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ORIGINAL PAPER

The sensitivity of reported effects of EMF on childhood leukemia to uncontrolled confounding by residential mobility: a hybrid simulation study and an empirical analysis using CAPS data

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Abstract

Purpose Residential mobility is considered as a potential source of confounding in studies assessing environmental exposures, including in studies of electromagnetic field (EMF) exposures and childhood leukemia.

Methods We present a hybrid simulation study where we simulate a synthetic dataset based on an existing study and use it to assess the sensitivity of EMF–leukemia associations to different scenarios of uncontrolled confounding by mobility under two major hypotheses of the infectious etiology of childhood leukemia. We then used the findings to conduct sensitivity analysis and empirically offset the potential bias due to unmeasured mobility in the California Power Line Study dataset.

Results As expected, the stronger the assumed relationship between mobility and exposure and outcome, the greater the potential bias. However, no scenario created a bias strong enough to completely explain away previously observed associations.

Conclusions We conclude that uncontrolled confounding by residential mobility had some impact on the estimated effect of EMF exposures on childhood leukemia, but that it was unlikely to be the primary explanation behind previously observed largely consistent, but unexplained associations.

Keywords Childhood leukemia · Simulation · Residential mobility · Electromagnetic fields

Introduction

Residential mobility is considered as a potential source of bias in studies assessing environmental exposures since the majority of studies consider exposures at only a single residential address. Mobility has been hypothesized to explain observed association [1] between electromagnetic fields (EMF) and childhood leukemia. Mobility can affect an association through study selection and participation, through exposure misclassification, or even as a confounder [2, 3].

Mobility has been known to be associated with characteristics such as lower socioeconomic status (SES) [4], which are related to a subject's exposure to magnetic fields [5, 6]. SES can be related to the type, quality, and number of appliances within a home, as well as the location of the home with regards to overhead powerlines [5, 6]. Type of dwelling (single-family home vs. apartment) is also associated with exposure to EMF [7, 8] as well as with mobility [3, 9].

Increased mobility is also associated with older age of child at diagnosis, and younger maternal age at birth [4] which can impact a child's risk for leukemia. Mobility may also be related to increased exposure to viruses or other infections possibly associated with risk of childhood leukemia [1, 10, 11]. There are two competing theories on the possible infectious etiology of childhood leukemia. In the "population mixing" hypothesis, the disease can develop as a rare response to a relatively common infection introduced to a previously isolated population [10]. In such a case,

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exposure to infections would be associated with a greater risk of childhood leukemia. Alternatively, the "delayed infection" hypothesis suggests a protective effect of infections in early childhood in the development of leukemia through normal immune system development [12]. Possible routes of early childhood infection include having older siblings, breastfeeding, and attending daycare [13–17].

We previously attempted to assess the effect of mobility on the EMF–leukemia relationship in a California Power Lines Study (CAPS) [3]. As the information on mobility was available only for cases, we determined variables predictive of mobility among cases: child's age, maternal age at birth, SES, race/ethnicity, parity, and dwelling type. We used a variety of approaches, including propensity score methods to control for those variables. Given the limitations in the available data and previous work, we extend this effort by simulation and sensitivity analysis.

In this paper, we present a hybrid simulation study [18] assessing the impact of unmeasured residential mobility on EMF–leukemia associations. The aims of this study are (1) to simulate a synthetic case–control study based on available CAPS data, and to use it to assess the sensitivity of the plausible EMF–leukemia associations to different scenarios of uncontrolled confounding by mobility, and (2) to use the simulation findings to conduct sensitivity analysis and offset the potential bias due to uncontrolled confounding by mobility in the empirical study of the associations between EMF exposures on childhood leukemia in CAPS.

Methods

We first conducted a simulation study that generated case–control data using inputs on the interrelations of childhood leukemia, EMF, and mobility conditional on other covariates from an existing case–control study, CAPS. We then analyzed the simulated dataset to investigate the extent to which not adjusting for various scenarios of confounding by mobility could explain the magnitude and the direction of the associations between EMF exposures and childhood leukemia. Finally, we assessed the empirical relationship between EMF exposures and childhood leukemia in CAPS by offsetting potential confounding by mobility as seen in the simulation study.

CAPS is a case–control study that enrolled childhood leukemia cases younger than 16 years diagnosed in California between 1988 and 2008. Cases were identified from the California Cancer Registry (CCR; www.ccrcal.org) and matched to the California Birth Registry (CBR; California Department of Public Health, Vital Statistics Branch). Controls were randomly selected from the CBR and matched to cases 1:1. Controls were excluded if they were diagnosed with any type of cancer in California before the matched case's date of diagnosis. Out of 6,645 eligible childhood leukemia cases identified from the CCR, 4,879 were matched to birth records and had accurate geocoding of both birth and diagnosis addresses. Similarly, 4,835 controls met these criteria (for birth address only). Details of this study have been previously described [19]. Cases were required to be

Table 1 Input values for the relationship between the covariates and distance to powerlines, calculated magnetic fields, and leukemia in CAPS used to develop the synthetic cohort

Covariate	< 50 m to 200+ kV line (OR)[a]	≥ 0.4 μT (OR)[b]	Distance → leukemia (OR)[c]	CF → leukemia (OR)[d]	Prevalence in CAPS ($0 < p < 1$)
Male sex	1.01	0.37	0.96	0.96	0.56
Asian race (v. non-Hispanic White)	2.19	1.98	1.24	1.24	0.11
Black race (v. non-Hispanic White)	0.52[e]	1.34[e]	0.63	0.63	0.07
Hispanic (v. non-Hispanic White)	1.44	1.45	1.20	1.20	0.50
Other race (v. non-Hispanic White)	1.96[e]	N/A[e]	1.06	1.06	0.02
< 1 year old (v. 10–15 years old)	1.12[e]	1.11[e]	0.91	0.91	0.07
1–5 years old (v. 10–15 years old)	1.81	1.24	0.99	0.99	0.64
6–9 years old (v. 10–15 years old)	0.45	0.67	0.97	0.97	0.17
High SES	0.62	0.63	1.05	1.05	0.30

Mobility ORs not estimated due to no information for controls

CAPS California Powerlines Study, *m* meters, *kV* kilvolts, *μT* microTesla, *CF* calculated fields, *OR* odds ratio, *p* probability, *SES* socioeconomic status

[a]Effect of covariates on living < 50 m from a 200+ kV line, adjusted for all other covariates

[b]Effect of covariates on having ≥ 0.4, adjusted for all other covariates

[c]Effect of covariates on leukemia risk, adjusted for all other covariates and distance

[d]Effect of covariates on leukemia risk, adjusted for all other covariates and calculated fields

[e]Cells $n < 5$

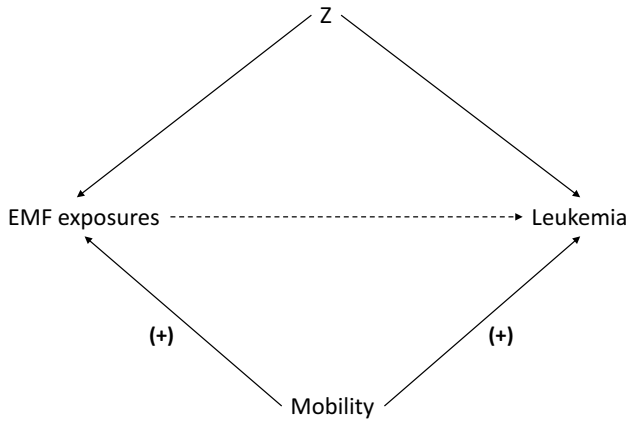

Fig. 1 DAG of a main causal structure under the population mixing hypothesis where mobility is positively associated with both EMF exposure and childhood leukemia and Z is the set of other associated measured factors. Z includes age, sex, SES, maternal age, parity, race/ethnicity, and dwelling type. *DAG* directed acyclic graph, *SES* socioeconomic status

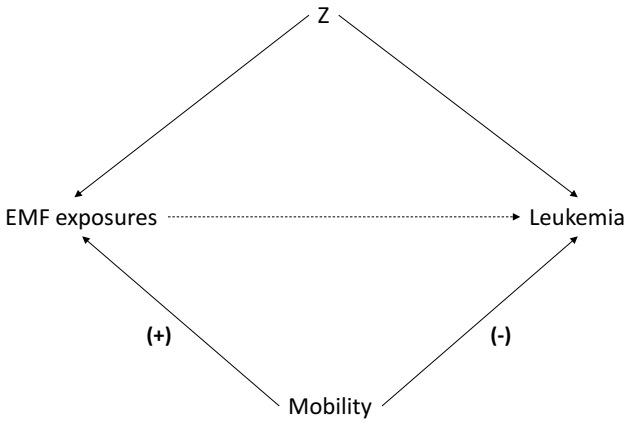

Fig. 2 DAG of a main causal structure under the delayed infection hypothesis where mobility is positively associated with EMF exposure and a protective factor for childhood leukemia and Z is the set of other associated measured factors. Z includes age, sex, SES, maternal age, parity, race/ethnicity, and dwelling type. *DAG* directed acyclic graph, *SES* socioeconomic status

both born and diagnosed in California, but as controls were selected from the CBR, they were not required to be residing in California at the time of their case's diagnosis. Hence, the mobility of controls is unknown.

First, we analyzed CAPS data to extract information on the prevalences of our EMF exposures: living < 50 m from an overhead powerline of 200 kV or greater and exposure to calculated magnetic fields of 0.4 μT or greater. The prevalence of childhood leukemia, as well as, residential mobility among cases, was also retrieved.

We used CAPS to estimate odds ratios (ORs) between the variables used in previous analyses [20, 21] and distance to high-voltage overhead powerlines, calculated magnetic fields, and childhood leukemia to the extent possible with the available data using both cases and controls. Table 1 lists the ORs and prevalences of our selected characteristics to both exposures of interest as well as to leukemia.

Second, we simulated data for a new mobility variable as well as new exposure and outcome variables using the parameters in Table 1 based on a causal structure of mobility as a confounder in the EMF–leukemia association shown in the two directed acyclic graphs (DAGs). These DAGs were used to depict plausible scenarios based on accepted theory or evidence. Figure 1 is based on the population mixing hypothesis while Fig. 2 is based on the delayed infection hypothesis. We simulated the new variables using equations with the defined parameter values in Table 1. All variables were binary. Mobility was drawn from a Bernoulli trial, B[1, p], where p was the probability of observing the variable as 1 (versus the reference 0) in the study. Since mobility information was not available for controls, we used the prevalence among cases for initial simulation values. In future analyses, mobility can be simulated using similar equations as those below taken from previous analyses [3]. For the exposures, we used indicator variables for the most highly exposed children (living < 50 m to a 200+ kV line; exposed to ≥ 0.4 μT calculated fields).

In particular, the probability of living < 50 m to an overhead powerline of 200 kV or greater used in the simulations was specified as:

$$
\begin{aligned}
&1/(1+\exp(-(\log-\ \text{odds}(\text{PL}_{\text{background}}=1)\\
&\quad+\log(\text{OR}_{\text{age}<1-\text{PL}})\times\text{age}<1\\
&\quad+\log(\text{OR}_{\text{age}\ 1-5-\text{PL}})\times\text{age}\ 1-5\\
&\quad+\log(\text{OR}_{\text{age}\ 6-9-\text{PL}})\times\text{age}\ 6-9\\
&\quad+\log(\text{OR}_{\text{male}-\text{PL}})\times\text{male}+\log(\text{OR}_{\text{high SES}-\text{PL}})\\
&\quad\times\text{high SES}+\log(\text{OR}_{\text{Hispanic}-\text{PL}})\times\text{Hispanic}\\
&\quad+\log(\text{OR}_{\text{other race}-\text{PL}})\times\text{other race}\\
&\quad+\log(\text{OR}_{\text{asian race}-\text{PL}})\times\text{asian race}\\
&\quad+\log(\text{OR}_{\text{black race}-\text{PL}})\times\text{black race}\\
&\quad+\log(\text{OR}_{\text{moved}-\text{PL}})\times\text{moved}
\end{aligned}
$$

where PL stands for powerlines

The corresponding equation for exposure to ≥ 0.4 μT calculated fields was:

$$1/(1+\exp(-(\log-\text{odds}(\text{CF}_{\text{background}}=1)+\log(\text{OR}_{\text{age}<1-\text{CF}})\times\text{age}<1+\log(\text{OR}_{\text{age}\,1-5-\text{CF}})\times\text{age}\,1-5+\log(\text{OR}_{\text{age}\,6-9-\text{CF}})\times\text{age}\,6-9+\log(\text{OR}_{\text{male}-\text{CF}})\times\text{male}+\log(\text{OR}_{\text{high SES}-\text{CF}})\times\text{high SES}+\log(\text{OR}_{\text{Hispanic}-\text{CF}})\times\text{Hispanic}+\log(\text{OR}_{\text{other race}-\text{CF}})\times\text{other race}+\log(\text{OR}_{\text{asian race}})*\text{asian race}+\log(\text{OR}_{\text{black race}})\times\text{black race}+\log(\text{OR}_{\text{moved}-\text{PL}})\times\text{moved}$$

where CF stands for calculated fields.

Similarly, the probability of leukemia given these exposures and the other variables was specified as:

$$1/(1+\exp(-(\log-\text{odds}(\text{Leuk}_{\text{background}}=1)+\log(\text{OR}_{\text{EMF}-\text{Leuk}})\times\text{newly generated EMF exposures}+\log(\text{OR}_{\text{age}<1-\text{Leuk}})\times\text{age}<1+\log(\text{OR}_{\text{age}\,1-5-\text{Leuk}})\times\text{age}1-5+\log(\text{OR}_{\text{age}\,6-9-\text{Leuk}})\times\text{age}6-9+\log(\text{OR}_{\text{male}-\text{Leuk}})\times\text{male}+\log(\text{OR}_{\text{high SES}-\text{Leuk}})\times\text{highSES}+\log(\text{OR}_{\text{Hispanic}-\text{Leuk}})\times\text{Hispanic}+\log(\text{OR}_{\text{other race}-\text{Leuk}})\times\text{otherrace}+\log(\text{OR}-_{\text{asian race}-\text{Leuk}})\times\text{asianrace}+\log(\text{OR}_{\text{black race}-\text{Leuk}})\times\text{blackrace}+\log(\text{OR}_{\text{moved}-\text{Leuk}})\times\text{moved.}$$

where EMF would be either distance or calculated fields.

The ORs for the covariates in the equations above are the same as Table 1, save for mobility, which is discussed below. The background prevalences of the exposure and outcome variables were based on their proportions in CAPS. To determine if confounding by mobility or other variables could affect previous findings of EMF–leukemia associations, we set the true effect of those associations as null.

We copied our dataset 1,000 times and simulated as many Monte Carlo samples of our new variables. We repeated this for different values for the association of mobility with leukemia ($\text{OR}_{\text{moved-Leuk}}$s) as well as mobility with the EMF exposures ($\text{OR}_{\text{moved-PL/CF}}$s). For the population mixing hypothesis (Fig. 1), we ran models where the association between mobility and outcome were assumed to be 1.3, 2.0, or 3.0 in accordance with moderate previous findings [10]. In the case of the delayed infection hypothesis (Fig. 2), we assumed the mobility-leukemia association to be negative and varied it at 0.3, 0.6 and 0.9 also based on the previous literature [22]. The mobility–EMF associations were the same under both hypotheses: they were assumed to be positive but small. We assessed scenarios of the EMF–mobility association at 1.3, 2.0 and 3.0 to simulate a small, moderate, or large effect of mobility, respectively. Each of the generated samples were run through a "fully-adjusted-minus-mobility" model that included all other variables except mobility. In this model, any difference from null in the coefficient of the exposure would be due to mobility. The resulting 1,000 ORs from each model of the 1,000 replicates of the hybrid simulated datasets were summarized using the median as the point estimate and the 2.5th and 97.5th percentiles as the lower and upper limits of the 95% simulation interval in each scenario.

Finally, to address the second main aim of this study, we used methods and formulas described by Arah et al. [23, 24] to obtain the estimated bias generated by uncontrolled mobility in our simulated dataset and used it as a fixed offset in the empirically estimated associations between EMF exposures and childhood leukemia based on the real CAPS dataset. The formula used to derive the offset was given by:

$\text{Offset}=\log(\text{OR}_{\text{EMF\_Leuk}})*\textit{Exposure}$ where $\text{OR}_{\text{EMF\_Leuk}}$ is the observed biased OR for the association between EMF and leukemia when all other variables, except for mobility, are accounted for in the simulated datasets wherein EMF had no effect on leukemia. The observed $\text{OR}_{\text{EMF\_Leuk}}$ from the simulated datasets could, thus, only be due to uncontrolled confounding by mobility and is a bias factor on the OR scale. Offsetting this bias factor from the empirically estimated EMF–leukemia OR is equivalent to dividing this biased empirical EMF–leukemia OR by the bias factor to obtain a mobility-adjusted EMF–leukemia OR [23, 24].

The main empirical analysis adjusted the variables sex, age, SES and race/ethnicity using a complete-case analysis. Sensitivity analyses involved using multiple imputations on observations with missing values for the variables SES and race/ethnicity (ten imputations per missing value). We also included other predictors of mobility documented previously [3]: maternal age at birth, parity, and dwelling type in complete-case scenarios.

All analyses were conducted using SAS software version 9.3. Copyright © 2017 SAS Institute Inc.

Results

The complete-case analysis included 9,244 subjects of which 4,659 were cases and 4,585 were controls. 61% of cases had moved between time of birth and diagnosis. The simulated impact of uncontrolled confounding by mobility on the associations between EMF exposures and childhood leukemia under the population mixing hypothesis is presented at the top of Table 2. For the analyses involving distance, removing mobility from the model increased the ORs up to 1.31. However, even with mobility associated with both exposure

Table 2 Complete-case analysis of the impact of mobility on the association between EMF exposures and childhood leukemia with additional variables: maternal age at birth and parity (n = 9,242)

Hypothesis	Varied inputs		< 50 m distance to 200+ kV power lines			≥ 0.4 μT calculated fields		
			Bias introduced	Offset analysis		Bias introduced	Offset analysis	
	Mobility → exposure (OR)	Mobility → leukemia (OR)	Distance → leukemia OR (95% CI)	Before adjustment OR (95% CI)	After adjustment OR (95% CI)	CF → leukemia OR (95% CI)	Before adjustment OR (95% CI)	After adjustment OR (95% CI)
Population mixing	1.30	1.30	1.03 (0.66–1.69)	1.39 (0.72–2.68)	1.34 (0.70–2.60)	1.06 (0.51–2.41)	1.49 (0.69–3.19)	1.40 (0.65–3.00)
	2.00	1.30	1.05 (0.72–1.60)		1.31 (0.68–2.54)	1.06 (0.55–2.14)		1.40 (0.65–3.01)
	3.00	1.30	1.08 (0.77–1.48)		1.29 (0.67–2.49)	1.06 (0.64–1.92)		1.40 (0.65–3.01)
	1.30	2.00	1.07 (0.66–1.79)		1.29 (0.67–2.50)	1.08 (0.49–2.81)		1.38 (0.64–2.97)
	2.00	2.00	1.13 (0.74–1.76)		1.22 (0.63–2.36)	1.14 (0.60–2.40)		1.30 (0.61–2.80)
	3.00	2.00	1.19 (0.83–1.70)		1.17 (0.60–2.26)	1.17 (0.72–2.25)		1.27 (0.59–2.72)
	1.30	3.00	1.08 (0.68–1.86)		1.28 (0.66–2.47)	1.14 (0.50–3.14)		1.31 (0.61–2.81)
	2.00	3.00	1.21 (0.78–1.94)		1.15 (0.59–2.22)	1.24 (0.64–2.81)		1.20 (0.56–2.57)
	3.00	3.00	1.31 (0.90–1.91)		1.06 (0.55–2.05)	1.30 (0.74–2.70)		1.14 (0.53–2.45)
Delayed infection	1.30	0.90	1.00 (0.62–1.67)	1.39 (0.72–2.68)	1.39 (0.72–2.68)	1.02 (0.49–2.42)	1.49 (0.69–3.19)	1.46 (0.68–3.13)
	2.00	0.90	1.00 (0.67–1.49)		1.38 (0.71–2.67)	1.01 (0.52–1.97)		1.48 (0.69–3.17)
	3.00	0.90	0.99 (0.70–1.37)		1.40 (0.72–2.70)	0.98 (0.56–1.74)		1.52 (0.71–3.25)
	1.30	0.60	0.98 (0.58–1.57)		1.42 (0.73–2.74)	0.99 (0.45–2.13)		1.51 (0.70–3.23)
	2.00	0.60	0.94 (0.62–1.40)		1.48 (0.76–2.86)	0.94 (0.47–1.85)		1.58 (0.74–3.39)
	3.00	0.60	0.91 (0.63–1.24)		1.52 (0.79–2.95)	0.89 (0.50–1.56)		1.67 (0.78–3.58)
	1.30	0.30	0.94 (0.54–1.50)		1.47 (0.76–2.84)	0.96 (0.40–2.02)		1.55 (0.72–3.33)
	2.00	0.30	0.85 (0.52–1.29)		1.64 (0.85–3.17)	0.85 (0.39–1.63)		1.75 (0.82–3.75)
	3.00	0.30	0.77 (0.52–1.06)		1.81 (0.93–3.49)	0.77 (0.39–1.29)		1.93 (0.90–4.14)

EMF electromagnetic fields, *m* meters, *kV* kilovolts, *μT* microTesla, *CF* calculated fields, *OR* odds ratio, *CI* confidence interval

All models were adjusted for age, sex, socioeconomic status, and race/ethnicity

and outcome with an OR of 3.0, there was not enough bias introduced to explain a previously observed association of 1.41 [21]. Naturally, as the effect of mobility increased, so did the amount of bias generated by leaving it out of the model. A similar trend was seen for calculated fields, where again, previously observed associations (such as OR of 1.50) were not reached [20].

The bottom of Table 2 shows the results of the simulations under the delayed infection hypothesis. It shows similar trends to the population mixing hypothesis but in the opposite direction. Scenario 3 with a mobility-exposure OR of 3.0 and mobility–leukemia exposure of 0.3 showed similar levels of bias to the maxed-out scenarios under the population mixing hypothesis. Several scenarios with mobility–leukemia at an OR of 0.9 showed almost no bias remaining in the model, even when mobility was omitted, but this could be due to the fact that the chosen association was so weak.

The results of using offsets in CAPS to account for the potential bias of mobility is also presented in Table 2. For the population mixing hypothesis, as expected, the greater the potential bias introduced by mobility, the closer to null the association became when accounting for it, for both distance and calculated fields. However, even in our scenario with the greatest bias introduced, the effect of large calculated fields on the incidence of childhood leukemia is not erased completely, even if the effect is imprecise. In the case of the delayed infection hypothesis, accounting for the bias pulled the ORs away from the null.

Using multiple imputation on the same variables did not change the results (results not shown). When maternal age at birth and parity were included in the model, the results were almost identical (Table S1), suggesting that although these variables are predictive of mobility, they do not appear to alter the EMF–leukemia relationship.

The associations were stronger for a site-visited subset: 1.73 (0.82–3.66) for distance and 1.99 (0.84–4.72) for magnetic fields. When site-visited dwelling classification was included, all the estimates increased in magnitude (Table S2), with the bias-adjusted distance ORs ranging from 1.28 to 1.62 for the population mixing hypothesis and from 1.66 to 2.25 under the delayed infection hypothesis. However, the sample size was greatly reduced for these analyses. In all cases, both exposures still showed associations with increased risk of childhood leukemia, even after accounting for the potential bias introduced by unmeasured mobility.

Discussion

In this paper, we created a synthetic case–control study based on information from CAPS on EMF exposures and childhood leukemia as well as related characteristics and used the computed bias from the simulation experiments to adjust the real CAPS dataset for uncontrolled confounding by residential mobility. We simulated different scenarios using the synthesized variables and examined whether the reported associations between EMF exposures and childhood leukemia could be affected by unmeasured residential mobility, which could represent either infectious etiology of childhood leukemia or other ways mobility could affect such a relationship.

In our study, although mobility appeared to be an important factor to adjust for, we find associations close to those previously found in CAPS: 1.41 for the association between living < 50 m from a high-voltage-powerline and 1.50 for the association between exposure to ≥ 0.4 μT of calculated magnetic fields, except for strong postulated associations between mobility and both exposure and outcome. For mobility were to be truly responsible for the observed associations, the relationship between mobility and both EMF exposures and childhood leukemia would have to be strong (ORs > 3.0 in both cases). However, as previously assessed among the cases in CAPS, mobility did not appear to be associated greatly with EMF exposures [3]. Stronger trends were seen under both hypotheses. Of note were scenarios in the delayed infection hypothesis where mobility-leukemia had an OR of 0.9. In the distance analyses, omitting mobility from the fully adjusted model still showed a null effect. For calculated fields, we saw an OR of 1.02 as well as 1.01. This does not lend support to the delayed infection hypothesis, at least in CAPS.

The most interesting finding was using the bias offsets in CAPS. It appeared as though mobility might play a role in the observed association between both EMF exposures and childhood leukemia. The 'unadjusted' ORs, however, were also lower than previously observed in CAPS analyses [20, 21]. Even with our "strongest mobility" scenario, neither bias-adjusted association of EMF exposure with leukemia appeared to be null, although the confidence intervals were relatively wider than before bias-adjustment. This further suggests that mobility alone might not completely explain away previously observed associations, unless the true associations are extreme. This also does not rule out other risk factors that could explain them away. Information on infections, for example, was not available in this study to assess the infectious etiology theories more rigorously.

The additional models with maternal age and parity included did not appear to change the results at all, suggesting that while they may be related to mobility, they are not substantially related to EMF exposures to have an effect on their relationship. Dwelling type, however, increased all ORs in magnitude, including the estimated bias introduced by mobility in the simulated datasets. This suggests that dwelling type is a major cofactor of mobility. Unfortunately, the subset for this analysis included only

240 subjects which also led to wide confidence intervals. Further analysis of dwelling type with additional identification of this information for subjects in CAPS is planned.

Strengths of this study include the use of CAPS, which itself has a relatively large sample size to increase power, and used population registries to obtain data, eliminating potential for participation bias due to self-selection. Exposure assessment was also conducted blindly with respect to case–control status, reducing the risk for information bias due to recorder bias.

Potential limitations of this study involve residential mobility itself. In CAPS, it was defined by the distance between a case's birth address and diagnosis address of more than 50 m, but this could be misclassified. Additionally, we used the prevalence of mobility only among cases because it was unavailable among controls which may not accurately reflect the source population distribution of residential mobility. In addition, previous studies have shown a discrepancy in mobility among cases and controls [25–27]. Finally, as only initial and final address information was available, it is possible for a case to have moved, then returned to their birth home before being diagnosed, but we expect this to be rare.

Conclusion

Uncontrolled confounding by residential mobility appears to have impact on the estimated effects of EMF exposures, namely proximity to high-voltage powerlines and increased magnetic field exposure, on childhood leukemia. However, it is unlikely to be the primary driving force behind previously observed largely consistent, but unexplained associations.

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Compliance with ethical standards

Conflict of interest The authors declare no conflicts of interest.

Ethical approval CAPS was approved by University of California, Los Angeles Office for the Protection of Research Subjects.

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