

Article

Incentivizing Innovation: The Causal Role of Government Subsidies on Lithium-Ion Battery Research and Development

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Abstract: Governments design and implement policies to achieve a variety of goals, but perhaps none are as pressing as shifting national economies away from non-renewable fuels and towards more sustainable, environmentally-friendly technologies. To incentivize such transitions, governments provide subsidies to private and public companies to innovate, i.e., to engage in research and development (R&D) to develop those technologies. However, the question of the companies is using government subsidies (GS) to perform R&D and its answer determines the effectiveness of government policies. Consequently, this paper seeks to answer this question through investigating Chinese lithium-ion battery (LiB) firms and the GS they receive through novel usage of information flow (IF). Hausman tests, fixed- and random-effects models confirmed a weak, though positive correlation between GS and R&D as determined by patent output (PO), but interestingly, observations of IF intimated that GS also affected other variables such as net profit (NP) and main business income (MBI). This suggests that firms are being awarded GS for higher PO, but a corresponding increase in R&D and its expected growth in company performance is not occurring. Thus, it is suggested that performance variables other than PO be used as firms may ab (use) this metric to apply for more GS, rather than performing R&D that leads to technological breakthroughs.

Keywords: innovation; lithium-ion batteries; governmental subsidies; Hausman test; information flow



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1. Introduction

The problem of global warming and associated pollution is multifaceted but is being addressed most prominently from the perspective of first minimizing and then eliminating the need for fossil fuels and is manifested by changing human behavior on both supply and demand sides for energy and transportation. Although solar and wind energy technologies have already begun displacing the usage of fossil fuels and are feeding electricity into grids on an ever-increasing scale and pace [1–4], as they are inherently intermittent, energy storage for when the sun is not shining, or the wind is not blowing remains a critical bottleneck in wider scale adoption. Lithium-ion batteries (LiBs) have emerged as a crucial technology to further renewable energy development [5–7] and not only serve to stabilize electrical grids [8–12] but are also highly desirable for the automotive industry promoting a new generation of electric vehicles (EVs) [13,14]. How to motivate such changes in behavior, whether achieved through reward or punishment (i.e., carrot and stick approaches), is a fundamental problem in economics and government policies [15–17]. Relevant for this study, to provide improvements in LiB energy density, reliability, and costs [8–21], in addition to studies assessing lithium resources and LiB environmental impact [22–24], governments provide subsidies, tax reduction and grant schemes to incentivize firm research and development (R&D) activities [25–29]. Additionally, the onset of the Fourth

Industrial Revolution that is concerned with the utilization of production factors such as the Internet (IoT), big data (new capital), artificial intelligence, and block chain (trust), argues for a stimulation of open innovation (future-oriented) and instruments focusing on entrepreneurship in what is called the experimental organized economy [30]. An example of research in open innovation comes from Tayal et al. that investigated computation of overall equipment effectiveness of machines in the automobile industry [31]. However, what is perhaps not well understood is the answer to the question of does GS motivate companies to invest more in innovation and the development of high-quality products, or does GS motivate companies to neglect actual innovation in favor of using acquired funds to perform other activities? This naturally leads to the question onto the actual effectiveness in GS in stimulating corporate innovation.

2. Literature Review

Subsidies are particularly useful as they may directly decrease financial pressure and risks of a company stimulating innovation activities and R&D investment [32]. Especially, at early stages when resources are limited, government can play a significant role. As industry grows and become mature, government provides ideas exchange between different innovation actors [33]. However, recent studies have identified that subsidy allocation are not having the intended effects. For example, Li et al. provided evidence that subsidies not being used by firms for improving their innovation capabilities, but for other purposes [34]. Lin and Luan suggested that although government subsidies (GS) can directly or indirectly improve a company's ability to improve their technological innovation capacity, crowding out effects as caused by GS may lead to companies not being as innovative as they used to be and thus GS could actually negatively affect innovation performance [35]. Lim et al. collected subsidy data on Chinese listed companies and found out that GS can negatively effect on firms' profitability even when it helps to lower a cost of debt [36]. Zhu and Liao supported the findings of Lim et al. [36] by analyzing Chinese renewable energy companies and the impact of GS on their financial performance [37]. The result show that the occurrence of subsidy-induced overcapacity, adverse selection and moral hazard weaken the effect of GS. Considering the acute importance of the shifting the global economy away from being powered by non-renewable fossil fuels, assessing the mechanisms by which this shift is performed is of equal importance.

As the one of the largest producers of lithium and a major consumer of LiBs [38–40], China is an extremely valuable laboratory to test the effect of subsidies on LiB innovation. This is due to GS being specifically designed to be intricately linked to technological metrics and performance indicators. Considering this, however Wu et al. studied the effects of RD on Chinese-listed firm innovation and found that no clear stimulating effect of RD subsidies could be found on innovation output and failed to find an optimal number of subsidies for these companies [41]. The authors nevertheless found that there was a marginal positive effect was identified given an increase in the number of RD subsidies. Zhang et al. studied the value of second use new energy vehicles (NEV), finding that in addition to battery cost and electricity prices, GS are another principal factor for the Chinese NEV battery industry [39]. Li et al. through analyses of dual credit policies and subsidies suggested that LiB manufacturers were competitively vulnerable unless government offered new financial subsidies [34]. Yu et al. studied the influence of GS on RD investment behavior for China's renewable energy sector and found that GS have a significant crowding out effect on RD investment behavior and this was influenced by enterprise ownership attributes [42]. Investigating 158 listed new energy power generation companies in China, Luo et al. found out that GS can have a negative impact on the short-term financial performance while on the long-term GS positively affects enterprises profitability [27]. However, Yang et al. used a panel threshold effect model to analyze the threshold effect of GS on renewable energy investment [25]. The results suggest that GS are the significant contribution and main supporting force for medium-, small-, and micro-sized renewable energy enterprises when energy consumption intensity and bank credit are greater.

Recent literature has suggested that in contrast to the conventional one-way causal relationship between patent number and RD investments, a bidirectional causal relationship may exist [43–45], necessitating the introduction of a methodology designed to study these processes. Information flow (IF) as rigorized by Liang [46], since the seminal study by Stips et al. [47], has been used in a wide variety of fields such as wave [48] and climate systems [49,50]. Other similar methods such as entropy transfer and Granger causality have been used to analyze IF [51,52], strongly suggesting that it can also be used to assess the relationship between RD investments, GS, and other relevant variables. For example, Nyasha and Odhiambo reviewed the causal relationship between government size and growth and identified that although the direction of causality between these two variables had four possible outcomes, each outcome had empirical support for their conclusions [53]. They also suggested that the causal relationship between government size and economic growth was not clear. Lawal et al. used Granger causality to examine the effect of government expenditure on Nigerian economic growth [54]. It was confirmed that total government expenditure and economic growth were not linked in the long term with regards to expenditure on agriculture, security, transport, and communication, however, a positive impact on Nigerian economic growth was observed. This study considers the introduction of IF in the characterization of the causal effect of GS, R&D investments, patent output on one another in the context of innovation and company performance. This is done because, to the best of the authors' knowledge, very few studies have attempted to establish a bidirectional causal relationship between GSs on LiB innovation in an attempt to definitively identify the effects GS has on LiB innovation. Moreover, the study seeks to uncover if, as was previously suggested, subsidies were used for other non-R&D purposes. Consequently, the rest of the paper is structured as follows. Section 2 provides a description of the dataset and methodology that includes fixed- and random-effect models, the Hausman test and IF. Section 3 gives the results and Section 4 provides policy recommendations and concludes this study.

3. Data and Methodology

3.1. Description of the Chinese Lithium-Ion Battery Market

Driven by the confluence of two goals of Chinese policy makers, i.e., environmental pollution reduction and conversion of low-cost, low-tech products to others that require higher levels of skills and technology to produce (the 'Made in China 2025' strategic national plan), LiB growth is largely dependent on the development of NEVs. Based on statistics provided by the Global Lithium-Ion Battery Supply Chain Ranking report [55], the Chinese LiB market is immense, and this is due primarily to large domestic battery demands, control of over 80% of the global raw material refining, 77% of cell capacity and 60% component manufacturing. The Battery—Global Market Trajectory & Analytics report [56] suggests that the China compound annual growth rate of the LiBs will be at 16.6% by 2027 and is estimated to be worth US\$61.1 billion. The same report goes on to classify Ningde Times Energy Technology Co., Ltd. (CATL), BYD Co. Ltd., Tianjin Lishen Battery Co., Ltd., Beijing Hezhong Pufang New Energy Technology Co., Ltd., the Wanxiang Group, China Aviation Lithium Battery (CALB), Gotion High-tech Co., Ltd. (formerly Hefei Guoxuan Hi-Tech Power Energy Co., Ltd.), OptimumNano, Coslight, and Microvast Power Systems as the leading power battery manufacturers in the country. Among these Beijing Hezhong Pufang New Energy Technology, Tianjin Lishen Battery Co., Ltd., Gotion High-tech Co., Ltd., CALB, OptimumNano, Coslight, and Microvast are private companies. BYD is also a private company but additionally relies on foreign investments. These and other companies have provided a third of global battery production capacity in 2019 and this trend is expected to remain up to 2025 [57], allowing Jin et al. to suggest that because of China's decade-long pilot and subsidy programs that were designed to drive EV technology advancement, the average battery capacity for pure electric cars increased from 35 to 44 kWh (approximately 23%) over the past five years, though this remains lower than in the United States and Europe in 2019 [58]. The dataset of companies used in

this paper includes a wide array of private, private and foreign invested, in addition to state-owned enterprises.

Based on research conducted by Zhang et al. [14], following the return of Hong Kong to the P.R.C. in 1997 and application of national policies concerning NEVs, EV battery technology patents grew exponentially, with this trend increasing annually. The authors suggest two policies, namely ‘The New Energy Infrastructure Project Management Interim Provisions’, and the ‘Decision on Speed Up the Cultivating and Developing Strategic Emerging Industries’, show that technological R&D is closely linked to national policy. Indeed, in a new report on China’s electric vehicle development, Jin et al. identify that China’s top-down management styles, i.e., its Five-Year-Plans, and resultant policies such as the ‘Ten Cities, Thousand Vehicles’ pilot projects, subsidy programs, tax breaks, and technical standards are largely responsible for the “strategic and policy continuity in China’s new energy vehicle development” [58]. The Chinese State Council Information Office on 2 November 2020 released the New Energy Vehicle Industry Development Plan (2021–2035) that proposed that by 2025, the sales volume of NEVs and intelligent connected vehicles should reach 25% and 30%, respectively [59]. Although the literature documents a wide array of Chinese government policies and subsidies meant to spur R&D into improving LiBs, which often encourages automakers to sell EVs below manufacturing costs [60,61], case studies on their effects on specific companies are scarce. Nonetheless, in 2012, China BAK Battery, a manufacturer of LiBs received a US\$1.9 million subsidy from the Chinese National Development and Reform Commission and MIIT [62] for its battery module project. As reported, government funds were slated to be used to enhance battery module efficiency for EVs and e-bikes. More recently, Scott and Ireland document that BYD and CATL are increasing their investments into battery production [63]. Masiero et al. in an examination of government subsidies on the largest Chinese EV manufacturer BYD, found that government subsidies (Table 1), combined with BYD-implemented strategies, could explain the successful expansion of the emerging industry in China [64]. Generally, China provides an average subsidy of \$10,000 per vehicle and with 770,000 EVs sold in 2017, China’s central and local governments spent a total of \$7.7 billion on EV subsidies that allowed the country to capture control of and dominate LiB manufacturing [65].

Table 1. Central government incentives for 2015.

Type of Vehicles	Technical Specifications	Incentives	
		RMB	US
BEV	80 km ≤ Autonomy < 150 km	31.5	5
	150 km ≤ Autonomy < 250 km	45	7.2
	Autonomy ≥ 250 km	54	8.6
PHEV	Autonomy ≥ 50 km	31	5
Fuel Cell Car	-	180	28.8
Plug-in Hybrid Bus	Length ≥ 10 m	250	40
Fuel Cell Commercial Vehicle	-	420	72.1
Super-capacitor/lithium Titanate Bus	-	150	24

Note: BEV is Battery Electric Vehicles and PHEV is plug-in hybrid electric vehicles.

3.2. Regression Analysis, Fixed and Random Effects Models and the Hausman Test

Regression analysis fixed and random effects models are widely used in the study of panel data to investigate the impact of government subsidies and firm R&D investments [66,67]. Consider the following cross-sectional multiple regression with explanatory variables X_1 and X_2 :

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + u_i; i = 1, 2, \dots, N. \quad (1)$$

where X_1 is the covariate of X_2 , and vice versa. Covariates act as governing factors for a given variable. When control variables are present, β are partial regression coefficients and

thus β_1 represents the marginal effects of X_1 on Y , keeping all other variables (e.g., X_2) constant. In keeping X_2 constant, the marginal effect of X_1 on Y is obtained after eliminating the linear effect of X_2 from both X_1 and Y . β_2 is explained identically. Consequently, multiple regression facilitates pure marginal effects to be obtained by including all relevant covariates and thus their heterogeneity can be controlled. If we further consider the multiple regression of the following time series with the same two explanatory variables, X_1 and X_2 :

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + u_t; \quad i = 1, 2, \dots, T. \quad (2)$$

We have the same explanation for the marginal effects but can now track the system's evolution over time. In order to account for time heterogeneity, we can combine Equations (1) and (2) to arrive at a pooled dataset, which forms panel data with the following panel regression:

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}; \quad i = 1, 2, \dots, N; \quad i = 1, 2, \dots, T. \quad (3)$$

Using a two-way error component assumption for perturbations, cross section and time heterogeneity can be controlled for:

$$u_{it} = \mu_i + \lambda_t + v_{it} \quad (4)$$

where μ_i is the unobserved individual (cross section) heterogeneity, λ_t is the unobserved time heterogeneity, and v_{it} is the remaining random error term. The μ_i and λ_t are the within components, and the v_{it} is the panel or between components. Based on the assumptions made concerning these error components, i.e., whether they are fixed, or random, fixed, or random effect models are formed. Specifically, if μ_i and λ_t are fixed parameters to be estimated and v_{it} is independently distributed with zero mean and constant variance, a two-way fixed effects model is built. If, however, μ_i and λ_t are random, identical to the error term, and are all independent of each other and of explanatory variables, a two-way random effects model is built. If only one component is considered at a time, one-way fixed or random effects models can be built by replacing μ_{it} (Equation (3)) and depending on either the fixed or random assumption of μ_i and λ_t , becomes:

$$u_{it} = \mu_i + v_{it} \quad (5)$$

$$u_{it} = \lambda_t + v_{it} \quad (6)$$

In this paper, innovation in LiB is measured by the level of research and development (RD) investments and by patent output (PO). RD investments, as the name suggests, is expressed as the funds invested by LiB companies into technological advancements and reflects the willingness of these companies to innovate. Patent output (PO), by contrast, is expressed in terms of the number of patents applied for due to technological breakthroughs, rather than the actual number of patents received as there is a lag between patent application and authorization phases [42,68]. Government subsidies (GS) was chosen as this study's main explanatory variable. If the growth of corporate RD investments is higher than the growth of GS, this implies that GS has a stimulating effect on RD investments. Correspondingly, if RD investments are lower than GS growth, this suggests that GS are not having their intended effect and subsidies should be redesigned. All variables are listed in Table 2.

Table 2. Variable descriptions.

Variables	Symbol	Variable Definition and Unit
RD investment	RD	Enterprise RD investment (Million Yuan)
Patent Output	PO	Number of enterprise invention patent applications
Government Subsidies	GS	Government subsidies in non-operating income (million yuan)
Main Business Income	MBI	Income from the company's main business (million yuan)
Asset-liability Ratio	LEV	Proportion of total liabilities to total assets (%)
Investment Ratio	DS	Proportion of RD investment in operating income (%)
Largest Shareholder Ratio	LSR	The ratio of the number of shares held by the shareholder with the most shares to the total number of shares (%)
Top Ten Shareholders Ratio	TTSR	The shareholding ratio of the top ten major shareholder (%)
Net Profit	NP	The amount of accounting profit a company has left over after paying off all its expenses (million yuan)

Among the control variables, the RD investment of lithium battery companies is mainly affected by the size and operating conditions of the company. Main business income (MBI) reflects the sales and market share of LiB companies and can be used as a representative variable reflecting the scale of the company. If the business is not operating well, it will lead to a debt crisis, and the company must prioritize repayment of principal and interest, thereby reducing RD investment. The asset-liability ratio (LEV) is used to reflect the business status of the enterprise, and it is expressed as the proportion of total liabilities to total assets. As an emerging industry, the innovation of lithium battery companies is also affected by the level of organizational knowledge. The patent output of lithium companies is mainly affected by the company's RD intensity. The RD investment ratio (DS) is used here to express the importance of LiB companies on RD. Generally, the greater the RD intensity of the company, more emphasis is placed on RD activities, the better the output of high-quality patents. The largest shareholders ratio (LSR) was chosen as an index, representing willingness of shareholders with the largest share in the company to invest in innovations, focusing on maximization of their income from selling high-quality inventions. Net Profit (NP) is used to reflect the amount of money that companies can spend directly on innovations and expresses the size of profit. Top 10 shareholders ratio (or major shareholders) (TTSR) as the largest shareholders ratio was used to represent the possible shareholders' contribution to RD, limited to within 10 main distributors [69].

To investigate the effects of GS on LiB innovation, we use a well-balanced panel dataset of 95 LiB-manufacturing companies that ranges from the year 2015 to 2018. To consider both fixed and random effects, the Hausman specification test is employed [70]:

$$RD_{it} = \mu + \beta_1 GS_{it} + \beta_2 MBI_{it} + \beta_3 LEV_{it} + \beta_4 LSR_{it} + u_{it} + \alpha_t \quad (7)$$

$$PO_{it} = \mu + \beta_1 GS_{it} + \beta_2 DS_{it} + \beta_3 TTSR_{it} + \beta_4 LSR_{it} + u_{it} + \alpha_t \quad (8)$$

where RD is RD investments and PO is the patent output; $i = 1, 2, \dots, n$, represents different enterprises; $t = 1, 2, \dots, n$, represents time, and $u_{it} + \alpha_{it}$ represents random effects. The data excludes the impact of price factors. Patent number was collected from the patent information service platform network [71], and the rest of the data comes from the China Stock Market & Accounting Research Database [72]. The data consists of the company name, company number, PO, total assets, total liabilities, etc. To guarantee model robustness, although there is data for 178 companies, data curation was performed to exclude companies that had large tracts of missing data, resulting in a total dataset of 95 companies.

According to Table 3, there is a large difference between the maximum value and the minimum value of RD investment, and the median is much smaller than the average value, indicating that the overall RD investment of LiB companies is relatively small, and the RD investment of a few lithium-ion battery companies has increased. The number of invention patents and RD investment shows a similar distribution, and the median is much lower

than the average, indicating that the overall output of invention patents of LiB companies is relatively small and unevenly distributed. With the aid of the econometric model, the influence of government subsidies on the RD investment of LiB companies can be further tested. Considering the large discrepancies in values between variables, before all further analyses were conducted, the data was normalized to a 0 to 1 range.

Table 3. Descriptive statistics before normalization.

Variables	Max.	Min.	Average	Median
RD	8535.9	0.04	309.5	99.2
PO	2856	1	146	38
GS	1248.5	0.005	41.9	11.5
MBI	100,492	0	5699.7	1172
LEV	0.77	0.1	0.48	0.49
DS	8.16	0	0.38	0.05
LSR	67.14	3	29.2	28.34
TTSR	94.33	9.15	50.97	51.7
NP	26,379	0	612.2	147.7

To determine the most appropriate model amongst the fixed and random effects models, the Hausman or Durbin-Wu-Hausman (DWH) test is performed on panel data and determines the presence of endogeneity (predictor variables) in the panel model. If the p -value is greater than 0.05 (>0.05) then the random effects model is chosen. Alternatively, if the p -value is less than 0.05 (<0.05), then null hypothesis is rejected, and the fixed effect model is chosen.

3.3. Information Flow

To ascertain the bidirectionality of causality between GS and other variables, information flow (IF) is applied and studied. IF is a real physical notion developed and rigorized Liang [43], to quantitatively assess causality between two time series. Causality is measured by the rate of information transfer from a given variable's time series, to another. Given two time series X_1 and X_2 , the maximum likelihood estimator of IF from X_2 to X_1 is:

$$T_{2 \rightarrow 1} = \frac{C_{11}C_{12}C_2, d_1 - C_{12}^2 C_1, d_1}{C_{11}^2 C_{22} - C_{11}C_{12}^2} \quad (9)$$

where C_{ij} is the sample covariance between X_i and X_j , and C_{ij, d_1} is the covariance between X_i and \dot{X}_j . Information flow in the opposite direction, i.e., $T_{1 \rightarrow 2}$, through switching the indices 1 and 2. The units are in natural units of information (nats). IF is used primarily to quantitatively assess causality between government subsidies and RD investment. For completeness, information flow is also calculated for all other variables and comparisons made. At this juncture, it is prudent to note that a standard procedure for testing the relative importance of a detected causality has been made available [73]:

$$Z_{2 \rightarrow 1} \equiv |T_{2 \rightarrow 1}| + \left| \frac{dH_1^*}{dt} \right| + \left| \frac{dH_1^{noise}}{dt} \right|, \tau_{2 \rightarrow 1} = \frac{T_{2 \rightarrow 1}}{Z_{2 \rightarrow 1}} \quad (10)$$

where the phase expansion in the X_1 direction is H_1^* and H_1^{noise} is the random effect (note: this is unrelated to the random effects model). The larger the value, the more significant the causal relationship between X_2 and X_1 . When the significance level is 0.1, $Z_{2 \rightarrow 1} > 0.1$ indicates that the causal relationship is significant. The relative importance of detected causality will also be measured.

4. Results

4.1. Hausman Test, Fixed and Random Effect Model Results

To estimate the correlation between the selected variables, fixed and random effect models were implemented in conjunction with performing the Hausman test. As shown below in Table 4, among the control variables, the MBI, reflecting the size of the company, passed the 1% significance level test, with a coefficient of 0.205 and 0.207. This indicates that LiB enterprise RD investment is positively correlated with company size. This is because LiB enterprises are important facets of the Chinese economy, and they often have the most complete RD investment mechanisms. LSR passed the significance test at the 1% level with correlation coefficients for the fixed and random effects being measured at 0.358 and 0.370, respectively. This indicates that with greater RD support from investors, these RD naturally activities become more intense due to higher investments.

Table 4. Regression results for RD investments.

Variable	Fixed Effects		Random Effects	
	Coefficient	<i>p</i>	Coefficient	<i>p</i>
GS	0.182	0.000	0.163	0.001
MBI	0.205	0.000	0.207	0.000
LEV	0.022	0.232	0.030	0.105
LSR	0.358	0.000	0.370	0.000
Cons	−0.057	0.000	−0.062	0.000
F/W Values	52.51 (F-value)		210.36 (W-value)	

In Table 5, it can be observed that as the P-value of the Hausman test is lower than 5%, again both fixed and random models can be used for estimation. The F- and W-values were measured at 41.05 and 158.32, respectively, indicating that the model's ability to estimate hidden effects is significant. Moreover, GS also passed the significance test at the level of 1% with the coefficient of 0.174 and 0.153, which suggests that there is a positive correlation between GS and PO. Combined with the regression results of the RD investment equation (Table 3), GS has a direct role in promoting RD. However, because the subsidies' policy focus on promoting continued investments, these results suggest that LiB enterprises are not being adequately motivated to engage in high-quality RD. Otherwise, among the control variables, RD investment ratio passed the significant test at the level of 1% with the coefficient of 0.124 and 0.119 for fixed and random effect models, respectively. This result demonstrates that the amount of money poured into RD is positively correlated with patent number. Enterprises with high RD investment ratios obviously would have higher proportions of their profits being diverted into RD, reflecting that enterprise's willingness to invest more in innovative research, leading to larger patent numbers. The quality of those innovations, however, remains unknown and will be discussed in a subsequent section. The LSR also passed the significance test at the 1% level, with a coefficient of 0.502 and 0.521 for the fixed and random effect models, respectively. Contrasted with managers that seek to maximize short-term benefits, shareholders, however, are more interested in securing and maximizing profits over the long-term and therefore are more willing to invest in risky RD activities [74,75].

Table 5. Patent output regression results.

Variable	Fixed Effects		Random Effects	
	Coefficient	<i>p</i>	Coefficient	<i>p</i>
GS	0.174	0.000	0.153	0.002
DS	0.124	0.003	0.119	0.004
TTSR	0.034	0.116	0.021	0.206
LSR	0.502	0.000	0.521	0.000
Cons	−0.089	0.000	−0.087	0.000
F/W Values	41.05 (F-value)		158.32 (W-value)	

4.2. Information Flow

In a deeper examination of the effect of GS on RD and other variables, IF was applied to time series of each variable to determine their interrelationships with results collated in Table 6. Observing Figure 1a that shows IF from each variable to GS, the most striking feature is its magnitude and polarity. This indicates that rather than information flowing from each variable to GS, GS had flows of information to each variable, suggesting that growth was stimulated, congruent with the results of either the fixed or random effects models, and results widely reported in the literature [76–79]. In Figure 1b where IF to each variable from GS shows that RD, PO, and NP are all strongly affected by GS, with MBI, LSR, LEV, DS, and TTSR being nearly completely overshadowed. A first inspection, while this result may suggest that because RD, PO, and NP are being stimulating by GS, actual innovation may not be occurring (or in other words, the classic notion that correlation does not imply causation). For example, Dang and Motohashi warned that although patent subsidy programs have increased the number of applications and grants by 30%, these subsidies have the negative side effect of encouraging low-quality patent applications and drive firms to narrow patent claims for easier grants [80]. Giarratana et al. agreed, terming the rewarding of low-quality inventions as ‘false positives’ and noted that high-quality inventions may be overlooked (false-negatives) [81]. Deeper research into the quality of patents is required to validate the causal influence of GS on innovation.

Table 6. Information flow to ($T_{1 \rightarrow 2}$) and from ($T_{2 \rightarrow 1}$) government subsidies with the corresponding statistically significant values at the 95% ($\tau_{1 \rightarrow 2(95\%)}$) and 99% ($\tau_{2 \rightarrow 1(99\%)}$) levels.

Variable	$T_{1 \rightarrow 2}$	$T_{2 \rightarrow 1}$	$\tau_{1 \rightarrow 2(95\%)}$	$\tau_{2 \rightarrow 1(95\%)}$	$\tau_{1 \rightarrow 2(99\%)}$	$\tau_{2 \rightarrow 1(99\%)}$
RD	2.2951	166.8535	0.0370	0.0341	0.0483	0.0446
PO	−51.1643	309.4262	0.0583	0.0587	0.0761	0.0767
MBI	−9.2132	22.6042	0.0101	0.0155	0.0132	0.0203
LSR	−1.1905	1.9735	0.0030	0.0040	0.0039	0.0052
LEV	9.8400	23.0154	0.0176	0.0196	0.0230	0.0256
DS	1.3364	5.8220	0.0085	0.0090	0.0111	0.0117
NP	−60.4489	242.9157	0.0463	0.0504	0.0605	0.0659
TTSR	−0.0720	3.7063	0.0063	0.0086	0.0082	0.0112

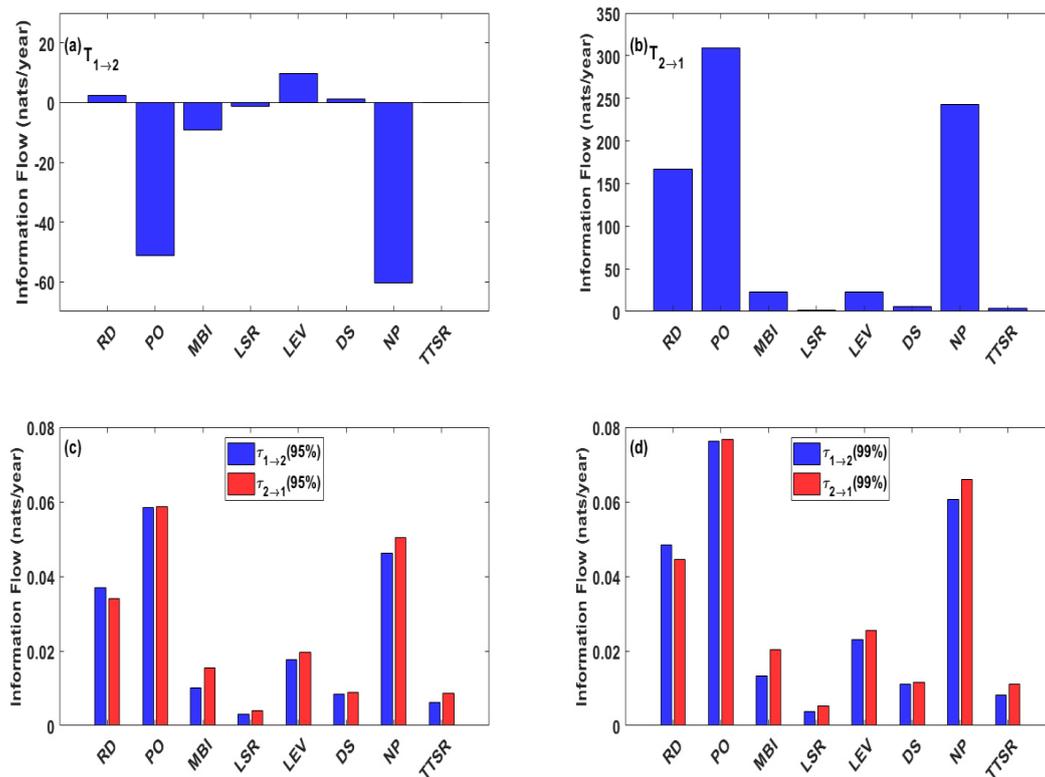


Figure 1. Information flow (a) from the variables to government subsidies ($T_{1 \rightarrow 2}$), (b) from government subsidies to the variables ($T_{2 \rightarrow 1}$), with the corresponding significant values (τ) at the (c) 95% and (d) 99% levels.

In Figure 1c, excluding RD, there was higher IF to variables from GS ($\tau_{2 \rightarrow 1}$) than to GS from each variable ($\tau_{1 \rightarrow 2}$) at the 95% confidence level. At the 99% confidence level, this trend continues identically to the 95% confidence level results. Through testing the bidirectional causal influence of GS to and from each variable by IF, the results strongly suggest that GS stimulate the variables, with RD, PO, and NP standing out. Their growth is being nurtured by GS as they are designed to do. Although, it should also be recognized that this effect may not necessarily be universal for the LiB industry. Recent observations by Wu et al. suggested that based on firm affiliation, those with higher-level governments contacts and those located in marketized regions were more likely to government financial support [41]. While the authors noted that they were able to confirm Chinese state intervention corrected market failure due to firms' RD activity, influence of subsidies had an ambiguous effect on this activity.

Using Equation (10), the relative importance of a detected causality is calculated with results plotted below in Figure 2. There it can be easily seen that amongst the variables, PO, followed by NP and then RD were influenced most strongly by GS, completely overshadowing every other variable. With regards to LSR, DS, and TTSR, as their values were negative, it can be suggested that not only are they are not crucial for GS, but may even restrict its growth, however it should be noted that excluding these variables, all others passed the 0.1 significance test, and thus more research is required to clarify their influence on GS for the LiB industry. In summary, while additional research will be required to ensure robustness, this result confirms the earlier fixed and random effects model observation that each variable, to varying degrees, were stimulated by GS.

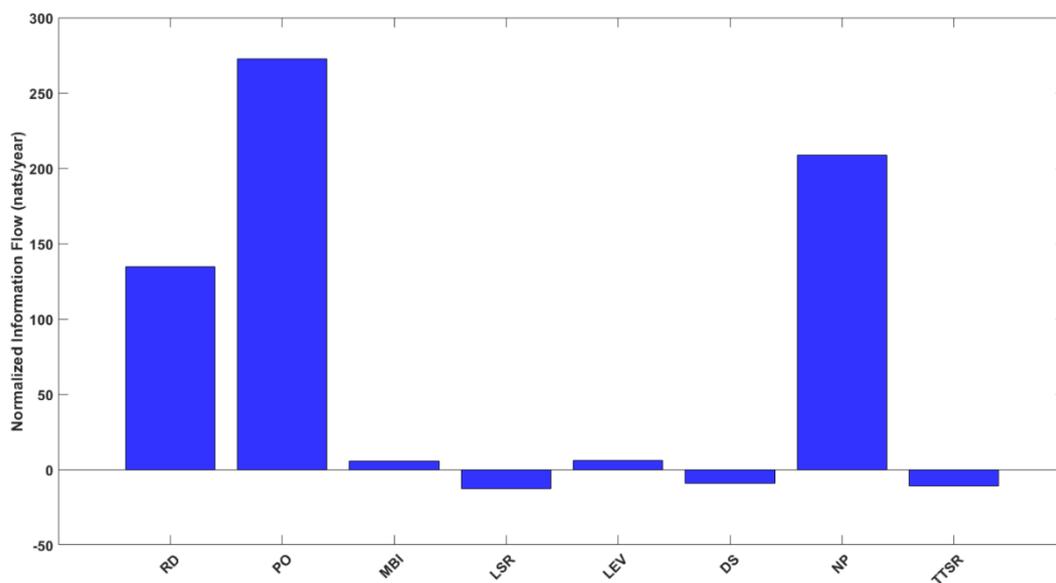


Figure 2. Relative importance of detected causality from the variables to government subsidies.

It is hypothesized that a selective pressure is exerted on companies to take greater risks and invest more into RD to apply for more patents and patent subsidies [82,83], but it must be additionally noted that some firms may do this rather than conducting RD to truly innovate [84]. These firms may be successful due to the awarding of GS, rather than their ability to innovate and bring new products to the market [41,83,85]. That is, the better companies do from an innovation perspective, and this is quantified by the number of patents, the more subsidies are allocated to their continued development [41,86,87]. Here, policymakers and special interest groups may be making decisions on which industries and technologies to subsidize and because they may not have neither the technical expertise nor desire to select firms based on their merits, misallocation of valuable capital is inevitable. Furthermore, it should also be noted that innovative inertia may engender firms to continue innovating even if government subsidies fail [67] and this may be the situation here. There is insufficient data to pursue this avenue to determine if this is indeed the case and can be studied in future research. Additionally, the causal relationship is not quite as simple as these results suggest since other factors not considered by this study could have affected the RD investments [45,88].

5. Conclusions

In the 21st century, innovation is amongst the main drivers of economic productivity and serve to advance the technology to solve problems that arose from previous centuries of development that were accompanied by pollution and carbon dioxide emissions. The promotion of electric vehicles placed increased pressure on LiB manufacturers to build safer, longer lasting and more energy dense batteries, which is inextricably linked to a firm's ability to innovate. Governments design and implement subsidies to engender innovations by providing financial incentives to conduct risky research and development activities. This is done primarily to steer markets to produce products and services beneficial for its citizenry. LiBs, from their abilities to store electricity generated by renewable energy, are currently the best technologies available to aid in stabilizing fluctuating energy production and with their inclusion into electric vehicles, help to reduce the burning of fossil fuels. This study sought to uncover the causal relationship between company performance as measured by the number of patents awarded through RD investments. It was found that while confirming the link between GS, PO and RD investments, the correlation between these variables was relatively weak as determined by the fixed and random effects models. However, through a novel application of IF to this kind of study, it can be clearly identified that the application of GS to firms led to greater investments in RD, that resulted in higher

PO and from this perspective, higher company performance. This is crucial for the LiB industry as higher levels of innovation results in safer, more efficient batteries for not only the electric vehicle that are currently dependent on them, but the entire renewable energy industry as energy storage is a critical bottleneck in widening the application of these and other technologies. Through measuring the relative importance of detected causality from GS to the measured variables, it was identified that GS influenced PO the greatest and this was followed by NP and then RD, with MBI, LEV having a significantly smaller influence. A negative influence on GS was detected for LSR, DS, and TTSR, which suggests that these variables may serve to restrict the application of GS for a given firm. Although this study confirmed the positive correlation between GS, RD and PO, an important caveat in the notion of causality where correlation may not imply causation, it cannot be overlooked that patents could have been applied for not when technological breakthroughs are made, but as padding to ensure that personal or firm evaluations are optimum, and GS can be acquired. In other words, GS could be awarded to firms with higher patent output, regardless if these patents led to increased company performance or not. This can be explained quite simply as just because innovation took place within an enterprise, the innovations themselves perhaps failed to lead to greater productivity and higher profits. Here, we can make a suggestion that not only should the subsidy structure be optimized, but more detailed targets and better supervision should be established as well. Alternative solutions to GS such as grants, tax credits, or allocation rules based on past performance can be implemented, but experimentation into the optimum design of these mechanisms to spur innovation is required. The minimization of crowding out effects should also be a priority for the government. Alongside these government-led policies, market-led, demand-oriented policy instruments to encourage innovation can and should be implemented. Based on the above research conclusions, the following countermeasures are proposed:

First, optimize the government's subsidy method for lithium-ion battery, and at the same time, improve the subsidy methods, such as granting more subsidies to companies with strong R&D capabilities, and guide companies to increase R&D investment and promote lithium-ion battery companies to improve their innovation capabilities.

Second, adopt incentive policies such as R&D tax credits to encourage enterprises to increase R&D investment. Compared with R&D subsidies, R&D tax incentives can mobilize market forces more. At present, the research and development of tax incentive tools has become a common method in many countries.

Third, promote the openness and transparency of government subsidy information, and establish and improve the government subsidy supervision system. At present, the Chinese government's policy of providing subsidies to lithium-ion battery has been implemented for a long time, but the openness of government subsidy information needs to be further strengthened. With the development of lithium-ion batteries, it is not only necessary to raise the standard for issuing government subsidies, but also to strengthen publicity before the issuance, and strengthen supervision after use, so as to guide social forces to supervise and improve the efficiency from the usage of subsidies funds.

Because of these observations, although LiB manufacturers took risks by making greater RD investments and GS were made available to incentivise these risks, no direct link between PO and company performance by IF can be confirmed due to additional variables not considered here. These variables, such as the number of employees and their corresponding levels of education may have a strong effect on assessing RD investments and patent output because the more highly educated employees a firm possesses and retains, products produced by said company may be higher. As a case in point, innovations that were made due to minor initial RD investments can have a disproportionately large effect on company and even market performance, and these come in the form of what are known as technological disruptors. Consequently, companies should primarily invest funds into increasing the quantity and quality of its technical and scientific expertise as only with greater theoretical and practical foundations, can a team of experts make

breakthroughs and improve innovation efficiency. This study is limited in that variable selection did not consider the influence of strategic alliance portfolios and characteristics of focal firm partners which has been shown by Jeong and Ko [89] to have a significant effect on R&D activities through the acquisition of knowledge and technologies from other firms. Moreover, the research doesn't consider some possibly influential variables such as tax credits (governmental tool to spur innovation in high-tech enterprises) which were used in the study by Jiang et al. [77] to create a threshold model investigating different effects of GS on R&D intensity of NEV enterprises. Additionally, open innovation approaches may also have an effect on firm R&D and innovation through the inclusion of big data [33,90], but there was currently insufficient data to consider its influence. Future research is required to provide evidence to support this hypothesis and can include an expanded quantity of companies, additional variables, and the inclusion of non-Chinese LiB manufacturers to broaden the theoretical foundation. Moreover, a deeper investigation into the causal role of government subsidies and open innovation in the Chinese NEV industry may lead to identification of strategies to overcome current rigidities in the allocation of GS. This perhaps may be useful as open innovation is a business management model for innovation that promotes collaboration with people and organizations outside the company and thus would involve people who have no direct financial incentive to merely apply for GS to support the firm. Improper activities can therefore be more easily identified as silo mentalities and the secrecy traditionally associated with corporate R&D culture can be minimized.

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References

1. Sahu, B.K. A study on global solar PV energy developments and policies with special focus on the top ten solar PV power producing countries. *Renew. Sustain. Energy Rev.* **2015**, *43*, 621–634. [[CrossRef](#)]
2. Padiyar, K.R.; Kulami, A.M. Solar Power Generation and Energy Storage. In *Dynamics and Control of Electric Transmission and Microgrids*; Wiley-IEEE Press: Hoboken, NJ, USA, 2019; pp. 391–414. [[CrossRef](#)]
3. Oakleaf, J.R.; Kennedy, C.M.; Baruch-Mordo, S.; Gerber, J.S.; West, P.C.; Johnson, J.A.; Kiesecker, J. Mapping global development potential for renewable energy, fossil fuels, mining and agriculture sectors. *Sci. Data* **2019**, *6*, 101. [[CrossRef](#)]
4. Bórawski, P.; Beldycka-Bórawski, A.; Jankowski, K.Z.; Dubis, B.; Dunn, J.W. Development of wind energy market in the European Union. *Renew. Energy* **2020**, *262*, 691–700. [[CrossRef](#)]
5. Guerra, O.J.; Zhang, J.; Eichman, J.; Denholm, P.; Kurtz, J.; Hodge, B. The value of seasonal energy storage technologies for the integration of wind and solar power. *Energy Environ. Sci.* **2020**, *13*, 1909–1922. [[CrossRef](#)]
6. Boretti, A. Integration of solar thermal and photovoltaic, wind, and battery energy storage through AI in NEOM city. *Energy AI* **2021**, *3*, 100038. [[CrossRef](#)]

7. Tong, F.; Yuan, M.; Lewis, N.S.; Davis, S.J.; Caldeira, K. Effects of Deep Reductions in Energy Storage Costs on Highly Reliable Wind and Solar Electricity Systems. *iScience* **2020**, *23*, 101484. [CrossRef]
8. Diouf, B.; Pode, R. Potential of lithium-ion batteries in renewable energy. *Renew. Energy* **2015**, *76*, 375–380. [CrossRef]
9. Trahey, L.; Brushett, F.R.; Balsara, N.P.; Ceder, B.; Cheng, L.; Chiang, Y.; Hahn, N.T. Energy storage emerging: A perspective from the Joint Center for Energy Storage Research. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 12550–12557. [CrossRef]
10. Chen, T.; Jin, Y.; Lv, H.; Yang, A.; Liu, M.; Chen, B.; Xie, Y.; Chen, Q. Applications of Lithium-Ion Batteries in Grid-Scale Energy Storage Systems. *Trans. Tianjin Univ.* **2020**, *26*, 208–217. [CrossRef]
11. Martin, J.; Miles, J. A techno-economic assessment of battery business models in the UK electricity market. *Energy Policy* **2021**, *148*, 111938. [CrossRef]
12. Goop, J.; Nyholm, E.; Odenberger, M.; Johnsson, F. Impact of electricity market feedback on investments in solar photovoltaic and battery systems in Swedish single-family dwellings. *Renew. Energy* **2021**, *163*, 1078–1091. [CrossRef]
13. Gong, S.; Ardeshiri, A.; Rashidi, T.H. Impact of government incentives on the market penetration of electric vehicles in Australia. *Transp. Res. D Transp. Environ.* **2020**, *83*, 102353. [CrossRef]
14. Zhang, Q.; Li, C.; Wu, Y. Analysis of Research and Development Trend of the Battery Technology in Electric Vehicle with the Perspective of Patent. *Energy Procedia* **2017**, *105*, 4274–4280. [CrossRef]
15. Johnson, W.H.A.; Medcof, J.W. Motivating proactive subsidiary innovation: Agent-based theory and socialization models in global R&D. *J. Int. Manag.* **2007**, *13*, 472–487.
16. D'Andria, D.; Savin, I. A Win-Win-Win? Motivating innovation in a knowledge economy with tax incentives. *Technol. Forecast Soc. Chang.* **2018**, *127*, 38–56. [CrossRef]
17. Zhao, X.M.; Bai, X.L. How to motivate the producers' green innovation in WEEE recycling in China?—An analysis based on evolutionary game theory. *Waste Manag.* **2021**, *122*, 26–35. [CrossRef]
18. Few, S.; Schmidt, O.; Offer, G.J.; Brandon, N.; Nelson, J.; Gambhir, A. Prospective improvements in cost and cycle life of off-grid lithium-ion battery packs: An analysis informed by expert elicitations. *Energy Policy* **2018**, *114*, 578–590. [CrossRef]
19. Penisa, X.N.; Castro, M.T.; Pascasio, J.D.A.; Esparcia, E.A., Jr.; Schmidt, O.; Ocon, J.D. Projecting the Price of Lithium-Ion NMC Battery Packs Using a Multifactor Learning Curve Model. *Energies* **2020**, *13*, 5276. [CrossRef]
20. Wu, F.; Maier, J.; Yu, Y. Guidelines and trends for next-generation rechargeable lithium and lithium-ion batteries. *Chem Soc. Rev.* **2020**, *49*, 1569–1614. [CrossRef]
21. Wang, W.; Yang, T.; Li, S.; Lu, J.; Zhao, X.; Fan, W.; Fan, C.; Zuo, X.; Tie, S.; Nan, J. 1,4-Phenylene diisocyanate (PPDI)-containing low H₂O/HF and multi-functional electrolyte for LiNi_{0.6}Co_{0.2}Mn_{0.2}O₂/graphite batteries with enhanced performances. *J. Power Sources* **2021**, *483*, 229172. [CrossRef]
22. Ballinger, B.; Stringer, M.; Schmeda-Lopez, D.R.; Kefford, B.; Parkinson, B.; Greig, C.; Smart, S. The vulnerability of electric vehicle deployment to critical mineral supply. *Appl. Energy* **2019**, *255*, 113844. [CrossRef]
23. Beaudet, A.; Larouche, F.; Amouzegar, K.; Brouhard, P.; Zaghbi, K. Key Challenges and Opportunities for Recycling Electric Vehicle Battery Materials. *Sustainability* **2020**, *12*, 5837. [CrossRef]
24. World Bank Group. *Reuse and Recycling: Environmental Sustainability of Lithium-Ion Battery Energy Storage Systems*; Energy Sector Management Assistance Program (ESMAP): Washington, DC, USA, 2020; Available online: <http://documents.worldbank.org/curated/en/593961599738208006/Reuse-and-Recycling-Environmental-Sustainability-of-Lithium-Ion-Battery-Energy-Storage-Systems> (accessed on 19 April 2021).
25. Yang, X.L.; He, L.Y.; Xia, Y.F.; Chen, Y.F. Effect of government subsidies on renewable energy investments: The threshold effect. *Energy Policy* **2019**, *132*, 156–166. [CrossRef]
26. Lin, B.; Luan, R. Are government subsidies effective in improving innovation efficiency? Based on the research of China's wind power industry. *Sci. Total Environ.* **2020**, *710*, 136369. [CrossRef]
27. Luo, G.L.; Liu, Y.X.; Zhang, L.P.; Xu, X.; Guo, Y.W. Do government subsidies improve the financial performance of China's new energy power generation enterprises? *Energy* **2021**, *227*, 120432. [CrossRef]
28. Wang, X.L.; Li, Z.Q.; Shaikh, R.; Ranjha, A.R.; Batala, L.K. Do government subsidies promote financial performance? Fresh evidence from China's new energy vehicle industry. *Sustain. Prod. Consum.* **2021**, *28*, 142–153. [CrossRef]
29. Yu, F.F.; Wang, L.T.; Li, X.T. The effects of government subsidies on new energy vehicle enterprises: The moderating role of intelligent transformation. *Energy Policy* **2020**, *141*, 111463. [CrossRef]
30. Lee, M.H.; Yun, J.H.J.; Pyka, A.; Won, D.K.; Kodama, F.; Schiuma, G.; Park, H.S.; Jeon, J.; Park, K.B.; Jung, K.H.; et al. How to Respond to the Fourth Industrial Revolution, or the Second Information Technology Revolution? Dynamic New Combinations between Technology, Market, and Society through Open Innovation. *J. Open Innov. Technol. Mark Complex* **2018**, *4*, 21. [CrossRef]
31. Tayal, A.; Kalsi, N.S.; Gupta, M.K.; Pimenov, D.Y.; Sarikaya, M.; Pruncu, C.I. Effectiveness Improvement in Manufacturing Industry; Trilogy Study and Open Innovation Dynamics. *J. Open Innov. Technol. Mark Complex* **2021**, *7*, 7. [CrossRef]
32. Liu, D.Y.; Chen, T.; Liu, X.Y.; Yu, Y.Z. Do more subsidies promote greater innovation? Evidence from the Chinese electronic manufacturing industry. *Econ. Model.* **2019**, *80*, 441–452. [CrossRef]
33. Liu, Z. The impact of Government Policy on Macro Dynamic Innovation of the Creative Industry: Studies of the UK's and China's Animation Sectors. *J. Open Innov. Technol. Mark Complex* **2021**, *7*, 168. [CrossRef]
34. Li, J.; Ku, Y.; Liu, C.; Zhou, Y. Dual credit policy: Promoting new energy vehicles with battery recycling in a competitive environment? *J. Clean Prod.* **2020**, *243*, 118456. [CrossRef]

35. Lin, B.; Luan, R. Do government subsidies promote efficiency in technological innovation of China's photovoltaic enterprises? *J. Clean Prod.* **2020**, *254*, 120108. [CrossRef]
36. Lim, C.Y.; Wang, J.W.; Zeng, C. China's "Mercantilist" Government Subsidies, the Cost of Debt and Firm Performance. *J. Bank Financ.* **2018**, *86*, 37–52. [CrossRef]
37. Zhu, Z.S.; Liao, H. Do subsidies improve the financial performance of renewable energy companies? Evidence from China. *Nat. Hazards* **2019**, *95*, 241–256. [CrossRef]
38. Chen, K.; Zhao, F.; Hao, H.; Liu, Z. Selection of Lithium-ion Battery Technologies for Electric Vehicles under China's New Energy Vehicle Credit Regulation. *Energy Procedia* **2019**, *158*, 3038–3044. [CrossRef]
39. Zhang, L.; Liu, Y.; Pang, B.; Sun, B.; Kokko, A. Second Use Value of China's New Energy Vehicle Battery: A View Based on Multi-Scenario Simulation. *Sustainability* **2020**, *12*, 341. [CrossRef]
40. Moreno-Brieva, F.; Merino-Moreno, C. Technology generation of lithium batteries in leading countries. *Environ. Sci. Pollut. Res.* **2021**, *8*, 28367–28380. [CrossRef]
41. Wu, R.; Liu, Z.; Ma, C.; Chen, X. Effect of government RD subsidies on firms' innovation in China. *Asian J. Technol. Innov.* **2019**, *28*, 1–18.
42. Yu, F.; Guo, Y.; Le-Nguyen, K.; Barnes, S.J.; Zhang, W. The impact of government subsidies and enterprises' RD investment: A panel data study from renewable energy in China. *Energy Policy* **2016**, *89*, 106–113. [CrossRef]
43. Otomo, P. The Impact of Patents on Research & Development Expenditure as a Percentage of Gross Domestic Products: A Case in the U.S. and EU Economies. Bachelor's Thesis, Skidmore College, Saratoga Springs, NY, USA, 2017.
44. Altuzarra, A. RD and patents: Is it a two-way street? *Econ. Innov. New Technol.* **2019**, *28*, 180–196. [CrossRef]
45. Das, R.C. Interplays among RD spending, patent and income growth: New empirical evidence from the panel of countries and groups. *J. Innov. Entrep.* **2020**, *9*, 1–22. [CrossRef]
46. Liang, X.S. Unraveling the cause-effect relation between time series. *Phys. Rev. E* **2014**, *90*, 052150. [CrossRef]
47. Stips, A.; Macias, D.; Coughlan, C.; Garcia-Gorritz, E.; Liang, X.S. On the causal structure between CO₂ and global temperature. *Sci. Rep.* **2016**, *6*, 21691. [CrossRef] [PubMed]
48. Li, M.; Liu, K. Probabilistic Prediction of Significant Wave Height Using Dynamic Bayesian Network and Information Flow. *Water* **2020**, *12*, 2075. [CrossRef]
49. Jiang, S.; Hu, H.; Zhang, N.; Lei, L.; Bai, H. Multi-source forcing effects analysis using Liang-Kleeman information flow method and the community atmosphere model (CAM4.0). *Clim. Dyn.* **2019**, *53*, 6035–6053. [CrossRef]
50. Hagan, D.F.T.; Wang, G.; San Liang, X.; Dolman, H.A.J. A Time-Varying Causality Formalism Based on the Liang-Kleeman Information Flow for Analyzing Directed Interactions in Nonstationary Climate Systems. *J. Clim.* **2019**, *32*, 7521–7537. [CrossRef]
51. Yao, C.Z. Information Flow Analysis between EPU and Other Financial Time Series. *Entropy* **2020**, *22*, 683. [CrossRef] [PubMed]
52. Nie, C. Dynamics of the price-volume information flow based on surrogate time series. *Chaos* **2021**, *31*, 013106. [CrossRef]
53. Nyasha, S.; Odhiambo, N.M. Government Size and Economic Growth: A Review of International Literature. *SAGE Open* **2019**, *9*, 215824401987720. [CrossRef]
54. Lawal, A.S.; Nenlat, R.; Jacob, H.U. The Granger Causality Tests on the Impact of Government Expenditure on Economic Growth in Nigeria. *Int. J. Res. Sci. Technol.* **2020**, *5*, 2454.
55. BloombergNEF. China Dominates the Lithium-ion Battery Supply Chain, but Europe is on the Rise. 2020. Available online: <https://about.bnef.com/blog/china-dominates-the-lithium-ion-battery-supply-chain-but-europe-is-on-the-rise/> (accessed on 16 April 2021).
56. RAM (Research and Markets). Battery–Global Market Trajectory & Analytics. 2021. Available online: www.researchandmarkets.com (accessed on 17 April 2021).
57. Slowik, P.; Lutsey, N.; Hsu, C. How Technology, Recycling, and Policy Can Mitigate Supply Risks to Long-Term Transition to Zero-Emission Vehicles. The International Council on Clean Transportation; 8 December 2020. Available online: <https://theicct.org/publications/mitigating-zev-supply-risks-dec2020> (accessed on 19 April 2021).
58. Jin, L.; He, H.; Cui, H.; Lutsey, N.; Wu, C.; Chu, Y.; Zhu, J.; Xiong, Y.; Liu, X. Driving a Green Future—A Retrospective Review of China's Electric Vehicle Development and Outlook for the Future. 2021. Available online: <https://theicct.org/sites/default/files/publications/China-green-future-ev-jan2021.pdf> (accessed on 17 April 2021).
59. Climate Cooperation. New Energy Vehicle Industry Development Plan (2021–2035). 2021. Available online: <https://climatecooperation.cn/climate/new-energy-vehicle-industry-development-plan-2021-2035/#:~:text=The%20New%20Energy%20Vehicle%20Industry,part%20of%20the%20comprehensive%20roadmap> (accessed on 19 April 2021).
60. Barrett, E. Government Subsidies Fueled China's Electric Vehicle Boom. Now They're Facing Intense Scrutiny. *Fortune*; 6 September 2019. Available online: <https://fortune.com/2019/09/06/government-subsidies-china-electric-vehicle-boom/> (accessed on 16 April 2021).
61. Moss, T. The Key to Electric Cars Is Batteries. One Chinese Firm Dominates the Industry. *The Wall Street Journal*; 3 November 2019. Available online: www.wsj.com/articles/how-china-positioned-itself-to-dominate-the-future-of-electric-cars11572804489?mod=searchresults&page=1&pos=15 (accessed on 19 April 2021).
62. ITS. China BAK Receives Government Subsidy for its Battery Module Project. 2015. Available online: www.itsinternational.com/news/china-bak-receives-government-subsidy-its-battery-module-project (accessed on 19 April 2021).

63. Scott, S.; Ireland, R. Lithium-Ion Battery Materials for Electric Vehicles and their Global Value Chains. Office of Industries Working Paper ID-068. 2020. Available online: www.usitc.gov/publications/332/working_papers/gvc_overview_scott_ireland_508_final_061120.pdf (accessed on 19 April 2021).
64. Masiero, G.; Ogasavara, M.H.; Jussani, A.C.; Risso, M.L. Electric vehicles in China: BYD strategies and government subsidies. *RAI Rev. Adm. Innov.* **2016**, *13*, 3. [[CrossRef](#)]
65. Mai, H.J. To Compete in the Global Battery Arms Race, the US Must Spur its Domestic Market, Analysts Say. 2019. Available online: www.utilitydive.com/news/creating-a-domestic-market-is-paramount-for-us-battery-industry-to-close-th/557339/ (accessed on 19 April 2021).
66. Bell, A.; Fairbrother, M.; Jones, K. Fixed and random effects models: Making an informed choice. *Qual. Quant.* **2019**, *53*, 1051–1074. [[CrossRef](#)]
67. Li, Q.; Wang, M.; Xiangli, L. Do government subsidies promote new-energy firms' innovation? Evidence from dynamic and threshold models. *J. Clean Prod.* **2020**, *286*, 124992. [[CrossRef](#)]
68. Bronzini, R.; Piselli, P. The impact of R&D subsidy on firm innovation. *Res. Policy* **2016**, *45*, 442–457.
69. Wu, A. The signal effect of Government R&D Subsidies in China: Does ownership matters? *Technol. Forecast. Soc. Chang.* **2017**, *117*, 339–345.
70. Hausman, J.A. Specification Tests in Econometrics. *Econometrica* **1978**, *46*, 1251–1271. [[CrossRef](#)]
71. Patent Information Service Platform Network. Available online: <http://pss-system.cnipa.gov.cn/sipopublicsearch/> (accessed on 20 January 2021).
72. China Stock Market & Accounting Research Database. Available online: <https://www.gtarsc.com/> (accessed on 23 January 2021).
73. Liang, S.X. Normalizing the causality between time series. *Phys. Rev. E* **2015**, *92*, 022126. [[CrossRef](#)]
74. Rossi, F.; Cebula, R.J. Ownership Structure and RD: An Empirical Analysis of Italian listed companies. *PSL Q Rev.* **2015**, *68*, 297–325.
75. Cherenksy, S.S. Shareholders, Managers, and Corporate RD Spending: An Agency Cost Model. *St. Clara High Technol. Law J.* **1994**, *10*, 299–346.
76. Hong, J.; Hong, S.; Wang, L.; Xu, Y.; Zhao, D. Government grants, private RD funding and innovation efficiency in transition economy. *Technol. Anal. Strateg. Manag.* **2015**, *27*, 1068–1096. [[CrossRef](#)]
77. Jiang, C.; Zhang, Y.; Bu, M.; Liu, W. The Effectiveness of Government Subsidies on Manufacturing Innovation: Evidence from the New Energy Vehicle Industry in China. *Sustainability* **2018**, *10*, 1692. [[CrossRef](#)]
78. Peng, H.; Liu, Y. How government subsidies promote the growth of entrepreneurial companies in clean energy industry: An empirical study in China. *J. Clean Prod.* **2018**, *188*, 508–520. [[CrossRef](#)]
79. Xu, J.; Wang, X.; Liu, F. Government subsidies, RD investment and innovation performance: Analysis from pharmaceutical sector in China. *Technol. Anal. Strateg. Manag.* **2020**, *33*, 535–553. [[CrossRef](#)]
80. Dang, J.W.; Motohashi, K. Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. *China Econ. Rev.* **2015**, *35*, 137–155. [[CrossRef](#)]
81. Giarratana, M.S.; Mariani, M.; Weller, I. Rewards for Patents and Inventor Behaviours in Industrial Research and Development. *Acad. Manag. J.* **2017**, *61*, 264–292. [[CrossRef](#)]
82. Gosens, J.; Lu, Y. From lagging to leading? Technological innovation systems in emerging economies and the case of Chinese wind power. *Energy Policy* **2013**, *60*, 234–250. [[CrossRef](#)]
83. Sun, X.; Yu, R.; Wang, Y.; Colombage, S.R.N. Do government subsidies stimulate firms' RD efforts? Empirical evidence from China. *Asian J. Technol Innov.* **2020**, *28*, 1–18. [[CrossRef](#)]
84. Lam, L.T.; Branstetter, L.; Azevedo, I.M.L. China's wind industry: Leading in development, lagging in innovation. *Energy Policy* **2017**, *106*, 588–599. [[CrossRef](#)]
85. Zhu, Z.; Zhu, Z.; Xu, P.; Xue, D. Exploring the impact of government subsidy and RD investment on financial competitiveness of China's new energy listed companies: An empirical study. *Energy Rep.* **2019**, *5*, 919–925. [[CrossRef](#)]
86. Li, X. Behind the recent surge of Chinese patenting: An institutional view. *Res. Policy* **2012**, *41*, 236–249. [[CrossRef](#)]
87. Lei, Z.; Sun, Z.; Wright, B. *Patent Subsidy and Patent Filing in China*; University of California: Berkeley, CA, USA, 2013.
88. Almeida, A.; Teixeira, A.A.C. *Does Patenting Negatively Impact on R&D Investment? An International Panel Data Assessment*; FEP Working Papers 255; Universidade do Porto, Faculdade de Economia do Porto: Porto, Portugal, 2007.
89. Jeong, H.J.; Ko, Y. Configuring an alliance portfolio for eco-friendly innovation in the car industry: Hyundai and Toyota. *J. Open Innov. Technol. Mark Complex* **2016**, *2*, 1–16. [[CrossRef](#)]
90. Kranzeeva, E.; Golovatsky, E.; Orlova, A.; Nyatina, N.; Burmakina, A. Assessing the effectiveness of Social and Political Innovations in the Development of Interaction between the Authorities and the Population during COVID-19: The Implication of Open Innovation. *J. Open Innov. Technol. Mark Complex* **2021**, *7*, 172. [[CrossRef](#)]