APPENDIX B:

Economic Analyses Supporting the Proposed Adjustment Factor

1. In the *5G Fund NPRM and Order*, the Commission proposed incorporating an adjustment factor that would assign a weight to specific geographic areas in the 5G Fund auction design as well as in the disaggregation of legacy high-cost support.[1] The adjustment factor would ensure that the 5G Fund support and legacy support are distributed to geographically and economically diverse areas.[2] The Commission directed the Office and the Bureau to propose specific values for the adjustment factor and to explain the underlying analyses used to develop the weights.[3] This appendix presents the technical descriptions of three economic analyses that inform our determination of the specific proposed adjustment factor values. The final datasets used in the three analyses are available for comment.

I. ENTRY MODEL ADJUSTMENT FACTOR

2. In this section, we present a simple entry model that estimates how various characteristics of a geographic area affect the likelihood that a carrier will choose to offer service in that area. Under the basic assumption that firms are profit-driven, economic theory predicts that firms will enter only those areas in which expected revenues (including subsidies) are greater than expected costs.[4] Building on this basic assumption, we use wireless carriers' reported coverage as a proxy for the expected profitability or "attractiveness" of any given area. In order to understand what drives any given area's attractiveness, we consider demographic characteristics, terrain and land use information, and universal service funding.[5] We model the number of wireless carriers providing service in an area as a function of these variables, which allows us to understand whether, and if so how, each variable affects the attractiveness of a geographic area. Using the model's estimates, we then calculate the adjustment factor that is necessary to make the areas equally attractive to prospective entrants, and holding all other factors that determine attractiveness equal, we set the probabilities of deploying service equally across geographic areas that differ only by income and terrain.

3. The analysis is conducted at the Census block group level,[6] and uses coverage data from each of the four national carriers.[7] A carrier is considered to have entered a Census block group if it

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[1] *5G Fund NPRM and Order* at 22, 67, paras. 66, 201-03.

[2] *Id.* at 22, para. 66.

[3] *Id.* at 67, paras. 201-03.

[4] *See, e.g.*, Andreu Mas-Colell, Michael D. Whinston & Jerry R. Green, Microeconomic Theory 405-11 (1995).

[5] *See infra* Appx. B.IV: Data Sources and Variable Construction for information on the data sources and construction of the variables.

[6] Ideally, the analysis would use a unit observation geography that is small enough to reveal a firm's site-by-site coverage decisions. We found that a census block group was the smallest geography for which the data we required could be constructed.

[7] We note that questions have arisen in various proceedings with respect to the accuracy and reliability of mobile broadband coverage data. *See generally Establishing the Digital Opportunity Data Collection; Modernizing the FCC Form 477 Data Program*, Report and Order and Second Further Notice of Proposed Rulemaking, 34 FCC Rcd 7505 (2019); *see also Connect America Fund; Universal Service Reform—Mobility Fund*, Report and Order and Further Notice of Proposed Rulemaking, 32 FCC Rcd 2152, 2175-2176, paras. 55-58 (2017) (*Mobility Fund Phase II Report and Order)*; *Rural Broadband Auctions Task Force Releases Mobility Fund Phase II Coverage Maps Investigation Staff Report*, GN Docket No. 19-367, Report, (OET, EB, WCB, OEA, WTB 2019). We use Mosaik mobile wireless coverage data by carrier and technology in all three economic analyses to maintain consistency of data used. Although the Commission collects similar coverage data through Form 477, we chose to rely upon Mosaik data for several reasons. First, the Commission did not begin collecting mobile coverage data until December 2014, which is after the timeframes of the other data used in the Auction Bidding (2012) and Cell Site Density (2013) models. Thus, using the Mosaik data is consistent with the timeframe of the other data sources.

(continued….)

covers at least 75% of the land area in the Census block group with 4G LTE.[8] We include in our sample those Census block groups that contain at least 50% rural blocks by land area,[9] and that have population densities of less than 100 persons per square mile[10] and GDPs of less than $100 million per square mile;[11] this procedure yields 28,519 observations.[12] Summary statistics are presented in Fig. B-1.

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Second, we acknowledge that the Commission and other parties have raised concerns about the accuracy of the Mosaik data in other contexts. *See, e.g., Mobility Fund Phase II Report and Order*, 32 FCC Rcd at 2177-78, para. 59. However, we have no evidence that these concerns would impact our estimated adjustment factors in any meaningful way. If coverage were overstated in the Mosaik data, it would likely be overstated in both flat and hillier terrain areas to similar degrees. The adjustment factor estimates will only be biased if the coverage data is systematically overstated in favor of one of the terrain categories. Since the adjustment factors reflect relative differences in costs across different areas, coverage being similarly overstated across these areas would have no effect on the relative differences. Third, while all three analyses are based on historic Mosaik coverage data of different vintages, we conclude that these analyses form a reasonable basis for setting current mobile wireless adjustment factors because the underlying economic and engineering principles on which these analyses are based are unlikely to have changed (i.e., the determinants of wireless signal propagation and economic profitability). Finally, extensive robustness checks on all three models, including alternative model specifications and using historic and more recent Form 477 data in place of Mosaik data, confirm these conclusions.

[8] In this analysis, we use January 2017 Mosaik 4G LTE coverage data. We use 4G LTE coverage data because as of that time, it is the baseline industry standard for the marketing of mobile broadband service. *Implementation of Section 6002(b) of the Omnibus Budget Reconciliation Act of 1993; Annual Report and Analysis of Competitive Market Conditions with Respect to Mobile Wireless, Including Commercial Mobile Services*, Eighteenth Report, 30 FCC Rcd, 14515, 14538-39, para. 35 (WTB 2015). We have also used Form 477 coverage data from December 2016 and June 2017 as robustness checks and found similar results. To simplify the analysis, our baseline specification focuses on the four nationwide carriers at that time: AT&T, Sprint, T-Mobile, and Verizon. However, in alternative specifications, we model the union of regional carriers' coverage as a fifth nationwide carrier and find that the qualitative results are largely unchanged. In all specifications, we also account for the presence of subsidized competitors in our estimation. Our baseline specification uses a coverage threshold of 75%, which generates roughly 750,000 square miles of uncovered area. It is unclear ex ante where the coverage threshold should be set, but to be certain that our analysis is not sensitive to the 75% threshold, we estimate the model using entrance thresholds of 50% and 90% in robustness checks. The 90% threshold is very strict and leads to significantly more area being considered uncovered, which should at least partially counteract any overstated coverage in the data.

[9] The U.S. Census Bureau designates rurality at the block level, which results in Census block groups that are made up of both rural and non-rural blocks. We selected a 50% rurality threshold to focus our analysis on block groups that are in the majority rural. As a robustness check, we have also conducted the analysis including and excluding all Census block groups with at least one rural block.

[10] For certain purposes, the Commission has previously characterized rural markets as having fewer than 100 people per square mile. *See, e.g., Facilitating the Provision of Spectrum-Based Services to Rural Areas and Promoting Opportunities for Rural Telephone Companies to Provide Spectrum-Based Services et al.*, Report and Order and Further Notice of Proposed Rulemaking, 19 FCC Rcd 19078, 19086-88, paras. 10-12 (2004).

[11] The GDP restriction removes 123 Census block groups that are significant outliers. These block groups are generally in close proximity to major cities and as such are not likely to be informative about areas that have historically lacked coverage or required universal service support to entice entry. For reference, the mean GDP per square mile of the Census block groups in the final sample is $3.73 million. We found that removing areas with GDP densities greater than $100 million produced a sample that was sufficient for estimating the effects of high levels of economic activity, while removing observations which may cause issues in the estimation procedure.

[12] We limit the dataset to sparsely populated rural areas to better reflect the areas under consideration in this proceeding. Firms' entry decisions in densely populated areas are unlikely to offer useful information about their decisions in areas that have historically lacked coverage or required universal service funding to incentivize entry. Nonetheless, we also present estimates with no population constraints. Further, we present estimates from a dataset that only contains observations from Census block groups with population densities less than 20 persons per square mile. We have previously described areas with less than 20 persons per square mile as "very rural." *See e.g.,*
(continued….)

4. *Analysis*. Carriers are expected to enter geographic areas when the incremental revenues from deploying are expected to exceed the incremental costs. In determining where to deploy, carriers likely consider demographic characteristics which may serve as demand proxies (i.e., population, level of economic activity, etc.), the costs associated with deploying coverage in the area, and the number of competitors also providing coverage. For example, providing service to 1000 individuals in a densely populated area with flat terrain is likely less costly than providing equivalent service to 1000 individuals over a larger more sparsely populated geographic area with mountainous terrain. The areas with higher demand and lower costs are thus more attractive to carriers, and therefore they likely have a greater number of mobile providers than mountainous areas with demand.

5. We fit an ordered logit model for the number of entrants on Census block group characteristics that reasonably could impact the attractiveness of entry.[13] Ordered logit models are used when there is a categorical outcome where category values have a meaningful sequential order.[14] In this case, the outcome of interest is the number of carriers providing coverage in a Census block group, and so the ordering is straightforward—one entrant implies more carriers providing service than zero, two entrants implies more carriers providing service than one, etc. We model the number of entrants as being determined by a latent attractiveness value for each Census block group. The model estimates the attractiveness thresholds required to induce entry by an additional mobile provider in each Census block group as shown below.

$$
\begin{aligned}
\text{Number of Entrants}_i &= 0 \;\; \text{if Attractiveness}_i < \text{Threshold}_1 \\
&= 1 \;\; \text{if Attractiveness}_i \geq \text{Threshold}_1 \;\&\; \text{Attractiveness}_i < \text{Threshold}_2 \\
&= 2 \;\; \text{if Attractiveness}_i \geq \text{Threshold}_2 \;\&\; \text{Attractiveness}_i < \text{Threshold}_3 \\
&= 3 \;\; \text{if Attractiveness}_i \geq \text{Threshold}_3 \;\&\; \text{Attractiveness}_i < \text{Threshold}_4 \\
&= 4 \;\; \text{if Attractiveness}_i \geq \text{Threshold}_4.
\end{aligned}
$$

6. While we do not observe a Census block group's attractiveness value, we can estimate the thresholds beyond which a Census block group would likely induce entry from a given number of carriers, as well as the impact of Census block group characteristics on attractiveness. The model assumes that the unobserved latent attractiveness of any given Census block group is the following linear function of revenue factors, cost factors, USF funding and an idiosyncratic error term specific to census block group i represented by ϵ_i.

$$
\begin{aligned}
\text{Attractiveness}_i = {} & \beta_0 + \beta_1 \text{Population Density}_i + \beta_2 \text{Road Density}_i + \beta_3 \text{GDP Density}_i \\
& + \gamma_1 \log(\text{Income}_i) + \gamma_2 \text{Dense Clutter}_i + \phi_{USF_i} + f_{terrain}(\text{Terrain}_i) + \epsilon_i,
\end{aligned}
$$

7. Census block groups vary significantly in land area. To account for this, the variables that proxy for demand—population, road miles, and local GDP—enter the latent attractiveness equation as per square mile densities. These demand density variables help characterize the potential additional subscribers that carriers could gain by providing service in these areas. Further, we include the natural log of median household income to capture the differences in entry related to differences in income across areas. In addition, the percentage of land area covered by dense clutter captures the effect of clutter on network deployment costs. Finally, universal service funding enters the model in two ways: i) dummy

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Application of AT&T Mobility Spectrum LLC and Fuego Wireless, LLC For Consent to Assign Licenses, Memorandum Opinion and Order, 31 FCC Rcd 13389, 13396, para. 18 (WTB 2016).

[13] We also estimate an alternative binary choice model where the dependent variable is simply a dummy for whether an area is covered by any carrier. However, the additional information conveyed by the number of entrants is valuable when estimating block group attractiveness

[14] For an introduction to ordered choice regression models, see William H. Greene, Econometric Analysis 784-90 (2003) (Greene (2003)).

variables are included for the number of national carriers receiving funding in the block group; and ii) a separate variable indicates whether a regional carrier receives funding in the Census block group.[15]

8. We note that propagation models exhibit a nonlinear relationship between terrain roughness and signal propagation.[16] It is ex-ante unclear how this relationship will translate to carriers' entry decisions, and for this reason, our baseline specification uses a piecewise linear spline to flexibly estimate the relationship between terrain roughness and entry appeal. A linear spline allows the linear slope parameter of an explanatory variable (e.g., the coefficient β) to vary across different ranges of values of that explanatory variable. Finally, if holding all else equal, we expect that large area Census block groups would require carriers to make a greater number of coverage decisions than small area Census block groups, and therefore our baseline specification weights observations by land area.[17]

9. *Adjustment Factor*. To calculate the adjustment factor, we solve for the adjustment to the land area in each Census block group necessary to equalize the differences in latent attractiveness values (i.e., entry probabilities) due solely to terrain, clutter, and income differences.[18] For example, if holding all else equal, mountainous areas with low median household incomes need to be three times smaller than flat areas with high median household incomes to induce the same number of expected entrants, then the mountainous-low income category will have an adjustment factor three times that of the flat-high income category.

10. We begin by constructing a representative block group for each category i. The representative block groups differ only in terrain roughness, clutter, and median household income. All other variables are set equal across categories. Next, we use the model estimates to assign predicted attractiveness values ($\widehat{A_i}$) to each representative block group from the model, and we set the baseline attractiveness value (A^*) equal to the largest of these values.[19] Finally, we solve for the set of constants m_i which when multiplied by the demand density variables (population density, road mile density, and GDP Density), offset the category specific income, clutter and terrain differences so that the latent attractiveness values all equal A^*. The estimated adjustment factor for category i is the m_i that solves:

$$A^* = \beta_1(m_i \times \widetilde{\text{pop den}}) + \beta_2(m_i \times \widetilde{\text{road den}}) + \beta_3(m_i \times \widetilde{\text{GDP den}}) + C_{im}$$

where $\widetilde{\text{pop den}}$, $\widetilde{\text{road den}}$, and $\widetilde{\text{GDP den}}$ are the median values of population density, road mile density, and local GDP density in the sample. The remaining variables in the latent attractiveness equation enter

[15] Universal service funding is currently distributed on a wire center basis. *Federal-State Joint Board on Universal Service*, Report and Order, CC Docket No. 96-45, 20 FCC Rcd 6371, 6806, para. 77 (2005). *Federal-State Joint Board on Universal Service; Highland Cellular, Inc. Petition for Designation as an Eligible Telecommunications Carrier for the Commonwealth of Virginia*, Memorandum Opinion and Order, CC Docket No. 96-45, 19 FCC Rcd 6422, 6438, para. 33 (2004). We designate a Census block group as receiving funding if at least 50% of the Census block group's land area falls within a wire center that receives funding. Because of the way funding is currently distributed, we cannot allocate funding levels directly to Census block groups and thus use dummy variables instead of directly using funding amounts.

[16] *See generally* Appx. A: Terrain Elevation.

[17] The ideal dataset would have the same variables at a uniformly sized geography. The largest Census block groups may require multiple cell sites to provide service to the entire area, while the land area of the smallest Census block group could be covered many times from a single site.

[18] A category is defined as a terrain level, income level combination. Since we consider three levels of terrain and three levels of income, there are nine categories. An alternative, but equivalent, way of thinking about the adjustment factor is that it represents the factor by which demand needs to be increased in order to offset the effects of terrain and income across categories, holding land area fixed.

[19] In practice, the flat terrain-high median household income category has the highest predicted attractiveness value due to its large potential revenues and low costs of deployment. By setting A^* equal to the largest $\widehat{A_i}$, we normalize the weight of the most attractive area to 1.

through C_i, a category-specific term that contains the category-specific median values of terrain roughness, clutter, and median household income.[20]

11. Solving for the multiplier m_i in each category we find:

$$A^* = \beta_1(m_i \times \widetilde{\text{pop den}}) + \beta_2(m_i \times \widetilde{\text{road den}}) + \beta_3(m_i \times \widetilde{\text{GDP den}}) + C_i$$
$$A^* - C_i = m_i\left(\beta_1(\widetilde{\text{pop den}}) + \beta_2(\widetilde{\text{road den}}) + \beta_3(\widetilde{\text{GDP den}})\right)$$
$$m_i = \frac{(A^* - C_i)}{\beta_1(\widetilde{\text{pop den}}) + \beta_2(\widetilde{\text{road den}}) + \beta_3(\widetilde{\text{GDP den}})}$$

12. To illustrate the procedure, we present the following numerical example. Suppose after estimation we find $\beta_1 = 5$, $\beta_2 = 4$, $\beta_3 = 2$ and $C_{\text{Flat, High}} = 250$, $C_{\text{Flat, Med}} = 200$, $C_{\text{Flat, Low}} = 150$, …, and $C_{\text{Mountainous, Low}} = 50$. Then, if the median values of $\widetilde{\text{pop den}}$, $\widetilde{\text{road den}}$, and $\widetilde{\text{GDP den}}$ are equal to 20, 15, and 10 respectively, we can construct the $\widehat{A}_i$'s:

$$\hat{A}_{\text{Flat, High}} = 5(20) + 4(15) + 2(10) + 250 = 430$$
$$\hat{A}_{\text{Flat, Med}} = 5(20) + 4(15) + 2(10) + 200 = 380$$
$$\hat{A}_{\text{Flat, Low}} = 5(20) + 4(15) + 2(10) + 150 = 330$$
$$\vdots$$
$$\hat{A}_{\text{Mountainous, Low}} = 5(20) + 4(15) + 2(10) + 50 = 230.$$

13. In this scenario, the flat terrain-high income category has the highest latent attractiveness value, thus $A^* = \hat{A}_{\text{Flat, High}}$ and, as a result, the adjustment factor for the flat-high income category is normalized to 1. With A^* established, we can now calculate adjustment factors for the remaining categories. Under our example values, the largest adjustment factor is associated with the mountainous-low median household income category, which is calculated as follows:

$$m_{\text{Mountainous, Low}} = \frac{(A^* - C_i)}{\beta_1(\widetilde{\text{pop den}}) + \beta_2(\widetilde{\text{road den}}) + \beta_3(\widetilde{\text{GDP den}})} = \frac{430 - 50}{5(20) + 4(15) + 2(10)}$$
$$= \frac{380}{180} = 2.11.$$

14. *Results*. Fig. B-2 presents estimation results from twelve specifications of the model. Columns 1-10 present ordered logit estimates in which the dependent variable is the number of entrants in the census block group. Our baseline specification is displayed in column 1. Column 2 aggregates regional carriers' coverage areas and considers them as a fifth potential entrant. Columns 3 and 4 add interactions between the demand density variables. Column 5 assumes that the terrain roughness effect has a logarithmic form. Columns 6 and 7 alter the population density population restriction whereby column 6 includes block groups with up to 500 persons per square mile and column 7 limits the sample to block groups with less than 20 persons per square mile. Column 8 uses the population density restriction in column 7 in lieu of land area weights. Columns 9 and 10 alter the coverage threshold by which census block groups are determined to be served, using 50% and 90% respectively. Columns 11 and 12 are simple logit specifications where the dependent variable is a dummy indicating the Census block group has one or more entrants. Column 11 is the logit analog of the baseline model, while column 12 considers the regional carriers as potential entrants. In addition to coefficients for the independent variables, Fig. B-

[20] We note that while the universal service dummy variables are theoretically included in C_i, we set the dummies to zero for the representative block groups and thus do not affect C_i.

2 also lists the estimated threshold values, which are the levels of latent attractiveness necessary to induce deployment by an additional provider.[21]

15. The estimated coefficients on the population, road mile, and local GDP density variables are positive and statistically significant in all specifications, indicating that Census block groups become more attractive to entrants when demand density increases and that our model is capturing factors relevant to carriers' entry decisions. Similarly, log income is positive and significant in all specifications, indicating that, all else equal, wealthy areas are more likely to be covered. The negative and significant dense clutter coefficient indicates that entry is less likely in high clutter areas with greater signal propagation losses. The estimates also suggest that the multiple carriers receiving universal service funding dummy variable is capturing otherwise unobserved characteristics that make an area "difficult to serve." Areas where multiple national carriers have received funding are likely to have fewer national carriers enter, however this effect disappears when we consider service as a binary outcome. The coefficient on the indicator for a regional carrier receiving funding in the area is also negative and significant. When regional carriers are included in the analysis, the coefficient decreases in magnitude, suggesting that the areas are unlikely to induce entry by multiple carriers.

16. Fig. B-3 shows the linear spline estimates of terrain roughness on block group attractiveness for the baseline specification. We find a negative relationship between terrain roughness and block group attractiveness with the marginal effects decreasing as terrain roughness increases. The shape of the non-linear relationship is robust across specifications.

17. Fig. B-4 presents the adjustment factor estimates for each category and the corresponding 95% confidence intervals produced by our baseline specification.[22] We generate the adjustment factors using terrain values of 10m, 70m, and 150m, and median household income values of $25,000, $35,000, and $65,000.[23] The baseline specification produces factors ranging from 1 to 4.06. Fig. B-5 presents the adjustment factors associated with each specification. Across all specifications, the largest factor is attributed to the mountainous-low median household income category. Top adjustment factors range from 3.08 to 4.29 with a median value of 3.84. The estimated adjustment factors are generally stable across specifications. The largest changes occur when we include interaction terms between demand density variables and when the sample is restricted to block groups with less than 20 persons per square mile.

[21] Note that the estimates in Fig. B-2 do not include a constant term; this is because the first cut point serves as a constant term in the model. An equivalent approach would be to report a constant term in the regression results and normalize the first cut point to zero. *See* Greene (2003) at 787-88.

[22] We bootstrap the standard errors to generate the 95% confidence intervals. *See* Greene (2003) at 652-55.

[23] 10m, 70m, and 150m are the land area weighted standard deviation of elevation medians of the terrain bins. Likewise, $25,000, $35,000, and $65,000 are the approximate median values of the income bins.

Fig. B-1: Summary Statistics

Variable		Observations	Mean	Std. Dev.	Min	Max
Population Density		28,519	40.2	27.32	0	100.00
Road Mile Density		28,519	2.49	0.88	0	11.93
Local GDP Density ($000,000)		28,519	3.73	7.44	0.01	99.53
Median Household Income ($000)		28,519	53.20	17.79	2.50	250.00
Terrain Roughness (Meters)		28,519	26.38	34.78	0.14	320.48
Land Area (Square Miles)		28,519	89.78	256.03	0.29	7503.21
Number of Entrants						
	0	28,519	0.06			
	1	28,519	0.10			
	2	28,519	0.20			
	3	28,519	0.33			
	4	28,519	0.31			
National Carriers Receiving USF Funding						
	0	28,519	0.66			
	1	28,519	0.31			
	2	28,519	0.03			
Regional Carrier Receiving USF Funding in Block Group						
	0	28,519	0.62			
	1	28,519	0.38			

Note: All densities are per square mile.

Fig. B-2: Estimation Results

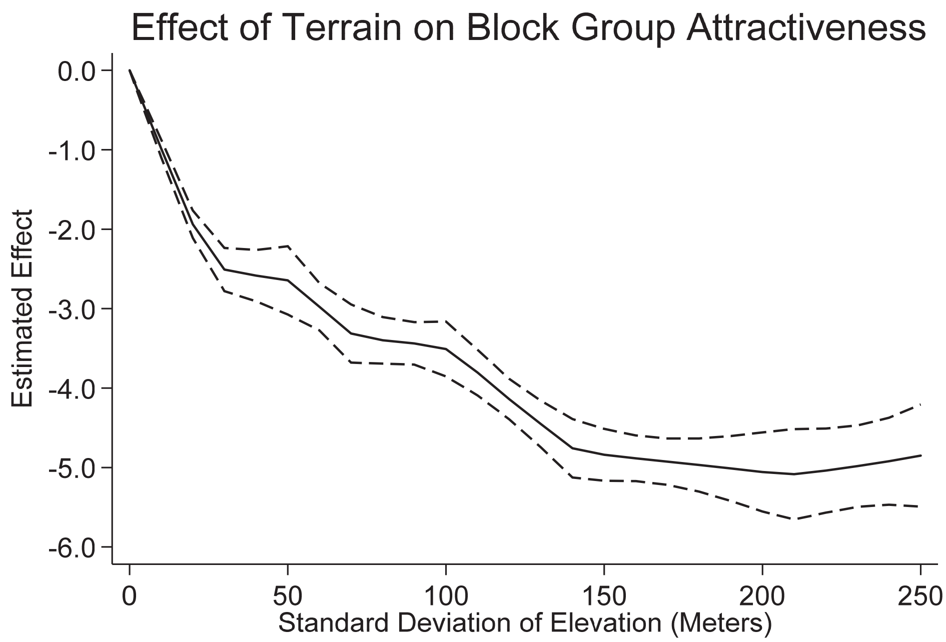
	Dependent Variable = Number of Entrants											
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Population Density	0.05***	0.04***	0.11***	0.11***	0.05***	0.02***	0.16***	0.12***	0.04***	0.05***	0.10***	0.12***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Road Mile Density	0.70***	0.78***	1.02***	1.16***	0.72***	0.79***	0.67***	0.27***	0.68***	0.74***	0.91***	0.94***
	(0.04)	(0.04)	(0.06)	(0.06)	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	(0.11)	(0.12)
Local GDP Density	0.04***	0.03***	0.05***	0.06***	0.04***	0.06***	0.03**	0.03**	0.07***	0.04***	0.08**	0.07**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.03)	(0.03)
log(Income)	0.51***	0.60***	0.49***	0.59***	0.52***	0.58***	0.32*	0.35***	0.45***	0.58***	0.73***	0.72**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.14)	(0.07)	(0.11)	(0.10)	(0.21)	(0.22)
% of Land Covered by Dense Clutter	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.01***	-0.02***	-0.02***	-0.01***	-0.02***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
National Carriers Receiving USF Funding												
One	0.23***	0.29***	0.14*	0.17**	0.22**	0.23***	0.18	-0.15**	0.28***	0.26***	0.07	-0.08
	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.11)	(0.05)	(0.07)	(0.06)	(0.16)	(0.18)
Two	-0.45***	-0.58***	-0.53***	-0.68***	-0.48***	-0.54***	-0.33*	-0.53***	-0.53***	-0.45***	0.10	-0.04
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.13)	(0.10)	(0.11)	(0.12)	(0.25)	(0.27)
Regional Carrier Receiving USF Funding	-0.99***	-0.28***	-1.02***	-0.30***	-0.96***	-0.98***	-0.97***	-1.23***	-1.02***	-0.95***	-0.35*	-0.28
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	(0.05)	(0.07)	(0.06)	(0.16)	(0.18)
Population Density # Road Mile Density	-	-	-0.00***	-0.00***	-	-	-	-	-	-	-	-
	-	-	(0.00)	(0.00)	-	-	-	-	-	-	-	-
Population Density # Local GDP Density	-	-	-0.02***	-0.02***	-	-	-	-	-	-	-	-
	-	-	(0.00)	(0.00)	-	-	-	-	-	-	-	-
Road Mile Density # Local GDP Density	-	-	0.01	0.01	-	-	-	-	-	-	-	-
	-	-	(0.00)	(0.00)	-	-	-	-	-	-	-	-

	Dependent Variable = Number of Entrants											
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
log(Terrain)	-	-	-	-	-1.15***	-	-	-	-	-	-	-
	-	-	-	-	(0.03)	-	-	-	-	-	-	-
Constant	-	-	-	-	-	-	-	-	-	-	-0.16	-0.24
	-	-	-	-	-	-	-	-	-	-	(0.91)	(0.98)
Terrain Spline	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation Weights	Land Area	Land Area	Land Area	Land Area	Land Area	Land Area	Land Area	None	Land Area	Land Area	Land Area	Land Area
Sample	<100 Pops	<100 Pops	<100 Pops	<100 Pops	<100 Pops	< 500 Pops	<20 Pops	<20 Pops	<100 Pops	<100 Pops	<100 Pops	<100 Pops
Regional Carriers Included	No	Yes	No	Yes	No	No	No	No	No	No	No	Yes
Coverage Threshold	75%	75%	75%	75%	75%	75%	75%	75%	50%	90%	75%	75%
Observations	28,519	28,519	28,519	28,519	28,519	53,041	8,397	8,397	28,519	28,519	28,519	28,519
Threshold 1	-1.33**	-0.54	-0.75	0.14	-2.43***	-0.75	-1.99***	-2.79***	-2.20***	-0.53	-	-
	(0.42)	(0.40)	(0.43)	(0.42)	(0.42)	(0.38)	(0.57)	(0.30)	(0.44)	(0.40)	-	-
Threshold 2	0.23	0.82*	0.86*	1.56***	-0.88*	0.73	-0.29	-1.14***	-0.36	1.14**	-	-
	(0.42)	(0.40)	(0.43)	(0.42)	(0.41)	(0.38)	(0.56)	(0.30)	(0.44)	(0.40)	-	-
Threshold 3	1.79***	2.33***	2.47***	3.15***	0.67	2.19***	1.37*	0.54	0.99*	2.82***	-	-
	(0.41)	(0.40)	(0.43)	(0.42)	(0.41)	(0.38)	(0.56)	(0.30)	(0.44)	(0.40)	-	-
Threshold 4	4.20***	4.47***	4.89***	5.33***	3.10***	4.38***	4.11***	2.89***	3.36***	5.18***	-	-
	(0.41)	(0.40)	(0.43)	(0.42)	(0.41)	(0.38)	(0.56)	(0.30)	(0.43)	(0.40)	-	-
Threshold 5	-	7.47***	-	8.26***	-	-	-	-	-	-	-	-
	-	(0.40)	-	(0.42)	-	-	-	-	-	-	-	-

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10

Specs (11) and (12) are logit models where the binary outcome is whether the block group is served by any carrier.

Fig. B-3: Terrain Spline Estimates (Specification 1)



Note: The dashed lines show the 95% confidence interval.

Fig. B-4: Adjustment Factor Estimates (Baseline Specification)

		Terrain Roughness		
		Flat	Hilly	Mountainous
Median Household Income	Low	1.35	2.81	4.06
		[1.25, 1.45]	[2.50, 3.12]	[3.69, 4.42]
	Medium	1.24	2.69	3.96
		[1.18, 1.30]	[2.40, 2.98]	[3.61, 4.30]
	High	1	2.40	3.67
			[2.14, 2.66]	[3.36, 3.98]

95% confidence intervals are shown in brackets.

Fig. B-5: Adjustment Factor Estimates (All Specifications)

Terrain Roughness

Median Household Income	Flat	Hilly	Mountainous	Flat	Hilly	Mountainous
		(1)			**(2)**	
Low	1.35	2.81	4.06	1.35	2.91	4.01
Medium	1.24	2.69	3.96	1.23	2.79	3.90
High	1	2.40	3.67	1	2.52	3.63
		(3)			**(4)**	
Low	1.25	2.19	3.13	1.27	2.25	3.08
Medium	1.18	2.11	3.06	1.19	2.16	3.01
High	1	1.90	2.86	1	1.95	2.80
		(5)			**(6)**	
Low	1.34	2.71	3.59	1.43	2.91	4.13
Medium	1.23	2.59	3.49	1.30	2.77	4.01
High	1	2.32	3.23	1	2.39	3.64
		(7)			**(8)**	
Low	1.16	2.15	3.27	1.30	2.80	4.29
Medium	1.11	2.10	3.23	1.20	2.70	4.21
High	1	1.97	3.10	1	2.45	3.96
		(9)			**(10)**	
Low	1.38	2.51	3.58	1.36	3.20	4.07
Medium	1.28	2.39	3.49	1.24	3.07	3.96
High	1	2.05	3.16	1	2.76	3.68
		(11)			**(12)**	
Low	1.36	2.86	3.84	1.32	2.90	3.83
Medium	1.25	2.74	3.75	1.22	2.79	3.74
High	1	2.42	3.44	1	2.50	3.47

II. CELL SITE DENSITY MODEL ADJUSTMENT FACTOR

18. In this section, we estimate the effect of terrain on the number of cell sites required to build out a mobile wireless network in rural areas. All else being equal, wireless network engineering principles indicate that greater variability of terrain in a given geographic area reduces the signal strength received by a mobile user,[24] which requires wireless carriers to build more sites to provide the same quality of service (e.g., speed). Based on county-level cell site counts and coverage data for each of the four largest national carriers in 2014, we estimate how many more sites must be built per square mile to cover the same land area in hillier terrain compared to flat areas, holding quality of service fixed.[25] If the

[24] Campbell Scientific Inc., *The Link Budget and Fade Margin*, (Sep. 2016), *available at* https://s.campbellsci.com/documents/us/technical-papers/link-budget.pdf; William C. Jakes, Microwave Mobile Communications 126-28 (IEEE Press 1993); Rappaport (2002) at 141-43.

[25] Our measure of terrain is the average standard deviation of elevation. *See* Appx. A: Terrain Elevation for more details.

cost of building a site is the same across terrain types, our adjustment factor provides an estimate of how much more costly it is to deploy mobile broadband in more mountainous areas relative to flatter areas.[26]

19. To estimate the adjustment factor, we first run a regression that controls for the terrain variation in the county as well as many other factors expected to affect the service area covered by a site. Next, from the estimated model, we predict the average number of square miles covered by a typical site in three terrain categories. Finally, we calculate an adjustment factor by dividing the estimated service area of a site in a flat area by the estimated service areas in each of the other two terrain categories. Our results suggest that the hilly terrain category is about 1.5 times more expensive to deploy while the mountainous terrain category is approximately 2.5-3 times as costly.[27]

20. Our dependent variable is the average square miles of service area per site in a county for each national carrier.[28] Our key explanatory variable is terrain variability, as measured by the standard deviation of elevation of the covered land area in a county for each carrier.[29] We note that another important factor to account for is the effect of demand on cell site service areas. In less rural areas with higher mobile data demand, the size of the cell site service area required to meet the carriers' minimum subscriber performance target may be determined by capacity constraints rather than signal propagation limitations. As a result, in areas of high demand, terrain may have almost no impact on the service area of a site since the site service area may already need to be quite small due to capacity limits, and therefore the signal strength would likely be strong throughout the service area of a site regardless of terrain. In Fig. B-6, we present summary statistics by different subsamples based on population densities for our dependent and independent variables. Fig. B-7 presents the sample means of our variables by terrain category and population density subsamples. Since our analysis is mainly concerned with the effect of terrain in rural areas that are less capacity constrained, we try to minimize the importance of capacity constraints by restricting the regression estimation to areas with population densities below the same thresholds that we used in Fig. B-7. Before setting out our regression specification, we briefly discuss the justification for the inclusion of each of the control variables and how we expect each to affect the expected squared miles served by a cell site.

A. Network Capacity Constraints

21. *Network capacity.* The amount of available spectrum bandwidth and the spectral efficiency of the deployed technology determines the maximum capacity of each site.[30] Bandwidth is determined by the number of megahertz of spectrum that each carrier has deployed per site; greater bandwidth reduces the number of sites required to serve the same amount of traffic.[31] Spectral efficiency is a function of signal quality and is measured by the bits per second that can be served per hertz of spectrum.[32] More recent technologies, such as 4G LTE and 5G-NR, allow more data to be transmitted over the same amount of spectrum, and this should allow a carrier to build fewer sites per square mile in

[26] If site construction, backhaul, and spectrum acquisition costs do vary by terrain, our estimated factors may not fully capture the effect of terrain on deployment costs.

[27] *See infra* Fig. B-9.

[28] *See* Appx. B.IV: Data Sources and Variable Construction for more details. Our analysis is restricted to 3,114 counties in the 48 states of the continental U.S., Hawaii, and Washington, D.C. Since our analysis includes the four largest mobile wireless carriers, we have a potential maximum of 12,456 observations in our sample. We also anonymize carriers as carrier A, carrier B, carrier C, and carrier D.

[29] *See* Appx. B.IV: Data Sources and Variable Construction for more details. We calculate terrain variation by carrier since the terrain in the actual land area covered by each carrier in a county may be very different.

[30] *See T-Mobile-Sprint Order*, 34 FCC Rcd at 10764, Appx. F: Technical Appendix, para. 11.

[31] *OBI Technical Paper No. 1*, Exh. 4-Q.

[32] *OBI Technical Paper No. 1*, at.63.

capacity constrained areas, all else equal.[33] Given a fixed number of sites, the approximate capacity of a cellular network is therefore given by the following formula.[34]

$$Capacity = Sites * \ Bandwidth\ per\ Site\ (MHz) * \ Efficiency$$

22. *Network Load.* Similarly, the network load in a geographic area should also affect the number of cell sites required.[35] If the network traffic served by a site reaches the site's capacity limit, this will result in congestion and a degradation in service quality.[36] To add capacity in order to maintain the minimum user speed target, the cell site may then be "split," which involves covering the same geographic area with two sites instead of one so that the deployed spectrum can be reused over two smaller service areas.[37] Therefore, for a given capacity per site and quality of service, more sites must be built closer together in an area with higher traffic demand compared to areas with lower demand.

23. If network capacity is equal to network load, it follows that:

$$\mathrm{Subscribers} * \mathrm{Usage/Subscriber} = Sites * \ Bandwidth\ per\ Site\ (MHz) * \ Efficiency$$

Taking the natural logarithm of both sides and rearranging terms yields the following estimation equation for the number of sites needed in a capacity constrained network environment for a given quality of service target:

$$\ln(Sites) = \ln\left(\frac{Subscribers}{Bandwidth\ per\ Sites}\right) + \ln(Usage/Subscriber) - \ln\ (Efficiency)$$

24. As the number of sites needed to address capacity constraints is a function of the number of subscribers per megahertz of spectrum, the usage per subscriber and the spectral efficiency of the deployed technology, we control for each of these factors in our regression model. To account for subscriber demand and the effect of bandwidth on network capacity, we include the natural logarithm of the subscribers per megahertz of deployed spectrum in each Cellular Market Area (CMA).[38] We would expect this variable to have a negative sign since, all else equal, more subscribers per MHz should result in a site being able to cover fewer square miles. We do not have a direct measure of usage per subscriber in our data sample, so to help alleviate any potential omitted variable bias, we include the natural logarithm of per capita income as a proxy for subscriber usage.[39] To account for spectral efficiency

[33] *Id*.

[34] *See* Applications of T-Mobile USA, Inc., and Sprint Corporation for Consent To Transfer Control of Licenses and Authorizations, ULS File No. 0008224209 (Lead Application) (filed June 18, 2018, amended July 5, 2018), Exh. 1—Description of the Transaction, Public Interest Statement, and Related Demonstrations at 30. This formula implies that if the number of sites, bandwidth per site or spectral efficiency doubles, then the overall network capacity would double as well.

[35] Network load is defined here as the product of the number of subscribers served by the site and their usage per subscriber. For a discussion of how average usage per subscriber maps into busy hour offered load, *see OBI Technical Paper No. 1*, at 111.

[36] *OBI Technical Paper No. 1*, at p.109-111.

[37] *See T-Mobile-Sprint Order*, 34 FCC Rcd at 10765, Appx. F: Technical Appendix, para. 14.

[38] *See* Appx. B.IV: Data Sources and Variable Construction for more details.

[39] We expect income to be correlated with per subscriber usage, and to be an effective proxy variable, it must also satisfy the untestable assumption that the regressors are now uncorrelated with the error term once the income variable is included in the regression. *See* Jeffrey M. Wooldridge, Introductory Econometrics: A Modern Approach (Wooldridge (2008)). If income does not sufficiently proxy for usage, the unobserved usage per subscriber variable could bias our estimated adjustment factors either upwards or downwards, depending on how usage varies with terrain. If usage is greater in flatter areas than mountainous areas, conditional on our other controls, then our model would not account for the greater usage shrinking cell coverage in flat areas, and this would tend to bias the

(continued….)

differences, we include the percent of the land area in each county that is covered by 4G LTE. We would generally expect greater spectral efficiency to increase the service area per site in any area that is capacity constrained but given that deploying more efficient technologies may also increase the unobserved usage per subscriber, the expected sign of this control variable is ex ante unclear. In order to measure which counties within a CMA are more likely to have higher network loading, we also include the natural logarithm of county population density and road mile density. We would expect both variables to have a negative sign since greater network loading should reduce the square miles covered by a site in capacity limited areas. Finally, we include the average download speed in each county by carrier, as measured by 2014 Ookla speed test data, to hold service quality fixed.

B. Network Coverage Constraints

25. *Propagation model*. We use a simple wireless engineering propagation model to inform our choice of included variables and functional form for our regression analysis. A general form of the Friis propagation formula for outdoor environments with pathloss due to terrain can be written as follows:[40]

$$P_r = P_t * k * \left(\frac{\lambda}{4\pi}\right)^2 * \frac{1}{d^{\alpha}};\ or\ d^{\alpha/2} = \left(\frac{P_t}{P_r} * k\right)^{1/2} * \frac{\lambda}{4\pi}$$

26. The received power, P_r, is a function of the transmitted power P_t, a constant of proportionality k that accounts for antennae gains, the transmission wavelength λ and inversely proportional to the distance from the transmitter d raised to the power α. The parameter α is called the pathloss exponent and is the focus of our analysis. It measures how quickly the received power declines as distance from the receiver to the transmitter increases and has a value of two in a free space environment without obstructions and higher values in more lossy environments. To express this formula in the logarithmic dB scale, we take the base-10 logarithm of both sides of the equation and then solve for the logarithm of the maximum distance (cell radius) given a minimum received power threshold.[41]

$$log_{10}(d_{max}) = \frac{2log_{10}\left(\left(\frac{P_t}{P_{r\_min}} * k\right)^{1/2} * \frac{\lambda}{4\pi}\right)}{\alpha}$$

27. The IEEE Stanford University Interim propagation loss model and its extensions expresses α as a linear function of antenna height and terrain category, where terrain reflects not only the variation in elevation, but also other factors that affect propagation such as buildings and foliage.[42] Therefore, in the Friis propagation model, the service area of a site in a coverage constrained outdoor environment is a function of, but not limited to, the wavelength (speed of light/frequency) of the deployed spectrum, tower height, terrain variation and other obstacles that reduce signal propagation such as trees, foliage, and building structures. Based on this formula we also multiply the logarithm of spectrum

(Continued from previous page)
estimated adjustment factor upwards. The terrain adjustment factor would be biased downwards if hillier terrain had higher usage than flatter areas.

[40] *See* Tony J. Rouphael, RF and Digital Signal Processing for Software-Defined Radio at Section 4.2.1 (2009). For free space where lambda=2, see Christopher Haslett, Essentials of Radio Wave Propagation at 5-7 (2009). *See also* Jyrki T.J. Penttinen, The Telecommunications Handbook, Engineering Guidelines for Fixed, Mobile and Satellite Systems at 596 (2015).

[41] The dB scale is expressed in base-10 logarithms, but we use natural logarithms in our regression analysis. To convert our estimated regression equations to base-10 logarithms, we would just multiply both sides by ln(10)=2.303 and this would have no effect on our estimated adjustment factors.

[42] V. Erceg et al., *An empirically based path loss model for wireless channels in suburban environments* 17 IEEE J. Select. Areas Comm. 1205 (1999).

frequency with the terrain variables in our regression analysis since the maximum radius is a multiplicative function of $\log_{10}(\lambda)$ and α.

28. *Terrain and Clutter*. The measure of terrain variability we use in our model is the standard deviation of elevation of the covered land area in a county for each carrier. In addition to terrain, radio propagation is affected by the number of man-made and natural obstructions in an area, since these block, absorb, diffract, and/or reflect radio waves which lead to losses.[43] In urban and suburban areas, signal loss may mostly be due to a greater number of structures that impede radio signals, while in more rural areas, natural structures such as trees and foliage may be more likely to reduce signal propagation. We control for "natural" clutter by including the percentage of land area in the county covered with forests. Clutter from other sources is accounted for by including the natural logarithms of county population density and business establishment density. We would expect that more densely built-up or forested areas would require a greater number of sites, and therefore, we expect the sign on these variables to be negative.[44]

29. *Spectrum Frequency and Tower Height.* Lower frequency spectrum can travel farther and better penetrate natural and other obstacles, which allows a carrier to cover a larger area with fewer sites absent capacity constraints.[45] We control for the frequency of spectrum deployed by including an indicator variable if the carrier has deployed low-band spectrum in the county and interact it with our measure of terrain variation and the percentage of forested area in the county to allow the effect of these variables on site coverage to vary by the frequency of deployed spectrum.

30. Tower height was not available in our cell site dataset, so to estimate the height of each tower in our sample, we compiled tower height information from publicly available tower company sources.[46] We first drop all towers with missing height information or a listed height over 500 feet in the tower company dataset since these are outliers that likely have inaccurate height information. We then match the towers in our sample to the closest tower in the public dataset and assign the tower height of the closest matched tower as long as that tower lies within 1 kilometer of the tower from the original data sample.[47] For towers that do not match within 1 kilometer, we assign the average tower height of the matched towers in the county for that carrier.

31. *Other Control Variables.* We also include carrier fixed effects in the model to capture any differences across carriers that do not vary at a sub-national level and eliminate potential bias from these unobserved differences across carriers. For example, if some carriers have higher data usage limits on their plans, and these plan characteristics are set nationally, then these carriers may have higher data usage per subscriber and would generally need more cell sites to serve their subscribers than a carrier with lower data limits, all else equal. Other important company-level policy differences across carriers such as

[43] *See OBI Technical Working Paper No. 1*, at 68.

[44] In addition to propagation, these variables may also be controlling for differences in demand that are not fully accounted for by our inclusion of CMA subscribers and the other demand measures noted above. These effects reinforce the propagation effects since we would also expect areas with greater demand to require more sites.

[45] *See OBI Technical Working Paper No. 1*, at 67.

[46] Tower site information was downloaded from 44 tower providers' websites in May 2018. Wireless Estimator, *Top 100 Tower Companies in the U.S.*, http://www.wirelessestimator.com/t_content.cfm?pagename=US-Cell-Tower-Companies-Complete-List (last visited May 15, 2020). Publicly available tower data with height information for the same time period as the BDS data was not available. However, we do not expect this to have much effect on our analysis since we are matching towers to themselves, and it is unlikely that many towers have been decommissioned in the intervening four years.

[47] A 1-kilometer buffer is used since differences in geocoding between the two data sources may result in a tower not matching exactly to itself. With this buffer, our match rate for towers within 1 km was approximately 82%.

the criteria they use to determine when a cell site needs to be split would also be captured in these carrier fixed effects.

32. In some of our specifications, we also add state fixed effects to the model so that only the variation in terrain within a state is being used to estimate the relationship between average square miles covered per site and terrain. Including state fixed effects will eliminate potential bias due to unobserved differences across states that impact site service areas and are correlated with our control variables. For example, if some states have more restrictive regulations on site deployment, then this could systematically lower the number of sites built in all counties located within that state. The inclusion of state fixed effects would ensure that such differences between states do not bias our adjustment factor estimates.

C. Regression Results

33. Each observation in our dataset is a county-carrier combination (e.g., Autauga County, carrier A), and our dependent variable is the natural logarithm of the average square miles served per site in the county for each carrier.[48] We take two approaches to account for the effect of subscriber demand and capacity constraints on the average per site service area. The first is to estimate a model with a flexible functional form that allows the effect of terrain to decline as capacity constraints increase by interacting the terrain variable with subscribers per megahertz of spectrum. We expect this interaction term to have a positive coefficient since per site service areas in counties with less spectrum per subscriber are more likely to be constrained for capacity reasons rather than coverage reasons related to propagation. The second approach, which we prefer, is to restrict our estimation sample to more rural counties. This is done by estimating the model on sub-samples of counties with population densities less than 100, 50 and 20 people. In the specifications run on the restricted samples, we expect the interaction between terrain and subscribers per MHz to be less important since in these areas of lower subscriber demand the service areas of these sites will more likely be propagation constrained rather than capacity constrained. The estimated model for the natural logarithm of the expected average service area per site in county *i* carrier *j,* in CMA *k,* and state *m* is as follows:

$$\begin{aligned}
\ln(CoverageAreaPerSite_{ijkm}) &= \beta_0 + \beta_1 Terrain_{ij} + \beta_2 PopDen_i + \beta_3 \ln(RMDen_i) + \beta_4 \ln(EstDen_i) \\
&+ \beta_5 \ln(Income_i) + \beta_6 \ln(SubsPerMHz_{jk}) + \beta_7 \ln(SubsPerMHz_{jk}) X\, Terrain_{ij} \\
&+ \beta_8 PercAreaLTE_{ij} + \beta_9 PercAreaForest_i + \beta_{10} LowBand_{ij} \\
&+ \beta_{11} LowBand_{ij} X\, PercAreaForest_i + \beta_{12} LowBand_{ij} X\, Terrain_{ij} \\
&+ \beta_{13} \ln(DownSpeed_{ij}) + \beta_{14} TowerHeight_{ij} + \beta_{15} Prov_j + \beta_{16} State_m + \varepsilon_{ij}
\end{aligned}$$

34. Fig. B-8 shows the regression results from models with and without state fixed effects on the full and population density restricted samples. The coefficients on nearly all variables are generally consistent with our expectations based on the Friis propagation formula we derived. The coefficients on both the terrain and the percentage of the county that is forested variables are negative and statistically significant, implying that the average service area of a site decreases as terrain becomes more mountainous and forested. Similarly, as the number of subscribers per megahertz of spectrum, density of establishments, road miles, or population increases, the expected average area served by a site decreases. Deploying low band spectrum both increases the expected average service area of a site and reduces the impact of terrain and clutter as shown by the positive sign on the interaction of low band spectrum and these variables. Finally, the percentage of area covered by 4G LTE and the income variables are generally insignificant and of indeterminant sign.

[48] We chose the county as our geographic unit of analysis because we do not observe the actual geographic service area of each site. The choice of county minimizes the number of sites with coverage that crosses the geographic boundary while still maintaining necessary terrain variation.

D. Adjustment Factor Estimates

35. We now predict the average service area of a site at various levels of terrain variation, setting population density, road mile density, establishment density, and subscribers per megahertz of deployed spectrum at the 5th percentile of the estimation sample restricted to less than 100 people per square mile. We chose to predict at the 5th percentiles to remove all potential capacity constraint issues from our estimated site service areas for each terrain category.[49]

36. The dependent variable in our regression is the natural logarithm of service area per site. However, in calculating the adjustment factor, we are interested in the level of service area per site, not the logarithm of the service area. In general, exponentiating the predicted service areas from the log model will not recover the correct predictions for service areas by terrain category.[50] As a result, when we exponentiate to form predicted service areas per site, we have to account for the expectation of exp[ε], or our predicted values for coverage will be biased downward. We assume that the error term has a log-normal distribution, which gives the following equation for our predicted coverage values:[51]

$$\hat{y} = \exp(\widehat{logy}) * \exp(0.5 * \sigma^2)$$

where $\widehat{logy}$ is the predicted logarithm of average county service area for each carrier and σ^2 is the root mean squared error (RMSE) of the model.

37. Fig. B-9 shows the predicted service areas from each specification, the implied radii, and adjustment factors and their 95% confidence intervals.[52] Our eight specifications produce consistent adjustment factors ranging from 2.13 to 2.96 for the mountainous terrain category, and our preferred specifications that restrict population density all produce mountainous adjustment factors of 2.49 or greater. For example, for our specification that includes state fixed effects and limits the sample to less than 20 people per square mile (bottom right panel), the high adjustment factor implies that a site in flat terrain (10m) can cover 2.96 times more area on average than the average land area covered by a site in a mountainous area (150m).

38. Using county level coverage and site data from each of the four largest carriers, we calculated adjustment factors based on a model that estimates how the average service area of a site changes according to the terrain of the surrounding area. If deployment costs are not affected by terrain, then our estimated adjustment factors will measure the cost differences of deploying a wireless network across terrain types. However, deployment costs most likely differ across terrain types, and therefore, our adjustment factors may not fully capture the cost differences. The direction of this bias is unclear. On the one hand, backhaul, power, and siting costs may be more expensive in hillier terrain compared to flatter areas. On the other hand, spectrum acquisition costs may be lower in mountainous areas compared to flatter, more populated areas. While the former considerations would imply that we are understating our adjustment factors, the latter would imply they are overstated. Despite this issue, we believe that our results can help inform the Commission regarding the magnitude of cost differences of deploying mobile

[49] The estimated adjustment factors are all measured relative to coverage per site in a flat area. For this reason, the values of the control variables at which we choose to predict the model generally do not affect the estimated adjustment factors. However, the low band indicator variable and subscribers per megahertz are interacted with terrain in the model so that the values chosen for these variables in predicting site service areas in each of the terrain categories do affect the estimated adjustment factors.

[50] *See* Arthur S. Goldberger, *The Interpretation and Estimation of Cobb-Douglas Functions*. 36 Econometrica 464 (1968).

[51] *See* Wooldridge (2008) at 210.

[52] We use a bootstrap procedure to calculate the confidence intervals for the adjustment factors. This procedure drew 1000 bootstrap replicates with replacement from the data and then re-estimated the regression model to estimate the sampling distribution from which we calculate the confidence intervals of the unknown parameters.

broadband services in different terrain types and provide the Commission with further evidence on what adjustment factors may be appropriate for the upcoming 5G Fund auction.

Fig. B-6: Summary Statistics by Population Density Subsample

	Mean				Minimum				Maximum			
	None	< 100	< 50	< 20	None	< 100	< 50	< 20	None	< 100	< 50	< 20
Coverage Area per Tower (Sq. Miles)	113	164	211	338	0.0	0.5	0.5	0.5	3,047	3,047	3,047	3,047
Terrain (Meters)	22	24	25	31	0.2	0.3	0.3	0.3	213	213	213	212
Population Density (Population per Sq. Mile)	348	39	23	9.2	0.2	0.2	0.2	0.2	71,481	100	50	20
Road Mile Density (Road Miles per Sq. Mile)	3.4	2.3	2.1	1.8	0.4	0.4	0.4	0.4	26	5.7	5.2	3.4
Establishment Density (Establishments Per Sq. Mile)	9.8	0.8	0.5	0.2	0.004	0.004	0.004	0.004	4,643	5.6	3.6	1.6
Median Household Income (Thousands of 2013 Dollars)	47	43	42	43	21	21	21	21	122	83	83	82
Subscribers per MHz Deployed Spectrum (CMA)	1,752	531	449	383	0.3	0.3	1.1	1.1	69,943	30,406	14,000	7,362
Pct. Area Covered by 4G-LTE	48%	40%	37%	34%	0%	0%	0%	0%	100%	100%	100%	100%
Pct. Area Covered by Forest	37%	37%	34%	24%	0.0%	0.0%	0.0%	0.0%	93%	93%	93%	93%
Pct. Counties with Low Band Spectrum Deployed	81%	83%	85%	87%	0%	0%	0%	0%	100%	100%	100%	100%
Avg. Download Speed (Mbps)	12	11	11	11	0.01	0.01	0.01	0.01	110	48	48	44
Avg. Tower Height (Meters)	66	73	75	74	4	4	4	4	152	152	152	152
Number of Observations	9,190	5,836	3,929	1,720								

Fig. B-7: Sample Means by Terrain Categories and Population Density Subsamples

	Flat Terrain (0-40m)				Hilly Terrain (40-115m)				Mountainous Terrain (115+m)			
	Population Density Restriction											
	None	< 100	< 50	< 20	None	< 100	< 50	< 20	None	< 100	< 50	< 20
Service Area per Site (Sq. Miles)	109	161	206	337	132	180	250	380	148	156	167	209
Terrain Roughness (Std. deviation of elevation)	12	11	11	12	68	70	71	73	142	143	145	144
Population Density (Population per Sq. Mile)	387	40	24	10	157	38	20	7.3	39	23	17	8.8
Road Mile Density (Road Miles per Sq. Mile)	3.5	2.4	2.2	1.9	2.8	2.2	1.9	1.5	1.9	1.7	1.6	1.4
Establishment Density (Establishments per Sq. Mile)	11.1	0.8	0.5	0.2	3.9	0.9	0.4	0.2	1.2	0.8	0.7	0.4
Median Household Income (Thousands of 2013 Dollars)	46.7	42.4	41.5	42.4	48.0	44.6	44.7	45.2	50.1	49.8	50.9	49.0
Subscribers per MHz Deployed Spectrum (CMA)	1,766	518	422	351	1,776	558	523	472	865	766	756	517
Pct. Area Covered by 4G-LTE	52%	44%	42%	40%	30%	22%	19%	16%	17%	15%	14%	10%
Pct. Area Covered by Forest	34%	34%	31%	19%	49%	49%	42%	31%	60%	60%	59%	56%
Pct. Counties with Low Band Spectrum Deployed	82%	84%	85%	88%	78%	79%	80%	82%	85%	85%	85%	88%
Avg. Download Speed (Mbps)	12	12	12	12	10	10	10	9.0	8.8	8.7	8.4	7.9
Avg. Tower Height (Meters)	70	79	82	85	47	49	47	43	32	31	30	30
Number of Observations	7,702	4,767	3,198	1,294	1,325	915	593	331	163	154	138	95

Fig. B-8: Regression Estimates of the Natural Logarithm of Average Coverage Area on Capacity and Coverage Factors

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
State Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Population Density Restriction	None	100	50	20	None	100	50	20
Carrier-Specific Terrain	-0.010	-0.011	-0.010	-0.008	-0.010	-0.011	-0.009	-0.009
	(.002)***	(.002)***	(.002)***	(.003)***	(.002)***	(.002)***	(.002)***	(.002)***
Log(Population Density)	-0.339	-0.398	-0.411	-0.336	-0.259	-0.304	-0.309	-0.257
	(.032)***	(.034)***	(.038)***	(.054)***	(.032)***	(.034)***	(.039)***	(.054)***
Log(Road Mile Density)	-0.389	-0.155	-0.169	-0.093	-0.335	-0.020	-0.043	0.040
	(.047)***	(.059)**	(.059)***	(.063)	(.035)***	(.041)	(.044)	(.060)
Log(Establishment Density)	-0.201	-0.087	-0.029	-0.028	-0.279	-0.183	-0.129	-0.107
	(.030)***	(.033)***	(.037)	(.048)	(.029)***	(.033)***	(.035)***	(.046)**
Log(Income)	0.013	-0.080	-0.055	0.030	0.036	-0.151	-0.157	-0.061
	(.045)	(.061)	(.072)	(.095)	(.040)	(.053)***	(.069)**	(.093)
Log(Subscribers per Deployed MHz) (CMA Level)	-0.100	-0.083	-0.067	-0.070	-0.101	-0.079	-0.066	-0.072
	(.012)***	(.013)***	(.017)***	(.025)***	(.010)***	(.012)***	(.016)***	(.023)***
Terrain*Log(Subscribers per Deployed MHz) (CMA Level)	0.001	0.002	0.001	0.001	0.001	0.002	0.001	0.001
	(.000)***	(.000)***	(.000)***	(.000)**	(.000)***	(.000)***	(.000)***	(.000)**
Percentage of Area Covered by 4G-LTE	0.035	0.051	-0.026	-0.162	0.015	0.049	-0.027	-0.113
	(.051)	(.058)	(.062)	(.116)	(.047)	(.057)	(.063)	(.117)
Percentage of Area Forested	-0.979	-1.309	-1.387	-1.489	-0.862	-1.139	-1.176	-1.086
	(.166)***	(.126)***	(.124)***	(.284)***	(.143)***	(.120)***	(.127)***	(.307)***
Low Band Spectrum Deployed Flag	-0.029	0.105	0.101	0.073	-0.054	0.063	0.050	0.069
	(.079)	(.084)	(.090)	(.127)	(.075)	(.095)	(.099)	(.137)
Low Band Spectrum Deployed Flag*Percentage of Area Forested	0.155	0.300	0.403	0.541	0.190	0.328	0.415	0.439
	(.178)	(.148)**	(.151)***	(.288)*	(.147)	(.132)**	(.141)***	(.287)
Low Band Spectrum Deployed Flag*Terrain	0.002	0.001	0.001	0.000	0.001	0.001	0.001	0.000
	(.002)	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)	(.002)
Log(Download Speed)	-0.061	-0.048	-0.060	-0.093	-0.055	-0.038	-0.045	-0.061
	(.014)***	(.013)***	(.015)***	(.023)***	(.012)***	(.012)***	(.014)***	(.023)***
Average Tower Height	0.004	0.002	0.002	0.000	0.003	0.003	0.002	0.001
	(.001)***	(.001)***	(.001)**	(.001)	(.001)***	(.001)***	(.001)***	(.001)
Sample Size	9,190	5,836	3,929	1,720	9,190	5,836	3,929	1,720
R-Squared	0.85	0.64	0.59	0.47	0.86	0.66	0.62	0.52

Robust standard errors in parentheses are clustered at the state-provider level.

***p<0.01, **p<0.05, *<0.1

Fig. B-9: Regression Model Predictions of Average Coverage Areas, Average Radius, and Terrain Factors

	Without State Fixed Effects					With State Fixed Effects				
Terrain Value	Cov. Area (Sq. Mile)	Radius (Miles)	Terrain Factor	95% CI LB	95% CI UB	Cov. Area (Sq. Mile)	Radius (Miles)	Terrain Factor	95% CI LB	95% CI UB
	No Population Density Restriction					**No Population Density Restriction**				
10	123	7	1.00	…	…	117	7	1.00	…	…
70	84	6	1.47	1.34	1.59	83	6	1.42	1.30	1.54
150	54	5	2.27	1.80	2.73	55	5	2.13	1.70	2.56
	< 100 Pops / Sq. Mile					**< 100 Pops / Sq. Mile**				
10	129	7	1.00	…	…	128	7	1.00	…	…
70	82	6	1.58	1.43	1.73	82	6	1.55	1.40	1.70
150	49	4	2.65	2.05	3.26	49	4	2.59	2.00	3.18
	< 50 Pops / Sq. Mile					**< 50 Pops / Sq. Mile**				
10	130	7	1.00	…	…	132	7	1.00	…	…
70	84	6	1.55	1.38	1.72	86	6	1.54	1.36	1.71
150	51	4	2.55	1.89	3.20	52	4	2.54	1.86	3.21
	< 20 Pops / Sq. Mile					**< 20 Pops / Sq. Mile**				
10	150	8	1.00	…	…	177	8	1.00	…	…
70	98	6	1.53	1.32	1.75	108	6	1.63	1.40	1.86
150	60	5	2.49	1.67	3.31	60	5	2.96	1.95	3.97

Evaluation Parameters: Population density, road mile density, establishment density, download speed, income, and tower height are evaluated at the mean of the < 100 pops sample; subscribers per deployed MHz is evaluated at the 5th percentile of the <100 pops sample; percentage forested is evaluated at the mean of each terrain category in the <100 pops sample; Low Band Spectrum Deployed Flag set to 1; Percentage of Area Covered by LTE set to 100%; Provided and state fixed effects are evaluated at means of regression samples.

Site radius calculations assume a hexagonal coverage areas equal to 2.598 the square of the radius.

95% confidence intervals calculations computed using bootstrap procedure and are based on 1000 replicates.

III. AUCTION BIDDING MODEL ADJUSTMENT FACTOR

39. This section uses Mobility Fund Phase I auction data to estimate the effects of terrain and other factors on the requested subsidy amounts for carriers to deploy mobile wireless infrastructure in previously unserved areas. The Mobility Fund Phase I auction was a reverse auction in which firms bid for subsidies to provide mobile service to all road miles in an unserved geographic area.[53] A higher bid means a higher subsidy is required for a firm to want to serve the area, which either means the cost to serve the area is high, the expected revenue is low, or the bidder expects less competition from other bidders. In this section, we regress the observed bids on area-specific variables that account for differences in expected costs and revenues to serve the area and competition in the auction. We find that terrain has a substantial and statistically significant effect on the requested subsidy amount requested by carriers.[54]

40. *Background.* In the Mobility Fund I proceeding, the Commission established Auctions 901 and 902 to distribute universal service funds to areas that lacked sufficient mobile service.[55] The analysis uses September 2012 bidding data from Auction 901. Bidders in the auction submitted sealed bids indicating the subsidy they would accept to serve all unserved road miles in a given geographic

[53] *Mobility Fund Phase I Auction Scheduled for September 27, 2012, Notice and Filing Requirements and Other Procedures For Auction 901*, Public Notice, 27 FCC Rcd 4725, 4729, para. 8 (2012) (*Auction 901 Procedures Public Notice*).

[54] We estimate the elasticity of bids amount to our measure of terrain roughness to be between 0.16-0.23. The small sample limits our ability to draw strong conclusions about the impact of other factors on bid amount.

[55] Auction 901 occurred for most areas on September 27, 2012 with a budget of $300 million, and Auction 902 occurred specifically for Tribal areas on February 25, 2014 with a budget of $50 million. *See Connect America Fund et al.*, Report and Order and Further Notice of Proposed Rulemaking, 26 FCC Rcd 17663, 17675, para. 28 (2011) (*USF/ICC Transformation Order*); *Auction 901 Procedures Public Notice*, 27 FCC Rcd at 4727, para. 1; *Tribal Mobility Fund Phase I Auction Rescheduled for February 25, 2014 Notice of Changes to Auction 902 Schedule Following Resumption of Normal Commission Operations*, Public Notice, 28 FCC Rcd 14656, 14656, para. 1 (2013). We do not consider Auction 902 because Tribal entities received bidding credits for Tribal areas, which would complicate the analysis, and we exclude Tribal areas in Auction 901 for the same reason.

area.[56] In our estimation sample, the geographic areas were all Census tract aggregations of unserved road miles.[57] The auction was conducted in a single round with bids simultaneously accepted for all areas and winning bids were determined by an algorithm that favored lower bids on a per road mile basis, but also kept total awarded bids within a budget.[58]

41. *Regression Specification.* Bids in an auction for subsidies should reflect the relative profitability of the geographic areas for auction. Those geographic areas that bring in more revenue and cost less to serve should require a lower subsidy to induce the bidder to serve, and, accordingly, such areas should receive lower bids, all else equal. We use linear regression to estimate the following specification of the effect of various revenue and cost factors on bids:

$$\ln(Bid_{ij}) = X_{ij}\beta + \phi_j + \epsilon_{ij}$$

42. We assume the natural logarithm of the dollar per road mile bid (log bids) is a function of expected revenue and cost factors, X_{ij}, plus bidder level fixed effects, ϕ_j, where *i* indicates a specific geographic area and *j* indicates the bidder. These factors include our measure of terrain roughness, area demographics and variables designed to capture competitive aspects of bidding and competition in the service market. The vector β represents the collective effects of the individual factors. We use log bids because the distribution of bids is highly skewed, and the log transformation makes the resulting data fit a normal distribution more closely, and thus better meets the classical assumptions for linear regression. In addition, because many skewed factors in X_{ij} are also log-transformed, most of the coefficients in β can be interpreted as elasticities; i.e. a coefficient β_k of a factor X_{ij}^k implies a β_k percent change of the dollars per road mile bid with a 1 percent change in that untransformed factor. The bidder-level fixed effects, ϕ_j, represent differences in costs and productivity that are entirely specific to the bidders themselves, and are not reducible to the observable characteristics of the geographic area or bidders. Finally, ϵ_{ij} represents the impact of any other determinants of bid level, such as cost or revenue factors specific to the area, that are not observed in any dataset to which we have access.

43. *Sample.* Our estimating equation is more likely to be appropriate when areas included in the data set are generally more comparable, so we exclude a variety of areas from the sample to maximize the comparability of geographic areas and bids.[59] The 5,695 potential areas generated 517 bids, with only 24 areas attracting more than 1 bid. Fifty-two areas with bids were not assigned any subsidy because the bids were so high the assignment algorithm could not grant them without exceeding the budget.

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[56] *Auction 901 Procedures Public Notice*, 27 FCC Rcd at 4761-65, paras. 131-141.

[57] Eligible areas were U.S. Census blocks that lacked 3G or better mobile coverage at the centroid of the block and contained road miles in any of six road categories. These blocks were identified by analyzing American Roamer coverage data (now called Mosaik). *USF/ICC Transformation Order*, 26 FCC Rcd at 17783-84, paras. 332, 334.

[58] The algorithm considered the lowest bids in an area to be tentatively winning bids. The algorithm then ranked the areas in ascending order by their tentatively winning bids on a per-road mile basis. As it went through the ranking, the algorithm awarded subsidies (equal to the per-road mile bid times the road mile service requirement) if that item had not been previously assigned and the total requested subsidies did not exceed the Mobility Fund Phase I budget. *Auction 901 Procedures Public Notice*, 27 FCC Rcd at 4765-66, paras. 143-44.

[59] Data on all Auction 901 results are available online. *Auction 901: Mobility Fund Phase I*, https://www.fcc.gov/auction/901 (last visited May 15, 2020). Specifically, the sample excludes: (1) areas in Alaska since these are especially large and not tract based; (2) awards to Tribal entities, since they received bidding credits for Tribal areas; (3) areas in Guam and the Northern Mariana Islands because we do not have terrain data there; (4) one very small area, T37171930102, for which it is difficult to calculate terrain roughness; and (5) area T37171930101 in North Carolina because it is made up of 3 disjoint and small parts. *Auction 901 Procedures Public Notice,* 27 FCC Rcd at 4763-64, paras. 138-40.

44. Out of 517 bids, 225 led to eventual defaults. It is unclear whether defaulted bids accurately reflect the true effect of cost and demand factors on bid amounts, as these bids may have greatly underestimated the required subsidy to make service of the given area viable. Similarly, bids that failed to receive subsidies may be systematically biased upwards given they may imply a higher estimate of costs or lower estimates of revenues than the bids that won subsidies. Given the difficulties in knowing whether to remove "potentially unreasonable" bids systematically, in addition to reporting results for the full sample, we will also report results for 1) the sample of bids with no defaults and 2) the sample of bids without defaults or losing bids.

45. Since they likely acted as a single strategic entity, we group subsidiaries into a single firm. This results in 19 active bidders for our subsample, 8 active bidders who bid outside of our subsample, and 9 bidders who applied but did not ultimately bid. Finally, we note that this sample of bids is a selected sample of only the areas that received at least one bid. If our cost and demand factors are correlated with the unobserved shock, ε_{ij} then our linear regression estimates will be biased. The decisions of bidders on where to bid could induce such correlation because observable factor combinations that would otherwise predict negative bids (low $X_{ij}\beta$) are included only if they have a high and positive, unobservable shock.[60] Therefore, our results should be interpreted with caution.

46. *Data.* The summary statistics are presented in Fig. B-10. The dependent variable is the dollar per road mile bid amount, which is how the bids were submitted.[61] Bids are right skewed, with winning bids having a mean of $8,135 per road mile and a median of $5,815 per road mile, while losing bids have a mean and median bid amount of $74,816 per road mile and a median of $49,312 per road mile, respectively. There was also substantial variation in bid amount. On a per road mile basis, the upper limit for winning bids was $41,523, but bids were as high as $429,695 and as low as $130.

47. We use many of the independent variables that were used in the Entry Model as described above as cost/revenue factors. These include logs of our measure of terrain roughness, population density, tract median household income, road miles, and percent forested land.[62] Terrain roughness will capture the effect of terrain on increased construction costs and reduced signal propagation distances. The other demographic and economic variables proxy for wireless demand for and cost variation caused by differences in economic development. Total road miles is also included to capture potential economies and diseconomies of scale in network infrastructure construction.

48. Our independent variables also include the fraction of a tract that is forested since forests would tend to reduce signal propagation and increase construction costs.[63] We also include separate variables for the fraction of the tract for which any service carrier and the bidder already provide some level of service, as measured by January 2012 coverage data.[64] If the surrounding area is well served by the bidder, we would expect they would have lower costs of expanding coverage. When the area is already well covered by other firms, represented by overall coverage, then rival firms are likely to be strong future competitors in the area to be served which may raise the required subsidy. We also include the number of carriers in the tract to measure local competition in the downstream market that would reduce revenues.[65] Similarly, we include the potential number of bidders as a covariate. While multiple

[60] The direction of the bias on estimated coefficients is only known under special circumstances. *See* Arthur S. Goldberger, *Linear regression after selection*, 15 J. Econometrics 357 (1981).

[61] *See infra* Appx. B.IV: Data Sources and Variable Construction for information on the data sources and construction of the variables.

[62] *Id.*

[63] *Id.*

[64] *Id.*

[65] *Id.*

bids for the same area were rare, the mere threat of a bid by a competitor may be enough to lower the bids that do occur. To calculate the number of potential bidders, we use bidder applications submitted to the Commission before the auction.[66]

49. Some of the independent variables, the average number of carriers, the number of carriers and the preexisting coverage variables, are calculated on a geographic basis.[67] Land area is the most common basis on which to calculate these variables, but since bidding was done on a road miles basis, the number of road miles basis may be the most relevant. We produce estimates using both approaches and find little difference between the results.

50. *Results.* We estimate six specifications, and our results are presented in Fig. B-11 below. Specifications (1)-(3) use the land area basis for some variables and (4)-(6) use the road miles basis. Specifications (1) and (4) include all observations, (2) and (4) exclude defaults, and (3) and (6) additionally exclude losing bids. Across all specifications, our terrain measure has between a 0.16 to 0.23 elasticity with respect to bids that is statistically significant across all specifications. That is, for every 1% increase in terrain roughness, we have a 0.16% to 0.23% increase in the dollar per road mile bid. Dividing terrain roughness into three categories of 0-40 m (flat), 40-115 m (hilly) and 115+ m (mountainous), we estimate the adjustment factor for each bin by estimating the impact of terrain roughness on the per road mile bids in levels at the same terrain values of 10m, 70m, and 150m used in the entry and cell site density analyses.[68] That is, the adjustment factor is the model predicted per road mile bid amount at one of these terrain levels over the predicted bid amount at 10 m. Holding all other variables fixed, this ratio will be constant for our formula across all possible areas and bidders.[69] Using the estimates of the full sample, the three categories would have adjustment factors of approximately 1.0 (0-40 m), 1.6 (40-115 m) and 1.9 (115+ m).

51. Several other covariates have statistically significant results over all or most of the specifications. Road miles has a negative impact on dollars per road mile, with an implied elasticity between -0.24 to -0.47. This result is consistent with economies in scale in road miles for wireless infrastructure, though the effect is not statistically significant in specification (6), the subsample with variables weighted over road miles and with no defaults or losing bids. Likewise, a bidder's current tract network coverage also seems to reduce costs, whereby an additional 1% network coverage is associated with between a 0.36% and 0.55% decrease in the bid, though the coefficient is not statistically significant for the sample with no defaults but no losing bids and using area-based variables. The percent coverage of the tract by forested land has a statistically significant large positive impact on bid amount, but not for specifications using the full sample. This may imply that defaulting bidders underestimated the importance of clutter in their bid calculations.

52. Other coefficients are too imprecisely estimated to draw further conclusions, probably due to the small sample size and limited variation of the sample. Population density has small implied elasticities between -0.2 and -0.7, which are only significant using the sample without defaults but with losing bids. The log count of carriers has coefficients that are mostly larger than the ones for terrain,

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[66] *Id*.

[67] Log count of carriers was calculated as a log of the weighted average count, not the weighted average of logs.

[68] These categories are consistent with the earlier categories used in the Entry Model and the Cell Site Density Model. *See supra* Appx. B.I: Entry Model Adjustment Factor and App. B II: Cell Site Density Model Adjustment Factor.

[69] If T is the terrain roughness in the comparison category, and α is the coefficient on the natural logarithm of terrain roughness, then the adjustment factor for this category is the expectation of the ratio between what a given bid would be if we changed the terrain roughness to T meters over that bid if we changed the terrain roughness to 10 meters: $E\left[\frac{Bid_{ij}\text{ at }T\text{ m}}{Bid_{ij}\text{ at }10\text{ m}}\right] = E\left[\frac{T^{\alpha}\,\exp(\beta X_{ij} - \alpha\ln(T_{ij}) + \phi_j + \varepsilon_{ij})}{10^{\alpha}\,\exp(\beta X_{ij} - \alpha\ln(T_{ij}) + \phi_j + \varepsilon_{ij})}\right] = \left(\frac{T}{10}\right)^{\alpha}$.

between 0.20 and 0.38, but are only statistically significant for specifications using the sample without defaults and losing bids, and for the specification using losing bids but no defaults and using area-based variables. Coverage by any carrier has relatively large negative coefficients using the full sample but no coefficient in any specification is statistically significant. Consistent with competition reducing bids, the coefficients on potential bidders are mostly negative, though only the coefficients on “Two bidders” were statistically significant and only for the sample removing defaults and losing bidders. Finally, log median household income always has a positive coefficient, which runs counter to the idea that more economic activity would make an area more profitable to deploy. While there may be other unobserved factors correlated with income involved, this finding might reflect that in areas with low economic development for the eligible areas of MF-I, the costs of setting up a network with a high enough quality level to serve a more developed area exceed any additional revenues. However, these coefficients are always imprecisely estimated so we do not rely on them for constructing adjustment factors.

Fig. B-10: Summary Statistics of Full Estimation Sample of Bids

VARIABLES	Mean	Median	Std. Dev.	Min.	Max.
Bid Per Road Mile ($)	17,856	5,953	41,271	130	429,695
Terrain Roughness (m)	38.9	17.5	41.9	0.8	223.6
Population Density (Per Land Area Mile^2)	33.6	12.8	100.0	0.0	1,723.4
Road Miles	167.4	36.2	414.5	0.0	4,227.4
Tract Median Household Income ($000s)	42,037	40,746	11,522	10,915	86,228
Fraction Tract Forest Land	0.52	0.59	0.28	0.00	0.94
Carriers Count (Tract Wt. Avg. by Land Area)	2.8	2.7	1.1	0.3	5.8
Carriers Count (Tract Wt. Avg. by Road Miles)	2.8	2.8	1.1	0.2	5.7
Fraction Service Coverage (Tract Wt. Avg. by Land Area)	0.95	1.00	0.11	0.24	1.00
Fraction Service Coverage (Tract Wt. Avg. by Road Miles)	0.95	1.00	0.10	0.18	1.00
Fraction Own Coverage (Tract Wt. Avg. by Land Area)	0.62	0.76	0.38	0.00	1.00
Fraction Own Coverage (Tract Wt. Avg. by Road Miles)	0.63	0.78	0.38	0.00	1.00
Potential Bidders	2.9	3.0	1.2	1.0	5.0

Fig. B-11: Estimation Results

DEPENDENT VARIABLE: LN(BID $/ROAD MILE)						
	SPECIFICATION					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log Terrain Roughness	0.23***	0.16*	0.20**	0.23***	0.16*	0.20**
	(0.06)	(0.09)	(0.09)	(0.06)	(0.08)	(0.09)
Log Population Density	-0.07	-0.06**	-0.02	-0.07	-0.06**	-0.02
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
Population is Zero Indicator	-0.63	-0.54	-0.29	-0.64	-0.56	-0.30
	(0.42)	(0.48)	(0.42)	(0.43)	(0.48)	(0.43)
Log Road Miles	-0.24*	-0.46***	-0.34***	-0.25*	-0.47***	-0.34***
	(0.12)	(0.12)	(0.11)	(0.13)	(0.12)	(0.11)
Log Tract Median Household Income ($000s)	0.25	0.05	0.15	0.26	0.06	0.15
	(0.16)	(0.17)	(0.25)	(0.16)	(0.17)	(0.25)
Fraction Tract Forest Land	0.36	0.75***	0.81**	0.34	0.73***	0.82**
	(0.40)	(0.21)	(0.30)	(0.39)	(0.22)	(0.31)
Log Carriers Count (Tract Wt. Avg)	0.24	0.30*	0.38**	0.20	0.25	0.33*
	(0.14)	(0.16)	(0.15)	(0.12)	(0.16)	(0.16)
Fraction Service Coverage (Tract Wt. Avg.)	-0.80	-0.18	-0.65	-0.80	0.05	-0.31
	(0.72)	(0.62)	(0.59)	(0.86)	(0.68)	(0.67)
Fraction Own Covered Area (Tract Wt. Avg)	-0.54**	-0.36	-0.39**	-0.55**	-0.44*	-0.46**
	(0.23)	(0.25)	(0.18)	(0.23)	(0.25)	(0.17)
Potential Bidders						
Two	-0.16	-0.11	-0.36**	-0.16	-0.12	-0.37**
	(0.24)	(0.28)	(0.14)	(0.24)	(0.27)	(0.13)
Three	-0.22	0.17	-0.04	-0.21	0.18	-0.02
	(0.28)	(0.28)	(0.44)	(0.27)	(0.28)	(0.45)
Four or More	-0.25	-0.00	-0.25	-0.24	0.01	-0.25
	(0.15)	(0.26)	(0.18)	(0.15)	(0.25)	-0.17
Bidder Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weighted Average Basis	Land Area	Land Area	Land Area	Road Miles	Road Miles	Road Miles
Sample	Full	No Defaults	No Defaults and Only Winning Bids	Full	No Defaults	No Defaults and Only Winning Bids
Observations	517	292	216	517	292	216
R^2	0.30	0.46	0.45	0.30	0.46	0.45

*** p-value<0.01, ** p-value <0.05, * p-value <0.1; standard errors clustered at the bidder level in parenthesis.

IV. DATA SOURCES AND VARIABLE CONSTRUCTION

53. In this section, we describe the data sources and variable construction for the three economic analyses informing our proposed adjustment factor values. We note that while the three analyses use the same data source for many variables, they rely on different vintages and geography for their specific analysis. Thus, the Entry Model analyzes 2017 coverage data at the Census block group

level, while the Cell Site Density Model analyzes cell site data from 2013 at the county level, and the Bidding Model analyzes 2012 bid data on partial areas of census tracts. Fig. B-12 provides a list of the data sources while Fig. B-13 describes the variables, the data vintages, and the geographies.

A. Dependent Variables

54. *Entry Analysis: Number of Entrants*. The number of entrants in a Census block group is constructed using Mosaik January 2017 coverage data. A carrier is considered to have entered a Census block group if it covers at least 75% of the land area within the Census block group with 4G LTE.

55. *Bidding Analysis ─ Bid Per Road Mile*. Bids in Mobility Fund Phase I were submitted on a per road mile basis for specific unserved areas and are publicly available.[70] Total subsidy amounts for an area are equal to the winning per road mile bid times the service requirement for road miles to be covered.

56. *Cell Site Density Analysis ─ Average Coverage Area Per Cell Site*. We calculate total coverage and the total number of cell sites in each county for each carrier and then divide each carrier's coverage by the number of cell sites to determine the average coverage area per cell site for each carrier. We include only counties where carriers report positive coverage and a positive number of cell sites, which gives us a maximum of 9,863 observations in any regression sample.[71]

- *Coverage.* We use the January 2014 Mosaik dataset and for each carrier, we calculate the percentage of area of each Census block covered by any technology (e.g., 3G, 4G LTE). Then, we multiply the percentage of the block covered by the land area in that block to determine the total covered area and aggregate the total covered area to the county level.[72]
- *Number of Cell Sites.* We use the December 2013 Business Data Service (BDS) Cell Site Database which contains 209,358 cell site locations (address and/or latitude-longitude coordinates) for four nationwide carriers. To identify which county each cell site is in, we use two approaches: (1) geocode the address to a Census block group and (2) use the coordinates to find the associated Census block.[73] We identify the block group and/or block for each cell site, and then count the number of cell sites in each county for each carrier.[74]

[70] *Auction 901: Mobility Fund Phase II*, https://www.fcc.gov/auction/901 (last visited May 15, 2020).

[71] 1,410 observations have positive coverage but zero cell sites which suggests that cell sites outside the county are covering areas in the county or that we are missing cell sites in that particular county. Three observations have zero coverage and a positive number of cell sites which suggests that these cell sites may not be in service or that they have been assigned to the wrong county. 1,183 observations have zero coverage and zero cell sites.

[72] We consider any technology because the BDS dataset does not include the technologies deployed on each cell site.

[73] Specifically, we used the Census Geocoder at "Find Geographies Using – Address Batch" with the "Public_AR_Census2010" Benchmark and the "Census2010_Census2010" Vintage which reported either a match, non-match, or tie for each inputted address. If the Geocoder produced a match, we assigned the associated county; if not, we relied on the BDS-reported coordinates to identify the county, using Geographic Information System (GIS) to join the 2010 Census block group shapefile with the coordinates of each cell site. *Census Geocoder Documentation*, https://www.census.gov/programs-surveys/geography/technical-documentation/complete-technical-documentation/census-geocoder.html (last visited May 15, 2020).

[74] Unfortunately, there are some cases where the two approaches assign different counties which could be due to inaccuracies with the BDS data (i.e., the reported address does not properly correspond with the reported coordinates), assuming the incorrect coordinate system for associating the coordinates to Census geographies, or we are not using the proper Census Geocoder Benchmark and/or Vintage. Because of these inconsistencies, we assign the county based on the geocoding and only used the result from the other approach if the geocoding failed. Cell sites that we could not assign to a Census geography via either approach are excluded from the analysis. This could result in an overstatement of the average coverage area per cell site in counties with missing cell sites.

B. Independent Variables

57. *Terrain.* Due to the signal loss caused by terrain variation, propagation models use a measure of terrain roughness to account for propagation losses.[75] As our measure of terrain roughness, we calculate the average standard deviation of terrain elevation.[76] To do this, we use the digital elevation model (DEM) of the conterminous U.S. and Hawaii which was published by the USGS in December 2012,[77] and a vector based shapefile of geographic units, which was either the Census Tiger Shapefile 2010 Block Groups[78] or a shapefile of Mobility Fund Phase I auction areas for the bidding analysis.[79] Most Mobility Fund Phase I auction areas (and all areas used in the Mobility Fund Phase I analysis) were constructed from U.S. Census blocks which the Commission determined lacked coverage that were then aggregated to the tract level.[80] In either case, we project the geographic unit geometries to match the raster dataset's projection.[81]

58. To calculate the average standard deviation of elevation for each analysis's geographic unit, we use two GIS processes. First, for each raster we define a circular neighborhood with a 2.5-kilometer radius centered at the centroid of that raster.[82] We then calculate the standard deviation of elevation of all rasters whose centroids are contained within the neighborhood.[83] Next, we use this raster layer as input data for the second GIS process, which for a particular geographic area, such as a Census tract, takes the average of the standard deviations for all rasters whose centroids lie within the geographic

[75] *See OBI Technical Paper No.* 1, at 50.

[76] This approach is similar to the approach taken in the National Broadband Plan (NBP) which calculated the standard deviation of elevation for block groups. *OBI Technical Paper No.* 1, at 50-52. Our approach differs from the NBP approach in that we calculate standard deviations over uniform geographic areas (in particular, we use a circular neighborhood of 2.5 kilometers) in order to produce a consistent measure across areas of different geographic size. We then calculate the average standard deviations in these areas (e.g., block groups, counties).

[77] These elevation data were derived from the National Elevation Dataset (NED) and are represented as a grid of 100-meter by 100-meter cells, called rasters, in the Albers Equal-Area Conic projection. Each raster is associated with an elevation, allowing us to measure very fine variations in terrain. In these data, all large water bodies such as oceans and the Great Lakes have elevation of zero meters above sea level; however, we know the Great Lakes elevations are above sea level. *USGS National Elevation Dataset*, https://catalog.data.gov/dataset/usgs-national-elevation-dataset-ned (last visited May 15, 2020). To minimize false variability in terrain because of the Great Lakes' zero elevation and their shores' relatively higher elevation, we exclude raster cells that have zero elevation. USGS, *Small Scale Data*, https://nationalmap.gov/small_scale/mld/elev100.html (last visited May 15, 2020).

[78] US Census Bureau, *TIGER/Line Shapefiles*, https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2010.html (last visited May 15, 2020).

[79] The shapefiles were created by staff based on available online data. *Auction 901: Mobility Fund Phase I*, https://www.fcc.gov/auction/901 (last visited May 15, 2020).

[80] *Auction 901 Procedures Public Notice*, 27 FCC Rcd at 4761-65, paras. 131-42.

[81] We used ArcGIS to recalculate the coordinate systems of the different geographic units to achieve the new projection.

[82] We chose a 2.5-kilometer radius because we wanted to measure terrain roughness over an area large enough to have some level of elevation variation but not too large to capture terrain that is irrelevant to a hypothetical cell site at the centroid of the raster. Since the immediate terrain surrounding a cell site is most relevant for propagation, we use a 2.5-kilometer radius as a conservative approach. As robustness checks, we also considered 1-kilometer, 5-kilometer, and 10-kilometer radii in the Entry Model and Cell Site Density Model and found similar results.

[83] We use the "Focal Statistics Tool," in ArcGIS to calculate this standard deviation. *See* ESRI, *How Focal Statistics Works*, http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/how-focal-statistics-works.htm (last visited May 15, 2020).

area.[84] This process produces an output table that contains each geographic area's average standard deviation of elevation based on the 2.5-kilometer circular neighborhood.

59. For the Entry Model analysis, average terrain roughness values are calculated for each block group. For the Auction Bidding Model analysis, we calculate a terrain value for each biddable area in the auction.[85] For the Cell Site Density Model analysis, we calculate carrier-specific terrain because each carrier does not necessarily cover the full county or cover the same areas as other carriers within a county. Specifically, from the block group level average standard deviation, we calculate the county level average for each carrier weighting by covered land area of each block group based on coverage data.

60. *Terrain Categories*. We categorize terrain into three groups as shown in Fig. B-14 below. To partition block groups into three groups, we use Jenks natural break clustering algorithm which minimizes within-cluster variances.[86] When evaluating the various analyses, we use the medians of each terrain category.

61. *Population Density.* For the Entry Model analysis, we use 2017 staff estimates to calculate population density by aggregating the total block level population to the block group and dividing by the total block group level land area.[87] For the Auction Bidding Model analysis, we aggregate the 2010 Census block level population and land area across all blocks in an area and divide to calculate the population density.[88] For the Cell Site Density Model analysis, we use 2014 county level Census population estimates and divide by the total land area to calculate the county level population density.

62. *Road Mile Density*. We use a previously developed dataset of the number of road miles per Census block which includes the following Census categories: Primary Road (S1100), Secondary Road (S1200), Local Neighborhood Road, Rural Road, City Street (S1400), Vehicular Trail [4WD] (S1500), Service Drive usually along a limited access highway (S1640), and Private Road for Service Vehicles (S1740).[89] In calculating the number of road miles associated with each Census block, we used two tables ("Faces" and "Edges"), published by the Census as part of the TIGER database.[90] We then sum the number of total road miles to higher geographies and divide by the land area to calculate the road mile density (number of road miles per square mile).

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[84] We use the "Zonal Statistics Tool" in ArcGIS to calculate this average. *See* ESRI, *How Zonal Statistics Works,* http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/h-how-zonal-statistics-works.htm (last visited May 15, 2020).

[85] The raster-level standard deviations of elevations within a 2.5-kilometer circular neighborhood were calculated for all raster cells in an area, and then the average taken for each area.

[86] We weight block groups by land area and use a Euclidean distance (L2) measure. Makles, A. (2012). Stata tip 110: How to get the optimal k-means cluster solution. *Stata Journal*. 12: 347–351.

[87] Staff creates these estimates by taking annual Census county level estimates of population and housing units and distributing any increases or decreases along eligible roads. *Staff Block Estimates*, https://www.fcc.gov/reports-research/data/staff-block-estimates (last updated Jan. 23, 2020).

[88] US Census Bureau, *Explore Census Data*, available at https://data.census.gov/cedsci/ (last visited May 15, 2020).

[89] US Census Bureau, *TIGER/Line® Shapefiles: Technical Documentation 2010* at F-192-3 (2012), *available at* https://www2.census.gov/geo/pdfs/maps-data/data/tiger/tgrshp2010/TGRSHP10SF1.pdf.

[90] A description of these relationship tables can be found at US Census Bureau, *Description of the Relationship Tables*, https://web.archive.org/web/20120526031804/http://www.census.gov/geo/www/tiger/rel_file_desc.pdf (last visited May 15, 2020). The datasets themselves are available in the FACES and EDGES directories, US Census Bureau, FTP, ftp://ftp2.census.gov/geo/tiger/TIGER2010/ (last visited May 15, 2020).

63. *GDP Density*. We use the Bureau of Economic Analysis (BEA) Gross Domestic Product (GDP) by county dataset to derive county level GDP per square mile.[91] These data provide GDP for most counties individually.[92] For the Entry Model analysis, we divide the annual real GDP by the total land area to get the GDP per square mile.

64. *Establishment Density*. We use the Census Bureau's County Business Patterns (CBP) dataset containing the number of establishments.[93] An establishment is defined as a single physical location at which business is conducted or services or industrial operations are performed.[94] For the Cell Site Density Model, we divide the total number of establishments by the total land area in each county.[95]

65. *Median Household Income*. We use the American Community Survey (ACS) five year estimates database published by the Census Bureau to derive median household income.[96] For each analysis, we use the vintage of data for which the final year of the ACS estimates matches with the relevant year in the analysis.[97]

66. *Subscribers Per Deployed MHz Spectrum (CMA Level).* In order to calculate the number of subscribers per deployed megahertz of spectrum for the Cell Site Density Model, we first analyze the December 2014 Form 477 data that indicates whether each carrier has deployed particular spectrum bands with at least one technology (e.g., LTE) in each county.[98] Second, we use Universal Licensing System (ULS) data which provides the amount of spectrum holdings (megahertz) for each carrier in each county and its associated radio service code.[99] We match the radio service codes with the Form 477 spectrum codes and sum the spectrum holdings over the radio service codes (see Fig. B-15 below). We then merge this with the Form 477 data from the first step. This produces a dataset that shows whether the carrier deploys on a given spectrum band (on any technology) in the county and the amount of spectrum holdings the carrier has in that particular spectrum band in that county.[100]

[91] Specifically, we use Real GDP (2012 Chained Dollars) of private industries only. Bureau of Economic Analysis, *GDP by County, Metro and Other Areas* (Dec. 12, 2019), https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas (last visited May 15, 2020).

[92] For some counties, however, BEA combines several counties or other jurisdictions for its estimates (e.g., Fairfax County, VA; Fairfax City, VA; and Falls Church, VA are a single BEA county). https://apps.bea.gov/regional/pdf/FIPSModifications.pdf. For those counties, we assume uniform GDP per capita across the combined counties.

[93] US Census Bureau, *County Business Patterns: 2014*, (Apr. 24, 2016), *available at* https://www.census.gov/data/datasets/2014/econ/cbp/2014-cbp.html.

[94] A more detailed definition is available at US Census Bureau, *Glossary*, https://www.census.gov/programs-surveys/cbp/about/glossary.html (last visited May 15, 2020).

[95] As there are no observations for King County, Texas, we assume that there are zero establishments in this county.

[96] US Census Bureau, *American Community Survey (ACS)*, https://www.census.gov/programs-surveys/acs (last visited May 15, 2020).

[97] For example, if the dependent variable in the model is from 2011, we would use the 2006-2011 ACS database.

[98] Because Mosaik does not provide data on where carriers have deployed specific spectrum bands, we use Form 477 data which does, on the other hand, indicate where carriers have deployed using different spectrum bands.

[99] Staff conducted its analysis using the December 2014 Universal Licensing System data.

[100] There are cases where the data suggest a carrier deploys on a particular spectrum band in a given county but does not have spectrum holdings.

67. To approximate the total deployed spectrum, we multiply the spectrum holdings by a binary variable that indicates if the carrier deploys on the given spectrum band in a given county.[101] Finally, we average total deployed spectrum to the CMA level weighting by 2014 county population. The final step uses Number Resource Utilization and Forecast (NRUF) data on the number of subscribers for each carrier in each county. Given issues associated with the use of NRUF data at the county level,[102] we aggregate to the CMA level and merge this with the total deployed spectrum and divide by the number of subscribers. This calculation produces an estimate of the subscribers per total deployed spectrum at the CMA level.

68. *Low Band Spectrum Flag.* For the Cell Site Density Model, we use the December 2014 Form 477 data to determine Census blocks in which each carrier deploys low band spectrum using any technology. We use the centroid method to identify which blocks are covered by low band. Then, we create a binary flag variable which equals one if the carrier deploys low band at the geographic centroid of at least one block in the county.

69. *Percentage of Area Covered.* Our coverage percentage data is constructed using Mosaik data by calculating coverage for each model's geographic unit of interest and then dividing it by the total area of the geographic unit. For the Cell Site Density Model analysis, we calculate the total area in each county covered by LTE by each carrier in January 2014. For the Auction Bidding Model, we use January 2012 Mosaik data.[103] In contrast to the Entry Model and Cell Site Density Model analyses, we use a "centroid-based" method to measure coverage in the Auction Bidding Model analysis. In line with the way coverage was measured in Auction 901, an entire Census block is counted as covered if the geographic centroid is covered.[104] In addition, "uncovered" areas in the Auction Bidding Model analysis sometimes do have coverage since an older vintage of Mosaik data was used to select the eligible blocks; and we use all types of coverage and not just 3G coverage as in the selection process of Mobility Fund Phase I. Some eligible blocks in MF-I were also included (or removed) due to challenges from commenters that revealed on-the-ground discrepancies in coverage compared with the Mosaik data.[105] We aggregated block area coverage to auction areas by adding the total land area of covered blocks within an auction area. We construct percentage coverage both for any carrier, by counting a block covered if it is covered by any carrier, and for each bidding carrier in the bid data, individually.

70. *Percentage of Road Miles Covered.* For the Auction Bidding Model, we calculated road miles covered analogously to the way area covered was calculated using the same road miles data used to calculate road mile density. Using any block we considered covered in the area calculation, we develop auction area coverage by adding road miles in these blocks, and dividing this figure by the total road miles in the auction area. Also like the area percentage coverage, we calculated this figure both for any carrier, by counting a block covered if it is covered by any carrier, and for each bidding carrier in the bid data, individually.

71. *Download Speed.* For the Cell Site Density Model, we use July through December 2014 Ookla Speedtest data to calculate average download speeds for each county for each carrier. First, we drop any test with non-positive download or upload speeds, tests taken over a WiFi connection, and tests

[101] Here we are assuming that if a carrier deploys on a particular spectrum band in a given county that the full amount of spectrum holdings is deployed. We only know whether or not spectrum has been deployed but not how much has been deployed. Using Form 477 data, we can exclude spectrum holdings in counties where the carrier has not deployed on a particular band on at least one technology.

[102] *2018 Communications Marketplace Report*, 33 FCC Rcd at 12582-83, para. 30 & n.94.

[103] The Entry Model uses the percentage of land covered by 4G LTE to construct its dependent variable, but does not use percentage of land covered as an independent variable.

[104] *USF/ICC Transformation Order,* 26 FCC Rcd at 17783-84 paras. 332, 334.

[105] *Auction 901 Procedures Public Notice*, 27 FCC Rcd at 4731-4756, paras. 13-22

with locations determined GEO-IP.[106] We then associate latitude and longitude coordinates to 2010 Census counties. Next, we calculate an average download speed for each device in each month and county for both Android and iPhone devices.[107] Finally, we calculate an overall carrier-county level average download speed weighting by the number of devices.

72. *Tower Height.* In the BDS data, tower height was not available, so to estimate the height of each tower in our sample, we compiled tower height information from publicly available tower company sources.[108] To calculate the average tower height in each county for each carrier, we first drop all towers with missing height information or a listed height over 500 feet and then match the towers in our sample to the closest towers in the public dataset. We then assign the tower height of the closest matched tower as long as that cell site lies within 1 kilometer of the tower from the original data sample. For towers that do not match within 1 kilometer, we assign the average tower height of the matched towers in the county for that carrier. Then, we calculate the average tower height for each county for each carrier.

73. *Land Cover (Clutter).* We use land cover data from the USGS 2011 National Land Cover Database (NLCD) to account for the role of clutter in radio wave propagation.[109] As we expect that most man-made clutter will be adequately proxied by population and establishment density, we only include a variable for naturally occurring dense clutter.[110] We condense the NLCD land use categories to create a natural "dense clutter" variable, based in part on the Commission's recommendations in the broadcast incentive auction.[111] The dense clutter category consists of the deciduous forest, evergreen forest, mixed forest, woody wetlands, and emergent herbaceous wetlands NLCD classifications. For each analysis we use the percentage of land area covered by these categories within the relevant geography. Each analysis uses 2011 NLCD data.

74. *USF Funding.* The Universal Service Fund (USF) distributes funding to subsidize mobile broadband service in high cost areas. To estimate areas that received funding in a particular area, we use internal Commission and USAC data to connect block groups to areas receiving Frozen High Cost Support or Mobility Fund Phase I support. Frozen High Cost Support is paid to firms via wire centers which do not have official geographic boundaries, so we use boundaries estimated by TomTom.[112] Mobility Fund Phase I areas included in our bidding analysis were defined by the Commission as part of

[106] Tests with non-positive download or upload speeds are assumed to be inaccurate. We exclude tests taken over a WiFi connection because we want to measure cell network quality and not a fixed broadband network's quality. Locations identified by GEO-IP are assumed to be inaccurate, and thus, tests with inaccurate location information are excluded.

[107] Instead of calculating a simple average of tests' download speeds, we calculate each device's monthly average download speed so users who take a large number of tests are not overrepresented.

[108] Tower site information was downloaded from 44 tower providers' websites in May 2018. Wireless Estimator, *Top 100 Tower Companies in the U.S.*, http://www.wirelessestimator.com/t_content.cfm?pagename=US-Cell-Tower-Companies-Complete-List (last visited May 15, 2020).

[109] USGS, *National Geospatial Program*, https://www.usgs.gov/core-science-systems/national-geospatial-program/land-cover (last visited May 15, 2020).

[110] *Office of Engineering and Technology Seeks to Supplement the Incentive Auction Proceeding Record Regarding Potential Interference Between Broadcast Television and Wireless Services*, Public Notice, 29 FCC Rcd 712, 735-37 (OET 2014). The Commission previously adapted the NLCD classifications to better reflect the propagation characteristics of the categories. *Id.*

[111] *Id*.

[112] TomTom data has been previously used, for example, to identify areas of subsidy in the Mobility Fund Phase II proceeding. *Procedures for the Mobility Fund Phase II Challenge Process,* Public Notice, 33 FCC Rcd 1985, Appx. A, n.4 (2018).

the auction.[113] Any block group whose centroid is within the boundary of a high cost wire center was counted as "subsidized."

75. *Carrier Count*. For the Auction Bidding Model analysis, we include the log of the weighted average of the number of carriers by tract. Using January 2012 America Roamer (now Mosaik) data, we determined the number of carriers covering the centroid of every Census block. We then calculated the weighted average of this number for each tract, weighting by either the block land area or road miles.[114]

76. *Number of Potential Bidders*. The bidding analysis also includes the *potential* number of bidders as a covariate. To calculate the number of potential bidders for each item, we use bidder applications submitted to the Commission before the Mobility Fund Phase I auction in which they indicate the areas they were interested in bidding.[115]

Fig. B-12: Data Sources

Data	Source Names	Source URL
Terrain	USGS - National Elevation Dataset	https://nationalmap.gov/small_scale/mld/elev100.html
Population	Census, FCC Staff Block Estimates	https://www.fcc.gov/reports-research/data/staff-block-estimates
Employment*	Census - County Business Patterns	https://www.census.gov/programs-surveys/cbp.html
Road Miles	Internal FCC Analysis of Census TIGER Data	
Gross Domestic Product	Bureau of Economic Analysis	https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas
Median Household Income	Census - American Community Survey	https://www.census.gov/programs-surveys/acs
Land Cover*	USGS - National Land Cover Database	https://www.mrlc.gov/data
Mobile Coverage	USGS - National Elevation Dataset	https://www.mosaik.com/network-experience-solutions/coverage/
Land Area	Census, FCC Staff Block Estimates	https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2010.html
Federal Land	Census - County Business Patterns	http://www.nationalatlas.gov/mld/fedlanp.html
Spectrum Holdings	Internal FCC Analysis of Census TIGER Data	https://www.fcc.gov/wireless/systems-utilities/universal-licensing-system
Subscribers	Bureau of Economic Analysis	Confidential FCC Data

[113] *Auction 901 Procedures Public Notice*, 27 FCC Rcd at 4761-65, paras. 131-42; *Auction 901: Mobility Fund Phase I*, https://www.fcc.gov/auction/901 (last visited May 15, 2020).

[114] Carrier count weighting is calculated on a land area and a road mile basis because coverage in the Auction Bidding Model is calculated both on a land area basis and a road mile basis for different specifications. To be consistent, we use land area weighting when using land area coverage and road miles weighting when using road miles coverage. *See supra* Appx. B.III: Auction Bidding Model Adjustment Factor.

[115] A carrier needed to have spectrum and ETC status to be able to bid on an area, and at the time of a bidder's short form application, the bidder had to designate what areas they had an interest in. *Auction 901 Procedures Public Notice*, 27 FCC Rcd at 4753-55, paras. 93-96. Applications can be accessed at *FCC Form 175 Search*, https://auctionfiling.fcc.gov/form175/search175/index.htm (last visited May 15, 2020).

Data	Source Names	Source URL
USF Funding	Census - American Community Survey	
MF I Auction Information	USGS - National Land Cover Database	https://www.fcc.gov/auction/901
Cell Site Counts	USGS - National Elevation Dataset	Confidential FCC Data
Download Speed	Census, FCC Staff Block Estimates	
Tower Heights	Census - County Business Patterns	

*Dataset downloaded from IPUMS NHGIS: Steven Manson, Jonathan Schroeder, David Van Riper, and Steven Ruggles. IPUMS National Historical Geographic Information System: Version 14.0 [Database]. Minneapolis, MN: IPUMS. 2019. http://doi.org/10.18128/D050.V14.0

Fig. B-13: Variables Used in Analyses

Variables	Entry Analysis		Cell Site Density Analysis		Auction Bidding Analysis	
Dependent Variables	**Vintage**	**Geography**	**Vintage**	**Geography**	**Vintage**	**Geography**
Number of Entrants	2017	Block Group				
Bid Per Road Mile					2012	Item*
Coverage Area Per Cell Site			Jan. 2014 / Dec. 2013	County**		
Independent Variables	**Vintage**	**Geography**	**Vintage**	**Geography**	**Vintage**	**Geography**
Terrain	2012	Block Group	2012	County**	2012	Item*
Employment Density						
Road Mile Density	2010	Block Group	2010	County	2010	Item*
GDP Density	2017	County				
Establishment Density			2014	County		
Median Household Income	2017	Block Group	2014	County	2011	Tract
Land Cover	2011	Tract			2011	Tract
Subscribers Per Deployed Spectrum			Dec. 2014 / Dec. 2013	CMA**		
Low Band Spectrum Flag			Dec. 2014	County**		
Download Speed			Jul.-Dec. 2014	County**		
Tower Height			May 2018	County**		
USF Funding	2016	Block Group				
Percentage Covered Land Area			Dec. 2014	County**	Jan. 2012	Tract
Percentage Covered Road Miles					Jan. 2012	Tract
Carrier Count					Jan. 2012	Tract
Number of Potential Bidders					2012	Item*

*An item is Mobility Fund I eligible area within a tract.

**Carrier-specific variable.

Fig. B-14: Terrain Categories

Category	Range	Median
Low	$0 \leq SD \leq 40$	10
Medium	$40 < SD \leq 115$	70
High	$SD > 115$	150

Note: Ranges and Medians were rounded

Fig. B-15: Relevant Form 477 Spectrum Codes and ULS Radio Service Codes

Form 477		ULS	Low, Mid, or
Code	Spectrum Band	Radio Service Codes	High Band
90	700 MHz Band	WU, WY, WZ	Low
91	Cellular Band	CL	Low
92	Specialized Mobile Radio (SMR) Band	SMR	Low
93	Advanced Wireless Services (AWS) 1 Band	AW	Mid
94	Broadband Personal Communications Service (PCS) Band	CW, CY	Mid
95	Wireless Communications Service (WCS) Band	WS	Mid
96	Broadband Radio Service / Educational Broadband Service Band	BRS-MBS, BRS-UB, EBS	Mid
Only Low Band and Mid-Band Spectrums Bands were deployed on by the four national carriers at this time period.			