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THE ROLE OF TECHNOLOGY EXTENSION AND TRANSFER IN FIRMS' INNOVATION AND PRODUCTIVITY IN PERU

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Departamento
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The Role of Technology Extension and Transfer in Firms' Innovation and Productivity in Peru*

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Abstract

This study examines how technology extension and transfer services (TETS) drive firm-level innovation and productivity. Since research and development (R&D) investments are subject to market failure, engaging with external agents enables firms to innovate at lower risk and cost. Using data from Peru's National Innovation Survey (ENI), we apply the Crépon, Duguet, and Mairesse (CDM) model alongside propensity score matching (PSM) to enhance the reliability of our results. Additionally, we employ the generalized propensity score (GPS) method to analyze the sensitivity of innovation and sales outcomes to varying investment levels. The findings confirm that investment in training and external R&D significantly enhances innovation, thereby boosting labor productivity. However, this relationship is nonlinear, suggesting the presence of investment thresholds required to maximize impact.

JEL Classification: L25, O32, O38

Keywords: Technology Transfer, Innovation, Productivity, R&D, CDM model

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El Rol de la Extensión y la Transferencia Tecnológica en la Innovación y la Productividad de las Empresas en Perú*

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Resumen

Este estudio examina cómo los servicios de extensión y transferencia tecnológica (SETT) impulsan la innovación y la productividad de las empresas. Dado que las inversiones en investigación y desarrollo (I+D) están sujetas a fallos de mercado, la colaboración con agentes externos permite a las empresas innovar con menor riesgo y coste. Utilizando datos de la Encuesta Nacional de Innovación (ENI) de Perú, aplicamos el modelo de Crépon, Duguet y Mairesse (CDM) junto con el emparejamiento por puntaje de propensión (PSM) para mejorar la fiabilidad de nuestros resultados. Además, empleamos el método de puntuación de propensión generalizada (GPS) para analizar la sensibilidad de los resultados de innovación y ventas a los distintos niveles de inversión. Los resultados confirman que la inversión en capacitación e I+D externa mejora significativamente la innovación, impulsando así la productividad laboral. Sin embargo, esta relación no es lineal, lo que sugiere la presencia de umbrales de inversión necesarios para maximizar el impacto.

Clasificación JEL: L25, O32, O38

Palabras Clave: Transferencia Tecnológica, Innovación, Productividad, I+D, Modelo CDM

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1. Introduction

Firms that invest in innovation follow one of four strategies (Lipczynski et al., 2017). An offensive strategy seeks to lead the market by introducing recent technology, requiring substantial investment in equipment and human capital. A defensive strategy is adopted to counteract a competitor's technological shift, ensuring survival in a changing market. An imitative strategy focuses on replicating existing innovations, typically through licensing agreements or by leveraging publicly available knowledge. A dependent strategy positions firms in a subordinate role, such as serving as suppliers or subcontractors, adopting technology provided by the contracting firm.

Research and development (R&D) plays a vital role among key innovation activities. Firms typically establish dedicated R&D units with specialized laboratories, qualified personnel, and structured research programs. However, a sizable proportion of firms—particularly small and medium-sized enterprises (SMEs)—lack the financial and organizational capacity to undertake such investments. High initial costs, risk exposure, and uncertainty regarding results create significant barriers. In addition, smaller firms face structural challenges in accessing financing, developing industry linkages, and attracting specialized human capital (Shapira and Youtie, 2016). These market failures constrain the emergence of potentially innovative firms and slow the pace of industrial innovation.

Innovation is a key driver of productivity growth (Syverson, 2011). One of the most widely used empirical frameworks for analyzing the relationship between R&D, innovation, and productivity is the Crépon, Duguet, and Mairesse (CDM) model (Crépon et al., 1998). This model has been extensively applied in demonstrating the positive link between innovation and productivity in advanced economies (Lööf et al., 2017). However, findings in emerging market economies (EMEs) have been mixed. While studies consistently confirm a direct relationship between innovation and productivity, the link between R&D investment and innovation is less robust (Fedyunina and Radosevic, 2022). This suggests that EME firms often engage in innovative processes through alternative investment pathways, such as collaborations with other firms or research institutions, rather than relying solely on in-house R&D.

These collaborative dynamics contribute to the formation of an innovation ecosystem, where firms leverage external knowledge while developing internal competencies—an approach known as open innovation. In the era of Industry 4.0, open innovation has become one of the most viable mechanisms for fostering both knowledge generation and technology commercialization. Within this framework, technology transfer—the process by which scientific and technological discoveries are transmitted from one organization to another for further development and commercialization—plays a crucial role in enhancing firms' absorptive capacity and strengthening innovation capabilities in EMEs (Alkhazaleh et al., 2022).

Similarly, technology extension services provide direct support to firms in technological upgrading and innovation adoption, with a particular focus on SMEs (Shapira et al., 2015). These services aim to enhance firms' competitiveness by improving business management practices, production processes, and access to specialized technological knowledge. They also provide targeted consulting services, technical assistance, workforce training, and support for the development of innovation-driven projects (De Groote, 2016).

Kolodny et al. (2001) differentiate between technology transfer, defined as the commercialization of complex technologies by research laboratories and R&D centers for large industrial firms, and technology extension, which focuses on providing applied technological support to SMEs. Two core components of these mechanisms are external R&D acquisition and training services for technology adoption. Firms that engage with these services benefit from greater access to innovative technology, the introduction of new products and services, and improvements in overall performance in the short and medium term (Shapira and Youtie, 2016).

As a developing economy, Peru faces structural constraints that hinder technological progress and productivity growth. Its total factor productivity (TFP) represents less than 30% of that of the U.S. (Loayza, 2016) and R&D investment accounts for just 0.11% of GDP, making it one of the lowest in Latin America (CONCYTEC, 2017). These low investment levels are reflected in Peru's performance in the Global Innovation Index (WIPO, 2021), where it ranked 70th out of 132 economies, with particularly weak results in knowledge and technology outputs (87th place).

This study quantifies the impact of technology extension and transfer services (TETS)—proxied by expenditures on innovation-related training and external R&D investment—on firms' innovation strategies and productivity performance, and seeks to answer the following hypotheses:

- H1: Does the decision to invest in TETS, and the amount invested, affect firms' innovation and productivity?
- H2: What are the differences and complementarities between TETS investment and internal R&D investment?

By addressing these questions, this study contributes to the expanding body of research on the role of TETS in fostering innovation and enhancing productivity in EME firms. From a methodological standpoint, the study employs an adjusted CDM model, conducting additional regressions on samples obtained and weighted using Propensity Score Matching (PSM) and Generalized Propensity Score (GPS).

The paper is structured as follows: Section 2 presents a review of the relevant literature; Section 3 describes the dataset and variables; Section 4 details the econometric methodology; Section 5 discusses the results and hypothesis validation; and finally, the study presents its main findings.

2. Literature Review

2.1. Relationship Between Innovation Activities, Innovation, and Productivity

Investing in innovation activities aims to create or expand knowledge within an organization. Pakes and Griliches (1984) highlight that in the transition between R&D investment and its effects on innovation and productivity, an unobservable variable—knowledge capital—plays a crucial role. This variable is defined as the economic value of technological knowledge. The accumulation of knowledge depends on R&D expenditures, underlying trends, and variations in research productivity. Investment in R&D affects knowledge capital with a time lag, accumulating over previous years. In turn, knowledge capital drives innovation outcomes.

Crépon et al. (1998) model the relationship between R&D, innovation, and productivity using a structural framework with three key linkages: (i) the relationship between R&D and its drivers, (ii) an innovation equation linked to R&D, and (iii) a productivity equation linked to innovation. Empirically, this is evaluated using a four-stage regression model, where the first two components relate to firms' decisions to invest in R&D and the scale of investment. Their findings for French firms indicate that both the decision to invest in R&D and the amount invested are influenced by firm size, market diversification, market share, demand conditions, and technological opportunities. Regarding innovation, they find positive effects of R&D investment, as well as a positive relationship between innovation and productivity.

Lööf and Heshmati (2006) extend the CDM model in a study on Swedish firms, evaluating the robustness of the results across different estimation techniques, testing for consistency in both services and manufacturing, verifying results across alternative data sources, and addressing potential distortions from outliers. Their results confirm that all findings remain statistically significant across model specifications.

Research on EMEs has yielded mixed results. Ramadani et al. (2019) apply the CDM model to Eastern European economies and find that external knowledge acquisition—used as a proxy for R&D—positively influences product innovation, which in turn enhances labor productivity. However, in a separate study on Eastern Europe, Fedyunina and Radosevic (2022) find no statistically significant relationship between R&D investment, innovation, and productivity. They argue that in EMEs, production capabilities are more critical than R&D investment and test this hypothesis using an alternative model in which the former replaces the latter. Their findings indicate that production capabilities do not significantly impact innovation but do influence productivity. They conclude that R&D investment and production capability development follow distinct processes and that in EMEs, the latter is more relevant for productivity growth.

Edeh and Acevedo (2021) identify access to financing as the most significant barrier for firms in EMEs such as Nigeria. Using the CDM model, they find that R&D investment positively affects product and marketing innovation but has no significant impact on process innovation. Their results also indicate that while government funding does not significantly influence R&D investment, it does have a positive effect on productivity.

In Peru, Tello (2020) examines the role of information and communication technologies (ICTs) adoption and differentiates between internal and external R&D investment. His findings indicate that decisions to invest in both types of R&D depend on firm size and whether the firm is part of a business group. The scale of investment is found to be significant for innovation outcomes, along with factors such as competitive pressure and mechanisms for protecting innovation. While productivity is positively influenced by innovation, its primary drivers are the capital-labor ratio and human capital accumulation. Internet use is also found to marginally increase the likelihood of innovation. The study concludes that firms are not fully capitalizing on the benefits of R&D and innovation activities.

García (2022) analyzes manufacturing firms to assess the impact of innovation and ICT adoption on productivity, measured using the Levinsohn and Petrin approach. Fixed-effects regression results indicate a positive relationship between investment in science, technology, and innovation (STI) and TFP. However, the effects of ICT adoption remain inconclusive, with significant results observed only for certain variables, such as local network usage, software acquisition, and the implementation of computerized management systems.

2.2. Relationship Between TETS and Productivity

Bell (1984) argues that technological change in firms is also driven by learning processes, which can occur internally or externally. He identifies three mechanisms through which this occurs: (i) learning-by-training, where firms acquire knowledge through employee training programs; (ii) learning-by-hiring, where firms gain knowledge by recruiting skilled personnel; and (iii) learning-by-searching, where firms engage in research activities. These mechanisms involve firms establishing linkages with other entities, including suppliers, research centers, universities, and specialized institutions. Acquiring external knowledge enhances cost efficiency and revitalizes firms' knowledge bases (Chen et al., 2015).

Jarmin (1999) evaluates a technology extension program in the U.S. using a two-stage model. In the first stage, he finds that firms with high prior growth, but low productivity are more likely to use these services.

The final results show positive effects on labor productivity, ranging from 3.4% to 16%. Ordowich et al. (2012) assess the same program using difference-in-differences and a lagged dependent variable model, also incorporating a firm survival model. Their results are inconclusive for the full sample, but a firm-size breakdown reveals positive effects. Finally, Lipscomb et al. (2018) conduct another evaluation of the program, incorporating updated datasets and methodological refinements. Their findings indicate that firms using these services see greater increases in sales and employment and are 18% less likely to exit the market.

Chen, Vanhaverbeke, and Du (2015) examine four distinct types of external knowledge acquisition and their impact on innovation in Chinese firms. When analyzed individually, each type shows positive effects, though horizontal linkages have a weaker impact. When assessed jointly, all remain statistically significant, except for horizontal linkages. Additionally, when the model includes an interaction term for internal R&D, the impact is stronger for firms collaborating with supply chain partners or technology service providers. However, for horizontal linkages, the only significant effect appears in the interaction term, whereas the opposite is observed for science-based partnerships.

Hottenrott and Lopes-Bento (2016) find a positive but nonlinear relationship between external R&D and innovation, with diminishing returns as firms increase their reliance on kind of investment. Their findings suggest that the optimal share of external R&D participation in projects is around 60%. Carboni and Medda (2021) report comparable results for Germany, France, Spain, and Italy, arguing that excessive reliance on external services can discourage firms from investing in in-house research and developing internal capabilities. However, when external R&D is sourced within a business group, it has the strongest impact on product innovation performance compared to acquiring it from universities or other firms.

Workforce training programs also contribute positively to innovation. Na (2021) finds that on-the-job training and employees' education levels enhance all types of innovation across Eastern Europe and Central Asia. This relationship is demonstrated using a two-stage Heckman regression model.

3. Research Design and Methodology

3.1. Dataset

This study uses data from the National Innovation Survey (ENI) for manufacturing and knowledge-intensive services, conducted by Peru's National Statistics Institute (INEI) in 2018. The survey covers Peruvian firms with annual sales exceeding USD 189,405 and includes 2,084 firms, selected based on two criteria: (i) a mandatory sample covering firms that account for 81% of net annual sales in their respective industries, and (ii) a randomly selected, non-mandatory sample drawn from the remaining firms. The survey collects data on firm characteristics, innovation activities, human resources, financing, obstacles, and outcomes for 2015, 2016, and 2017.

3.2. Variable Definitions

TETS adoption (gst_i) is measured based on whether a firm invested in external R&D and innovation-related training in 2015 and 2016. Investment intensity (rst_i) is calculated as the logarithm of total investment over both years, divided by the number of employees. Innovation is measured using two variables. The first is a binary (dummy) variable (pst_i) that equals 1 if the firm introduced an innovation and 0 otherwise. The second is an innovation intensity variable (nst_i), defined as the share of total sales generated by innovative products. Labor productivity is captured as net sales per worker (Y/L), expressed in logarithms for 2017.

The independent variables (x) follow the original CDM model and its extensions (Edeh and Acedo, 2021; Lööf et al., 2017; Lööf and Heshmati, 2006; Ramadani et al., 2019). To incorporate a localized perspective, this study also draws on Peruvian research, including Tello (2020) and García (2022).

Firm size is measured by the number of employees, while human capital is defined as the percentage of employees with higher education. Market concentration is assessed using the Herfindahl-Hirschman Index (HHI). Once calculated, a categorical variable is assigned, classifying firms as unconcentrated (HHI < 0.15), moderately concentrated (0.15 ≤ HHI ≤ 0.25), or highly concentrated (HHI > 0.25) (Nguyen et al., 2020). These variables are used to test Schumpeterian hypotheses, which propose that larger firms and those operating in concentrated markets are better positioned to engage in innovation activities.

The analysis also accounts for market constraints, incorporating variables related to financing constraints, risk aversion, and technological and demand-side barriers. Other firm characteristics include firm age, as well as external linkages and international market participation, measured through foreign capital ownership and export activity.

For the innovation equation, additional controls include intellectual property protection, such as patents and copyrights, and participation in government programs. In the final stage, the model incorporates physical capital per worker, a key driver of productivity, alongside labor and human capital (Lööf and Heshmati, 2006; Jarmin, 1999). Following Lööf and Heshmati (2006), all monetary variables are expressed on a per-worker basis. A consumer price index (CPI) deflator is applied to adjust values to real terms over the three-year period.

Across all model specifications, additional controls include firm location, particularly whether the firm operates in Lima, given the city's concentration of TETS providers and access to transportation and communication networks. The analysis distinguishes between services and manufacturing, with further subdivisions based on technology intensity (UNIDO, 2019).

All the variables mentioned in this section and used in the CDM model are described in detail in the Annex.

3.3. Methodology

To test H1, the analysis applies the CDM model. The explanatory variables include the decision to use TETS and the intensity of investment, both measured as cumulative values for 2015 and 2016. By 2017, firms are expected to exhibit results in terms of innovation and productivity.

Figure 1, constructed from the literature, summarizes the causal chain of how different innovation activities, both R&D and TETS, increase knowledge capital, which in turn will have an effect on innovation and business performance of firms.

A key challenge of the CDM model is the potential presence of endogeneity and selection bias (Crépon et al., 1998). This issue arises when the firms using TETS are not randomly selected but rather self-select into the program. As a result, the intensity of investment is only observed for firms that actively choose to engage with TETS, leading to a latent variable problem. To address this issue, the first stage of the analysis applies a Heckman selection model, where the decision to invest is treated as a latent variable (gst_i^*). The observed binary outcome (gst_i) takes a value of 1 if the firm chooses to invest and 0 otherwise:

$$gst_i = \begin{cases} 1 \; si \; gst_i^* > 0 \\ 0 \; si \; gst_i^* \leq 0 \end{cases} \qquad (1a)$$

The intensity of investment in TETS (rst_i^*) is also a latent variable. The observed investment level (rst_i) is only recorded if the firm has chosen to use these services:

$$rst_i = \begin{cases} r_i^* \; si \; gst_i^* > 0 \\ - \; si \; gst_i^* \leq 0 \end{cases} \quad (1b)$$

Thus, both equations are related. In the classical version of the model, the latent variables are derived from the following equations:

$$gst_i^* = x_{0i}b_0 + u_{0i} \quad (2)$$

$$rst_i^* = x_{1i}b_1 + u_{1i} \quad (3)$$

the error terms (u_{0i} and u_{1i}) are potentially correlated (ρ) and assumed to follow a joint normal distribution. The correlation coefficient (ρ) is crucial for determining the interdependence between Equations (2) and (3). If $\rho = 0$, then the error terms are uncorrelated, and Ordinary Least Squares (OLS) would be a more efficient alternative. To correct for heteroskedasticity, robust standard errors are applied.

As a result, the first stage produces a predicted value for investment intensity, which is used in the second stage to examine the relationship between innovation and TETS investment. product innovation (pst_i) is modeled as a binary variable that equals 1 if the firm introduced an innovation and 0 otherwise. The estimation applies a probit model with robust standard errors:

$$pst_i = \alpha_k rst_i^* + x_{2i}b_2 + u_{2i} \quad (4a)$$

A second innovation variable, innovation intensity, is defined as the share of sales from innovative products (nst_i) and estimated using OLS regression with robust standard errors.

$$nst_i = \alpha_k nst_i^* + x_{2i}b_2 + v_{2i} \quad (4b)$$

Both models consider innovation at all levels (internal, market, and international), following De Groote (2016), who argues that technology services, particularly TETS, primarily drive internal innovation rather than market-oriented innovation.

In the third stage, the analysis examines the relationship between predicted innovation outcomes (pst_{ji}^*) and labor productivity (q). The productivity measure is based on first differences between 2015 and 2017, following Pakes and Griliches (1984), who model R&D investments as lagged and cumulative inputs. This approach is also consistent with Jarmin (1999), assuming a Cobb-Douglas production function.

$$\Delta \ln q_i = \Delta \ln \frac{Y_i}{L_i} = \ln \frac{Y_{i,2017}}{L_{i,2017}} - \ln \frac{Y_{i,2015}}{L_{i,2015}} \quad (5)$$

where Y_i represents the net sales of firm i and L_i denotes the number of employees. First differences are also applied to physical capital per worker (K_i), employment (L_i), and human capital (H_i). following Lööf and Heshmati (2006):

$$\Delta \ln q_i = \Delta \ln \frac{Y_i}{L_i} = \alpha pst_i^* + \delta \Delta \ln \left(\frac{K_i}{L_i}\right) + \theta \Delta \ln(L_i) + \pi \Delta(H_i) + x_{3i}b_3 + u_{3i} \quad (6a)$$

$$\Delta \ln q_i = \Delta \ln \frac{Y_i}{L_i} = \alpha nst_i^* + \delta \Delta \ln \left(\frac{K_i}{L_i}\right) + \theta \Delta \ln(L_i) + \pi \Delta(H_i) + x_{3i}b_3 + u_{3i} \quad (6b)$$

To assess the robustness of the results, the model is replicated on a subsample consisting of firms that used TETS, compared to a control group of non-users with similar observable characteristics. The matching procedure applies PSM, which estimates the probability of using TETS based on observable firm attributes. This method is commonly used to approximate causal inference, as applied in Gallego and Gutiérrez (2017) to evaluate the impact of quality certification on labor productivity, and the results are «as good as randomization» (Heinrich et al., 2010).

The propensity score ($P(x_0)$) is estimated as the probability of using TETS (d), conditional on observable characteristics (x_0) (Becker and Ichino, 2002). Next, a balance test is performed to ensure that variable differences are not statistically significant within each distribution block.

$$P(x_0) = \Pr(d = 1|x_0) \tag{6}$$

Firms are matched using Nearest-Neighbor Matching (NNM), selecting a set of control firms ($c(i)$) with the closest propensity scores within a pre-defined threshold (k). Each treated firm is matched with four control firms, using weighting $\omega_1(i,j)$ to construct the comparison group:

$$c(i) = \{j \in D = 0 \mid \|P_i(x_0) - P_j(x_0)\| \leq k\} \tag{7}$$

Additionally, Kernel Matching is applied to assign weighted averages to both treated and control firms, minimizing sample loss. The weighting function follows:

$$\omega_2(i,j) = \frac{K\left(\frac{P_j(X) - P_i(X)}{a_n}\right)}{\sum_{k\epsilon C} K\left(\frac{P_j(X) - P_i(X)}{a_n}\right)} \tag{8}$$

where $\omega_2(i,j)$ represents the weight and K(.) is the Kernel function.

Once the subsample is defined, the CDM model is replicated, applying the associated weights ($\omega_2(i,j)$) to each firm identified as a counterfactual, and the results are compared.

To test H2, the CDM model is compared to an alternative specification incorporating internal R&D (gid_i) in Equation (2). Subsequently, Equations (3) to (6) are replicated. Internal R&D expenditure is used to measure investment intensity (rid). In the second and third stages, the predicted variables for expenditure intensity (pid_i) and innovation (INN^*_{ji}) are included.

To assess the cost-effectiveness of investing in R&D versus ETTS, the dose-response function is estimated using the GPS method. This technique evaluates the impact of a treatment when it is continuous rather than binary or discrete, allowing for an analysis of treatment intensity (Bia and Mattei, 2008). The core idea is to obtain a potential outcome (Y) for each potential treatment level (t). Thus, the set of potential outcomes for a range of treatments (τ) is defined as $\{Y_i(t)\}_{t\in\tau}$. This methodology consists of three steps:

- In the first stage, the GPS score $R = r(T, X)$ is estimated as the conditional density of the treatment level T given the covariates X.
- In the second stage, the expected conditional outcome parameter is obtained: $\beta(t, x) = E(Y|T = t, R = r)$.
- In the third stage, the dose-response function is estimated as $\mu(t) = E[\beta(t, r(t, X))], t \in \tau$

The goal is to estimate the percentage change in sales for each percentage change in R&D or ETTS expenditure. Confidence intervals are constructed using Bootstrap. Dai and Cheng (2015) apply this methodology to investigate the impact of public subsidies on R&D investment in Chinese manufacturing firms.

4. Results

4.1. Descriptive Statistics

Table 1 shows the main descriptive statistics of the variables used in the models. Between 2015 and 2016, 12.7% of firms used TETS. A total of 30% introduced a product innovation, with sales from innovative products averaging 14.3% of total sales. Sales per worker—in Peruvian soles (PEN)—declined, from PEN 481,000 in 2015 to PEN 444,000 in 2017.

On average, firms had 18.2 years of operation and employed 227 workers. Innovation-related linkages were weak, with the highest being firm-to-firm collaborations (4%). Most firms operated in diversified markets (34% in highly competitive industries and 53% in unconcentrated industries) with low market shares. Physical capital per worker increased by 56%.

4.2. Decision to Invest in TETS and Investment Intensity

The first stage of the CDM model examines firms' decision to use TETS and investment intensity. The estimated rho ($\hat{\rho}$) is statistically significant, indicating selection bias, which has been addressed. The results are shown in Table 2, the third column corresponds to the results of the decision to invest in TETS, while the second one refers to the intensity of spending, both cases referring to the total sample. Columns 4 to 7 repeat both regressions for the samples using the Kernel and Nearest Neighbor matching methods.

The number of employees has a positive effect on the decision to invest but a negative effect on investment intensity, consistent with findings for Peru (García, 2022; Tello, 2020). Market concentration is not significant in either stage, except for moderate concentration, which is significant for investment decisions. Firms may pursue these investments for various reasons (Lipczynski et al., 2017): while large firms have greater resources, they may also face bureaucratic barriers or exhibit a complacent attitude. In contrast, firms in competitive markets may invest in TETS to enhance their competitiveness.

The share of qualified workers has a positive effect, in line with Lööf and Heshmati (2006) and Ramadani et al. (2019). Technological barriers influence investment decisions, as firms rely on external sources to acquire unavailable technologies. Market constraints, particularly demand-side challenges, may also encourage firms to innovate—especially those following a defensive R&D strategy (Lipczynski et al., 2017).

For investment intensity, firm age exhibits a quadratic relationship: positive in early years but declining over time. TETS programs typically target smaller firms and focus on transferring existing technology. Initially, these services are essential, but as firms establish themselves and develop internal expertise, their reliance on TETS declines.

Linkages with other entities are not significant, although belonging to a business group has a positive effect. This supports Díaz and Kuramoto (2010), who note that Peru's National Innovation System remains underdeveloped, with weak coordination between industry and scientific institutions.

For the matched sample, all variables in the first stage of the model are not significant, as expected, since they were used for matching. However, $\hat{\rho}$ still indicates selection bias.

For investment intensity, coefficients for firm age, employment, and share of qualified workers are similar in sign and magnitude to those in the full sample, making them the only statistically significant variables. Physical capital per worker is not significant in this case.

4.3. Innovation Outcomes

Table 3 shows the results of the innovation equation (Eq. 4). The analysis considers two innovation variables: product innovation and the share of total sales from innovative products. In both cases, the predicted TETS investment intensity variable is positive and significant. Similar findings are reported by Ramadani et al. (2019) and Martin and Nguyen-Thi (2015), who use external knowledge acquisition as a proxy for innovation activities, as well as by Na (2021) in the context of workforce training.

Some variables are also positively significant, including the number of employees, consistent with other research (Edeh and Acedo, 2021; Ramadani et al., 2019); software development/acquisition, a proxy for ICT use, which plays a key role in innovation processes, (Martin and Nguyen-Thi, 2015) intellectual property protection (Ramadani et al., 2019); and SME status. Regarding the latter, smaller firms may find it easier to introduce new products more quickly due to fewer bureaucratic barriers (Lipczynski et al., 2017). Additionally, in Peru, SMEs benefit from more flexible labor and tax regulations and are prioritized in public R&D&I subsidy programs.

For product innovation, demand-side constraints prove relevant, suggesting that firms innovate as a defensive strategy in response to market restrictions. Access to government R&D&I programs also has a positive effect, aligning with Edeh and Acedo (2021). The coefficient for the main product's sales share is negative, indicating that more diversified firms are more likely to engage in innovation. However, this variable is not significant for the second innovation measure, implying that while it affects innovation achievement, it does not necessarily translate into commercial success.

For the matched sample, product innovation coefficients remain significant and similar in magnitude. Other variables show consistent patterns, except for software development, access to R&D&I programs, and the main product's sales ratio. Regarding the share of sales from innovative products, TETS investment intensity remains significant, but some discrepancies arise across matching methods. Under NNM, intellectual property protection, foreign capital participation, and software acquisition are not significant. In contrast, under Kernel Matching, risk perception is not significant, whereas software development and foreign capital participation are.

4.4. Productivity Outcomes

The primary finding is the positive significance of predicted innovation, a result consistent with Lööf and Heshmati (2006), who also measure differences in sales per worker. Jarmin (1999) and Lipscomb et al. (2018) directly assess the impact of technology extension programs on productivity and find positive effects. As shown in columns 2 and 3 of Table 4

Regarding production factors, physical capital exhibits a positive and significant effect, aligning with previous literature. However, labor is significant but negatively correlated—a finding similar to Edeh and Acedo (2021) for process and marketing innovation. Crépon et al (1998), Lööf and Heshmati (2006), and Tello (2020) do not report significance for this variable. The share of employees with higher education is only significant at the 10% level. Financial constraints also emerge as a relevant factor.

For the matched sample (columns 3 to 6 of Table 4), innovation variables remain significant only for the sales share measure, with coefficients similar to those found in the full sample. Among production factors, capital and the number of employees remain significant, whereas skilled labor is not. The country's high occupational mismatch may explain these results. Compared to the previous stage, the matched sample shows a better model fit, particularly under NNM.

4.5. Comparison Between Models Using TETS and Internal R&D

An additional regression was conducted for firms investing in internal R&D. The decision to invest in internal R&D aligns with the decision to invest in TETS in terms of the relevance of the number of employees, skilled labor, export status, physical capital investment, and market-related constraints regarding technology access and demand, consistent with the literature. Notably, membership in a business group and firm diversification play a significant role, suggesting that investment is driven by market expansion, aligning with an offensive strategy.

Regarding investment intensity, some differences emerge. Firm age, the number of employees, and market concentration lose significance. Meanwhile, skilled labor and capital remain significant and positive. However, firm linkages become significant but negative, indicating that inter-firm collaboration primarily involves services for ready-to-use technologies, where knowledge transfer follows a one-way flow from provider to client (Carboni and Medda, 2021), reducing the need for an internal R&D process.

In the second stage, as with TETS, predicted expenditure remains significant for innovation, though with smaller marginal effects. Most variables maintain their sign and significance, except for employment in the sales ratio model and foreign capital participation in product innovation.

Regarding the impact on performance, the coefficients for predicted innovation remain significant for both internal R&D and TETS. The coefficients for other variables are also similar, suggesting that both serve as strong predictors of innovation, in line with Ramadani et al. (2019). However, on average, firms invest more than twice as much per worker in internal R&D compared to TETS.

The dose-response function, estimated using the GPS method, quantifies the marginal effect of both types of investment on innovation and labor productivity outcomes (See Figure 2). Examining the relationship between the probability of product innovation and investment in TETS and internal R&D, the findings first highlight a rapid increase in innovation likelihood at low levels of TETS investment, followed by a gradual decline, plateauing around PEN 8,000 per worker, after which it begins to decrease. This pattern reflects the quadratic relationship in external knowledge acquisition documented by previous studies (Carboni and Medda, 2021; Hottenrott and and Lopes-Bento, 2016). Excessive investment in TETS may become counterproductive by increasing coordination, management, and oversight costs while potentially constraining a firm's ability to develop internal knowledge. In contrast, internal R&D—although showing a lower slope in certain segments—maintains a consistently upward trend.

The effect of investment on sales growth also reveals a positive relationship between TETS spending and increased sales, but only at moderate investment levels. Similar to the innovation probability curve, the effect diminishes around PEN 8,000 per worker. For internal R&D, however, once this investment threshold is exceeded, the sales impact accelerates significantly.

5. Conclusions

Innovation is a key driver of firm productivity. However, investing in internal R&D can be prohibitively expensive due to the substantial financial commitment and associated risks. As a result, many firms choose to acquire knowledge externally, which allows them to share risk with other actors, foster technology transfer, and enhance their commercial and organizational capabilities. In EMEs, external knowledge acquisition also facilitates access to proven technologies in a shorter timeframe.

The decision to invest in TETS is influenced by firm size, human capital, and market constraints. This finding suggests that firms adopt a defensive innovation strategy to maintain competitiveness. In contrast, investing in internal R&D is associated with factors such as market structure, business linkages, and product diversification—suggesting an offensive innovation strategy aimed at market expansion.

Regarding TETS investment intensity, firm age plays a relevant role, though the relationship is nonlinear. Initially, firms that invest in TETS benefit from greater experience, improved internal capabilities, and enhanced access to external knowledge providers (Chen et al., 2015). However, as firms gain expertise, they may transition away from TETS, opting instead to develop in-house knowledge.

Firm linkages were not found to be significant in explaining TETS investment intensity, possibly due to the weak integration and coordination within the National Innovation System (Díaz and Kuramoto, 2010). This underutilization of collaborative innovation opportunities could be a missed opportunity, particularly in the context of Industry 4.0, where rapidly evolving market needs demand open innovation strategies (Alkhazaleh et al., 2022).

The results confirm that TETS investment significantly contributes to innovation, even when controlling for selection bias. Other variables positively associated with innovation include firm size, intellectual property expenditure, and R&D investment. Additionally, the inverse relationship between risk perception and export status with innovation suggests that firms with lower risk tolerance may be more cautious in pursuing innovation.

Innovation was also found to have a significant impact on sales performance. However, in the matched sample, the only significant effect was observed for the share of sales from innovative products. This implies that while the direct relationship between innovation and labor productivity remains unclear, successful innovations—measured through their contribution to sales—are clearly linked to better firm performance. In this regard, the sales share of innovative products is widely recognized as a key indicator of innovation success (Carboni and Medda, 2021).

The dose-response function indicates that TETS investments yield positive effects at moderate levels; however, as spending increases, the growth rate turns negative. This suggests a quadratic relationship between external knowledge acquisition and firm performance. This pattern does not hold for internal R&D, where the trend remains consistently positive.

TETS investment represents a viable strategy for firms facing multiple constraints in accumulating and transforming knowledge into innovation. This is particularly relevant for younger firms seeking to invest cautiously and at lower risk.

More broadly, investment in innovation activities emerges as a viable strategy for enhancing firm performance. In the short term, both TETS and internal R&D yield similar results, with both serving as strong predictors of innovation. This allows firms to pursue innovation strategies without bearing the full risks associated with in-house knowledge development.

Finally, this study has certain limitations. The analysis is constrained to a three-year period due to the scope of available data in the ENI, preventing an assessment of long-term effects. Additionally, the measurement of TETS is limited to external R&D and innovation-related training, as these are the only activities explicitly identified as externally acquired in the dataset. Other relevant services, such as engineering and design, could not be distinguished between internal and external investment. Furthermore, data constraints prevented the inclusion of more comprehensive productivity indicators, notably TFP.

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Table 1. Descriptive statistics of the variables

Variable	*Mean*	*Standard Deviation*	*Minimun*	*Maximun*
Dependent variables				
Invested in TETS 2015-2016	0.13	0.333	0	1
Invested in internal R&D 2015-2016	0.12	0.323	0	1
Product innovation	0.3	0.46	0	1
Percentage of sales from innovative products 2017	14.28	30.394	0	100
Difference in sales per worker	-0.09	0.568	-5	3.3
Independent variables				
Firm age	18.23	14.761	1	108
Foreign capital	0.16	0.363	0	1
Employees in 2015	227.65	740.773	1	16578
Exporter in 2015	0.37	0.482	0	1
Qualified workers in 2015	0.26	0.257	0	1
Financial constraints	0.46	0.498	0	1
Linkage (companies)	0.04	0.191	0	1
Linkage (consulting firms)	0.02	0.135	0	1
Linkage (institutes and universities)	0.02	0.123	0	1
Market share	0.02	0.087	0	1
Technology obstacles	0.32	0.466	0	1
Demand obstacles	0.59	0.492	0	1
Risk perception	0.43	0.495	0	1
Accessed R&D&I program	0.03	0.169	0	1
Concentration (highly competitive)	0.34	0.475	0	1
Concentration (not concentrated)	0.53	0.499	0	1
Concentration (moderate)	0.11	0.308	0	1
Manufacturing/low technology	0.44	0.496	0	1
Manufacturing/medium technology	0.14	0.346	0	1
Manufacturing/medium-high technology	0.13	0.337	0	1
Knowledge-intensive services (KIS)	0.29	0.454	0	1
Business group	0.18	0.386	0	1
Main product ratio 2015	80.38	25.894	0	100
Acquired or developed software	0.13	0.334	0	1
Invested in R&D in 2015	0.1	0.304	0	1
SME in 2015	0.36	0.479	0	1
Intellectual property	0.04	0.201	0	1
Difference in capital per worker	0.56	4.446	-16.2	17.3
Difference in workers	0.04	0.378	-4.1	3.4
Difference in % of skills	0.01	0.068	-0.4	0.8

Note: Statistics based on the sample of 2,032 companies
Source: National Innovation Survey (NIS) 2018.

Table 2. Estimation of the first stage, decision and intensity of spending on technology extension and transfer services

Variables	***Total sample***		***Matched sample (NNM)***		***Matched sample (Kernel)***	
	log(spending on TETS)	***decision to invest in TETS***	***log(spending on TETS)***	***decision to invest in TETS***	***log(spending on TETS)***	***decision to invest in TETS***
log(firm age)	7.729***	0.065	7.416***	0.042	7.087**	0.0154
	(2.723)	(0.051)	(2.753)	(0.075)	(2.808)	(0.683)
log(firm age)^2	-3.913***		-3.787***		-3.623**	
	(1.416)		(1.434)		(1.461)	
log(employees 2015)	-0.365***	0.096***	-0.471***	0.053	-0.457***	0.062
	(0.107)	(0.028)	(0.105)	(0.044)	(0.104)	(0.041)
linkage (companies)	-0.014		-0.018		-0.021	
	(0.290)		(0.296)		(0.295)	
linkage (consulting firms)	0.375		0.384		0.337	
	(0.458)		(0.453)		(0.454)	
linkage (institutes and universities)	0.448		0.447		0.434	
	(0.549)		(0.529)		(0.530)	
linkage (innovation centers and government)	0.419		0.538		0.548	
	(0.573)		(0.599)		(0.598)	
qualified workers	2.710***	0.477***	1.792***	-0.134	1.952***	0.009
	(0.702)	(0.173)	(0.657)	(0.267)	(0.673)	(0.261)
exporting company 2015	0.197	0.205**	-0.318	-0.142	-0.333	-0.151
	(0.307)	(0.085)	(0.285)	(0.126)	(0.278)	(0.115)
foreign capital	0.418	0.116	0.261	0.0541	0.228	0.0383
	(0.358)	(0.101)	(0.340)	(0.149)	(0.333)	(0.139)
not concentrated	-0.515*	-0.112	-0.314	-0.009	-0.376	-0.058
	(0.291)	(0.104)	(0.286)	(0.142)	(0.274)	(0.128)
moderate concentration	0.797**	0.032	0.811**	0.021	0.826**	0.038
	(0.406)	(0.139)	(0.401)	(0.188)	(0.390)	(0.171)
high concentration	-0.393	-0.127	-0.218	-0.158	-0.205	-0.105
	(0.722)	(0.249)	(0.739)	(0.341)	(0.717)	(0.322)
main product ratio 2015	-0.004	-0.002	-0.002	-0.001	-0.002	-0.001
	(0.005)	(0.001)	(0.005)	(0.002)	(0.004)	(0.002)
government funding	0.152		0.095		0.099	
	(0.560)		(0.563)		(0.565)	
financial constraints	0.195	0.064	0.085	0.023	0.071	-0.013
	(0.260)	(0.086)	(0.257)	(0.118)	(0.253)	(0.110)
risk perception	0.231	0.0458	0.065	-0.087	0.117	-0.062
	(0.291)	(0.085)	(0.286)	(0.121)	(0.281)	(0.112)
log(capital 2015)	0.063*	0.029***	0.023	0.010	0.020	0.007
	(0.033)	(0.009)	(0.032)	(0.014)	(0.031)	(0.012)
technology obstacles	0.258	0.208**	0.098	0.164	0.064	0.117
	(0.300)	(0.086)	(0.293)	(0.124)	(0.285)	(0.115)
demand obstacles	0.244	0.185**	-0.112	-0.018	-0.074	0.026
	(0.310)	(0.090)	(0.312)	(0.133)	(0.304)	(0.122)
business group	0.773***	0.118	0.454	-0.083	0.466*	-0.109
	(0.278)	(0.093)	(0.279)	(0.134)	(0.274)	(0.125)
$\hat{\rho}$		1.358***		1.178***		1.165***
		(0.216)		(0.230)		(0.228)
Constant	2.702**	-2.017***	6.207***	-0.198	6.143***	-0.162
	(1.306)	(0.248)	(0.964)	(0.372)	(0.952)	(0.345)
Observations	2,032	2,032	781	781	1,856	1,856

Note: Controlled for industry type and geographic factors.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: National Innovation Survey (NIS) 2018

Table 3. Estimation of the second stage, innovation outcomes

Variables	*Total sample*		*Matched sample (NNM)*		*Matched sample (Kernel)*	
	log(spending on TETS)	*decision to invest in TETS*	*log(spending on TETS)*	*decision to invest in TETS*	*log(spending on TETS)*	*decision to invest in TETS*
predicted spending on SETT	0.036*** (0.012)	2.208*** (0.781)	0.123*** (0.039)	7.384** (3.905)	0.101*** (0.034)	6.880** (2.854)
log(employees 2015)	0.033*** (0.009)	1.624** (0.648)	0.086*** (0.026)	6.162*** (2.110)	0.071*** (0.023)	4.999*** (1.894)
technology obstacles	0.004 (0.022)	2.005 (1.560)	0.042 (0.044)	6.142* (3.634)	0.035 (0.040)	6.225* (3.429)
demand obstacles	0.069*** (0.022)	1.930 (1.545)	0.127*** (0.046)	2.558 (3.781)	0.115*** (0.041)	2.265 (3.540)
foreign capital	-0.043 (0.029)	-4.027** (1.971)	-0.068 (0.057)	-6.252 (4.350)	-0.064 (0.051)	-6.649* (3.994)
risk perception	-0.040* (0.021)	-2.748* (1.480)	-0.082* (0.043)	-6.161* (3.574)	-0.067* (0.039)	-5.185 (3.359)
not concentrated	0.003 (0.026)	0.071 (1.824)	-0.011 (0.054)	-0.363 (4.818)	-0.009 (0.049)	0.541 (4.426)
moderate concentration	0.004 (0.033)	0.875 (0.646)	-0.082 (0.077)	-4.664 (6.835)	-0.041 (0.067)	-3.147 (6.288)
high concentration	0.074 (0.071)	4.700 (5.431)	0.086 (0.110)	0.581 (11.190)	0.139 (0.091)	4.876 (10.730)
acquired or developed software	0.173*** (0.027)	14.660*** (2.657)	0.040 (0.044)	5.541 (3.728)	0.033 (0.040)	6.520* (3.569)
accessed R&D&I program	0.216*** (0.064)	6.903 (4.950)	0.057 (0.088)	-4.574 (6.447)	0.049 (0.082)	-4.151 (6.618)
invested in R&D in 2015	0.284*** (0.031)	13.74*** (3.025)	0.167*** (0.045)	6.010 (3.843)	0.163*** (0.043)	6.121 (3.755)
main product ratio 2015	-0.001*** (0.000)	-0.043 (0.028)	-0.001 (0.001)	-0.030 (0.063)	-0.001 (0.001)	-0.024 (0.062)
SME	0.079*** (0.027)	5.021** (2.049)	0.171*** (0.058)	17.740*** (5.331)	0.126** (0.051)	12.830*** (4.951)
intellectual property	0.245*** (0.057)	7.759* (4.468)	0.124* (0.071)	-2.576 (4.875)	0.180*** (0.064)	1.037 (4.810)
Constant		2.575 (5.336)		-29.150 (23.790)		-21.170 (21.940)
Observations	2,032	2,032	781	781	1,856	1,856
R^2	0.161	0.091	0.103	0.070	0.102	0.058

Notes: Controlled for industry type and geographic factors. The probit model shows marginal effects and MacFadden R^2.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: National Innovation Survey (NIS) 2018

Table 4. Estimation of Firm Performance

Variables	*Total sample*		*Matched sample (NNM)*		*Matched sample (Kernel)*	
	log(spending on TETS)	*decision to invest in TETS*	*log(spending on TETS)*	*decision to invest in TETS*	*log(spending on TETS)*	*decision to invest in TETS*
Predicted innovation	0.222*** (0.052)	0.005*** (0.001)	0.086 (0.116)	0.004* (0.002)	0.088 (0.105)	0.004** (0.002)
Difference in log capital per worker	0.015*** (0.003)	0.015*** (0.004)	0.016*** (0.006)	0.016*** (0.006)	0.016*** (0.005)	0.016*** (0.005)
Difference in log of labor	-0.427*** (0.092)	-0.428*** (0.091)	-0.538*** (0.072)	-0.537*** (0.071)	-0.525*** (0.070)	-0.527*** (0.068)
Difference in % of qualified workers	0.437* (0.264)	0.444* (0.264)	0.179 (0.422)	0.190 (0.418)	0.359 (0.363)	0.369 (0.360)
Log seniority	-0.026 (0.018)	-0.026 (0.018)	0.002 (0.025)	0.005 (0.025)	-0.015 (0.025)	-0.013 (0.025)
Financial constraints	-0.042* (0.024)	-0.044* (0.024)	-0.085** (0.036)	-0.097*** (0.036)	-0.064* (0.036)	-0.075** (0.036)
Constant	-0.090 (0.069)	-0.129* (0.071)	-0.067 (0.129)	-0.197 (0.162)	-0.033 (0.115)	-0.163 (0.145)
Observations	2,032	2,032	781	781	1,856	1,856
R^2	0.104	0.104	0.164	0.169	0.153	0.157

Notes: Controlled by industry type and geographic factors.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: NIS 2018

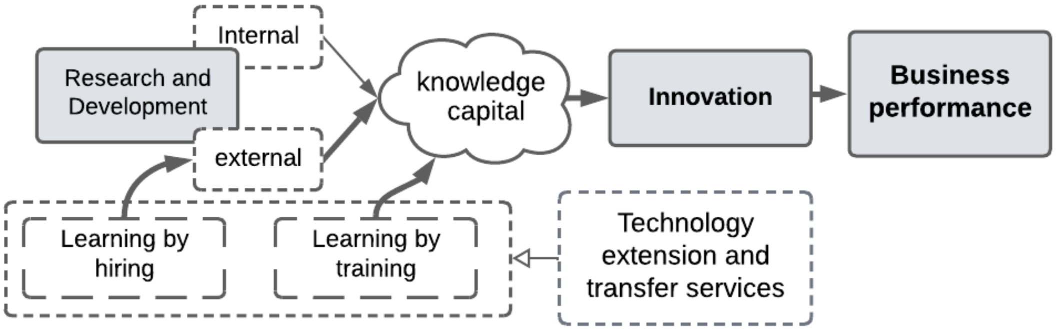
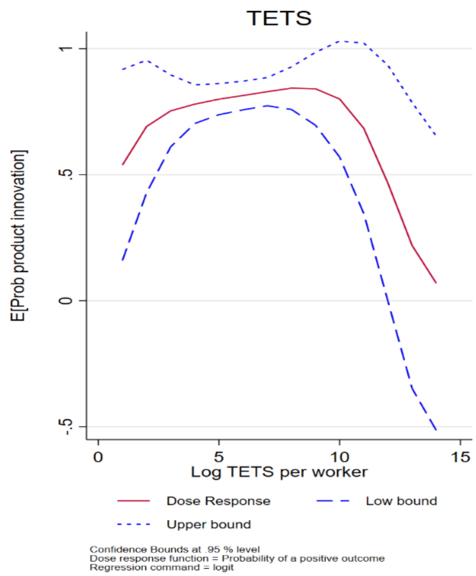
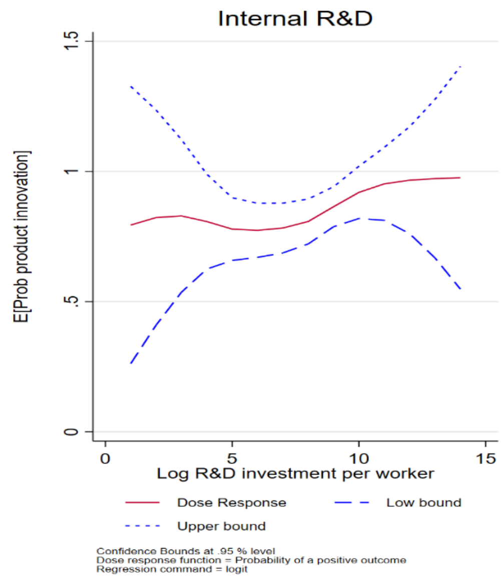


Figure 1. Process of R&D, TETS and innovation
Own elaboration based on Bell (1984) and Crépon et al. (1998)



(a)



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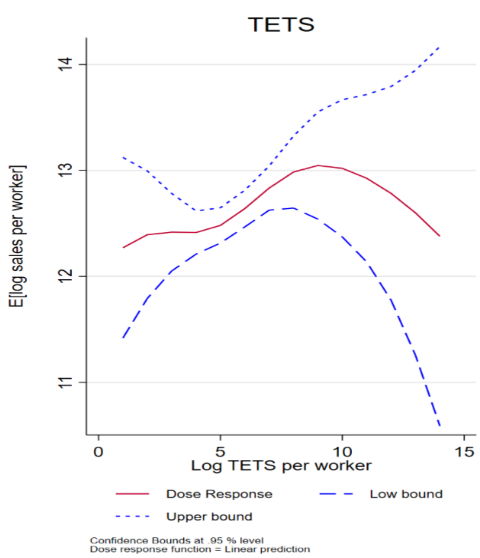

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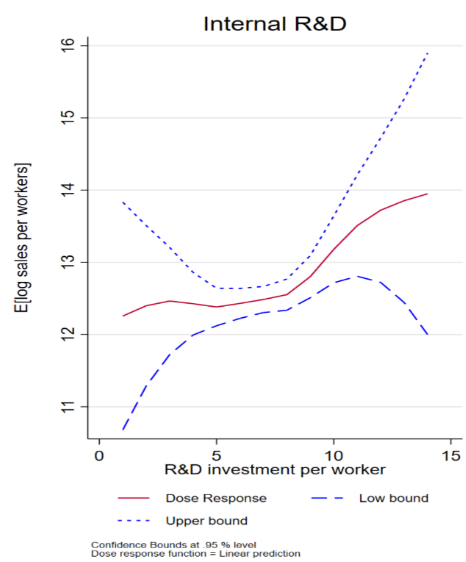

(d)

Figure 2. Dose-Response Function of Expenditure on TETS and Internal R&D
Source: NIS 2018

Annex: Variables Used in the CDM Models

Variable	Name	Type	Definition
Dependent Variables			
Decision to invest in TETS	st1516	Qualitative (Dummy)	1 if the company invested in TETS, 0 if it did not. For the years 2015 and 2016.
Investment in TETS per worker	lstrab_1516	Quantitative	Logarithm of the amount of investment in TETS per worker.
Product innovation results	inn_prod	Qualitative (Dummy)	1 if the company carried out product innovations, 0 if it did not.
Percentage of innovations on sales	pvent_inn	Quantitative	Percentage of sales corresponding to innovations in 2017.
Sales per worker	lventrab_17	Quantitative	Logarithm of net sales per worker in the year 2017.
Difference in sales per worker	d_lventast	Quantitative	Difference in the logarithm of net sales between 2015 and 2017.
Explanatory Variables			
Market Participation			
Market share	cuota	Quantitative	Ratio between the company's total sales and the total sales of the sector by macro-region.
Market concentration	nivhhi	Qualitative	1 for diversified industry; 2 for moderate concentration; 3 for concentrated industry. Based on Herfindahl-Hirschman Index (HHI) values.
Diversification	princ	Quantitative	Percentage of sales from the main product relative to total sales in 2015.
Experience	lantig	Quantitative	Years of company operation from its start until the survey date.
Firm Size			
Firm size	sme_15	Qualitative	1 for small and medium-sized enterprises; 0 for large enterprises.
Workers	lemp_15	Quantitative	Logarithm of the number of workers in 2015.
Sectoral Effects			
Economic sector	act_econ	Qualitative	1 for low-tech industry; 2 for medium-tech industry; 3 for medium-high-tech industry; 4 for knowledge-intensive services (According to UNIDO classification).
Region	lima	Qualitative	1 for Lima and Callao; 0 for other regions.
Demand Pull			
Demand pull	dempull	Qualitative (Dummy)	1 for medium to high obstacles due to uncertainty regarding demand for innovative goods and services, markets dominated by established firms, and small market size; 0 otherwise.

Variable	Name	Type	Definition
Risk aversion	riesgo	Qualitative (Dummy)	1 for perception of economic risk; 0 otherwise.
Participation in international markets	emp_exp15	Qualitative (Dummy)	1 if the company exported during the analysis period; 0 otherwise.
Sectoral Technological Level			
Intellectual property	propint	Qualitative	1 if the company invested in intellectual property; 0 otherwise.
Participation in STI support programs	programa	Qualitative (Dummy)	1 if the company participated in any program; 0 otherwise.
Financing obstacles	rfin	Qualitative (Dummy)	1 if the company reported obstacles to financing innovation activities; 0 otherwise.
Technology push	tecpush	Qualitative (Dummy)	1 if the company faced limited technological opportunities; 0 otherwise.
Foreign capital	kext_15	Qualitative (Dummy)	1 if the company received foreign capital in 2015; 0 otherwise.
Active linkages	vinc*	Qualitative	1 with related companies; 2 with specialized firms; 3 with research centers and universities; 4 with innovation centers and government.
Physical Capital Intensity			
Capital investment	lcaptrab_15	Quantitative	Logarithm of capital investment in 2015.
Variation in capital investment	dlcap_1517	Quantitative	Difference in the logarithm of capital investment between 2015 and 2017.
Workforce Quality			
Skilled personnel	skill_15	Quantitative	Percentage of workers with higher education in 2015.

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