Do female cadres improve clean energy accessibility in villages? Evidence from rural China

Abstract

The active role of female cadres in promoting clean energy has received considerable attention while existing research fails to provide robust evidence. This study investigates how female village cadres stimulate clean energy accessibility in villages. Using large-scale survey data from the Third Agricultural Census in China, this study presents a strong effect of female cadres on clean energy accessibility in villages and plausible mechanisms. Results show that female cadres increase the natural gas connection and connection rate within the village by 1.7% and 1.4%, respectively. Moreover, heterogeneity analyses reveal that the positive effect of female cadres is more significant for villages in mountainous areas. Additionally, female cadres can effectively improve clean energy accessibility when the proportion of female cadres in the village is around 87%. The contributions of female cadres are more considerable when the village is more likely to elect female cadres. Furthermore, mechanism identifications suggest that female cadres improve clean energy accessibility by promoting entrepreneurship, developing the collective economy, and providing elderly care services. Based on these findings, several policy implications are proposed to facilitate the adoption of clean energy in rural areas.

Keywords: *female cadres; clean energy accessibility; heterogeneity; mechanisms; rural China*

1. Introduction

With the rapid growth of the Chinese economy, there has been a notable improvement in the living standards of the populace. Urban denizens have transitioned from using solid fuels such as coal, straw, and fuelwood to cleaner energy sources in their daily lives. However, the use of traditional solid fuel-based energy is still prevalent among the rural populace (Li et al., 2022a). The combustion of these fuels emits toxic gases such as carbon monoxide, sulfur dioxide, and soot particles, which adversely affect the quality of the environment. The long-term exposure of rural residents to these harmful substances is particularly detrimental to their respiratory health (Bonjour et al., 2013; Sharma et al., 2020). Furthermore, the excessive use of solid fuel-based energy sources can result in severe ecological damage (Huang et al., 2019), which includes amplified global carbon dioxide emissions, a rise in average earth temperatures, the melting of glaciers, and the frequent occurrence of extreme weather events (Mahapatra et al., 2021).

Before China implemented the reform and opening-up policy, energy construction primarily served cities and industries. The rural areas, however, experienced an energy shortage and were forced to rely on crop straws and fuel wood for their energy supply and consumption. Subsequently, the central government recognized the importance of rural energy issues and introduced a series of policies to regulate environmental behaviors. As a result, rural energy issues have been elevated to the level of national security. In the 21st century, energy consumption has become a pressing global issue, and China is faced with the vital task of optimizing its energy structure and developing new and renewable energy sources. The Outline of the Tenth Five-Year Plan for National Economic and Social Development, adopted in 2001, emphasized the necessity of developing new energy sources and energy-saving technologies, such as biogas and energy-efficient stoves. Additionally, it stressed the importance of strengthening the comprehensive construction of rural energy sources. Based on the data obtained from the Second National Agricultural Census conducted in 2006, it can be inferred that the energy consumption patterns among the rural population of China were relatively homogeneous. The majority of the energy was derived from four sources: firewood, coal, gas, and natural gas, accounting for 60.2%, 26.1%, 11.9%, and 0.8%, respectively. However, in recent years, there has been a significant shift in the energy consumption patterns of rural households, driven by the national focus on environmental protection and rural development. As a result, there has been a remarkable transformation in the rural landscape and household energy consumption structure. According to the data provided by the Third National Agricultural Census conducted in 2016, there has been a gradual diversification in the energy consumption patterns of Chinese rural households. The consumption of efficient, sustainable, and clean energy sources, such as electricity and natural gas, has increased, accounting for 58.6% and 49.3%, respectively. Moreover, the proportion of traditional solid fuels, such as fuelwood and coal, has declined, accounting for 44.2% and 23.9%, respectively. Despite the significant changes in the rural energy structure, it is apparent that the consumption of traditional solid fuels still accounts for a substantial proportion of daily energy consumption (Niu et al., 2019).

Many Chinese rural households still face energy poverty, including low energy use, poor structure, and weak capacity (Tang and Liao, 2014; Jiang et al., 2020). The lack of awareness and lower-income level make farmers "non-economically rational" in their energy consumption (Gould and Urpelainen, 2018), leading to more severe harm (Sharma et al., 2020). People in rural areas are more likely to fall into the energy poverty trap. Rural households' low-income level often prevents them from accessing adequate domestic energy and energy services, limiting their choice of efficient and clean energy sources (Gertler et al., 2016; Chaton and Lacroix, 2018). In addition, gender has a different impact on the structure of energy consumption due to the difference in the frequency of energy use between women and men (Tarhini et al., 2014; Fathallah and Pyakurel, 2020). In the process of China's economic development, it is easy to notice a great change in the structure of the rural population. China's Seventh Census Bulletin indicated that the rural population shows an obvious development trend of having fewer children and aging, the phenomenon of young-adult population exodus and lack of local talents are still serious, and the rural resident population shows feminization characteristics. Women have become the main body of the rural population and revitalization. In the background, an increasing number of women are participating in village governance as village cadres. Data from the third national agricultural census showed that at the end of 2016, nearly 80% of villages had female cadres. Female cadres are emerging as an important force in promoting the welfare of women and other vulnerable groups by providing public goods (Chattopadhyay and Duflo, 2004; Kumar and Prakash, 2017; Gottlieb et al., 2018). However, it remains unclear whether female cadres affect the accessibility of clean energy in villages, which warrants further investigation.

Existing studies have revealed that women exhibit a greater sensitivity toward environmental issues than their male counterparts (Dietz et al., 2002; McCright, 2010). Studies on energy and gender have highlighted the significant disparities in energy consumption patterns, preferences, and accessibility across gender lines (Anfinsen and Heidenreich, 2017). Notably, enhancing female participation in the energy sector has been shown to yield high returns and promote low carbon emissions. Several governments, including those of Zambia, Uganda, and Botswana, have acknowledged the valuable contributions of female professionals in the energy field toward achieving sustainable development (Karlsson, 2007). Further, Norgaard and York (2005) have documented that countries with a substantial representation of female decision-makers are more responsive to environmental concerns and tend to adopt more environmental protection regulations. Correspondingly, departments with a higher proportion of women tend to comply more readily with national environmental policies (Liu, 2018). Moreover, women in executive positions have been found to be more effective in improving corporate energy efficiency, increasing investments in renewable energy, and ultimately facilitating low-carbon development (Zaman et al., 2021). It is worth noting that communities with educated female decision-makers are more inclined towards adopting and promoting eco-friendly products and tend to prioritize environmental conservation (Kwauk and Braga, 2017). These findings collectively suggest that female leaders appear to outperform men in areas such as environmental awareness and environmental behavior. However, research on the association between female leadership and clean energy accessibility in developing countries has been scarce (Pachauri and Rao, 2013; Tang and Liao, 2014). This paper aims to address this literature gap. This paper introduces the concept of clean energy accessibility and constructs an econometric model to examine the relationship between female cadres and clean energy accessibility. The empirical results demonstrate that female cadres can enhance clean energy accessibility in villages. Furthermore, we explore the mechanisms through which female cadres influence clean energy accessibility. Heterogeneity analysis indicates that the positive impact of female cadres on clean energy accessibility varies significantly depending on village topography, the proportion of female cadres, and the tendency of villages to elect female cadres. Mechanism tests show that female cadres promote clean energy accessibility through three channels: promoting entrepreneurship, developing the collective economy, and providing elderly care services. Compared with existing studies, the marginal contributions of this paper are as follows:

First, this study contributes to the literature on gender differences and energy transition (Pachauri and Rao, 2013; Kumar and Prakash, 2017; Ngarava et al., 2022). With the increased status of women in the new period, examining the decision-making preferences of female leaders has become a popular topic. Studies have explored the influence of female officials on local public policy (Besley and Case, 2003; Chattopadhyay and Duflo, 2004; Gajwani and Zhang, 2008; Kumar and Prakash, 2017) and the decision-making behavior of female leaders in business (Tate and Yang, 2015; Harjoto et al., 2020). Based on these studies, this paper focuses on the role of female village cadres in the village energy transition in rural China, trying to reveal the potential causal relationship between female village cadres and village clean energy accessibility and enrich the research on the relationship between female village cadres and village energy transition.

Second, considering that the influence of female village cadres on village energy accessibility varies across scenarios, this paper identifies heterogeneous effects due to different village topography, the proportion of female cadres within the village, and the propensity to elect female cadres. In addition, this paper identifies three channels through which female cadres influence clean energy accessibility, both theoretically and empirically, which is one of the breakthroughs of this study. The identification of heterogeneous treatment effects and influence channels can help us better understand the relationship between female village cadres and village clean energy accessibility.

Third, this paper puts forward some policy suggestions to promote rural energy transition from the perspective of village cadres' gender, which can provide a reference for promoting rural energy transition in developing countries. In the particular context of the large proportion of the female population and the increasing status of women in rural areas of China, our findings emphasize the positive role of female cadres in village energy transition and advocate the creation of a gender-equal and inclusive political environment to promote village energy transition by improving the gender structure of village cadres.

The remainder of this paper is arranged as follows: Section 2 presents the theoretical analysis; Section 3 introduces data and variable selection; Section 4 states empirical methods; Section 5 shows the empirical results; Section 6 is a discussion and Section 7 makes a conclusion.

2. Theoretical analysis

The development of clean energy is an increasingly significant global trend (Wei et al., 2021). However, approximately three billion people worldwide lack access to clean energy fuels and energy technologies (United Nations, 2019). In particular, the diffusion of clean energy in rural areas of developing countries presents a significant challenge (Sovacool, 2012; Li et al., 2022b). In China, most rural households rely on polluting solid fuels for cooking (Tang and Liao, 2014), such as fuelwood, coal, and other biomass fuels. The traditional social division of labor is "men outside the home and women inside," in which women are responsible for the care of the household while men are responsible for external income-earning activities (Eagly, 2013). This traditional social division of labor has long created stereotypes about the domestic and social behaviors that different genders are expected to exhibit (Harjoto et al., 2020). In most cases, women and girls bear the brunt of household energy work, including fuel collection, cooking, heating, and lighting (International Energy Agency, 2009; Sovacool, 2012). Women are the main users of solid fuel energy and also the biggest victims of energy poverty (Wickramasinghe, 2003; Oparaocha and Dutta, 2011; Ngarava et al., 2022). Men, however, are less concerned about the nitty-gritty of household tasks and therefore spend little money on cleaning cookware or installing kitchen cleaning facilities for the women in the household (Moniruzzaman and Day, 2020; Makan, 1995). To some extent, the traditional division of labor has led to the unequal status of men and women (Fan, 2003; MacPhail and Dong, 2007). Women are disadvantaged in society and the family (Huber and Spitze, 1981). In particular, full-time housewives have a lower status in the household because they do not have the financial independence and sense of achievement in earning money and are almost dependent on the salary earned by men for household expenses (Davis and Robinson, 1991). Therefore, women have weak bargaining power within their households and lack the power to make decisions about energy choices (Stuhlmacher and Walters, 1999; Pachauri and Rao, 2013; Dim, 2023). Women in weaker positions in the household are often left with no choice but to rely on cheap and non-clean energy (Lewis and Pattanayak, 2012; Kishore and Spears, 2012; Pachauri and Rao, 2013).

In recent years, a growing body of research has explored the potential economic and social advantages of empowering women, advancing gender equality, and expanding women's roles in society. Building on this prior work, it can be inferred that female cadres can play a crucial role in improving access to clean energy in rural areas through three key channels: fostering entrepreneurship and employment, promoting the development of the collective economy, and providing elderly care services.

Female cadres have the potential to increase the accessibility of clean energy in rural areas by promoting entrepreneurship. Entrepreneurship poses a greater challenge for women and other marginalized groups, and female cadres can help to overcome these challenges by creating a supportive entrepreneurial environment. Specifically, female cadres may establish social networks to support entrepreneurship in the community (Kyrö and Sundin, 2008). One such example is the women's cooperatives in India, which are voluntary organizations of women providing information channels and employment opportunities for women to start businesses, intending to help impoverished families (Datta and Gailey, 2012). Furthermore, female cadres' participation in political decision-making processes may have a positive impact on social welfare, as they are more likely to formulate and implement policies that are conducive to gender equality and family-friendly practices (Clots-Figueras, 2011; Beaman et al., 2012; Kumar and Prakash, 2017). Policies such as increasing employment opportunities for women and supporting women's entrepreneurship enable women to generate income, enhance their family status and bargaining power within the household (Austin and Mejia, 2017; Agrawal et al., 2021), and ultimately increase their autonomy in choosing to use clean energy (Permana et al., 2015; Choudhuri and Desai, 2020). In addition, the Energy Ladder Theory suggests that households transition to using more advanced and cleaner fuels as their income rises (Hosier and Dowd, 1987; Van der Kroon et al., 2013). Therefore, by promoting community entrepreneurship and increasing household income, female cadres may contribute to the greater adoption of cleaner and more efficient energy sources in the community.

In addition to entrepreneurship, female cadres promote access to clean energy in rural areas by developing the village collective economy. In China, rural collective economy refers to a form of socialist public ownership economy in which collective members utilize collective resources through cooperation and joint efforts to achieve common development (Chen, 2016). Developing rural collective economy is the path to gradually realizing common prosperity and rural revitalization for farmers (Xiao and Chen, 2021). On the one hand, female cadres are more concerned about the family and social status of women in villages and play a role model in changing women's attitudes and courageously expressing group demands (Kumar and Prakash, 2017). Specifically, they further promote the development of the collective economy (Barron et al., 2020; Dutta, 2020), which embeds the formation of women's status into the local economic and social structure and family structure. The development of village collective economy helps to fully absorb women into employment (Wojan, 2000; Venkatesh, 2013; Briones, 2013), enabling women and men to enjoy equal distribution of collective welfare. That is to say, the expansion of the collective economy not only guarantees women's social and family status but also to some extent meets the demand for clean energy use among women. On the other hand, the expansion of the collective economy provides a solid material foundation for the supply of public goods in villages (Briones, 2013; He et al., 2016). In the context of the continuous growth of the collective economy, the possibility of fully supplying clean energy as an important public good will be greater. Therefore, female cadres promote the development of the village collective economy to facilitate the connection between clean energy and households, leading to a shift towards the use of clean energy in rural areas.

Moreover, female cadres are enhancing clean energy accessibility in villages by providing elderly care services. Within households, the care of the elderly is typically undertaken by co-residing daughters-in-law. If female elders lose their ability to work, their domestic burden is shifted onto daughters-in-law, which reduces the possibility of females engaging in formal employment (Heitmueller and Inglis, 2007; Sugawara and Nakamura, 2014). Unlike male cadres, female cadres tend to invest in public services that are needed by women and other vulnerable groups (Chattopadhyay and Duflo, 2004; Kumar and Prakash, 2017). As rural populations continue to age, female cadres can leverage their platforms and influence to advance the development of community-based day care centers and group-living centers for the elderly (Feng et al., 2020). This approach has two benefits: on the one hand, rural elderly care services reduce the pressure on households to care for the elderly, releasing more labor to seek livelihoods (Sugawara and Nakamura, 2014), which greatly increases household income. Furthermore, households will have more funds available to invest in energy improvement, leading to a corresponding increase in demand for clean energy (Van der Kroon et al., 2013). On the other hand, the implementation of rural elderly care services improves the quality of life for the elderly, including support for better healthcare, nutrition, and entertainment (Wen et al., 2020; Tang, 2021). This indirectly encourages rural households to adopt healthy lifestyles and invest more time and money in improving their living environment, including the use of cleaner fuels (Zahno et al., 2020). Therefore, female cadres are promoting the use of clean energy by providing elderly care services.

As previously mentioned, female village cadres have the potential to improve clean energy accessibility in villages. Figure 1 illustrates the framework of theoretical analysis, and the empirical section will test the validity of the three plausible mechanisms outlined above.

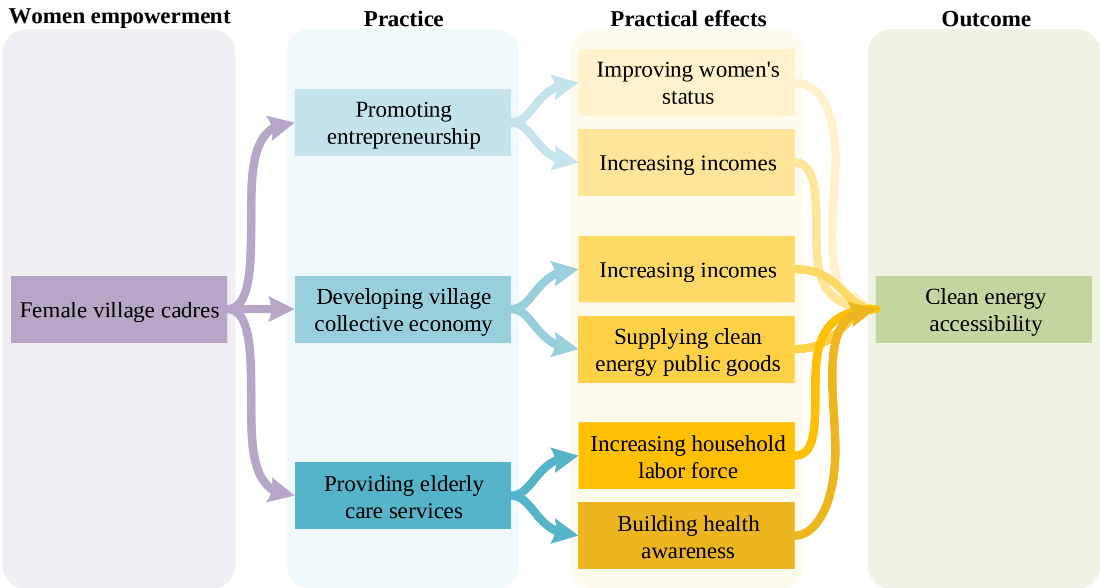


Figure 1: The framework of theoretical analysis

3. Data and variables

3.1. Data source

The data used in this paper are mainly from the administrative village census data from the Third National Agricultural Census conducted in 2016. China's agricultural census aims to gain a comprehensive understanding of the development of agriculture, rural area, and farmers and has been conducted three times since 1997. This research provides a large amount of statistical information for agricultural production operators and the public and provides a basis for China to study and formulate rural economic and social development plans and new rural construction policies. In December 2016, the census team adopted a comprehensive survey approach under the State Council's and local governments' guidance. It adopted the method of census officers visiting households and units directly to register and comprehensively collect information about rural areas, agriculture, and dwellers. Its census includes ordinary farm households, large-scale agricultural operations, agricultural business units, administrative villages, and township administrative districts.

To analyze the impact of female cadres on clean energy accessibility, this paper uses administrative village census data. The administrative village census questionnaire mainly includes the basic information module, demographic information module, basic social service information module, and village cadre information module of the administrative village. The data used in this paper is the sub-sample data randomly selected by the subject group from the administrative village census data in the national agricultural census. A total of 54,596 administrative villages sample data has a strong national representation. Figure 2 depicts the sample distribution.

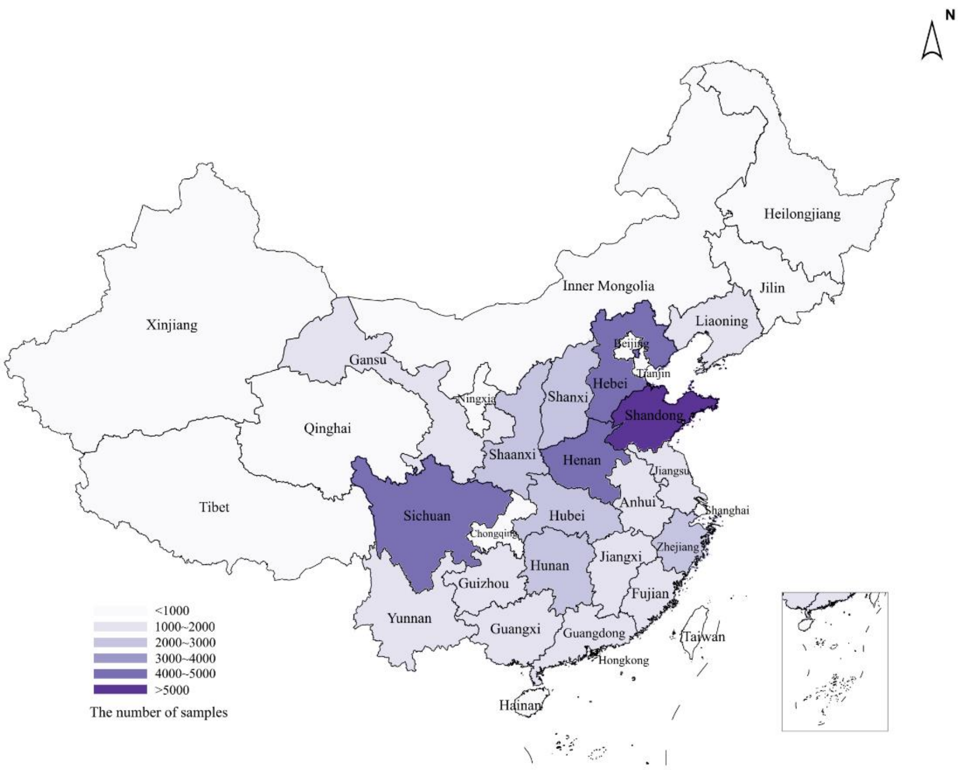


Figure 2: The sample distribution

3.2. Variable construction

The explained variable, clean energy accessibility, is measured by two variables: (1) whether the village connects to natural gas. Assigning a value of 1 if the village is connected to natural gas, and 0 otherwise; (2) the connected rate of natural gas within the village, which is calculated as the proportion of natural villages and settlements in the village that are connected to natural gas, divided by the total number of natural villages and settlements in the village. Also, it is necessary to explain the concept of natural villages here. Natural villages are primarily spontaneous settlements formed due to family, bloodline, or surname affiliations, and serve as the basic unit of daily life for rural residents. While administrative villages are grassroots self-governing units established according to national laws and may contain several natural villages within their boundaries. Additionally, this paper sets a variable that whether the village has external population as an instrument, and involves it in an endogenous treatment effect model to address the endogeneity problem of female cadres.

The core explanatory variable is whether there are female cadres in the village, and this dummy variable is assigned a value of 1 if there are, and 0 otherwise. In addition, this paper mainly includes two sets of control variables. The individual characteristics variables mainly include the annual salary of the village branch secretary, age, education level, and the number of positions. Moreover, the village characteristics variables include village topography, roads, population, whether the village is a national tourism village, village area, and the number of natural villages. Furthermore, village characteristics also include four variables used for mechanism identification, including collective economic income, the number of comprehensive stores or supermarkets, the number of formal restaurants, and the number of elderly people receiving centralized care in the village. The specific definitions of selected variables are shown in Table 1.

Table 1: The definitions of variables

Variables	Definitions
Gas	Whether the village connected to natural gas? Yes=1, 0 otherwise.

RGas	The rate of natural villages or settlements within the village connected to natural gas (%).
Female cadre	Whether the village has female cadres? Yes=1, 0 otherwise.
Migration	Is there external population in the village? Yes=1, 0 otherwise.
Plain	Is the village topography plain? Yes=1, 0 otherwise.
Hilly	Is the village topography hilly? Yes=1, 0 otherwise.
Mountain	Is the village topography mountain? Yes=1, 0 otherwise.
Asphalt road	Is the village road asphalt? Yes=1, 0 otherwise.
Concrete road	Is the village road concrete? Yes=1, 0 otherwise.
Slate road	Is the village road slate? Yes=1, 0 otherwise.
Gravel road	Is the village road gravel? Yes=1, 0 otherwise.
Other roads	Is the village road other? Yes=1, 0 otherwise.
Ln(population)	The natural logarithm of the resident population in the village.
Tourism village	Whether the village is a national tourism village? Yes=1, 0 otherwise.
Natural village	The number of natural villages in the administrative village.
Ln(village area)	The natural logarithm of the village area.
Ln(collective income)	The natural logarithm of (the collective economy income of the whole village).
Ln(store)	The natural logarithm of (the number of comprehensive stores or supermarkets with a business area of 50 square meters or more).
Ln(restaurant)	The natural logarithm of (the number of restaurants with business licenses).
Ln(elderly care)	The natural logarithm of (the number of elderly people receiving centralized care in the village).
Ln(salary)	The natural logarithm of the annual salary of the village branch secretary.
No schooling	Is the village branch secretary no schooling? Yes=1, 0 otherwise.
Primary schooling	Is the education of the village branch secretary a primary school? Yes=1, 0 otherwise.
Middle schooling	Is the education of the village branch secretary a middle school? Yes=1, 0 otherwise.
High schooling	Is the education of the village branch secretary a high school? Yes=1, 0 otherwise.
College schooling or above	Is the education of the village branch secretary a college school or above? Yes=1, 0 otherwise.
Ln(age)	The natural logarithm of the age of village branch secretary.
Holding two positions	Whether the village branch secretary holds a director position on the villager committee? Yes=1, 0 otherwise.

3.3. Descriptive statistics

Table 2 reports the results of descriptive statistics. As shown in Table 1, 10% of the surveyed villages were connected to natural gas, and the natural gas connectivity within these villages was only 8.1%. It is surprising that 79.9% of the villages have female cadres. In the sample, 44.2% of villages have external population. The topography of the sample villages covered all plains, hills, and mountains, with a relatively balanced share of each. The overall road condition of the villages was sound, with 77.6% of the villages having asphalt roads and 19.2% of the villages having concrete roads as their main roads. On average, each administrative village had an area of 730 hectares and consisted of 5 natural villages with 1,055 permanent residents. Only 0.4% of the villages were national characteristic tourism villages. In addition, the average village collective economic income was 90,000. The number of people who were centrally cared for within the village ranged from 0 to 1800, with a large variation between villages. Each village had an average of 1 restaurant and 1 store or supermarket, but there was also wide variation in this indicator. For the village branch secretaries, the average age was 50, and 63.8% had a high school education or above, with an average annual salary of about 21,767 yuan. 30.5% of the village branch secretaries also held a village director position on the villager committee.

Table 2: The results of descriptive statistics

Variable	Max	Min	Mean	Std.Dev.
Gas	1	0	0.100	0.300
RGas	1	0	0.081	0.261
Female cadre	1	0	0.799	0.401
Migration	0	1	0.442	0.497
Plain	1	0	0.397	0.489
Hilly	1	0	0.301	0.458
Mountain	1	0	0.303	0.459
Asphalt road	1	0	0.776	0.417
Concrete road	1	0	0.192	0.394
Slate road	1	0	0.02	0.140
Gravel road	1	0	0.005	0.069
Other roads	1	0	0.007	0.082
Ln(population)	9.859	0	6.962	0.908
Tourism village	1	0	0.004	0.066
Ln(village area)	9.210	-1.609	5.959	1.160
Ln(collective income)	12.642	0	2.310	1.522
Ln(store)	4.025	0	0.549	0.709
Ln(restaurant)	6.043	0	0.352	0.705
Ln(elderly care)	7.496	0	0.430	0.758

Natural village	59	0	5.248	5.882
Ln(salary)	13.13	0	9.726	1.207
No schooling	1	0	0.003	0.052
Primary schooling	1	0	0.038	0.190
Middle schooling	1	0	0.322	0.467
High schooling	1	0	0.435	0.496
College schooling or above	1	0	0.203	0.403
Ln(age)	4.419	2.890	3.915	0.168
Holding two positions	1	0	0.305	0.460

Figure 3 displays the natural gas connection rate in rural areas across different provinces, revealing that more rural residents in the central region use natural gas. The average natural gas connection rate in villages in Sichuan province is the highest, reaching 43.47%. Provinces such as Beijing, Hebei, Shanghai, and Ningxia follow closely behind with natural gas connection rates exceeding 10%. In contrast, rural natural gas usage is relatively low in other provinces. The connection and usage of natural gas are related to the region's geography, topography, energy policies, and market demand. Taking Sichuan province as an example, frequent geological activity and abundant natural gas resources make it a significant base for natural gas production in China. In recent years, the government has vigorously promoted clean energy in rural areas and the "coal-to-gas" project, allowing Sichuan province to take the lead in promoting clean energy in rural areas due to its rich endowments of resources.

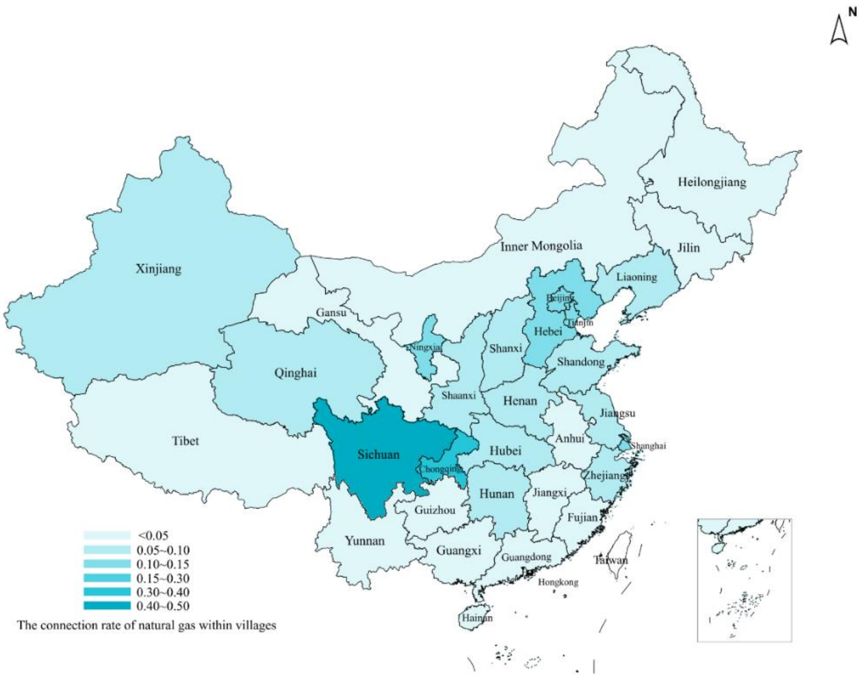


Figure 3: The connection rate of natural gas within villages

4. Empirical strategy

4.1. Benchmark regression

The purpose of this study is to explore the causal relationship between female cadres and clean energy accessibility in villages. We used two explained variables to measure village clean energy accessibility. One is whether the village is connected to natural gas (Gas), which is set as a dummy variable. 1 indicates that the village is connected to gas and 0 indicates otherwise. The other is the rate of natural villages or settlements within the village connected to natural gas (RGas), which is a non-negative number. In addition, the explanatory variable is whether the village has female cadres (T_i), which is also a dummy variable. If the village has female cadres, it takes the value of 1, otherwise, it is 0. The models for estimating Gas and RGas are given below:

$$Gas = \alpha_1 + \beta_1 T_i + \gamma_1 X_i + \varepsilon_1 \quad (1)$$

$$RGas = \alpha_2 + \beta_2 T_i + \gamma_2 X_i + \varepsilon_2 \quad (2)$$

Where X_i is the vector of control variables, including individual characteristics and village characteristics. β_1 and β_2 are interesting coefficients that measure the effects of female cadres on the accessibility to clean energy in the village. γ_1 and γ_2 are two coefficients. α_1 and α_2 are constant terms. ε_1 and ε_2 are random error terms. Since whether the village is connected to natural gas is a binary variable and the cumulative distribution function $F(T_i,\ \beta_1)$ obeys the standard normal distribution, the Probit model is used, and the correlation coefficient in equation (1) and the marginal effects are estimated by the maximum likelihood method. Additionally, the rate of natural villages or settlements within villages connected to natural gas is non-negative, i.e., RGas are roughly continuously distributed over positive values, but contain a fraction of observations that take the value of zero with positive probability. Therefore, we chose the Tobit model and employ the maximum likelihood method to estimate the correlation coefficient in equation (2).

However, the selection of village cadres is not random but by holding a village assembly for voting and there might be a reverse causality from the female cadres to clean energy accessibility (Das et al., 2020), which results in a correlativity between the error terms ε and the covariates X_i. That is, some endogeneity problems such as unobserved omitted variables, self-selection, and reverse causality in equations (1) and (2) would lead to biased estimation results. Thus, this paper introduces the exogenous treatment effect models and the endogenous treatment effect models, and the heteroskedasticity-based identification strategy to address these endogeneity problems.

4.2. Treatment effect model

The gender of village cadres is not necessarily randomly assigned, and there are many factors affecting gender in practice. To overcome the estimation bias in the model due to the self-selection problem, several exogenous treatment effect models such as the propensity score matching (PSM), Nearest-neighbor matching (NNM), Regression adjustment (RA), Inverse-probability weights (IPW), and Inverse-probability weights regression adjustment (IPWRA) are used to evaluate the treatment effect of female cadres on clean energy accessibility.

We estimate the propensity score to have a female cadre in villages using the Probit model. Next, we calculate the effect of female cadres on clean energy accessibility by estimating the expected treatment effect for each group. Assuming that Y_{1i} denotes clean energy accessibility in village i with female cadres and Y_{0i} represents clean energy accessibility in village i without female cadres. Then the average treatment effect on the treated (ATT) and the average treatment effect (ATE) can be expressed as:

$$ATT = E(Y_{1i}|T_i = 1) - E(Y_{0i}|T_i = 1) \tag{3}$$

$$ATE = E(Y_{1i}|T_i = 1) - E(Y_{0i}|T_i = 0) \tag{4}$$

Considering that the proportion of villages with female cadres among samples is 79.9%, we adopt the NNM and set the ratio at 1:1 and 1:7 respectively to estimate the ATE, and make a comparison with other results.

In addition to the matching methods above, estimators such as RA, IPW, and IPWRA are employed to evaluate the treatment effects of female cadres on clean energy accessibility. These estimators also could address the problem of self-selection bias (Wooldridge, 2010). The IPWRA estimator combines the IPW estimator with the RA estimator. The IPW is mainly used to model the presence of female cadres in villages, and RA is mainly used to analyze the results, thus avoiding errors in the results caused by self-selection bias and perturbation factors. The above method is known as "doubly robust" because only one of the two equations needs to be correctly identified to obtain consistent estimation results (Wooldridge, 2010), thus reducing the chance of error.

However, the endogeneity of treatment assignment in relation to potential outcomes violates the conditional mean independence assumption of the exogenous treatment effect model described above. The endogenous treatment effect model estimates the ATE of female cadres on clean energy accessibility from observational data when treatment assignment is correlated with the potential outcomes. Das et al. (2020) mentioned that there is likely a bidirectional causality between female village cadres and clean energy accessibility, and hence this paper uses the endogenous treatment effect model to tackle the endogeneity problem. The endogenous treatment effect model controls for the endogeneity of treatment assignment by using a control function approach. Specifically, the method incorporates instrumental variables into the control variables in the first step and regresses the explanatory variable (female cadres) to obtain the generalized residual. Next, the generalized residual is treated as a regressor in the models for the potential outcome, therefore using the sample averages of the conditional means to estimate the unconditional ATE (Wooldridge, 2010). During this process, whether the village has external population is set as an instrumental variable. External population affects political participation within the village but hardly affects clean energy accessibility directly. Research suggests that migrants are more likely to support political change (Jones-Correa, 1998) because they lose their previous status by moving away from their original family and social networks. Moreover, female migrants are more inclined to play a political role in community organizations than men (Pardo, 1990; Hardy-Fanta, 1993). However, there is no direct causality between external population and clean energy availability, at least there is no evidence to suggest so far. Therefore, it is reasonable to use the external population in the village as an instrumental variable.

4.3. Heteroskedasticity-based identification strategy

As a complement to the above research methods, this paper also uses the heteroskedasticity-based identification method of Lewbel (2012). We use the data from the model to build tools as simple functions. This method can be used in the absence of external tool variables. In addition, both constructed and external tools can also be used when performing data analysis to improve estimation efficiency (Baum and Lewbel, 2019). The model and estimation methods are as follows：

$$Y_1 = X\delta + Y_2\mu + \epsilon_1 \tag{5}$$

$$Y_2 = X\eta + \epsilon_2 \tag{6}$$

Where there is a possible correlation between the random perturbation terms ϵ_1 and ϵ_2. Lewbel's (2012) heteroskedasticity-based identification method breaks the restriction that traditional instrumental variable estimates must satisfy exclusionary constraints. In traditional instrumental variable strategy estimation, the number of exogenous variables needs to satisfy the condition that they are at least equal to the number of endogenous individuals. That is, all endogenous variables must have associated instrumental variables. Lewbel's (2012) heteroskedasticity-based identification method only needs to satisfy the assumption that the error is heteroskedastic and does not require external instrumental variables.

We make assumptions based on the standard regression model. First, we assume that the sum is a fixed constant. Second, we assume that X is a standard exogenous variable, $(X_{\epsilon_1}) = E(X_{\epsilon_2}) = 0$, and $E(XX')$ is non-heterogeneous. Third, when estimating based on heteroskedasticity, we cannot ignore $Cov(\mathrm{Z}, \epsilon_1\epsilon_2) = 0$ and $Cov(\mathrm{Z}, \epsilon_2^2) \neq 0$, where $Z = X$ or Z is a subset of X. The heterogeneity-based identification strategy can then be summarized in the following two steps：First, using the ordinary least squares (OLS) linear regression of Y_2 on X to estimate $\hat{\eta}$ and the estimated residuals $\widehat{\epsilon_2} = Y_2 - X'\hat{\eta}$ are acquired. Second, supposing $Z = X$ or Z is a subset of X (excluding the constant term), then use the ordinary two-stage least squares (TSLS) linear regression of Y_1 on X and Y_2 to estimate δ and μ. The instruments in this linear regression are X and $(Z - \bar{Z})\widehat{\epsilon_2}$, where $\bar{Z}$ is the sample mean of Z.

4.4. Generalized propensity score matching

The benchmark results are based on the premise that the number of female cadres is linear in reflecting marginal utility, while the role of female cadres may be non-linear in impact. Therefore, this paper uses the generalized propensity score matching method (GPSM) to estimate the marginal utility of female cadres on clean energy accessibility. GPSM extends the restriction that PSM treatment variables must be binary selection variables while retaining the advantage of PSM in eliminating self-selection effects (Bia and Mattei, 2008). The endogeneity problem can be better addressed when more valid information is available (Kluve et al., 2012).

First, the conditional probability density of treatment intensity is estimated based on covariates X_i. Then we estimate the conditional probability density of performance expectation:

$$F(X_i\theta) = \frac{\exp(X_i\omega)}{1 + \exp(X_i\omega)} \quad (7)$$

The probability density of the village i can be estimated:

$$\widehat{R_i} = [F(X_i\widehat{\omega})]^{T_i} \times [1 - F(X_i\widehat{\omega})]^{1-T_i} \quad (8)$$

Second, a model is constructed using the treatment variable T_i (whether the village has female cadres) and the generalized propensity score $\widehat{R_i}$ estimated in the previous step to calculate the conditional expectation (clean energy accessibility) of the outcome variable Y_i (Hirano and Imbens, 2004):

$$E(Y_i | T_i, \widehat{R_i}) = \lambda_0 + \lambda_1 T_i + \lambda_2 T_i^2 + \lambda_3 \widehat{R_i} + \lambda_4 \widehat{R}_i^2 + \lambda_5 T_i \widehat{R_i} \quad (9)$$

Third, the expected value of the outcome variable Y_i could be obtained:

$$\hat{E} = [Y(d)] = \frac{1}{N}\sum_{i=1}^{n}\left[\hat{\lambda}_0 + \hat{\lambda}_1 t + \hat{\lambda}_2 t^2 + \hat{\lambda}_3 \hat{r}(t, X_i) + \hat{\lambda}_4 \hat{r}(t, X_i)^2 + \hat{\lambda}_5 t\hat{r}(t, X_i)\right] \quad (10)$$

Next, the sample is divided into different subintervals $\bar{T}_s (s = 1,2,3 \ldots)$according to the range of values of the treatment variables $T = [t_{min}, t_{max}]$ and in each subinterval, the causal effect between the treatment (whether the village has female cadres) and the outcome (clean energy accessibility) can be estimated. Finally, the generalized propensity score can present the image of the dose-response function between them. In the process, the explanatory variable (female cadres) is considered an endogenous binary indicator that may be based on the self-selection of the village leadership, resulting in a high bias when using OLS estimation. Therefore, we address the endogeneity problem of female cadres by employing the control function approach because the first-stage Probit regression is more accurate.

5. Results

5.1. Benchmark results

Table 3 and Table 4 present the regression results by introducing the Probit model and the Tobit model, respectively. The marginal effects show that female village cadres increase the possibility of natural gas connection in the village by 1.7% and improve the natural gas connection rate in the village by 1.4%. That is, the female cadre can facilitate clean energy accessibility in villages. The results are consistent with the theoretical analysis presented earlier. In the theoretical analysis section, we inferred that there are three potential channels (promoting entrepreneurship, developing the collective economy, and providing elderly care services) through which female cadres may improve clean energy accessibility in villages. However, as previous studies did not involve the causal relationship between female cadres and clean energy use in villages, we cannot yet provide a convincing explanation for the baseline regression results. In Section 5.4, the three channels will be verified.

Additionally, the regression with control variables provides some interesting results. The village topography significantly affects the accessibility of clean energy, indicating that villages in plain and hilly areas are more likely to have access to natural gas. The types of roads within the village also have a significant positive effect on natural gas connection, suggesting that good road conditions are conducive to the spread of natural gas. This is in line with the findings of Islam et al. (2022) and Hamed et al. (2012) that good infrastructure can meet the use of clean energy at a lower cost and thus is more conducive to the diffusion of clean energy. Moreover, the village population and the age of the village branch secretaries also had a significant positive effect on the connection to natural gas. The education level of the village branch secretaries has a significant positive effect on the connection to natural gas (individuals with a university education and above are taken as controls, thus the regression results are negative). However, the administrative area of the village also has a significant negative effect on the natural gas connection.

Table 3: Regression results based on the Probit model

Variables	Probit	Probit	Probit	OLS
	Gas	Gas	Margins	Gas
Female cadre	0.194^{***}	0.121^{***}	0.017^{***}	0.017^{***}
	(0.022)	(0.023)	(0.003)	(0.003)
Plain		0.272^{***}	0.038^{***}	0.033^{***}
		(0.033)	(0.005)	(0.004)
Hilly		0.304^{***}	0.042^{***}	0.048^{***}
		(0.029)	(0.004)	(0.003)

Asphalt road		0.505***	0.070***	0.069***
		(0.145)	(0.020)	(0.012)
Concrete road		0.676***	0.094***	0.096***
		(0.146)	(0.020)	(0.012)
Slate road		0.142	0.021	0.035**
		(0.170)	(0.024)	(0.013)
Gravel road		0.418**	0.058**	0.061***
		(0.200)	(0.028)	(0.018)
Ln(population)		0.292***	0.041***	0.035***
		(0.016)	(0.002)	(0.002)
Tourism village		0.219*	0.031*	0.032*
		(0.120)	(0.017)	(0.018)
Ln(salary)		0.017*	0.002*	0.002*
		(0.010)	(0.001)	(0.001)
No schooling		-0.540**	-0.075**	-0.102***
		(0.219)	(0.030)	(0.021)
Primary schooling		-0.346***	-0.048***	-0.072***
		(0.056)	(0.008)	(0.007)
Middle schooling		-0.242***	-0.034***	-0.041***
		(0.025)	(0.003)	(0.004)
High schooling		-0.160***	-0.022***	-0.028***
		(0.022)	(0.003)	(0.004)
Ln(age)		0.257***	0.036***	0.047***
		(0.054)	(0.008)	(0.008)
Ln(village area)		-0.290***	-0.040***	-0.044***
		(0.011)	(0.001)	(0.002)
Natural village		-0.004**	-0.001**	0.001***
		(0.002)	(0.000)	(0.000)
Holding two positions		-0.034	-0.005	-0.005*
		(0.022)	(0.003)	(0.003)
Provincial fixed effect		Yes	Yes	Yes
Constant	-1.299***	-3.614***		-0.182***
	(0.085)	(0.301)		(0.039)
Observations	54,596	54,596	54,596	54,596
R-squared	0.15	0.216	0.216	0.173

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

Table 4: Regression results based on the Tobit model

Variables	Tobit	Tobit	Tobit	OLS
	RGas	RGas	Margins	RGas
Female cadre	0.727***	0.426***	0.014***	0.015***
	(0.085)	(0.082)	(0.003)	(0.003)

Plain		0.948^{***}	0.032^{***}	0.028^{***}
		(0.121)	(0.004)	(0.003)
Hilly		0.988^{***}	0.033^{***}	0.036^{***}
		(0.101)	(0.003)	(0.003)
Asphalt road		1.871^{***}	0.062^{***}	0.060^{***}
		(0.494)	(0.016)	(0.009)
Concrete road		2.407^{***}	0.080^{***}	0.078^{***}
		(0.499)	(0.017)	(0.009)
Slate road		0.687	0.023	0.035^{***}
		(0.578)	(0.019)	(0.010)
Gravel road		1.497^{**}	0.050^{**}	0.053^{***}
		(0.720)	(0.024)	(0.016)
Ln(population)		1.029^{***}	0.034^{***}	0.029^{***}
		(0.060)	(0.002)	(0.002)
Tourism village		0.764^{*}	0.025^{*}	0.031^{*}
		(0.430)	(0.014)	(0.016)
Ln(salary)		0.072^{**}	0.002^{**}	0.002^{**}
		(0.035)	(0.001)	(0.001)
No schooling		-1.759^{**}	-0.059^{**}	-0.078^{***}
		(0.777)	(0.026)	(0.018)
Primary schooling		-1.190^{***}	-0.040^{***}	-0.055^{***}
		(0.204)	(0.007)	(0.006)
Middle schooling		-0.837^{***}	-0.028^{***}	-0.033^{***}
		(0.091)	(0.003)	(0.003)
High schooling		-0.557^{***}	-0.019^{***}	-0.023^{***}
		(0.079)	(0.003)	(0.003)
Ln(age)		0.812^{***}	0.027^{***}	0.036^{***}
		(0.195)	(0.006)	(0.007)
Ln(village area)		-1.053^{***}	-0.035^{***}	-0.038^{***}
		(0.046)	(0.001)	(0.001)
Natural village		-0.038^{***}	-0.001^{***}	-0.001^{***}
		(0.008)	(0.000)	(0.000)
Holding two positions		-0.101	-0.003	-0.003
		(0.083)	(0.003)	(0.003)
Provincial fixed effect		Yes	Yes	Yes
var(e.rgas)	15.612^{***}	13.455^{***}		
	(0.737)	(0.635)		
Constant	-4.874^{***}	-12.262^{***}		-0.114^{***}
	(0.363)	(1.101)		(0.035)
Observations	54,585	54,585	54,585	54,585
R-squared	0.109	0.163	0.163	0.127

Notes: Robust standard errors in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

5.2. Robustness tests

5.2.1. Treatment effect model

There may be a problem of self-selection bias in the selection of female cadres in villages. Villages with poor economic conditions are managed by women. In addition, there may be omitted variables that affect female village cadre selection and clean energy accessibility, which is easy to bring about endogeneity problems. To address these endogeneity problems, we adopted a series of exogenous treatment effect models and endogenous treatment effect models to further identify the relationship between female cadres and clean energy accessibility. For the endogenous treatment effect model, this paper introduces an instrumental variable, whether the village has external population, to deal with the endogeneity problems of female cadres. The reason for selecting the instrumental variable is described in Section 4. For the binary outcome Gas, we use the control function approach to estimate the ATE. For the bilateral limited outcome $RGas$, we employ both the control function approach, the Two-step consistent estimator, and the maximum likelihood estimator to evaluate the ATEs (the complete results see Appendix Table A3, Table A4, Table A5, and Table A6). Table 5(a) and Table 5(b) show that the ATEs of female cadres on natural gas connection and natural gas connection rate in the village are all significantly positive. This suggests that female cadres are a great boost in facilitating clean energy accessibility in villages.

It's necessary to show the validity in some treatment effect models. The quality of the PSM results is mainly evaluated by the results of the common support, balance test, and sensitivity analysis, which are reported in Appendix Figure A1, Figure A2, Table A1, and Table A2, respectively. Figure A1 shows only a small number of samples are excluded from the common support, and the exclusion has little effect on the whole. Figure A2 shows the matching balance between the treatment and control groups, indicating a good matching quality. Additionally, we use Rosenbaum boundary analysis to examine the sensitivity of matching results to unobservable factors. Matching results are considered reliable if they are insensitive to unobservable factors. We perform a sensitivity analysis with Gamma ranging from 1 to 3. With the larger values of Gamma, the influence of unobservable factors is greater. The sensitive analysis shows that the results are still not significant on the 95% confidence interval when Gamma equals 3, which implies that the matching results are not sensitive to unobservable factors.

Table 5(a): The average treatment effects for Gas

Methods	ATE	S.E.	p-value
Nearest-neighbor matching (1:7)	0.023^{***}	0.004	0.000
Nearest-neighbor matching (1:1)	0.023^{***}	0.006	0.000
Propensity-score matching	0.015^{***}	0.006	0.005
IPW regression adjustment	0.014^{***}	0.005	0.006
Inverse-probability weights	0.017^{***}	0.006	0.004
Regression adjustment	0.014^{***}	0.005	0.002
Endogenous treatment-effects (CF)	0.154^{***}	0.024	0.000

Notes: ***p<0.01, **p<0.05, *p<0.1. "CF" denotes the control function approach.

Table 5(b): The average treatment effects for RGas

Methods	ATE	S.E.	p-value
Nearest-neighbor matching (1:7)	0.015^{***}	0.004	0.000
Nearest-neighbor matching (1:1)	0.016^{***}	0.005	0.003
Propensity-score matching	0.015^{***}	0.005	0.005
IPW regression adjustment	0.009^{**}	0.005	0.048
Inverse-probability weights	0.010^{**}	0.005	0.024
Regression adjustment	0.009^{**}	0.004	0.038
Endogenous treatment effects (CF)	0.158^{***}	0.059	0.007
Endogenous treatment effects (Two-step)	0.119^{***}	0.018	0.000
Endogenous treatment effects (ML)	0.035^{***}	0.008	0.000

Notes: ***p<0.01, **p<0.05, *p<0.1. "CF" denotes the control function approach; "Two-step" denotes the Two-step consistent estimator; and "ML" denotes the maximum likelihood estimator.

5.2.2. Heteroskedasticity-based identification strategy

This paper also uses Lewbel's heteroskedasticity-based identification strategy to estimate the impact of female cadres on clean energy accessibility. We constructed internal instrumental variables using a subset of the control variables from the article and performed a regression analysis of the results using two-stage least squares (2SLS). Table 6 reports the estimation results of the heteroskedasticity-based identification strategy. The Breusch-Pagan test is significant at a 1% level, indicating heteroskedasticity of the error term in the regression model. In addition, the p-value of the Hansen J statistic is not significant, indicating the validity of the internal instrument. Based on the results, female cadres can increase the connection of natural gas in villages by 4.1% and the connection rate of natural gas in villages by 3.6%. In summary, our estimation is very robust.

Table 6: Results of the heteroskedasticity-based identification strategy

Variables	Gas	RGas
Female cadre	0.041^{***}	0.036^{***}
	(0.015)	(0.014)
Control variables	Yes	Yes
Provincial fixed effect	Yes	Yes
Constant	-0.226^{***}	-0.172^{***}
	(0.036)	(0.032)
Endogeneity test (p-value)	0.089	0.098
Hansen J statistic (p-value)	0.521	0.426
Cragg-Donald Wald Fstatistic	1356.250	1356.144
Breusch-Pagan (p-value)	0.000	0.000
Observations	54,596	54,585
R-squared	0.172	0.126

Notes: Robust standard errors in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

5.2.3. Placebo test

The election of village cadres may not be random, which can lead to serious estimation bias. In other words, we cannot completely rule out the influence of other unobserved factors on clean energy accessibility in the village. To demonstrate the validity of causal inference, this paper introduces the placebo test to check whether the estimation results are affected by other unobservable factors. Similar to the method of Ji et al. (2023), we perform 1000 random assignments of the village cadres' gender and involve the gender in regression. If the gender of village officials as a random variable does not affect the outcome variable, it indicates that the baseline regression results are not influenced by other events or unobserved factors.

Figure 4 shows the scatter plot and the kernel density curve of the regression coefficients obtained from 1000 random samples. It is easy to see that most of the regression coefficients are distributed around zero, which is inconsistent with the baseline results. More importantly, the p-values of these coefficients are not significant at the 10% level. Therefore, the results of the placebo test are sufficient to prove that the estimation results are unbiased and effective, and are unlikely to be influenced by other events or unobserved factors.

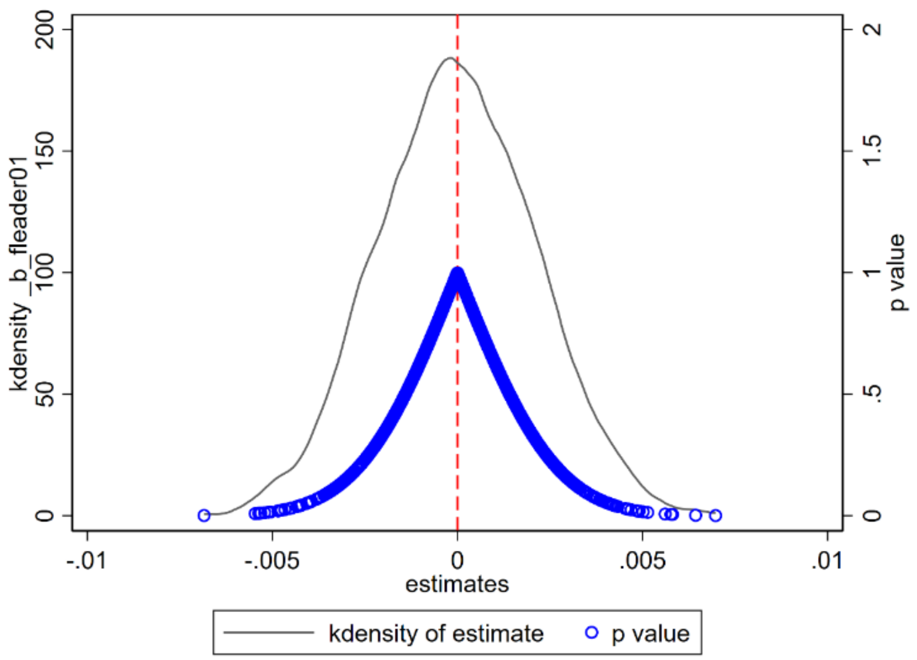


Figure 4: Results of the placebo test

5.3. Heterogeneity analyses

5.3.1. Heterogeneity from the village topography

To further explore the relationship between female cadres and clean energy accessibility, we analyzed the moderating effects of two factors in plain and hilly areas. The above variables formed interaction terms with female cadres as two variables and were involved in the regression. In Table 7, all coefficients of the "Female cadre×Plain" and "Female cadre×Hilly" are negative, respectively, suggesting that the topography of plain and hilly can weaken the positive effect of female cadres on clean energy accessibility.

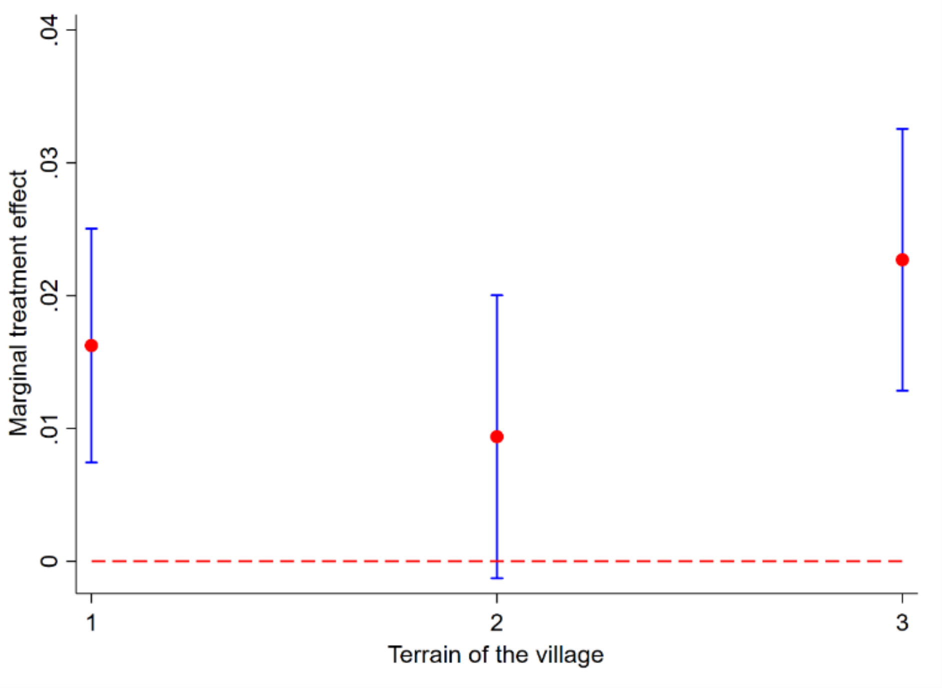
In addition, Figure 5 describes the moderating effects of village topography, where the 1, 2, and 3 on the axis of abscissas represent the topography of plains, hills, and mountains, respectively. There is a negative moderating effect between female cadres and clean energy accessibility when the topography is plain. Figure 5(a) shows the moderating effect of village topography on the relationship between female cadres and the natural gas connection in villages. And Figure 5(b) portrays the moderating effect of village topography on the correlation between female cadres and the connection rate of natural gas in villages. We found that all three topologies, plains, hills, and mountains, weakened the positive effect of female cadres on village clean energy accessibility, but the weakening effect of plain and hilly topography on the effect of female cadres and village clean energy accessibility is greater than that of the mountain. This may be because the flatter the topography, the more likely that farmers are to use clean energy, and therefore the role of female cadres in promoting clean energy accessibility in villages is less prominent. Conversely, the steeper the topography, the lower the clean energy accessibility. The role of women in promoting clean energy adoption in villages is more pronounced when women are elected as village cadres in mountainous villages.

Table 7: The results of moderating effects of village topography

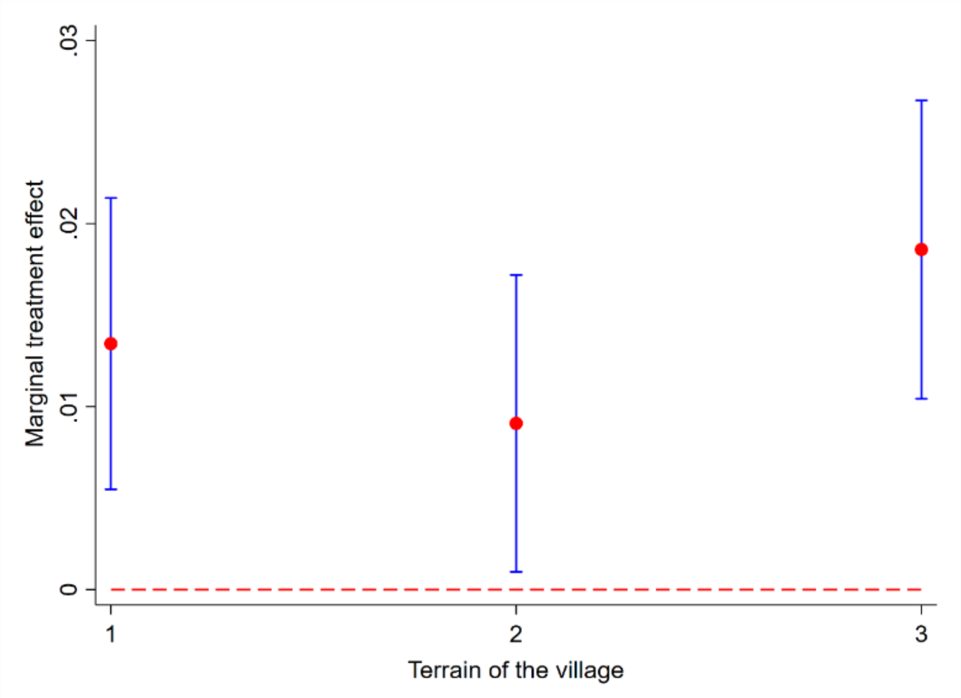
Variables	Gas	RGas
Female cadre	0.228^{***}	0.788^{***}

	(0.054)	(0.191)
Female cadre×Plain	-0.113*	-0.394*
	(0.063)	(0.226)
Female cadre×Hilly	-0.165**	-0.529**
	(0.065)	(0.222)
Control variables	Yes	Yes
Provincial fixed effect	Yes	Yes
Constant	-3.696***	-12.544***
	(0.303)	(1.110)
Observations	54,596	54,585

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



5(a) Gas



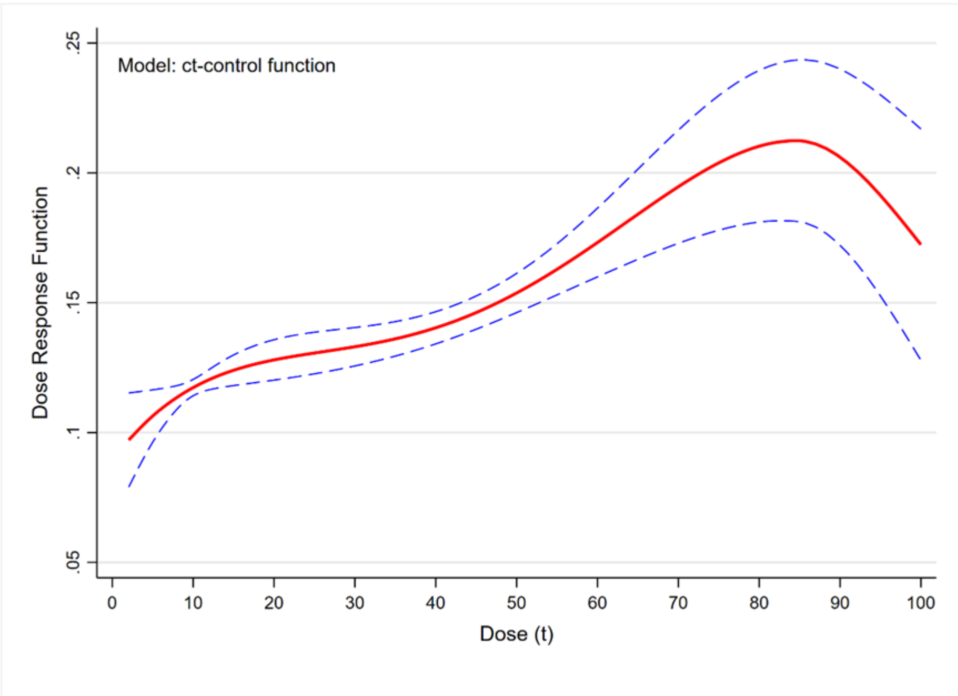
5(b) RGas

Figure 5: The moderating effects of village topography

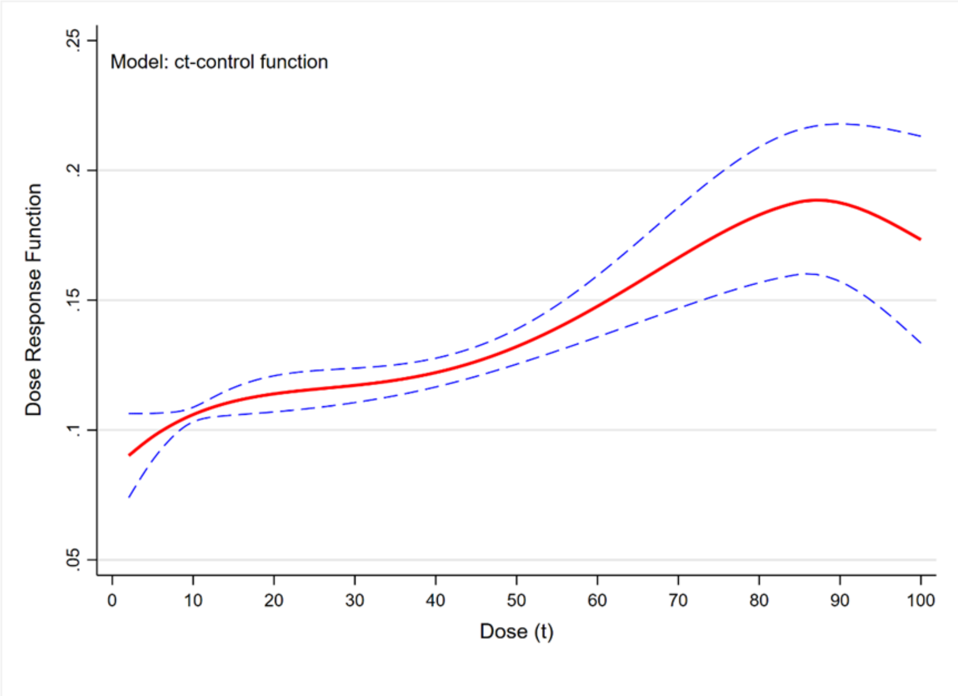
5.3.2. Heterogeneity from the proportion of female cadres

The above empirical results suggest that female cadres can significantly contribute to clean energy accessibility in villages. The matching results above are only the average treatment effect of female cadres driving village clean energy development and cannot reflect the heterogeneous effect of the proportion of female cadres on village clean energy development. The baseline results are based on a linear hypothesis, while the impact of female cadres on clean energy accessibility in villages is non-linear. Therefore, this paper uses the generalized propensity score matching (GPSM) to estimate the heterogeneous effects of the proportion of female cadres. The explanatory variable (female cadres) is a binary variable and is endogenous because the election of female village cadres is most likely dependent on the preferences of the village leadership team. For example, female discrimination and competence denial by the leadership team can affect the employment of female cadres, and these influence factors are often difficult to observe. Thus, using OLS to estimate the impact of female cadres on clean energy accessibility is subject to bias. To obtain more precise estimates, this paper uses a two-step control function approach for estimation because the results obtained in the first step using Probit regression are more accurate.

Figure 6 shows the relationship between the proportion of female cadres and clean energy accessibility obtained by the GPSM method. Figure 6(a) plots the dose-response function of female cadres to the natural gas connection in villages, and Figure 6(b) shows the dose-response of female cadres to the connection rate of natural gas in villages. There is a non-linear relationship between female cadres and clean energy accessibility. With the increase in the proportion of female cadres, the marginal treatment effects rise gradually and hit the highest value, which corresponds to 87% of the proportion of female cadres. While the marginal treatment effects of female cadres reduce with the continuous increase of the proportion of female cadres. Therefore, we argue that the optimal proportion of female cadres in villages is about 87%, which helps villages improve clean energy accessibility.



6(a) Gas



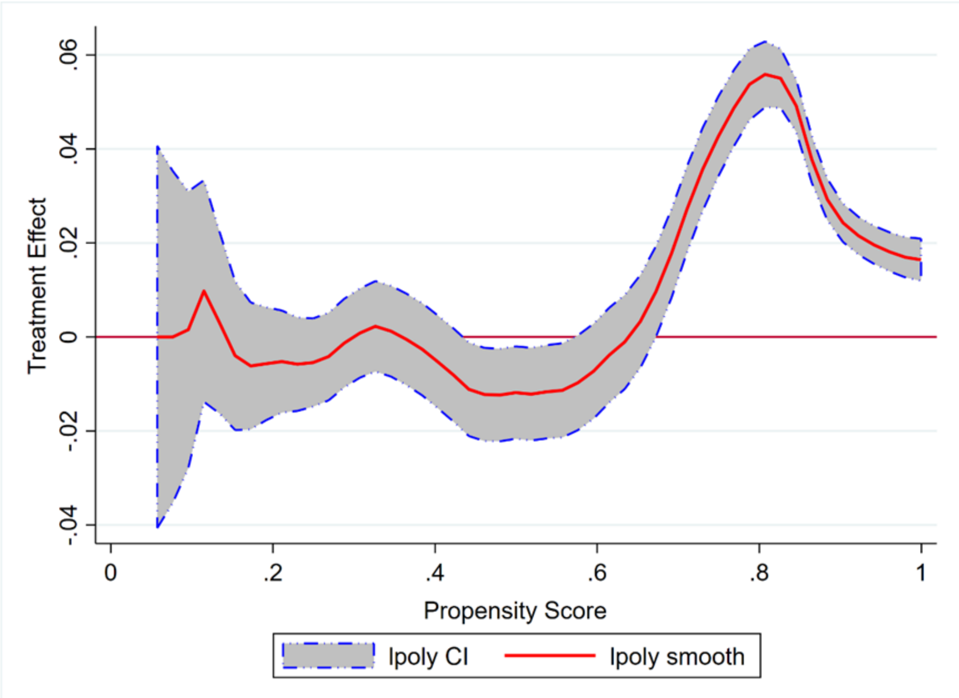
6(b) RGas

Figure 6: Dose-response of female cadres to clean energy accessibility in villages

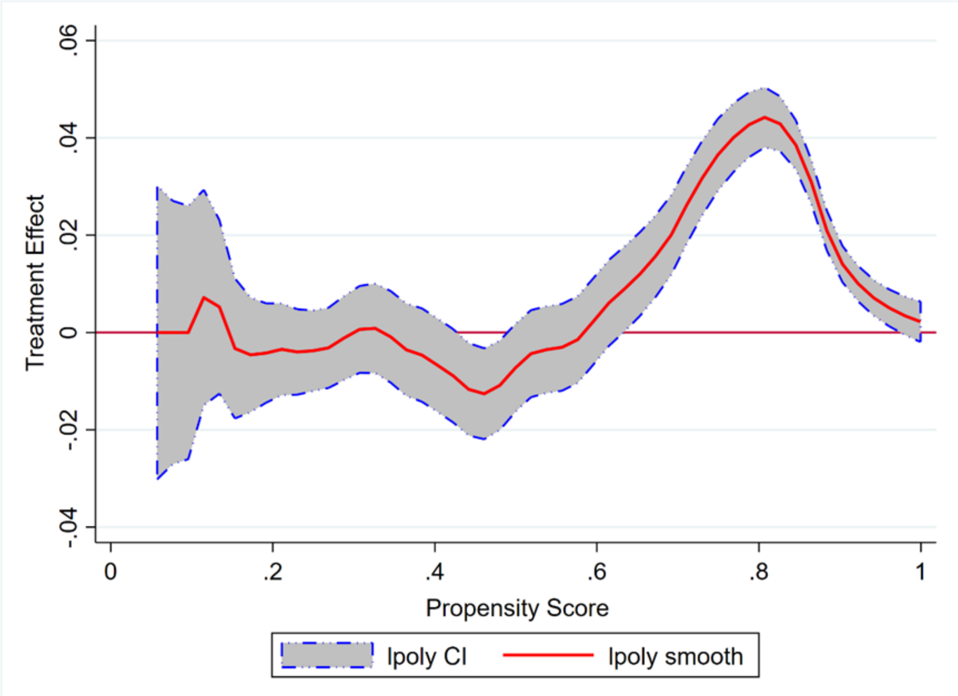
5.3.3. Heterogeneity from the propensity to elect female cadres

In addition to the observable background characteristics mentioned in the above two sub-sections, individual differences also lie in the way they respond to a particular treatment. The treatment effect of female cadres on clean energy accessibility in villages may vary depending on the change in the propensity to accept the treatment. Thus, we introduce the matching-smoothing (MS) method (Xie et al., 2012) to further explore the heterogeneous treatment effects of female cadres on clean energy accessibility due to the different propensity to elect female cadres. The advantage of this method is that individual-level information can be preserved before cross-individual comparisons are made to detect heterogeneous treatment effects. Individuals in the treatment and control groups are matched on the basis of propensity scores to obtain differences among individuals, and these differences are then used to plot nonparametric smoothing curves for analyzing heterogeneous treatment effects.

Figures 7(a) and 7(b) depict the treatment effects corresponding to villages with different propensities to elect female cadres. 95% confidence intervals do not contain zero mainly at the right half tail of the curve, and the treatment effect corresponds to the maximum when the propensity score is around 0.81. That is, the positive effect of female cadres on clean energy accessibility in villages is greatest when the probability of electing female cadres in villages is 81%. In contrast, for villages where the probability of electing female cadres is lower than 66% and higher than 97%, the effect of female cadres on clean energy accessibility in villages is not significant.



7(a) Gas



7(b) RGas

Figure 7: The heterogeneous treatment effects due to the propensity to elect female cadres

5.4. Mechanism identification

Although the theoretical analysis section has elaborated on how female cadres can improve clean energy accessibility in villages through three channels including promoting entrepreneurship, developing the rural collective economy, and providing elderly care services, our conjectures should be tested by empirical methods.

First, this study chooses two variables to measure the entrepreneurial situation within the villages: the natural logarithm of the number of comprehensive stores or supermarkets with a business area of 50 square meters or more, and the natural logarithm of the number of restaurants with business licenses. Table 8 reports the impact of female cadres on village entrepreneurship. It is found that having female cadres in the village can increase the number of stores or supermarkets by about 8.46% and increase the number of restaurants with business licenses by 9.13% (the average of all estimation results). These results are significant at the 1% level. Thus, the channel of female cadres to enhance village clean energy accessibility by promoting inner village entrepreneurship is supported by the data.

Table 8: The treatment effect of female cadres on entrepreneurship within the village

Methods	Stores or supermarkets			Restaurants with business licenses		
	ATE	S. E.	p>|z|	ATE	S. E.	p>|z|
Nearest-neighbor matching (1:7)	0.101***	0.014	0.000	0.114***	0.010	0.000
Nearest-neighbor matching (1:1)	0.091***	0.015	0.000	0.096***	0.014	0.000
Propensity-score matching	0.089***	0.013	0.000	0.094***	0.015	0.000
IPW regression adjustment	0.080***	0.013	0.000	0.083***	0.012	0.000
Inverse-probability weights	0.074***	0.015	0.000	0.075***	0.016	0.000
Regression adjustment	0.071***	0.012	0.000	0.085***	0.011	0.000

Notes: ***p<0.01, **p<0.05, *p<0.1

Second, the rural collective economy is measured by the natural logarithm of the collective economic income of the whole village. As reported in Table 9, the estimation results show that female cadres significantly increase rural collective economy income by approximately 27.1% (the average of all estimation results). This result corroborates the theoretical analysis in this paper, indicating that female cadres have a significant positive impact on rural collective economic income, thereby indirectly improving clean energy accessibility in villages.

Table 9: The treatment effect of female cadre on collective economic income

Methods	ATE	S. E.	p>|z|
Nearest-neighbor matching (1:7)	0.353***	0.024	0.000
Nearest-neighbor matching (1:1)	0.302***	0.027	0.000
Propensity-score matching	0.314***	0.034	0.000
IPW regression adjustment	0.261***	0.027	0.000
Inverse-probability weights	0.193**	0.077	0.012
Regression adjustment	0.281***	0.027	0.000

Notes: ***p<0.01, **p<0.05, *p<0.1

Third, to verify the channel through which female cadres improve clean energy accessibility in villages through providing elderly care services, this study measures the situation of elderly care services in the village by the natural logarithm of the number of people who are centrally cared for within the village. The estimation results for the treatment effect of female cadres on elderly care services are reported in Table 10, showing that female cadres could increase the number of people participating in centralized elderly care in the village by about 4.43% (the average of all estimation results). This result indicates that female cadres effectively improve clean energy accessibility in villages by providing elderly care services, and the corresponding theoretical analysis has received empirical support.

Table 10: The treatment effect of female cadre on elderly care services.

Method	ATE	S. E.	p>|z|
Nearest-neighbor matching (1:7)	0.068***	0.014	0.000
Nearest-neighbor matching (1:1)	0.053***	0.015	0.001
Propensity-score matching	0.039**	0.017	0.018
IPW regression adjustment	0.043***	0.014	0.002
Inverse-probability weights	0.032*	0.018	0.077
regression adjustment	0.037***	0.014	0.006

Notes: ***p<0.01, **p<0.05, *p<0.1

6. Discussion

In recent years, carbon emissions have received widespread attention in the world (Ang and Su, 2016; Mallapaty, 2020; Li et al., 2021). In 2020, the Chinese government proposed to achieve "peak carbon emissions" by 2030 and "carbon neutrality" by 2060, advocating a green, environmentally friendly, low-carbon lifestyle and adjusting the industrial and energy structures. In this context, this paper focuses on household energy consumption in rural areas. Most rural households use unclean cooking fuels, which emit pollutants that can harm human health (Bonjour et al., 2013; Sharma et al., 2020).

The situation in rural areas of China is special in that due to the accelerated industrialization and urbanization, the rural male labor force continues to migrate to the non-farm sector, resulting in a predominantly female resident population in rural areas (Zhao et al., 1999; Chang et al., 2011). As a result, more and more women are engaging in rural management, such as being elected as village cadres. Can female cadres improve clean energy accessibility in villages? What are the potential mechanisms? These questions are mainly explored in this paper. We established a theoretical framework for how female cadres can influence the accessibility of clean energy in rural villages. Subsequently, we used big data from the Third Agricultural Census to estimate the impact of female cadres on clean energy accessibility and identified the underlying mechanisms.

First, we found that female cadres can significantly improve the accessibility of clean energy in villages. On the one hand, female cadres can facilitate the natural gas connection in villages. On the other hand, female cadres can increase the proportion of residents within villages connected to natural gas. These estimates are tested by robustness tests such as treatment effect models and the heteroskedasticity-based identification strategy. Owing to traditional norms of gender division of labor in the household (Imelda and Verma, 2019), women are usually responsible for cooking and are the major users of fuel in the household (Li et al., 2022b) and are victims of unclean energy and energy poverty (Oparaocha and Dutta, 2011). Therefore, from the demand perspective, female cadres have a stronger willingness to adopt clean energy than men. From a psychological perspective, women have altruistic traits and higher health and environmental awareness levels, making them more likely to generate environmental motivation and behavioral decisions (Andreoni and Esterlund, 2001; Casaló and Escario, 2018).

Second, this paper also investigated the heterogeneous effect of female cadres on clean energy accessibility in villages. We found that the effect of female cadres on clean energy accessibility is more pronounced for villages with uneven topography, while the opposite is true for plain areas. The possible reason is that the level of clean energy accessibility is higher in flatter areas (Wu et al., 2022), thus replacing some of the positive effects of female cadres on clean energy accessibility. This is in line with Islam et al. (2022), Mahama (2012), and Mondiale (2008), where areas with better infrastructure access to clean energy are less costly and more attractive for clean energy investments when the effect of cadre gender is not considered. In addition, we find that the positive effect of female cadres in improving access to clean energy in villages is greatest when the proportion of female cadres in villages is about 87%. Furthermore, the results of the SD method suggest that female cadres are more able to play a role in promoting clean energy access for villages that are more likely to elect women as cadres.

We identified three channels through which female cadres can influence the accessibility of clean energy in rural villages. We found that female cadres can promote entrepreneurship within the village. By supporting female entrepreneurship, female cadres can enhance the social and family status of women, increase women's income (Datta and Gailey, 2012; Kumar and Prakash, 2017), and empower them to choose their family's fuel (Agrawal et al., 2021). Moreover, female cadres can contribute to the development of the rural collective economy. The development of the rural collective economy can lead to more employment opportunities and increased household income (Barron et al., 2020; Dutta, 2020). The Energy ladder theory suggests that as household income increases, household fuel consumption tends to shift towards cleaner fuels (Van der Kroon et al., 2013). Additionally, the development of the rural collective economy can contribute to the provision of public goods within the village, such as clean energy (He et al., 2016). Furthermore, female cadres tend to provide elderly care services, which can release more eligible labor force to work and increase household income (Sugawara and Nakamura, 2014). The provision of elderly care services in the village can also enhance the health awareness of families (Zahno et al., 2020), leading to more households choosing to use clean energy.

This paper contributes to the existing literature by studying the effects of female cadres on clean energy accessibility in villages, and this research perspective is innovative. This study confirms that female cadres play an important role in promoting clean energy use in villages. At the same time, the identification of heterogeneous treatment effects and influence channels can help us gain a deeper understanding of the positive effects of female cadres on clean energy accessibility in villages and provide a basis for government departments to formulate policies to upgrade the structure of rural energy consumption and improve the rural living environment. However, we must acknowledge that this study has some limitations. Our findings cannot be fully generalized to all countries or regions, as this study is based on the particular scenario of China. Our findings may be applicable to developing countries such as Asia and Africa, which also face the problem of rural household energy poverty, and their household energy consumption structure needs to be improved.

7. Conclusion

Based on the data from the Third Agricultural Census of China, this paper analyzes the effect of female cadres on clean energy accessibility and inner mechanisms. The results show that female cadres can significantly contribute to the improvement of clean energy accessibility. Compared with villages without female cadres, villages with female cadres are more likely to have access to natural gas, and their residential areas have a higher natural gas connection rate. Additionally, the positive relationship between female cadres and clean energy accessibility shows heterogeneity due to village topography, the proportion of female cadres, and the propensity to elect female cadres in villages. The contribution of female cadres to clean energy accessibility is weakened in villages with plain terrain. Also, the role of female cadres in promoting clean energy accessibility in villages is greatest when the proportion of female cadres in villages is around 87%. In addition, for villages that are more likely to elect female cadres, female cadres are more likely to promote clean energy accessibility. Furthermore, female cadres contribute to clean energy accessibility by promoting entrepreneurship, developing the collective economy, and providing elderly care services.

Based on these findings, some policy implications are proposed. First, grassroots units should recognize the significant role of women in rural environmental governance. As female cadres are capable of improving the accessibility of clean energy, they should be assigned to positions in environmental management or public welfare where they can leverage their gender advantages. Second, it is recommended that the village committee should refer to the optimal female representation of 87% to reasonably arrange the gender proportion of the cadre team, enabling female cadres to maximize their role in improving the accessibility of clean energy. For villages that have gender biases and are not inclined to elect female cadres, relevant government departments should guide them to be more inclusive and accepting of female cadres. Additionally, it is important to enhance women's awareness of participation in rural governance and provide more training and development opportunities for them to better contribute to environmental governance. Finally, female cadres are essential for natural gas connectivity in mountainous areas.

References

Agrawal, A., Gandhi, P., & Khare, P. (2021). Women empowerment through entrepreneurship: case study of a social entrepreneurial intervention in rural India. International Journal of Organizational Analysis, 4(31), 1122-1142.

Andreoni, J., & Vesterlund, L. (2001). Which is the fair sex? Gender differences in preferences. The Quarterly Journal of Economics, 116(1), 292-312.

Anfinsen, M., & Heidenreich, S. (2017). Energy & gender-a social sciences and humanities crosscutting theme report. Cambridge: SHAPE ENERGY.

Ang, B. W., & Su, B. (2016). Carbon emission intensity in electricity production: A global analysis. Energy Policy, 94, 56-63.

Austin, K. F., & Mejia, M. T. (2017). Household air pollution as a silent killer: women's status and solid fuel use in developing nations. Population and Environment, 39, 1-25.

Barron, M., Philip Clarke, R., B Elam, A., A Klege, R., Shankar, A., & Visser, M. (2020). Gender and entrepreneurship in the renewable energy sector of Rwanda. IDS bulletin, 51, 53-69.

Baum, C. F., & Lewbel, A. (2019). Advice on using heteroskedasticity-based identification. The Stata Journal, 19(4), 757-767.

Beaman, L., Duflo, E., Pande, R., & Topalova, P. (2012). Female leadership raises aspirations and educational attainment for girls: A policy experiment in India. science, 335(6068), 582-586.

Besley, T., & Case, A. (2003). Political institutions and policy choices: evidence from the United States. Journal of Economic Literature, 41(1), 7-73.

Bia, M., & Mattei, A. (2008). A Stata package for the estimation of the dose-response function through adjustment for the generalized propensity score. The Stata Journal, 8(3), 354-373.

Bonjour, S., Adair-Rohani, H., Wolf, J., Bruce, N. G., Mehta, S., Prüss-Ustün, A., ... & Smith, K. R. (2013). Solid fuel use for household cooking: country and regional estimates for 1980–2010. Environmental health perspectives, 121(7), 784-790.

Briones, R. M. (2013). Agriculture, rural employment, and inclusive growth (No. 2013-39). PIDS Discussion Paper Series.

Casaló, L. V., & Escario, J. J. (2018). Heterogeneity in the association between environmental attitudes and pro-environmental behavior: A multilevel regression approach. Journal of Cleaner Production, 175, 155-163.

Chang, H., Dong, X. Y., & MacPhail, F. (2011). Labor migration and time use patterns of the left-behind children and elderly in rural China. World Development, 39(12), 2199-2210.

Chaton, C., & Lacroix, E. (2018). Does France have a fuel poverty trap?. Energy Policy, 113, 258-268.

Chattopadhyay, R., & Duflo, E. (2004). Women as policy makers: Evidence from a randomized policy experiment in India. Econometrica, 72(5), 1409-1443.

Chen, A. (2016). The politics of the shareholding collective economy in China's rural villages. The Journal of Peasant Studies, 43(4), 828-849.

Choudhuri, P., & Desai, S. (2020). Gender inequalities and household fuel choice in India. Journal of cleaner production, 265, 121487.

Clots-Figueras, I. (2011). Women in politics: Evidence from the Indian States. Journal of public Economics, 95(7-8), 664-690.

Das, I., Klug, T., Krishnapriya, P., Plutshack, V., Saparapa, R., Scott, S., & Pattanayak, S. K. (2020). A Virtuous Cycle? Reviewing the evidence on women's empowerment and energy access, frameworks, metrics and methods. White Paper.

Datta, P. B., & Gailey, R. (2012). Empowering women through social entrepreneurship: Case study of a women's cooperative in India. Entrepreneurship theory and Practice, 36(3), 569-587.

Davis, N. J., & Robinson, R. V. (1991). Men's and women's consciousness of gender inequality: Austria, West Germany, Great Britain, and the United States. American Sociological Review, 72-84.

Dietz, T., Kalof, L., & Stern, P. C. (2002). Gender, values, and environmentalism. Social science quarterly, 83(1), 353-364.

Dim, J. U. (2023). Gender, Energy Expenditure and Household Cooking Fuel Choice in Nigeria. The Energy Journal, 44(5), 1-17.

Dutta, S. (2020). Promoting women's entrepreneurship in distribution of energy technologies: lessons from ENERGIA's WEE programme. IDS Bulletin, 51(1), 71-90.

Eagly, A. H. (2013). Sex differences in social behavior: A social-role interpretation. Psychology Press.

Fan, C. C. (2003). Rural-urban migration and gender division of labor in transitional China. International Journal of Urban and Regional Research, 27(1), 24-47.

Fathallah, J., & Pyakurel, P. (2020). Addressing gender in energy studies. Energy

Research & Social Science, 65, 101461.

Feng, Z., Glinskaya, E., Chen, H., Gong, S., Qiu, Y., Xu, J., & Yip, W. (2020). Long-term care system for older adults in China: policy landscape, challenges, and future prospects. The Lancet, 396(10259), 1362-1372.

Gajwani, K., & Zhang, X. (2008). Gender, caste, and public goods provision in Indian village governments (Vol. 807). Intl Food Policy Res Inst.

Gertler, P. J., Shelef, O., Wolfram, C. D., & Fuchs, A. (2016). The demand for energy-using assets among the world's rising middle classes. American Economic Review, 106(6), 1366-1401.

Gottlieb, J., Grossman, G., & Robinson, A. L. (2018). Do men and women have different policy preferences in Africa? Determinants and implications of gender gaps in policy prioritization. British Journal of Political Science, 48(3), 611-636.

Gould, C. F., & Urpelainen, J. (2018). LPG as a clean cooking fuel: Adoption, use, and impact in rural India. Energy Policy, 122, 395-408.

Hamed, T. A., Flamm, H., & Azraq, M. (2012). Renewable energy in the Palestinian Territories: Opportunities and challenges. Renewable and Sustainable Energy Reviews, 16(1), 1082-1088.

Hardy-Fanta, C. (1993). Latina politics, Latino politics: Gender, culture, and political participation in Boston. Temple University Press.

Harjoto, M. A., Laksmana, I., & Lee, W. E. (2020). Female leadership in corporate social responsibility reporting: Effects on writing, readability and future social performance. Advances in accounting, 49, 100475.

He, C., Peng, L., Liu, S., Xu, D., & Xue, P. (2016). Factors influencing the efficiency of rural public goods investments in mountainous areas of China——based on micro panel data from three periods. Journal of Rural Studies, 47, 612-621.

Heitmueller, A., & Inglis, K. (2007). The earnings of informal carers: Wage differentials and opportunity costs. Journal of health economics, 26(4), 821-841.

Hirano, K., & Imbens, G. W. (2004). The propensity score with continuous treatments. Applied Bayesian modeling and causal inference from incomplete-data perspectives, 226164, 73-84.

Hosier, R. H., & Dowd, J. (1987). Household fuel choice in Zimbabwe: an empirical test of the energy ladder hypothesis. Resources and energy, 9(4), 347-361.

Huang, A., Xu, Y., Sun, P., Zhou, G., Liu, C., Lu, L., & Wang, H. (2019). Land use/land cover changes and its impact on ecosystem services in ecologically fragile zone:

A case study of Zhangjiakou City, Hebei Province, China. Ecological Indicators, 104, 604-614.

Huber, J., & Spitze, G. (1981). Wives' employment, household behaviors, and sex-role attitudes. Social Forces, 60(1), 150-169.

Imelda, I., & Verma, A. P. (2019). Clean energy access: gender disparity, health, and labor supply. Universidad Carlos III de Madrid, Departamento de Economía , 29397, 1-58.

International Energy Agency (2009). World energy outlook (p. 17). Paris: OECD/IEA.

Islam, M. M., Irfan, M., Shahbaz, M., & Vo, X. V. (2022). Renewable and non-renewable energy consumption in Bangladesh: The relative influencing profiles of economic factors, urbanization, physical infrastructure and institutional quality. Renewable Energy, 184, 1130-1149.

Ji, X., Xu, J., & Zhang, H. (2023). Environmental effects of rural E-commerce: A case study of chemical fertilizer reduction in China. Journal of Environmental Management, 326, 116713.

Jiang, L., Yu, L., Xue, B., Chen, X., & Mi, Z. (2020). Who is energy poor? Evidence from the least developed regions in China. Energy Policy, 137, 111122.

Jones-Correa, M. (1998). Different paths: Gender, immigration and political participation. International migration review, 32(2), 326-349.

Karlsson, G. (2007). Where energy is women's business. National and regional reports from Africa, Asia, Latin America and the Pacific', ENERGIA, Leusden.

Kishore, A., & Spears, D. (2012, May). Clean cooking fuel, women's intrahousehold status, and son preference in rural India. In Poster presentation, Population Association of America annual meeting, San Francisco.

Kluve, J., Schneider, H., Uhlendorff, A., & Zhao, Z. (2012). Evaluating continuous training programmes by using the generalized propensity score. Journal of the Royal Statistical Society: Series A (Statistics in Society), 175(2), 587-617.

Kumar, S., & Prakash, N. (2017). Effect of political decentralization and female leadership on institutional births and child mortality in rural Bihar, India. Social Science & Medicine, 185, 171-178.

Kwauk, C., & Braga, A. (2017). Three platforms for girls' education in climate strategies. Washington, DC: Brookings.

Kyrö, P., & Sundin, E. (2008). Women entrepreneurship and social capital: A dialogue and construction. Copenhagen Business School Press DK.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. Journal of Business & Economic Statistics, 30(1), 67-80.

Lewis, J. J., & Pattanayak, S. K. (2012). Who adopts improved fuels and cookstoves? A systematic review. Environmental health perspectives, 120(5), 637-645.

Li, L., Fan, F., & Liu, X. (2022a). Determinants of rural household clean energy adoption intention: Evidence from 72 typical villages in ecologically fragile regions of western China. Journal of Cleaner Production, 347, 131296.

Li, N., Zhang, G., Zhang, L., Zhou, Y., & Zhang, N. (2022b). Improving rural women's health in China: Cooking with clean energy. Environmental Science and Pollution Research, 29(14), 20906-20920.

Li, Z. Z., Li, R. Y. M., Malik, M. Y., Murshed, M., Khan, Z., & Umar, M. (2021). Determinants of carbon emission in China: how good is green investment?. Sustainable Production and Consumption, 27, 392-401.

Liu, C. (2018). Are women greener? Corporate gender diversity and environmental violations. Journal of Corporate Finance, 52, 118-142.

MacPhail, F., & Dong, X. Y. (2007). Women's market work and household status in rural China: Evidence from Jiangsu and Shandong in the late 1990s. Feminist Economics, 13(3-4), 93-124.

Mahama, A. (2012). 2012 international year for sustainable energy for all: African Frontrunnership in rural electrification. Energy policy, 48, 76-82.

Mahapatra, S., Kumar, D., Singh, B., & Sachan, P. K. (2021). Biofuels and their sources of production: A review on cleaner sustainable alternative against conventional fuel, in the framework of the food and energy nexus. Energy Nexus, 4, 100036.

Makan, A. (1995). Power for women and men: towards a gendered approach to domestic energy policy and planning in South Africa. Third World Planning Review, 17(2), 183-198.

Mallapaty, S. (2020). How China could be carbon neutral by mid-century. Nature, 586(7830), 482-484.

McCright, A. M. (2010). The effects of gender on climate change knowledge and concern in the American public. Population and Environment, 32(1), 66-87.

Mondiale, B. (2008). Designing sustainable off-grid rural electrification projects: principles and practices. The World Bank.

Moniruzzaman, M., & Day, R. (2020). Gendered energy poverty and energy justice in

rural Bangladesh. Energy Policy, 144, 111554.
Ngarava, S., Zhou, L., Ningi, T., Chari, M. M., & Mdiya, L. (2022). Gender and ethnic disparities in energy poverty: The case of South Africa. Energy policy, 161, 112755.
Niu, S., Li, Z., Qiu, X., Dai, R., Wang, X., Qiang, W., & Hong, Z. (2019). Measurement of effective energy consumption in China's rural household sector and policy implication. Energy policy, 128, 553-564.
Norgaard, K., & York, R. (2005). Gender equality and state environmentalism. Gender & Society, 19(4), 506-522.
Oparaocha, S., & Dutta, S. (2011). Gender and energy for sustainable development. Current Opinion in Environmental Sustainability, 3(4), 265-271.
Pachauri, S., & Rao, N. D. (2013). Gender impacts and determinants of energy poverty: are we asking the right questions?. Current Opinion in Environmental Sustainability, 5(2), 205-215.
Pardo, M. (1990). Mexican American Women Grassroots Community Activists:" Mothers of East Los Angeles". Frontiers: A Journal of Women Studies, 1(11), 1-7.
Permana, A. S., Aziz, N. A., & Siong, H. C. (2015). Is mom energy efficient? A study of gender, household energy consumption and family decision making in Indonesia. Energy research & social science, 6, 78-86.
Sharma, D., Ravindra, K., Kaur, M., Prinja, S., & Mor, S. (2020). Cost evaluation of different household fuels and identification of the barriers for the choice of clean cooking fuels in India. Sustainable Cities and Society, 52, 101825.
Sovacool, B. K. (2012). The political economy of energy poverty: A review of key challenges. Energy for Sustainable Development, 16(3), 272-282.
Stuhlmacher, A. F., & Walters, A. E. (1999). Gender differences in negotiation outcome: A meta-analysis. Personnel Psychology, 52(3), 653-677.
Sugawara, S., & Nakamura, J. (2014). Can formal elderly care stimulate female labor supply? The Japanese experience. Journal of the Japanese and International Economies, 34, 98-115.
Tang, X., & Liao, H. (2014). Energy poverty and solid fuels use in rural China: Analysis based on national population census. Energy for Sustainable Development, 23, 122-129.
Tarhini, A., Hone, K., & Liu, X. (2014). Measuring the moderating effect of gender and age on e-learning acceptance in England: A structural equation modeling approach

for an extended technology acceptance model. Journal of Educational Computing Research, 51(2), 163-184.

Tate, G., & Yang, L. (2015). Female leadership and gender equity: Evidence from plant closure. Journal of Financial Economics, 117(1), 77-97.

United Nations. (2016). Sustainable development goals report 2016. UN.

uz Zaman, Q., Wang, Z., Zaman, S., & Rasool, S. F. (2021). Investigating the nexus between education expenditure, female employers, renewable energy consumption and CO_2 emission: Evidence from China. Journal of Cleaner Production, 312, 127824.

Van der Kroon, B., Brouwer, R., & Van Beukering, P. J. (2013). The energy ladder: Theoretical myth or empirical truth? Results from a meta-analysis. Renewable and sustainable energy reviews, 20, 504-513.

Venkatesh, P. (2013). Recent trends in rural employment and wages in India: has the growth benefitted the agricultural labours?. Agricultural Economics Research Review, 26(347-2016-17099), 13-20.

Wei, J., Duan, H., & Yan, Q. (2021). Shale gas: Will it become a new type of clean energy in China?—A perspective of development potential. Journal of Cleaner Production, 294, 126257.

Wen, X., Cui, L., Yuan, F., Liu, X., Ouyang, M., Sun, Y., ... & Yuan, Z. (2020). Study on the utilization of inpatient Services for Middle-Aged and Elderly Rural Females in less developed regions of China. International Journal of Environmental Research and Public Health, 17(2), 514.

Wickramasinghe, A. (2003). Gender and health issues in the biomass energy cycle: impediments to sustainable development. Energy for Sustainable Development, 7(3), 51-61.

Wojan, T. R. (2000). The composition of rural employment growth in the "new economy". American Journal of Agricultural Economics, 82(3), 594-605.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT press.

Wu, Y., Liao, Y., Xu, M., He, J., Tao, Y., Zhou, J., & Chen, W. (2022). Barriers identification, analysis and solutions to rural clean energy infrastructures development in China: Government perspective. Sustainable Cities and Society, 86, 104106.

Xiao, H., Chen, M. (2021). The development situation, typical case analysis, some thoughts and its measures of new rural collective economy. Issues in Agricultural Economy, 12, 104-115. (In Chinese)

Xie, Y., Brand, J. E., & Jann, B. (2012). Estimating heterogeneous treatment effects with observational data. Sociological methodology, 42(1), 314-347.

Zahno, M., Michaelowa, K., Dasgupta, P., & Sachdeva, I. (2020). Health awareness and the transition towards clean cooking fuels: Evidence from Rajasthan. PloS one, 15(4), e0231931.

Zhao, Y. (1999). Labor migration and earnings differences: the case of rural China. Economic Development and Cultural Change, 47(4), 767-782.

Appendix

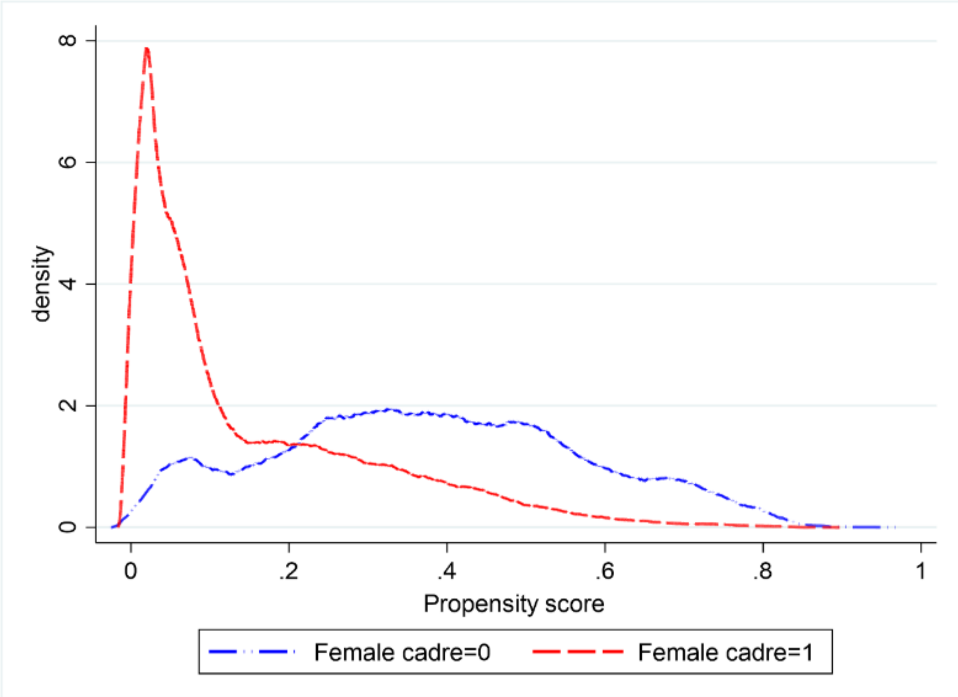


Figure A1: Common support

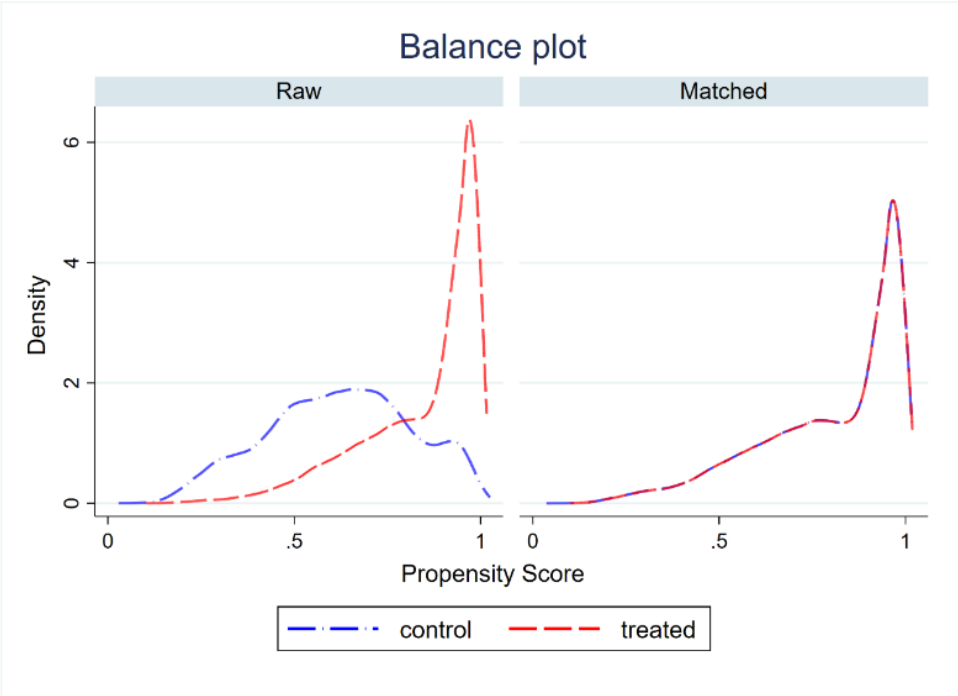


Figure A2: Balance test

Table A1: Results of the Rosenbaum sensitivity analysis for Gas

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	1	1	-0.065132	-0.065132	-0.06546	-0.064807
1.05	1	1	-0.065863	-0.064399	-0.066187	-0.064076
1.1	1	1	-0.066563	-0.0637	-0.066898	-0.063374
1.15	1	1	-0.067246	-0.063034	-0.067581	-0.062713
1.2	1	1	-0.067903	-0.0062411	-0.068249	-0.062098
1.25	1	1	-0.068555	-0.061834	-0.06891	-0.061539
1.3	1	1	-0.069195	-0.061314	-0.069565	-0.061037
1.35	1	1	-0.069835	-0.060849	-0.070217	-0.060616
1.4	1	1	-0.07047	-0.060467	-0.07086	-0.060245
1.45	1	1	-0.07109	-0.060117	-0.071481	-0.059904
1.5	1	1	-0.071688	-0.059793	-0.072077	-0.059603
1.55	1	1	-0.072262	-0.059517	-0.072646	-0.059354
1.6	1	1	-0.072807	-0.05928	-0.073189	-0.059087
1.65	1	1	-0.073331	-0.059011	-0.073709	-0.058794
1.7	1	1	-0.073831	-0.058716	-0.074192	-0.058468
1.75	1	1	-0.074293	-0.058393	-0.074638	-0.058116
1.8	1	1	-0.074722	-0.058046	-0.075056	-0.057747
1.85	1	1	-0.075123	-0.057683	-0.075446	-0.057363
1.9	1	1	-0.0755	-0.057307	-0.075807	-0.056968
1.95	1	1	-0.075849	-0.056921	-0.076148	-0.056567
2	1	1	-0.076177	-0.056529	-0.076469	-0.056159
2.05	1	1	-0.07649	-0.056134	-0.076787	-0.055749
2.1	1	1	-0.0768	-0.055734	-0.077153	-0.055342
2.15	1	1	-0.077158	-0.055338	-0.078011	-0.054935
2.2	1	1	-0.077993	-0.054941	-0.07904	-0.054525
2.25	1	1	-0.078996	-0.054543	-0.080034	-0.054118
2.3	1	1	-0.079962	-0.054147	-0.080988	-0.053717
2.35	1	1	-0.080894	-0.053756	-0.081917	-0.053317
2.4	1	1	-0.0818	-0.053367	-0.082816	-0.052922
2.45	1	1	-0.082677	-0.052984	-0.083682	-0.052532
2.5	1	1	-0.083525	-0.052604	-0.084509	-0.052148
2.55	1	1	-0.084336	-0.05223	-0.085286	-0.05177
2.6	1	1	-0.085103	-0.051861	-0.086037	-0.051393
2.65	1	1	-0.085834	-0.051495	-0.086776	-0.051022
2.7	1	1	-0.086554	-0.051134	-0.087505	-0.050647
2.75	1	1	-0.087265	-0.050771	-0.088208	-0.050274
2.8	1	1	-0.087957	-0.050409	-0.088882	-0.049901
2.85	1	1	-0.088622	-0.050047	-0.089525	-0.04952
2.9	1	1	-0.089258	-0.049684	-0.090147	-0.049134
2.95	1	1	-0.089867	-0.049309	-0.090745	-0.048742
3	1	1	-0.090457	-0.048931	-0.091328	-0.048355

Notes: Gamma: log odds of differential assignment due to unobserved factors; sig+: upper bound significance level; sig-: lower bound significance level; t-hat+: upper bound Hodges-Lehman point estimate; t-hat-: lower bound Hodges-Lehman point estimate; CI+: upper bound confidence interval of 95%; CI-: lower bound confidence interval of 95%.

Table A2: Results of the Rosenbaum sensitivity analysis for RGas

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	1	1	-0.06088	-0.06088	-0.061224	-0.060527
1.05	1	1	-0.061655	-0.060091	-0.061995	-0.059745
1.1	1	1	-0.062378	-0.059352	-0.062695	-0.059014
1.15	1	1	-0.063024	-0.058666	-0.063346	-0.058344
1.2	1	1	-0.063656	-0.058051	-0.063982	-0.057759
1.25	1	1	-0.064271	-0.057532	-0.064594	-0.057283
1.3	1	1	-0.064847	-0.057083	-0.065161	-0.05683
1.35	1	1	-0.065387	-0.056647	-0.065711	-0.056389
1.4	1	1	-0.065932	-0.056218	-0.066274	-0.055961
1.45	1	1	-0.06648	-0.055808	-0.066836	-0.05555
1.5	1	1	-0.06703	-0.055411	-0.067397	-0.055159
1.55	1	1	-0.067573	-0.055039	-0.067947	-0.054813
1.6	1	1	-0.068108	-0.054731	-0.068483	-0.054501
1.65	1	1	-0.068625	-0.054408	-0.069	-0.054143
1.7	1	1	-0.069124	-0.05405	-0.069499	-0.053748
1.75	1	1	-0.069608	-0.053658	-0.069982	-0.05333
1.8	1	1	-0.070074	-0.053245	-0.070452	-0.052898
1.85	1	1	-0.07053	-0.052823	-0.070898	-0.052457
1.9	1	1	-0.070962	-0.052393	-0.071333	-0.05201
1.95	1	1	-0.071383	-0.051958	-0.071754	-0.051558
2	1	1	-0.071793	-0.051517	-0.072159	-0.051103
2.05	1	1	-0.072184	-0.051073	-0.072541	-0.050649
2.1	1	1	-0.072554	-0.050632	-0.072897	-0.050198
2.15	1	1	-0.072901	-0.050194	-0.073238	-0.049754
2.2	1	1	-0.073232	-0.049761	-0.073563	-0.049314
2.25	1	1	-0.073549	-0.049334	-0.073873	-0.048877
2.3	1	1	-0.07385	-0.048908	-0.07417	-0.048448
2.35	1	1	-0.074141	-0.048492	-0.07445	-0.048028
2.4	1	1	-0.074414	-0.048082	-0.074717	-0.047615
2.45	1	1	-0.074677	-0.047679	-0.074971	-0.047211
2.5	1	1	-0.074926	-0.047285	-0.075212	-0.046815
2.55	1	1	-0.075161	-0.046898	-0.075441	-0.046427
2.6	1	1	-0.075386	-0.04652	-0.075666	-0.046044
2.65	1	1	-0.075604	-0.046149	-0.075899	-0.04566
2.7	1	1	-0.075827	-0.045776	-0.076153	-0.045281
2.75	1	1	-0.076066	-0.045405	-0.076666	-0.044908
2.8	1	1	-0.076468	-0.045043	-0.077208	-0.04454

2.85	1	1	-0.076997	-0.044685	-0.077732	-0.044174
2.9	1	1	-0.077513	-0.044328	-0.078234	-0.043801
2.95	1	1	-0.078008	-0.043972	-0.078717	-0.043421
3	1	1	-0.078486	-0.043605	-0.07918	-0.043032

Note: Gamma: log odds of differential assignment due to unobserved factors; sig+: upper bound significance level; sig-: lower bound significance level; t-hat+: upper bound Hodges-Lehman point estimate; t-hat-: lower bound Hodges-Lehman point estimate; CI+: upper bound confidence interval of 95%; CI-: lower bound confidence interval of 95%.

Table A3: Results of the control function approach for Gas

Variables	ATE	TME1	OME0	OME1
ATE	**0.154*** **			
	(0.024)			
Plain		-0.026	0.274***	0.256***
		(0.024)	(0.079)	(0.038)
Hilly		0.058***	0.432***	0.245***
		(0.021)	(0.067)	(0.033)
Asphalt road		0.208***	0.219	0.500**
		(0.073)	(0.188)	(0.220)
Concrete road		0.228***	0.331*	0.663***
		(0.074)	(0.195)	(0.221)
Slate road		0.038	-0.140	0.237
		(0.086)	(0.245)	(0.244)
Gravel road		-0.033	0.234	0.461
		(0.112)	(0.271)	(0.300)
Ln(population)		0.187***	0.232***	0.221***
		(0.010)	(0.052)	(0.022)
Tourism village		0.465***	0.102	0.109
		(0.156)	(0.663)	(0.128)
Ln(salary)		0.036***	0.016	0.003
		(0.006)	(0.027)	(0.010)

No schooling		-0.270**	-0.190	-0.518**
		(0.130)	(0.430)	(0.258)
Primary schooling		-0.381***	-0.060	-0.223***
		(0.039)	(0.131)	(0.075)
Middle schooling		-0.245***	-0.093	-0.166***
		(0.022)	(0.080)	(0.031)
High schooling		-0.151***	-0.040	-0.120***
		(0.021)	(0.066)	(0.026)
Ln(age)		0.021	0.240*	0.248***
		(0.044)	(0.126)	(0.063)
Ln(village area)		0.031***	-0.327***	-0.296***
		(0.009)	(0.027)	(0.012)
Natural village		0.006***	0.002	-0.007***
		(0.002)	(0.008)	(0.002)
Holding two positions		0.004	-0.064	-0.036
		(0.019)	(0.057)	(0.025)
Provincial fixed effect		Yes	Yes	Yes
Migration		0.202***		
		(0.015)		
TEOM0			-0.917*	
			(0.540)	
TEOM1				-1.741***
				(0.289)
Constant		0.359	-1.980*	-2.787***
		(0.301)	(1.117)	(0.400)
Observations	54,596	54,596	54,596	54,596

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

Table A4: Results of the control function approach for RGas

Variables	ATE	TME1	OME0	OME1
ATE	**0.158*** **			
	(0.059)			
Plain		-0.026	0.030***	0.027***
		(0.024)	(0.007)	(0.004)
Hilly		0.058***	0.059***	0.027***
		(0.021)	(0.007)	(0.003)
Asphalt road		0.208***	0.033***	0.048***
		(0.073)	(0.013)	(0.014)
Concrete road		0.228***	0.040***	0.066***
		(0.074)	(0.014)	(0.014)
Slate road		0.037	0.017	0.035**
		(0.086)	(0.014)	(0.015)
Gravel road		-0.033	0.033	0.057***
		(0.112)	(0.028)	(0.021)
Ln(population)		0.187***	0.017***	0.018***
		(0.010)	(0.006)	(0.003)
Tourism village		0.465***	0.010	0.014
		(0.156)	(0.074)	(0.018)
Ln(salary)		0.036***	0.002	-0.000
		(0.006)	(0.003)	(0.001)
No schooling		-0.270**	-0.044	-0.065***
		(0.130)	(0.034)	(0.023)
Primary schooling		-0.381***	-0.014	-0.036***
		(0.039)	(0.015)	(0.008)
Middle schooling		-0.245***	-0.008	-0.022***
		(0.022)	(0.010)	(0.004)
High schooling		-0.151***	-0.002	-0.018***

		(0.021)	(0.009)	(0.004)
Ln(age)		0.021	0.025*	0.037***
		(0.044)	(0.015)	(0.008)
Ln(village area)		0.031***	-0.038***	-0.040***
		(0.009)	(0.003)	(0.002)
Natural village		0.006***	0.001	-0.001***
		(0.002)	(0.001)	(0.000)
Holding two positions		0.004	-0.006	-0.003
		(0.019)	(0.007)	(0.003)
Provincial fixed effect		Yes	Yes	Yes
Migration		0.202***		
		(0.015)		
TEOM0			-0.115	
			(0.072)	
TEOM1				-0.284***
				(0.038)
Constant		0.359	0.181	0.013
		(0.301)	(0.297)	(0.044)
Observations	54,585	54,585	54,585	54,585

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

Table A5: Results of the Two-step consistent estimator for RGas

Variables	RGas	Female cadre
Plain	0.029***	-0.026
	(0.004)	(0.024)
Hilly	0.035***	0.058***
	(0.003)	(0.021)
Asphalt road	0.052***	0.208***
	(0.013)	(0.072)

Concrete road	0.069***	0.228***
	(0.013)	(0.074)
Slate road	0.031**	0.037
	(0.015)	(0.085)
Gravel road	0.054***	-0.033
	(0.020)	(0.115)
Ln(population)	0.023***	0.187***
	(0.002)	(0.010)
Tourism village	0.024	0.465***
	(0.016)	(0.147)
Ln(salary)	0.001	0.036***
	(0.001)	(0.006)
No schooling	-0.071***	-0.270**
	(0.021)	(0.131)
Primary schooling	-0.045***	-0.381***
	(0.007)	(0.039)
Middle schooling	-0.027***	-0.245***
	(0.003)	(0.022)
High schooling	-0.020***	-0.151***
	(0.003)	(0.021)
Ln(age)	0.035***	0.021
	(0.007)	(0.044)
Ln(village area)	-0.039***	0.031***
	(0.001)	(0.009)
Natural village	-0.001***	0.006***
	(0.000)	(0.002)
Holding two positions	-0.003	0.004
	(0.003)	(0.019)
Provincial fixed effect	Yes	Yes

ATE	**0.119*****	
	(0.018)	
Migration		0.202***
		(0.015)
Hazard(lambda)		-0.061***
		(0.011)
Constant	-0.162***	0.359
	(0.036)	(0.302)
Observations	54,585	54,585

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

Table A6: Results of the maximum likelihood estimator for RGas

Variables	RGas	Female cadre
Plain	0.028***	-0.024
	(0.004)	(0.024)
Hilly	0.035***	0.061***
	(0.003)	(0.021)
Asphalt road	0.059***	0.208***
	(0.013)	(0.072)
Concrete road	0.076***	0.229***
	(0.013)	(0.074)
Slate road	0.034**	0.038
	(0.015)	(0.085)
Gravel road	0.053***	-0.032
	(0.020)	(0.115)
Ln(population)	0.028***	0.186***
	(0.002)	(0.010)
Tourism village	0.029*	0.463***

	(0.016)	(0.147)
Ln(salary)	0.002**	0.036***
	(0.001)	(0.006)
No schooling	-0.077***	-0.270**
	(0.021)	(0.131)
Primary schooling	-0.053***	-0.381***
	(0.006)	(0.039)
Middle schooling	-0.032***	-0.245***
	(0.003)	(0.022)
High schooling	-0.022***	-0.150***
	(0.003)	(0.021)
Ln(age)	0.036***	0.022
	(0.007)	(0.044)
Ln(village area)	-0.038***	0.031***
	(0.001)	(0.009)
Natural village	-0.001***	0.006***
	(0.000)	(0.002)
Holding two positions	-0.003	0.004
	(0.003)	(0.019)
Provincial fixed effect	Yes	Yes
ATE	**0.035***	
	(0.008)	
Migration		0.206***
		(0.015)
athrho		-0.049***
		(0.017)
lnsigma		-1.411***
		(0.003)
Constant	-0.124***	0.373

	(0.034)	(0.304)
Observations	54,585	54,585

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