REJOINDER: "SPATIAL ACCESSIBILITY OF PEDIATRIC PRIMARY HEALTHCARE: MEASUREMENT AND INFERENCE"

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We first would like to thank all discussants for their thoughtful comments. We appreciate the additional insights regarding our findings and the suggestions on future directions relevant to the estimation of and inference on healthcare access. In our rejoinder, we emphasize three discussion threads addressing challenges and limitations of the proposed methodology, and addressing further considerations in the interpretation of our models with implications in informed decision making.

Local estimates and targeted interventions. In recent years, the fields of healthcare services research and health policy have acknowledged and stressed the significance of applying operations research methodology to understand and manage the complexity of healthcare [Rouse and Serban (2014)]. The methodology can emphasize impact and improvements at different levels—individuals, communities, processes, providers, organizations and/or the entire ecosystem of care. Depending on what actions are targeted in improving healthcare delivery, one may assess individual-level improvements (e.g., personalized medicine) or system-wide effects (e.g., health policy), for example. Our study primarily emphasizes health policy, while not losing sight of its potential unintended consequences at the community level. In policy decision making, low geographic granularity inferences, block or census tracts, are desirable over coarser geographic aggregations such as county because they will capture the diversity of populations in need of better care and the diversity of environments of care delivery.

Making inferences at low geographic granularity, specifically local assessments of systematic disparities, is not a new research direction in the medical literature, although one will find novel modeling contributions in recent years with the advancement of computational approaches in the area of geographic economics and environmental studies.

An immediate application of local disparity inferences is suggesting targeted actions to improve various aspects of healthcare. We divide such actions into policy and network interventions. For example, in the discussion paper, we primarily focus on *policy interventions*, which commonly involve designing, implementing or translating a health policy. On the other hand, *network interventions* refer to actions that involve altering an existing network of care, including location and allocation of sites. Designing and evaluating such interventions require understanding healthcare access and its impact on health outcomes at the community level along with

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advanced mathematical modeling, including location-allocation models [Daskin and Dean (2004)] and discrete simulations [Jacobson, Hall and Swisher (2006)], for optimal allocation of resources while achieving high levels of equity and quality of care.

Because we find that the policy interventions explored in our study have limited impact in improving access, the discussants have suggested two possible network interventions. One intervention is to consider new service locations for primary care to reduce geographic inequities and/or reduce the disparities between the Medicaid and non-Medicaid population. A second intervention is to incentivize providers to consider satellite care opportunities in more remote areas than otherwise preferred. The two interventions, however, can be considered together by designing alternative care opportunities including mobile clinics and telemedicine, which can use the expertise of physicians in densely served areas to provide care to patients in underserved and unserved areas. The optimization and statistical models developed in our study can be used to derive optimal assignments between providers and areas in need for care under such alternative care approaches. The optimal allocation of limited resources can be based on equity and effectiveness objectives jointly [Graber, Carter and Verter (2014)]. We are examining each of these interventions in our ongoing research.

Data uncertainty. A third thread of comments refers to data uncertainties in informing the optimization model for measuring access. We reiterate their importance by providing additional insights and discussions.

In our study, one emphasis is to develop optimization-based measurement models for estimating spatial access because we recognize that the existing approaches provide inaccurate estimates due to deficiencies of the models employed, particularly because of their lack of incorporating knowledge about the trade-offs and realistic constraints in the care system. However, errors in the spatial access measures are also largely driven by uncertainties as a potential deficiency that is due to lack of knowledge; in statistical terms, these are called estimation errors. All existing spatial access measures, regardless of whether they are derived using simple approaches or obtained using more sophisticated models, are point estimates derived using uncertain data, and thus they are limited in terms of the ability of making inferences on spatial access. To the best of our knowledge, this important aspect is overlooked in the existing literature of spatial access.

Particularly, the optimization assignment model used to measure spatial access relies on a set of parameters that are assumed fixed and known, including the maximum willingness to travel for patients with or without a car, and Medicaid participation along with the maximum caseload devoted to Medicaid patients of pediatricians in the network of care. These parameters are specified based on either subjective care delivery recommendations or sources of data observed with uncertainty. Moreover, there are also uncertainties in the supply (providers) and demand (patients) data, due to irregularities in the reporting of providers and their taxonomy (supply uncertainty) and because of the estimation error in population

counts derived by the Census Bureau (demand uncertainty). Last, the travel distance from a community to a provider will vary depending on where patients in the respective community live and depending on the variations in alternative travel routes. Such uncertainties may also be different in rural areas than in urban areas. Thus, the spatial access measures derived from the optimization models are point estimates, with an estimation error varying across space and compounding many sources of uncertainty.

We have made an attempt to reduce the uncertainty due to physician participation in the Medicaid insurance program and we have studied the sensitivity of our model to small variations in the model parameters; however, we have also overlooked the error quantification due to other sources of uncertainty. The discussants have rightly so stressed the importance of considering quantification of the estimation error in a principled manner, as it is key in making inferences on local disparities in spatial access.

Uncertainty quantification has broadly been studied in experimental design and simulations [Barton, Nelson and Xie (2014); Smith (2013); Snyder (2006)]. But in studies relying on deterministic optimization models, the presence of the estimation error due to data uncertainty is rarely acknowledged. In such models, the effect of uncertainties of the model parameters on the estimates derived from the optimization model is often evaluated using sensitivity analysis and running the model with different input values; however, quantification of the overall estimation error is overlooked. Thus, there is an immediate need for developing methodology to address the need of quantifying the estimation error not only for spatial access measures, but also for decision variables and solutions derived from deterministic optimization models more generally that rely on uncertain data and uncertain parameters.

Interpretation of the results. The discussants suggested several interesting directions for interpretation of the results of our model. First, as mentioned in the paper and highlighted in the discussion, there are strong correlations between dimensions of access to healthcare. Indeed, the state-wide spatial correlation between average distance traveled and percent covered is -0.92. The correlation between distance and congestion is 0.51 and between congestion and coverage is -0.45. In some regions and for some sub-populations, these correlations will be stronger. Understanding the small scale correlations is especially important since they indicate where improving access for some access dimension or population groups may have unintended consequences. The type or magnitude of correlation can also be useful in thinking about the type of intervention appropriate in a particular area.

Each discussant suggested further analysis of the striking differences between access in urban and rural areas of Georgia. In our optimization model specifications, we chose to set some parameters constant throughout the state. For example, the parameter for maximum distance families are willing to travel is specified to be consistent with policy makers' goal for accessible primary care. If the research objective is to identify areas with access below a certain threshold, or locations

which experience inequities, this modeling approach may be sufficient. However, as the discussants correctly point out, this parameter value will surely vary by location since many families living in rural areas will tolerate driving further than those living in urban areas to reach medical services. Therefore, the current approach might underestimate access in rural areas relative to urban areas and fail to identify locations that face the strongest spatial inequities in access. Allowing this parameter and other inputs to the optimization model to vary across space would result in more accurate measures of access to healthcare in vulnerable regions.

Additional investigation into the local effects of potential policies is another important next step for this research. Facility location methodology could be used to identify regions where a policy would have the largest effect on the local population. It might also be useful to understand the degree to which a policy would need to be implemented before access improves in a particular rural region. The concentration of need or demand for healthcare will impact a policy's potential effectiveness. For example, under a fixed budget, a policy maker may have to choose between an intervention that slightly improves access for many patients in an urban area and an intervention that dramatically improves access for a smaller number of patients in a rural area. Analysis which allows policy makers to better understand these types of trade-offs would allow for more informed decision making.

Finally, as one discussant noted, further work could be done to consider the policy implications of the effects of covariates across the multiple regression models. For example, we found that when population density had a nonconstant effect on distance traveled, segregation levels typically had a significant and constant effect. However, in models where population density had a constant effect, segregation levels took on a nonconstant effect. Further exploration of these types of relationships might help policy makers understand the complex dynamics of access to healthcare. To our knowledge, little work has been done to develop methodologies that systematically identify and effectively convey these types of relationships. Further work in this area has the potential to offer contributions to this line of work and many other domains.

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