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How Supply Chain Integration Affects Innovation in a Digital Age: Moderating Effects of Sustainable Policy

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Abstract: With the rapid development of digital technologies and increasing public attention on environmental problems, it has become a new challenge for global enterprises to manage supply chains responsibly, so as to improve their innovation performance for sustainability. Prior works have identified the effects of supply chain integration on firm innovation in advanced economies; however, so far, there has been limited research on the relationships between supply chain integration and firm innovation in emerging and developing countries. Hence, building upon transaction cost and resource dependence theories, this study used China's manufacturing industry as the research setting, probing the dynamic mechanisms between supply chain integration and firm innovation. The results show that the degree of supply chain integration positively relates to firms' patent output but negatively relates to their innovation efficiency, and that a sustainable policy moderates the foregoing associations. Our study enriches the body of knowledge regarding responsible supply chain integration in a new digital age with growing ecological concerns and thereby offers insightful practical implications for practitioners and policy makers.

Keywords: supply chain integration; policy; innovation efficiency; sustainable development; patent

1. Introduction

The continuous degradation of the ecological environment has gained an increasing amount of attention from global enterprises in recent years. Thus, promoting the sustainable development of the supply chain by strengthening energy-saving measures and corporate social responsibility (CSR) has become an important topic [1,2]. The conventional concept of supply chain integration (SCI) refers to the degree to which a manufacturer, with the aim of reducing costs as well as enhancing efficiency and economic value, strategically collaborates with its various partners (e.g., suppliers, customers, and other stakeholders) by integrating their materials, information, and capital flows and synchronizing their inter- and intraorganizational processes into a more comprehensive system [3]. Traditionally, SCI did not place much emphasis on CSR concerns. However, as mentioned at the outset, the implementation of environmental and social policies in SCI has become a prominent trend nowadays [2], and the governments of many countries have enacted policies to support the establishment of sustainable supply chains [4]. It is thus vital to further investigate the effect of sustainable policies on SCI-related issues in this new era.

In the past, SCI, which comprises planning, sourcing, production, and distribution, often required some time to configure and integrate different types of resources [5]. However, with the rise of Industry

Version 4.0, various types of advanced technologies, for example, cloud computing, big data, and block chain, have largely simplified the complex structure and accelerated the speed of SCI [3–5]. In this vein, focal companies of the supply chain today are expected to more easily draw on the integration of a wide range of knowledge and information at the global level to conduct innovation. Nevertheless, hitherto existing evidence regarding SCI-innovation associations mostly comes from the manufacturing industry of developed countries, and research focusing on developing or emerging economies is still limited [6,7]. Given that quite a few emerging and developing nations with the advantage of a large amount of surplus labor (e.g., India, China, and Vietnam) have gained increasing importance in global supply chains [7], it is imperative to obtain a better understanding of the impact of SCI upon firm innovation in such a context.

Considering the foregoing arguments, the main purpose of this paper is to fill the above-mentioned gap by exploring the mechanisms among SCI, firm innovation, and sustainable policies within a non-developed, highly digitalized context with growing ecological concerns. As China is the world's biggest emerging economy and there is an ongoing transformation of this nation's manufacturing industry, we used China's manufacturing sector as the background to conduct our research. It is worth noting that the Chinese government always plays a dominant role in the allocation and distribution of crucial resources to firms by launching policies [1,6,7]. We thus also tested the moderating effect of the most relevant sustainable policy (i.e., strategic emerging industry policy in our case) on SCI–innovation relations.

Overall, this study makes three main contributions: First, incorporating the perspectives of transaction cost and resource dependency, we provide valuable evidence from a non-Western context (i.e., China), thus enriching the body of knowledge regarding how responsible management of SCI (i.e., responsible SCI), which refers to broadening the boundaries of companies' social responsibilities to their SCI [2], impacts firm innovation in such a new digital era riddled with CSR concerns. Second, to a certain extent, we distinguish "innovation quality" from "innovation quantity" by using both "innovation efficiency" and "patent output" as our measures, which deepens our understanding of relevant issues. Third, we examine the moderating effect of China's recent sustainable policy on SCI-innovation mechanisms, thereby offering insightful practical implications for practitioners and policy makers.

2. Literature Review and Hypotheses Development

2.1. SCI and Innovation With Ecological Concerns: Resource Dependency and Transaction Cost Theories

In terms of SCI practice, traditionally, there was usually one large-size enterprise (mostly a famous brand or a multinational corporation) as a focal organization to preside over the entire supply chain process, which covered raw material procurement, manufacturing and assembly of finished products, transportation of products, and delivery to the end user [4,5]. Such SCI in general pays particular attention to the process-oriented internal synthesis of production, logistics, and marketing activities within or dominated by the leading/core firm [8]. However, along with the coming of the new digital age, advanced technologies have enabled firms to synchronously share and process a massive amount of information and knowledge across organizational and national borders. More specifically, all functional units within the supply chain can be integrated into a more complex virtual system in which research and development (R&D), manufacturing, logistics, and marketing activities are completed through the coordination of a variety of independent modules that include one or more organizations [8,9]. This new, modern type of SCI often involves both internal (e.g., intraorganizational integration) and external (e.g., customer and supplier integration) dimensions [5], whereby firms can concentrate on their specialized areas and complete other functions through strategic alliance and cooperation with diverse partners along the supply chain. Such SCI goes beyond organizational boundaries, thus enabling firms to effectively avoid making costly (and probably risky) investments, particularly those highly asset-specific and customized ones because not all critical activities and services need to be carried out independently in-house [8–10].

To a certain extent, the foregoing arguments echo the perspective of the transaction cost theory (TCT) [11], which has been used to explain how the focal/leading company of the supply chain, based on the associated transaction costs, decides whether a specific activity (e.g., design, manufacture, and logistics) as an economic exchange should be managed internally within the organization or contracted out to its external strategic partner (i.e., outsourcing) [12]. The literature also indicates that the resource dependence theory (RDT) [11] can be employed to address why some focal firms of the supply chain decided not to increase dependence on external strategic partners for expense saving but to invest in keeping key resources in their own hands to create distinctive competitive advantages [13–15]. Due to the popularity of digitalized SCI coupled with rising ecological considerations, when engaging in innovation, leading firms of the supply chain have to confront new challenges about how to achieve a better trade-off between reducing transaction costs and gaining more critical resources over rivals. Taking into account the foregoing contentions, TCT and RDT can be deemed as two important perspectives for investigating the relationship between SCI and firm innovation. We therefore applied TCT and RDT to develop our theoretical logic presented below.

2.2. Hypotheses Development

It is widely recognized that R&D efficiency and number of patents are key indicators to measure innovation performance in the supply chain [15–19]. However, in terms of the relationships between SCI and firm innovation, the current research shows inconsistent results. For instance, Lahiri et al. (2013) claimed that the level of SCI is negatively related to focal firms' patent numbers but positively related to their net incomes [18]. Li et al. (2010) discovered that the SCI level of information technology (IT) enterprises has an inverted U-shaped relationship with the quality level of patents [19]. Such discrepancies may be attributed to the crucial challenges caused by the deepening of the green supply chain concept coupled with the popularization of the Internet and technology. On the one hand, this leads focal firms to more easily manage their strategic partners and to increase the sustainability of their supply chains; on the other hand, this also implies a huge amount of investment into the implementation of more stringent environmental standards that may increase operation risks.

China's manufacturing sector, where industrial upgrading has led firms to build new digital platforms for SCI, is suffering from increasingly critical environmental pollution issues. Manufacturing firms in this context are confronted with serious pressure to coordinate CSR and commercial performance. According to the TCT, the growing prominence of ecological concerns in SCI coupled with the emerging trend of digitalization indicates that more asset-specific investments and rising transaction costs related to CSR and IT are required in the economic exchanges among supply chain partners. Firms must introduce new digital technology with environmental and social considerations by recruiting knowledgeable IT specialists and purchasing environmentally friendly equipment. Hence, it is plausible that the R&D time and expenses during the integration of the supply chain will increase, and SCI may thereby exert a negative impact on firm innovation efficiency. We thus posit.

Hypothesis 1a. *In Chinese manufacturing, SCI negatively relates to firm innovation efficiency. Nevertheless, from the perspective of RDT, with the use of advanced digital technologies, leading enterprises today can effectively combine the diversified resources of its stakeholders at the early phase of product R&D, at which point it may be easier to overcome the institutional constraints of immature markets and to create worldwide competitive advantages in a more green, sustainable way [20,21]. Adhering this logic, some aspiring entrepreneurs in Chinese manufacturing have indeed sought a long-term superior position by making best use of their vital resources to create distinctive competitive advantages that are difficult to imitate and replicate, such as producing and acquiring patents with ecological awareness (e.g., products that reduce energy consumption or can be recycled) [22,23]. More specifically, the logic of the RDT allows us to further argue that the quality of innovation as a more valuable, rare, and not easily substituted resource is more important than the quantity of innovation in*

SCI nowadays. It is plausible that the prevalence of achieving sustainable SCI may encourage firms to create more product patents. We thus hypothesize the following:

Hypothesis 1b. *In Chinese manufacturing, SCI positively relates to firm patent outcome.*

Our research framework is shown as Figure 1.

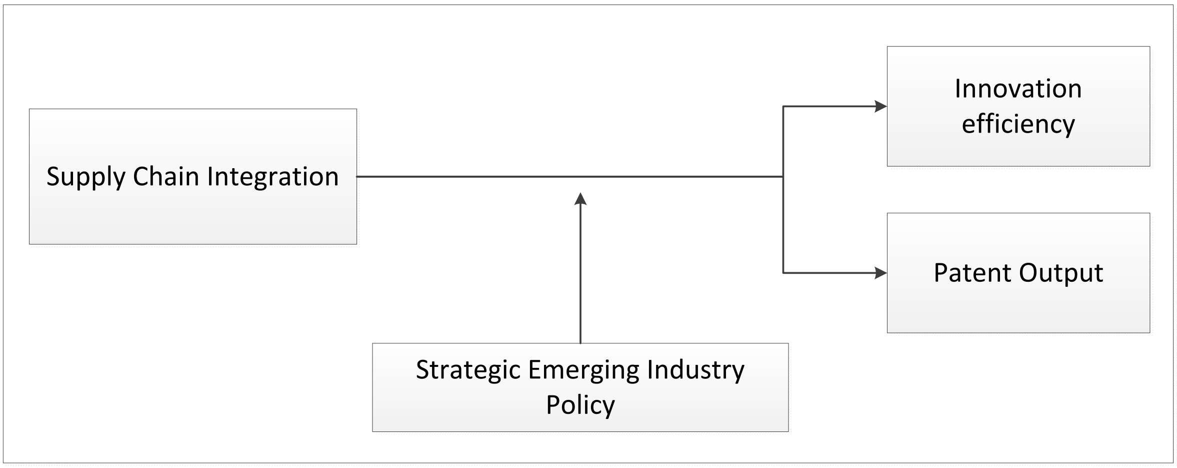

Figure 1. Conceptual Framework.

2.3. The Moderating Effect of Sustainable Policy on SCI–Innovation Relations

In terms of the Chinese manufacturing sector, the central government promulgated the strategic emerging industry policy in 2010, in which the establishment and responsible management of sustainable supply chains has been seen as one of the strategic priorities [24]. This sustainable policy, which requires firms to fully comply with more stringent environmental standards, provides strong support to nine industries characterized by low material and resource consumption, as well as high growth potential and comprehensive benefits (i.e., new-generation IT industry, high-end equipment manufacturing industry, new materials industry, biological industry, new-energy automotive industry, new-energy industry, energy-saving and environmental protection industry, digital creative industry, and relevant services industry). Echoing this policy, China's manufacturing sector has paid a considerable amount of attention to the implementation of green supply chain management [25,26].

It is widely recognized that in China's unique institutional environment, the government always intervenes in the market by means of industrial policy that controls the distribution and allocation of critical natural resources [22,23]. According to the RDT, it is thus imperative for Chinese organizations to abide by the newly launched policies as soon as possible, so as to gain access to scarce and valuable strategic resources from the government for innovation and competition [23–26]. However, evidence also shows that in order to take greater advantage of the policy, some firms may frequently choose to engage in rent-seeking behaviors rather than dedicating themselves to the public welfare [26,27]. Scholars indicate that in China, excessive governmental interference into the market mechanism sometimes elicits quite a few side effects that often impede organizational innovation and even lead to political corruption [5,23]. In light of these debates, we contend that industrial policies may kindle or hinder corporate innovation in the Chinese context, which is a topic that requires further, deeper investigation.

As far as the relationship between SCI and firm innovation is concerned, some scholars have employed the TCT to discuss relevant issues in the Chinese context. For instance, Yang et al. (2015), based on a sample from the Bohai Rim region of China [28,29], and Julan et al. (2012), using the World Bank database of the Chinese manufacturing industry [25], both discovered that in an emerging market such as China, where the protection of intellectual property rights and asset specificity are weak and contract enforcement is imperfect, SCI is conducive to reducing transaction costs and the potential for opportunism. This is because SCI helps firms to act more agilely and to adapt more quickly to the ongoing technological changes and economic uncertainties; thus, they can better secure innovation outcomes [26].

China's strategic emerging industry policy allocates and directs abundant public resources to specifically selected industries and organizations according to the government's preference. Firms that are supported by such policies in general enjoy various tax exemption treatments and fiscal subsidies and have unique competitive advantages for innovation. Considering the foregoing discussion, we thus argue that the strategic emerging industry policy, as an important sustainable policy, may moderate SCI–innovation relationships:

Hypothesis 2a. *The sustainable policy moderates the negative relationship between SCI and firm innovation efficiency, such that the negative SCI–innovation relationship is stronger in the presence of the sustainable policy;*

Hypothesis 2b. *The sustainable policy moderates the positive relationship between SCI and firm patent outcome, such that the positive SCI–patent relationship is stronger in the presence of the sustainable policy.*

3. Research Design and Methodology

3.1. Sample Selection

We used a sample of the listed companies in China's manufacturing sector at the Shanghai and Shenzhen stock exchanges from 2011 to 2017. Raw data were selected from the Win.d database (please refer to https://www.wind.com.cn/en/Default.html) and supplemented by the China Stock Market & Accounting Research Database (CSMAR). Win.d is a renowned financial data and analytics tool provider which helped us obtain comprehensive corporate financial information, as its database includes more than 90% of Chinese listed enterprises. To control for extraneous variance, we referred to previous research [30], excluding financial companies (e.g., insurance companies and banks), nonprofit organizations, and special treatment (ST) companies. Also, companies with missing variable data were eliminated. We finally obtained 1722 usable data points for formal analysis and trimmed all the firm-level variables at the 1st and 99th percentiles to avoid outliers that would have distorted our results.

3.2. Measures

3.2.1. Dependent Variables

Referring to previous research [31], we used innovation efficiency (labeled PTE) and the proportion of the number of a firm's authorized patents to the average number of granted patents per firm in the manufacturing sector (labeled GPA11) to measure firm innovation performance.

The method of data envelopment analysis (DEA) was first proposed by Charnes et al. (1978) [32]. It is a non-parametric mathematical programming method using linear programming and convex analysis as tools to calculate the relative efficiency between the evaluated units [33]. Considering that there exist multiple inputs and outputs in a real production situation, the DEA method, which is capable of offering a comprehensive optimal input–output scheme out of the decision-making unit, is especially appropriate for measuring innovation efficiency [34,35].

In light of Bai's (2011) study [36], we created an aggregate patent measure (labeled GPA) with three indicators to evaluate firms' total innovation output. Three indicators (i.e., invention, utility model, and design patents) were given weights of 0.5, 0.3, and 0.2, respectively.

3.2.2. Independent Variable

Referring to previous research [19], SCI level (labeled VI) was measured as shown below:

$$VI = VAS = \frac{\text{Added value}}{\text{Total output}}. \quad (1)$$

3.2.3. Moderator

Based on the main business activities and product portfolios disclosed in the annual reports, a firm supported by the strategic emerging industry policy was coded as 1; otherwise, it was coded as 0 (labeled IP).

3.2.4. Control Variables

Referring to prior studies [6,37], we controlled for the following variables: earnings before interest and tax (labeled EBIT), operating cash flow (labeled CF), property nature (labeled property), company age (labeled age), firm size (labeled size), long-term debt ratio (labeled Lev), sales expense (labeled Adv), R&D expense (labeled RDs), and return on equity (labeled ROE). Referring to the literature [38–40], we also controlled for complementary assets (labeled CAS), which are believed to influence firm innovation performance.

3.3. Model Specification

According to the theoretical hypotheses, we constructed the following two regression models (please refer to Table 1 for more details).

Table 1. Definitions of variables.

Variable		Definition and Measurement
Dependent Variables	PTE	Innovation efficiency is calculated by the DEA method as illustrated above.
	GPA11	The proportion of the number of a firm's authorized patent to the average number of the granted patents per firm in the manufacturing sector as described above.
	GPA_invent	The number of invention patent authorizations.
	GPA_design	The number of design patent authorizations.
	GPA_utility	The number of utility model patent authorizations.
Independent Variable	VI	The degree of SCI, VI = VAS = added value/total output.
Moderator	IP	Firm supported by the policy is 1 and 0 otherwise (dummy variable).
Control Variables	EBIT	Earnings before interest and tax, EBIT = Earnings before interest and tax/operating income.
	CF	Operating cash flow, CF = operating cash flow/total assets.
	CAS	complementary assets, CAS = (machine and equipment value + sales expense + cash paid to and for staffs)/commodity and labor cash incomes
	Property	Property nature, which is 1 for state-owned enterprises and 0 otherwise.
	Age	Company age, Age = (observation year − incorporation year) + 1.
	Size	Enterprise size, size = ln total assets.
	Lev	Long-term debt ratio, Lev = long-term debts/assets.
	Adv	Sales expense, Adv = sales expense/operating income.
	ROE	Return on equity, ROE = net returns/net assets.
	RDs	R&D expense, RDs = R&D expense/operating income.

Model 1 was built for testing Hypotheses 1a and 1b. The standard error of robustness was adopted to avoid heteroskedasticity [41,42]:

$$\begin{aligned} PTE_{i,t}/GPA_{i,t} &= \alpha_0 + \alpha_1 VI_{i,t} + \alpha_2 EBIT_{i,t} + \alpha_3 CF_{i,t} + \alpha_4 CAS_{i,t} + \alpha_5 Property_{i,t} \\ &+ \alpha_6 Age_{i,t} + \alpha_7 Size_{i,t} + \alpha_8 Lev_{i,t} + \alpha_9 Adv_{i,t} + \alpha_{10} ROE_{i,t} + \alpha_{11} RDs_{i,t} \end{aligned} \tag{2}$$

Model 2 was built for testing Hypotheses 2a and 2b. VI* IP, as the interaction term, represents the moderating effect. If the result of α_1 is significant, the moderating effect is valid:

$$\begin{aligned} \frac{PTE_{i,t}}{GPA_{i,t}} &= \alpha_0 + \alpha_1 VI_{i,t} \times IP_{i,t-1} + \alpha_2 VI_{i,t} + \alpha_3 IP_{i,t-1} + \alpha_4 EBIT_{i,t} + \alpha_5 CF_{i,t} \\ &+ \alpha_6 CAS_{i,t} + \alpha_7 Property_{i,t} + \alpha_8 Age_{i,t} + \alpha_9 Size_{i,t} + \alpha_{10} Lev_{i,t} \\ &+ \alpha_{11} Adv_{i,t} + \alpha_{12} ROE_{i,t} + \alpha_{13} RDs_{i,t} \end{aligned} \tag{3}$$

In Models 2 and 3, $PTE_{i,t}$ is the innovation efficiency of firm i at period t; $GPA11_{i,t}$ is the proportion of the number of a firm's authorized patents to the average number of the granted patents per firm in the manufacturing sector; $VI_{i,t}$ is the degree of SCI of firm i at period t; and $EBIT_{i,t}$, $CF_{i,t}$, $CAS_{i,t}$, $Property_{i,t}$, $Age_{i,t}$, $Size_{i,t}$, $Lev_{i,t}$, $Adv_{i,t}$, $ROE_{i,t}$, and $RDs_{i,t}$ represent earnings before interest and tax, operating cash flow, complementary assets, property nature, enterprise age, enterprise size, long-term debt ratio, sales expense, return on equity, and R&D expense of firm i at period t, respectively (please refer to Table 1). In addition, in Model 3 $IP_{i,t-1}$ is the policy support of firm i at period t − 1.

Scholars argue that a hysteresis effect should be taken into consideration in the relationship between policy implementation and firm performance [43]. Therefore, we lagged all variables for one year to examine the impact of the sustainable policy on corporate innovation output.

PTE (innovation efficiency); the proportion of the number of a firm's authorized patents to the average number of the granted patents per firm in the manufacturing sector as described above (GPA11); VI (supply chain integration); IP (strategic emerging industry policy virtual variable); EBIT (earnings before interest and tax); CF (operating cash flow); CAS (complementary assets); property (property nature); Age (company age); Size (enterprise scale); Lev (long-term debt ratio); Adv (sales expense); ROE (return on equity); RDs (R&D expense).

4. Empirical Analysis

4.1. Descriptive Statistics

Table 2 reports information and descriptive results of the main variables. As Table 2 shows, the mean value of PTE was 0.081, its standard deviation was 0.108, the minimum value was 0.003, and the maximum value was 0.742. These results indicate that the innovation efficiency of our sample firms is generally low. However, the mean of GPA11 was 1.345 and the standard deviation was 2.569, indicating there may be large differences among the samples in terms of patent output. As for the control variables, the standard deviations of enterprise age and scale were 4.437 and 1.154, respectively. This shows that the age and size of the enterprise are quite different among the sample companies, and that the age difference of the enterprise is greater than the difference of the scale of the enterprise.

Table 2. Statistic description of related variables.

Variable	Observation Value	Mean Value	Standard Deviation	Minimum Value	Maximum Value
PTE	1418	0.0806062	0.1076341	0.00338	0.742187
GPA11	1425	1.345114	2.569318	0	19.4731
VI	1405	0.1491569	0.0694938	0.019481	0.4085363
IP	1441	0.5100625	0.5000723	0	1
Moderator	1405	0.0764787	0.0876301	0	0.4085363
EBIT	1409	0.0698222	0.0851894	−0.143194	0.5788783
CF	1416	0.042758	0.0607939	−0.138388	0.2417022
CAS	1410	0.6096447	0.3899659	0.0586145	2.351202
Property	1441	0.6766135	0.4679312	0	1
Age	1441	18.93963	4.436571	5	38
Size	1414	22.53074	1.154382	20.05804	25.94896
Lev	1427	0.0827147	0.0763854	0	0.3315441
Adv	1411	0.0685278	0.0767476	0.00282	0.4277569
ROE	1410	0.0712884	0.0852229	−0.297101	0.3617772
RDs	1401	0.0278511	0.01875	0.0005302	0.1010012

4.2. Regression Result Analysis

Table 3 shows the models addressing the SCI–innovation relationships and the moderating effects of the sustainable policy on such relationships.

Table 3. Regression results.

Variable	Innovation Efficiency (Model 1a)	Patent Output (Model 1b)	Innovation Efficiency (Model 2a) With Moderator	Patent Output (Model 2b) With Moderator
Moderator			−0.269 *** −0.0714	−3.208 * −1.6400
IP			0.0492 *** −0.0138	0.545 * −0.2960
VI	−0.223 *** −0.0631	3.779 ** −1.5490	−0.110 * −0.0651	5.143 *** −1.4100
EBIT	−0.114 *** −0.0366	−5.190 *** −0.8690	−0.117 *** −0.0369	−5.213 *** −0.8650
CF	−0.108 ** −0.0515	−4.168 *** −1.0450	−0.100 * −0.0512	−4.103 *** −1.0560
CAS	−0.0406 *** −0.0072	−0.985 *** −0.1390	−0.0385 *** −0.0072	−0.971 *** −0.1400
Property	−0.0117 * −0.0067	−0.1420 −0.1150	−0.0110 * −0.0066	−0.1360 −0.1150
Age	−0.0007 −0.0007	−0.0102 −0.0144	−0.0006 −0.0007	−0.0091 −0.0144
Size	0.0110 *** −0.0035	1.163 *** −0.0906	0.00975 *** −0.0036	1.151 *** −0.0941
Lev	−0.0078 −0.0458	0.7450 −1.0070	−0.0089 −0.0451	0.7380 −1.0030
Adv	0.0202 −0.0284	−0.7930 −0.5090	0.0238 −0.0284	−0.7670 −0.5110
ROE	0.198 *** −0.0489	3.998 *** −1.4240	0.217 *** −0.0505	4.186 *** −1.4720
RDs	0.1410 −0.1570	25.84 *** −3.7440	0.0958 −0.1620	25.49 *** −4.0530
Constant	−0.0964 −0.0766	−24.99 *** -2.0660	−0.0948 −0.0785	−25.01 *** −2.0960
Observations R^2	1220.0000 0.0780	1229.0000 0.3500	1220.0000 0.0870	1229.0000 0.3520

Note: (1) The upper figure is the estimation coefficient and the lower figure is the cluster robustness standard error in the table; (2) ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively.

Models 1a and 1b explain the associations between SCI and firm innovation performance. In Model 1a, we ran an Ordinary Least Square (OLS) model to test the effect of SCI on PTE and discovered that the coefficient of VI was significantly negative (α = –0.223, $p < 0.001$). Hypothesis 1a is thus supported. In Model 1b, we tested the effect of SCI on GPA11, and the coefficient of VI was found to be significantly positive (α = 3.779, $p < 0.05$). The results provide support for Hypothesis 1b.

Models 2a and 2b explain the moderating effect of the sustainable policy on the SCI–innovation associations. In order to introduce the moderator, all main variables were mean-centered. Taking a closer look at our models, we found that the model fit of Model 2a and 2b (R^2 = 0.08 and 0.352, respectively) was better than that of Model 1a and 1b (R^2 = 0.078 and 0.350, respectively). As Model 2a shows, the regression coefficient of the moderator was significantly negative (α = –0.269, $p < 0.001$), while Model 2b reveals that the regression coefficient of the moderator was significantly negative (α = –3.208, $p < 0.1$). We therefore validated the moderating effects of the strategic emerging industry policy on both SCI–PTE and SCI–GPA11associations. Hypotheses 2a and 2b are supported as well.

In order to more clearly characterize the moderating mechanisms, simple slope tests were used to evaluate whether the relationship (slope) between SCI and innovation performance is significant at a particular value of our moderator. To perform the simple slope test, the slope itself was calculated by substituting the value of our moderator into the regression equation. Figure 2 shows that the support of the strategic emerging industry policy can weaken the negative correlation of SCI and innovation efficiency. Figure 3 shows that SCI and patent output have stronger positive correlations with the presence of the strategic emerging industry policy. Our hypotheses are further validated.

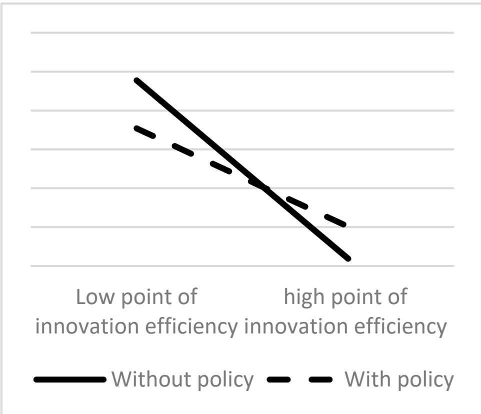

Figure 2. Regulatory effects of SCI-PTE.

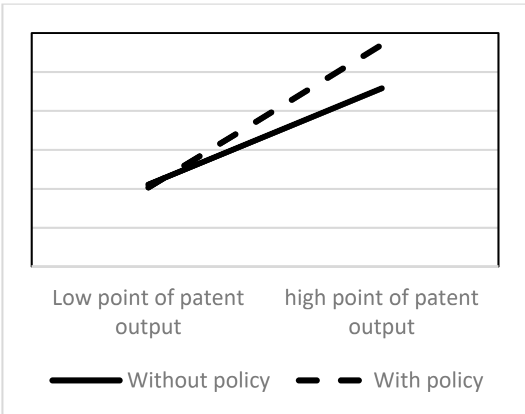

Figure 3. Regulatory effects of SCI-GPA11.

Regarding the control variables, earnings before interest and tax (EBIT) and complementary assets (CAS) had a significant negative correlation with innovation efficiency, and enterprise size (Size) and return on equity (ROE) had a significant positive correlation with innovation efficiency in Models 1a and 2a. In Models 1b and 2b, earnings before interest and tax (EBIT) and complementary assets

(CAS) had a significant negative correlation with innovation patent output, and enterprise size (Size), return on equity (ROE), and R&D expense (RDs) had a significant positive correlation with innovation patent output.

4.3. Robustness Check

In order to enhance the methodological rigor, we double-checked the model fit and accuracy of our OLS regression results by employing another two statistical techniques to validate our assumptions. Considering our variable "patent output" (GPA11) is zero-inflated count data, we built a zero-inflated Poisson regression model to re-examine part of our findings on patent output [44], whereas the Tobit analysis may complement the deficiency of the OLS model in terms of measuring production and innovation efficiency [45]; we thus also employed the Tobit approach to further verify our findings on innovation efficiency (PTE). In Table 4, Models 1a and 2a show the results of the Tobit regression analysis while Models 1b and 2b show the results of the zero-inflated Poisson regression model. According to Models 1a, 2a and 1b, H1a ($p < 0.01$), H2a ($p < 0.01$) and H1b ($p < 0.05$) are fully supported; although H2b ($p > 0.1$) is not supported, the correlation direction is still the same. Given the foregoing outcomes, we argue that it is appropriate to proceed to conduct the robustness check.

Table 4. Alternative Approaches.

Variable	Innovation Efficiency (Model 1a)	Patent Output (Model 1b)	Innovation Efficiency (Model 2a) With Moderator	Patent Output (Model 2b) With Moderator
Moderator			−0.269 *** −0.085	−1.372 −1.837
IP			0.0492 *** −0.0143	1.333 −529.1
VI	−0.223 *** −0.0718	2.664 ** −1.339	−0.11 −0.0799	3.672 * −1.899
EBIT	−0.114 ** −0.0526	−1.934 * −1.172	−0.117 ** −0.0524	−2.005 * −1.176
CF	−0.108 * −0.0572	0.772 −0.72	−0.100 * −0.0571	0.81 −0.721
CAS	−0.0406 *** −0.00838	0.184 −0.257	−0.0385 *** −0.00839	0.174 −0.257
Property	−0.0117 * −0.00639	0.311 −607.2	−0.0110 * −0.00636	0.169 −630.6
Age	−0.000695 −0.000698	−0.0903 *** −0.0287	−0.000557 −0.000696	−0.0898 *** −0.0287
Size	0.0110 *** −0.00293	0.840 *** −0.158	0.00975 *** −0.00295	0.846 *** −0.158
Lev	−0.00777 −0.0451	−0.462 −0.64	−0.00886 −0.0449	−0.54 −0.648
Adv	0.0202 −0.0394	0.317 −2.391	0.0238 −0.0392	0.409 −2.39
ROE	0.198 *** −0.0658	−1.552 * −0.87	0.217 *** −0.0657	−1.533 * −0.87
RDs	0.141 −0.159	1.374 −2.961	0.0958 −0.161	1.405 −2.959
Constant	−0.0964 −0.0676	−0.339 −531.8	−0.0903 −0.0678	−0.744 −529.9
Observations	1220	1222	1220	1222

Note: (1) The upper figure is the estimation coefficient and the lower figure is the cluster robustness standard error in the table; (2) ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively.

In order to check the sensitivity of our findings to the changes of the values of the key variables [46], three types of robustness checks were conducted to further validate our results. First, scholars have suggested adopting more diversified scales to evaluate firm innovation efficiency and performance, so as to draw more convincing conclusions [47–50]

As shown in Table 5, we thus used two different variables to measure innovation performance, namely, the proportion of the number of patent authorizations to the R&D input (labeled Effc), and the number of total patent authorizations (labeled GPA) to replace original innovation efficiency and patent output variables. Second, as mentioned above, due to the presence of time hysteresis, a longer lag period should be taken into consideration when measuring SCI–innovation associations [51] and confirming the moderating effect of policy implementation on such relations [52]. Hence, as shown in Table 6, we used two-year lag data (from 2012 to 2017) to test the hypotheses. Third, for the sake of prudence, as shown in Table 7, we combined the two methods described above.

Table 5. Robustness Check 1.

Variable	Innovation Efficiency (Effc)	Patent Output (GPA)	Innovation Efficiency (Effc) With Moderator	Patent Output (GPA) With Moderator
Moderator			-7.72×10^{-7} *** -2.62×10^{-7}	−82.94 *** −28.7
IP			1.95×10^{-7} *** -4.78×10^{-8}	14.89 *** −5.249
VI	-6.00×10^{-7} ** -2.48×10^{-7}	59.77 ** −24.54	-2.75×10^{-7} -2.41×10^{-7}	94.91 *** −24.45
EBIT	2.13×10^{-7} -1.63×10^{-7}	−83.33 *** −16.12	1.85×10^{-7} -1.59×10^{-7}	−84.08 *** −16.15
CF	-3.29×10^{-7} * -1.85×10^{-7}	−55.88 *** −18.74	-2.64×10^{-7} -1.87×10^{-7}	−53.51 *** −18.78
CAS	2.49×10^{-8} -2.99×10^{-8}	−18.20 *** −2.558	3.80×10^{-7} -3.04×10^{-8}	−17.71 *** −2.585
Property	-2.07×10^{-8} -2.36×10^{-8}	−3.555 −2.198	-1.62×10^{-8} -2.33×10^{-8}	−3.378 −2.208
Age	-4.44×10^{-9} -2.73×10^{-9}	0.185 −0.283	-3.83×10^{-9} -2.70×10^{-9}	0.22 −0.284
Size	-5.48×10^{-8} *** -1.17×10^{-8}	20.68 *** −1.484	-6.19×10^{-8} *** -1.15×10^{-8}	20.31 *** −1.513
Lev	-3.31×10^{-7} ** -1.31×10^{-7}	24.04 −18.12	-3.14×10^{-7} ** -1.28×10^{-7}	24.21 −17.93
Adv	5.51×10^{-8} -1.15×10^{-7}	−20.01 ** −9.426	7.90×10^{-8} -1.14×10^{-7}	−19.12 ** −9.493
ROE	1.35×10^{-7} -2.58×10^{-7}	62.91 *** −22.98	1.85×10^{-7} -2.56×10^{-7}	67.78 *** −23.66
RDs	-6.30×10^{-6} *** -7.40×10^{-7}	465.3 *** −62.11	-6.67×10^{-6} *** -7.52×10^{-7}	451.7 *** −65.96
Constant	1.84×10^{-6} *** -2.71×10^{-7}	−449.5 *** −33.69	1.89×10^{-6} *** -2.67×10^{-7}	−449.0 *** −34.04
Observations	1240	1224	1240	1224
R^2	0.125	0.357	0.14	0.362

Note: (1) The upper figure is the estimation coefficient and the lower figure is the cluster robustness standard error in the table; (2) ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively.

Table 6. Robustness Check 2.

Variable	Innovation Efficiency (PTE)	Patent Output (GPA11)	Innovation Efficiency (PTE) with Moderator	Patent Output (GPA11) with Moderator
Moderator			−0.283 *** −0.0712	−3.382 ** −1.47
IP			0.0457 *** −0.0134	0.45 −0.294
VI	−0.167 *** −0.0595	3.796 *** −1.13	−0.0537 −0.0625	5.138 *** −1.213
EBIT	−0.104 *** −0.0342	−4.711 *** −0.852	−0.105 *** −0.0345	−4.698 *** −0.85
CF	−0.121 ** −0.0539	−4.094 *** −1.073	−0.117 ** −0.0542	−4.116 *** −1.088
CAS	−0.0458 *** −0.00712	−1.083 *** −0.127	−0.0448 *** −0.0072	−1.089 *** −0.131
Property	−0.0119 * −0.00637	-1.38×10^{-1} -1.14×10^{-1}	−0.0113 * −0.00633	-1.35×10^{-1} -1.14×10^{-1}
Age	−0.000889 −0.000789	−0.0148 −0.0155	−0.000774 −0.000793	−0.014 −0.0156
Size	0.0131 *** −0.00347	1.182 *** −0.0917	0.0122 *** −0.00357	1.178 *** −0.0965
Lev	−0.00338 −0.0438	0.779 −0.995	−0.00488 −0.043	0.745 −0.989
Adv	−0.0235 −0.0245	−1.209 *** −0.465	−0.0216 −0.0245	−1.224 *** −0.469
ROE	0.156 *** −0.0478	2.795 ** −1.281	0.173 *** −0.0489	2.965 ** −1.302
RDs	0.281 * −0.152	28.05 *** −3.801	0.25 −0.155	28.15 *** −4.147
Constant	−0.144 * −0.0775	−25.38 *** −2.1	−0.147 * −0.0796	−25.50 *** −2.154
Observations	1219	1232	1219	1232
R^2	0.092	0.357	0.101	0.359

Note: (1) The upper figure is the estimation coefficient and the lower figure is the cluster robustness standard error in the table; (2) ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively. (3) The time period of this regression is 2012–2017.

Table 7. Robustness Check 3.

Variable	Innovation Efficiency (Effc)	Patent Output (GPA)	Innovation Efficiency (Effc) Introduction of Moderator	Patent Output (GPA) Introduction of Moderator
Moderator			-5.60×10^{-7} *** -1.93×10^{-7}	−94.61 *** −29.27
IP			1.38×10^{-7} *** -3.57×10^{-8}	15.99 *** −5.472
VI	-5.77×10^{-7} *** -2.00×10^{-7}	70.11 *** −22.17	-3.48×10^{-7} * -1.83×10^{-7}	107.8 *** −24.15
EBIT	3.86×10^{-8} -9.73×10^{-8}	−79.96 *** −16.41	2.33×10^{-8} -9.49×10^{-8}	−80.32 *** −16.54
CF	-2.39×10^{-7} -1.49×10^{-7}	−69.58 *** −20.77	-1.92×10^{-7} -1.52×10^{-7}	−67.35 *** −20.83

Table 7. *Cont.*

Variable	Innovation Efficiency (Effc)	Patent Output (GPA)	Innovation Efficiency (Effc) Introduction of Moderator	Patent Output (GPA) Introduction of Moderator
CAS	1.04×10^{-8} -2.59×10^{-8}	−21.98 *** −2.611	1.91×10^{-8} -2.65×10^{-8}	−21.63 *** −2.657
Property	3.93×10^{-9} -1.63×10^{-8}	−4.072 * −2.306	6.97×10^{-9} -1.62×10^{-8}	−3.890 * −2.306
Age	-5.05×10^{-9} ** -2.26×10^{-9}	0.109 −0.341	-4.63×10^{-9} ** -2.24×10^{-9}	0.147 −0.342
Size	-4.04×10^{-8} *** -1.19×10^{-8}	22.79 *** −1.619	-4.57×10^{-8} *** -1.16×10^{-8}	22.41 *** −1.641
Lev	-3.41×10^{-7} *** -1.20×10^{-7}	24.38 −19.14	-3.28×10^{-7} *** -1.17×10^{-7}	24.68 −18.89
Adv	-7.67×10^{-9} -7.99×10^{-8}	−32.77 *** −9.457	1.08×10^{-8} -8.08×10^{-8}	−32.05 *** −9.553
ROE	1.72×10^{-7} -2.30×10^{-7}	49.31 ** −24.92	2.03×10^{-7} -2.32×10^{-7}	54.16 ** −25.43
RDs	-4.41×10^{-6}*** -5.90×10^{-7}	499.8 *** −65.77	-4.69×10^{-6} *** -5.94×10^{-7}	485.4 *** −69.51
Constant	1.46×10^{-6}*** -2.60×10^{-7}	−493.5 *** −37.2	1.50×10^{-6} *** -2.57×10^{-7}	−492.8 *** −37.56
Observations	1242	1226	1242	1226
R^2	0.103	0.372	0.114	0.377

Note: (1) The upper figure is the estimation coefficient and the lower figure is the cluster robustness standard error in the table; (2) ***, ** and * indicate a significance level of 1%, 5% and 10%, respectively. (3) The time period of this regression is 2012–2017.

It is obvious from analyzing Tables 5–7 that all of our hypotheses are still fully supported. The correlation direction and significance level between the main variables have not substantially changed, which further validates the robustness of our research. Moreover, in Table 3, the chi-squared values of the four models are 0.078, 0.087, 0.35, and 0.352; in Table 5, the chi-squared values of the four models are 0.125, 0.14, 0.357, and 0.362; in Table 6, the chi-squared values of the four models are 0.0923, 0.101, 0.357, and 0.359; and in Table 7, the chi-squared values of the four models are 0.103, 0.114, 0.372, and 0.377. As a result, the regression results of the three robustness tests do not show significant differences with those in Table 3. The robustness of our results is thus assured.

5. Conclusions

5.1. Discussion

All four hypotheses were fully supported. With the sample of China's listed companies in the manufacturing sector, our empirical findings thus offer fresh insights into understanding the complex links between SCI and firm innovation performance considering the moderating role of the sustainable policy in affecting such relationships.

In terms of theoretical contributions, first and foremost, our results show that in Chinese manufacturing with intensifying environmental and social concerns, the degree of SCI negatively relates to firm innovation efficiency but positively relates to firm patent outcomes, which, to a certain extent, reflects the paradoxes between the pursuit of innovation quality and quantity and between CSR investment and innovation efficiency. To a certain extent, our findings, based on the theories of strategic management (i.e., RDT) and economics (i.e., TCT), are a response to the calls of operations management scholars for employing multiple domains to study SCI-related issues [12,23]. In light of the inconsistent results regarding the impact of SCI on firm innovation found in previous studies [1–3], we have therefore contributed to the supply chain literature by providing new, context-specific evidence and fruitful cross-disciplinary understanding. Additionally, our study implies that the rise of ecological concerns coupled with the popularity of digital technologies may result in the emergence of more dynamic mechanisms between the responsible management of SCI and organizational innovation among all stakeholders of the supply chain.

Second, according to Figures 1 and 2, our findings illustrate the positive and significant impact of the strategic emerging industry policy on SCI–innovation relationships. This sustainable policy weakens the negative association between SCI and innovation efficiency but strengthens the positive link between SCI and firm patent output. In line with the literature [23,29,30]; this study also highlights the predominate role the Chinese government plays in guiding firms' strategic direction and the importance of leveraging policy support to obtain more precious public resources over their rivals in a non-Western context. Despite Chinese firms being used to engaging in politically correct behaviors and complying with the national initiative, it is worth noting that the lack of effective policy implementation may still hamper the achievement of sustainable SCI [2].

As for the practical implications, our research offers novel insights for global managers and policy makers into understanding the complex interactions of firm sustainability and innovation in SCI. While for the past decades, numerous Chinese manufacturing firms had merely focused on increasing productivity and achieving economies of scale, our results shed some light on how these firms can capitalize on digital technology to more rapidly adapt to dynamic market changes and consumer demands, so as to cope with the new green challenges for sustainable innovation in the manufacturing sector. Viewed from this angle, we also provide practical implications about how manufacturing firms can adopt SCI as an effective means to deal with intensifying competition coupled with more serious CSR considerations in a new digitalized way. In addition, while green policy-induced innovation has gained much prominence in Europe, we expect that such sustainability-oriented innovation may also become a common practice in the Chinese context.

5.2. Limitations of the Research and the Future Outlook

This study is still subject to certain limitations and future research should take these into consideration. While the implementation of China's strategic emerging industry policy is a relatively recent phenomenon, we can only measure the short-term changes in innovation efficiency and patent output. Future research should consider a longitudinal research design, whereby the intricate relationships between SCI and innovation performance can be more clearly characterized.

We only used data from the manufacturing sector in mainland China as our sample, so future research should include a greater variety of industries and more regions because the characteristics of other industries are different and innovation cultures in different regions of China (e.g., Hong Kong, Taiwan, and Macao) may vary. Furthermore, while firm innovation should take into account the heterogeneities of SCI, it would be rather interesting to identify the multidimensional concept of SCI in the future.

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