Energy Constraint in China at the Expense of Profitability?
Perspectives of Green Technology Innovation

Lijun Jia, Shanghai University, China
Yunjie Hao, Shanghai University, China*
Wuyang Hu, The Ohio State University, USA

ABSTRACT

Although energy constraints, green technology innovation increment, and corporate profitability are issues of central importance to enterprise management and the environment, many aspects of these elements have been neglected in the present work. Using data from listed manufacturing firms in China, this study presents two major findings. First, the authors identify a u-shaped relationship between city-specific energy constraints and business profitability. Second, they find green technology innovation can significantly drive profitability in different types of industries. In addition, the profitability of certain enterprises, such as those that are smaller and younger can be more drastically affected by energy constraints. To develop a green innovation-driven strategy to allow manufacturing enterprises to achieve greater profitability and promote ecological improvements, they recommend energy policies be more individualized to guide "energy-constraint sensitive” enterprises to success.

KEYWORDS

Central Cities, China, Energy Use, Energy-Constraint Sensitive, Enterprise Profitability, Government Policy, Manufacturing Industry, Pollution Management, Sustainable Development, U-Shaped Curve

INTRODUCTION

Benefiting from the market-oriented reforms since 1978, China has made remarkable economic progresses for over 30 years. However, like the price most other ascending developing countries have paid, according to the Bulletin of China’s Environment Status, the total discharge of wastewater, waste gas, and industrial solid waste in China has been high for years. Many rivers and lakes have been polluted to varying degrees and the groundwater quality also raises concerns in some regions. Signified by urban smog, China’s environmental problems have been continuously exposed.

The Chinese government is increasingly restricting enterprises’ energy use and emission. Sun et al. (2020) concluded that by 2016, China had added 67 new environmental protection-related laws and regulations from the 358 items in 2013. Facing stricter energy restrictions, enterprises need to make additional efforts to reduce emission. Given the limited governmental subsidies for environmental innovation, the environmental constraints enterprises face can be reflected in the rising production costs, limited access to energy, and operational difficulties. Some scholars believe that even tighter enterprise energy restrictions could fail to tackle the problems at their sources and cause enterprises
to shrink or relocate (Hu et al. 2008; Li 2015; Wang et al. 2018). As such, research and development of more advanced green energy technology have been an international focus (Ramos-Martin 2001). Considering the technological progress of China’s manufacturing industry (Xiu 2016), green energy use and emission reduction also need to be improved.

Continuous industrialization and urbanization have increased China’s energy demand and caused unbalances across regions (Marti-Ballester 2020). Therefore, some scholars see how to coordinate the development between energy and economy as a central theme under the “new normal” background of China (Arnold and Hockerts 2011). High enterprise energy limitations may lead to a decline in corporate profitability, increase bankruptcy probability, and bring challenges to the macroeconomy. Enterprises need to pay attention to the tradeoff between economic development and energy constraints. There are many difficulties enterprises need to handle under limited resources and this is a common problem encountered by all enterprises, but especially for manufacturing industries.

How is enterprise profitability affected by the energy restriction? Can an enterprise achieve a win-win situation between profitability and technological progress with limited energy access? These explorations are of great significance to enterprises and countries seeking a balance between energy consumption and stable economic expansion. This paper uses the data of listed manufacturing enterprises in China from 2007 to 2020 to analyze the impact of green technology innovation on profitability under energy constraints. As enterprises differ in multiple respects, this paper further discusses the heterogeneous effects of energy constraint and green innovation on profitability from three perspectives: industry, region, and individual enterprises.

Our possible contributions are as follows. First, the research on the relation between economic development and resource constraints has tested these connections at the macro level, focusing on countries or regions, but ignoring micro-level analysis. As a result, this research makes a contribution to focus on the micro-level analysis of resource constraints and the energy consumption of manufacturing enterprises. Second, although energy constraints, green technology innovation increment, and corporate profitability are issues of central importance to enterprise management and the environment, the present work examines each aspect separately instead of treating them as related elements in a system. Our research fills this void. Finally, this paper uses the comprehensive index to quantify city-level energy constraints and expand the related research on enterprise energy constraints and usage.

**BACKGROUND**

The literature is scarce on the definition and understanding of energy constraints. Duncan (2001) regards energy resources as “short-board resources” that could pose constraints to social and economic development. Tilley and Comar (2006) mention that “energy constraint” is derived from the constraint theory. It refers to the constraints of energy stock, energy flow, energy utilization efficiency, energy conversion technology, and energy control that result in limited economic progress. Wang et al. (2020) explain energy constraints based on the constraint theory and indicate that although energy promotes economic and social development, it could limit expansion because of its scarcity. Total energy consumption that rises with an increasingly booming world economy could exacerbate energy constraints. Tilley and Comar (2006) also believe that energy constraints for enterprises are reflected in multiple dimensions, such as energy acquisition and use, energy efficiency constraints, and energy conversion technology constraints.

Methods quantifying energy constraints are also limited in the literature. Marti-Ballester (2020), Jeon, Taisch, and Prabhu (2015), Lambert (1997), and others use total energy consumption as the proxy for energy constraints. The energy constraint theory developed by Tilley and Comar (2006) and others also emphasizes the aspects apart from constraints in energy stock. On the relationship between energy constraint and corporate profitability, Wang et al. (2018) recognize the urgent need to balance the environment and profitability under energy constraints. The authors take a theoretical approach and find that corporate emissions are jointly affected by energy constraints, enterprise scale, and technology progress. The
literature has little to say on the relationship between energy constraints and enterprise management, and the remaining few are conducted from the macro perspective of larger regions and metropolitan areas.

Scholars have paid more attention to the impact of green technology innovation on enterprise management. Green technology innovation is often defined as a type of technology, processes, and products that could minimize pollution and minimize the destruction of the ecological system (European Commission 2013; Gasbarro, Rizzi, and Frey 2016). Many scholars have found that green technology innovation can improve enterprise operations. Chertow and Zhu (2017) note that green consumption has been acknowledged more as a trend or necessity by the general public. Energy-saving and environmental-friendly products would contribute to corporate social responsibility and a better corporate image thus can enhance corporate competitiveness. Actively pursuing pollution-control technology could reduce energy consumption and the “compliance cost” under energy constraints. From the perspective of signal theory, Junbo et al. (2018) argue that enterprises engaging in new green innovation will be able to convert positive social responsibility signals to the trust and support of stakeholders and long-term development. Based on the data of Chinese electronic manufacturing companies, Wong (2012) identifies green process innovation and green product innovation as an inner impetus of enterprise performance and growth.

ISSUES, CONTROVERSIES, PROBLEMS

In practice, Chinese manufacturing enterprises have long faced high energy constraints. As shown in Figure 1, the energy constraints faced by Chinese manufacturing enterprises continued to increase from 2008 to 2015 but decreased significantly in 2016. This may be due to the fact that since 2016, China has imposed policy constraints, such as energy conservation and emission reduction, and achieved promising environmental results. However, energy constraints continue to increase from 2016 to 2020, indicating that energy use and constraints are a long-term problem difficult to solve in short run. In addition, the energy constraints in central and western inland areas are generally higher than those on the southeast coastal regions.

As shown in Figure 2, although the level of green technology innovation fluctuated, the values were all around 0 prior to 2018. There were large increases since 2019, but it was negative again in 2020. Overall, the level of green technology innovation is still relatively low in China.
Existing research suggests that energy constraints are often erroneously measured as energy consumption (Quinn, Spreitzer, and Lam 2012). We treat these as separate but closely related concepts. Our current research attempts to discuss the implications of energy constraints and green technology innovation on enterprise profitability from the perspective of optimal energy allocation and technology. On the one hand, energy constraints and green technology innovation facilitate alternative products development, energy efficiency, and the utilization of clean energy. On the other hand, energy conversion and upgrading production technology can reduce energy consumption, alleviate energy constraints, and improve enterprise profitability (Duncan 2001). This analysis examines enterprise green innovation under energy constraints and means to allocate energy more effectively among R&D, production, and overall management.

**METHODS**

As a pillar industry of the economy, China’s manufacturing GDP often accounts for about 30% of the country’s total GDP (Wong, Wong, and Boon-Itt 2020). With the rapid development of the manufacturing industry, energy consumption has been at a high level, and together with other sectors, the dependence on resources and the environment is increasingly severe (Zhang et al. 2020). This paper takes Chinese manufacturing listed companies as a case of examination. We build a regression model to explore the impact of energy constraints on the performance of Chinese manufacturing enterprises.

**Data**

There are 37,477 entries of Chinese manufacturing enterprises listed in Shanghai and Shenzhen A-shares since 2007 after matching the China Stock Market & Accounting Research (CSMAR) database and the database maintained by Wind information Co. Ltd (WIND). The status of corporate pollutant discharge and compliance largely depends on the disclosure requirements but is rarely published; therefore, these data are collected at the prefectural-city level. Companies with largely missing data are discarded, and individual missing values are filled by the mean interpolation method (Zhong et al. 2018). Additional data cleaning is performed as follows:

1. Remove companies without enterprise codes
2. Remove companies less than one-year old
Step 3: Remove companies with less than eight employees
Step 4: Remove companies not meeting the basic accounting standards

Following these procedures, we obtain enterprise-level data across 33 manufacturing sub-industries.

Model

We present the relationship between energy constraints, green technology innovation, and corporate profitability as follows:

$$\ln(\text{probability})_{it} = \beta_0 + \beta_1 ec_{it} + \beta_2 ec^2_{it} + \beta_3 gti_{it} + \varphi X_{it} + \theta_m + \theta_r + \epsilon_{it}$$

(1)

In Equation (1), $i$ and $t$ represent enterprise and time, respectively. Profitability represents corporate profitability, while $ec$, $ec^2$ and $gti$ represent the energy constraint, its quadratic term, and the increment of green technology innovation, respectively. $X$ is a set of control variables. $\beta_0$, $\beta_1$, $\beta_2$ and $\beta_3$ represent regression coefficients, while $\varphi$ a coefficient matrix of control variables. $\theta_m$, $\theta_r$ and $\epsilon$ respectively represent industry fixed effect, regional fixed effect, and the residual.

Variables

Profitability of enterprises (profitability). Business profit is a major index to measure profitability, and it can be classified into relative index and absolute index. A discrete measure may also be used but it may require special models to detail with long tails in the data such as enterprises with very low or high profits (Hu, 2006). Following Wu (2017), we use the logarithm of the annual operating profit of listed companies.

Energy constraints (ec). Although directly quantifying energy constraints as energy consumption has the advantage of simplicity, it suffers from the lack of comprehensiveness and representativeness. Therefore, following Wang et al. (2018) and Quinn, Spreitzer, and Lam (2012), we use the comprehensive index method to construct manufacturing enterprise energy constraints. Considering the scant and selective disclosure of energy use and emission data at the micro-level and the substantial territorial differences in local energy policies, we quantify energy constraints based on the prefecture-level cities where the enterprises in our data are located. Specifically, industrial wastewater discharge compliance, sulfur dioxide, and soot removal rates are selected as the main evaluation factors. The comprehensive utilization rate of industrial solid waste, domestic sewage treatment, and domestic garbage harmless treatment are used as secondary indexes.

The increment of green technology innovation (gti). Scholars have different measures for green technology innovation, the quantification of which at the micro-level tends to fall into three categories. The first is to divide green technology innovation into green product innovation and green process innovation and then measure them separately before summing them up. In these articles, green product innovation is mainly calculated by the sales revenue and total energy consumption associated with green innovation products. There are two approaches to measure green process innovation: using internal R&D expenditure and technical transformation investment funds; or using total industrial output value as well as the industrial “three wastes” including waste liquids, solids, and gases (Zameer 2021; Kazamias et al. 2017; Wong, Wong, and Boon-Itt 2020; Chertow and Zhu 2017). The second method to quantify green technology innovation is to use the ratio between R&D investment and energy consumption (Li 2019). The third way of quantification is to use the operating income divided by the green R&D expenditure (Junbo et al. 2018).

The above three methods have merits, but some scholars consider it is rather one-sided to use R&D investment as the proxy variable of green technology innovation because R&D investment is missing detailed information such as developer inputs and machine inputs. Chen and Hung (2014) put forward intangible assets mainly covering non-patented technologies and patents following the new
Chinese accounting standards in 2007. The new index could reflect the achievements of corporate innovation investment. Therefore, this study uses the ratio between intangible assets increment and operating income as the index of green technology innovation increment. We remove the data before 2007 due to accounting standard change.

Control variables. Based on data availability on listed companies in China, we refer to Jovanovic (1999), Amore and Bennedsen (2016), Woo (2014) and select the control variables. Variable definitions are shown in Table 1.

### Table 1. Variable definition and descriptive statistics

| Variable Name | Variable Definition | Calculation (Unit) | Mean | Std. Dev. | Number of Observations |
|---------------|---------------------|--------------------|------|-----------|------------------------|
| profitability | Enterprise profitability | ln (annual operating profit) (in yuan) | 18.564 | 1.518 | 24,922 |
| ec            | Energy constraints  | An index of industrial wastewater discharge compliance rate, sulfur dioxide removal rate, soot removal rate, comprehensive utilization rate of industrial solid waste, domestic sewage treatment rate, and domestic garbage harmless treatment rate | 0.213 | 0.400 | 29,158 |
| ec²           | Energy constraints' quadratic term | | 0.206 | 0.423 | 29,158 |
| gti           | Green technology innovation | Intangible assets increment/operating income | -0.092 | 3.515 | 29,144 |
| ownership     | Enterprise ownership | If the company is a state-owned enterprise, it is valued as 1; otherwise, it is valued as 0 | 0.363 | 0.481 | 29,137 |
| size          | Enterprise scale     | In (employees) (number of people) | 7.589 | 1.198 | 27,782 |
| alr           | Asset-liability ratio | total liabilities/total assets | 3.552 | 4.386 | 29,143 |
| capitalintensity | Capital intensity  | Net fixed assets/(employees*1000000) | 0.281 | 2.152 | 27,636 |
| age           | Enterprise age       | ln (2021-openning year) | 23.859 | 5.378 | 28,998 |
| age²          | Age’s quadratic term | | 598.175 | 287.900 | 28,998 |

Source: (authors)

**EMPIRICAL RESULTS AND ANALYSIS**

The empirical analysis includes three parts: benchmark results, heterogeneity, and additional robustness check.

**Benchmark Results**

The results of benchmark regression are shown in Table 2. Column (1) shows that the estimated coefficient of the energy constraint, its quadratic term, and the green technology innovation increment are all significant at the 1% significance level. The energy constraint and its quadratic term have negative and positive coefficients, respectively. With relatively loose energy constraints in the early stage, profitability will decline with increases in energy constraints. In the later period, when enterprises are forced to carry out green innovation and R&D under energy pressure, profitability rises instead. As a result, the impact of energy constraints represents a U-shaped curve. The positive coefficient of green
technology innovation increment preliminarily demonstrates that corporations with more attention to energy conservation and clean production could be associated with higher profitability.

Column (2) to Column (4) of Table 2 add control variables in turn. Observing the results of these columns, the signs of the main explanatory variable coefficients do not change, and they are still significant at the 1% significance level. According to the complete estimation model in Column (4), the profitability of state-owned enterprises is lower compared to other enterprises. Chinese state-owned enterprises have both profit and non-profit targets. This angle can explain state-owned enterprises’ low efficiency and low profitability (Chertow and Zhu 2017). Enterprises with a larger scale could obtain higher profitability, and the relationship is significant at the 1% significance level. This can be reasonable, as larger enterprises could have higher industry competitiveness, a more significant status on the market, and higher profitability. The asset-liability ratio also positively correlates with profitability and is significant at the 1% significance level. Benefits and risks can be jointly considered, and a certain proportion of debt operating leverage can enhance profitability (Chen 2014). Coefficient of the capital density variable is significantly positive at the 1% significance level. Capital-intensive enterprises could have high labor productivity and a more significant status on the market, and higher profitability. The asset-liability ratio also positively correlates with profitability and is significant at the 1% significance level. Benefits and risks can be jointly considered, and a certain proportion of debt operating leverage can enhance profitability (Chen 2014). Capital-intensive enterprises could have high labor productivity and strong competitiveness (Junbo et al. 2018). Enterprise age has a U-shaped relationship with profitability. Companies may initially face essential difficulties in operation due to lack of experience and human and social resources. However, after a few years, their profitability could rise (Huang and Li 2016).

**Heterogeneity**

To better test the robustness of our findings and identify the difference in profitability affected by different green technology innovation under energy constraints, we analyze heterogeneity from three levels: industry, region, and individual enterprise. Industry-level heterogeneity examines whether the technology innovation under energy constraints has different effects on the profitability in industries with various pollution levels, technology levels, and resource types. Region-level heterogeneity studies the diverse influence on enterprises due to their geographic location. Finally, dissimilarity in profitability among enterprises with different sizes and ages is conducted at the enterprise level.

1. **Industry-level heterogeneity.** In terms of pollution, according to Jeon, Taisch, and Prabhu (2015) and Quinn, Spreitzer, and Lam (2012), manufacturing industries could be classified into lightly polluting industries ($\gamma_i \leq 0.0151$), moderately polluting industries ($0.0151 < \gamma_i \leq 0.4079$), and heavily polluting industries ($\gamma_i > 0.4079$). The regression results based on the three levels of pollution are shown in Table 3. The green technology innovation coefficients are positive and significant at the 1%, 1%, and 10% significance levels, respectively, for the three categories of industries but are generally consistent with the benchmark model results.

The energy constraint coefficient in highly polluting industries is not significant. The U-shaped curve of lightly polluting industries has tighter spread, and enterprises in lightly and moderately polluting industries (especially the former) are more affected by energy constraints and green technology innovation. Because the fixed cost of enterprises in low- and medium-pollution industries is not high compared to total investment, fund allocation may be more flexible (Tong Jian et al. 2016). These enterprises may invest more rapidly in green innovation technology and products when energy constraint intensity increases (Ramos-Martin 2001). The expense may also climb faster, resulting in a faster decline in the early stage and a corresponding recovery in the later stage in profitability.

In terms of industry technical level, in line with Hall and Helmers (2013) and Foster-McGregor et al. (2013), manufacturing enterprises could be grouped under medium-high technology (MHT) industries and medium-low technology (MLT) industries. The regression results are shown in Columns (4) and (5) of Table 3 (continued). The coefficients of energy constraint in MHT industries and MLT industries are negative, significant at the 1% and 5%, respectively. The quadratic coefficients are positive, significant at the 1% and 5% significance level, respectively. It corroborates the benchmark regression results of an un-linear relationship between energy constraints and profitability.
The coefficients of green technology innovation are all positive and significant at the 1% significance level. Green technology innovation can bring less relative energy consumption and higher energy efficiency resulting in possibly less environmental costs but higher profitability. The coefficient estimates and underlying U-shaped curve demonstrate that MLT enterprises maintain larger coefficients of green technology innovation and quadratic energy constraints than enterprises in the MHT industries. The former has a relatively narrow U-shaped curve between energy constraint intensity and enterprise profitability. In other words, when the energy constraint intensity changes by the same unit, the profitability of MLT-industry enterprises fluctuates more rapidly and more intensely compared to MHT-industry enterprises. This result is consistent with the findings of other studies that, all other things equal, enterprises with lower technical levels will be subject to greater actual cost constraints. MLT-industry enterprises’ lack of technology access can be an entry barrier, so these enterprises may find themselves hard-pressed to survive or compete when the intensity of energy constraints grows (Geng and Chang 2020). The enterprises will be more motivated to carry out technological innovation, green energy adoption, and emission mitigation so that their labor productivity and profitability level could rise more rapidly and to a greater extent (Hamamoto 2006).

Table 2. Benchmark estimation results

| Variable          | (1)        | (2)        | (3)        | (4)        |
|-------------------|------------|------------|------------|------------|
| $ec$              | 0.016***   | 0.044***   | 0.045***   | 0.045***   |
|                   | (0.002)    | (0.005)    | (0.005)    | (0.005)    |
| $ec^2$            | -1.611***  | -1.376***  | -1.345***  | -1.306***  |
|                   | (0.108)    | (0.101)    | (0.101)    | (0.101)    |
| $gti$             | 1.039***   | 0.957***   | 0.938***   | 0.918***   |
|                   | (0.101)    | (0.095)    | (0.094)    | (0.094)    |
| ownership         | -0.229***  | -0.239***  | -0.154***  |
|                   | (0.040)    | (0.039)    | (0.039)    |
| size              | 0.548***   | 0.571***   | 0.583***   |
|                   | (0.009)    | (0.010)    | (0.010)    |
| $alr$             | 0.004**    | 0.004**    |
|                   | (0.002)    | (0.002)    |
| capitalintensity  | 0.036***   | 0.037***   |
|                   | (0.003)    | (0.003)    |
| age               | -0.091***  |            |
|                   | (0.010)    |            |
| age$^2$           | 0.001***   |
|                   | (0.000)    |
| constant          | 17.966***  | 12.986***  | 12.769***  | 14.088***  |
|                   | (0.928)    | (0.745)    | (0.723)    | (0.718)    |
| Industry effect   | Yes        | Yes        | Yes        | Yes        |
| Regional effect   | Yes        | Yes        | Yes        | Yes        |
| Hausman           | 0.003      | 0.000      | 0.000      | 0.000      |
| Sample size       | 24 268     | 24 268     | 24 268     | 24 268     |
| $R^2$             | 0.077      | 0.323      | 0.332      | 0.342      |

Note: Standard errors are shown in brackets. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. The $p$ values of the Hausman test are all less than 0.01, so the null hypothesis is rejected at 1%, and it is more reasonable to use the fixed effects model.
In terms of resource types, following Wong, Wong, and Boon-Itt (2020), we separate manufacturing industries between resource-based and non-resource-based. The results are shown in Columns (6) and (7) of Table 3. The coefficients are mostly significant at the 1% significance level, and the signs are consistent with the benchmark results. Comparing the coefficients, the green technology innovation coefficients of the two groups are close, while the quadratic energy constraints in non-resource-based industries have a larger coefficient. The U-shaped curve of energy constraints and profitability in non-resource-based industries are steeper. Corporate earnings in non-resource-based industries are more responsive to changing energy constraint intensity, and green technology innovation may drive profitability more effectively. Enterprises in the resource-based industry group rely more on natural resources such as minerals and metals. From a supply chain perspective, most resource-based industries are located at the low end of the value chain. Lacking core technologies and vital production-process parts, most products these enterprises produce are low value-added, resulting in insufficient corporate motivation for independent innovation (Li 2017). Meanwhile, fixed assets

| Variable | (1) Low-pollution industries | (2) Medium-pollution industries | (3) High-pollution industries |
|----------|-----------------------------|-------------------------------|-------------------------------|
| ec       | 0.096***                    | 0.037***                     | 0.037***                     |
|          | (0.015)                     | (0.007)                      | (0.009)                      |
| ec²      | -1.525***                   | -1.261***                    | -1.239***                    |
|          | (0.225)                     | (0.158)                      | (0.178)                      |
| gti      | 1.154***                    | 0.847***                     | 0.848***                     |
|          | (0.211)                     | (0.145)                      | (0.167)                      |
| ownership| -0.266***                   | -0.043                       | -0.236***                    |
|          | (0.082)                     | (0.075)                      | (0.060)                      |
| size     | 0.680***                    | 0.588***                     | 0.551***                     |
|          | (0.020)                     | (0.016)                      | (0.016)                      |
| alr      | 0.014***                    | -0.003                       | 0.005*                       |
|          | (0.004)                     | (0.003)                      | (0.003)                      |
| capitalintensity | 0.297***      | 0.023***                     | 0.096***                     |
|          | (0.036)                     | (0.003)                      | (0.008)                      |
| age      | -0.201***                   | -0.079***                    | -0.077***                    |
|          | (0.036)                     | (0.017)                      | (0.015)                      |
| age²     | 0.004***                    | 0.001***                     | 0.001***                     |
|          | (0.001)                     | (0.000)                      | (0.000)                      |
| constant | 17.076***                   | 15.509***                    | -                            |
|          | (0.857)                     | (0.421)                      | -                            |
| Industry effect | Yes      | Yes                          | Yes                          |
| Regional effect | Yes      | Yes                          | Yes                          |
| Sample size | 5,472   | 7,001                        | 9,602                        |
| R²       | 0.445                        | 0.370                        | 0.284                        |

Note: Standard errors are shown in brackets. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively.
account for a relatively high proportion and render the energy constraint intensity unmanageable and reduce profitability improvement.

2. Region-level heterogeneity. In terms of cities, there are multifaceted disparities across city sizes and administrative levels. This brings different impacts that energy constraints and green technology innovation have on profitability. Based on the concept of “central city” by Zameer (2021), we further define general prefecture-level cities or below as “non-central cities,” and provincial capitals as well as sub-provincial cities as “central cities”. Sub-sample regression results are shown in Columns (1) and (2) of Table 4.

Table 4. (Table 3 continued). Industry heterogeneity results

| Variable     | (4) Medium-high-tech industries | (5) Medium-low-tech industries | (6) Resource-based industries | (7) Non-resource-based industries |
|--------------|---------------------------------|---------------------------------|-------------------------------|---------------------------------|
| ec           | 0.051*** (0.007)                | 0.038*** (0.008)                | 0.048*** (0.007)              | 0.045*** (0.009)                |
| ec^2         | -1.224*** (0.141)              | -1.412*** (0.145)              | -1.234*** (0.108)            | -1.787*** (0.364)              |
| gti          | 0.870*** (0.132)                | 0.978*** (0.133)                | 0.862*** (0.100)              | 1.330*** (0.348)               |
| ownership    | -0.160*** (0.049)              | -0.182*** (0.064)              | -0.120*** (0.042)            | -0.434*** (0.138)              |
| size         | 0.599*** (0.013)                | 0.579*** (0.015)                | 0.593*** (0.010)              | 0.603*** (0.031)               |
| alr          | 0.007*** (0.003)                | 0.000                           | 0.005** (0.002)               | -0.002 (0.007)                 |
| capitalintensity | 0.035*** (0.003)            | 0.165*** (0.022)                | 0.035*** (0.003)              | 0.141*** (0.025)               |
| age          | -0.083*** (0.013)              | -0.107*** (0.016)              | -0.094*** (0.011)            | -0.070 (0.060)                 |
| age^2        | 0.001*** (0.000)                | 0.002*** (0.000)                | 0.001*** (0.000)              | 0.001 (0.001)                  |
| constant     | -14.295*** (0.761)             | 14.074*** (0.722)              | -                               |                                 |

Note: Standard errors are shown in brackets. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively.

Mostly, the coefficients of energy constraint and green technology innovation are significant at the 1% significance level. The enterprises will not actively pursue green R&D before the energy constraint intensity reaches the inflection point (Zhang et al. 2011) since it could add to the burden
on enterprise operation and profitability. After the turning point, however, the enterprises have more incentives, accompanied by climbing energy constraints, to invest in green technology innovation (Geng and Li 2019). A higher level of energy conservation and emission reduction could raise the company’s profitability (Lannelongue et al. 2017).

Compared to enterprises in central cities, the profitability of enterprises in non-central cities could be more sensitive to energy constraints, and the green technology innovation also matters more. As central cities, provincial capitals, and sub-provincial cities are often first movers of policy implementation (Arnold and Hockerts 2011). These central cities can gather green innovation elements under the national or provincial development strategy of energy conservation, emission reduction, and innovation. This phenomenon, coupled with the convenience of technological innovation, scale advantage, and knowledge spillover generated by economic development, facilitates corporate innovation potential in central cities. Lacking awareness of energy conservation and emission reduction

Table 5. Results of regional heterogeneity

| Variable         | (1) Central cities | (2) Non-central cities | (3) Southeast coast | (4) Central and western inland |
|------------------|--------------------|------------------------|---------------------|-------------------------------|
| \( ec \)         | 0.038***           | 0.047***               | 0.055***            | 0.042***                      |
|                  | (0.011)            | (0.006)                | (0.012)             | (0.006)                       |
| \( ec^2 \)       | -1.038***          | -1.970***              | -1.055***           | -2.344***                     |
|                  | (0.121)            | (0.194)                | (0.111)             | (0.257)                       |
| \( gti \)        | 0.669***           | 1.575***               | 0.692***            | 1.949***                      |
|                  | (0.108)            | (0.189)                | (0.100)             | (0.254)                       |
| ownership        | -0.008             | -0.277***              | -0.118**            | -0.234***                     |
|                  | (0.062)            | (0.050)                | (0.048)             | (0.070)                       |
| size             | 0.567***           | 0.618***               | 0.602***            | 0.561***                      |
|                  | (0.014)            | (0.013)                | (0.011)             | (0.018)                       |
| \( alr \)        | 0.007**            | 0.003                  | 0.000               | 0.018***                      |
|                  | (0.003)            | (0.002)                | (0.002)             | (0.005)                       |
| capitalintensity | 0.026***           | 0.164***               | 0.071***            | 0.025***                      |
|                  | (0.003)            | (0.012)                | (0.006)             | (0.004)                       |
| age              | -0.095***          | -0.080***              | -0.085***           | -0.105***                     |
|                  | (0.014)            | (0.014)                | (0.010)             | (0.035)                       |
| age^2            | 0.001***           | 0.001***               | 0.001***            | 0.001*                        |
|                  | (0.000)            | (0.000)                | (0.000)             | (0.001)                       |
| constant         | 14.353***          | 15.050***              | 13.833***           | 15.733***                     |
|                  | (0.729)            | (0.781)                | (0.704)             | (0.917)                       |
| Industry effect  | Yes                | Yes                    | Yes                 | Yes                           |
| Regional effect  | Yes                | Yes                    | Yes                 | Yes                           |
| Sample size      | 8 744              | 14 272                 | 15 556              | 7 460                         |
| \( R^2 \)        | 0.398              | 0.324                  | 0.366               | 0.321                         |

Note: Standard errors are shown in brackets. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively.
technology, enterprises in non-central cities usually start later in technological innovation. Their profitability could be more determined by energy constraints and green technological innovation.

According to Gao et al. (2018), the manufacturing enterprises could be categorized under two classes from the geographical perspective: southeast coastal areas as well as central and western inland areas. Similarly, the regression results of sub-samples support the explanation above, as shown in Columns (3) and (4) of Table 4. It suggests that due to the high level of opening-up, southeast coastal areas, with better-structured, more resource-rich, and managed industries, achieve a rather high level of green innovation (Liu et al. 2018; Jiang 2020). Thus, energy constraints and green technology innovation in the southeast coastal areas have a relatively small marginal impact on profitability. In contrast, these factors matter more for the enterprises in the central and western inland areas.

3. Enterprise-level heterogeneity. In terms of business scale, our sampled enterprises are divided into large and small enterprises according to the CSMAR Database. The regression results are shown in Columns (1) and (2) of Table 5. The profitability of small enterprises remains more responsive to energy constraints since the main factor affecting business performance for growing small enterprises lies in technological innovation (Min 2013). As well as having more flexible capital allocation (Tong et al. 2016), small enterprises can react more quickly to energy constraint change. In terms of enterprise age, based on Hall and Helmers (2013), the older 50% (age>23) enterprises are identified as high-age enterprises, and the younger 50% (age<23) are termed young enterprises. The regression results are shown in Columns (3) and (4) of Table 5. Young enterprises can respond more quickly under strict energy constraints, and this is reflected in the regression results that the profitability fluctuates faster. Green technology innovation has a larger coefficient. Enterprises operating for a longer time are less influenced by energy policy control, possibly owing to the green technology accumulation by these older enterprises themselves, and the changes of energy constraints have little impact on the profitability of such enterprises.

The study replaces some crucial variables in the regression model in four ways to further examine the robustness of our findings.

**Method One:** Enterprise profitability is replaced by a new index (i.e., the net profit and total profit distributed to shareholders), and the regression results are shown in Columns (1) and (2) of Table 6.

**Method Two:** We use a new index of annual intangible asset improvement divided by total assets at the end of the year to substitute the incremental green technology innovation (Chen and Hung 2014), as shown in Column (3).

**Method Three:** Considering the inertia effect or sunk cost of enterprise decision-making, enterprises’ profitability that lags one period is added to the model as an additional explanatory variable as in Hall and Helmers (2013). The fourth column of Table 6 lists the regression results.

**Method Four:** Combining the index replacement method with the variable lagging method and using lag-1 profitability as an explanatory variable for regression, Column (5) gives the coefficients estimates. All models in Table 6 show that the results of energy constraint and green technology innovation are consistent with the benchmark analysis, primarily significant at the 1% level and not affected by the replacement of indicators or the lag of variables.

**Additional Robustness Check**

Although adding control variables in turn in addition to benchmark estimation and heterogeneity analysis can reflect some robustness, we continue to analyze from two aspects. First, due to possible reverse causality, there can be an endogeneity problem in the impact of energy constraints and green technology innovation on profitability. The rising profitability, for example, may foster green technology innovation and relieve energy constraints.

In addition, limited disclosure of manufacturing enterprises provides no guarantee that all essential variables can be included in the model. Therefore, this paper refers to other articles such as Fu and Li (2010) and selects lag-1 to lag-3 of coal-equivalent energy consumption and energy constraints in
various provinces and cities as instrument variables (IVs). 2SLS, two-step optimal GMM, and iterative GMM methods are utilized to test the endogeneity of the model and the results are shown in Table 7. The IVs successively pass the weak IV test and over-identification test, proving the rationality of IV selection. The coefficients are significant at the 1% or 5% significance levels. Compared to the benchmark model, the main explanatory variables’ signs are consistent with the previous results. After controlling for endogeneity, we still observe a U-shaped relationship between energy constraints and profitability. Green technology innovation has a positive relationship with the growth of profitability.

Table 6. Results reflecting enterprise heterogeneity

| Variable     | (1) Small enterprises | (2) Large enterprises | (3) Senior enterprises | (4) Young enterprises |
|--------------|------------------------|-----------------------|------------------------|-----------------------|
| $ec$         | 0.061***               | 0.028***              | 0.036***               | 0.047***              |
|              | (0.007)                | (0.010)               | (0.010)                | (0.006)               |
| $ec^2$       | -1.320***              | -0.512                | -1.22***               | -1.423***             |
|              | (0.113)                | (0.466)               | (0.143)                | (0.143)               |
| $gti$        | 0.961***               | 0.650                 | 0.789***               | 1.092***              |
|              | (0.105)                | (0.417)               | (0.133)                | (0.134)               |
| ownership    | -0.258***              | 0.590**               | -0.096                 | -0.230***             |
|              | (0.045)                | (0.295)               | (0.065)                | (0.051)               |
| size         | 0.643***               | 0.055                 | 0.529***               | 0.672***              |
|              | (0.011)                | (0.054)               | (0.014)                | (0.013)               |
| $alr$        | 0.013***               | -0.008                | -0.003                 | 0.014***              |
|              | (0.003)                | (0.008)               | (0.003)                | (0.003)               |
| capitalintensity | 0.038*** | -0.097              | 0.030***               | 0.436***              |
|              | (0.003)                | (0.233)               | (0.003)                | (0.031)               |
| age          | -0.078***              | -0.006                | -0.059*                | -0.047                |
|              | (0.012)                | (0.124)               | (0.034)                | (0.041)               |
| age$^2$      | 0.001***               | -0.001                | 0.001*                 | 0.000                 |
|              | (0.000)                | (0.003)               | (0.000)                | (0.001)               |
| constant     | 13.289***              | -                    | 16.171***              | 12.996***             |
|              | (0.748)                | (10.024)              | (0.740)                | (0.740)               |
| industry effect | Yes                  | Yes                  | Yes                   | Yes                   |
| regional effect | Yes                  | Yes                  | Yes                   | Yes                   |
| sample size  | 18 194                 | 530                  | 10 426                 | 12 590                |
| $R^2$        | 0.340                  | 0.336                 | 0.333                  | 0.385                 |

Note: Standard errors are shown in brackets. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively.
In this study, the relationship between energy constraint, green technology innovation, and enterprise profitability is discussed and tested for Chinese manufacturing enterprises in 2007-2020 based on the CSMAR and WIND databases. The results generally suggest a U-shaped relationship between energy constraints and profitability, and the improvement in green technology innovation could boost business earnings. Among the control variables, business age, business scale, and asset-liability ratio are positively associated with profitability.

The increase in green technology innovation could be associated with heterogeneous profitability growth in industries with different pollution levels, technological levels, and resource use types. The regression models after differentiating industry types indicate a steeper U-shaped curve between energy constraint and profitability in low-pollution, medium-low-tech, and non-resource-based industries. The profitability of enterprises in these industries is more sensitive to the change of energy constraint intensity. There is no U-shaped relationship in high-pollution industries.

Further classifying regional differences and enterprise types, the U-shaped curve between energy constraint and profitability of non-central cities, central and western inland areas, and smaller and younger enterprises is steeper. The profitability of these types of enterprises could react more to changing energy constraints. There is no U-shaped curve relationship between energy constraints and the profitability of large enterprises. Corporate earnings could be enhanced more following the increment of green technology innovation when the enterprises are in non-central cities as well as in central and western inland areas. The effects can be subdivided into regional heterogeneity and

Table 7. Regression results of replacing indicators

| Variable          | (1) Replacing profitability -1 | (2) Replacing profitability -2 | (3) Replacing green technology innovation | (4) Profitability lag-1 | (5) Replacing profitability & lag-1 |
|-------------------|--------------------------------|--------------------------------|------------------------------------------|------------------------|-----------------------------------|
| $ec$              | -0.422***                      | -0.463***                      | -0.364***                                | -0.281***              | -0.336***                         |
|                   | (0.095)                        | (0.106)                        | (0.097)                                  | (0.096)                | (0.099)                           |
| $ec^2$            | 0.414***                       | 0.472***                       | 0.399***                                 | 0.365***               | 0.408***                          |
|                   | (0.087)                        | (0.097)                        | (0.090)                                  | (0.088)                | (0.091)                           |
| $gti$             | 0.014***                       | 0.013**                        | 0.082***                                 | 0.079***               | 0.079***                          |
|                   | (0.005)                        | (0.005)                        | (0.006)                                  | (0.006)                | (0.006)                           |
| $gti^2$           |                                |                                | 0.064***                                 |                        |                                   |
|                   |                                |                                | (0.019)                                  |                        |                                   |
| $\text{L.log (profitability)}$ |                          |                                | 0.498***                                 |                        |                                   |
|                   |                                |                                | (0.006)                                  |                        |                                   |
| $\text{L.log (profitability 2)}$ |                       |                                | 0.487***                                 |                        |                                   |
|                   |                                |                                | (0.006)                                  |                        |                                   |
| Constant term     | 14.545***                      | 14.926***                      | 15.075***                                | 6.800***               | 7.016***                          |
|                   | (0.674)                        | (0.714)                        | (0.697)                                  | (0.437)                | (0.441)                           |
| Industry effect   | Yes                            | Yes                            | Yes                                      | Yes                    | Yes                               |
| Regional effect   | Yes                            | Yes                            | Yes                                      | Yes                    | Yes                               |
| Sample size       | 24 231                         | 23 253                         | 23 019                                   | 21 133                 | 21 034                            |
| $R^2$             | 0.117                          | 0.302                          | 0.114                                    | 0.114                  | 0.305                             |

Note: Standard errors are shown in brackets. *, **, and *** indicate significant at the 10%, 5%, and 1% significance levels, respectively.

CONCLUSION

In this study, the relationship between energy constraint, green technology innovation, and enterprise profitability is discussed and tested for Chinese manufacturing enterprises in 2007-2020 based on the CSMAR and WIND databases. The results generally suggest a U-shaped relationship between energy constraints and profitability, and the improvement in green technology innovation could boost business earnings. Among the control variables, business age, business scale, and asset-liability ratio are positively associated with profitability.

The increase in green technology innovation could be associated with heterogeneous profitability growth in industries with different pollution levels, technological levels, and resource use types. The regression models after differentiating industry types indicate a steeper U-shaped curve between energy constraint and profitability in low-pollution, medium-low-tech, and non-resource-based industries. The profitability of enterprises in these industries is more sensitive to the change of energy constraint intensity. There is no U-shaped relationship in high-pollution industries.

Further classifying regional differences and enterprise types, the U-shaped curve between energy constraint and profitability of non-central cities, central and western inland areas, and smaller and younger enterprises is steeper. The profitability of these types of enterprises could react more to changing energy constraints. There is no U-shaped curve relationship between energy constraints and the profitability of large enterprises. Corporate earnings could be enhanced more following the increment of green technology innovation when the enterprises are in non-central cities as well as in central and western inland areas. The effects can be subdivided into regional heterogeneity and
enterprise heterogeneity. For enterprises of these characteristics, the increase of green technology innovation could also have more positive relationship with profitability.

Generally, enterprises under certain energy constraint intensity can develop green technology innovation without profitability losses. Green innovation may even promote profitability to a great extent. Our analysis verifies this through the lens energy policies, showing that green technology innovation can be implemented without threatening enterprises’ survival and, therefore, achieve win-win results. However, we also show that there exists an inflection point in the relationship between energy constraints and profitability. Enterprises may suffer from profitability decline before reaching the inflection point. Only after this point will their profitability rise with energy constraints.

Accordingly, we provide the following policy recommendations. As we show, some industries (lightly polluted industries, low- and medium-tech industries, and/or non-resource-based industries), regions (non-central cities and/or central-western inland areas), or enterprises (smaller and/or younger enterprises) are more responsive to and are disproportionately affected by severe energy conservation and emission reduction policies. These policies could cause a frequent adverse impact on these enterprises, such as rising operating costs and bankruptcy. Therefore, the first recommendation is that for these “energy-constraint sensitive” industries or enterprises, local government could consider options to avoid a “one-size-fits-all” approach in their energy policy. Instead, some level of flexibility should be
permitted to allow these industries and enterprises to build up their competitiveness and capabilities to cope with the possibly stricter energy use constraints and green technology requirements in the future.

Since our results show that green technology innovation can help enterprises resolve the dilemma associated with energy constraints, our second recommendation is that the government should actively enable and facilitate enterprises to invest in green technology innovation. This may be achieved through tax reduction and low-interest loans. Owing to their high level of green technology adoption, for industries, regions, or enterprises that are not sensitive to tightening energy constraints, local governments can maintain the existing policies or pursue stricter energy policies to stimulate enterprises to develop further and adopt more efficient production management and processes. Driving all enterprises in all regions or industries to carry out green innovation may also improve synergy.

This study also has limitations. First, only Chinese enterprises are analyzed, so the conclusion may not apply to other countries. Second, because of the economic importance of the manufacturing industry, high dependence on resources, and the need for technological progress, we select manufacturing enterprises for research. Therefore, results and policy recommendations may not reflect all industrial sectors in China, including the resource industries. In terms of research methods and data, other methods to quantify and analyze energy constraints may be considered. Research may also be conducted from a microscopic perspective of energy constraints, such as at the enterprise level.

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ENDNOTES

1  The vertical axis in Figure 1 represents the energy constraints. See *Variables* for a specific calculation.
2  The vertical axis in Figure 2 represents green technology innovation. See *Variables* for a specific calculation.

Lijun Jia is the director of the Department of Economics and Finance of SILC Business School, Shanghai University. She is also an associate professor and a tutor for graduate students. Jia’s main research interests are international economy and cooperation, energy and environmental economy.

Yunjie Hao is a graduate student in the Department of Economics and Finance of Shanghai University, majoring in regional economics. Her research mainly focuses on tourism economics, environmental economics, and corporate analysis both from theoretical and empirical perspectives.

Wuyang Hu earned his PhD in agricultural and resource economics from the University of Alberta, Canada in 2004. He is currently a professor in the Department of Agricultural, Environmental, and Development Economics at The Ohio State University.