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Although much progress has been made in relating brain activations to choice behavior, evidence that neural measures could actually be useful for predicting the success of marketing actions remains limited. To be of added value, neural measures should significantly increase predictive power, beyond conventional measures. In the present study, the authors obtain both stated preference measures and neural measures (electroencephalography; EEG) in response to advertisements for commercially released movies (i.e., movie trailers) to probe their potential to provide insight into participants' individual preferences as well as movie sales in the general population. The results show that EEG measures (beta and gamma oscillations), beyond stated preference measures, provide unique information regarding individual and population-wide preference and can thus, in principle, be used as a neural marker for commercial success. As such, these results provide the first evidence that EEG measures are related to real-world outcomes and that these neural measures can significantly add to models predicting choice behavior relative to models that include only stated preference measures.

Keywords: neuromarketing, consumer neuroscience, electroencephalography, beta, gamma

Brain Responses to Movie Trailers Predict Individual Preferences for Movies and Their Population-Wide Commercial Success

Consumer neuroscience, that is, applying neuroscience methods to marketing, has gained considerable popularity in recent years among scholars and practitioners alike (Smidts et al. 2014; Yoon et al. 2012). As Ariely and Berns (2010) note, there seem to be good reasons for this enthusiasm. First, because brain data are considered less noisy than data obtained through conventional marketing methods, data from smaller samples are believed to generate more accurate predictions, making neuroscience methods cheaper and faster than traditional methods. Second, it is believed that neuroimaging methods could provide marketers with information that is not obtainable through conventional marketing methods. This idea is based on the assumption that people cannot fully articulate their preferences when asked to express them explicitly and that consumers' brains contain hidden information about their true preferences.

Indeed, several decades of research have shown that many important mental processes occur below the surface of consciousness (Dijksterhuis 2004; Zajonc 1980), leaving people very limited in their ability to predict their own future behavior and to accurately identify their internal mental states through verbal or written self-reports (Nisbett and Wilson 1977). Complicating matters further, explicitly asking participants to reflect on such internal mental states

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and the process leading to choice has been shown to actually alter the outcome and quality of their judgments (Morwitz and Fitzsimons 2004; Wilson and Schooler 1991). Thus, suffering from such biases, traditional approaches to marketing may indeed provide data that are not very accurate (Griffin and Hauser 1993). Yet can neuroscientific measurements provide less biased data?

Evidence from neuroscience suggests that, in particular, the ventromedial aspect of the prefrontal cortex (vmPFC) is implicated in implicit valuation and processing preferences and goals, independent of conscious awareness (Damasio 1996; D'Argembeau et al. 2010; Hare, Malmaud, and Rangel 2011; Levy et al. 2011; McClure et al. 2004). Importantly, these neural indicators of implicit preference have been shown to be predictive of the actual choices people make (Falk et al. 2011; Knutson et al. 2007; Tusche, Bode, and Haynes 2010; for a recent meta-analysis, see also Bartra, McGuire, and Kable 2013). In addition, research has shown activity in the vmPFC in response to products or advertisements in a small sample of participants (a "neural focus group") to be predictive of population-wide commercial success (Berns and Moore 2012; Falk, Berkman, and Lieberman 2012). Thus, evidence exists that (1) neuroimaging methods can provide marketers with information that is not obtainable through conventional marketing methods, (2) such neural markers can be reliably obtained from a relatively small sample of participants, and (3) these neural markers are actually predictive of commercial success.

There are, however, also reasons to be somewhat less optimistic about the usefulness of neural data in marketing practice. First, although consumers are often not very good at stating their own preferences and predicting their own future behavior, it is not the case that stated preferences are completely unrelated to actual choice. There is a wealth of data showing that measures such as willingness to pay (WTP) perform quite well in predicting observed choice. Second, evidence on the predictive value of neural measures stems mainly from functional magnetic resonance imaging (fMRI). The MRI machine is not the most natural environment; it is uncomfortable (participants lie in a narrow tube) and very noisy (noise levels typically exceed 90 dB). Evidence exists that such adverse environmental characteristics may have a substantial (negative) impact on cognition and choice (Arnsten and Goldman-Rakic 1998; Szalma and Hancock 2011), thus potentially distorting any relationship between brain and (population) behavior.

To resolve these issues, we primarily need to show not only that our neural measures predict consumer choices but also that these measures actually provide unique added value in terms of predictive power beyond traditional measures. That is, because we acknowledge that traditional self-report measures often perform quite well in predicting preferences and choice, we therefore need to demonstrate that neural data can actually capture unique information about marketing stimuli that can be of additive value in combination with traditional measures. Moreover, we need to measure brain activity in relatively natural settings to achieve maximal generalizability to real-world situations. This is what we set out to achieve in the present study.

We obtained both stated preference measures and neural measures in response to advertisements for commercially released movies (i.e., movie trailers). With a global box office return of approximately $35 billion (Motion Picture Association of America [MPAA] 2012), the movie industry is a market with tremendous prospects for profit, but it is also a risky market: 75% of movies earn a net loss during their run in theaters (De Vany and Walls 1999). With such high variance in profit, the stakes for attracting audiences to the theater are high indeed. Promotion expenditures for a major movie release average more than $40 million (MPAA 2012). Comparing this number with the $70 million average budget to produce a movie makes it clear that advertising is extremely important for the motion picture industry. Movies are advertised through many channels but most prominently through theatrical trailers, which reach their audience through cinemas, rented media, and the Internet. These movie trailers are the preferred source of information for consumers to determine which movie they will actually go to see (Gazley, Clark, and Sinha 2011). Therefore, increasing the probability of success by pretesting and optimizing movie trailers by means of neuroimaging methods could be of great benefit to the industry. In this study, we investigated the brain response to cinematic trailers using electroencephalography (EEG) to probe its potential to predict individual purchase decisions in our participants as well as movie sales in the population at large, beyond stated preferences.

In addition to its high temporal resolution, an important benefit of using EEG is that it allows for relatively naturalistic viewing conditions: participants can be seated in a comfortable chair, viewing a relatively large screen with surround-sound cinematic acoustics. In addition, the cost of a complete EEG setup is approximately .5% of that of an fMRI machine (typically approximately $10,000), and typical per-hour charges are also much lower. Indeed, for these reasons, EEG is the method of choice for most neuromarketing companies; only a handful of such companies use fMRI (Smidts et al. 2014). The use of EEG in marketing research already dates back several decades (for a review, see Wang and Minor 2008). Most of this research has focused on investigating the memorability of commercial messages (Rossiter et al. 2001; Rothschild and Hyun 1990) and their ability to capture viewers' attention (Smith and Gevins 2004). However, no study to date has related EEG measures to observed preferences and choices.

Research has shown that medial-frontal EEG oscillations (regular cyclic voltage changes) in the beta frequency range (12–30 Hz; Cohen, Elger, and Ranganath 2007; HajiHosseini, Rodríguez-Fornells, and Marco-Pallarés 2012; Kawasaki and Yamaguchi 2013; Marco-Pallares et al. 2008; Van de Vijver, Ridderinkhof, and Cohen 2011) are associated with reward processing, while lower frequencies (most prominently theta, 4–8 Hz) are more related to losses and other negative outcomes (Cavanagh, Cohen, and Allen 2009; Cavanagh et al. 2010; Cohen, Elger, and Ranganath 2007; Marco-Pallares et al. 2008; Van de Vijver, Ridderinkhof, and Cohen 2011). Indeed, Lucchiari and Pravettoni (2012) recently observed that beta activity seems to be modulated by the experience of pleasure associated with a favorite brand, whereas theta modulation seems to reflect the lack of this experience.

Although it is notoriously difficult to localize the source of EEG activity (indeed, this is the main drawback of EEG

compared with fMRI, which has excellent spatial resolution), it is believed that these beta oscillations originate from brain areas involved in reward processing, most notably the vmPFC (Hlinka et al. 2010; Jann et al. 2010; Mantini et al. 2007; Marco-Pallares et al. 2008). More specifically, a possible role of beta-band oscillations might be the synchronization of neural populations over long distances to functionally couple the different areas of the brain involved in reward processing, such as the vmPFC, striatum, and posterior cingulate cortex (Berns et al. 2001; Marco-Pallares et al. 2008; Steriade 2006).

In summary, we set out to investigate whether neural measures could make a valuable and significant contribution to the prediction of commercial success, beyond stated preference measures, under naturalistic viewing conditions. We obtained EEG and stated preference measures from a small sample of participants while they viewed movie trailers and related these measures to observed individual preferences and population-wide commercial success (U.S. box office results). We predicted that particularly high-frequency components of the EEG (e.g., beta band oscillations) would be related to preference and that these high-frequency oscillations would significantly add predictive power to stated preference measures. Although we predicted that beta power on electrode sites above the medial prefrontal cortex in particular would be related to preference, we did not restrict our analyses only to this frequency range and topography. Instead, we used high-density, high-sampling-rate EEG recordings to conduct whole-brain, broad-spectrum analyses on our EEG data.

METHODS

Participants

Thirty-two participants were recruited from the university population and paid €25 for their participation. Participants had no history of neurological illness or damage, were not using drugs or psychiatric medication, and had normal or corrected-to-normal vision. Written informed consent was obtained before the study. We failed to record data from one participant due to EEG equipment failure, and two participants had to be excluded because of excessive artifacts in their EEG recordings resulting from a problem with the recordings. The final sample consisted of 29 participants (16 men) between 18 and 28 years of age (M = 21.5 years, SD = 2.8).

Procedure

After arriving at the lab, participants received detailed written and verbal instructions on all the tasks they were going to perform in the experiment. We then proceeded to apply the EEG electrodes and seated participants in a dimly lit, sound-attenuated, electrically shielded room at 1.80 meters from a 19-inch PC monitor. To familiarize participants with the task, we had them complete one (short) practice trial.

The task was as follows (for a graphic representation, see Figure 1): Participants viewed 18 movie trailers in random order (see the "Stimuli" subsection) while their EEG was recorded. Each trial began with a presentation of the DVD cover of the movie featured in the upcoming trailer (for 6 seconds), followed by a blank screen for 2.5 seconds. Then, the trailer was presented (for approximately 2.5–3 minutes). After viewing the trailer, participants indicated how much they would like the movie featured in the trailer they had just seen and how much they would be willing to pay for the DVD of this movie (see the "Behavioral Measures" subsection). These questions were self-paced and were preceded and followed by a blank screen for 2.5 seconds, after which the next trial started.

After participants viewed the 18 trailers (lasting approximately 50 minutes in total), the task ended. Participants were taken out of the EEG cubicle, and the electrodes were removed. They were then led to a table on which we had piled a stack of DVDs of the 18 movies featured in the trailers they had just viewed. We asked them to sort these DVDs into descending order of preference, which was logged by the experimenter. Finally, the Becker–DeGroot–Marschak (BDM) auction was resolved (see the "Behavioral Measures" subsection). Each participant was then given the three most preferred DVDs plus the DVD purchased in the BDM auction to take home.

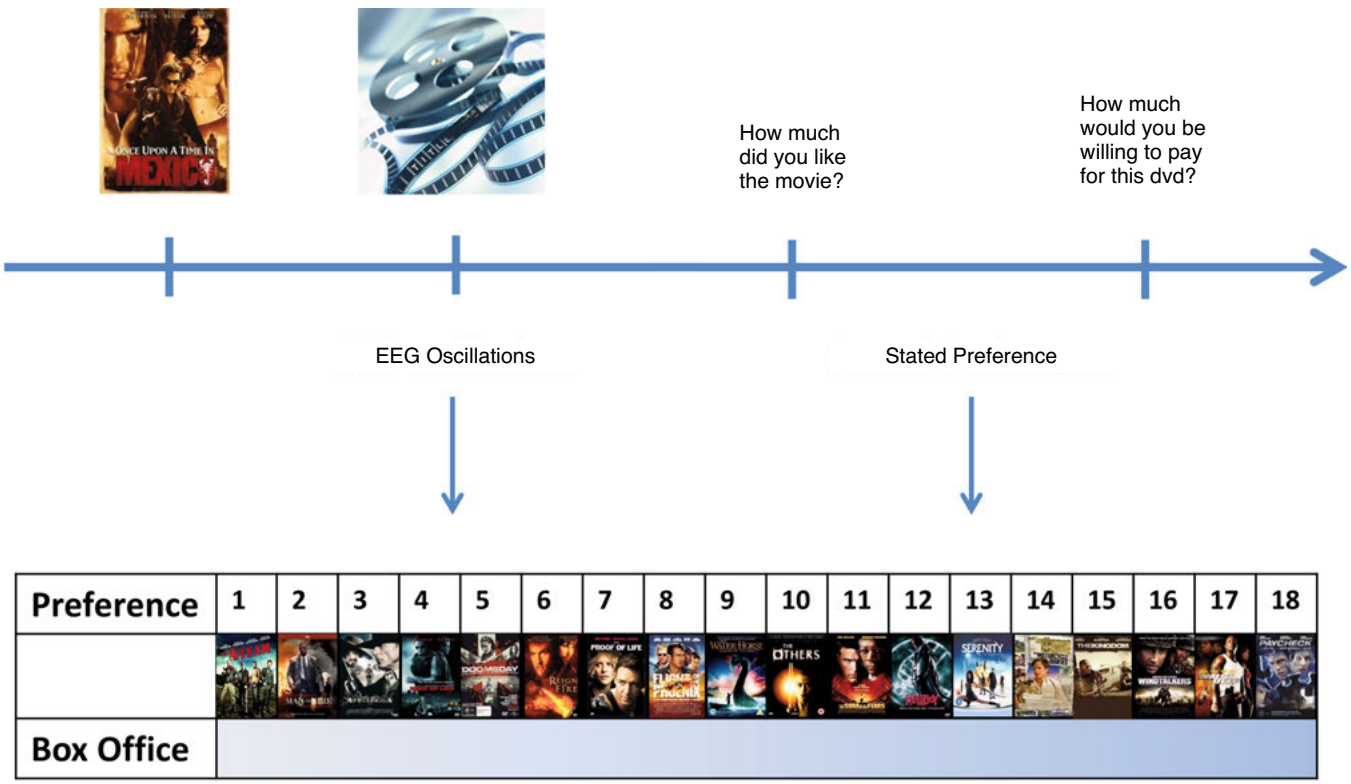
Stimuli

We constructed a database of 56 movies from four genres (action, drama, adventure, and thriller), released between 2000 and 2010. To be included in our database, movies had to have received a rating of 5.5 stars or higher (on the Internet Movie Database [IMDb.com]) based on 1,000 votes or more. We did this so that only movies of at least reasonable quality were included in our set. In addition, we did not include animated movies and cartoons, 3D movies, and remakes or sequels in our set. Finally, the official trailer had to be in English and 2–2.5 minutes in length. Movies were selected on the basis of their U.S. box office result, such that we took the box office ranking of all movies in each genre from IMDb.com and selected for inclusion the movies with rank 150, 200, 250, and so on. If a particular movie did not meet the criteria, the movie ranked one slot lower would be selected. This way, we constructed a set of movies that varied considerably in commercial success. We did not select any of the best 150 movies to avoid including movies that most participants would either have already seen or at least be very familiar with.

To construct a set of trailers to present to the participants in the experiment, we first asked participants to indicate their least-preferred movie genre (i.e., action, drama, adventure, or thriller). Movies from the indicated genre were then excluded from the set for that participant. We then asked participants to indicate whether they had already seen each of the remaining 42 movies. We then excluded previously seen movies from the set. From the remaining set, we randomly selected six movies from each of the three genres. The trailers of these final 18 movies were presented to the participant in the experiment.

Across participants, 56 trailers were presented in the experiment, indicating that all trailers in our database were presented at least once. The median number of views of a specific trailer was 10, with a minimum number of 2 and a maximum number of 15 participants having viewed the same trailer. The commercial success (in terms of U.S. box office results) of the movies these trailers promoted was rather diverse (between $4.4 million and $121 million; M = $47 million), and they also differed quite a bit in audience

Figure 1
SCHEMATIC REPRESENTATION OF THE EXPERIMENT



Notes: Each trial began with the presentation of the cover of the DVD for the trailer that participants were going to see in that trial. Then, the trailer was presented, and participants indicated how much they liked the movie and how much they would be willing to pay for the DVD (stated preference measures). Participants completed 18 of these trials. Afterward, they sorted the DVDs of the movie trailers they had just viewed in descending order of preference. We used EEG recordings during trailer viewing and stated preference measures to predict individual preference for movies (ordered preference) and population-level popularity (U.S. box office results).

evaluation (IMDb score ranged between 5.6 and 8.3; M = 6.7 on a 10-point scale). Importantly, there were no significant differences in terms of box office ($F(3, 52) = .60$, $p = .60$) or IMDb ratings ($F(3, 52) = 1.87$, $p = .15$) between the four genres.

Behavioral Measures

Liking. After viewing a trailer, participants saw a screen asking them to indicate how much they thought they would like the movie featured in the trailer they had just seen. They could indicate their preference on an 11-point scale (0–10) using the cursor keys.

WTP. Following the liking question, participants indicated how much they would be willing to pay for the DVD of the movie whose trailer they had just seen. We used the BDM method (Becker, DeGroot, and Marschak 1964; Wertenbroch and Skiera 2002), an incentive-compatible procedure frequently used in experimental economics, to get a true estimate of their WTP. In short, before the start of the experiment, participants received €5, which they could use to buy a DVD of one of the movies they would see in the experiment. After every trailer, they bid an amount (between €0 and €5) corresponding to the maximum amount they would be willing to pay for that particular DVD. At the end of the experiment, one movie was randomly selected from the 18 trailers the participant viewed in the experiment. Then, participants were presented with an urn containing ten balls. Inside each ball was a note marked €0, €0.50, €1, €1.50, €2, €2.50, €3, €3.50, €4, €4.50, or €5. If the participant's bid was greater than or equal to the drawn amount, he or she would buy the DVD (with the €5 received at the start of the experiment) for the price drawn from the urn, keeping the remainder of the €5. If the bid was less than the amount drawn from the urn, the participant would not buy the DVD and would keep the entire €5. The optimal strategy in the BDM procedure is for participants to bid their actual WTP—no more, no less.

Ordered preference. To obtain a measure of relative preference for every movie in comparison to the other movies viewed in the experiment, we asked participants to sort the 18 movies they had seen into descending order of preference.

EEG Measures

We recorded EEG from 64 active Ag–AgCl electrodes (Biosemi ActiveTwo) mounted in an elastic cap. We recorded horizontal electro-oculogram (EOG) from two electrodes placed at the outer canthi of both eyes to measure the electrical activity generated by horizontal eye movements. We

recorded vertical EOGs from electrodes on the infraorbital and supraorbital regions of the right eye placed in line with the pupil to measure vertical eye movements and blinks. The EEG and EOG signals were sampled at a rate of 512 Hz, digitally low-pass filtered with a 128 Hz cutoff (3 dB), and offline rereferenced to an averaged mastoid reference.

We performed all processing of EEG signals using the Brain Vision Analyzer software (Brain Products). The data were down-sampled to 256 Hz and further filtered with a 1 Hz high-pass filter with a slope of 48 dB/oct and a 50 Hz notch filter. The continuous data were then divided into 18 segments (one for each trailer). Each segment started at the beginning of a trailer and lasted the duration of that specific trailer (between 2 and 2.5 minutes). We then further separated each segment into 256-data-point, 50% overlapping segments. Eye-movement artifacts were corrected using independent component analysis, as implemented in the Brain Vision Analyzer software. Standard artifact detection and rejection procedures were applied to the 256 data point segments, rejecting channels within segments containing jumps larger than 30μV/ms, segments with amplitude differences that exceeded 150μV/200ms, and segments with amplitude differences that did not exceed .5μV/200ms. Note that we did not reject entire segments when artifacts were detected, only the channels in which artifacts were found within a given segment. Doing so results in a very low dropout of data from artifact rejection (M = .1% [SE = .1] rejected data per participant). The preprocessed data were then submitted to a fast Fourier transform algorithm, using a standard 100% Hanning window. We averaged the resulting spectral EEG data per trailer for all participants individually. Averaged segments were then log-transformed to normalize the distributions and were exported to MATLAB (www.mathworks.com) and R (www.R-project.org) for statistical analyses.

Statistical Analyses

Using a mass univariate regression, we regressed the dependent variables (DVs) of interest (i.e., ordered preference and box office) onto EEG data from all electrodes and spectral points, using a multilevel approach. At the first level (i.e., the participant level), we performed regressions to test whether the EEG data were related to our DVs. We then tested the resulting betas at the second level for significant group effects, using one-sample t-tests. We used cluster-based permutation testing as a stringent control for multiple comparisons (Maris and Oostenveld 2007). Briefly, for every sample (a [channel, frequency] pair), we quantified the experimental effect by a t-value. We selected samples for which the t-value was larger than a given threshold (here, $p < .01$) for potential inclusion in a cluster. Note that the threshold used does not affect the false alarm rate of the final statistical test; it only sets a threshold for considering a sample as a candidate member of a cluster. We subsequently clustered selected samples in connected sets on the basis of temporal and spectral adjacency, and we calculated cluster-level statistics by taking the sum of the t-values within every cluster. We then performed permutation testing using the Monte Carlo method to calculate the posterior significance probability of our observed effect (Maris and Oostenveld 2007). We report results significant at the $\alpha = .05$ level, family-wise-error (FWE) corrected for multiple comparisons.

Next, we wanted to determine whether the EEG measures that related to our DVs of interest actually provide unique information regarding individual and population preference, beyond self-report measures. To do so, we reduced the observed EEG effects (which span multiple electrode sites and frequencies) into measures of the "EEG effect" by taking the average EEG signal across the data points (electrode-frequency pairs) within the observed clusters that survived thresholding at $p < .05$ FWE (analogous to a "region of interest" in fMRI research). We then used mixed-model regression analyses to test whether the EEG data added significantly to the models that included only the behavioral measures in predicting our DVs. For predicting individual preference (i.e., the ordered preference), we entered both stated preference[1] (WTP) and the EEG effect in a mixed ordinal regression model (cumulative link mixed model; Hedeker and Gibbons 1994; Tutz and Hennevogl 1996) fitted with the adaptive Gauss–Hermite quadrature approximation (the CLMM function from the R:ORDINAL package) with random intercepts. For predicting box office, we entered both stated preference and the EEG effect in a linear mixed model regression analysis (LMER function from the R:LME4 package) with random intercept and random slopes for WTP and EEG. We report the fixed predictor effects from these models, including t or z statistics and associated *p*-values (based on a Satterthwaite [1946] approximation for denominator degrees of freedom). In addition, we report pseudo R-square measures of fit (Nakagawa and Schielzeth 2013) as a measure of usefulness of including EEG measures as a predictor of choice.[2]

RESULTS

There was a good amount of variance in how much participants liked the movies featured in the trailers they watched. Liking scores ranged between 0 and 10 (M = 5.4, SD = 2.4) and WTP ranged between €0 and €5 (M = €1.80, SD = 1.4; the actual price of the DVDs ranged between €2.50 and €10.75 [M = €4.86]).

EEG Results

The mass univariate regression with the EEG data as predictor and the individual ordered preference as the response variable revealed that a cluster of EEG activity in the beta range (16–18 Hz) on midfrontal sites (surviving thresholding at $p < .05$ FWE on electrodes AFz, F2, FC1, FCz; see Figure 2) was a significant predictor of individual prefer-

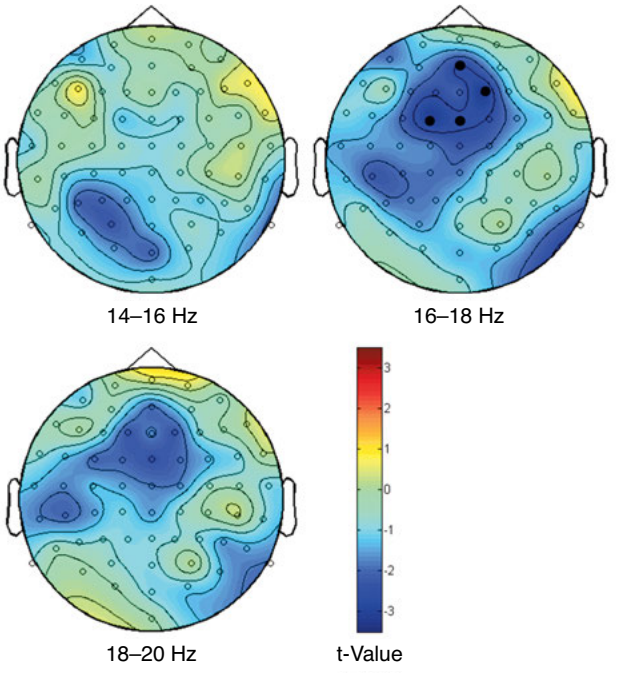
[1]For predicting both ordered preference and box office, because WTP and liking scores were highly correlated (r = .87), we used only WTP as a stated preference measure in these analyses to avoid problems with colinearity of predictors. The same models including liking instead of WTP yielded virtually identical results.

[2]For mixed models it is, strictly speaking, not possible to calculate a measure indicating explained variance, analogous to ordinary least square regression models. Nevertheless, because it is a specific aim of this article to provide insight into the added contribution of EEG measures in predicting consumer choice, we calculated a pseudo R-square measure to provide at least some indication of how much information EEG measures add to stated preference. The exact numbers, however, should be interpreted with caution and should merely be taken as an indication of variance explained.

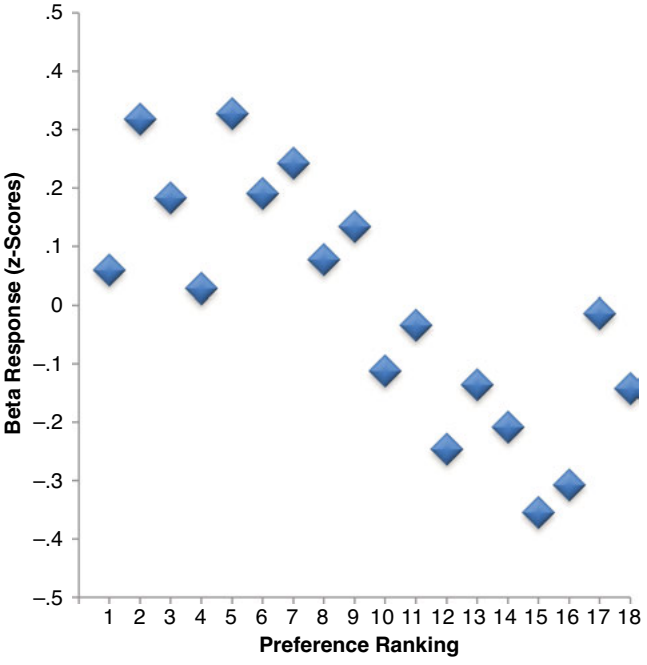
Figure 2

EEG OSCILLATIONS IN THE BETA RANGE (16–18 Hz) PREDICT INDIVIDUAL PREFERENCES

A: Topographic Maps of the Relationship Between Power in the Beta Band and Preference[a]



B: Scatterplot of the Relationship Between Beta Power and Ordered Preference for the 18 Movies[b]



[a]Colors represent t-values. Electrodes that showed above-threshold activations ($p < .05$, FWE corrected) are marked. Note that the most preferred movies have the lowest numerical rank, so that beta power and rank are negatively related. However, increased beta power predicts increased preference.

[b]Because of substantial individual differences, beta power from all significant electrode-frequency pairs was transformed to z-scores and averaged across participants here, for illustrational purposes only.

ence: we found that high beta activity during viewing of the trailer was related to a high preference for that movie.

Regressing the population preference on the EEG data revealed a cluster of EEG activity that was a significant predictor of U.S. box office in the gamma range, clustered around frontocentral sites (surviving thresholding at $p < .05$ FWE in the 60–100 Hz range, on electrodes F1, F2, F4, FC3, FC1, FCz, FC2, FC4, C5, C3, C1, C4, and CP5; see Figure 3): the higher this frontal gamma activity in our participants during the viewing of the trailers, the more money this movie generated at the box office.

Having established that individual and population preferences are associated with specific components of the EEG, we next turn to the question of whether these EEG measures actually provide unique information regarding individual preference and commercial success, beyond stated preference measures.

Individual Preference

Not surprisingly, the model including only WTP as a predictor of ordered preference revealed that stated preference was a highly significant predictor of the final individual preference (b = –2.16, z = –18.14, $p < .001$, pseudo R^2 = .57). In replicating the EEG results described previously, when adding EEG data (from the cluster in the beta range) to the model, we found that EEG was an additional significant predictor of individual preference: high beta activity (controlling for WTP) during viewing of the trailer was related to a high preference for that movie (b = –.25, z = –2.74, $p <$ .01). Importantly, adding this frontocentral beta activity as a predictor significantly increased the fit of the model predicting individual choice, compared with the model including the stated preference only ($\chi^2(1) = 7.49$, $p < .01$). These results indicate that there is unique information in the EEG measures that is not captured by stated preference and that including both EEG and stated preference measures significantly improves prediction of observed individual preference. The actual improvement in fit, however, was small (pseudo R^2_{change} = .01), and the actual proportion of the individual preference accounted for by beta EEG alone was also limited, though highly significant (b = –.2676, z = –2.991, $p < .005$, pseudo R^2 = .02).

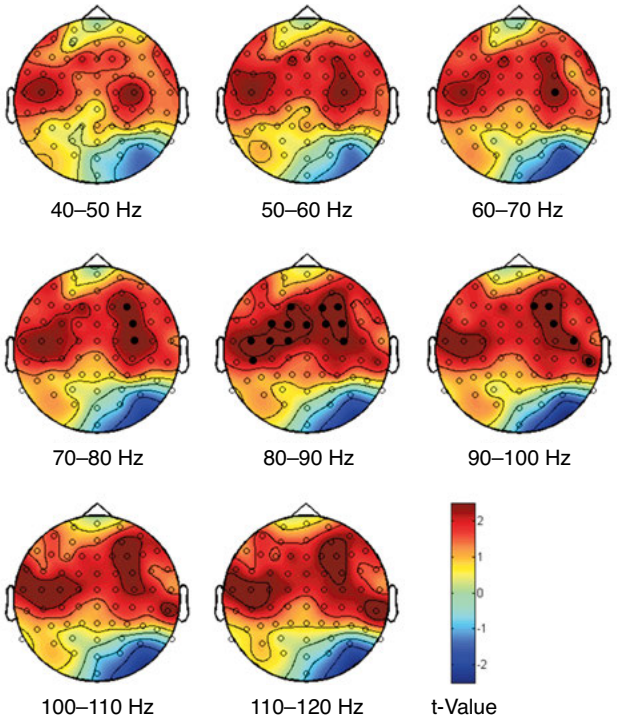
Population Preference

The model including only stated preference revealed that WTP was not a significant predictor of population preference (i.e., U.S. box office; b = 2.52, t(30.13) = 1.87, $p = .07$, pseudo R^2 = .01). Again replicating the EEG results described previously, including EEG (from the cluster in the gamma range) as a predictor in the model revealed that EEG provided a strong predictor of population preference (b = 3.92, t(33.45) = 2.88, $p < .005$) in the form of frontal gamma activity. The higher this frontal gamma activity (controlling for WTP) in our participants during the viewing of the trailers, the more money this movie generated at the box office. This gamma activity added significantly to the model predicting population preference (in addition to stated preference, which was unrelated to population preference; pseudo R^2_{change} = .02, $\chi^2(1) = 7.41$, $p < .01$), indicating that EEG gamma activity in response to viewing a trailer for a par-

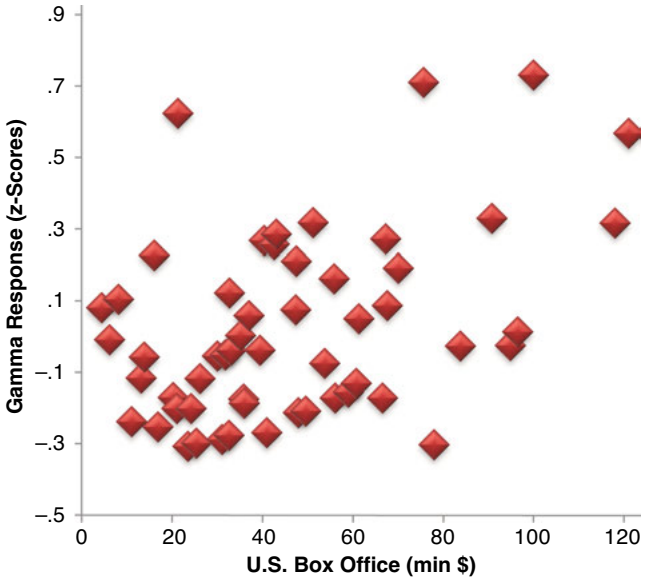
Figure 3

EEG OSCILLATIONS IN THE GAMMA RANGE (>60 Hz) PREDICT POPULATION-LEVEL PREFERENCES

A: Topographic Maps of the Relationship Between Power in the Gamma Band and Commercial Success[a]



B: Scatterplot of the Relationship Between Gamma Power and U.S. Box Office of the 56 Movies[b]



[a]Colors represent t-values; electrodes that showed above-threshold activations ($p < .05$, FWE corrected) are marked.

[b]Relatively high power in the gamma band was related to increased box office results. Because of substantial individual differences, gamma power from all significant electrode-frequency pairs was transformed to z-scores and averaged across trailers here, for illustrational purposes only.

ticular movie significantly enhances predictions of commercial success for that movie.

To test whether EEG gamma is predictive of box office success across genres, we added genre as a fixed-effect predictor in the regression model. The results showed that even though the genre predicts the box office to a certain extent (adventure has a negative effect, whereas the other genres have a positive effect, on box office), the effect of EEG gamma remains significant ($b = 3.57$, $t(508.30) = 2.86$, $p < .005$), independent of genre.

DISCUSSION

In the present study, we aimed to investigate whether neural measures could make a valuable and significant contribution to the prediction of individual choice behavior and population-wide commercial success. Importantly, we wanted to show that these neural measures could provide unique information beyond stated preference measures. Therefore, we obtained EEG and stated preference measures from a small sample of participants while they viewed movie trailers and related these measures to observed individual choices and population-wide commercial success (U.S. box office results). We predicted that particularly high-frequency components of the EEG (e.g., beta band oscillations) would be related to preference.

The results show that medial-frontal beta power is indeed related to individual preference: the higher the amplitude of EEG oscillations in the beta frequency range (16–18 Hz) during viewing of the movie trailer, the higher participants ranked that particular movie relative to the other movies for which they viewed trailers. These findings are highly consistent with the literature, which has linked medial-frontal beta to reward processing; increased beta power has been observed during reward anticipation and reward delivery (Cohen, Elger, and Ranganath 2007; Kawasaki and Yamaguchi 2013; Marco-Pallares et al. 2008), while its medial-frontal distribution is suggestive of a source in the medial frontal cortex (Mantini et al. 2007; Marco-Pallares et al. 2008), a key hub in the neural reward system that has been strongly implicated in reward evaluation and choice in previous studies (Berns and Moore 2012; Falk, Berkman, and Lieberman 2011; Falk et al. 2011; Knutson et al. 2007).

In addition to the vmPFC, reward processing is carried out by an extensive network of brain areas, including the striatum and posterior cingulate cortex (Bartra, McGuire, and Kable 2013). Such an extensive and distributed network requires an integration mechanism that allows for the coordination of and communication between the different areas involved. Brain oscillations are an effective mechanism to accomplish such a task (Akam and Kullmann 2010; Engel, Fries, and Singer 2001; Womelsdorf et al. 2007). Specifically, high-frequency oscillations (beta and gamma bands) are well suited to synchronize these different components of the reward network because they allow for the communication and integration of information across distant brain areas.

In the present study, we observed increased amplitudes of beta oscillations when participants viewed movie trailers that they ranked highly in terms of preference at the end of the experiment, after viewing all the trailers. Previous research has shown that power in the beta band is not only a

passive correlate of reward anticipation or delivery but also related to subsequent behavior. Beta oscillations upon reward delivery have been related to improved learning of stimulus materials or task contingencies (i.e., reinforcement learning; Cohen, Elger, and Ranganath 2007); the increase in beta band oscillations following positive reinforcement has been suggested to function as a mechanism to strengthen the current representations of value and reward, thereby influencing future behavior (Van de Vijver, Ridderinkhof, and Cohen 2011). Indeed, beta oscillations following reward delivery have been found to be predictive of improved memory performance for the rewarded stimuli (Kawasaki and Yamaguchi 2013). Taken together, increased amplitudes of beta oscillations evoked by movie trailers seem to indicate that these trailers may be experienced as motivationally rewarding and that the rewarding aspects of that particular movie are transferred to memory, such that relatively stable and lasting memory traces of this preference are formed.

Importantly, we found that beta power is related to individual preference, beyond stated preference measures. Not surprisingly, simply asking participants how much they would be willing to pay for a movie immediately after having viewed the trailer was already highly predictive of their final ordered preference of all the movies they saw in the experiment. Nevertheless, adding the EEG data to the model increases the explained variance by a significant (albeit small) amount, indicating that these neural measures do add something unique to the prediction of choice behavior. These observations correspond well with previous fMRI work relating neural activation to individual choice: in Knutson et al. (2007), neural measures (activity in the striatum and vmPFC) significantly increased predications of individual choices, but the authors also find that the increase in predictive power was approximately 1%. We note that in our experiment, we measured WTP and final preference very close together in time (within one hour), which likely contributes to the strong association between these two measures and the relatively small additional contribution of EEG. One might speculate that if stated preference and final preference or choice were observed further apart in time, the contribution of EEG could potentially be more substantial.

When relating our neural data to commercial success of the viewed movies, we found a relationship with very high-frequency oscillations in the gamma range (>60 Hz), with a frontal and a somewhat bilateral distribution. Traditionally, gamma band activity has been related to states of enhanced arousal and focused attention, even in the absence of a specific task such as in the present experiment (Engel, Fries, and Singer 2001; Fries 2001; Von Stein, Chiang, and König 2000). Researchers have proposed that gamma synchronization between higher-order and lower-order areas of the brain reflects top-down control of attention, thereby enhancing relevant stimulus representations (Rodriguez et al. 1999; Steinmetz et al. 2000; Tallon-Baudry et al. 1997) while suppressing irrelevant stimuli (Fries 2005; Jensen and Mazaheri 2010). Indeed, previous research has shown enhanced high-frequency EEG components during attentive listening (Tiitinen et al. 1993), visual search (Tallon-Baudry et al. 1997), and attention to moving visual stimuli (Gruber et al. 1999). Moreover, gamma band activity has been found to be enhanced in task situations involving object recognition (Rodriguez et al. 1999) and emotional evaluation (Müller, Gruber, and Keil 2000), processes that are most likely engaged during the viewing of movie clips. Taken together, these findings may suggest that the more participants were engaged in viewing the movie trailer, the more popular or successful the movie ultimately was at the population level, independent from individual preference, which did not show any relationship with gamma power.

Importantly, Mantini et al. (2007) find that gamma power is most strongly related to activations of the medial PFC, which corresponds well with previous fMRI studies showing that the medial PFC in particular is related to population-wide preferences and choice (Berns and Moore 2012; Falk, Berkman, and Lieberman 2012). In this context, it is worthwhile to note that gamma power relates not only to engagement during passive viewing but also to the further processing of the viewed materials; increased gamma power has been found to be related to associative learning (Miltner et al. 1999) and to committing viewed material to memory (Howard et al. 2003; Mainy et al. 2007). Indeed, the medial PFC is strongly connected to the hippocampus (a brain area critically involved in memory formation; Gilbert and Fiez 2004; Pochon et al. 2002), and intracranial depth electrode recordings in epileptic patients have demonstrated that local gamma frequency activity in the hippocampus and gamma synchronization between hippocampus and other brain areas were correlated with successful encoding into long-term memory (Fell et al. 2001). Taken together, these findings may suggest that increased amplitudes of oscillations in the gamma band evoked by movie trailers relate to their capacity to capture the viewers' attention, increasing memorability of the viewed material, which in turn increases the probability that people will actually go see the movie, thus increasing box office returns.

Again, we found that gamma power is related to population preference independent of stated preference measures. We found that it is difficult to predict box office returns by simply asking participants how much they would be willing to pay for the movie (explained variance was not significant and only 1%).[3] Importantly, adding the EEG data to the model increases predictive power significantly, to 3%.[4] Of course, predictive power in absolute terms is still quite low when we include EEG gamma power as a predictor. However, an increase of two percentage points (which represents a 200% increase in predictive power) may actually be meaningful when we consider the enormous stakes (the average budget for producing a movie is $70 million and promotion expenditures for a major movie release average more than $40 million [MPAA 2012]) involved in movie releases.

[3]We note that the sample size in the present study was much smaller than what is common when using traditional measures for marketing research, which in some ways puts these traditional measures at a relative disadvantage compared with the EEG measures. Therefore, this result should be taken as a lower limit of predictive accuracy using traditional measures only.

[4]Note that this percentage should be taken as an upper limit of the variance in box office that can be explained by EEG measures because the EEG gamma effect, as entered as a predictor in the regression, is derived from the EEG signal that relates most strongly to box office (the same is true for the effect on individual preference). Although this approach is valid in the current study, taking the same frequency range and electrodes to predict commercial success in future studies may result in lower predictive accuracy.

Being that much more accurate in judging how well the movie will do in cinemas—or, indeed, gauging the effectiveness of the promotional trailer—could lead to better-informed decisions on which trailer to release and how much money to invest in promoting a particular movie, potentially decreasing costs and increasing revenues tremendously.

In the current study, we found that particularly high-frequency EEG components were related to both individual preference (beta) and population preference (gamma). As discussed previously, our findings fit well with previous literature relating power in beta and gamma bands to reward and attentional processes, respectively. However, in practice, it may actually not be that crucial to know what these different neural measures reflect in terms of psychological processes. Instead, in many cases it will be sufficient to know *that* these measures relate to real-world outcomes such as individual and population-wide preferences and choices. Herein, we report evidence that high-frequency oscillations provide such neural markers of commercial success, indicating that increased power in these frequency bands is indicative of a "better" movie trailer, commercial, or product, irrespective of what these oscillations actually reflect. Importantly, more experimental results are needed to establish the robustness of these findings and determine whether they extend to different types of commercials and products. In addition, whereas in the present study we averaged EEG activity over the trailer, future studies could take advantage of the high temporal resolution of EEG to investigate the time course of EEG within trailers to pinpoint the key scenes within a trailer that predict movie success (see, e.g., Vecchiato et al. 2010, 2011). Because participants all saw different trailers in the present study, leading to a low number of observations per trailer (and thus relatively low signal-to-noise ratio per individual trailer), doing so was not possible here.

In summary, the current study demonstrates that EEG measures (beta and gamma oscillations) capture unique information regarding both individual and population-wide preference and can thus be used as a neural marker for commercial success. As such, we provide the first evidence that such EEG activations in response to marketing stimuli are related to real-world outcomes. In addition, we are the first to show that such neural measures significantly add to models predicting choice behavior compared with models that include only stated preference measures. Finally, because EEG measures are relatively cheap to obtain, and because even a small increase in accuracy in estimating the successfulness of products or marketing stimuli can result in a substantial increases in revenue, we suggest that including such measures in marketing strategies may actually be cost effective.

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