Field experimental evidence of how social relations shape behavior that promotes energy conservation

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Highlights
- Social relations shape households’ electricity consumption patterns
- Existence of social relations leads to heterogeneity in the electricity conservation
- Targeted relations generate 12.35% more energy conservation
- Future demographic transitions for households decrease the demand response potential

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Field experimental evidence of how social relations shape behavior that promotes energy conservation

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SUMMARY
Energy demand-side management is essential for deep decarbonization. However, while we target people as discrete and isolated individuals, we ignore the fact that energy consumption occurs in intricate webs of pre-existing social relations. This study examines an emergency demand response (EDR) program in China involving more than 180,000 households based on relations with family members, communities, and identity. The results indicate that the existence of social relations can promote energy conservation behavior and there is a large degree of heterogeneity. Targeted relations, such as single-living residents, small-scale households, city dweller etc., show greater electricity savings with 12.35% increase in overall effect, which benefit when demographics change in the next few decades. Such heterogeneous changes put forward the pressing need for policymakers to focus on social relations as a unit in future intervention designs to decarbonize the energy system.

INTRODUCTION
Energy demand-side management is crucial for deep decarbonization. Globally, there have been widespread incentives for electrification, and electricity consumption has increased dramatically, with growth in the residential sector accounting for 26.6% (IEA, 2021).1 The surge in household electricity demand means pressures such as increased peak load, widening peak-to-valley gap, which creates challenges in matching supply with demand. The traditional approach is to increase the output of the generator set when the demand is high, which leads to a large amount of unnecessary carbon emissions, and the peak load duration in a year is only 5% or less. Consequently, there is growing interest in demand-side interventions to reduce peak-hour electricity consumption, such as demand response measures.

However, current measures to change energy demand behavior ignore the fact that energy use occurs in places such as homes and communities in which complex networks tend to treat people as discrete and isolated individuals (Hargreaves et al., 2020).2 Households are typically been considered simply as the site where energy consumption occurs, and thus programs and policies aimed at reducing energy consumption use in the house, office, or building as the unit of analysis, but the analysis of people within the structure and their interactions is still limited (Ellsworth et al., 2015).3 For example, in the recently developed shared socioeconomic pathways, in their framework of climate-related scenario setting, the analysis unit is population; people are seen as discrete and isolated individuals, rather than treating people as being entangled in a web of relations with family members, communities, or their own identities (Calvin et al., 2017).4 Social relations fundamentally affect people’s daily lives and when, why, and how they consume energy. Individuals’ energy use decisions are shaped not only by their own preferences and attitudes but also by taking into account the needs and desires of others (Elder, 1994; Burningham et al., 2017).5,6 In this study, we follow the social relations framework built by Hargreaves et al. (2020),7 and focus on how social relations with family, communities, and relations of identity shape energy use. On the other hand, intervening in residents’ electricity consumption behavior requires high-frequency data collection through devices such as smart meters. However, widespread adoption of intelligent equipment is an expensive cost. If the purpose of load reduction could be achieved earlier with limited funds and time, we need to intervene in targeted residents with more energy-saving potential to avoid delays in the realization of the urgent purpose.
First, the key social relations in households are those with family, which are related to the composition of family members, resulting in different energy usage habits through a series of family practices. Residents who live alone have more freedom and less negotiation in the way they consume energy than those who live with their families. In households with infants and young children, there is a non-negotiable need for naps, feedings, or bedtimes (Burningham et al., 2017; Nicholls et al., 2015). In households with school-aged children, such concerns have gradually evolved to include regular schedules for school hours, homework, and after-school activities (Powells et al., 2014), and a growing need for autonomy and privacy, with children having separate bedrooms in the home (Gibson et al., 2011; Shirani, 2015). Caring for an elderly relative is another critical stage, often increasing energy demand for cooling and heating (Shirani et al., 2017). More individuals are living in their parents’ homes as a result of broader socioeconomic trends including increased home purchase costs and growing divorce rates (Sandra et al., 2015), associated effects on energy use. People have to negotiate with the elderly over thermostat settings for different comfort concerns, or increasingly discuss whether lights or smart devices should be turned on or off (Hargreaves et al., 2016), given frugal living habits.

Second, the landlord-tenant relation is one of the most commonly discussed social relations with the community. The challenge for them is who will do more to reduce energy bills, such as the installation or updating of energy-efficient equipment, if tenants are reluctant to raise weatherization concerns with their property owner for fear of being evicted. In the current policy environment, landlords are not strictly required by rental agents, energy providers, or utility agencies. Due to a lack of trust, most homeowners are unable to accept smart meters or sockets, leading to positive resistance and low participation rates in energy efficiency interventions (Darby, 2010; Hess, 2014). For example, a British energy policy named Green Deal was effectively terminated after 2.5 years (Rosenow et al., 2016). The community scale is also essential for determining reactions to interventions in energy usage and the adoption and implementation of sustainable energy technology, which may be closely related to peer effects. For example, the adoption decisions of residential solar photovoltaic panels have a peer effect, with each new installation increasing the likelihood that others on the same street would follow suit by 0.78% points (Bryan et al., 2012), which may be due to clustered environmental preferences (Kahn et al., 2009). Larger scale communities allow residents a greater probability of seeing the visible application of energy policies in the community, just as longer commutes within a community may mean more driving time to see the installation of solar photovoltaic panels.

Third, the identities of individuals influence how policymakers and decision-makers understand and target (or do not target) them (Hargreaves et al., 2020). Social identity can be defined by the geographic location in which a person lives and demographic characteristics (gender, education, occupation, ethnicity, etc.). These social identities, in turn, denote group membership, which can also influence energy behavior in the form of peer effects. For example, the energy demands of people who work in the same office or share a common attitude toward energy and environmental topics because the same occupation is correlated (Whittle et al., 2015; Hargreaves et al., 2016). Individuals’ reactions to their own identities are significant because they may frustrate interventions; people respond in unforeseen ways based on their own self-awareness. Residents with high income levels may mean a reluctance to lower comfort levels in response to power-saving policies, as this does not fit their self-identity that they do not care about the meager monetary incentives because they are “rich”. Similarly, gender and generation can also affect the levels and patterns of energy demand (Sahakian et al., 2018; Hansen et al., 2019). These three forms of relations interact and intersect with one another.

Despite the increasing interest in how relations shape energy demand, their impact and implications in developed countries have not yet been studied empirically. There has been abundant literature identifying the factors influencing heterogeneous energy demand, such as time-of-use (White et al., 2018), building performance (Aghniaey et al., 2019), individual consumer attributes such as environmental awareness (Tiefenbeek et al., 2019), and income (Rosa et al., 2012). However, there is a dearth of empirical research on social relations, especially social relations in the homes and with family, as an analytical unit and how it shapes or intervenes in energy use. Such empirical evidence is extremely important for policymakers to pre-judge the potential of demand-side management rather than considering isolated individuals as analytical units which are energy consumption scenario errors. This is not how energy was decided to be consumed. Our analysis recognizes the various and diversified types of social participation in sustainable energy transitions that are now in place and calculates the costs and benefits of targeting and more active
This study makes three major contributions. First, we consider the interdependent nature of energy demand focuses on social relations as a research unit and conducted a large-scale randomized experiment in China, where we offered empirical evidence of how social relations influence energy usage practices in this case response to reduce load peaks. Second, high-frequency data make it possible to link changes in the electricity consumption of residents with different relations to other important outcomes in the society system, such as sociodemographic structure, which provides a reference for the priority of future home electrical intelligence construction, which is crucial for a country like China that has barely equipped with home energy management system (HEMS) which is vital in demand-side management. Finally, we estimate the change of volume of demand response resource pool with future demographic changes for households. Since impact of family on energy use can last for generations. This provides reference for future energy demand-side management, which has become increasingly important with further utilization of renewable energy.

Our results indicate that emergency demand response (EDR) reduces electricity use by up to 3.42% in households that are directly incentivized by rebate coverage. If we target specific relations, such as living alone, living in a mid-sized community, living in their own house, city dweller, etc., the reduction effect increases up to 12.35%. The EDR potential will decline after peaking around 2050 due to demographic transitions. In particular, relative to 2020, the future demand response of households with infants or children will experience an accumulated decline of −43.3% and −40.3%, respectively, in the year 2100. There will be household size decline and more elderly individuals in the future family structure, which will result in further higher losses after peaking. Note that this is only the impact of future demographic changes in the family structure scenario. While, paying attention to the targeted relations groups can substantially makeup this loss, and the effect of demand response is expected to increase by 45.37%–52.18% compared with those indiscriminate invitations. This study accounts for the relational nature of energy demand, focuses on social relations as a research unit, and puts forward the pressing need for future intervention designs to decarbonize the energy system.

RESULTS

Our data come from a utility agency in the southwest regional division of State Grid. In our final sample for analysis, there are 15,233 households who participated in EDR rebate program and these households form our treatment group. 90,547 non-participated households form the control group. Demographic characteristics data come from survey and are matched with electricity consumption data. The sample size of the survey is 7773. All households in the treatment group had access to monetary rebates if they met the requirements of the EDR program. Details of the program procedure, with assignment process, sample distribution, and summary statistics, can be found in Program and data section in the main text and Figure S2 and Table S2 in the supplementary information. We quantify the influence of social relations on EDR-promoting energy conservation behaviors using a difference-in-difference model. Details of the models and data can be found in STAR Methods.

Baseline estimation results for the effect of EDR

We first analyze the average electricity conservation broken out by social relations between pre-treatment and post-treatment (Figure S3), which provide visual evidence that EDR rebate program has altered the electricity usage patterns of households. During the pre-treatment period, the difference in electricity usage between the treatment and control groups for each relation is not significant. This verifies the parallel trend assumption for the difference-in-difference (DID) analysis, indicating that the treatment and control households had comparable electricity consumption trends prior to the start of EDR program. During the post-treatment phase, the treatment group changed electricity consumption behavior to promote electricity conservation. This indicates that after participating in the EDR program, households use less electricity during declared period in accordance with a generally believed idea supported by modeling.

We estimate the average effect of the EDR rebate program on household electricity consumption during on-peak times. The introduction of a clean control enables us to assess the baseline effects of EDR (Figure S2). This is done by comparing households who are access to monetary incentives (i.e., EDR treatment group) with those who will never realize its existence (i.e., comparison group). Table 1 shows the changes in electricity consumption due to EDR rebate program based on the average profiles of all 107,770 households. Column (1) contains individual fixed effects. Column (2) uses ordinary least squares (OLS) regression.
with adding individual-level control variables, and column (3) uses an estimation strategy with dynamic time warping (DTW)-matching clustering (see STAR Methods). First, comparing fixed effect (FE) model and DTW model, the results using fixed effects are very similar to the results using DTW-matching clustering. Thus, we focus our discussion on the results using DTW-matching clustering as it takes into account the similarity of electricity consumption behavior patterns (Yang W et al., 202226). Second, comparing among models (FE, OLS, & DTW), the results are generally consistent. EDR rebate coverage decreases electricity consumption by 0.1026 kWh (p < 0.001; Table 1) during on-peak times, a 3.42% (p < 0.001; Table S6) reduction relative to the control mean. Results are statistically significant and robust (we adopted identification strategies such as intent-to-treat, instrumental variable approach, and placebo test to solve the endogeneity problem, see STAR Methods, Tables S3–S5) which demonstrating the effectiveness of demand response across the total population.

Overall, the findings suggest that EDR rebate program encourages households to consume less electricity during peak demand hours, which aids utilities in reducing the system load pressure so that load curves may be more effectively flattened and grid stability can be more effectively assured. In the next three parts, we evaluate whether the actions of consumer are compatible with the incentives among different social relations. Figure S4 shows the results of electricity conservation profile from heterogeneous social relations households induced by the EDR rebate program. Although there are many differences among social relations, comparison between cases does reveal similarities. Most notable is the reduction in load across cases; EDR groups are observed to more electricity conservation. Differences in behavioral changes among social relations are consistent with the regression results.

### Relations with family members’ impact on EDR

Small-scale households and households with elderly individuals promote more electricity conservation. On the basis of Equation 1, we considered the effects of social relations with family members in shaping EDR behavior. We obtained the number and structure of family members through a survey (Table S8 in...
supplemental information), and then divided the households into different subgroups, namely LA (live alone, the number of family members is 1), SHZ (small household size, the number of family members is 2–5), and LHZ (large household size, the number of family members is 6 and above). Details can be found in Table S1.

Figure 1. Mean change in electricity conservation by relations with family members and EDR assignment
Change in electricity conservation (treatment day minus benchmark day) for the control, and EDR treatment groups for each targeted relations indicator with standard error bars.
(A) Live alone (control, n = 3,172; EDR, n = 568).
(B) Small household size (control, n = 11,616; EDR, n = 1,928).
(C) Large household size (control, n = 4,368; EDR, n = 560).
(D) Households with baby (control, n = 4,322; EDR, n = 618).
(E) Households with children (control, n = 11,158; EDR, n = 1,792).
(F) Households with elderly (control, n = 7,442; EDR, n = 1,262). Boxes indicate significant positive double difference terms that indicate a greater increase in electricity conservation for EDR versus control groups among targeted relations population. Solid boxes denote that the value is higher than the overall average effect of the population; dashed boxes denote that the value is lower than the average effect of the population (see Table 1 and Table 2).
Figure 1 provides visual evidence that EDR assignments and relations group have different electricity conservation. The estimated DID coefficients in Table 2 for the LA, SHZ, and LHZ groups were \(-0.2130\) (p = 0.017), \(-0.1002\) (p = 0.002), and \(-0.0599\) (p = 0.294), respectively. This indicates that the EDR measure has a significant load reduction on small-sized households, whereas there is no significant effect on households with six or more family members. More importantly, the coefficient of the empirical p value shows that the targeted LA participants are significantly more sensitive to the EDR measure than that of SHZ and LHZ. Small-scale families have more flexibility to adjust their electricity consumption behavior, and single-living residents can respond more positively by changing their energy usage patterns without negotiation with others.

Among households with different family structures, EDR measures have a significant effect on load reduction in households with babies (HB) and households with elderly (HE), but there is no significant evidence that EDR measures are effective for households with children (HC). In addition, the coefficient of the empirical p value shows that the targeted HE participants are significantly more sensitive to the EDR measure than that of HC. Households with elderly individuals saving more electricity may be related to long-standing frugal habits (Kavousian et al., 2013). Declining fertility, mortality and morbidity, partnering and parenthood are delayed, divorces and family dissolutions rise, and the number of multi-generational household decreases are important determinants of energy consumption and carbon emissions per capita (Underwood et al., 2015). Increasing house size and simultaneous demographic trends of reducing family size have resulted in a worldwide movement toward greater domestic space per person, which brings fresh issues with consequences for energy usage per capita (Lorek et al., 2019). We briefly discussed the impact of changes in household demographics on future demand response potential in the subsequent section and focus on the improvement of targeted relations in reducing peak load.

Further, we focused on the relations with family members of above the average treatment effect, including residents living alone, households with baby, and households with elderly (marked by solid boxes in Figure 1). Note that for the same number of participants (10,380 in our sample), if we target these designated households, we could expect an increase of electricity savings by 54.54% (Table S7 in supplemental information), relative to the indiscriminate invitation in the whole society.

### Table 2. Regression results for dividend relations with family members

| Household size               | Coef. \((T_i \times P_i)\) | SE   | \(R^2\) | Number of observations |
|------------------------------|-----------------------------|------|---------|------------------------|
| LA (live alone)              | \(-0.2130^{**}\)            | 0.0873 | 0.0204  | 2,276                  |
| SHZ (small household size, 2-5) | \(-0.1002^{***}\)          | 0.0321 | 0.0223  | 8,130                  |
| LHZ (large household size, 6+) | \(-0.0599\)                | 0.0567 | 0.0465  | 2,870                  |

| Family structures            | Coef. \((T_i \times P_i)\) | SE   | \(R^2\) | Number of observations |
|------------------------------|-----------------------------|------|---------|------------------------|
| HB (Households with baby, 0-3) | \(-0.1133^{**}\)            | 0.0531 | 0.0285  | 2,906                  |
| HC (Households with children, 4-18) | \(-0.0469\)               | 0.0362 | 0.0282  | 7,690                  |
| HE (Households with elderly, 60+) | \(-0.1612^{***}\)          | 0.0524 | 0.0180  | 5,198                  |

The empirical p values were determined using the simulation procedure described in STAR Methods. These are estimated based on the null hypothesis that the coefficients are equal for the two groups under consideration. For example, the p value of 0.319 in the coefficient column for LHZ versus SHZ suggests that the DID coefficient for the LHZ group differs from that of the SHZ group at the 31.9% significance level. The 0.029 p value suggests that the coefficient estimate for the DID measure is different between the HE and HC groups (at the 2.9% level of significance). Standard errors were clustered at the household-group level. Significance is at ***p < 0.01, **p < 0.05, *p < 0.1.

Figure 1 provides visual evidence that EDR assignments and relations group have different electricity conservation. The estimated DID coefficients in Table 2 for the LA, SHZ, and LHZ groups were \(-0.2130\) (p = 0.017), \(-0.1002\) (p = 0.002), and \(-0.0599\) (p = 0.294), respectively. This indicates that the EDR measure has a significant load reduction on small-sized households, whereas there is no significant effect on households with six or more family members. More importantly, the coefficient of the empirical p value shows that the targeted LA participants are significantly more sensitive to the EDR measure than that of SHZ and LHZ. Small-scale families have more flexibility to adjust their electricity consumption behavior, and single-living residents can respond more positively by changing their energy usage patterns without negotiation with others.

Among households with different family structures, EDR measures have a significant effect on load reduction in households with babies (HB) and households with elderly (HE), but there is no significant evidence that EDR measures are effective for households with children (HC). In addition, the coefficient of the empirical p value shows that the targeted HE participants are significantly more sensitive to the EDR measure than that of HC. Households with elderly individuals saving more electricity may be related to long-standing frugal habits (Kavousian et al., 2013). Declining fertility, mortality and morbidity, partnering and parenthood are delayed, divorces and family dissolutions rise, and the number of multi-generational household decreases are important determinants of energy consumption and carbon emissions per capita (Underwood et al., 2015). Increasing house size and simultaneous demographic trends of reducing family size have resulted in a worldwide movement toward greater domestic space per person, which brings fresh issues with consequences for energy usage per capita (Lorek et al., 2019). We briefly discussed the impact of changes in household demographics on future demand response potential in the subsequent section and focus on the improvement of targeted relations in reducing peak load.

Further, we focused on the relations with family members of above the average treatment effect, including residents living alone, households with baby, and households with elderly (marked by solid boxes in Figure 1). Note that for the same number of participants (10,380 in our sample), if we target these designated households, we could expect an increase of electricity savings by 54.54% (Table S7 in supplemental information), relative to the indiscriminate invitation in the whole society.
Table 3. Regression results for dividend relations with communities

| Regression estimates | Coef. (T, \times P_i) | SE  | R^2  | Number of observations |
|----------------------|------------------------|-----|------|------------------------|
| House type           |                        |     |      |                        |
| Owner                | –0.1106***             | 0.0286 | 0.0247 | 12,412                 |
| Rent                 | –0.1947                | 0.1395 | 0.0237 | 864                    |
| Community scale      |                        |     |      |                        |
| SSC (small-scale community) | –0.0794***             | 0.0221 | 0.0212 | 36,506                 |
| MSC (medium-scale community) | –0.1080***             | 0.0117 | 0.0125 | 165,040                |
| LSC (large-scale community) | –0.0676                | 0.0535 | 0.0306 | 9,994                  |
| Empirical p values   |                        |     |      |                        |
| Owner versus Rent    | 0.223                  |     |      |                        |
| MSC versus SSC       | 0.025                  |     |      |                        |
| LSC versus SSC       | 0.417                  |     |      |                        |
| LSC versus MSC       | 0.191                  |     |      |                        |

Note: The empirical p values were determined using the simulation procedure described in STAR Methods. These are estimated based on the null hypothesis that the coefficients are equal for the two groups under consideration. Standard errors are clustered at the household-group level. Significance is at ***p < 0.01, **p < 0.05, *p < 0.1.

Relations with communities’ impact on EDR

Households living in their own houses and in small or medium-sized communities have greater potential for demand response. We estimate the effect of social relations with communities in shaping EDR behavior. First, we estimated the differences between the two types of housing occupancy. The EDR measure led to a significant load reduction in households living in their own houses (coef. = –0.1106, p < 0.001, Table 3 and Figure 2). In our experimental areas, tenants had no significant load reduction incentivized by the EDR measure, although they also needed to bear their own electricity bills. This is a long-standing energy equipment negotiation problem between landlords and tenants. Landlords are reluctant to install or update energy-saving equipment due to economic cost, which makes it difficult for tenants to effectively participate in energy-saving programs (Sovacool et al., 2017).30

Additionally, we estimated the effect of the EDR measure across different community sizes. Small-scale communities (SSC), medium-scale communities (MSC), and large-scale communities (LSC) groups were formed by sorting all households according to the number of residents in their community. The communities with the lowest number of residents (the bottom one-third) were categorized as small-scale communities, the next one-third were categorized as medium-scale communities, and the top one-third were categorized as large-scale communities. The results show that the EDR measure had a significant load reduction in the SSC and MSC groups (Table 3 and Figure 2), and the estimated coefficients for the SSC and MSC groups were –0.0794 (p < 0.001) and –0.1080 (p < 0.001), respectively. The word-of-mouth of community residents appears to contribute to social interactions that lead to further adoption, and comparing a household’s electricity bill to that of its neighbors has been shown to reduce home energy use (Allcott, 2011).31 Considering the spatial spillover, this word-of-mouth communication is more advantageous in small and medium-sized communities (Godes, 2016).32 More importantly, the coefficient of the empirical p value shows that the MSC participants are significantly more sensitive to the EDR measure than that of the SSC and LSC.

Residents living in their own houses, and households living in medium-scale communities had higher than average treatment effects (marked by solid boxes in Figure 2). Note that for the same number of participants (177,452 in our sample), if we target these designated households, we could expect an increase of electricity savings by 5.44% (Table S7 in supplemental information), relative to the indiscriminate invitation in the whole society.

Relations of identity’s impact on EDR

Households with higher income and highly educated households are more active in reducing electricity consumption. We report the regression results using different per capita income regions and educational level identities as analysis samples in Table 4. In China, the per capita income levels of villages, countryside,
Figure 2. Mean change in electricity conservation by relations with communities and EDR assignment

Change in electricity conservation (treatment day minus benchmark day) for the control, and EDR groups for each targeted relations indicator with standard error bars.

(A) Owner-occupied home (control, n = 17,810; EDR, n = 2,982).
(B) Small-scale community (control, n = 60,098; EDR, n = 4,136).
Counties, and cities range from low to high (note that a village, in China, is an administrative unit populated mainly by agricultural populations. The difference between village and countryside is that village is smaller in area, population, and weaker in economic development). The results show that the estimated coefficients are negative in each regional sample, which are $-0.0550$ ($p = 0.010$), $-0.0908$ ($p = 0.007$), $-0.0899$ ($p < 0.001$), and $-0.1236$ ($p < 0.001$), respectively (Figure 3). These indicate that the EDR program is a significant determinant of the peak load reduction (at least at the 1 percent significance level) for all regions with different levels of per capita income. The coefficient of the empirical p value shows that the city participants are significantly more sensitive to the EDR program than that of other groups, which may be related to their own resource endowments. Households with higher incomes may have more household appliances (Guo et al., 2018; Yohanis et al., 2008), leading to more demand for electricity use and thus a greater electricity conservation potential.

We divided the samples into EJH (junior high school and below), EH (high school), and EU+ (university and above), based on the highest education of family members. Table 4 shows that the EDR measure has no significant effect on EJH (coef. = $0.0102$, $p = 0.839$), but it had a peak load reduction effect on EH (coef. = $-0.1102$) and EU+ (coef. = $-0.1408$) at the 0.014% and 0.002% level of significance, respectively (Figure 3). The coefficient of the empirical p value shows that, compared with EJH, the effect of the EDR measure on load reduction for EH and EU+ is more obvious.

City citizens, households with high school education and above had higher than average treatment effects (marked by solid boxes in Figure 3). Note that for the same number of participants (97,147 in our sample), if we target these designated households, we could expect an increase of electricity savings by 20.47% (Table S7 in supplemental information), relative to the indiscriminate invitation in the whole society.

Table 4. Regression results for dividend relations of identity

| Regression estimates | Coef. ($T_i \times P_j$) | SE | $R^2$ | Number of observations |
|----------------------|--------------------------|----|-------|------------------------|
| **Region**           |                          |    |       |                        |
| Village              | $-0.0550^{***}$          | 0.0210 | 0.0200 | 38,560                 |
| Countryside          | $-0.0908^{***}$          | 0.0329 | 0.0275 | 15,030                 |
| County               | $-0.0899^{***}$          | 0.0193 | 0.0147 | 42,862                 |
| City                 | $-0.1236^{***}$          | 0.0124 | 0.0083 | 115,088                |
| **Education**        |                          |    |       |                        |
| EJH (Junior high school and below) | $-0.0102$         | 0.0503 | 0.0362 | 2,266                  |
| EH (High school)     | $-0.1102^{**}$           | 0.0439 | 0.0248 | 5,298                  |
| EU+ (University and above) | $-0.1408^{***}$      | 0.0450 | 0.0195 | 5,712                  |
| **Empirical p values** |                      |    |       |                        |
| Countryside versus Village | 0.034               |     |       |                        |
| County versus Village | 0.049                   |     |       |                        |
| City versus Village  | 0.000                   |     |       |                        |
| EH versus EJH        | 0.028                   |     |       |                        |
| EU+ versus EJH       | 0.056                   |     |       |                        |
| EU+ versus EH        | 0.381                   |     |       |                        |

The empirical p values were determined using the simulation procedure described in STAR Methods. These are estimated based on the null hypothesis that the coefficients are equal for the two groups under consideration. Standard errors were clustered at the household-group level. Significance is at ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. 

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Change of EDR potential due to targeted relations and demographic transitions

Focusing on targeted relations can improve demand-side management efficiency. We consider above average treatment effect as households with targeted relations, including living alone, households with elderly, living in a mid-sized community, living in an own house, city dweller, etc. If we target these specific

Figure 3. Mean change in electricity conservation by relations of identity and EDR assignment
Change in electricity conservation (treatment day minus benchmark day) for the control, and EDR groups for each targeted relations indicator with standard error bars. (A) Village (control, n = 66,436; EDR, n = 2,758). (B) Countryside (control, n = 24,526; EDR, n = 1,906). (C) County (control, n = 69,018; EDR, n = 5,946). (D) City (control, n = 176,430; EDR, n = 19,863). (E) Junior high school and below (control, n = 3,520; EDR, n = 400). (F) High school (control, n = 7,926; EDR, n = 1,104). (G) University and above (control, n = 7,710; EDR, n = 1,606). Boxes indicate significant positive double difference terms that indicate a greater increase in electricity conservation for EDR versus control groups among targeted relations population. Solid boxes denote that the value is higher than the overall average effect of the population; dashed boxes denote that the value is lower than the average effect of the population (Table 1 and Table 4).
relations, the reduction effect will increase up to 12.35% with the same volume of participants in the demand response (Table S7 in supplemental information), which provides precise guidance for the implementation of demand response when time and cost are limited. Furthermore, this also provides crucial reference for the HEMS installation priority setting in China who barely has any intelligent home energy management system.

In addition, we estimate the reduction in demand response potential due to future demographic changes, which emphasizes the neglect of families in development studies, is consistent with findings from household and environmental demographics, and implies that household size is frequently a stronger predictor of carbon emissions than population size. Based on data provided in the World Population Prospects 2019 published by the United Nations (Affairs, 2019), even if social and economic progress frequently reduces the rate of population expansion (e.g., a lowering total fertility rate), it also results in an increase in the number of smaller households. We estimate that demographic changes in China, such as aging, will be expected to cause a decline in demand response pool after peaking in the next few decades. In particular, for households with infants or children, relative to 2020, their future demand response declines dropped from −9.0% and 0.4% to −43.3% and −40.3%, respectively (Figure 4). This is only the impact of future demographic changes in the same family structure scenario. As the number of families members increases, the number of households decreases, which will result in higher further losses. However, paying attention to the targeted relations groups (including households with infants and elderly individuals) can substantially makeup this loss, and the demand response is expected to increase by 45.37%–52.18% compared with those indiscriminate invitations (Figure 4).

DISCUSSION

Policymakers need to estimate the demand response behavior according to individual’s social relations, culture, electricity bills, and consumption patterns to design the most efficient incentive programs. This can improve grid resilience and achieve carbon emission reduction goals in a systematic manner while meeting the demand-side and supply-side balance of the grid. The majority of research about demand respond policy target people as discrete and isolated individuals, ignoring that energy consumption occurs in intricate webs of social relations. This paper adds to the discussion of demand-side management and potential challenges to power system decarbonization by providing empirical evidence on how social
relation can shape power demand response and the associated projection of how future demographic changes will further influence it in China.

This study investigates the relations with family members, communities, and identity based on a dataset from a large-scale EDR rebate program in China involving more than 180,000 households to provide empirical evidence on how social relation can shape behavior that promotes energy conservation. High-resolution households level power consumption data have been collected to identify real power-saving behavior. Three kinds of social relations have been identified from matching questionnaires: We find that EDR rebate coverage decreases electricity consumption by 0.1026 kWh during on-peak times, which account for 3.42% reduction relative to the control mean. Such a negative impact is economically significant. Regarding relations with family members, communities, and identity, small-scale households, households with elderly individuals, households living in their own houses in small or medium-sized communities, and urban participants have greater electricity conservation. If we target these specific relations for the implementation of demand response with the same volume of participants, the reduction effect will increase up to 12.35%. Demographic transitions in future China can create a depressed energy response for up to a decade. However, paying attention to the targeted relations can substantially makeup this loss by around 50% compared with those indiscriminate invitation. Please note that this is only the impact from changes of family structure. Further decrease in the number of families in more years will generate much higher impact. This study addresses the neglecting of social relations in energy conservation and emission reduction, and suggests that household size and social relations is often a better predictor of energy conservation than focus on population size and isolated individuals.

Our results have important implications for the demand-side management, not only for China but also for any country or region that is seeking to realize decarbonization through electrifications. Policy instruments and social dimension measures have been taken worldwide to facilitate more rapid electrification and demand-side management. With the acceleration of urbanization and household electrification, and extreme weather events occur more frequently as global temperatures rise, electricity fluctuations caused by irregular surges in household power consumption could cause more challenges for the power system in the near future. This situation will worsen as the proportion of new energy sources increases. Demand-side management for household will play an increasingly important role in this process. Our results highlight that social relationships can better shape energy consumption behavior. Guiding a clean and low-carbon lifestyle of social relations can not only reduce direct energy use but also help staggered energy use by balancing supply and demand in the power which further help power systems to realize deep decarbonization. The sixth IPPC assessment report points out the importance of keeping temperature rise within 1.5°C. All society should take each and every effort, from both social and economic dimensions, to cope with the challenge of global warming. Policymakers need to estimate the energy-saving behavior according to regions’ culture, consumption custom, sense of values etc., which might affect the way social relationships work in order to adopt efficient policies to meet demand-side and supply-side balance while also improving grid resilience and meeting the carbon emissions reduction targets in the systematic way. This paper adds to the discussion of demand-side management and potential challenges to power system decarbonization by providing empirical evidence on how social relation can shape power demand response and the associated projection of how future demographic changes will further influence it in China.

Several measures and policy approaches can be adopted to facilitate social relations to play a better role in demand-side management. First, integrate the households demand response into the demand-side management pool, taking households and social relationships as the unit of analysis, conduct comprehensive and systematic regulation strategy together with the industrial load, mobilize all the resources that can be mobilized, and formulate the response optimization strategy under the constraints of the balanced operation of the power grid. Second, accelerate the popularization of smart energy systems for households in developing countries. The characteristics of small households or community load, strong randomness and high uncertainty require intelligent regulation and centralized scheduling. Third, develop customized demand-side management strategies according to different social relations and regional cultural characteristics, rather than a one-size-fits-all strategy. Vulnerable groups, especially in extreme weather situations, need special attention to avoid further energy poverty.

Limitations of the study
This study still has a few remaining limitations. Given the complexity of social relations, residents’ identity varies across different environments, and they are cross-integrated. For example, people have multiple identities such
as fathers, husbands, and colleagues at the same time. It is difficult to regard them as tools to achieve predetermined policy goals. We also wish to avoid limiting instrumental indicators and assessments that prescribe particular roles for individuals and communities in the energy transition (Smith et al., 2016), and we prefer that future energy intervention policies inspire and nurture more active energy citizens (Chilvers et al., 2018). In addition, due to the data availability, we only focus on the impact of future demographic changes in the same family structure scenario, and cannot consider electrification, new energy vehicle adoption in the future, which may increase electricity consumption and possibly more demand response adjustment potential.

**STAR METHODS**

Detailed methods are provided in the online version of this paper and include the following:

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**SUPPLEMENTAL INFORMATION**

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.105456.

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**AUTHOR CONTRIBUTIONS**

Z.W., B.W., and B.L. designed the study; B.L. and Z.W. completed data processing and visualization; B.L., Y.Q., B.W., and J.L. completed econometric model related work; Z.W., B.L., and B.W. wrote the first draft; Z.W., B.W., Y.Q., and B.Z. contributed to the interpretation of the results.

**DECLARATION OF INTERESTS**

Yueming Lucy Qiu is a member of the journal advisory board for iScience.

**INCLUSION AND DIVERSITY**

The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

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STAR METHODS

KEY RESOURCES TABLE

| REAGENT or RESOURCE | SOURCE | IDENTIFIER |
|---------------------|--------|------------|
| Deposited data      |        |            |
| World population data | United Nations | https://population.un.org/wpp/ |
| Hourly meteorological data | China Meteorological Data Service Center | http://www.nmic.cn/ |
| Hourly electricity usage data | This paper | N/A |
| Survey data         | This paper | N/A |

Software and algorithms

| STATA 15         | 15MP | https://www.stata.com/ |
| Python           | 3.5.7| https://www.python.org/ |

RESOURCE AVAILABILITY

Lead contact
Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Bo Wang (51022080@qq.com).

Materials availability
This study did not generate new unique reagents.

Data and code availability
- World population data and aggregated data for households’ electricity use have been deposited at Mendeley Data (https://doi.org/10.17632/dgkfhtnspw.3) and are publicly available as of the date of publication.
- This paper does not report original code, which is available for academic purposes from the lead contact upon reasonable request.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

METHOD DETAILS

Program and data
We conducted a large-scale randomized experiment, named EDR rebate program, in July and August 2019, in the monsoon-influenced humid subtropical environment of southwestern China. Experimenting with household emergency demand response during high summer temperature is highly typical, given that increased electricity consumption owing to high temperature is the primary source of power grid peaks. We were granted access to the smart meter data of households participating in this incentive program. Figure S1 illustrates the daily peak load of the power grid in experimental regions from July 18, to August 21, 2019. We discovered that the peak hours usually appear between 8 pm and 9.30 pm, which are called on-peak times. In order to reduce peak load and explore the energy-saving potential of households during on-peak times, we set the period for EDR rebate program to 8 pm - 9.30 pm.

The time scope of our electricity consumption data is from January 2016 to August 2019, from a utility company in the southwest regional division of State Grid. EDR rebate program was implemented on August 19, 2019. We obtained monthly electricity usage data for each household throughout the time scope, and collected electricity usage data for a week both the pre-treatment and post-treatment periods at 15-min intervals by high-speed power line communication (HPLC) smart meters. Details of the data can be found in STAR Methods. The program’s specific procedure is as described below. First, we adopted the clustered randomization method to randomly select the regions (divided by communities) of the EDR rebate
program, and then installed HPLC smart meters. We preprocessed the electricity consumption data (vacant homes that were always at 0 kWh were removed) and deleted the households with missing values due to HPLC smart meters’ collection and transmission. Then, we randomly assigned permission to apply for the EDR rebate program. Interviewed households, named assignment winners, were allocated to either a treatment group (also called the targeted group or the EDR subjects) or an untargeted group, with 15,233 households in the treatment group and 77,658 in the untargeted group. An additional comparison group with 90,547 households who did not receive any treatment were as seen as the pure control group (see Figure S2). Table S2 in supplementary information provides a summary statistic of the electricity using patterns.

All households in the treatment group had access to monetary rebates if they met the requirements of the EDR program for a specific time. The electricity consumption decrease resulted in a cash subsidy of $0.143/kWh (equal to 1 in RMB) distributes as bill credits for every 1 kWh less than the declared on-peak times on the benchmark day compared to treatment day.

We conducted a survey investigating the demographic features of the households and assessing their electricity consumption patterns from July to December in 2019 (see Table S2). The survey included questions on socio-economic characteristics, electric facilities, and behavioral actions toward electricity conservation, and personal values. We conducted this survey mainly through online forms, and the scope of the survey was randomly selected households in the EDR pilot. In our final analysis sample, there are 7773 households forming the survey data. Table S2 summarized the electricity consumption and decrease throughout experimental period of 1.5 h for each group. Because of the random assignment, the electricity usage is balanced across the groups.

**Empirical strategy for identifying emergency demand respond effects**

The causal effects of policy evaluations are difficult to identify. The identification of causal effects is often complicated by three factors: endogenous group formation resulting in self-selection of participant (homophily), correlated unobservable, and simultaneity.

The most natural way to estimate the effect of the energy usage intervention strategy on the energy-saving behavior is to compare the difference in energy consumption between each household before and after the experiment. However, this outcome may be modified by things that occur concurrently with the energy policy. For the EDR measures, participants’ motivation to respond affirmatively to invitations is likely indicative of interest in energy issues, the ability to reduce their electric usage, or potentially financial motivation. Typically used in the empirical analysis, the difference-in-difference (DID) method is utilized to exclude the influence of other synchronic factors. On the basis of a counter-factual framework, we adopt clustered randomization method to select regions for our EDR program and randomly assign permission to apply for the program to compare the difference in electricity consumption of households who participated in EDR versus those who did not. A base model is as follows:

$$ Elec_{it} = \beta_0 + \beta_1 (EDR_i \times P_t) + \beta_2 EDR_i + \beta_3 P_t + \alpha_i + X_{it} + \varepsilon_{it} $$

(Equation 1)

where $Elec_{it}$ is the electricity usage of households during the declared on-peak times. $EDR_i$ is a dichotomous variable set to 1 if the household participated in the EDR program. $P_t$ is a dichotomous variable set to 1 if the date is the treatment day and 0 for the benchmark day. $\beta_1$ is the DID estimate of the treatment effect. The term $\alpha_i$ denotes individual fixed effects. The term $X_{it}$ represents the control variables, including temperature, wind direction, wind speed, relative humidity, pressure, the average monthly electricity use of households and other factors related to household characteristics. $\varepsilon_{it}$ is an idiosyncratic error term.

There are two identification assumptions that require attention when using the DID method. First, an unbiased estimate of $\beta$ requires that the control group provide a reasonable counterfactual for the treatment group that reflects the performance of the treatment group without the intervention. Therefore, fixed effects and control variables were added to the regression model to reduce the difference between the treatment and control groups. Additionally, standard errors are clustered at the cluster-group level to allow for arbitrary serial correlation and correlation across households within the cluster groups. In addition, if the treatment group and the control group have good comparability, there should be no significant difference before the intervention, and our results have also passed the parallel trend hypothesis test.
The precondition for using the DID method is that the experimental group and the control group are comparable before the policy, that is, to satisfy the parallel trend test. It is difficult for traditional matching methods (such as propensity score matching) to capture all of the factors that affect the electricity use behavior during on-peak times through the covariates. We adopted matching approaches based on dynamic time warping (DTW) to overcome the issue of parallel trends between the treatment group and the control group. Our underlying assumption is that households with similar long term (36 months) and short term (15 min) electricity use patterns before the experiment should be comparable. This process is carried out in two steps. The first step is matching the households’ electricity use data and the meteorological data. The second step is using the DTW method based on monthly electricity use data and high-frequency 15-min electricity use data, and the households are divided into 100 groups of electricity use patterns to ensure that the treatment was randomly distributed within the group. There are some differences in electricity use among the groups, and the households in each group are relatively similar in terms of electricity use trends (Figures S5 and S6).

Determination of significance levels. This research is primarily concerned with comparing the sensitivity of EDR measure across various groups of households. We divided all samples into different subgroups based on their social relationships. Whether there is a significant difference in the DID estimation coefficients between the groups is our basis for judgment. However, conventional tests meant to identify variations in coefficients are inapplicable due to the likelihood that the error terms break the requisite assumptions. For instance, the Chow test requires that the disturbance be same for both regressions, whereas the standard Wald test needs the error terms be independent. The panel data residuals are unlikely to satisfy these constraints. This study used simulation data to investigate the relevance of the observed disparities in coefficient estimations. The null hypothesis is $H_0 : d = 0$, which states that there is no significant difference in the subsamples’ coefficient estimations. Bootstrapping is used to create empirical $p$ values that assess the probability of seeing observed variations in coefficient estimates if the real coefficients are equal. Suppose that the total sample is divided into two subsamples $S_A, S_B$ according to social relations. The steps to obtain the empirical $p$ value are as follows: (1) The number of households from the two subsamples is $n_A$ and $n_B$, respectively. (2) In each round of simulation, randomly select $n_A$ and $n_B$ households from the existing samples, and define them as $S_{A,i}$ and $S_{B,i}$ respectively, that is, to obtain the empirical sample. (3) Estimate the coefficient values in the two groups respectively, and record the coefficient difference statistic $d_i$ between the groups. (4) Steps 2 and 3 are repeated $k$ times (set to 1000 times in this study) to obtain the empirical distribution. The empirical $p$ value is the proportion of simulations in which the difference between estimated coefficients $d_i (i = 1, 2, ..., k)$ exceeds the observed difference in coefficient estimates $d$.

**Intent-to-treat test for the effect of assignment selection**

The potential problem in our experimental design is that the EDR measure may cause changes in the composition of participants. We randomly assigned permission to apply for the EDR rebate program, but for ethical and logistical reasons, we cannot force all experimental households to follow the randomized treatment assignment. For instance, some in the treatment group refused to take the treatment, which was called noncompliance, such as untargeted group in our trial. We can estimate the effect of assignment selection by fitting difference-in-difference regressions and comparing the average outcome for households selected in the assignment (treatment group and untargeted group in our trial, which we called assignment winners) to the average outcome for comparison group (those not selected by the assignment). This approach provides an intent-to-treat estimate. The coefficient on $T_i \times X_{pi}$ (same as Equation 1 settings) is the main coefficient of interest, which is interpreted as the impact of being able to apply for the EDR rebate program. The estimated DID coefficients is significant (coef. $= -0.0120$, $p = 0.002$, Table S3), which is consistent with the main conclusion.

**Instrumental variable two-stage approach test**

The intent-to-treat estimates provide an estimate of the causal effect of winning the assignment (i.e., winning permission to apply for the EDR trial). This provides a net effect assessment for extending access to EDR, which may lead to conservative effects of the treatment. We are also interested in the effect of EDR coverage itself. In this section, we adopt an instrumental variable two-stage approach to estimate the effect of the treatment - not just assignment to treatment - that must account for noncompliance. To adjust for noncompliance, one can use assignment to treatment as an instrument for treatment receipt since the initial assignment was random, similar to the approach taken in existing studies such as (Taubman et al., 201416). We evaluate the effects of EDR by fitting two-stage least squares regressions (with assignment
selection as an instrument for EDR coverage) and estimating the local average treatment effect of EDR coverage. We model this as follows:

\[ \text{Elec}_t = \pi_0 + \pi_1 \text{Treatment}_{it} + \alpha_i + X_{it} + \epsilon_t \]  

(Equation 2)

where \( \text{Treatment}_{it} \) is defined as participating in the EDR program during the research period. All remaining variables are specified in Equation 1. We estimate Equation 2 using regression with instrumental variable and the following first-stage Equation 3:

\[ \text{Treatment}_{it} = \pi_0 + \beta_1 \text{IV}_{\text{assignment}} + \alpha_i + X_{it} + \nu_{it} \]  

(Equation 3)

in which the excluded instrument is the variable \( \text{IV}_{\text{assignment}} \) that is a dichotomous variable set to 1 if the household was assigned to the EDR and 0 for others.

We interpret the coefficient on \( \text{Treatment}_{it} \) from the instrumental variable estimation of Equation 2 as the local average treatment effect of EDR. In other words, our estimate of \( \pi_1 \) identifies the causal effect of EDR among the subgroup of households who participated in the EDR upon winning the assignment but who would not participate in EDR without winning the assignment (i.e., the compliers). The results in Table S4 show that the coefficient is 0.0747 (\( p = 0.009 \)), which is consistent with the conclusion.

**Placebo test**

We adopted a placebo test to conduct a counterfactual test by altering the EDR’s implementation time. Specifically, we created fictitious treatment and control groups and a fictitious EDR program implementation period. On non-EDR days (August 15, 2019, and August 16, 2019, that is, assuming the EDR was implemented some days in advance), we chose the electricity use data of the same households. The households that participated in the EDR served as the hypothetical treatment group, while the other households served as the hypothetical control group. The regression results (Table S5) indicate that, with the exception of a few groups, the estimated coefficients for the majority groups are not statistically significant, which means that there were no systematic differences in the changes in electricity use between the treatment and control groups after removing the EDR program. This conclusion demonstrates the reliability of our previous estimate results.