A real-time signal of brand equity and sales from Twitter data

Executive Summary

- Kantar TNS and Twitter have pioneered a new form of social media modeling that integrates survey data with Twitter data to reliably predict changes in brand equity
- Extensive research from Kantar TNS proves that these models can accurately predict the results of brand tracker surveys months in advance — providing vital early warning of brand performance
- By evolving these models we were able to develop a stand-alone index of brand health generated solely from Twitter data, which accurately predicts how the Twitter conversation impacts sales
- The diagnostics that we have developed show how brand activity on Twitter influences the conversation — and the actions that brands can take to respond to changes in equity as they occur

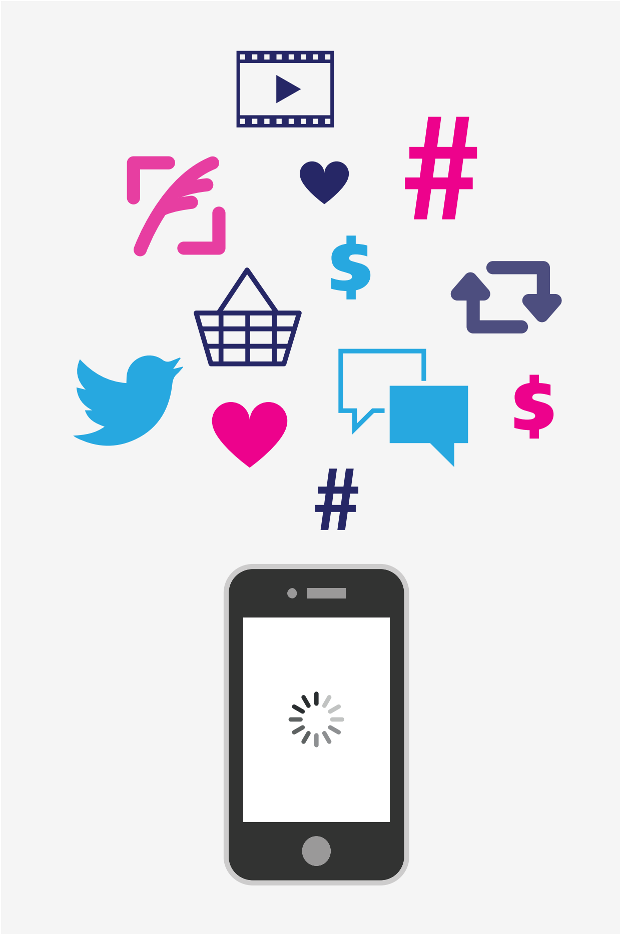
Background

In an ideal world, no brand manager wants to know today what his or her brand's health was a month ago, nor would they ask to know the thoughts and feelings of only those who are prepared to spend time answering a brand questionnaire.

Marketers want a full picture of what is really happening to their brand, in the moment, and they want to know in time to do something about it.

That has always been the promise of social media. Up to now though, marketers have had serious doubts about whether a meaningful signal can be detected amid the social media noise. There have also been concerns that social media data can never be fully representative — since not everybody is active on social, and some are far more vocal about brands than others.

In truth, representativeness is a concern only because it affects our ability to predict future outcomes accurately. The real goal of market research is to reveal the situation in as rapid and efficient a way as possible. The test, therefore, is not whether social data captures the representative views of every single consumer out there; it is whether we can accurately separate out a signal and predict changes in brand equity on the basis of the data that we have. A unique partnership between Twitter and Kantar TNS has proved that we can. In doing so, it opens up exciting new opportunities for brands seeking to understand their performance in real-time — and seeking actionable insight to improve it.



Translating Twitter data into a signal of brand health

In order to explore how Twitter data correlates with shifts in brand equity and sales performance, we drew on extensive research that Kantar TNS has conducted into the relationship between social media and brand health. We used this research to build accurate models for integrating historic survey data and Twitter data, in order to predict movements in brand equity up to 12 weeks in advance.

We then built on this research to explore the possibilities for using Twitter data alone to predict changes in brand equity and sales performance. This approach provides several important potential advantages for marketers: it can be simpler, quicker and more cost-effective, it leverages a potentially rich source of both qualitative and quantitative insight, and it provides readily actionable insight by looking at how brand activity on Twitter directly influences equity and sales.

We followed a six-stage process for exploring the correlation of Twitter data with shifts in brand equity and sales performance:

- Aggregating, cleaning and categorizing Twitter data to isolate genuinely relevant content, developing a taxonomy for brands and identifying key themes within the Twitter data for each category
- Integrating this cleaned Twitter data with previous brand equity studies for brands to identify the big data signals that would correspond to shifts in brand equity
- Testing whether this model could have predicted shifts in brand equity that had taken place in the past
- Exploring whether we could develop a meaningful metric of brand health from Twitter data alone, and how this metric correlated with sales data
- Identifying key diagnostics within the Twitter data that explain movements in brand equity, including changes in sentiment around the key themes and attributes for the brand
- Analyzing the role of paid and owned brand activity on Twitter in shifting the brand metrics that were modeled

The results of this six-stage process are very exciting. Our models have consistently predicted more than 85% of the variance in brand equity revealed in brand equity surveys—and have done so up to 12 weeks in advance of when these changes appeared in survey results. Twitter data transforms retrospective brand equity insights into real-time brand equity signals.

That is just the start. When we looked deeper, we found that the themes related to brands that were identified from the Twitter data correlated far more closely with actual brand equity than did the attributes listed in surveys. This provides yet more evidence that the ability of Twitter to predict brand equity is no fluke—it is a natural outcome of data that appears to be more robust and more predictive at every level than traditional surveys. In fact, when data on brand marketing spend is combined with the Twitter data, we are able to make very accurate predictions about sales performance without any recourse to survey data at all.

Our approach to curating Twitter data

These exciting results were made possible by the approach that we took to curating Twitter data. We knew that integrating contextual understanding into the isolation, analysis and modeling of the data was essential for overcoming concerns about separating a meaningful signal from the social media noise.

We developed a unique, iterative process that combined human intervention with machine-based learning, training our algorithms to think like people in detecting nuances such as sarcasm, idioms and unique Twitter phrasing.

Doing so enabled us to deliver a clean set of data with positive, neutral and negative sentiments coded accurately, and with the speed and scalability required.

In the real-time world that social media listening enables, the shape and nature of the conversation change quite quickly. Because of this, the ability of our model to detect emerging trends and adjust to track them can be hugely important. The launch of a new product such as the Apple Watch introduces entirely new themes to the social media and search conversation, and new attributes that are relevant to both the new product and others in its category. Our approach to data curation was able to adapt to this.

Other important elements in the data curation process included targeting the right markets, de-duping the data, removing the distortions that result from coupon activity and ensuring that content is genuinely relevant to the category (whether 'Apple' refers to fruit or technology, for example).

After cleaning out bot-generated and promotional posts, we created two separate data sets: one including only consumer-generated content, and the other including both consumer and brand-generated content. Comparing these two sets enabled us to understand the role of marketer activity in affecting brand perception, sentiment and ultimately brand heath.

In summary, the data preparation process included the following seven key steps:

1. Defining the query criteria, in order to identify a corpus of Twitter data with broad, relevant applicability to the brand(s) in scope

2. Using a social listening platform to launch and optimize the search query and store the data

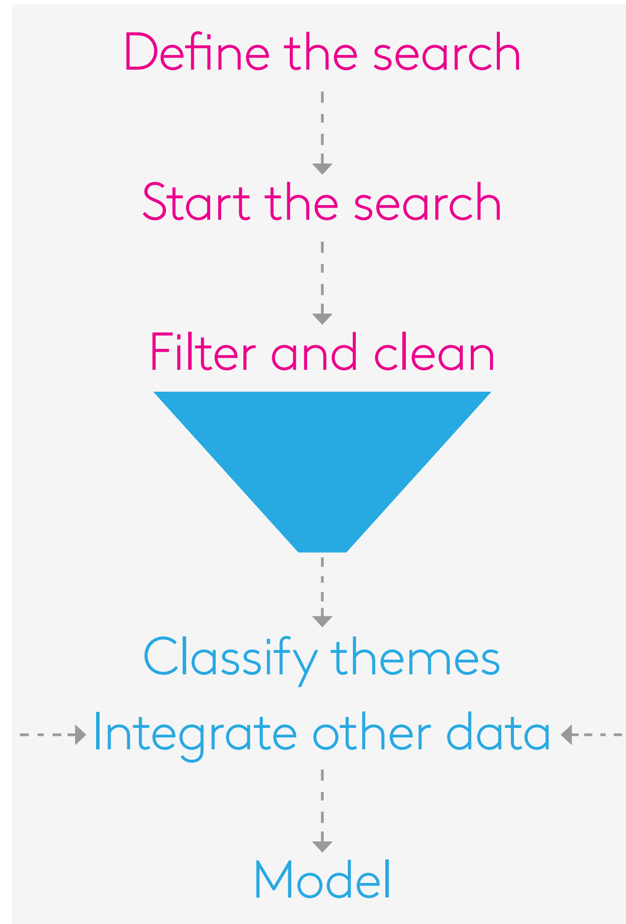
3. Cleaning and filtering the data

4. Classifying and coding the data into content-related categories

5. Reviewing category relevance and sentiment accuracy

6. Incorporating variables from other sources such as brand data, media data or sales data

7. Modeling the relationship between the Twitter data and the brand health data, as captured in a brand tracking survey



Building the model

Our approach to building a Twitter-based model for brand equity aimed to relate social media sentiment and content to survey-based measures of brand equity.

We did this retrospectively, using time-series data from both Twitter and brand surveys. By establishing the relationship between the two, we could reduce marketer's reliance on expensive survey data and lessen the impact of weaknesses in surveys such as an over-dependence on respondents' memories. We could also gain a greater insight into what drives changes in brand equity, by relating changes to key themes and sentiments within the Twitter data.

We Combine:

Survey-based brand health/equity tracking data + Twitter data

Which results in:

A predictive model
Brand Health/Equity = f(Twitter data)

That provides: Brand health/equity predictions for upcoming time periods with their underlying causes

And we can take it further with:

A predictive marketing mix model
Sales = f(marketing inputs + Twitter data)

That provides: A market simulator and planning tool

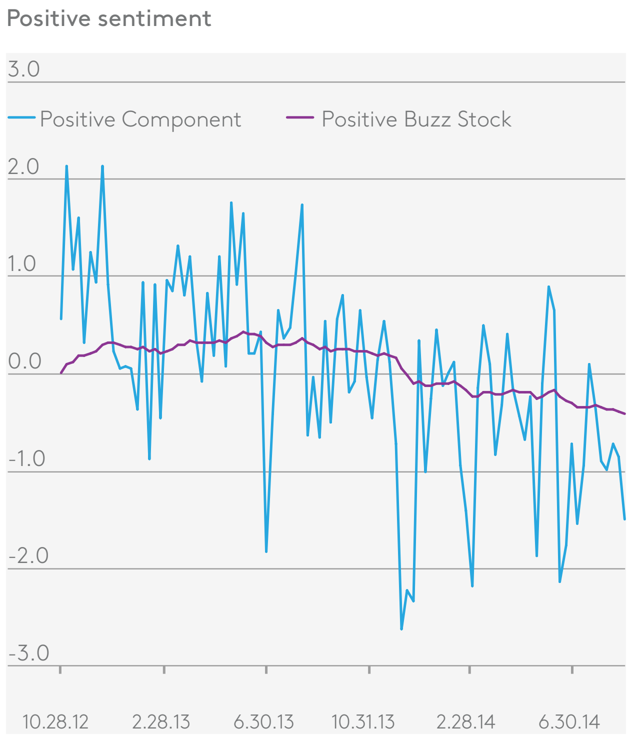
The Importance of Data Transformation and Smoothing

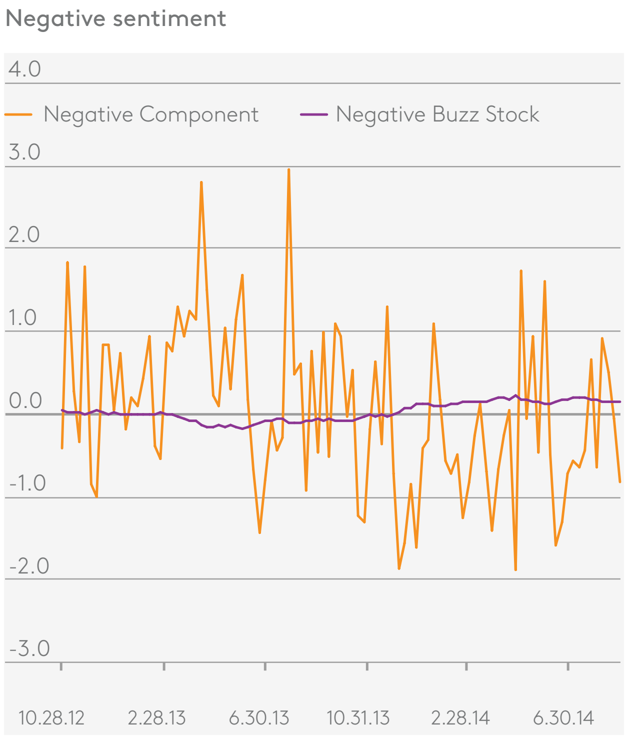
We used advanced time-series modeling and smoothing techniques to improve our model's diagnostic and predictive powers. This included applying a concept known as "BuzzStock" which allows for the fact that Twitter conversations remain influential after the point at which they occur.

Conversations about a topic have a buildup and carryover effect that decays over time, much like the impact of media weight in advertising.

The charts below show the impact of data smoothing on weekly Twitter data:

Example: Raw vs. Smoothed Twitter Metrics





The Importance of Data Transformation and Smoothing

Our data requirements

In order to build a stable, predictive model, we had several requirements for both survey and Twitter data:

For survey data, we required two years of historical data, measured weekly, for all of the survey-based brand equity measures and all of the Twitter data (approximately 100 time-series data points in all). Alternatively we required continuously collected data that could be used and "rolled" on a weekly basis. As an absolute minimum, we required one year of back data measured weekly or two years of back data measured monthly.

For Twitter data, we required 200 posts per topic per week, with an average of 40 to 50 posts per brand per theme each week for a maximum of 15 to 20 themes in total. We applied quality control checks to 200 random posts, checking that sentiments were coded and themes categorized accurately. We required accuracy of 90% for brand relevancy, 80% for sentiment and 60% for theme relevancy.

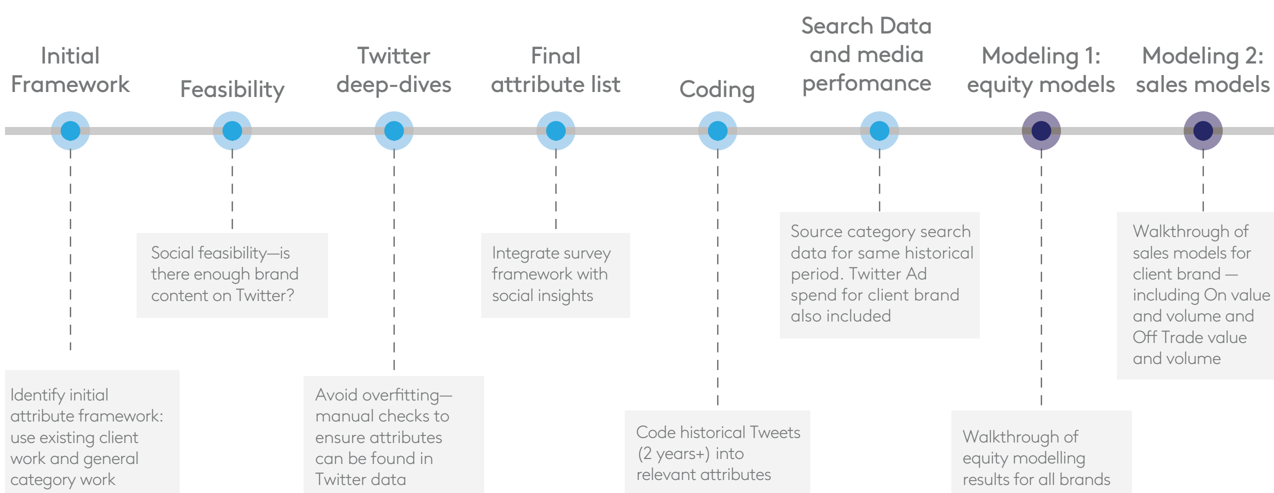
The model in action: an in-depth study of the UK beer market

To test the various applications of the model, we applied it to time-series Twitter and survey data for the UK beer market, testing its ability to predict brand equity and sales for key brands.

The diagram below describes the overall process:

Using Netbase as our social media listening platform, we collected two years of historical Twitter data on these brands. Via our curation process, we identified several key themes that were relevant to the Twitter conversation about beer in the UK: Affordability, Refreshing, Occasions, Availability, Preference, Taste, Innovation, Heritage, and Brand Character/Sponsorship.

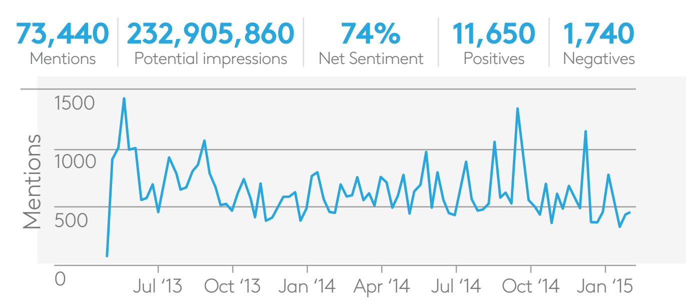
Modeling journey



For each brand, the query specification that we used to identify the relevant universe of Tweets was broad and inclusive.

The end result was over 70,000 qualified mentions of our client brand on Twitter in the UK over the last 2 years, which were then categorized into the aforementioned themes. This volume of mentions, while low in terms of absolute numbers, is highly relevant due to curation of Twitter data to remove non-relevant content (e.g., bot-based posts). Relevance is further enhanced by limiting the data set to posts from users who self-identify as being from the UK in their Twitter profile.

Client Brand Twitter conversations



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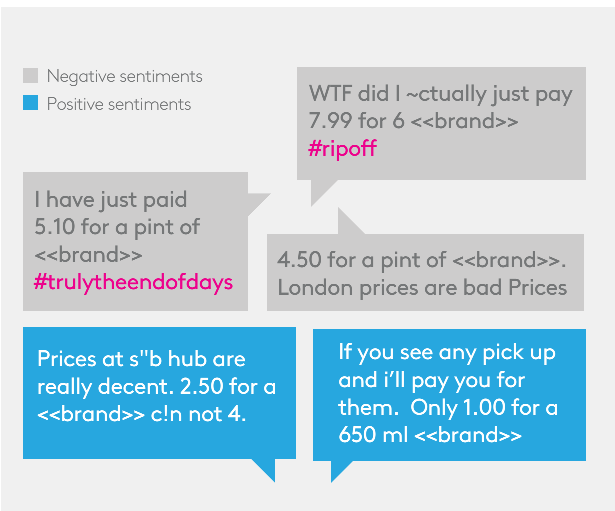
We then categorized all of these brand-relevant Tweets into themes. From a market research perspective, this is significantly different to recording brand attributes through a survey, since people do not naturally communicate on social media in the same way that they respond to survey questions — as shown below:

Because of the nature of the classification challenge, we looked at over 5,000 Tweets manually to validate our list of themes. Manually evaluating these Tweets allowed us to determine which themes it was feasible for us to code for, producing the following list:

An example of “Affordability” Tweets



An example of “Taste Performance” Tweets

An example of “Taste Performance” Tweets

Macro theme	Sub-theme
Commitment	Prefer
Heritage	Heritage
Innovation	Innovation
Performance	Refreshing
Performance	Taste
Recommended	Recommend
Special occasions	Occasions

Note: Example Tweets were anonymized using random characters to comply with Kantar TNS standards to protect Personally Identifiable Information and individual authors’ ownership of their content.

We then coded over two years' worth of Twitter data against this general list. Below is an example theme query and output from Netbase. Queries reflect the way that we found consumers talking about beer brands on Twitter — and as a result, they include some "colorful" descriptions.

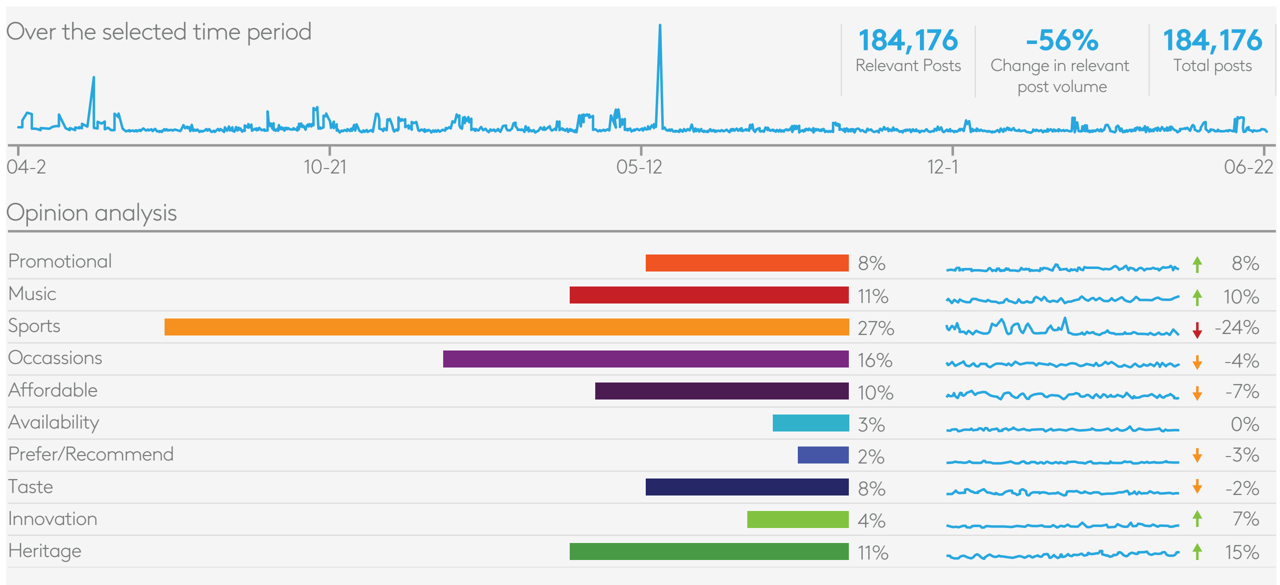
In order to understand the impact of organic consumer-generated Tweets versus promoted Tweets, we included promotional content in our modeling. This was done by incorporating performance data supplied by Twitter on sponsored brand Tweets, where clients consented for us to do so.

Query for Taste:

Themes:

awful taste terrible taste tastes terrible best cider best beer best light beer best taste bitter bland can't beat the taste can't wait to taste delicious disgusting taste enjoy the taste love the taste flavourless great flavor horrible taste like milk like mushy peas like nothing i've tasted lousy taste lovely taste nice taste nice beer no taste overly sweet satisfying flavour smooth strong taste sweet taste tastes like glue tastes fabulous too sweet unique taste tastes like urine wated down tastes weak worst i've tasted tastes yummy

Theme Output:



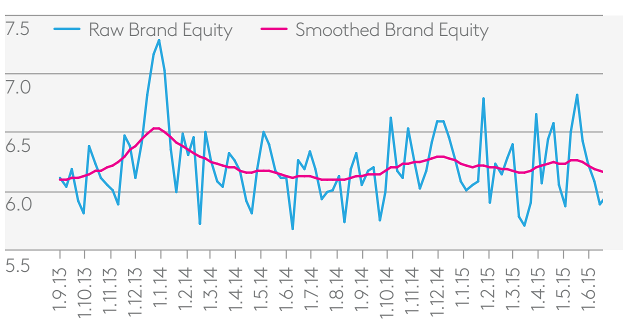
The model in action: an in-depth study of the UK beer market

An example of the modeling results

The models we produced for each brand were based on exploring the relationship between a dependent variable (brand equity) and two independent variables: Twitter data, coded for sentiment and theme, and Twitter promotional activity as captured through Twitter ad spend and the volume of promoted Tweets for the client brand.

The following graph shows how the brand equity for one of our clients was smoothed to provide the dependent variable for the model:

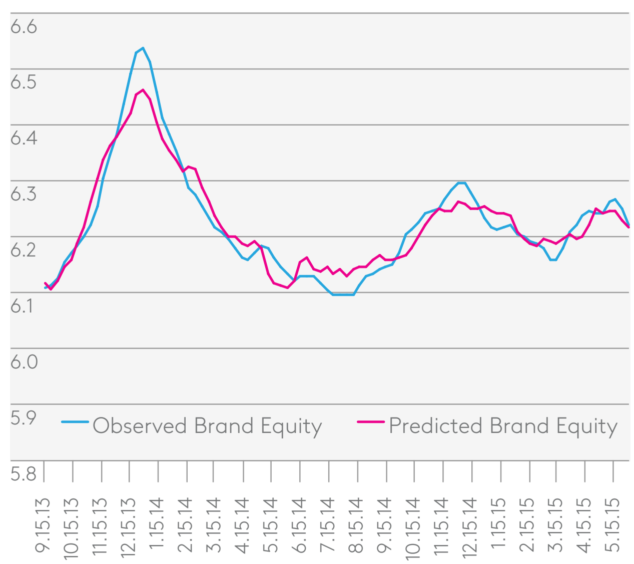
Client Brand Twitter conversations



Model Output – Predicted vs. Observed Brand Equity:

The graph below then shows how predicted brand equity based on the two independent variables related to observed brand equity:

Client Brand: Observed Versus Predicted Brand Equity



We can therefore see how coded Twitter data combined with Twitter promotional activity provided an accurate model of brand equity. In establishing the relationship between the dependent and independent variables, we observed several interesting dynamics:

a. Movements in positive and negative sentiment on Twitter anticipated changes in equity as revealed in brand surveys by nearly a month; in order to produce an accurate prediction of equity, we therefore had to introduce a 4 week "lag" into our model.

b. Both sentiment and Twitter ad spend had carry-over effects. What this means is that, like media weight, there is a lingering impact of Twitter buzz/volume and Twitter ad spend beyond the period in which it takes place.

c. When evaluating Twitter ad spend and promotional Tweet volume, we found ad spend to be a contributor to the model, whereas promoted Tweet volume was not. We believe these two metrics are in fact highly correlated, and as a result adding more than one into the model does not result in more accurate predictions.

Interpreting the results

We can draw the following conclusions from these results:

- The model fit is excellent with an R^2 of 92.7%, a very accurate model prediction.
- About 70% of ad spend and sentiment impact on equity is carried over to the following week and the impact of both decays at a constant rate.
- Sentiment is a leading indicator of changes in brand equity. Changes in sentiment today will be reflected in tracking data four weeks from now.
- Twitter Ad spend correlates more meaningfully with changes in brand equity than volume of promoted Tweets, and is therefore a more useful input for our model.
- Twitter Ad effects occur immediately and decay over time.

This leads us to the conclusion that Twitter is indeed an effective source of signal for brand health, and that marketing activity within Twitter has a demonstrable impact on overall brand health.

Uncovering the themes behind the sentiment

In addition to predicting shifts in brand equity, we wanted to explore whether Twitter data could reveal which particular conversational themes were driving these changes. We used an approach featuring Principal Components Analysis (PCA) to isolate the impact themes.

Principal Components Analysis is a procedure for identifying a smaller number of uncorrelated variables, called "principal components", from a large set of data, in order to determine the impact of these different variables. The goal of PCA is to explain the maximum amount of variance with the fewest number of principal components.

Similar to factor analysis, PCA creates composite metrics to which we can compare themes, to see what the contribution of those themes are to the metrics in question. In this case we used PCA to isolate two main composite measures as our key metrics — one based on positive themes and one based on negative themes — and to identify the contribution of each theme to those composites/factors.

Below is an example analysis of the influence of these themes on sentiment — weighted by importance:

Positive		Negative	
Brand character	**31.0%**	Availability	**17.5%**
Sponsorship	**30.8%**	Heritage	**16.7%**
Occasions	7.1%	Refreshing	**16.5%**
Promotions	5.7%	Price	**16.1%**
Price	5.3%	Occasions	10.2%
Taste	5.1%	Taste	7.9%
Availability	5.0%	Sponsorship	6.2%
Refreshing	4.3%	Brand character	5.4%
Innovation	3.2%	Preference	3.3%
Preference	1.8%	Innovation	0.2%
Heritage	0.7%	Promotions	0.0%

The model in action: an in-depth study of the UK beer market

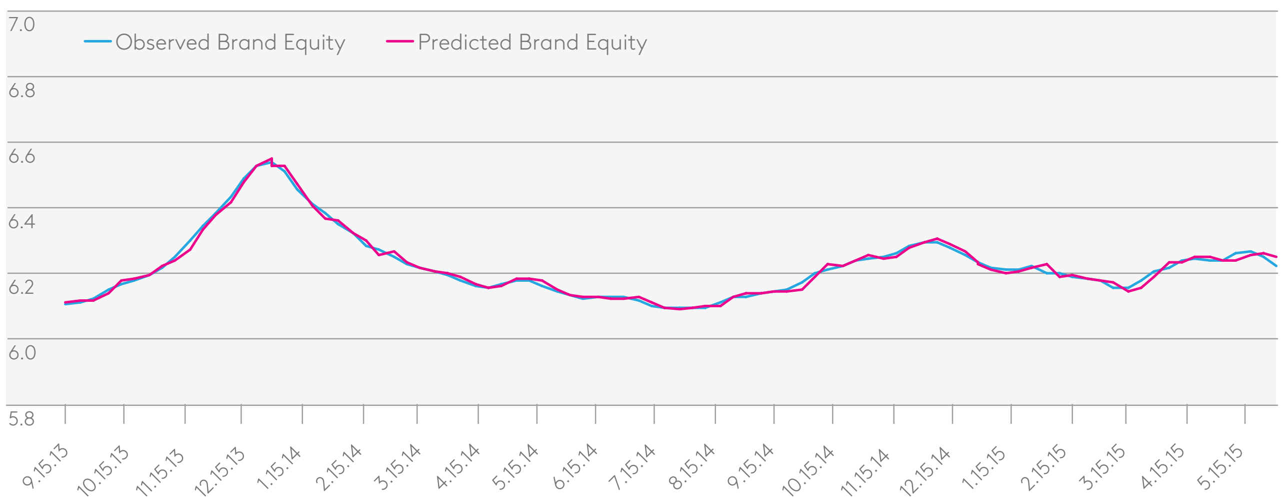
Forecasting future fovements in equity:

In addition to predicting a brand's equity accurately in any given period, we wanted to explore how well Twitter data could forecast future movements in equity. To do this, we conducted a "holdout" validation, whereby we would model predictions of the survey-based equity measure 2, 4, and 8 weeks ahead of the timeframe for the Twitter data we had collected. This was the cast-iron test of our model's validity: could it predict future brand equity movements as effectively as it predicted brand equity movements in the past? In other words — could Twitter data provide not just a real-time view of brand equity, but a predictive view of its future movement?

We found our model predictions to be very accurate for the holdout period. The model predicted brand equity for our client 8 weeks into the future. The subsequent survey results showed a mean absolute percent error (MAPE) of 0.3%, well below Kantar TNS's threshold of +/- 5.0% for a good model fit.

We found our model predictions to be very accurate for the holdout period.

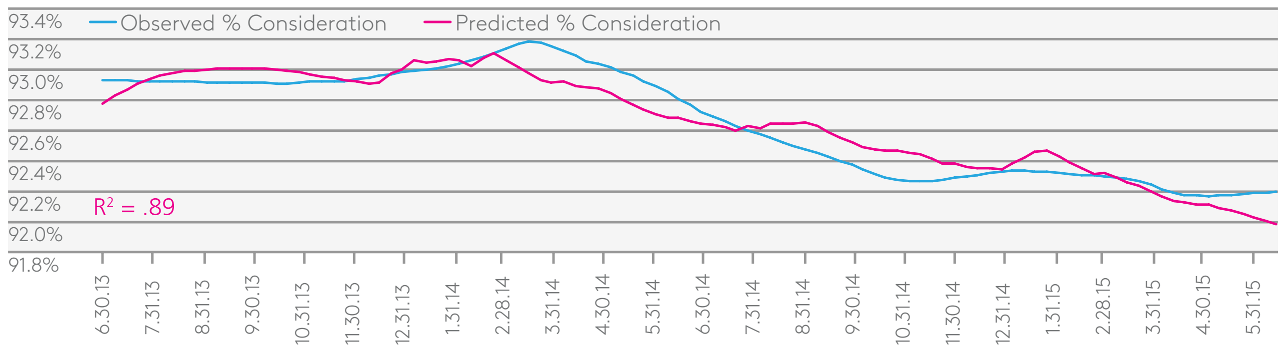
Client Brand: Model predictions on training and holdout data



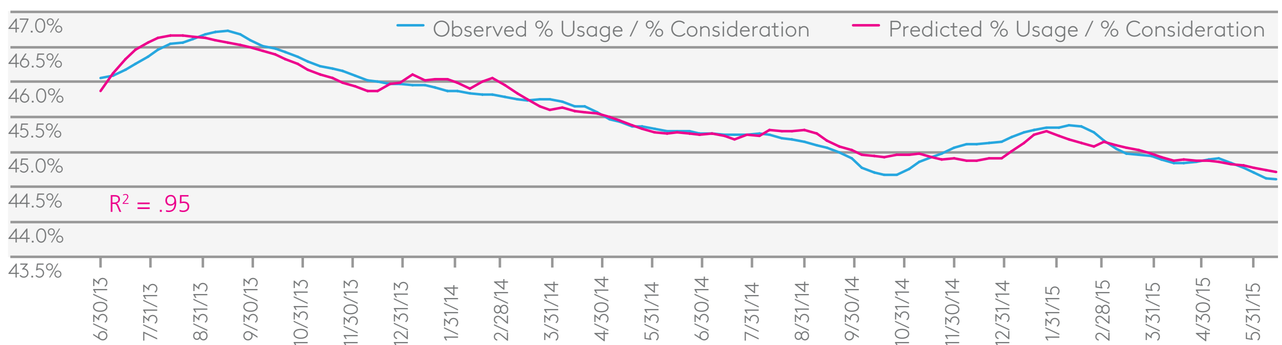
Testing the relationships between Twitter activity, consideration and usage

In addition to equity, another key metric in brand tracking studies is the percentage of people who consider the brand and then use it. Could our model predict consideration and usage for a brand? To answer this question, we examined whether Twitter ad spend and positive Twitter sentiment correlated with increased consideration and usage for the beer brands in the study. Once again, we found a statistically significant correlation between these different variables.

Twitter relationship to brand consideration:



Twitter relationship to conversion from consideration to usage:



The model in action: an in-depth study of the UK beer market

Could our Twitter model predict sales?

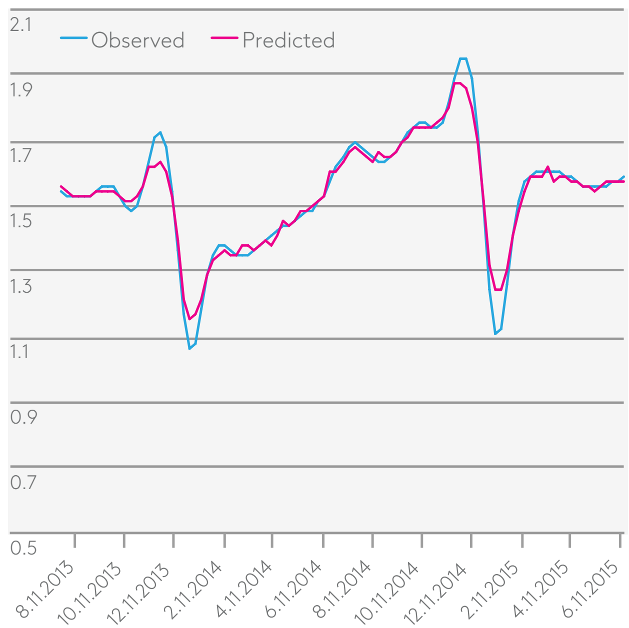
The next step of the study involved testing the value of our model for predicting actual sales of beer brands. This is usually done by building a marketing mix model that includes all of the relevant marketing variables that impact sales: advertising spending (and schedule), promotion events and distribution levels, for example. The test for our model was whether it could make accurate sales predictions without all of these inputs, using only Twitter data and the brand equity signal that our Twitter-based model produced.

Our marketing mix model used volume and currency sales (on-premise, such as in bars, and off-premise, such as beer bought in a supermarket and consumed at home) as our dependent variable, and attempted to predict these using only our Twitter-based brand equity signal and the Twitter ad spend of our client brand, plus search data, and the percentage of consumers converting from consideration to usage, as revealed in surveys.

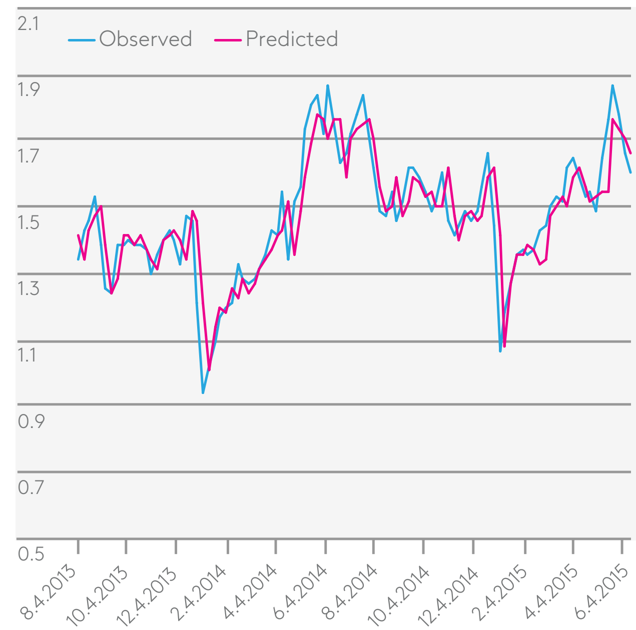
The results were striking. Our model showed a very strong ability to predict sales both on and off premise accurately, as shown in the graphs below. Our hold-out results are also very strong, with mean average percent error (MAPE) of between 3-4% for on-premise and off-premise volume.

Brand on-premise volume:

On trade



Off trade



Implications of the sales findings

Our model predicted sales accurately without using data on the full range of a brand's marketing programs because Twitter data is an excellent surrogate for the net impact of a brand's comprehensive marketing programs. In other words, properly curated Twitter data can clearly signal the impact of all of a brand's marketing activity, not just its marketing activity on Twitter itself.

In typical mix models, collecting and formatting all the marketing data is a laborious and time-consuming process. Our model results suggest that accurate sales models can be built without this data — making the process of generating mix models, projecting the impact of brand activity, and optimizing marketing plans faster and more cost-effective.

This is not to say that there will not be advantages to including all of the detailed elements of the marketing plan when this data is available. Such details will improve the model's diagnostic power — and detailed scenario planning requires it.

Despite this, our "shortcut" method illustrates the power of leveraging consumer conversations on Twitter for a near real-time view of brand equity and sales trends – and a vital early warning as to whether a marketing plan is delivering against its objectives.

An alternative to survey-based predictions: the Brand Health Index

There are key requirements that must be met in order to model survey-based equity from Twitter data. We need many months of data in a stable, consistent survey, in order to have enough observations available to create the model.

The next test of our modeling approach explored what is possible when detailed survey data is not available. Could we create a "synthetic" measure of brand health from Twitter data alone – a meaningful "Brand Health Index" (BHI) using benchmarks from within Twitter itself?

Kantar TNS set about building a BHI using a multivariate analysis of Twitter data:

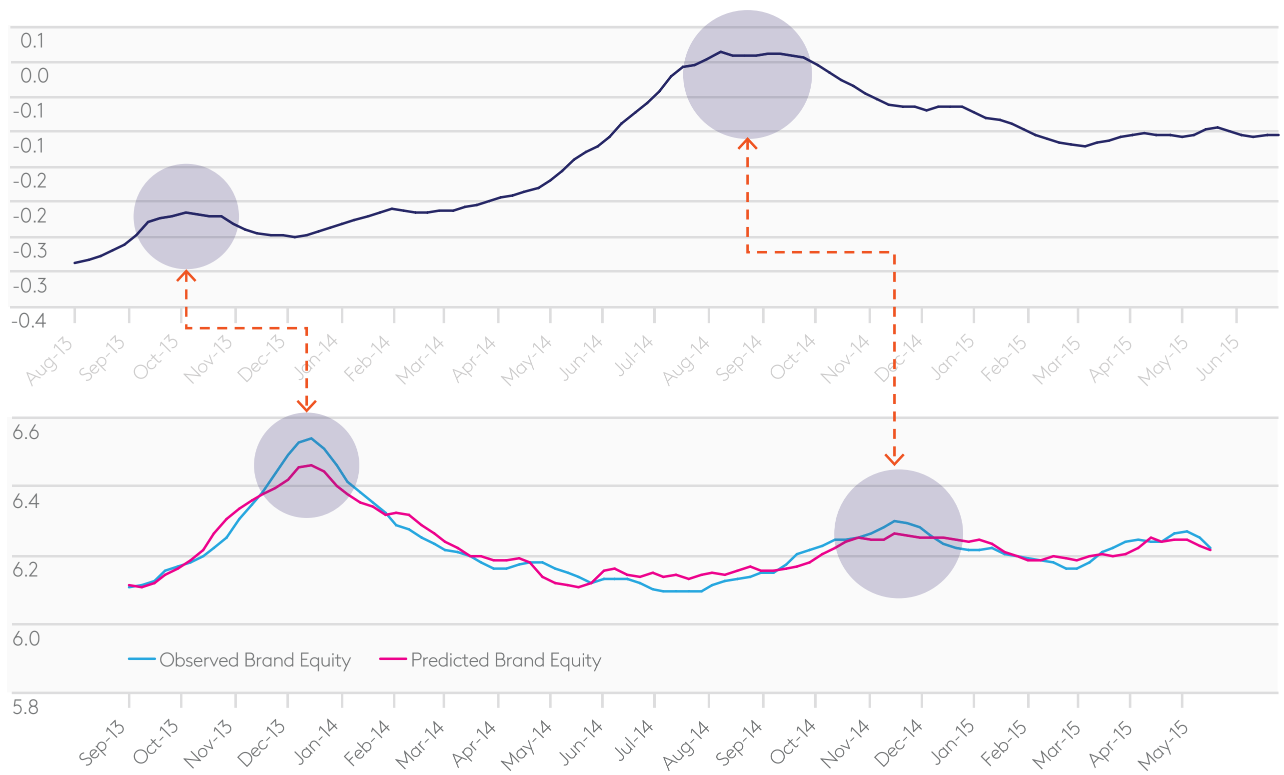
- Identifying the trends or patterns in Twitter themes within and across brands in a category
- Creating an overall category trend, and then comparing the trend for each brand to this category trend, to derive an index for a brand's performance (the BHI)
- Determining the contribution of each individual theme to the BHI, by analyzing how that theme varies over time, and if it varies independently from other themes

The model in action: an in-depth study of the UK beer market

Kantar TNS compared the BHI-based predictions for the UK beer market to the predictions that our model had already generated. Again the results were striking. BHI produced an earlier signal of changes in brand equity. This was less precise than the predictions of our model (which used brand survey data as a key to help interpret patterns within Twitter data), however it did capture the general direction and momentum of brand equity and provided a meaningful early warning of what was happening to brand health.

BHI show effects a bit earlier and with different levels of impact.

Comparison of BHI to survey-based predictions



KANTAR TNS.

The advantages of a meaningful BHI generated solely from Twitter data are clear:

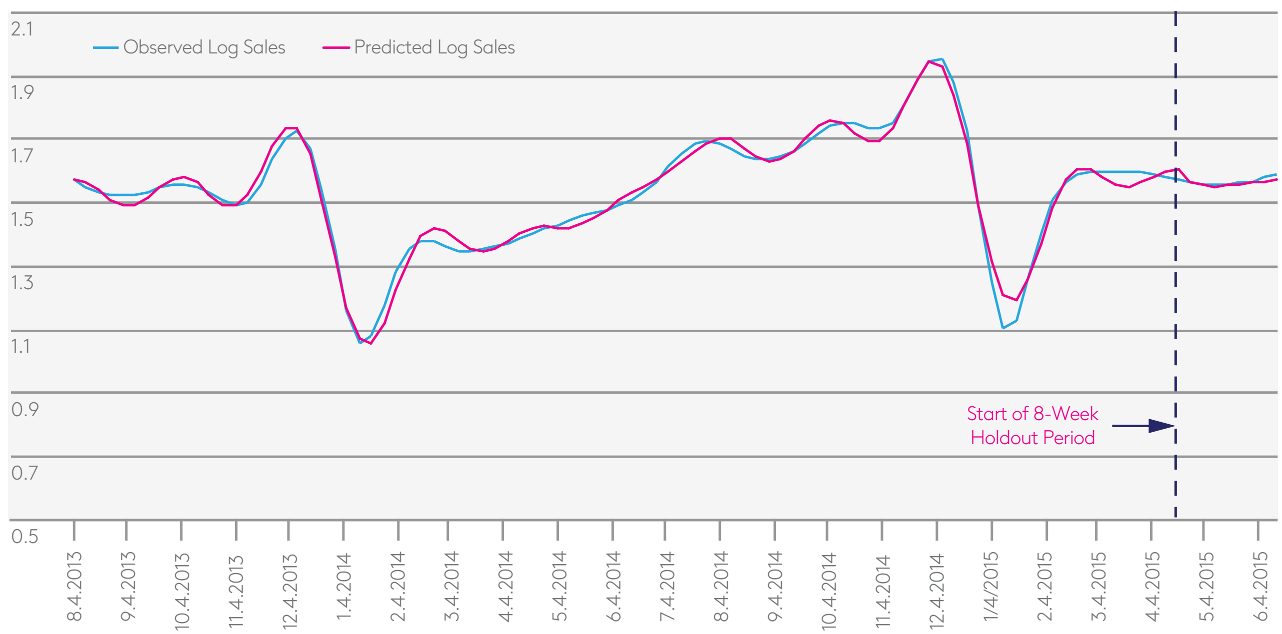
- No survey data is required, and the only constraint is the amount of relevant Twitter content in the category and brands we wish to analyze.
- The modeling process is much faster and more scalable.
- There is much less need to reformat or transform the data.
- The BHI creates a consistent measure across multiple categories.
- We can index all brands in a category so that they can be easily compared.

Without survey data, how could a brand be certain that its BHI predictions were accurate? The obvious answer here was to compare the BHI signal with a brand's sales performance. When Kantar TNS compared BHI to sales, the results were extremely exciting. BHI predicts sales even more accurately than it predicts brand equity — and almost as accurately as the outputs from our full model.

Sales Models using BHI as an input work well

Example: Client Brand On-Trade Volume

Model Statistics	Fit Metrics for 8-Week Holdout Period
R^2: **97.1%**	MAPE: **0.3%**



The key findings of our UK beer market study

What have we learned about predicting equity and sales?

- Trends in Twitter sentiment are an excellent predictor of brand health, consideration and conversion to purchase.
- Twitter data can be categorized into themes that help explain changes in brand equity/health.
- Twitter marketing activity is a key contributor to overall brand health and sales projections.

What have we learned about the process?

- Accurate curation and categorization of the Twitter data is critical to good modeling results. Existing social listening platforms are not equal when it comes to this – we chose Netbase for this study because it provides for more effective categorization and analysis of the data.
- Modeling sentiment first then using alternative methods to uncover the contribution of individual themes is a much simpler and more scalable process than modeling directly from themes. The same process can be used for any category.
- Modeling to survey data produces accurate results but slows the process down and makes the modeling less scalable. However, it is possible to use the patterns of Twitter data across all key brands in a category to create "synthetic" measure of brand equity (BHI) – and these measures have very strong relationships to sales.

Summary and Implications

The conclusions of our research are clear: Twitter data can provide marketers with valuable, real-time data on the overall momentum for their brands. When incorporated with historical survey data, it can accurately predict survey-based approaches up to 12 weeks in advance. It can also be used to produce a real-time, solely Twitter-based Brand Health index (BHI) that gives a sense of brand performance relative to the category.

We also showed that marketing activity within Twitter has a direct relationship to brand health. Marketers with an effective Twitter strategy shape the consumer conversation, and this can play a role in driving the brand's overall momentum.

Finally, modeling survey-based brand health data from Twitter can be used to create very accurate models of sales, even in categories with complex routes to market such as the beer category. Twitter data can provide a clear signal that, when viewed alongside other elements of the marketing mix, makes market modeling a real-time exercise. In an exciting development, the purely Twitter-based BHI signal, as an alternative for clients who do not have sufficient historical survey data also shows a very strong correlation with sales data.

The outputs from these kinds of analysis can easily be incorporated into marketers' dashboards and activity systems. These models enable them to see the impact of their and their competitors' activity on overall brand health and sales, as well as changes in tone, message and strategy on Twitter that could accelerate growth in both brand equity and sales.

Twitter data can provide marketers with valuable, real-time data on the overall momentum for their brands.

Get in touch

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About Kantar TNS

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With expertise in innovation, brand and communication, shopper activation and customer relationships we help our clients identify, optimize and activate the moments that matter to drive growth for their business.

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