ORIGIN VID MODEL PROOF OF CONCEPT
Stage 1: Integration of TV

A report prepared for:

ISBA

August 2021

RSMB Limited, Savoy Hill House 7-10 Savoy Hill London WC2R 0BU
Tel: + 44 (0)20 7808 3600 Email: contact@rsmb.co.uk Web: www.rsmb.co.uk
Registered office as above. Registered in England and Wales No. 2173860

Table of Contents

Page

Contents

1. Introduction

Origin is a cross industry initiative led by ISBA on behalf of UK advertisers to establish a cross media measurement service for campaign planning, reporting and evaluation, and aligned to the WFA Framework for cross media measurement.

As part of this initiative, Origin seeks to test and validate key components proposed as part of a technical blueprint that can provide for advertisers needs. One of these key components is the Virtual ID Model.

RSMB had previously completed a comprehensive methodology review and concept assessment concluding that the approach had potential merit and a recommended proof of concept (POC) be established to test the Virtual ID Model including how measured panel data for Linear TV advertising data could be integrated into the framework. This reflects the scope of the BARB universe for their TV advertising currency, which is driven by the broadcast TV commercial logs used as input to this POC. In particular it excludes non-linear BVOD and addressable advertising. Return path data and BVOD census data are not a feature of this currency.

RSMB were commissioned by ISBA to undertake this Proof of Concept. The proof of concept consisted of two stages:

Stage 1 — Integration of TV data

The first stage was to evaluate how data from a television panel could be adapted into a Virtual ID model and how well this would retain results seen in the original data. Given the hypothesis that channels could be taken as surrogates for websites, another important corollary outcome from this work was whether the VID model could work for online. Campaigns are restricted to spots on broadcast TV.

Stage 2 — Integration of TV data with Online

The second stage is to evaluate if the Virtual ID model could be successfully extended across TV and Online data. The work would compare various scenarios to understand if any could retain cross media campaign relationships.

This interim report relates to work undertaken and completed for Stage 1 only. Campaigns were restricted to television only.

2. Executive Summary

The Proof on Concept (POC) was to test the Virtual ID component of the WFA technical blueprint for cross media measurement. The first stage (and the basis for this interim report) was to evaluate how well data from a TV panel can be integrated into this VID framework preserving TV campaign results. A secondary outcome from this TV data would be an indication whether the model would potentially work for online given the relationship between channels across campaigns may be analogous to relationships between websites.

The TV campaign data related to linear campaigns only; return path data, addressable advertising and BVOD are not part of the BARB commercial campaign currency and were not part of this evaluation. The POC used data from Ipsos MORI's Compass panel. For the first stage only data for television linear campaigns was used. (For the second stage online campaign viewing data would also be assessed in conjunction with the TV campaigns). Panel data was treated as census data in the design of the experiment in order to evaluate the model against 'true' census data. Campaigns were restricted to spots from 6 key channels for simplicity.

The WFA proposed VID model allocates individuals to website impressions based on a probabilistic rate and potentially a website cookie. For this first stage of the POC, 4 different scenarios were evaluated based on 2 types of rates and using a 'cookie' (i.e. panel ID) and, finally, not using a 'cookie'. The two types of rates were as follows:

Abstract	follows WFA framework and based on theoretical rates designed to give closest results by training the model using campaign results.
Real	calculated relative propensity to view for each individual based on panel data.

The 'with cookie' scenario was utilised within a single channel only. A further option of using across all channels was redundant for the work undertaken in Stage 1 as by definition it will preserve television data the best but will be evaluated in Stage 2 to establish whether this inhibits cross-media measurement.

For total campaign reach all models performed well. The model with abstract rates and 'with cookie' returned results closest to the benchmark 'census' data. It over predicted slightly for campaigns of low and very high weight and under predicted slightly for campaigns of medium to high weight. The model with real rates and 'with cookie' was the next best with the models without 'cookies' showing more variability although results were acceptable.

Attribution was undertaken within gender and age demographics and this resulted in fairly good retention of demographic profiles for campaigns from the modelled data.

Week to week build of campaigns was largely preserved and showed a similar degree of differences for each modelling scenario as was seen across the full period of the campaign.

Campaigns were grouped according to their delivery in time segments and days to evaluate whether the models had any deficiencies for campaigns with a particular type of laydown. There was no significant differential performance for any particular type of campaign.

As would be expected, in general the true campaigns exhibited non-random overall reach (i.e. reach between channels was correlated). Regression to the mean measurements were used to evaluate if and how much the modelled results moved away from this toward random reach. For smaller campaigns inevitably sampling error made assessment difficult but for the larger robust campaigns regression to the mean ranged from very low to acceptable for the four scenarios.

The abstract rates with cookies showed the best results. However, it must be noted that for Stage 1 this was a small scale test and this technique would have benefited from this; on a larger scale the results would be expected to weaken. Although the scale will not really be expanded significantly, a sterner test for this model will occur for Stage 2 with the introduction of digital campaigns and the creation of model parameters from a period independent to the domain of evaluation.

In summary, the Proof of Concept for Stage 1 has yielded the following findings:

> The allocation model is able to address marked duplications seen across television campaigns producing acceptable results for key components (e.g. overall, reach build, demographic profile, channel's unique contributions). The model closest to the WFA specification performed best but the other scenarios performed satisfactorily and will therefore also continue to be assessed for Stage 2 as they could provide better cross media estimates when online campaigns are introduced into the assessment.

The standalone results for television only campaigns have produced encouraging signs that the approach may preserve duplications between TV channels and websites for joint media campaigns given similar interdependent relationships between TV channels may also exist between TV channels and websites.

3. Methodology recap

The framework set out by the WFA has a multitude of components in the cross media solution. However, at the heart of the solution is the Virtual ID model. This is the focus of the Proof of Concept.

The Virtual ID model is straightforward in nature. It can broadly be described as follows:

A 'respondent' ID listing is created equal to the Census population.

Gender and Age Group classifications are assigned to these based on universes sizes.

A homogeneous group indicator is assigned to these indicating groups of similar behaviour for channels in the media campaign.

Relative rates of advertising exposure to each channel are assigned to these homogeneous groups.

Given Census campaign impressions, these are assigned in a probabilistic way using an allocation algorithm.

Cookie information collected for the Census impressions may also be used in this allocation process.

The inputs for this process are acquired by training the model using Single Source Panel (SSP) data.

The framework allows and invites modifications to the process for example, in terms of how these rates and groups are created and whether cookie usage is beneficial.

4. Dataset

In order to conduct this evaluation a Single Source Panel dataset is required that is able to measure campaign data for both Television and Online. The Compass panel run by Ipsos MORI was used for this process. The panel consists of around 3,000 respondents aged 18+. Data is measured across TV, Radio and Online. For Stage 1, only data for the TV element was used.

The data used was for 4 w/e 31st January 2021. For this Proof of Concept, for simplicity, the TV channels were restricted to the following channels:

ITV

Channel 4

Channel 5

ITV2

Sky 1

Dave

Data was extracted for every single campaign spot transmitted during this period for these channels. It was accepted that some of these would constitute only partial campaigns but this data was still useful for training the model and calculating propensity to view for panel members. In the actual evaluation of the models only campaigns that consisted of an appreciable proportion of the original campaign were used.

The demographics used in the test were as follows:

Men 18-34	Women 18-34
Men 35-54	Women 35-54
Men 55+	Women 55+

For simplicity, the sample was restricted to a consistent cohort of Adults who had reported for at least 21 days out of the 28 days.

For reference, a campaign reach of 50% would have the following sampling errors:

- All Adults Sampling error = 0.8 95% Confidence Interval = (48.4,51.6)
- Demographic Sampling error = 2.2 95% Confidence Interval = (45.6,54.4)

5. Design of Experiment

Stage 1 of the Proof of Concept related to the integration of television data into the VID model.

For this stage, the evaluation was mainly concerned with how the panel data could be transformed into the Virtual ID framework, using elements of the methodology that was set out, while still retaining the general viewing metrics of the original source. In order to evaluate this, the panel data was treated as though it came from a census population. The allocation process could then be applied to the impressions measured using the allocation algorithms and compared back to this 'Census' benchmark.

There were two key inputs to the allocation process: the determination of individual rates and the use of a 'cookie' (to help control the reach currency), which for TV panel data was the respondent ID.

5.1 Individual rates

For this evaluation two types of rates were used: Abstract and Real rates.

Abstract rates

These followed the protocols set out in the WFA framework. Essentially these were designed to be based (or rather trained) on the panel campaign aggregate results rather than using any personal panel rates per se. So essentially an optimisation routine was undertaken to segment the VID population into groups with equal rates such that the expected results from the allocation process would be as close as possible on average to campaign data. The data was optimised with respect to the following reach components of the campaigns:

- Total campaign
- Demographics (Gender by Age Group)
- Weekly build
- Pairwise Channels

It is accepted that this level of training was achievable for this experiment but may be more challenging for a larger scale application.

Real rates

The real rates used were much simpler. Here each respondent was effectively in their own unique group and generated a unique rate based on their propensity to view advertising on that media channel across the campaigns.

Note that in both cases, the VID model is guaranteed to replicate the impressions currency for each demographic group.

5.2 'Cookie'

In the WFA framework for Online the cookie information was utilised and the recommendation for the algorithm was to use this in the allocation process rather than treat the data as individual separate impressions. For TV data there is no such thing as a 'Cookie' but analogously the unique panel identifier can be used, principally to retain observed campaign frequencies by individuals. For the end-to-end project, 3 options related to cookies are considered:

No Cookie

Here, each television impact is treated independently in the process. Clearly, under this method by definition there is a loss in preservation of the measured television campaign reach and frequency data with spots viewed by the same individual not accounted for directly. However, this option is considered as the loss here may be offset if there are gains in accuracy of modelled cross media interactions, which will be considered in Stage 2. So, it is useful to see what is lost in the standalone TV campaigns.

Cookies within Channels

Here, each television impact uses the respondent ID for campaign spots within the same channel. So, for example if two spots were watched on a channel by a single respondent, the Virtual ID respondents that were allocated the first spot would also have the second. This method aligns more closely with what happens on website data for the allocation model if a cookie is used as it can only be done so within the website.

Cookies across Channels

The final option is where each television impact uses the respondent ID across all campaign spots. This option by definition preserves the campaign data seen for the panel so is redundant for Stage 1 as it will match exactly. However, it will be an important option in Stage 2 where it will need to be evaluated whether this option, although perfect for standalone television data, inhibits the accuracy of the cross media measurement.

So, for Stage 1 the following 4 scenarios are considered:

	Pros	Cons
Scenario 1: **Abstract/Cookies**	Follows WFA Framework	Dependent on availability of cookies. Rates based on training – limit to how much can be controlled.
Scenario 2: **Abstract/No Cookies**	Not dependent on availability of cookies.	Rates based on training – limit to how much can be controlled. Loses the benefit of cookie information.
Scenario 3: **Real/Cookies**	Uses observed data.	Dependent on availability of cookies Range and mixture of rates limited by panel sample size.
Scenario 4: **Real/No Cookies**	Not dependent on availability of cookies Uses observed data	Loses the benefit of cookie information

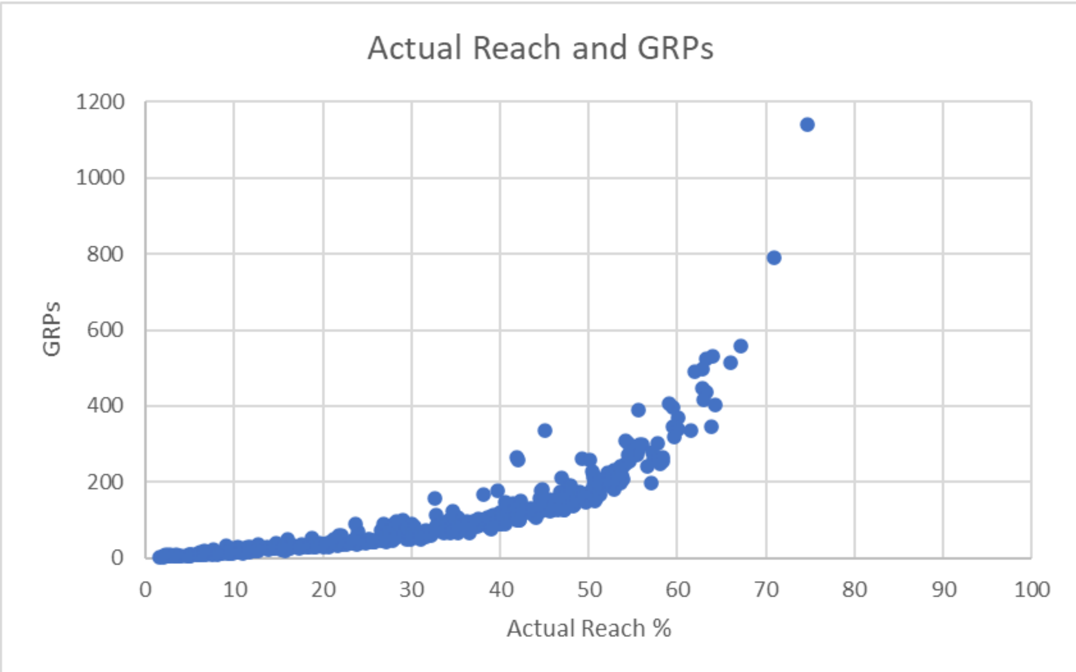
Work was undertaken to produce the two types of rates. Allocation algorithms as specified in the WFA framework were then applied using the appropriate inputs and protocols for the four scenarios.

6. Results

Although all commercial spots across the channels were used in the determination of rates in order to utilise the data fully, for the evaluation schedules were only used if the spots broadcast across the selected channels and time period were a sufficient proportion of the original schedule. This meant the campaigns were both closer to full campaigns and also findings would not be contaminated by erratic variation from schedules with limited data. All four scenarios were evaluated for 459 campaigns.

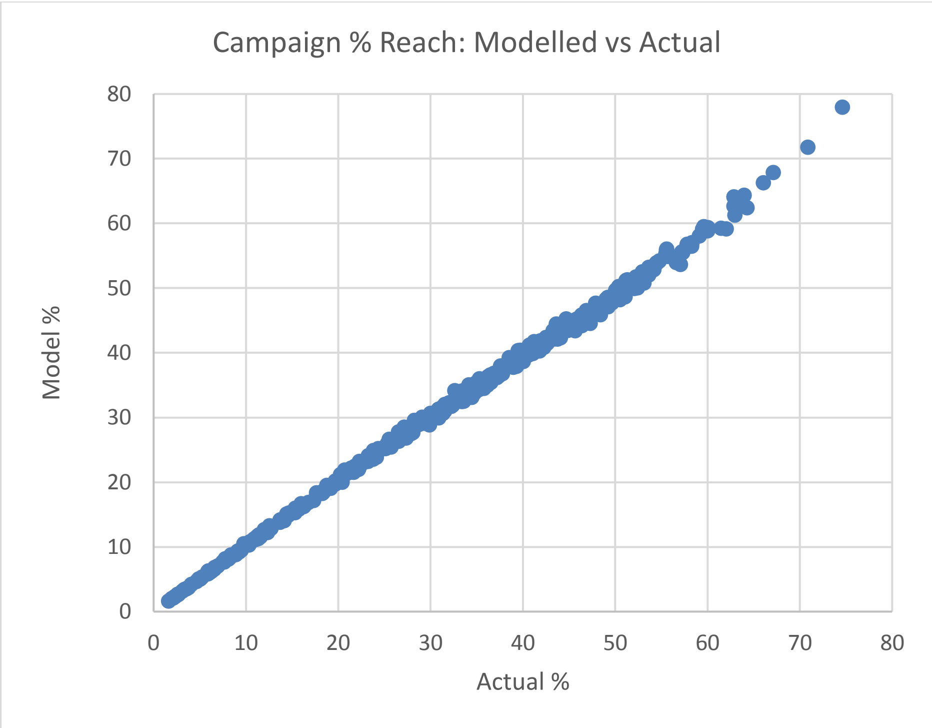
6.1 Total Campaign Reach

A key requirement of the model is that it produces credible estimates for the overall campaign reach. The actual reach of each campaign compared to GRPs is shown below:



As with all statistical evaluations, the proof of concept can only assess model performance within the bounds of the input data. There is a clear relationship between Reach and GRPs but there is some noticeable variation in reach around the underlying curve. For example, at around 200 GRPs the reach ranges from 40% to 57%, with an average spread of around plus or minus 5 points. This significantly exceeds the sampling errors and confidence intervals cited in section 3 and reassures that the dispersion within the domain of study is systematic rather than random. Essentially the model has to work hard to reflect systematic variations in the reach to frequency relationships and the relatively low sampling error means that the test is quite powerful. Inevitably, systematic variations within demographics are more confounded with sampling error.

The below charts the percentage reach from the allocation against the actual reach for **Scenario 1 (Abstract/Cookie):**

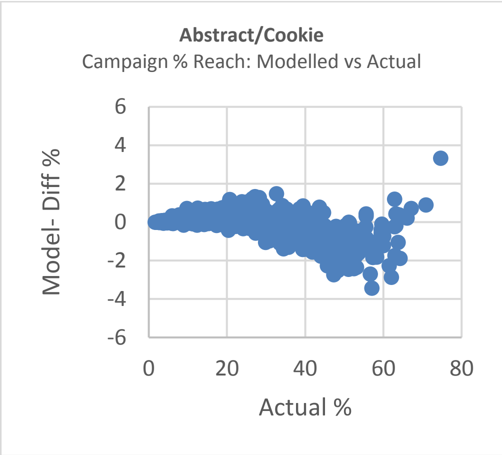


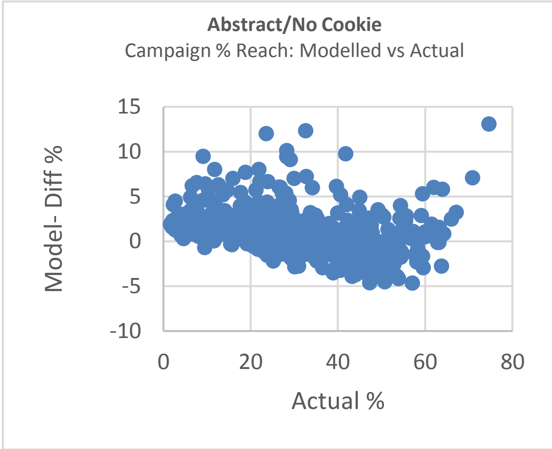
From the above, it can be seen that the modelled reach is close to actual reach.

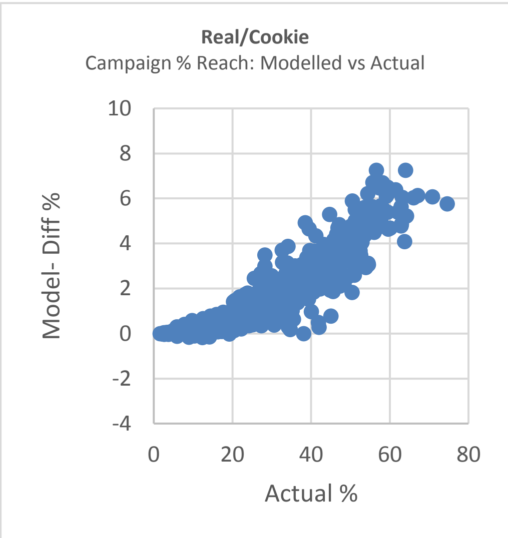
The other scenarios show a similar pattern.

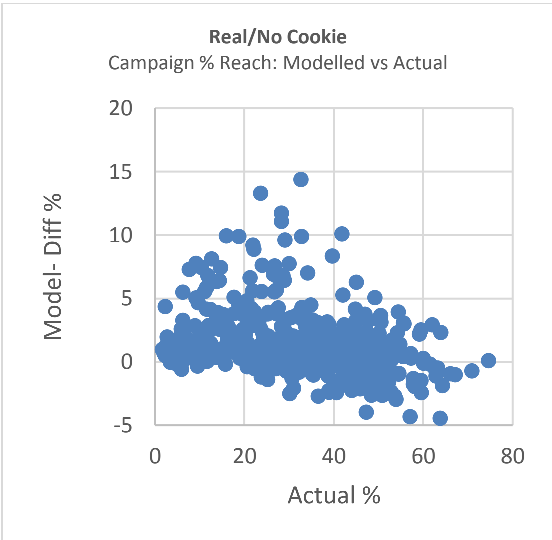
However, the key differences in goodness of fit are imperceptible from these types of charts. A better chart to focus on the goodness of fit is to plot the (Model – Actual) vs the Actual reach. This will better show any differences in the precision of modelled estimates between the scenarios and also any biases within the scenarios.

The below shows these for the 4 scenarios. Note that the y-axis is in terms of percentage points (e.g. if modelled reach was 11% and actual reach was 10% then Model – Diff % would be 1%):





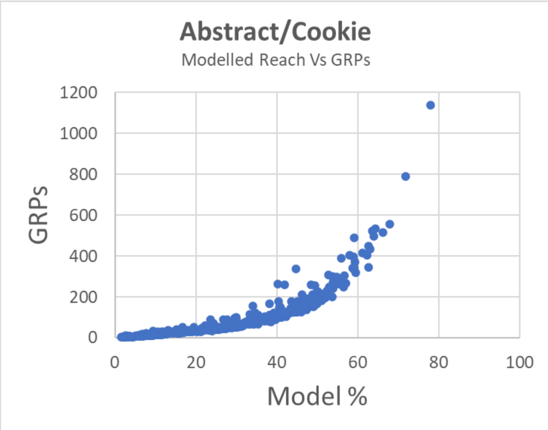


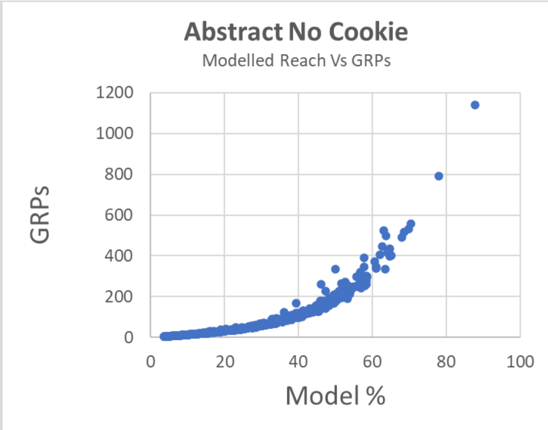


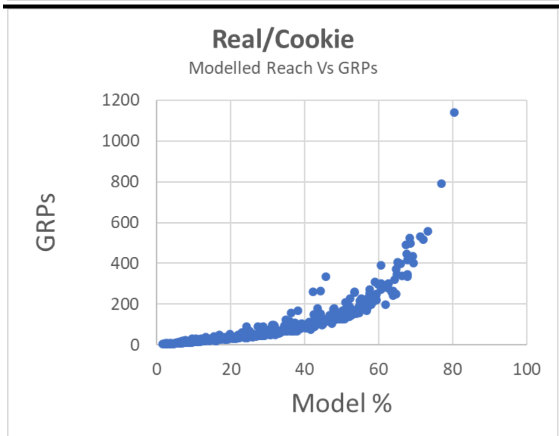
A brief summary of the above:

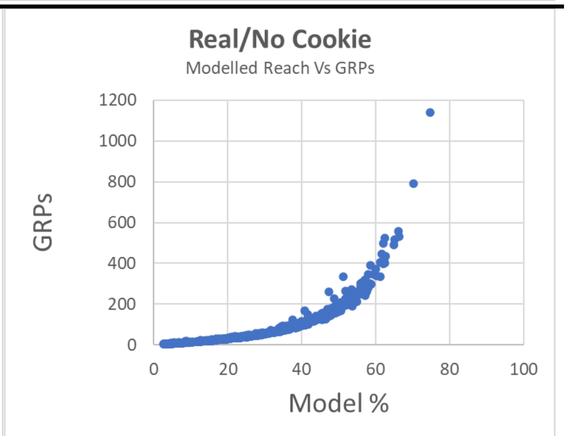
Scenario 1: Abstract/Cookies	Closest fit.
Scenario 2: Abstract/No Cookies	More variability, slight tendency towards underestimating the higher reach campaigns.
Scenario 3: Real/Cookies	Reasonably close fit, tendency towards over reporting.
Scenario 4: Real/No Cookies	More variability, slight tendency towards underestimating the higher reach campaigns.

The modelled reaches when compared to GRPs look as follows:









All methods show a similar shape to the actual reach, however the “no cookie” models seem to show less dispersion than the actual reach curve has which could indicate that the no cookie models aren’t able to model the variation in reach as well as the cookie models are (which is also supported by the “no cookie” models having more variation in the Model Difference charts).

The table below summarises the performance across all scenarios for the 459 campaigns.

	Rates	Cookie used	Diff	Abs Diff
Scenario 1:	Abstract	Yes	-0.3	0.6
Scenario 2:	Abstract	No	1.0	2.1
Scenario 3:	Real	Yes	1.6	1.6
Scenario 4:	Real	No	1.4	2.0

Although averages can mask what happens at an individual level, all scenarios perform well in terms of reach. The average difference shows that Abstract/Cookie has the least bias overall, although the chart illustrates where the biases were more marked. With the abstract model, because the rates are determined by fitting to campaigns there is probably potential to adjust this process to target some of these biases. The other scenarios show a similar level of closeness of fit, although for Scenario 3 the consistent figures for difference and absolute differences reinforce the findings seen in the charts whereby there is a consistent over estimation. It should be noted that in our opinion the differences seen in all scenarios are acceptably close for a modelled solution within the training campaigns examined, with the performance of the Abstract/Cookie scenario model particularly impressive. It should be noted however that this is a modelled solution and the goodness of fit is based on intended use cases; specialist planned campaigns which fall outside the reach to frequency relationships seen in the input dataset of actual executed campaigns may not produce as accurate a reach figure since the rates will not have been trained on these types of less common campaign (although this is an issue that can also affect panel based solutions). The Abstract/Cookie scenario is designed to produce rates to minimise differences in reach between the model and the panel for these campaigns at both an overall level but more importantly for various components. In this small scale experiment a higher level could be applied than usual, so caution is needed regarding whether it is much better than the other scenarios. Further to this, the true test is how well it will preserve cross-media duplications in Stage 2. Nonetheless, the rest of the following results below will largely focus on this scenario as it is the method that most follows the WFA initiative but also because the pattern of results for the other scenarios generally replicates the findings (albeit relative to their top line results).

6.2 Reach by Channel

Another important characteristic to evaluate is how well the model preserves the channel components within the campaigns themselves. This will be analogous to how well the model will preserve data for individual websites.

Again, the overall average differences are examined to determine if there are any marked differences between performance for channels. For the scenarios that use ‘cookies’ this exercise is redundant because this ‘cookie’ is used within channels and it will therefore perfectly preserve reach (and frequency) at this level so differences will be zero. The table below details the differences for the other scenarios:

	Abstract without Cookie		Real without Cookie	
	Diff	**Abs diff**	**Diff**	**Abs diff**
All	**1.0**	**2.1**	**1.4**	**2.0**
ITV	-0.3	2.0	0.5	1.8
Channel 4	0.1	0.9	0.5	0.9
Channel 5	0.1	1.1	1.0	1.2
ITV2	0.7	0.7	0.2	0.3
Sky 1	0.9	0.9	0.2	0.3
Dave	1.1	1.1	0.2	0.3

For abstract without cookie for ITV, Channel 4 and Channel 5 there is little bias with ITV showing larger differences. This may relate to ITV constituting a heavier element of the campaign so relative to reach the difference may not be so marked. It should be noted that for ITV2, Sky 1 and Dave the average difference and the average absolute difference are the same, which indicates that whatever bias does exist in these channels it is almost always an overestimation in reach.

For 'real without cookie' the average differences across channels are small and more consistent with little bias. For ITV, Channel 4 and Channel 5 there are larger absolute differences but as noted before this may relate more to weight of these channels within the campaign. For ITV2, Sky 1 and Dave differences are small both in terms of bias and fit, and it can be noted that the real rates have a closer fit to the reach compared to the abstract rates for these channels.

6.3 Reach by Demographic

For this proof of concept the allocation process for TV campaign data was undertaken at a demographic level. The breakdown was as follow:

Men/Women * Age (18-34, 35-54, 55+)

Similar, to the channel data it is intuitive to examine if there are any differences in the allocation process.

Data analyses were undertaken for all scenarios but only the Abstract/Cookie scenario is detailed below.

	Abstract/Cookie	
	Diff	**Abs diff**
All	**-0.3**	**0.6**
Men 18-34	0.5	0.9
Men 35-54	-0.4	0.9
Men 55+	-0.4	1.0
Women 18-34	0.1	0.8
Women 35-54	-0.7	1.1
Women 55+	-0.3	1.0

There is not much difference across demographics in terms of goodness of fit for bias or absolute difference.

As noted, the Abstracts/Cookie scenario is focused on here as it most closely aligns with the recommended approach in the WFA framework. However, for the other scenarios there were no key differences observed for any particular demographic.

Given there are no key differences this is encouraging as it should mean that the true reach demographic profiles of the campaign are preserved. The following shows an example campaign and it can be seen that this largely stands:

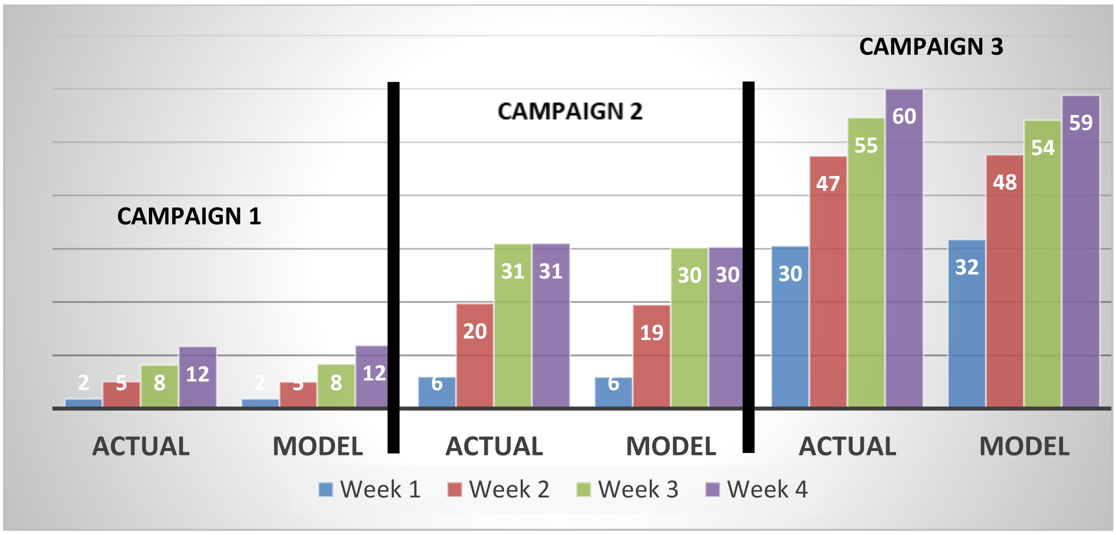
Abstract/Cookie: Example campaign

	Actual	**Model**	**Diff**
All	**100**	**100**	**0**
Men 18-34	4	4	0
Men 35-54	17	16	0
Men 55+	26	26	0
Women 18-34	8	8	0
Women 35-54	21	20	-1
Women 55+	25	26	1

It is perhaps not surprising that profiles are preserved well given that the allocation is done within the demographics themselves but there was potential that differences could arise if there was differences in the preservation of duplications across channel for any particular demographic which could have skewed the profile.

6.4 Reach build by Week

A key component in the Advertiser 'North Star' requirements was that the modelling solution should be dissectible and results consistent as the campaigns build. As part of the evaluation therefore the 4 week campaigns were evaluated by examining the weekly build for the allocation model and comparing to the real results. In general, the results were encouraging with weekly builds aligning. The below shows examples for 3 campaigns of different weight for the Abstract/Cookie model.



These were typical of the comparisons seen with the level and direction of differences for each scenario mirroring that seen overall.

6.5 Type of Campaign

Another challenge for the allocation model is for campaigns with a particular laydown. An example of this is if the model could cope with a campaign schedule that was heavily delivered in weekday afternoon when availability to view may be different (e.g. for full time workers). All four scenarios had no direct component in the calculation of rates to directly address this (although the cookie models preserved spots viewed within channels so arguably addressed some correlation in personal viewing of spots).

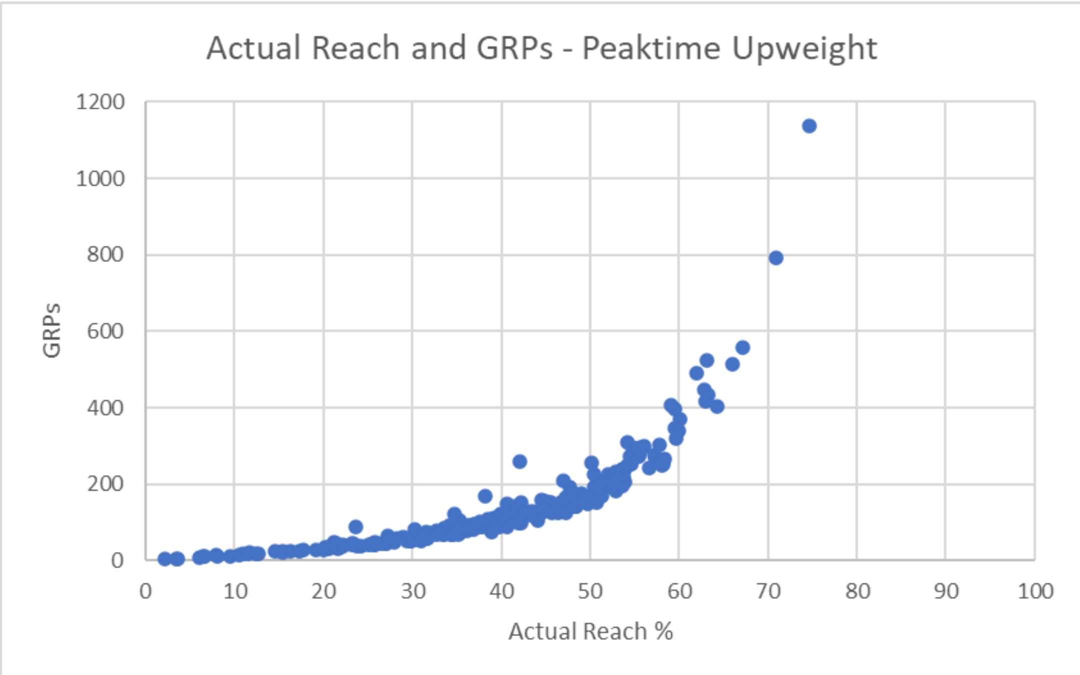
RSMB undertook a cluster analysis for the 459 television campaigns using time segments and days that spots were broadcast in order to separate them out into different types of campaigns. Three types of campaigns were identified:

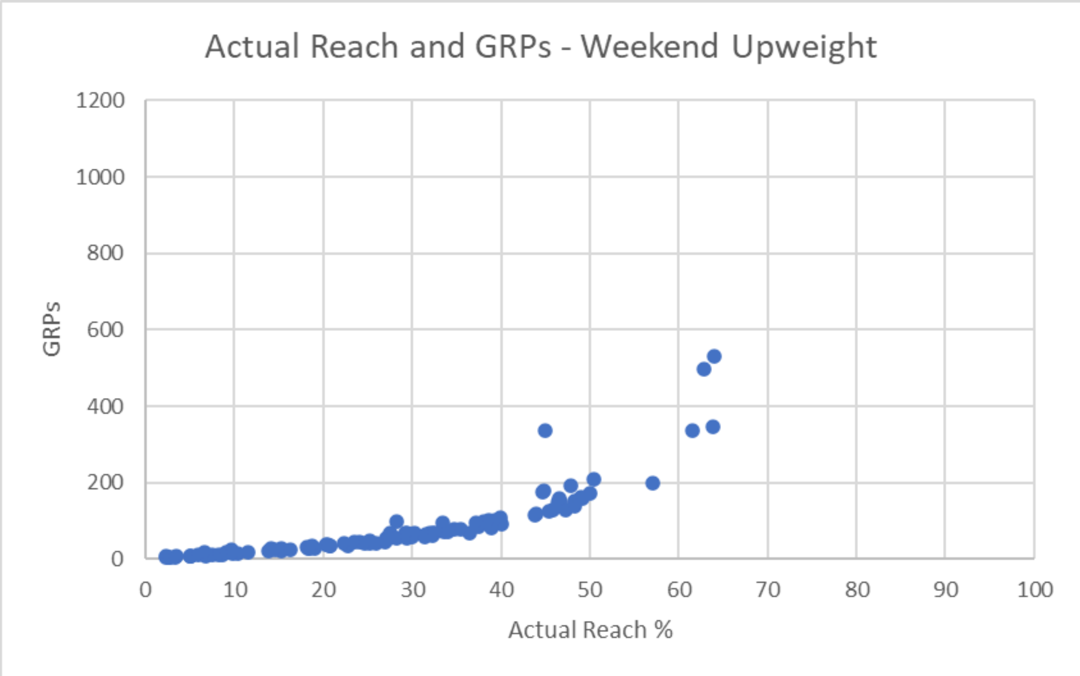
Peaktime upweight

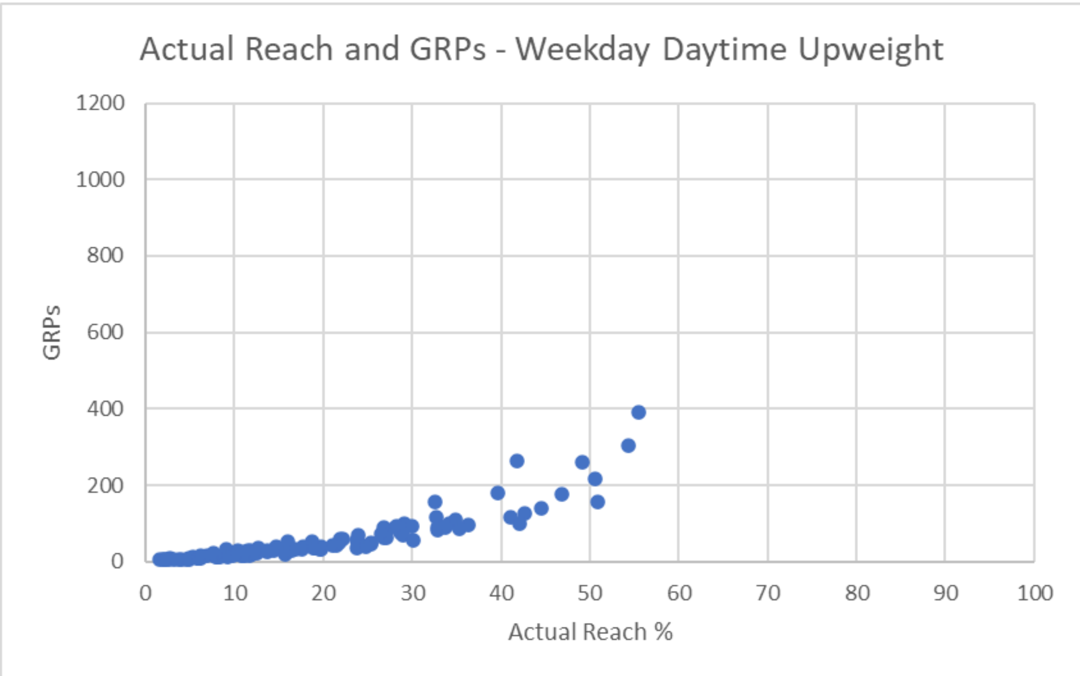
Weekend upweight

Weekday Daytime upweight

We can note from the reach curves that each cluster has a clear relationship with GRPs (with less dispersion than when looking at all campaigns), although as the relationship is broadly similar in each cluster the model would not have needed to stretch too much to meet the needs of each type:







The table below shows the performance of the allocation model across these campaigns for the Abstract/Cookie model.

Scenario 1: Abstract/Cookie

Type	Campaigns	Diff	Abs diff
All	**459**	**-0.3**	**0.6**
Peaktime	109	0.2	0.4
Weekend	99	-0.2	0.5
Weekday Daytime	251	-0.6	0.8

The Weekday/Daytime schedules were slightly worse in terms of bias and size of differences. Although these clusters identified types of campaign where it was suspected that the model may struggle, differences were minimal and the model coped well with the three types of campaign. It should be noted though that the relationship between reach and GRPs was similar with all three campaign types, if more specialised campaigns exist in the real world (that have a different relationship to that observed in the data) then the performance may differ from the domain of study.

6.6 Overall Reach – Regression to the Mean

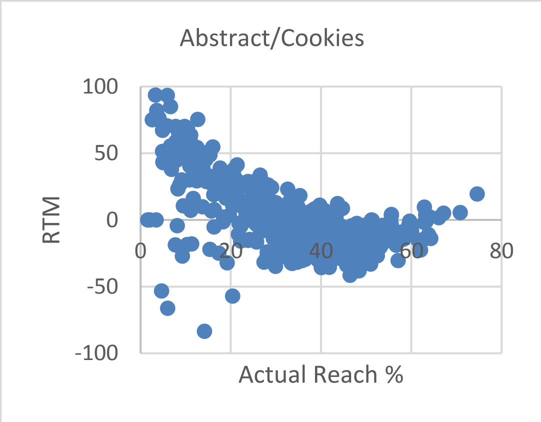
The danger with many modelled solutions is that although the top-line results are strong, the solution fails to pick up marked discrimination and tends towards a random solution. In the context of this experiment the test here is whether the modelled solution picks up and retains the non-random element of viewership across channel spots. It is best illustrated by a real example:

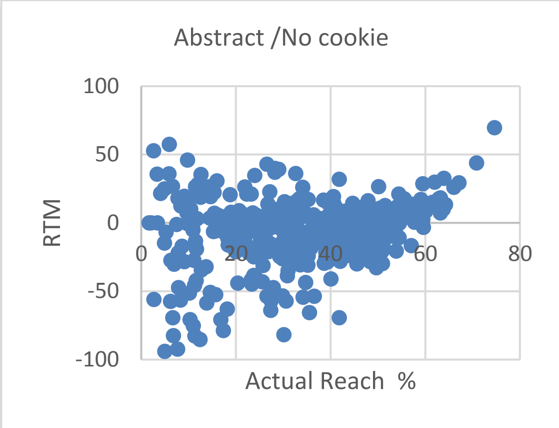
Scenario 3: Abstract/Cookie

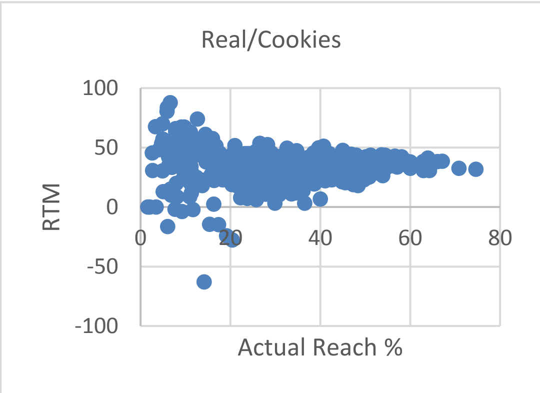
Random reach	=	55%
Actual total panel reach	=	47%
Model reach	=	50%
RTM	=	(47-50)/(47-55) = 38%

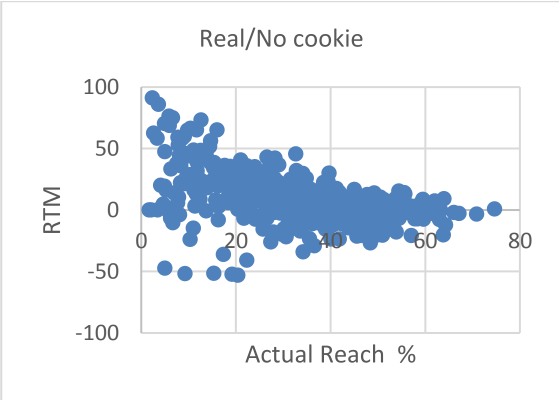
So, in the above case the random reach would be 55%. This is calculated by assuming each measured separate channel campaign reach was independent. The real reach is 47%. This is therefore 8 percentage points from random. The model reach is 50%. This has ‘moved’ 3 points (out of 8 points) from the actual towards random so a regression to the mean of 38%. The complement of this – and perhaps more positive – is that 62% of the discrimination is retained.

This calculation was undertaken for all 459 campaigns for each scenario. The following charts compare the regression to the mean against the size of campaign (using reach as the metric):









It must be acknowledged that at low reach levels, small absolute levels of regression-to-the-mean are large in percentage terms. Differences between actual and random are more likely to be within the bounds of sampling error, therefore it might be expected that RTM is overstated. Plotting RTM against Actual Reach allows the larger/more robust reach data points to be differentiated.

A brief summary of the above:

> Scenario 1: Abstract/Cookies – High regression to the mean for smaller campaigns. For larger campaigns regression to the mean is smaller and actually tends slightly towards negative regression to the mean. This would mean reach is slightly underestimated.

Scenario 2: Abstract/No Cookies – More variability in regression to the mean but broadly averages around zero regression to the mean.

Scenario 3: Real/Cookies – High regression to the mean for smaller campaigns. Regression to the mean tends towards 40% meaning this model retains 60% of discrimination on average.

Scenario 4: Real/No Cookies – This largely mirrors the regression to the mean seen in Scenario 1 albeit with less tendency towards regression to the mean.

The results across scenarios are quite different. The abstract/cookie and real/no cookie perform best in terms of limiting regression to the mean but even the worst scenario produces regression to the mean statistics that are in our opinion acceptable for a modelled solution.

The results indicate two important findings ahead of Stage 2:

1. The allocation model is able to preserve marked duplications seen across broadcast television campaigns.
2. Encouraging signs it may also then preserve duplications between TV channels and websites for joint media campaigns.

Although the Abstract Cookie scenario performed best, for Stage 2 all the scenarios will be carried forward and evaluated as results may have been enhanced for the Abstract Cookie scenario due to the level of control that could be applied and also because the other scenarios may produce better cross media results.

6.7 Unique Contribution to Reach

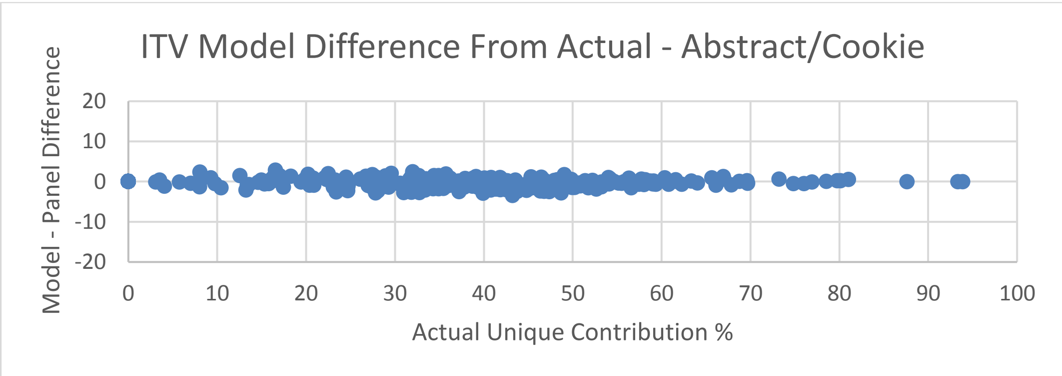
In addition to preserving the reach of stations it is important that the unique contributions each station makes to the overall reach of a campaign is preserved. A station's unique contribution to reach is the reach of the overall campaign that would be lost if that the spots on that station were removed. The average unique reach (as a % of census population) each station contributes for each of the 4 methods is as follows:

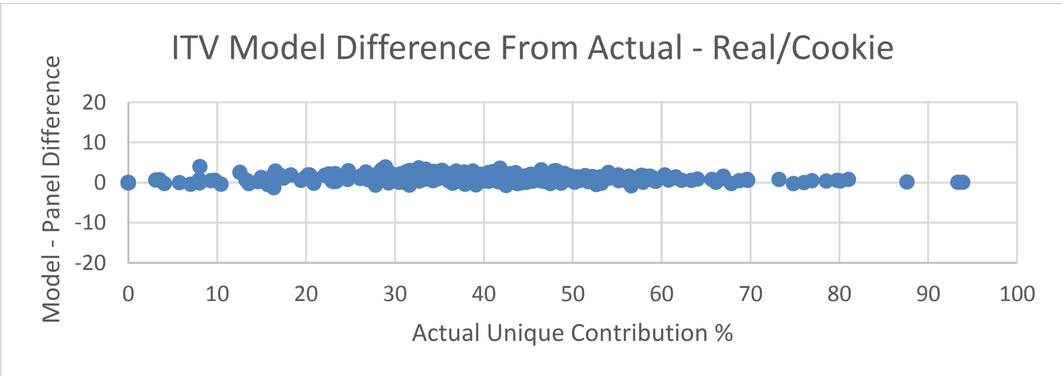
Unique contribution to reach – Absolute percentage points

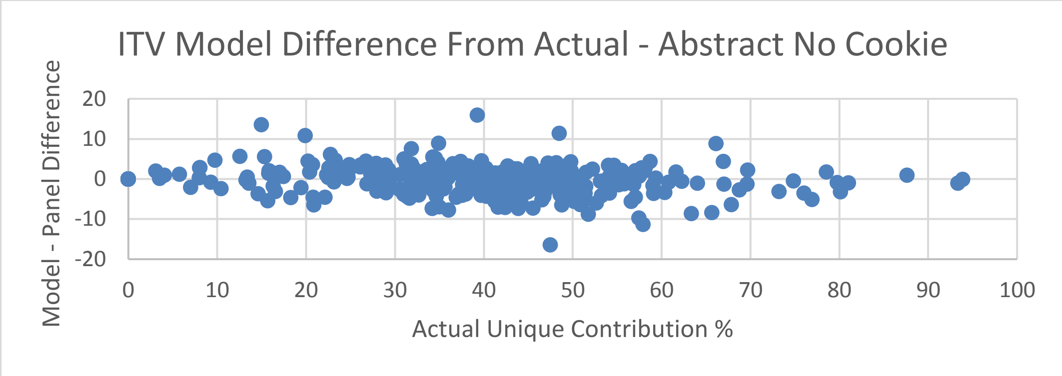
	Actual	Abstract/ Cookies	Abstract/No Cookies	Real/Cookies	Real/No Cookies
ITV	**15.0**	14.6	15.2	16.2	15.0
Channel 4	**5.4**	5.1	5.8	6.3	5.6
Channel 5	**3.7**	3.5	3.7	4.3	4.2
ITV2	**1.5**	1.4	1.3	1.6	1.6
Sky 1	**0.7**	0.8	1.0	0.8	0.8
Dave	**1.5**	1.6	1.8	1.6	1.6

All models on average seem to preserve the unique contribution to reach well albeit the Real/Cookies scenario consistently overestimates and to a higher degree.

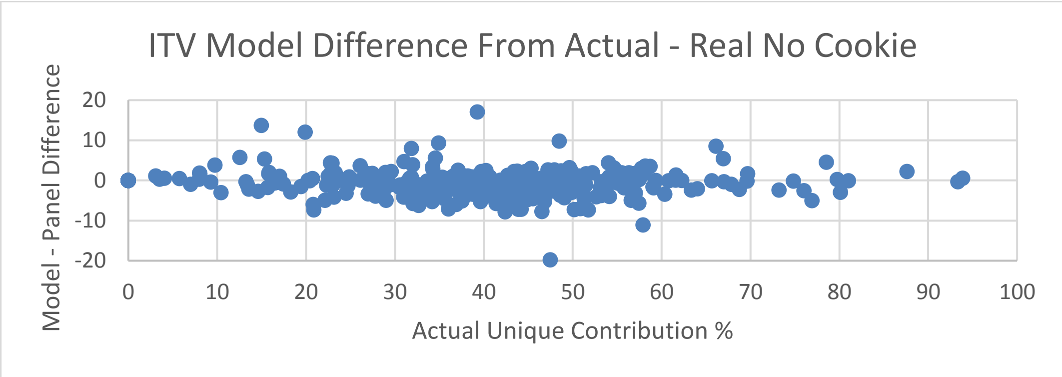
However, an examination of all individual campaigns shows that the cookie based models do a better job of preserving unique contribution to reach as they show the least variance between actual and modelled unique contribution to reach, with abstract/cookie performing the best (only ITV is shown but results are similar for the other stations):







ITV Model Difference From Actual - Abstract No Cookie
Model - Panel Difference
20
10
0
-10
-20
0
10
20
30
40
50
60
70
80
90
100
Actual Unique Contribution %



ITV Model Difference From Actual - Real No Cookie
Model - Panel Difference
20
10
0
-10
-20
0
10
20
30
40
50
60
70
80
90
100
Actual Unique Contribution %

7. Summary

Using the Compass panel (run by Ipsos MORI) Phase 1 of Origin was evaluated by treating the panel as a census and applying the methodology to a set of real TV campaigns known to have been broadcast in the period of the dataset. Four scenarios were assessed (Abstract rates to assign cookies; abstract rates to assign impressions; panel based rates to assign cookies; and panel based rates to assign impressions) and their performance evaluated. Performance was assessed at a top line level for reach as well as by demographic, station, type and week by week.

Results were encouraging in all methods, broadly conserving systematic variations in TV campaign reach across channels within the VID model. The preservation of reach suggests potential for the model to work well across TV and website campaigns, as well as website campaigns themselves, although nothing conclusive can be said until these types of campaigns are directly tested. Results indicated that abstract rates with cookies saw the smallest discrepancies between actual and modelled reach. However, it should be caveated that, for clarity in the POC, the evaluation has been limited to 6 larger channels and that abstract rates may be harder to devise in the presence of a long tail of channels. It may also be the case that to optimise the VID model for cross-media estimation, it is necessary to break down the cookie beyond separation of channels. In our opinion, the "no cookie" scenario results suggest that there is indeed some leeway without significantly distorting the TAM panel reach and frequency relationships within the linear advertising measurement. Therefore all 4 methods will continue to be assessed in Phase 2.

In addition, Phase 2 will evaluate the scenario in which the TAM panel ID creates a "cookie" which transcends campaign viewing across all channels in a campaign. By definition, this will preserve the TAM panel reach and frequency currency in the VID model. The trade-off will be the degree to which this might distort the cross-media duplications.

The technique used for evaluation is based upon goodness-of-fit, in the sense that one set of training campaigns are used to both fit and then evaluate the performance of the VID model. A second set of broadcast TV campaigns, in a different time period, will be available for phase 2 of the POC. It will be prudent to evaluate the set 1 trained model in terms of the set 2 campaign outcomes.