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How Digital Transformation Promotes China's Energy Transition: An Empirical Study Based on a Quasi-experiment

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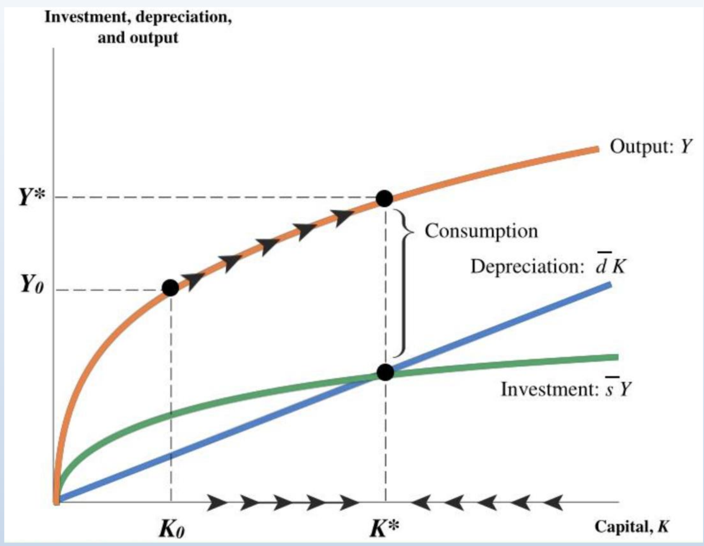
Introduction

- Having become the world's largest energy consumer and carbon emitter over the past few decades, China urgently needs to transition towards a more sustainable and green energy system.
- The digital transformation brought about by the emerging technologies is not only about the application of technology, but also a profound process of change.
- Though digital transformation theoretically seems to be beneficial for energy transformation, further research and verification are needed to evaluate its effectiveness in practical applications, particularly in energy transition.
- Empirical evidence in the context of a major country like China will be of great value for both policy-making and practical implementation.

Theoretical Foundation

- **Solow Growth Model**

  The Solow growth model in economics assumes that the marginal returns to investment are diminishing, meaning that beyond a certain level, producing more results in lower efficiency. In the long run, technological progress is the only source of economic growth. This theory lays the economic rationale and foundation for energy transition, as it implies that continuing reliance on conventional energy sources with diminishing returns necessitates shifting towards technological progress and innovation in renewable energy to sustain long-term growth.



- **System Dynamics Model**

  The system dynamics model of digitalization and energy efficiency considers the interactions between various factors in complex systems. This model can be utilized to describe how digital technologies can optimize energy utilization. Its widespread application has led to the development of many theoretical frameworks on the relationship between digitalization and energy efficiency, which have provided valuable insights for the mechanism analysis in this study.

- **Technology Acceptance Model (TAM) theory**

  Beyond facilitating evaluations of acceptance, the intrinsic value of the digitalization Technology Acceptance Model in energy transition research lies in its capability to identify barriers and drivers. This feature positions it as one of the dependable sources for indicator development.

Analysis

- **Baseline Regression Model**

$$Y_{it} = \alpha + \beta \cdot Treat_i + \gamma \cdot Post_t + \delta \cdot (Treat_i \times Post_t) + X'_{it}\theta + \varepsilon_{it}$$

Where:

Y_{it}: Represents the energy transition indicator for city i in period t

$Treat_i$: A dummy variable equal to 1 for cities that underwent digital transformation and 0 otherwise.

$Post_t$: A dummy variable equal to 1 for periods after the treatment and 0 otherwise.

$Treat_i \times Post_t$: The interaction term. The coefficient δ provides our DiD estimate of interest.

$X'_{it}\theta$: A set of control variables, e.g., city GDP, per capita income, etc.

ε_{it} : The error term.

- **Parallel Trends Test Model:**

$$Y_{it} = \alpha + \beta \cdot Treat_i + \sum_k \gamma_k (Treat_i \times PreYear_{kt}) + X'_{it}\theta + \varepsilon_{it}$$

Where:

$PreYear_{kt}$: Refers to a series of dummy variables pointing to each pre-treatment period.

γ_k : The coefficients associated with each interaction term $PreYear_{kt}$. For the parallel trends assumption to hold, we expect these coefficients to be statistically insignificant.

Methodology

- **Research Plan**

  This study plans a quasi-experiment design and to form a panel data from 286 prefecture-level cities in China to estimate the causal effects of digital transformation on sectoral energy consumption.

- **Research Framework:**

  To thoroughly investigate the causal impact of digital transformation on China's energy transition, we mainly employ the Difference-in-Differences (DiD) method. This approach capitalizes on comparing changes over time between groups that are exposed to the digital transformation and those that are not, allowing us to infer causal effects amidst potential confounding factors.

- **Data Sources:**

  The panel data from 286 prefecture-level cities in China utilized for this research predominantly originate from official Chinese statistical repositories, complemented by information from international energy and technological research institutions. This encompasses data concerning energy consumption, modes of production, and the prevalence and application of digital technologies across various provinces in China. (Data collection is in progress)

- **Model Specification:**

  We set forth a DiD econometric model wherein the dependent variable signifies indicators of energy transition progress across provinces, and the independent variables encapsulate the extent and rate of digital technology applications. To account for other potential confounders, a series of control variables such as provincial GDP, per capita income, and industrial structures have been incorporated.

- **Causal Inference:**

  Leveraging a quasi-experimental design, we identify certain instrumental variables besides the DiD method to aid in establishing the causal linkage between digital transformation and energy transition. For instance, sudden surges in digital investments within certain provinces over specific timeframes are considered as instrumental variables, addressing potential endogeneity concerns.

- **Statistical Analysis:**

  A battery of statistical tools, encompassing OLS regression, 2SLS, and fixed-effects models, have been planned for our statistical analyses. These instruments aim to extract meaningful insights from the data, anchoring the relationship between digitalization and energy transition.

- **Robustness Tests:**

  To ensure the robustness of the output, we plan to undertake various robustness checks. These encompass modifications in model specifications, using different data subsets, and exploring alternative statistical approaches. In particular, parallel trends assumption, alternative control groups, alternative time windows, placebo tests, heterogeneous treatment effects would be employed.

Discussion

- The study has potential to conclude that digital transformation significantly reduces the energy intensity of China's industrial, transportation, and service sectors, with the largest effect observed in the industrial sector. Results from certain robustness tests address peripheral questions pertaining to this research intention. The study may suggest that digital transformation is becoming an important driver for promoting China's energy structure optimization and green low-carbon transition.

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