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Impact of firm-level innovation on productivity of manufacturing and service firms in Sub-Saharan Africa

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ABSTRACT

This study investigates the impact of firm-level research and innovation on the productivity of Sub-Saharan African firms in 2014–2018. This study utilizes World Bank Enterprise Surveys on 2,867 manufacturing and service firms conducted in SSA in 2018/19. Endogenous Switching Regression (ESR) was used as the primary estimation methodology. The results indicated that Research and Development spending positively and significantly impacts manufacturing firms' productivity. In addition, service innovation has a positive and significant effect on the productivity of service firms. In contrast, product innovation is insignificant to manufacturing firms' productivity. Lastly, process innovation is significant only to the manufacturing firms and not the service firms. These results suggest that Sub-Saharan African firms did not realize maximum innovation productivity gains during the study period. Nonetheless, the results imply that other than the conventional factor-driven production, Sub-Saharan African firms have the potential to drive their productivity through semi-endogenous firm-level innovation.

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Sub-Saharan Africa; impact evaluation; firm-level innovation; productivity; propensity score matching; endogenous switching regression

Introduction

Firms face a highly volatile business environment characterized by rapid globalization, cutthroat competition, and rapid demand change. As a result, the global trend is that firms are heavily investing in Science, Technology, and Innovation (ST&I) and Research and Development (R&D) to remain competitive (Sukumar et al. 2020). Innovation and adoption of science and technology have become effective strategies to improve firm productivity, competitiveness, labour productivity, industry value-added, and exporting capacity (Seclen-Luna et al. 2020; Twumasi Baffour, Quartey, and Adu-Danso 2022). On the other hand, a firm's output may stagnate or decline due to non-adoption of R&D initiatives, poor utilization of novel ideas, organizational failure to manage the innovation process, ineffective ST&I policies, and poor commercialization of innovations and knowledge outputs (Vu and Asongu 2020).

In light of the competitive global market and volatile business environment in Sub-Saharan Africa (SSA), this study investigated the impact of innovative firm-level

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strategies on the productivity of SSA firms. Firm-level innovation was measured using three indicators; spending on R&D, product/service innovation, and process innovation, following the guidelines by OECD & Eurostat (2018). Based on the available study data, firm productivity was measured using labour productivity or the industry value-added per worker. Then using treatment effects approaches, the study investigated whether innovative firms' productivity differed significantly from that of non-innovating firms.

The productivity of firms in SSA lagged behind other regions globally during the study period. For instance, industry value-added as a percentage of GDP in 2019 was 26.9% for SSA, while the world average stood at 28%. Additionally, SSA industry value-added as a percentage of GDP was better compared to OECD members (22.2%), Latin and Caribbean (23.3%), and EU (22.2%). However, SSA was lagging behind the Middle East and North Africa (42.4%) and the Arab world (43.6%) (The World Bank, 2020a). Additionally, SSA lagged behind all other regions regarding industry value-added per worker—a measure of labour productivity in US dollars. The industry value-added per worker was US$10,320 for SSA against a world average of US$ 25,917. This performance was below that of all other regions, for instance, OECD members (US$76,126), Middle East and North Africa (US$46,021), Latin America and the Caribbean (US$24,605), European Union (US$74,364), and Arab world (US$42, 643) (The World Bank, 2020b).

The productivity of SSA firms in terms of industry value-added was at par with other developing regions such as Latin and the Caribbean. However, it lagged behind all regions in labour productivity measured as value-added per worker. We argue that firm-level semi-endogenous innovation can enhance firms' productivity in SSA. Subsequently, firm-level innovation best practices can improve SSA firms' productivity, enabling them to be among the most productive globally. Therefore, using firm-level data from six SSA countries, the study explored the impact of firm-level internal R&D spending and innovation on firms' productivity. Specifically, a treatment effect model —Endogenous Switching Regression (ESR), was used to investigate the impact of firm-level innovation on their productivity. Propensity Score Matching (PSM) was used for robustness testing.

The study on the impact evaluation of innovation on firms' productivity in SSA is still not comprehensive. A few studies have attempted to investigate the effect of innovation on firms' productivity in Africa and SSA. For instance, Cherif et al. (2020), Cirera, Lage, and Sabetti (2016), and Morsy and Amira (2020) have attempted to investigate the effect of firm-level innovation on the productivity of firms using the Generalized Structural Equation Model (GSEM) by Crepon-Duguet-Mareisse (CDM) (1998). This paper extends the impact of innovation on firm productivity in SSA discourse by using treatment effects approaches such as the ESR and PSM. The treatment effects approaches, as opposed to GSEM-CDM, are better adapted to handle endogeneity and unobservable firm or country effects, particularly in the absence of baseline data.

This paper contributes to innovation and productivity literature in developing countries, especially SSA, in three unique ways. First, the study evaluated whether innovating firms' productivity was better than non-innovating firms' productivity in SSA and compared innovation performance among the manufacturing and service firms. By comparing the two sectors' innovation activities, it is possible to gauge the strength of SSA innovation across the sectors, compare the industry with the highest impact of innovation, and use the results to develop pertinent policies. Secondly, the paper employs a counterfactual analysis approach in evaluating innovation impacts using the treatment effects model, which has not been applied in the SSA context. Further, impact analysis helps determine whether or not the current firm-level innovation strategies have been effective or not. Therefore, the findings of this study are essential in describing the efficacy of firm-level innovation measures in SSA. The rest of the paper proceeds as follows; literature review and hypothesis development are presented in section 2. The empirical strategy and descriptive statistics are presented in section 3. Section 4 provides the results and discussion. Lastly, Section 5 offers conclusions and policy implications of the study.

2. Theoretical framework and hypothesis development

2.1. The link between firm-level R&D, innovation, and productivity

Firm-level innovation in this study entails spending on R&D, product/service, and process innovation. R&D involves the development, dissemination, transfer, and utilization of ST&I in all national development sectors. Successful investments in R&D lead to the realization of innovations (Albis et al. 2021). On the other hand, innovation is the introduction of novel ideas and methods to a firm, country, or workplace and includes imitations (Hall et al. 2014). At the firm level, innovations are measured by analyzing whether or not a firm launched a new-to-the-firm service or product, new organizational procedures, new production processes, and new marketing strategies (Baumann and Kritikos 2016). Besides, firm-level innovation can be measured by considering the financial gains realized from commercializing innovations and licensing or owning intellectual property rights (OECD & Eurostat 2018). Consequently, successful investment in firm-level innovation leads to the realization of innovations that increase firm productivity (Fiorentino, Longobardi, and Scaletti 2020).

Successful R&D and innovation leading to enhanced firm productivity can be described as a semi-endogenous process (Comite 2015). Therefore, a firm's stock of knowledge is assumed to be semi-endogenous. Consequently, apart from the novel expertise developed within the firm, other innovation players significantly influence a firm's R&D and innovation investment process through technical collaborations (Jun, Yoo, and Hwang 2021). Technical cooperation may be between the firm and government, other firms, the R&D sector, society, and the rest of the world (Natera 2015).

The government influences a firm's R&D and innovation investment through subsidies and taxes (Teng et al. 2020). The subsidies can be provided as a tax credit to the households on their receipts from knowledge outputs. Tax credits on knowledge output (patents) may encourage more highly-skilled workers to participate in R&D and innovations (Xu, Wang, and Liu 2021). The government can also encourage investment in R&D by reducing the tax levied on knowledge outputs such as patents, or it can pay a wage incentive to R&D highly-skilled workers. The government can boost firm-level investment in R&D and innovation by reducing fixed costs faced by the firms, such as energy and bandwidth costs (Comite and Kancs 2015; Xu, Wang, and Liu 2021). The government plays a crucial role in stimulating innovations in a country, mainly in developing countries. It can directly influence R&D investment and innovation in given sectors of the economy through taxes, subsidies, and other relevant R&D policies (Crespi et al. 2020; Fiorentin, Suárez, and Yoguel 2021).

Comite and Kancs (2015) posits that the R&D sector is comprised of a research institute (national private, or public), institutions (academia), or a research department within a firm. The R&D sector hires highly-skilled workers and utilizes R&D-intensive capital to produce novel ideas. In creating novel ideas, the R&D segment uses the prevailing domestic and foreign stock of knowledge (Yu et al. 2021). A country's or firm's R&D capacity is determined by the supply of highly skilled workers and the quality of the labour force (Ren and Song 2021). Highly-skilled workers comprise mainly the technical workers and graduates of tertiary institutions. The public expenditure on higher education and education policies influences the quality of countries' human capital (Ren and Song 2021).

A firm's interaction with the rest of the world through knowledge spillovers and international trade also influences its R&D investment and innovation (Comite and Kancs 2015). Domestic or foreign knowledge spillover from one firm, local or global, to another may be experienced through domestic or international trade with other trading partners (Gkypali, Arvanitis, and Tsekouras 2018). The ability of a firm to adopt foreign technology is also critical in its R&D investment and innovation (Fatima 2017). Furthermore, innovation partnerships among firms for joint product/service innovation and joint use of R&D infrastructure may influence firm-level R&D intensity (Albors-Garrigos, Igartua, and Peiro 2018). Figure 1: shows the framework of interactions in a semi-endogenous firm-level innovation process.

Figure 1 shows that apart from the endogenous knowledge produced by highly-skilled workers, the firms also depend on ability emanating from external sources. External knowledge arises from interaction with other innovation players, such as the spillover from other firms, links with academia, and the national ST&I infrastructure and policies. The political governance and business environment influence the knowledge-generation process (Aklobo and Ahodode 2022). The realized knowledge outputs are utilized as inputs in producing goods and services, leading to improved productivity by the firm.

The framework described in figure 1 relies on the CDM-GSEM, a crucial theoretical framework for studies investigating the impact of innovation on firm productivity for the past two decades. According to Lööf, Mairesse, and Mohnen (2017), hundreds of papers

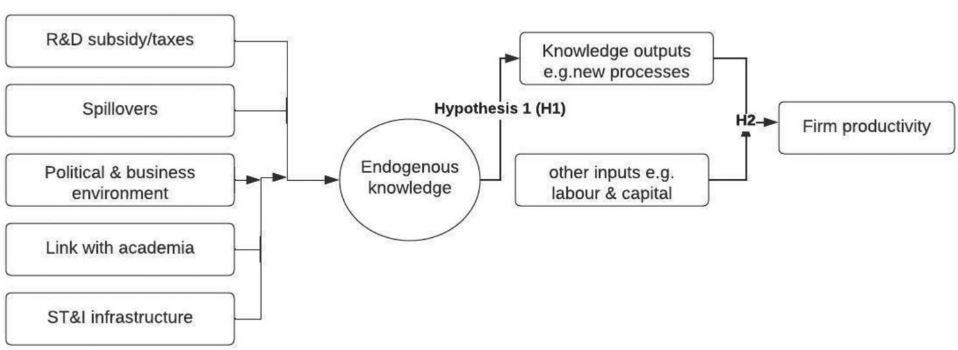

Figure 1. Diagrammatic Representation of Semi-Endogenous Innovation Process and its Link to Firm Productivity.

have studied the CDM-GSEM model in over 40 countries. The four equations of the mathematical form of the CDM-GSEM have been analyzed using different econometric methodologies. They include; Instrumental Variable (IV) estimation, Bivariate Probit, two-stage least squares, Panel data models, and treatment effect models (Lööf, Mairesse, and Mohnen 2017). The impact of innovation on firm productivity has been widely researched in developed regions. However, in the SSA, the impact of innovation on firm productivity has not been adequately analyzed especially using treatment effects approaches. The CDM-GSEM cannot analyze counterfactual innovation outcomes; therefore, in this study, we use it as a basis to develop treatment effects estimation. Prior research has tried linking augmented CDM to treatment effects models such as the Endogenous Switching Regression (ERS) (Crowley and McCann 2018; Damijan, Kostevc, and Rojec 2011).

2.2. Firm-level R&D and innovation challenges in Sub-Saharan Africa

Firm-level R&D and innovation investment can be costly to individual firms. A substantial amount of money is needed to purchase the R&D intensive capital, pay highly skilled workers, conduct market surveys, acquire intellectual properties, and cater to other innovation-related expenses (Cornell University INSEAD & WIPO 2020). Most SSA firms are less competitive than firms from different global regions, notwithstanding SSA's fluctuating business cycles and environment (Cherif et al. 2020). As a result, most firms have insufficient funds to exhaustively meet the cost of all internal R&D and innovation activities. Consequently, only a few firms engage in internal R&D and innovation activities (Lema, Kraemer-Mbula, and Rakas 2021).

Various firm-level and external factors and challenges influence firm-level innovation in SSA. For instance, in most of these countries, the national innovation systems are still in their infancy; therefore, ST&I policies are still being developed (African Union–New Partnership for Africa's Development, 2019). In most of these countries, there are fewer R&D researchers and insufficient funding for research activities. Industry-academia linkage in most SSA countries is still ineffective (Yongabo and Göransson 2022). Additionally, in most of these countries, there is a mismatch between the quality of graduates and industry requirements. The commercialization of innovation and the ability to tap into spillovers is still ineffectual compared to developed economies. Lastly, some countries' political, business, and market environments are volatile (Egbetokun et al. 2016; United Nations Conference on Trade and Development 2021).

When producing innovative products/services, firms, especially in developing regions like SSA, are constrained by institutional, technological, and resource-based factors (Abbey and Adu-Danso 2022). These constraints affect the intensity of firm-level R&D investment and, by extension, firm-level innovation (Barasa et al. 2017; Divisekera and Nguyen 2018). Subsequently, concrete technical cooperation among the innovation players, such as the national STI infrastructure and policies, spillovers from other firms, access to finance, and link with the academia, is necessary to augment firm-level innovation initiatives (Carayannis and Rakhmatullin 2014).

Despite the challenges facing the SSA firms' semi-endogenous innovation process, this paper argues that effective technical partnerships are essential in enhancing SSA firms' efforts to invest in R&D and innovation. Linking a firm's innovation performance to technical associations may enhance joint innovations and knowledge sharing, improving productivity. The improved firm productivity may be manifested through increased sales growth, operational and innovation efficiency, labour productivity, exporting capacity, and total factor productivity (Siepel and Dejardin 2020). This paper investigated the counterfactual innovation impacts on firm productivity. The study's central hypothesis is that despite the institutional, technological, and resource-based constraints, firm-level semi-endogenous R&D and innovation enhance the productivity of SSA manufacturing and service firms. The study's central hypothesis implies that;

H1: Endogenous knowledge plus technical cooperation significantly affect firm-level R&D and innovation in SSA.

H2: Firm-level R&D and innovation significantly impact a firm's productivity in SSA.

3. Methodology and data

3.1. Econometric model and estimation strategy

Based on the available data set in this study, firm-level innovation entails R&D spending, product/service innovation, and process innovation. The *augmented* Generalized Structural Equations Model (GSEM) by Crepon-Duguet-Mareisse (CDM) (1998) provides an empirical framework for linking firm productivity to firm-level R&D and innovation (Hall and Sena 2017). The mathematical form of the GSEM-CDM provides a structural model with four equations.

$$rd_i^* = \begin{cases} 1 \text{ } if \text{ } rd_i = Z_i\alpha + u_i > 0 \\ 0 \text{ } if \text{ } rd_i = Z_i\alpha + u_i \leq 0 \end{cases} \tag{1}$$

$$rd_i = \begin{cases} \beta X_i + u_i \text{ } if \text{ } rd_i^* = 1 \\ 0 \qquad\qquad if \text{ } rd_i^* = 0 \end{cases} \tag{2}$$

$$INNO_i = \phi rd_i^* + \theta x_i + \varepsilon_i \tag{3}$$

$$Y_i = A + \alpha_k k_i + \alpha_l l_i + \delta_1 rd_i + \delta_2 INN0_i^* + v_i \tag{4}$$

When investigating the firm's research behaviour, the first equation (1) is the participation equation, and it helps explain the likelihood that a particular firm will participate in R&D and innovation undertakings. Equation (2) is the research participation outcome equation that describes the intensity of R&D activities. Z_i and X_i are vectors of explanatory variables that explain the research participation and intensity, respectively, β and α are vectors of parameters to be estimated. Equation (3) is the innovation equation, where, $INNO_i$ is innovation output in the form of new-to-the-firm products or services, new organizational procedures, new production processes, and new marketing strategies. $INNO_i$ is a function of R&D spending rd_i^* and other explanatory variables x_i, ϕ and θ are vectors of parameters to be evaluated. Equation (4) is the productivity equation expressed as a Cobb–Douglas production function. The productivity equation is a function of intangible (unobserved endogenous) inputs, including R&D, innovation, and tangible inputs like labour, raw materials and capital.

This study estimates the productivity equation (4) of the augmented GSEM-CDM model to evaluate the impact of R&D spending (Equation 2), product/service innovation, and process innovation (Equation 3) on a firm's productivity. The study employed a random treatment assignment model. A randomized treatment assignment model such as the ESR and PSM was preferred because it accounts for selection bias and heterogeneous treatment effect bias in the estimation process when baseline data is unavailable. Additionally, unlike the canonical CDM, the ESR can model endogeneity between output and innovation in addition to modelling counterfactual innovation outcomes. Further, Even though the standard CDM model helps model endogeneity between R&D and innovation, ESR treats R&D and innovation as randomized treatments and focuses on their counterfactual impacts (Crowley and McCann 2018; Damijan, Kostevc, and Rojec 2011).

The study hypothesized three randomized treatments for the sampled firms. Y in equation four was treated as the potential outcome variable measured as a firm's value-added per worker. Let the three treatments be $i = A, B, C,$ where treatment A = firms that engaged in R&D spending and the control group be non-R&D spending firms. Treatment B = firms involved in product or service innovation and the control group as non-innovative firms; treatment C = firms engaged in process innovation and the control group as non-process innovators. In general, for i^{th} randomized treatment $i = A, B, C,$ $Y_{1i} =$ treatment outcome; Y_{0i} = non- treatment outcome; Then,

$$Y_{1i} = Y_{0i} - \delta_i \text{ or } \delta_i = Y_{1i} - Y_{0i} \tag{5}$$

Where, δ_i is the i^{th} randomized treatment effect; the objective of the randomized treatment effect models is to obtain an estimate of the value of the i^{th} randomized treatment effect δ_i. The study defined a dummy $D = 1$, if a firm had received treatment; $D = 0$, if a firm had not received treatment. Then, $E(Y_{1i}\ |D = 1)$, was the value-added per worker expected value of firms that had received treatment; $E(Y_{0i}\ |D = 1)$, was the value-added per worker expected value that would have been if those who have received treatment had not gone through it. The randomized treatment effect across all firms was estimated by equation (6). Randomization ensures that firms in the control group are matched to similar firms in the treatment group. Randomization ensures that there is no difference between these two groups on average on any characteristics other than their treatment. As a result, randomization eliminates any confounders/omitted variable bias/ or heterogeneity effects that may be present in the data before randomization (Ismay et al. 2020).

$$\hat{\delta} = E(Y_{1i}|D = 1) - E(Y_{0i}\ |D = 1) \tag{6}$$

Since $E(Y_{0i}\ |D = 1)$ is not observable for the same firm that received treatment, counterfactuals needed to be evaluated by defining two parameters. One is the Average Treatment Effect (ATE), the mean impact of treatment obtained by averaging the impact across all firms in the population, as shown by equation (7) (Heinrich, Maffioli, and Vázquez 2010).

$$ATE = E(\delta) = E(Y_{1i} - Y_{0i}) \tag{7}$$

The second parameter which had to be defined is the Average Treatment Effect on the Treated (ATT) equation (8) which is the impact of treatment on those firms that participated.

$$ATT = E(Y_{1i} - Y_{0i}|\ D = 1) \ = \ E(Y_{1i}|\ D = 1) - E(Y_{0i}\ |D = 1) \tag{8}$$

3.2. Data sources and variables of interest

This study benefited from World Bank Enterprise Surveys (WBES) conducted in SSA in 2018/19, where manufacturing and service firms were surveyed on their innovation activities (2014–18). Six enterprise surveys were conducted in six countries, covering; 1,001 firms from Kenya, 153 from Chad, 151 from the Gambia, 601 from Mozambique, 360 from Rwanda, and 601 from Zambia. The combined sample contained 2,867 firms, 1,172 manufacturing firms, and 1,695 service firms. Innovation input and output variables were extracted following empirical literature and the available data set. Table 1 summarizes the definition and measurement of the control variables including country dummies, innovation outputs, and inputs. Firm productivity was measured using industry value-added, and all monetary units were standardized to US Dollars. Regarding innovation inputs, we include firm-level factors and indicators of technical associations, such as foreign technology adoption, credit access, and business-government relations.

3.3. Descriptive statistics

The descriptive results are presented in Tables 2 and 3. Table 2 shows the number of firms surveyed in the six countries and the proportion of innovating firms. 35% of all the firms had introduced a new product/service into the market. 11% of all firms had spent on R&D, and 17% had launched new processes. The three measures of innovation also show the proportion of treated firms. Therefore, the innovative firms were assumed to be in the treatment group, and the non-innovative firms were considered in the control group.

Table 2 further revealed that nearly half of the firms in the manufacturing and service sectors had participated in product innovation. Gambia, Kenya, and Zambia had the highest numbers of innovating firms. In addition, the descriptive statistics revealed no difference in the distribution of innovation activities among the manufacturing and service firms. Lastly, Table 2 shows that the proportion of firms engaged in innovation activities was below average during the study period. On the other hand, Table 3 summarizes descriptive statistics.

Table 3 indicates that the mean value-added per worker was approximately USD 45,000, ranging between USD negative one million and ten million USD. The service firms had a slightly higher mean value-added than the manufacturing firms. Further descriptive results revealed that the distribution of international certification, foreign technology adoption, exporting capacity, and hiring of highly trained workers differed substantially among the service and manufacturing firms. For instance, 17% of manufacturing firms had received international certification compared to 9% of service firms, while 15% had adopted foreign technology compared to 1% of firms in the service

Table1. Definition and Measurement of Variables.

Variables	Definition and Measurement
Control variables	
Industry	A firm's main activity is manufacturing, or retail, and other services.
Firm age	Number of years since the establishment was started until the survey year
Manager experience	Number of years of service of the establishment's top management
Country Dummies	
Kenya	1 if a firm is from Kenya, 0 if otherwise
Zambia	1 if a firm is from Zambia, 0 if otherwise
Chad	1 if a firm is from Chad, 0 if otherwise
Gambia	1 if a firm is from Gambia, 0 if otherwise
Mozambique	1 if a firm is from Mozambique, 0 if otherwise
Rwanda	1 if a firm is from Rwanda, 0 if otherwise
Innovation outputs	
Product/service innovation	1 if a firm launched a new product/service into the market, 0 if otherwise.
Process innovation	1 if a firm introduced a new process in producing goods or service delivery, 0 if otherwise.
R&D propensity	1 if a firm spent on R&D activities, either in-house or contracted with other companies, excluding market research surveys, 0 if otherwise.
Firm productivity measure	
Value-added per worker	The total annual sales for all products and services less the cost of goods/services sold divided by the number of workers.
Independent variables-innovation inputs	
Internet access	1 if an establishment has an official operational website, 0 if otherwise.
Spending on physical capital	1 if a firm spent on physical capital purchasing new machinery equipment etc., 0 if otherwise.
International certification	1 if a firm is licensed by international standards bodies like ISO: 9001, 0 if otherwise.
Foreign technology adoption	1 if the firm uses technology licensed from foreign-owned companies, 0 if otherwise.
Exporting capacity	1 if a firm engaged in direct and indirect exports, 0 if national sales only.
Credit access	1 if a firm borrowed from financial intuitions, 0 if otherwise.
Business-government relations	1 if a firm secured a government contract at the county or national government level, 0 if otherwise.
Employee training	1 if a firm formally trained employees on developing or introducing new products/services, 0 if otherwise.
Hiring highly skilled workers	1 if a firm hires professionals whose tasks require extensive theoretical and technical knowledge, 0 if otherwise.
Expenditure on raw materials	Log total annual expenditure on raw materials
Expenditure on labour	Log total annual expenses on labour

Source: World Bank Enterprise Survey (WBES) 2018/19 data, (Countries; Zambia, Rwanda, Mozambique, Kenya, Chad and Gambia).

Table 2. Proportion of innovating firms in the sample.

	Kenya	Chad	Gambia	Mozambique	Rwanda	Zambia	Total
Manufacturing firms (N)	**455**	**72**	**63**	**287**	**120**	**175**	**1,172**
R&D Spenders (%)	22	8	11	7	7	14	12
Product /service innovator (%)	47	36	48	34	12	38	36
Process innovator (%)	32	22	27	18	7	22	21
Service firms (N)	**546**	**81**	**88**	**314**	**240**	**426**	**1,695**
R&D Spenders (%)	15	15	9	11	4	11	11
Product /service innovator (%)	47	37	48	32	15	31	35
Process innovator (%)	21	10	16	17	8	11	14
All firm (N)	**1,001**	**153**	**151**	**601**	**360**	**601**	**2,867**
R&D Spenders (%)	18	12	10	9	5	12	11
Product /service innovator (%)	46	37	47	33	14	33	35
Process innovator (%)	26	16	21	17	8	14	17

Source: Authors' computations from the WBES data.

Table 3. Descriptive Statistics.

	All firms N=2,867				Manufacturing firms N=1,172				Service firms N=1,695			
Variable	Mean	Std. dev	Min	max	Mean	Std. dev	Min	max	Mean	Std. dev	Min	max
Firm age	19	15	1	126	23	16	2	109	17	14	1	126
Manager experience	16	10	1	70	18	11	1	70	14	10	1	60
Value-added per worker	46,731	284,381	−1,369,478	10,400,000	37,215	339,332	−9,900,99	10,400,000	53,330	238,858	−1,369,478	5,422,696
Internet access	0.453	0.497	0	1	0.437	0.496	0	1	0.465	0.499	0	1
Spending on physical capital	0.387	0.487	0	1	0.415	0.493	0	1	0.368	0.482	0	1
International certification	0.131	0.337	0	1	0.178	0.382	0	1	0.098	0.297	0	1
Foreign technology adoption	0.071	0.255	0	1	0.151	0.359	0	1	0.013	0.115	0	1
Exporting capacity	0.229	0.421	0	1	0.311	0.463	0	1	0.172	0.377	0	1
Credit access	0.244	0.429	0	1	0.260	0.439	0	1	0.232	0.423	0	1
Business-government relations	0.197	0.398	0	1	0.163	0.370	0	1	0.221	0.415	0	1
Employee training	0.332	0.471	0	1	0.326	0.469	0	1	0.337	0.472	0	1
Hiring highly skilled workers	0.339	0.473	0	1	0.827	0.377	0	1	0	0	0	0

Source: Authors' computations from the WBES data.

sector. Moreover, 31% of manufacturing firms, compared to 17% of service firms, exported goods and services during the study period.

Table 3 further indicates that hiring highly trained workers was mainly concentrated among the manufacturing firms. Generally, the results of the descriptive statistics show below-average innovation activities and a large-scale heterogeneity among the firms since, for most variables, the standard deviation is more than the mean. As a result, in the regression analysis, the study separates manufacturing and service firms to investigate counterfactual innovation impacts properly. Further, the PSM estimation approach matched firms in the treatment group with the most similar firms in the control group and the ESR estimation employed country dummies to control country level effects.

4. Empirical results and discussion

This paper investigates the impact of semi-endogenous innovation on firm productivity using ESR/PSM treatment effects approaches. The ESR was used as the primary estimation method and PSM as the test for robustness.

4.1. Endogenous switching regression results

Endogenous Switching regression (ESR) has been applied in empirical literature for causal inference investigation of the impact of firm-level innovation on productivity using cross-sectional data (Crowley and McCann 2018; Dvouletý and Blažková 2019). In the ESR, which uses Full Information Maximum Likelihood (FIML) estimation, the behaviour of a firm is described with two outcome equations and a selection function that defines which regime (treatment or control) the firm faces. ESR controls for selection bias and unobserved heterogeneity. Further, the ESR can be used to evaluate distinct values for ATT. The main demerits of the ESR are difficulty in achieving convergence, primarily when there is a weak model selection (Fazlıoğlu, Dalgıç, and Yereli 2018).

The selection results under different treatment regimes are shown in Tables 4–6. The selection equation is based on the factors that influence firm-level innovation. The outcome equation on the other hand is based on the fundamental knowledge of a Cobb–Douglas production function (equation 4). The outcome variable is the value-added per worker and the independent variables are the usual inputs in the Cobb–Douglas production function such as labour, capital and raw material. In addition to control for country level unobserved factors we include country dummies in the ERS regression. Lokshin and Sajaia (2004) suggest that for the ERS estimation the selection equation (equations 2 and 3) includes a set of instruments that help identify the model and when dependent variables of selection equations are different, a different selection equation need to be specified. Table 4 shows the results of the selection function for participation and non-participation in R&D spending activities.

This study argues that a firm's R&D and innovation process follows a semi-endogenous process, where partnerships with other innovation players are essential. Consequently, the choice innovation inputs include variables that are indicators of associations with other innovation players. The results in Table 4, for instance, indicate that foreign technology adoption and access to credit increase the possibility of manufacturing firms participating in R&D spending activities by 48% and 23%, respectively. In

Table 4. Endogenous Switching Regression with R&D Spending as the Treatment.

	Manufacturing Firms			Service Firms		
	Value-added perworker_1	Value-added perworker_0	R&D spending participation	Value-added perworker_1	Value-added perworker_0	R&D spending participation
Firm age						−0.002
						(0.003)
Internet access			0.126			0.466***
			(0.118)			(0.092)
Physical capital spending	19,609.64	−4,382.10	0.440***	1,703.135	4,044.252	0.395***
	(15,229.88)	(10,304.88)	(0.106)	(7,349.046)	(10,897.64)	(0.091)
International certification			0.311***			0.111
			(0.126)			(0.132)
Foreign technology adoption			0.481***			0.451
			(0.136)			(0.365)
Exporting capacity			0.0306			0.311**
			(0.118)			(0.108)
Credit access			0.228**			0.186
			(0.113)			(0.103)*
Business-government relation			0.287**			0.306**
			(0.128)			(0.097)
Employee training			0.501***			0.401***
			(0.110)			(0.092)
Log expenditure on raw materials	−13,641.64	−6,306.084	−0.002	8,953.926*	14,248.14**	0.044
	(9,620.149)	(7,234.108)	(0.077)	(4,803.558)	(7,077.987)	(0.062)
Log expenditure on labour	13,332,66	14,330.66	0.116	1,258.144	3,218.047***	0.130*
	(12,960.89)	(8,622.32)	(0.097)	(5,525.676)	(808.370)	(0.074)
Country Dummies	yes	yes	yes	yes	yes	yes
Sigma	13.612***	11.921***		12.997***	12.153***	
	(0591)	(0.022)		(0.062)	(0.018)	
Rho	−0.191	0.030		−0.271	0.051	
	(0.157)	(0.097)		(0.180)	(0.072)	
Likelihood test of independence of equations	chi2(1) = 1.14 Prob. > chi2 = 0.2866			chi2(1) = 28.09 Prob. > chi2 = 0.0000		
N		1,172			1,695	

Note: ***, **, and *denote 1%, 5%, and 10% significance levels, respectively. LR test of independence of equations tests whether the selection in both regimes is potentially exogenous or not. Country dummies are included to control for differences across countries but results show that probability of participation to treatment was not significantly affected by country differences.
Source: Authors' computations from the WBES data.

addition, doing business with the government increases the likelihood of manufacturing firms' participation in R&D by 28% and service firms by 30%. Table 5 shows the results of the selection function to participate or not participate in product/service innovation.

The fitted model results in Table 5 indicate that partnerships such as business-government relations, credit access and foreign technology are crucial factors influencing the probability of product innovation among the manufacturing firms. Doing business

Table 5. Endogenous Switching Regression with Product/Service Innovation as the Treatment.

	Manufacturing Firms			Service Firms		
	Value-added perworker_1	Value-added perworker_0	Product/ service innovation participation	Value-added perworker_1	Value-added perworker_0	Product/ service innovation participation
Internet access			0.238**			−0.018
			(0.093)			(0.039)
Physical capital spending	3,194.478	−13,420.76	0.549***	13,681.79***	−1,443.311	0.395***
	(5,589.571)	(13,148.98)	(0.082)	(2,709.678)	(11,639.34)	(0.065)
International certification			−0.108			−0.019
			(0.114)			(0.061)
Foreign technology adoption			0.228**			0.078
			(0.117)			(0.148)
Exporting capacity			−0.027			0.008
			(0.097)			(0.049)
Credit access			0.208**			0.013
			(0.096)			(0.045)
Business-government relation			0.187*			0.003
			(0.109)			(0.044)
Employee training			0.104			0.130**
			(0.092)			(0.041)
Log expenditure on raw materials	−3,263.921	11,569.91	−0.052	5,553.70**	1,499.44**	0.136**
	(3,594.394)	(8,653.806)	(0.060)	(1,796.824)	(7,770.067)	(0.043)
Log expenditure on labour	7,826.483*	2,809.981	0.190**	3,428.939	3,478.00***	0.191***
	(4,706.135)	(10,266.56)	(0.073)	(2,121.74)	(8,496.267)	(0.051)
Country Dummies	yes	yes	yes	yes	yes	yes
Sigma	13.138***	11.929***		12.926***	12.015***	
	(0.034)	(0.027)		(0.034).	(0.021)	
Rho	−0.079	0.080		0.970	−0.007	
	(0.122)	(0.091)		(0.003)	(0.098)	
Likelihood test of independence of eqns.	chi2(1) = 0.77 Prob. > chi2 = 0.3792			chi2(1) = 444.01 Prob. > chi2 = 0.0000		
N		1,172			1,695	

Note: ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. LR test of independence of equations tests whether the selection in both regimes is potentially exogenous or not. Country dummies are included to control for differences across countries but results show that probability of participation to treatment was not significantly affected by country differences.
Source: Authors' computations from the WBES data.

with government, credit access and adoption of foreign technology will increase the chances of a manufacturing firm to engage in product innovation by 19%, 21% and 23% respectively. Spending on physical capital, employee training and raw materials were significant drivers of service innovation among the service firms. Table 6 presents the selection function for participation and non-participation in process innovation results.

Technical cooperation leading to a novel process, for instance, foreign technology adoption and business-government relations, seem more effective in the manufacturing than in the service firms. Business-government relation is a significant driver of process innovation among service firms, while highly trained workers do not matter significantly among the manufacturing firms. For the three treatments, employee training and

Table 6. Endogenous Switching Regression with Process Innovation as the Treatment.

All firms	Manufacturing Firms			Service Firms		
	Value-added perworker_1	Value-added perworker_0	Process innovation participation	Value-added perworker_1	Value-added perworker_0	Process innovation participation
Internet access			-0.171			0.034
			(0.102)			(0.083)
Physical capital spending	−913.823	−2,468.933	0.430***	−794.716	974.58	0.436***
	(8,885.439)	(10,280.31)	(0.089)	(5,597)	(1,157)	(0.082)
International certification			0.206*			0.273***
			(0.117)			(0.118)
Foreign technology adoption			0.227*			0.435
			(0.123)			(0.331)
Exporting capacity			−0.108			0.058
			(0.105)			(0.103)
Credit access			0.282***			0.126
			(0.101)			(0.092)
Business-government relations			0.149			0.267***
			(0.116)			(0.090)
Employee training			0.469***			0.369***
			(0.096)			(0.085)
Highly skilled workers			0.107			
			(0.119)			
Log expenditure on raw materials	−3,563.918	467.350	0.146**	423.660	1,860.176***	0,063
	(6,148.86)	(726.713)	(0.066)	(344.81)	(748.863)	(0.056)
Log expenditure on labour	852.652	214.131***	−0.191**	389.89	299.160***	0.043
	(778.456)	(85.77)	(0.081)	(438.28)	(83.64)	(0.067)
Country Dummies	yes	yes	yes	yes	yes	yes
Sigma	13.380***	11.860***		12.863***	12.183***	
	(0.045)	(0.023)		(0.058)	(0.018)	
Rho	−0.154	0.083		−0.298	0.048	
	(0.130)	(0.082)		(0.148)	(0.071)	
Likelihood test of independence of eqns.	chi2(1) = 1.63 Prob. > chi2 = 0.2020			chi2(1) = 28.93 Prob. > chi2 = 0.000		
N	1,172			1,695		

Note: ***, **, and *denote 1%, 5%, and 10% significance levels, respectively. LR test of independence of equations tests whether the selection in both regimes is potentially exogenous or not. Country dummies are included to control for differences across countries but results show that probability of participation to treatment was not significantly affected by country differences.
Source: Authors' computations from the WBES data.

spending on physical capital are the most significant internal factors influencing firm-level innovation.

Lastly, the paper analyzed the impact of actualized innovations on a firm's productivity (equation 5). Accordingly, Table 7 shows the participation and non-participation mean and the ATT of the three innovation measures.

Table 7. Endogenous Switching Regression Treatment Effects Results.

	Manufacturing Firms			Service Firms		
Treatment	Participation Mean	Non-Participation Mean	Treatment Effect (ATT)	Participation Mean	Non-Participation Mean	Treatment Effect (ATT)
R&D Spending firms	87,126	53,476	33,650***	96,684	85,520	11,164
Product/service innovators	56,463	51,143	5,19	146,306	56,777	89,529***
Process innovators	72,486	54,242	18,244***	74,419	85,226	−10,807

Note: ATT = the difference in participation and non-participation means of firms in the treatment group, ***, indicates significance at ATT at 1%.
Source: Authors' computations from the WBES data.

The results in Table 7 indicate that participation in R&D spending would significantly improve manufacturing firms' value-added by USD 35,650. Participating in product or service innovation did not considerably affect manufacturing firms' value-added. In contrast, product/service innovation significantly affected the service firms' value-added by USD 89,529. Lastly, participating in process innovation significantly affected the manufacturing firms' value-added by USD 18,244 and did not affect service firms value-added.

4.2. Robustness test

Two critical assumptions of the PSM model need to hold for the PSM model to be successfully employed in counterfactual impact evaluation. The assumptions are validation of selection on observables and the common support requirement. The selection on observables assumption of the PSM assumes that selection is based on observed variables in the study data. It is, however, essential to note that this assumption cannot be validated empirically (Cunningham 2021). The only alternative is to use a conceptual argument for why we think the observable characteristics sufficiently explain who received the treatment.

Common support is the second PSM assumption that needs to be satisfied. The common support assumption ensures that the control and treatment groups are comparable conditional on the observed factors. The balancing property ensures that the control and treatment groups are compared conditional on the observed factors identified in the respective selection Probit model. Table 8 shows the results of the Probit selection model of firms for each of the three treatments.

Results in Table 8 indicate that internal factors plus technical associations enhance firm-level R&D and innovation. Particularly adoption of foreign technology is significant only to manufacturing firms. In addition, business-government relations are more meaningful to the service firms, while credit access is essential to all firms, and hiring highly skilled workers does not matter significantly. On the other hand, spending on physical capital and training employees are the primary internal drivers of firm-level innovation and R&D.

Once the balancing property was satisfied and the PSM assumptions validated, four algorithms were used to match the P-Score of the control and treatment groups to analyze the ATT. The matching algorithms include the Nearest Neighborhood, Radius,

Table 8. Results of Selection into the Treatment Sample Probit Models.

Variables	Manufacturing Firms			Service Firms		
	R&D Spend	Product/service innovation	Process Innovation	R&D Spend	Product/service innovation.	Process Innovation
Firm age		0.005**			0.003	
		(0.002)			(0.002)	
Internet access	0.159	0.230***	−0.161*	0.444***	0.142**	0.020
	(0.112)	(0.088)	(0.097)	(0.092)	(0.068)	(0.082)
Physical capital spending	0.435***	0.598***	0.454***	0.430***	0.383***	0.452***
	(0.103)	(0.080)	(0.087)	(0.088)	(0.067)	(0.079)
International certification	0.377***	−0.058	0.267***	0.191	0.267*	0.323**
	(0.122)	(0.111)	(0.113)	(0.126)	(0.106)	(0.166)
Foreign technology adoption	0.339***	0.177	0.153	0.344	0.412	0.342
	(0.126)	(0.111)	(0.117)	(0.344)	(0.275)	(0.306)
Exporting capacity	0.104	−0.022	−0.072	0.224**	0.018	0.064
	(0.113)	(0.094)	(0.101)	(0.102)	(0.085)	(0.099)
Credit access	0.313***	0.209**	0.306***	0.184*	0.168*	0.162**
	(0.108)	(0.090)	(0.095)	(0.096)	(0.076)	(0.088)
Business-government relations	0.215*	0.133	0.054	0.283***	0.177*	0.233***
	(0.123)	(0.103)	(0.111)	(0.095)	(0.078)	(0.088)
Employee training	0.482***	0.051	0.435***	0.414***	0.322***	0.410***
	(0.106)	(0.089)	(0.094)	(0.089)	(0.070)	(0.082)
Highly skilled workers	0.019	−0.068	0.093			
	(0.143)	(0.104)	(0.116)			
N-Treated	166	448	277	146	400	174
N- Control	1,008	726	897	971	719	945
LR chi2	154.72	117	101.93	106.80	77.69	90
Pro>chi2	0	0	0	0	0	0
Balancing property	Satisfied	Satisfied	Satisfied	Satisfied	Satisfied	Satisfied

Note: Balancing property must be satisfied for generating the P-score; *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.
Source: Authors' computations from the WBES data.

Stratification, and Kernel-based matching. Each treatment firm was compared to the most similar control firm using the P-Score's nearest neighbourhood matching criteria. Further, the study matched each treatment firm to all control firms with greater weight than those with more similar P-Scores in the Kernel matching. Stratification matching balances covariates by finding strata with no difference in mean covariate values. Then those strata are used to calculate differences in means and sum over suitably weighted strata (Cunningham 2021). In radius-based matching, each P-score is matched with the control group units whose propensity scores are in a predefined neighbourhood of the propensity score of the treatment unit. Table 9 reports the matching results, including the Average Treatment Effect on the Treated (ATT), bootstrapped standard errors, and t-test of each treatment.

The matching results in Table 9 reveal that the manufacturing firms' R&D spending, product or service innovation, and process innovation had a positive but insignificant ATT of approximately USD 48,000, USD 34,000, and USD 46,000, respectively. On the other hand, the ATT due to product/service innovation was positive and significant among the service firms using the four matching approaches at 5% and 1%. This result means that participation in product/service innovation would significantly improve the value-added per worker by approximately USD 35,000. Participating in R&D spending and process innovation by service firms had a positive but insignificant ATT of around USD 31,000 and USD 13,000, respectively.

Table 9. Matching Treatment Effects Results.

Treatment	Manufacturing Firms				Service Firms			
Treatment	Nearest Neighborhood Matching	Radius Matching Method (0.1)	Stratification Matching	Kernel-Based Matching	Nearest Neighborhood Matching	Radius Matching Method (0.1)	Stratification Matching	Kernel-Based Matching
A. R&D spending								
ATT.	32,908	59,627	48,712	49,090	36,466	21,464	19,776	48,403
Bootstrapped Std. Error	66,724	58,733	59,880	66,319	36,042	15,299	15,227	32,792
t-statistic	0.493	1.015	0.813	0.740	1.012	1.403	1.299	1.476
B. Prod/serv. innovation								
ATT.	35,645	31,949	35,412	34,848	45,969**	32,676***	30,148***	39,461**
Bootstrapped Std. Error	23,023	20,475	30,279	24,139	18,675	18,818	10,663	15,272
t-statistic	1.548	1.560	1.170	1.444	2.461	2.765	2.827	2.584
C. Process innovation								
ATT.	47,559	48,336	45,956	47,596	26,149	5,317	299	22,175
Bootstrapped Std. Error	36,157	40,327	42,985	38,224	26,313	13,394	13,209	27,695
t-statistic	1.315	1.199	1.069	1.245	0.994	0.397	0.023	0.801

Note: ATT-Average treatment effect on the treated is expected to be significant at 10%, 5%, and 1% significance levels when the t-test statistic is more than 1.64, 1.95, and 2.64, respectively.
Source: Authors' computations from the WBES data.

4.3. Results discussion

SSA firms' productivity is still not at its maximum potential compared with other global areas such as the developed economies. This study argues that firm-level innovation augmented with technical alliances may enhance joint innovations and knowledge sharing, enhancing a firm's productivity. The study's central hypothesis is that notwithstanding the challenges SSA manufacturing and service firms encounter, firm-level R&D and innovation plus technical associations lead to increased innovation outputs that enhance their productivity. Consequently, the study analyzes the counterfactual impact of firm-level innovation on firm productivity.

The results confirm that partnership with other innovation players is crucial in the innovation process. For instance, adopting foreign technology, access to finance, and doing business with the government are significant associations influencing firm-level innovation. In addition, internal drivers of firm-level innovation include employee training and spending on physical capital. The result also indicated that, technical partnerships increased the probability of firm-level innovation to a bigger extent among the manufacturing firms compared to the service firms. Further, the results revealed that R&D spending significantly impacted manufacturing firms' productivity. Service innovation significantly impacted service firms' productivity. On the other hand, product innovation did not matter considerably to the manufacturing firms' productivity, while process innovation significantly affected their productivity. In contrast to service firms, process innovation did not influence their productivity significantly.

The results suggest that manufacturing firms did not realize full benefits from product innovation, while service firms had challenges realizing financial gains from R&D

spending and process innovation. Most R&D spending by manufacturing firms involves novel manufactured products, while a significant share of R&D expenditure by service firms is devoted to developing new and improved processes (Biemans and Griffin 2018). Therefore, when SSA manufacturing firms experience ineffectual product innovation and service firms face ineffective process innovation is an indicator of unrealized R&D and innovation gains. One possible explanation for this result could be the innovation challenges of developing countries discussed in section 2.2, which may hamper full innovation gains. For instance, this could be attributed to the lack of uniqueness of the new innovation, because just a small percentage of innovations in developing countries are new to the world. Sometimes lack of uniqueness may fail to produce a major shift in demand (Egbetokun et al. 2016).

The impact of innovation on firm productivity was not directly comparable to other studies in Africa because no prior studies were virtually available employing programme evaluation methods. However, Empirical literature from other developing and developed regions employing different estimation methodologies indicates that innovation positively impacts firm productivity. For instance, Morsy and Amira (2020), using 52 countries from developing economies and 15 from Africa, found that innovation significantly affected productivity. Using Tobit regression, Fu, Mohnen, and Zanello (2018) found that innovation positively affected formal and informal firms in Ghana. Fazlıoğlu, Dalgıç, and Yereli (2018), who used ESR, found that innovation positively affected firm productivity among Turkish firms. Fiorentino, Longobardi, and Scaletti (2020), who employed a PSM estimation, found that innovation positively affected the productivity of Italian start-up firms.

5. Conclusion, implication to policy, and areas of further research

This paper investigated the impact of innovation on firm productivity using manufacturing and service firms in SSA. Firm-level innovation was measured by R&D spending, product/service, and process innovation. Firm productivity was measured using a firm's value-added per worker, and the study relied upon ESR/PSM estimation methodologies. The study findings indicated some evidence that innovation positively and significantly impacted firms' productivity in SSA. Further results showed that manufacturing firms struggled with product innovation, and service firms experienced difficulties with process innovation. These results suggest that SSA manufacturing firms were experiencing problems converting product innovations into profitable outputs. Similarly, service firms experienced difficulties realizing financial gains from process innovation.

On the other hand, impact evaluation indicates the effectiveness of the intervention measures of a programme. Therefore the study's results also demonstrate the efficacy of firm-level innovation efforts and strategies in SSA during the study period. The results indicate evidence of some innovation measures' positive and significant impact. The results also suggest that manufacturing firms had challenges with product innovation, and service firms had challenges with process innovation. Therefore it can be claimed that firm-level innovation strategies have been somehow effective even though there is potential for improvement to ensure maximum innovation gains are realized from firm-level innovation.

Therefore, there is a need to re-evaluate firm-level innovation strategies in SSA to realize maximum innovation benefits. This study argues that intensified adoption of R&D and semi-endogenous innovation best practices may increase productivity in SSA's manufacturing and service sectors. The implication to the policy of the study findings is that first, other than the conventional factor-driven production, Sub-Saharan African firms have the potential to drive their productivity through firm-level R&D and innovation. Secondly, Technical partnerships are essential, considering that R&D and innovation activities are expensive, notwithstanding the challenges facing SSA's firm being a developing region. For instance, developing regions such as the SSA are characterized by volatile business, market, and political environments, affecting the maximum productivity of firms. Therefore, effective technical partnerships among the innovation actors in SSA can help stimulate more firms to participate in R&D and innovation activities, significantly reduce the cost of R&D and innovation to firms, and simultaneously maximize innovation benefits in the region (African Union–New Partnership for Africa's Development, 2014).

Finally, this study experienced a few challenges- a common occurrence with many technical studies- raising further areas for future research. First is the high degree of missing observation on some variables in the available data sets. Secondly, due to the nature of WBES, it was impossible to create pseudo panel data for the Sub-Saharan African firms. Lastly, the ESR/PSM estimation methods have their limitations. Due to these limitations, future research avenues arise. First, to analyze counterfactual innovation impacts using extensive panel data and robust panel data models such as the Generalized Method of Moments (GMM), Difference in Differences (DID), and fixed and random-effects models. Secondly, to use a comprehensive, robust dataset to analyze innovation impacts on all economic agents using full general equilibrium models such as Bayesian approaches.

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