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From Neural Responses to Population Behavior: Neural Focus Group Predicts Population-Level Media Effects

Emily B. Falk[1], Elliot T. Berkman[2], and Matthew D. Lieberman[3]
[1]University of Michigan, [2]University of Oregon, and [3]University of California, Los Angeles

Abstract

Can neural responses of a small group of individuals predict the behavior of large-scale populations? In this investigation, brain activations were recorded while smokers viewed three different television campaigns promoting the National Cancer Institute's telephone hotline to help smokers quit (1-800-QUIT-NOW). The smokers also provided self-report predictions of the campaigns' relative effectiveness. Population measures of the success of each campaign were computed by comparing call volume to 1-800-QUIT-NOW in the month before and the month after the launch of each campaign. This approach allowed us to directly compare the predictive value of self-reports with neural predictors of message effectiveness. Neural activity in a medial prefrontal region of interest, previously associated with individual behavior change, predicted the population response, whereas self-report judgments did not. This finding suggests a novel way of connecting neural signals to population responses that has not been previously demonstrated and provides information that may be difficult to obtain otherwise.

Keywords

mass media, neuroimaging, health, cognitive neuroscience, neuromarketing, health communication, smoking

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Can small groups of individuals efficiently predict population-level behavior? People are notoriously limited in their ability to predict their own future behavior and accurately identify their internal mental states through verbal and written self-reports (Nisbett & Wilson, 1977). Furthermore, explicitly asking participants to reflect on such internal mental states (e.g., "Why do you like this?") has been shown to alter the outcome and quality of judgments (Wilson & Schooler, 1991). Thus, it is not surprising that public-health media messages selected using traditional focus groups—which rely on these forms of self-report—are also imperfect predictors of population-level responses (Noar, 2006).

Recent research has identified neural indicators of individuals' future behavior that may be inaccessible using self-reports (Berns & Moore, 2012; Brewer, Worhunsky, Carroll, Rounsaville, & Potenza, 2008; Falk, Berkman, Mann, Harrison, & Lieberman, 2010; Knutson, Rick, Wimmer, Prelec, & Loewenstein, 2007; Kosten et al., 2006; Paulus, Tapert, & Schuckit, 2005; Tusche, Bode, & Haynes, 2010). However, it has not been previously demonstrated whether neural responses to persuasive messages in a small group of individuals also forecast behavioral responses at the population level (e.g., in a city or state).

To examine this question, we partnered with public health organizations that had produced television ads designed to help smokers quit. We used ads from three campaigns in a functional MRI (fMRI) investigation conducted in a separate location from where the ads were aired. Participants in our study (smokers who intended to quit) viewed ads from each campaign while their neural activity was measured. In a previous study, we used the same task and sample to demonstrate that overall neural activity across all the ads predicted individual smoking reduction in the month following the scan, above and beyond the participants' self-reports of intention to quit, quitting-related self-efficacy, and their ability to relate to the ads (Falk, Berkman, Whalen, & Lieberman, 2011). In the analyses reported here, we used those data together with new

Corresponding Authors:
Matthew D. Lieberman, University of California, Franz Hall, Los Angeles, CA 90095-1563
E-mail: lieber@ucla.edu

Emily B. Falk, University of Michigan, 426 Thompson St., Ann Arbor, MI 48104
E-mail: ebfalk@umich.edu

data (about population-level outcomes) to answer an orthogonal question: Would neural activity in response to the different ad campaigns predict the effectiveness of the campaigns among a larger group of new individuals? To address this question, we used the fMRI data and self-report predictions of the ads' effectiveness to rank the campaigns. We then compared these rankings with the actual population-level success of the campaigns. Neither this analysis, the brain-activation-based and self-report measures of the ads reported in this article, nor the population data were reported in the previous study. The approach described here is novel because it directly links neural responses with behavioral responses to the ads at the population level.

Method

Participants

Thirty-one right-handed participants (15 female, 16 male) were recruited from a quit-smoking program in the greater Los Angeles area. One male participant was excluded for excessive motion during the fMRI session. All participants were heavy smokers with a strong intention to quit (Biener & Abrams, 1991); thus baseline intentions to quit were held relatively constant across this sample. Participants varied in age from 28 to 69 years (M = 44.4 years, SD = 10.1) and were ethnically and socioeconomically diverse. Participants were paid $80 for completion of the fMRI portion of the study. The study was approved by the University of California, Los Angeles institutional review board, and all participants provided written informed consent. (See Additional Participant Details in the Supplemental Material available online for further information about the sample.)

Procedure

The ads task. The task during the fMRI session consisted of viewing professionally developed television ads designed to help smokers quit smoking. We focused on three ad campaigns (designated here as Campaigns A, B, and C). All of the ads were selected to target smokers who had decided to quit. All ads lasted 30 s, with the exception of two ads that were 15 s. All participants viewed a series of 16 ads, 10 of which ended by displaying the National Cancer Institute's Smoking Quitline phone number (1-800-QUIT-NOW). These 10 advertisements are the subject of the current study; three of these ads appeared in Campaign A, three appeared in Campaign B, and four appeared in Campaign C. All campaigns included a total of 90 s of ad time. (For additional information, see Organization of the fMRI Task in the Supplemental Material.)

Population-level measures. To measure the population-level success of each advertising campaign, we compared Quitline call volume from the month before and the month after each ad aired. (Call volume after the ads aired was directly attributable to the launch of the media campaign.) We drew these data from the media market in which the ads were run, and we controlled for factors such as media weight purchased (i.e., the size of the audience the ads were expected to reach).

Self-report measures of ads. After the fMRI procedure, participants completed a survey, in which they ranked the projected effectiveness of all of the ads they viewed during the scanner session. Participants also ranked the ads from least favorite to most favorite and evaluated each ad's effectiveness using a 10-item scale. This scale was developed based on questions used to evaluate similar ads in other settings and based on theoretical constructs such as internal motivation and social norms (Table 1). The items on this scale showed high internal consistency (Cronbach's α = .95). Response options were 1, *strongly disagree*; 2, *disagree somewhat*; 3, *agree somewhat*; and 4, *strongly agree*. There was a high degree of consistency across all three types of self-report. (For additional information, see Self-Report Projections of Ad Effectiveness in the Supplemental Material.)

fMRI data acquisition and analysis

Imaging data were acquired on a 3-T Siemens Trio scanner using standard acquisition parameters and were preprocessed and quality-checked according to standardized procedures. One participant was excluded because of extreme head motion. The task was modeled separately for each subject using a block design in Statistical Parametric Mapping software (SPM5; Wellcome Trust Centre for Neuroimaging, London, England). Initial analyses modeled brain activation during exposure to each ad campaign compared with a fixation baseline. Corresponding random-effects models calculated averages across results at the single-subject level. (See fMRI Data Acquisition and Analysis in the Supplemental Material for more information about acquisition, preprocessing, and analysis of fMRI data.)

A priori region of interest (ROI). The primary ROI was constructed using MarsBaR (Brett, Anton, Valabregue, & Poline,

Table 1. Items on the Self-Report Scale of Ad Effectiveness

This ad motivates me to quit.
This ad is discouraging. (reverse-coded)
This ad is helpful.
This ad is persuasive.
This ad is believable.
This ad grabbed my attention.
This ad is powerful.
This ad is confusing. (reverse-coded)
This ad highlights for me that people who care about me want me to quit.
This ad made me stop and think.

Note: Response options were 1, *strongly disagree*; 2, *disagree somewhat*; 3, *agree somewhat*; and 4, *strongly agree*. These items showed high internal consistency (Cronbach's α = .95).

2002); it encompassed a ventral subregion of medial prefrontal cortex (MPFC) in Brodmann's area (BA) 10. This region was selected because it was the cluster most highly associated with individual behavior change in a previous independent study (Falk et al., 2010; Fig. 1a). It was also predictive of individual behavior change within the same cohort of smokers (Falk et al., 2011) in analyses orthogonal to the current investigation. Average parameter estimates of activity were extracted at the group level using MarsBaR in order to compute a ranked prediction of ad effectiveness (in which higher levels of neural activity in the a priori ROI were hypothesized to correspond with greater ad success).

Control ROIs. To confirm that results in our primary ROI were not due to uniformly increased neural activity during certain ad campaigns (i.e., to establish discriminant validity), we subsequently constructed control ROIs in regions not hypothesized to respond differentially to the ad campaigns, including primary visual cortex, primary motor cortex, and right and left frontal eye fields. We also included results from ventral striatum because of its prominence in the behavioral economics literature. (For more information about the construction of the control ROIs, see fMRI Data Acquisition and Analysis in the Supplemental Material; results pertaining to these control ROIs are shown in Fig. 2 and in Fig. S1 in the Supplemental Material).

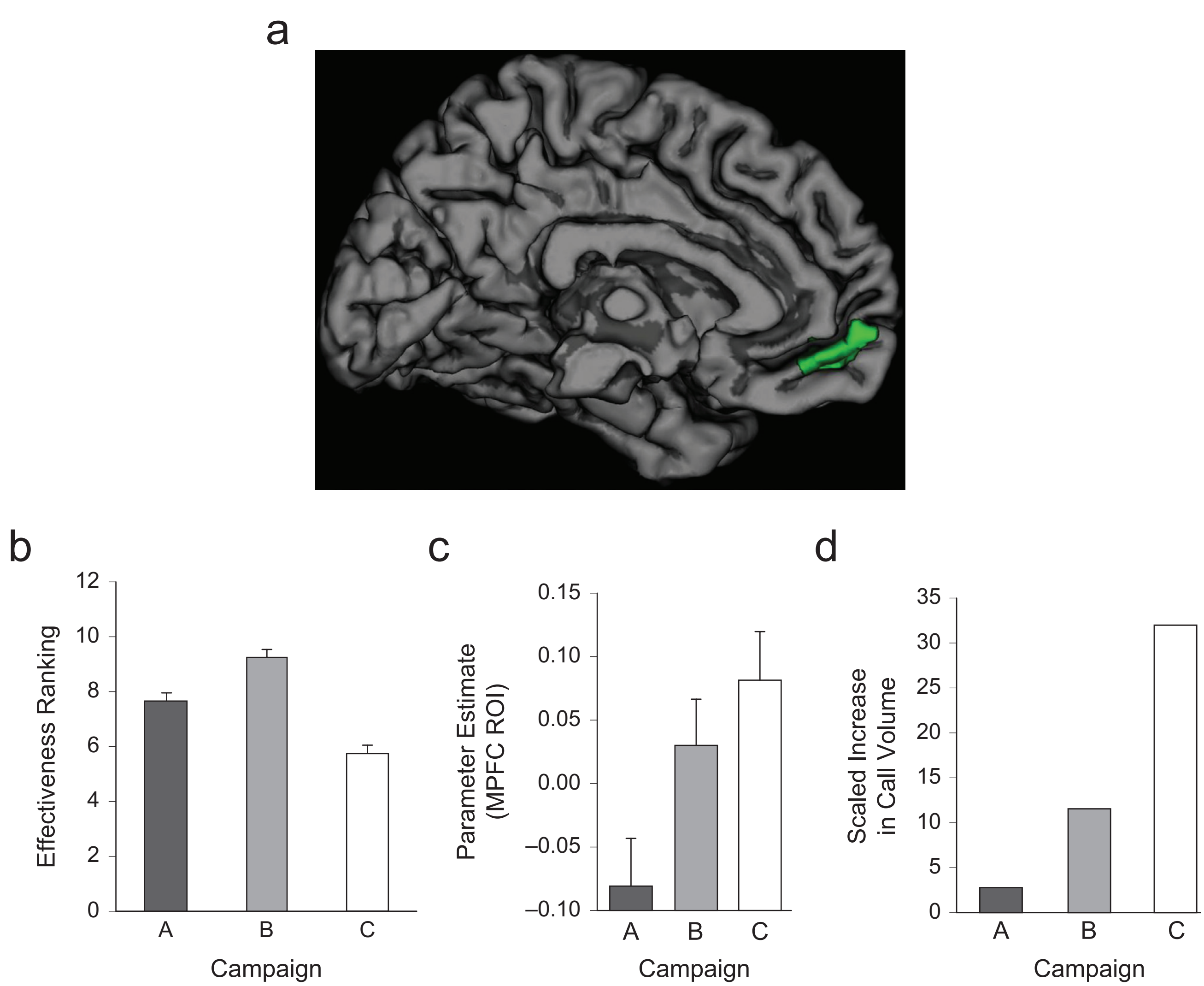

Fig. 1. Illustration of the medial prefrontal cortex (MPFC) region of interest (ROI) and three measures of the effectiveness of the antismoking ad campaigns promoting the National Cancer Institute's Smoking Quitline. The top panel (a) shows the MPFC ROI examined in the study; this region predicted individual behavior change in prior work (Falk, Berkman, Mann, Harrison, & Lieberman, 2010; Falk, Berkman, Whalen, & Lieberman, 2011). The graphs show (b) mean effectiveness ranking, (c) mean activity in the MPFC ROI, and (d) scaled percentage increase in call volume to the National Cancer Institute's Smoking Quitline for the three ad campaigns. Error bars in (b) and (c) represent pooled standard errors of the mean. Error bars are not shown in (d) because these values represent population change and not a sample from that population.

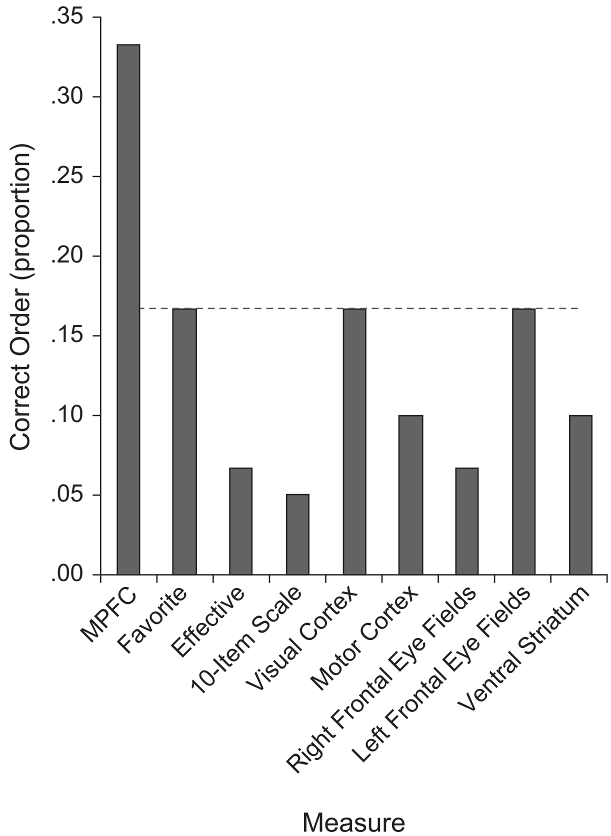

Fig. 2. Proportion of cases in which responses produced the correct ordering of campaigns (C > B > A) as a function of measurement type. The measures used were activity in the primary region of interest (medial prefrontal cortex, or MPFC), self-reports (ranking of favorite ad campaigns, ranking of most effective ad campaign, and evaluation of each ad campaign on a 10-item scale), and activity in control regions of interest (visual cortex, motor cortex, right frontal eye fields, left frontal eye fields, and ventral striatum). The dashed line represents chance performance.

Self-report and neural projections of ad-campaign success

Parameter estimates of neural activity in the MPFC ROI were extracted using MarsBaR. Individual self-report measures of ads within each campaign were averaged to compute self-report rankings of campaign effectiveness for each participant. Each subject's data were converted to rankings attributed to each data source using MATLAB 7.10.0 (The MathWorks, Natick, MA). We examined the data in three ways. We first examined the overall ordering of ad campaigns suggested by mean ratings. We next used a chi-square test to compare the proportion of individuals who produced each possible ranking with what would be expected by chance (1/6). Finally, we confirmed the reliability of the proportion-based predictions using weighted Kendall's taus (τ_w; Critchlow, Fligner, & Verducci, 1991; Lee & Yu, 2010; Shieh, 1998; see Kendall's Tau Distance Based Metric for Ranking Data in the Supplemental Materials for details and formulas).

Results

All three measures of participants' self-reported projections of ad effectiveness produced the same mean ranking of the ad campaigns (Table 2): Campaign B was ranked highest, followed by Campaign A, and then Campaign C (Fig. 1b). Industry experts who were familiar with the campaigns also ranked Campaigns B and A above C. In contrast with the self-report measures, the prediction based on the participants' mean neural activity in the MPFC ROI during ad exposure suggested a different campaign order: C > B > A (Table 2; Fig. 1c).

Given that there are six possible ways to order the three campaigns, each ordering has a 1/6 probability of occurring by chance. Therefore, in addition to examining group means, we also examined the frequency with which each ordering occurred across subjects (Fig. 2). Consistent with the mean ratings, our results showed that 33% of the individual rankings based on MPFC activity suggested the order C > B > A. A chi-square test confirmed that the proportion of C > B > A orderings suggested by MPFC activation was significantly above chance, $\chi^2(1, N = 30) = 5.97$, $p = .015$, whereas no other ordering of MPFC data appeared above chance level (16.67%). This result also indicates that C > B > A was selected more frequently than any other order, providing an unambiguous prediction from MPFC activity. The proportion of self-report rankings mirrored the ordering suggested by mean self-report ratings across self-report metrics (see Fig. S2 in the Supplemental Material for results of each self-report metric), which suggests a different, unambiguous prediction (B > A > C) from self-report data. In other words, MPFC and self-report metrics each produced clear but discrepant predictions of the population-level response.

At the population level, each of the ad campaigns led to increases in call volume to the National Cancer Institute's Smoking Quitline, ranging from 2.8- to 32-fold increases (Table 2; Fig. 1d) compared with the month prior to the launch of each campaign. Increases in call volume to the Quitline in the month after the campaigns were launched were taken as a proxy for the population-level success of each campaign. The ordering of population-level success (based on call-volume increase) was C > B > A, which was consistent with the neural predictions (C > B > A) but different from the self-report predictions (B > A > C). This ordering remained the same both before and after adjusting for a variety of potential differences between media markets, including media weight purchased, time of year, unemployment rate, smoking rate, and tobacco-control policies.

Thus, both the average and most frequently observed neural responses in our MPFC ROI correctly ordered the success of the ad groups at the population level, whereas self-reports of our participants and anecdotal evaluations of industry experts did not. To confirm the reliability of this result, we examined the distances between individual MPFC rankings and the modal (correct) ordering using a distance-based metric for ranked data, weighted Kendall's tau. To the degree that

Table 2. Self-Report Measures, Medial Prefrontal Cortex (MPFC) Region-of-Interest Parameter Estimates, and Population-Level Change in Quitline Call Volume for the Three Ad Campaigns

Dependent variable	Campaign A	Campaign B	Campaign C
Self-report measure			
Mean effectiveness ranking	7.64_a (0.630)	9.24_b (0.451)	5.75_c (0.502)
Mean favorite ranking	7.93_a (0.646)	9.21_b (0.423)	5.52_c (0.494)
Mean evaluation rating (1–10)	2.40_a (0.122)	2.59_b (0.111)	2.05_c (0.117)
Neural activity			
Mean MPFC parameter estimate	-0.08_a (0.079)	$0.03_{a,b}$ (0.059)	0.08_b (0.057)
Population response			
Scaled by media weight	2.8	11.5	32.0
Unscaled by media weight	2.3	11.5	45.0

Note: Standard errors of the mean are given in parentheses; within a row, values with different subscripts are significantly different ($p < .05$). Population-level increases in call volume to the National Cancer Institute's Smoking Quitline were assessed by comparing data from 1 month prior with data from 1 month after each campaign aired. These numbers are presented as raw percentage increases and scaled by media weight purchased (the size of the audience the ads were expected to reach). Mean effectiveness rankings, mean MPFC parameter estimates, and population responses scaled by media weight are presented in Figure 1.

individual MPFC rankings consistently favored one prediction (in this case, selecting the best ad campaigns), the average distance between observed individual rankings and the modal response should be smaller than the distance between rankings obtained by chance and any modal ranking. Results of this analysis supported the hypothesis that MPFC activations provided a more consistent ranking of the best ads than what would be expected by chance: τ_w = .3667, mean expected τ_w = .5, $t(29) = -2.0708$, $p = .0474$ (or, given the strong directional nature of our hypothesis, $p = .0237$, one-tailed).

Discussion

Activity in an a priori MPFC ROI clearly predicted the real-world success of different advertising campaigns at the population level, whereas self-reports and the control ROIs did not. Why did our MPFC ROI provide insight regarding the success of ads at the population level (when self-reports were misleading)? In our previous work using neural activity to predict individual behavior change (Falk et al., 2010), we chose to examine the MPFC because prominent theories of behavior change (Ajzen & Fishbein, 1980; Fishbein et al., 2001; Strecher & Rosenstock, 1997) touch on self-related processing of different varieties, and activity in MPFC (BA 10) is implicated in nearly all studies of self-related processing (Lieberman, 2010). We now propose that MPFC activity in this context may index a less explicit process than we originally hypothesized. We report elsewhere (Falk et al., 2011) that in an effort to determine whether the relation between MPFC activity and individual behavior change is explained by participants' ability to relate to ads (an explicit, self-related process), we included a measure (i.e., "To what extent can you relate to this advertisement") as a control variable in a model predicting individual change in smoking behavior using MPFC activity. We found that these explicit "self" variables did not mediate the relationship between neural activity and individual behavior change. Thus, it is likely that a different psychological mechanism was at play.

Similar regions of MPFC are implicated in implicit valuation and affective judgments, independent of conscious awareness (Damasio, 1996), in processing implicit preferences (McClure et al., 2004), implicit self-relevance (Moran, Heatherton, & Kelley, 2009; Rameson, Satpute, & Lieberman, 2010), considerations of personally relevant future goals (D'Argembeau et al., 2010), and valuations of stimuli in terms of expected outcomes with respect to current situations (Cunningham, Zelazo, Packer, & Van Bavel, 2007). Similar portions of MPFC have also been implicated in implicit integration of value signals associated with choices and preferences (Hare, Malmaud, & Rangel, 2011; Knutson et al., 2007). Thus, it is plausible that self-related processes, or a value signal, outside conscious awareness but tracked by neural signals may both predispose individuals to behavior change and provide an index of similar processes likely to occur when larger groups of people are shown the same messages. However, an important theoretical direction for future work is to disentangle which of these processes, if any, are reflected by the predictive activation observed here.

The current study broadens the use of fMRI data from predicting individual behavior (Berkman, Falk, & Lieberman, 2011; Berns & Moore, 2012; Brewer et al., 2008; Falk et al., 2010; Falk et al., 2011; Knutson et al., 2007; Kosten et al., 2006; Paulus et al., 2005; Tusche et al., 2010) to tracking the responses of large groups of people at the population level; future studies comparing larger numbers of population outcomes, and within identical media markets, will provide insight into the boundary conditions and selectivity of the effects observed. Inspired by recent advances in neuroimaging analysis, including pattern classification and other brain-as-predictor approaches (Bandettini, 2009; Haxby et al., 2001), the current study suggests that, using a priori ROIs, behavioral responses of entire populations whose brains are never examined may be inferred from the brain activations of a small neural focus group.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Supplemental Material

Additional supporting information may be found at http://pss.sagepub.com/content/by/supplemental-data

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Supplemental Material

From neural responses to population behavior:
Neural focus group predicts population-level media effects

Emily B. Falk, University of Michigan
Elliot T. Berkman, University of Oregon
Matthew D. Lieberman, University of California, Los Angeles

Supplemental Methods

Additional Participant Details

All participants were heavy smokers with the intention to quit. Participants were considered heavy smokers if they smoked at least 10 cigarettes per day, 7 days per week, for at least one year, and had urinary cotinine levels of at least 1000 ng/mL. In addition to enrollment in a cessation program, quitting intentions were assessed via scores >9 out of 10 on the Contemplation Ladder, a single-item measure of intentions to quit (Biener & Abrams, 1991), thus holding baseline intentions to quit relatively constant across this sample. Participants were ethnically diverse: 50% were Caucasian, 27% Hispanic, 20% African American, and 4% other, and socioeconomically diverse: participant mean annual income = \$31,000 (range = \$0-\$200,000); 60% completed some form of college, and 28% received a bachelor's degree or higher. Participants were excluded if they were left-handed, did not speak English, were pregnant, claustrophobic, or had any other condition contraindicated for MRI. Participants were also excluded if they consumed more than 10 alcoholic drinks per week, or had any of the following conditions: dependence on substances other than nicotine, dependence on substances within one year of the scan date, neurological or psychiatric disorders, cardiovascular disease.

Self-report projections of ad effectiveness

Following the fMRI procedure, participants completed a survey in which they rank ordered their projected efficacy for each of the ads viewed during the scanner session. In addition to providing self-report rankings of ad efficacy, participants also rank ordered the ads from least favorite to most favorite, and evaluated each ad using a 10 item scale developed based on questions used to evaluate ads in other settings (e.g. the Legacy Media Tracking Survey: www.legacyforhealth.org/2141.aspx), and based on theoretical constructs of interest such as the power of internal motivation, and the power of social norms (e.g., "This ad motivates me to quit", "This ad highlights for me that people who care about me want me to quit"; see Table 1 for all scale items). This scale produced a high degree of internal reliability (Cronbach's alpha = .95). The average ratings of the individual ads were highly consistent across the three self report measures; the correlation between average ratings of the 10 ads, across participants, using the two rank ordering scales (most effective to least effective and most favorite to least favorite) was $r(8)=.94$, $p<.001$; and the correlations between the 10-item scale and each of the rank order scales, respectively, were $r(8)=.93, p<.001$, and $r(8)=.95, p<.001$.

Organization of the fMRI task

Within our fMRI study, the campaigns were presented in a counter-balanced, pseudo-randomized order, ensuring that ads from different campaigns followed one another across subjects. At the population level, individuals in a given market were exposed to exactly one of the three ad groups. The population data we have access to are naturalistic in that we obtained quit line call volume in regions after the campaigns were aired, and hence the campaigns were not rotated in markets. The content of the three ad campaigns was similar in that all promoted the National Cancer Institute's 1-800-QUIT-NOW call line. Across campaigns, the ads differed in the strategies used to persuade, but all followed a similar theme (e.g. we know it's hard to quit, but there are resources that can help you quit, call 1-800-QUIT-NOW).

fMRI Data Acquisition and Analysis

Acquisition. High-resolution structural T2-weighted echo-planar images (spin-echo; TR=5000ms; TE=34ms; matrix size 128x128; 34 axial slices; FOV = 192mm; 4mm thick) were acquired coplanar with the functional scans. One functional scan lasting 11.5 minutes (351 volumes) was acquired during the task (echo-planar T2*-weighted gradient-echo, TR=2000ms, TE=30ms, flip angle=90°, matrix size 64x64, 34 axial slices, FOV=192mm; 4mm thick).

Preprocessing. Images were brain-extracted using BET (FSL's Brain Extraction Tool) and realigned within runs using MCFLIRT (FSL's Motion Correction using FMRIB's Linear Image Registration Tool), then checked for residual motion and noise spikes using a custom automated diagnostic tool (thresholded at 2mm motion or 2% global signal change from one image to the next). In SPM8, all functional and anatomical images were reoriented to set the origin to the anterior commissure and the horizontal (*y*) axis parallel to the AC-PC line. Functional images were then corrected for slice acquisition timing differences within volumes, realigned within and between runs to correct for residual head motion, and coregistered to the matched-bandwidth structural scan using a 6-parameter rigid body transformation. The coregistered structural scan was then normalized into the Montreal Neurological Institute (MNI) standard stereotactic space and these parameters were applied to all functional images. Finally, the normalized functional images were smoothed (8mm FWHM Gaussian kernel).

Analysis. The task was modeled separately for each subject, using a block design in SPM5 (Wellcome Department of Cognitive Neurology, Institute for Neurology, London, UK). Initial analyses modeled ad exposure to each campaign compared to a fixation baseline. Corresponding random effects models averaged across results at the single subject level. All functional imaging results are reported in MNI coordinates. Average parameter estimates of activity in our MPFC ROI were extracted at the group level using Marsbar in order to compute a rank-ordered prediction of ad efficacy (where higher levels of neural activity in the *a priori* ROI were hypothesized to correspond to greater ad success). An outlier analysis was conducted, and data points falling greater than 2.5 standard deviations away from the mean for each ad group were excluded in comparing means parametrically (this included 3 data points out of 90 parameter estimates extracted); the ranking of means and substantive conclusions remain unchanged with or without inclusion of potential outliers.

Construction of control ROIs. In order to confirm that results in our primary region of interest were not due to uniformly increased neural activity during certain ad groups (for discriminant validity), we subsequently constructed control regions of interest in regions not hypothesized to respond differentially to the ad groups. In particular, using the wfu pickatlas and Marsbar, we constructed ROIs in primary visual cortex (BA 17), primary motor cortex (BAs 1,2,3), and right and left frontal eye fields (defined as 20mm cubes around 40,0,44 and -40,0,44, respectively, based on mean coordinates for this region reported in the Brede Database: http://neuro.imm.dtu.dk/services/jerne/brede/WOROI_434.html). As with our primary MPFC ROI, average parameter estimates of activity in our control ROIs were extracted at the group level using Marsbar in order to compute a rank-ordered prediction of ad efficacy. In response to an insightful reviewer who suggested that ventral striatum might also predict important outcomes (given it's prominent role in the decision neuroscience literature), we also constructed an anatomically defined ventral striatum ROI. Ventral striatum ROIs were structurally defined a priori using the Wake Forest University Pickatlas Tool (Maldjian, Laurienti, Kraft, & Burdette, 2003) based on the Automated Anatomical Labeling atlas (Tzourio-Mazoyer et al., 2002) and constrained in the following way: $-12<x<12$, $4<y<18$, and $-12<z<0$ (Eisenberger et al., 2010). We then used the Marsbar toolbox (http://marsbar.sourceforge.net) to extract mean parameter estimates.

Kendall's Tau Distance Based Metric for Ranking Data

In order to confirm the reliability of the rank ordering suggested by MPFC, we examined whether the average distance between orderings obtained in our data and the modal (and correct) ordering is smaller that the average distance that would be expected by chance. More specifically, our metric, based on Kendall's Tau, computes pairwise comparisons between each item that has been ranked, and further compares each observed ordering to the modal/correct ranking: $T_{UW} (\pi, \sigma) = \sum\sum I \{[\pi (i) - \pi (j)][\sigma (i) - \sigma (j)] < 0\}$. Here, π represents the mapping function from item *i* (out of a total of k items ordered) to the observed ranking for that item; e.g., $\pi(1)=2$ indicates that the first item is ranked second; σ represents the comparison ranking, for example, the modal ranking or the correct, population level ranking. $I\{\}$ is the indicator function (Critchlow, Fligner, & Verducci, 1991; Lee & Yu, 2010; Shieh, 1998). An extension of this metric, weighted Kendall's Tau, proposed by Shieh (1998), allows different ranks to be assigned weights based on theoretical questions of interest: $T_w (\pi, \sigma) = \sum\sum w\pi 0 (i)\, w\pi 0 (j)\, I \{[\pi (i) - \pi (j)][\sigma (i) - \sigma (j)] < 0\}$. Given that we are most interested in selection of campaigns that are likely to be most effective in reducing smoking, we chose weights that preference correct selection of the best ad campaign $w = [.6\ .2\ .2]$, reported in the main body of the manuscript. The unweighted metric $w = [1\ 1\ 1]$ is also consistent with the hypothesis that the pairwise distances between our individual MPFC ratings, and the modal response is smaller than what would be expected by chance.

Supplemental Results

Figure S1. Whereas activity in the hypothesized medial prefrontal cortex region-of-interest, previously associated with persuasion-induced behavior change, mirrored the relative effectiveness of the three ad campaigns at the population level, neural activity in control regions of interest did not.

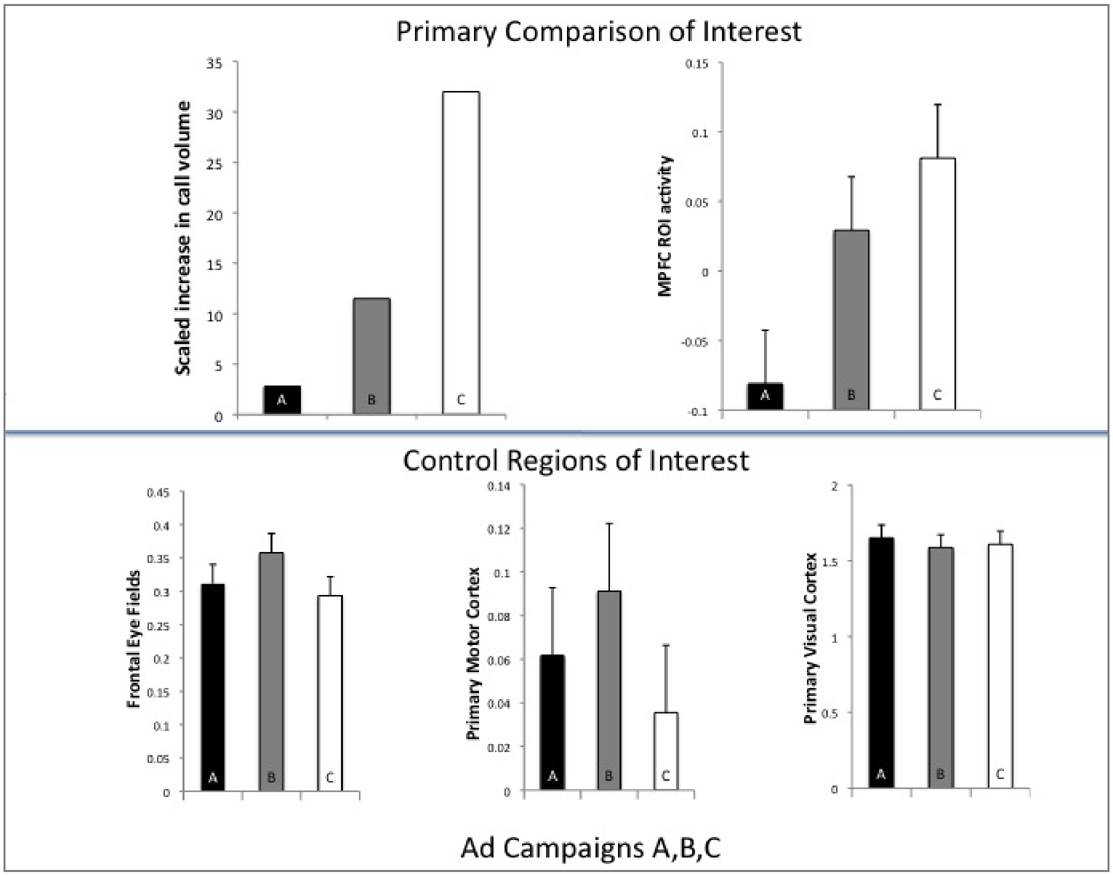
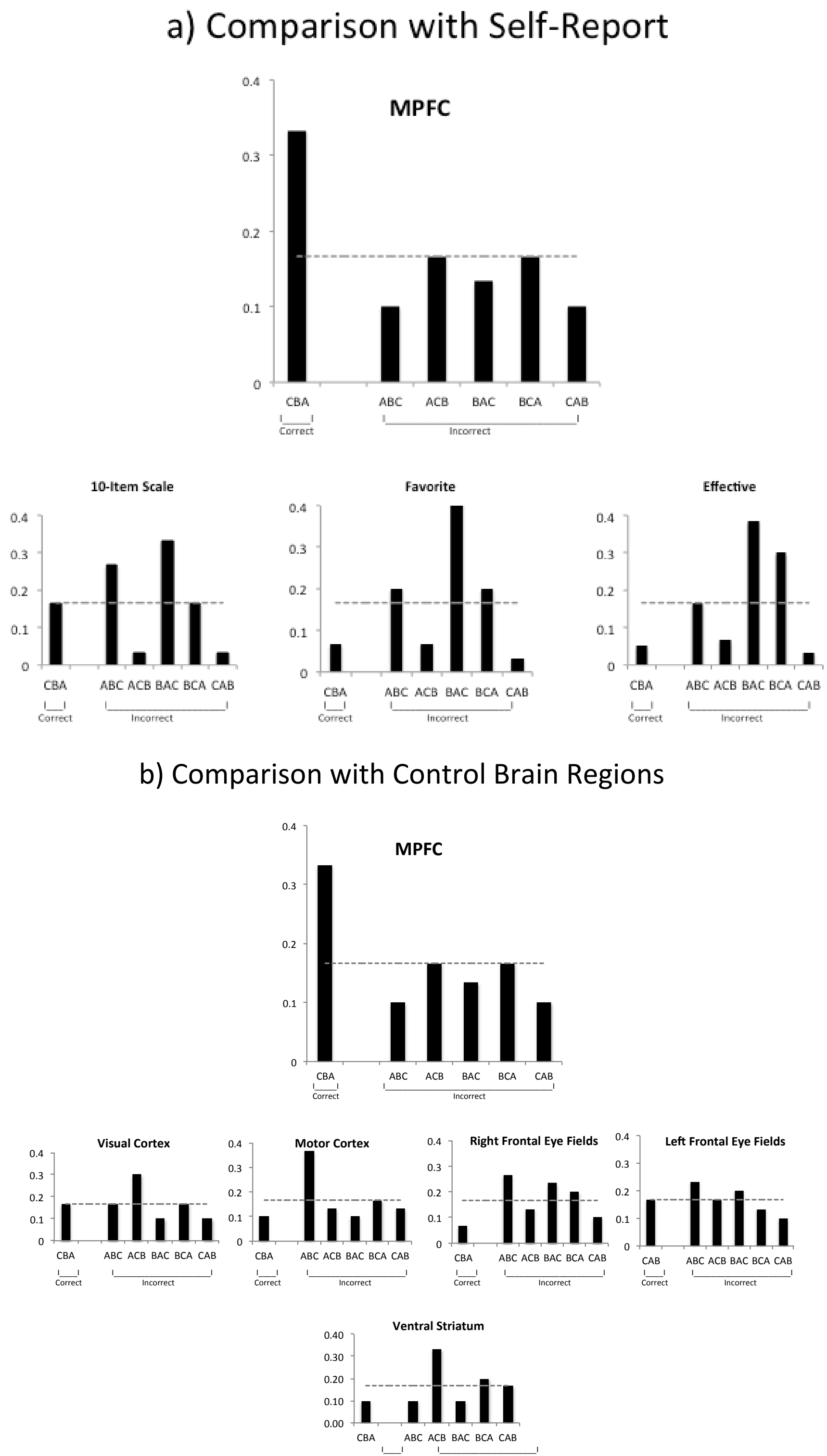


Figure S2. The proportion of cases in which each of the 6 possible orderings appeared for each type of measurement. Notably, participants' MPFC responses most frequently ordered the campaigns correctly, whereas other measurement types including (a) all three types of self-report, and (b) neural activity in control regions produced incorrect orderings as their most frequent outcome. Black bars indicate the proportion of cases suggesting each ordering permutation. Grey dashed lines indicate chance level.



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