Content Growth and Attention Contagion in Information Networks: Addressing Information Poverty on Wikipedia

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Abstract

Open collaboration platforms have fundamentally changed the way knowledge is produced, disseminated and consumed. In these systems, contributions arise organically with little to no central governance. While such decentralization provides many benefits, a lack of broad oversight and coordination can leave questions of information poverty and skewness to the mercy of the system's natural dynamics. Unfortunately, we still lack a basic understanding of the dynamics at play in these systems, and specifically, how contribution and attention interact and propagate through information networks. We leverage a large-scale natural experiment to study how exogenous content contributions to Wikipedia articles affect the attention they attract and how that attention spills over to other articles in the network. Results reveal that exogenously added content leads to significant, substantial and long-term increases in both content consumption and subsequent contributions. Furthermore, we find significant attention spillover to downstream hyperlinked articles. Through both analytical estimation and empirically-informed simulation, we evaluate policies to harness this attention contagion to address the problem of information poverty and skewness. We find that harnessing attention contagion can lead to as much as a twofold increase in the total attention flow to clusters of disadvantaged articles. Our findings have important policy implications for open collaboration platforms and information networks.

Keywords: user-generated content, open collaboration platforms, information consumption, attention contagion, spillover effect

1. Introduction

Wikipedia is one of the most successful examples of open collaboration platforms, serving millions of information seekers daily. It is both a repository of free knowledge and the most-visited educational resource on the planet[1]. By the end of 2017, a mere sixteen years since its inception, the English language Wikipedia alone contained over 5.5 million articles and a total of over 3.1 billion words, over 60 times as many as the next largest English-language encyclopedia, *Encyclopædia Britannica*[2]. It consists of millions of articles written by a global network of volunteers and is accessible to anyone with an internet connection. Wikipedia represents a new generation of internet-based collaborative tools that strives to be open, accessible, and egalitarian.

However, Wikipedia's reliance on open and distributed collaboration as well as community governance is not without its problems. As noted by Wikipedia itself, volunteers don't always contribute to the content that people need the most[3]. A large proportion of articles are incomplete or insufficiently supported with references[4]. Because of Wikipedia's open and distributed production model, it is difficult to direct contributors' attention to articles that most need improvement. Hence, not only are these articles incomplete, but they are likely to remain so. As a consequence, the coverage and depth of knowledge in Wikipedia articles is uneven. While well-developed articles are considerably longer than their analogues in *Encyclopædia Britannica*, many articles are still of poor quality and are on average half as long as their professionally edited analogues[5]. Importantly, coverage also appears to be uneven across both geographical areas and knowledge domains (Graham et al. 2014, Halavais and Lackaff 2008, Kittur et al. 2009). For example, Wikipedia has strong coverage of military history and political events in America, but articles on biology, law, medicine, and information on developing countries are often absent or underdeveloped[6].

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[1] It is the 5th most visited website in the world, according to Alexa.
[2] https://en.wikipedia.org/wiki/Wikipedia:Size_of_Wikipedia
[3] https://wikiedu.org/changing/wikipedia/
[4] http://time.com/4180414/wikipedia-15th-anniversary/
[5] https://en.wikipedia.org/wiki/Wikipedia:Size_comparisons
[6] https://en.wikipedia.org/wiki/Criticism_of_Wikipedia

Left unchecked, the societal implications of uneven coverage are deeply troubling. Despite the openness of Wikipedia, there are growing concerns that geographical areas and knowledge domains that are left out or underrepresented will remain so or become even further underrepresented relative to the growing knowledge base in a kind of poor-get-poorer phenomenon. Geographical informational skews can act to further limit our understandings of, attention to, and interactions with impoverished areas in terms of regional economic, social, political, and cultural concerns (Forman et al. 2012, Graham et al. 2014, Norris 2001, Yu 2006). Knowledge-domain information skews can compound insularity, lead to domain-based siloing, and push information seekers towards alternative, domain-specific information platforms that are less open and not free. Informational skew may reinforce or even compound existing biases in worldviews and exacerbate information poverty. Existing research has shown that information (un)availability has a surprisingly strong impact on real-world outcomes in financial markets, scientific advancement, and the tourist industry (Hinnosaar et al. 2017, Thompson and Hanley 2017, Xiaoquan and Lihong 2015, Xu and Zhang 2013). These studies further emphasize the salience of the skewed coverage problem in Wikipedia. Importantly, while we focus on Wikipedia, concerns of uneven coverage exist in a variety of platforms that facilitate collaborative content production, including open-source software (e.g. GitHub), knowledge markets (e.g. Stack Overflow or Quora), and product reviews (e.g. Amazon or Steam).

It is unclear whether Wikipedia's uneven coverage is driven by selection effects on the part of Wikipedia editors due to their intrinsic interests (Kuznetsov 2006, Nov 2007), natural emerging trends and exogenous factors (Kämpf et al. 2012, 2015, Keegan et al. 2013) or a systematic tendency for well-developed articles to continue to receive more attention via the "rich-get-richer" dynamic (Aaltonen and Seiler 2016, Barabási and Albert 1999). Most existing work on knowledge contribution behavior on Wikipedia has focused primarily on the motivation of its *editors* (Gallus 2016, Harhoff et al. 2003, Lampe et al. 2012, Nov 2007, Zhang and Zhu 2011, Zhu et al. 2013). However, it is critical that we understand the factors that govern the evolution and lifecycle of *articles*, which are central to the dynamics of Wikipedia as a system. Such factors are also likely important determinants of uneven coverage.

Unfortunately, our understanding of how open collaboration platforms evolve and attract attention is still very limited.

There are three streams of research in the literature that are relevant to our study. The first stream of research emphasizes the dynamic co-evolution of knowledge consumption and knowledge production. The open collaboration model allows consumers of knowledge to react to existing content and potentially also become contributors. But, how does production and consumption of knowledge interact in this complex dynamic system (Kämpf et al. 2012, Wilkinson and Huberman 2007)? Aaltonen and Seiler (2016) find that longer Wikipedia articles tend to receive more editing in the future. Kummer (2019) studied how attention shocks arising from natural disasters affect contributions. Kane and Ransbotham (2016) investigate the feedback loop between consumption and contribution of articles in WikiProject Medicine and find that the state of content moderates this feedback loop. It is noteworthy that they argue that this feedback loop in open collaboration platforms has been under-researched and that a deeper understanding is warranted.

The second stream of research emphasizes the network perspective by recognizing that, similar to the web as a whole, Wikipedia is an information network of hyperlinked articles. This has important implications: at least some of the traffic (attention) arriving at a particular article flows outward along links to other downstream articles. The importance of this network perspective derives from a long tradition of relating a node's relative importance to its network properties -- an assumption that is implicit to the well-known PageRank algorithm. The overall exposure of an article in Wikipedia is determined by the various ways that an information seeker can arrive at it via both external (e.g., search engines) and internal sources (upstream Wikipedia articles). Previous research has shown that the network position of an article is correlated with its content consumption and production (Kane 2009, Kummer et al. 2016, Ransbotham et al. 2012). Moreover, the structural embeddedness of an article in the content-contributor network is positively related to its viewership and information quality (Kane and Ransbotham 2016, Ransbotham et al. 2012). Beyond information networks, Lin et al. (2017) examined a product recommendation network and found that both network diversity and stability are significantly associated with product demand. These findings suggest that articles that are disadvantaged in terms of network position may receive less attention, further limiting their future evolution.

The third stream of research focuses on attention flow or spillover in information networks and policies to optimally leverage spillover. West and Leskovec (2012) used an experimental game to study the dynamics of attention flow in Wikipedia through the lens of goal-oriented search. Kummer (2014) studied spillovers from articles that are featured on the home page of German Wikipedia. Wu and Huberman (2007) study the dynamics of attention to articles on the news aggregator Digg.com and show how attention to articles decays with their novelty. Several works have focused on how content, and particularly perception of its importance, can drive attention. Salganik et al. (2006) conducted a series of randomized online experiments to determine the impact of music track ranking on consumption. Muchnik et al. (2013) demonstrated that perceived popularity of comments not only attract attention and additional votes but can lead to herding phenomena where “likes” beget additional “likes.” Carmi et al. (2017) carried this idea further and studied how demand shocks generate not only attention but attention spillover in the product recommendation networks of Amazon.com, yielding substantial benefits to downstream recommended products. Finally, Aral et al. (2013) studied seeding strategies for policies that leverage spillover in the context of social networks. These studies suggest that attention spillover has a significant impact on real-world outcomes and policies that leverage spillover can be beneficial.

While all three streams of research have enriched our understanding of knowledge production and consumption in information networks, much of the work on open collaboration platforms like Wikipedia relies on endogenous observational data, making it difficult to draw valid causal conclusions. In addition, existing work has focused only on the local direct effect of attention spillover. It has not addressed how heterogeneous characteristics of articles moderate spillover. Nor has it considered the systemic effect of spillover and its broader policy implications.

Yet, a rigorous understanding of the dynamics at play in the Wikipedia network and collaborative information systems in general is indispensable for understanding how information evolves in these systems. Such an understanding is vital to the mission of global empowerment through open knowledge production and dissemination. Moreover, it is an important precursor to the development of sound policies, such as incentivizing contributions to achieve more robust coverage[7]. Randomized controlled experiments are the gold standard for causal inference but are difficult to conduct on platforms like Wikipedia. Apart from the technical challenges and ethical concerns associated with experiments in this context, the continued survival and operations of these platforms depend completely upon the community of contributors, who are highly sensitive to sudden and unvetted policy changes. On the other hand, natural experiments that create exogenous variation in otherwise endogenous relationships can also permit valid causal inference.

In this study, we leverage a natural experiment to examine how exogenous content contributions to a Wikipedia article affect future activities surrounding the article in terms of both pageview dynamics and editing behavior. More interestingly, we examine how the attention an article attracts can spill over to other articles it links to and hence further propagate through the network. Furthermore, we consider the broader policy implications of spillover. We conduct policy simulations to understand how spillovers concentrated in the clusters of the network, which we term *attention contagion*, could impact the evolution of Wikipedia as a system and how it could be harnessed and incorporated into policies to address impoverished regions in information networks.

The goal of the policy simulation is to integrate our findings into an empirically-calibrated attention diffusion model and to guide policy decisions through the analysis of counterfactuals. While the platform can answer some policy questions through analysis of observational data and through experimentation, many relevant counterfactuals for policy recommendation are not directly recoverable from direct estimates. They may be too costly or even impossible to test. In our context, interpreting the spillover effect of individual articles on the whole system is not straightforward. In particular, the effect of spillovers might

[7] https://meta.wikimedia.org/wiki/Research:Increasing_article_coverage

be amplified when editorial efforts are directed at a group of interconnected articles. The key idea behind the policy simulation approach is that reduced-form analysis is used to estimate parameters of a model of the system so that the model can be used to extrapolate findings to more complex or more interesting policies, at the cost of imposing additional model assumptions (Taylor and Eckles 2018).

Our study provides three major contributions. First, we confirm and obtain causal estimates of the feedback loop between contribution and attention. We find that contribution drives sustained increase in future attention (12% on average, with stronger impact for more significant contributions) and future contributions (3.6 more edits and 2 more unique editors over a 6-month period). Second, we determine the article and network characteristics that most amplify spillover or attention contagion. We find that spillovers have the most impact (as much as 22%) for less popular articles that are hyperlinked from focal articles through newly created links. Third, we provide insights from comparisons of policies to address information-impoverished regions of the network based on analytic derivation and empirically-calibrated simulations. We demonstrate that a policy designed to leverage attention contagion can yield substantial increases in attention (as much as a twofold) to impoverished regions of information networks. These results are directly relevant to concerns of societal equity and have managerial importance for collaborative information platforms.

2. Natural Experiment and Data

Since 2010, the Wikipedia Education Foundation has been collaborating with university course instructors to encourage students in the United States and Canada to expand and improve Wikipedia articles through course assignments. The mission of this endeavor is to cultivate students' skills such as media literacy, writing, and critical thinking, while leveraging student effort to fill content gaps on Wikipedia. Since its launch, university instructors participating in the program have guided their students to add content to approximately 46,000 course-related articles on Wikipedia. About 35,000 students have contributed more than 35 million words to Wikipedia, equivalent to 22 volumes of a printed encyclopedia. These student-edited articles have collectively received 282 million views by the end of 2017[8].

In this study, we leverage the exogenous content contributions that result from this campaign to enrich our understanding of the dynamics in open collaboration platforms. The identification derives from the assumption that the content contributions by students are exogenous to the natural evolution of the articles and would not have occurred during the same time period in the absence of the Wiki Education campaign. This is likely to hold for two reasons: first, many of the treated articles pertain to topics that do not naturally relate to current events (e.g., detailed topics in fundamental sciences, such as properties of molecules, etc.); Second, the timing of contribution is exogenous. The content addition occurs during a fixed time period that corresponds to an arbitrary class period – that is to say that the contribution would not have occurred during the same time period in the absence of the assignment. We seek to learn three things from this natural experiment: First, whether efforts that focus on developing underdeveloped pages can lead to long-term, sustained impact; Second, more generally, how contribution and attention dynamically interact and how this interaction depends upon article attributes; Third, whether and to what extent attention propagates through the information network, i.e. the phenomenon of *attention contagion*. Finally, we seek to combine insights in order to synthesize and assess policies that address information poverty and skewness.

For this study, we collected all the articles that received content contribution from students through this campaign in the year of 2016[9]. For each article, we retrieved its title, URL, the time period of the course (i.e. the shock period), and the number of characters added to the article by the assigned student from the website of Wiki Education Dashboard[10]. In our analysis, we retain only articles that existed prior to the campaign (excluding new articles created by students) and those that received substantive contributions (of

[8] https://wikiedu.org/changing/wikipedia/
[9] Wikimedia changed their measurement of "pageviews" in May 2015 to better filter out bot traffic and incorporate the visits from mobile devices. Looking at the articles edited in 2016 guarantee we have a consistent measure of pageviews in the 6 months before and after the content shock.
[10] https://dashboard.wikiedu.org/

at least 500 added characters during the shock period). This leaves us with 3,296 unique treated articles in the sample.

To assess the impact of the content shock, we consider the number of pageviews of an article, a widely-used measure of information consumption. In addition, we parse the complete revision history of each article to obtain the time series of edits and authorship (i.e., the number of unique editors that worked on the article over time). Both the pageviews and revisions are collected through the public API developed and maintained by the Wikimedia Foundation[11].

2.1. Matching and control group

Rates of Wikipedia content creation and consumption are subject to seasonality and other temporal patterns. A simple comparison of quantities of interest (e.g. pageviews and revisions) before and after the content shock may therefore be misleading. Observed changes can be attributed to alteration of the page content, but also to naturally occurring trends. Statistical modeling techniques alone are often insufficient to fully account for seasonality and other complex temporal patterns of article activity. We address this issue by constructing a sample of treated and control articles, matched across multiple attributes. The control group is used to identify the average outcomes corresponding to the counterfactual state that would have occurred for articles in the treatment group had they not received the content contribution during the shock period.

The control group is chosen via the following procedure. First, we pick candidates for the control group by choosing a random sample of 100,000 Wikipedia articles that did not receive content contribution from students. Next, we define the hypothetical shock period for each control article by randomly sampling from the pool of shock periods of treated articles and measure the pre-shock article characteristics for control articles. Finally, we use Coarsened Exact Matching (CEM) (Iacus et al. 2012) based on each article's pre-shock characteristics of tenure, size and popularity (calculated based on average historical pageviews) to obtain a matched sample by pruning articles that have no close match in the treated and control group. We

[11] https://www.mediawiki.org/wiki/API:Main_page

opt for a k-to-k matching solution (i.e., an equal number of treated and control units), which is accomplished by pruning observations from a CEM solution within each stratum until the solution contains the same number of treated and control units in all strata. Pruning occurs within a stratum through nearest neighbor selection using a Euclidean distance function.

Matching is a frequently used technique for drawing causal conclusions from observational data based on the assumption of selection on observables (Ho et al. 2007, Rosenbaum and Rubin 1983). It emulates a randomized experiment, after the data has been collected, by constructing a balanced dataset in which samples in the control group are similar to the samples in the treated set in observed characteristics. We confirm that the constructed control group closely mirrors the treatment group in seasonality and natural time trends. This can be verified in the model-free plots of pageviews over time in Section 2.3 and by comparing article attributes in each group as displayed in Table 1. The average of all three covariates are very close across groups and t-tests fails to reject the null hypothesis that they have the same mean value. In addition, this between-group panel research design lends itself neatly to a standard Difference-in-Difference estimation of the effect of content contribution.

Table 1: Balanced Check for Matched Sample

	Size (characters)	Popularity (weekly pageviews)	Tenure (weeks)
Control	16,228	1,575	506
Treatment	16,255	1,574	506
t-test (p-value)	0.70	0.93	0.51

Table 1 illustrates the quality of our matching procedure. It compares pre-shock characteristics of articles in the matched groups. T-tests indicate that we cannot reject the null hypothesis that articles in treatment and control group have the same mean across all three characteristics.

The above procedure yields 2,766 pairs of matched treated and control articles. For each article, we construct a panel of weekly pageviews from 26 weeks before the shock to 26 weeks after (excluding the shock period itself). Our final sample consists of a balanced panel of 52 periods for 5,532 articles or 287,664 observations at the article-week level. Our results are robust to other matching procedure choices. For example, we evaluated an alternative matching procedure that incorporates matching on article topic and find that the direct effect results are qualitatively similar with only small changes in the magnitude of effect sizes. In addition, we also demonstrate that our results are robust to matching based on network characteristics of articles (see Appendix for further details).

2.2. Links and hyperlink articles

Because we are also interested in attention spillovers from treated articles to downstream hyperlinked articles, we parse content revisions to retrieve the outgoing hyperlinks from focal articles. Following the links, we retrieve all articles linked to by treated and control articles. There are millions of such hyperlinked articles. To avoid confounds that may arise from multiple exposures to the treatment, we retain only hyperlinked articles that are linked to from one and only one treated article (Walker and Muchnik 2014). For parity, we treat articles downstream of control articles in the same manner. This allows us to obtain a clean estimate of the spillover effect from each link. This procedure yields 131,974 hyperlinked articles that are downstream from directly treated articles. The spillover treated and spillover control articles constitute our sample for analyzing the spillover effect of the content contribution. This is illustrated in Figure 1.

Figure 1: Research Design - Direct Effect and Spillover Effect

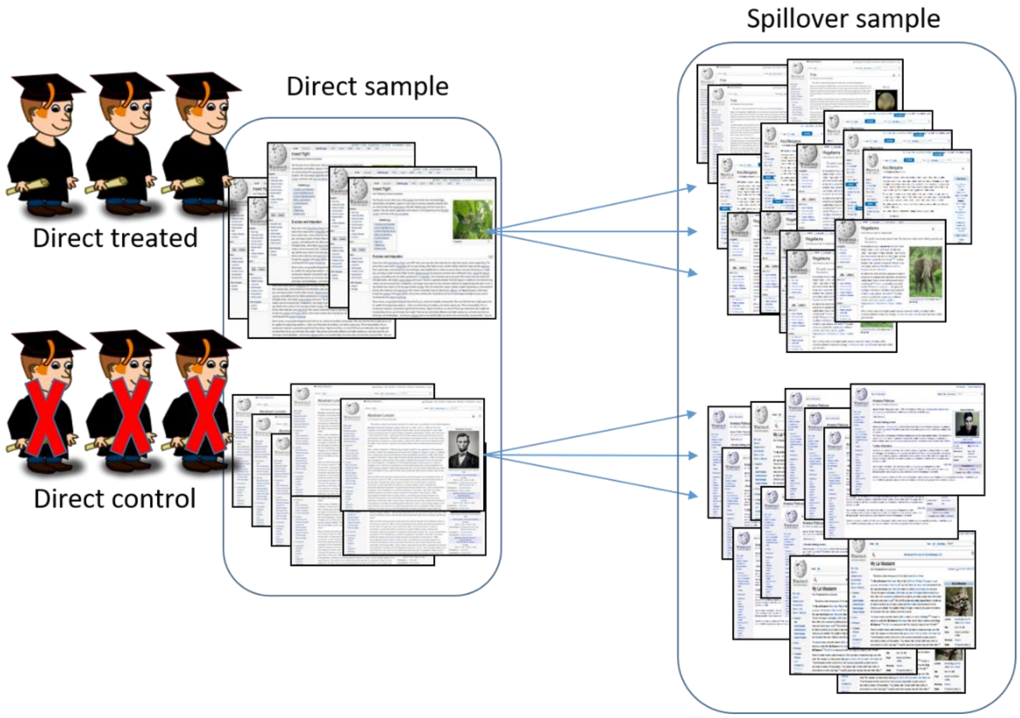

Figure 1 illustrates the direct treated and direct control articles, which constitute our matched sample for analyzing the direct effect of the treatment. Similarly, the spillover treated and spillover control articles constitute our sample for analyzing the spillover effect of the content contribution.

2.3. Model-free evidence

In this section, we present model-free evidence regarding the direct and spillover impact of the content shock, in terms of both pageview dynamics and editing behavior. A model-free examination of the evidence can reveal important effects while avoiding modeling assumptions.

Pageviews dynamic

Because articles are highly heterogeneous, they experienced a large variance in activities (such as pageviews) even prior to treatment, a phenomenon that is typical for complex social systems (Muchnik et al. 2013) To compensate for large baseline variation, we scaled pageviews for each article relative to its own pre-shock popularity, which is computed as average weekly pageviews over 26 weeks (about 6 months) prior to its shock period[12]:

$$scaledPageview_{i,t} = \frac{pageview_{i,t}}{preShockPopularity_i} \ (eq\ 1)$$

Where $preShockPopularity_i = 1/26 \sum_{\mu=1}^{26} pageview_{i,\tau-\mu}$ and τ is the week when the content shock begins for article i. Because courses in our sample begin at different weeks and have different durations, we align their start dates and exclude the duration of shock period itself from the analysis. We consider relative time before or after the shock. Figure 2 plots the mean and standard deviation of weekly scaled pageviews in the 6 months prior to and after the shock period for treated and control articles.

Figure 2

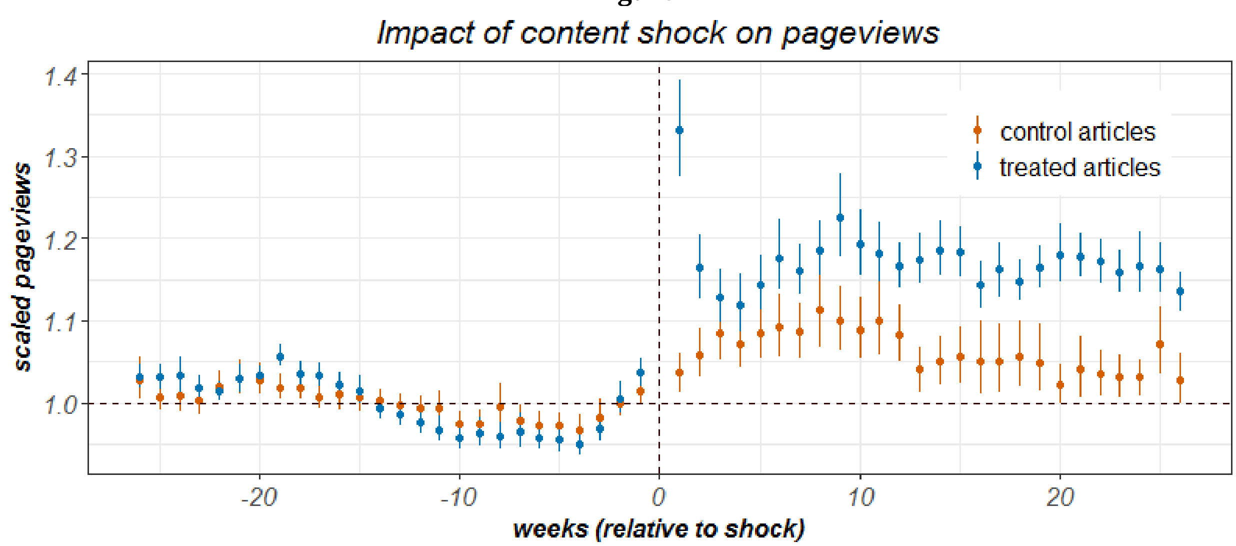

Figure 2 displays the pageviews dynamics for articles in the treatment and control group. Time is measured relative to the shock period (which is excluded), up to 26 weeks before and after. Dots and whiskers represent the mean and standard deviation of scaled pageviews in each bin, respectively.

This model-free view of the data displays a clear seasonal trend for both treatment and control group articles, indicating the need for careful construction of a control group as a counterfactual. Prior to the shock, articles in the control group mimic the time trend of those in the treatment group well, highlighting the success of our CEM procedure. We can also see the significant and relatively long-lasting impact of the

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[12] Note that this normalization simply scales the time series of pageviews of each article by a constant. Examination of the model-free evidence for scaled and unscaled pageviews reveals that this scaling is appropriate.

treatment on post-shock pageviews. Treated articles received approximately 10% more traffic than control articles, and this effect persisted for at least 26 weeks after the contribution shock. Evidently, Wikimedia's campaign efforts to develop underdeveloped pages both worked and had a relatively long-term impact, suggesting the potential for a policy approach to fill impoverished regions in Wikipedia's information network.

Figure 3 plots the mean and standard deviation of weekly scaled pageviews in the 26 weeks prior to and after the shock period for articles in the spillover treated and spillover control groups. While pageviews of spillover treated articles seem to exceed those of spillover control articles after week 10, it is unclear from this model-free evidence alone whether the effect is significant. It should be noted that there is little doubt that spillover of attention occurs on Wikipedia– this can be seen explicitly from published clickstream data of actual traffic flowing over hyperlinks from one article to another (see *Sources of Increased Attention* in section 3 for further discussion). What is unclear is the extent and heterogeneity of treatment spillover effect and whether it can be teased out. Downstream articles, by virtue of being selectively linked to, tend to be more popular and have a larger variance in pageviews, suggesting that the effect, if it exists, may require econometric strategies to uncover. For example, it could be the case that the spillover is significant for only less popular articles, which may themselves be underdeveloped.

Figure 3

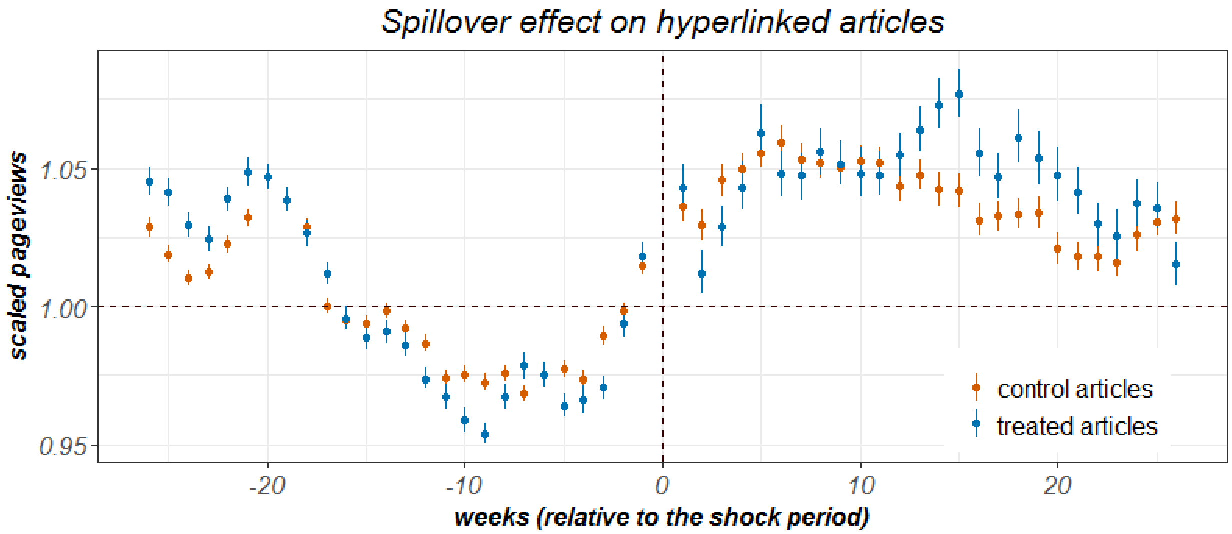


Figure 3 displays the pageviews dynamics for articles to which treatment and control group articles link. Time is measured relative to the shock period (which is excluded), up to 26 weeks before and after. Dots and whiskers represent the mean and standard deviation of scaled pageviews in each bin, respectively.

During the shock period, students also added new links to downstream pages, as part of their contribution efforts. Newly added links are interesting in terms of attention spillover, because they may function to "open the valve" of attention flow between articles. Intuitively, old links can convey only changes in attention to downstream articles. In contrast, a newly added link can convey the totality of attention to downstream articles. This is illustrated in a simple conceptual model:

$$\Delta pageviews_{i,j}^{spillover} \propto pageviews_i * newLink_{i,j} + \Delta pageviews_i^{treated} \; (eq\ 2)$$

Where $newLink_{i,j}$ can be thought of as an indicator variable (equal to 1 for new links, and 0 for old links). This suggests that attention spillover may be more clearly visible in model-free evidence if we look only at newly-linked downstream articles (i.e., those downstream articles that were linked to from treated articles *during the shock period*). Figure 4 is similar to Figure 3 but distinguishes spillover populations by whether the link from the directly treated article was pre-existing (old link) or was added during the shock period (new link). New link articles in the spillover control group are not displayed because they did not receive sufficient new links during the shock period.

Figure 4

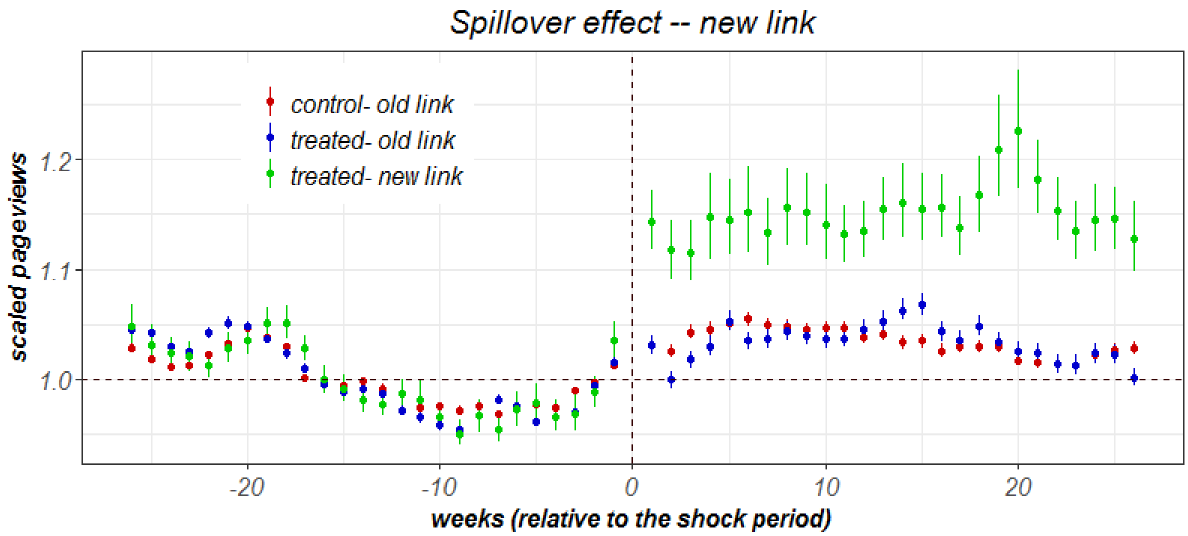


Figure 4 displays the pageviews dynamics for hyperlink articles based on whether the downstream article is connected through a new link or an old link. The time period is from 26 weeks prior to the contribution shock to 26 weeks after. Dots represent mean value of scaled pageviews in each bin and whiskers represent the corresponding standard deviation.

The model-free plot of the spillover effect for new links confirms our reasoning. Spillover of attention across newly created links is clearly significant and the temporal pattern of spillover closely follows the pattern of the post-shock pageviews of directly treated articles. Compared to an old link, a new link can convey an additional 15% pageviews to target articles on average.

Editing behaviors

Prior research has suggested that content contributions are self-promoting – that, in addition to boosting future attention (consumption), they also drive future contributions. We examine model-free evidence to determine whether the exogenous content contribution to articles leads to future contributions to those articles. We retrieved the full revision history of all articles in our sample and constructed two measures of editing behavior, the number of total edits and the number of unique editors in the six months prior to and after the shock period for each article. Because contribution behavior is relatively rare, we collapse the time series into a "pre" and "post" period. For each article, we look at the editing behavior before and after the content shock and their difference across treatment and control groups.

Table 2: Editing behavior before and after the shock period

	Total edits			Unique editors		
	Before	After	Δ	Before	After	Δ
Control	11.2	11.3	0.1	6.2	6.5	0.2
Treatment	11.7	15.4	3.7	6.7	9	2.2
t-test (p-value)	0.45	-	<1e-9	0.36	-	<1e-16

Note: The values display under the columns "Before" and "After" are counts of total edits and unique editors in the 6 months before and after the shock period. Δ = After - Before. The values in the row "t-test" are p-values from a two-sided t-test of the null hypothesis that control and treatment group have the same mean.

Editing behavior is similar across treatment and control groups during the pre-shock period, as expected: t-tests fail to reject the null hypothesis that the treatment and control group have the same mean number of total edits ($p = 0.45$) and number of unique editors ($p = 0.36$) prior to the shock. For treated articles, in the 6-month period after the contribution shock, the number of total edits increased by 3.7 (p<1e-9) and the number of unique editors increased by 2.2 persons (p<1e-16). In contrast, control group articles did not experience any significant increase in number of total edits or number of unique editors. These results confirm that exogenous content shocks significantly drive future editing behavior.

Overall the model-free evidence confirms that exogenous content contributions drive future attention and editing behavior and that spillover of attention occurs significantly for newly added links. To capture the impact of varying intensity of treatment and heterogenous treatment impact, we turn to econometric modeling.

3. Empirical Methods

3.1. Direct Impact of Contribution Shock

In this section, we use econometric models to infer how differing intensities of content shocks affected treated articles contingent on article characteristics, in terms of future content consumption and future editing behavior. We further investigate the source of attention increases to treated articles by analyzing the internal and external inbound traffic to treated pages.

Content Consumption

We estimate the average treatment effect on the treated (ATT) for content consumption using the following simple specification as the baseline model:

$$Pageviews_{it} = \alpha PostShock_{it} + \gamma_i + \delta_t + e_{it} \quad (eq\ 3)$$

where i is a Wikipedia article and t indexes the week. The dependent variable $Pageviews_{it}$ is the scaled pageviews for article i at week t as defined in $eq\ 1$. For brevity, we have defined $PostShock_{it} = PostShockPeriod_t * Treatment_i$, a dummy variable equal to 1 if the period t is after shock and the article i is a treated article, and 0 otherwise. We include article and week fixed effects (γ_i and δ_t) to account for article level heterogeneity and common pageviews trends over time on the platform. Equation (3) estimates a simple Difference-in-Difference model of the impact of exogenous content contribution.

However, content contribution may have different impacts on articles with different characteristics. For example, less popular articles (with less average attention prior to the shock) may have been more or less affected. Article characteristics include article length, tenure and popularity (defined as average pageviews over the 6 months period before the shock). Moreover, not all treated pages received equal contributions during the shock period. Actual contributions varied significantly across treated articles, ranging from hundreds to tens of thousands of characters added through the course of student edits. To account for varying treatment intensity and to allow for heterogeneous treatment effects, we estimate the following model:

$$Pageviews_{it} = \beta_1 PostShock_{it} * \log(charCount_i) + \beta_2 PostShock_{it} * X_i$$

$$+\gamma_i + \delta_t + e_{it} \quad (eq\ 4)$$

where $\log(charCount_i)$ is the logarithm of number of characters added to article i by a student during the shock period[13]. It represents the variation of treatment intensity. X_i is a vector of article characteristics measured before the content shock, including article tenure, size, and popularity. To provide better interpretability of model estimates and to avoid the assumption of linearity, we bin these three continuous variables to low and high levels by their median value and include dummy variables that are equal to 1 when the value is high and 0 otherwise (i.e. older article, longer article, and more popular article) in the vector X_i. Diagnostic tests show that two bins for our continuous variable is a reasonable choice (see Appendix for more detail). The interaction term of $PostShock_{it}$ and X_i allows us to investigate heterogeneous treatment effects. We retain article fixed effects and week fixed effects. The parameters of interest are β_1 and β_2.

We use linear regression to estimate the above models and results are reported in Table 3. Because we scale the pageviews of each article with respect to its average pageviews over the six months prior to the shock, all estimates can be conveniently interpreted as the percent changes of pageviews relative to their pre-shock average. Following the suggestion of Bertrand et al.(2004), all reported standard errors allow for arbitrary serial correlation across time and heteroscedasticity across articles to properly gauge the uncertainty around the estimates for serially correlated outcomes in panel data.

Overall, we find post-shock pageviews for treated article increased by 12% on average. The magnitude of the treatment effect is positively correlated with treatment intensity and the impact is stronger for articles that are younger and less popular. The effect is both economically and statistically significant. Based on the model estimates in (3), a relatively young and less popular article with 6000 characters added (the average number of characters added for treated articles in our sample) during the shock period experienced a 25% boost in post-shock pageviews. The impact is even larger for similar articles that received a more intense treatment.

[13] For articles in the control group, the value of $\log(charCount_i)$ is set to zero.

Table 3: The Impact of Content Contribution on Consumption

	Scaled pageviews		
	(1)	(2)	(3)
PostShock	0.119***		
	(0.017)		
PostShock*log(char count)[14]		0.035***	0.065***
		(0.005)	(0.008)
PostShock*old article			-0.041*
			(0.024)
PostShock*popular article			-0.142***
			(0.025)
PostShock*long article			-0.015
			(0.025)
Article fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Observations	287,664	287,664	287,664
Adjusted R^2	0.122	0.122	0.124
Notes:	***Significant at the 1 percent level.		
	**Significant at the 5 percent level.		
	*Significant at the 10 percent level.		

We perform diagnostics to assess our modeling assumptions in terms of linear interaction effects and common support. Results show that both assumptions are satisfied. For robustness, we also estimated alternative specifications. Using linear regression, we drop article fixed effects γ_i and retain only a simple treatment indicator, and all estimates are similar (see the Appendix for more details).

Editing Behavior

Beyond the impact on attention, we are also interested in whether exogenous content contributions spur future editing behavior. Because editing behavior is typically sparse for a Wikipedia article, for modeling purposes, we collapse the time series into just "pre" and "post" periods for the 6 months prior to and after

[14] Note that in models 2 and 3, we include PostShock*log(char count) and exclude a bare PostShock term because log(char count) captures the intensity of a treatment (and every article that received a contribution as a consequence of treatment had some number of characters added).

the contribution shock. For each article, this yields two 6-month time periods during which we count the number of total edits and number of unique editors and these comprise the dependent variables. Compared to alternative approaches (such as multistage, zero-inflated models), this transformation permits a simpler linear model which retains interpretability and avoids more restrictive modeling assumptions (such as distributional assumptions on the error term that are required by Poisson or Negative Binomial regression). In addition, as suggested by (Bertrand et al. 2004), the “pre” and “post” time series collapse allows us to obtain a consistent estimator for the standard errors of the treatment effect in the Difference-in-Difference model. The models estimated here are similar to models in equation (3) and (4) for content consumption, apart from the time period collapse and the exchange of the dependent variable for editing behavior. For the sake of interpretability, we report the results from a linear regression, but results from Poisson regression and Negative Binomial regression are qualitatively similar (see Appendix for details).

Table 4: The Impact of Contribution Shock on Future Editing behavior

	Number of total edits			Number of unique editors		
	(1)	(2)	(3)	(4)	(5)	(6)
PostShock	3.596***			1.996***		
	(0.855)			(0.243)		
PostShock *log(char count)		1.173***	1.186***		0.640***	0.606***
		(0.229)	(0.234)		(0.068)	(0.065)
PostShock *old article			1.446			0.691**
			(0.957)			(0.339)
PostShock *long article			-1.840**			-0.829***
			(0.926)			(0.305)
PostShock *popular article			0.241			0.333
			(0.856)			(0.326)
Article Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,964	10,964	10,964	10,964	10,964	10,964
Adjusted R^2	0.63	0.63	0.63	0.82	0.82	0.82

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

As we can see from Table 4, the contribution shock has a significant impact on future editing behavior in terms of both number of total edits and number of unique editors. Based on model estimates from column (1) and (4) in Table 4, an article that received content contribution in the shock period had approximately 3.6 more edits and 2 more unique editors in the 6 months after the shock period, compared to articles that did not receive exogenous content contribution. Similar to our findings for content consumption, the magnitude of the treatment effect increases with treatment intensity. Based on the estimates from column (2) and (4), an article with 6000 characters added during the shock period attracts 4.5 more edits and 2.5 editors in the 6 months post-shock period. As for heterogeneous treatment effects, the most significant factor we weaker impact for articles that already have a substantial amount of content.

Sources of Increased Attention

Both model-free results and estimates from statistical models confirm that exogenous contributions to articles drive future attention. But from where does this increased attention originate? In general, articles can receive attention directly from external sources (e.g., traffic arriving to an article from outside of the information network, such as through search engine discovery or links from external websites) and internal sources (e.g. traffic flowing to an article from another upstream article). This distinction is interesting and meaningful from a policy perspective as some articles may act to pull attention into the information network from external sources, thereby increasing the overall attention to the platform. Articles also play a role in the redistribution of attention throughout the platform, which is relevant from the standpoint of information equity. An article’s role in the flow of attention on the information network is illustrated in Figure 5.

Figure 5

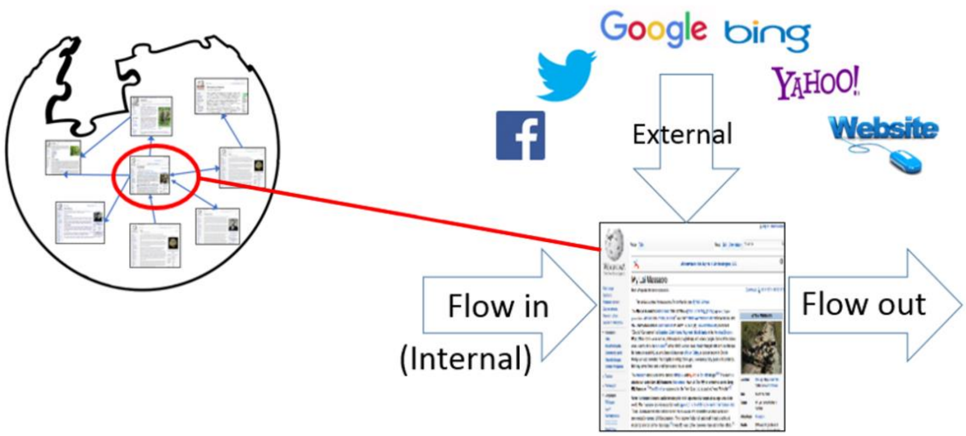


Figure 5 illustrates the flow of attention on information networks with respect to a particular article in terms of flow in (internal and external) and flow out.

For many large-scale real-world information systems, we cannot directly observe the detailed flow of attention (traffic). However, recently released data of monthly Wikipedia clickstream[15] snapshots provide exactly this level of detail for all Wikipedia articles. The clickstream data show how users arrive at an article and what links they click on within the article over the course of a given month, aggregated at the article level. They contain counts of (referrer, resource) pairs extracted from the Wikipedia HTTP request logs, where a referrer is an HTTP header field that identifies the address of the webpage that linked to the resource being requested. In other words, the clickstream data gives a weighted network of articles and external sites, where the weight of each edge corresponds to the traffic flow along that edge. These counts are aggregated at the monthly level and any (referrer, resource) pair with greater than 10 observations in a month are included in the dataset. To give a sense of the scale of the data, the August 2016 release contains 25.8 million (referrer, resource) pairs from a total of 7.5 billion requests for about 4.4 million English Wikipedia articles. Figure 6 displays an example from the Wikimedia website, which illustrates incoming and outgoing traffic to the page “London” on English Wikipedia.

[15] https://meta.wikimedia.org/wiki/Research:Wikipedia_clickstream

Figure 6

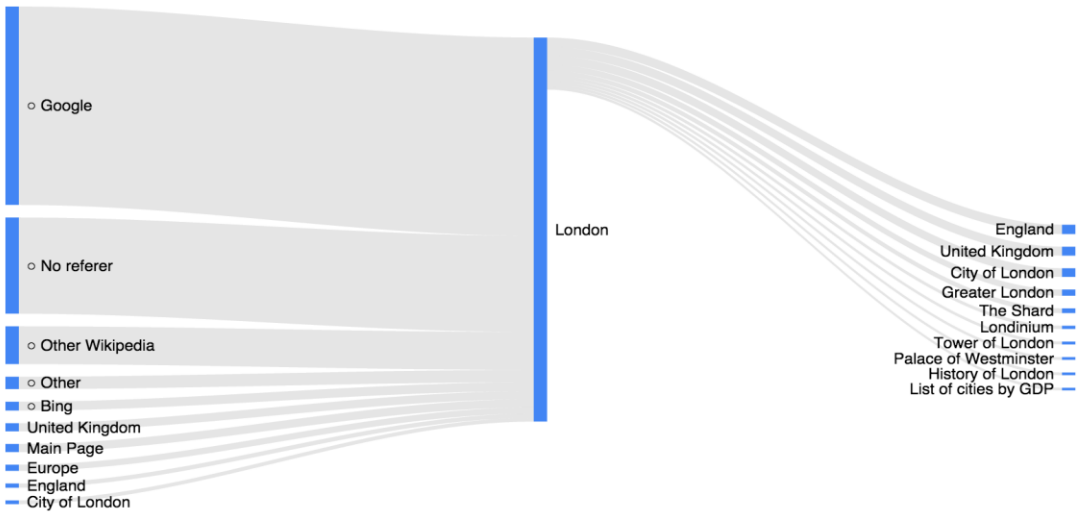


Figure 6 displays the sources of incoming and outgoing traffic for the "London" Wikipedia article, as determined from the clickstream monthly data snapshots provided by the Wikimedia foundation.

We leverage this data to shed light on the sources from which increased attention originate. The clickstream data snapshots are only available for a limited number of months during the period of our natural experiment. To look at the change of traffic flow, we need to compare snapshots before and after the shock period. Fortunately, the Wikimedia Foundation released clickstream snapshots for both August 2016 and January 2017, which are just before and after articles were treated in the fall semester of 2016.

For each article, we calculate its total inbound traffic (combined internal and external traffic arriving at the article), total outbound traffic (traffic leaving the article), internal inbound traffic[16] (traffic flow to the article from other articles in the network) and external inbound traffic (traffic flow to the article from a search engine or other external website). We use CEM to ensure that articles in the treatment group and control group are comparable across all traffic measures prior to the start of the natural experiment (i.e. in the August 2016 snapshot). The k-to-k CEM procedure leaves us with 1,017 articles in both the treatment and control group (see Appendix for distribution and balance checks for clickstream data).

First, we look at changes in network structure in terms of newly created incoming links. During the shock period, it is likely that links to articles in either the treatment or control group were created, either by

[16] The link traffic only includes links from other Wikipedia articles. The link traffic from other website outside of the ecosystem of Wikipedia were classified under the "external traffic" category.

student editors or as part of the natural evolution of the information network. Matching the 2,024 treatment and control articles in our sample with the clickstream data snapshots (for August 2016 and January 2017), we find that the number of active incoming links[17] for treated articles grew significantly faster as compared to control group articles. As we see in Table 5, articles in the treatment group received on average 0.9 more active links during the shock period (compared to 0.4 for articles in control group). New incoming links make an article more discoverable by creating new channels to capture attention flow within the network. These increased channels may explain how contributions ultimately drive attention.

Table 5: Number of incoming links

	Number of incoming links per articles		
	Before	After	Δ
Control	6.6	7.0	0.4
Treatment	6.6	7.5	0.9
t-test (p-value)	0.96	-	< 1e-15

Notes: The values display under the columns "Before" and "After" are the average number of incoming links per articles in the 6 months before and after the shock period. Δ = After - Before. The values in the row "t-test" are p-values from a two-sided t-test of the null hypothesis that control and treatment groups have the same mean.

Attention from external sources can also explain the attention increases we observed. To determine the extent to which observed attention increases derive from internal or external sources, we compare pre/post shock changes in internal, external, and total incoming traffic across treatment and control articles in Table 6. The control group serves as a counterfactual to account for natural fluctuations arising from seasonal or other pageview trends, leading to a simple DID style estimator:

Table 6: Incoming traffic breakdown

	Total incoming traffic	internal traffic ($T^{internal}$)	external traffic ($T^{external}$)

[17] We define an active incoming link as one that conveys at least 10 pageviews in a month. The monthly clickstream data snapshots filter out any (referrer, resource) pairs that do not meet this criterion.

	Before	After	Δ	Before	After	Δ	Before	After	Δ
Control	45.4	53.6	8.2	10.2	12.2	2.0	35.2	41.4	6.0
Treated	44.7	59.3	14.6	10.2	14.0	3.8	34.4	45.2	10.8
t-test (p-value)	0.85	-	0.01	0.97	-	0.05	0.80	-	0.03

Notes: The values display under the columns "Before" and "After" are the average traffic per article per day in the 6 months before and after the shock period. Δ = After - Before. The values in the row "t-test" are p-values from a two-sided t-test of the null hypothesis that control and treatment groups have the same mean.

From Table 6, we see that the total incoming traffic increased by 14.6 pageviews per article per day for the treatment group relative to 8.2 for the control group. The extra 6.4 pageviews can be interpreted as the Average Treatment Effect on the Treated (ATT), which is about a 14% increase relative to the pre-shock average. This result is consistent with our prior estimates, which were based on article-level pageviews data. Hence, we demonstrate the impact of content shock using two different data sources (clickstream data and pageviews data) and find similar effect sizes. We can also see that both internal and external sources conveyed increased attention, indicating that content contributions yield attention gains from within the information network and from without. We suggest that attention gains from external sources are likely the result of increased visibility of the articles in search engine results[18]. Modern search engine algorithms are clearly sensitive to the recency of content changes. Though we do not know the actual details of search engine ranking algorithms (proprietary information), more incoming hyperlinks to a page convey a higher ranking in ordinary PageRank. We define the ratio of internal to external traffic as $R(T) = T^{internal}/T^{external}$. New traffic has a higher ratio, ($R(\Delta T) = 0.4$) relative to the pre-shock ratio ($R\left(T_{Before}\right) = 0.3$), indicating that new traffic originates slightly more from internal sources.

3.2. Attention Spillover

The impact of content shocks is not limited to directly treated articles. Attention resulting from the shock can also spillover onto other downstream articles through the hyperlink network. Conceptually, we can

[18] Search engines traffic dominates other external sources such as external websites in external traffic.

think of the spillover as a dyadic relationship between each source (directly treated or control) and target article. As our consideration of model-free evidence showed, new links, which build bridges between source and target articles, seem to play a critical role in facilitating spillover. It also seems plausible that the popularity of source and target articles may moderate the extent of the spillover. We test these hypotheses with the following model:

$$Pageviews_{it} = \beta_0 PostShock_{it} + \beta_1 PostShock_{it} * stPopularity_i + \beta_2 PostShock_{it} * newLink_i + \beta_3 PostShock_{it} * stPopularity_i * newLink_i + \gamma_i + \delta_t + e_{it} \quad (eq\ 5)$$

Where i is a target article and t is the week. $stPopularity_i$ is a 2-dimension vector $(sourcePopularity_i, targetPopularity_i)$, representing the popularity of the source article (i.e., the treated article that received an exogenous content contribution) and the target article (that was linked to from the treated article), respectively. The indicator $newLink_i$ is equal to 1 if the link between source article and target article was added during the treatment period, 0 otherwise. The parameters of interest are $\beta_1, \beta_2, \beta_3$. We include each term in successive models gradually to investigate how they parcel out the overall spillover effect. The results are displayed in Table 7.

Table 7: The Attention Spillover of Contribution Shock

	Scaled pageviews			
	(1)	(2)	(3)	(4)
PostShock	0.008***	0.027***	-0.006	-0.005
	(0.003)	(0.006)	(0.004)	(0.007)
PostShock*popularTargetArticle		-0.013**		-0.004
		(0.005)		(0.005)
PostShock*popularSourceArticle		-0.016**		0.000
		(0.007)		(0.007)

PostShock*newLink			0.129***	0.148***
			(0.012)	(0.018)
PostShock*popularTargetArticle*newLink				-0.138***
				(0.023)
PostShock*popularSourceArticle*newLink				0.073***
				(0.023)
Article fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Observations	6,862,648	6,862,648	6,862,648	6,862,648
Adjusted R^2	0.104	0.104	0.104	0.104

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

We can see from column (1) of Table 7 that the overall effect (i.e., when averaged over all articles) is small but significant. This result is consistent with the model-free evidence and our intuition given the large heterogeneity across articles. Column (2) of Table 7 shows how the treatment effect varies with the popularity of source and target articles. Evidently, spillover from low popularity source articles to low popularity target articles yielded a 2.7% increase in pageviews ($p<0.01$). While this effect size may initially seem small, it is measured with respect to a single outgoing link from the treated article to one target article. In general, treated articles link to multiple downstream target articles, suggesting that the overall collective effect of spillover can be quite substantial. Interestingly, spillover is enhanced when both source and target articles are less popular, which is a typical scenario for underdeveloped pages, particularly in informationally impoverished regions in the Wikipedia network.

A more interesting insight emerges when we consider whether the link between source and target articles was new. Surprisingly, for new links, the impact of the spillover can be as large as around 13%, which is close in magnitude to the average direct effect. As illustrated in our discussion of model-free evidence, the rationale is that a new link can "open the valve" between source and target article and convey both the preexisting and increased attention from the source to the target. We note that old links clearly convey attention (as the clickstream data illustrate). However, they convey only increased attention from the source to the target and we lack the statistical power to see it directly in this model. Finally, the attention spillover is even larger (14.8%) for new links between less popular source and target articles. As underdeveloped regions of information networks likely satisfy all these criteria (i.e. low popularity of articles and lack of preexisting link structures between articles), policies that focus on promoting such regions can benefit from strategies that harness spillover.

4. Policy Simulation of Attention Contagion

Our spillover results indicate that attention shocks in Wikipedia have a local network effect. Articles in the system benefit when upstream articles receive attention. Some spillovers direct attention to downstream articles that already receive significant exposure. On the other hand, some of this attention may increase exposure to underdeveloped articles. This begs the question: By focusing attention on connected sets of underdeveloped articles, can we optimally harness spillovers in order to redirect attention to articles that would benefit the most from increased exposure?

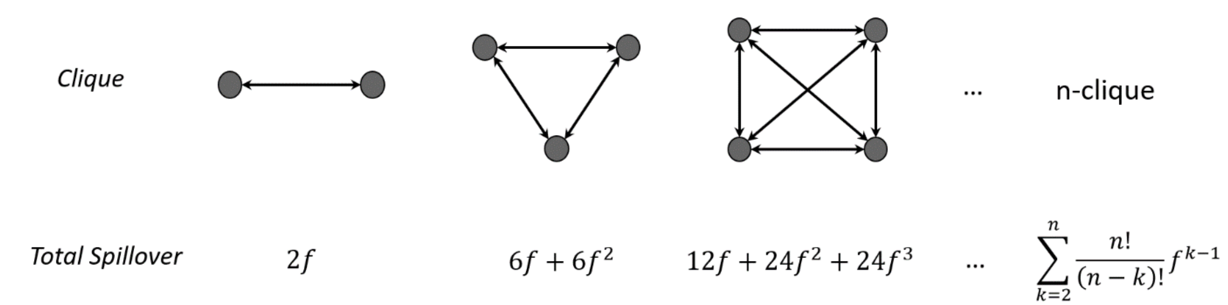
To better understand this question, we conduct policy simulations in which we integrate our findings from the econometric estimates into an empirically-calibrated attention diffusion model and to guide policy decisions through the analysis of counterfactuals. We propose a policy in which editors are encouraged to focus their editorial efforts on a set of targeted underdeveloped articles that are intimately related to one another, in order to harness attention contagion and maximize joint exposure. Targeted sets of related articles will be well-connected either at the outset (i.e., a set of stub articles that are already well-connected but remain underdeveloped) or will become well-connected as a consequence of directed editorial efforts. That is, the links between sets of related articles need not exist prior to being edited but can arise as a consequence. The rationale is that attention spillovers to underdeveloped articles are more valuable to the platform (in terms of the information equity that they convey) than spillovers to articles that are already well-developed.

4.1 Intuition – a Mean-field Estimation

We begin by providing an intuition for how network structure can impact attention spillover using a mean-field estimation. To represent a set of related and highly connected articles in a manner that is simple, we consider network cliques, defined as a set of n completely connected nodes in a network. To demonstrate our intuition, we analytically calculate the spillover in cliques of size n using mean-field assumptions.

For an n-clique, assuming each node receives direct traffic T and where spillover over a single step is given by $T_{spillover} = fT$, the total spillover exposure gain is given by: $\sum_{\boldsymbol{k=2}}^{\boldsymbol{n}} \frac{\boldsymbol{n}!}{(\boldsymbol{n-k})!} f^{\boldsymbol{k-1}}$. The summand represents all partial permutations of a set of at k nodes, describing the paths of length $k-1$ that successive spillovers take (each contributing a multiplicative factor of f) from each starting node to each other ending node. Figure 7 displays the total spillover gain for all articles in the clique (i.e., the total additional exposure gained from spillover from each article in the clique onto all other articles).

Figure 7



For example, for a mean spillover of $f = 0.10$ and for cliques of sizes n=3, 4, 5, the total spillover exposure gain is 0.66, 1.46, and 2.73, respectively, as measured in units of proportion of incident direct traffic. This estimate assumes constant spillover (f), and equal traffic from any node in the clique to any other, which is unlikely to hold in the real world. Fortunately, we can relax these assumptions by using exact and fine-grained data on traffic flowing on all links in Wikipedia and traffic to all pages from external sources (e.g., traffic from search engines that arrive at Wikipedia pages) from the monthly Clickstream snapshots[19]. We leverage this data to estimate spillover and assess policies designed to capture spillover through empirically-calibrated simulations.

4.2 Diffusion Simulation

Our mean-field estimation is useful to obtain stylized estimates of policies that focus attention on clusters of well-connected articles and to develop an intuition about why this might work, but it does not account for real-world heterogeneity in actual traffic flow on the links between articles. To address this, we test policies more realistically and comprehensively through simulations of traffic flow that arise from attention perturbations. We define perturbations as increases in incident traffic from external sources. These policy simulations make use of highly detailed clickstream data for calibration, to ensure that traffic flow changes follow pathways in proportion to real-world patterns on Wikipedia. To accomplish this, we use a generalization of the personalized PageRank algorithm[20]. PageRank is widely recognized as one of the most important algorithms used for network-based information retrieval. It represents traffic flow as a random walk process on the information network, and is given in the iterative form by:

$$\vec{r}_{t+1} = (1-\alpha)\vec{r}_0 + \alpha G \cdot \vec{r}_t \quad (eq\ 6)$$

Where $\vec{r}_t$ is a vector of the traffic (attention) landing on article i for the t-th iteration of the diffusion process; $\vec{r}_0$ is a vector of the initial distribution of traffic or whenever the process involves "hopping" rather than following a hyperlink from an article to a downstream article. The "hopping" occurs with probability $(1-\alpha)$ – the so-called damping factor. G is a matrix of normalized out-flow of traffic from any article i that hyperlinks to an article j. Convergence of the iterative form of PageRank is achieved for some $\vec{r} \equiv \vec{r}_{t+1}$ when $|\vec{r}_{t+1} - \vec{r}_t| < \epsilon$, for a small choice of ϵ. The converged vector $\vec{r}$ represents the normalized

[19] Ellery Wulczyn, Dario Taraborelli (2015). Wikipedia Clickstream. https://meta.wikimedia.org/wiki/Research:Wikipedia_clickstream

[20] Personalized PageRank has recently been *formally* related to the task of community detection in networks (Kloumann et al. 2016)

accumulated traffic to each article i that results from the simulated random walk process. We represent this simulation process functionally as: $\vec{r} = PR(\vec{r}_0, G, \alpha, \epsilon)$.

Ordinary PageRank assumes an equal initial distribution of traffic, $\vec{r}_0 = 1/N$, and equal probability of out-flow along all links, $G_{ij} = A_{ij}/k_j$ where A_{ij} is the adjacency matrix and k_j is the degree of article j. The damping factor is conventionally chosen as $(1-\alpha) = 0.15$. Personalized PageRank relaxes the assumption of equal initial distribution of traffic for an arbitrary normalized $\vec{r}_0$. To guarantee realism, we relax these assumptions even further and leverage the clickstream data (see section 3, *Sources of Increased Attention* for a description) to empirically calibrate internal and external traffic flows in the simulation[21]. In personalized PageRank, we set the vector $\vec{r}_0$ to the normalized empirical distribution of external incident traffic on each article i, and the matrix G to the normalized empirical distribution of out-flow traffic from article i to article j. Having defined the simulation process, we are now in a position to assess how perturbations to attention (i.e. increases in incident traffic from external sources—for example, arising from content contribution shocks) drive accumulated attention to all articles in the network. We represent a general perturbation to some set of articles S as $\vec{r}_{0p}^{\,S} = \vec{r}_0 + \overrightarrow{\delta r}_{0p}^{\,S}$ and set the perturbation according to:

$$\left(\delta r_{0p}\right)_i = (r_0)_i \begin{cases} p, & \text{for } i \in \mathrm{S} \\ 0, & \text{otherwise} \end{cases} \qquad (eq\ 7)$$

where $p > 0$ represents a constant percentage increase of attention shock to affected articles (those in the chosen perturbed set S). In other words, we create relative perturbations of attention that are correlated across a set S of chosen articles. For each perturbation, we calculate the resultant PageRank vector $\vec{r}_p^{\,S} = PR(\vec{r}_{0p}^{\,S}, G, \alpha, \epsilon)$ and compare it to the unperturbed PageRank vector $\vec{r} = PR(\vec{r}_0, G, \alpha, \epsilon)$. Specifically, we are interested in the resultant *excess attention* (EA) received by underdeveloped articles which comprise the articles in the perturbed set:

[21] In prior research, others have calibrated PageRank with internal traffic from Wikipedia clickstream data (Dimitrov et al. 2017), but have not accounted for variation in external traffic.

$$EA(S,p) = \sum_{i \in S} \frac{r_{p,i}^{S} - r_i}{r_i} \qquad (eq\ 8)$$

Because any perturbation of a set of articles will result in those articles receiving excess attention, we compare excess attention across two different policies: i. an *Attention Contagion Policy* (ACP) where editorial efforts are focused on clusters of well-connected, underdeveloped articles; ii. an *Undirected Attention Policy* (UAP) where editorial efforts are focused on randomly chosen underdeveloped articles that are not necessarily (but may incidentally be) connected to one another. The random selection of underdeveloped articles under this latter UAP policy will lead to contributions to articles that are more spread out across the information network as compared to the ACP policy.[22] The two policies are illustrated in Figure 8. The UAP policy represents a simple and useful baseline for comparison. It may be that without guidance editors already cluster their editorial focus to some extent. However, we do not parametrize clustering under UAP to avoid introducing unnecessary assumptions and additional complexity.

Figure 8

[22] In fact, because UAP spreads out editorial focus through the network, it conveys excess attention to more unique articles. But, under ACP more articles receive a larger share of excess attention. For more details see Fig A11 and the related discussion in the Appendix.

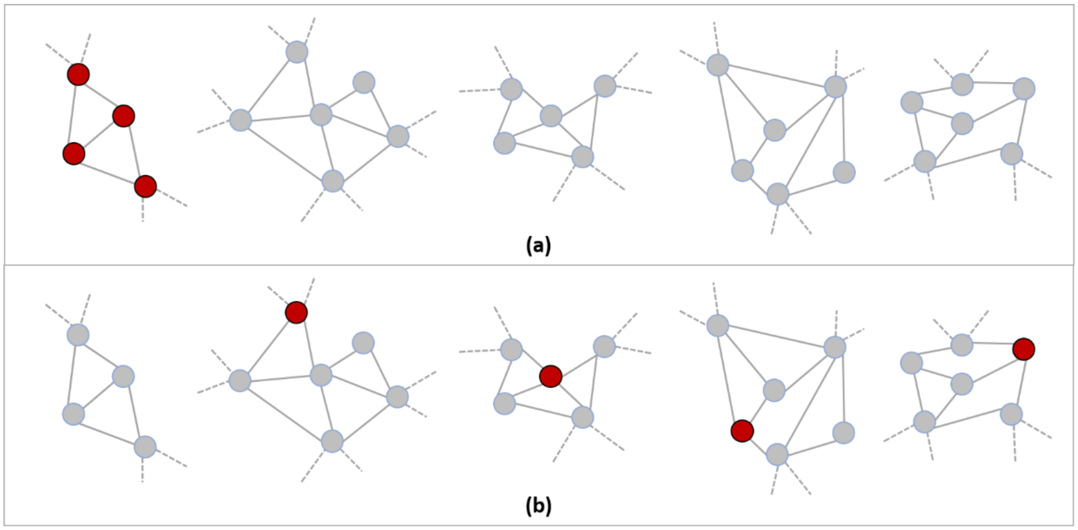


Figure 8 illustrates concentration of attention across network communities or cliques for the two policies. Red nodes receive increased attention (perturbed). Panel (a) illustrates the Attention Contagion Policy (ACP), where attention to red nodes (which constitute the perturbed set S_c^{ACP} for a given clique or community, c) is clustered within a community or clique. Panel (b) illustrates the Undirected Attention Policy (UAP), where attention is spread out randomly across communities or cliques in the network. To compare policies fairly, red nodes in panel (a) are matched one-to-one to red nodes in panel (b), (comprising the set $S_{m_c}^{UAP}$, as described in the text).

To compare these two policies, we first need to identify sets of well-connected articles in Wikipedia that appear in clickstream data and are good empirical proxies for underdeveloped articles. Importantly, many actual sets of related, underdeveloped articles will likely lack the linking structure that would naturally arise from directed editorial focus. That is to say, while these underdeveloped pages are related to one another, they do not *yet* possess the linking structure to connect them. To avoid making unnecessary and potentially ill-informed assumptions about unobserved network structure and its relationship to content, we instead focus only on actual links that appear in the clickstream data and that experienced actual traffic flow. To accomplish this, we use the weighted directed graph of traffic flow between articles and seek tightly connected sets of nodes in the form of both cliques and communities. To find cliques, we computed a large sample of maximal cliques via depth-first-search with Bron-Kerbosh style pruning (Tomita et al. 2006). To find communities, we modify the well-known label propagation algorithm (LBA) (Raghavan et al. 2007): to address the instability of the original LBA, we perform the algorithm 200 times and assign articles to the same community if and only if they were assigned to the same community in at least 95% of the runs. This approach produces stable, tightly connected communities with minimal noise. It is also efficient, fast and able to cope with networks of millions of nodes. We filter maximal cliques and communities and retain only those of small to moderate size ($2 \leq n \leq 6$). For each such clique or community, we match each article to another article in a different clique or community with the closest external incident traffic. This yielded a set of well-connected articles to perturb according to the *Attention Contagion Policy*, S_c^{ACP}, and a corresponding matched set of articles to be used in the *Undirected Attention Policy*, $S_{m_c}^{UAP}$, where c labels the clique or community and m_c labels the matched set. Note that the articles in S_c^{ACP} belong to the same clique or community (c), whereas articles in $S_{m_c}^{UAP}$ can belong to many different cliques or communities. Because testing large numbers of perturbations is computationally intense, we select a random subset of 600 cliques and communities and, for each clique or community, we simulate the perturbations for both policies and compare the distribution of excess attention $EA(S_c^{ACP}, p)$ to $EA(S_{m_c}^{UAP}, p)$. The results are displayed in figure 9 for cliques (panel a) and communities (panel b) for simulation with $p = 0.1$.

Figure 9

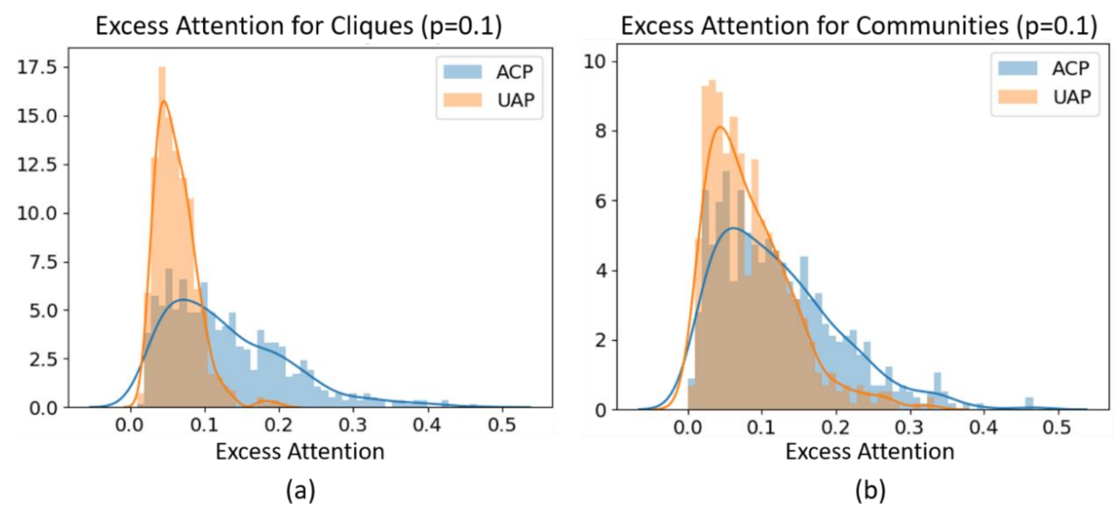


Figure 9 displays the distribution and kernel density estimates of Excess Attention for perturbative simulations (p=0.1) of the *Attention Contagion Policy* (ACP) and *Undirected Attention Policy* (UAP) for 600 cliques (a) and communities (b). The ACP policy leads to significantly more excess attention.

The *Attention Contagion Policy* clearly leads to significant excess attention directed towards underdeveloped pages as compared to the *Undirected Attention Policy*, yielding a relative increase of mean excess attention (ACP over UAP) of 106% for cliques and 44.2% for communities (p<1e-71 from two-sided t-test)[23]. Because editors may already cluster their editorial attention to some extent even without a guidance policy, our results should be interpreted as an upper bound to the value conveyed by the Attention Contagion Policy. Excess attention scales linearly with the size of the perturbation, which follows from the definition of excess attention and the expansion of the iterative perturbed PageRank equation. The shape of the distributions of excess attention for either policy is determined entirely from the network structure around the perturbation set, implying that the results are identical up to a scale factor (p) for different choices of perturbation size. Results are also robust to different random samples of cliques or communities (see Appendix for details).

5. Conclusion

Open collaborative platforms have fundamentally changed the way that knowledge is produced, disseminated and consumed in the digital era. This study directly contributes to our understanding of the interaction between production and consumption of information and the phenomenon of attention contagion on Wikipedia, arguably the largest and most successful example of such platforms. To conduct valid causal inference so that we can inform policy with high confidence, we employed a battery of methods including natural experiment, matching, econometric modeling, and empirically-informed simulation. We found that real-world exogenous contributions increase future attention by 12% on average with stronger impact for more significant contributions. They also increase future contribution by 3.6 more edits and 2 more unique editors to affected articles over a 6-month period. This impact is both economically significant and persists for a long time. In addition, we obtained causal estimates of the extent of spillover impact and identified characteristics of articles and links between them that receive the most benefit from spillovers. Specifically, we find that spillover is greatest across new links that point to less popular target articles, yielding an impact as high as 22% for new links from popular source articles to unpopular target articles and 15% for new links from less popular source articles to less popular target articles.

[23] Alternatively, two sample KS-tests reject the null hypothesis that the distributions are equal with $p<1e-63$

Overall, our results confirm the existence of positive feedback loops of production and consumption of information on Wikipedia. This, unfortunately, also implies that underdeveloped articles experience a poor-get-poorer phenomenon and are therefore naturally disadvantaged in the cumulative development process. This observation is deeply troubling because it suggests that impoverished regions in collaborative information systems will remain impoverished in the absence of policies that are specifically designed to address this problem. More importantly, because information poverty is often correlated with economic poverty (Forman et al. 2012, Graham et al. 2014, Norris 2001, Yu 2006), this phenomenon can act to exacerbate economic, social, political, and cultural inequalities. Fortunately, our findings suggest that less developed regions of information networks can benefit substantially from spillovers. We carry this insight further and propose and compare policies that drive editorial attention using diffusion simulations that are based on real-world traffic flows on Wikipedia. We evaluate the Attention Contagion Policy that leverages spillovers to stimulate development of impoverished regions. We find that this policy can yield up to a twofold increase in excess attention relative to the baseline Undirected Attention Policy. These results are directly relevant to concerns of information equity and have managerial implication for collaborative information platforms. Although we focus on Wikipedia, our findings are relevant to the uneven coverage problem that exists in many platforms that facilitate collaborative content production in domains such as open-source software creation (e.g., GitHub), knowledge markets (e.g., Stack Overflow or Quora), and product reviews (e.g., Amazon or Steam).

Our results suggest that two policies can be effective for encouraging the development of underdeveloped articles or impoverished regions in the information network. First, editors may be encouraged to identify popular articles that should naturally (semantically) link to a focal underdeveloped article. Our results show that creating such a link can harness the largest attention spillover (as much as 22%). Although care should be taken to ensure that added links are semantically meaningful. Second, and perhaps more importantly, Wikipedia should consider encouraging coherent development of impoverished regions. Our results show that underdeveloped regions, which typically lack both attention and the linking structure to connect related articles, are precisely positioned to benefit from attention contagion policies. Currently, the quality and importance of Wikipedia articles is assessed through a tagging system implemented on talk pages. Tools exist that use these metrics to allow editors to search for specific articles that are both important and in need of attention. Additional features could be added to these tools to encourage a coherent focus for individual editors or even groups of editors.

This work is not without limitations. This work tackles causality by leveraging a natural experiment, matching, econometric techniques and empirically-informed simulation. However, cleaner causal inference could be achieved in future work through controlled randomized experiments. As we examine attention spillover due to a second order shock to attention (that itself is driven by a contribution shock), we may miss subtle heterogeneous spillover effects. Future work could consider perturbations to link structure and real-world experimental tests of attention contagion policies. Furthermore, Wikipedia is subject to other natural experiments that may be discoverable. In particular, examination of clickstream data may permit the discovery of natural experiments that can help us better understand attention flow in information networks.

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Appendix
Data and Descriptive Statistics

Table A1: Distribution of Article Characteristics

Statistic	N	Min	Pctl(25)	Median	Pctl(75)	Max
Popularity	5,532	2	96	392	1,617	48,850
Size	5,532	19	3,678.8	8,788.5	22,122	147,469
Tenure	5,532	18	422.8	538	627	808
CharCount	2,766	501	1,331	3,180	7,292	159,912

Note: 1. We display the min, max and each 25 percentile values for popularity, size, and tenure which are all pre-shock article characteristics (in both treatment and matched control groups). Binary variables used in main analysis are binned by corresponding median values; 2. CharCount for control group is defined as zero and the distribution displayed above is only for articles in the treatment group.

Table A2: Distribution of Traffic Flow of Matched Articles in Clickstream Data

Statistic	N	Min	Pctl(25)	Median	Pctl(75)	Max
Inbound	2,034	14	251.2	869	2,329.8	53,088
Outbound	2,034	3	3	40	219.8	10,778
Link Count	2,034	0	1	3	7	149
Link Share	2,034	0.001	0.054	0.114	0.214	0.647

Note: We display the min, max and each 25 percentile values for Inbound traffic, Outbound traffic, Link Count (number of incoming links), and Link Share (the proportion of link traffic in the inbound traffic).

Table A3: Balance Checks for Clickstream Matching

	Inbound	Outbound	Link Count	Link Share
Control	1916	192	5.5	0.15
Treatment	1915	192	5.6	0.15
t-test (p-value)	0.99	0.99	0.78	0.99

Note: The table illustrates the quality of our matching procedure for clickstream data. “Inflow” and “Outflow” are traffic per month per article. “Link Count” is number of incoming links per article. “Link Share” is the proportion of link traffic in the total inflow traffic for each article. T-tests indicated that we cannot reject the null hypothesis that articles in treatment and control group have the same mean across all four characteristics.

Matching on Article Topics

The model-free plot in Figure 2 indicates that the control articles matched on pre-shock article characteristics closely mirror the treated articles in seasonality and natural time trends prior to the shock. This constitutes strong evidence that the controls serve as good counterfactuals for treated articles and capture what would have happened had they not received exogenous content contributions. Despite this, one may still have the concern that the topic distribution of treated and control groups may not be exactly the same. In this section, we reproduce our analysis with an alternative control sample that matches with treated articles on topics in addition to the other pre-shock article characteristics of popularity, size, and tenure. The results are qualitatively similar with only very small differences in magnitudes compared with the results presented in the main analysis of the paper, giving us strong confidence that our results are insensitive to matching procedure choices. The major challenge of topic matching is that each Wikipedia article is associated with multiple topics or categories and collectively the topic distribution of all treated articles resides in a high dimensional space. No traditional matching method is designed to deal with this problem. We adopt a novel two-step procedure to tackle this unconventional matching problem and ensure that we can match reasonably well on topics.

In the first step, we construct a pool of candidate control articles to use for matching through a random sampling procedure that leverages the "Category" information associated with each article. Each Wikipedia article has a set of "Category" labels added by its editors. Because category labels are user-defined, they are prone to errors and not subject to sanitization, e.g. very few articles have exactly the same set of labels and very few labels appear multiple times in a randomly selected set of articles. We adopt a strategy to leverage category information in our sampling procedure that avoids potential pitfalls. To do this, we randomly draw articles only from the categories to which our treated articles belong, where the number of draws from each category is proportional to the category frequency in the treated sample. This sampling procedure can achieve sample-level matching on categories but does not guarantee a direct correspondence between each individual control and treated article. For simplicity, we refer to this category-matched sample as "the control sample" in the remainder of this discussion.

In the second step, to better account for direct topic matching, we turn to the popular text-mining technique of Latent Dirichlet Allocation (LDA) topic modeling. Topic modeling is a frequently used machine learning tool for discovering hidden semantic structures in a corpus of text. We use LDA topic modeling to discover the latent topics from the text of each article in an unsupervised fashion and then match each treated article with a control article in the latent topic space. We train our topic model with the complete text of English Wikipedia (about 5.3 million articles and 15 GB) extracted from the October 2018 Wikipedia data dump. The number of topics is set to 100, though our method is robust to different choices. Manual inspection of word distribution of each topic indicates that our model captures coherent latent topics from the texts. Some example topics from our topic model are displayed in Figure A1. Next, we apply the topic model to treated and control articles to obtain their topic distribution in the latent topic space. Using this, we generate a tailored pool of candidate control articles C_i for each treated article T_i by searching for all articles in the control sample that are sufficiently similar on topic, according to the cosine similarity $\cos\left(\overrightarrow{Topic}[C_i], \overrightarrow{Topic}[T_i]\right) > 0.6$. We experimented with different cosine similarity thresholds and the results are robust to the choice of threshold; naturally, the size of the matched sample monotonically decreases with a stricter similarity requirement. Finally, we use Coarsen Exact Matching on the treated and topically similar control samples to further match on the other pre-shock article characteristics of popularity, size, and tenure. We opt for a k-to-k matching solution by choosing the closest matched control article in terms of Euclidean distance. The above procedure yields 2,747 pairs of matched treated and control articles. For each article, we construct a panel of weekly pageviews from 26 weeks before the shock to 26 weeks after (excluding the shock period itself). Our final sample consists of a balanced panel of 52 periods for 5,494 articles, or 285,688 observations at the article-week level. Finally, we redo our analysis of direct effect on this new sample -- the results are displayed in the table A4.

Figure A1: Some Example Topics

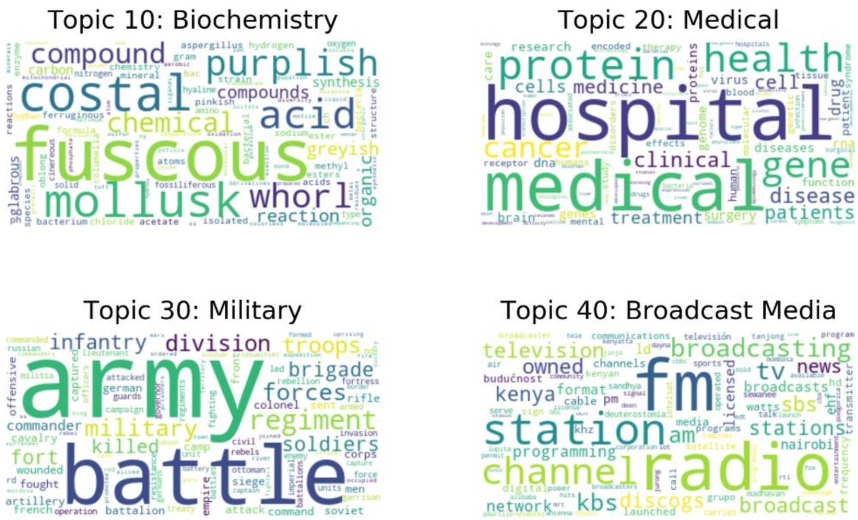


Table A4: Direct Effect with Matching on Topic

	Scaled pageviews		
	(1)	(2)	(3)
PostShock	0.106***		
	(0.016)		
PostShock*log(char count)		0.032***	0.060***
		(0.004)	(0.006)
PostShock*old article			-0.060**
			(0.024)
PostShock*popular article			-0.116***
			(0.024)
PostShock*long article			-0.030
			(0.025)
Article fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Observations	285,688	285,688	285,688
Adjusted R^2	0.172	0.172	0.174

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Matching on Network Characteristics

In this section, we replicated our analysis for direct effect of content contribution based on a sample that is matched on network characteristics. We note that the so-called curse of dimensionality affects every matching method - as the number of covariates over which we match grows, the chance of finding matches with similar values of all covariates rapidly goes to zero (King and Nielsen, 2019). Hence, we were very careful about selecting matching variables in the main analysis because adding variables to the matching procedure comes at a cost of lowering the chance of finding good matches and reducing the size of matched sample. We think the most important variable to match on is pre-popularity of an article as it conveys the information about how much attention an article receives prior to the treatment period and we want to compare the impact for treated and control articles that receive the similar amount baseline attention.

Some of the network characteristics, e.g. in-degree, incoming internal traffic, or incoming external traffic, carry information about how the attention arrives at an article, not the amount of attention arriving, which is already accounted for by pre-popularity. We therefore regarded these to be less relevant to the matching procedure and analysis. Still, matching on in-degree and in-traffic might be appropriate, as it allows us to compare treated articles to control articles that receive attention at the same proportion through channels both internal and external to Wikipedia. We would like to demonstrate that our results are also robust to matching based on network characteristics.

We conducted additional analysis and show that the results are very similar when we match on some of the network characteristics of the articles. We conducted Coarsened Exact Matching (CEM) on three network characteristics of an article, i.e. in-degree, average incoming external traffic, average incoming internal traffic. The matched sample consists of 2,058 treated articles and control article, respectively. We did a balance check and it shows that we cannot reject the null hypothesis that articles in treatment group and control group have the same mean values across number of incoming links, internal traffic from other pages in Wikipedia and external traffic (See Table A5). We replicated our analysis of direct effect with this new matched sample and the results are very similar as in the original (See Table A6). The original model, however, is preferable as: 1) we are matching on characteristics on which we evaluate heterogeneous treatment effects; and 2) pre-popularity is already a very good control for incoming traffic and in-degree.

Table A5: Balanced Check for Matched Sample of Network Characteristics

	Number of Incoming links	Internal traffic/month	External traffic/month
Control	7.20	447	2014
Treatment	7.20	446	2015
t-test (p-value)	0.96	0.90	0.96

Table A5 illustrates the quality of our matching procedure. It compares pre-shock network characteristics of articles in the matched groups. T-tests indicate that we cannot reject the null hypothesis that articles in treatment and control group have the same mean across all three network characteristics.

Table A6: Direct Effect with Matching on Network Characteristics

	Normalized pageviews		
	(1)	(2)	(3)
PostShock	0.118***		
	(0.015)		
PostShock*log(char count)		0.037***	0.068***
		(0.004)	(0.006)
PostShock*old article			-0.074***
			(0.026)
PostShock*popular article			-0.140***
			(0.027)
PostShock*long article			-0.023
			(0.024)
Article fixed effect	Yes	Yes	Yes
Week fixed effect	Yes	Yes	Yes
Observations	214,032	214,032	214,032
Adjusted R^2	0.138	0.139	0.141

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Checks of Modeling Assumptions for Multiplicative Interactions

Binning Estimates

The plots below serve as a diagnostic tool for two main modeling assumptions: common support and linear interaction effect. The distribution of the covariate presented at the bottom of each plot demonstrates that the assumption of common support, which is needed for a multiplicative interaction model, is satisfied. Moreover, the number of bins in the plot is two and equal-sized bins are created based on the distribution of each covariate. The plots confirm that using two bins to represent low/high values for the covariates is a reasonable choice. We provide a set of diagnostic statistics to further justify that choice in Table A7.

Figure A2

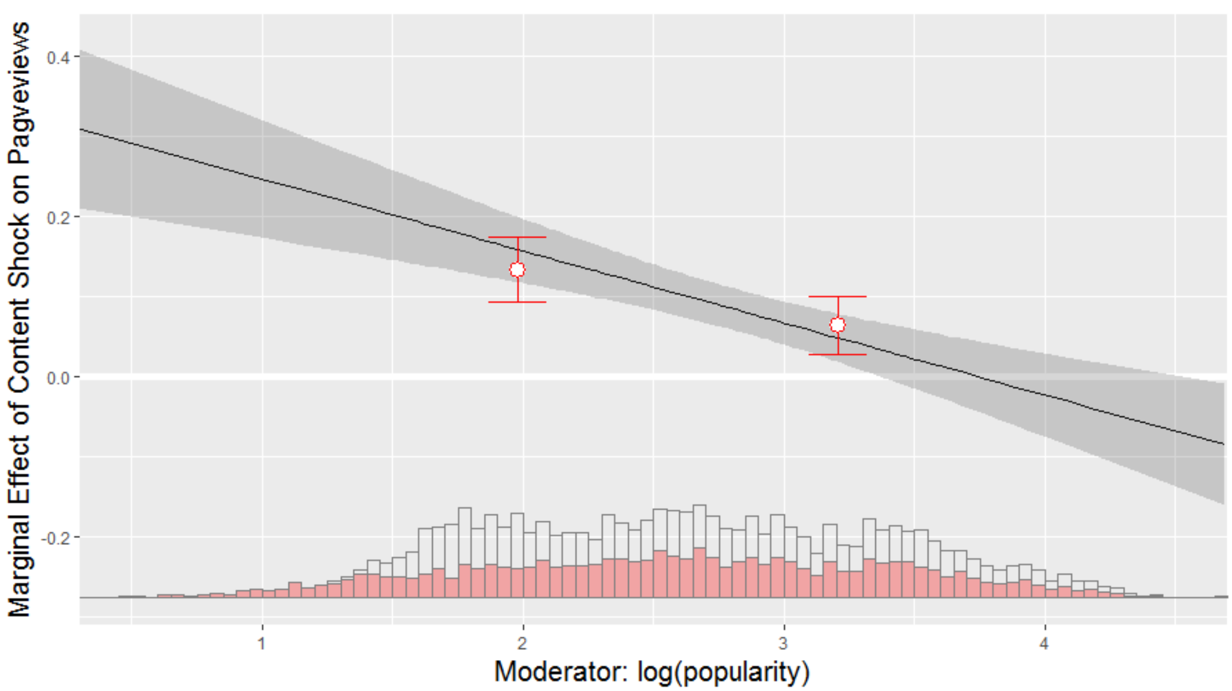


Figure A3

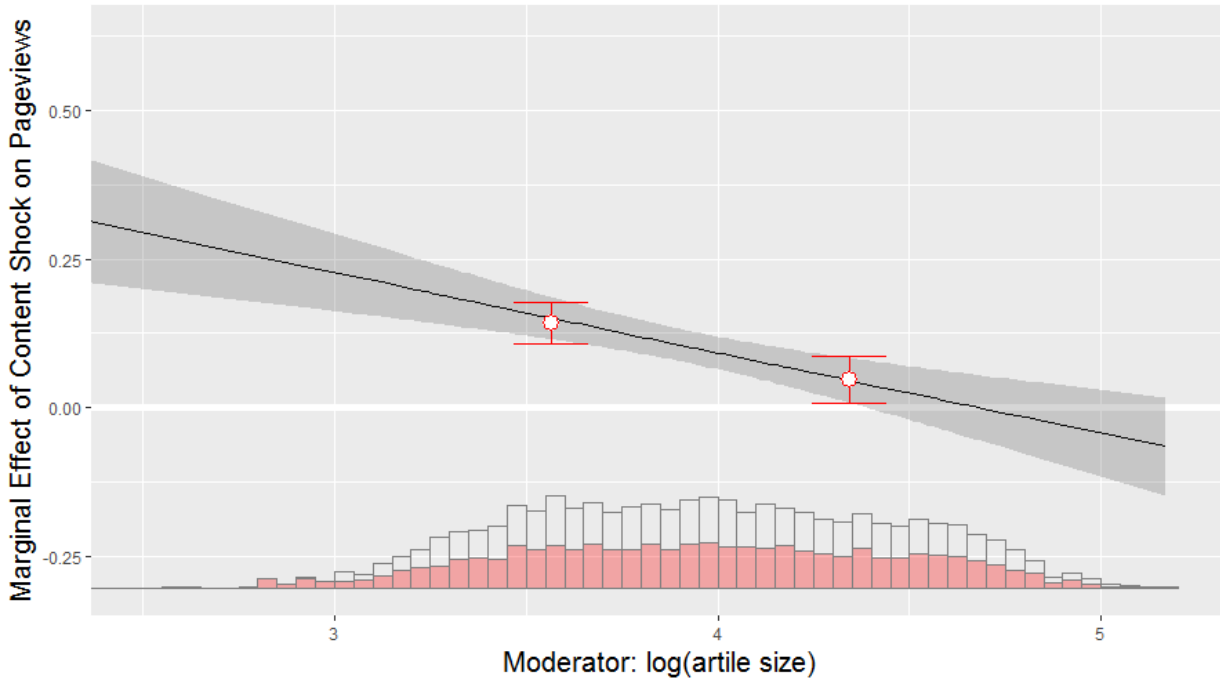


Figure A4

Table A7: Model Estimates and Test Statistics of Binning Estimators

	range	median	coef	se	CI_lower	CI_upper	t-test
log(popularity):high	[0.23, 2.59]	1.980	0.133	0.021	0.093	0.173	0.012
log(popularity):low	(2.59, 4.69]	3.209	0.064	0.019	0.027	0.099	
log(article size):high	[1.28, 3.94]	3.566	0.143	0.018	0.108	0.177	3e-04
log(article size):low	(3.94, 5.17]	4.345	0.048	0.020	0.009	0.087	
articlue tenure:high	[18,538]	424	0.109	0.021	0.068	0.149	0.09
articlue tenure:low	(538,808]	627	0.063	0.017	0.029	0.097	

Note: 1. The binning estimates for the three article characteristics correspond to the above three plots; 2. The column "t-test" displays the p-value of t-test for the two binning estimates.

Kernel Estimates

The kernel method produces non-linear marginal effects that are much more flexible and closer to the effects implied by the true data-generating process. The standard errors are produced by a non-parametric bootstrap. The below kernel plots show that covariates exhibit linear behavior over most of their range provide further evidence that our linear interaction model with two bins well approximates the more flexible models while also maintain good interpretability.

Figure A5

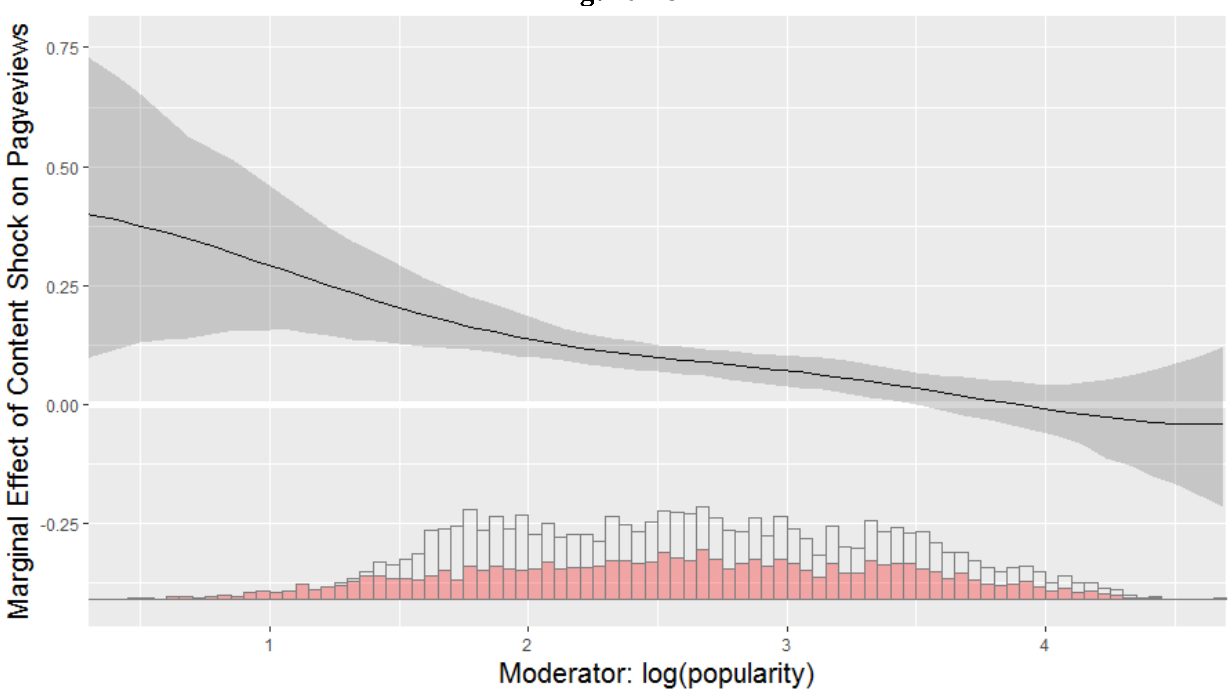


Figure A6

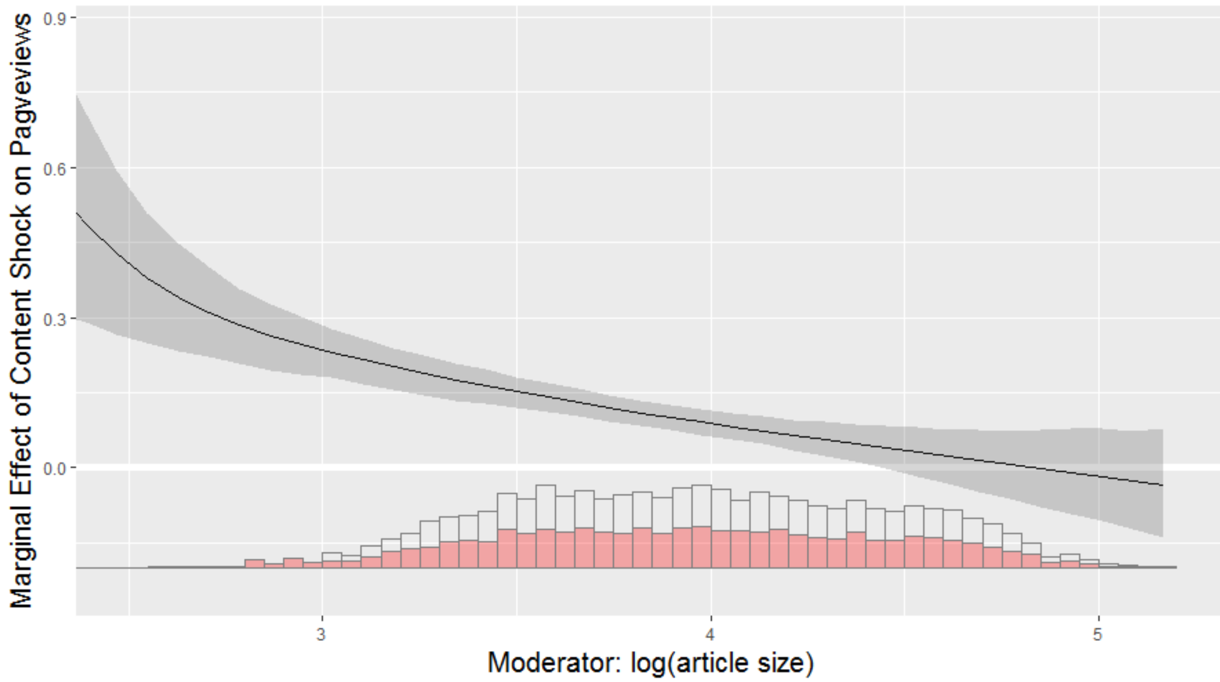
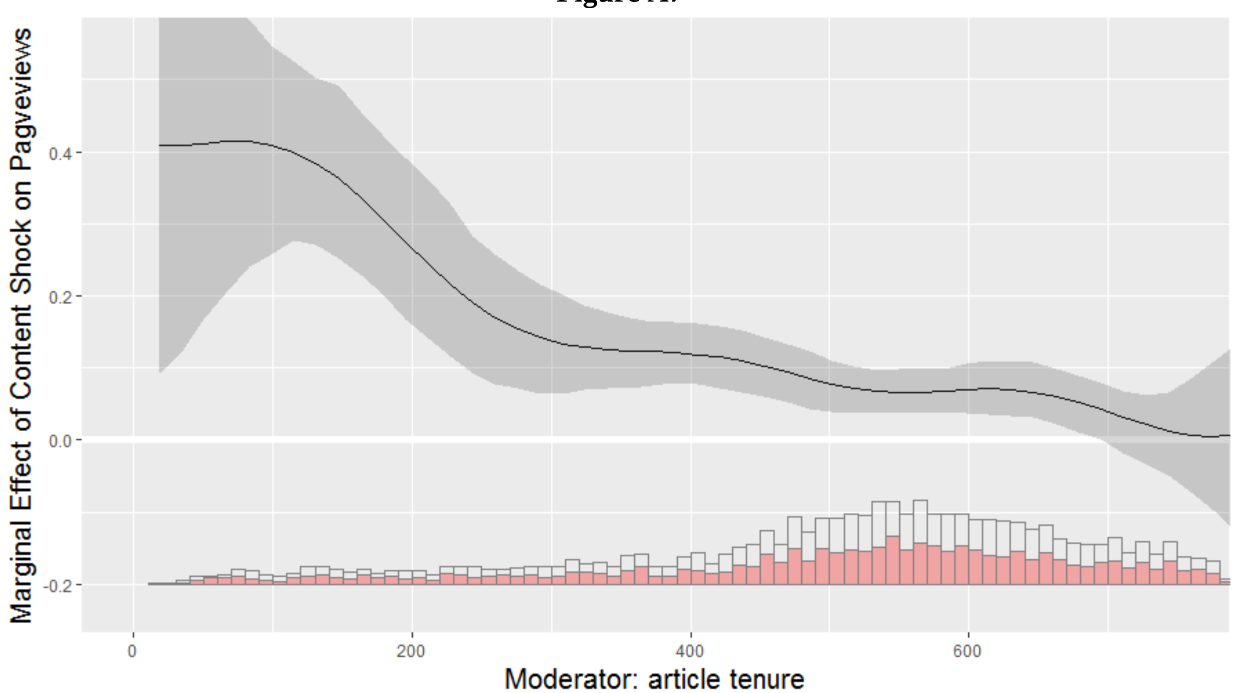


Figure A7



Checks of Model Specification

No Fixed Effect

Because they do not account for heterogeneity across articles, models without fixed effects tend to overestimate effect sizes. However, we find that they lead to qualitatively similar results. We provide the model estimates as robustness checks in Tables A8-A9.

Table A8: Direct impact of content shock -- No Fixed Effect

	Scaled pageviews		
	(1)	(2)	(3)
Post	0.062***	0.056***	0.062***
	(0.004)	(0.004)	(0.004)
Treated	0.000	-0.006	0.000
	(0.004)	(0.004)	(0.004)
PostShock	0.111***		
	(0.005)		
PostShock*log(charCount)		0.035***	0.062***
		(0.002)	(0.002)
PostShock*old article			-0.030***
			(0.006)
PostShock*popular article			-0.150***
			(0.007)
PostShock*long article			-0.010
			(0.006)
Article fixed effect	No	No	No
Week fixed effect	No	No	No
Observations	287,664	287,664	287,664
Adjusted R^2	0.009	0.010	0.013

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table A9: Spillover Effect – No Fixed Effects

	Scaled pageviews			
	(1)	(2)	(3)	(4)
Post	0.039***	0.039***	0.039***	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)
Treated	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
PostShock	0.008***	0.014***	-0.002	-0.002
	(0.001)	(0.002)	(0.002)	(0.003)
PostShock*popularTargetArticle		-0.015***	-0.022***	-0.005***
		(0.002)	(0.002)	(0.002)
PostShock*popularSourceArticle		-0.002	0.029***	0.014***
		(0.002)	(0.002)	(0.003)
PostShock*newLink			0.128***	0.143***
			(0.002)	(0.005)
PostShock*popularTargetArticle*newLink				-0.137***
				(0.005)
PostShock*popularSourceArticle*newLink				0.069***
				(0.005)
Article fixed effect	No	No	No	No
Week fixed effect	No	No	No	No
Observations	6,862,648	6,862,648	6,862,648	6,862,648
Adjusted R^2	0.001	0.001	0.001	0.001

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Spillover models with treatment intensity

Multiway interaction models require more restrictive modeling assumptions and are not easily interpretable. We did not incorporate the treatment intensity in our main spillover models for this reason. As a robustness check, we present the result for the spillover model that accounts for both treatment intensity and new link indicators. We did not estimate a model that simultaneously incorporates treatment intensity, new link indicators, and target and source popularity, as these would involve complex four-way interactions that are difficult to interpret. Estimates for this model are displayed in Table A10.

Table A10: Spillover Model with Treatment intensity

	Scaled pageviews		
	(1)	(2)	(3)
PostShock*log(charCount)	0.002***	0.008***	-0.002
	(0.001)	(0.002)	(0.002)
PostShock*log(charCount)*popularTargetArticle		-0.003**	
		(0.002)	
PostShock*log(charCount)*popularSourceArticle		-0.005***	
		(0.002)	
PostShock*log(charCount)*newLink			0.032***
			(0.004)
Article fixed effect	Yes	Yes	Yes
Week fixed effect	Yes	Yes	Yes
Observations	6,862,648	6,862,648	6,862,648
Adjusted R^2	0.104	0.104	0.104

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Poisson and Negative Binomial Regression for Editing Behavior

Editing behaviors (i.e. the number of total edits and number of unique editors) in a certain period (6 months) are counting processes. We show below that Poisson regression and Negative Binomial regression produce qualitatively similar results as the linear regression that we use in the main analysis.

Table A11: Number of Total Edits

	Number of Total Edits					
	Poisson Regression			Negative Binomial Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Postshock	0.278***			0.526***		
	(0.007)			(0.020)		
Postshock*log(charCount)		0.093***	0.240***		0.157***	0.191***
		(0.003)	(0.006)		(0.006)	(0.010)
Postshock*old article			0.105***			0.093**
			(0.020)			(0.046)
Postshock*long article			-0.454***			-0.290***
			(0.022)			(0.046)
Postshock*popular article			-0.292***			0.002
			(0.025)			(0.051)
Article Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,964	10,964	10,964	10,964	10,964	10,964
Log Likelihood	-43,202.5	-43,060.7	-42,497.8	-35,368.3	-35,326.3	-35,303.4

Notes:

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table A12: Number of Unique Editors

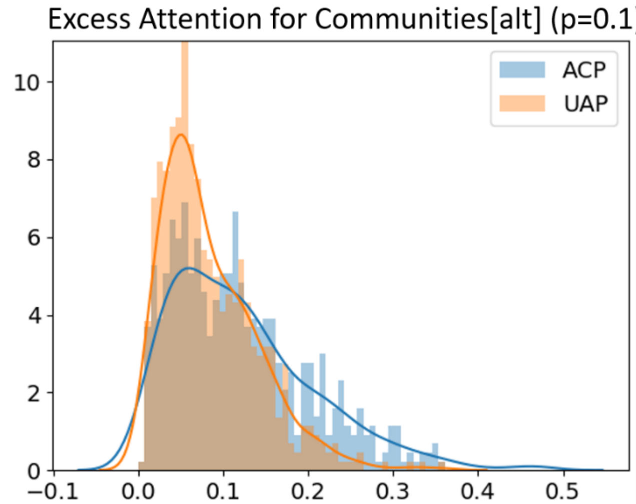
	Number of Unique Editors					
	Poisson Regression			Negative Binomial Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Postshock	0.290^{***}			0.411^{***}		
	(0.016)			(0.015)		
Postshock*log(charCount)		0.090^{***}	0.178^{***}		0.123^{***}	0.158^{***}
		(0.003)	(0.007)		(0.004)	(0.008)
Postshock*old article			0.059^{**}			0.087^{**}
			(0.026)			(0.034)
Postshock*long article			-0.301^{***}			-0.234^{***}
			(0.027)			(0.035)
Postshock*popular article			-0.142^{***}			-0.040
			(0.031)			(0.039)
Article Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,964	10,964	10,964	10,964	10,964	10,964
Log Likelihood	-30,997.0	-30,928.4	-30,789.9	-30,230.1	-30,184.3	-30,154.1

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Robustness of Simulation

The results on distribution of excess attention for the ACP and UAP policies are similar for different choices of cliques or communities. While we perturbed all 600 cliques that met our size criteria, there are significantly more communities that do so. We repeated the analysis for an alternate set of communities. Results are displayed in Figure A7 and are qualitatively similar to the main results. Differences in excess attention arise from differences in network structure, though ACP consistently captures more attention than UAP on average.

Figure A8



As described in the text, the shape of the distribution of excess attention is entirely a consequence of the network structure around the perturbation set, where the size of perturbation p acts as a simple scaling factor. This can be seen by iteratively expanding the PageRank equation and examining only the elements of the PageRank vector that correspond to the nodes of the perturbed set. For this set of nodes, p is a common factor which can be factored out. We verify that our distributions are consistent with this reasoning by examining two other choices perturbation size $p = 0.25, 0.5$ for the same set of chosen cliques or communities, as displayed in Figures A8, A9.

Figure A9

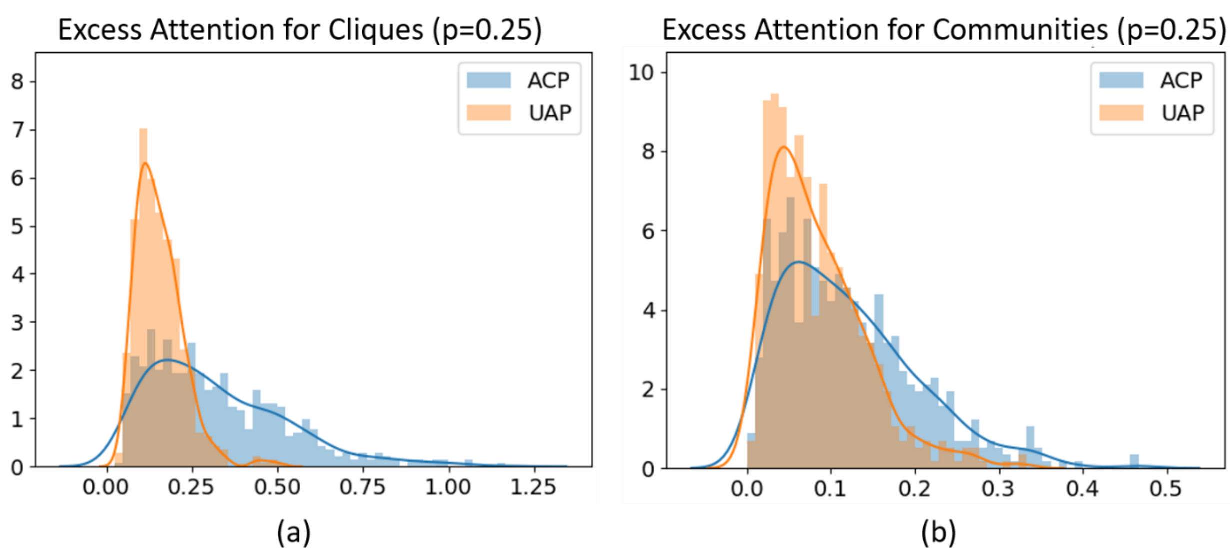
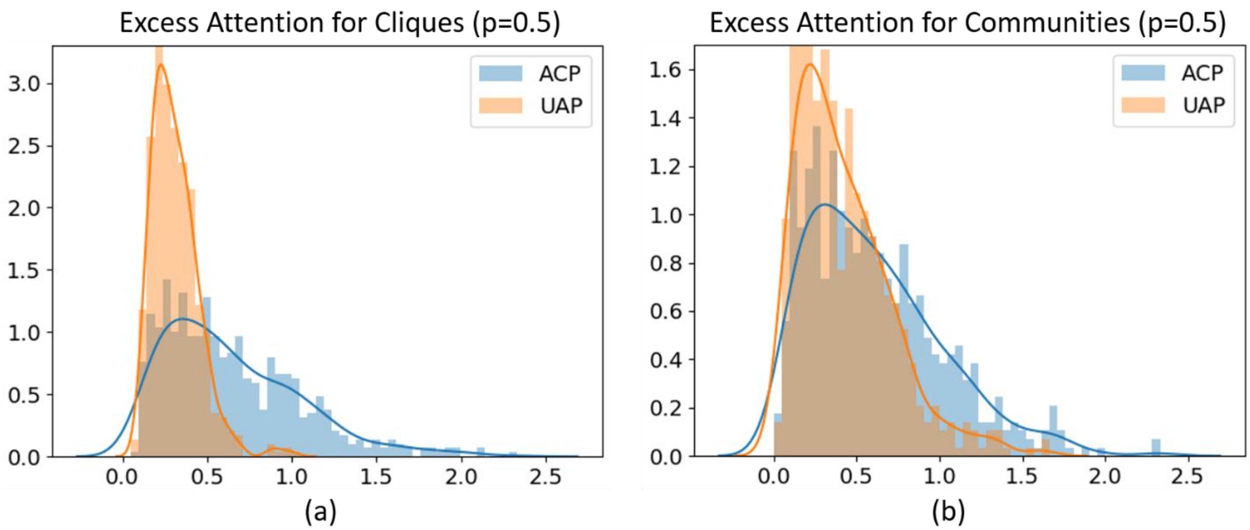


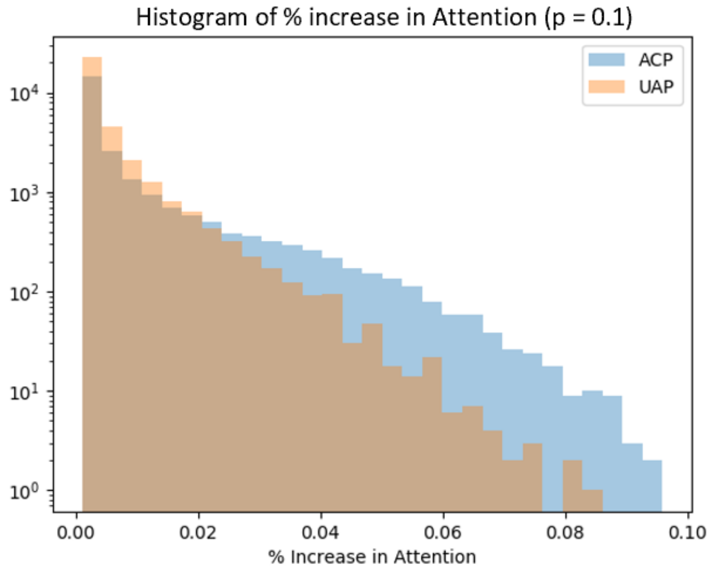
Figure A10



Excess Attention Conveyed by ACP vs UAP

The aim of the Attention Contagion Policy (ACP) is to bring attention to specific (underdeveloped) regions of the information network that could benefit from it the most. When editors cluster the focus of their editorial attention under ACP, spillovers compound, conveying excess attention locally. In contrast, the undirected - or essentially random – editorial focus of the Undirected Attention Policy (UAP) will convey excess attention more widely across the information network. In other words, UAP will convey significant excess attention to more unique articles overall. But, under ACP, more articles receive a larger share of excess attention. This is illustrated in Figure A11, which shows the distribution of percentage increase in attention across *all* articles under both policies. It is clear that ACP shifts the weight of the distribution to the right relative to UAP.

Figure A11


Histogram of % increase in Attention (p = 0.1)
ACP
UAP
10^4
10^3
10^2
10^1
10^0
0.00
0.02
0.04
0.06
0.08
0.10
% Increase in Attention