Department for Education

Your Future | Their Future: impact of the Department for Education's marketing campaign

Technical annex

January 2019

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Acknowledgements

We would like to acknowledge the useful guidance and feedback provided by the Department for Education (DfE) and their marketing contractors throughout this research. In particular, we would like to thank Nicola Keane and Vanessa Clements for supplying and providing clarifications on much of the data that was employed in our analysis. We would also like to extend our gratitude to Khalida Choudhury who was the DfE project manager, as well as Oliver Anderson and Simon Palmer for their methodological suggestions. A number of marketing specialists working with the DfE also provided invaluable insights and suggestions on how to overcome some of the methodological challenges in the research. Responsibility for the contents of this report remains with London Economics.

Contents

List of figures

List of tables

A1 Technical Annex

This Annex provides a more detailed description of the data collected and the econometric model developed for analysis.

A1.1 Data

The first stage of the project involved gathering all necessary data for the econometric modelling and collating it into a clean and consistent dataset covering the full modelling period. Data was collected from a number of sources, including the DfE marketing department and their commissioned marketing agencies, The Universities and Colleges Admissions Service (UCAS), as well as publicly-available national statistics sources (e.g. the Office for National Statistics (ONS) and Department for Education).

The final dataset compiled covers data for the period from 1st September 2012 to 31st January 2016, thus covering three full recruitment cycles and the first part of the 2015/16 recruitment cycle. The data was either collected at (or converted into) 'week commencing Monday' format. The choice of weekly data frequency was informed by the feasibility study. The motivation for this choice was twofold: firstly, the majority of marketing variables were available on a weekly basis; and secondly, a higher frequency data (i.e. monthly) would have provided fewer data points, which would have resulted in an insufficient level of variation for subsequent econometric modelling.

A1.1.1 Outcomes of interest

The feasibility study identified a number of key outcomes of interest across the entire customer journey undertaken by prospective teachers[1] for which data could be collected in the required format for subsequent analysis. These outcome variables included website visits, website registrations and UCAS applications, acceptances, ITT entries and NQTs, and are discussed in greater detail overleaf.

Shortage subjects

In addition, the DfE identified certain harder-to-fill subject areas, whereby graduates eligible to apply for these subjects might have a very different customer journey (as well as competing opportunities in the wider graduate labour market). In addition to the outcome variable 'all secondary subjects', a number of outcome variables were also defined for *shortage*[2] ITT subjects. Two versions of the 'shortage subjects' outcome variables were considered: one which followed the definition of shortage subjects over time, thereby reflecting the *changing* set of subjects considered shortage; and a second classification that only included those subjects classified as a shortage subject continuously over the entire duration of the modelling period. These are referred to as

[1] The process from learning about ITT opportunities, through considering them, to taking action towards applying for such opportunities.

[2] Shortage subjects included chemistry, mathematics, physics, computer sciences, modern foreign languages and design & technology for the recruitment cycles from 2012/13 to 2014/15. For the 2015/16 recruitment cycle, this definition has been updated to exclude design & technology and instead include biology and geography.

‘core shortage’ subjects (chemistry, mathematics, physics, computer science and modern foreign languages)). With the limited length of the time series data available, we wanted to avoid the inherent structural break issue[3] that the extended classification of the variable carries. Therefore, throughout the analysis, we modelled the core shortage classification.

Outcome variables

- Website visits are the first (*intermediate*) stage of the customer engagement process. DfE’s marketing strategy aims to initially engage with prospective teachers and encourage them to visit the *Get Into Teaching* website, which provides information on the routes into and benefits of the teaching profession. Data on the number of website visits was provided directly by DfE’s marketing department in weekly format, covering the full modelling period.
- Website registrations are the next *intermediate* outcome modelled, representing the number of individuals who have filled in the online interest form once they had visited the *Get Into Teaching* website. Data on this outcome was supplied by DfE’s marketing department in daily format and aggregated up to weekly format to match the format of the wider dataset (again covering the full modelling period). The website registration form includes a field on ‘subject of interest’, which allows number of registrations to be collected both for shortage subjects as well as for all subjects.
- UCAS applications are a crucial outcome associated with reaching the targeted number of ITT entrants in a given year, as the majority of applications to Initial Teacher Training positions come through UCAS. Moreover, this is the last outcome variable in the customer journey process which is solely dependent on the customer as opposed to the course provider. Weekly data on the number of UCAS applications, by subject, was supplied by UCAS through a data sharing agreement. We have modelled UCAS applications, both for all shortage subjects and core shortage subjects.

  However, over the course of the data analysis it became evident that these outcome variables exhibit a *highly seasonal pattern*[4] and a significantly delayed response. Therefore, due to the nature of the applications variable, the results from the econometric modelling are not sufficiently reliable to be used for marketing planning purposes. Nevertheless, for completeness, they are presented in detail in section A3 of the Annex of results.
- Acceptances, ITT entries and NQTs are the ultimate outcomes concluding the customer journey. Although these are the outcomes of most importance, they are very *distant,* both in timing and in character, to the decisions in the initial stages of the customer journey. In addition, the number of ITT entries and NQTs are only

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[3] Changing the subjects included as shortage to exclude design & technology and instead include biology and geography would have led to a jump in outcome variable between the 2014/2015 and 2015/2016 academic years. Such discontinuity in the data does not allow to produce reliable estimates over a short time scale.

[4] The number of new UCAS applications is highly dependent on the time of the year, and the pattern of the UCAS applications over time is very similar each year. The pattern observed is that he level of new UCAS applications increases very sharply within the first few weeks when the UCAS application process opens, and then gradually declines over the course of the academic year until the applications close.

observed annually. Therefore, these outcomes are unsuitable for evaluation using time-series econometrics and have instead been analysed as long-term outcomes using a set of assumptions. These results are presented in section A4 of the Annex of results.

A1.1.2 Marketing activities

Multiple marketing activities were undertaken throughout the duration of the modelling period, with varying intensity. One of the key challenges of the analysis related to *disentangling* the impact of each activity given the fact that many of the activities appear (deliberately) in bursts and at similar times. Data on each of the activities undertaken was provided by the DfE's marketing team and their contractors, and a number of alternative measures of the impact of each activity have been tested whenever available:

Table 1 Marketing activities data

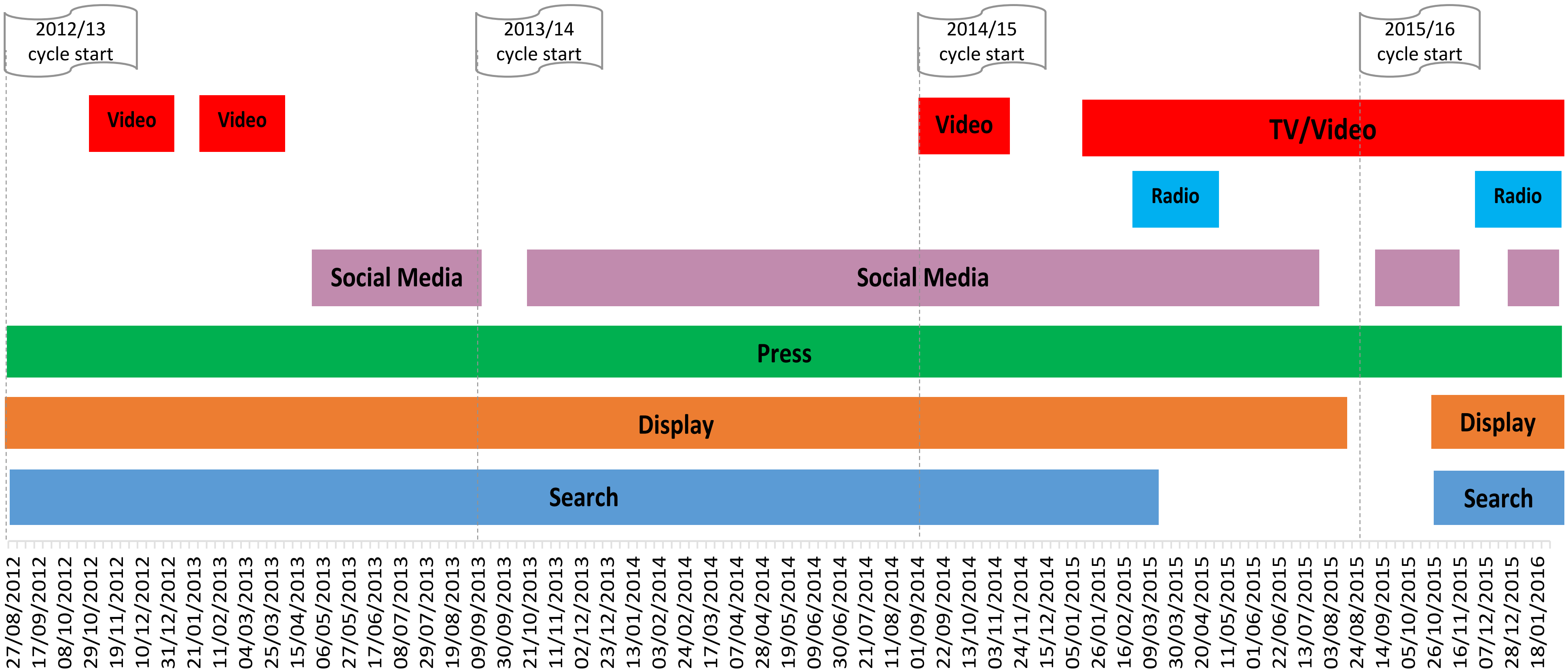
Activity	Measures
TV	• TV rating points (TVRs) • branded Search[5] (paid and organic) web sessions • branded Search (paid and organic) clicks
Press	• circulations • inserts • branded Search (paid and organic) web sessions • branded Search (paid and organic) clicks
Paid search (generic)	• clicks
Radio	• impacts • gross rating points (GRPs)
Digital Radio	• impressions • clicks
Display	• impressions • clicks
Video-on-Demand/ YouTube	• clicks
Social media marketing (Facebook, Twitter, LinkedIn, Instagram)	• a range of response and engagement measures
Out-of-home advertising (OOH)	• number of panels
Emails	• opens • sends • deliveries • click-throughs

Source: London Economics

[5] Branded Search refers to search for the 'call-to-action' phrase 'get into teaching' which appears on Press ads until 2015 and in the TV and Video film thereafter. As such, it is assumed to be used by customers who have seen the Press/TV/Video ad and therefore has been used as an explanatory variable to identify the impact of Press up to the beginning of January 2015, and that of TV & Video afterwards. In this fashion, branded Search provides a way to directly track these channels the impact of which is otherwise more difficult to measure.

An overview of the timing of the major groups of marketing activities (with varying levels of activity) is presented below in Figure 1:

Figure 1: Timing of alternative marketing activities



Source: London Economics summary of DfE marketing data

A1.1.3 Contextual factors

In addition to the information on the main activities undertaken as part of the marketing campaign and associated outcome measures, data was collected on a range of wider contextual factors, as these factors can impact an individual's decision to express an interest and apply for a teacher training course, either in the presence or in the absence of marketing activities. In econometric literature, such factors are usually referred to as 'control variables'.

Table 2 describes the set of control variables that were considered for inclusion in the econometric model. They represent factors that economic theory and the Department for Education's experience have shown might influence the number of trainee teachers entering ITT courses.

Table 2 Contextual factors data

Contextual factor	Source	Time coverage and frequency
Macro-economic factors[6]		
GDP growth	ONS key economic time series data	1955 Q1 – 2015 Q2; quarterly
Unemployment	ONS key economic time series data	05/2001 – 07/2015; monthly
Labour market conditions		
Percentage of graduates in the population	ONS 'Graduates in the UK Labour Market' publication based on Labour Force Survey Person Dataset data	1992 Q2 – 2015 Q3; quarterly
Graduates employed in non-graduate roles (recent and non-recent)		2001 Q2 – 2015 Q2; quarterly
Graduate unemployment (recent and non-recent)		1992 Q2 – 2015 Q3; quarterly
Number of allocated places / ITT targets	Department for Education	Annual
Cost-related factors		
Teacher pay and its levels relative to other competing professions[7]	Labour Force survey; Department for Education; annual editions of 'The Graduate Market' reports;	Quarterly average levels (LFS); Annual average levels (reports)
Tuition fees	Department for Education	Annual
ITT bursaries/scholarships by subject	Department for Education	Annual
Other deterministic factors		
Time trends and seasonality	Google Analytics	Pre-2010; weekly
Holidays and other events	Gov.uk	2012 – 2015; daily

Source: London Economics

Seasonality

Seasonality is a common characteristic of time-series data and as such, was also tested for in the model. Given the nature of the academic year, seasonality might be a particular concern in this analysis. Specifically, given the fact that the university applications cycle

[6] Macro-economic data needs to be lagged according to the data of publication, e.g. if unemployment data was announced to the public with a 12-week delay compared to the period it refers to, the data will be included with a lag of 12 periods (weeks).
[7] In reality, individuals obtain their information on salaries according to professions based on job advertisements, rather than reports, which means that (apart from annually-determined graduate position salaries), individuals observe salary changes in near-real time. The best available estimation of salary levels they might have observed by profession at a certain time would be based on the Labour Force Survey, which is issued quarterly.

(and associated deadlines etc.) traditionally takes place during particular calendar months, there may be a significant degree of seasonality in the process.

Given that the data spans only three and a half academic years, stripping out the seasonal pattern from the data would have taken away much of the variation truly contributed by marketing activity and therefore potentially misrepresented the estimated impact. Instead, seasonality variables were created and tested using data on the incidence of key teacher training-related search terms from Google Analytics over the course of a number of academic years prior to the implementation of the *Your Future | Their Future* marketing campaign. This approach was undertaken to generate an initial understanding of applicant awareness or engagement in the absence of any marketing activity.

Data on these search terms were only used prior to the modelling-period start point, so as to avoid these search terms being themselves impacted by observed marketing activities.

Holidays and major calendar events

Christmas, Easter and other major calendar events can disrupt the normal pattern of an individual's behaviour. For instance, it was observed that website visits and registrations were less frequent over the Christmas period. Creating indicators (or dummy variables) for holiday periods and other major calendar events can help explain disturbances in the data which otherwise appear random but have an effect on the estimated impact of other variables.

A1.2 Analysis

A1.2.1 Econometric analysis

General econometric framework

The DfE is interested in understanding what contribution their latest marketing campaign *Your Future | Their Future* has made towards teacher recruitment, and which specific marketing channels had a key contributory role. Econometric analysis provides a useful tool for disentangling the impact of the different marketing activities on recruitment outcomes from the impact of the contextual factors. In addition to establishing what level of outcome would have been achieved in the absence of marketing, the econometric modelling results were used to measure the impact of each marketing channel separately.

The formula below describes a simple econometric model. The brackets below list the outcome variables modelled, as well as some of the marketing activities and contextual factors considered.

Figure 2: General form of the econometric model

$$Outcome_t = \alpha + \beta \times Marketing\ activities_t + \gamma \times Contextual\ factors_t + \varepsilon$$

- Website sessions
- Website registrations - all secondary subjects
- Website registrations – core shortage subjects
- Registration starts
- UCAS applications – all secondary subjects
- UCAS applications – core shortage subjects

- TV
- Press
- Search
- Display
- Social media
- Video
- Radio
- Outdoor
- CRM

- Seasonality
- Holidays and notable events
- Graduate unemployment
- Salaries of competing profession in the public and private sectors
- Average secondary teacher salary
- ITT bursaries

Source: London Economics

An econometric model attempts to determine the relationship between the variables on the right-hand side of the equation and the variable(s) on the left-hand side. The left-hand side variable, referred in econometric literature as the dependent variable, is the outcome variable that is being estimated. A separate model was estimated for each of the outcomes of interest.

The right-hand side of the equation contains a selection of factors which potentially influence the value of the modelled variable (known as independent or explanatory variables). In this example, the independent variables include the measureable marketing variables, as well as the contextual factors of importance. β represents the coefficients of most interest in this study, which provide an indication of the impact of each marketing channel on the outcome of interest.

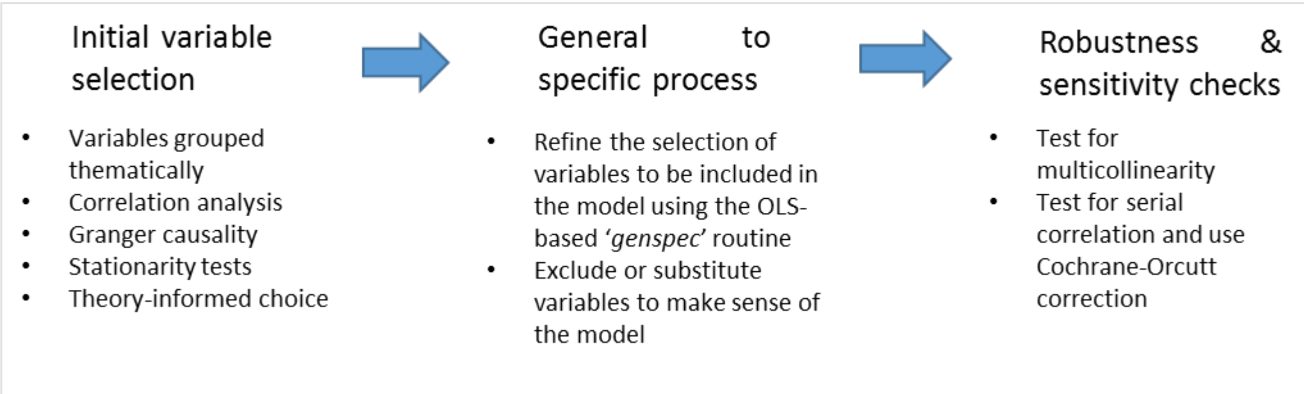
The outputs of this model can then be used to compare incremental impacts from each channel; examine the impact of the campaign as a whole; and to generate cost effectiveness measures for each channel.

Variable selection procedure

The main challenge in modelling the outcome variables was to select the set of explanatory variables that 'best' explain the observed outcomes. Goodness-of-fit statistical test statistics (e.g. adjusted R-squared) were used in combination with economic and marketing reasoning (e.g. whether the sign and magnitude of the estimated coefficients is plausible given the interpretation of the explanatory variables) to judge how well a set of variables explained the modelled outcome.

Figure 3 represents the process undertaken to arrive at the final selection of explanatory variables. Although five different models were estimated (i.e. one for each of the outcomes of interest), the same over-arching variable selection process (denoted below) was used throughout.

Figure 3: Variable selection procedure



Source: London Economics

The selection of explanatory variables started with preparatory correlation analysis, and was then driven by the general-to-specific method, in which the evaluator starts with a large number of candidate variables and narrows them down to a set of key explanatory variables, without the model losing statistical power. Complementing this method, various transformations of the explanatory variables were tested within the model to mimic various behavioural response patterns. Verification checks and robustness checks accompanied the econometric estimation.

Multicollinearity and grouping of marketing activity variables

In order to detect and avoid potential multicollinearity problems in the estimation, a partial correlation matrix was produced for all marketing activity variables tested in the model. Multicollinearity is a statistical phenomenon in which two or more explanatory variables in a multi-variate regression model are highly correlated, meaning that one can be linearly predicted from the other with a substantial degree of accuracy. This could occur if two marketing activities, for instance Press and TV, were regularly undertaken over the same time periods.

Multicollinearity is an issue as it increases the variance of coefficient estimates and makes them very sensitive to minor changes in the model specification. This can make it difficult to choose the optimal model specification and can produce estimates that can be difficult to interpret (e.g. estimates that suggest that one of the marketing activities has a *negative* effect on the outcome, which is generally very unlikely).

If marketing activity variables represent similar types of marketing activities (e.g. social media marketing/digital marketing/ video-on-demand) and are measured in the same way (e.g. impressions/clicks/landings), these variables can be grouped together into one aggregate variable (e.g. Facebook impressions + Twitter impressions + LinkedIn impressions = Social media impressions). Grouping variables in such a manner reduced the multi-collinearity problem, avoided a potential omitted variable problem[8], and captured the impact of both activities at the same time in the model.

Correlation analysis

Correlation analysis was further used in order to reduce the number of variables entering the general-to-specific routine and to avoid overfitting the data[9]. A correlation coefficient was computed for each explanatory variable with each of the dependent variables. These correlation coefficients provided an initial idea of potential candidates to be used as explanatory variables in the econometric models. However, it is important to remember that correlation analysis identifies the association between the two variables, but does not provide causality links, and acts predominantly as important preparatory work for the subsequent econometric estimation.

Stationarity tests

One of the most likely issues associated with applying OLS to time series data is that of non-stationary variables. Firstly, given the raw data for each variable, it is necessary to test whether each variable is stationary[10].

Before commencing the econometric modelling, we performed three stationarity tests on each of the outcome variables. Stationarity tests help detect the presence of a trend and structural breaks in the data, which are issues that are common to time-series analysis and which would result in OLS estimates lacking robustness.

Looking at the combined evidence from the three tests, there is no strong evidence that unit-roots or time trends are present in the website sessions and registrations outcome variables.

[8] This problem occurs if an important marketing factor is not captured in the model. The model might 'compensate' for this missing factor by overestimating the effect of one of the other factors.
[9] In econometric terms, if a model is overly complicated and incorporates too many variables given the number of data points, the model might suggest a relationship between a variable being tested and the outcome, where no such underlying relationship exists.
[10] Stationary variables have constant statistical properties (e.g. mean, variance) over time. A variable is not stationary, for example, when it has a structural break in its data generating process.

Three stationarity (unit root) tests were considered:

- the Augmented-Dickey Fuller (ADF) test;
- the Phillips-Perron (PP) test; and,
- the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) test.

Each has its merits and downsides: the ADF test corrects for higher-order serial correlation by adding differenced terms of the lagged variable as determinants. However, including differenced lags reduces the power of the ADF text and as such the ADF test has a low power differentiating between true unit-root processes and near unit-root process. The PP test accounts for serial correlations by using corrected t-statistics of the coefficients of the lagged variables. The advantage of the PP test vis-à-vis ADF is that it assumes no functional form for the error process of the variables which can help account for autocorrelation.

Finally, the KPSS tests for trend and level stationarity uses different numbers of lags of the residuals as explanatory variables. The advantage of using the KPSS test alongside the ADF and PPP tests is that it allows to distinguish whether a series is stationary, has a unit root or is insufficiently informative. Moreover, it can also be used to investigate whether a series is fractionally integrated.

The Schwert criterion is used to select the maximum number of lags included in the tests.[11] If presence of a unit root is suspected, the data can be transformed using first differences.

If the test statistics are larger than the critical values, the result would be that all the variables are trend or level non-stationary (to a certain number of lags).

The three classes of stationarity tests were performed on all outcome variables modelled, namely website sessions, website registrations for all secondary subjects and for core shortage subjects, and UCAS applications for all secondary subjects and for core shortage subjects. Tests were performed both for trend- and constant-stationarity, on lags 0 to 3. Although the results from the three different tests yield some minor discrepancies, the overall set of results shows no concerns over the stationarity of any of the outcome variables modelled.

General-to-specific approach

Our approach to building the econometric models departs from the General-to-Specific (G-S) modelling. Specifically, the G-S approach is a statistically rigorous approach to building an econometric model. It is particularly useful in cases where there are a large

[11] The Schwert criterion is the default method used by statistical programmes such as STATA.

number of potential explanatory variables and it is not clear a priori which explanatory variables should be included in the regression model[12].

Model refinements implemented in this analysis

One drawback of the general-to-specific approach is that it is entirely data driven. Given the relatively small number of data points in the sample and the relatively large number of explanatory variables to be tested (even after the restrictions imposed by variable grouping and correlation analysis), the general-to-specific approach might produce the best results in terms of goodness-of-fit; however, the results may not necessarily have any sensible economic and marketing interpretation. For this reason, the general-to-specific model results serve only as a starting point for the building of the model.

Each of the variables selected by the *'genspec'* routine were examined for the sign, magnitude and statistical significance of their estimated coefficient of impact. The approach adopted in determining which variables to hold and which to remove was as follows:

1. Contextual factors: If the sign of a contextual factor is not justified by economic theory, or the coefficient is not statistically significant, the variable was removed as there was no strong evidence of causal relationship between the contextual factor and the modelled outcome.
2. Marketing activities: If the sign of the coefficient of a marketing activity was negative (usually coupled with lack of statistical significance), the variable was removed as none of the marketing activities would be expected to have a negative impact on customer awareness or engagement. If the sign was positive but the coefficient was not statistically significant, the variable was retained in the model, as the variable still potentially had an impact.

Adaptation of the model for time-series data

In this study, the standard OLS approach was adapted for time-series data by allowing for seasonality, time trends and lagged variables.

The econometric model was also adapted to incorporate behavioural response to marketing. At the individual level, some individuals might respond to advertising immediately or in the same week, but others might exhibit delayed response in their actions. Incorporating a simple marketing variable that only has measureable values in the weeks it actually occurs would therefore underestimate the actual impact of the activity.

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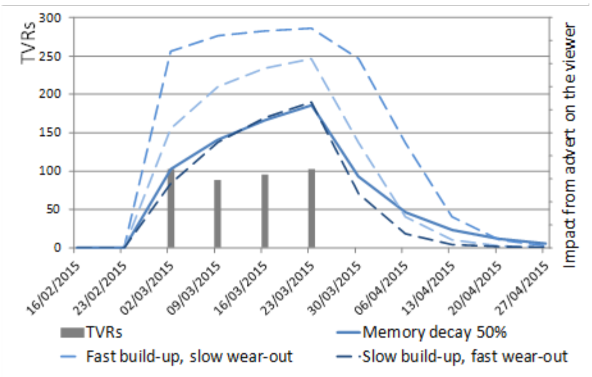
[12] The general-to-specific approach used was the 'genspec' command in **STATA**. This approach removes the least statistically significant variable at each stage in an **iterative process**, until either all variables remaining in the model are statistically significant (Clarke, D. (2014). *General-to-specific modeling in Stata*. Stata Journal, 14(4), 895-908.)

To address this issue, the set of marketing response variables tested in the econometric model was expanded to accommodate behavioural factors[13] that may arise in the individuals' decision-making process. These variables were constructed through a variety of mathematical transformations of the marketing variables[14]. Figure 4 demonstrates how these transformations can mimic a variety of shapes of point-wise response levels to TV advertising over time, all of which are induced by the same amount of TVRs[15] of the DfE teacher marketing campaign.

Figure 4: Behavioural impact of advertising – constructing alternative variables for testing



Source: London Economics and DfE TV marketing data

Robustness checks

Due to the time series characteristics of the data, visual and statistical checks for multicollinearity, stationarity[16] and autocorrelation[17] were implemented to ensure the robustness of the results.

- Stationarity tests, as described earlier in this section, were run on the dependant variables before modelling in order to identify whether OLS was an appropriate approach to use. Stationarity tests were also run on the macroeconomic variables prior to the group selection procedure in order to pre-select only those which satisfy the stationary requirements
- A *variance inflation factor* test was performed on the *'genspec'* model results using the *'vif'* STATA command in order to test for multicollinearity issues. The rule of thumb is that if a variable has an individual *vif* test statistic greater than 10[18], it is

[13] Behavioural factors can arise from the audience's decision making process (e.g. how much consideration people need on average to change their decision on choice of career) as well as the advert characteristics, such as how frequently an add needs to be seen to trigger response, what speed of built the advert has, and how quickly the audience's memory of the advert decays.
[14] These transformations include: lags to account for time delays in response; variable decays to test for time-persistent but declining impacts of the activity after it has ended; and sets of (arctangent) function transformations of the decay variables to test for a different speed of build and wear-out of response for the same marketing activity output levels.
[15] TV rating points – defined as a given percentage of a base population watching a TV programme where that base is defined as a given target audience in a given geographical area.
[16] Stationary variables have constant statistical properties (e.g. mean, variance) over time. A variable is not stationary, for example, when it has a structural break in its data generating process.
[17] Autocorrelation arises when past values of a variable directly impact future values of the same variable.
[18] http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter2/statareg2.htm

likely to cause multicollinearity problems. Such variables were eliminated or substituted one by one until all problems were eliminated.

- As is often the case in time series data modelling, autocorrelation was observed in most of the estimated models. However, choosing an alternative model specification (e.g. an AR process) would not have provided a good indication of the incremental impact from marketing over time. Therefore, Cochrane-Orcutt correction for serially correlated error terms was used to produce robust standard errors in all models with an autocorrelation problem, using the '*prais'* STATA command to re-estimate the model with the same chosen set of variables based on the OLS specification.

A1.2.2 Derivation of incremental impact figures

The econometric model of each outcome variable provides information on:

1. which of the observed factors explain the outcome in a meaningful way; and
2. by how much the outcome variable would change given a unit change in the explanatory variable (the $\boldsymbol{\beta}$ coefficients estimated by the model).

Knowing the level of each explanatory variable in each week, we estimated the incremental impact on the outcome variable under consideration for a given marketing activity *i* using the following equation:

Figure 5: Estimation of the impact from marketing using econometric results

$$Incremental\ impact from\ marketing\ activity_{\ i,t}\ =\ \beta_i * Level\ of\ marketing\ activity_{\ i,t}$$

Source: London Economics

A1.2.3 Cost effectiveness analysis

Costs data

The costs included in the marketing analysis were gross costs incurred by the DfE marketing department, wherever these were available.

It should be noted that the costs of creating the advertising campaign itself were not included in our cost estimates. It should also be noted that costs for both on-campus and graduate fair advertising and Customer Relationship Management (CRM)[19] were not included in the cost estimates as these costs were not provided to London Economics.

Costs of top-level channels are calculated as the sum of the costs of all the marketing activities included in the top-level channel, regardless of whether all activities falling

[19] Customer Relationship Management in this context includes, for instance, emails, text messages and calls to website subscribers to assist them in filling in an application.

within that channel had been found to be statistically significant (e.g. all social media costs were considered even if only Facebook was found to have an impact).

Comparisons of cost effectiveness of each channel

When calculating cost effectiveness of marketing for a given outcome, all costs have been allocated to that outcome. In reality, a marketing activity may have affected multiple outcomes (e.g. a TV advert induces an individual to visit the website, register and apply for initial teacher training). However, this assumption is necessary since it is not possible to disentangle the costs of the activity by ultimate outcome. Therefore, when discussing cost effectiveness of marketing for one outcome (website sessions, for example), it should be noted that the same marketing activities are also likely to have induced the other outcomes (e.g. website registrations, UCAS applications and further outcomes). Therefore, some degree of caution should be applied when considering the notional cost effectiveness of different marketing activities associated with different outcomes.

A1.2.4 Caveats

Challenges of the chosen econometric approach

The OLS approach for time series data estimates a linear model as described in Section 2.2. One assumption of this econometric approach is the timeliness of the impact of a marketing activity on the outcome, or the extent to which a lagged impact can be identified. However, a more substantial delay in impact, for instance months rather than weeks, is difficult to disentangle from the impact of other factors due to issues of multicollinearity and spurious correlation. This is the main reason why applications related outcome variables were the most challenging to model, and the results from these models were insufficiently robust.

In addition, despite grouping variables within groups, multicollinearity still presents a problem given that many marketing activities only occur in very short time-periods and in parallel. As discussed in section 2.2.1, the variance inflation factor (VIF) test was used during the model selection procedure to identify and eliminate explanatory variables with high levels of multicollinearity. Therefore, the presented models do not suffer from this statistical issue. However, a remaining limitation is that we might not be able to capture the impact of every marketing channel that has been a part of the campaign.

Limitations of the marketing data

There are further issues associated with the quality of the marketing activities data.

Firstly, in December 2014 there was a three week period of data loss when the DfE switched between marketing agencies. In turn, this period could not be included in the modelling.

Secondly, there are some concerns about the quality of the data of a few of the marketing activities:

- Display data: There is no granular Display data for the academic year 2012/2013 and the variation in Display could not be modelled over this period. Therefore, a flat distribution of the aggregate Display figures was used implying that the impact of Display might not have been captured accurately.
- Press data here is an inherent difficulty in measuring the impact of Press on outcome variables because of the lack of immediacy of the response by individuals to press advertising. For instance, an advert in a monthly magazine could be read anytime in a month.

  Furthermore, the impact of press activity was measured using data on Branded Search for the period 2012-2015. Branded Search refers to search for the 'call-to-action' phrase "Get into Teaching" which appears on the advert. As such, it is assumed to be used by customers who have seen the Press advertisement, and therefore has been used as an explanatory variable to identify the impact of Press up to the beginning of January 2015. However, in the 2015/2016 academic year, the 'call-to-action' phrase was placed in the TV/Video advertisement and the Press campaign started using user-friendly URLs instead. Given that people might not search for the exact URL in the same way as a 'call-to-action' phrase, this reduced the ability to measure the effectiveness of the Press campaign.

- Outdoor advertising: Outdoor advertising shares similar problems in tracking customer-reach as Press advertising, specifically the fact that it is difficult to measure how many people have seen the outdoor advert in a given week.

Department
for Education

Reference: DFE-RR624

ISBN: 978-1-78105-983-8

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