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Electricity Outages and Health Outcomes of Children: Empirical Evidence from Transition Economy

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Abstract:
The electricity prices in developing countries are relatively low to recover its costs of generation and provision. This results in under-investment in infrastructure, which usually leads to frequent outages or rolling blackouts by the electricity suppliers. Outages may have an adverse impact on the household's welfare including the health of household members. Using household-level panel data "Life in Kyrgyzstan" (LIK), and a coarsened exact matching (cem) procedure this paper investigates whether there is a relationship between outages and the health of children. Specifically, I study the differences in the anthropometric outcomes of children aged 5 and below (given by the z-scores) living in households that experience frequent outages and those which do not. I find that the children living in the households with frequent outages have z-scores of height-for-age that are -0.334 units lower, and z-scores of weight-for-age that are -0.157 units lower than compared to the children living in the observationally identical households but without frequent outages.

JEL: I12, I14, J13, P36, Q53, Q41
Keywords: electricity outages; child health; height-forage; weight-for-age; developing countries; transition economies

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1. Introduction

Access to energy is essential for development and poverty reduction. However many countries in the developing world still deal with a lack of access to reliable energy sources like electricity due to outages, poor infrastructure, or high prices. All these, force consumers to adopt certain behavior of energy consumption patterns, which shapes the overall electricity demand and may affect a household's wellbeing.

Various studies have observed the benefits of access to electricity on a range of socio-economic characteristics of the household like health, education, and employment. The vast majority of these studies, however, are employing aggregate-level data.

Employing aggregated household data from demographic and health surveys and World Development Indicators (WDI) for a sample of 41 developing countries Wang (2003) finds strong evidence of a reduction in child mortality when GDP per capita, urbanization level, and access to electricity is higher. The author also shows that access to electricity has an even greater impact than the availability of safe water and sanitation.

According to Wang (2003) electrification has a significant and independent (of income) impact on mortality. The use of electricity for cooking, lighting and heating decreases indoor air pollution (Barnes, Krutilla, & Hyde, 2005; World Bank, 2003), while regular use of wood fuel creates the incidence of respiratory infections, mostly affecting women and children that spend a considerable part of their time indoors. Additionally, electrification allows for refrigeration and boiling water, which has a decisive role in reducing infectious diseases among young children. Wang (2003) concludes that the effect of income on health in previous studies has been overestimated due to omitted information about electrification.

Brenneman (2002) also underlines the relationship between health, transport, and electricity. Claiming that electricity allows school year children to study more, which in turn may be linked with better health outcomes.

Fay et al., (2005) empirically analyze the determinants of three child-health outcomes: the infant mortality rate, the child mortality rate, and the prevalence of malnutrition. Their findings suggest that apart from traditional variables like income, assets, education, and direct health interventions, better access to basic infrastructure services including electricity has an important role in improving child health outcomes.

Meles, (2020) underlines the importance of reliability of electricity supply. The study estimates the average monthly defensive expenditures of the household for the given monthly hours of power outages. Findings also suggest that power outages could contribute to indoor air pollution, deforestation, and global warming through the use of traditional fuels as a backup mechanism.

Despite the documented evidence of the impact of electrification on health (see, for instance, Clay, Lewis, and Severnini, 2016; Lewis, 2018) there is relatively small documented empirical evidence on how the reliability of supply affects health outcomes of the households. Some studies examined the impacts of power outages at the firm level (see, for instance, Andersen and Dalgaard, 2013; Fisher-Vanden et al., 2015; Allcott et al., 2016). However, there is relatively little attention given to the impact of power outages at the household level. This is partly due to the lack of household-level data where frequent power outages are a documented phenomenon.

This paper aims to close this gap in the literature by investigating the relationship between the frequent electricity outages and health outcomes of children under the age of five. The study employs household-level panel data for Kyrgyzstan. Like other post-Soviet countries in a region, Kyrgyzstan has nearly complete country coverage with electricity connections (Gassmann, 2014). Thus, the energy connection per se is not an issue, as in some other developing countries. However, the electricity tariff is well below the cost-recovery level. As a consequence, reliability, service quality, and the efficiency of sector operations are struggling.

In Kyrgyzstan "*the climate is continental, with cold winters, often frosty, and warm and sunny summers, sometimes scorchingly hot*[1]". The daily temperature in summer in some of the regions may fluctuate anywhere between 20 to 40 degrees Celsius (peaking up to 43 degrees sometimes), while in winter it can get as low as negative 25 degrees Celsius[2].

In winter supply reliability is poor and is characterized by frequent outages and emergency shut-downs of assets (The World Bank 2014). As a result, households use traditional fuels (e.g. charcoal, firewood, liquefied petroleum gas (LPG)) as a backup mechanism for heating and cooking. This in turn significantly increases indoor air pollution which is a catalyst of various respiratory diseases (Akhmetov, 2014), especially among children that spend most of their time indoors.

In summer, frequent electricity outages may create sizeable problems for the households in terms of storing food and cooling their households as the work of refrigerators and AC's is constantly interrupted. Under these conditions, the stored food spoils faster driving the household to consume it under potentially serious health problems. Moreover, households with frequent electricity outages may strategically opt for food that is more weather prone and does not require much refrigeration. This in turn may also affect their health (especially in the case of children) negatively as they basically will have to exclude such high protein foods like meat, dairy

[1] https://www.climatestotravel.com/climate/kyrgyzstan
[2] ibid

prodcuts , fish, and eggs from their daily intake. These products are essential for the child's development, and without it, children can grow up smaller, less strong and less intelligent (Hopkin, 2005).

Childrens' health is assessed by the growth and general nutritional status using standardized age- and sex-specific growth references to calculate height-for-age *Z*-scores (haz), and weight-for-age *Z*-scores (waz) in accordance with the recommendations of the World Health Organization (WHO, 2006).

Using the coarsened exact matching technique, and fixed effects panel regression I show that the children in the households which experience frequent outages have a lower haz, and waz indicators than the children in comparable households but without frequent outages. In particular, I find that the children living in the households with frequent outages have z-scores of height-for-age that are -0.334 units lower, and z-scores of weight-for-age that are -0.157 units lower than compared to the children living in the observationally identical households but without frequent outages.

The rest of the paper is structured as follows. The next section describes the energy sector of the Kyrgyz Republic, while Section 3 presents the data employed and the descriptive statistics of the employed sample. In Section 4 I describe the empirical methodology. The results are outlined in Section 5. Section 6 concludes.

2 Kyrgyz Republic's Energy Sector

Among five Central Asian countries, Turkmenistan Kazakhstan, and Uzbekistan depend mainly on natural gas or oil reserves, while Kyrgyzstan and Tajikistan rely on hydropower (mainly in summer), and energy imports during the winter. Kyrgyzstan experienced 58-percent growth in residential consumption of electricity from 2007-2016 along with a 12-percent growth in the number of residential consumers. Access to centralized heating is limited and mainly available in urban areas[3]. Increasing use of electricity as a heating source in the residential sector makes electricity demand more seasonal. Higher winter peaks relative to average demand result in frequent outages and emergency shut-downs of assets (World Bank, 2017).

Economic growth, higher living standards, and social justice need a reliable and affordable energy supply. The Kyrgyz Republic is rich in renewable energy sources. From 2007 to 2014 more than 80% of the total installed power generation capacity come from Naryn cascade hydropower. The rest comes from two combined heat and power (CHP) plants, Bishkek CHP and Osh CHP, which produce electricity as a byproduct (Asian Development Bank, 2016). Kyrgyzstan is exporting electricity generated by hydropower plants and importing fossil fuels. Thermal plants are the largest users of coal, which is produced in the country, but Bishkek CHP uses imported coal due to technological constraints. These plants work mainly from November to March, to meet the increasing electricity demand. Households not connected to the district heating network burn considerably large amounts of coal, which turns into a significant problem with air pollution.

Residential tariffs in the Kyrgyz Republic are one of the lowest in the world. They are even below the actual cost of power generation due to social consideration and affordability. Price for the electricity increased twice in 2010 and became Som1.50 (0.032 USD) per kWh, but due to public pressure, it was reduced, in the same year, to Som0.70 (0.015USD) per kWh for households and Som1.32 (0.028 USD) per kWh for all other customers. In 2015, rising public

[3] According World Bank (2017) less than 1/5 of the population has access to central heating

awareness of the benefits of sector reforms helped the government to increase the price to Som0.77 (0.012 USD) per kWh for households that use below 700kWh and Som2.16(0.035USD) per kWh for above 700kWh. Meanwhile, the price for businesses became Som2.24 (0.036USD)per kWh (Asian Development Bank, 2016).

The low tariffs result in low quality of power supply reliability and quality of service due to old and under-maintained assets operating beyond their economic life. The sector is characterized by inadequate cost recovery and high losses. Residential electricity demand has risen by almost 60% since 2010, with no major investment in the capacity of power generation. This, in turn, creates a supply gap, particularly in the winter months. Unfortunately, I do not possess information on the duration of these outages; however, rolling blackouts by the electricity suppliers aimed to manage the difference in supply and demand are a documented phenomenon in this region, and according to the World Bank from 2009 to 2012, distribution companies reported around two outages per hour (see, World Bank, 2017).

3 Data

The paper utilizes household-level data for Kyrgyzstan. Longitudinal survey study 'Life in Kyrgyzstan' (LiK) tracks the same 3,000 households and 8,000 individuals in all major Kyrgyz regions. The LiK is a nationally representative, longitudinal household and individual survey. The data collection process was administered by several institutions in Central Asia and Europe with the German Institute for Economic Research (DIW Berlin) as the consortium leader. Currently, LiK is administered by IZA's International Data Service Center (IDSC).

The survey was for the first time conducted in 2010 and it has been repeated five times in 2011, 2012, 2013, 2016, and 2019. For my particular study, I use three waves of LiK from 2011 to

2013, since the data collection was conducted uninterruptedly during this period and because information on outages has been recorded since the second wave of LiK.

The initial 2010 sample contained responses from 8,160 adult individuals from 3,000 households. The data were collected using a two-stage stratified random sampling approach based on the 2009 population census. No weights were applied to the data, as the survey had been collated according to population points in 16 strata, together with Bishkek city, Osh city, and the rural and urban areas of the seven regions (oblasts)[4]. About 80.6 percent of the initial sample of households that participated in the survey in 2010, also participated in the following three years.

The survey collects information regarding household demographics, assets, expenditure, migration, employment, agricultural markets, shocks, social networks, well-being, health, and many other factors. One reference person provides information on the household characteristics and particularly about children under age 18.

For the empirical analyses, we use households that have at least one child age from 0 to 5 and have access to the grid. This results in a total of 3743 observations for children and 1326 households in three years, in all major Kyrgyz regions. Among many other socio-economic characteristics of the households, data also reports information about how often the electricity supply to a household was disrupted (our main variable of interest).

It is a quite regular phenomenon in Kyrgyzstan to have regular electricity disruptions (see Figure 1), and usually, the frequency of outages differs from one dwelling to another, even if they are located in the same neighborhood. Respondents can choose among six different options

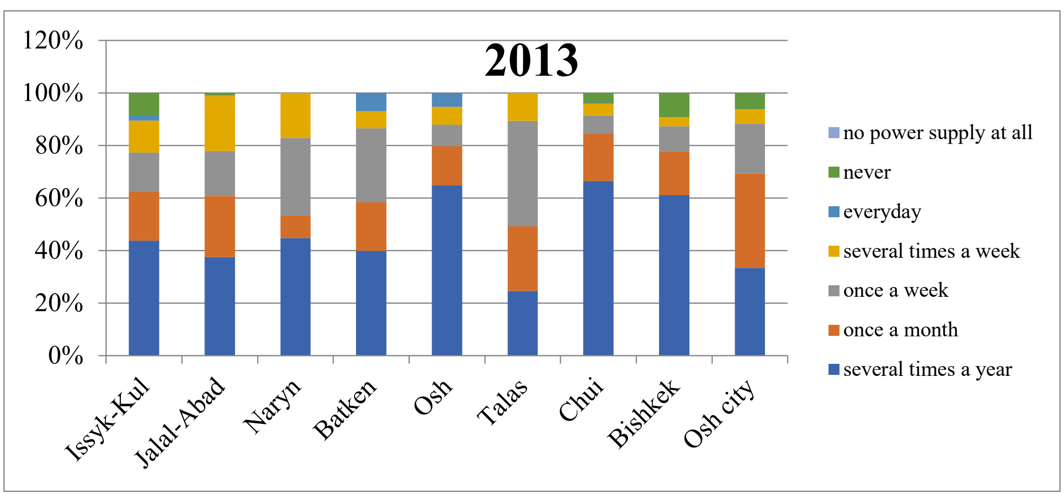
[4] Kyrgyzstan is divided into seven regions (oblasts). Two cities (Bishkek and Osh City) are independent cities with status equivalent to a region.

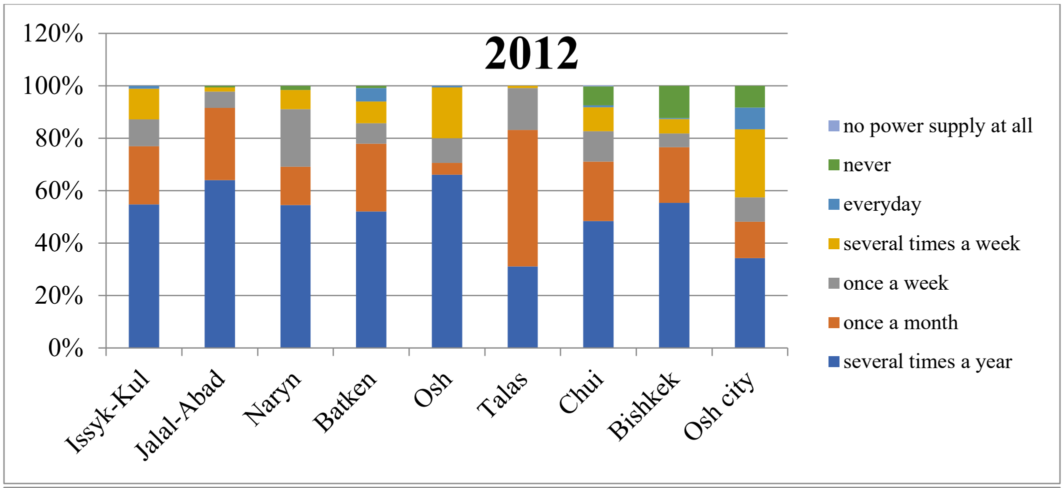
starting from "never" to "every day". Also, since the households where the outages occur every day are quite rare (1.36% of our sample, see Table 1), I use a binary indicator which equals one (=1) if the outages occur more than once a month, and zero (=0) otherwise as my dependent variable.

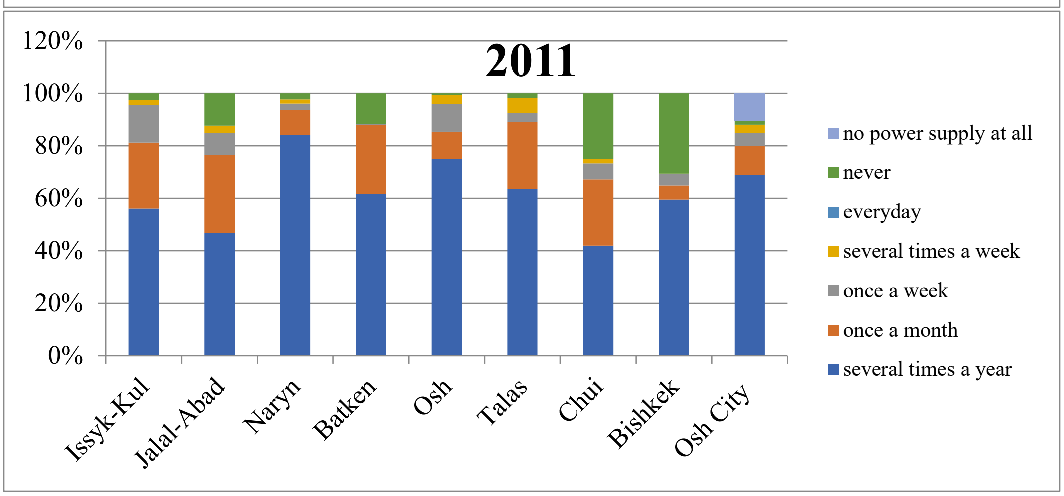
Table 1: Frequency of electricity disruption

Variable	Percent of the Sample
Never	6.0%
Several times a year	54.70%
Once a month	19.78%
Once a week	11.28%
Several times a week	6.87%
Everyday	1.36%

Figure 1: Electricity disruption in all regions of Kyrgyzstan, from 2011-2013







Panel A of Table 2 compares characteristics of households with electricity disruption once a month or less, and households with electricity disruption more than once a month. Some dimensions, such as the number of rooms in a dwelling, drinking water, and heating conditions are significantly better for the households with fewer outages. Overall, both groups heavily rely on stoves using solid fuel for heating. There are also some differences between the two groups with regards to almost all household characteristics, except the height of the child's parents and ethnicity (reported in Panel B and respectfully). I address this problem by implementing coarsened exact matching procedure (see Methodology section for details).

Table 2: Child and household characteristics by group

	Electricity disruption once a month or less[1]	Electricity disruption more than once a month[2]	Difference [1]-[2]=[3]
Panel A: Household characteristics			
Number of rooms	2.70	2.30	0.394***
	(2.03)	(2.23)	
Drinking water inside the dwelling	0.44	0.36	0.077***
	(0.49)	(0.48)	
Central heating	0.08	0.02	0.054***
	(0.27)	(0.16)	
Electric heating (installed-type)	0.05	0.06	-0.01
	(0.21)	(0.23)	
Electric heating (transportable-type)	0.05	0.02	0.031***
	(0.21)	(0.13)	
Solid fuel stove heating	0.80	0.89	-0.086***
	(0.40)	(0.31)	
Gas heating	0.02	0.00	0.016***
	(0.13)	(0.04)	
Food expenditure per capita	411.19	392.02	19.17**
	(190.0)	(161.7)	
Income per capita	756.9	806.1	-49.21*
	(505.7)	(519.0)	
Number of working-age adults in household	3.54	3.78	-0.235***
	(1.80)	(1.95)	
Household size	6.79	7.24	-0.45***
	(2.41)	(2.55)	
Panel B: Child characteristics			
Weight-for-age Z-score	0.36	0.27	0.094**
	(1.10)	(1.09)	
Weight	13.99	14.14	
	(3.73)	(3.59)	
Age in months	34.40	35.60	-1.2*
	(17.90)	(17.50)	
Male	0.50	0.52	-0.02
	(0.50)	(0.49)	
Height-for-age Z-score	-0.26	-0.43	0.169*
	(1.70)	(1.86)	
Height	90.64	91.29	
	(13.97)	(13.83)	

Mother's height (centimeters)	161.40	162.60	-1.15***
	(9.73)	(5.80)	
Father's height (centimeters)	171.52	172.52	-1*
	(9.24)	(6.73)	
Panel C: Ethnicity			
Kyrgyz	0.69	0.75	-0.059*
	(0.45)	(0.42)	
Uzbek	0.12	0.15	-0.023
	(0.33)	(0.35)	
Russian	0.05	0.02	0.024
	(0.21)	(0.14)	
Dungan	0.06	0.04	0.017
	(0.23)	(0.19)	
Uighur	0.03	0.01	0.020
	(0.15)	(0.07)	
Tajik	0.00	0.01	-0.001
	(0.07)	(0.07)	
Kazakh	0.01	0.00	0.005
	(0.08)	(0.04)	
Other	0.03	0.02	0.017
	(0.18)	(0.12)	

Note: Standard deviation in brackets, * significant at 10%, ** significant at 5%, and *** significant at 1%. Children with a height-for-age Z-score below -2 are considered stunted

4. Methodology

The health status of children is measured in our study by generally-known anthropometric indiators, namely height-for-age and weight-for-age. We compute Z-scores for each child's height-for-age, weight-for-age indicators, where the Z-score is defined as the difference between the child's anthropometric value (i.e. weight and height) and the mean value of corresponding measure for the same aged international reference population, divided by the standard deviation of the reference population[5]. . An international reference is useful since the growth in height and

[5] We use global child growth standards for infants and children up to the age of 5 years introduced by the World Health Organization(WHO) in April 2006.

weight of well-fed, healthy children under 5 years of age from different ethnic backgrounds and different continents is reasonably similar (Graitcer and Gentry, 1981, Habicht et al., 1974).

On average, in our sample, children's height-for-age z-scores (haz) are 0.29 standard deviations below the average height-for-age of a reference child, and 15.7% considered stunted[6]. The weight-for-age Z-score (waz) is on average 0.34 standard deviations above the reference group and 7.8% of children in our sample are overweight.

In the absence of experimental data, one has to rely on other techniques to derive the causal relationships between variables of interest. In particular, one of the most popular techniques to derive the causal relationship from the observational data is matching. Matching is a nonparametric technique of controlling for the confounding effect of the pretreatment control variables in observational studies. The goal of matching is to reduce existing imbalance (prune the data) between treatment and control groups. Ideally, if the data is perfectly balanced controlling further for any covariates is unnecessary, and a simple difference in means of the outcomes on the matched data can estimate the causal effect (see, for instance, Heckman et al., 1997).

Various types of matching techniques were developed in the literature. In this study, I use the "coarsened exact matching" (cem) method. The cem matching technique belongs to the newly developed class of Monotonic Imbalance Bounding'' (MIB) class of matching methods developed by Iacus et al., (2012) from which cem is derived.

Previously popular class of "equal percent bias reducing''(EPBR) matching methods from which for example the "propensity score matching" technique is derived, do not guarantee any

[6] Children with height-for-age Z-scores below -2 are considered stunted

level of imbalance reduction in any given data set. Their properties only hold on average across samples and even then, only by assuming a set of normally unverifiable assumptions about the data generating process (King & Nielsen, 2019). Contrary to EPBR matching techniques, cem works in a given sample and requires no assumptions regarding the data generating process except the common ignoribility assumption (ibid).

Moreover, cem was shown to dominate existing (EPBR and other) matching methods in its ability to reduce imbalance, model dependence, estimation error, bias, variance, mean square error, and other important criteria in a wide range of real and simulated data (see, for instance, Iacus et al., 2009, 2011).

Although the cem matching algorithm is quite different from its EPBR counterparts, the end goal of the cem is the same, to estimate the sample average treatment effect on the treated (SATT):

$$SATT = \frac{1}{n_T} \sum_{i \ni T} TE_i \qquad (1)$$

TE_i stands for the treatment effect for unit i, and $n_T = \sum_{i=1}^{n} T_i$ and $T = \{1 \leq i \leq n : T_i = 1\}$, where T_i is an indicator variable with the value $T_i = 1$ if unit i receives the treatment, and $T_i = 0$ otherwise.

As stated above cem matching algorithm implies that the assignment of the treatment is ignorable conditional on a set of observed covariates. Formally, this can be depicted as:

$$P\big(T \big| X, Y(0), Y(1)\big) = P(T|X) \qquad (2)$$

Where $Y(0)$ indicates the outcome variable in case of no treatment, and $Y(1)$ indicates the outcome variable in the case when treatment is received. The vector X stands for the covariates on which the matching algorithm is implemented.

I match treatment and control groups on the various household characteristics. More specifically, I match on the per capita income of the household, per capita household spending on food, household size, whether the household receives any remittances from abroad, whether the household using the stove on the solid fuels for heating, and whether it uses an outdoor clay oven (tandyr) for cooking. I also match on various location dummies. In particular, I match on each of the nine locations available in the dataset (seven regions, and two major cities), along with an indicator for whether the dwelling is located in a rural or urban area.

As outlined above if the matching algorithm achieves a perfect balance of covariates between treatment and control groups, the conditioning on the covariates is not necessary. However, it is rather hard to achieve a perfect balance in a real-world application. Therefore, it is recommended to control for any potentially confounding variables in the preceding method of estimation.

Thus, in this study I analyze the effect of electricity outages on health outcomes of children aged from 0 to 5 using the following fixed effects econometric model for each of the anthropometric outcomes of interest:

$$WAZ_{it} = \beta_1\, outages_{it} + \beta_2\, X_{it} + a'_{1i} + a'_{2t} + e_{it} \qquad (3)$$

$$\mathrm{HAZ}_{\mathrm{it}} = \delta_1\, outages_{it} + \delta_2\, X_{it} + \gamma_1{'}_{\mathrm{i}} + \gamma_2{'}_{\mathrm{t}} + \mathrm{u}_{\mathrm{it}} \qquad (4)$$

Where i and t stand for household and time subscripts. Our main variable of interest (treatment indicator) is a binary indicator for the frequency of outages occurring more than once a month.

The panel nature of our data allows us to control for all observed and unobserved fixed individual characteristics via the fixed effects indicators in our regression a'_{1i} and $\gamma_1{'}_{\mathrm{i}}$. The included fixed effects complement our cem matching algorithm implemented prior, as it should capture any time-invariant unobserved and/or omitted variables that can potentially invalidate our results.

My empirical specification also includes time-varying variables given by the vector *X* that can potentially affect the anthropometric outcomes of children. In particular, I control for the (natural logarithm of) per capita household food expenditure, (natural logarithm of) per capita income, number of dependent household members defined as the number of children below the age of 18, and number of adults of a non-working age residing within the household. I also control for the age of the child under consideration. The year fixed effects given by a'_{2t} and $\gamma_2{'}_t$ control for any aggregate time shocks.

5. Results

I start by examining the overall balance of the covariates between households that experience frequent outages (T=1), and those which do not (T=0). As the measure of imbalance of the covariates between the groups, I use the overall imbalance indicator introduced by Iacus et al., (2008). It is based on the comprehensive imbalance measure L1, the difference between the multidimensional histogram of all pretreatment covariates in the treated group and that in the control group given by:

$$L_1(f, g) = \frac{1}{2}\sum_{l_1 \dots l_k} | f_{l_1 \dots l_k} - g_{l_1 \dots l_k} | \quad (5)$$

Where $f_{l_1 \dots l_k}$ and $g_{l_1 \dots l_k}$ are the *k*-dimensional relative frequencies for the treated and control groups respectively calculated from the cross-tabulation of the discretized (coarsened) covariates.

Naturally, the inherent trade-off of matching is reflected in cem too: more coarsening of the covariates will result in fewer strata. Fewer strata will result in more diverse observations within the same strata and, therefore, higher imbalance. Moreover, unlike some other methods of matching, cem prunes both treatment, and control units, therefore, changing the quantity of the interest for the treatment effect in the post-matching subsample. This procedure, however, proved to be justified as long as the decision is transparent (see, for instance, Crump et al., 2006).

To avoid any ambiguity, I use cem's automated binning algorithm in Stata-16 software. This automated algorithm is based on the scott break method for imbalance (see Scott, 1979), rather than user-defined cut-off values. The overall imbalance statistics for the chosen variables between the households which experience frequent outages and those which do not is presented in table 3 below.

Table 3: The imbalance statistics of the full sample

Multivariate L1 distance: 0.974	**Univariate imbalance:**						
N=3743	**L1**	**mean**	**min**	**25%**	**50%**	**75%**	**max**
Per capita Income	0.0892	49.213	22.433	28.151	23.23	105.12	-1218.4
Per capita Food Exp	0.11274	-19.183	23.552	-1.8041	-22.788	-5.2514	-35.668
Household size	0.08899	0.46243	0	0	1	1	0
Heating with Stove	0.08617	0.08617	0	0	0	0	0
Cooking with tandyr	0.00845	-0.00845	0	0	0	0	0
Rural households	0.07931	0.07931	0	1	0	0	0
Receiving remittance	0.02532	0.02532	0	0	0	0	0
Issyk_kul region	0.02427	0.02427	0	0	0	0	0
Jalal_abad region	0.02325	0.02325	0	0	0	0	0
Naryn region	0.01545	0.01545	0	0	0	0	0
Batken region	0.00666	-0.00666	0	0	0	0	0
Osh region	0.03425	0.03425	0	0	0	0	0
Osh city	0.03134	0.03134	0	0	0	0	0
Talas region	0.02908	0.02908	0	0	0	0	0
Chui region	0.07042	-0.07042	0	0	0	0	0
Bishkek city	0.08056	-0.08056	0	0	0	0	0

As can be seen, the overall measure of the imbalance indicates that our data is highly unbalanced. The comprehensive measure of imbalance L1 is equal to 0.974 which indicates almost a perfect separation (=1) of the covariates between treatment and control groups. Therefore, the matching procedure proves to be necessary in this case. The column labeled as *L1*, reports the individual L1 measure for the *j*th variable separately, the column labeled *mean*, reports the difference in means between treatment and control groups. The rest of the columns indicate the difference in the empirical quantiles of the distribution of the two groups for the 0^{th}(min), 25^{th}, 50^{th}, and 100^{th} (max) percentiles for each covariate. We can see that there is also some substantial imbalance between the individual L1 scores of the selected variables.

Next, I present the imbalance statistics after the cem matching algorithm was implemented (see table 4).

We can see that out of 3743 households 489 from the control group, and 306 from the treatment group were matched, making it 795 observations in total. Taking into consideration that there are overall 16 variables involved in the matching algorithm, the number of pruned households is quite tolerable.

We can see that there is a considerable improvement both in overall multivariate balancing, as well as the individual univariate balance of the covariates. The comprehensive measure of global imbalance L1 is equal to 0.806 indicating that compared to the baseline reference value of 0.974 for the unmatched data, there was a substantial improvement[7]. The individual L1 imbalance measures are also extremely low and close to zero in most of the cases, indicating near a perfect

[7] It should be noted that the absolute values of the L1 statistics mean less than comparisons between the matching solutions. In this sense, the L1 statistics works for imbalance as R-squared works for the model fit.

balance between the two groups. Although we cannot observe much improvement in the individual imbalance L1 statistics for the per capita income, and the per capita food expenditure, there is a substantial improvement in the difference in the empirical quantiles, showing that there is a minimal difference between the treatment and control groups.

Table 4: The imbalance statistics of the matched sample

Number of strata	1810	
Number of matched strata	177	
Observations	**Treatment=0**	**Treatment=1**
All	3013	730
Matched	489	306
Unmatched	2524	424

Multivariate L1 distance: 0.806	**Univariate imbalance:**						
	L1	**mean**	**min**	**25%**	**50%**	**75%**	**max**
Per capita Income	0.09114	2.1306	20.19	0.69675	34.055	-19.64	0
Per capita Food Exp	0.12805	0.41018	18.808	6.2274	-10.839	13.627	0
Household size	0.01089	0.00871	0	0	0	0	1
Heating with Stove	3.50E-18	0	0	0	0	0	0
Cooking with tandyr	1.10E-16	-2.20E-16	0	0	0	0	0
Rural households	1.70E-16	2.20E-16	0	0	0	0	0
Receiving remittance	1.10E-16	6.90E-18	0	0	0	0	0
Issyk_kul region	2.90E-16	-2.80E-17	0	0	0	0	0
Jalal_abad region	6.90E-17	2.80E-17	0	0	0	0	0
Naryn region	5.60E-17	0	0	0	0	0	0
Batken region	1.30E-16	-4.20E-17	0	0	0	0	0
Osh region	4.20E-16	5.60E-17	0	0	0	0	0
Osh city	1.70E-16	6.90E-18	0	0	0	0	0
Talas region	5.90E-17	-6.90E-18	0	0	0	0	0
Chui region	2.30E-16	-1.40E-17	0	0	0	0	0
Bishkek city	1.20E-16	-1.40E-17	0	0	0	0	0

Next, I present the fixed effects estimation results both for a matched sample of households, and the full sample for comparison purposes. The estimation results for the fixed effects regressions for haz and waz for children aged 0 to 5 are presented in Table 5. Columns 1 and 2 present estimation results for the matched households, while Columns 3 and 4 present results for the full sample of households. When running the regressions for the full sample of the households, we can see that the coefficients on electricity disruptions both in the case of haz and waz are close to zero and highly statistically insignificant. These regression results should serve only as a point of reference and comparison, as this sample is highly unbalanced, and therefore likely biased.

Table 5: Fixed effects regressions

	(1) Height for age Z-score matched	(2) Weight for age Z-score matched	(3) Height for age Z-score full sample	(4) Weight for age Z-score Full sample
el_disruption	-0.334**	-0.157*	-0.041	0.046
	(0.155)	(0.086)	(0.071)	(0.046)
ln_Income	-0.065	-0.387	-0.011	-0.028
	(0.331)	(0.269)	(0.093)	(0.059)
ln_FoodExp	0.131	-0.001	-0.026	-0.007
	(0.175)	(0.116)	(0.062)	(0.041)
Age	-1.428***	-0.821***	-2.254***	-1.201***
	(0.436)	(0.221)	(0.180)	(0.092)
n_of_dependent household members	-0.044	-0.095	0.144***	0.062*
	(0.140)	(0.071)	(0.054)	(0.032)
year2013	1.792*	0.997**	2.858***	1.556***
	(0.978)	(0.496)	(0.385)	(0.199)
year2012	1.369***	0.654**	1.780***	1.009***
	(0.527)	(0.275)	(0.204)	(0.111)
_cons	2.538	4.771***	4.440***	2.954***
	(2.228)	(1.844)	(0.664)	(0.439)
N	795	795	3743	3743
adj. R^2	0.398	0.404	0.457	0.378
F	32.598	17.869	218.577	142.522
p	0.000	0.000	0.000	0.000

Standard errors are clustered at the household level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The relationship between frequent outages and anthropometric outcomes of children for the sample of matched households is negative and statistically significant at 5-percent, and 10-percent in the case of haz and waz respectively. Overall, the height for age z-scores of children in the households which experience frequent outages is 0.334 standard deviations behind, and weight for age z-scores is 0.157 standard deviations behind the children living in the similar household but which do not experience frequent outages.

Although frequent electricity disruptions seem to affect both haz and waz indicators, the coefficient on the dummy indicating frequent outages in the case of haz is more than twice the size of the waz coefficient (-0.335 vs -0.157). These results may be supported by the fact that stunting is a more prevalent issue than wasting in the context of our dataset, as well as generally across developing countries (see, for instance, Wild et al., 2015).

It is interesting to note that the logarithm of the per-capita income and the logarithm of the per-capita food expenditure included in the regressions are statistically insignificant. This can potentially be attributed to the fact that matching ensures that only the households with a balanced income and food expenditures are taking part in the regressions as these variables are also included in the matching algorithm. However, taking into account that per capita income and per capita food expenditures are also insignificant in a context of a full sample, this can also be potentially attributed to the documented general misreporting of income, and expenditures in the household surveys (Bound et al., 2001; and Moore et al., 2000, provide reviews of the literature).

In addition, the insignificant association of income with the anthropometric outcomes of children is supported by the previous studies as well. For instance, Cooper (2018) shows on a sample of household data for three developing countries (Ghana, Zambia, and Bangladesh) that income is an insignificant determinant of height-for-age indicator. The results hold even when proxying for the household income with household's "asset index".

Age of the child is negative and highly statistically significant determinant of the anthropometric outcomes of children across regression specifications. This result is in line with the general evidence that the variation in the anthropometric outcomes of children tends to increase with their age (Cooper, 2018; Wild et al., 2015).

On the other hand, the number of dependent household members is insignificant determinant of child's anthropometric outcomes. This result is also in line with previous studies (see, for instance, Cooper, 2018), and expected since the logarithm of per-capita income is also insignificant in our regression specification.

Finally, we can also observe a generally positive trend for the anthropometric outcomes of children estimated by the year fixed effects dummy variables. We can attribute this to the generally improving overall economic situation as well general development indicators for the Kyrgyz Republic during the 2011-2013 period (The World Bank, 2018), which are known to be associated positively with the general health status of children.

6. Conclusion

Access to reliable energy services is a fundamental prerequisite for poverty reduction and sustainable development of poor countries. Unlike many other developing countries, Kyrgyzstan has a nearly complete country coverage of electricity connections. Therefore, the connection to the electricity grid perse is not a problem in Kyrgyzstan.

However, like in some other developing countries, energy prices are relatively low in Kyrgyzstan. The low energy prices result in the deterioration of energy infrastructure due to a lack of sector investments. This often results in a rolling blackout by the energy suppliers aimed to manage the difference between demand and supply. In the harsh climate of Kyrgyzstan, the disruptions in energy supply may affect the health status of the household negatively, as access to reliable heating, and other energy sources become essential.

In this paper, I explore the possible links between the frequent electricity outages and the anthropometric outcomes, which serve as a proxy for the health status, of children aged 0 to 5. Using panel household data (LiK) and coarsened exact matching technique implemented before the fixed effects regression I find that outages have a negative, and statistically significant effect both on the height for age, and weight for age z-scores of children in the Kyrgyz households. This study documents that, on average, the height for age z-scores of children living in the households which experience frequent outages are 0.334 standard deviations behind, and weight for age z-scores are 0.157 standard deviations behind the children living in the identical household but which do not experience the frequent outages.

Several limitations of this study have to be noted as well. Even though I control for a rich set of household and individual characteristics via the matching procedure, and inclusion of individual fixed effects into the regression, I cannot claim that this study fully accounts for the possible endogeneity of the outages, owing to the lack of suitable instruments, my conclusions are indicative of associations, not causations.

I also do not study the relationship between the outages and well-being indicators of children (and the household in general) other than the anthropometric outcomes. This may be an avenue for future research.

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