Can Technological Innovation Bring an Economic and Environmental Benefit to Energy Firms: An Evidence from China?

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Abstract: This paper investigates whether technological innovation can bring some economic and environmental benefits to energy firms. By analyzing data for energy firms in China from 2009 to 2017, this paper finds that technological innovation is not always beneficial to the multi-interests of energy firms. First, technological innovation does not necessarily fully promote the benefit-based performance of energy firms in China. Actually, technological innovation increases the excess returns but inhibits the operational efficiency of energy firms, and has no a significant impact on the firm value of energy firms. Moreover, technological innovation exacerbates the crash risks of energy firms, which is not conductive to the stability of energy financial market. Second, technological innovation may significantly reduce carbon emissions intensity and play an important role in improving the environmental performance of energy firms in China. Finally, a sharp rise in energy prices may inhibit technological innovation activities, and thus influencing the performance of energy firms.

Keywords: Technological innovation; Energy firms; Firm performance; Truncated regression model; Treatment effect model

JEL Classification: Q55; M14; O13; L25

1 Introduction

Addressing climate change has increasingly become a global consensus with the new round of industrial revolution. As the main source of greenhouse gas, energy industry has received much attention, especially for the improvement in the areas of energy conversion, energy efficiency and low-carbon energy, in responding to the negative environmental externalities stemming from energy sources. In this situation, accelerating technological innovation in the energy industry is considered as a key force in addressing environmental issues worldwide,

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and has been universally concerned (Chan et al., 2017; Doblinger et al., 2019). For example, governments in many industrialized countries and emerging economies have expanded their support for developing advanced energy-supply and energy-demand technologies (Anadón, 2012). Among them, the exploration and utilization of new energy systems have been receiving extensive attention in the field of energy technology innovation, such as wind, solar, and other renewables (Rogge and Schleich, 2018; Noailly and Smeets, 2015), but their high costs and technological barrier hamper the widespread usage of renewable energy resources (Verdolini and Galeotti, 2011). Moreover, as stated by Jewell et al. (2018), the renewable energy is unlikely to increase even though removing the fossil fuel subsidies. Therefore, the affordable and reliable fossil energy is still the main concern for energy development, and the cornerstone to sustain global economic growth in the near future (Chu and Majumdar, 2012). Especially for China, fossil energy consumption accounts for more than 85% of total energy consumption. Although China has been committed to cleaning energy consumption structure and improving energy efficiency, traditional energy sources, such as oil, coal, and natural gas, still play an important role in the energy mix. According to the new plan for energy technology innovation issued by the National Energy Administration of China in 2016,[1] in addition to the utilization of new energy and nuclear energy, the efficient exploration, transformation and utilization of fossil energy are also still the main focus for energy technology in China.

However, the national energy strategy requires cleaning the structure of energy production and clean consumption, the survival advantages of Chinese traditional energy companies have been severely challenged. Specifically, oil and gas producers need to expand production to ensure their profits when the oil prices are high, and at this time, the goals of production and profit are consistent. However, when the oil prices tend to be low, some problems may appear, such as insufficient capability of technological innovation, small profit margins caused by high mining costs, and focusing on scale but ignoring efficiency. For coal firms, clean and efficient energy development strategies have forced coal to be replaced, which may impair the long-term benefits for coal firms. As for power firms, because more than 70% of China's power generation is mainly dominated by thermal power, under the influence of coal cleanliness, power firms have to find a way to both meet the national strategic demand of energy transformation and benefit their own survival.

[1] http://zfxxgk.nea.gov.cn/auto83/201701/P020170113571241558665.pdf.

Fortunately, the rapid development of innovative technologies may bring new opportunities for energy firms. Technological innovation is not only an important driver for economic growth, but also helpful to establish the competitive advantage of firms (Porter, 1992), it plays an important role in the firms' survival, and thus, has been of wide interests (Rubera and Kirca, 2012). Given that energy firms need to balance the multi-interests of different stakeholders and fulfill corporate social responsibility in their business, their competitive advantage should have broader scope. In a transparent market, the managers of a firm need to consider the firm performance in the financial market to enhance investor confidence and obtain long-term financing when trying to obtain firm internal profits to gain market advantage. Meanwhile, they also need to establish a good image by fulfilling social responsibilities, and thus obtaining competitive advantage. Unfortunately, it is difficult for a firm to achieve multiple goals at the same time, and the results of technological innovation are highly uncertain. To get an insight about these circumstances, this paper examines whether technological innovation can bring competitive advantage to traditional energy firms in the complex energy market environment. Specifically, the impact of technological innovation on energy firms' benefit-based performance, risk performance, and environmental performance is investigated in detail. There are three main reasons on why these performances can be treated as the crucial competitiveness of energy firms and affected by technological innovation.

First, obtaining long-term benefits is the main purpose of most business strategies such as technological innovation activities for an energy firm. For energy firms, the premise of improving competitiveness through innovation strategies is whether technological innovation can help them achieve their profit goals. Generally, reducing costs and increasing revenue are the main goals for firms' business operations. However, owing to the instability of energy supply and demand in China, overcapacity will be exacerbated if energy firms dilute costs by increasing their production. Therefore, enhancing firm competitiveness through technological innovation provides a possible path for the low-cost development of energy firms. Since whether energy firms will enhance their competitiveness through large-scale technological innovation activities depends on whether technological innovation can bring enough benefits to them or not, focusing on how the benefit-based performance is affected by technological innovation is critical for energy firms. Firm benefits include many aspects, such as productivity, sales, return on assets, and so on. This paper selects three indicators, i.e., operational efficiency, Tobin's Q, and excess returns, which involve both the accounting-based performance and financial performance, to represent the benefit-based performances of energy firms in China, and further investigate how technological innovation affect them.

Second, the uncertainty of the results of technological innovation exacerbates the risks of firms. Specifically, technological innovation has the characteristics of a high failure rate, and may make energy firms face the volatility of their future cash flow, leading to high volatility in stock prices and, thus, high risk (Titman and Grinblatt, 2002). Moreover, with uncertain returns investing in technological innovation activities, relevant energy firms may be pressured by myopic investors to generate short-term profits, which could be detrimental to long-term innovation and further exacerbate the stock price risk of firms (Stein, 1989; Acharya and Xu, 2017). However, if the economic benefits or other benefits can be generated from technological innovation after considering the increase in risks caused by innovation activities, relevant stakeholders are willing to support related innovation activities (Sorescu and Spanjol, 2008). On the contrary, if technological innovation brings great risks, then even if they bring weak economic benefits, technological innovation activities as a whole should be regarded as a failure. Therefore, while considering the above-mentioned benefit-based performance, this paper incorporates firm risk into the performance system of energy firms, aiming to investigate whether technological innovation will exacerbate the risks of energy firms and how much.

Finally, technological innovation plays an important role in energy conservation and emissions reduction. Energy firms as both energy producers and consumers, are closely related to some key environmental pollutants, like carbon emissions (Hille and Möbius, 2019), thus, concerning environmental issues is also their urgent social responsibility. Recently, resource constraints, social pressures, and regulatory policies drive the need towards a more balanced approach to economic growth force and environmental issue (Tang et al., 2018). From the perspective of corporate social responsibility, the key principle is that energy firms are responsible for the environmental problems that they either cause or are associated with (Starik and Marcus, 2000). Therefore, energy firm managers are increasingly focused on maximizing energy savings and emissions reduction without reducing the accounting performance. Fortunately, technological innovation can lead to technological advancement, which helps to increase the energy efficiency and energy savings, and reduce the negative environmental consequences of energy production and consumption (Sagar and Holdren, 2002). Recently, the attention to global competitiveness and environmental issues poses challenges to technological innovation in the energy industry (Anadón, 2012; Anadón at al., 2016). This is because the extraction, transportation, and refining of energy resources are accompanied by huge energy consumption and carbon dioxide emissions. According to China Energy Statistical Yearbook, the total energy consumption in mining oil and coal, processing, and power production industries reached 67.723 million tons of coal equivalent in 2017, which accounts for approximately 18.9% of the total energy production.[2] Thus, this paper concerns whether technological innovation are beneficial to environmental performance of energy firms in China.

Overall, to better understand whether technological innovation brings economic and environmental benefits to energy firms, this paper examines the impact of technological innovation on multiple performance indicators (benefits-based performance, risk performance, and environmental performance) of energy firms in China. Specifically, the main purpose of this paper is to detect whether technological innovation can improve the benefits-based performance of energy firms, whether it can reduce the risks that energy firms face, and whether it can reduce the carbon emissions intensity of energy firms. To this end, this paper first proposes three types of performance indicators, i.e., benefits-based performance (operational efficiency, firm value, and excess returns), risk performance (firm risk), and environmental performance (carbon emissions intensity), to examine the impact of technological innovation on the performances of energy firms. Meanwhile, this paper also identifies several factors that affect the performance of energy firms, including firm size, ownership, economic environment, financial environment, and firm age. Second, based on the operational efficiency calculated by the bootstrap based data envelopment analysis (Odeck, 2009) model in this paper, the truncated regression method is used to estimate the impact of technological innovation on operational efficiency. Finally, to ensure the reliability of the empirical results, this paper conducts a series of robustness tests, including variable substitution, endogeneity problems, and the dynamic impact of technological innovation on the performance of energy firms.

This paper contributes to the literature in three ways. First, this paper extends the exiting literature of measuring firm performance, and finds that technological innovation does not necessarily fully promote the benefit-based performance of energy firms in China, but it

[2] National Bureau of Statistics of China, http://www.stats.gov.cn/.

may significantly increase their crack risks and improve the environmental performance. The extended firm performances is conductive to investors making investment decisions, managers formulating management strategies, and relevant institutions building supervision plans. Second, this paper obtains a new result of the role of energy price changes on technological innovation. We find that the sharp rise of energy prices can inhibit innovation activities, which is contrary to the common statement that "energy prices may amplify the incentives for innovation" in the literature (Popp, 2002; Newell et al., 1999). The previous relevant literature often considers the increase in energy price as a change in cost, and thus affecting firm's decision and direction of technological innovation. However, the change of energy prices also has another role for energy firms, that is, energy prices are directly associated with the revenue of energy firms. Also, the paper draws on a novel method of processing energy prices, and explores another possibility of the impact of energy prices on the technological innovation of energy firms. Finally, this paper uses the firm-level data to reveal the more micro-level issues that concern investors and firm managers. For example, the environment issues have always been a hot topic for researchers at a macro level, which offers the general trend of environment development but lacks the micro evidences of energy firms. However, these micro evidences are of great value for relevant investors and managers to make their decisions.

The remainder of this paper is organized as follows. Section 2 is devoted to the literature review. Section 3 introduces the methods used for the empirical analysis. Section 4 describes the data and variables and Section 5 calculates the operational efficiency of energy firms, analyzes the impact of technological innovation on the performance of energy firms, and conducts a series of robustness tests. Section 6 concludes the paper.

2 Literature review

With the development of economic growth theory and the availability of firm-level data, there have been many studies to highlight the importance of technological innovation for firm performance. For example, technological innovation plays an important role in increasing productivity (Hashi and Stojčić, 2013) and firm growth (Rubera and Kirca, 2012). In particular, numerous studies have found that technological innovation has a positive impact on firm performance (e.g., Li and Atuahene-Gima, 2002). However, some research supports the argument that technological innovation does not affect firm performance (e.g., Mansury and

Love, 2008), and even finds negative performance implications of technological innovation (e.g., Artz et al., 2010). This may be the reason that innovation activities often take up many firm resources (Li and Atuahene-Gima, 2001) and may imply increasing uncertainties and risks (Wang et al., 2010). Furthermore, successful technological innovation activities may be affected by many factors. For instance, it requires special compensation incentives and organizational learning to stimulate technological innovation and enable firms to obtain the value generated from their technological innovation (Ederer and Manso, 2013). In brief, the overall impact of technological innovation on firm performance is an aggregate from both positive and negative mediating effects (Rosenbusch et al., 2011), which makes the final results become uncertain. For this reason, this paper aims to examine how technological innovation affects performances of energy firms in China.

As for the impact of technological innovation on firm performance, due to different measurement criteria and access sources, there are many variables used for technological innovation activities, such as patent-based innovation (e.g., patents granted, citations, generality, and originality), and R&D-based innovation (e.g., R&D expenses and R&D intensity). Meanwhile, there are some different representative variables for the performance that distinct stakeholders concern, such as accounting-based performance and financial performance.

In view of the input and output processes of technological innovation activities, there are two common approaches used to measure technological innovation. The first approach uses R&D expenditure as a proxy for technological innovation input (Thornhill, 2006). There are two problems associated with this approach: for one thing, not all R&D expenditure ends in technological innovation outputs to market, as this measure reflects only the resources committed to producing innovation output but not the innovation process or ultimate result of innovation (Leeuwen, 2008). For another, performing R&D might not be enough to introduce new products to market, especially in developing countries, where firms often generate technological advances in informal R&D process, i.e., many firms can acquire embedded technology by purchasing machinery and hardware. In this case, R&D will not capture the true extent of innovative efforts (Wadho and Chaudhry, 2018). The second approach is to use patents as an indicator for technological innovation output. This approach also has some limitations, i.e., not all technological innovations occurred in firms will be the subject of patent applications, and not all patents can represent the technological innovation performance of firms. However, patents are the direct result of technological inventions and are expected to have an attractive commercial prospect, so patents prove an appropriate indicator for better reflecting a firm's innovation capability since they can capture technological change and competition capability.

As for firm performance, most relevant studies are more concerned about accounting performance, such as productivity, profit, and income. In fact, financial performance also receives widespread attention. For example, Simeth and Cincera (2015) use Tobin's Q to measure firm performance, and find the positive impact of scientific publications on firm market value. Errunza and Senbet (1981) use excess returns to measure firm performance. Moreover, with the complex financial conditions and high requirements for corporate social responsibility, scholars have started to concern more generalized firm performance in recent years, such as operational efficiency, firm risk, and environmental performance.

First, operational efficiency is often used as an indicator for firm performance. For example, Un and Asakawa (2015) state that one of the main goals of technological innovation is to improve the operational efficiency of firms, whereas Chan et al. (2016) consider operational efficiency in performance measurement together with profitability, but they measure this efficiency only from the cost-efficiency perspective. Actually, the operation of a firm is a process from input to output, and the role of technological innovation should not only be to reduce costs. If the firm can obtain higher output at a given cost, it also indicates the success of innovation activities. Thus, it is important to consider both input and output factors when studying the impact of technological innovation on the operational efficiency of a firm. This paper uses the data envelopment analysis (DEA) approach, a nonparametric method in operations research and economics for the estimation of production frontiers, to measure the operational efficiency of energy firms in China to better understand how technological innovation effectively transforms human, material and capital resources into income.

Second, the firm risk has been a wide concern and become increasingly important to investors and management. Specifically, firm risk is inversely related to a firm's general survival probability, and firms at high risk levels tend to have greater probabilities of experiencing financial distress, which is almost always unfavorable for creditors, management, customers, and employees (Sorescu and Spanjol, 2008). Thus, more relevant studies focused on the impact of internal controls (Ashbaugh-Skaife et al., 2009), management discretion (Li and Tang, 2010), and tax avoidance on firm risks (Kim et al., 2011). In view of the high failure and high risk of innovation activities, and the sensitivity of financial markets to firm's major activities, firm risk has been used as an indicator for firm performance (Köhler and Som, 2014). This paper uses the crack risks as a proxy of firm risk for energy firms, to investigate how it is affected by the technological innovation.

Third, global warming, especially the deterioration of environmental quality in developing countries, has placed energy firms under enormous environmental pressures from markets and regulators. Competition in ecological innovation and environmental sustainability is particularly important for the survival of energy firms, and has attracted wide attention of scholars and policy makers. For example, Long et al. (2017) use carbon emissions to measure the environmental performance and confirm that innovation has a greater impact on environmental performance than financial performance, whereas Carrión-Flores and Innes (2010) concern the toxic emissions in environmental performance and find that innovation is an important driver of reducing toxic emissions in the United States. Therefore, technological innovation may be an effective method for energy firms to relieve environmental pressure and improve their environmental performance, and this paper will give reliable evidence.

To sum up, existing relevant studies have explored the impact of technological innovation on firm performance, but they have not paid sufficient attention to whether energy firms can always benefit from their innovative strategies and activities. This is mainly reflected in the following aspects: on the one hand, the firm's benefits should serve different stakeholders, and these stakeholders may concern different firm performances. For example, firm managers may pay more attention to whether technological innovation can improve the finance and operation of firms under an unstable energy market. Investors are more concerned about whether the innovation investment conflicts with either their long-term or short-term benefits, regulators need to supervise firm social responsibility (e.g., the responsibility of reducing emissions) in an innovative environment, and policy makers need to consider the interests of each entity and formulate the next strategic plan (e.g., innovation strategy) that is in line with the development of firms, economy and society. Therefore, to understand how technological innovation affects the performance of energy firms under the national innovation-driven development strategy in China, this paper examines the impact of technological innovation on multiple performance indicators (benefits-based performance, risk performance, and environmental performance) of energy firms. On the other hand, the impact of technological innovation on firm performance is heterogeneous across industries and regions. This paper focuses on Chinese energy industry and incorporates industry-specific variables, namely the change of energy prices, to better understand how changes in the energy market affect the relationship between technological innovation and firm performance.

3 Methodologies

To study the impact of technological innovation on the performances of energy firms in China, this paper specifies the following basic model:

$$y_{it} = \alpha + \beta_1 P_{it} + \beta_2^\top x_{it} + \epsilon_{it}, \tag{1}$$

where y_{it} includes operational efficiency, Tobin's Q, excess returns, firm risks, which is defined in Section 4.2.1 (see later), and environmental performance, P_{it} is a technological innovation variable represented by the natural logarithm of number of patents granted, x_{it} denotes the set of control variables, including firm age (i.e., the natural logarithm of the number of years a firm has existed), firm size (i.e., the natural logarithm of total assets), ownership (i.e., 1 for state-owned=1 and 0 otherwise), unemployment rate and GDP per capita (i.e., the natural logarithm of GDP per capita), leverage (i.e., the natural logarithm of leverage), and energy price (i.e., the dummy variable of a net increase of energy price), defined in Section 4.2.2 (see later).

Since the values of operational efficiency are calculated by the bootstrap-DEA model proposed by Simar and Wilson (1998) and distributed between 0 and 1, thus, we use the truncated regression model to estimate (1), when the firm performance is represented by operational efficiency (Simar and Wilson, 2007).[3] In other models, specifically, when the firm performance in (1) refers to Tobin's Q, excess returns, firm risks, and environmental performance, respectively, the ordinary least squares (OLS) method can be used for estimating (1).

3.1 Operational Efficiency Measurement of Energy Firms

To study whether technological innovation can effectively transform energy firm resources, such as human, material, and capital resources, into income, this paper employs the DEA method to calculate the operational efficiency of energy firms in China. Considering the small sample size, and traditional DEA models with sample sensitivity may cause biased

[3]When identifying drivers of firm efficiency, Simar and Wilson (2007) suggest using a two-stage procedure for a truncated regression technique and show that the proposed estimation is consistent under some mild assumptions.

estimation with small samples (Odeck, 2009), this paper uses the bootstrap-DEA method to calculate the operational efficiency. First, the simple DEA model is used to calculate the original efficiency θ for each decision unit, and then, the bootstrap approach is used to extract a simple sample θ^b with the scale of n, where b is the number of iterations of bootstrap sampling and is set as $1,000$ in this paper. Finally, the kernel density estimation method is used to smooth the samples obtained by bootstrap, and the processed samples are used to correct the input indicators (fixed assets, operating costs, and number of employees) of the original samples, and the adjusted input indicators are obtained and combined with the original output data (sales) to calculate the adjusted operational efficiency values.

3.2 Treatment Effect Model of Technological Innovation and Energy Firm Performance

Because a firm's decision to engage in innovative activities is an endogenous choice driven by other observed and unobserved factors, there may be endogenous problem due to selectivity bias in this paper. To test whether this endogeneity could change the effect of technological innovation on energy firm performance, this paper uses the idea similar to the treatment effect model to test the robustness of the estimated results concerning technological innovation and firm performance.

We set the technological innovation variable P_{it} as a dummy variable IP_{it} (defined below) in the following treatment effect model. Specifically, the observation value with patents granted greater than 0 is recorded as 1, otherwise, 0. For energy firms, the decision as to whether to carry out technological innovation activities is not random, and the effect of treatment (i.e., technological innovation activities) could differ across firms and could affect the decisions made regarding firm's innovative activities. Therefore, we need to control unobservable factors that could drive both the performance and the decision to conduct technological innovation. Specifically, the treatment effect model for the impact of technological innovation on energy firm performance includes two main equations. The first equation is the outcome equation as follows

$$y_{it} = \alpha + \beta_1 IP_{it} + \beta_2^\top x_{it} + \epsilon_{it}, \tag{2}$$

where the dummy variable IP_{it} indicates the treatment condition and the coefficient β_1 can be regarded as the average treatment effect, and the second equation is the selection equation

$$IP_{it} = I(P_{it}^* > 0), \quad \text{and} \quad P_{it}^* = \pi + \delta^\top Z_{it} + v_{it} \tag{3}$$

where $I(A)$ is the indicator function of event A and Z_{it} denotes a set of firm characteristic variables that affect a firm's decision to carry out innovation activities, including ownership, firm age, energy price, and an exogenous instrumental variable – the number of firm technicians. The treatment effect model is estimated using the two-step approach in this paper: the first step is to estimate (3), and the second step is to estimate (2) containing the dummy variable, so that the impact of technological innovation on the performance of energy firm is obtained.

4 Data and Variable Descriptions

4.1 Data Descriptions

Because of the difficulty in collecting financial data and performance data of small or unlisted energy firms in China, this paper focuses on the listed and large energy firms (including listed oil and gas firms, coal firms, and power firms) and a full sample range from 2009 to 2017. We further select the firms which have more than one patent in total during the period 2009-2017. In the selected sample, the number of patents is set to zero when no patent is available in some years (Acharya and Xu, 2017). The data on patents are compiled from two databases: patents granted come from the CSMAR database,[4] and patent citations come from the State Intellectual Property Office of China.[5] Except for the data of Tobin's Q from the CSMAR database, other accounting data and financial data in this paper are from the Flush Financial Database (iFind).[6] Data about the economic indicators, such as GDP per capita and unemployment rate, are derived from the National Bureau of Statistics of China.[7] After eliminating the missing data, this paper obtains 639 observations to examine the impact of technological innovation on operational efficiency, and when studying the impact of technological innovation on firm value, excess returns, firm risks, and carbon emissions intensity, it obtains 549, 522, 576, and 666 observations, respectively.

[4]CSMAR: http://cn.gtadata.com.
[5]National Intellectual Property Administration, PRC: http://www.sipo.gov.cn/.
[6]iFind: http://www.51ifind.com/.
[7]National Bureau of Statistics of China, http://www.stats.gov.cn/.

4.2 Variable Descriptions

4.2.1 Dependent Variables

Considering the performance indicators are differ from stakeholders of energy firms, and the impacts of innovation on those distinct performances may different markedly (Sorescu and Spanjol, 2008), this paper introduces benefits-based performance (operational efficiency, firm value, and excess returns), firm risks, and environmental performance to investigate the effect of technological innovation on them.

As for operational efficiency, this paper uses the bootstrap-DEA approach to calculate the operational efficiency of energy firms in China. Compared to the accounting-based performance (such as price-to-book ratio), Tobin's Q takes into account both book value and market value, and is widely used as financial performance to represent firm value in literature (Bharadwaj et al., 1999). Thus, this paper uses Tobin's Q as an indicator of firm value of energy firms. As for excess returns, producing excess returns is one of the goals for a firm, and the innovation-related activities, as a kind of scarce resource, can lead to the change of expected excess returns (Garleanu et al., 2012). Therefore, this paper refers to Firth et al. (2014) and uses the one-year lending rate as the risk-free rate to calculate the excess returns of energy firms.[8] Meanwhile, reducing firm risks is one way to increase the survival probability of energy firms. Therefore, this paper uses firm risks as one of the performance indicators of energy firms, to further determine whether technological innovation can reduce or increase energy firm risks. This paper focuses on the crash risks of energy firms and measures this risk by negative return skewness (Kim et al., 2011; Chen et al., 2001) foreach firm i in year t, which can be expressed as:

$$\mathrm{FirmRisk_{it}} = -\frac{n(n-1)^{3/2}\sum \mathrm{WR}_{it}^{3}}{(n-1)(n-2)\left[\sum \mathrm{WR}_{it}^{2}\right]^{3/2}},$$

where WR_{it} denotes firm-specific weekly return.[9] Besides, this paper uses carbon emissions intensity to represent environmental performance and measure it using the ratio of carbon dioxide emissions to the sales of energy firms (Alam et al., 2019).

[8] Excess return$_{it}$ = $R_{it} - R_m$, where R_{it} denotes the stock return of energy firm i and R_m means the risk-free rate.

[9] As Chen et al. (2001) note that stock market returns are asymmetrically distributed, and exhibit negative skewness, they use negative conditional return skewness to examine this asymmetric volatility. Later, Kim et al. (2011) regard this asymmetric volatility as the crack risk of firm-specific stock price.

4.2.2 Independent Variables and Control Variables

This paper uses the number of patents granted from the State Intellectual Property Office of China to measure the technological innovation level of each energy firm.[10] There are two reasons for using China's patent data rather than internationally recognized patent data, such as US patent data, to measure the level of technological innovation of energy firms in China. One reason is that the US patent database for China's firm data is updated only to 2006, and it cannot reflect the technological innovation situation after the innovation-driven development strategy proposed in China in 2012. The second reason is that the process and costs of patent registration may differ from countries, thus we use the patents from China rather than others to avoid bias caused by these differences, which is more conducive to truly reflecting the firm's technological innovation in China (Choi et al., 2011).

This paper also considers the impact of some control variables on energy firm performance, such as energy price, economic factors, and firm ownership. Among them, the impact of energy price on energy firm performance is often studied in two main ways. One is the direct impact of price on firm performance. Price, sales and cost constitute the main factors of firm decision-making. Therefore, energy price directly impacts on firm performance. The second way concerns the effect of energy price on firm performance through influencing technological innovation. The induced innovation theory proves that element scarcity induces technological innovation, and price can reflect the scarcity of factors and the demand of products and, thus, it will have an impact on technological innovation (Lichtenberg, 1986; Popp, 2002). By following Kilian and Vigfusson (2017) and Hamilton (2003), we use the net increase in energy price to study its impact on energy firm performance as follows

$$\Delta p_{it}^{net,+,3year} = \max\{0, p_{it} - p_{it}^*\},$$

where p_{it} is the real energy price at time t and p_{it}^* is the highest price for the previous three years. Because the different types of energy firms are included in our sample, their price units are distinct, and it is impossible to measure the price of one product by that of another. Therefore, a dummy variable is used to represent the net increase in energy prices, i.e., $EnergyPrice = 1$ if $p_t > \max\{p_{t-3}, p_{t-2}, p_{t-1}\}$, and $EnergyPrice = 0$, otherwise.[11]

[10] The data of patents granted are derived from the CSMAR database, which are originally published by the State Intellectual Property Office of China.

[11] The net increase of natural gas prices and oil prices are almost identical when they are represented by our dummy variable, so we use the net increase in oil prices to represent the increase of energy prices correspond-

Besides, this paper uses the logarithm of the firm's total assets to represent firm size; firm age is represented by the natural logarithm of the number of years a firm has existed; the ownership is set as a dummy variable for whether the firm is state-owned, i.e., it equals 1 if the firm is state-owned, otherwise 0; macroeconomic variables include unemployment rate and GDP per capita, which are expressed in 2012 constant price; and the leverage is denoted by the ratio of debt book value to total assets.

5 Empirical Results

5.1 Operational Efficiency of Energy Firms in China

To study the impact of technological innovation on the operational efficiency of energy firms, this paper calculates the operational efficiency of energy firms using the bootstrap-DEA method as mentioned in Section 3.1, and the results are shown in Table 1. We can find that the efficiency of China's energy firms is relatively low, with an average value of 0.5878. Specifically, the operational efficiencies of oil and gas firms, coal firms, and power firms are 0.6471, 0.5590, and 0.5562, respectively.

Table 1: Descriptive statistics on operational efficiency of energy firms in China.

Range of efficiency value		Observation		Proportion (%)
$E \in (0.2, 0.3)$		5		0.78
$E \in (0.3, 0.4)$		50		7.82
$E \in (0.4, 0.5)$		182		28.48
$E \in (0.5, 0.6)$		157		24.57
$E \in (0.6, 0.7)$		93		14.55
$E \in (0.7, 0.8)$		61		9.55
$E \in (0.8, 0.9)$		55		8.61
$E \in (0.9, 1.0)$		26		7.50
$E = 1$		10		4.07
Mean of efficiency	Full sample	Oil and gas firms	Coal firms	Power firms
	0.5878	0.6471	0.5590	0.5562

also, we find that the average value operational efficiency of coal firms and power firms

ing to oil and gas firms. The oil price data use WTI spot prices (https://www.eia.gov/), coal price data use the closing prices of Qinhuangdao Datong mixed coal 5500 (Q5500K) in China (https://www.wind.com.cn/), and electricity price data use the average selling prices in China (https://www.wind.com.cn/).

are relatively similar, and both are lower than oil and gas firms by nearly 15.8%, which is about 0.1 units. This may be due to the higher proportion of state-owned firms in coal firms and power firms. In our sample data, the proportions of state-owned firms in the oil and gas, coal, and power industries are 41.7%, 71.4%, and 88.5%, respectively. It has been proven that state-owned firms in China are significantly less efficient than private firms due to both low investment efficiency and technical efficiency (Chen et al., 2011). Compared to private firms whose main goal is to make great profits, state-owned firms need to balance multi-missions, such as profitability, employment, and resource sustainability (Hartley and Medlock, 2008), and thus, their operational efficiency is lower. Additionally, from the perspective of energy market, the internationalization and marketization of oil prices have improved the operational efficiency of Chinese oil and gas firms. However, for power firms, given China's coal-fired power generation, when technology has not made significant progress to reduce emissions, the only choice for them is to add more desulfurization and dust-removing equipment. This would consume additional energy and increase the cost of power generation (Song and Wang, 2018), which is coupled with unchanged terminal electricity prices and would reduce power firms' operational efficiency. Meanwhile, the government has implemented subsidy policies while controlling coal prices, which will inevitably lead to inefficiencies in coal firms. In this situation, when studying the impact of technological innovation on operational efficiency, the state-owned attributes of energy firms will be included in the research framework as one of the factors affecting operational efficiency.

5.2 Impact of Technological Innovation on the Performance of Energy Firms in China

This paper examines energy firm performance in China using five indicators for benefits-based performance, risk performance, and environmental performance. According to (1), we estimate the impact of technological innovation on the performance of energy firms. The results are shown in Table 2 with 5 models for the dependent variable y_{it} being operational efficiency (Model I), firm value (Model II), excess returns (Model III), firm risks (Model IV), and log of carbon emissions intensity (Model V), respectively, and the findings are summarized as follows.

First, technological innovation does not always improve the benefits-based performance of China's energy firms in our sample, but it still significantly increases the excess returns.

Table 2: Estimated results of performance of energy firms in China.

	I	II	III	IV	V
	Operational efficiency	Firm value	Excess returns	Firm risks	log(Carbon emissions intensity)
log(Patents)	**-0.0096****	**0.0062**	**3.7448*****	**0.1815*****	**-0.0416****
log(Age)	-0.0178	-0.5047***	24.9561***	-0.0486	-0.0028
Ownership	-0.1181***	-0.2655***	0.6550	0.5032***	-0.3929***
log(Assets)	0.0504***	-0.2227***	-3.1908**	-0.1476***	-0.9292***
log(Leverage)	-0.1109***	-1.1852***	-2.7203	0.1415	0.0363
Energy price	0.0051	-0.1376*	-0.1889	0.3250***	0.1402**
Unemployment	0.1037	0.8797***	235.2845***	0.1690	-1.4346***
log(GDP)	0.0156	1.0290***	54.2485***	0.3133	0.0490
Constant	0.0019	5.4918***	-1068.4770***	-0.7597	14.9951***
Adj-R^2/Log-L	330.2863	0.5069	0.2737	0.0547	0.8679
Observation	639	549	522	576	666

Note: The second row in the table represents five different dependent variables. The operational efficiency is calculated by the bootstrap-DEA approach. The firm value is represented by Tobin's Q based on the total asset from the CSMAR database. The excess returns mean the stock returns of energy firms over the risk-free rate. Firm risks are represented by negative conditional return skewness, and the carbon emissions intensity is the natural logarithm of the ratio of the total carbon emissions to the sales of firms. Model I with operational efficiency as dependent variable is estimated by the truncated regression approach, and the rest models (Models II - V) are estimated by the OLS approach. The Log-L (i.e., Log likelihood) statistic is reported for the truncated regression approach, while the adj-R^2 (i.e., Adjusted R^2) statistic is obtained from the OLS approach. $***$, $**$, and $*$ denote the significance at the 1%, 5% and 10% levels, respectively.

Model I in Table 2 shows that technological innovation has significant negative impact on the operational efficiency of energy firms (i.e., the coefficient is -0.0096), which means that technological innovation does not effectively convert limited human, material, and capital resources into income for energy firms. There may be three reasons for this result: the low conversion efficiency of patents from research to practice, the level of technological innovation not reaching the threshold that can bring commercial value to firms; and firms either having not fully integrated the environment needed for technological innovation to create value or the existing environment having not yet adapted to technological innovation. Meanwhile, Model II in Table 2 shows that technological innovation has no significant impact on firm value, indicating that the efforts of technological innovation in China's energy firms have not been recognized by the stock market.

However, it can be seen from Model III in Table 2 that technological innovation significantly promotes the excess returns of energy firms, with the coefficient 3.7448. This is because, for one thing, investors often underestimate the implied positive abnormal cash flow arising from technological innovation, and the subsequent excess returns are derived from positive earnings' surprises, and for another, excess returns are compensation for the increased risks to firm cash flows associated with innovation investment (Chambers et al., 2002). The results above prove that there are both positive and negative impacts of technological innovation on the benefits-based performance of energy firms, which is why many articles draw different conclusions concerning the impact of technological innovation on some firm performances. In addition to the firm responses to technological innovation differing in various industries, we also find that different performance indicators, even if they all belong to benefits-based performance, are affected by technological innovation in significantly different ways.

Second, innovation activities may increase the crash risks of energy firms in China in our sample. Specifically, it can be seen from Model IV in Table 2 that innovation activities have significant positive impact on firm risks, the crash risks of energy firms will increase by 0.1815 when the number of patents granted rises by 1%. This result means that innovation activities do not necessarily translate into an increase in profits, because the technological innovation takes up large amounts of resources that may bring stable income if they are invested in other projects, which may intensify the fluctuation of stock prices, and thus, increase the firm risks.

Third, innovation activities may improve the environmental performance of energy firms in China during the sample period. From the results in Model V in Table 2, we can see that the carbon emissions intensity of energy firms is reduced by 0.0416% when the number of patents granted rises by 1%. This result means that innovation activities can reduce the carbon emissions intensity of energy firms in China, and effectively improve their environmental performance. This is consistent with the finding in Alam et al. (2019) that patents represent knowledge and technology, and technological advances play an important role in improving the transformation and utilization of traditional energy, thereby improving the effectiveness of energy use.

Fourth, as shown from the coefficient of firm size, the laws of scale to return differ among firm performances. Specifically, the coefficient of firm size for operational efficiency in Model

I is significantly positive (0.0504), indicating that the operational efficiency in the energy firms will increase with the increment of firm size; this is in line with the increasing law of scale return. However, this rule does not apply to the other two benefit-based performance indicators (Tobin's Q and excess returns). From Models II and III in Table 2, we can see that the coefficients of firm size for Tobin's Q and excess returns are significantly negative, i.e., -0.2227 and -3.1908, respectively, which means that the Tobin's Q and excess returns of energy firms in China may decrease as the firm size increases. Meanwhile, the coefficients of firm size for firm risks in Model IV and carbon emissions intensity in Model V are -0.1476 and -0.9286, respectively, indicating that large energy firms are significantly better than small firms at reducing firm risks and carbon emissions intensity.

Fifth, the sharp rise of energy prices can reduce firm value while exacerbating firm risks and increasing carbon emissions intensity of energy firms in China. From Table 2, we can see that energy prices have negative impact on Tobin's Q in Model II, with the coefficient -0.1376, indicating that the firm value of energy firms declines with a sharp rise in energy prices. The price rise can increase the stock market value of energy firms, but can also increase the replacement costs of energy firms. When the growth rate of replacement costs is greater than that of stock market value, the Tobin's Q of firms will decrease as energy prices rise. The coefficients of energy prices in Model IV is significantly positive (i.e., 0.3250), which means that rising energy prices may exacerbate firm risks. Besides, the coefficient of energy prices in Models V is 0.1244, which denotes that the sharp rise of energy prices may increase the carbon emissions intensity. This is because the rising energy prices can stimulate suppliers to extract and produce energy, which is often accompanied by considerable energy consumption, and thus promoting the increase of carbon emissions intensity.

Finally, state-owned energy firms tend to have lower operational efficiency, firm value, and carbon emissions intensity than private firms. It can be seen from Table 2 that the coefficients of ownership in both Models I and II are significantly negative, i.e., -0.1181 and -0.2655, respectively, which means that state-owned energy firms have relatively lower operational efficiency and lower firm value (Wei et al., 2005). Meanwhile, the coefficient in Model V is significantly negative (i.e., -0.3936), indicating that the carbon emissions intensity of state-owned energy firms is also lower. As energy is a strategic resource, state-owned energy firms have to take into account more tasks for sustainable development, such as energy security, energy conservation and emissions reduction. In particular, the mining plan for non-renewable energy and the implementation of energy trade plans signed with other countries may affect the operational efficiency of state-owned energy firms. Moreover, the ambitious policy goals for energy conservation and emissions reduction in China also promote China's state-owned energy firms have lower carbon emissions intensity, because the state-owned firms have stronger environmental responsibility and stricter environmental disclosure systems (Elmagrhi et al., 2019).

5.3 Robustness Checks

5.3.1 Substitution of Technological Innovation Variables and Performance Variables

To test whether the variable selection would change the impact of technological innovation on energy firm performance, we re-define technological innovation variables and performance variables separately in this paper. First, we use patent citations as a surrogate variable of patents granted to test the stability of the impact of technological innovation on firm performance. The patent citations can measure the importance of patents and distinguish the breakthrough technological innovations from the progressive technology discoveries (Acharya and Xu, 2017). Table 3 displays the estimated results for technological innovation represented by patent citations.

It can be seen that, except for the coefficient of technological innovation on operational efficiency not being significant, the remaining coefficients of Tobin's Q, excess returns, firm risks, and carbon emissions intensity are consistent with the results in Table 2.

Moreover, we re-define the dependent variables to test the robustness of the impact of technological innovation on energy firm performances. Specifically, for the operational efficiency, as seen from Table 1, the efficiency value of the decision-making unit is equal to 1 in many years. Thus, we recalculate the operational efficiency of energy firms using the super-efficiency DEA approach (Zhu, 2001). The new firm value is represented by the Tobin's Q based on the total assets without including the net value of the intangible asset. For the excess returns, because the risk-free rate is also commonly expressed by the treasury bond rate (Campbell and Vuolteenaho, 2004), we recalculate the excess returns of energy firm using the one-year treasury bond rate as the risk-free rate. For the firm risks, we use the standard deviation of firm returns to re-define firm risks, referring to Sorescu and Spanjol (2008). For the environmental efficiency, as carbon dioxide is a by-product of energy consumption, this paper uses energy consumption intensity to re-define carbon emissions intensity to measure

Table 3: Results of robustness test - substitution of innovative variables.

	I	II	III	IV	V
	Operational efficiency	Firm value	Excess returns	Firm risks	log(Carbon emissions intensity)
log(Citations)	**0.0036**	**0.0269**	**2.6461****	**0.0780***	**-0.0987****
log(Age)	-0.0715**	-0.5679**	33.3316***	0.7868**	0.1963
Ownership	-0.1314***	-0.1127	3.8294	0.3586	-0.0440
log(Assets)	0.0411***	-0.2568***	-2.1784	0.0116	-0.9344***
log(Leverage)	-0.0828***	-1.1089***	-2.5078	-0.3060	-0.1741**
Energy price	0.0120	-0.0512	2.9121	0.5589***	0.0158
Unemployment	0.1163	1.0338*	220.9922***	1.4583	-1.3841***
log(GDP)	0.0567	1.2191***	61.9259***	0.1643	-0.0684
Constant	-0.0027	4.7552	-1061.2120***	-8.2145*	15.2411***
Adj-R^2/Log-L	163.3951	0.5797	0.2650	0.0299	0.8904
Observation	6360	279	287	252	405

Note: The second row represents five different dependent variables. The operational efficiency is calculated by the bootstrap-DEA approach. The Log-L (i.e., Log likelihood) statistic is reported for the truncated regression approach, while the Adj-R^2 (i.e., Adjusted R^2) statistic is obtained from the OLS approach. $***$, $**$, and $*$ denote the significance at the 1%, 5% and 10% levels, respectively.

environmental efficiency of energy firms in China, where energy consumption intensity is expressed as the ratio of total energy consumption to the sales of energy firms. The estimated results after re-defining each performance variable of energy firms are given in Table 4.

It can be found that, except for the effect of technological innovation on firm risks not being significant, the other estimated results are similar to those in Table 2. The impact of technological innovation on carbon emissions intensity here is consistent with the finding in Alam et al. (2019). Based on this result, we believe that it is not only specific environmental innovations that play an important role in environmental issues (Carrión-Flores and Innes, 2010), but that all the innovation activities contribute to the reduction of carbon emissions intensity. Specifically, innovation activities that benefit the environment can contribute directly to the reduction of carbon emissions by promoting the development of clean energy. Meanwhile, the innovation activities that intend to strengthen the long-term development of energy firms, can indirectly improve energy conservation and emissions reduction through increasing the energy utilization rate for energy firms.

Table 4: Results of robustness test - substitution of dependent variables.

	I	II	III	IV	V
	Operational efficiency	Firm value	Excess returns	Firm risks	log(Carbon emissions intensity)
log(Patents)	**-0.0156*****	**0.0012**	**3.6809*****	**-0.0494**	**-0.0402****
log(Age)	-0.0164	-0.6075***	23.8845***	-0.1802	0.0084
Ownership	-0.1126***	-0.2182***	0.5587	-0.7276	-0.3936***
log(Assets)	0.0448***	-0.2251***	-3.2072**	-0.8502***	-0.9286***
log(Leverage)	-0.1124***	-1.2195***	-2.7929	1.2722**	0.0411
Energy price	0.0061	-0.1376***	0.4979	-2.4705***	0.1244**
Unemployment	0.0692	0.9556**	238.9673***	11.9690***	-1.7225***
log(GDP)	0.0264	1.0903***	54.5931***	2.1412*	0.1093
Constant	0.2136	5.5689***	-1081.2260***	-30.5391**	19.8399***
Adj-R^2/Log-L	314.2535	0.5658	0.2849	0.1538	0.8656
Observation	639	549	522	576	666

Note: The second row represents five different dependent variables. The operational efficiency is calculated by the bootstrap-DEA approach. The Log-L (i.e., Log likelihood) statistic is reported for the truncated regression approach, while the Adj-R^2 (i.e., Adjusted R2) statistic is obtained from the OLS approach. $***$, $**$, and $*$ denote the significance at the 1%, 5% and 10% levels, respectively.

5.3.2 Robustness Checks for the Endogenous Problem

The explanatory variable - log(Patents) - may face potential endogenous bias, which may result from funds' shortage, business cycle or other industrial factors, such as industrial concentration. As stated by Acs and Audretsch (1987), firms are more likely to innovate in industries that are highly concentrated and have entry barriers. Owing to the distinct resource endowments and the changes in energy demand during the development of economic-environment system, the concentration may differ among energy sources. In this way, the technological innovation in this paper may be affected by industrial concentration, which, in turn, affects the impact of technological innovation on firm performance. To avoid this potential bias, we add HHI (Herfindahl index based on sales), which represents the industrial concentration among oil and gas, coal, and power firms in China, and then re-estimate Models I to V. The results are presented in Table 5, which are basically consistent with those in Table 2. That is, technological innovation inhibits the operational efficiency and environmental efficiency but promotes the excess returns and firm risks.

Table 5: Results of robustness test - adding HHI.

	I	II	III	IV	V
	Operational efficiency	Firm value	Excess returns	Firm risks	log(Carbon emissions intensity)
log(Patents)	**-0.0147*****	**0.0200**	**3.9295*****	**0.18953*****	**-0.0059**
log(Age)	0.0018	-0.3862***	23.7380***	-0.0684	-0.0752
Ownership	-0.0969***	-0.1769*	-0.2837	0.4852***	-0.5062***
log(Assets)	0.0563***	-0.2257***	-3.3587**	-0.1511***	-0.9725***
log(Leverage)	-0.1050***	-1.1284***	-2.9744	0.1365	-0.0032
Energy price	0.0302**	-0.0317	-1.2848	0.3081**	0.0033
Unemployment	0.1025	0.9858**	235.3556***	0.1689	-1.3520***
log(GDP)	0.0217	1.0740***	53.8721***	0.3073	0.0121
HHI	0.2549***	0.9567***	-11.2303	-0.1860	-1.4763***
Constant	-0.2387	4.1292**	-1058.1720***	-0.5725	16.0918***
Adj-R^2/Log-L	3347.0951	0.5165	0.2733	0.0533	0.8777
Observation	639	549	522	576	666

Note: The second row represents five different dependent variables. The operational efficiency is calculated by the bootstrap-DEA approach. The Log-L (i.e., Log likelihood) statistic is reported for the truncated regression approach, while the Adj-R^2 (i.e., Adjusted R^2) statistic is obtained from the OLS approach. $***$, $**$, and $*$ denote the significance at the 1%, 5% and 10% levels, respectively.

Moreover, as energy firms with greater performance are more inclined or more likely to engage in innovation activities, this might cause the endogenous problem in the model concerning the impact of innovation activities on energy firm performance. To avoid this endogeneity bias, this paper uses the instrumental variable approach for a robustness check. In addition to choosing the one-year lagged technological innovation variables ($Patent_{i,t-1}$) as instrumental variables (Morrison, 1970), this paper also uses the number of firm's technicians ($Technician_{it}$) and the number of employees with graduate and undergraduate degrees ($Educations_{it}$) as other two instrumental variables. The technological innovation capability of energy firms is defined as the skills and knowledge needed to effectively absorb, master and improve existing technologies and create new ones (Lall, 1992). Thus, the technical staffs with high skills are critical to the development of technological innovation (Hoffman, 1998). The direct impact of high-quality employees and technicians on energy firm performance is uncertain, and they might influence energy firm performance through their impact on technological innovation.

This paper uses the F test and over-identification test to assess the appropriateness of the instrumental variables. The results are reported in Table 6, from which, one can see that the null hypotheses that instrumental variables are valid, can not be rejected, and they are closely related to the technological innovation variables. After minimizing the endogeneity concern, the main empirical results in Table 6 are consistent with those in Table 2. In other words, we can infer that the impact of technological innovation activities on energy firm performance is robust.

Table 6: Results of robustness test –instrumental variables method.

	I	II	III	IV	V
	Operational efficiency	Firm value	Excess returns	Firm risks	log(Carbon emissions intensity)
log(Patents)	**-0.0994***	**0.0640***	**3.9320****	**0.2356*****	**-0.3064*****
log(Age)	-0.0289	-0.3947**	28.0508***	-0.0933	0.0946
Ownership	-0.1207***	-0.3053***	-0.0548	0.5808***	-0.3974***
log(Assets)	0.1151***	-0.2673***	-2.5982	-0.2074***	-0.7470***
log(Leverage)	-0.2011***	-1.0337***	-3.4618	0.2479	-0.2358**
Energy price	0.0602	-0.0393	8.7564**	0.3900***	-0.0794
Unemployment	-0.1504	1.9364***	95.6946***	1.5580	-2.1792***
log(GDP)	-0.0302	1.2575***	25.5910***	-0.1074	-0.0665
Constant	0.8004	0.4564	-477.8922***	7.2365	17.1098***
Observation	639	540	513	549	648
1st-stage F test (p-value)	0.0773	0.0000	0.0000	0.0000	0.0000
Overidentification test (p-value)	0.3413	0.2015	0.1202	0.1504	0.2702

Note: The second row represents five different dependent variables. The instrumental variables of technological innovation variable in Models I to V include the number of technicians and the number of employees with graduate undergraduate degrees, while in Models II to IV, the instrumental variables include one-year lagged technological innovation variable, the number of technicians and the number of employees with graduate undergraduate degrees. The 2-stage least squares (2SLS) approach is used to estimate them, and the over-identification test reports the p-value of the Sargan statistic. $***$, $**$, and $*$ denote the significance at the 1%, 5% and 10% levels, respectively.

Furthermore, this paper uses the treatment effect model to avoid endogenous problem due to selectivity bias, and thus, to test the robustness of the impact of innovation activities on the performance of energy firms. We refer to previous research to determine the factors affecting technological innovation, including ownership (Choi et al., 2011), firm age (Hashi and Stojčić, 2013) and energy prices. Furthermore, we choose the number of firm technicians ($technician_{it}$) as the instrumental variable influencing technological innovation, and use the two-step approach to estimate the treatment effect model. The estimated results are summarized in Table 7.

Table 7: Results of robustness test –treatment effect model.

	I	II	III	IV	V
	Operational efficiency	Firm value	Excess returns	Firm risks	log(Carbon emissions intensity)
Panel A: Treatment effect model - first step					
log(Age)	-0.7851***	0.8343**	0.9759***	0.8306	0.9639
Ownership	0.2766**	0.3550**	0.6695***	0.27688*	0.1988
Energy price	-0.4684**	-0.4676**	-0.5457**	-0.4334***	-0.5431**
Technicians	0.1191***	0.1524***	0.1472**	0.1660***	0.1861***
Panel B: Treatment effect model - second step					
IP	**-0.2582***	**-0.3990**	**26.1807**	**0.8271**	**-0.7374**
Unemployment	0.0217	0.5720***	227.6761***	0.3125	-1.4065***
log(GDP)	0.0036	1.0410***	51.7639***	0.1379	0.0364
log(Age)	0.0316	-0.4050***	17.4431***	-0.3513	0.1923***
log(Assets)	0.0401***	-0.2187***	-1.2622	-0.0187	-0.9744***
log(Leverage)	-0.1286***	-1.2689***	-6.0426	0.0777	0.0565
Constant	0.5363*	6.7670***	-1037.6840***	0.8271	15.1746***

Note: The second row represents five different dependent variables. $***$, $**$, and $*$ denote the significance at the 1%, 5% and 10% levels, respectively.

We can find that first, as shown in Panel A in Table 7, firm age and ownership have positive impacts on technological innovation, whereas the energy prices may inhibit technological innovation. Among them, the positive impact of firm age on technological innovation means that the innovation activities of mature energy firms are more active than are those of younger firms. Ownership has positive impact on technological innovation but negative impact on operational efficiency, as shown in Table 2. This means that state-owned energy firms in China can obtain patents more easily than private energy firms, but they tend to be not efficient at converting patents into practice that can benefit their operational efficiency. From the coefficient of energy prices, it can be seen that a sharp rise in energy prices has negative impact on technological innovation. A sharp rise in energy prices is generally accompanied by short supply in the energy market. In this situation, there exists market advantage for the supplier, and they can easily earn the income only by expanding production, but tend to ignore technological innovation. This result is different from the idea that a rise of energy prices promotes technological innovation, as in the "induction theory" (Lichtenberg, 1986). This is because previous researchers see energy as a raw material cost for the firm, and they conduct innovation activities to reduce costs. Therefore, rising energy prices can stimulate energy firms to increase their innovation activities. However, for the energy firms in this paper, an increase in energy prices would increase their income. Therefore, energy firms tend not to expand innovation activities because they can guarantee their benefits when the prices of energy products rise sharply. Second, as seen in Panel B in Table 7, except for the insignificant impact of technological innovation on firm value, the remaining coefficients for the impact of technological innovation on firm performance are statistically significant, which are similar to those in Table 2.

5.3.3 Robustness Checks for the Dynamic Impact of Technological Innovation on Firm Performance

As patents require some time delay to influence firm performance, many patents may not be put into practice soon after authorization. Therefore, we use one-year lagged patents granted to test the dynamic impact of technological innovation on firm performance, and the results are shown in Table 8. It can be seen that the findings are statistically similar to those in Table 2; that is, innovation activities significantly promote the excess returns and firm risks of energy firms, but they may curb the operational efficiency and carbon emissions intensity. Meanwhile, the impacts can continue to the next period.

6 Concluding Remarks

Cleaning the structure of energy production and consumption poses great challenges to traditional fossil energy firms in China, but the national innovation-driven development strategy brings appealing opportunities for them. Technological innovation has become an increasingly important way for energy firms to seek survival advantage and competitiveness. Considering not only the performance indicators differ among energy firms' stakeholders, but also the influencing mechanisms of technological innovation on those performances are distinct, this paper examines the impact of technological innovation on multiple performances

Table 8: Results of robustness test –lagging one year for patents.

	I	II	III	IV	V
	Operational efficiency	Firm value	Excess returns	Firm risks	log(Carbon emissions intensity)
log(Patents)(-1)	**-0.0087****	**0.0235**	**2.8999*****	**0.1793*****	**-0.0468****
log(Age)	-0.0140	-0.4129***	28.0443***	-0.0857	-0.0072
Ownership	-0.1172***	-0.3084***	-0.1386	0.5658***	-0.3595***
log(Assets)	0.0511***	-0.2283***	-1.6433	-0.1551***	-0.9368***
log(Leverage)	-0.1014***	-1.1037***	-4.2861	0.1639	0.0144
Energy price	0.0127	-0.0636	8.8715**	0.3856***	0.0584
Unemployment	0.0979	1.8317**	90.2774***	-1.6823	-2.0247***
log(GDP)	0.0204	1.2236***	24.9144**	-0.1496	-0.0579
Constant	-0.0490	0.8105	-462.6714***	7.5308	17.7625***
Adj-R^2/Log-L	301.1783	0.4639	0.0411	0.0607	0.8655
Observation	639	549	522	576	666

Note: The second row represents five different dependent variables, i.e., operational efficiency, firm value, excess returns, firm risks, and log(Carbon emissions intensity). The operational efficiency is calculated by the bootstrap-DEA approach. The Log-L (Log likelihood) statistic is reported for the truncated regression approach, while the Adj-R^2 (i.e., Adjusted R^2) statistic is obtained from the OLS approach. $***$, $**$, and $*$ denote the significance at the 1%, 5% and 10% levels, respectively.

of energy firms (i.e., benefits-based performance, risk performance, and environmental performance). The main conclusions are drawn as follows:

First, technological innovation does not necessarily fully promote the benefits-based performance of energy firms in China, but it significantly increases the firm risks of energy firms. Specifically, for one thing, the promotion of technological innovation to firm value (Tobin's Q) is not significant. For another, although technological innovation can create higher excess returns for energy firms, it requires huge investment, together with the sunk cost caused by the squeezing of limited resources. As a result, technological innovation may not bring net benefits over cost for energy firms, even inhibits the operational efficiency of energy firms. These negative effects may be amplified and accumulated in the stock market, together with the uncertainty of technological innovation itself, ultimately, exacerbating the crack risks of energy firms. Second, technological innovation brings environmental benefits to energy firms in China, and it improves their environmental performance. Specifically, both carbon emission intensity and energy consumption intensity can be significantly reduced by about 0.04%

for every 1% increase in the number of patent applications representing technological innovation, which confirms that technological innovation plays an important role in improving the environmental performance of energy firms in China.

Finally, the sharp rise in energy prices may inhibit the technological innovation activities of energy firms in China. The robustness checks in this paper reveal that the mature and state-owned energy firms have more active technological innovation activities, but energy price rise may inhibit innovation activities, because energy firms tend to expand their production to ensure the profits in this case.

The conclusions above have significant policy implications for energy firm managers, investors, and regulators. First, energy firm managers are expected to integrate the firm resources and further improve the conversion efficiency of patents granted to practice, thus gaining the value of technological innovation strategies. Second, investors need to consider multiple performance indicators when making investment decisions on energy firms with reference to relevant information about technological innovation activities. In particular, the long-term investors, while paying attention to the positive impact brought by technological innovation to firms, should not neglect their negative impact on stock market performance and the more serious consequences of the negative impact after the long-term accumulation. Finally, regulators should pay attention to the role of firm technological innovation in improving environmental performance. In addition to encouraging energy firms with lower innovation intensity to intensify their technological innovation and granting them special funds for technological innovation, regulators can set up corresponding energy technological innovation institutions to provide sustainable consulting service for energy firms, such as the establishment of a public-private partnership in the United Kingdom to accelerate the development of low-carbon technologies (Chan et al., 2017). Meanwhile, they need to initiate the cooperation with financial institutions (such as trust institution) to ensure stable financial support and guarantee the sustainability of technological innovation in environmental protection.

In the future, there is much relevant research to be done further. For instance, future research can use survey data and other variables, such as R&D investment, to explore the role of technological innovation in firm performance when the data are available, and can also examine whether the price changes of alternative energy sources would affect the implementation of technological innovation strategy. In addition, future research can consider the heterogeneous characteristics of different industries when the impact of technological innovation on firm performance is concerned. Finally, it can also discuss whether the impact of technological innovation may differ from various types of innovation activities, such as exploratory innovation, exploitative innovation, and progressive innovation, so as to provide more specific help for energy firms to achieve technological innovation dividend and contribute to the national target for low-carbon development and global climate change mitigation.

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