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The impact of the green energy infrastructure on firm productivity: Evidence from the three gorges project in the People's Republic of China

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ADB Working Paper Series

**THE IMPACT OF THE GREEN
ENERGY INFRASTRUCTURE ON
FIRM PRODUCTIVITY: EVIDENCE
FROM THE THREE GORGES
PROJECT IN THE PEOPLE'S
REPUBLIC OF CHINA**

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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, might affect the productivity of manufacturing firms in the province where the project is located. The empirical results statistically and economically reveal the significant positive impact of the TGP on manufacturing firms' productivity, and various robustness checks confirm the soundness of our findings. We also verify the three channels, the capital deepening effect, the scale effect, and the competition effect, robustly. This productivity impact reveals that hydropower projects have one economic benefit in addition to the other well-known ones, such as flood control and an improvement of the shipping capacity. The findings imply that policy makers need to consider the broad benefits of green renewable energy beyond the conventional cost–benefit trade-off and could implement many green energy projects and technology that marginally fail to pass the cost–benefit analysis.

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

JEL Classification: C33, D24, O18, Q56

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Highlights

- First study to investigate whether hydropower projects affect firm productivity using micro data
- First comprehensive study of the production-side economic impacts of the PRC's TGP
- The TGP has significantly and robustly 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 could not only inform national policy debates on green energy infrastructure investment but also help to mitigate global carbon emissions. 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. 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 the non-energy benefits, especially externalities, such as enhancing firm productivity, would 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, Duflo, and Qian 2012; Barzin, D'Costa, and Graham 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 accounted for 15.8% of the total power generation, whereas the other renewables collectively only accounted 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), Ghani, Goswami, and Kerr (2016), Holl (2016), Gibbons et al. (2019); information and communication technology (ICT), such as Garicano and Heaton (2010), Mitra, Sharma, and Véganzonès-Varoudakis (2016), Mohamad et al. (2017); DeStefano, Kneller, and Timmis (2018), and Mithas et al. (2018); and pure electricity infrastructure, such as Abeberese (2017), Cole et al. (2018), and Fisher-Vanden, Mansur, and Wang (2015). Zheng et al. (2016) studied the role of the TGP in the People's Republic of China (PRC) but only focused on its role in relieving the electricity shortage and did not consider more comprehensive production-side economic impacts, such as enhancing productivity.

Many existing studies have found 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) discovered that infrastructure investment imposes a significantly positive effect on manufacturing firms' productive efficiency in the United States (US). In addition, the main channel for generating such a positive effect is the cost-saving benefits. Cohen and Paul (2004) used the manufacturing data of the US, covering the period from 1982 to 1996, to investigate the impact of public highway infrastructure investment on firms' productivity. They also found 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, Sahni, and Biswal (2004) employed the annual data from 1961 to 1995 at the sectoral level in Canada and found that public infrastructure investment had a significant effect on the productivity of 12 two-digit Canadian manufacturing industries. Holl (2012) used various estimation methods and determined 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, Pollin, and Garrett-Peltier (2009) argued that improving the US infrastructure in transportation, public schools, water management, and energy transmission will improve the US's competitiveness. Li, Wu, and Chen (2017) found 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, Bennathan, and Srinivasan (2006) found 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) used 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 concluded 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) found 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, Sharma, and Végazonès-Varoudakis (2016) examined the role of infrastructure and information and communication technology (ICT) investment in total factor productivity (TFP). The findings showed 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 applied comprehensive micro data 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 found that the TGP has significantly improved firm productivity through channels including capital deepening, the scale effect, and the competition effect.

This study adds to the existing literature in three respects. First, it is the first study to estimate the green energy infrastructure's impact on firm productivity. Although a few studies have estimated the cost and benefit of infrastructure investment in hydropower stations, there is no study about the impact of the construction of a hydropower station on firm production side performance, such as productivity. 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, it is the first paper to propose and test empirically the three channels through which infrastructure affects firm productivity. The proposed channels, specifically capital deepening, the scale effect, and the competition effect, are applicable to studying the productivity impact of other green energy infrastructure investment. 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 findings 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

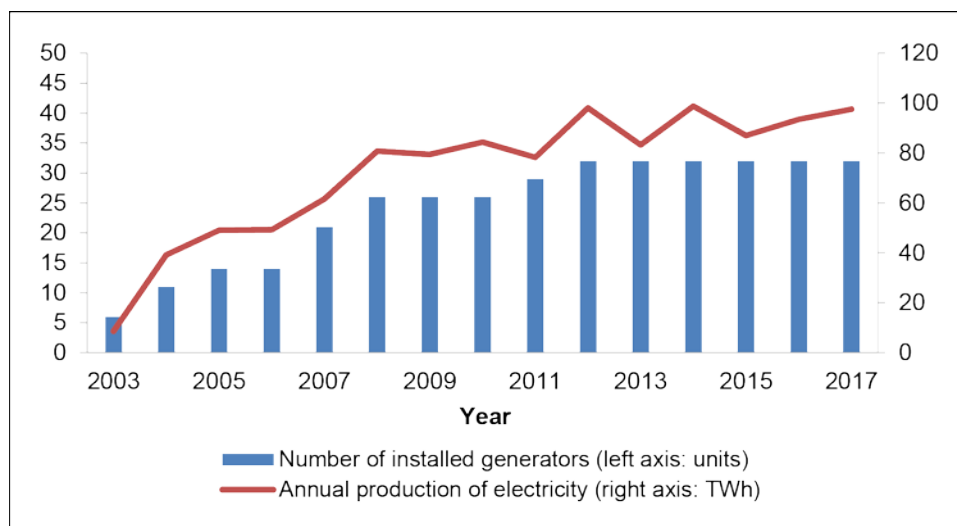
The Three Gorges Dam (TGP) is a hydroelectric project that spans the Yangtze River in Yichang, Hubei province, the PRC. The total capacity of the TGP is 22,500 MW. It is the largest hydroelectric power project in the world and contains 34 generators. The capacity of 32 hydropower generators is 700 MW 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 PRC 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 TGD 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 TGD 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 used the average flow rate at the dam

site, assuming 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).

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



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, which altogether serve Hubei, Henan, Anhui, Jiangxi, Zhejiang, Guangdong, Chongqing, and Shanghai (Zheng et al. 2016). 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 inspired 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 selected Hebei province in the northern PRC to be the location for our control group of firms. Further discussion on how we chose 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, like that in the TGP, would affect firm productivity. We conducted a survey of a wide range of existing studies related to our research question. Basing on the relevant literature, we found 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. However, they are particularly difficult to obtain in developing countries (Cole et al. 2018). Considering that electricity is the 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. Abeberese (2019) argued 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 investment in self-generation, which will crowd out other investment opportunities and obviously reduce their productivity. Fisher-Vanden, Mansur, and Wang (2015) used Chinese energy-intensive firms' data covering the period 1999–2004 and found 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) provided evidence on how electricity shortages and the electricity price affect firms' productivity growth in India. She found that, in response to an exogenous increase in the electricity price, which is a typical production cost, firms switch to less electricity-intensive production processes and thus reduce their productivity growth rates. Allcott, Collard-Wexler, and O'Connell (2016) estimated the effects of electricity shortages on manufacturing firms in India and concluded 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) argued that, against the backdrop of rapid economic growth and an 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) provided a case study of the TGP in the PRC. They found 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 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 could 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 might greatly improve the enterprise production efficiency. At the industry level, this means that the industry is becoming more capital intensive.

Hypothesis 1. *The operating of the TGP encourages 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 and 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, Kneller, and Timmis (2018) investigated the impacts of broadband infrastructure and information and communication technology on firm performance in the UK. They argued 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) investigated the average causal impact of infrastructure investment (e.g., road improvements) on British enterprises' productivity. The estimated results indicated that road improvement has a larger positive effect

on firms' productivity than previous studies have reported (Ghani, Goswami, and Kerr 2016) via the channel of the market potential effect. They argued 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. 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 help firms in Hubei to increase their size. 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 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., 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 like 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 could improve manufacturing productivity through the channel of increased competition and competitiveness. For example, Heintz, Pollin, and Garrett-Peltier (2009) argued 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 could then lead to higher productivity. Holl (2016) used a geo-coded micro-level panel data set for Spain from 1997 to 2007 and investigated the effect of infrastructure investment on firm-level productivity. He found that infrastructure investment could 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 also increases the productivity of firms via the channel of the competition effect (Garicano and Heaton 2010). Some studies have argued 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, thus pushing our treated firms (i.e., firms in Hubei) to raise their productivity for the purpose of 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 regressed firm productivity (which we measured using the estimated TFP, which 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. We should note that our TFP measure is already in log form, so we could interpret the coefficient estimates as percentage changes or elasticities, depending on whether the regressor is discrete or continuous.

In our baseline regressions, we also included a reasonable set of firm characteristics that might correlate with firm productivity, such as firm age, size, and financial conditions. We further included high-dimensional fixed effects to control for macroeconomic, sectoral, and ownership-specific shocks. Those fixed effects are the four-digit industry multiplying year fixed effect (θ_{st} , where s denotes the sector) and the ownership multiplying year fixed effect (ς_{ot} , where o denotes ownership). In total, our baseline sample contained around 390 four-digit industries. Turning to specifics, we specified our baseline regression equation as follows:

$$tfp_{it} = \beta_0 + \beta_1 * post + \beta_2 * treat + \beta_3 * post * treat + \beta_j * control_{it} + \theta_{st} + \varsigma_{ot} + e_{it}. \quad (1)$$

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 (the milestone is the start of the TGP’s electricity supply on 10 July 2003). We expected 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 checked our standard errors by clustering them at the four-digit industry level.

3.2 Data

We employed the comprehensive micro data 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 of 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 focused on two rather comparable provinces: Hubei and Hebei. The two provinces were similar in total GDP (370.4 billion yuan versus 425.6 billion yuan), total population (59.1 million versus 65.7 million people), and thus GDP per capita (6,271 yuan versus 6,479 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 provided us with an ideal setting to evaluate the effect of this giant infrastructure project on firm performance. Accordingly, we identified firms from the ASIP in Hubei as the treated group and those in Hebei as the control group.

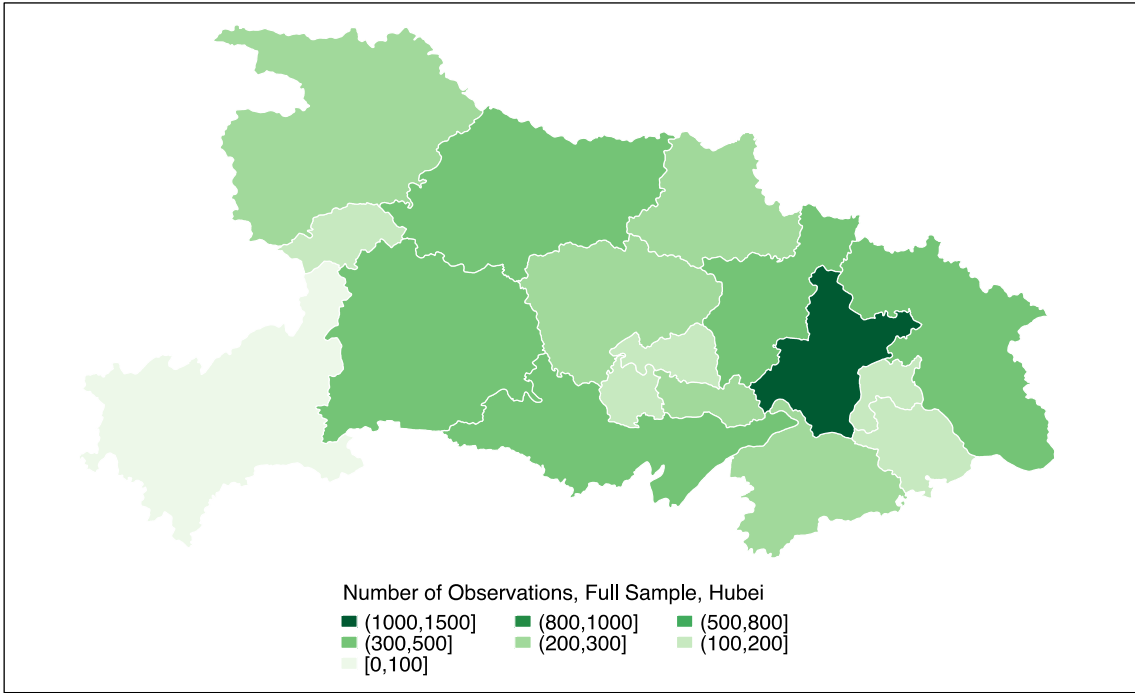
We employed a DID design that compares the growth in firm productivity among treated firms with that among control firms during our sample period. In our baseline sample, there are 46,272 firms in the treated group and 56,920 firms in the control group. The number of observations is quite comparable 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 employed a propensity score matching (PSM) approach to match our Hubei firms to more comparable Hebei firms. The PSM approach that we followed is in the spirit of nearest-neighbor matching (Dehejia and Wahba 2002). Using data prior to the TGP's construction, we first implemented 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 could be state owned, collectively owned (domestic), privately owned (domestic), or foreign owned. Our underlying assumption was 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 matched 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 generated a PSM sample from the baseline sample with 38,583 firms in the treated group and 23,682 firms in the control group. Not surprisingly, we will show later that the firms in the PSM sample are more comparable between the treated and the control group in terms of many explanatory variables (such as firm input–output information and financial conditions) that we use in our empirical studies.

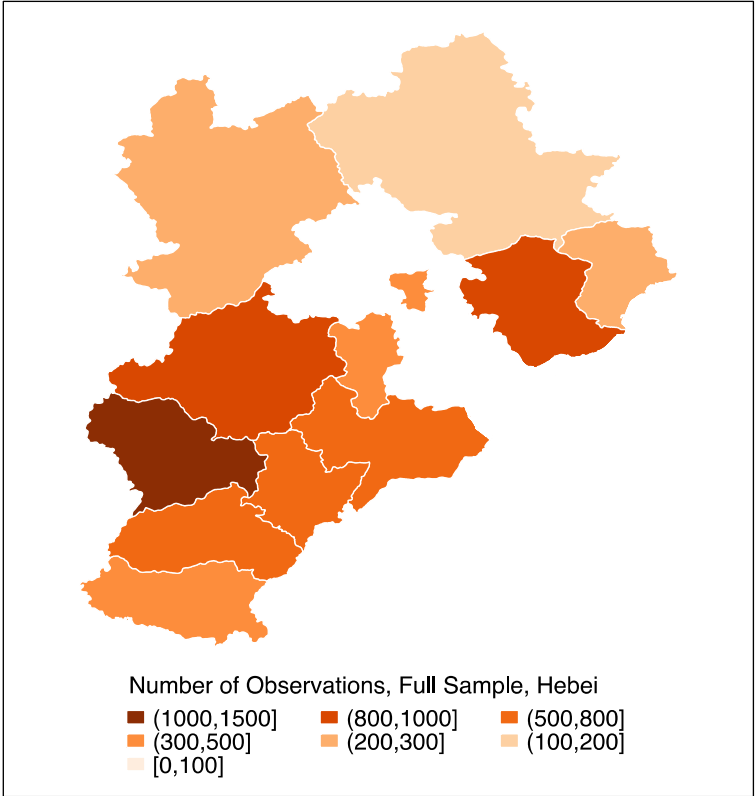
Figures 2–3 and 4–5 further present the geographical distribution of our baseline and PSM samples, respectively. Two quick observations from the figures are the following: first, though the number of observations is associated with local development at the prefecture level, the sample is fairly well distributed across locations; second, the geographical distribution of firms is largely maintained when we use the PSM sample to replace the baseline sample.

Figure 2: Prefecture-Level Distribution of Firms in Hubei, Full Sample



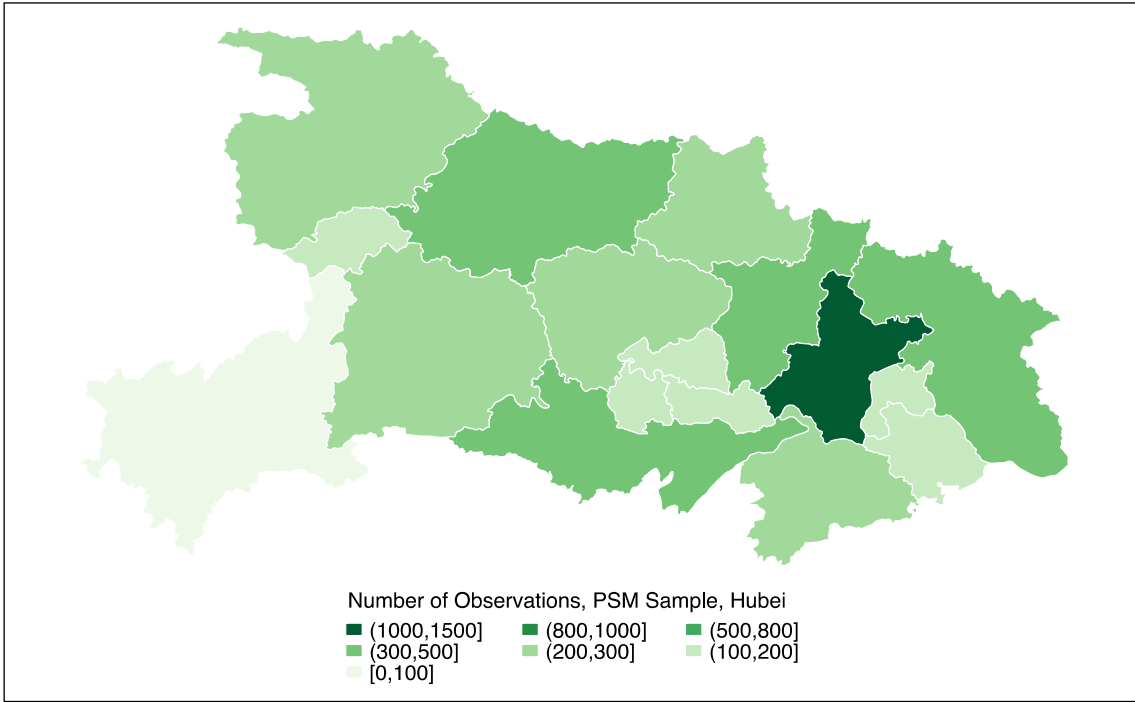
Note: Number of observations means the annual average number of firms over the period 1998–2006 in the full sample.

Figure 3: Prefecture-Level Distribution of Firms in Hebei, Full Sample



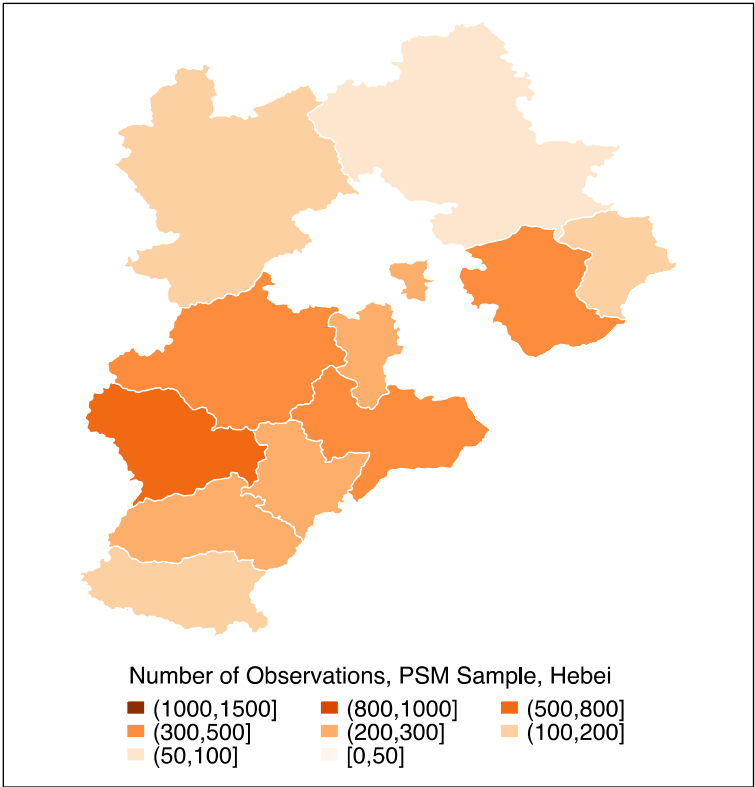
Note: Number of observations means the annual average number of firms over the period 1998–2006 in the full sample.

Figure 4: 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 5: 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.

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 major variables.

Our primary explained variable in this empirical study is firm productivity. To measure firm productivity, we employed the state-of-the-art method, which estimates firm total factor productivity (TFP) using a widely recognized semi-parametric approach, as Akerberg, Caves, and Frazer (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 Olley and Pakes (1996), Levinsohn and Petrin (2003), and Wooldridge (2009). Intuitively, the TFP measures the efficiency of firms in utilizing labor, capital, and intermediate inputs. 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:

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

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 $(v_{it}, \varepsilon_{it})$ 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 the firm-level TFP, including firm gross revenue, employment, capital stock, and intermediate inputs. Except for employment, measured as the number of workers, we measured them in Chinese yuan. Note that we included intermediate inputs in the TFP estimation; thus, we needed the gross revenue rather than the value added.

In addition to the TFP and the variables used to compute the TFP, we constructed a group of control variables for the empirical analysis. We calculated age as the length of a firm's operating years since its establishment and two financial conditions following Berman and Héricourt (2010) and Guariglia, Liu, and Song (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.

Tables 1 and 2 tabulate the summary statistics for our major 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. 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 did 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 reasonable comparable treatment and control groups for DID analysis.

Table 1: Descriptive Statistics for the Full Sample

	Full-Sample Treatment Firms				Full-Sample Control Firms			
	N	Mean	Media n	Std Dev.	N	Mean	Media n	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	Media n	Std Dev.	N	Mean	Media n	Std Dev.
TFP	38,583	0.827	0.743	0.626	23,682	0.726	0.695	0.437

	38,58	58,72			23,68	69,79		
Gross Revenue	3	4	16,975	456,620	2	2	18,582	405,682
	38,58	25,58			23,68	26,48		
Capital Stock	3	6	3,637	403,561	2	8	4,240	231,074
	38,58				23,68			
Employment	3	306	120	1,486	2	311	120	1,343
	38,58	41,67			23,68	52,48		
Intermediates	3	7	10,951	361,988	2	0	12,926	332,465
	38,50				23,67			
Age (Years)	5	13.50	8	13.90	6	12.30	8	12.60
	38,58				23,68			
External Finance (%)	3	0.623	0.597	0.378	2	0.608	0.601	0.381
	38,58				23,68			
Internal Finance (%)	3	0.495	0.483	0.329	2	0.495	0.490	0.244

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

4. EMPIRICAL RESULTS

We present the empirical results in this section. We show two important dimensions. First, in terms of the sample used, in the baseline estimation, we used the full sample, whereas, in the robustness checks, we used the PSM sample rather than the baseline full sample. The second dimension speaks to the underlying channels for our baseline estimation results, in which we empirically tested the three channels proposed in Section 2.

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

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 did not control for firm-level characteristics. It shows a significant coefficient for *post* TFP ($\hat{\beta}_1 = 0.1206$), meaning that the control firms (firms in Hebei with no relevant direct connections with the TGP) experienced about a 12.82% ($e^{0.1206} - 1 \approx 0.1282$) 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) had higher productivity than our control firms before 2003, when the TGP started supplying electricity. Specifically, the treated firms were on average 9.01% ($e^{0.0863} - 1 \approx 0.0901$) more productive than the control firms before 2003. This finding is also consistent with our summary descriptive tables, which show a higher mean TFP for the treated group.

More importantly, we found that the coefficient for the interaction term, *post*treat*, is significantly positive. It suggests that firms in Hubei, relative to firms in Hebei, experienced 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 3.24% ($e^{0.0319} - 1 \approx 0.0324$). 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). Though the magnitudes of some estimates show a drop, they are still statistically and

economically significant. We also achieved 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 found 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.

Table 3: Baseline DID Results with the Full Sample

	(1) Log(TFP)	(2) Log(TFP)	(3) Log(TFP)	(4) Log(TFP)
Post	0.121*** [0.004]	0.092*** [0.004]		
Treat	0.086*** [0.005]	0.099*** [0.005]	0.081*** [0.004]	0.081*** [0.007]
Post # Treat	0.032*** [0.007]	0.020*** [0.007]	0.024*** [0.007]	0.024* [0.013]
Log(Age)		-0.018*** [0.002]	-0.005*** [0.002]	-0.005** [0.002]
Log(Size)		-0.040*** [0.002]	-0.022*** [0.002]	-0.022*** [0.003]
External Finance		-0.113*** [0.006]	-0.089*** [0.005]	-0.089*** [0.008]
Internal Finance		0.058*** [0.009]	0.011** [0.006]	0.011 [0.007]
Constant	0.653*** [0.003]	0.943*** [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.

4.2 Three Channels for Baseline DID Estimation Results

Our baseline finding in the DID analysis is that, relative to firms in Hebei, firms in Hubei experienced 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 capital deepening, 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 tested this channel through a similar DID analysis in which we implemented firm productivity in the baseline DID analysis. Turning to specifics, we replaced the TFP in Equation (1) with the log capital–labor ratio. As discussed in Hypothesis 1, we expected the capital deepening regression to show that, relative to firms in Hebei, firms in Hubei have experienced 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 did 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* the log capital–labor ratio ($\hat{\beta}_1 = 0.2694$), indicating that the control firms

experienced around a 30.92% ($e^{0.2694} - 1 \approx 0.3092$) increase in the capital–labor ratio following the implementation of the TGP in 2003. This is in line with the fact that Huang, Ju, and Yue (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 experienced a lower capital–labor ratio increase than our control firms before the operation of the TGP in 2003. Particularly, the firms in Hubei were on average 19.25% ($e^{-0.2138} - 1 \approx -0.1925$) less capital intensive than the firms in Hebei before 2003. The result implies that, prior to the operating of the TGP, firms in Hubei had more space to improve their capital intensity once they had 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 ($\hat{\beta}_3 = 0.1043$).

Third, the coefficient for the interacted term indicates that, relative to firms in Hebei, firms in Hubei have experienced a rise in the capital–labor ratio as large as 10.99% ($e^{0.1043} - 1 \approx 0.1099$) 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 and more fixed effects or cluster standard errors.

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*** [0.010]	0.196*** [0.010]		
Treat	−0.214*** [0.010]	−0.195*** [0.012]	−0.165*** [0.012]	−0.165*** [0.025]
Post # Treat	0.104*** [0.016]	0.089*** [0.016]	0.056*** [0.016]	0.056** [0.028]
Log(Age)		−0.026*** [0.004]	−0.000 [0.004]	−0.000 [0.011]
Log(Size)		−0.099*** [0.004]	−0.111*** [0.004]	−0.111*** [0.017]
External Finance		−0.112*** [0.019]	−0.205*** [0.019]	−0.205*** [0.027]
Internal Finance		−1.339*** [0.153]	−1.314*** [0.106]	−1.314*** [0.135]
Constant	3.422*** [0.007]	4.729*** [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.

4.2.2 The Second Channel: The Scale Effect

Formally, we tested the following hypothesis for the scale effect channel: relative to firms in Hebei, firms in Hubei have experienced a jump in relative firm size since the TGP commenced operation in 2003. We defined the relative size of firms as the gross revenue share. Specifically, it is the share of firms' gross revenue in the industry-prefecture-level total gross revenue. A larger share means that the firm has a larger relative scale. Again, we implemented a similar DID analysis with respect to firms' gross revenue share to examine the scale effect channel.

Table 5 presents the DID regression results for the gross revenue share. Note that the explained variable is the log gross revenue share. We followed 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 obtained a significant estimate of $\hat{\beta}_1 = -0.4185$, indicating that the control firms experienced around a 34.20% ($e^{-0.4185} - 1 \approx -0.3420$) decline in relative firm size (gross revenue share) following the start of the TGP's operations in 2003. This might reflect that the firm entry has been very high in Hebei province 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*, $\hat{\beta}_2 = 0.1636$, is significantly positive, which means that our treated firms experienced a 17.77% ($e^{0.1636} - 1 \approx 0.1777$) larger gross revenue share increase than our control firms before the operation of the TGP in 2003.

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

	(1) Log(GV_S)	(2) Log(GV_S)	(3) Log(GV_S)	(4) Log(GV_S)
Post	-0.419*** [0.016]	-0.322*** [0.016]		
Treat	0.164*** [0.016]	0.189*** [0.017]	0.276*** [0.015]	0.276*** [0.102]
Post # Treat	0.243*** [0.023]	0.228*** [0.024]	0.155*** [0.021]	0.155*** [0.048]
Log(Age)		0.088*** [0.006]	0.016*** [0.005]	0.016 [0.010]
Log(Size)		0.340*** [0.005]	0.509*** [0.005]	0.509*** [0.027]
External Finance		-0.164*** [0.018]	-0.146*** [0.015]	-0.146*** [0.050]
Internal Finance		0.182*** [0.023]	0.009 [0.016]	0.009 [0.030]
Constant	-2.456*** [0.010]	-4.303*** [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

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

The operating of the TGP accelerated the relatively higher growth of the gross revenue share in Hubei relative to that in Hebei. The coefficient for the interaction term, $post * treat$, $\hat{\beta}_3 = 0.2426$, is significantly positive, suggesting that, compared with firms in Hebei, firms in Hubei have experienced a 27.46% ($e^{0.2426} - 1 \approx 0.2746$) rise in relative firm size (gross revenue share) 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.

4.2.3 The Third Channel: The Competition Effect

To test this hypothesis, we formally conducted 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 defined the mirror image side of firm competition pressure as the firm market concentration index. Turning to the specifics, we constructed 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 did not control for firm characteristics or high-dimensional fixed effects or cluster standard errors. The coefficient for $post$ has a significantly positive estimate of $\hat{\beta}_1 = 0.3402$, meaning that the control firms (firms in Hebei) experienced around a 40.52% ($e^{0.3402} - 1 \approx 0.4052$) 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, $\hat{\beta}_2 = -0.1600$, indicating that our treated firms (firms in Hubei, where the TGP is located) experienced a 14.79% ($e^{-0.1600} - 1 \approx -0.1479$) lower market concentration index increase than our 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 became even fiercer when the TGP started to operate in 2003. The coefficient for the interaction term, $post * treat$, $\hat{\beta}_3 = -0.1692$, is significantly negative, indicating that, relative to firms in Hebei (control firms), firms in Hubei (treated firms) experienced a 15.57% ($e^{-0.1692} - 1 \approx -0.1557$) 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 stayed unchanged when we controlled for firm characteristics and more fixed effects or clustered standard errors.

In sum, all the three channels that we hypothesized to be important for understanding the baseline productivity DID results have supportive evidence in the micro data and thus helped us to conclude that they are relevant channels, through which the operation of the TGP has promoted firm productivity since 2003.

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*** [0.015]	0.258*** [0.015]		
Treat	-0.160*** [0.014]	-0.182*** [0.015]	-0.240*** [0.014]	-0.240** [0.103]
Post # Treat	-0.169*** [0.021]	-0.157*** [0.022]	-0.116*** [0.020]	-0.116** [0.056]
Log(Age)		-0.073*** [0.005]	-0.014*** [0.004]	-0.014 [0.010]
Log(Size)		-0.329*** [0.004]	-0.502*** [0.004]	-0.502*** [0.028]
External Finance		0.265*** [0.017]	0.216*** [0.015]	0.216*** [0.052]
Internal Finance		-0.185*** [0.022]	-0.045*** [0.015]	-0.045 [0.029]
Constant	1.714*** [0.009]	3.411*** [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.

4.3 Robustness Checks

In this subsection, we conduct a battery of robustness checks for our baseline DID analysis. We first reran all the DID regressions, including those for productivity, the capital–labor ratio, the gross revenue share, and the market concentration index, using the PSM sample rather than the baseline full sample. Tables 7–10 present the PSM sample results. 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.

Table 7: Baseline DID Results with the PSM Sample

	(1) Log(TFP)	(2) Log(TFP)	(3) Log(TFP)	(4) Log(TFP)
Post	0.117*** [0.005]	0.095*** [0.005]		
Treat	0.093*** [0.006]	0.098*** [0.006]	0.080*** [0.005]	0.080*** [0.007]
Post # Treat	0.026*** [0.008]	0.016* [0.008]	0.023*** [0.007]	0.023* [0.013]
Log(Age)		-0.017*** [0.002]	-0.003* [0.002]	-0.003 [0.002]
Log(Size)		-0.044*** [0.002]	-0.027*** [0.002]	-0.027*** [0.003]
External Finance		-0.105*** [0.007]	-0.083*** [0.006]	-0.083*** [0.008]
Internal Finance		0.040*** [0.009]	-0.000 [0.006]	-0.000 [0.008]
Constant	0.660*** [0.004]	0.968*** [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 8: 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*** [0.015]	0.196*** [0.014]		
Treat	-0.200*** [0.014]	-0.192*** [0.014]	-0.161*** [0.014]	-0.161*** [0.026]
Post # Treat	0.103*** [0.020]	0.087*** [0.019]	0.058*** [0.019]	0.058** [0.029]
Log(Age)		-0.024*** [0.004]	-0.002 [0.005]	-0.002 [0.011]
Log(Size)		-0.098*** [0.005]	-0.112*** [0.005]	-0.112*** [0.016]
External Finance		-0.136*** [0.018]	-0.219*** [0.018]	-0.219*** [0.028]
Internal Finance		-1.255*** [0.182]	-1.213*** [0.125]	-1.213*** [0.159]
Constant	3.440*** [0.011]	4.695*** [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 9: Scale Effect Channel (Channel 2) with the PSM Sample

	(1) Log(GV_S)	(2) Log(GV_S)	(3) Log(GV_S)	(4) Log(GV_S)
Post	-0.376*** [0.023]	-0.311*** [0.023]		
Treat	0.202*** [0.021]	0.193*** [0.021]	0.355*** [0.018]	0.355*** [0.105]
Post # Treat	0.171*** [0.030]	0.207*** [0.029]	0.174*** [0.025]	0.174*** [0.048]
Log(Age)		0.082*** [0.006]	0.020*** [0.005]	0.020* [0.010]
Log(Size)		0.325*** [0.006]	0.493*** [0.005]	0.493*** [0.026]
External Finance		-0.201*** [0.022]	-0.143*** [0.017]	-0.143*** [0.053]
Internal Finance		0.128*** [0.022]	0.003 [0.018]	0.003 [0.031]
Constant	-2.434*** [0.017]	-4.168*** [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

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

Table 10: 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*** [0.022]	0.247*** [0.021]		
Treat	-0.190*** [0.019]	-0.186*** [0.019]	-0.304*** [0.017]	-0.304*** [0.106]
Post # Treat	-0.107*** [0.027]	-0.135*** [0.027]	-0.124*** [0.024]	-0.124*** [0.055]
Log(Age)		-0.063*** [0.006]	-0.016*** [0.005]	-0.016 [0.010]
Log(Size)		-0.317*** [0.006]	-0.488*** [0.005]	-0.488*** [0.026]
External Finance		0.286*** [0.021]	0.208*** [0.018]	0.208*** [0.056]
Internal Finance		-0.140*** [0.022]	-0.046*** [0.017]	-0.046 [0.029]
Constant	1.693*** [0.016]	3.296*** [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.

Next, we examine the sample reliability issue further. As Brandt, Van Biesebroeck, and Zhang (2014) documented, the consistent recording of the ASIP data officially started in 1998. However, they found that the total number of firms in the ASIP dropped in 1999 compared with 1998, which suggests that there might be a data reliability issue for these two years. We accounted for this issue by focusing on the sample for 2000–2006 only. Column 1 of Table 11 presents our baseline DID analysis for firm productivity when we restricted the sample to the years 2000–2006. The coefficient for the interaction term, $post * treat$, $\hat{\beta}_3 = 0.0357$, 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.

Table 11: Robustness Checks for the Baseline DID Results

	(1) Log(TFP)	(2) Log(TFP)	(3) Log(TFP)
Hubei	0.070*** [0.005]	0.082*** [0.005]	0.081*** [0.008]
Post # Treat	0.036*** [0.007]	0.023*** [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]
Y2003 # Treat			0.020* [0.012]
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

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

Furthermore, we consider the differential impact of trade liberalization on the treated and control groups, since the two provinces (Hebei and Hubei) may have very different exposure to trade and foreign investment. Since Hebei has seaports, for instance, it might have more foreign direct investment (FDI), and the advanced technology that FDI brings in could introduce some differences in productivity growth for the two provinces, especially after the PRC entered the WTO in December 2001. One way that we could address this issue using the micro data is to exclude all foreign firms in the manufacturing sector. Column 2 of Table 11 shows that the interaction term, $post * treat$

, with $\hat{\beta}_3 = 0.0357$, is still significantly positive, indicating that the trade and foreign investment issue is not a relevant problem for this empirical study (though it somehow dampens the magnitude of our DID result).

Finally, we performed 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 11 presents the paralleling trend test results, which clearly show 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 2003, 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 statistically more significant. This makes sense given that productivity-enhancing activities generally involve long-term adjustments, like the time to build, for capital deepening.

5. CONCLUDING REMARKS

Studying the productivity impact of the green energy infrastructure could 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.

In this paper, we fill the gap by estimating whether and how the TGP, the world's largest hydropower project, may affect manufacturing firm productivity. We proposed three channels through which the TGP could affect firm productivity, which is another contribution. We employed manufacturers' data from the PRC's Annual Survey of Industrial Production (ASIP) between 1998 and 2006. We proposed 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. We also adopted the state-of-the-art method to measure the TFP (e.g., Akerberg, Caves, and Frazer 2015).

Our empirical results revealed a significant positive impact of the TGP on manufacturing firms' productivity, and various robust checks confirmed the credibility of the baseline findings. This empirical study also empirically tested the three channels, the capital deepening effect, the scale effect, and the competition effect, and the analyses are robust as well.

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. More broadly, the findings suggest that policy makers need to consider the broad benefits of green renewable 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 might be implementable, and thus the global plan for mitigating carbon emissions could be more ambitious.

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 would also be possible to extend the study to other green energy projects, for instance wind and solar, which would help policy makers in gauging their decisions regarding the development.

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