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"Attention Allocation in Information-Rich Environments: The Case of News Aggregators"

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Abstract

News aggregators have emerged as an important component of digital content ecosystems, attracting traffic by hosting curated collections of links to third party content, but also inciting conflict with content producers. Aggregators provide titles and short summaries (snippets) of articles they link to. Content producers claim that their presence deprives them of traffic that would otherwise flow to their sites. In light of this controversy, we conduct a series of field experiments whose objective is to provide insight with respect to how readers allocate their attention between a news aggregator and the original articles it links to. Our experiments are based on manipulating elements of the user interface of a Swiss mobile news aggregator. We examine how key design parameters, such as the length of the text snippet that an aggregator provides about articles, the presence of associated images, and the number of related articles on the same story, affect a reader's propensity to visit the content producer's site and read the full article. Our findings suggest the presence of a substitution relationship between the amount of information that aggregators offer about articles and the probability that readers will opt to read the full articles at the content producer sites. Interestingly, however, when several related article outlines compete for user attention, a longer snippet and the inclusion of an image increases the probability that an article will be chosen over its competitors.

Keywords: digital content, media curation, media economics, news aggregator, click-through rate

Figure 1: Example of a news aggregator article entry

1 Introduction

The overwhelming amount of news content available online has increased the importance of *curation and aggregation*, that is, of interfaces and services that help readers filter and make sense of the subset of content that is important to them. Historically such functions used to be the realm of professional editors. Editors not only commissioned the production of content but also decided what content would be included in a newspaper and how it would be organized.

Web technologies allow this important function to be unbundled from content production. Specifically, the web's ability to place hyperlinks across content has enabled new types of players, commonly referred to as *content aggregators*, to successfully enter professional content ecosystems, attracting traffic and revenue by hosting collections of links to the content of others (Dellarocas et al. 2013; Dewan et al. 2004). Content aggregators produce little or no original content; they usually provide titles and excerpts (hereafter called *snippets*) of the articles they link to (Figure 1). Examples of well known aggregators include Google News, the Drudge Report, and the Huffington Post. Google News (news.google.com) is a search engine of many of the world's news sources; it algorithmically aggregates headlines and groups similar articles together. The Drudge Report (www.drudgereport.com) aggregates selected hyperlinks to news websites all over the world; each link carries a headline written by the site's editors. The Huffington Post (www.huffingtonpost.com) is a hybrid of news aggregator and original content creator.

Facing severe financial pressures, some content creators have turned against content aggregators, accusing them of stealing their revenues by free riding on their content.[1] Media tycoon Rupert Murdoch has been particularly outspoken on this issue, referring to aggregators as "parasites" and selectively blocking some from indexing the content of media sites he owns.[2] In late 2012 some countries were considering imposing a tax on news aggregators

[1] The 2009 dispute between the Associated Press and News Corporation with Google is a representative example. See http://www.forbes.com/2009/04/06/google-ap-newspapers-business-media-copyright.html

[2] http://www.mediaite.com/online/rupert-murdoch-begins-blocking-new-aggregators-search-engines/

and distributing the revenue to content producers.[3] Other market actors point out that, in today's link economy, links bring valuable additional traffic to their target nodes. Therefore content creators should be happy that aggregators exist and direct consumers to their sites (Jarvis 2008; Karp 2007). Key aggregator executives, such as Google's Eric Schmidt, assert that it is to their interest to see content creators thrive, since the value of links (and aggregators) is directly related to the quality of content that these point to.[4]

A central aspect of the debate focuses on the complex economic implications of the process of placing (for the most part) free hyperlinks across content nodes. The main argument in favor of aggregators is that, if links are chosen well, then they point to good quality content; as a result, they reduce the search costs of the consumers, which may lead to more traffic for higher quality sites. The main argument against aggregators is that some consumers satisfy their curiosity by reading an aggregator's short snippet of a linked-to article and never click through to the article itself. In fact, the question of whether aggregators are legally permitted to reproduce an article's title and snippet without obtaining permission from (and possibly paying) the content producer, is still unresolved.[5]

The question of whether the current generation of news aggregators is beneficial or harmful to content ecosystems remains open (Athey and Mobius 2012; Chiou and Tucker 2011). Nevertheless, we believe that the ever-increasing volume of available content makes some form of aggregation an inevitable, and valuable, component of every content ecosystem. The key question, therefore, is not whether aggregators should exist, but rather how the, partly symbiotic and partly competitive, relationship between aggregators and content creators, can be optimized for the benefit of both parties.

To provide insights to these questions, we examine the distribution of readers' attention between a news aggregator and the original articles it links to. The focus of our interest is a user's decision to follow the provided link towards the content producer's site and read the full text of an aggregated article. Our objective is to understand how key aggregator design parameters, such as the length of the text snippet that an aggregator provides about an article, the presence of associated images, and the presence of other related articles on the same topic, affect a reader's propensity to click on an article. We offer both theoretical modeling of these relationships, as well as a set of field experiments with smartphone and tablet versions of a Swiss news aggregator application.

[3] The Economist magazine, Newspapers versus Google: Taxing times, November 10, 2012.

[4] "CEO Eric Schmidt wishes he could rescue newspapers", Fortune January 7, 2009.

[5] Aggregators claim that the reproduction of titles and short snippets of text falls under the "fair use" provisions of copyright law. However, as stated by Isbell (2010), "for all of the attention that news aggregators have received, no case in the United States has yet definitively addressed the question of whether their activities are legal."

We find evidence for the presence of a substitution relationship between the amount of information that aggregators display about an article and the probability that readers will opt to read its full text at the content producer sites. Our results suggest that an article's headline provides all the information users need to decide if an article is close enough to their interests. Any additional information provided by aggregators, in the form of text snippets or images, apparently satiates the appetite of some readers and can only serve to decrease click-through rates. Interestingly, however, when several related articles compete for user attention, a longer snippet and the inclusion of an image increases the probability that an article will be chosen over its competitors.

Besides contributing to research, the findings of this study are valuable for aggregators seeking to optimize their traffic patterns, as well as in terms of informing the public discourse between aggregators and content creators on the need for equitable business agreements between the two parties.

2 Related Work

The relationship between news aggregators and content producers is the subject of a small, but growing, body of scholarly work. Dellarocas et al. (2013) model how the ability to place costless hyperlinks to third party content affects the behavior of competing content producers, who can now choose between spending effort to write an original article on a story and simply linking to an article that someone else has written. They view aggregators as a limiting case of content nodes who are inefficient in original content production and, therefore, can only attract readers by placing links to interesting third-party content. The paper shows that the impact of an aggregator on the content ecosystems is the sum of two opposite effects. On one hand, a search cost reduction effect arises from the fact that aggregators generally place links to well-chosen content and provide some information (snippet) about this content that helps users decide whether it matches their interests. This effect is positive; it increases the overall consumption of content in the entire ecosystem and primarily benefits high quality content producers. On the other hand, a free riding effect is due to readers who browse aggregator headlines and snippets, and never click through to the original articles. The free riding effect is at the core of the controversy between aggregators and original content producers. It reduces the content producers' profits and incentives to produce quality content.

Chiou and Tucker (2011) offer an empirical contribution to the discourse about the net impact of aggregators. They empirically examine the effect of the removal of all hosted articles by The Associated Press from Google News at the end of 2009 (due to a dispute in licensing negotiations) on what sites consumers visited. They find that the removal of The Associated Press's content was correlated with a decline in subsequent visits to traditional news sites (immediately after visiting Google News) as compared to other news aggregators that continued to host The Associated Press content. The results suggest the presence of a complementary relationship between aggregators and content producers, whereby article summaries hosted by aggregators induce readers to seek more news on those stories after visiting the aggregator.

In another empirical paper with a similar objective, Athey and Mobius (2012) look at how the addition of a localization feature on Google News affects the consumption of local content. They find that the addition of this feature increases local news consumption, including the number of direct visits to such sites (that presumably users discover via Google News and then begin to visit directly). However, the effect diminishes over time.

Hong (2011) focuses on the potential for aggregators to induce information cascades that concentrate traffic to a few "popular" sites. The author provides evidence of an association between the number of visitors to a news aggregator site and the online traffic concentration of that site. The author suggests design interventions for alleviating the adverse impact of such phenomena.

Our work also relates to the broader discourse on how readers allocate their attention in content networks. For example, Wu and Huberman (2008) analyze the role that popularity and novelty play in attracting the attention of users to dynamic websites. Agarwal et al. (2009) propose novel spatial-temporal models to estimate click-through rates in the context of content recommendation. Roos et al. (2011) propose a model of browsing behavior in hyperlinked media that takes into consideration a user's utility and beliefs about the quality of cross-linked content.

Compared to this broader literature, our aims are more focused, looking specifically on how consumers allocate attention between news aggregators and news articles and how design parameters of the aggregator affect this allocation.

3 Modeling Attention Allocation

Assume that newspaper articles are uniformly distributed in a Salop circle of radius R. Each point of the circle represents a combination of article attributes, such as topic, style, political orientation, etc. Users are, similarly, assumed to be uniformly distributed in the same circle. A user's location in the circle represents the center of mass of her interests.[6] The user's

[6]The assumption of uniformly distributed users and articles is without loss of generality, since any set of random variables can be converted to random variables having a uniform distribution via the probability

utility from reading an entire article is $u = U - d$, where d represents the distance between the user's and the article's locations and U is the ex-ante expected utility that a user can receive from reading an article that exactly matches her interests. This utility includes the variable cost of reading the article. To limit the complexity of the subsequent analysis, we assume that all articles offer the same ex-ante expected maximum utility U and focus our attention on a user's uncertainty regarding an article's fit with her interests.

Clicking on a news aggregator link incurs a fixed cost $c < U$. This cost is associated with waiting for the new page to load and reorienting oneself to a different screen layout.

Because of symmetry, we can simplify the analysis by considering the perspective of a single user. In that case, we can collapse the circle into a line segment $[-D, D]$, $D = \pi R$. We assume that our user is located at 0 and that articles are located on either side of the user.[7]

If aggregators offer no information about an article, our user expects d to be equal to the average distance d_0 between her and a randomly chosen article. She, thus, expects utility $U - d_0$ from clicking on the aggregator link and will do so if and only if $U - d_0 > c$.

3.1 Impact of snippet length on click-through rates

The presence of snippets (headlines plus article text excerpts) on news aggregators has two effects on the expected utility from reading an article. First, snippets provide some information about an article's true location. Second, snippets give away some of the content contained in the full article. We will consider each effect individually and will then examine their combined impact on click-through probabilities.

First Effect: Snippets provide information about an article's location. Assume that each snippet provides a location signal x, drawn from a Normal distribution that is centered at an article's true location y and whose precision $t = t(\ell)$ is an increasing function of snippet length ℓ (Figure 2). In the rest of this section we will, therefore, use signal precision as a proxy for snippet length. Bayesian belief updating theory predicts that a user's posterior beliefs about an article's expected distance to herself can usually be expressed as a convex combination $\delta = f(t)|x| + (1 - f(t))d_0$ of her prior d_0 and absolute signal $|x|$, where $f(t)$ is an

integral transform. The key assumption, therefore, is that the distribution of articles matches the distribution of user interests. We argue that such an assumption is plausible in a competitive marketplace where content producers act strategically with the aim of capturing as much user attention as possible.

[7]The correspondence of the line segment to the circle is, of course, approximate, since the line segment does not account for the wrap-around effect at the two far ends of the circle. We assume that far away articles are not interesting to users located at 0 so whether the wrap-around effect is explicitly modeled or not has no impact on user behavior.

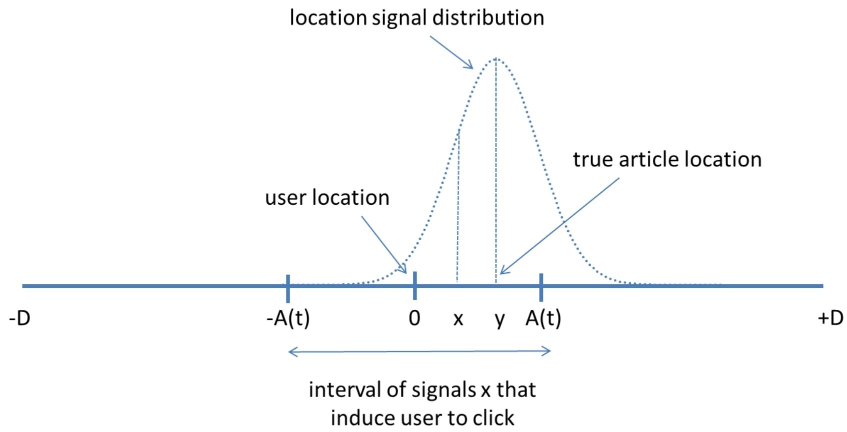


Figure 2: Snippets provide a signal about an article's true location.

increasing function of snippet precision; we will assume that this is the case in this analysis.[8] The presence of the snippet changes the user's expected utility to $U - \delta$. The user will click the aggregator link if and only if $U - \delta > c$. This happens if the distance signal satisfies $|x| < d_0 + \frac{U-d_0-c}{f(t)}$, or, equivalently, if $x \in (-A(t),\ A(t))$, where $A(t) = \max\left(0,\ d_0 + \frac{U-d_0-c}{f(t)}\right)$. Assuming that $A(t) > 0$, if an article's true location is y, the probability of this occurring is $\Phi\left([A(t) - y]\sqrt{t}\right) - \Phi\left([-A(t) - y]\sqrt{t}\right)$, where $\Phi(\cdot)$ is the Gaussian cumulative distribution function. The expected click-through probability for a randomly chosen article is then:

$$\kappa(t) = \frac{1}{2D}\int_{-D}^{D}\left[\Phi\left([A(t) - y]\sqrt{t}\right) - \Phi\left([-A(t) - y]\sqrt{t}\right)\right]dy$$

The impact of snippet length on this first effect is captured by the sign of $\kappa'(t)$. The following Lemma is proven in the appendix.

Lemma 1: *If $A'(t) \geq 0$ then $\kappa'(t) \geq 0$, whereas, there is a threshold b such that, if $A'(t) \leq -b$ then $\kappa'(t) \leq 0$.*

There are two cases of interest:

Case I: $U - d_0 - c < 0$. When this case applies, in the absence of snippets, the user will not click on any article, because, on average, a randomly chosen article is located too far away from her interests to make clicking worthwhile. Given the information overload that most users experience, we believe that this case reflects the behavior of the majority of the population, as well as an important rationale for the emergence of news aggregators.

[8]The intuition here is that new information shifts beliefs from the prior towards the signal; the higher the precision of the new information, the bigger the shift.

It is then $A(t) = \max\left(0,\ d_0 - \frac{|U-d_0-c|}{f(t)}\right)$ and the presence of a snippet of precision t, where $f(t) > \frac{|U-d_0-c|}{d_0}$, is required in order for any user to click on the article. For snippets longer than this threshold, it is $A'(t) = \frac{|U-d_0-c|}{(f(t))^2} f'(t) \geq 0$. Intuitively, as snippets provide more precise information about the article, the interval $(-A(t),\ A(t))$ of signals that make the user confident enough to click on the link, gets wider. By Lemma 1, this implies $\kappa'(t) \geq 0$, that is, as the snippet length increases, the click-through probability for a randomly chosen article also increases.

Case II: $U - d_0 - c > 0$**.** When this case applies, in the absence of snippets, the user will click on every article. We consider this case to be less common in practice, but include it for completeness. In this case $A(t) = d_0 + \frac{|U-d_0-c|}{f(t)}$ and $A'(t) = -\frac{|U-d_0-c|}{(f(t))^2} f'(t) \leq 0$. Additionally, it is $\lim_{t\to 0} A'(t) = -\infty$. From Lemma 1 this implies that, at least when t is not very large, it is $\kappa'(t) \leq 0$. Intuitively, as snippets get more informative, there is an increasing probability that the user, who, in the absence of any information is willing to give every article a try, will realize that some articles are not interesting to her and will choose not to read them.

Second effect: Snippets give away part of an article's content. In most practical cases, snippets are excerpts of actual full articles and give away part of the content that is available in the full article. By doing so, they decrease a user's residual utility from reading the full article. Assume that the utility of reading the first ℓ words of an article is given by $g(t(\ell))u$, where $u = U - d$ is the expected utility of reading the entire article, $t(\ell)$ is the corresponding information precision, and $0 \leq g(t) \leq 1$, $g(0) = 0$, $g'(t) > 0$, $\lim_{t\to\infty} g(t) = 1$. The residual utility of reading the full article, after having read the snippet, is $(1 - g(t))u$. This second effect reduces the expected utility of clicking the aggregator link.

To combine the two effects, we set $u = U - \delta$, where $\delta = f(t)|x| + (1 - f(t))d_0$. Users will click if and only if $(1 - g(t))(U - \delta) > c$. Substituting and rearranging, we find that this happens when $|x| < d_0 + \frac{1}{f(t)}\left(U - d_0 - c - \frac{g(t)}{1-g(t)}c\right) = A(t)$. The following result holds:

Lemma 2: *If $U - d_0 - c < 0$ then there are thresholds $0 < t_0 \leq t_1$, such that $A'(t) \geq 0$ for $t \leq t_0$ and $A'(t) \leq 0$ for $t \geq t_1$. If $U - d_0 - c > 0$ then it is $A'(t) \leq 0$ for all t.*

In all our hypotheses we will assume that the majority of the user population satisfies $U - d_0 - c < 0$. Lemma 2, in conjunction with Lemma 1, lead to our first pair of hypotheses.

Hypothesis 1a: *There exists a threshold snippet length ℓ_0 such that, as long as $\ell < \ell_0$, news aggregator article click-through rates are increasing with snippet length ℓ.*

Hypothesis 1b: *There exists a threshold snippet length ℓ_1 such that, as long as $\ell > \ell_1$, news aggregator article click-through rates are decreasing with snippet length ℓ.*

3.2 Impact of the presence of multiple snippets on group click-through rates

Popular stories typically have multiple newspaper articles written about them. News aggregators collect such articles together and display their snippets next to each other. This is an interesting aspect of aggregator behavior, whose implications have not yet received sufficient attention. We denote *group click-through* rate the probability that a user will click at least one article from among a group of related articles. Of particular interest is to explore how the number of article snippets related to the same story affects group click-through rates.

We assume that users read all snippets and then decide whether the story is interesting enough for them to click at least one article and find out more about it. Each story has a location z and each article about that story has a location $y_i = z + e_i$, where e_i is a zero mean Normal error term reflecting an individual article's political orientation, writing style, etc. As before, snippets provide signals $x_i = y_i + \eta_i$ about each article's location as well as some information about the article/story itself; η_i represents another zero mean Normal error term. Observe that it is $x_i = z + e_i + \eta_i$, that is, snippets simultaneously provide signals about the story's location. The display of multiple snippets modifies the analysis of Section 3.1 in the following ways:

1. In terms of belief updating, receiving multiple (independently drawn) signals about the same quantity is approximately equivalent to receiving a single signal of higher precision. Therefore, the impact of increasing the number of displayed snippets on a user's posterior beliefs about the story's location, is mathematically (approximately) equivalent to providing a signal of higher precision t.

2. Because of complementarities among the content of snippets, the presence of multiple snippets is likely to give away more details of the story than what is contained in any single snippet. Therefore, the residual utility from clicking and reading any single article is likely to be lower, relative to settings where only one snippet is displayed.

In summary, the mathematics of Section 3.1 also apply to a setting with multiple snippets if we simply assume that the precision $t = t(\ell, n)$ is a function of both snippet length and number of snippets, and that it is $\frac{\partial}{\partial \ell} t(\ell, n) \geq 0$ and $\frac{\partial}{\partial n} t(\ell, n) \geq 0$. Therefore, the effect of displaying more snippets is mathematically equivalent to the effect of displaying a single longer snippet. This allows us to modify Hypotheses 1a/1b and generate the following hypotheses:

Hypothesis 2a: *When their total number n is below a threshold n_0, the presence of additional articles about the same story increases the group click-through rate.*

Hypothesis 2b: *When their total number n exceeds a threshold n_1, the presence of additional articles about the same story decreases the group click-through rate.*

3.3 Impact of snippet length on an article's choice probability

For stories that have multiple articles competing for user attention, another important question is what factors make users choose among the competing articles. It is well documented here that position matters a lot. The higher the article is on the list, the higher the probability that it will be chosen (see, for example, Ghose and Yang 2009). What has not been researched is the impact of an article's snippet length on the choice probability. To construct hypotheses around this, we build on the analysis of the previous section as follows:

Assume that, after reading all available snippets, a user has decided that a story is worth reading more about. If we ignore position effects, a rational user will click on the article that offers the highest expected residual utility $(1 - g(t_1, .., t_n))(U - \delta_i)$, where $g(t_1, .., t_n)$ represents the utility gained from reading all the available snippets and δ_i denotes the user's posterior beliefs about article i's expected distance to herself. Since the term $(1-g(t_1, .., t_n))$ is common to all choices, the user will simply choose the article that is associated with the highest $U - \delta_i$ or, equivalently, the smallest δ_i. Recall that δ_i can be expressed as a convex combination $\delta_i = f(t_i)|x_i| + (1 - f(t_i))d_0$ of the prior d_0 and absolute signal $|x_i|$, where the weight $f(t_i)$ is an increasing function of snippet precision. For a given story, say, located at z, the expected value $E(|x_i|)$ across all articles will be a constant (close to, but not equal to, z). If we assume that $U - d_0 - c < 0$, stories that induce the user to click must have $E(|x_i|) < d_0$, that is, they must be located closer to her interests than the average story that is available online. In such cases, $E(\delta_i) = f(t_i)E(|x_i|) + (1 - f(t_i))d_0$ is a declining function of $f(t_i)$ and, therefore, of t_i. This implies that, for stories that are indeed close to the user's interests, articles with longer, more informative, snippets are, on average, more likely to be perceived as being closest to the user's interests and, therefore, chosen. The above line of reasoning leads to the following hypothesis:

Hypothesis 3: *When several articles about the same story compete for user attention, controlling for position, readers are, on average, more likely to click on articles whose snippet*

Name	Website	Language	Circulation*	Free/Paid*	Log frequency**
Blick	blick.ch	German	275,000	Paid	1,492 (5%)
Neue Zürcher Zeitung	nzz.ch	German	330,000	Paid	2,729 (10%)
20 Minuten	20min.ch	German	329,000	Free	5,034 (18%)
Tages Anzeiger	tagesanzeiger.ch	German	216,000	Paid	3,400 (12%)
Basler Zeitung	bazonline.ch	German	165,000	Paid	1,546 (5%)
Berner Zeitung	bernerzeitun.ch	German	165,000	Paid	2,064 (7%)
24 Heures	24heures.ch	French	86,000	Paid	1,266 (4%)
Le Matin	lematin.ch	French	69,000	Paid	802 (3%)
20 minutes	20min.ch/ro/	French	221,000	Free	1,208 (4%)
Tribune de Genève	tdg.ch	French	67,000	Paid	665 (2%)
TIO (Ticino Online)	tio.ch	Italian	N/A	Free	2,591 (9%)
Corriere del Ticino	cdt.ch	Italian	40,000	Paid	3,002 (10%)
Ticino News	ticinonews.ch	Italian	N/A	Free	2,807 (10%)

* Circulation and Free/Paid refer to print edition; N/A implies no print edition.
** Instances and percentage of article access sessions in the iPhone data set.

Table 1: List of Newscron news sources.

lengths are longer.

4 Field Experiment Setting

Our field experiments are conducted on a Swiss news aggregator application called Newscron. The front-end of the app consists of two separate client versions (for iPhones and iPads respectively) that can be freely downloaded from Apple's App Store. The back-end of the app is a server that collects and organizes news articles. The server collects all news articles published online by every major newspaper in Switzerland (in all three national languages: German, French, and Italian) on daily basis (Table 1). The server performs a semantic analysis of article texts to group them together into topics (stories). Topics are, further, classified as belonging to one of 9 categories: international, local, business, technology, entertainment, sports, life, motors, and culture. This leads to the following data structure: every article belongs to a topic; a topic contains one or more articles and is assigned to a category.

The iPhone and iPad client versions of Newscron provide distinct user interfaces with different features and different strengths and limitations vis-à-vis the research questions that motivate this work. We have, therefore, conducted separate experiments on each version of the app to obtain complementary insights. In the rest of the section we describe each client version, the experiments we conducted on it, and the properties of the resulting data sets.

(a) First level: Topics (b) Second level: Article outlines (c) Third level: Full article

Figure 3: Newscron iPhone user interface

4.1 iPhone client and experiments

User interaction with the iPhone version of Newscron is designed as a three step process (Figure 3). First, the user is presented with a list of topics (news stories), organized by category (Figure 3a). When the user clicks on a topic, she sees all articles related to the particular topic, sorted by their publication dates (i.e., the most recent articles are displayed first). Only an outline (headline, snippet, and - if available - picture) of each article is displayed (Figure 3b). Snippets in Newscron are simply the first characters of each article. By clicking on the article's dedicated and labeled button at the bottom of the article's outline (the button is labeled "Ganzen Artikel Lesen" in Figure 3b), the user is directed to the newspaper's website to read the full article (Figure 3c).

To test our hypotheses, we manipulated the length of article snippets at the second level of the user interface (Figure 3b). The default snippet length used in our app is equal to 245 characters, which is the average number of characters of snippets at Google News. We reduced/increased this default snippet length in increments of 20%, which is twice the standard deviation of snippets in Google News. We, thus, defined six different snippet lengths ranging from -60% to +40% of the default length (see Figure 4). We chose -60% because it is the shortest length that is supported by the user interface and +40% because it is the longest snippet possible subject to copyright agreements we have with the news providers. During our experiment the snippet length that was displayed when user i accessed article j was randomized. This means that different users might encounter the same article with different snippet lengths and the same user may encounter different articles with different snippet lengths. Furthermore, different articles within the same topic group could be displayed with

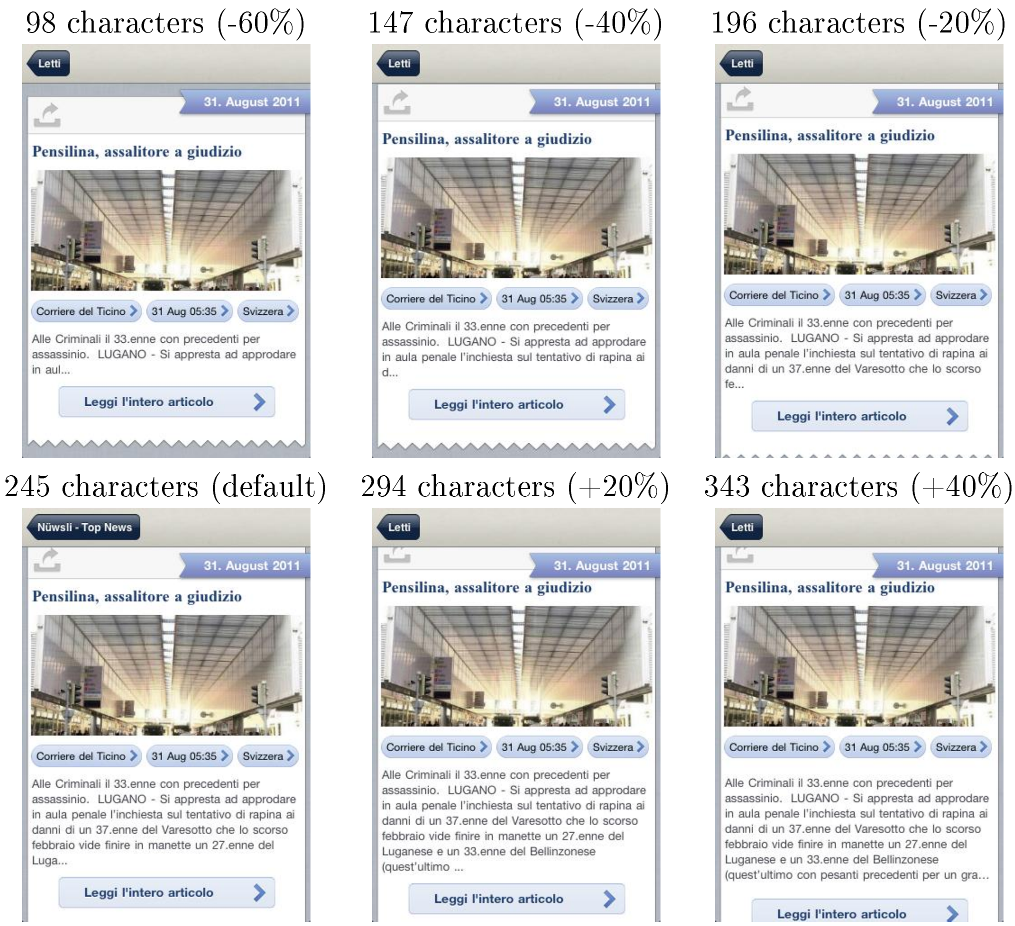


Figure 4: Preview of different snippet lengths

different snippet lengths.

Our main variable of interest is the *click-through rate*, which is the probability that a user will click through to an article linked to through the aggregator and will proceed to read it in its entirety at the content producer's site. We are interested in measuring two types of click-through: individual and group.

An *individual click-through rate* stands for the click-through rate of a single article and is defined as the ratio of the number of times users click the button at the bottom of an article's outline (Figure 3b) and move to reading the full article at the publisher's site (Figure 3c) over the number of times that the article's outline is displayed to the users.

Popular stories typically have multiple newspaper articles written about them. Newscron collects such articles together under a topic and displays their outlines next to each other. We denote *group click-through rate* the probability that a user will click *at least one* article from among a group of related articles. In such cases we are, additionally, interested in understanding *which* article(s) users choose to read.

Age Interval	Percent of Users
13-17	5%
18-24	10%
25-34	21%
35-54	52%
55+	12%

Gender	Percent of Users
Male	73%
Female	27%

Table 2: User demographics

Measurement	Value	Units
Average application launches	1.9	launches/day
Users launching once per day	55%	
Users launching twice per day	21%	
Users launching 3-4 times per day	15%	
Users launching more than 4 times per day	9%	
Average time spent on application	2.7	minutes/day
Average topics opened	3.44	topics/day
Average displayed article outlines	4.18	outlines/day
Average articles clicked-through	2.18	articles/day

Table 3: iPhone app usage statistics

The field experiment lasted for two weeks in the Spring of 2012 during which we had 2,016 users interacting with the Newscron app. The user population demographics are shown in Table 2. The application was opened on average 1.9 times per day, accumulating 2.7 minutes of average daily usage. Users select on average 3.44 topics per day, containing around 1.21 articles per topic. Table 3 shows detailed application usage statistics.

The field experiment data set is organized in *topics* (first level, Figure 3a), each topic containing one or several articles (second level, Figure 3b). An article can belong to only one topic throughout the experiment. During the two week period of the experiment, each user opened 12.21 topics on average. Decision time is the elapsed time between the time an article's outline is displayed on a user's display and the time the user either clicks-through to the publisher's page or goes back to the list of topics. On average, users clicked-through 54% of article outlines with an average decision time of 12.41 seconds. Conditional on clicking, the average full article reading time was 82.77 seconds. Table 4 summarizes the data set parameters described here.

Measurement	Value
Total unique users	2,016
Total unique topics	3,420
Total unique articles	4,909
Total articles having an image	3,641
Total topic access events	24,614
Total article click-through events	15,413
Average number of topic access per user	12.21
Average decision time (in seconds)	12.41
Average reading time (in seconds)	82.77

Table 4: iPhone data set parameters

4.2 iPad client and experiments

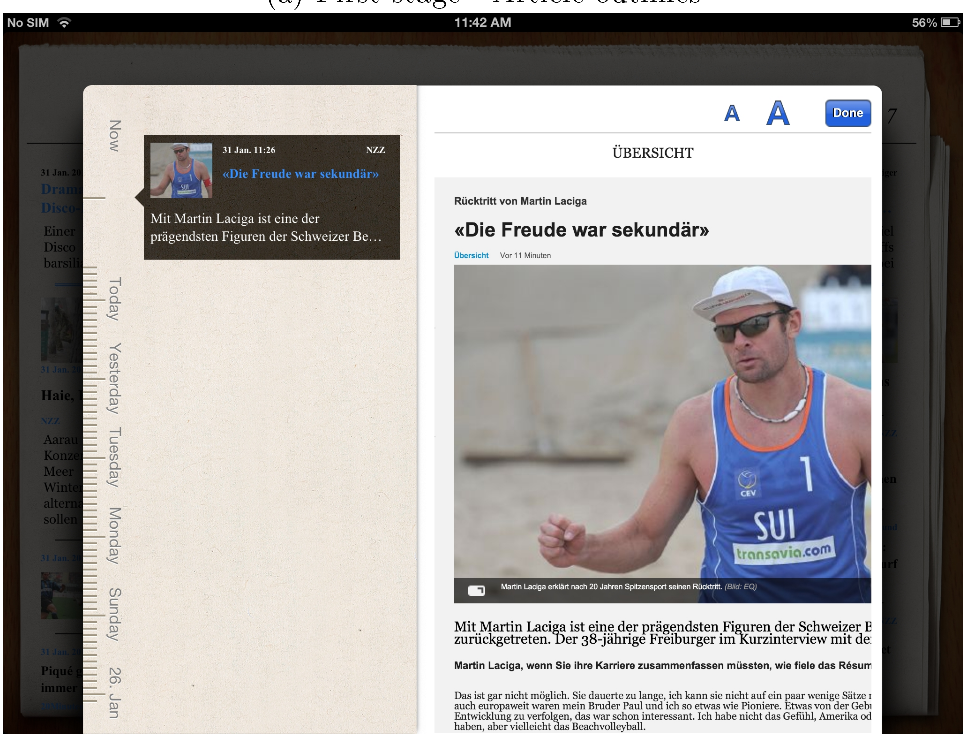
On the iPad, user interaction is designed as a two-stage process (Figure 5) that attempts to mimic the process of reading a traditional newspaper. The app's entry page aims to mimic the front page of a traditional newspaper: the user is presented with the outline (i.e. headline, snippet and photo) of a lead article at the center of the page. To the left of the lead article, a secondary article outline is displayed. Around these two article outlines, the app lists the headlines and images of 6-10 more articles (Figure 5a). Each section is displayed as a separate page, with a structure that is very similar to that of the front page. Upon clicking on one of the articles, a pop up window covers the screen displaying the publisher's website with the full content of the article on the right, and any related articles on the left, on a timeline (see Figure 5b).

To test our hypotheses, we manipulated the lead article's snippet length at the front page as well as at every category page (Figure 5a). During our experiment, the lead article snippet length that was displayed when user i accessed a page of the app was randomized. The snippet length shown to the user was either zero (i.e., no snippet was displayed, only the image and the title of the news) or one of the following lengths (in characters): 98, 147, 196, 245, 294 and 343, as reasoned in the iPhone experiment case. Compared to the iPhone experiment, where the smallest snippet length was 98 characters, the iPad experiment adds the possibility of articles without snippets.

The second manipulation investigates the effect of images on the click-through. The secondary article outline (Figure 5a) is manipulated to randomly display or hide its image. The application then logs whether the article was displaying an image or not and whether it was clicked by the user. On the iPhone version this manipulation was not possible.

The iPad experiment ran for 16 weeks in 2012, during which 1,399 users interacted with

(a) First stage - Article outlines



(b) Second stage - Full article text and timeline of related articles

Figure 5: Newscron iPad user interface and manipulations

Measurement	Value	Units
Average application launches	1.43	launches/day
Users launching once per day	64%	
Users launching twice per day	28%	
Users launching 3-4 times per day	7%	
Users launching more than 4 times per day	<1%	
Average time spent on application	6.63	minutes/session
Average first level category pages visited	8.25	pages/session
Average articles clicked-through	2.87	articles/session

Table 5: iPad app usage statistics

Measurement	Value
Total unique users	1,399
Total unique lead articles	15,920
Total unique secondary articles	13,613
Total topic display events	65,906
Total lead article click-through events	2,783
Total secondary article click-through events	1,109
Average decision time (in seconds)	15.58
Average reading time (in seconds)	65.48

Table 6: iPad data set parameters

the application, generating 65,906 topic display events. A topic display event represents displaying the first level page of a certain news category (see Figure 5a) which gathers data for both a snippet length manipulation (on the lead article) as well as an image display manipulation (on the secondary article). The average user launched the application 1.43 times a day, each time scrolling through 8.25 categories (and thus seeing 8.25 lead and 8.25 secondary articles), on which she clicked only 2.87 times (1.98 times on the lead article and 0.87 times on the secondary article) after spending 15.58 seconds deciding; average reading time for clicked articles was 65.48 seconds. Tables 5 and 6 summarize this information.

4.3 Why we used both clients

Each of the two client apps allows us to investigate complementary aspects of user news reading behavior in the presence of aggregators. The iPhone app is the most mature of the two and has the largest user base. Of the two apps, only the iPhone app allows us to investigate how aggregating snippets of related articles affects user choice.[9] On the other hand, technical limitations on the iPhone app's architecture do not allow us to reduce snippet lengths below 98 characters or to manipulate the presence of images.

The iPad app allows us to reduce snippet length to zero and to manipulate the presence/absence of an image associated with an article headline. It also offers a richer interface that is closer to that of a web browser, and can, therefore be used as a robustness check to make sure that the effects observed on the iPhone app are not due to idiosyncrasies or limitations of mobile interfaces.

Overall, performing similar experiments on two substantially different user interfaces and finding similar results increases our confidence that our findings represent fundamental aspects of online news consumption behavior.

5 Results

5.1 Impact of snippet length on click-through rate

We used logistic regression to analyze how individual click-through rates on the iPhone data set are affected by snippet length and by the presence of photos. To filter out any side effects from other articles on the same topic, we restricted this analysis to topics that contain a single article. We used random effects to account for any systematic differences in the click-through rates of individual users and articles.

The regression results are summarized in Table 7. Our key independent variables (*snippet-nnn*) are dummy variables that are equal to 1 if the article outline that corresponds to an access record was displayed using a snippet of *nnn* characters (*nnn*=98, 147, 196, 245, 294, 343). *Has-image* specifies whether the article outline had an associated image. We include control variables for article language, article category, topic age (time elapsed between the publication of the earliest article on a topic and the timestamp of an access record) and time of day when an article was accessed (*morning*=5-8am, *lunch*=11am-1pm, *afterwork*=3pm-6pm, *afterdinner*=8pm-11pm).

Our key finding is that click-through rates *monotonically decrease* with snippet length, i.e. longer snippets are associated with lower click-through rates. The effect appears to be concave: the difference of adjacent coefficients of variables *snippet-nnn* shrinks as snippet lengths increase. The presence of an accompanying image *further reduces* the click-through

[9] On the iPad app, when a user clicks on an story outline at the top level, even when there are multiple articles associated with the story, the app automatically displays the full text of the topmost (most recent, at the time of access) article.

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	1.030208	0.061986	16.620	< 2e-16	***
snippet-98	(baseline)				
snippet-147	-0.249254	0.052386	-4.758	1.96e-06	***
snippet-196	-0.444536	0.051574	-8.619	< 2e-16	***
snippet-245	-0.578196	0.050783	-11.386	< 2e-16	***
snippet-294	-0.726413	0.050767	-14.309	< 2e-16	***
snippet-343	-0.744078	0.050221	-14.816	< 2e-16	***
has-image	-0.241077	0.037197	-6.481	9.11e-11	***
category-international	(baseline)				
category-local	0.077055	0.040390	1.908	0.056421	
category-business	-0.059181	0.053064	-1.115	0.264730	
category-technology	0.374787	0.055426	6.762	1.36e-11	***
category-entertainment	0.370899	0.050919	7.284	3.24e-13	***
category-sports	0.263547	0.063824	4.129	3.64e-05	***
category-life	0.497000	0.073357	6.775	1.24e-11	***
category-motors	0.028857	0.115271	0.250	0.802325	
category-culture	0.262356	0.077894	3.368	0.000757	***
language-german	(baseline)				
language-french	-0.208344	0.043546	-4.785	1.71e-06	***
language-italian	-0.126199	0.033507	-3.766	0.000166	***
time-other	(baseline)				
time-morning	0.131129	0.043539	3.012	0.002597	**
time-lunch	0.067304	0.046317	1.453	0.146189	
time-afterwork	-0.098537	0.046658	-2.112	0.034696	*
time-afterdinner	0.001074	0.044570	0.024	0.980774	
topic-age	-0.008143	0.003427	-2.376	0.017485	*

--- Significance codes: *** = 0.001, ** = 0.01, * = 0.05
Null deviance: 28529 on 21395 degrees of freedom
Residual deviance: 27973 on 21374 degrees of freedom
AIC: 28017

Table 7: iPhone individual click-through rate regression

rate by an amount that is roughly equivalent to increasing the snippet length by 50-100 characters.

The above results are consistent with Hypothesis 1b. Specifically, it appears that a snippet length of 98 characters is already longer than the threshold snippet length ℓ_1 mentioned in Hypothesis 1b. In that case, any additional information provided to users via longer snippets, or through the inclusion of an image, only serves to satiate the appetite of some users for the full story, resulting in lower population-level click-through rates.[10]

Examining the interaction between snippet length and inclusion of an image suggests that these two effects are independent of each other (Table 8). Specifically, the curves of the interaction term coefficients for different snippet lengths with and without images have very similar shape (Figure 6). The coefficients are uniformly higher when no image is displayed.

Repeating the above analysis on the iPad data set provides the benefit of examining what happens when snippet size goes down to zero. In addition, recall that the iPhone snippet length manipulation takes place at the second level of the user interface (Figure 3b), when users have already expressed an interest for the topic (by clicking through the top level,

[10] An examination of our control variables offers additional insights into online news reading behavior. In the Appendix we comment on these relationships and present some additional analyses.

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.055424	0.055890	0.992	0.321362	
snippet-98:No image	1.044143	0.098396	10.612	< 2e-16	***
snippet-147:No image	0.779328	0.092055	8.466	< 2e-16	***
snippet-196:No image	0.495665	0.089490	5.539	3.05e-08	***
snippet-245:No image	0.455335	0.084926	5.362	8.25e-08	***
snippet-294:No image	0.168800	0.085090	1.984	0.047278	*
snippet-343:No image	0.188969	0.083554	2.262	0.023720	*
snippet-98:Yes image	0.719147	0.055535	12.949	< 2e-16	***
snippet-147:Yes image	0.472253	0.054525	8.661	< 2e-16	***
snippet-196:Yes image	0.297351	0.053536	5.554	2.79e-08	***
snippet-245:Yes image	0.141160	0.052820	2.672	0.007530	**
snippet-294:Yes image	0.027131	0.052746	0.514	0.606995	
snippet-343:Yes image	NA	NA	NA	NA	
category-intl	(baseline)				
category-local	0.076270	0.040404	1.888	0.059066	.
category-business	-0.059878	0.053099	-1.128	0.259459	
category-technology	0.374798	0.055422	6.763	1.35e-11	***
category-entertain	0.369889	0.050922	7.264	3.76e-13	***
category-sports	0.263135	0.063822	4.123	3.74e-05	***
category-life	0.495586	0.073356	6.756	1.42e-11	***
category-motors	0.027456	0.115281	0.238	0.811754	
category-culture	0.262002	0.077931	3.362	0.000774	***
language-german	(baseline)				
language-french	-0.208548	0.043559	-4.788	1.69e-06	***
language-italian	-0.125852	0.033514	-3.755	0.000173	***
time-other	(baseline)				
time-morning	0.131889	0.043545	3.029	0.002456	**
time-lunch	0.066761	0.046324	1.441	0.149535	
time-afterwork	-0.098123	0.046667	-2.103	0.035497	*
time-afterdinner	0.001554	0.044582	0.035	0.972189	
topicage	-0.008188	0.003426	-2.390	0.016838	*

```
--- Significance codes:  *** = 0.001, ** = 0.01,  * = 0.05
Null deviance: 28529  on 21395  degrees of freedom
Residual deviance: 27969  on 21369  degrees of freedom
AIC: 28023
```

Table 8: Snippet length and image interaction analysis: regression results.

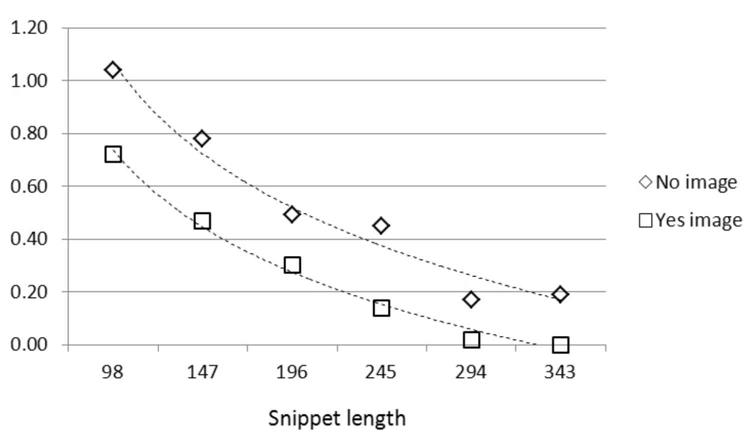


Figure 6: Snippet length and image interaction analysis: coefficient plot.

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-3.4029375	0.0774879	-43.916	< 2e-16	***
snippet-0	(baseline)				
snippet-98	-0.0405066	0.0698282	-0.580	0.561854	
snippet-147	-0.0716769	0.0700058	-1.024	0.305896	
snippet-196	-0.1309776	0.0712253	-1.839	0.065927	
snippet-245	-0.1713780	0.0725527	-2.362	0.018171	*
snippet-294	-0.2193421	0.0729460	-3.007	0.002639	**
snippet-343	-0.2551973	0.0732455	-3.484	0.000494	***
category-intl	(baseline)				
category-local	0.7576408	0.0596889	12.693	< 2e-16	***
category-business	0.3392168	0.0811333	4.181	2.90e-05	***
category-technology	0.6164478	0.0722908	8.527	< 2e-16	***
category-entertain	0.8242345	0.0705485	11.683	< 2e-16	***
category-sports	0.4552858	0.0797088	5.712	1.12e-08	***
category-life	0.6261332	0.0788313	7.943	1.98e-15	***
category-motors	0.2027030	0.0985593	2.057	0.039719	*
category-culture	-0.2057773	0.0986723	-2.085	0.037027	*
language-german	(baseline)				
language-french	0.0247296	0.0544382	0.454	0.649636	
language-italian	0.1168826	0.0446224	2.619	0.008809	**
time-other	(baseline)				
time-morning	0.1598024	0.0591375	2.702	0.006888	**
time-lunch	-0.0004208	0.0663752	-0.006	0.994942	
time-afterwork	-0.2309352	0.0659358	-3.502	0.000461	***
time-afterdinner	-0.1219484	0.0595255	-2.049	0.040494	*

--- Significance codes: *** = 0.001, ** = 0.01, * = 0.05
Null deviance: 22959 on 65509 degrees of freedom
Residual deviance: 22600 on 65489 degrees of freedom
AIC: 22642

Table 9: iPad lead article click-through rate regression (snippet length manipulation)

Figure 3a). In contrast, the iPad snippet length manipulation takes place at the lead article. at the top level of the interface (Figure 5a), at which point users have seen nothing else about the article. The iPad experiment, therefore, corresponds a bit closer to the theoretical setting of Section 3.1.

Table 9 shows the results of performing logistic regression on the click-through rates of the iPad lead articles. The key finding of the iPad experiment is that, compared to the baseline case where an article headline but no snippet is displayed, increasing snippet length has no statistically significant effect on click-through rates until snippet lengths reach 196 characters, from which point on the effect is decreasing. This result is consistent with what we found from the iPhone experiment, even though the sensitivity of click-through rates on snippet lengths is lower on the iPad.

One concern of the iPhone experiment is that the result regarding the presence of an image could be biased, as an image is displayed only when it is available (in other words, it is not randomized). In the iPad experiment, we randomized the presence of an image at the secondary article that was displayed to the left of the lead article in each section (Figure 5a). Table 10 shows the results of performing logistic regression on the click-through rates of the iPad secondary articles. The results confirm the finding that the presence of an image

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-4.32016	0.13929	-31.016	< 2e-16	***
has-image	-0.39339	0.06435	6.113	9.75e-10	***
category-intl	(baseline)				
category-local	0.78051	0.12664	6.163	7.12e-10	***
category-business	0.55620	0.14848	3.746	0.000180	***
category-technology	0.64842	0.13663	4.746	2.08e-06	***
category-entertain	0.75546	0.13738	5.499	3.82e-08	***
category-sports	0.52206	0.14365	3.634	0.000279	***
category-life	0.60388	0.14732	4.099	4.15e-05	***
category-motors	0.13692	0.18245	0.750	0.452981	
category-culture	0.12542	0.16031	0.782	0.434009	
language-german	(baseline)				
language-french	-0.07784	0.08300	-0.938	0.348316	
language-italian	0.03388	0.07225	0.469	0.639122	
time-other	(baseline)				
time-morning	0.01511	0.09388	0.161	0.872100	
time-lunch	-0.08523	0.10392	-0.820	0.412102	
time-afterwork	-0.24351	0.10143	-2.401	0.016361	*
time-afterdinner	-0.08983	0.09037	-0.994	0.320236	

--- Significance codes: *** = 0.001, ** = 0.01, * = 0.05
Null deviance: 10315 on 43249 degrees of freedom
Residual deviance: 10190 on 43233 degrees of freedom
AIC: 10224

Table 10: iPad secondary article click-through rate regression (image manipulation)

reduces the probability that users will click on the article. Thus the presence of image has the same effect with the increase in snippet length.

If we relate the above results to the theoretical model of Section 3.1 together they suggest that an article's headline provides all the information users need to decide if the article is close enough to their interests. Any additional information provided by aggregators, in the form of snippets or images, apparently satiates the appetite of some readers and can only serve to decrease click-through rates.

5.2 Impact of the presence of multiple snippets on group click-through rate

An important function of aggregators is to group together related articles on the same topic. Since the aggregator displays a snippet for each article, it is important to know how the presence of multiple articles affects the probability that any article in the group is clicked on. To answer this question we collapsed each topic (story) access session into a single record and performed logistic regression. Our key independent variables (*related-articles*, *related-articles^2*) capture the first and second powers respectively of the number of related articles displayed during each topic access. Our dependent variable records whether *at least one* article within that topic was clicked by the user during that session.

In real life, news stories evolve and publishers report updates on important stories, usually on a daily basis. This means that the same topic can grow in the number of associated articles

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-0.562992	0.093168	-6.043	1.52e-09	***
related-articles	0.789094	0.058075	13.588	< 2e-16	***
related-articles^2	-0.088047	0.008527	-10.326	< 2e-16	***
topicage	-0.054185	0.009658	-5.610	2.02e-08	***
category-intl	(baseline)				
category-local	0.087998	0.058496	1.504	0.132494	
category-business	0.045385	0.069022	0.658	0.510828	
category-technology	0.366267	0.089880	4.075	4.60e-05	***
category-entertain	0.417372	0.087755	4.756	1.97e-06	***
category-sports	0.304854	0.082667	3.688	0.000226	***
category-life	0.496969	0.188897	2.631	0.008516	**
category-culture	0.366240	0.144492	2.535	0.011255	*
time-other	(baseline)				
time-morning	0.193964	0.066802	2.904	0.003689	**
time-lunch	0.054098	0.069278	0.781	0.434877	
time-afterwork	-0.034349	0.069624	-0.493	0.621763	
time-afterdinner	-0.057925	0.066991	-0.865	0.387217	
language-german	(baseline)				
language-french	-0.204459	0.064962	-3.147	0.001647	**
language-italian	-0.058165	0.052597	-1.106	0.268790	

--- Significance codes: *** = 0.001, ** = 0.01, * = 0.05
Null deviance: 12758 on 9503 degrees of freedom
Residual deviance: 12427 on 9487 degrees of freedom
AIC: 12461

Table 11: iPhone group click-through rate regression

over time. Our data set contains several examples where a user has opened a topic to find that it contains 1 article, while another user has opened the same topic a short while later to find that it contains 2 or more articles. Our data set, therefore, naturally contains variation in the number of articles contained within the same topic. Of course, topics with many articles also tend to be older and topic age, as opposed to number of articles, might be the true driver of click-through patterns. We control for this possibility by including a variable (*topic-age*) that captures the time between the publication of the first article on the topic and the time of the current user access. As before, we used random effects to account for systematic differences across topics and users. The results are shown in Table 11.

Our principal finding is that the number of related articles has an inverse U-shaped relationship with the group click through rate. Click-through rates attained their maximum value when a topic had around 4 related articles. Hypotheses 2a and 2b are therefore supported. We discuss this finding further in Section 6.

5.3 Impact of snippet length on whether an article is chosen

Besides knowing how the presence of multiple articles affects the probability that at least one article in the group is clicked on, it is equally important to find out what factors determine *which* article is chosen. To answer this question, we performed discrete choice analysis. Specifically, we looked at article topic groups containing 2 or more article outlines and where

```
                   Estimate Std. Error  t-value  Pr(>|t|)
snippet-shorter     (baseline)
snippet-average    -0.18513    0.48055  -0.3852   0.70005
snippet-longer      0.26561    0.11250   2.3609   0.01823 *
position-top        (baseline)
position-second    -2.07819    0.11189 -18.5743 < 2.2e-16 ***
position-low       -2.02229    0.17956 -11.2626 < 2.2e-16 ***
has-image           2.07634    0.25813   8.0437 8.882e-16 ***
--- Significance codes:  *** = 0.001, ** = 0.01,  * = 0.05

Log-Likelihood: -320.3
```

Table 12: iPhone multinomial logit regression.

one or more linked articles were clicked. We used a multinomial logit regression model to identify which covariates of each choice alternative had a statistically significant association with the probability that the alternative in question would be clicked on by the user. For this analysis, we replaced absolute snippet lengths with dummy variables that indicated whether an article's snippet was longer than (*snippet-longer*), equal to (*snippet-average*) or shorter than (*snipper-shorter*) the group's average snippet length. We also added control variables that indicated an article's position in the group (*position-top*, *position-second*, *position-low*, the latter variable indicating third or lower position).

The regression results are shown in Table 12. As expected, an article's position has a very important effect on it being chosen, with the topmost article being chosen most often. Interestingly, an article's snippet length relative to the group's average snippet length was also found to be a significant predictor. The baseline case corresponds to the case where the snippet length is shorter than average. Compared to the baseline case, we notice that having longer than average snippets has a small but statistically significant positive effect on the choice probability. Moreover, the presence of an image increases an article's within-group choice probability. The effect of having an image is strong and comparable to moving from second to first position on the list of related articles. This finding is interesting and should be contrasted with the fact (see Section 5.1) that the presence of an image is associated with a decrease in an article's absolute click-through rate when there are no related articles. Overall, the above findings provide support for Hypothesis 3.

6 Discussion and Implications

News aggregators have emerged as an important component of the digital content ecosystem. A better understanding of how their design parameters affect the allocation of reader attention is useful, both in terms of informing aggregator design, as well as in terms of informing the current controversy that exists between aggregators and content producers. In

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	1.8386894	0.0075861	242.377	< 2e-16	***
snippet-98	(baseline)				
snippet-147	0.1526484	0.0062659	24.362	< 2e-16	***
snippet-196	0.2426397	0.0061228	39.629	< 2e-16	***
snippet-245	0.3386749	0.0059745	56.687	< 2e-16	***
snippet-294	0.4337354	0.0058979	73.541	< 2e-16	***
snippet-343	0.4815978	0.0057670	83.509	< 2e-16	***
has-image	0.2112578	0.0043892	48.131	< 2e-16	***
no-clicks	0.1538788	0.0033701	45.659	< 2e-16	***
category-intl	(baseline)				
category-local	-0.0398357	0.0044209	-9.011	< 2e-16	***
category-business	-0.1507134	0.0056415	-26.715	< 2e-16	***
category-technology	-0.0851998	0.0063192	-13.483	< 2e-16	***
category-entertain	-0.0806296	0.0060836	-13.254	< 2e-16	***
category-sports	-0.1704977	0.0066929	-25.474	< 2e-16	***
category-life	-0.1447068	0.0093500	-15.477	< 2e-16	***
category-motors	-0.2186243	0.0177057	-12.348	< 2e-16	***
category-life	-0.0746151	0.0096425	-7.738	1.01e-14	***
language-german	(baseline)				
language-french	0.0035077	0.0047479	0.739	0.4600	
language-italian	0.0068764	0.0038222	1.799	0.0720	
time-other	(baseline)				
time-morning	0.0341617	0.0049091	6.959	3.43e-12	***
time-lunch	-0.0255825	0.0052240	-4.897	9.73e-07	***
time-afterwork	0.0068274	0.0052735	1.295	0.1954	
time-afterdinner	0.0213642	0.0049762	4.293	1.76e-05	***
topic-age	0.0011026	0.0004426	2.491	0.0127	*

Significance codes: *** = 0.001, ** = 0.01, * = 0.05
Null deviance: 149938 on 21395 degrees of freedom
Residual deviance: 129988 on 21373 degrees of freedom
AIC: 214935

Table 13: iPhone decision time regression.

this study, we conducted field experiments with that objective in mind.

Our first set of results (Section 5.1) show that there is a negative relationship between an article's snippet length at the aggregator and the probability that a user will click on the link and visit the original article site. That is, the longer the snippet, the lower the click-through rate. We obtained additional perspective on these results by conducting a post-hoc analysis on the amount of time users spend at the aggregator, browsing article outlines related to a single topic. The dependent variable of this additional analysis (decision time) is the amount of time elapsing between the initial display of a topic group (group of related article outlines, Figure 3b) and a user's decision to either click an article of that group or to move back to the top level interface (Figure 3a) of the aggregator. We performed Poisson regression, since our dependent variable is a time-to-event quantity and we did not find evidence of overdispersion (decision time mean=12.41 seconds, variance=13.02 seconds).

The regression results (Table 13) are almost a mirror image of the results of Table 7: we find that people spend *more* time on the aggregator when snippets are longer, when there are images, and when they do not click on the article link (*no-clicks*=1). This analysis, together with the analyses of Section 5.1 on click-through rates, provide evidence for the substitution effect of news aggregators on the content ecosystem. Interestingly, the presence of an image on an article outline has the same substitution effect to that of increasing the snippet length: it is associated with a decrease in click-through rate and an increase in the time spent at the aggregator.

Based on the above results, content producers have a point in terms of challenging the currently prevailing view that the reproduction of headlines and article snippets by aggregators falls under the "fair use" provisions of U.S. copyright laws (Copyright Act of 1976, 17 U.S.C. § 107).[11] Specifically, one of the factors for fair use set forth by current law is "the effect of the use upon the potential market for or value of the copyrighted work." Our study shows that such an effect, indeed, exists. Furthermore, this effect is very sensitive to the amount of information that is reproduced by aggregators – practically every character makes a difference to click-through rates.

Aggregators typically group together articles that refer to the same story, thus increasing competition among related articles. In this study, we also examined how the aggregation of articles into topic groups affects the allocation of readers' attention. We found an inverse U-shaped relationship between the number of articles in a topic group and the probability that readers will click on at least one article from that group. This is a previously unnoticed side effect of news aggregators that deserves more attention.

One tentative explanation for this finding (see Section 3.2) is that, the more articles are available on a topic, the more likely it is that a user will find at least one of them appealing. However, when there are many related articles, we speculate that the combined information contained in their snippets might satisfy the readers' curiosity who then may not feel the need to click on any of the linked articles. We proceeded to test this hypothesis by quantifying the degree of content complementarity of snippets belonging to every one of the topics that were displayed to users during our two-week iPhone experiment. We employed two student coders for snippets in German, Italian, and French language respectively (six coders in total). Coders were tasked with characterizing each snippet belonging to a topic as being either a *replica* (containing identical or essentially the same information), an *alternative* (containing complementary information about the same event), or an *update* (containing new developments in the story) relative to the information contained in the snippet that was displayed immediately before it. The average inter-coder reliability was 76%.

We consider the number of alternatives and updates contained in a topic group as proxies of the degree to which the snippets of the group collectively reveal more information about the story, relative to any single snippet. A correlation check attests that these variables contain distinct information, not captured by other variables in our regression (Cor(*related-articles*,

[11] See http://en.wikipedia.org/wiki/Fair_use

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-0.417185	0.094955	-4.393	1.12e-05	***
related-articles	0.611610	0.062762	9.745	< 2e-16	***
related-articles^2	0.069399	0.008560	-8.108	5.17e-16	***
topic-age	-0.053540	0.009786	-5.471	4.47e-08	***
alternatives	0.365729	0.079032	4.628	3.70e-06	***
updates	0.248030	0.060859	4.075	4.59e-05	***
category-intl	(baseline)				
category-local	0.086275	0.058656	1.471	0.141323	
category-business	0.052379	0.069094	0.758	0.448397	
category-technology	0.386705	0.089971	4.298	1.72e-05	***
category-entertain	0.435848	0.087867	4.960	7.04e-07	***
category-sports	0.312408	0.082842	3.771	0.000163	***
category-life	0.521353	0.188912	2.760	0.005784	**
category-culture	0.334574	0.145478	2.300	0.021458	*
language-german	(baseline)				
language-french	-0.210655	0.066026	-3.190	0.001420	**
language-italian	-0.062373	0.052825	-1.181	0.237703	
time-other	(baseline)				
time-morning	0.192996	0.066931	2.884	0.003933	**
time-lunch	0.053053	0.069401	0.764	0.444607	
time-afterwork	-0.038461	0.069764	-0.551	0.581433	
time-afterdinner	-0.060044	0.067122	-0.895	0.371027	

--- Significance codes: *** = 0.001, ** = 0.01, * = 0.05
Null deviance: 12758 on 9503 degrees of freedom
Residual deviance: 12388 on 9485 degrees of freedom
AIC: 12426

Table 14: iPhone group click-through rate regression with content analysis variables.

alternatives)=0.01, Cor(*related-articles*, *updates*)=0.18, Cor(*alternatives*, *updates*)=0.10). We added the number of alternatives and updates of each topic as additional independent variables and repeated the regression of Table 11. We found a significant positive relationship between the number of updates and alternatives on the group click-through rates (see Table 14). However when we split the analysis between topics with 4 or less articles and topics with more than 4 articles, we found that the number of alternatives and updates was not significant on group click-through rate when there are 4 or more articles in a topic.

The findings of this additional analysis go *against* our speculative hypothesis of complementary snippet information being responsible for the reduction in group click-through rates when groups have more than 4 articles. Support for that hypothesis would have required a *negative* effect of alternatives and updates on click-through rates. Instead we found a *positive* effect that loses significance when there are more than 4 articles per group. We must, therefore, conclude that the reason for the drop in group click-through rates past 4 articles is due to other factors, such as cognitive overload. Aggregator designers must take this effect into consideration when designing their interfaces.

With respect to the competition among related articles, we examined what factors determine which article(s) in a topic group are more likely to be chosen by readers. As expected, articles positioned at the top of the list were chosen most often. Controlling for position, articles with an image and articles whose snippet length was longer than the average snippet length of related articles were more likely to be chosen. These findings are consistent with our theoretical predictions (Section 3.3) but stand in contrast to the findings for individual click-through rates, where longer snippets and presence of an image correlate with lower rates. Taken together, they reinforce the difficult position in which content producers are placed by aggregators – on one hand, our findings on individual click-through rates suggest that content producers might want to place limits on the amount of article text/graphics that an aggregator is allowed to reproduce. On the other hand, our findings on competition click-through rates show that, doing so unilaterally may place a publisher's content at a disadvantage vis-à-vis the content of competing publishers who choose to not impose such limits. This argument is consistent with the theoretical predictions of Dellarocas et al. (2013) regarding the prisoner's dilemma situation that competing content producers are facing in their negotiations with aggregators. The above discussion suggests the need for industry-wide (as opposed to one-on-one) negotiations between content producers and news aggregators with respect to the terms of their relationship.

7 Concluding Remarks

As with any study, the findings of this paper should be viewed with regard to the study limitations. Although this work offers novel insight into the relationship between news aggregators and content producers, its objective is not to provide answers to the question of whether aggregators are, on balance, beneficial or harmful to content ecosystems. What the current work establishes is that aggregators extract an "attention tax" from content producers, in the form of users who never click through to the original articles. We demonstrate that the fraction of such users depends on the design parameters of the aggregator and that there is a substitution relationship between the amount of information that aggregators offer about articles and the probability that readers will opt to read the full articles at the content producer sites. We further show that competitive pressure might limit the extent to which individual content producers might find it beneficial to deviate from an aggregator's norms: our multinomial logit results suggest that a publisher's unilateral decision to shorten the snippet lengths of its articles and/or disallow the reproduction of images might put them at disadvantage in situations where there are several related articles on the same topics.

What is outside the scope of the current research is the impact that aggregators have on increasing the overall consumption of content (e.g. because they reduce search costs by organizing content). Despite notable recent attempts to provide answers to the latter question (Athey and Mobius 2012; Chiou and Tucker 2011), a balanced examination of the cumulative impact of aggregators, that takes into consideration both the search cost reduction and the attention tax effects, still remains an elusive and interesting empirical question for future research.

From a methodological perspective, this work highlights the feasibility of conducting field experiments using apps developed in research labs and then released to the public. Our results suggest that experiments with even a few thousands of users can expose many of the effects that are also present in much larger scale applications. There is, thus, an interesting methodological discussion to be had on the merits of working with larger, but less flexible, secondary data sets obtained from third-parties vs. with primary data sets obtained from smaller scale apps developed for the purpose of conducting experimental studies.

References

Agarwal, D., B-C. Chen, P. Elango. 2009. Spatio-temporal models for estimating click-through rate. *Proc. of the 18th Int. Conf. on World Wide Web (WWW'09)*, Madrid, Spain, 21-30.

Athey, S., M. Mobius. 2012. The impact of news aggregators on internet news consumption: The case of localization. Working Paper, Microsoft Research.

Chiou, L., C. Tucker. 2011. Copyright, digitization, and aggregation. NET Institute Working Paper No. 11-18. Available at SSRN: http://ssrn.com/abstract=1864203 or doi:10.2139/ssrn.1864203

Dellarocas, C., Z. Katona, W. Rand. 2013. Media, aggregators and the link economy: Strategic hyperlink formation in content networks. *Management Sci.* forthcoming.

Dewan, R. M., M. L. Freimer, A. Seidmann, J. Zhang. 2004. Web portals: Evidence and analysis of media concentration. *J. Management Info. Sys.* **21**(2) 181-199.

Ghose, A., S. Yang. 2009. An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Sci.* **55**(10) 1605-1622.

Hong, S. 2011. A simple model of news aggregators, information cascades, and online traffic. Working Paper. Available at SSRN: http://ssrn.com/abstract=1927035

Isbell, K. 2010. The rise of the news aggregator: Legal implications and best practices. Research Publication No. 2010-10, Berkman Center.

Jarvis, J. 2008. The link economy vs. the content economy. Buzzmachine blog, June 18, 2008. (http://www.buzzmachine.com)

Karp, S. 2007. The web's link-driven attention economy. Publishing 2.0, December 15, 2007. (http://publishing2.com/)

Roos, J., C. F. Mela, R. Shachar. 2011. Hyper-media search and consumption. Working Paper, Duke University.

Wu, F., B. Huberman. 2008. Popularity, novelty and attention. *Proc. of the 9th ACM Conf. on Electronic Commerce (EC'08)*, Chicago, USA, 240-245.

Proof of Lemma 1

Substituting $\Phi(x) = \frac{1}{2}\left[1 + \text{erf}\left(\frac{x}{\sqrt{2}}\right)\right]$, where $\text{erf}(\cdot)$ is the error function, we obtain

$$\kappa(t) = \frac{1}{4D}\int_{-D}^{D}\left[\text{erf}\left([A(t)-y]\frac{\sqrt{t}}{\sqrt{2}}\right) - \text{erf}\left([-A(t)-y]\frac{\sqrt{t}}{\sqrt{2}}\right)\right]dy$$

Integration and differentiation with respect to t gives:

$$\begin{aligned}\kappa'(t) = {} & \tfrac{1}{2D}A'(t)\left[\text{erf}([D-A(t)]\tfrac{\sqrt{t}}{\sqrt{2}}) + \text{erf}([D+A(t)]\tfrac{\sqrt{t}}{\sqrt{2}})\right] \\ & + \tfrac{\sqrt{2}}{4Dt^{\frac{3}{2}}\sqrt{\pi}}\left[e^{-\frac{1}{2}t(D-A(t))^2} - e^{-\frac{1}{2}t(D+A(t))^2}\right]\end{aligned}$$

The above expression is the sum of two terms. These terms capture the two effects of changing signal precision in our model. First, as signal precision grows, the size of the interval $(-A(t), A(t))$ of signals that induce click-throughs changes as well (grows or shrinks). The first term captures the change in click-through rates because of the change in the size of that interval (a broader interval results in higher rates, a narrower interval to lower). Second, as precision grows, signals become more concentrated around their mean. Given an interval $(-A(t), A(t))$, if a signal's true mean falls inside the interval, the probability that the signal will also fall inside the interval grows. Conversely, if a signal's true mean falls outside the interval, the probability that the signal will fall inside the interval shrinks. The second term captures the net result of the second effect.

Because $D > A(t) \geq 0$, the argument of both error functions in the above expression is positive. Since it is $\text{erf}(x) > 0$ for all $x > 0$, this implies that the functions always have a positive value. Hence, the term inside the first pair of square brackets is positive. Furthermore, it is always $D - A(t) < D + A(t)$, which implies that the difference of negative exponential terms inside the second pair of square brackets is also positive. Overall, if $A'(t) \geq 0$ then it is also $\kappa'(t) \geq 0$, whereas, if $A'(t) < 0$, the first term of the above expression is negative and the second is positive (but very small, especially as t grows), so for $A'(t)$ sufficiently negative, $\kappa'(t)$ also becomes negative.

Proof of Lemma 2

If $U - d_0 - c < 0$ then $A(t) = d_0 - \alpha(t)\beta(t)$, where

$$\alpha(t) = \frac{1}{f(t)}, \alpha(0) = \infty,\ \alpha(\infty) = 1, \alpha'(t) \leq 0$$

$$\beta(t) = |U - d_0 - c| + \frac{g(t)}{1 - g(t)}c, \beta(0) = |U - d_0 - c|,\ \beta(\infty) = \infty, \beta'(t) \geq 0$$

It is, therefore, $A(0) = -\infty$, $A(\infty) = -\infty$ and $A(t)$ finite for all finite t. By continuity this implies that there is a region $t \in [0, t_0]$ where $A(t)$ monotonically grows and a region $t \in [t_1, \infty)$ where $A(t)$ declines towards $-\infty$. Furthermore, it is $\lim_{t\to\infty} \beta'(t) = \lim_{t\to\infty} \frac{g'(t)}{(1-g(t))^2}c = \infty$, which also implies $\lim_{t\to\infty} A'(t) = -\infty$.

If $U - d_0 - c > 0$ then $A(t) = d_0 + \alpha(t)\beta(t)$, where

$$\alpha(t) = \frac{1}{f(t)}, \alpha(0) = \infty,\ \alpha(\infty) = 1, \alpha'(t) \leq 0$$

$$\beta(t) = |U - d_0 - c| - \frac{g(t)}{1 - g(t)}c, \beta(0) = |U - d_0 - c|,\ \beta(\infty) = -\infty, \beta'(t) \leq 0$$

Therefore, $A(t)$ is the sum of a constant term plus the product of two monotonically declining functions. So it is $A'(t) \leq 0$ for all t. Furthermore, it is $\lim_{t\to\infty} \beta'(t) = \lim_{t\to\infty} -\frac{g'(t)}{(1-g(t))^2}c = -\infty$, which also implies $\lim_{t\to\infty} A'(t) = -\infty$.

Appendix: Additional Insights into Online News Reading Behavior

An examination of the control variables in Table 7 provides additional insight into online news reading behavior. These findings are not directly related to our main research questions but interesting enough to merit a brief discussion in this appendix. We observe the following:

1. Average click-through rates for technology, entertainment, sports, life and culture news are higher than those for local, international, business and motor news. Our explanation for this finding is that the former group consists of stories that people tend to personally identify and engage more with. Readers are, then, more likely to seek additional information (beyond what is listed in the article outline) for such stories. On the other hand, local, international and business news tend to be more “impersonal” - most people are interested in knowing that an event happened nationally or internationally but not in finding out more details about it.

2. Click-through rates generally decline as news topics get older. This is an intuitive finding and a useful control for some of our later analyses, but see some interesting nuances below.

3. Average click-through rates are higher during the morning commute hours and lower during the end of the work day/evening commute hours, relative to other times of the day. It appears that the majority of our users are most focused on reading the news during their morning commute and least engaged with news near the end of their work day.

4. Average click-through rates were lower for French and Italian-speaking users, relative to German-speaking users. We do not have an explanation for this finding - it might be due to idiosyncrasies of our user population or to some cultural factor yet to be identified. We note it here as an interesting opportunity for future research.

We obtained deeper insight into some of these findings by adding appropriate interaction terms. The inclusion of interaction terms allows us to examine how the click-through rates of different news categories are impacted differently by (a) the length of the snippet, (b) the presence of an image and (c) the age of the news topic. For this analysis, we replaced the six dummy variables *snippet-nnn* that were used in all other regressions with a single numerical variable *snippet-length* that contains the length of the snippet in characters.

The regression results are shown in Table 15. Our key insights are the following:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	1.4764287	0.0628378	23.496	< 2e-16	***
snippet-length	-0.0033217	0.0002509	-13.239	< 2e-16	***
has-image	-0.3237663	0.0583047	-5.553	2.81e-08	***
language-french	-0.1975523	0.0439954	-4.490	7.11e-06	***
language-italian	-0.1180109	0.0344644	-3.424	0.000617	***
time-morning	0.1373963	0.0437872	3.138	0.001702	**
time-lunch	0.0607560	0.0465908	1.304	0.192221	
time-afterwork	-0.1161362	0.0468908	-2.477	0.013259	*
time-afterdinner	0.0041697	0.0448021	0.093	0.925849	
snippet-length:local	-0.0002898	0.0002981	-0.972	0.331091	
snippet-length:business	-0.0001976	0.0003680	-0.537	0.591283	
snippet-length:technology	0.0008371	0.0004574	1.830	0.067212	
snippet-length:entertain	0.0004240	0.0004353	0.974	0.330028	
snippet-length:sports	0.0013651	0.0005158	2.646	0.008140	**
snippet-length:life	0.0010619	0.0006925	1.534	0.125146	
snippet-length:motors	0.0015413	0.0010069	1.531	0.125824	
snippet-length:culture	0.0008449	0.0005879	1.437	0.150696	
has-image:local	0.1798261	0.0819824	2.193	0.028273	*
has-image:business	0.0954138	0.1025981	0.930	0.352383	
has-image:technology	0.0372704	0.1202121	0.310	0.756532	
has-image:entertain	0.2626888	0.1151244	2.282	0.022502	*
has-image:sports	0.0155368	0.1382637	0.112	0.910529	
has-image:life	0.0751486	0.1757078	0.428	0.668876	
has-image:motors	-0.6007551	0.2586951	-2.322	0.020219	*
has-image:culture	-0.2257698	0.1553179	-1.454	0.146058	
topic-age:intl	-0.1118874	0.0149521	-7.483	7.26e-14	***
topic-age:local	-0.2282627	0.0320993	-7.111	1.15e-12	***
topic-age:business	-0.2454063	0.0349461	-7.022	2.18e-12	***
topic-age:technology	0.0050178	0.0039793	1.261	0.207319	
topic-age:entertain	-0.0679701	0.0312803	-2.173	0.029785	*
topic-age:sports	-0.2207185	0.0457769	-4.822	1.42e-06	***
topic-age:life	0.0553013	0.0347850	1.590	0.111879	
topic-age:motors	0.0096235	0.0269463	0.357	0.720989	
topic-age:culture	0.0582648	0.0347938	1.675	0.094018	

--- Significance codes: *** = 0.001, ** = 0.01, * = 0.05
Null deviance: 28529 on 21395 degrees of freedom
Residual deviance: 27777 on 21362 degrees of freedom
AIC: 27845

Table 15: Understanding the impact of snippet length, images and topic age on different news categories.

1. Snippet lengths have a negative impact on the click-through rates of all news categories (the coefficient of *snippet-length* is negative and of substantially higher magnitude than any of the positive coefficients of interaction terms *snippet-length:{category}*). Interestingly, however, the click-through rates of sports news appear to be less severely affected by increases in snippet length, relative to other types of news.

2. Displaying an image has a negative impact on the click-through rates of all news categories (the coefficient of *has-image* is negative and of substantially higher magnitude than any of the positive coefficients of interaction terms *has-image:{category}*). This impact is more severe than average for motor news (where, usually, the image pretty much tells the whole story) and less severe than average for entertainment news (where an image often engages people to find out more about the story) and for local news.

3. Topic age has a different impact on different news categories. The impact is negative and more severe for local, business and sports news, negative and less severe for international and entertainment news. Topic age has no statistically significant impact on technology, life, motors and culture news. The latter group of news tends to be less time sensitive and of more lasting interest.