March 14, 2019

VIA ECFS

Marlene H. Dortch
Secretary
Federal Communications Commission
445 Twelfth Street, S.W.
Washington, DC 20554

REDACTED – FOR PUBLIC INSPECTION

Re: Applications of T-Mobile US, Inc. and Sprint Corporation for Consent to Transfer Control of Licenses and Authorizations, WT Docket No. 18-197

Dear Ms. Dortch:

T-Mobile US, Inc. and Sprint Corporation (collectively, "Applicants") submit this letter to report serious false statements in the submissions of DISH Network Corporation and three economists affiliated with the Brattle Group, Coleman Bazelon, Jeremy Verlinda, and William Zakaras (the "Brattle Economists"), dated February 19, 2019 and February 25, 2019 (the "February DISH Submissions").[1] In these submissions, DISH has presented an economic study that fabricates harms on low income consumers where none exist. These misrepresentations were identified only through an extensive, time-intensive, and detailed review of the Brattle Economists' back-up materials by the Applicants' expert economists. The effect of these false statements is so significant to the positions promulgated by DISH and the Brattle Economists that their submissions should be excluded from the record and given no weight in this merger review.

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[1] Letter from Pantelis Michalopoulos, Counsel to DISH Network Corp., to Marlene Dortch, Secretary, Federal Communications Commission, WT Docket No. 18-197 (Feb. 19, 2019) ("DISH February 19, 2019 Letter"); Coleman Bazelon, Jeremy Verlinda, and William Zarakas, "Reply to Cornerstone 'Response to Dish and CWA Comments,'" Attachment A to DISH February 19, 2019 Letter ("Bazelon, Verlinda, and Zarakas February 19 Submission"); and Coleman Bazelon, Jeremy Verlinda, and William Zarakas, "Economic Analysis of the Proposed Sprint/T-Mobile Merger Presented to Federal Communications Commission," February 25, 2019, Attachment B to Letter from Pantelis Michalopoulos, Counsel to DISH Network Corp., to Marlene Dortch, Secretary, Federal Communications Commission, WT Docket No. 18-197 (Feb. 27, 2019) ("Bazelon, Verlinda, and Zarakas February 25 Presentation"). Notably, Professor Joseph Harrington, who was a co-author with the Brattle Economists of a declaration submitted in support of DISH's filings in this proceeding in August and October 2018, has not subscribed to the December, January, and February DISH submissions criticizing the ABH work.

The February DISH Submissions criticize the work of Drs. John Asker, Timothy Bresnahan, and Kostis Hatzitaskos (collectively, "ABH") for using U.S. Census data on median incomes in their demand estimation procedure and, by extension, in computing diversion ratios. The Brattle Economists claim that when they used "actual subscriber incomes" instead of U.S. Census data they were able to generate "much higher diversion ratios among the non-premium brands, and significantly higher price increases from the merger."[2]

Through time-consuming efforts to understand the source of the divergent conclusions, ABH have discovered that the Brattle Economists fabricated subscriber incomes rather than using actual subscriber incomes as represented. The effect of this manufactured data is to mislead the Commission and other interested consumer groups that its findings were based on better "data" and show merger harm when, in fact, the real data shows benefits:

- The Brattle Economists' demand modeling *did not utilize any* "actual subscriber incomes," available in the Nielsen Mobile Performance ("NMP") survey. Instead, they manufactured income "data" to support their desired conclusions, wholly inconsistent with accepted economic practice.
- The "data" the Brattle Economists used is far different from any real world income data, including data submitted by Free Press in its Petition to Deny in this very proceeding.
- Had the Brattle Economists actually used in their demand modeling the data that they purported to use, they would have come to the same result as ABH—that the proposed merger is procompetitive.

These false submissions went well beyond the bounds of aggressive advocacy. The Applicants, therefore, request that the Commission direct DISH to withdraw the February DISH Submissions or, in the alternative, that the Commission give no weight to them.

DISH and the Brattle Economists' Misrepresentations

In the February DISH Submissions, DISH and the Brattle Economists explicitly state on multiple occasions that the Brattle Economists used "actual" data from NMP in their analysis of the ABH merger simulation and demand estimation:

> [T]he majority of Nielsen Mobile Performance ("NMP") respondents have actually reported income information. Use of that information produces more credible

[2] Bazelon, Verlinda, and Zarakas February 19 Submission at 7.

> diversion results. Brattle has implemented Cornerstone's merger simulation *using reported income information* . . . .[3]
>
> As it happens, the majority of the users covered by the NMP data did report their actual individual income. In its report, *Brattle used that reported income information* instead of the cookie cutter median number used by Cornerstone.[4]
>
> We show that using *actual subscriber incomes* in the Cornerstone demand model would likely indicate significantly greater segmentation between premium- and non-premium brands . . . .[5]
>
> We implemented Cornerstone's merger simulation using the demand and diversion estimates from the *panelist income information*.[6]

These representations are simply false. As ABH's attached declaration explains in detail, the Brattle Economists attempted to statistically "predict" the income for all of the NMP panelists.[7] They then used the resulting "predicted income" to re-estimate the Cornerstone demand model. This method results in entirely manufactured "data."

The method the Brattle Economists used to create this "data" falls far short of any acceptable standard of economic analysis, and they made no effort to demonstrate that their method produces accurate results. In fact, for the 28,113 NMP panelists who "did report their actual, individual income," as DISH and the Brattle Economists repeatedly emphasized, the Brattle Economists' regression predicted the *wrong* income bin for *76.9%* of them.[8] Despite this fact, the Brattle Economists *threw out all* of the actual NMP income survey data, replacing it with manufactured "data" for all NMP panelists, even for those 28,113 NMP panelists for whom they had actual income data. Put differently, given the choice between actual data and manufactured "data," the Brattle Economists chose to use their manufactured "data" despite their explicit representations to the contrary.

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[3] DISH February 19, 2019 Letter at 3 (emphasis added).

[4] *Id.* at 8 (emphasis added).

[5] Bazelon, Verlinda, and Zarakas February 19 Submission at 7 (emphasis added).

[6] *Id.* at 28 (emphasis added).

[7] Attachment A, Exhibit 4.

[8] Subscribers are divided into six income bins – [redacted]

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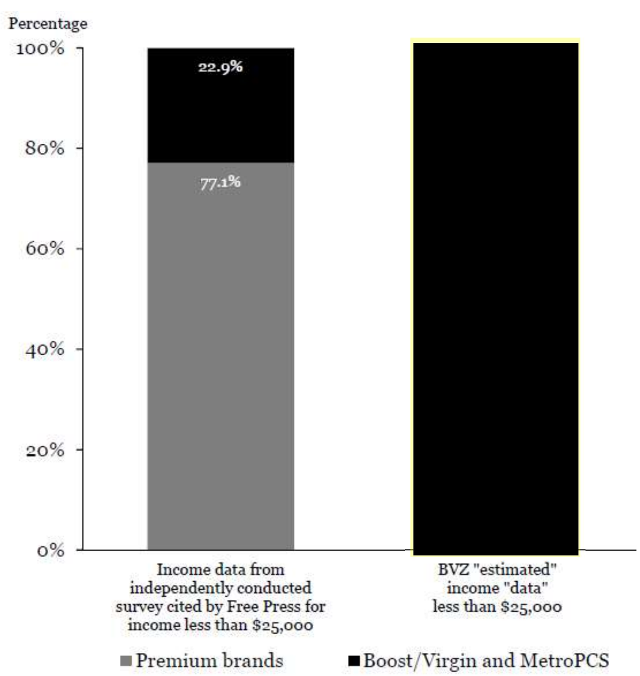
The Brattle Economists' "Data" Is Not Consistent with Any Actual Data

As ABH also explain, the Brattle Economists' "data" has no basis in reality. For example, their "data" would indicate that only about [redacted] of subscribers with incomes below $25,000 choose premium brands.[9] This result bears no relation to actual real-world data. Revealingly, Free Press, one of the *opponents* of the proposed merger, provided data on brand choices for consumers with income below $25,000. Comparing Free Press's data to the Brattle Economists "data" shows a far different picture—just under 80% of subscribers with income below $25,000 choose premium brands.[10]

EXHIBIT 1
Consumer choices among those with annual income less than $25,000 according to survey income data used by Free Press and the "estimated" income "data" BVZ used



Source: KPMG Streamshare Data; Petition to Deny of Free Press, August 27, 2018, Figure 10, "Percent of Each Carrier's Customers that Report Annual Income Below $25,000"; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission

The Brattle Economists' manufactured "data" also produce other results dramatically different from the choices reported in the NMP survey data, as well as the results reached using other actual

[9] Attachment A at 2, Exhibit 1.

[10] Attachment A at 2.

real world data sources.[11] Those other data sources produce results that are much more consistent with the Free Press survey data than with the Brattle Economists' manufactured "data."

If the Brattle Economists Had Used the "Actual" NMP Survey Data They Purported to Use, Their Results Would Have Been the Same as ABH's

As ABH explain, had the Brattle Economists used the NMP income data they purported to use, the results would mirror the ABH results. Indeed, as ABH discuss, "[e]very real-world demographic dataset we are aware of (including the survey data the Brattle Economists claim to use but do not actually use) supports our prior findings regarding diversion and segmentation. They also all support our ultimate conclusion: that the proposed merger is likely to be procompetitive."[12]

Conclusion

In sum, the very foundation of the DISH February Submissions is based upon falsehoods and material omissions. The work of the Brattle Economists fails to meet recognized professional standards. Accordingly, the Applicants request that the Commission direct DISH to withdraw the February DISH Submissions or, in the alternative, that the Commission give no weight to them.

* * * * *

This filing contains information that is "Highly Confidential" pursuant to the Protective Order filed in WT Docket No. 18-197.[13] Accordingly, pursuant to the procedures set forth in the Protective Order, a copy of the filing is being provided to the Secretary's Office. In addition, two copies of the Highly Confidential Filing are being delivered to Kathy Harris, Wireless Telecommunications Bureau. A copy of the Redacted Highly Confidential Filing is being filed electronically through the Commission's Electronic Comment Filing System.

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[11] Attachment A at 3-4.

[12] Attachment A at 7.

[13] Applications of T-Mobile US, Inc., and Sprint Corporation for Consent to Assign Licenses, Protective Order, WT Docket No. 18-197 (June 15, 2018).

Please direct any questions regarding the foregoing to the undersigned.

Respectfully submitted,

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CORNERSTONE RESEARCH
ECONOMIC AND FINANCIAL CONSULTING AND EXPERT TESTIMONY

RESPONSE TO DISH'S FEBRUARY 19 AND 25 SUBMISSIONS

By John Asker,* Timothy F. Bresnahan,† and Kostis Hatzitaskos ‡

March 13, 2019

* John Asker is a Professor of Economics at the University of California at Los Angeles, where he holds the Armen A. Alchian Chair in Economic Theory.

† Timothy Bresnahan is a Professor of Economics at Stanford University, where he holds the Landau Professorship in Technology and the Economy.

‡ Kostis Hatzitaskos is a Vice President in the Chicago office of Cornerstone Research.

1. Introduction and summary

1. In their February 19 and 25 submissions on behalf of DISH,[1] Bazelon, Verlinda, and Zarakas of The Brattle Group ("BVZ") claim that "actual" survey income data differ from the census zip code income data that we use in our analysis,[2] and that using "actual" data would materially change our results:

> "We show that using *actual subscriber incomes* in the Cornerstone demand model would likely indicate significantly greater segmentation between premium- and non-premium brands, much higher diversion ratios among the non-premium brands…."[3] (emphasis added)

2. What they say is false and misleading. The BVZ analysis does not use actual income data to re-estimate our demand model. BVZ have replaced all income information with biased "data" that BVZ simply manufactured. They admit this replacement later in their submission, when they variously refer to the income "data" they use to re-estimate the demand model as "estimated,"[4] "predicted,"[5] or "imputed" income.[6] The analysis BVZ presented is distorted by their "data," misleading, and falls far short of any acceptable standard of economic analysis.

3. As we explain further below, BVZ do not use the NMP survey income data to re-estimate the demand model. They only "use" NMP survey income data to inaccurately "estimate" their own income "data" (§ 2, p. 5). Their income "data" are demonstrably biased, making any analysis that relies on them fundamentally unreliable and misleading. In particular, their "data" (a) falsely create an appearance of strong brand choice segmentation by income, and (b)

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[1] Coleman Bazelon, Jeremy Verlinda, and William Zarakas, "Reply to Cornerstone 'Response to Dish and CWA Comments,'" February 19, 2019 ("Bazelon, Verlinda, and Zarakas February 19 Submission"); and Coleman Bazelon, Jeremy Verlinda, and William Zarakas, "Economic Analysis of the Proposed Sprint/T-Mobile Merger Presented to Federal Communications Commission," February 25, 2019 ("Bazelon, Verlinda, and Zarakas February 25 Presentation").

[2] Bazelon, Verlinda, and Zarakas February 19 Submission, p. 23 ("However, Cornerstone ignores the self-reported income data in the NMP survey. … Figure 1 and Figure 2 highlight the significant differences in the two income variables.").

[3] Bazelon, Verlinda, and Zarakas February 19 Submission, p. 7.

[4] Bazelon, Verlinda, and Zarakas February 19 Submission, pp. 25 ("…we *estimate* a regression model of panelists' reported income…"), 26 ("…to *estimate* income for all panelists."), 27 ("Figure 3: Diversion Ratios with Income *Estimated* from NMP Responses … a higher value under the model with *estimated* incomes … a lower diversion ratio under the model with *estimated* incomes…."), 28 ("…the estimated diversion ratios under the *estimated* income information … in the original model than in the model with *estimated* panelist income."), and fn. 63 ("…necessitating use of interval regression techniques for the income *estimation* model.") (emphasis added).

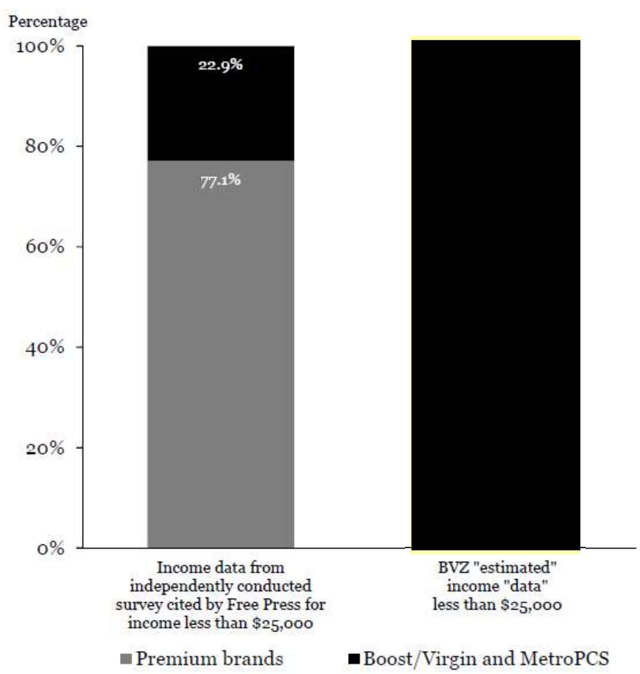
[5] Bazelon, Verlinda, and Zarakas February 19 Submission, p. 26 ("… replacing census median income information with *predicted* panelist income….") (emphasis added).

[6] Bazelon, Verlinda, and Zarakas February 19 Submission, fn. 65 ("…for the matched sample and the full sample with *imputed* income.") (emphasis added).

are starkly different from all available real-world income data sources, including data provided by other opponents of the proposed merger and the NMP survey data BVZ claim to use. Put differently, the BVZ income “data” purport to show that consumers with incomes below a certain level are extremely likely to choose non-premium brands. But this is simply not true (§ 3, p. 9). Using any of the available real-world income data sources, the results in our initial and subsequent white papers are unchanged (§ 4, p. 11).

4. Before we describe the erroneous process by which BVZ “estimate” their income “data,” we demonstrate the bias they introduce in Exhibit 1, where we compare their “data” to data presented by another opponent of the merger. In particular, we ask the following question: among consumers with income under $25,000 according to either (a) the survey data Free Press presented in their Petition to Deny (bar on the left), and (b) the income “data” BVZ use to re-estimate our demand model (bar on the right), what share choose AT&T, Sprint, T-Mobile, or Verizon as opposed to Boost/Virgin or MetroPCS?

EXHIBIT 1
Consumer choices among those with annual income less than $25,000 according to survey income data used by Free Press and the “estimated” income “data” BVZ used



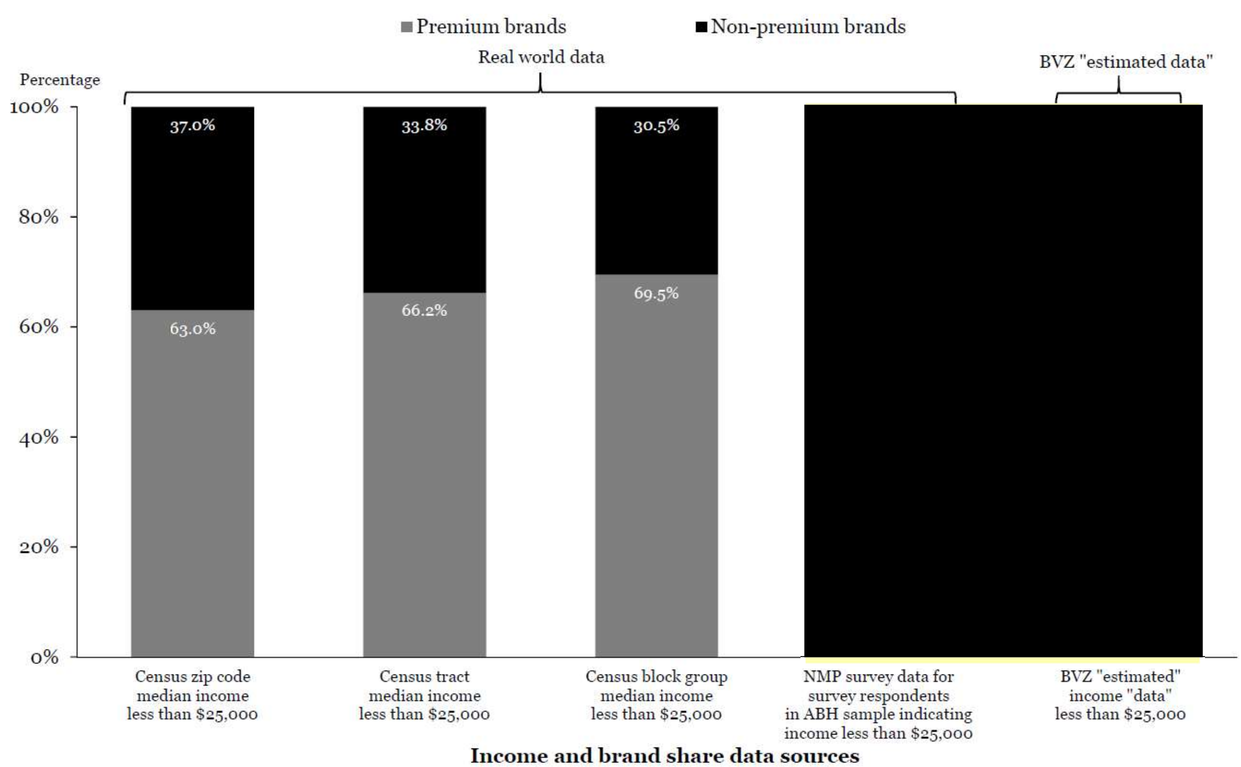
Source: KPMG Streamshare Data; Petition to Deny of Free Press, August 27, 2018, Figure 10, “Percent of Each Carrier’s Customers that Report Annual Income Below $25,000;” Backup of Bazelon, Verlinda, and Zarakas February 19 Submission

Note: For details on the BVZ income “data,” see § 2. For details on the income data used by Free Press, see Appendix § 5. Analysis limited to the Verizon, AT&T, T-Mobile, Sprint, Boost/Virgin, and MetroPCS brands. The data presented by FreePress does not include information on the share of consumers with incomes below $25,000 for any other brands.

5. The BVZ income "data" are starkly different from the Free Press data. The income "data" BVZ use have almost all consumers with income below $25,000 choosing Boost/Virgin or MetroPCS (the black portion of the bar on the right). This is entirely inconsistent with the subscriber shares implied by the data presented by Free Press, which shows Boost/Virgin and MetroPCS to be a distinct minority choice among such low-income consumers.

6. The BVZ income "data" are also starkly different from the NMP survey data, as well as all other real-world income data of which we are aware. In Exhibit 2 we add Cricket, MVNOs, and regional carriers to the analysis (omitted by Free Press and, hence, from Exhibit 1) and present premium and non-premium subscriber shares among Nielsen Mobile Performance ("NMP") consumers with income under $25,000 according to several sources. First we present four real-world sources of income data (three from the census and, as a fourth, the NMP survey data). In the rightmost bar, we present shares among the consumers to whom BVZ have assigned "income" below $25,000.

EXHIBIT 2
Consumer choices among those with annual income less than $25,000 according to four real-world income data sources and the "estimated" income "data" BVZ use



Source: KPMG StreamShare Data; Nielsen Mobile Performance Data; Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission; U.S. Census Bureau American Community Survey, 2016

Note: For details on the BVZ income "data," see § 2. For details on the real-world income data, see Appendix §§ 5, 7.

7. The income "data" BVZ use are the outliers, clearly standing out from any source of real-world income data of which we are aware. BVZ also claim to have conducted a "robustness check" to their analysis, stating:

> "As a robustness check, we also calculated the diversion ratios using *only* the NMP respondents *who reported their income*. We find similar market segmentation patterns for the matched sample and the full sample with imputed income."[7] (emphasis added)

8. To be clear, BVZ's backup reveals that even in their "robustness check," which focuses only on those individuals who provided income data to the survey ("the matched sample"), BVZ do not use the self-reported NMP survey income data to re-estimate the demand model and calculate diversion ratios. Instead, BVZ throw out the income data consumers self-reported (corresponding to the fourth bar in Exhibit 2) and replace them with their erroneously "estimated" income "data" (corresponding to the last bar in Exhibit 2, which looks nothing like the NMP survey data).

9. In the rest of this reply, we explain the erroneous process by which BVZ have "estimated" their biased income "data" (§ 2, p. 5); further demonstrate the ways in which the BVZ biased "data" create an artificial appearance of strong segmentation of brand choice by income (§ 3, p. 9); demonstrate that using any of the available real-world data sources, including the NMP survey data, supports the results and conclusions of our initial and subsequent white papers (§ 4, p. 11); and provide further details on data, results, and relevant academic literature in five appendices (starting on p. 17).

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[7] Bazelon, Verlinda, and Zarakas February 19 Submission, fn. 65.

2. BVZ do not clearly explain their methodology, which erroneously replaces survey income data with "estimates" of income

10. In their submission, BVZ do not clearly explain the process by which they "estimate" the income "data" they use to re-estimate our demand model.[8] However, they have provided backup and code, which we have used to understand and explain their process in detail within this section. BVZ have made no attempt to demonstrate their process is accurate. We explain in this section that their "estimation" exercise is not accurate.

11. First, BVZ start with income data from an optional survey that is administered to consumers contributing data to the NMP dataset. Consumers self-report income within a range, e.g., [redacted].[9]

12. Second, BVZ try to "estimate" the income responses of consumers for whom they have survey income data using other observable information about the consumers. They use (a) the wireless service brand the consumer chose, (b) the demographics of the consumer's home zip code, (c) the consumer's daily data usage in megabytes, (d) how geographically mobile they are, and (e) the number of days they are in the NMP data.[10]

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[8] BVZ describe their "estimation" approach in three short sentences and a footnote towards the end of their submission (on pp. 25–26, including fn. 63). These come between Figure 2 (which presents data from the NMP survey that they do not use to re-estimate our demand model) and Figure 3 (which present the diversion ratio results of their analysis where they re-estimate our demand model using their income "data"). In its entirety, including the footnote text, their explanation reads as follows: "In order to explore the potential effect of this issue, we consider a sensitivity analysis in which we estimate a regression model of panelists' reported income as a function of other information observed across the Cornerstone sample. NMP panelist reported income is recorded as income intervals [redacted], necessitating use of interval regression techniques for the income estimation model. We then use the regression results to estimate income for all panelists. We then re-estimate Cornerstone's demand model, replacing census median income information with predicted panelist income while preserving all other variables in the original Cornerstone report." Notably, while BVZ choose to report the data they *did not use* (Figure 2), they fail to report the income "data" they actually used. (We omit another footnote, fn. 64, which defends the survey but does not explain their process.)

[9] The income response brackets in the NMP survey are [redacted]. These data have important limitations and inconsistencies. Many consumers never report income. Of those that do, many offer contradicting responses over time. For more detail on the NMP survey data and their issues and limitations, see Appendix § 5 and Asker, Bresnahan, and Hatzitaskos November 6 White Paper, fn. 121. BVZ acknowledge (but proceed to sidestep) the inconsistent responses within their backup and code. See Backup of Bazelon, Verlinda, and Zarakas February 19 Submission, file "\Tables 4, 5 Figures 1-3, 6 NMP Income\2 NMP Survey Data\code\Clean NMP csv files.do." Since the survey dataset often includes multiple surveys filled by the same consumer, BVZ's approach keeps the latest answer any given consumer has given to the survey. Additionally, in lines 38–39, in the event that multiple responses are given by the same consumer in the same day, BVZ keep only the highest response. See Appendix 6 for additional details. Where we use the NMP survey income data (rather than the BVZ income "data"), we use the data as prepared by BVZ.

[10] Specifically, BVZ use Stata's "*intreg*" command to run an (unweighted) interval regression, which requires two dependent variables (the lower limit and the upper limit for each income interval). The interval regression assumes that consumers' incomes are a linear function of the explanatory variables. The *intreg* command attempts to predict a specific level of income for each consumer, based on the survey data and other observed

13. BVZ do not describe this list of variables, nor do they offer any argument that the list of variables is appropriate or sufficient to "estimate" income. Most importantly, BVZ do not (and cannot) justify their problematic and circular choice to (a) "estimate" income "data" based on brand choice, and to then (b) model brand choice using these income "data."[11] Put more starkly, BVZ appear to have "estimated" their "data" using a process that leads specifically to their incorrect "finding" of high diversion between Boost/Virgin and MetroPCS.

EXHIBIT 3
The overwhelming majority of income "data" that BVZ "estimate" are demonstrably different than the NMP survey data they are supposed to be predicting

Share of BVZ "estimation" of income falling outside of actual NMP survey income bracket

[redacted]

Source: Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission

Note: This analysis compares BVZ's assigned income "data" (*inc_estimated*) to the survey income bracket (*panelistincome*) of each demand estimation consumer that answered the survey.

variables. BVZ amend the model to predict the log of income. After estimating the interval regression model, they find predicted log incomes for every consumer in the sample. Finally, BVZ takes the exponential of each consumer's log incomes to get predicted income levels.

[11] Including brand choice in the set of conditioning variables in the interval regression to "estimate" income "data" induces correlation between the income "data" and unobserved determinants of brand choice in the choice model. This then leads to bias when BVZ rerun the demand model and exacerbates the effect of their income "data." That is, BVZ use a linear function of brand choice to predict brand choice. See Joshua D. Angrist and Jorn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, (Princeton, NJ: Princeton University Press, 2009), p. 64 ("Some variables are bad controls and should not be included in a regression model.... Bad controls are variables that are themselves outcome variables.... That is, bad controls might just as well be dependent variables too.").

14. Third, BVZ proceed without making any attempt to demonstrate that the "estimation" process that generates their income "data" is accurate. In fact, it is not accurate. The BVZ "estimates" bear little resemblance to the NMP survey data that they purportedly try to estimate. More specifically, in Exhibit 3 we show that the BVZ "estimate" gets the income bracket wrong for 76.9 percent of the [redacted] consumers for whom they have NMP survey income data. For example, BVZ erroneously "estimate":

- Income *above* $25,000 for 83.9 percent of the [redacted] consumers who report incomes *below* $25,000 in the NMP survey data.
- Income below $100,000 for *all* of the [redacted] consumers who report incomes above $100,000 in the NMP survey data.[12]

15. These are serious departures from the original NMP survey data. Several income brackets span $15,000 or more. By routinely "estimating" income incorrectly even by a single bracket, the BVZ "estimation" exercise mispredicts income for individuals by many thousands of dollars. In fact, BVZ incorrectly "estimate" income by two or more brackets for 35.2 percent of consumers who report income in the NMP survey data.[13]

16. Fourth, BVZ rely on this error-prone process instead of using the real-world survey data that they "estimate."[14] BVZ use their income "estimates" to replace the actual survey data, even where they have survey data. So BVZ replace real income data with "estimated" income "data" that tend to be far from the actual data.

17. Note that while BVZ once refer to their "data" as "imputed" rather than "estimated" income,[15] what they have done is not imputation. Economists and statisticians refer to imputation as the process of filling in missing data.[16] What BVZ have done instead is use an erroneous process to *replace all data* with

[12] See our workpapers.

[13] See our workpapers.

[14] Bazelon, Verlinda, and Zarakas February 19 Submission, p. 7 ("Alternatively, a significant fraction of NMP respondents provided [redacted] income information as part of the survey.... We show that using actual subscriber incomes in the Cornerstone demand model would likely indicate significantly greater segmentation between premium- and non-premium brands, much higher diversion ratios among the non-premium brands, and significantly higher price increases from the merger.").

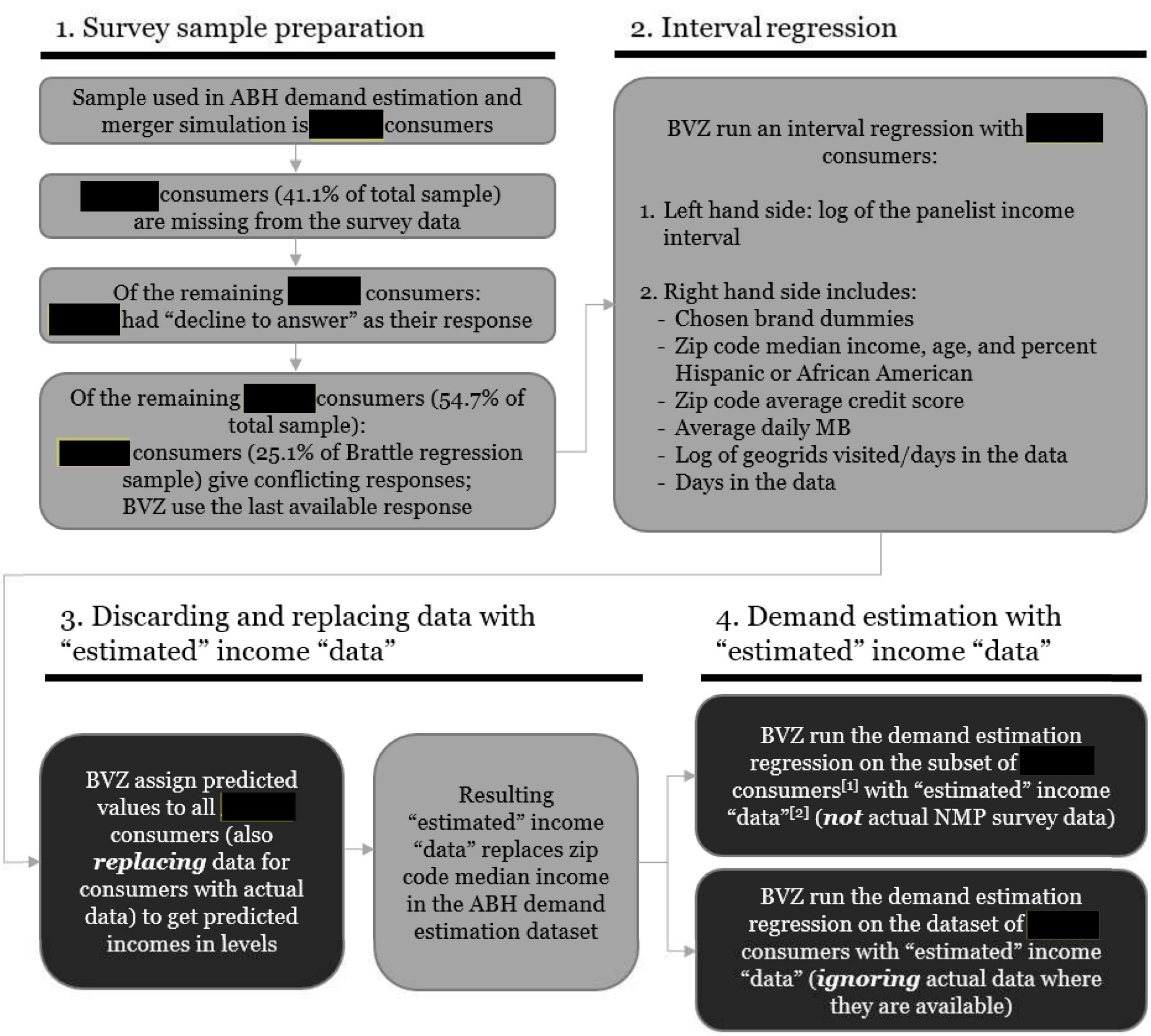
[15] Bazelon, Verlinda, and Zarakas February 19 Submission, fn. 65.

[16] See Appendix § 9 for examples from five econometrics and statistics textbooks. We ourselves have (properly) applied imputation within our analysis, as we explain clearly in some detail in our initial white paper. See Asker, Bresnahan, and Hatzitaskos November 6 White Paper, § 5.1.6, "Imputing missing data for non-premium brands." In particular, we use imputation to fill in missing network quality data for non-premium brands when that data are missing but when data are available for the premium brand that runs on the same network.

biased data, not to fill in missing data with appropriately estimated imputed data.

18. Finally, we summarize in a schematic that we present in Exhibit 4 the process by which BVZ "estimate" the income "data" that they use to re-estimate our demand model.

EXHIBIT 4
Steps taken by BVZ to "estimate" their inaccurate and misleading income "data"



Source: KPMG StreamShare Data; Nielsen Mobile Performance Data; Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission

Note:

[1] [redacted] users (with reported survey incomes greater than $100,000) are dropped from the subset of [redacted] users with survey income data because of a BVZ coding error, resulting in a regression on only [redacted] users.

[2] When running the regression on the subset of [redacted] users, BVZ incorrectly maintain the weights used to make the sample of [redacted] users nationally representative because of a BVZ coding error.

3. The income "data" that Bazelon, Verlinda, and Zarakas "estimate" are biased

19. The BVZ income "data" are biased in a way that has the effect of artificially segmenting brand choice by income. Real-world income data do not show such segmentation.[17] Put differently, the BVZ data purport to show that consumers with incomes below a certain level are, contrary to fact, extremely likely to choose non-premium brands. Consider that:

- According to the BVZ income "data," Boost, MetroPCS, and Cricket hold [redacted] percent share among consumers with income below $25,000. This is about four times their share of this segment according to the NMP survey data, which indicate their share is only [redacted] percent.
- According to the BVZ income "data," AT&T and Verizon hold just [redacted] percent share among consumers with income below $25,000. This is about an *order of magnitude* less than their share according to NMP survey data, which indicate that their share of this segment is [redacted] percent.[18]

20. To make this clearer, in Exhibit 5 we compare the actual NMP survey data BVZ claim to use to the income "data" that they actually use to re-estimate our demand model. The stark difference between the two explains the BVZ "finding" of high diversion between the Boost/Virgin and MetroPCS brands.[19]

21. In particular, the top panel in Exhibit 5 reproduces BVZ's Figure 2. These are the survey data BVZ present but do not use to re-estimate our demand model.[20] The lighter bars show the distribution of income among consumers who have chosen the premium AT&T, Sprint, T-Mobile, or Verizon brands. The darker bars show the distribution of income among consumers who have chosen the Boost/Virgin, Cricket, MetroPCS, and "other" brands.[21]

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[17] We present details on each real-world income data source in Appendix § 5.

[18] See Exhibit 14 in Appendix § 7.

[19] In the next section we also explain that this "finding" cannot be reproduced using any real-world income data sources of which we are aware.

[20] As we explain in the next section, using these data to re-estimate our demand model reproduces the results we reported in our initial white paper. Where we use the NMP survey income data (rather than the BVZ income), we use the data as prepared by BVZ for their Figure 2.

[21] Note that, even among low-income groups, more consumers choose premium brands than non-premium brands. Even though some of the darker bars are higher than the corresponding lighter bars, premium brands hold a majority share even among low-income consumers, consistent with Exhibit 1 and Exhibit 2. For example, [redacted] consumers who self-reported income below $25,000 in the NMP survey chose non-premium brands, while [redacted] consumers with the same level of self-reported income chose premium brands. See Appendix § 6 and Exhibit 11 for details.

22. BVZ take the data in the top panel, run them through their "estimation" process, and generate the "data" on the bottom panel of Exhibit 5. The bottom panel shows the "data" BVZ use to re-estimate our demand model and calculate diversion ratios in their Figure 3 analysis, which purports to "find" high diversion between Boost/Virgin and MetroPCS. BVZ do not present the "data" in the bottom panel of Exhibit 5, which look nothing like the data they are supposed to be "estimating" (shown in the top panel).

EXHIBIT 5
Distribution of income among consumers choosing premium and non-premium brands: actual NMP survey data BVZ claim to use vs. the income "data" BVZ actually use

[redacted]

Source: Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission
Note: [1] Dark-colored bars show the percentage of non-premium consumers assigned to each income bracket, out of all non-premium consumers. Ligher-colored bars show the percentage of premium consumers in each income bracket, out of all premium consumers. For example, in the NMP survey data, [redacted] of all premium brand consumers who reported income stated their income was below $25,000. In the BVZ "data," only [redacted] of all premium consumers were assigned an income of less than $25,000.

23. It is instructive to compare the two panels of Exhibit 5 and note how the bottom panel artificially separates consumers who choose premium and non-premium brands in a way not present in the NMP survey data.

- In the top panel, the NMP survey income data, there are as many lower-income consumers choosing premium brands as there are higher-income consumers: [redacted] percent of premium brand consumers have incomes below $25,000, while [redacted] percent have incomes above $75,000. There are also higher-income consumers who choose non-premium brands: [redacted] percent of non-premium brand consumers have incomes above $75,000.
- In the bottom panel, the BVZ income "data" artificially separate the two distributions. BVZ "estimate" that only [redacted] percent of consumers who choose premium brands have incomes below $35,000 and that only [redacted] percent have incomes below $25,000. In contrast, they "estimate" that only [redacted] percent of consumers who choose non-premium brands have incomes above $35,000.[22]

24. Whereas the NMP survey data show substantial overlap in the incomes of consumers who choose premium and non-premium brands, the BVZ income "data" impose a strong separation between the two groups. It is not surprising that BVZ "find" that there is strong segmentation by income when they re-estimate our demand model using their "data," which artificially impose important income differences on consumers who choose premium and non-premium brands. Their "finding" follows from their analyzing erroneous and misleading "data." As we show in the next section, their "finding" cannot be reproduced with actual real-world income data.

4. Every available real-world income data source, including the NMP survey data, confirms the findings and conclusions of our initial white paper

25. We have undertaken the analysis that BVZ claim to conduct, using more disaggregated or individual income data in our demand model than we used in our initial white paper. Every real-world demographic dataset of which we are aware (including the NMP survey data) supports our prior findings regarding

[22] They also predict that only [redacted] consumers have income above $100,000 and that they [redacted] choose AT&T. In the actual NMP survey data, [redacted] consumers report incomes above $100,000 and [redacted] percent of them choose AT&T. See our workpapers.

diversion and segmentation. They also all support our ultimate conclusion: that the proposed merger is likely to be procompetitive.

26. We first test whether using less aggregated census measures of income has any effect, specifically census tract or census block group median incomes.[23] We find no change to our results. We then test whether there is any effect from using the individual-level NMP survey income data that BVZ do not actually use in re-estimating our demand model. We again find no change to our results.

27. To illustrate the differences between zip codes (which our initial white paper uses), tracts, and block groups (which are more granular than zip codes), we present an example in Exhibit 6 for zip code 20009, in Washington, DC.

- In Exhibit 6, the entire *zip code* is represented by light gray and covers an area of approximately 1.3 square miles, a population of approximately 48,000 and a median income of approximately $98,000.
- Each zip code can be further subdivided into *census tracts*. Census tracts are generally designed to contain 1,200 to 8,000 people.[24] The dashed line illustrates one census tract within zip code 20009. Its irregular shape covers approximately 0.08 square miles, with a population of approximately 4,000 and a median income of $105,000.
- Finally, census tracts can be further subdivided into *census block groups*. These are significantly smaller, generally designed to contain 600 to 3,000 people.[25] For example, the darker gray rectangle within the outlined census tract represents a single census block group that covers

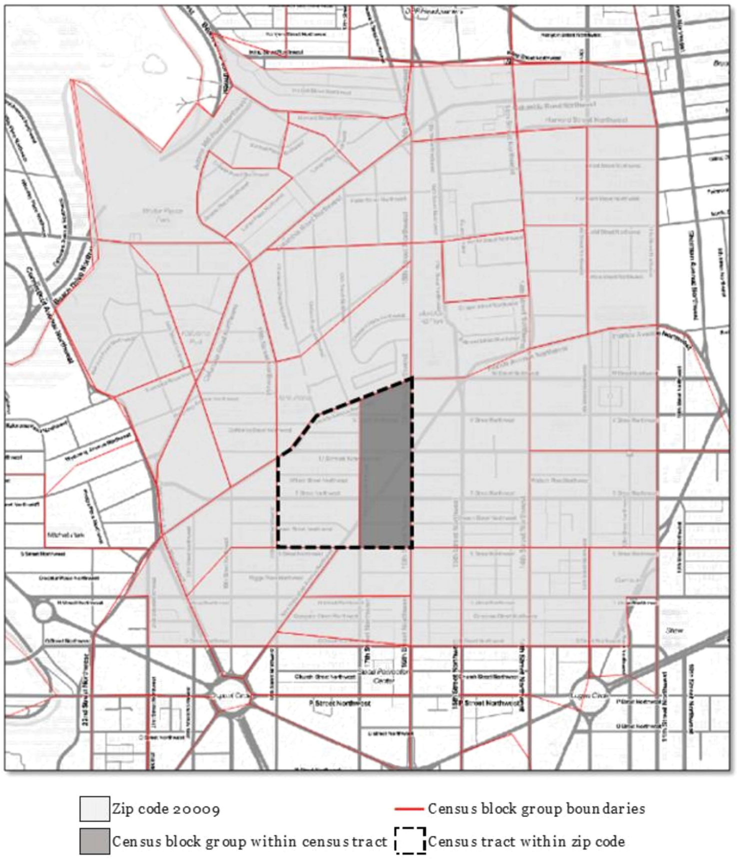
[23] Our initial white paper uses census demographics at the zip code level. The academic literature frequently uses census demographics at the zip code level, as we do, or at even more aggregate levels, such as media Designated Market Areas ("DMAs") or commuting zones. For example, see Gregory J. Martin and Ali Yurukoglu, "Bias in Cable News: Persuasion and Polarization," American Economic Review, Vol. 107, No. 9, September 2017, pp. 2565–2599 at 2571; Gregory S. Crawford and Ali Yurukoglu, "The Welfare Effects of Bundling in Multichannel Television Markets," American Economic Review, Vol. 102, No. 2, February 2012, pp. 643–685 at 653; Raj Chetty, Nathaniel Hendren, and Lawrence F. Katz, "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment," American Economic Review, Vol. 106, No. 4, April 2016, pp. 855–902 at 863; David Figlio, Jonathan Guryan, Krzysztof Karbownik, and Jeffrey Roth, "The Effects of Poor Neonatal Health on Children's Cognitive Development," American Economic Review, Vol. 104, No. 12, December 2014, pp. 3921–3955 at 3941; Amy Finkelstein, Matthew Gentzkow, and Heidi Williams, "Sources of Geographic Variation in Health Care: Evidence from Patient Migration," The Quarterly Journal of Economics, Vol. 131, No. 4, November 2016, pp. 1681–1726 at 1697, 1716; David H. Autor, David Dorn and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," American Economic Review, Vol. 103, No .6, October 2013, pp. 2121–2168 at 2132–2133.

[24] United States Census Bureau, "Geographic Terms and Concepts – Census Tract," available at https://www.census.gov/geo/reference/gtc/gtc_ct.html, accessed on March 5, 2019.

[25] United States Census Bureau, "Geographic Terms and Concepts – Block Groups," available at https://www.census.gov/geo/reference/gtc/gtc_bg.html, accessed on March 5, 2019.

approximately 0.04 square miles, with a population of approximately 1,500 people and a median income of $84,000.[26]

EXHIBIT 6
Census tracts and block groups for zip code 20009 in Washington, DC



Source: U.S. Census Bureau – Cartographic Boundary Shapefiles – ZIP Code Tabulation Areas (ZCTAs), available at: https://www.census.gov/geo/mapsdata/data/cbf/cbf_zcta.html, accessed October 12, 2018; U.S. Census Bureau – Cartographic Boundary Shapefiles – Census Tracts, available at: https://www.census.gov/geo/maps-data/data/cbf/cbf_tracts.html, access March 1, 2019; U.S. Census Bureau – Cartographic Boundary Shapefiles – Block Groups, available at https://www.census.gov/geo/maps-data/data/cbf/cbf_blkgrp.html, accessed March 1, 2019

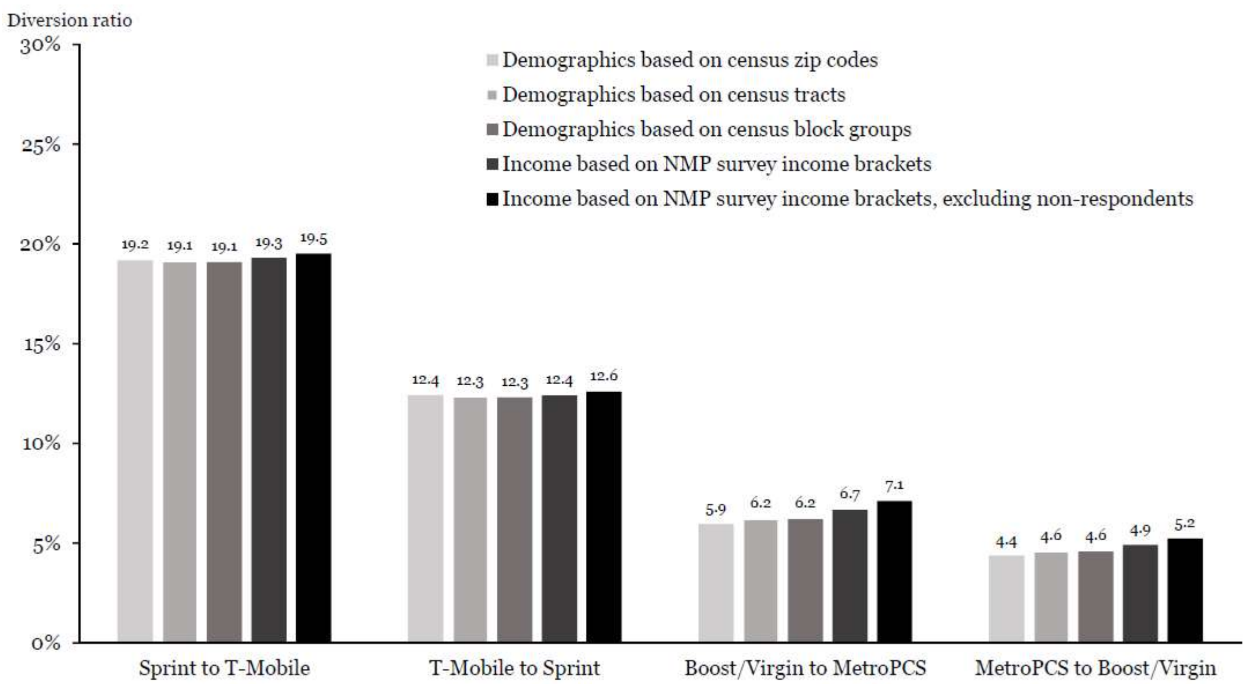
28. As we explain below, using demographic information at any census level has no meaningful effect on the diversion ratios we calculate or on the merger simulation results. Our results also do not change if instead of census-based data we use NMP survey income data. We do this in two ways, neither of which changes our results. First, we conduct our analysis using only the subset of consumers who have provided income information in the NMP survey. Second, we conduct our analysis on all consumers, flexibly allowing consumers who did

[26] See our workpapers.

not provide income information in the survey to have their own set of preferences over brands.[27]

29. In Exhibit 7 we present the diversion ratios between various merging party brands under our baseline specification using census zip code data and each of the alternatives we described above. Using more granular real-world income data does not meaningfully affect the estimated diversion ratios.[28]

EXHIBIT 7
Diversion ratios between the merging party brands are similar regardless of whether we assign demographics at the census zip code, tract, or block group level, or whether we replace census income with NMP self-reported survey income brackets



Source: KPMG StreamShare Data; Nielsen Mobile Performance Data; Nielsen Mobile Performance Survey Data.
Note: Diversion from brand j to brand k is calculated for individual consumers as the change in share of brand k divided by the change in share of brand j due to a $1 increase in price of brand j. See Appendix § 5 for a discussion of the different demographic and income data.

30. We also conduct our merger simulation using these different methods of assigning demographics for the conservative scenario where Sprint catches up

[27] See Appendix § 8.

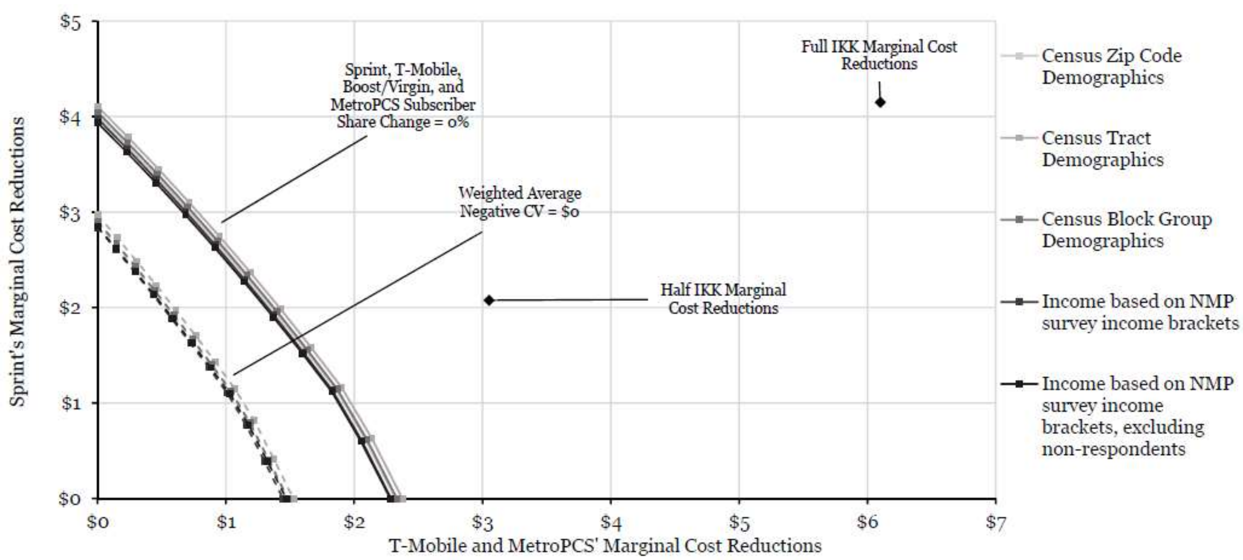
[28] We provide full diversion ratio tables between all brands as well as detailed demand estimation results in our workpapers. Free Press provides the within-brand share of individuals with income under $25,000. We therefore cannot re-estimate our entire analysis using the Free Press data, which lacks more granular information on consumer choices for consumers with income above $25,000. See Appendix § 5.

to T-Mobile on coverage and T-Mobile catches up to Sprint on speed.[29] Our results are robust to using any of the available real-world income data sources.

31. In Exhibit 8 we present the critical marginal cost reductions for procompetitive outcomes under which (a) the merging party brands gain share, or (b) consumer welfare increases. Regardless of how we assign demographics, the results do not qualitatively change. In each case, the marginal cost reductions estimated by Israel, Katz, and Keating are well above the critical marginal cost reductions, even if conservatively cut in half.[30]

EXHIBIT 8

Merger simulations using census zip code, tract, block group, and NMP survey demographics all yield nearly identical results: Critical marginal cost efficiencies with best-of-both scenario



Source: KPMG StreamShare Data; Nielsen Mobile Performance Data

Note: [1] The subscriber share of NewCo is weighted by post-merger choice probabilities across brands and consumer weights (based on SOS) and Sprint, T-Mobile, Boost/Virgin, and MetroPCS' combined subscriber share in the standalone scenario is weighted by the standalone choice probabilities across brands and consumer weights (based on SOS). The weighted average negative compensating variation reflects the difference in expected consumer utility in the standalone scenario and expected consumer utility in the merger scenario expressed in monetary terms, weighted by consumer weights (based on SOS).
[2] In the merger scenario, Sprint's measure of percent of time on LTE is equal to T-Mobile's measure of percent of time on LTE at the geogrid level if its standalone value is less than T-Mobile's. Boost/Virgin's measure of percent of time on LTE is imputed from Sprint's measure at the geogrid level if it is greater than its standalone value. T-Mobile's measure of download speed is equal to Sprint's measure of download speed at the geogrid level if its standalone value is less than Sprint's. MetroPCS' measure of download speed is imputed from T-Mobile's measure at the geogrid level if it is greater than its standalone value. Boost/Virgin's cost reductions are $1 less than the indicated Sprint marginal cost reduction, unless it goes below $0. In this case, marginal cost reductions are $0.
[3] See Asker, Bresnahan, and Hatzitaskos November 6 White Paper for details on the data, processing, and variable definitions.

[29] For a detailed description of this scenario, see Asker, Bresnahan, and Hatzitaskos November 6 White Paper, § 4.2.4, "Critical marginal cost efficiencies assuming conservative improvements for Sprint in coverage and for T-Mobile in speed."

[30] Declaration of Mark Israel, Michael Katz, and Bryan Keating, September 17, 2018.

32. BVZ's own estimation results refute their repeated, false assertions that our model must find diversion proportional to shares.[31] When BVZ re-estimate our demand model using their income "data," which are unlike real-world data, they validate that our model is entirely capable of finding diversion ratios between Boost/Virgin and MetroPCS that are "drastically different" from shares even in the aggregate.[32]

33. By contrast, the robustness of our results to using real-world income data demonstrates that, as we have previously explained, our findings are driven by the data, not assumptions.[33] All real-world data of which we are aware indicate that the proposed merger is likely to enhance competition and benefit consumers.[34]

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[31] Coleman Bazelon, Jeremy Verlinda, and William Zarakas, "Response to Applicant Filings on Diversion Ratios," January 28, 2019 ("Bazelon, Verlinda, and Zarakas January 28 Submission"), p. 23 ("…the model does not 'find' approximate share proportionality, but instead just assumes it."), p. 24 ("Cornerstone's demand model is built on an underlying assumption of share-proportional diversion."), p. 24 ("…its reproduction of share-proportional diversion is pre-determined by the model's underlying assumptions…"), p. 25 ("…because the individual choice probabilities still add up to observed shares, we would still expect diversion under the Cornerstone model specification to be approximately close to share proportionality."), p. 26 ("It is, effectively, an alternative calculation for determining diversion as proportional to shares."), p. 28 ("The Cornerstone demand model is incapable of capturing market segmentation that would allow for subsets of products to be closer substitutes than their aggregate wireless shares."); Bazelon, Verlinda, and Zarakas February 19 Submission, p. 22 ("…the claimed attractiveness of Cornerstone's model—that it is an individual-level logit demand model based on detailed data—is negated by its limited ability to identify switching behavior other than in proportion to the carriers' shares.").

[32] Bazelon, Verlinda, and Zarakas January 28 Submission; Bazelon, Verlinda, and Zarakas February 19 Submission, p. 26, ("We then re-estimate Cornerstone's demand model, replacing census median income information with predicted panelist income while preserving all other variables in the original Cornerstone report. The resulting diversion ratio estimates are *drastically different* from those of the original Cornerstone model…," emphasis added).

[33] Asker, Bresnahan, and Hatzitaskos February 6 White Paper, § 2.1, "Our analysis estimates diversion ratios at the individual level that deviate sharply from share-based diversion."

[34] Furthermore, in our first response to BVZ, we pointed out that their critiques were incomplete. BVZ had modified our demand model but failed to run their modifications through a complete merger simulation analysis. Doing so demonstrated that the bottom-line metrics that inform whether the proposed merger is procompetitive did not change – even under their modifications, the proposed merger was procompetitive. See Asker, Bresnahan, and Hatzitaskos December 18 White Paper, ¶ 63. This is the case here once again. Even if one were to accept the erroneous BVZ income "data" (despite the fact that these "data" are inconsistent with all sources of real-world income data of which we are aware), it is still the case that a merger simulation shows the proposed merger to be procompetitive under a wide range of assumptions regarding marginal cost efficiencies and network quality improvements. See our workpapers.

5. Appendix: details on different real-world sources of income data

34. **Census data at the zip code, tract, and block group level.** We use census-based data at the zip code, tract, and block group level to assign demographic information to consumers. The U.S features approximately 33,000 zip code tabulation areas,[35] 73,000 census tracts, and 218,000 census block groups.[36] Census tracts are designed to "provide a stable set of geographic units for the presentation of statistical data" and are generally smaller than zip codes, designed to have 1,200 to 8,000 people.[37] Census tracts vary widely in spatial size due to differences in population density.[38] Census block groups represent a cluster of blocks within the same census tract, and are therefore smaller than census tracts, generally containing between 600 and 3,000 people.[39]

35. As we discussed in our initial white paper, in order to assign demographic information to consumers based on census demographic information at the zip code level, we assume that consumers are most likely to be home during the night and early morning hours.[40] We define a home zip code as the zip code in which the consumer has the most events between the hours of 2am and 6am. If the consumer has no events between 2am and 6am, we extend the window and identify the zip code in which the consumer has the most events from 10pm to 10am. We designate this to be the home zip code for the particular consumer.

36. We assign demographic information to consumers based on census data at the census tract and census block group levels in the same way. When census tract level demographic information is censored, for privacy or statistical reasons, we use the demographic information assigned based on the

[35] In mapping demographics, our methodology uses zip code tabulation areas (ZCTAs) instead of zip codes. See United States Census Bureau, "Zip Code Tabulation Areas," available at https://www.census.gov/geo/reference/zctas.html, accessed on March 5, 2019. See also, United States Census Bureau, "2010 Census National Geographic Tallies," available at https://www.census.gov/geo/maps-data/data/tallies/national_geo_tallies.html, accessed on March 7, 2019.

[36] United States Census Bureau, "2010 Census Tallies of Census Tracts, Block Groups & Blocks," available at https://www.census.gov/geo/maps-data/data/tallies/tractblock.html, accessed on March 5, 2019.

[37] United States Census Bureau, "Geographic Terms and Concepts – Census Tract," available at https://www.census.gov/geo/reference/gtc/gtc_ct.html, accessed on March 5, 2019.

[38] United States Census Bureau, "Geographic Terms and Concepts – Census Tract," available at https://www.census.gov/geo/reference/gtc/gtc_ct.html, accessed on March 5, 2019.

[39] United States Census Bureau, "Geographic Terms and Concepts – Block Groups," available at https://www.census.gov/geo/reference/gtc/gtc_bg.html, accessed on March 5, 2019.

[40] See Asker, Bresnahan, and Hatzitaskos November 6 White Paper § 5.1.8.

consumers' home zip code. This happens for at least one demographic variable for about 0.3 percent of NMP consumers in our demand estimation sample.[41]

37. When census block group level demographic information is censored, we use the demographic information assigned to the consumer based on the consumers home census tract, which happens for at least one demographic variable for 2.3 percent of consumers in our demand estimation sample.[42] The variables we use to calculate share African-American or Hispanic are always censored at the block group level, so we instead calculate this share at the census tract level.

38. **Free Press data.** In its Petition to Deny, Free Press provides a figure that shows the percent of each carrier's customers who report annual incomes below $25,000.[43] Free Press shows these percentages only for the following carriers: AT&T, Verizon, T-Mobile, Sprint, Boost, Virgin, and MetroPCS.

39. Free Press cites a February 2018 S&P Global Market Intelligence MediaCensus survey of 10,000 U.S. internet adults as the source for the figure. We find subscriber shares by multiplying the number of subscribers per brand based on KPMG data by the percent of each brand's customers that have annual incomes less than $25,000 in Figure 10 of Free Press' Petition to Deny.[44]

40. **NMP survey data.** Finally, the last real-world demographic data source we employ is the one that BVZ use to erroneously "estimate" their income "data," namely, the NMP survey data included with the rich network quality and consumer behavior data that we employ in our analysis.

41. As we have previously noted,[45] the NMP data contain surveys with measures of customer satisfaction, self-reported income, and education. NMP consumers have multiple opportunities to respond to these survey questions and many respond more than once. However, many consumers never respond. Those that

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[41] See our workpapers.

[42] See our workpapers.

[43] Petition to Deny of Free Press, August 27, 2018, Figure 10, "Percent of Each Carrier's Customers that Report Annual Income Below $25,000"

[44] Free Press reports separate percentages for Boost and Virgin, 34 and 26 percent, respectively, while our dataset combines these brands into one. We calculate the combined Boost/Virgin brand to have 33.1 percent of their subscribers with annual incomes below $25,000, the weighted average share of the two brands. See our workpapers.

[45] Asker, Bresnahan, and Hatzitaskos November 6 White Paper, fn. 121 and § 5.1.1, "The NMP data."

respond multiple times frequently report inconsistent data for information that should be relatively stable within a three-month period.

- Among those who responded, [redacted] percent reported income on multiple occasions and gave inconsistent answers.
- Another [redacted] percent of respondents gave multiple inconsistent answers on their education level.[46]

42. In Exhibit 9 and Exhibit 10, we provide examples of specific individual responses in successive months to the survey questions on income and education. For example:

- [redacted]
- [redacted]

EXHIBIT 9
Examples of inconsistent NMP survey responses for income

[redacted]

[46] See our workpapers.
[47] The specific wording of the survey questions was provided by Nielsen.
[48] The specific wording of the survey questions was provided by Nielsen.

EXHIBIT 10
Examples of inconsistent NMP survey responses for education

[redacted]

6. Appendix: detail on premium and non-premium choices by income bracket

43. In Exhibit 11 we present the data underlying Exhibit 5 to make clear that, even within the NMP survey income data that BVZ use to "estimate" their income "data," a majority of low-income consumers choose premium brands.

44. In particular, BVZ's Figure 2 (recreated as the top panel of Exhibit 5) presents the fraction of consumers that choose premium (or non-premium) brands that have income within a given range according to the NMP survey data. In other words, the denominator is the total number of consumers who choose premium (or non-premium) brands, *not* the number of consumers with income in some range, e.g., under $25,000. Put differently, the two bars within each income range do not add up to 100 percent. Instead, the bars of a single color add up to 100 percent across all income ranges.

45. In the top panel of Exhibit 11 we present the counts of consumers who provide income information in response to the NMP survey. This clarifies that even lower-income consumers are more likely than not to choose premium brands. For example, among those who reported incomes below $25,000, [redacted] chose non-premium brands, while [redacted] chose premium brands.

46. In the bottom panel of Exhibit 11 we present the counts of consumers who choose premium and non-premium brands according to the erroneous income "estimation" process that yields the income "data" BVZ actually use to re-estimate our demand model. It is clear that these "data" look nothing like the income data in the NMP survey they are supposed to be "estimating."

EXHIBIT 11
Count of survey respondents of premium and non-premium brands, by income bracket: actual NMP survey data vs. BVZ income "data"

[redacted]

Source: Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission
Note: On the top panel, dark-colored bars show the count of non-premium subscribers in each income bracket based on survey responses, while lighter-colored bars show the count of premium subscribers in each income bracket. The lower panel shows the equivalent counts in BVZ's income "data," for the same set of respondents that had answered the survey. For example, in the NMP survey data, [redacted] subscribers in a premium brand reported income below $25,000. In the BVZ "data," only [redacted] premium subscribers were assigned income of less than $25,000.

47. To underscore how badly BVZ "estimate" the NMP survey data, we present these data in a different format and broken out by individual brand in Exhibit 12. In particular:

- The top panel shows the distribution of income brackets for each brand according to the actual NMP survey data. Each brand, including Verizon, has more than [redacted] percent of its consumers with self-reported incomes below $25,000. Conversely, each brand, including non-premium brands, has at least [redacted] percent of its consumers who self-report incomes that are above $75,000.

- The bottom panel shows how the BVZ "estimation" process distorts the data in the top panel. The BVZ income "data" purport to show that each brand has at least [redacted] percent of its consumers within just two income brackets.

EXHIBIT 12
Distribution of income bracket by brand: actual NMP survey data vs. BVZ income "data"

[redacted]

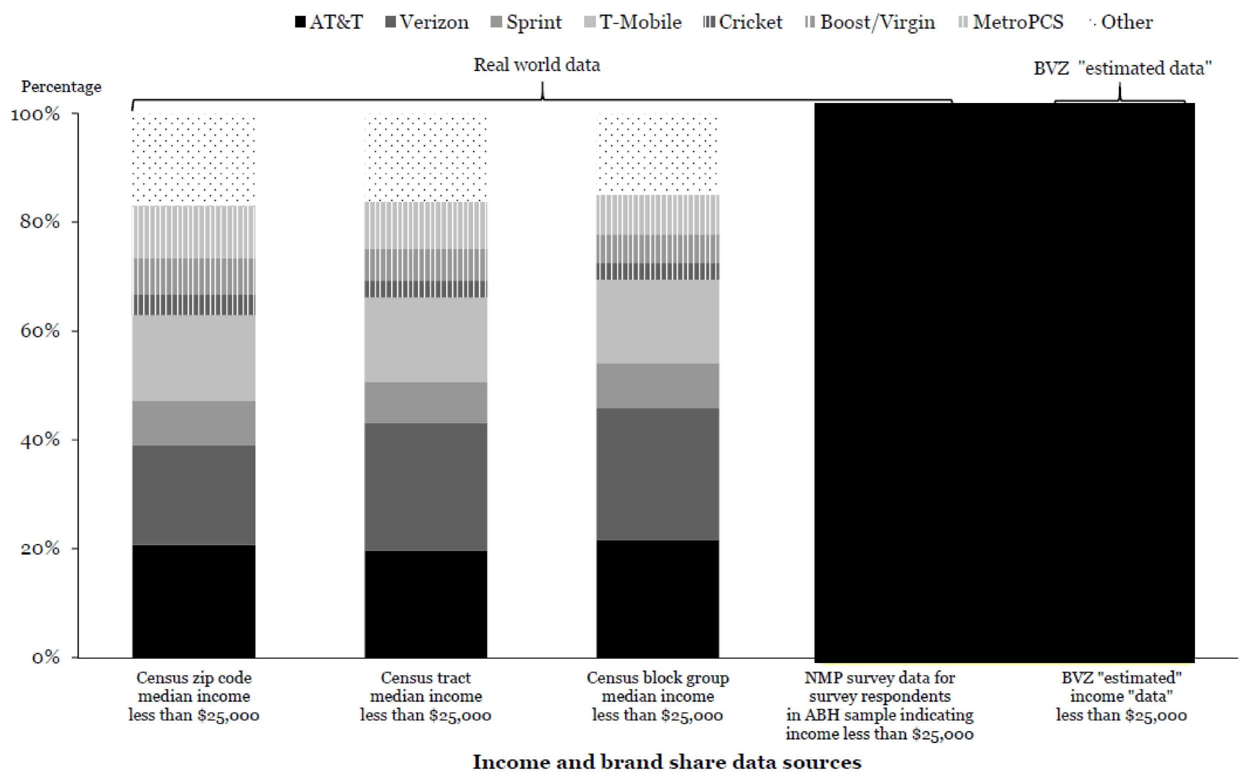
Source: KPMG StreamShare Data; Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission

Note: Only consumers who respond to the NMP survey are included in this analysis. Consumers are weighted by the KPMG subscriber shares. We rely on the same methodology used by BVZ to assign income to consumers based on their survey responses. The most recent survey response is used. In the case that a consumer responded to the same survey on the same day, the higher income level is used.

7. Appendix: detail on share data for consumers with income under $25,000

48. In Exhibit 13 we disaggregate the results in Exhibit 2 by brand. In Exhibit 14 we provide the numerical values underlying Exhibit 13.

EXHIBIT 13
Brand share of subscribers with annual income less than $25,000 according to four real-world income data sources and the income "data" BVZ actually use



Source: KPMG StreamShare Data; Nielsen Mobile Performance Data; Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission; U.S.Census Bureau American Community Survey, 2016
Note: For details on the BVZ income "data," see § 2. For details on the real-world income data, see Appendix § 5.

EXHIBIT 14
Underlying data on share of consumers with annual income less than $25,000 according to four real-world income data sources and the income "data" BVZ actually use

Income/brand share data source	AT&T	Verizon	Sprint	T-Mobile	Cricket	Boost/Virgin	MetroPCS	Other	Total
Census zip code median income less than $25,000	20.7%	18.3%	8.2%	15.9%	3.7%	6.8%	9.5%	17.0%	100.0%
Census tract median income less than $25,000	19.7%	23.4%	7.5%	15.6%	3.0%	5.9%	8.7%	16.3%	100.0%
Census block group median income less than $25,000	21.7%	24.1%	8.2%	15.5%	3.0%	5.3%	7.2%	15.0%	100.0%
NMP survey data for survey respondents in ABH sample indicating income less than $25,000	[redacted]								100.0%
BVZ "estimated" income "data" less than $25,000									100.0%

Source: KPMG StreamShare Data; Nielsen Mobile Performance Data; Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission; U.S.Census Bureau American Community Survey, 2016
Note: For details on the BVZ income "data," see § 2. For details on the real-world income data, see Appendix § 5.

8. Appendix: detailed demand estimation results using actual NMP survey income data

49. To test the assertion by BVZ that using the NMP survey income data may change our results, we present demand estimates where we flexibly allow for different survey income levels to affect brand preferences.

50. In particular, we replace the census zip code income variable with a series of dummy variables, one for each of the NMP self-reported survey income brackets. We then conduct our demand estimation in two alternative ways: either including individuals who did not respond to the survey (or responded but declined to provide income information) as a "missing" category, or by focusing entirely on the subset of individuals who provided income data.

51. These two specifications, which we report in Exhibit 15 and Exhibit 16, respectively, do not materially change the results of our demand model. The following notes apply to both exhibits.

- [1] See Initial White Paper Appendix for details on the data, processing, and variable definitions. Light, medium, and heavy data user shares are [redacted] percent, [redacted] percent, and [redacted] percent respectively.
- [2] Consumer characteristics other than income are measured at the census zip code level and correspond to the individual's home zip code.
- [4] The McFadden R2 is a standard measure of goodness of fit in models estimated using the maximum likelihood estimation method. The McFadden R2 falls between 0 and 1, and a higher McFadden R2 value indicates better model fitness.
- [5] Change in R2 relative to FE only compares the McFadden R2 in the model to the McFadden R2 in a model only with location-brand and brand fixed effects.

52. The following note applies to Exhibit 15.

- [3] This model specification includes interacting dummies for survey data income brackets. The omitted category for survey data income brackets is "missing," i.e., those consumers who did not answer the income question.

EXHIBIT 15

Estimates from demand model assigning income using NMP survey income brackets, including "missing" response as an omitted category

	Variable	Coefficient [1]		
		Light Data Users	Medium Data Users	Heavy Data Users
1.	Speed	0.260**	1.225***	2.920***
		(0.105)	(0.0928)	(0.0787)
2.	Percent of Time on LTE	0.422***	1.976***	3.631***
		(0.124)	(0.165)	(0.187)
3.	Worst Speed	-0.166*	0.425***	0.379***
		(0.0949)	(0.0899)	(0.0936)
4.	Worst Percent of Time on LTE	0.292***	0.219***	0.150***
		(0.0703)	(0.0615)	(0.0578)

	Brand Variable	Consumer Characteristics Variable [2]			
		Percent Hispanic or African American	Median Age	Mobility	Average Credit Score
5.	AT&T	-0.003	-0.012	0.277***	0.562**
		(0.004)	(0.010)	(0.047)	(0.255)
6.	Boost/Virgin	-0.002	0.003	0.011	-0.888***
		(0.005)	(0.012)	(0.053)	(0.310)
7.	Cricket	-0.001	-0.009	0.171***	-0.187
		(0.005)	(0.013)	(0.063)	(0.317)
8.	MetroPCS	0.007*	-0.014	0.075	-0.271
		(0.004)	(0.010)	(0.048)	(0.263)
9.	Sprint	0.003	-0.021**	0.319***	0.582**
		(0.004)	(0.009)	(0.047)	(0.264)
10.	T-Mobile	0.011***	-0.025***	0.284***	1.078***
		(0.004)	(0.009)	(0.047)	(0.260)
11.	Verizon	-0.007*	-0.007	0.298***	0.609**
		(0.004)	(0.009)	(0.044)	(0.249)

	Brand Variable	Survey Data Income Bracket Variables [3]					
		< $25,000	$25,000 – $34,999	$35,000 – $49,999	$50,000 – $74,999	$75,000 – $99,999	≥ $100,000
12.	AT&T	-0.599***	-0.314***	-0.245	-0.114	0.108	0.574***
		(0.087)	(0.121)	(0.149)	(0.137)	(0.175)	(0.218)
13.	Boost/Virgin	0.252**	0.146	-0.409**	-0.476***	-0.591**	-0.540*
		(0.108)	(0.148)	(0.181)	(0.174)	(0.248)	(0.303)
14.	Cricket	0.144	0.134	0.013	-0.122	-0.447	0.099
		(0.127)	(0.156)	(0.187)	(0.195)	(0.327)	(0.361)
15.	MetroPCS	0.201**	0.079	-0.285*	-0.426***	-0.751***	-0.519**
		(0.092)	(0.128)	(0.153)	(0.157)	(0.212)	(0.254)
16.	Sprint	-0.594***	-0.306**	-0.158	0.056	0.148	0.429*
		(0.096)	(0.124)	(0.148)	(0.142)	(0.172)	(0.229)
17.	T-Mobile	-0.458***	-0.186	-0.076	-0.008	-0.024	0.512**
		(0.096)	(0.117)	(0.148)	(0.141)	(0.178)	(0.223)
18.	Verizon	-0.584***	-0.292**	-0.156	0.072	0.250	0.776***
		(0.088)	(0.117)	(0.143)	(0.134)	(0.166)	(0.228)

	General	
19.	Number of Consumers	[redacted]
20.	McFadden R2 [4]	0.124
21.	Change in R2 relative to FE only [5]	0.0799

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: KPMG StreamShare Data; Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission

53. The following note applies to Exhibit 16.

- [3] This model specification includes interacting dummies for survey data income brackets. The omitted category for survey data income brackets is "< $25,000."

EXHIBIT 16
Estimates from demand model assigning income using NMP survey income brackets, omitting individuals that did not provide survey income data

	Variable	Coefficient [1]		
		Light Data Users	Medium Data Users	Heavy Data Users
1.	Speed	0.362***	1.181***	2.745***
		(0.120)	(0.127)	(0.0964)
2.	Percent of Time on LTE	0.551***	1.866***	3.935***
		(0.149)	(0.201)	(0.233)
3.	Worst Speed	-0.226*	0.531***	0.371***
		(0.131)	(0.123)	(0.107)
4.	Worst Percent of Time on LTE	0.228**	0.246***	0.143*
		(0.0936)	(0.0806)	(0.0730)

	Brand Variable	Consumer Characteristics Variable [2]			
		Percent Hispanic or African American	Median Age	Mobility	Average Credit Score
5.	AT&T	-0.001	0.001	0.338***	0.701**
		(0.004)	(0.011)	(0.069)	(0.297)
6.	Boost/Virgin	0.004	0.010	0.112	-0.362
		(0.005)	(0.014)	(0.081)	(0.382)
7.	Cricket	-0.001	0.008	0.280***	-0.218
		(0.005)	(0.015)	(0.090)	(0.388)
8.	MetroPCS	0.009**	-0.003	0.150**	-0.109
		(0.004)	(0.011)	(0.074)	(0.313)
9.	Sprint	0.007	-0.012	0.399***	0.707**
		(0.005)	(0.011)	(0.072)	(0.324)
10.	T-Mobile	0.015***	-0.014	0.375***	1.213***
		(0.004)	(0.011)	(0.075)	(0.303)
11.	Verizon	-0.006	0.006	0.340***	0.641**
		(0.004)	(0.010)	(0.068)	(0.286)

	Brand Variable	Survey Data Income Bracket Variables [3]				
		\$25,000 – \$34,999	\$35,000 – \$49,999	\$50,000 – \$74,999	\$75,000 – \$99,999	≥ \$100,000
12.	AT&T	0.338***	0.387**	0.508***	0.784***	1.170***
		(0.128)	(0.153)	(0.133)	(0.188)	(0.231)
13.	Boost/Virgin	-0.059	-0.657***	-0.765***	-0.855***	-0.859***
		(0.141)	(0.173)	(0.154)	(0.260)	(0.329)
14.	Cricket	0.007	-0.133	-0.215	-0.837***	-0.123
		(0.166)	(0.204)	(0.202)	(0.303)	(0.385)
15.	MetroPCS	-0.114	-0.444***	-0.653***	-0.893***	-0.761***
		(0.138)	(0.160)	(0.150)	(0.222)	(0.265)
16.	Sprint	0.337***	0.470***	0.669***	0.817***	1.027***
		(0.125)	(0.158)	(0.143)	(0.190)	(0.249)
17.	T-Mobile	0.316**	0.421***	0.462***	0.491**	0.980***
		(0.126)	(0.150)	(0.137)	(0.204)	(0.246)
18.	Verizon	0.342***	0.490***	0.709***	0.947***	1.389***
		(0.123)	(0.153)	(0.130)	(0.179)	(0.243)

	General	
19.	Number of Consumers	[redacted]
20.	McFadden R2 [4]	0.130
21.	Change in R2 relative to FE only [5]	0.0864

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: KPMG StreamShare Data; Nielsen Mobile Performance Survey Data; Backup of Bazelon, Verlinda, and Zarakas February 19 Submission

9. Appendix: textbook citations clarifying that imputation is the process of filling in missing data, not throwing out actual data

54. Economists and statisticians refer to imputation as the process of filling in missing data, as made clear in the following five textbook citations. This is different from what BVZ have done, which is to use an erroneous process to replace all data, not just fill in missing data.

> "Regression imputation replaces missing values with predicted scores from a regression equation … The basic idea behind this approach is intuitively appealing: use information from the complete variables to fill in the incomplete variables. Variables tend to be correlated, so it makes good sense to generate imputations that borrow information from the observed data … The first step of the imputation process is to estimate a set of regression equations that predict the incomplete variables from the complete variables. A complete-case analysis usually generates these estimates. The second step is to generate predicted values for the incomplete variables. These predicted scores fill in the missing values and produce a complete data set."
>
> Craig K. Enders, *Applied Missing Data Analysis*, The Guilford Press, 2010, ch. 2.7, p. 44.

> "The problem of missing data in survey data is one of long standing, arising from nonresponse or partial response to survey questions. Reasons for nonresponse include unwillingness to provide the information asked for, difficulty of recall of events that occurred in the past, and not knowing the correct response. Imputation is the process of estimating or predicting the missing observations."
>
> A. Colin Cameron and Pravin K. Trivedi, *Microeconometrics: Methods and Applications*, Cambridge University Press, 2005, ch. 27, p. 923

"Imputation ('filling in') is a general and flexible alternative to the complete case analysis. The missing values in the data matrix D are replaced by guesses or correlation-based predictors transforming D to a complete matrix. The completed data then can be analyzed by standard procedures."

C. Radhakrishna Rao and Helge Toutenburg, *Linear Models: Least Squares and Alternatives*, Second Edition, 1999, ch. 8, p. 243

"Imputation methods assign to each sample member with a missing realization of y some logically possible value, say, y*. This done, E[g(y)] is estimated by the sample average which uses the actual value of y when available and the imputation otherwise."

Charles F. Manski, *Identification for Prediction and Decision*, Harvard University Press, 2007, ch. 3, p. 74

"Next we write a little function to create a completed dataset by imputing the predictions into the missing values … and use this to impute missing earnings."

Andrew Gelman and Jennifer Hill, *Data Analysis Using Regression and Multilevel/Hierarchical Models*, Cambridge University Press, 2007, ch. 25, p. 535