

PUBLIC FINANCIAL SUPPORT AND INBOUND OPEN INNOVATION IN DEVELOPING ECONOMIES: EVIDENCE FROM MOROCCAN FIRMS

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ABSTRACT

The objective of this study is to quantitatively examine the impact of public financial support (PFS) on the adoption of inbound open innovation (IOI). The study is based on data from the World Bank survey of 1,096 Moroccan firms (WBES, 2020). Inbound open innovation is measured by two indicators, namely the acquisition of external knowledge and the use of licensed foreign technologies. Given the nature of the data, we apply two complementary methods to control for the potential endogeneity problem associated with access to public funding: logistic regression and propensity score matching (PSM). The results show that firms benefiting from public financial support are more likely to adopt inbound open innovation (IOI), i.e., the acquisition of external knowledge and the use of licensed foreign technologies. This result highlights the strategic role of public innovation policy, particularly public financial support, in supporting innovation in developing countries (DCs). Our study concludes that targeted financing mechanisms can strengthen the absorptive capacity of companies, particularly in contexts where private investment in research and development (R&D) and technological knowledge remains limited. This can generate positive spin-offs not only for companies benefiting from public financial support (PFS), but also for the economy as a whole, by improving productivity, boosting competitiveness, and helping to bridge the technology gap with advanced countries.

Keywords: *Inbound Open Innovation, Public Financial Support, Absorption Capacity, Propensity Score Matching (PSM)*

1. INTRODUCTION

Innovation is a key factor in the economic development, growth, and competitiveness of firms and nations (Schumpeter, 1934). Numerous researchers have studied the conditions conducive to the development of innovation. Early studies on innovation focused on factors internal to firms, such as R&D expenditure, size, age, and management structure. Subsequently, attention turned to external factors, introducing the concept of open innovation (OI) (Chesbrough, 2003; Laursen and Salter, 2006; Cassiman and Veugelers, 2006). A major conclusion of the OI literature is that firms seeking to innovate must integrate external knowledge, technologies, and resources, a process known as inbound open innovation (IOI) (Greco et al., 2017; Jugend et al., 2018). IOI enables firms to access the resources they need, reduce internal development times

and risks, broaden their technological knowledge, gain access to cutting-edge technology, and catch up on these technological advances (Sabando-Vera et al., 2022; Jesus & Jugend, 2023).

However, the emergence of acquisition costs such as transactional, organizational and cognitive costs can hinder firms from adopting IOI (Laursen & Salter, 2006; Greco et al., 2017; Hewitt-Dundas & Roper, 2018; Chesbrough & Vanhaverbeke, 2018; Ardito et al., 2018; Leckel et al., 2020; Costa & Moreira, 2022; Zaghdoud, 2025), especially firms in developing countries (DCs), which generally lack these resources (Elia et al., 2020; Haddoud et al., 2023).

In many DCs, the market alone is not enough to provide the resources needed for successful IOI (Jugend et al., 2020). As a result, governments are striving to stimulate this model (Cano-Kollmann et al., 2017; Chesbrough & Vanhaverbeke, 2018; Jugend et al., 2020). Public support is needed because of market failures, such as difficulties in accessing R&D and innovation funding, problems of information asymmetry and network issues (Hewitt-Dundas & Roper, 2018; Jugend et al., 2020). This makes the adoption of external technologies more affordable, especially for firms that do not have the resources to directly fund expensive external technologies (Jugend et al., 2020; Costa & Moreira, 2022).

Although the empirical literature has confirmed that public financial support (PFS) has a beneficial effect on OI (Kang and Park, 2012; Canno-Kollmann et al., 2017; Greco et al., 2017; Jugend et al., 2018 ; Ahn et al., 2020), we note that it does not specifically address IOI or the geographical context of acquired external technological knowledge. This distinction is particularly important in the context of firms in DCs, which often lag behind their advanced-country counterparts technologically and face greater resource constraints (Awate et al., 2015; Perri et al., 2017; Elia et al., 2020). Moreover, the existing literature on PFS and OI focuses mainly on developed countries (Rosario et al., 2022), leaving a gap regarding the realities and specificities of DCs, where barriers to innovation are often more complex.

This article aims to fill these gaps by analyzing the impact of public support on IOI in the context of the Moroccan economy, where the majority of firms are SMEs (WBES, 2020). This country, marked by low productivity, low absorptive capacity and major challenges in terms of access to finance (WBES, 2020), is a representative developing context in which to examine this relationship. Moreover, to accurately assess the impact of public support, we need to take into account selection bias and the endogeneity problem, often overlooked in previous research. To address these issues, our paper uses a quasi-experimental estimation technique called propensity score matching (PSM).

The article thus makes several contributions to the literature. On the theoretical level, it enriches the literature on OI by specifically exploring the role of PFS in IOI in DCs, based on a representative sample of 1,096 firms. In addition, it contributes to research on absorptive capacity by demonstrating the role of public policies in enhancing this essential capacity. Secondly, as a complement to previous empirical studies that were limited to examining OI in its entirety, this study focuses specifically on IOI as measured by the acquisition of external knowledge and the use of licensed foreign technologies, thus broadening the literature on OI by distinguishing the origin of technological knowledge. Methodologically, the study combines logistic regression and propensity score matching (PSM). This innovative approach offers three major advantages: Firstly, it controls for selection bias, an aspect often neglected in previous studies. Secondly, it enables a more accurate assessment of the effects of PFS on IOI, by comparing firms with similar characteristics but different access to public support. Finally, it identifies the factors influencing access to public funding. An in-depth explanation of the gaps and our contribution is presented in Section 2.

The remainder of this article is structured as follows: Section 2 sets out the theoretical frame-

work and empirical work. Section 3 describes the methodology adopted. Section 4 presents the results of the model estimations. Section 5 offers an in-depth discussion of the results obtained. Finally, Section 6 concludes the article.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

2. 1. INBOUND OPEN INNOVATION (IOI)

Even large, innovative firms increasingly realize that their in-house knowledge is insufficient to sustain innovation and remain competitive (Chesbrough, 2006; Cassiman and Veugelers, 2006). The concept of « IOI », popularized by Chesbrough (2003), describes how firms seek ideas and knowledge beyond their own borders to drive their development. Unlike outbound OI, which involves sharing internal knowledge outwards, IOI refers to a flow of knowledge from outside to inside the firm (Hewitt-Dundas and Roper, 2018; Bogers et al., 2020).

Input knowledge flows are associated with mechanisms such as licensing, acquisitions, spinning, innovation and incubation, user-driven innovations and supplier/competitor-driven innovation, among others (Costa & Moreira, 2022). This concept is preceded by the presupposition that firms need knowledge and technology, recognizing that they are beyond their internal capabilities (Jesus & Jugend, 2023). Consequently, IOI aims to meet this need and improve a given firm's capacity for innovation (Laursen and Salter, 2006).

The role of integrating external knowledge and technologies has been widely documented. In terms of learning and innovation, it enables firms to broaden their technological knowledge base (Cohen & Levinthal, 1989; Bakracheva, 2025). In addition, collaboration with technology partners enables firms to leverage their expertise and increase their competitiveness (Teece, 1992). It also offers strategic advantages, such as reduced internal development costs, rapid access to cutting-edge technologies, and accelerated growth (Tsai & Wang, 2008).

The important role that the integration of external knowledge and technologies can play has also attracted growing interest in the empirical literature. For example, Lopez (2008) found a positive and significant impact on productivity, while Elia et al. (2020) found a positive effect on stock market returns. For their part, Li-Ying et al. (2013), Li-Ying and Wang (2015), Wang and Li-Ying (2015), and Haddoud et al. (2023) found positive effects on innovation.

2. 2. JUSTIFYING PUBLIC FINANCIAL SUPPORT (PFS) FOR INBOUND OPEN INNOVATION (IOI) IN DEVELOPING COUNTRIES (DCS)

IOI relies on combining the external knowledge and technologies of close stakeholders such as suppliers, customers, and competitors with those of external sources such as universities, research institutes, consultants, investors, governments, and foreign firms (Costa & Moreira, 2022 ; Jesus & Jugend, 2023 ; Haddoud et al., 2023). However, the emergence of acquisition costs may prompt firms to avoid adopting this strategy (Cano-Kollmann et al., 2017; Ardito et al., 2018). For example, the acquisition of external national or international knowledge and technologies requires significant transaction costs (Hewitt-Dundas & Roper, 2018 ; Chesbrough & Vanhaverbeke, 2018 ; Ahn et al., 2020 ; Moreira et al., 2020). Indeed, finding suitable partners with technologies that match firms' competitive strategies is difficult and costly because technological knowledge is context-dependent (Tsai & Wang, 2009 ; Hewitt-Dundas & Roper, 2018). Today's technologies are being developed in an increasing variety of geographical areas, and their acquisition costs can be higher in a globalized context due to the emergence of geographical and cultural barriers between countries (Ardito et al., 2018; Trifunović et al., 2025).

In addition, one of the main expenses comes from the acquisition of licenses and intellectual property rights, as access to technologies or knowledge protected by patents often involves

high licensing fees, such as transaction costs, agency costs, and ownership and integration costs, including upfront payments and recurring royalties (Arora et al., 2013 ; Chesbrough & Vanhaverbeke, 2018 ; Cabaleiro-Cerviño & Burcharth, 2018 ; Hewitt-Dundas & Roper, 2018 ; Perri et al., 2017 ; Cano-Kollmann et al., 2017; Mastilo et al., 2025).

A firm's absorptive capacity, i.e., their ability to recognize, assimilate, and exploit external technological knowledge, must also be taken into account in the IOI (Jesus and Jugend, 2023), as acquiring external national or international knowledge and technology requires significant cognitive costs (Ardito et al., 2018). Indeed, technology developed in advanced countries is generally adapted to the factor endowments specific to these economies, such as natural resources, labor, capital, and entrepreneurship, as well as to their market structure and customer preferences (Acemoglu, 2002). Consequently, this technology may not be immediately applicable to developing countries, where economic endowments and conditions differ considerably (Wang and Li-Ying, 2015). This suggests that firms need a certain level of related technological knowledge before they can benefit from external technologies (Cohen & Levinthal, 1990; Cassiman & Veugelers, 2006). This capacity is largely based on internal R&D (Cohen & Levinthal, 1990; Tsai & Wang, 2009). However, in developing countries, private-sector investment in R&D is often insufficient due to the difficulty firms have in financing their R&D activities (Jugend et al., 2020). At the same time, the integration of new technologies often requires additional efforts in staff training, incurring significant costs in terms of time and skilled human resources (Bianchi & Lejarraga, 2016).

Integrating external technologies would also require the absorption of external knowledge and its integration into the internal knowledge base, which is a costly and difficult task (Wang & Li-Ying, 2015; Cabaleiro-Cerviño & Burcharth, 2018).

These various costs can slow down the adoption of IOI by firms in developing countries, particularly SMEs (Topić – Pavković, 2024). In this context, we argue that PFS can play a key role in reducing these costs. The crucial role of government in innovation has been widely studied in the context of various economic and management theories, including business and innovation ecosystems (Mazzucato and Robinson, 2018), the triple helix (Ranga and Etzkowitz, 2013), and innovation systems theory (Edquist, 2001).

Empirical literature is paying increasing attention to the role of government assistance in promoting OI. Analysis of this work shows that PFS stimulates in-house R&D and collaborations (Kang & Park, 2012; Greco et al., 2017; Radicic et al., 2020), increases the degree of openness of firms (Canno-Kollmann et al., 2017), and plays a moderating role in the relationship between OI and innovation (Jugend et al., 2018). Ahn et al. (2020) have also shown that PFS for R&D encourages firms to choose partners in a more adventurous context.

2. 3. RESEARCH GAP

Although these studies (Kang & Park, 2012; Greco et al., 2017; Radicic et al., 2020; Canno-Kollmann et al., 2017; Jugend et al., 2018; Ahn et al., 2020) have examined the role of public support in different aspects of OI, we find that they focus mainly on developed countries. Jugend et al. (2020) and Rosario et al. (2022) have shown that the majority of research work is mainly concentrated in Europe and China. Our work brings a new perspective on the Moroccan economy, a DC where the majority of firms are SMEs and where the challenges associated with innovation and OI differ considerably due to specific institutional, economic, and technological constraints (WBES, 2020). Morocco, as a developing country, faces a number of challenges in encouraging innovation. Although initiatives such as the Plan Maroc Numérique 2020 and the Stratégie Maroc Innovant have been put in place to encourage innovation and technological development, Moroccan firms face significant obstacles, such as limited access to private funding

and a still-developing R&D ecosystem. In this context, PFS plays a crucial role in facilitating the integration of IOI into Moroccan firms.

In addition, previous work has focused on IOI as a whole, encompassing both incoming and outgoing IOI (Jesus & Jugend, 2023). However, this study focuses specifically on IOI. IOI is based on the assumption that firms require knowledge and technologies, recognizing that they exceed their internal capabilities (Jesus & Jugend, 2023). This is especially the case for firms located in developing countries such as Morocco, where they face specific challenges (WBES, 2020).

The use of « licensed foreign technologies » and « acquisition of external knowledge » as measures of IOI (Costa & Moreira, 2022) also reinforces the originality of our work, as it departs from studies that focus solely on IOI in terms of the degree or intensity of collaborations (Canno-Kollmann et al., 2017; Greco et al., 2017; Jugend et al., 2018). In addition, by using foreign technology licenses, our article is distinguished by taking into account the geography of the partner firms with which firms collaborate. Thus, this variable offers us the opportunity to accurately assess the scope and nature of collaborations between Moroccan firms and their associates abroad, particularly in terms of advanced technology acquisition.

By using the matching method (PSM), our article provides an important methodological improvement. Indeed, the major challenge in impact assessment of public support is that the decision to grant public support is endogenous and self-selective. Consequently, including public support in a linear regression could lead to inconsistent estimates if it is correlated with the error term (Almus & Czarnitzki, 2003). To estimate the real effects of granting public financial support, it is therefore necessary to answer the central question of impact assessment: how much effort would recipient firms have devoted to IOI in the absence of public support? In fact, most studies on the impact of public support do not attempt to model this counterfactual situation, i.e., they pay no attention to this type of selection bias. We will use the propensity score matching (PSM) method, which goes back to the potential outcomes model developed by Rubin (1974). This approach will help us to estimate the adoption of IOI that recipient firms would have made had they not received assistance, using the sub-sample of non-participants and accounting for selection or endogeneity and other firm-specific characteristics to provide evidence of how the provision of assistance affects IOI. The matching method enables us to accurately determine the effect associated with receiving assistance, as it allows us to examine a situation in which there is no difference between firms that receive assistance and those that do not in terms of characteristics influencing the probability of obtaining public funding. The literature on OI has largely neglected the analysis of characteristics influencing access to PFS. In our paper, we draw on work on the determinants of access to public funds to identify the various factors likely to increase the probability of accessing public funds in order to construct the sub-sample of non-recipient firms (Almus & Carnitzki, 2003; Afcha, 2011; Antonelli & Crespi, 2013; Mardones & Zapata, 2019; Barajas et al., 2021; Elhassan, 2025). In line with the aforementioned studies, we suggest the hypothesis that firms benefiting from PFS are more inclined to adopt IOI than those that do not.

3. METHODOLOGY

3.1. DATA AND SAMPLE

Our study uses data from the World Bank Enterprise Survey for the year 2020 (WBES, 2020). It is a nationally representative survey of business owners and managers. It consists of a survey of a representative private sector sample of 1,096 Moroccan firms. It provides an overview of many aspects of the business environment, such as access to finance, corruption, infrastructure, and performance, among others. The WBES is organized around a global approach, using

standardized survey instruments and a homogeneous sampling methodology. Stratified random sampling is used to select a sample that reflects the private sector of the economy. Categories include firm size, age, and field of activity (Table 1).

Table 1. Firm Characteristics

Characteristic	Frequency	Percent	Cumulative percent
By size			
Small	418	38.14	38.14
Medium	375	34.22	72.35
Large	303	27.65	100
By age			
Young (Up to 5 years)	100	9.99	9.99
Mature (Between 6 and 15 years)	355	35.46	45.45
Older (Above 15 years)	546	54.55	100
By sector			
Manufacturing	463	42.24	42.24
Retail	189	17.24	59.48
Services	444	40.52	100

Source: Author's calculation

3. 2. MODEL, VARIABLES AND ESTIMATION METHOD

To account for the potential endogeneity of PFS, the framework of this study refers to the standard econometric evaluation model, i.e., Rubin's (1974) model of potential outcomes. This involves estimating the parameter "Average Treatment Effect on the Treated (ATT)," which indicates the difference in results for treated firms (i.e., firms receiving PFS) with and without treatment and can be written as follows:

$$ATT = E(Y^1 | T = 1) - E(Y^0 | T = 1) \quad (1)$$

Where $E(Y^1 | T = 1)$ represents the expected outcome for the group of treated firms, while the term $E(Y^0 | T = 1)$ is the expected outcome if the treated firms had not received public financial support (i.e., the counterfactual situation). For variable (T), i.e., PFS, WBES (2020) offers a binary variable indicating whether the firm received PFS or not. So $T=1$ in case of treatment (the firm has received PFS) and 0 otherwise. Y^1 is the result in case of treatment; Y^0 is the result in case of non-treatment. The outcome variable (Y) in this case is the adoption of IOI. IOI is an outside-in process, i.e., technology and knowledge move from outside to inside the firm (Hewitt-Dundas & Roper, 2018; Jesus & Jugend, 2023). Inbound flows are associated with mechanisms such as licensing, acquisitions, short-term grants, spinning, innovation and incubation, user-driven innovations, and supplier/competitor-driven innovation (Costa & Moreira, 2022). WBES (2020) offers two binary variables indicating whether the firm has adopted IOI or not. The first is the use of foreign-licensed technologies, excluding office software. It takes 1 if the firm has used foreign-licensed technology and 0 otherwise. The second variable is the acquisition of external knowledge. This includes the purchase or licensing of patents and non-patented inventions, know-how, and other types of knowledge from other firms or organizations. It takes 1 if the firm has acquired external knowledge and 0 otherwise.

Since $E(Y^0 | T = 1)$ is unobservable, we use the matching method to estimate model (1). This is the most commonly used evaluation method in innovation studies (Radicic et al., 2020). Matching has a major advantage over standard linear regression models. Indeed, it allows us to take into account the endogeneity problem without the need for valid instruments. This approach

involves two identification assumptions (Imbens & Wooldridge, 2009 ; Ouakil et al., 2024):

$$(Y^1, Y^0) \perp T \mid X \quad (2)$$

$$0 < \Pr (T = 1 \mid X) < 1 \quad (3)$$

Assumption (2), known as conditional independence (CIA), postulates that the outcome in the absence of treatment (Y^0) is independent of treatment assignment but depends on the X_i . This implies that all differences between treatment and control groups can be eliminated by including the appropriate X_i . This assumption is similar to that of unbiased omitted variables in linear regression. However, this assumption is strong and difficult to verify directly. Thus, estimates from matching methods should be interpreted with caution, as statistical associations rather than causal effects. Assumption (3) implies the existence of overlap (common support) between the two groups, meaning that they must be comparable in terms of characteristics (Ouakil et al., 2024). This condition guarantees the possibility of finding similar individuals in both groups. It is easier to test and is an advantage of matching over standard linear regression in ensuring this overlap (Imbens & Wooldridge, 2009). However, when the number of features X_i is large, a “dimensionality curse” (Heckman et al., 1997) could affect the width of the common support. To overcome this problem, Rosenbaum & Rubin (1983) propose to match treated and untreated individuals not on the basis of X but on the basis of the propensity score $p(X)$. We therefore have:

$$\Pr (X \mid T = 1, p(X))(Y^1, Y^0) \perp T \mid p(X) \quad (4)$$

$$0 < \Pr (T = 1 \mid p(X)) < 1 \quad (5)$$

The $p(X)$ score is defined as the probability of receiving public support based on characteristics X_i . To estimate this probability, researchers can choose any model, as probit and logit models generally give similar results (Radicic, 2019; Radicic et al., 2020). We use a probit model to estimate this probability on the basis of various X characteristics. Statistically, the propensity score $p(X_i)$ estimates, for each firm « i », the conditional probability P of receiving the treatment under study T , given its initial characteristics (X_i), is given as follows:

$$p(X_i) = P(T_i = 1 \mid X_i) = \beta_i X_i + \varepsilon_i \quad (6)$$

Where the variable $X_i = x_1, x_2, \dots, x_p$ represents the characteristics that affect the probability of receiving PFS. β_i is a vector of parameters to be estimated. ε_i is a random error term.

As for the choice of covariates X , it is recommended to introduce into the model all variables that have a significant impact on both the probabilities of belonging to the treated group and on the outcome variables to credibly satisfy the CIA assumption (Radicic, 2019; Radicic et al., 2020). The matching literature suggests the inclusion even of covariates that are statistically insignificant, as their inclusion does not increase bias in subsequent matching estimates (Radicic, 2019; Radicic et al., 2020). For the selection of X_i characteristics, recourse was made to articles that have studied the determinants of access to PFS (Almus & Carnitzki, 2003; Afcha, 2011; Antonelli & Crespi, 2013; Mardones & Zapata, 2019; Barajas et al., 2021) and the determinants of the acquisition of external technological knowledge (Dohse et al., 2019). Based on data availability and these articles, we have 8 variables. Consequently, the Probit model that takes into account various explanatory variables affecting the probability of receiving PFS(X_i) is developed as follows:

$$p(X_i) = \beta_0 + \beta_1 \text{Comp}_i + \beta_2 \text{Age}_i + \beta_3 \text{MH\_Tech}_i + \beta_4 \text{ICT}_i + \beta_5 \text{Obs\_Pol}_i + \beta_6 \text{Skill}_i + \beta_7 \text{LogSize}_i + \beta_8 \text{Obs\_Tax}_i + \varepsilon_i \quad (7)$$

Table 2 shows the definitions of all the selected variables.

Another important contribution of the estimation procedure used in this study is that we can use the results of the Probit model estimation to analyze and identify the determinants of access to public support (Almus & Czarnitzki, 2003). In addition to the estimated parameters, marginal effects are also used to interpret the results (Almus & Czarnitzki, 2003). In other words, we analyze the impact of marginal variations in X characteristics on the probability of receiving public support. The marginal effects of the probit model are calculated as follows (Wooldridge, 2002):

$$\frac{\partial \Pr[T=1/X=x]}{\partial x_p} = \frac{\partial \phi(x'\beta)}{\partial x_p} = \phi(x'\beta)\beta_i \quad (8)$$

Where $\phi(\bullet)$ represents the probability density function of the standard normal distribution.

Once the propensity score has been estimated, we need to choose the appropriate matching estimator. Indeed, it is pointed out that many matching estimators are suggested in the literature (e.g., nearest neighbor, kernel, stratification). When it comes to choosing the best estimator, the available literature argues that there is no such thing as a “winning” estimator (Imbens & Wooldridge, 2009). Consequently, this study mainly uses the Nearest Neighbor Matching method, whereby the treated agent is matched with the agent in the control group that has the closest propensity score estimate (Imbens & Wooldridge, 2009), while applying kernel and stratification methods to test the robustness of the results.

The aim of matching is to balance the observed covariates between the two groups. Therefore, before choosing the matching technique, we need to perform a balancing test. The purpose of this test is to check the extent to which the estimated propensity score has succeeded in balancing the Xi. This involves checking that there are no statistically significant differences between the propensity score means of treated and untreated firms. If the difference between the means is not statistically significant, the Xi are well balanced between the matched pairs (Radicic, 2019; Radicic et al., 2020). Several methods can be used to test the quality of PSM. The first is based on comparing means between treatment and control groups, before and after matching, to ensure that initially significant differences are no longer significant. The second is based on bias reduction, calculated by comparing standardized mean differences before and after matching. Good matching quality is achieved if these differences are reduced. Finally, another method consists in estimating the pseudo-R² of the propensity score model only on matched individuals: a low pseudo-R² after matching indicates a good match.

Finally, we calculate the ATT by taking the average difference between the two groups' outcome variables. The IPTW (inverse probability of treatment weighting) method popularized by Hirano et al. (2003) will also be used to validate the results obtained by the PSM method (Radicic, 2019).

4. RESULTS

4. 1. DESCRIPTIVE STATISTICS

Table 2. Descriptive Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
PFS	DV=1 for firms having public financial support, 0 otherwise.	.093	.29	0	1
Know_Ext	DV=1 if the firm has acquired external knowledge, 0 otherwise.	.098	.297	0	1
Tech_Lic	DV=1 if the firm uses technology licensed from a foreign firm, 0 otherwise.	.185	.389	0	1
Comp	DV=1 if competing with unregistered or informal firms, 0 otherwise.	.425	.495	0	1
Age	Age of establishment in years	20.073	14.23	2	92
MH_Tech	DV=1 if the firm belongs to the medium/high-tech sector, 0 otherwise. (A Classification according to the OECD)	.254	.435	0	1
ICT	DV=1 if the firm owns its own website; 0 otherwise	.464	.499	0	1
Obst_Pol	DV=1 if political instability is considered sever or major, 0 otherwise.	.329	.47	0	1
Skill	DV=1 if the obstacle of inadequately educated workforce is sever or major, 0 otherwise.	.224	.417	0	1
LogSize	Natural log of the number of permanent full-time employees.	1.602	.677	.699	3.90
Obs_Tax	DV=1 if tax rates are perceived as a sever or major obstacle, 0 otherwise.	.379	.485	0	1

Source: Author's calculation

4. 2. CORRELATIONS AND MULTICOLLINEARITY PROBLEM

Before calculating propensity scores, a multicollinearity study between Xi was carried out to check for the absence of high correlations likely to distort the interpretation of individual effects. We calculated correlation coefficients and the variance inflation factor (VIF) (Table 3). The results reveal low correlations and VIFs below 2, with an average of 1.16 (Wooldridge, 2002). These results confirm that there is no multicollinearity.

Table 3. Matrix of correlations and multicollinearity problem (Variance inflation factor)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Tech_Lic	1.000										
(2) Know_Ext	0.254	1.000									
(3) PFS	0.351	0.376	1.000								
(4) Comp	0.146	0.057	0.063	1.000							
(5) Age	-0.05	-0.06	-0.15	-0.02	1.000						
(6) MH_Tech	-0.04	0.074	0.012	0.015	0.034	1.000					
(7) ICT	0.104	0.030	0.021	0.134	0.031	0.052	1.000				
(8) Obst_Pol	0.022	-0.05	-0.12	0.004	0.107	0.028	0.018	1.000			
(9) SKill	0.122	0.065	-0.04	0.045	0.008	0.032	0.099	0.345	1.000		
(10) LogSize	0.148	-0.03	-0.05	0.032	0.201	-0.01	0.176	0.016	0.118	1.000	
(11) Obs_Tax	-0.01	-0.08	-0.10	-0.02	0.064	-0.03	0.050	0.528	0.311	-0.03	1.000
VIF	/	/	/	1.03	1.04	1.01	1.07	1.46	1.19	1.07	1.39
1/VIF	/	/	/	0.975	0.961	0.987	0.932	0.684	0.838	0.934	0.717

Source: Author's calculation

4. 3. PROPENSITY SCORE ESTIMATION

The Probit model revealed significant trends in access to PFS. In addition to the estimated parameters, marginal effects are also used to interpret the results (Table 4). Indeed, competition, firm age, ICT investment, and political stability are factors impacting access to PFS. With regard to competition, the results show that it positively and significantly influences access to public support ($\hat{\beta}_1 = .532$). According to marginal effects, the results show that, all other things being equal, a competitive market increases the chance of accessing public support by 5.7%. As for firm age, we note that its coefficient is negative and significant ($\hat{\beta}_2 = -.016$). This means that new firms are more likely to access public support. According to marginal effects, all other things being equal, firm age decreases the probability of accessing public support by 0.02%. Furthermore, the results show that investment in ICT positively and significantly impacts access to public support ($\hat{\beta}_4 = .48$). According to marginal effects, the results indicate that investment in ICT increases the probability of accessing public support by 5.2%. Finally, the results show that political instability negatively impacts access to public support ($\hat{\beta}_5 = -.370$). According to marginal effects, the results indicate that it decreases the probability of receiving public support by 4%.

Table 4. Propensity score estimation (Probit model and marginal effects at the mean)

Variables	Coef.	Standard errors	dy/dx	Standard errors
Comp	.532***	(.156)	.057***	(.017)
Age	-.016**	(.0062)	-.002**	(.0006)
MH_Tech	.11	(.170)	.013	(.018)
ICT	.48***	(.163)	.052***	(.018)
Obs_Pol	-.37*	(.208)	-.040*	(.022)
Skill	.002	(.201)	.0003	(.021)
LogSize	.03	(.116)	-.003	(.012)
Obs_Tax	-.145	(.187)	-.015	(.020)
_cons	-1.71	(.233)		
Pseudo R2 = 0.1038				
Prob > chi2 = 0.0000				
LR chi2(8) = 36.8				
Log likelihood = -158.93				

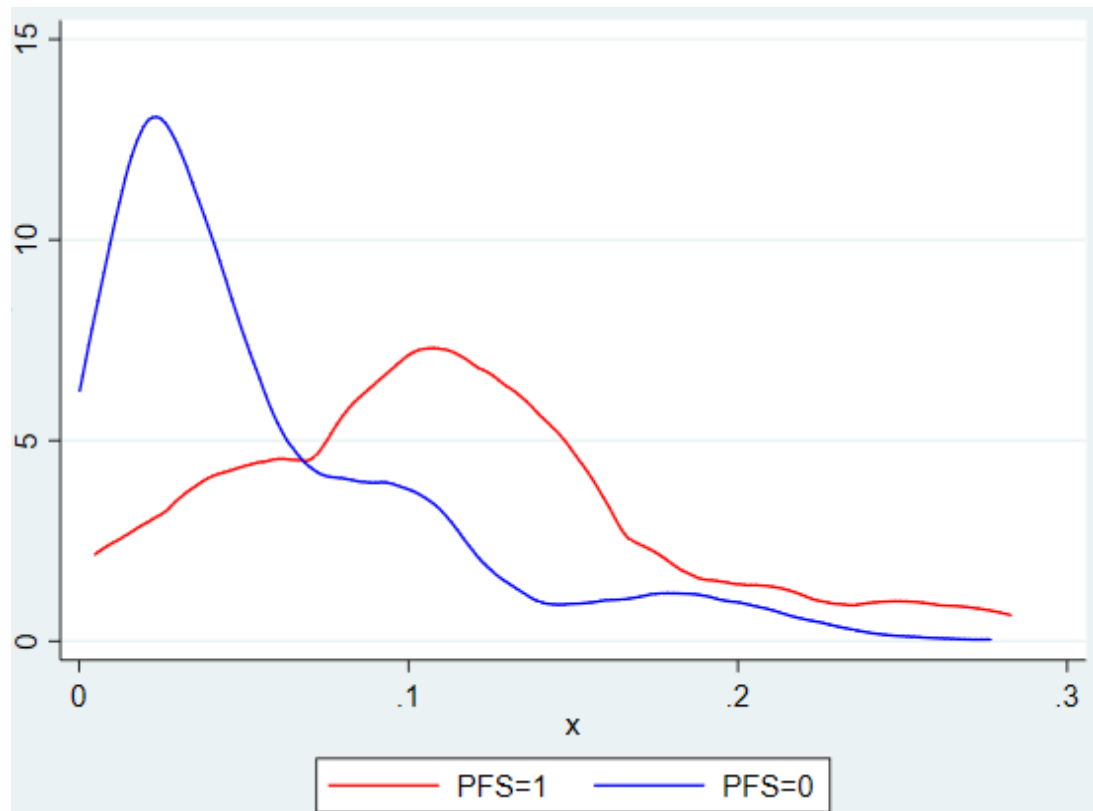
Note: * statistically significant at $p=.1$, ** at $p = .05$ and *** at $p = .01$. Dependent variable: the probability of receiving PFS

Source: Author's calculation

4. 4. COMMON SUPPORT

The impact of the treatment (public financial support) of any estimator based on propensity score is only estimated in the common support zone (see equation (5)). We must therefore check the overlap of the propensity score between the two groups after matching. The approach adopted is based on determining a minimum and maximum propensity score and eliminating observations whose propensity scores in the treatment group are below the minimum threshold and above the maximum propensity score in the comparison group. In this research, common support lies between [.004824, .28279623] (Figure 1). There is therefore a good overlap.

Figure 1. Checking the overlap condition



Source: Author's calculation, STATA-15 software

4. 5. BALANCING TEST

The aim of the balancing test is to ensure that matching reduces the biases observed at the out-set. Table 5 shows, for example, that before matching, 64% of firms in the treatment group are in competition, compared with 39% in the control group. This difference is significant ($p < 5\%$). After matching, 63% of firms in the treatment group and 56% of firms in the control group are in competition. The difference is no longer significant. The bias is reduced by 72.6%. Overall, bias is reduced on all variables considered, and for these variables, no significant difference remains between the two groups after matching ($p > 5\%$). Thus, the quality of nearest-neighbor matching on propensity score is satisfactory for these data. Moreover, the pseudo- R^2 is close to zero, suggesting that the quality of the matching is high. These results confirm that the propensity score used in the matching process is appropriate and that comparisons between the two groups are valid (Table 6).

Table 5. Balancing covariates test

Covariate (Xi)	Matched	Mean		%Reduction		T-test	
		Treated	Controls	%bias	bias	T	p> t
Comp	U	.64444	.39554	51.1		3.31	0.001
	M	.63636	.56818	14.0	72.6	0.65	0.519
Age	U	16.4	21.327	-33.5		-2.18	0.030
	M	16.727	16.091	4.3	87.1	0.25	0.805
MH_Tech	U	.28889	.25348	7.9		0.53	0.598
	M	.27273	.27273	0.0	100.0	0.00	1.000
ICT	U	.66667	.43175	48.3		3.09	0.002
	M	.65909	.68182	-4.7	90.3	-0.22	0.823
Obs_Pol	U	.17778	.35655	-41.1		-2.45	0.014
	M	.18182	.18182	0.0	100.0	-0.00	1.000
Skill	U	.2	.23816	-9.2		-0.58	0.559
	M	.20455	.20455	0.0	100.0	-0.00	1.000
LogSize	U	1.9333	1.9095	2.8		0.19	0.848
	M	1.9545	1.6003	8.1	19.1	0.38	0.708
Obs_Tax	U	.26667	.41226	-30.9		-1.93	0.054
	M	.27273	.20455	14.5	53.2	0.74	0.459

Source: Author's calculation

Table 6. Rubin's R and B test

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med. Bias	B	R	%Var
Unmatched	0.099	33.87	0.000	29.0	32.2	93.9	0.69	0
Matched	0.011	1.35	0.995	5.7	4.5	24.6	0.92	50

Source: Author's calculation

4. 6. ATT ESTIMATION WITH NEAREST NEIGHBOR MATCHING METHOD

The results of the estimation show that the impact of PFS on IOI is positive and significant (Table 7). In practice, this means that firms receiving PFS are much more likely to acquire external knowledge and licensed foreign technologies, given that firms in the two groups do not differ with regard to the exogenous variables influencing the probability of receiving PFS. More specifically, the probability of these firms using foreign-licensed technologies is 38.5% higher than that of firms not receiving this type of funding (ATT = 0.385). The results also show that the probability of these firms acquiring external knowledge increases by 41.7% compared to that of firms not receiving this type of funding (ATT = 0.417).

Table 7. ATT estimation with Nearest Neighbor Matching method

Result variables	n. treat.	n. contr.	ATT	Std. Err.	T-stat
Tech_Lic	47	36	0.385***	0.108	3.557
Know_Ext	47	18	0.417***	0.115	3.627

Note: *** statistically significant at p = .01

Source: Author's calculation

4. 7. ROBUSTNESS CHECK

4. 7. 1. CHANGE MATCHING METHOD

The application of kernel matching, which takes into account a finer weighting of untreated individuals according to their similarity to treated individuals (Table 8), and stratification, which divides individuals into subgroups according to their propensity scores (Table 9), did not significantly alter the ATT estimates. These results reveal that the findings are not sensitive to methodological variations and that the relationship between public support and IOI is robust.

Table 8. ATT estimation with the Kernel Matching method

Result variables	n. treat.	n. contr.	ATT	T-stat	Observed	Bias	[95% Conf. Interval]
Tech_Lic	47	701	0.538***	10.348	.538	.008	[.433; .642] (N) [.467; .656] (P) [.459; .656] (BC)
Know_Ext	47	701	0.447***	3.916	.446	-.018	[.217; .676] (N) [.238; .669] (P) [.294; .678] (BC)

Note: Bootstrapped standard errors are reported for kernel matching, the number of replications is 50. N = normal; P = percentile; BC = bias-corrected. *** statistically significant at $p = .01$

Source: Author's calculation

Table 9. ATT estimation with the Stratification method

Result variables	n. treat.	n. contr.	ATT	Std. Err.	T-stat
Tech_Lic	47	704	0.529***	0.066	8.006
Know_Ext	47	704	0.412***	0.074	5.539

Note: *** statistically significant at $p = .01$

Source: Author's calculation

4. 7. 2. CHANGE ESTIMATION METHOD

The IPTW method popularized by [Hirano et al. \(2003\)](#) was used to validate the results obtained by the PSM method (Table 10). The IPTW estimator comprises three steps: first, the propensity score is estimated. Second, the inverse of the estimated propensity scores is used as a weight in the regression analysis. Third, the ATT is calculated as the difference between the weighted means of the predicted outcomes ([Wooldridge, 2002](#)). The results obtained with IPTW confirmed our initial findings: the effect of PFS on the adoption of IOI, measured by the use of licensed foreign technologies, is positive and significant (Coef.=0.521), showing strong consistency between the two approaches.

Table 10. Treatment-effects estimation (IPTW)

Res. Var.: Tech Lic	Coef.	St.Err.	t-value	p-value	[95% Conf Interval]	Sig
PFS						
1	.521	.071	7.36	0	.382; .66	***
0	.168	.024	6.94	0	.12; .215	***
Covariates (Xi)						
Comp	1.054	.338	3.12	.002	.391; 1.716	***
Age	-.035	.018	-1.95	.051	-.071; 0	*
MH Tech	.217	.354	0.61	.541	-.478; .912	
ICT	.906	.316	2.86	.004	.286; 1.527	***
Obs Pol	-.747	.506	-1.48	.14	-1.737; .244	
Skill	.022	.461	0.05	.962	-.882; .925	
Size	.093	.257	0.36	.719	-.411; .596	
Obs Tax	-.426	.415	-1.03	.304	-1.239; .387	
Constant	-3.044	.625	-4.87	0	-4.269; -1.818	***

*** $p < .01$, ** $p < .05$, * $p < .1$

Source: Author's calculation

5. DISCUSSION

This article analyzes the impact of PFS on IOI. The empirical approach applied in this study is characterized by the combination of logistic regression and propensity score matching (PSM).

The finding that firms benefiting from PFS are more inclined to adopt external technologies and knowledge reinforces and complements the findings of previous research highlighting that PFS can mitigate barriers to the adoption of open innovation, including IOI (Kang and Park, 2012; Canno-Kollmann et al., 2017; Greco et al., 2017; Radicic et al., 2020; Jugend et al., 2018; Ahn et al., 2020). Indeed, IOI, which is defined by the incorporation of technologies and knowledge from outside the firm, frequently requires substantial financial resources for its application and progress.

For the Moroccan economy, where small and medium-sized enterprises (SMEs) predominate and access to finance, firms' absorptive capacity, and access to advanced knowledge and technologies are limited (WBES, 2020), the PFS can be used as a crucial instrument of public innovation policy to facilitate the adoption of IOI (the acquisition of external knowledge and the use of licensed foreign technologies). Our conclusion confirms that of Jugend et al. (2020), who emphasized that research and development (R&D) and innovation result from the interaction between companies, government institutions, universities, and research centers. They showed that the PFS has the capacity to foster this dynamic by offering firms access to resources inaccessible by their own means. In addition, the use of cutting-edge technologies frequently presents risks, including significant expenditure and unpredictable returns on investment (Ardito et al., 2018). PFS can act as a lever for firms, offering them the financial security to explore new technological solutions without fear of significant losses (Felipe and Carlos, 2019; Jugend et al., 2020). In addition, PFS can improve firms' absorptive capacity by investing in research and development (R&D) and staff training (Crespi et al., 2015). In sum, this finding highlights the crucial role of public action in mitigating the difficulties associated with adopting external technologies and knowledge while at the same time supporting Moroccan firms in their innovation drive.

The approach used also enabled us to identify the key factors in access to PFS (Almus and Czarnitzki, 2003). As for the other characteristics considered, the results indicate that firm age, competition, and information and communication technologies (ICT) investment prove to be key elements influencing access to PFS. Our conclusion indicates that, although funding is based on the feasibility of innovation projects and the ability to use and integrate external knowledge and technologies, observable firm characteristics have a significant influence on access to PFS. This confirms the findings of other studies on factors influencing access to PFS (Almus and Carnitzki, 2003; Afcha, 2011; Antonelli and Crespi, 2013; Mardones and Zapata, 2019; Barajas et al., 2021). For example, the conclusions drawn from the probit model indicate that firm age is a determining factor in access to PFS. Indeed, the probability of taking advantage of it decreases as the age of the firm increases. This result is in line with Schumpeter's theory (1934) that new companies are the essential generators of new products and processes. The young companies are more likely candidates for innovation and investment in the assimilation of external technological knowledge than older companies. Moreover, various empirical studies show that investment in innovation is less likely as age increases (e.g., Rajapathirana and Hui, 2018). In addition, younger companies face greater financial constraints, along with greater incentives to apply for and acquire them.

The probit model also shows that competition increases the chances of receiving PFS. This result can be explained by the fact that companies facing competition have a greater incentive to integrate external technological knowledge. According to Arrow (1962), incentives to innovate are stronger in a competitive situation than in a monopoly. Indeed, the development of new products by competitors can destabilize a firm's sector position (Moreira et al., 2020). Faced

with competition, a firm may intensify its internal research and development (R&D) efforts or collaborate with other firms. In this context, the acquisition of licensed technologies becomes an effective reactive strategy, as it enables rapid adaptation to technological changes in the market without the delays or uncertainties associated with complex collaborations or long-term in-house projects (Moreira et al., 2020). This dynamic justifies the commitment of public authorities in granting financial aid to firms operating in a competitive environment to improve their ability to compete by facilitating the adoption of new knowledge and technologies.

The results also show that investment in information and communication technologies (ICT), particularly websites, increases the chances of receiving PFS. Indeed, a website helps to strengthen a company's digital position, reduce transaction costs, information asymmetry and innovation efficiency, while reducing the proximity between producers and consumers. This conclusion is corroborated by the research of Dewan et al. (2003), according to which the Internet reduces the cost of information search and enables a better understanding of consumer needs. This offers firms the opportunity to create products more closely aligned with customer tastes and market requirements, thereby increasing the quality and feasibility of projects submitted for funding. In addition, online platforms facilitate the exchange of information and networking with potential partners, which is essential in an inbound open innovation (IOI) approach. Research by Zhang and Xiaofeng (2023) and Rizov et al. (2022) shows that firms using websites are more likely to demonstrate innovation capabilities. By facilitating access to information, networking, and interaction with various players in the entrepreneurial ecosystem, these digital tools enhance firms' innovation capabilities.

Finally, the estimation results also show that low institutional quality, as measured by political instability, acts as a barrier to access to PFS. This result suggests that institutional stability is an indispensable condition for guaranteeing effective implementation of public innovation policies. In developing countries, where administrative capacities are sometimes limited, this instability can create an environment of uncertainty, reducing the scope and effectiveness of aid programs.

6. CONCLUSION

The main objective of this research is to quantitatively examine the impact of the PFS on the adoption of inbound open innovation (IOI) as measured by the acquisition of external knowledge and the use of licensed foreign technologies. Our study is based on a representative sample of 1,096 Moroccan companies. By combining logistic regression and propensity score matching (PSM), we were able to draw two major conclusions. Firstly, the PSM analysis shows that the PFS favors the adoption of inbound open innovation (IOI) by Moroccan companies. Secondly, logistic regression highlights several factors influencing access to PFS, including age, competition, ICT investment and political instability.

These results have significant implications. This research offers several theoretical contributions in the field of OI, public innovation policies, and absorptive capacity. Firstly, by making a contribution to theoretical research on OI, this study broadens the scope of scientific study on this strategy by focusing on IOI. This idea is based on the assumption that firms require knowledge and technology, admitting that they outperform their internal capabilities (Jesus & Jugend, 2023), which is the reality for many firms in developing countries (DCs). Secondly, the research proposes a novel vision of how government aid stimulates the absorptive capacity of Moroccan firms to integrate external technological knowledge.

The results of our study also have implications for management. Indeed, our research indicates that it is crucial for firm leaders to improve their financing capacity to mitigate financial restrictions and their adverse effects on IOI implementation by changing their behavior. According to

our research and various empirical works, the behavior and specificities of firms, such as their size, foreign location, belonging to the high-tech industrial field, market structure, presence of an R&D department, previous R&D experience, and increased labor productivity, are essential to obtain public funding (Almus & Carnitzki, 2003; Antonelli & Crespi, 2013; Barajas et al., 2021). In conclusion, from a policy point of view, this study highlights the crucial role of public authority intervention in fostering the adoption of IOI. According to Antonelli & Crespi (2013), the government should introduce specific assistance strategies, particularly for employee training, R&D support, and access to finance, while ensuring an efficient allocation of public resources to firms with the greatest potential. The results of the probit model suggest that public innovation policies should also target dynamic, early-stage firms often facing significant adaptation and development challenges. Start-ups, which are generally under-resourced and exposed to high risk, benefit from this support to strengthen their long-term viability. Similarly, firms investing in ICT should also be targeted by PFS. For example, Rizov et al. (2022) argue that firms that use websites are more likely to demonstrate innovative capabilities. The study by Rizov et al. (2022) used website adoption as a directly observable indicator of firms' innovative behavior. This conclusion is also supported by Zhang and Xiaofeng (2023), who showed that Internet applications, including websites, are important catalysts of business innovation. By using a website, firms can not only promote their products and services but also demonstrate their ability to innovate and adapt to market trends, thereby increasing their chances of obtaining PFS. ICT reduces the distance between producers and consumers. ICTs can reduce the risk of entrepreneurs making bad decisions by enabling information to circulate quickly and cheaply. With this in mind, it would be appropriate to strengthen the support mechanisms designed to accompany the digital transformation of businesses, particularly small structures that do not always have the technical or human resources to go digital. The results of our model also suggest supporting firms exposed to competition. Strengthening firms' competitiveness in the face of growing competitive pressure makes it possible to support their efforts to adapt, innovate, and move upmarket in order to preserve their market position.

Despite these implications, our study has a number of limitations. The first limitation concerns the nature of the data used. We used cross-sectional data from the World Bank Enterprise Survey (WBES, 2020). Despite the challenges associated with collecting longitudinal data for microeconomic research, future dynamic studies could reveal the role of public financial support in the adoption of inbound open innovation over time. The second limitation concerns the methodology adopted to answer the central question of our study. While the PSM method took observable firm characteristics into account, unobservable characteristics were not. To overcome this constraint, future research could merge the matching approach (PSM) and the double-difference technique (DID). Finally, the third limitation concerns the research sample, which is limited to a single country (1096 Moroccan firms). Future studies could gather panel data from firms in various countries to analyze the link between public financial support and the adoption of inbound open innovation in other situations.

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