, which supports the fact that the difference of coefficients between OLS, FE and GMM result from removing the simultaneous effects of inputs and output.

I also consider translog production function, which is a flexible functional forms for the production functions, to remove rigid assumptions in cobb-douglas product function, such as linear relationship between factor inputs and output, and perfect substitution between production factors (in other words, perfect competition on the production factors market), however, did not include it due to the high collinearity among regressors.[18]

The collinearity among regressors in the traslog specification is seen as "harmful" if the sign of at least one estimated parameter is contrary to the sign of the coefficient of correlation between the resultative variable and the analyzed explanatory variable (Pavelescu, 2010b). Using equations (3) in the translog function[19], I find that, when other inputs are in the mean, the marginal effect of labor is 0.309, the marginal effect of capital is 0.158, the marginal effect of intermediate inputs is 0.694 and the marginal effect of innovation is -0.072. Likewise, equations (4) is measured with translog function. When other inputs are in the mean, the marginal effect of labor is 0.296, the marginal effect of capital is 0.104, the marginal effect of intermediate inputs is 0.690 and the marginal effect of internal innovation is -0.036 and the marginal effect of internal innovation is -0.068. The negative coefficients for innovation variables seem to be caused by collinearity among explanatory variables, which is a major constraint to estimate the translog production function.

Meanwhile, if a firm, which would have invested in innovation, decides not to under a certain threshold (z = 0), the observed innovation value Z_{ijt} is censored around zero. To address this issue, I use tobit for the censored dependent variables. Table 1.7 provides estimation results using Tobit regression as described in equations (9) and (10).

Table 1.7 Determinants of Innovation Using Tobit Methods

Dep. Var. { U_{ijt} }	(1) Internal	(2) External	(3) Total innov
Firm size	1.881***	0.957***	0.912***
	(0.000)	(0.000)	(0.000)
Tech staff ratio	-1.491***	0.060	0.045
	(0.000)	(0.835)	(0.869)
Ln (ave wage)	2.758***	1.547***	1.467***
	(0.000)	(0.000)	(0.000)
Export status	0.861***	0.830***	0.880***
	(0.000)	(0.000)	(0.000)

[18] The translog production function can be used for the second order approximation of a linear-homogenous production and allows to estimate not only the elasticity of input but also the elasticity of scale, which is equal to the marginal product (Ferguson, 1979; .Klacek, et al., 2007).

[19] For instance, equations (3) is now measured as; Y=f(K,L,I, T) = l k m t l2 lk lm lt k2 km kt m2 mt t2 lkm lkt lmt kmt lkmt y1997-y2009. Now the marginal product of innovation to be potentially non-linear and a function of other inputs; dY/dN= _b[t]+_b[lt]*l+_b[kt]*k+2*_b[t2]*t+_b[mt]*m+_b[lkt]*lk+_b[lmt]*lm+_b[kmt]*km+_b[lkmt]*lkm.

FDI_stat	-0.980***	-0.756***	-0.687***
	(0.000)	(0.000)	(0.000)
Firm age	-0.008	-0.018***	-0.017**
	(0.282)	(0.001)	(0.001)
Dominance	-4.911**	2.377	1.743
	(0.007)	(0.054)	(0.156)
Observations	13,257	13,257	13,257
*N*_uncensored	4,995	8,384	8,875
*N*_left censored	8,262	4,873	4,382
Pseudo R^2	0.028	0.014	0.013
Log pseudo likelihood	-23,400	-32,568	-33,724
Sigma	8.919	6.530	6.343
Sigma standard error	0.069	0.053	0.053

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (White's correction for heteroskedasticity); *p*-values in parentheses: Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

Tobit regression coefficients are estimated in a similar way to Probit regression coefficients in pooled regression, except that the linear effect is on the uncensored latent variable, not the observed outcome. As expected, the direction and statistical significance of coefficients in table 1.7 are similar to the results in columns (2), (4), and (6) in table B.1 in Appendix II. Meanwhile, the magnitude of coefficients is changed when considering the censoring issue in table 1.7. For instance, the positive effects of firm size, average wage, and export become much larger in table 1.7 than in table B.1. Also, the negative coefficient of technical staff ratio and dominance on internal innovation investment, and negative coefficient of FDI on any type of innovation become much larger in table 1.7, compared to table B.1.

Among the observations of 13,257 firms, the uncensored observations are 4,995, 8,384, and 8,875; observations left censored, which are for the firms that reported zero innovation investment, are 8,262, 4,873, and 4,382, depending on sources of innovation, in columns (1) to (3). The pseudo *R*-square is between 0.013 and 0.028, which is less than the *p*-value of *R*-square in table 1.3 — that is, between 0.020 and 0.056. Sigma value, which is in the range 6.343 to 8.919 in columns (1) to (3), is comparable to the root mean squared error in an OLS regression that estimates the average of the squares of the difference between the estimator and what is estimated. The significance of the Tobit "sigma" parameter can tell whether the results of the Tobit model fit the data considerably better (González and Jaumandreu 1998).[20] This finding supports the

20. González and Jaumandreu (1998) integrate analysis of the decision to undertake R&D activities with analysis of the decision of the level of the R&D investment when this investment is carried out. The framework assumes existence of minimum required R&D expenditure. This assumption, combined with demand characteristics and technological opportunities, determine threshold level of R&D expenditure

assumption that there is a minimum required innovation investment. In fact, sizable thresholds exist, which are systematically related to determinants of innovation, that is, demand and technological factors.

Table 1.8 provides the estimation results of equations (11), (12), and (13) system GMM with lag 2 and 3, while using the predicted value of innovation investment, obtained from the Tobit regression above.

Table 1.8 Innovation Impact on Output, GMM, and Predicted Value

Dep. Var. ln revenue	(1) Total innov	(2) Internal vs. external	(3) Synergies
ln_labor	0.041	-0.112	-0.162
	(0.473)	(0.340)	(0.167)
ln_capital_d	-0.070	0.009	0.050
	(0.137)	(0.906)	(0.495)
ln_intermed_d	0.247***	0.215***	0.189***
	(0.000)	(0.000)	(0.001)
Innov_hat	0.857***		
	(0.000)		
Inter_hat		-0.275	-0.230
		(0.180)	(0.249)
Exter_hat		1.374**	1.477***
		(0.001)	(0.000)
Int_ext_hat			-0.026
			(0.062)
Export_stat	-0.529***	-0.768**	-0.870***
	(0.000)	(0.002)	(0.000)
FDI_stat	0.530***	0.652***	0.643***
	(0.000)	(0.000)	(0.000)
# of obs.	12,764	12,764	12,764
# of group	3,210	3,210	3,210

under which firms do not find it profitable to invest. This framework leads naturally to a Tobit model aimed at estimating thresholds, which the study authors applied to more than 2,000 Spanish manufacturing firms, many among those without R&D expenditure.

Sum of coefficient	1.075	1.211	1.298
AR2 (p-value)	0.000	0.001	0.003
Hansen (p-value)	0.000	0.000	0.001

Note: Year and industry dummies were included but not reported. Standard errors are clustered and robust (White's correction for heteroskedasticity); *p*-values in parentheses. Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

The main interest in this table is the coefficients of the predicted value of innovation investments. Like table 1.5, overall innovation (innov_hat) and external innovation have positive and statistically significant effects on final output, while internal innovation and synergy between two sources of innovation are statistically insignificant. Surprisingly, the magnitude of the coefficients became much larger when using the predicted value, so that the coefficient of overall innovation is 0.857 in column (1), and external innovation is 1.374 in column (2) and 1.477 in column (3), which makes the 1 percent increase in either external or overall innovation investment have a larger effect on final output than the 1 percent increase of other factors, such as intermediary inputs. Also, an increase in innovation investment has a larger effect on final output than if a firm receives foreign investment or becomes an exporter. Therefore, the overall and external innovation effects on final output become much larger when considering the minimum requirement of innovation investment (threshold); however, internal innovation still has an insignificant effect on final output, and there is no synergy in investing in both sources of innovation. The results of table 1.9 further support the results of table 1.5.

When predicted values of innovation are used, the coefficients of labor become insignificant, and the coefficients of capital remain insignificant. Meanwhile, the coefficients of intermediary inputs are still positive and statistically significant. The coefficients of exports now become negative while FDI status still remains positive and significant.

Table 1.9 provides the estimation results when I used TFP, instead of final output (revenue), as a dependent variable, which is a direct test of the effect of different sources of innovation on productivity.

Table 1.9 Using TFP as a Dependent Variable, GMM

Dep. Var Ln TFP $_{ijt}$	(1) Innov	(2) Internal vs. external	(3) Synergies
ln_n_innovationinv	0.063^{***}		
	(0.001)		
ln_n_internalino		0.024	0.034
		(0.110)	(0.307)

ln_n_externalino		0.045*	0.039*
		(0.015)	(0.047)
ln_n_internal and ln_n_external			-0.001
			(0.853)
Export_stat	0.635***	0.611***	0.528***
	(0.000)	(0.000)	(0.000)
FDI_stat	0.807***	0.782***	0.704***
	(0.000)	(0.000)	(0.000)
# of obs.	15,735	15,735	15,735
# of group	4,255	4,255	4,255
AR2 (p-value)	0.607	0.534	0.509
Sargan (p-value)	0.000	0.000	0.000
Hansen (p-value)	0.001	0.002	0.000

Note: Year and industry dummies were included but not reported. Standard errors are clustered, and robust (White's correction for heteroskedasticity); *p*-values in parentheses, Significance level: * = 5 percent, ** = 1 percent, *** = 0.1 percent

The instrument set for the differenced equation consists of TFP, the log of innovation investment (for all, internal, and external innovation), in levels, in periods t-2 and t-3 (for which missing values are treated as zero, and instruments for each period are collapsed), export and FDI status, and year and industry dummies, differenced. The instrument set for the levels equation consists of TFP, the log of innovation investment (for all, internal and external innovation), export and FDI status, a constant, and year and industry dummies.

Test results for the AR (equation 2) are quite large, between 0.509 and 0.607, and fail to reject the null hypothesis that the differenced residuals in period t and t-2 are uncorrelated; therefore, autocorrelation in levels might not be a serious concern in this system GMM measurement. However, the p-value of the Sargan/Hansen test of over identifying restrictions for GMM estimators are close to zero, rejecting the null hypothesis that instruments are exogenous. This might have been caused by the fact that the instrument is exactly identified. The difference-in-Sargan/Hansen test fails to reject similar results that these additional instruments are valid.

The overall innovation has a positive and significant effect on TFP, as seen in column (1) in table 1.9. The coefficient of internal innovation is statistically insignificant while the coefficient of external innovation is positive and statistically significant in column (2). Lastly, using both sources of innovation at the same time (synergy) does not have a significant effect on TFP. These results are also consistent with the results of table 1.5, which support innovation effects on final output via TFP.

6. Conclusion

In this paper, I first identified the determinants of innovation investment and analyzed whether those determinants are different for internal and external sources of innovation for a large number of representative samples of Tunisian manufacturing firms from 1997 to 2007.

As in previous literature on determinants of innovation, my estimation results showed that in Tunisia, larger firms that pay higher wages and participate in exports are more likely to invest in innovation. Meanwhile, having more technicians and larger market share are statistically insignificant determinants of all and external innovation decisions, and they reduce the probability of firms engaging in internal innovation. Firm age has a negative and statistically significant coefficient, but the magnitude is small and close to zero.

Interestingly, FDI firms are less likely to invest in innovation, although FDI has a positive effect on final output, which might be explained by the fact that most foreign investment in Tunisia is driven by cost-saving purposes, rather than longer-term strategic vision, and is consistent with previous findings of the negative effects of FDI on technological upgrading in domestic firms (OECD 2002). Determinants of innovation investment work in the opposite way for firms that invest in only one source of innovation, implying that those firms that invest in only one type of innovation are very different from those that invest in both sources of innovation.

The major determinants of the innovation decision are consistent, using either the Probit model or firm fixed effects in panel data. Also, the estimation results with innovation intensity (innovation investment amount) as a dependent variable reveal that the decision related to innovation (whether to innovate or not) and the decision related to innovation intensity (how much to innovate) are similar for external innovation but quite different for internal innovation investment in Tunisia.

I then tested which sources of innovation contribute more to final output (via productivity) in Tunisian manufacturing firms. The results are summarized below.

First, innovation, overall, has a positive and statistically significant effect on final output via productivity increase (output productivity), but different types of innovation investment has different effect on productivity. The coefficient of the innovation (all) variable is 0.027, implying that 1.0 percent increase of innovation investment would be associated with 2.7 percent increase of final output, controlling other inputs and export/FDI status as well as simultaneity issues between innovation and final output, using GMM methods.

Second, internal innovation has an insignificant effect on final output, while external innovation has a positive and statistically significant effect on it. Specifically, when separately testing the effect of each source of innovation on final output, it is found that the coefficient of external innovation is 0.021; demonstrating that external innovation contributes most to the overall effect on output productivity. These results are also documented in the previous study on Tunisian firms using a different data set, such as the innovation survey. Hence, it is more efficient for Tunisian manufacturing firms simply to acquire foreign technology created externally to enhance their output productivity during the period of data coverage.

Third, external innovation's effect on final output is larger for those firms that invest in only external sources of innovation than for firms that invest in both sources of innovation. When the interaction terms of the internal and external innovation investment are added, the coefficient of external innovation becomes larger while the coefficient of internal innovation remains insignificant.

Fourth, there is no synergy from using both sources of innovation simultaneously. The coefficient of the interaction term is close to zero and statistically insignificant. This result might suggest that internal innovation does not play a role in absorptive capacity in Tunisia. The results further support my argument that for a developing country like Tunisia, where firms face resource constraints and have limited internal skills and limited capability to innovate, it is better to invest more in only external innovation, rather than dividing resources between two sources of innovation.

Fifth, the estimation result using the Tobit model supports the assumption that a minimum innovation investment is required. When considering the censoring issue of innovation variables, using Tobit methods to analyze determinants of innovation investment, the direction and statistical significance of coefficients are consistent with the main specification, but the magnitude of the coefficients becomes larger. It appears that the Tobit model fits the data considerably better given that a large number of observations have been left censored (zero innovation investment) and the significant sigma values of Tobit regression. In fact, sizable thresholds exist, which are systematically related to determinants of innovation, that is, demand and technological factors.

Lastly, the overall and external innovation effects on output productivity become much larger when considering this minimum requirement of innovation investment (threshold), using the predicted value from the Tobit regression. Meanwhile, the internal innovation and synergy of using both sources of innovation still have an insignificant effect on final output when using the predicted values.

The above results are also borne out through other econometric methods, such as OLS, FE, and LP, confirming that GMM results are in the credible range. Also, the results were consistent when I used TFP as a dependent variable, which confirms the innovation effect on productivity via TFP.

These results provide valuable information in designing innovation policy in Tunisia.

The findings suggest that innovation policy should emphasize technology adoption and adaptation, rather that technology creation. In particular, the innovation policies should focus on facilitating firms' purchase of foreign technology and external innovation since external innovation contributes most to the overall effect on output productivity, and there is no synergy in using both sources of innovation simultaneously. Specifically, to encourage firms' investment in external innovation, the Tunisian government can promote exports and workers' skills (average wage can be a proxy of workers' skills), but providing incentives, such as subsidies, to firms to hire more technicians, and FDI promotion are not the best ways to encourage firms' investment in innovation.

Moreover, the finding that so-called "high-tech" industries are not the most innovative industries in Tunisia suggests that innovation policy should not narrowly focus on those "high-tech" industries. In addition, the fact that there is a minimum requirement (threshold) for innovation investment suggests that policies that aim to reduce this threshold or to support firms around this threshold could catalyse the innovation investment of certain firms. The findings are particularly important since there is little empirical evidence that quantifies innovation outsourcing's effect on firms' output productivity, especially in developing countries.

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