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Do China's Industrial Clusters Increase Energy Efficiency?

1. Introduction

China's national leadership has made ambitious plans to achieve carbon neutrality by 2060.[1] To support these goals while sustaining a high speed of economic growth, the national government has made plans to improve China's energy efficiency by establishing industrial clusters which are seen as key to driving structural transformation and industrial upgrading.

This study examines how local energy efficiency is impacted by industrial clusters. Existing studies have praised the economic success of industrial zones in China in their ability to accumulate productive capabilities,[2] adopt modern management practices,[3] increase industrial competitiveness,[4] enhance structural transformation,[5] and facilitate China's overall integration into the world economy.[6] However, beyond their economic impact, how effective have these industrial clusters been in driving energy efficiency gains?

To understand the relationship between industrial clusters and energy efficiency, this study looks at the role of high-tech industrial development zones (HTIDZs) in facilitating local energy efficiency gains. By 2022, China had established a total of 169 HTIDZs nationwide. These national HTIDZs share very similar preferential policies set by the national government and have similar stated goals to 'adjust industrial structure, drive traditional industrial transformation, and increase international competitiveness',[7] but they are established in regions with vastly different local socio-economic contexts. By focusing on these HTIDZs, this research allows for a meaningful comparison of how a similar national set-up of industrial clusters differ in their effectiveness in driving energy efficiency gains based on the local conditions and given China's wide regional variations.

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[1] McGrath, M. (2020). Climate change: China aims for 'carbon neutrality by 2060'. *BBC News*. 22 September 2020.

[2] Felipe, J., et al. (2013). 'Why Has China Succeeded? And Why It Will Continue To Do So', *Cambridge Journal of Economics* 37(4), 791–818.

[3] Zeng, D. (2010). *Building engines for growth and competitiveness in China: Experience with special economic zones and industrial clusters*. World Bank Publications.

[4] World Bank (2008). 'Special Economic Zones: performance, lessons, learning, and implications for zone development', *World Bank Foreign Investment Advisory Service (FIAS).*

[5] Lin, J., Xu, J., and Xia, J. (2020). 'Explaining Reform and Special Economic Zones in China', *The Oxford Handbook of Industrial Hubs and Economic Development.*

[6] Rodrik, D. (2008). 'Second-Best Institutions', *American Economic Review* 98(2), 100–4.

[7] MOST (2021) 'High-Tech Industrial Development Zones', *Ministry of Science and Technology of the People's Republic of China*. Available at: http://www.most.gov.cn/gxjscykfq

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This research helps to advance current research on China's energy efficiency by examining empirical evidence on the ways local socio-economic contexts interact with a nation-wide industrial policy. It employs quantitative analysis while recognizing the significant heterogeneity across China's. To do so, this research looks at a sample of 276 prefecture-level cities which had reported data over the period of 2003–2018.[8] The cities in the sample represent 88.6 per cent of China's total population, 86.2 per cent of its total GDP, 94.4 per cent of its total secondary sector output, and 84.1 per cent of its total energy usage as at 2018. These cities house 161 of the total 169 HTIDZs in China.[9]

The period covered in this paper coincides with a period of huge expansion in HTIDZs across China. In 2003, only 44 cities had a HTIDZ, a figure which more than tripled to 146 by 2018. By looking at the implementation of HTIDZs in Chinese cities and how they relate to energy efficiency patterns, this paper draws a comparison across both temporal and spatial dimensions to better understand the effectiveness of industrial clusters in driving energy efficiency gains at the local municipality level.

This research finds no evidence that industrial clusters by themselves drive local energy efficiency gains. However, when established in cities with a high level of technical human capital, industrial clusters can be effective in driving energy efficiency improvements, even after controlling for other factors such as GDP per capita, whether the city is located in a coastal region, the city's industrial structure, and the region's energy mix. The results ultimately suggest that while industrial clusters play a role in providing the potential for energy efficiency gains, they are not a sufficient factor. What matters is the city's 'software', particularly its technical human capital. To achieve its environmental pledge while maintaining a high growth rate, China needs to address institutional imbalances between cities by improving local human capital to ensure that energy efficiency gains can be realized in cities outside of provincial capitals. In other words, this research cautions against studies that use China's successful experience with industrial zones to cast these clusters as a panacea that can improve energy efficiency by itself. Instead, China's experience shows that technical capability matters for industrial clusters to realize their intended energy efficiency gains.

2. Energy efficiency and total-factor energy efficiency

Energy efficiency is defined as the practice of using less energy to perform a task, such as obtaining a productive output.[10] By contrast, energy intensity measures the quantity of energy required per unit output, such that using less energy to produce a product reduces the energy intensity.[11] Energy intensity is the inverse of energy efficiency, where a reduction in energy intensity is a proxy for energy efficiency improvements, holding fuel mix and economic structure constant.

Environmentally, energy efficiency plays a central role in the outcome of carbon neutral targets. The International Energy Agency (IEA) estimates that energy efficiency improvements could deliver one-third of the greenhouse gas emissions required to stabilize climate change.[12] However, energy

[8] The municipal-level data for this paper comes from the China City Statistical Yearbook (中国城市统计年鉴), which records data for 276 prefecture-level cities, out of a total of 293 prefecture-level administrative areas as at 2018. The omitted sample is due to the requirement of the total-factor energy efficiency method used by this paper for a balanced dataset. Therefore, all new prefecture-level cities created after 2003 are omitted from the data. The yearbook also omits ten autonomous prefectures, leagues, and prefectures, which are usually set up in ethnic minority areas on China's border regions. These autonomous administrations are nominally governed by ethnic minorities and have different sets of political institutions. Furthermore, the four directly administered municipalities of Beijing, Shanghai, Tianjin, and Chongqing are omitted from the dataset. While they are cities by name, they have province-level status in China's political system and are therefore subjected to a different set of political constrains compared to the prefecture-level cities in the sample.

[9] The other eight HTIDZs are located in Beijing (1), Tianjin (1), Shanghai (2), and Chongqing (4). Two prefecture-level cities have more than one HTIDZ in their jurisdiction. Changchun has two HTDIZs (长春高新技术产业开发区 and 长春净月高新技术产业开发区). Suzhou has three (苏州高新技术产业开发区, 苏州工业园区, and 昆山高新技术产业开发区). All other cities have a maximum of one HTIDZ.

[10] Environmental and Energy Study Institute (2022). 'Energy Efficiency', *EESI.*

[11] US Department of Energy (2022). 'Energy Efficiency vs Energy Intensity', *Office of Energy Efficiency & Renewable Energy.*

[12] IEA & OECD (2018). 'Electric power transmission and distribution losses (per cent of output) dataset', http://data.worldbank.org/indicator/EG.ELC.LOSS.ZS.

efficiency has importance beyond environmental implications. Economically, existing literature has recognized the potential of energy efficiency improvements in driving high-quality development through increasing industrial productivity,[13] improving macroeconomic stability through strengthening energy security,[14] and reducing public expenditure on energy infrastructure, thereby enhancing fiscal balance.[15] Socially, energy efficiency gains alleviate poverty by improving access to energy services,[16] and increasing energy affordability.[17]

Despite the society-wide impact of energy efficiency gains, the existing literature finds significant untapped potential within industrial sectors. In a 2005 report, the IEA calculated that the energy intensity of most industrial processes was at least 50 per cent higher than the theoretical minimum globally.[18] Since then, energy efficiency has improved significantly due to technological or managerial improvements. On one hand, technological innovation such as process improvement,[19] reduction of electrical and mechanical transmission loss,[20] or energy recovery technologies[21] can significantly increase energy efficiency. On the other hand, management and operational optimization can also improve energy efficiency through energy and material management,[22] maintenance investments,[23] and more streamlined industrial management practices.[24]

To measure energy efficiency, this paper uses an economic indicator of total-factor energy efficiency (TFEE). This indicator is different from more traditional measurements of energy efficiency which use GDP divided by energy consumption. While the traditional measurement is more straightforward and is easier to measure, it only considers energy as a single input that produces the economic output, thereby ignoring other key inputs such as capital and labour. Since there is a substitution effect between energy and other inputs, a traditional measurement of energy inputs can lead to misleading estimates.[25] In other words, since energy alone cannot produce outputs, a more sophisticated measurement of energy efficiency taking into account a multiple-input model of energy, capital, and labour can be applied to assess a region's energy efficiency more accurately.[26]

To calculate this multi-input model, this paper uses the data envelopment analysis (DEA) to work out the TFEE. The DEA calculates the amount of inefficient energy usage and computes slack and radial adjustments to produce an index of the TFEE that is constructed as the ratio of the most efficient energy input calculated by the DEA to the actual energy inputs in a region. To obtain the raw data required to calculate the TFEE, this paper uses data from the China City Statistical Yearbook to provide information on each city's factor inputs of labour, capital, and energy for a given year. These factor data are then

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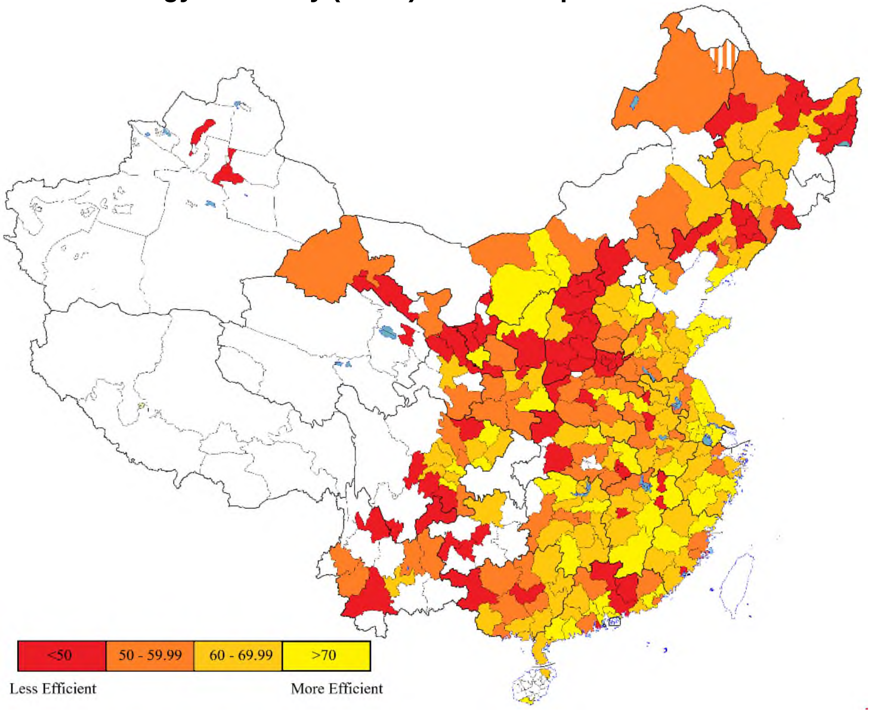
[13] Worrell, E., Laitner, J. A., Ruth, M., and Finman, H. (2001). 'Productivity Benefits of Industrial Energy Efficiency Measures', Ernest Orlando Lawrence Berkeley National Laboratory. http://ies.lbl.gov/iespubs/productivitybenefits.pdf
[14] Kruyt, B., van Vuuren, D. P., de Vries, H.J.M., and Groenenberg, H. (2009). 'Indicators for Energy Security', *Energy Policy*. 37(6), 2166–2181.
[15] Ryan, L., and Campbell, N. (2012). 'Spreading the net: the multiple benefits of energy efficiency improvements', International Energy Agency Report.
[16] Heffner, G., and Campbell, N. (2011). 'Evaluating the Co-benefits of Low-Income Energy Efficiency Programmes', OECD Workshop Report.
[17] Dubois, U., and Meier, H. (2016). 'Energy affordability and energy inequality in Europe: Implications for policymaking', *Energy Research & Social Science* 18, 21–35.
[18] Worrell, E., et al. (2009). 'Industrial energy efficiency and climate change mitigation', *Energy Efficiency* 2(2).
[19] IEA (2006), 'Energy technology perspectives 2006: Scenarios and strategies to 2050', International Energy Agency.
[20] Xenergy, Inc. (1998). 'Evaluation of the US Department of Energy Motor Challenge Program'.
[21] Bergmeier, M. (2003). 'The history of waste energy recovery in Germany since 1920', *Energy*, 28, 1359–1374.
[22] Okazaki, T., Nakamura, M., and Kotani, K. (2004). 'Voluntary initiatives of Japan's steel industry against global warming', paper presented at IPCC Industrial Expert Meeting (ITDT) in Tokyo.
[23] UNIDO (2001). 'Africa industry and climate change project proceedings', UN Industrial Development Organization.
[24] Barats, C. (2005), 'Managing greenhouse gas risk: A roadmap for moving forward', presented at Risk and Insurance Management Society Annual Meeting.
[25] For example, see Hu, J.L., and Wang, S.C. (2006). 'Total-factor energy efficiency of regions in China', *Energy policy* 34(17), 3206–3217.
[26] Zhang, X. P., et al. (2011). 'Total-factor energy efficiency in developing countries', *Energy Policy* 39(2), 644–650.

entered into a DEA software to obtain the TFEE estimates. For a more technical explanation of TFEE and the data used, see Appendix B.

Figure 1: Total-factor energy efficiency (TFEE) in China's prefecture-level cities in 2018



Source: input data from the China City Statistical Yearbook and calculated by the author using the data envelopment DEAP 2.1 tool provided by Coelli (1996).[27] The TFEE indicator is a value between 0 and 100, with 100 being the most efficient.

After obtaining the TFEE scores that allows more meaningful comparison between different Chinese prefecture-level cities with different local socio-economic contexts, this research examines the trends of energy efficiency changes in China at the local level.

3. Energy efficiency and China

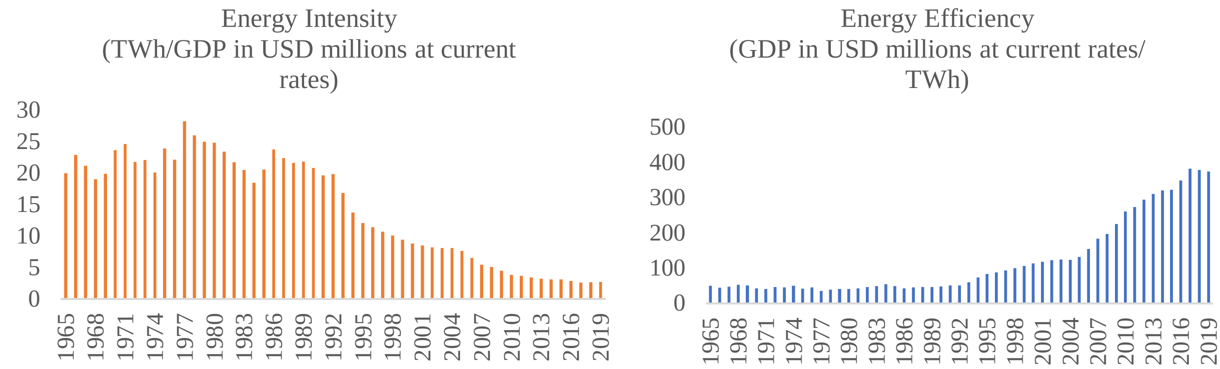
Since market liberalization, which started in the 1980s, China has made significant gains in energy efficiency while maintaining high economic growth. Up to 1979, China followed a Soviet-style energy policy with subsidized energy prices and central planning favouring heavy industry in energy allocation. However, starting from the Sixth Five-Year Plan (1981-1985), China moved towards energy price reform and reducing energy intensity.[28] Subsequent state-directed reform from the 1980s to the 1990s led to greater privatization, creating firms that were more sensitive to energy prices and leading to a rapid adoption of energy-efficient technology. At the same time, the Chinese government made significant gains in driving structural transformation and reducing its reliance on coal by moving to alternative energy sources.[29]

The decline of energy intensity in the 1980s and 1990s was largely due to productivity gains within industries, which were more important in driving efficiency improvements than structural changes in

[27] Coelli, T. (1996). 'A guide to DEAP version 2.1: a data envelopment analysis (computer) program', *Centre for Efficiency and Productivity Analysis, University of New England, Australia* 96(08), 1–49.
[28] Sinton, J. E., Levine, M.D., and Qingyi, W. (1998). 'Energy efficiency in China: accomplishments and challenges', *Energy Policy* 26(11), 813–829.
[29] Andrews-Speed, P. (2009). 'China's ongoing energy efficiency drive: Origins, progress and prospects', *Energy Policy* 37(4), 1331–1344.

China's economy.[30] China made significant improvements during this period, particularly in energy-intensive sectors such as the metallurgy, cement, and oil-processing industries.[31] However, the extent of the efficiency gains varies between regions, with the more economically developed coastal areas driving significant efficiency gains, while those in the western regions experienced slower efficiency improvements.[32]

Figure 2: Energy Intensity and Energy Efficiency in China 1965–2019



Source: data from Our World in Data (2021) and World Development Indicator (2021).

Despite initial efficiency gains, by the 2000s improvements in industrial energy intensity started to deteriorate. Between 2002 and 2005, China experienced a reversal from earlier trends of energy efficiency gains and started to see accelerated energy demands.[33] This was due to a triple factor of (1) the rapid growth of energy-intensive industries causing a structural shift in the economy,[34] (2) lower investment in energy-efficient technologies,[35] and (3) an increase in the share of coal in the energy mix at the expense of other more energy-efficient fuel sources such as oil, gas, and hydroelectricity.[36]

To address these bottlenecks, the national government accelerated existing projects to create knowledge-intensive industrial clusters, which started with the Beijing Zhongguancun National High-Tech Industrial Development Zone, to improve energy efficiency and facilitate industrial upgrades. The Ministry of Science and Technology describes HTIDZs as 'a major strategic plan made by the Party leadership and the State Council' to 'adjust industrial structure, drive traditional industrial transformation, and increase international competitiveness'.[37] Businesses in the HTIDZs are supposed to be 'innovation driven' with 'private enterprises'.[38] These industrial zones help to alleviate the first two limiting factors mentioned above by driving structural transformation through the establishment of knowledge-based industries with low energy intensity, and by encouraging spillover effects facilitating the adoption of energy-efficient technologies within these industrial clusters.

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[30] Fisher-Vanden, K., et al. (2004). 'What is driving China's decline in energy intensity?', *Resource and Energy Economics* 26(1), 77–97.
[31] Andrews-Speed, P. (2009). 'China's ongoing energy efficiency drive: Origins, progress and prospects', *Energy Policy* 37(4), 1331–1344.
[32] Hu, J. L., and Wang, S.C. (2006). 'Total-factor energy efficiency of regions in China', *Energy Policy* 34(17), 3206–3217.
[33] Naughton, B.J. (2006). *The Chinese economy: Transitions and growth*. MIT Press.
[34] Liu, M., and Zhu, L. (2006). 'A study on coordinated growth among industry structure adjustment, energy supply and consumption in China', *Energy of China* 28(1), 11–14.
[35] Lin, J. (2007). 'Energy conservation investments: A comparison between China and the US', *Energy policy* 35(2), 916–924.
[36] Han, Z. Y., et al. (2007). 'Energy structure, marginal efficiency and substitution rate: An empirical study of China', *Energy* 32(6), 935–942.
[37] MOST. 2021. High-Tech Industrial Development Zones. *Ministry of Science and Technology of the People's Republic of China*. Available at: http://www.most.gov.cn/gxjscykfq
[38] Ibid.

The projects for industrial clusters were further strengthened during subsequent national economic plans. The Eleventh Five-Year Plan (2006–2010), aimed to reduce energy intensity by 20 per cent in 5 years through strong monitoring channels of industrial energy use, financial incentives, information services, education and training programmes, and research and development investments into industrial zones.[39] The Twelfth Five-Year Plan (2011–2015) placed a greater focus on industrial upgrading. The plan targeted large industrial companies, aiming to phase out inefficient industries, and support higher energy productivity through industrial clustering. By 2022, 169 HTIDZs had been established across China.

Looking at China's experience with these HTIDZs, how effective have these industrial clusters been in driving energy efficiency gains, particularly in inland regions, given China's wide regional disparity in energy efficiency?

4. Industrial clusters and energy efficiency

The existing literature views industrial clusters as networks of production that form within a spatial location, where the agglomeration of firms and institutions helps to create forms of commonality and improve the frequency and impact of interactions.[40] Industrial clusters usually have three important attributes. First, they create economic linkages among cluster firms owing to their geographical proximity. Second, individual firms within industrial clusters share forms of commonality, such as access to specialized factors, supply of intermediate products, infrastructure, and cultural embeddedness, all of which create a common stock of knowledge that is shared and embedded within the cluster. Lastly, clusters often create interaction that reflects the acquisition of knowledge, and the sharing, diffusion, and creation of technology.[41]

From an economic standpoint, industrial clusters take advantage of economies of scale to reduce transaction costs, search costs, and learning costs.[42] As a policy tool, industrial clusters play a major role in transforming the rules of industrial competition.[43] Instead of focusing solely on large enterprises in driving national industrial upgrading, geographical clusters of firms can promote a competitive environment that drives long-term economic growth.

Looking at the experience of industrial agglomerates in China, industrial clusters have the potential to improve energy efficiency through three main mechanisms.

First, industrial clusters enhance the ability of firms to maximize their efficiency of scale. Firms within an industrial cluster benefit from access to an improved infrastructure and a supply network that helps them to achieve increasing returns to scale of energy factors,[44] thereby improving the energy efficiency of their production process. In cities that are promoting industrial upgrading into less energy-intensive sectors, industrial clusters can quickly achieve the scale in these new sectors to allow firms to become profitable and transition away from their previous industrial production structure.

Second, industrial clusters create technology spillover effects by building diffusion networks, thereby facilitating inter-industry technology spillover.[45] Economists find that a greater density of industrial firms in an area increases the process of learning, thereby building stronger capacity for technological

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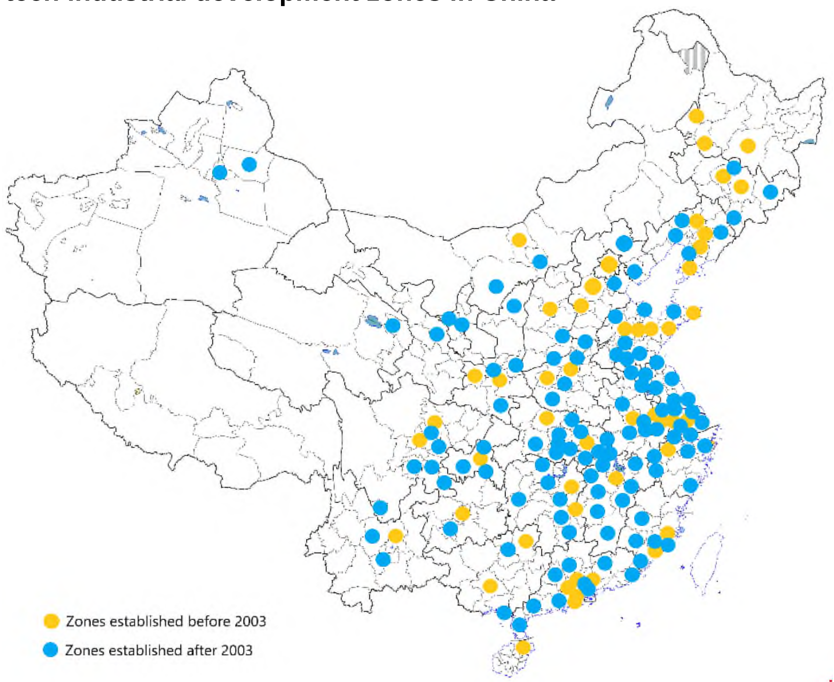
[39] Zhou, N., Levine, M., and Price, L. (2010). 'Overview of current energy-efficiency policies in China', *Energy Policy* 38(11), 6439–6452.
[40] Porter, M. (2011). *Competitive advantage of nations: creating and sustaining superior performance*, Simon and Schuster.
[41] Guo, B., and Guo, J. (2011). 'Patterns of technological learning within the knowledge systems of industrial clusters in emerging economies: Evidence from China', *Technovation* 31(2–3), 87–104.
[42] Greenwald, B., and Stiglitz, J. (1986). 'Externalities in economies with imperfect information and incomplete markets', *The Quarterly Journal of Economics* 101(2), 229–264.
[43] Giuliani, E. (2007). 'The selective nature of knowledge networks in clusters: evidence from the wine industry', *Journal of Economic Geography* 7(2), 139–168.
[44] Krugman, P. (1991). 'Increasing returns and economic geography', *Journal of political economy* 99(3), 483–499.
[45] Pan, W., Yang, D., and Lin, M. (2012). 'Inter-industry Technology Spillover Effects in China: Evidence from 35 Industrial Sectors', *China & World Economy* 20(2), 23–40.

innovation.[46] In this way, different firms within an industrial cluster benefit from knowledge diffusion, thereby lowering the information costs associated with more energy-efficient technologies and facilitating their adoption. These observations have been supported by studies drawing on the concept of 'social capital', where industrial clusters create social networks that improve trust, reliability, and information, which ultimately help clustered organizations to secure resource complementarity through cooperation and communication.[47] Furthermore, beyond the spillover effect from greater social interactions, industrial clusters drive inter-industry productivity gains through network organization independent of production factor allocation such as capital and labour.[48] Existing literature has found that even with the same factor endowments, a more optimal spatial organization of firms can increase their productive capabilities.[49] In other words, even with no changes in employees or investment patterns, simply by moving firms closer to one another can, as empirical evidence shows, change their positionality within the productive network and in turn improve their productive patterns. In this way, industrial clusters can help create an efficient spatial distribution of firms that help them improve the production process and lower their energy efficiency.

Lastly, industrial clusters increase competition between firms, forcing them to adopt more efficient technology that reduces their energy intensity. Industrial clusters create a setting of 'imperfect competition', where firms compete with each other in both price and differentiated products.[50] This setting can increase the incentive for firms to invest in energy-saving technologies to improve their production process, thereby becoming more competitive in the market.

Figure 2: High-tech industrial development zones in China



Source: data from the China City Statistical Yearbook and drawn by the author. The figure shows the location of 169 HTIDZs in China as at 2022. Yellow dots represent zones established prior to the sample years used in this paper from 2003. Blue dots represent zones established during the sample years in this paper from 2003 to 2018.

[46] Duranton, G., and Strange, W. (1986). *Handbook of regional and urban economics: applied urban economics Volume 3*. Elsevier.

[47] Putnam, R (1993). *Making democracy work: Civic traditions in modern Italy*, Princeton, NJ: Princeton University Press.

[48] Capello, R. (2015). *Regional economics*, Routledge.

[49] Capello, R. (2015). *Regional economics*, Routledge.

[50] Cohen, F., Glachant, M., and Söderberg, M. (2017) 'Consumer myopia, imperfect competition and the energy efficiency gap: Evidence from the UK refrigerator market', *European Economic Review* 93, 1–23.

These impacts are not limited to firms within the industrial zones, but instead extend beyond the zones' boundaries. This is because industrial zones account for a significant portion of industrial activity in an area, and can cause gains to diffuse through its linkages with the rest of the economy. For example, the HTIDZ in Zhuzhou, an average-size inland city in China's Hunan Province, accounts for around 22 per cent of the total number of industrial firms above a designated size,[51] and around 13 per cent of the total fixed assets of industrial firms in the city districts.[52] New technology or best practices acquired by these firms can then travel through their supply networks to the wider economy. On top of this direct channel, diffusion can occur indirectly since these HTIDZs provide tour visits and invite media reports, which further help to publicize best practices, thereby extending energy efficiency gains to firms outside of the zones' boundaries.

However, despite these positive impacts of industrial clusters, excessive agglomeration of industrial capacity may also have a negative impact on energy efficiency. The existing literature finds that excessive agglomeration increases the price of factors of production, leading to higher land rents and higher labour costs, which decrease the firms' abilities to invest in energy-efficient technology. In this way, by crowding in firms, excessive agglomeration can burden them with additional costs that may decrease their investment capability.[53] Furthermore, greater agglomeration can also cause excessive competition between firms producing similar products, leading to overcapacity and further weakening firms' incentives to invest in technology to lower their energy intensity.

Thus, industrial clusters can have important but ambiguous effects on regional energy efficiency. Looking at the impact of the 169 HTIDZs can help understand the way industrial clusters drive energy efficiency changes across the different regions in China. Understanding the role of industrial clusters can be especially important in the context of China's inland regions, which currently lag behind in energy efficiency and have significant potential to catch up on the energy efficiency of their counterparts in China's coastal regions. The section below analyses the impact of industrial clusters across four different dimensions.

5. Regional variations and industrial clusters

To understand the impact of HTIDZs in China, one needs to take into account the high regional variation between different regions. This study looks at a sample of 275 prefecture-level cities out of a total of 299 such administrative divisions. The cities in the sample are selected based on reliable data reporting during the years 2003–2018 to offer a balanced dataset for analysis.

Given China's wide regional variations in local conditions, this research considers the role of industrial clusters in driving energy efficiency gains at the local level given four dimensions: (1) levels of economic development, (2) industrial structure (3) energy mix, and (4) local technological capability. This research looks at each dimension in turn to examine the mechanisms of how national HTIDZs can impact energy efficiency gains across regional variations in that factor. It then uses a series of statistical regressions to verify the mechanisms.

5.1 Level of economic development

China has an unequal distribution of economic development at the city level. Generally, China's coastal regions enjoy higher GDP per capita than that of its inland cities. The level of energy efficiency correlates with regional economic differences in the country. As the graph below shows, there is a positive correlation between the level of economic development, measured by GDP per capita, and the level of TFEE in the 275 prefecture-level cities in the sample. The relation is not statistically significant at the 10 per cent level, with a p-value of 0.263 and an adjusted R-square of 0.1268.

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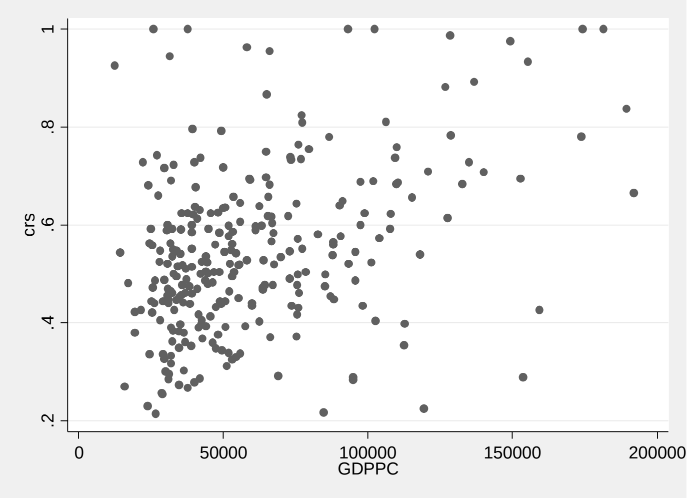
[51] Defined by China's Statistics Bureau as firms with an annual revenue above CNY 20 million (USD 3 million). For example, see: http://gxt.shandong.gov.cn/col/col15232/index.html

[52] Data obtained by author using Chinese government reports.

[53] Brülhart, M., and Mathys, N.A. (2008). 'Sectoral agglomeration economies in a panel of European regions.' *Regional Science and Urban Economics* 38(4), 348–362.

Figure 3: TFEE and GDP per capita in prefecture-level cities (2018)



Source: data from the China City Statistical Yearbook and prepared by the author. The y-axis represents a TFEE ranging from 0 to 1. The x-axis represents the GDP per capita of prefecture-level cities in China. The figure shows a positive relationship between the GDP per capita and the TFEE.

The level of economic development can impact energy efficiency in two ways. First, the Porter hypothesis predicts that regions with higher levels of economic development can have stricter environmental regulations that facilitate the adoption of more innovative technology. Firms invest in more energy-efficient technology to compensate for the compliance cost associated with environmental regulations, thereby increasing their energy efficiency during production.[54]

Second, similar to the Porter hypothesis, the pollution haven hypothesis claims that energy-intensive industries relocate from regions with higher economic development and therefore more environmental regulations to regions that are less developed and have fewer regulations.[55] The relocation of industry thus creates a reallocation of industry that further improves the energy efficiency of the richer coastal regions at the expense of the inland regions.

Both of these theories assume that higher levels of economic development are associated with stronger environmental regulations. This assumption has been supported by empirical data from China, which suggests that there is considerable variation in environmental regulation between regions[56] and that Chinese firms have taken advantage of this regulatory disparity to relocate their energy-intensive firms, often from more developed coastal regions to less developed inland and western regions.[57] The exodus of energy-intensive firms from coastal to inland regions accelerated in particular after 2005.[58]

In terms of the role of industrial clusters, the theories mentioned above suggest that regions with high levels of economic development will already benefit from greater adoption of innovative technology. Therefore, the agglomeration effect of industrial clusters can be greater in regions with lower levels of

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[54] Shapiro, M. A. (2014). 'Regionalism's challenge to the pollution haven hypothesis: a study of Northeast Asia and China', *The Pacific Review* 27(1), 27–47.

[55] Dou, J., and Han, X. (2019). 'How does the industry mobility affect pollution industry transfer in China: Empirical test on Pollution Haven Hypothesis and Porter Hypothesis', *Journal of cleaner production* 217, 105–115.

[56] Zhang, J., and Fu, X. (2008). 'FDI and environmental regulations in China', *Journal of the Asia Pacific Economy* 13(3), 332–353.

[57] Liu, L. (2013) 'Geographic approaches to resolving environmental problems in search of the path to sustainability: The case of polluting plant relocation in China', *Applied Geography* 45, 138–146.

[58] Yao, S., Luo, D., and Rooker, T. (2012) 'Energy efficiency and economic development in China', *Asian Economic Papers* 11(2), 99–117.

economic development since they have more room to benefit from the increase in innovative capacity. Therefore, the theory leads to the hypothesis:

Hypothesis 1: Industrial clusters are more effective in improving energy efficiency in municipalities with lower economic development due to greater potential in innovation gains.

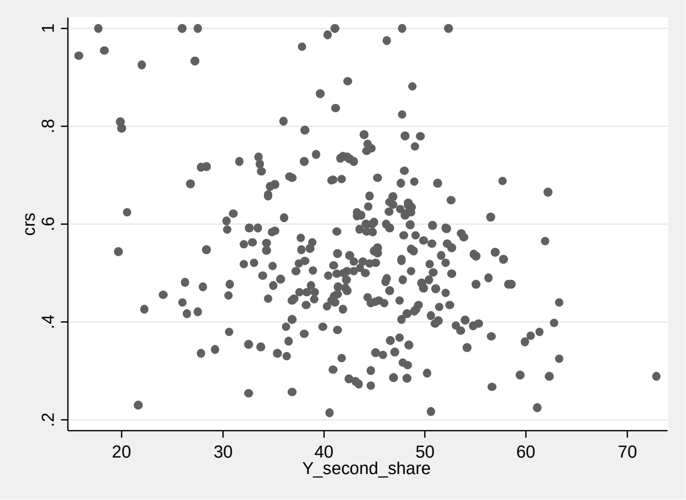
5.2 Industrial structure

Another key determinant of energy efficiency is the region's industrial structure. Since there is a large difference in productivity between industries, when the allocation of energy changes from a low productivity industry to a high productivity industry, this structural adjustment can improve the region's total energy efficiency.[59] Generally, existing studies have found that energy efficiency is negatively correlated with the share of secondary industry as a percentage of GDP,[60] as shown in the figure below. In the data used in this paper, there is a strong statistical correlation between the share of secondary industry and energy efficiency, significant at the 1 per cent level. The R-square is 0.3397.

Even between different types of industries, there is a significant variation in energy intensity of production. Out of more than 40 industrial subsectors in China, eight subsectors alone account for 35 per cent of industrial output and 60 per cent of the energy consumption. These subsectors are non-metallic mineral products, petroleum, coking, nuclear fuel, paper and paper products, ferrous and non-ferrous metals, metal products, textiles, and chemical products.[61]

In terms of regional variation, China's coastal regions generally have a higher level of secondary industry share as part of the economy compared with the northeast and western regions, which have lower degrees of industrialization. However, many coastal cities have also transitioned to a greater share of the service sector, thereby changing their industrial clusters by phasing out energy-intensive industries.

Figure 4: TFEE and share of secondary industry in GDP in prefecture-level cities (2018)



Source: data from the China City Statistical Yearbook and prepared by the author. The y-axis represents a TFEE ranging from 0 to 100. The x-axis represents the share of secondary industry output as a percentage of total GDP output of the prefecture-level city as a percentage. The figure shows a negative relationship between a higher share of secondary industry and the TFEE.

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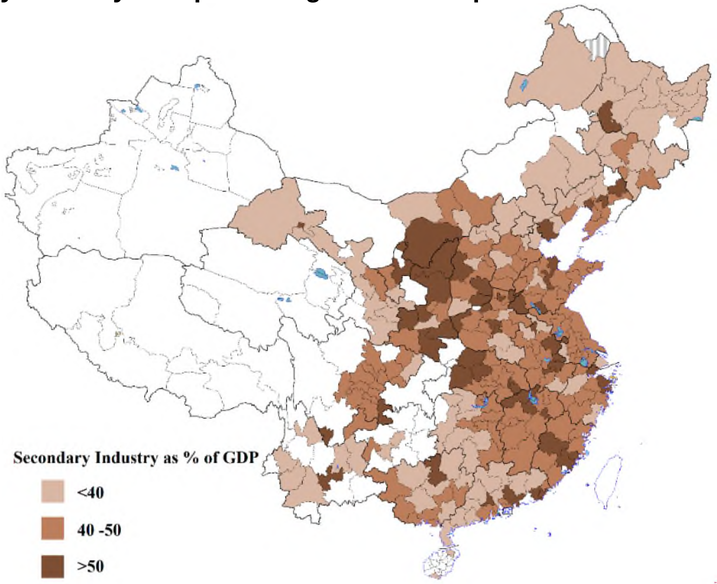
[59] Liu, J., Cheng, Z., and Zhang, H. (2017). 'Does industrial agglomeration promote the increase of energy efficiency in China?', *Journal of Cleaner Production* 164, 30–37.
[60] Wei, C., Ni, J., and Shen, M. (2009). 'Empirical analysis of provincial energy efficiency in China', *China & World Economy* 17(5), 88–103.
[61] Yao, S., Luo D., and Rooker, T. (2012). 'Energy efficiency and economic development in China', *Asian Economic Papers* 11(2), 99–117.

Figure 5: Secondary industry as a percentage of GDP in prefecture-level cities (2018)



Source: data from the China City Statistical Yearbook and drawn by the author. The figure shows the share of secondary industry as a percentage of GDP in 275 prefecture-level cities in China.

Looking at the impact of industrial clusters, agglomeration effects can be more effective in regions with a high share of secondary industry. In regions with a strong manufacturing base, industrial clusters push for industrial upgrading and greater knowledge-intensive sectors, thereby improving energy efficiency. Thus the hypothesis for this factor is:

Hypothesis 2: Industrial clusters are more effective in improving energy efficiency in municipalities with a higher share of secondary industry as a percentage of GDP, due to their higher manufacturing base that can benefit more from industrial upgrading.

5.3 Energy mix and energy price

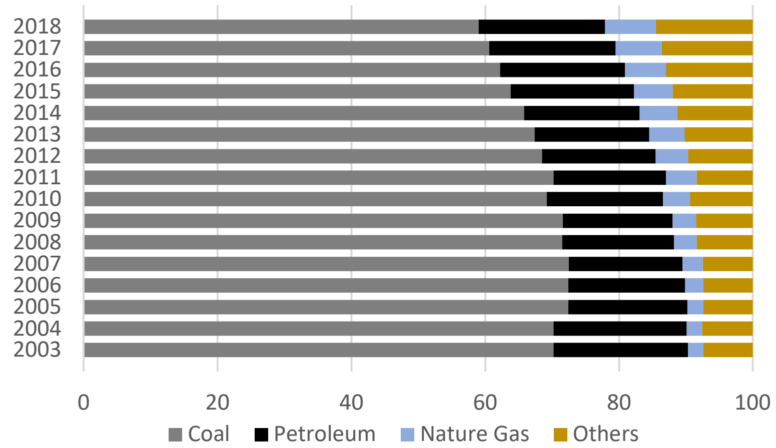
At the national level, China's energy mix is heavily dependent on coal. However, China has experienced a slow transition away from coal as the dominant source of total energy consumption, dropping from 70 per cent to 59 per cent between 2003 and 2018.[62] Meanwhile, the country has experienced rapid growth of gas and hydro power as a share of total energy consumption, while simultaneously developing alternative energy sources, especially wind and solar, to help reduce its reliance on coal.

At the regional level, China's northern provinces are particularly reliant on coal as a source of energy. This reliance is partly due to a strong endowment of coal reserves, where the four northern provinces of Shanxi, Inner Mongolia, Xinjiang, and Shaanxi alone account for 70 per cent of the national coal reserves.[63]

[62] Sourced from the China Energy Statistical Yearbook 2019. The figures have been calculated using a coal equivalent calculation.

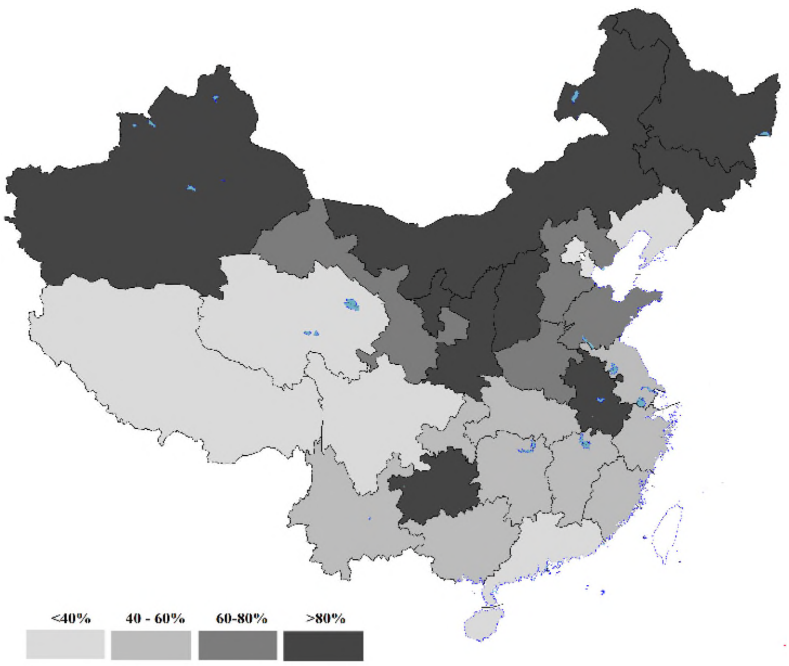
[63] Jiang, P., Yang H., and Ma, X. (2019). 'Coal production and consumption analysis, and forecasting of related carbon emission: evidence from China', *Carbon Management* 10(2), 189–208.

Figure 6: Energy mix in China for primary energy consumption (2003–2018)



Source: data from the China Energy Statistical Yearbook and prepared by the author. The figure shows the change in energy mix for primary energy consumption between 2003 and 2018, with a steady decrease in coal and an increase in natural gas and alternative renewable energy sources in the energy mix.

Figure 7: The share of coal as the primary source of energy in Chinese provinces (2018)



Source: data from the China Energy Statistical Yearbook and prepared by the author. The figure shows the percentage of coal as the source of primary energy consumption in Chinese provinces.

Since the 1980s, two major trends in China's energy mix have helped drive down its energy intensity. First, the reduction of coal's share in the primary energy supply helped to improve energy efficiency, since coal has lower conversion efficiency compared to alternative sources of energy, such as natural gas or hydropower sources.[64] Second, China's industrial sector has increased the share of electricity in end usage instead of drawing on primary energy sources for end usage.[65] This complements China's energy mix transition to drive down energy intensity. Therefore, regions with a lower dependency on coal should have higher energy efficiency.

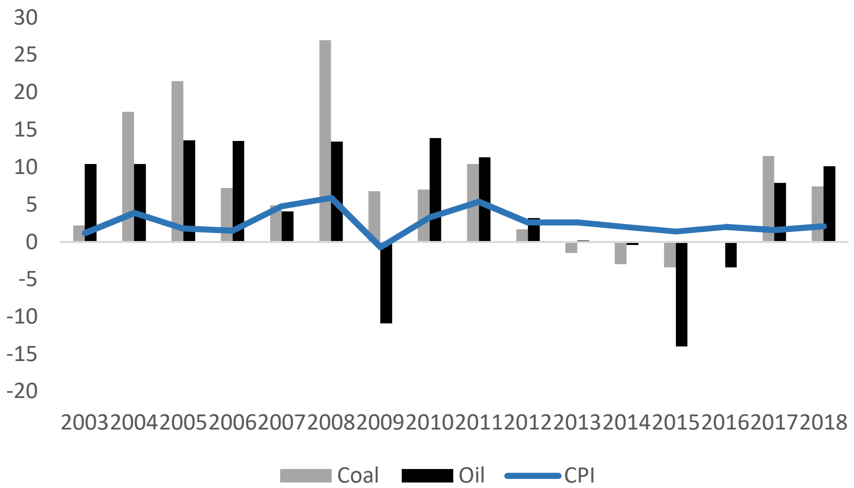
Furthermore, the energy price also plays a role in pushing for energy efficiency gains. When energy prices are high, firms have greater returns from investing in energy abatement technology that reduces the cost of energy inputs. In China, coal and oil prices have largely moved together, with high increases in energy prices before 2009, and a drop in energy prices between 2013 and 2017.

Given these dynamics, this research predicts that industrial clusters can be more effective in cities experiencing high energy prices. These clusters' knowledge spillover is potentially more powerful during periods of high energy prices, since firms have more incentives to adopt more energy-efficient technology given the high cost of energy. However, since firms are unlikely to play a major role in deciding the energy mix in their region, industrial clusters should not discriminate between regions with varying dependency on coal.

Hypothesis 3: Industrial clusters are more effective in improving energy efficiency in regions with higher energy prices due to a greater return to investment in energy abatement technology.

Hypothesis 4: Industrial clusters should not discriminate between regions with a higher dependency on coal since firms play a limited role in deciding the region's energy mix.

Figure 8: Annual change of coal and oil prices in China (2003–2018)



Source: data from the China Energy Statistical Yearbook and prepared by the author. The figure shows the year-to-year change in the price of coal and oil in China between 2003 and 2018. The change in CPI, a proxy for inflation, is included to compare the change in overall prices in the economy.

5.4 Technical human capital

Existing studies suggest that the level of human capital plays a role in energy efficiency changes.[66] At the industry-level, higher proportions of people with technical education are associated with energy efficiency improvements. This can occur through two channels. First, firms with higher education levels

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[64] Song, C., et al. (2015). 'A data envelopment analysis for energy efficiency of coal-fired power units in China', *Energy Conversion and Management* 102, 121–130.

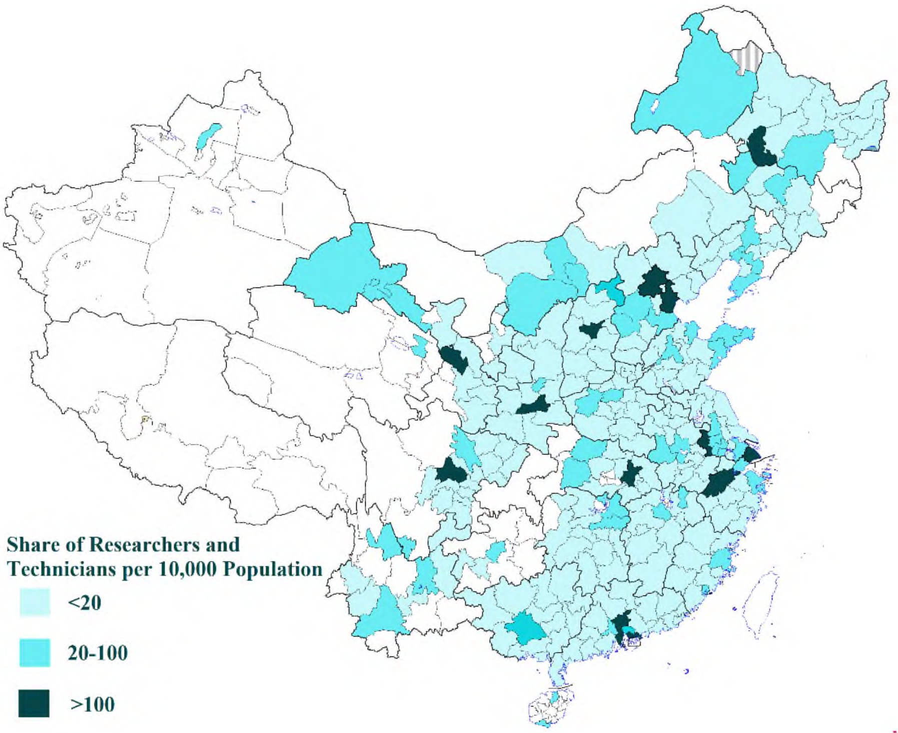
[65] Andrews-Speed, P. (2009). 'China's ongoing energy efficiency drive: Origins, progress and prospects', *Energy Policy* 37(4), 1331–1344.

[66] Salim, R., Yao, Y., and Chen, G.S. (2017). 'Does human capital matter for energy consumption in China?', *Energy Economics* 67, 49–59.

facilitate the adoption of existing energy-efficient technologies.[67] In a world with imperfect information, firms may not always adopt the most up to date technologies, even if these existing technologies save energy and help increase the firm's profit. Therefore, industrial firm employees with better technical know-how can help to identify these new technologies and facilitate their adoption. To this end, the International Energy Agency estimates that the full adoption of technology can reduce global primary energy consumption from 18 to 26 per cent, and improved human capital can help to realize this potential.[68]

Second, other than adopting existing technologies, higher human capital facilitates the innovative capacity of industrial firms to improve their production efficiency through process innovation. This occurs through learning-by-doing, on-the-job training, and experience. Firms with more researchers and technicians can in turn take advantage of these mechanisms to improve their production processes and energy efficiency.

Figure 9: Researchers and technicians as a share of the total population in prefecture-level cities (2018)



Source: data from the China City Statistical Yearbook and prepared by the author. The figure shows the number of people employed as researchers or technicians, calculated based on the city's total population. The figure shows a high share of researchers and technicians, proxy for technical human capital, in provincial capitals. It also shows an unequal distribution of technical human capital between core provincial capitals and more peripheral provincial cities.

Industrial clusters in turn build on these two mechanisms. As mentioned in the previous section, the agglomeration effect of industrial clusters helps to create channels to facilitate technology spillover and enhances competition, leading to process innovation. Therefore, industrial clusters in regions with

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[67] Li, K., Lin B. (2016). 'Impact of energy technology patents in China: evidence from a panel cointegration and error correction model', *Energy Policy* 89, 214–223.

[68] IEA (2008). 'Worldwide trends in energy use and efficiency', *Iea. Org*.

higher human capital can take better advantage of these mechanisms and enhance its effectiveness in pushing for energy efficiency gains.

One challenge with measuring human capital is that indicators of human capital sometimes overemphasize years of schooling or university education, thereby glossing over variations in education quality, as well as favouring formal university training over vocational education.[69] However, vocational and technical training play crucial roles in the actual learning-by-doing and technological adoption mechanisms of achieving energy efficiency.

Therefore, this study defines human capital as the number of researchers and technicians employed in a municipality. Unfortunately, there is no disaggregated data between these two employment types. But this indicator is a good proxy for the technical capacity of the municipality both to adopt existing technologies, and to innovate and improve through learning-by-doing. Based on these considerations, this research advances the final hypothesis that:

Hypothesis 5: Industrial clusters are more effective in improving energy efficiency in municipalities with higher technical human capital, due to their better capacity to adopt existing energy-efficient technologies and to improve production efficiency through new innovation.

6. Findings: industrial clusters improve energy efficiency in regions with higher technical human capital

This study employs the data of 275 cities between 2003 and 2018 to measure their relationship with energy efficiency. Interaction variables are used for each of the four factors mentioned above to measure how the combination of industrial clusters and that specific factor impact energy efficiency.

Statistical analysis shows that the presence of an industrial cluster does not have a statistically significant relationship with energy efficiency, suggesting that an industrial cluster by itself is not sufficient to improve energy efficiency. Appendix A reports the regression results of a fixed effects model looking at prefecture-level municipalities in a sample over the 2013–2018 period. Regression (1) provides a baseline estimate of the correlation between the TFEE energy efficiency score and industrial zone, controlling for city population and whether or not the city is in a coastal region. The result shows that the presence of industrial clusters alone does not have a statistically significant correlation with energy efficiency levels.

Regression (2) adds in the four regional variation variables considered in this paper, using the logarithm of GDP per capita and its square to allow for non-linear relations, secondary industry share of GDP, share of coal in energy consumption as well as the price of coal, and the number of researchers and technicians per capita and its square to allow for non-linear relations. The control variables from regression (1) are also included. The result shows that other than GDP per capita, the other three variables have a statistically significant negative relation with energy efficiency levels.

Regression (3) to regression (6) consider each of the four regional variation variables in turn, but also adding in interaction variables between the regional variation variables and whether there is an industrial zone present. The control variables from regression (1) are also included. The inclusion of these interaction variables help to gauge the role industrial zones play for each of these variables. The results show that only the researcher and technician per capita interaction variable are statistically significant. This shows that given the higher per capita numbers of researchers and technicians, the presence of an industrial zone increases energy efficiency levels.

Regression (7) includes all regional variation variables, their interaction variables, and the control variables. The results show that the observation from regression (6) on per capita researchers and

[69] Benos, N., and Zotou, S. (2014). 'Education and economic growth: A meta-regression analysis', *World Development* 64, 669–689.

technicians is still statistically significant, thereby showing that the relation between the per capita number of researchers and technicians and energy efficiency is robust.

Overall, the results show that out of the four factors discussed in this paper, only the technical human capital of the municipality has a strong positive relationship with energy efficiency. Even after controlling for GDP per capita, whether the municipality is in a coastal region, and other socio-economic indicators, the number of researchers and technicians per capita still has a statistically significant relationship with energy efficiency. Furthermore, this relationship is convex, suggesting an increasing return to scale of technical human capital to energy efficiency. In other words, a one unit increase in technical human capital improves energy efficiency by more than one unit.

The results suggest that local technical capability matters for industrial clusters to realize their intended energy efficiency gains. Without technical human capital to adopt existing energy-efficient technology and innovate through on-the-job learning-by-doing, industrial clusters might not always be able to achieve energy efficiency results.

Therefore, while HTIDZs offer an opportunity to increase energy efficiency, it is not a sufficient condition to do so. Energy efficiency increases through technological know-how, and combining available technology with existing production procedures. Without the technical human capital to facilitate this transformation, policy alone does not always achieve the results.

As the finding suggests, technical human resources matter. However, China's human resources are not evenly distributed. Technical human capital tends to be concentrated in the provincial capitals. However, the industrial areas outside the provincial capitals with high potential for energy efficiency improvements are also the ones with the fewest researchers and technicians working in their area. This inequality of human capital is not unique to China. Many other parts of the world, such as the United Kingdom, also see a concentration of human resources in a specific region while other peripheral regions lag behind.[70] Nonetheless, this heavy concentration of technical human capital remains one of the major hurdles for China's energy efficiency future. Without a more equitable distribution of technological talents, China might have difficulty realizing gains in many of its regions with the highest potential for energy efficiency improvement. Even with national policies such as HTIDZs, China might still have trouble developing knowledge-intensive industries in certain areas.

7. Conclusion: industrial clusters and China's energy efficiency future

Given President Xi's pledge to achieve carbon neutrality by 2060,[71] China requires major improvements to its energy efficiency to lower energy intensity while still sustaining economic growth. Industrial policies, such as HTIDZs, can be key to drive industrial upgrading and realize China's energy efficiency potential. However, industrial policy itself might not always be enough if the relevant local technical human capital is not present.

This conclusion points to a major hurdle in China's current energy efficiency transition. Since 'reform and opening-up', China's economic growth has been highly unbalanced. National industrial policy concentrated resources in a few urban centres while growth trickled down from provincial capitals to regional towns, and from coastal areas to inland cities. So far, this top-down approach has been successful in lifting millions out of poverty. But this strategy has also created an imbalance in China's human resources and local technological infrastructure. China's provincial capitals have high levels of socio-economic development, allowing them to employ a high number of talented technical staff and giving regional capitals an advantage in reaping the benefits of industrial policies to push for industrial upgrades. By contrast, cities outside of China's provincial capitals can find it difficult to attract and retain

[70] Coyle, D., and Sensier, M. (2019). 'The imperial treasury: appraisal methodology and regional economic performance in the UK', *Regional Studies*.
[71] Myers, S.L. (2020). 'China's Pledge to Be Carbon Neutral by 2060: What It Means', https://www.nytimes.com/2020/09/23/world/asia/china-climate-change.html

technical human capital, thereby struggling to improve energy efficiency even though they have high energy gain potential.

As mentioned before, this dynamic is not unique to China. Across developing and developed countries, human resources tend to concentrate in a few major cities, while more minor towns struggle to attract talent and employ a large pool of researchers and technicians. However, this dynamic has been especially true for China, given the unequal pace of economic development. To achieve the stated purpose of HTIDZs to 'adjust industrial structure, drive traditional industrial transformation, and increase international competitiveness',[72] the impact of industrial clusters may depend on local technical human capital. Therefore, the implementation of HTIDZs should be preceded or accompanied by the boosting of local education and training facilities. While industrial clusters can play a role in facilitating better spatial organization of firms, the task of long-term energy efficiency gains across China's regions may be difficult if policies focus solely on the 'hardware' of industrial clusters, on industrial structures, and infrastructure, without consideration for the 'software' of human capital.[73]

This finding ultimately suggests that China might need to address its institutional imbalance to realize energy efficiency gains. Energy efficiency touches on a wider institutional challenge for China. Industrial policy provides an opportunity for local players to realize energy efficiency potentials. But without other necessary conditions, some cities might struggle with energy efficiency gains, even with significant policy support from central government.

[72] MOST (2021). High-Tech Industrial Development Zones. *Ministry of Science and Technology of the People's Republic of China*. Available at: http://www.most.gov.cn/gxjscykfq

[73] Hove, A., Meidan, M., and Andrews-Speed, P. (2021) *Software vs. Hardware: how China's institutional setting helps and hinders the clean energy transition,* Oxford Institute for Energy Studies.

Appendix A: Regression results

			Industrial Cluster as Interaction Variable				
VARIABLES	(1) Energy Efficiency	(2) Energy Efficiency	(3) Energy Efficiency	(4) Energy Efficiency	(5) Energy Efficiency	(6) Energy Efficiency	(7) Energy Efficiency
Presence of industrial zone	0.0126 (0.0132)	0.00481 (0.0117)	-0.558 (1.332)	-0.0517 (0.0538)		-0.0350** (0.0177)	-0.894 (1.326)
Regional variation variables							
log (GDP per capita)		-0.0542 (0.174)	-0.316** (0.144)				0.0640 (0.189)
log (GDP per capita) square		0.00675 (0.00845)	0.0146** (0.00692)				0.00127 (0.00900)
Secondary industry share of GDP		-0.00759*** (0.000943)		0.00683*** (0.000802)			0.00771*** (0.000982)
Share of coal in final energy consumption		0.196** (0.0849)			-0.879* (0.485)		0.190** (0.0853)
Price of coal		-0.00122*** (0.000375)			-0.00286 (0.00257)		-0.000249 (0.000485)
# of researcher & technicians per capita		-20.06** (8.722)				-39.89*** (12.91)	-42.55*** (11.93)
# of researcher & technicians per capita square		745.8** (346.1)				2,281*** (735.6)	2,057*** (639.5)
Interaction variables							
Industrial zone*log (GDP per capita)			0.0624 (0.253)				0.111 (0.257)
Industrial zone*log (GDP per capita) square			-0.000935 (0.0121)				-0.00318 (0.0124)
Industrial zone*secondary industry share of GDP				0.00121 (0.000998)			0.000967 (0.000850)
Industrial zone*share of coal in final energy consumption					-0.111 (0.295)		-0.0104 (0.0486)

Industrial zone * price of coal					0.00887 (0.00890)		-0.00404** (0.00195)
Industrial zone* # of researcher & technicians per capita						36.24*** (10.55)	22.68** (9.513)
Industrial zone* # of researcher & technicians per capita square						-1,926*** (650.0)	-1,422** (562.1)
Control variables							
Population	-4.87e-05 (0.000154)	-7.30e-05 (0.000116)	-0.000152 (0.000153)	-5.50e-05 (0.000139)	-4.48e-06 (0.000180)	-0.000155 (0.000146)	-0.000121 (0.000119)
City in coastal region	0.224*** (0.0328)	0.196*** (0.0289)	0.247*** (0.0335)	0.228*** (0.0294)	0.0376 (0.147)	0.237*** (0.0310)	0.194*** (0.0277)
Constant	0.343*** (0.0115)	0.530 (0.914)	2.025*** (0.744)	0.669*** (0.0395)	3.263*** (0.570)	0.398*** (0.0196)	-0.0390 (0.993)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,397	4,369	4,381	4,391	4,400	4,386	4,369
R-squared	0.759	0.792	0.768	0.782	0.884	0.763	0.796

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix B: Total-factor energy efficiency (TFEE) and data envelopment analysis (DEA)

As mentioned above, this paper uses an economic indicator of the TFEE which measures energy efficiency given three inputs of energy, labour, and capital. To measure this multi-input indicator, the paper uses the DEA calculator DEAP 2.1 developed by Coelli (1996).[74] This appendix explains the technical aspects of the DEA and how the TFEE is calculated.

Data for the calculation comes from China City Statistical Yearbooks for the years 2003–2018. The yearbook is published by the Chinese Statistics Bureau on an annual basis and contains data disaggregated at the city level for various economic and environmental indicators. The following data is extracted from the yearbooks for the TFEE calculations:

Table 1: Summary statistics of data extracted

Factor	English Name	Chinese Name	Unit	Mean	Max	Min
Y	Local total GDP	地区生产总值	CNY 10 000	1.47e+07	317731	2.42e+08
	GDP share of secondary industry	第二产业占GDP比重	%	48.12	9	90.97
K	Total fixed assets	固定资产净值	CNY 10 000	7035273	18750	1.20e+08
L	Persons employed in urban units at year end	单位从业人数	10 000 persons	44.11	4.05	613.54
	Share of secondary industry in employment	第二产业从业人员比重	%	43.92	4.46	84.4
E	Industrial electricity usage	工业用电量	10 000 kWh	560914.5	1016	1.23e+07

Using the data above, factor endowments for each city in a given year are then calculated. For capital (K) and energy I, the paper uses the corresponding data from the yearbook. For output (Y), the observations are obtained by multiplying the total GDP by the GDP share of secondary industry. For labour (L), the observation is obtained by multiplying the total number of persons employed in urban units by the share of secondary industry in employment. The reason for the multiplication is to ensure that the data reflects industrial activities as closely as possible and reduces noise from other sectors.

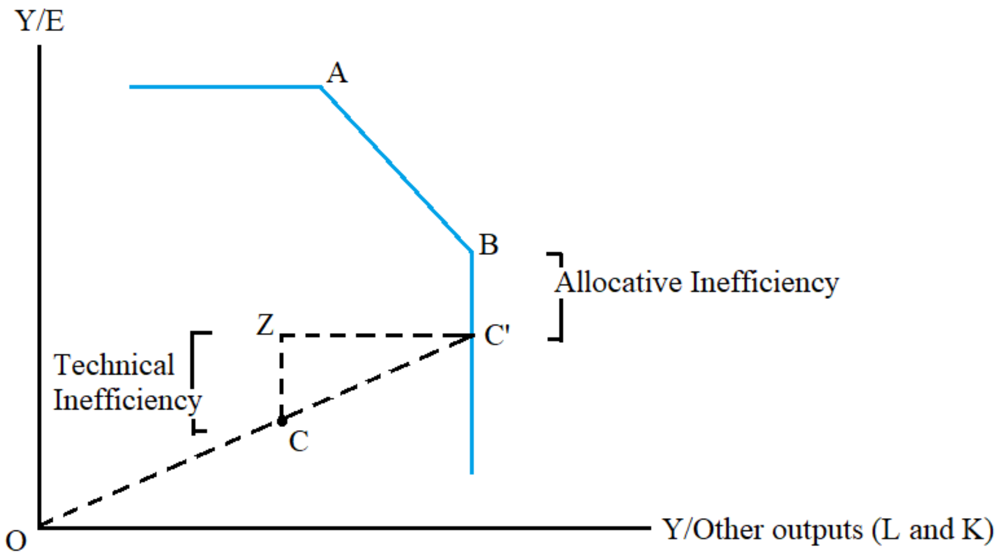
The data is then entered into DEAP 2.1 developed by Coelli (1996) using the data envelopment analysis (DEA) analysis to obtain efficiency scores.

The DEA is a non-parametric model commonly used to evaluate the relative efficiency of decision-making units, which in this paper are prefecture-level cities in China, using multiple inputs and outputs.[75]

[74] Coelli, T. (1996). 'A guide to DEAP version 2.1: a data envelopment analysis (computer) program', *Centre for Efficiency and Productivity Analysis, University of New England, Australia* 96(08), 1–49.
[75] Cooper, W., Seiford L., and Zhu, J. (2000). 'A unified additive model approach for evaluating inefficiency and congestion with associated measures in DEA', *Socio-Economic Planning Sciences*. 34(1), 1–25.

To calculate the TFEE, the DEA constructs a non-parametric envelopment frontier over all sample data of 275 prefecture-level cities for a specific year. All observed data is either on or below the frontier. The data points on the frontier are considered the best performers, and have a TFEE value of 100, creating a benchmark relative to other sample points. Data below the points takes a value between 0 and 100 based on the distance to the frontier.

Figure 10: TFEE in a constant return to scale, input-oriented model



Source: figure drawn by the author.

In the example above, using the constant return to scale (CRS) model, each prefecture-level city employs input energy, capital, and labour to produce a unit of output. The blue line is an isoquant that represents the efficiency frontier, where points A and B lie. Therefore, A and B have a TFEE value of 100. There is also a point C that is inefficient compared to A and B, and a point C' that is the point on the frontier extending from the line OC between C and origin O. We can obtain the technical efficiency of point C as OC/OC', since the same output can be maintained by reducing the radial adjustment CC'. However, C' is not an optimized point since point B uses the same amount of labour and capital, but has higher output Y per energy input E. In other words, point C' has excessive energy inputs compared with point B. Therefore, the quantity of energy input loss can be broken down into two portions. The first is the point ZC, representing technical inefficiency for each input. The technical efficiency measures the proportion of inputs into C that can be replaced to produce the same output. The other part is the allocative inefficiency indicated by the slack BC'. The sum of CZ and BC' is the energy that can be saved for C to reach the more efficient frontier of B. Using this figure, we can define the TFEE of each prefecture-level city *i* in year *t* using the equation:

$$TFEE_{i,t} = \frac{Actual\ Energy\ Input_{i,t} - Lost\ Energy\ Input_{i,t}}{Actual\ Energy\ Input_{i,t}} = 1 - \frac{Lost\ Energy\ Input_{i,t}}{Actual\ Energy\ Input_{i,t}} \quad (1)$$

Where the actual energy input is the energy usage of the prefecture-level city, and lost energy input is the sum of CZ and BC'. This can also be written as:

$$TFEE_{i,t} = \frac{Target\ Energy\ Input_{i,t}}{Actual\ Energy\ Input_{i,t}} \quad (2)$$

Where the target energy input is the optimized point B, divided by the actual energy input.

If the score of the TFEE is 100, then that prefecture-level city is at the frontier of energy efficiency compared to those in the data. A score of 100 does not mean that the city is free from any energy inefficiency in the production process, rather, compared to all those in the sample-year, that the city is able to produce the same level of output using relatively fewer energy inputs. Therefore, the TFEE for the same city can change from year to year, depending on the other cities in the sample.

The result of the energy efficiency score is as follows:

Table 2: Summary statistics of the TFEE calculated

Variable	Observation	Mean	Standard Deviation	Min.	Max.
TFEE	4400	0.518	0.212	0.031	1