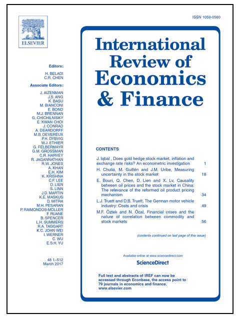
Journal Pre-proof



The impact of the green energy infrastructure on firm productivity: Evidence from the Three Gorges Project in the People's Republic of China

Dong Cheng, Xunpeng Shi, Jian Yu

PII: S1059-0560(20)30224-0

DOI: https://doi.org/10.1016/j.iref.2020.09.022

Reference: REVECO 2056

To appear in: *International Review of Economics and Finance*

Received Date: 30 March 2020

Revised Date: 18 September 2020

Accepted Date: 21 September 2020

The authors declare no conflict of interest.

The Impact of the Green Energy Infrastructure on Firm Productivity: Evidence from the Three Gorges Project in the People's Republic of China

Dong Cheng[1], Xunpeng Shi[2], Jian Yu[3*]

1. Department of Economics, Union College, email: chengd@union.edu.

2. Australia-China Relations Institute, University of Technology Sydney, NSW 2007, Australia; Center of Hubei Cooperative Innovation for Emissions Trading System & School of Low Carbon Economics, Hubei University of Economics, Wuhan, Hubei Province 430205, China, email: xunpeng.shi@uts.edu.au

3*. (Corresponding author). School of Economics, Central University of Finance and Economics, Beijing 102206, China, email: jianyu@cufe.edu.cn.

Acknowledgement

Xunpeng Shi acknowledges financial support from the National Natural Science Foundation of China (71828401, 71873029). Jian Yu acknowledges financial support from the Beijing Social Science Fund Project (19LJB001).

The Impact of the Green Energy Infrastructure on Firm Productivity: Evidence from the Three Gorges Project in the People's Republic of China

Abstract:

Despite the dominant role of hydropower in the global power generation mix and the popularity of studying the productivity impact of infrastructure investment, there is a lack of research regarding the impact of hydropower projects on firm productivity. Such a positive impact could promote a more ambitious action plan for mitigating carbon emissions. This study investigates whether and how the People's Republic of China's Three Gorges Project (TGP), the world's largest hydropower project, may affect the productivity of manufacturing firms in the province where the project is located. The empirical results reveal a statistically and economically significant positive impact of the TGP on manufacturing firms' productivity, and various robustness checks confirm the soundness of our findings. We also verify three channels, the capital deepening effect, the scale effect, and the competition effect, robustly. This productivity impact suggests that hydropower projects have an economic benefit in addition to the other well-known ones, such as flood control and improvement of the shipping capacity. The findings imply that policy makers need to consider the broad benefits of green energy beyond the conventional cost-benefit tradeoff, which can help justify some marginal green energy projects and technologies.

Keywords: infrastructure investment; productivity; DID; Three Gorges Project; hydropower

Highlights

- First micro study to investigate whether hydropower project affects firm productivity
- First comprehensive study of the production-side economic impact of the PRC's TGP
- The TGP has significantly improved the productivity of manufacturing firms in Hubei province
- The study proposes and verifies three channels, the capital deepening, scale, and competition effects
- New empirical evidence for additional economic benefits of the PRC's giant infrastructure investment

1. Introduction

Studying the productivity impact of green energy infrastructure can not only inform national policy debates on green energy infrastructure investment, but also help to mitigate global carbon emissions (Wu et al., 2020; D. Zhang et al., 2019). Given the global efforts toward mitigating the carbon emissions from increasing energy use, the adoption of low-carbon or green energy resources, including hydropower, is a key solution (Wang et al., 2020). However, such kinds of green energy often face cost disadvantages compared with fossil fuels and thus appear less attractive to national policy makers. In fact, infrastructure investment has many benefits beyond economic returns, that is, positive externalities, such as reducing transportation costs, fostering economic integration, stimulating competition, and improving access to new markets (Gibbons et al., 2019). Understanding non-energy benefits, especially externalities, such as enhancing firm productivity, will provide further support for low-carbon energy and thus facilitate its earlier and larger-scale adoption. Such an ambitious low-carbon energy development plan is critical, because the existing Intended Nationally Determined Contributions (INDCs) are far from sufficient (Gao et al., 2019), and all of them collectively can only limit the warming by 2.6-3.1 degrees Celsius by 2100 (Rogelj et al., 2016). With the consideration of the positive externalities of low-carbon energy, national governments might make more ambitious emission reduction targets than their current commitment to the INDCs.

Policy makers and researchers have been paying increased attention to the effects of infrastructure investment on economic outcomes, including productivity (Banerjee et al., 2012; Barzin et al., 2018). However, there is a lack of studies on the response of firm performance to hydropower infrastructure even though hydro accounts for the lion's share of the non-fossil fuel electricity generation. Globally, in 2018, hydropower accounts for 15.8% of the total power generation, whereas the other renewables collectively only account for 9.3% (British Petroleum (BP), 2019). The prevailing literature on the productivity effect of infrastructure focuses on road infrastructure, such as Cohen and Paul (2004), Holl (2016), Ghani et al. (2016), Gibbons et al. (2019); information and communications technology (ICT), such as DeStefano et al. (2018), Garicano and Heaton (2010), Mithas et al. (2018), Mitra et al. (2016), Mohamad et al. (2017); and pure electricity infrastructure, such as Abeberese (2017), Cole et al. (2018), and Fisher-Vanden et al. (2015). Zheng et al. (2016) study the role of the TGP in the People's Republic of China (PRC) but only focus on its role in relieving electricity shortage and does not consider more comprehensive production-side economic impacts, such as enhancing productivity.

Many existing studies find that infrastructure investment positively influences the productivity of firms in both developed and developing countries (Fernald, 1999; Ghani et al., 2016). Morrison and Schwartz (1996) discover that infrastructure investment imposes a significantly positive effect on manufacturing firms' productive efficiency in the US. In addition, the main channel for generating such a positive effect is the cost-saving benefits. Cohen and Paul (2004) use the manufacturing data of the US from 1982 to 1996 to investigate the impact of public highway infrastructure investment on firms' productivity. They also find that public highway infrastructure investment exerts a positive effect on manufacturing firms' productivity via its cost-saving. Moreover, there is a spatial spillover effect, and infrastructure investment in neighboring states increases the value of own-state public infrastructure investment as well as directly affecting manufacturing firms' productivity. Paul et al. (2004) employ the annual data from 1961 to 1995 at the sectoral level in Canada and find that public infrastructure investment has a significant effect on the productivity of 12 two-digit Canadian manufacturing industries. Holl (2012) uses various estimation methods and determines that infrastructure investment generates a market-potential effect on Spanish firms' productivity.

The literature has also heavily explored infrastructure in various forms, primarily road, electricity, and irrigation. Heintz et al. (2009) argue that improving the US infrastructure in transportation, public school, water management, and energy transmission will improve the US's competitiveness. Li et al. (2017) find that infrastructure investment (e.g., road investment) in the PRC has contributed to an increase in manufacturing firms' productivity by using data of Chinese manufacturing firms during the period 1998-2007. With data of manufacturing firms in India from 1972 to 1992, Hulten et al. (2006) find that the growth of road and electricity generation capacity investment has accounted for nearly half of the growth of the productivity residual of India's registered manufacturing firms. Zhang and Fan (2004) use a panel data set at the district level in rural India from 1971 to 1994 to investigate the relationship between productivity and infrastructure investment. They conclude that sector-specific infrastructure investment (e.g., irrigation investment) in India mainly enhances yields and moves the agricultural production frontiers outward. Mohamad et al. (2017) find that the information technology infrastructure has a significant positive effect on the performance of electrical and electronic manufacturing firms in Malaysia. Using data of the India manufacturing sector for the period 1994-2010, Mitra et al. (2016) examine the role of infrastructure and information and communication technology (ICT) investment in total factor productivity (TFP). The findings show that the elasticity of TFP with respect to total infrastructure investment is around 0.32 and that the dramatic growth of ICT investment in India has a significant effect on manufacturing firms' productivity. However, to the best of our knowledge, there is no study on the impact of any hydropower project, regardless of its size, on firm production-side performance and especially on productivity.

This study fills the gap by estimating the impact of the PRC's TGP on the productivity of firms in Hubei, where the project is located. We apply comprehensive microdata on Chinese manufacturing firms from 1998 to 2006 and a state-of-the-art productivity measurement in a difference-in-differences (DID) setting. The study finds that the TGP has significantly improved firm productivity through channels including the capital deepening effect, the scale effect, and the competition effect.

This study adds to the existing literature in three respects. First, although existing studies have found that infrastructure investment has many benefits including reducing transportation costs, fostering economic integration, and stimulating competition, this article is the first one to investigate whether the world's largest hydropower project (e.g., the Three Gorges Project) has a positive effect on firm performance from the perspective of production side using micro-survey data from China. This paper reports the most comprehensive research about the impact of the TGP on firm performance and, in particular, firm production efficiency (i.e., productivity). Second, to the best of our knowledge, this study is the first paper to propose and test empirically the three channels through which infrastructure affects firm productivity. The proposed channels, specifically the capital deepening effect, the scale effect, and the competition effect, are applicable to studying the productivity impact of other green energy infrastructure investments. Third, our application of the DID method is clean and innovative for hydropower station studies and researchers can apply it to study the impact of other energy infrastructure investment projects.

The rest of the paper is organized as follows. After this introduction, Section 2 presents some background information on the TGP and then proposes three hypotheses for the underlying channels through which the TGP affects firm productivity, building on the conceptual frameworks from the existing studies. Section 3 introduces the empirical methodology, data, and variables. Section 4 presents and explains the estimation results. The last section concludes this paper.

2. Background and Hypotheses

2.1. The TGP: An Overview

The Three Gorges Project (TGP) is a hydroelectric project that spans the Yangtze River in Yichang, Hubei province, the PRC. The total capacity of the TGP is 22,500 MW. It is the largest hydroelectric power project in the world and contains 34 generators. The capacity of 32 hydropower generators is 700 MW each, and the capacity of the two auxiliary supply generators is 50 MW each (Cleveland and Morris, 2013). Among those 32 hydropower generators, 14 are located on the north (or left) side, 12 are located on the south (or right) side, and the last 6 are underground in the north.

The TGP began generating electricity in 2003, when the first north-side generator (No. 2) started operation on 10 July 2003. This milestone is also the year that we selected as the first year in which the project took effect in our DID analysis, that is, the first year of the post-project period. The north side became completely operational on 7 September 2005 with the commission of generator No. 9. However, the full capacity of the north side (9,800 MW) was only reached on 18 October 2006, after the water level reached 156 meters (Government of the People's Republic of China, 2006). The 12 south-side main generators are also in operation. The south-side generators started operation with No. 22 on 11 June 2007, and No. 15 started working on 30 October 2008. The 6th (No. 17) began operation on 18 December 2007, raising the total capacity to 14.1 GW, and then the TGP project surpassed Itaipu (14.0 GW) to be the largest hydropower plant in the world. On 23 May 2012, with the commissioning of the last main generator (No. 27), the TGP reached its full capacity of 22.5 GW.

Figure 1 shows that the annual production of electricity and the number of installed generators of the TGP have increased steadily from 2003 to 2017. In July 2008, the TGP generated 10.3 TWh of electricity, its first month over 10 TWh. When there is sufficient water flow, the power output can reach the generation capacity of the plant. The calculation of the maximum power output curves uses the average flow rate at the dam site, and assumes that the water level is 175 meters and the plant gross efficiency is 90.15%. During the dry season, from November to May, the river's flow rate restricts the power output. The TGP reached its designed maximum reservoir water level of 175 meters for the first time on 26 October 2010, when it also realized the intended annual power generation capacity of 84.7 TWh. In 2012, the TGP's 32 generating units created an electricity record of 98.1 TWh, which accounts for 14% of hydro generation in the PRC (Zheng et al., 2016).

[Insert Figure 1 here]

Figure 2 indicates that there are 10 provinces and municipalities in China served with electricity by the TGP. They are Hubei, Henan, Hunan, Jiangxi, Chongqing, Shanghai, Jiangsu, Zhejiang, Anhui and Guangdong. It is shown that the electricity service area of the TGP includes provinces and municipalities belonging to different power grids. We have highlighted the serviced provinces belonging to the China Southern Power Grid, East China Power Grid, and Central China Power Grid with brown, purple, and green background colors, respectively. To avoid the effect of the TGP on manufacturing productivity through electricity supply, we will pick up a province outside of the electricity service area of the TGP to act as the control province for the treatment province, Hubei.

[Insert Figure 2 here]

In Figure 2, we already present that the intent of the project is to transmit the electricity that the TGP generates to the Central China Power Grid, the East China Power Grid, and the China Southern Power Grid. However, the North China Power Grid is not part of the plan. Therefore, provinces in the northern PRC, such as Hebei, have no direct connection to the TGP. This inspires us to find a comparable province for Hubei province, where the TGP is located and has supplied electricity since 2003, to implement a DID analysis for the assessment of how the hydropower infrastructure affects firm production efficiency (productivity). To be specific, we select Hebei province in the northern PRC to be the location for our control group of firms. Further discussion on how we choose the control province appears in section 3.

2.2. The TGP and Firm Productivity: Hypothesized Channels

In this subsection, we aim to review the existing literature with the hope of finding relevant testable channels through which hydropower investment such as that in the TGP, will affect firm productivity. We conduct a survey of a wide range of existing studies related to our research question. Basing on the conceptual frameworks in the relevant literature, we find that the TGP can potentially affect firm productivity through the following three channels.

The first channel is the capital deepening effect. In other words, hydropower plants can speed up the process of capital deepening and improve the production efficiency of enterprises by relaxing the constraint of the electricity supply. Resource availability and input factor reliability play an important role in improving manufacturing firms' productivity (D. Zhang et al., 2020). However, they are particularly difficult to obtain in developing countries (Cole et al., 2018). Considering that electricity is one of the most important sources of energy for manufacturing firms in developing countries, electricity shortages can exert a significant negative impact on their productivity (Cheong et al., 2019; Shaikh et al., 2015; T. Zhang et al., 2019). Abeberese (2020) argues that electricity shortages have a significantly negative effect on capital investment in Ghana through the channel of reducing capital productivity or durability. In the case of an electricity shortage, manufacturing firms have to invest in self-generation, which will crowd out other investment opportunities and obviously reduce their productivity. Fisher-Vanden et al. (2015) use Chinese energy-intensive firms' data covering the period 1999-2004 and find that the unit production cost increased by 8% in response to the increase in electricity shortages from 1999 onward, and this is harmful to firm productivity. Abeberese (2017) provides evidence on how electricity shortages and the electricity price affect firms' productivity growth in India. She finds that, in response to an exogenous increase in electricity price, which is a typical production cost, firms switch to less electricity-intensive production processes and thus reduce their productivity growth rates. Allcott et al. (2016) estimate the effects of electricity shortages on manufacturing firms in India and conclude that electricity shortages reduce plants' revenues and producer surplus by 5 to 10% on average and impose a smaller negative effect on productivity.

Hydropower plants have played a key role in generating affordable electricity in developing countries, such as the PRC, India, and Brazil. Tang et al. (2019) argue that, against the backdrop of rapid economic growth and insufficient energy supply in Malaysia, Indonesia, Thailand, and Myanmar, hydropower is the best choice to satisfy the increasing demand in those countries. Zheng et al. (2016) provide a case study of the TGP in the PRC. They find that it has been delivering electricity continuously to Hubei, Henan, Jiangxi, Anhui, Zhejiang, Guangdong, Shanghai, and other provinces in the eastern and central PRC since 2003 and has greatly relieved the power shortage for enterprises in those provinces. In fact, the construction of hydropower plants can significantly alleviate an insufficient supply and eliminate power outages. If enterprises can obtain a steady and reliable supply of external electricity, they do not need to buy power production equipment for self-generation, and the cost of self-generated power is generally higher. Furthermore, enterprises can use that money for different investments, such as financing more advanced machinery and equipment. The capital deepening effect induced by the reduction of power shortages may greatly improve the enterprise production efficiency. At the more aggregate industry level, this means that the industry is becoming more capital intensive.

Hypothesis 1. *The operating of the TGP encourages treated firms (i.e., manufacturing firms in Hubei) to increase their capital intensity, which tends to raise firm productivity directly.*

The second channel is the scale effect, which works in the following way: if a firm experiences an increase in its relative size within a location and industry, it tends to have more bargaining power in the local input markets and more interest in resources for long-term technology-enhancing investment (e.g., R&D investment) because of its increase in local economic importance. These newly gained advantages then raise the firm's productivity by lowering its input prices or improving its technology directly. DeStefano et al. (2018) investigate the impacts of broadband infrastructure and information and communication technology on firm performance in the UK. They argue that infrastructure investment has a market potential effect on firm productivity, which features a bigger firm size captured by either sales or employment. Gibbons et al. (2019) investigate the average causal impact of infrastructure investment (e.g., road improvements) on British enterprises' productivity. The estimated results indicate that road improvement has a larger positive effect on firms' productivity than previous studies have reported (Ghani et al., 2016) via the channel of the market potential effect. They argue that road improvement in Britain has a positive effect on the employment size in places that have better access to the network. A 1% gain in accessibility leads to 0.3-0.5% more employment, which researchers can use to measure the market potential effect indirectly.

Moreover, in the PRC, banks (especially state-owned banks) prefer to lend to large firms, and thus the increased scale that the TGP induces will also earn favorable financial positions for manufacturing firms in the impacted area (Xu et al., 2020; Yu et al., 2019). The giant infrastructure project will also bring many additional resources (such as labor, capital, intermediate inputs, and advanced technology) to Hubei, where the TGP is located, and the increased availability of inputs and technology will further help firms in Hubei to increase their size.[1] Unlike the existing studies, we characterize the scale effect using firms' relative size in their industry and locality because the bargaining power story (or economic importance and market potential story) that we propose is industry-specific and more likely to hold within a locality. Therefore, we can form the second hypothesis:

Hypothesis 2. *The operation of the TGP will encourage the treated firms* (i.e., manufacturing firms in Hubei) *to increase their (relative) scales, which will help them to gain access to more resources and raise their bargaining power in the input markets, and their productivity will increase accordingly.*

The third channel is the competition effect, by which we mean that: when a firm faces more competition within a location and industry, it will be forced to improve its productivity through methods such as better management to survive. Increased competition will consequently drive the least-productive firms out of the market and simultaneously raise the pressure on the surviving firms to raise their productivity, so the average productivity will increase (Melitz, 2003; Melitz and Polanec, 2015). Public infrastructure investment can improve manufacturing productivity through the channel of increased competition and competitiveness. For example, Heintz et al. (2009) argue that improving the US infrastructure in four primary areas, which consist of transportation systems, public school buildings, water management, and energy transmission, will improve the market competition and firm competitiveness in the US by contributing to a lower-cost environment against the aging infrastructure stock. There are many benefits from improvements of the transportation infrastructure arising from increases in connectivity, owing to the reduction in travel time and travel costs for both goods and people. These can then lead to higher productivity. Holl (2016) uses a geo-coded micro-level panel data set for Spain from 1997 to 2007 and investigates the effect of infrastructure

[1] The Chinese government has provided many funds and preferential policies for the construction of the TGP in Hubei province. For example, in order to make the TGP into a world-class hydropower station, the central government has provided Hubei province with a large amount of non-repayable funds, professionals, and advanced equipment. Many Chinese commercial banks (e.g., China Construction Bank, Industrial and Commercial Bank of China, and Bank of Communications) have also provided loans of more than 11 billion RMB for the construction of the TGP at a rate of 10% lower than the benchmark interest rate. Moreover, the surrounding provinces of Hubei also have provided a lot of conveniences in the resettlement of immigrants. These additional resources and conveniences not only greatly enhanced the status of Hubei province in China, but also provided positive externalities that cannot be ignored for enhancing the development of enterprises in Hubei.

investment on firm-level productivity. He finds that infrastructure investment can improve competition among firms via savings in transportation costs and travel time and then raise firm-level productivity indirectly through the competition effect. Research has also discovered that information technology infrastructure investment can increase the productivity of firms via the channel of the competition effect (Garicano and Heaton, 2010). Some studies argue that IT enables organizational change, which leads to productivity gains (Mithas et al., 2012).

Hypothesis 3. *The operation of the TGP will increase firm entry and create more local competition within industries, thus pushing our treated firms (i.e., manufacturing firms in Hubei) to raise their productivity for survival.*

3. Methodology and Data

3.1. Methodology

Our primary research question aims to understand the effect of the giant infrastructure (hydropower) project, the TGP (which we can view as "green infrastructure" in the sense that it is less polluting than thermal power stations), on firm-level productivity. Toward this end, we regress firm productivity (which is measured with the estimated TFP that we discuss below and denote as tfp_{it} for firm i in year t) on a time dummy, which indicates whether the time is post-TGP ($post$, we choose 2003 as the first post-TGP year because it is the year when the TGP started to supply electricity to several provinces, including Hubei); a dummy variable that indicates whether the firm is in Hubei, where the TGP makes a difference and has a direct impact through the supply of electricity among many others ($treat$); and the interaction term of the time and location dummies. Our TFP measure is already in log form, so we can interpret the coefficient estimates as percentage changes or elasticities, depending on whether the regressor is discrete or continuous.

In our baseline regressions, we also include a reasonable set of firm characteristics that might correlate with firm productivity, such as firm age, size, and financial conditions. Cheng et al. (2019), Cheng, Tan, et al. (2020) and Shi and Grafton (2010) demonstrate that those controls are important factors associating with important dimensions of manufacturing firm performance such as exporting and productivity. We further include high-dimensional fixed effects to control for macroeconomic, sectoral, and ownership-specific shocks. Those fixed effects are the four-digit industry in multiplication with year fixed effect (θ_{st}, where s denotes the sector) and the ownership in multiplication with year fixed effect (ς_{ot}, where o denotes ownership). In total, our baseline sample contains around 390 four-digit industries. Turning to specifics, we specify baseline regression equation as follows:

$$tfp_{it} = \beta_0 + \beta_1 \times post + \beta_2 \times treat + \beta_3 \times post \times treat + \beta_j \times control_{it} + \theta_{st} + \varsigma_{ot} + e_{it}. \tag{1}$$

Note that e_{it} is the error term, and there are four additional control variables on the right-hand side: age, size (measured through total employment of the firm), external finance, and internal finance.

The parameter of interest is β_3, which is associated with the interaction term and captures the growth in firm productivity for our treated firms, relative to that growth for our control firms, following the operation of the TGP in 2003 (in particular, the milestone is the start of the TGP's electricity supply on 10 July 2003). We expect a positive coefficient for β_3, because it indicates an increase in firm productivity after the commencement of operation of the TGP. In addition to robust standard errors in all the regressions, we further check our standard errors by clustering them at the four-digit industry level.

3.2. Data

We employ comprehensive microdata on Chinese manufacturing firms from the Annual Survey of Industrial Production (ASIP) to examine the effect of the TGP on firm productivity. The National Bureau of Statistics of China (NBS) conducts the ASIP annually and it covers all state-owned manufacturers and private firms with sales no less than 5 million Chinese yuan (roughly $650,000). The data set contains detailed information on firm characteristics (such as location, ownership, sector, etc.), input and output (such as labor, intermediate inputs, capital stock, total production, production of new products, etc.), balance sheet (such as total assets, cash, total liabilities, etc.), taxes, and so on.

Our sample spans from 1998 to 2006. To estimate the effect of the TGP on firm productivity accurately, we focus on two rather comparable provinces: Hubei and Hebei. The two provinces are similar in total GDP (311.4 billion yuan versus 425.6 billion yuan), total population (59.1 million versus 65.7 million people), and thus GDP per capita (5,269 yuan versus 6,478 yuan) in 1998 (the starting year of our sample). Therefore, it would be reasonable to say that they are at the same stage of economic development initially. The TGP is in Hubei and has no significant relationship with Hebei. It does not provide electricity to Hebei or change the river and other water systems in Hebei. The differential connections between the TGP and the two different provinces thus provide us an ideal setting to evaluate the effect of this giant infrastructure project on firm performance. Accordingly, we identify firms from the ASIP in Hubei as the treated group and those in Hebei as the control group (see Figure 2 for the locations of these two provinces). In the robustness check, we replace Hebei with Shanxi to test the potential difference that Hubei is a landlocked province while Hebei, despite many similarities, is a coastal province. Also note that neither Hebei nor Shanxi is geographically adjacent to Hubei, which helps to reduce the possibility that the TGP can have spillover effects on the control province through channels other than electricity supply.

We employ a DID design that compares the growth in firm productivity among treated firms with that among control firms during our sample period. In our baseline sample, there are 46,272 firms in the treated group and 56,920 firms in the control group. The number of observations is quite comparable across different groups, and thus reduces the concern of unbalanced sample splitting in the DID analysis.

To alleviate the concern that the selection of our treated group was not random, we employ a propensity-score-matching (PSM) approach to match our Hubei firms to more comparable Hebei firms. The PSM approach that we follow is in the spirit of nearest-neighbor matching (Dehejia and Wahba, 2002). Using data prior to the TGP's construction, we first implement a standard logit regression to compute the probability of being a treated firm (i.e., being a firm in Hubei). The set of explanatory variables in the logit regression included: (1) firm age, measured as the number of operating years since the firm's establishment; (2) firm size, measured as a firm's total number of workers; (3) financial conditions, including external and internal finance, in which external finance is the ratio of total assets to total liabilities while internal finance is the ratio of total cash to total assets; (4) firm industry code, which represents the industry to which the firm belongs, such as textiles, chemicals, machinery, and so on; and (5) firm ownership, measuring using the firm's ownership, which can be state-owned, collectively-owned (domestic), privately-owned (domestic), or foreign-owned. Our underlying assumption is that those observable factors are the main determinants of firm location choice between the two provinces, Hubei and Hebei.

Following the first-step logit regression, we then match each treated firm to a control firm using the nearest-neighbor matching method with replacement, and set the caliper to 0.25 multiplying the standard error of the propensity score (Dehejia and Wahba, 2002). This matching procedure generates a PSM sample from the baseline sample with 38,583 firms in the treated group and 23,682 firms in the control group. The effectiveness of the PSM procedure is presented in Table A.1 of the Appendix. It shows clearly that the matching is reasonably effective in terms of the four continuous variables we include in the first-step logit regression.[2]

Figures 3-4 and 5-6 further present the geographical distribution of our baseline and PSM samples, respectively. Two quick observations from the figures are the following: first, although the number of observations is associated with local development at the prefecture level, the sample is fairly well-distributed across locations; second, the geographical distribution of firms is largely maintained when we use the PSM sample to replace the baseline sample.

[Insert Figure 3 here]

[2] Not surprisingly, we show later in Table 2 that the firms in the PSM sample are more comparable between the treated and control groups, in terms of many explanatory variables (such as firm input-output information and financial conditions) that we use in our empirical studies.

[Insert Figure 4 here]

[Insert Figure 5 here]

[Insert Figure 6 here]

3.3. Variable Construction

This subsection discusses the construction of the main variables that we employ in our empirical analysis. We also present here the summary statistics of those key variables.

Our primary explained variable in this empirical study is firm productivity. To measure firm productivity, we employ the state-of-the-art method, which estimates firm total factor productivity (TFP) using a widely recognized semi-parametric approach, as Ackerberg et al. (2015) introduced. For simplicity, we refer to it as the ACF method. The ACF method is the most updated and advanced version of firm-level production function estimation that utilizes information on firms' first-order conditions with respect to input (such as labor and intermediate input) demands to infer the firm-level unobserved productivity or TFP. By allowing for more general assumptions on input demand functions and improving the efficiency of the estimators, the ACF method has greatly refined many representative studies in this strand of literature, including Levinsohn and Petrin (2003), Olley and Pakes (1996), and Wooldridge (2009).[3] Intuitively, the TFP measures the efficiency of firms in utilizing labor, capital, and intermediate inputs to produce output. A higher TFP means that a firm is more efficient in utilizing the same amount of labor, capital and intermediate inputs, than another firm and thus can produce more products.

Mathematically, the TFP is the combination of two unobserved residual terms (for econometricians) in the typical firm-level Cobb-Douglas production function specification,

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + v_{it} + \varepsilon_{it}. \tag{2}$$

[3] See Cheng, Yu, et al. (2020) for a more detailed survey of the TFP estimation methods. We also compute TFP using the other methods listed in Cheng, Yu, et al. (2020) and get consistent results.

Note that $(y_{it}, k_{it}, l_{it}, m_{it})$ are the log gross output (not value added), log capital stock, log labor, and log intermediate input, and $(\nu_{it}, \varepsilon_{it})$ are the two unobserved residual terms for econometricians, among which the former is partially observable for firms and the latter is unobservable for both firms and econometricians. The goal of the firm-level production function estimation is thus to estimate $(\beta_0, \beta_k, \beta_l, \beta_m)$ consistently and precisely. With those valid parameter estimates, we can easily compute and estimate the firm productivity or TFP as the difference between y_{it} and $\hat{\beta}_0 + \hat{\beta}_k k_{it} + \hat{\beta}_l l_{it} + \hat{\beta}_m m_{it}$.

Another group of relevant variables in this paper contains those needed to infer firm-level TFP, including firm gross revenue, employment, capital stock, and intermediate inputs. Except for employment, measured as the number of workers, we measure them in Chinese yuan. Note again that we include intermediate inputs in the TFP estimation, so we need the gross revenue rather than the value added.

In addition to the TFP and the variables used to compute the TFP, we construct a group of control variables for the empirical analysis. We calculate age as the length of a firm's operating years since its establishment and two financial conditions following Berman and Héricourt (2010) and Guariglia et al. (2011), external finance as the ratio of firm liabilities to assets, and internal finance as the firm cash assets to total assets. The two financial measures are able to capture a firm's ability to borrow externally and finance its expenses internally. Higher external finance means a lower capability to borrow from external sources, and higher internal finance means that a firm has a higher capability to finance internally with its own liquid assets. Cheng et al. (2019) and Cheng, Tan, et al. (2020) provide extensive empirical evidence that these financial conditions are important determinants for firm performance, and can affect firm productivity directly through channels such as long-term investment (such as technology upgrading) and indirectly through learning by exporting.

Tables 1 and 2 tabulate the summary statistics for our key variables in the baseline full sample and the PSM sample, respectively. To mitigate the concern of outliers, we winsorized the top and bottom 0.5% of all the variables from their distributions. Table 1 shows that the mean TFP during our sample period is 0.808 for the treated firms and 0.714 for the control firms. It also exhibits that the average firm is larger in Hebei than in Hubei in terms of gross revenue (67,072 versus 54,211 yuan), capital stock (26,088 versus 24,143 yuan), employment (311 versus 305 employees), and intermediate inputs (50,646 versus 38,544 yuan). Thus, it implies that firms in the treated group are relatively smaller yet more productive. Moreover, the treatment firms are a little older (12.9 versus 11.6 years old) than those in the control group. The mean internal finance is almost the same in the two groups (0.494 versus 0.493), suggesting no significant difference in the ability to finance internally. However, we can see a notable difference in their capability to borrow externally, as the mean external finance is much higher in the treated group (0.631 versus 0.588), which implies a more difficult condition for firms in Hubei to borrow externally.

Table 2 shows similar results to Table 1. The main mean comparison results from Table 1 remain unchanged. In Table A.2 of the Appendix, we also provide mean difference of the primary variables used in our regression analysis between treatment and control firms, for both full and PSM samples. The significance of the mean difference in Table A.2 further corroborates the results we find in Tables 1 and 2. However, it is worth mentioning that all the other variables are more comparable between the treated and the control group in terms of means, except that the mean productivity (TFP) diverges slightly more. We do not include the TFP in the propensity score matching process, as it is an inferred variable. We can conclude that our PSM method produces very reasonably comparable treatment and control groups for DID analysis.

[Insert Table 1 here]

[Insert Table 2 here]

4. Empirical Results

Our empirical strategy includes two parts. The first is about the data used. In the baseline estimation, we use the full sample. While in the robustness checks, we use the PSM sample instead. The second part follows the baseline full sample estimation, where we further test the three channels that are proposed in section 2.

4.1. The Effect of the TGP on Firm Productivity: Full Sample Baseline Estimation

Table 3 presents the baseline results of our regressions for the baseline full sample. Columns 1-2 show the regression results without controlling for fixed effects and clustering standard errors. Column 1 is the simplest case in which we do not control for firm-level characteristics. It shows a significant coefficient for $post$ ($\hat{\beta}_1 = 0.121$), meaning that the control firms (firms in Hebei with no relevant direct connections with the TGP) experience about a 12.86% ($e^{0.121} - 1 \approx 0.1286$) increase in productivity or TFP after 2003. Such a time trend is normal in productivity growth. Similarly, the coefficient for $treat$ is significantly positive, indicating that our treated firms (firms in Hubei that have received an electricity supply from the TGP since 2003) have higher productivity than our control firms before 2003, when the TGP started supplying electricity. Specifically, the treated firms are on average 9% ($e^{0.086} - 1 \approx 0.09$) more productive than the control firms before 2003. This finding is also consistent with our descriptive summary tables, which show a higher mean TFP for the treated group.

More importantly, we find that the coefficient for the interaction term, $post * treat$, is significantly positive. It suggests that firms in Hubei, relative to firms in Hebei, experience an increase in productivity after the TGP commenced operation in 2003. This increase is economically significant as well, with the numerical magnitude being as large as 3.25% ($e^{0.032} - 1 \approx 0.0325$). Note that our results in Column 1 are robust to including firm-level characteristics (Column 2), controlling for high-dimensional fixed effects (Column 3), and clustering standard errors at the four-digit industry level (Column 4). Although the magnitudes of some estimates show a drop, they are still statistically and economically significant. We also achieve gains by including more regressors and fixed effects, and Columns 3-4 show a big increase in the adjusted R-squared when compared with Columns 1-2. Furthermore, we find that younger firms are more productive than older ones, firms with fewer employees are more productive than bigger firms, and firms with better financial conditions (lower external finance and higher internal finance) are more productive.[4]

[Insert Table 3 here]

4.2. Channels for Baseline DID Result

Our baseline finding in the DID analysis is that, relative to firms in Hebei, firms in Hubei experience an increase in productivity (2%-3%) due to the operation of the TGP in 2003 (the milestone is the beginning of the electricity supply in that year). To understand this finding, we explore several possible channels that have been discussed in Section 2, including the capital deepening effect, the scale effect, and the competition effect.

4.2.1. The First Channel: The Capital Deepening Effect

Here we define capital deepening as an increase in the capital–labor ratio, indicating that the amount of capital per worker rises. We test this channel through a similar DID analysis. Turning to specifics, we replace TFP in Equation (1) with log capital–labor ratio. As discussed in Hypothesis 1, we expect the capital deepening regression to show that, relative to firms in Hebei, firms in Hubei experience a rise in the capital–labor ratio since the beginning of operation of the TGP in 2003.

Table 4 presents the regression results for the capital deepening channel. Similar to the strategy in the baseline analysis, Column 1 is the simplest case in which we do not control for firm characteristics and high-dimensional fixed effects. Three quick observations from Column 1 are as follows. First, there is a significant coefficient for $post$ ($\hat{\beta}_1 = 0.269$), indicating that the control firms experience around a 30.9% ($e^{0.269} - 1 \approx 0.309$) increase in the capital–labor ratio following the implementation of the TGP in 2003. This is

[4] Note that the sign of coefficient of size on firm productivity is not uniform in all regressions estimated in this paper. We do not expect it to be decisive simply because that we do not guarantee any causation for this variable. Most studies in the literature might suggest a positive sign for size, however, they are also studies finding a negative sign for it, such as Dhawan (2001).

in line with the fact that Huang et al. (2017) documented: the Chinese manufacturing production became more capital intensive over time.

Second, the coefficient for $treat$ is significantly negative, indicating that our treated firms experience a lower capital–labor ratio increase than control firms before the operation of the TGP in 2003. Particularly, the firms in Hubei are on average 19.3% ($e^{-0.214}-1\approx-0.193$) less capital intensive than the firms in Hebei before 2003. The result implies that prior to the operating of the TGP, firms in Hubei have more space to improve their capital intensity once they have obtained the opportunities and resources. Our DID result for capital deepening, represented by the coefficient for the interacted term, $post*treat$, further confirms this implication that the coefficient is significantly positive ($\hat{\beta}_3 = 0.104$).

Third, the coefficient for the interacted term indicates that, relative to firms in Hebei, firms in Hubei experience a rise in the capital–labor ratio as large as 11% ($e^{0.104}-1\approx 0.11$) since the operation of the TGP in 2003. In a nutshell, our DID results for capital deepening strongly support the conjecture that this giant infrastructure, the TGP, significantly favors the capital deepening process in Hubei province, which then contributes to faster productivity growth in Hubei. Note that all the qualitative and quantitative results remain basically the same when we control for firm characteristics, more fixed effects, or cluster standard errors at the four-digit industry level.

[Insert Table 4 here]

4.2.2. The Second Channel: The Scale Effect

Formally, we test the following hypothesis for the scale effect channel: relative to firms in Hebei, firms in Hubei experience a jump in relative firm size since the TGP commenced operation in 2003. We define the relative size of firms as the gross revenue ratio. Specifically, it is the ratio of firms' gross revenue to industry-prefecture-level median gross revenue. A higher ratio means that the firm has a larger relative scale.

Again, we implement a similar DID analysis with respect to firms' gross revenue ratio to examine the scale effect channel.

Table 5 presents the DID regression results for the gross revenue share. Note that the explained variable is log gross revenue ratio. We follow the same method in interpreting the baseline DID results and the results for the first channel to understand the estimated coefficients in Column 1, which considers the simplest case. As for the coefficient for $post$, we obtain a significant estimate of $\hat{\beta}_1 = 0.02$, indicating that the control firms experience around a 2% ($e^{0.02} - 1 \approx 0.02$) increase in relative firm size (gross revenue ratio) following the start of the TGP's operations in 2003. This may reflect that the prevalent firm growth across China since 2003, which is consistent with the high and vibrant economic growth rate in the PRC during the first decade of the 21st century. The coefficient for $treat$, $\hat{\beta}_2 = -0.02$, is significantly negative, which means that our treated firms experience 2% ($e^{-0.02} - 1 \approx -0.02$) lower gross revenue ratio growth than our control firms before the operation of the TGP in 2003.

The operating of the TGP accelerates the relatively higher growth of the gross revenue ratio in Hubei, relative to that in Hebei. The coefficient for the interaction term, $post * treat$, $\hat{\beta}_3 = 0.052$, is significantly positive, suggesting that, compared with firms in Hebei, firms in Hubei have experienced a 5.3 % ($e^{0.052} - 1 \approx 0.053$) rise in relative firm size (gross revenue ratio) since the TGP commenced operation in 2003.

This result is very much in line with Hypothesis 2, which stated that the operating of the TGP encourages firms in Hubei consciously to improve their relative firm size to grasp the opportunities that the giant infrastructure project induces in terms of more resources (inputs) and better technology. As a consequence, the scale effect channel works in the expected direct to support our baseline DID results for firm productivity. Again, note that all the qualitative and quantitative results barely change when we control for firm characteristics, and high-dimensional fixed effects or cluster standard errors at the four-digit industry level. In Table A.3 of the Appendix, we provide the estimation results for an alternative measure of scale effect, where we define it as the share of firm's gross revenue in industry-prefecture-level total gross revenue. It shows that the results are in line with what we get using the current gross revenue ratio definition.

[Insert Table 5 here]

4.2.3. The Third Channel: The Competition Effect

To test this hypothesis, we formally conduct a DID analysis for firm competition pressure similar to the baseline DID analysis for firm productivity.

To align with the widely used Herfindahl-Hirschman Index (HHI) in industrial organization, we define the mirror-image side of firm competition pressure as the firm market concentration index. Turning to the specifics, we construct the firm market concentration index as the ratio of the top 5% firms (sorted by sales) at the industry-prefecture-level to the firm-level total sales. A lower ratio means that the market concentration that the firm faces at the industry-prefecture-level is lower; thus, the market is more competitive (with high firm competition pressure). Table 6 presents our DID regression results for the firm market concentration index. Note that the market concentration index is in log values.

Column 1, again, contains the simplest case of DID regression in which we do not control for firm characteristics or high-dimensional fixed effects or cluster standard errors. The coefficient for $post$ has a significantly positive estimate of $\hat{\beta}_1 = 0.34$, meaning that the control firms (firms in Hebei) experience around a 40.5% ($e^{0.34} - 1 \approx 0.405$) increase in the firm market concentration index (or the mirror-image of firm competition pressure) following the start of the TGP's operation in 2003. On the contrary, the coefficient for $treat$ is significantly negative, $\hat{\beta}_2 = -0.16$, indicating that our treated firms (firms in Hubei where the TGP is located) experienced a 14.8% ($e^{-0.16} - 1 \approx 0.148$) lower market concentration index increase than control firms (firms in Hebei) before the TGP started operating in 2003. This suggests a more competitive market in the manufacturing sector of Hubei even before the TGP entered service.

The local competition in Hubei becomes even fiercer when the TGP started to operate in 2003. The coefficient for the interaction term, $post*treat$, $\hat{\beta}_3 = -0.169$, is significantly negative, indicating that, relative to firms in Hebei (control firms), firms in Hubei (treated firms) experience a 15.5% ($e^{-0.169} - 1 \approx -0.155$) decline in the firm market concentration index (the opposite side of firm competition pressure) since the operation of the TGP began in 2003. Therefore, our DID regression results for the firm market concentration index substantiate Hypothesis 3, which stated that the TGP operation increases local competition and thus helps to push firms to increase their own productivity to survive in the increased competition. Note that all the qualitative and quantitative results stay unchanged when we controlled for firm characteristics and more fixed effects or clustered standard errors.

In sum, all the three channels that we hypothesize to be important for understanding the baseline productivity DID results have supportive evidence in the microdata and thus help us to conclude that they are relevant channels, through which the operation of the TGP promotes firm productivity since 2003.

[Insert Table 6 here]

4.2.4. The Effect of Three Channels on TFP

This subsection presents the estimation results for the effect of the proposed three channels (the capital deepening effect, the scale effect, and the competition effect) on firm productivity. We assess the impacts of those channels in three steps. First, we show how the three channels are separately correlated with firm productivity. Second, we include the three channels in the same regression to evaluate their impacts on firm productivity under a general multivariate setting. Third, we introduce the three channels into our baseline DID regression to formally examine their contributions to firm productivity in the context of the TGP.

Table 7 presents the estimation results for the three steps above. Columns 1-3 show that capital deepening is positively correlated with firm TFP; firm relative size (measured by gross revenue ratio) is positively correlated with firm TFP; and firm market concentration index (the mirror image of firm competition pressure) is negatively correlated with TFP. These correlations are all significant at the 1% level. When we include these three channels into the same regression in Column 4, their impacts on firm TFP stay significant and the signs stay the same, although the magnitudes of capital deepening effect and scale effect are inflated somehow. When more firm-level controls are introduced, the effects of those three channels shrink in magnitudes, and the impact of competition effect becomes less significant both economically and statistically.

Column 7 compiles the results for the case when the three channels are directly taken into the baseline DID regression. This specification formally assesses how the three channels intermediate the effects of the TGP on firm productivity. It shows that the coefficient on the interaction term, $post*treat$, is still significantly positive. However, the magnitude of the coefficient on the interaction declines significantly when compared with Column 4 in Table 3 (0.008 versus 0.024). This suggests that the introduction of the three channels is effective because a significant part of the effect of the TGP on firm productivity estimated in Table 3 is working through the three proposed channels. Moreover, the magnitude and statistical significance of the coefficients for the three channels stay consistent with their separate correlation estimates in Columns 1-3. Combined with the DID results for the three channels in Tables 4-6, it indicates that the TGP increases firm capital deepening (i.e., capital-labor ratio increases), enlarges firm scale (i.e., gross revenue ratio increases), and intensifies firm competition (i.e., firm market concentration index declines), which all in turn boost firm productivity.

[Insert Table 7 here]

4.3. Robustness Checks

In this subsection, we conduct a battery of robustness checks for our baseline DID analysis. We first redo all the DID regressions, including those for productivity, the capital-labor ratio, the gross revenue ratio, and the market concentration index, using the PSM sample rather than the baseline full sample.[5] The PSM sample results are presented in Tables 8-11. We can observe from those PSM results that the main qualitative and quantitative results that we obtained from the baseline full sample still hold, when we account for the comparability of treated and control firms more seriously. We also want to mention that, even though the sample size is much smaller in the PSM sample than in the full sample, our regression results do not alter much, suggesting that the regression results in this empirical study do not suffer from a noticeable sample selection issue. Again, in Table A.4 of the Appendix, we present the estimation results for an alternative measure of scale effect, where we get consistent results.

[Insert Table 8 here]

[Insert Table 9 here]

[Insert Table 10 here]

[Insert Table 11 here]

Next, we examine the sample reliability issue further. As Brandt et al. (2014) documented, the consistent recording of the ASIP data officially starts in 1998. However, they find that the total number of firms in the ASIP drops in 1999 compared with 1998, which suggests that there might be a data reliability issue for these two years. We account for this issue by focusing on the sample for 2000-2006 only. Column 1 of Table 12 presents our baseline DID analysis for firm productivity when we restrict the sample to the years 2000–2006. The coefficient for the interaction term, $post*treat$, $\hat{\beta}_3 = 0.036$, is still significantly positive, which is very consistent with the findings in the baseline case. Therefore, our baseline DID regression for firm productivity does not suffer from any known data reliability concern.

[Insert Table 12 here]

[5] We also examined the potential impact of heterogeneity in industrial policy across regions by adding prefecture-sector fixed effects. The results are the same as our baseline results. To save space, we did not report the results, which are available upon request.

Furthermore, we consider the differential impact of trade liberalization on the treated and control groups as the two provinces (Hebei and Hubei) may have very different exposure to trade and foreign investment. Since Hebei has seaports, for instance, it may have more foreign direct investment (FDI), and the advanced technology that FDI brings in can introduce some differences in productivity growth for the two provinces, especially after the PRC entered the WTO in December 2001. One way that we can address this issue using the microdata is to exclude all foreign firms in the manufacturing sector. Column 2 of Table 12 shows that the interaction term, $post*treat$, with $\hat{\beta}_3 = 0.023$, is still significantly positive, indicating that the trade and foreign investment issue is not a major problem for this empirical study although it somehow dampens the magnitude of our DID results.

Fourthly, we perform paralleling trend tests for our baseline DID results using the method that Autor (2003) proposed. The method basically estimates the interaction terms of treatment and all lead-and-lag years. If the interaction terms for the lag years are not significant but significant for the lead years, then there will be no significant evidence indicating that our DID analysis violates the paralleling trend assumption. Column 3 of Table 12 presents the paralleling trend test results, which clearly shows that the interacted terms of the treatment and lag years of 2003 (including 1999, 2000, 2001, and 2002, while 1998 is dropped due to collinearity) are all statistically insignificant. However, the interacted terms of treatment with the lead years of 2003 (including 2004, 2005, and 2006) are all significant. In addition, the effect of the TGP on firm productivity mainly manifests in the years 2005 and 2006, since the estimated coefficients for the interaction terms are larger and more statistically significant. This makes sense given that productivity-enhancing activities generally involve long-term adjustments, such as the time-to-build for capital deepening.

Finally, to deal with the potential impact due to the fact that Hebei is a coastal province whereas Hubei is landlocked, we replace Hebei with Shanxi (which is also a landlocked province) in our robustness checks. This robustness check can mitigate the concern that coastal provinces have experienced different shocks to manufacturing productivity than the landlocked ones ever since China's WTO accession in December 2001. We choose Shanxi because it has the closet GDP per capita (5,107 yuan in 1998) to Hubei and locates outside of the electricity service area of the TGP, although the aggregate GDP volume and population size of Shanxi are much smaller than Hubei. To save space of the main text, the empirical results with Shanxi as the control province are presented in Table A.5 and A.6 of the Appendix.

5. Concluding Remarks

Studying the productivity impact of the green energy infrastructure can not only inform national policy debates on green energy infrastructure investment, but also help to mitigate global carbon emissions. Although hydropower is the primary component of low-carbon generation sources, and there are many studies on the productivity impact of infrastructure investment, there is still a lack of research focusing on the response of firm productivity to hydropower projects.

This paper employs manufacturing data from the PRC's Annual Survey of Industrial Production (ASIP) between 1998 and 2006, and proposes firms from another province (Hebei province) that is similar to the province (Hubei province) where the project is located but much less likely to experience effects from the TGP as a control group in an innovative DID setting. This paper fills the gap by estimating whether and how the TGP may affect manufacturing firm productivity and proposes three channels through which the TGP can affect firm productivity, which is another contribution. The main findings of this article are fourfold.

Firstly, our empirical results reveal that there is a significant positive impact of the TGP on manufacturing firms' productivity, and its effect is between 2%-3%. This positive productivity impact reveals that hydropower projects have an economic benefit in addition to other well-known benefits, for instance flood control and the improvement in shipping capacity. This further justifies the development of hydro projects when everything else is constant.

Secondly, we use capital-labor ratio to measure the capital deepening effect, and find that firms in Hubei province experience an increase in capital-labor ratio after the operation of the TGP in 2003. The positive effect of TGP on firms' capital deepening is about 6% after controlling the fixed effects and clustering standard errors. This result indicates that the increased availability of electricity helps to improve manufacturing capital intensity in Hubei province.

Thirdly, based on the stylized fact that firms in Hubei experienced a jump in relative firm size since the TGP commenced operation in 2003 from the Chinese manufacturing survey data, we measure the relative size of firms with the gross revenue ratio and employ it to test the scale effect channel of TGP on firm productivity. The results show that there exists the scale effect channel and firms in Hubei have experienced a 5% rise in relative firm size (gross revenue ratio) since the TGP commenced operation in 2003.

Finally, this paper tests the third channel (the competition effect) of TGP on firm productivity. The empirical result shows that the firm market concentration index of Hubei decreased by 16% since the operation of the TGP in 2003. That is to say, the TGP operation increases local competition and thus helps to push firms in Hubei to increase their own productivity to survive in the increased competition.

Based on the new findings above, we can conclude that the three channels including the capital deepening effect, the scale effect, and the competition effect are tested robustly in this article. The new findings suggest that policy makers need to consider the broad benefits of green energy, which are beyond the conventional cost-benefit trade-off. Some green energy projects and technology that marginally fail to pass a cost-benefit analysis may be implementable, and thus the global plan for mitigating carbon emissions can be more ambitious.

The new findings in this article also provide important policy implications. The first one is that policy makers need to be aware of extra externalities when making decisions on giant infrastructure projects. A good example is the TGP, which brings many additional resources to Hubei, such as a large amount of non-repayable funds, professionals, and advanced equipment. These additional resources not only greatly enhanced the importance of Hubei province in China, but also provided positive externalities that cannot be ignored by improving the performance of enterprises in Hubei. The second one is that governments need to notice the spillover effects of green energy investment on local firm performance. For example, the TGP has a positive effect on firm productivity through three channels including the capital deepening effect, the scale effect, and the competition effect. Lastly, the Chinese government should pay attention to both the short-term and long-term benefits of green energy investment. In the short-term, a green energy project can bring more job opportunities and better infrastructure. In the long-term, green energy investment can provide a more reliable power supply and higher productivity for the local manufacturing firms. Additionally, the implications, while drawn from a case study in China, are applicable to other countries. Particularly, while large hydrogen projects have controversies due to its adverse environmental impact, such positive externalities revealed by our study should be counted in justifying future projects.

One potential caveat of this study is the controversial surroundings of large hydro projects. This, however, is one negative side that is beyond the scope of the present study, which only aims to reveal an additional benefit of large hydro projects. It will also be possible to extend the study to other green energy projects, for instance wind and solar, which can help policy makers in gauging their decisions regarding the development.

References

Abeberese, A. B. (2017). Electricity cost and firm performance: Evidence from India. *Review of Economics and Statistics*, *99*(5), 839–852.

Abeberese, A. B. (2020). The effect of electricity shortages on firm investment: Evidence from Ghana. *Journal of African Economies*, *29*(1), 46–62.

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, *83*(6), 2411–2451.

Allcott, H., Collard-Wexler, A., & O'Connell, S. D. (2016). How do electricity shortages affect productivity? Evidence from India. *American Economic Review*, *106*(3), 587–624.

Autor, D. H. (2003). The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, *21*, 1–42.

Banerjee, A., Duflo, E., & Qian, N. (2020). On the road: Access to transportation infrastructure and economic growth in China. *Journal of Development Economics*, *145*. https://doi.org/10.1016/j.jdeveco.2020.102442

Barzin, S., D'Costa, S., & Graham, D. J. (2018). A pseudo – panel approach to estimating dynamic effects of road infrastructure on firm performance in a developing country context. *Regional Science and Urban Economics*, *70*(5), 20–34.

Berman, N., & Héricourt, J. (2010). Financial factors and the margins of trade: Evidence from cross-country firm-level data. *Journal of Development Economics*, *93*(2), 206–217.

Brandt, L., Van Biesebroeck, J., & Zhang, Y. (2014). Challenges of working with the Chinese NBS firm-level data. *China Economic Review*, *30*(9), 339–352.

British Petroleum (BP). (2019). BP statistical review of world energy. In *British Petroleum* (Issue 66). British Petroleum. https://doi.org/http://www.bp.com/content/dam/bp/en/corporate/pdf/energy-economics/statistical-review-2017/bp-statistical-review-of-world-energy-2017-full-report.pdf

Cheng, D., Hu, Z., & Tan, Y. (2019). Heterogeneous impacts of finance on firm exports: Evidence from export deregulation in a large developing country. *SSRN Working Paper*. https://doi.org/https://ssrn.com/abstract=3014528

Cheng, D., Tan, Y., & Yu, J. (2020). Credit rationing and firm exports: Microeconomic evidence from small and medium-sized enterprises in China. *World Economy*, *00*, 1–26.

Cheng, D., Yu, J., Zhang, D., & Zheng, W. (2020). Is heterogeneous capital depreciation important for estimating firm-level productivity ? Evidence from Chinese manufacturing firms. *Research in International Business and Finance*, *52*, 101146.

Cheong, T. S., Li, V. J., & Shi, X. (2019). Regional disparity and convergence of electricity consumption in China: A distribution dynamics approach. *China Economic Review*, *58*, 101154.

Cleveland, C. J., & Morris, C. G. (2013). *Handbook of Energy: Chronologies, Top Ten Lists, and Word Clouds* (1 edition). Elsevier Science.

Cohen, J. P., & Paul, C. J. M. (2004). Public infrastructure investment, interstate spatial spillovers, and manufacturing costs. *Review of Economics and Statistics*, *86*(2), 551–560.

Cole, M. A., Elliott, R. J. R., Occhiali, G., & Strobl, E. (2018). Power outages and firm performance in Sub-Saharan Africa. *Journal of Development Economics*, *134*(9), 150–159.

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, *84*(1), 151–161.

DeStefano, T., Kneller, R., & Timmis, J. (2018). Broadband infrastructure, ICT use and firm performance: Evidence for UK firms. *Journal of Economic Behavior and Organization*, *155*, 110–139.

Dhawan, R. (2001). Firm size and productivity differential: Theory and evidence from a panel of US firms. *Journal of Economic Behavior and Organization*, *44*(3), 269–293.

Fernald, J. G. (1999). Roads to prosperity? Assessing the link between public capital and productivity. *American Economic Review*, *89*(3), 619–638.

Fisher-Vanden, K., Mansur, E. T., & Wang, Q. J. (2015). Electricity shortages and firm productivity: Evidence from China's industrial firms. *Journal of Development Economics*, *114*(5), 172–188.

Gao, G., Chen, M., Wang, J., Yang, K., Xian, Y., Shi, X., & Wang, K. (2019). Sufficient or insufficient : Assessment of the intended nationally determined contributions (INDCs) of the world's major greenhouse gas emitters. *Frontiers in Engineering Management*, *6*(1), 19–37.

Garicano, L., & Heaton, P. (2010). Information technology, organization, and productivity in the public sector: Evidence from police departments. *Journal of Labor Economics*, *28*(1), 167–201.

Ghani, E., Goswami, A. G., & Kerr, W. R. (2016). Highway to success: The impact of the golden quadrilateral project for the location and performance of Indian manufacturing. *Economic Journal*, *126*(591), 317–357.

Gibbons, S., Lyytikäinen, T., Overman, H. G., & Sanchis-Guarner, R. (2019). New road infrastructure: The effects on firms. *Journal of Urban Economics*, *110*, 35–50.

Government of the People's Republic of China. (2006). *Three Gorges Dam (in Chinese)*. http://www.gov.cn/jrzg/2006-10/18/content_416256.htm

Guariglia, A., Liu, X., & Song, L. (2011). Internal finance and growth: Microeconometric evidence on Chinese firms. *Journal of Development Economics*, *96*(1), 79–94.

Heintz, J., Pollin, R., & Garrett-Peltier, H. (2009). How infrastructure investments support the U.S. economy: Employment, productivity and growth. In *Amherst: University of Massachusetts*. http://www.peri.umass.edu/fileadmin/pdf/other_publication_types/green_economics/PERI_Infrastructure_Investments

Holl, A. (2012). Market potential and firm-level productivity in Spain. *Journal of Economic Geography*, *12*(6), 1191–1215.

Holl, A. (2016). Highways and productivity in manufacturing firms. *Journal of Urban Economics*, *93*, 131–151.

Huang, H., Ju, J., & Yue, V. Z. (2017). Structural adjustments and international trade: Theory and evidence from China. *Mimeo*.

Hulten, C. R., Bennathan, E., & Srinivasan, S. (2006). Infrastructure, externalities, and economic development: A study of the Indian manufacturing industry. *World Bank Economic Review*, *20*(2), 291–308.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, *70*(2), 317–341.

Li, Z., Wu, M., & Chen, B. R. (2017). Is road infrastructure investment in China excessive? Evidence from productivity of firms. *Regional Science and Urban Economics*, *65*, 116–126.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *71*(6), 1695–1725.

Melitz, M. J., & Polanec, S. (2015). Dynamic Olley-Pakes productivity decomposition with entry and exit. *RAND Journal of Economics*, *46*(2), 362–375.

Mithas, Tafti, Bardhan, & Goh. (2012). Information technology and firm profitability: Mechanisms and empirical evidence. *MIS Quarterly*, *36*(1), 205–224.

Mitra, A., Sharma, C., & Véganzonès-Varoudakis, M. A. (2016). Infrastructure, information & communication technology and firms' productive performance of the Indian manufacturing. *Journal of Policy Modeling*, *38*, 353–371.

Mohamad, A., Zainuddin, Y., Alam, N., & Kendall, G. (2017). Does decentralized decision making increase company performance through its Information Technology infrastructure investment? *International Journal of Accounting Information Systems*, *27*(11), 1–15.

Morrison, C. J., & Schwartz, A. E. (1996). State infrastructure and productive performance. *American Economic Review*, *86*(5), 1095–1111.

Olley, G. S., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, *64*(6), 1263–1297.

Paul, S., Sahni, B. S., & Biswal, B. P. (2004). Public infrastructure and the productive performance of Canadian manufacturing industries. *Southern Economic Journal*, *70*(4), 998–1011.

Rogelj, J., Elzen, M. den, Höhne, N., Fransen, T., Fekete, H., Winkler, H., Schaeffer, R., Sha, F., Riahi, K., & Meinshausen, M. (2016). Paris Agreement climate proposals need a boost to keep warming well below 2 °c. *Nature, 534*(6), 631–639.

Shaikh, F., Ji, Q., & Fan, Y. (2015). The diagnosis of an electricity crisis and alternative energy development in Pakistan. *Renewable and Sustainable Energy Reviews*. *52*, 1172-1185.

Shi, X., & Grafton, R. Q. (2010). Efficiency impacts of the Chinese industrial transition: A quantitative evaluation of reforms in the coal industry. *Economic Change and Restructuring*, *43*(1), 1–19.

Tang, S., Chen, J., Sun, P., Li, Y., Yu, P., & Chen, E. (2019). Current and future hydropower development in Southeast Asia countries (Malaysia, Indonesia, Thailand and Myanmar). *Energy Policy*, *129*(6), 239–249.

Wang, Y., Zhang, D., Ji, Q., & Shi, X. (2020). Regional renewable energy development in China: A multidimensional assessment. *Renewable and Sustainable Energy Reviews*, *124*. 109797.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, *104*(3), 112–114.

Wu, H., Hao, Y., & Ren, S. (2020). How do environmental regulation and environmental decentralization affect green total factor energy efficiency: Evidence from China. *Energy Economics*, *91*, 104880.

Xu, L., Zhang, Q., Wang, K., & Shi, X. (2020). Subsidies, loans, and companies' performance: evidence from China's photovoltaic industry. *Applied Energy*, *260*, 114280.

Yu, J., Shi, X., & Laurenceson, J. (2019). Will the Chinese economy be more volatile in the future? Insights from urban household survey data. *International Journal of Emerging Markets*, *15*(4), 790–808.

Zhang, D., Li, J., & Ji, Q. (2020). Does better access to credit help reduce energy intensity in China? Evidence from manufacturing firms. *Energy Policy*. *145*, 111710.

Zhang, D., Rong, Z., & Ji, Q. (2019). Green innovation and firm performance: Evidence from listed companies in China. *Resources, Conservation and Recycling*, *144*, 48–55.

Zhang, T., Shi, X., Zhang, D., & Xiao, J. (2019). Socio-economic development and electricity access in developing economies: A long-run model averaging approach. *Energy Policy*, *132*, 223–231.

Zhang, X., & Fan, S. (2004). How productive is infrastructure ? A new approach and evidence from rural India. *American Journal of Agricultural Economics*, *86*(2), 492–501.

Zheng, T., Qiang, M., Chen, W., Xia, B., & Wang, J. (2016). An externality evaluation model for hydropower projects: A case study of the Three Gorges Project. *Energy*, *108*(8), 74–85.

Tables

Table 1: Descriptive Statistics for the Full Sample

	Full Sample Treatment Firms				Full Sample Control Firms			
	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.
TFP	46,272	0.808	0.730	0.622	56,920	0.714	0.682	0.435
Gross Revenue	46,272	54,211	15,699	424,089	56,920	67,072	17,400	381,087
Capital Stock	46,272	24,143	3,502	381,452	56,920	26,088	4,200	214,264
Employment	46,272	305	120	1,465	56,920	311	120	1,201
Intermediates	46,272	38,544	10,274	335,297	56,920	50,646	12,150	317,320
Age (years)	40,326	12.90	7	13.90	51,029	11.60	7	14.70
External Finance	46,270	0.631	0.604	0.381	56,920	0.588	0.593	0.374
Internal Finance	46,270	0.494	0.480	0.341	56,920	0.493	0.484	0.273

Note: All the monetary values are in units of thousand Chinese yuan.

Table 2: Descriptive Statistics for the PSM Sample

	PSM Sample Treatment Firms				PSM Sample Control Firms			
	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.
TFP	38,583	0.827	0.743	0.626	23,682	0.726	0.695	0.437
Gross Revenue	38,583	58,724	16,975	456,620	23,682	69,792	18,582	405,682
Capital Stock	38,583	25,586	3,637	403,561	23,682	26,488	4,240	231,074
Employment	38,583	306	120	1,486	23,682	311	120	1,343
Intermediates	38,583	41,677	10,951	361,988	23,682	52,480	12,926	332,465
Age (years)	38,505	13.50	8	13.90	23,676	12.30	8	12.60
External Finance	38,583	0.623	0.597	0.378	23,682	0.608	0.601	0.381
Internal Finance	38,583	0.495	0.483	0.329	23,682	0.495	0.490	0.244

Note: All the monetary values are in units of thousand Chinese yuan.

Table 3: Baseline DID Results with the Full Sample

	(1) Log(TFP)	(2) Log(TFP)	(3) Log(TFP)	(4) Log(TFP)
Post	0.121***	0.092***		
	[0.004]	[0.004]		
Treat	0.086***	0.099***	0.081***	0.081***
	[0.005]	[0.005]	[0.004]	[0.007]
Post # Treat	**0.032*** **	**0.020*** **	**0.024*** **	**0.024* **
	[0.007]	[0.007]	[0.007]	[0.013]
Log(Age)		-0.018***	-0.005***	-0.005**
		[0.002]	[0.002]	[0.002]
Log(Size)		-0.040***	-0.022***	-0.022***
		[0.002]	[0.002]	[0.003]
External Finance		-0.113***	-0.089***	-0.089***
		[0.006]	[0.005]	[0.008]
Internal Finance		0.058***	0.011**	0.011
		[0.009]	[0.006]	[0.007]
Constant	0.653***	0.943***		
	[0.003]	[0.010]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	103,192	87,635	87,520	87,520
Adjusted R-Squared	0.024	0.043	0.369	0.369

Notes. Fixed effects are high dimensional, including *4-digit industry* × *year* and *ownership* × *year*. We cluster standard errors at the four-digit industry level when indicated. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 4: Capital Deepening Channel (Channel 1) with the Full Sample

	(1) Log(K/L)	(2) Log(K/L)	(3) Log(K/L)	(4) Log(K/L)
Post	0.269***	0.196***		
	[0.010]	[0.010]		
Treat	-0.214***	-0.195***	-0.165***	-0.165***
	[0.010]	[0.012]	[0.012]	[0.025]
Post # Treat	**0.104*** **	**0.089*** **	**0.056*** **	**0.056** **
	[0.016]	[0.016]	[0.016]	[0.028]
Log(Age)		-0.026***	-0.000	-0.000
		[0.004]	[0.004]	[0.011]
Log(Size)		-0.099***	-0.111***	-0.111***
		[0.004]	[0.004]	[0.017]
External Finance		-0.112***	-0.205***	-0.205***
		[0.019]	[0.019]	[0.027]
Internal Finance		-1.339***	-1.314***	-1.314***
		[0.153]	[0.106]	[0.135]
Constant	3.422***	4.729***		
	[0.007]	[0.076]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	103,192	87,635	87,520	87,520
Adjusted R-Squared	0.021	0.123	0.259	0.259

Notes. K/L is the capital-labor ratio. A higher value means more capital deepening. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 5: Scale Effect Channel (Channel 2) with the Full Sample

	(1) Log(GV_R)	(2) Log(GV_R)	(3) Log(GV_R)	(4) Log(GV_R)
Post	0.020**	0.080***		
	[0.009]	[0.009]		
Treat	-0.020**	-0.003	0.005	0.005
	[0.010]	[0.010]	[0.010]	[0.016]
Post # Treat	**0.052*** **	**0.053*** **	**0.041*** **	**0.041** **
	[0.014]	[0.013]	[0.014]	[0.019]
Log(Age)		-0.033***	-0.017***	-0.017**
		[0.003]	[0.004]	[0.008]
Log(Size)		0.454***	0.548***	0.548***
		[0.004]	[0.004]	[0.023]
External Finance		-0.335***	-0.298***	-0.298***
		[0.013]	[0.013]	[0.021]
Internal Finance		0.102***	0.063***	0.063***
		[0.014]	[0.011]	[0.023]
Constant	-0.036***	-2.042***		
	[0.007]	[0.020]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	103,192	87,635	87,520	87,520
Adjusted R-Squared	0.000	0.228	0.271	0.271

Notes. GV_R is the ratio of firm's gross revenue to industry-prefecture-level median gross revenue. A larger ratio means that the firm has a larger relative scale. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 6: Competition Effect Channel (Channel 3) with the Full Sample

	(1) Log(CON_R)	(2) Log(CON_R)	(3) Log(CON_R)	(4) Log(CON_R)
Post	0.340***	0.258***		
	[0.015]	[0.015]		
Treat	-0.160***	-0.182***	-0.240***	-0.240**
	[0.014]	[0.015]	[0.014]	[0.103]
Post # Treat	**-0.169*** **	**-0.157*** **	**-0.116*** **	**-0.116** **
	[0.021]	[0.022]	[0.020]	[0.056]
Log(Age)		-0.073***	-0.014***	-0.014
		[0.005]	[0.004]	[0.010]
Log(Size)		-0.329***	-0.502***	-0.502***
		[0.004]	[0.004]	[0.028]
External Finance		0.265***	0.216***	0.216***
		[0.017]	[0.015]	[0.052]
Internal Finance		-0.185***	-0.045***	-0.045
		[0.022]	[0.015]	[0.029]
Constant	1.714***	3.411***		
	[0.009]	[0.029]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	103,108	87,573	87,458	87,458
Adjusted R-Squared	0.012	0.068	0.389	0.389

Notes. CON_R is the ratio of top 5% firms (sorted by sales) at the industry-prefecture-level to the firm-level total sales. A higher ratio means that the market concentration that the firm faces at the industry-prefecture-level is higher; thus, the market is less competitive. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 7: The Effects of Three Channels on TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(TFP)	Log(TFP)	Log(TFP)	Log(TFP)	Log(TFP)	Log(TFP)	Log(TFP)
Log(K/L)	0.022***			0.044***	0.022***	0.022***	**0.019*** **
	[0.001]			[0.001]	[0.002]	[0.003]	[0.003]
Log(GV_R)		0.055***		0.108***	0.101***	0.089***	**0.092*** **
		[0.002]		[0.002]	[0.002]	[0.005]	[0.005]
Log(CON_R)			-0.007***	-0.006***	-0.001**	-0.001*	**-0.006* **
			[0.001]	[0.001]	[0.000]	[0.000]	[0.003]
Log(Age)					-0.023***	-0.005**	-0.003
					[0.002]	[0.002]	[0.002]
Log(Size)					-0.045***	-0.029***	-0.033***
					[0.004]	[0.006]	[0.006]
External Finance					-0.086***	-0.064***	-0.067***
					[0.005]	[0.008]	[0.008]
Internal Finance					0.021***	-0.022***	-0.020***
					[0.007]	[0.007]	[0.007]
Treat							**0.078*** **
							[0.007]
Post # Treat							**0.008* **
							[0.005]
Constant	1.051***	0.758***	0.786***	1.329***	1.367***		
	[0.009]	[0.002]	[0.002]	[0.011]	[0.014]		
Fixed Effects?	N	N	N	N	N	Y	Y
Clustering SE?	N	N	N	N	N	N	Y
Observations	103192	103192	103108	103108	87573	87458	87458
Adjusted R-Squared	0.011	0.013	0.003	0.047	0.055	0.385	0.391

Notes. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 8: Baseline DID Results with the PSM Sample

	(1) Log(TFP)	(2) Log(TFP)	(3) Log(TFP)	(4) Log(TFP)
Post	0.117***	0.095***		
	[0.005]	[0.005]		
Treat	0.093***	0.098***	0.080***	0.080***
	[0.006]	[0.006]	[0.005]	[0.007]
Post # Treat	**0.026*** **	**0.016***	**0.023*** **	**0.023***
	[0.008]	[0.008]	[0.007]	[0.013]
Log(Age)		-0.017***	-0.003*	-0.003
		[0.002]	[0.002]	[0.002]
Log(Size)		-0.044***	-0.027***	-0.027***
		[0.002]	[0.002]	[0.003]
External Finance		-0.105***	-0.083***	-0.083***
		[0.007]	[0.006]	[0.008]
Internal Finance		0.040***	-0.000	-0.000
		[0.009]	[0.006]	[0.008]
Constant	0.660***	0.968***		
	[0.004]	[0.012]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	62,265	62,265	62,114	62,114
Adjusted R-Squared	0.022	0.040	0.341	0.341

Notes. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 9: Capital Deepening Channel (Channel 1) with the PSM Sample

	(1) Log(K/L)	(2) Log(K/L)	(3) Log(K/L)	(4) Log(K/L)
Post	0.232***	0.196***		
	[0.015]	[0.014]		
Treat	-0.200***	-0.192***	-0.161***	-0.161***
	[0.014]	[0.014]	[0.014]	[0.026]
Post # Treat	**0.103*** **	**0.087*** **	**0.058*** **	**0.058** **
	[0.020]	[0.019]	[0.019]	[0.029]
Log(Age)		-0.024***	-0.002	-0.002
		[0.004]	[0.005]	[0.011]
Log(Size)		-0.098***	-0.112***	-0.112***
		[0.005]	[0.005]	[0.016]
External Finance		-0.136***	-0.219***	-0.219***
		[0.018]	[0.018]	[0.028]
Internal Finance		-1.255***	-1.213***	-1.213***
		[0.182]	[0.125]	[0.159]
Constant	3.440***	4.695***		
	[0.011]	[0.092]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	62,265	62,265	62,114	62,114
Adjusted R-Squared	0.018	0.118	0.258	0.258

Notes. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 10. Scale Effect Channel (Channel 2) with the PSM Sample

	(1) Log(GV_R)	(2) Log(GV_R)	(3) Log(GV_R)	(4) Log(GV_R)
Post	0.042***	0.085***		
	[0.014]	[0.013]		
Treat	-0.009	0.005	0.011	0.011
	[0.013]	[0.012]	[0.013]	[0.020]
Post # Treat	**0.051*****	**0.048*****	**0.040****	**0.040***
	[0.018]	[0.016]	[0.017]	[0.022]
Log(Age)		-0.034***	-0.017***	-0.017**
		[0.004]	[0.004]	[0.008]
Log(Size)		0.445***	0.540***	0.540***
		[0.004]	[0.005]	[0.023]
External Finance		-0.317***	-0.281***	-0.281***
		[0.015]	[0.014]	[0.023]
Internal Finance		0.103***	0.069***	0.069***
		[0.017]	[0.013]	[0.023]
Constant	-0.030***	-2.015***		
	[0.011]	[0.025]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	62,265	62,265	62,114	62,114
Adjusted R-Squared	0.001	0.226	0.268	0.268

Notes. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 11. Competition Effect Channel (Channel 3) with the PSM Sample

	(1) Log(GV_S)	(2) Log(GV_S)	(3) Log(GV_S)	(4) Log(GV_S)
Post	0.298***	0.247***		
	[0.022]	[0.021]		
Treat	-0.190***	-0.186***	-0.304***	-0.304***
	[0.019]	[0.019]	[0.017]	[0.106]
Post # Treat	**-0.107*** **	**-0.135*** **	**-0.124*** **	**-0.124** **
	[0.027]	[0.027]	[0.024]	[0.055]
Log(Age)		-0.063***	-0.016***	-0.016
		[0.006]	[0.005]	[0.010]
Log(Size)		-0.317***	-0.488***	-0.488***
		[0.006]	[0.005]	[0.026]
External Finance		0.286***	0.208***	0.208***
		[0.021]	[0.018]	[0.056]
Internal Finance		-0.140***	-0.046***	-0.046
		[0.022]	[0.017]	[0.029]
Constant	1.693***	3.296***		
	[0.016]	[0.036]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	62,229	62,229	62,078	62,078
Adjusted R-Squared	0.011	0.064	0.380	0.380

Notes. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table 12. Robustness Checks for Baseline DID Results

	(1) Log(TFP)	(2) Log(TFP)	(3) Log(TFP)
Hubei	0.070***	0.082***	0.081***
	[0.005]	[0.005]	[0.008]
Post # Treat	**0.036*** **	**0.023*** **	
	[0.007]	[0.007]	
Y1999 # Treat			0.031
			[0.042]
Y2000 # Treat			-0.031
			[0.026]
Y2001 # Treat			-0.017
			[0.012]
Y2002 # Treat			0.017
			[0.011]
Y2004 # Treat			**0.023***
			[0.013]
Y2005 # Treat			**0.048*** **
			[0.013]
Y2006 # Treat			**0.025** **
			[0.012]
Fixed Effects?	Y	Y	Y
Firm-level Controls?	Y	Y	Y
Observations	76,763	78,993	87,520
Adjusted R-Squared	0.375	0.368	0.369

Note. Column 1 eliminates data before 2000 to account for the issue of data reliability. Column 2 eliminates foreign firms to account for the effect of FDI. Column 3 employs the products of year dummies and tries to account for the issue of paralleling trends, where 2003 is the base year and 1998 is dropped due to collinearity. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Figures

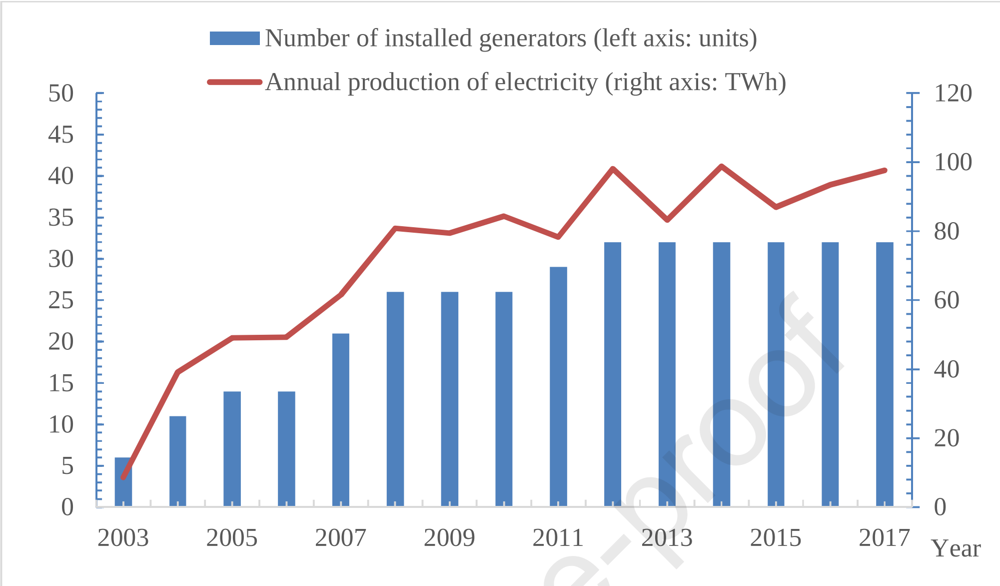


Figure 1. The Number of Installed Generators and the Annual Electricity Production of the TGP: 2003-2017

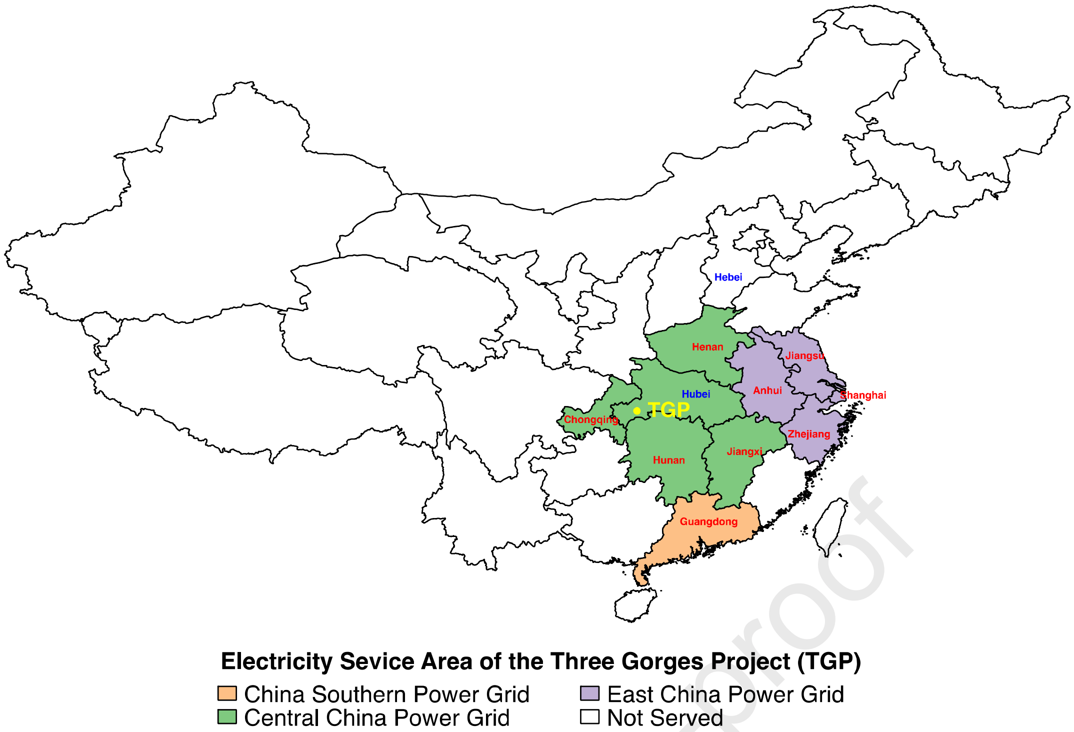


Figure 2. Electricity Service Area of the Three Gorges Project (TGP)

Note. The location and name of the TGP are marked with yellow color. The names of the treatment and control provinces (Hubei and Hebei) are marked with blue color. And the names of all other provinces served with electricity by the TGP are marked with red color. Also note that the electricity service area of the TGP includes provinces belonging to different power grids. We have highlighted the serviced provinces belonging to the China Southern Power Grid, East China Power Grid, and Central China Power Grid with brown, purple, and green background color, respectively.

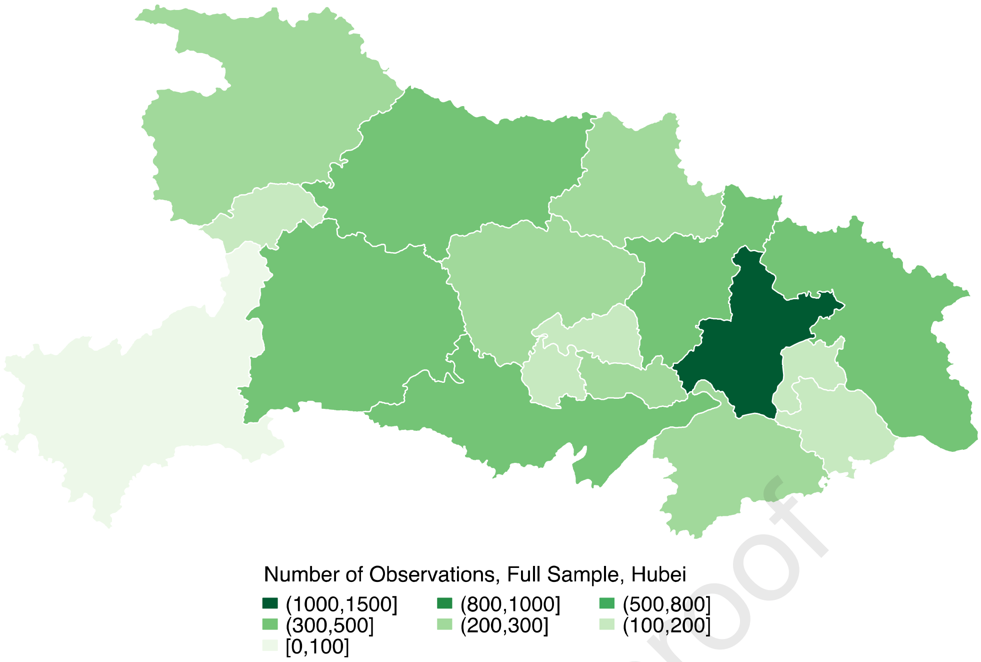


Figure 3. Prefecture-level Distribution of Firms in Hubei, Full Sample

Note. Number of observations means the annual average number of firms over the period 1998-2006 in the full sample.

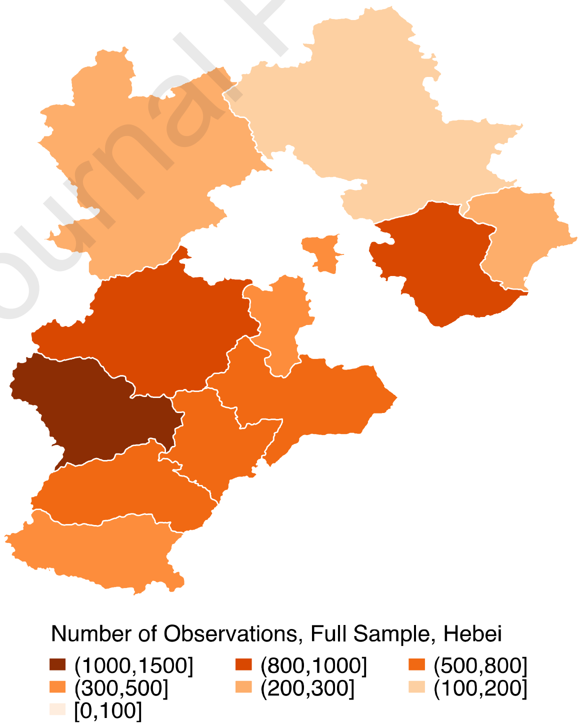


Figure 4. Prefecture-level Distribution of Firms in Hebei, Full Sample

Note. Number of observations means the annual average number of firms over the period 1998-2006 in the full sample.

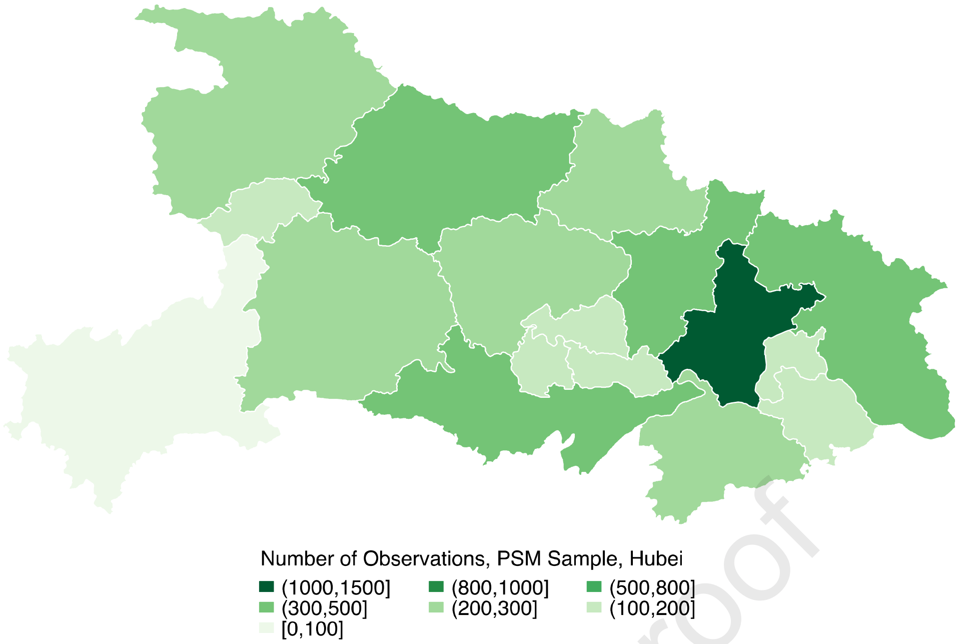


Figure 5. Prefecture-level Distribution of Firms in Hubei, PSM Sample

Note. Number of observations means the annual average number of firms over the period 1998-2006 in the PSM sample.

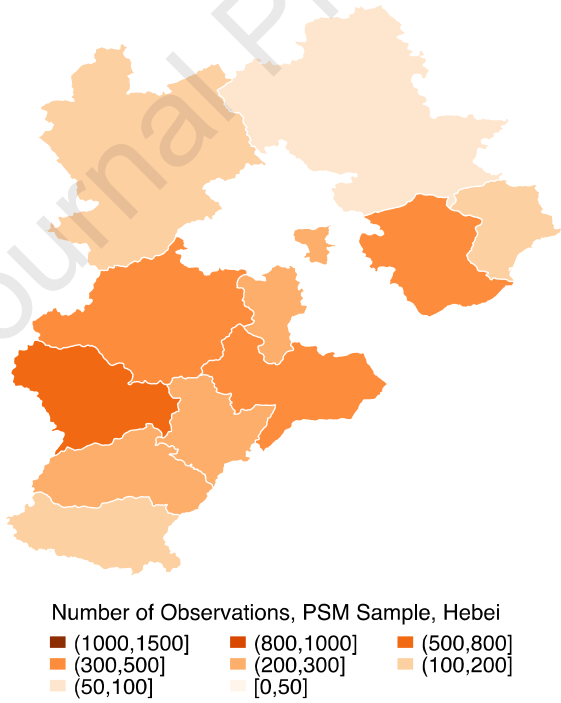


Figure 6. Prefecture-level Distribution of Firms in Hebei, PSM Sample

Note. Number of observations means the annual average number of firms over the period 1998-2006 in the PSM sample.

Appendix

A.1. The Effectiveness of the Propensity Score Matches

Table A.1 presents the test of the effectiveness of the propensity score matches. We include four firm-level variables in the logic regression; thus, we tabulate the test results for them in Table A.1. Note ** and *** indicate significance at the 5% and 1% levels (two-tailed), respectively. The logit regression results are also available upon request.

Table A.1. The Effectiveness of the PSM

Variable		Mean, treated firms (1)	Mean, control firms (2)	Difference (1)-(2)
Log(Age)	Pre-match	2.041	2.004	0.037***
	Post-match	2.042	2.017	0.024***
Log(Size)	Pre-match	4.860	4.881	-0.021***
	Post-match	4.866	4.877	-0.011**
External finance	Pre-match	0.631	0.588	0.043***
	Post-match	0.623	0.608	0.016***
Internal finance	Pre-match	0.494	0.493	0.001
	Post-match	0.495	0.495	0.000

A.2. Mean Difference of Key Variables between Treatment and Control Firms for Full and PSM Samples

Table A.2 presents the mean difference of key variables employed in this empirical study between the treated and control groups for full and PSM samples. We provide the mean difference with significance levels. Note *** indicates significance at the 1% level (two-tailed).

Table A.2. Mean Difference of Key Variables between Treated and Control Firms

Variable		Mean, treated firms (1)	Mean, control firms (2)	Difference (1)-(2)
TFP	Full sample	0.808	0.714	0.095***
	PSM sample	0.827	0.726	0.111***
Gross Revenue	Full sample	54211	67072	-12861***
	PSM sample	58724	69792	-11063***
Capital Stock	Full sample	24143	26088	-1946
	PSM sample	25586	26488	-901
Employment	Full sample	305	311	-5.558
	PSM sample	306	311	-4.763
Age (years)	Full sample	12.928	11.623	1.304***
	PSM sample	13.542	12.286	1.256***
External finance	Full sample	0.631	0.588	0.043***
	PSM sample	0.623	0.608	0.016***
Internal finance	Full sample	0.494	0.493	0.001
	PSM sample	0.495	0.495	0.000

A.3. Scale Effect Channel (Channel 2) with Full Sample and Alternative Measurement

Table A.3 presents the full sample estimation results for the Channel 2, Scale Effect Channel, with an alternative measure for scale effect. The alternative measure is the GV_S, the share of firm's gross revenue in industry-prefecture-level total gross revenue. A higher share means the firm has a larger relative scale. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table A.3. Scale Effect Channel (Channel 2) with Full Sample

	(1) Log(GV_S)	(2) Log(GV_S)	(3) Log(GV_S)	(4) Log(GV_S)
Post	-0.419***	-0.322***		
	[0.016]	[0.016]		
Treat	0.164***	0.189***	0.276***	0.276***
	[0.016]	[0.017]	[0.015]	[0.102]
Post # Treat	**0.243*****	**0.228*****	**0.155*****	**0.155*****
	[0.023]	[0.024]	[0.021]	[0.048]
Log(Age)		0.088***	0.016***	0.016
		[0.006]	[0.005]	[0.010]
Log(Size)		0.340***	0.509***	0.509***
		[0.005]	[0.005]	[0.027]
External Finance		-0.164***	-0.146***	-0.146***
		[0.018]	[0.015]	[0.050]
Internal Finance		0.182***	0.009	0.009
		[0.023]	[0.016]	[0.030]
Constant	-2.456***	-4.303***		
	[0.010]	[0.032]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	103,192	87,635	87,520	87,520
Adjusted R-squared	0.014	0.066	0.454	0.454

A.4. Scale Effect Channel (Channel 2) with PSM Sample and Alternative Measurement

Table A.4 presents the PSM sample estimation results for the Channel 2, Scale Effect Channel, with an alternative measure for scale effect. The alternative measure is the GV_S, the share of firm's gross revenue in industry-prefecture-level total gross revenue. A higher share means the firm has a larger relative scale. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table A.4. Scale Effect Channel (Channel 2) with PSM Sample

	(1) Log(GV_S)	(2) Log(GV_S)	(3) Log(GV_S)	(4) Log(GV_S)
Post	-0.376***	-0.311***		
	[0.023]	[0.023]		
Treat	0.202***	0.193***	0.355***	0.355***
	[0.021]	[0.021]	[0.018]	[0.105]
Post # Treat	**0.171*** **	**0.207*** **	**0.174*** **	**0.174*** **
	[0.030]	[0.029]	[0.025]	[0.048]
Log(Age)		0.082***	0.020***	0.020*
		[0.006]	[0.005]	[0.010]
Log(Size)		0.325***	0.493***	0.493***
		[0.006]	[0.005]	[0.026]
External Finance		-0.201***	-0.143***	-0.143***
		[0.022]	[0.017]	[0.053]
Internal Finance		0.128***	0.003	0.003
		[0.022]	[0.018]	[0.031]
Constant	-2.434***	-4.168***		
	[0.017]	[0.038]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	62,265	62,265	62,114	62,114
Adjusted R-squared	0.012	0.060	0.448	0.448

A.5. Baseline DID Results with Full Sample and Shanxi as the Control Province

Table A.5 presents the full sample baseline DID estimation results with Shanxi as the control province. Note fixed effects are high dimensional, including *4-digit industry* × *year* and *ownership* × *year*. We cluster standard errors at the 4-digit industry level when indicated. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table A.5. Baseline DID Results with Full Sample and Shanxi as the Control Province

	(1) Log(TFP)	(2) Log(TFP)	(3) Log(TFP)	(4) Log(TFP)
Post	0.074***	0.059***		
	[0.006]	[0.006]		
Treat	0.155***	0.147***	0.105***	0.105***
	[0.005]	[0.006]	[0.006]	[0.010]
Post # Treat	**0.079*** **	**0.055*** **	**0.037*** **	**0.037*** **
	[0.008]	[0.009]	[0.009]	[0.013]
Log(Age)		-0.017***	-0.006***	-0.006**
		[0.002]	[0.002]	[0.003]
Log(Size)		-0.041***	-0.030***	-0.030***
		[0.002]	[0.002]	[0.003]
External Finance		-0.101***	-0.077***	-0.077***
		[0.008]	[0.007]	[0.011]
Internal Finance		0.034***	0.007	0.007
		[0.009]	[0.007]	[0.008]
Constant	0.584***	0.902***		
	[0.004]	[0.015]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	62,814	52,552	52,331	52,331
Adjusted R-squared	0.035	0.051	0.335	0.335

A.6. Baseline DID Results with PSM Sample and Shanxi as the Control Province

Table A.6 presents the PSM sample baseline DID estimation results with Shanxi as the control province. Note fixed effects are high dimensional, including *4-digit industry* × *year* and *ownership* × *year*. We cluster standard errors at the 4-digit industry level when indicated. Standard errors are in brackets. *p<0.10, **p<0.05, ***p<0.01.

Table A.6. Baseline DID Results with PSM Sample Shanxi as the Control Province

	(1) Log(TFP)	(2) Log(TFP)	(3) Log(TFP)	(4) Log(TFP)
Post	0.064***	0.049***		
	[0.007]	[0.007]		
Treat	0.159***	0.146***	0.101***	0.101***
	[0.007]	[0.007]	[0.007]	[0.010]
Post # Treat	**0.081*****	**0.064*****	**0.045*****	**0.045*****
	[0.009]	[0.009]	[0.010]	[0.013]
Log(Age)		-0.017***	-0.005**	-0.005
		[0.002]	[0.002]	[0.003]
Log(Size)		-0.043***	-0.032***	-0.032***
		[0.002]	[0.002]	[0.004]
External Finance		-0.099***	-0.076***	-0.076***
		[0.008]	[0.007]	[0.011]
Internal Finance		0.032***	0.007	0.007
		[0.009]	[0.007]	[0.009]
Constant	0.595***	0.915***		
	[0.005]	[0.016]		
Fixed Effects?	N	N	Y	Y
Clustering SE?	N	N	N	Y
Observations	49,739	49,739	49,518	49,518
Adjusted R-squared	0.033	0.048	0.331	0.331