

# Spillovers in Networks of User Generated Content \*

- Evidence from 23 Natural Experiments on Wikipedia

Michael E. Kummer<sup>†</sup>

## Working Paper

June 1, 2014

### Abstract

How do networks generate externalities, such as spillovers or peer effects? Quantifying these externalities is challenging due to the endogeneity in network formation. I tackle this problem by exploiting local exogenous shocks on a small number of nodes in the network and investigate spillovers of attention on the German Wikipedia. I show how the link network between articles influences the attention that articles receive and how the additional attention is converted into content.

Exogenous variation is generated by natural and technical disasters or by articles being advertised on Wikipedia's start page. The effects on neighboring pages are substantial: They generate an increase in views of almost 100 percent and content generation is affected similarly. Aggregated over all neighbors, a view on a treated article converts one for one into a view on a neighboring article. My approach applies even if, absent network data, identification through partial overlaps in the network structure fails. It thus helps to bridge the gap between the experimental and social network literatures on peer effects.

**Keywords:** Social Media, Information, Knowledge, Spillovers, Networks, Natural Experiment

**JEL Classification Numbers:** L17, D62, D85, D29

---

\*I thank the selection committee of the IIIrd ICT Conference in Munich for awarding a very early version of this paper the 2nd Prize in the "Best PhD Paper Award." The author is grateful to the Wikimedia Foundation and Frédéric Schütz for access to the Wikipedia data. Thanks to Thorsten Doherr and Manfred Knobloch for support with data processing and to George Giorgidze for help with DSH. I benefitted from discussions with Irene Bertschek, Christoph Breunig, Luis Cabral, Jörg Claussen, Ulrike Cress, Habiba Djebbari, Neil Gandal, Avi Goldfarb, Sanjeev Goyal, Shane Greenstein, Thorsten Grohsjean, Maximilian Kasy, Francois Laisney, Jose Luis Moraga-Gonzalez, Kathy Nosal, Gal Oestreicher-Singer, Martin Peitz, Marianne Saam, Philipp Schmidt-Dengler, Olga Slivko, Yossi Spiegel, Joel Waldfogel, Michael Ward and Andrea Weber. The participants in several seminars at ZEW and U Mannheim, U Linz, U Kaiserslautern and WU Wien and of the 11<sup>th</sup> ICT-Conference (ZEW, Mannheim), the EARIE 2013 (Évora), the 11<sup>th</sup> conference of Media Economics (Tel Aviv) and the IIIrd ICTCM (Munich) provided valuable input. James Binfield, Timo Schäffer and Daniel Bergman provided outstanding research assistance. Financial support from the WissenschaftsCampus Tübingen is gratefully acknowledged.

<sup>†</sup>University of Mannheim and Centre for European Economic Research (ZEW); L7 1; 68181 Mannheim, Germany; Kummer@zew.de.

# 1 Introduction

Over the last decade, it was surprising to witness how large numbers of volunteers coordinated to produce Wikipedia. It is now the world’s most consulted reference for encyclopedic information, highlighting the potential of collaborative “peer production”.<sup>1</sup> The amount and quality of voluntary contributions to online public goods, such as Wikipedia or open source software, is of great economic interest: Leveraging this potential in other settings could be very beneficial to society, but requires understanding how exactly peer production works. In this paper I analyze spillovers of attention, transmitted through links in the German Wikipedia and how attention affects contribution effort.

How much attention can be channeled by links and how much of this attention is converted to action? These questions are key to understanding peer production and matter in other important contexts, such as public decision making or advertisement, where channeling attention is essential. However, they cannot easily be answered empirically, because most outcome variables of interest might themselves drive the network structure.<sup>2</sup> I circumvent this endogeneity problem by exploiting local exogenous shocks in the attention to single nodes in Wikipedia’s article network. The resulting attention spillovers to neighboring nodes generate exogenous variation to attention that is independent of the production process. As initial shocks I use natural and technical disasters or when a neighbor is advertised on Wikipedia’s start page for 24 hours. Both are shown to affect traffic and allow applying difference-in-differences to measure direct and indirect treatment effects. Moreover, I formally show how to relate these treatment effects to the structural parameter that measures attention spillovers.

Considering the network formed by Wikipedia’s articles (as nodes) and the hyperlinks between articles (as directed links), I obtain a dataset on 57 primary news and attention shocks, which contains daily information on views and content generation of almost 13,000 articles and more than 700,000 observations.<sup>3</sup> I document a large initial attention spillover, independent of whether the initial shock is generated by a disaster or by advertisement on the start page. I find that the initial increase of attention to neighboring pages of featured articles translates to substantial content generation (= editing activity). Views of neighbors doubled on average, and editing activity almost doubled.

---

<sup>1</sup>Its quality is sufficient to almost completely drive previous incumbents out of existence: Encyclopedia Britannica was the most prominent English encyclopedia and the “Brockhaus” dominated in Germany. Both have suffered considerable losses in sales and market share.

<sup>2</sup>In my case the outcomes of interest are attention (= clicks) and new edits, but the problem applies in general. Both processes, like supply and demand, may be driven by unobserved dynamics. The resulting methodological issues are a constant obstacle in a wide range of applications that try to measure peer effects or the role of social networks in generating externalities. Examples are interpersonal connections and the take up of micro-finance, or peer effects in schooling, aid programs or health interventions.

<sup>3</sup>23 large-scale media events such as natural disasters and 34 articles that were advertised on Wikipedia’s main page for 24 hours, and all their respective network neighbors. The information was obtained 14 days before and after the events. Details are provided in Section 4 and Appendix 4.1.

Furthermore, the number of authors increased, indicating that new authors contributed.

Distinguishing articles by their length I find that the spillovers of attention do not depend on the length of the link's target, whereas content generation *does*. Like the average article, short articles were visited 35 times more, on average, but these additional visits resulted in substantially fewer new edits and a smaller increase in length than in the full sample. In short, citation links matter for the attention that nodes receive, but much less for the content that is generated on such nodes. This may be justified given the maturity the German Wikipedia had reached by 2007.

To relate the measured effects to the structural spillover parameter, I extend a standard model of peer effects by Bramoullé et al. (2009) to allow for the incorporation of local exogenous shocks. I show how the spillover parameter can be uncovered in two steps: (i) by applying a difference-in-differences strategy to obtain estimates for the indirect treatment effect (as in Kuhn et al. (2011)) and (ii) by discounting for higher order spillovers in the network. I also show that bounds can be derived if the network information cannot be used to account for higher order spillovers. This illustrates why the estimation strategy is robust to both endogenous network formation and Manski's (1993) reflection problem. The resulting model provides a notation to nest approaches for identifying social effects that are based on exploiting exogenous (pseudo-) experimental variation<sup>4</sup> into a framework which considers network structure. I apply these techniques to my data and obtain an interval estimator for the structural spillover parameter of interest. I find that an average increase of ten views on the neighboring pages results in an increase of 2.22 to 2.92 views on the page in the center. These bounds are computed using extreme (benchmark) assumptions on the network, and can be computed even when no information on the link structure is available. My method for deriving these bounds is an additional contribution to the literature.

My findings allow for a more abstract reading. The hyperlink network between articles can be interpreted as a citation network and Wikipedia as a peer production tool for the documentation of human knowledge. Consequently the relevance of my findings extends to other settings of peer production including open source software or scientific research. While it is true that my strategy requires a lot from the data<sup>5</sup>, recent advances in data handling techniques and the increasing availability of data on social interactions will provide further applications for this strategy.

In the next section (2) I discuss the relevant literature and this paper's contributions. The methodological approach is discussed in Section 3, which extends the linear peer

---

<sup>4</sup>Partial population treatments (Moffitt (2001)) or impact evaluation studies based on a two-stage randomization over sub-populations (villages) and then individuals inside sub-populations.

<sup>5</sup>Exogenous treatments of individuals in networks (or groups) could rarely be observed in previous studies. Researchers often have the network structure and no exogenous source of identification, or exogenous variation yet no information on the network structure. However, such data are increasingly available from field experiments or online sources.

effects model and describes identification through local treatments in networks. Detailed derivations of the estimator and the bounds are in Appendix C. Section 4 discusses the data collection and the relevant variables. The empirical results and how to relate my reduced form estimates to the structural model are described in Section 5. Limitations and avenues for further research are offered in Section 6 and Section 7 concludes. The appendices contains summary statistics, robustness checks, additional figures and a discussion of why network neighbors should not react to their neighbor's treatment.

## 2 Literature

Coase's (1937) insight that production should either be organized in a free market if market frictions are low, or in a firm if they are high, was fundamentally challenged by the success of Open Source Software production and Wikipedia. The new coordinating principle, by which large numbers of people distribute small modules of the total workload via the web is referred to as commons-based peer production (Benkler 2002 and 2006). The extraordinary past achievements of this production mode illustrate the deep impact its emergence might have on the economic process and even society as a whole. This paper contributes to the literature in several ways. First, I document the role of the network for spillovers of attention and for content production in a relevant setting of peer production - the German Wikipedia. Second, I measure attention spillovers and quantify how attention is converted into action (contributing content). Finally, I analyze the heterogeneities in the spillovers in the network. In what follows, I discuss the streams of the literature that each of these contributions add to.

By analyzing the role of the network for content production in Wikipedia, I add to previous research, which has analyzed the correlation between a node's position in a network and the outcomes of interest (Fershtman and Gandal (2011), Claussen et al. (2012) or Kummer et al. (2012)). Economists have asked how social networks influence economic real world outcomes for (at least) two reasons: First, it is important to understand how a network's structure affects individuals' outcomes and to quantify the resulting overall value of a network and its links. Second, it matters whether the outcome of our connections or peers influences us, be it positively or negatively. My paper quantifies the causal effect of the average attention of a focal articles's neighbors on the attention of the focal article. Previous research has struggled with the following empirical problems: The outcome variable might itself drive network position, thus giving rise to the classic endogeneity problem. Moreover, the reflection problem laid out by Manski (1993) applies, since nodes influence each other like peers (Bramoullé et al. (2009)). This paper circumvents both problems by exploiting local exogenous treatments of single nodes in Wikipedia's article network.

A second contribution to the literature is the econometric approach to quantifying

attention spillovers between Wikipedia articles. My formal framework combines existing approaches and extends it in a novel way. I analyze treatments of neighbors *in a network*, but instead of focusing on the effect of treatment I focus on the *spillovers* of these treatments and use them as sources of exogenous variation in the *attention* to such articles. Moreover, I use the fact that exogenous treatment sometimes affects only a single node. Such local treatments are analogous to the Partial Population Treatment that Moffitt (2001) suggested for the analysis of peer effects - not in the context of network analysis - to solve the reflection problem Manski (1993).<sup>6</sup> There is also a close relationship to studies that added a higher layer of randomization, which allows the computation of *indirect* treatment effects.<sup>7</sup> An example is Crépon et al. (2013), who randomize over cities and vary the treatment intensity to study whether labor market programs have a negative impact on the non-eligible. Studies that use exogenous local shocks to single individuals could be called “Mini Population Treatments” and this idea is used increasingly often in recent studies that use network information (Aral and Walker (2011), Banerjee et al. (2012), Carmi et al. (2012)).

Following the analysis of attention spillovers, I analyze how attention translates into action. I find a conversion rate of 1000 clicks for 1 edit. These findings highlight the need of adding an important extra ingredient to modularity and strong leadership (Benkler and Nissenbaum (2006), Lerner and Tirole (2002)), to guarantee the success of peer production: If the individuals contribute infrequently, a high overall frequency of visits is necessary. This reaffirms the potential of ICTs to enable peer production through their ability to drastically reduce coordination costs. To guarantee that the content production is exclusively due to attention, I exploit sudden exogenous spikes in the attention to a neighbor, which affect not only the shocked nodes in a network, but are also transmitted across links (Carmi et al. (2012)). Such spikes are generated by large-scale events like natural disasters and accidents or the advertisement of featured articles on Wikipedia’s start page. Little is known about how attention influences the decision to contribute to a public good. Several papers show that attention through blogs or reviews, even negative, can be positively related to purchase and investment decisions (Barber and Odean (2008), Berger et al. (2010), Hu et al. (2013)). However, it is typically impossible to measure the amount of attention generated by the publicity and how it is converted to action.<sup>8</sup>

---

<sup>6</sup>Dahl et al. (2012) provide an example of such an experiment. An alternative approach is to exogenously vary the composition of peer groups: Zhang and Zhu (2011) uses the fact almost all Chinese Wikipedia users in mainland China were blocked by the government’s “Chinese fire wall”, to measure the effect on the incentives to contribute. Also disasters or fatal accidents are frequently used in similar settings. (Sacerdote (2001), Imberman et al. (2009)), Ashenfelter and Greenstone (2004)). Keegan et al. (2013), who analyze the structure and dynamics of Wikipedia’s coverage of breaking news events.

<sup>7</sup>When social effects or spillovers are present, a violation of Stable Unit Treatment Value Assumption (SUTVA) compromises the validity of the control group (Ferracci et al. (2012)). Depending on the application, a second layer (classrooms, villages, districts etc.) can remedy the issue. (Miguel and Kremer (2003), Angelucci and De Giorgi (2009), Kuhn et al. (2011) and many more).

<sup>8</sup>Altruism and social image concerns are important drivers of voluntary provision (non-monetary)

The last contribution of this paper consists of analyzing whether attention spill uniformly or whether there are large heterogeneities. I analyze the drivers of the attention spillovers and subsequent content generation. Only a few papers study what determines whether spillovers take place or not. Carmi et al. (2012) pioneering analysis finds that the network structure does well in predicting spillovers on Amazon’s recommendation network, but their findings are challenged by the fact that spillovers are also an important driver of Amazon’s algorithm that places and sorts the links.<sup>9</sup> I distinguish articles by their length, by how they are generally linked, and by how closely they are linked to the shocked articles. Concerning drivers of individual attention to an item, only few studies have analyzed which items receive collective attention. (Hoffman and Ocasio (2001), Wu and Huberman (2007)).<sup>10</sup> I contribute by analyzing what users choose, when presented with several options for a click and the subsequent conversion of awareness to making a voluntary (non-monetary) contribution to a public good.

In conclusion, this paper provides new insights into the dynamics of user activity in the world’s largest knowledge repository, measures how users allocate their attention, and how these effects are mediated by node characteristics. It shows how treatments diffuse across networks if the content items are linked and how attention is converted into contributions of effort. To the best of my knowledge my results are the first to show how a citation network influences users’ contributions through channeling attention.

### 3 The Empirical Model

In this section I discuss the empirical model. I first give a basic and informal intuition of my estimation approach (Subsection 3.1). Next I discuss the assumptions made to identify the effect of the exogenous treatments I use (Subsection 3.2) and the reduced form estimation of the regressions (Subsection 3.3). The last and most extensive subsection (3.4) describes the extended linear peer effects model: I discuss how and under which assumptions the researcher can identify the structural parameter that measures spillovers from the reduced form estimates if she observes the network information. In the same section I also show how to compute an upper and a lower bound for the coefficient when the network information is not available. An important case where my arguments do

---

of a public good in offline contexts (Carpenter and Myers (2010)). Social effects and attention to the individual contribution also matter in peer productivity (Shang and Croson (2009), Huberman et al. (2009)). Yet, studies that precisely quantify how attention converts to contributions and that disentangle this effect from the other relevant drivers of contributions are rare.

<sup>9</sup>Carmi et al. (2012) analyze the effect of the external shocks of recommendations by Oprah Winfrey on the product network of books on Amazon. They find that a recommendation not only triggers a spike in sales of the recommended book but also of books adjacent in Amazon’s recommendation network.

<sup>10</sup>Viral Marketing studies are concerned with the diffusion of information in a social network, i.e. mediated by social propagation, rather than repeated individual decisions.(e.g. Aral and Walker (2011), Ho and Dempsey (2010), Hinz et al. (2011))

not apply are situations where the neighbors of the treated nodes/individuals observe the treatment and adjust their outcome as a reaction.<sup>11</sup> Appendix D shows, how the model would have to be extended to include such a possibility and which challenges to identification of the spillover parameter would emerge as a result.

### 3.1 Basic Intuition - Throwing Stones into a Pond

This subsection provides an intuitive explanation of the data structure and the estimation approach. The basic idea of the research approach can be imagined as “throwing stones into a pond and tracing out the ripples”. The design of this paper uses the fact that certain nodes were affected by a large increase of attention, that this was exogenous, and that ex-post it is known to the researcher when exactly the pseudo-experiment occurred. Moreover, since the link structure is also known, it is possible to observe what happens to the directly or indirectly neighboring nodes. As in a pond, we would expect the largest effect on the directly hit node and a decreasing amount of additional attention the further away an article is from the epicenter.

The schematic representation in Figure 1 shows how the data is structured. Wikipedia articles are the nodes of the network. They are represented by a circle with a letter inside. Each circle represents a different article in the German Wikipedia. Articles are connected to each other via links, which are visible on Wikipedia as highlighted blue text. Clicking on such text forwards the reader to the next article and these links form the edges of my directed network. Such links are represented by a line between two nodes. An important aspect of my identification strategy requires the observation of two disconnected subnetworks at the same time. This is represented by network  $L$  and network  $C$  shown facing each other. I maintain this notation in all derivations that follow.

I focus on subnetworks around a start node. These start nodes are denoted by subscript 0. Hence, the start node of the two networks are denoted by  $\ell 0$  and  $c0$ . Consider “today’s featured articles” for a moment: start nodes  $\ell 0$  and  $c0$  could both be featured articles, so both are eligible for treatment. However, only one of them can be selected to become “today’s featured article” on any given day. The nodes that receive a direct link from a start node (direct neighbors) in network  $L$  form the set of direct neighbors  $L_1$  and a focal node from that set is sometimes denoted as  $\ell 1$ .<sup>12</sup> The set of indirect neighbors<sup>13</sup> in the network  $L$  forms  $L_2$  and so on. Analogously the set  $C_1$  is the direct neighbors of the start node in network  $C$ , and  $C_2$  is the indirect neighbors of node  $c0$ .

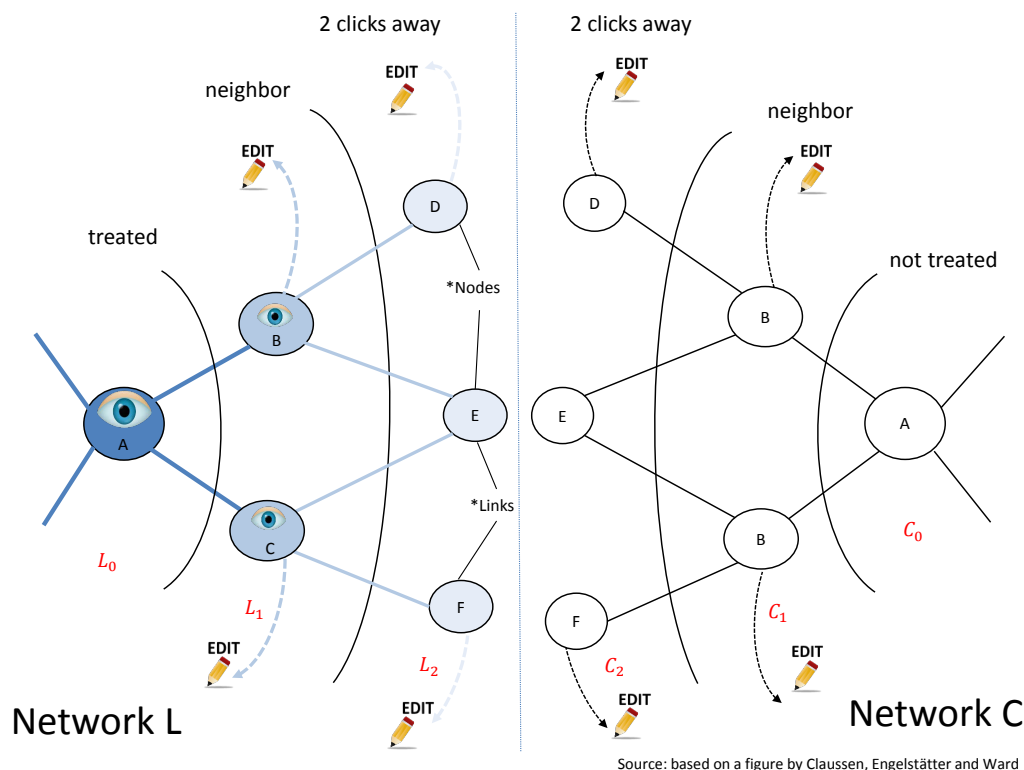
In a typical network in which the outcome of the individual nodes depends on the outcome of their neighbors we would observe many correlations and cross influences.

<sup>11</sup>E.g. classmates, that react with protest to an unfair punishment of their peer.

<sup>12</sup>While the set  $L_0$  consists only of one node ( $L_0 = \{\ell 0\}$ ), set  $L_1$  consists of multiple nodes.

<sup>13</sup>Indirect neighbors are defined as receiving at least one link from a node in set  $L_1$  without themselves being in  $L_1$ . Hence the shortest path from the start node to an indirect neighbor is via two clicks.

Figure 1: Schematic representation of a local treatment, which affects only one of the two subnetworks and there only a single node directly.



NOTES: The figure illustrates the structure of the data. Wikipedia articles are the nodes of the network. Each circle with a letter inside represents a different article in the German Wikipedia. The eye icons represent attention, while the pencil illustrate a decision to contribute an edit. Articles are connected to each other via links, which are represented as lines. The design of this paper uses the fact that certain nodes were affected by a large and exogenous increase of attention, and that it is known to the researcher when the pseudo-experiment occurred. In this setting this is represented by the two subnetworks L and C. Both, nodes in  $L_0$  and  $C_0$ , could be hit by a disaster (or are featured articles). Hence they are eligible for treatment. Yet, only one is actually hit (or becomes “today’s featured article”) at any given day. The coloring illustrates the effect of such a large local shock on Wikipedia, which affects only subnetwork L. The shocked node is colored in dark blue, the direct neighbors are colored in light blue and so on. If we observe a valid second network from which it is possible to infer what the outcomes would have been if no treatment had taken place, we can use these outcomes for comparing the size of the outcomes layer by layer. In general the network may be directed or undirected (Wikipedia articles are directed). The figure draws on a representation in a working paper on network formation by Claussen, Engelstaetter and Ward.

However, it would be difficult to discern where they originate from or whether they are due to underlying and unobserved background factors which merely affect the nodes in similar ways. The coloring in Figure 1 illustrates the mechanism of local exogenous shocks (“the stone in a pond”). The shocked node is colored in dark blue, the direct neighbors are colored in light blue and so on. As I will show formally in the next sections, identification of the spillover hinges on the ability to observe a valid counterfactual from which to infer what the outcomes would have been if no treatment had taken place. If this is possible, we can compare the outcomes layer by layer. More information about how the layers are identified and obtained is provided in Section 4.



## 3.2 Identifying Assumptions for the Treatment Effects

The spillover parameter will be evaluated by estimating difference-in-differences for each layer separately. To clarify the assumptions in the reduced form estimation by layer, I use the control-treatment notation from the impact evaluation literature (cf. Angrist and Pischke (2008)). First, this highlights similarities to the Partial Population Treatment (cf. Moffitt (2001)). Second, it aids the understanding of the assumptions made here. Terminology and notation are inspired by Kuhn et al. (2011).<sup>14</sup>

**Direct Effect of Treatment:** Consider a node in network  $i \in \{\ell, c\}$  in period  $t$ . The direct treatment effect measures the effect of treatment on the treated. We would like to compare the observed outcome after treatment to the unobservable outcome of the same individual if we had not treated them.

$$(1) \quad \mathbf{E}[y_{\ell 0,t}^1 | d_{\ell 0,t} = 1] - \mathbf{E}[y_{\ell 0,t}^0 | d_{\ell 0,t} = 1]$$

$\ell$  denotes the subnetwork which is treated in period  $t$  and  $c$  the subnetwork that is not.  $d_{i,t}$  indicates if node  $i$  itself was directly treated. Superscript 1 denotes the outcome of a treated observation and 0 the outcome of the untreated counterpart.  $\mathbf{E}[y_{\ell 0,t}^0 | d_{\ell 0,t} = 1]$  is the unobservable counterfactual.

We estimate this counterfactual term using a comparable node<sup>15</sup> in a period where it is not treated. I take two approaches to obtain such an estimate: (i) a simple approach compares the observation “before and after” the treatment. It attributes all observed changes in outcomes to the treatment.<sup>16</sup>

**Assumption Direct Treatment Effect before-after:**

$$(2) \quad \mathbf{E}[y_{\ell 0,t}^0 | d_{\ell 0,t} = 1] = \mathbf{E}[y_{\ell 0,t-1}^0 | d_{\ell 0,t-1} = 0]$$

The “before and after” counterfactual estimate maximizes the similarity between the treated and untreated observations. However, it will fail to capture any period-specific effects that would have affected all nodes even absent treatment. Any weekday fluctuations, shocks etc. will be attributed to the treatment. (ii) Alternatively, “difference-in-differences” uses individuals in the same populations, which were not eligible for treatment, or here, eligible individuals in untreated subpopulations. The unobservable counterfactual outcomes of the treated nodes are assumed to be the treated nodes’ pre-treatment outcome *plus* the *change* of the non-treated control observation.

<sup>14</sup>Readers who know the estimation of direct and indirect treatment effects might wish to merely browse the formulas or skip this subsection. The identifying assumption will be: Absent treatment, the control observations have a similar rate of change across time to the treated subnetworks. They must grow at similar rates and be affected similarly by any Wikipedia wide dynamics such as weekdays etc.

<sup>15</sup>A node, which is believed to be affected by treatment in similar ways.

<sup>16</sup>If the object/individual was observed more than once before treatment it might be possible to further improve this approach by accounting for trends in the outcomes etc.

**Assumption Direct Treatment Effect-DiD:**

$$(3) \quad \mathbf{E}[y_{\ell 0,t}^0 | d_{\ell 0,t} = 1] = \mathbf{E}[y_{\ell 0,t-1}^0 | d_{\ell 0,t-1} = 0] + \\ + \{ \mathbf{E}[y_{c 0,t}^0 | d_{c 0,t} = 0] - \mathbf{E}[y_{c 0,t-1}^0 | d_{c 0,t-1} = 0] \}$$

Note that in the context of Wikipedia articles, the crucial assumption is not that articles *are* very similar but that they *evolve* in a similar way. On average they have similar growth in readership and edits and are subject to similar intertemporal fluctuations.

**Indirect Treatment Effects:** The *ITE* measures the spillover or externality effect of treatment of eligibles on the outcomes of non-eligibles. As for the direct treatment effect, we cannot observe the outcome of the non-eligibles had the eligibles not been treated. Knowing the distance to the treatment’s epicenter, I can compare the nodes of the subnetworks by layer.  $ITE_1$  refers to the effect on direct neighbors,  $ITE_2$  for indirect neighbors and so on.<sup>17</sup> My dataset requires even more involved notation because I differentiate nodes along four dimensions (treatment, time, distance and subnetwork). I use  $D_{xr,t}$  as shorthand that takes the value 1 if both of the following conditions are simultaneously satisfied: (i) subnetwork  $x$  was treated and (ii) there exists a treated node exactly  $r$  steps away by the shortest route. For direct neighbors we have:

$$(4) \quad ITE_1 = \mathbf{E}[y_{\ell 1,t}^1 | D_{\ell 1,t}^1, d_{i,t}^0] - \mathbf{E}[y_{\ell 1,t}^0 | D_{\ell 1,t}^1, d_{i,t}^0]$$

As before,  $d_{i,t}^1$  indicates if node  $i$  was directly treated in period  $t$ .<sup>18</sup>  $y_{\ell r,t}^1$  is now the outcome if *some neighbor* in  $D_{xr}$  was treated in  $t$ , and  $y_{\ell r,t}^0$  denotes the outcome if nobody in that set was treated.

The object of interest is the  $ITE_r$ , Generally, for any range  $r$ :

$$(5) \quad ITE_r = \mathbf{E}[y_{\ell r,t}^1 | D_{\ell r,t}^1, d_{i,t}^0] - \mathbf{E}[y_{\ell r,t}^0 | D_{\ell r,t}^1, d_{i,t}^0]$$

As in the direct treatment effect, I have to estimate the counterfactual outcome using two methods: (i) a “before and after” comparison (ii) a difference-in-differences between neighbors in the comparison subnetwork.

**Assumption  $ITE_r$ -before-after:**

$$(6) \quad \mathbf{E}[y_{\ell r,t}^0 | D_{\ell r,t}^1, d_{i,t}^0] = \mathbf{E}[y_{\ell r,t-1}^0 | D_{\ell r,t-1}^0, d_{i,t-1}^0]$$

---

<sup>17</sup>Well known papers that estimate  $ITE_1$ s are Angelucci and De Giorgi (2009), Kuhn et al. (2011) or Crépon et al. (2013), to name a few. Miguel and Kremer (2003) include distance layers in the estimation to incorporate a similar notion of distance to treatment in a real world setup.

<sup>18</sup>To save space treatment status is indicated by superscripts,  $d_{i,t}^0$  otherwise. Notation has to be more involved here, because it is no longer possible to talk of a single node, as the treated nodes can have many different neighbors.

Estimating an  $ITE_r$  from a “before and after” estimation has the same advantages and drawbacks as the direct treatment effect. Analogously, the drawbacks can be accounted for by computing a difference-in-differences estimator. In the context of an  $ITE$ , we need to observe comparable, but untreated, subpopulations.<sup>19</sup>

**Assumption  $ITE_r$ -DiD:**

$$(7) \quad \mathbf{E}[y_{\ell_r,t}^0 | D_{\ell_r,t}^1, d_{i,t}^0] = \mathbf{E}[y_{\ell_r,t-1}^0 | D_{\ell_r,t-1}^0, d_{i,t-1}^0] + \\ + \{ \mathbf{E}[y_{cr,t}^0 | D_{cr,t}^0, d_{i,t}^0] - \mathbf{E}[y_{cr,t-1}^0 | D_{cr,t-1}^0, d_{i,t-1}^0] \}$$

The counterfactual is estimated by last period’s value *plus* the comparison group’s rate of change. The same assumptions apply as for the direct treatment effect difference-in-differences. Before moving on to the econometric specification, I conclude this section by summarizing the identification result in terms of the difference-in-differences estimator:

**Conclusion  $ITE_r$  DiD:** If Assumption  $ITE_r$ -DiD holds, the difference below identifies the  $ITE_r$ .

$$(8) \quad ITE_r = \mathbf{E}[y_{\ell_r,t}^1 | D_{\ell_r,t}^1, d_{i,t}^0] - \{ \mathbf{E}[y_{\ell_r,t-1}^0 | D_{\ell_r,t-1}^0, d_{i,t-1}^0] + \\ + ( \mathbf{E}[y_{cr,t}^0 | D_{cr,t}^0, d_{i,t}^0] - \mathbf{E}[y_{cr,t-1}^0 | D_{cr,t-1}^0, d_{i,t-1}^0] ) \}$$

Hence, our estimator of the  $ITE_1$  is based on the pre-treatment outcomes and comparing the *change* in the outcomes of direct neighbors of the eligible nodes in a *treated* subnetwork to the direct neighbors of the eligible nodes in the *non-treated* subnetwork. Thus, (indirectly) treated and control observations must grow at similar rates and be affected similarly by any dynamics that affect the entire Wikipedia (weekday dynamics etc.). Note that this conclusion also applies to the direct treatment effect, when setting  $r$  to 0.

### 3.3 Reduced Form Analysis

To obtain the  $ITEs$  for each layer, I apply reduced form regressions which allow the understanding of the impact of the local treatment on both the treated pages and their neighbors. These are very similar in spirit to the analysis in Carmi et al. (2012). The idea is to compare pages grouped by their distance to the page which experiences treatment to their analogue in the control group ( $L_0$  to  $C_0$ ,  $L_1$  to  $C_1, \dots$ ). I denote all reduced form coefficients by  $\phi$ . Furthermore, I define “treatment” for each set of pages along the lines of the indirect treatment effects ( $ITE_r$ ) in the previous section.<sup>20</sup> I let  $s$  indicate the day relative to day 0, the day when the treatment is administered. Hence  $s$  runs from -14

<sup>19</sup> Ideally we would like to observe a random selection of the subpopulations in which any treatments are to be administered, and in the second step we administer treatment to the eligible nodes. Moreover, we observe both subpopulations before the treatment of one takes place.

<sup>20</sup>The dummy in the regression for the neighbors (sets  $L_1$  and  $C_1$ ) takes the value 1, not if the node was itself treated, but if the corresponding start node ( $\ell_0$ ) was treated in  $t$  (and 0 otherwise).

to 14.  $\lambda_s$  is an indicator, which takes the value 1 if  $t = s$  and 0 otherwise. Each set of pages that corresponds to one layer in the network is regressed separately. So if I focus on the treated nodes, the neighbors and the indirect neighbors, it results in the following system of fixed effect regression equations, which all are based only on dummy variables:

$L_0$ .) Difference in Differences specification at level  $L_0$ <sup>21</sup>:

$$(9) \quad y_{it} = \phi_i^{L_0} + \sum_{s \in S} \phi_{1,s}^{L_0} \lambda_s + \sum_{s \in S} \phi_{2,s}^{L_0} (\lambda_s * treat_{L_0,i}) + \xi_{it}$$

... $treat_{L_0}$ : treatment on the very page;  $S = \{-14, \dots, 14\}$

$L_1$ .) At level  $L_1$  ( $treat_{L_1}$  means the shock is 1 click away):

$$(10) \quad y_{it} = \phi_i^{L_1} + \sum_{s \in S} \phi_{1,s}^{L_1} \lambda_s + \sum_{s \in S} \phi_{2,s}^{L_1} (\lambda_s * treat_{L_1,i}) + \xi_{it}$$

$L_2$ .) At level  $L_2$  ( $treat_{L_2}$  means the shock is 2 clicks away):

$$(11) \quad y_{it} = \phi_i^{L_2} + \sum_{s \in S} \phi_{1,s}^{L_2} \lambda_s + \sum_{s \in S} \phi_{2,s}^{L_2} (\lambda_s * treat_{L_2,i}) + \xi_{it}$$

In words, I run the same difference-in-differences on three levels (on  $L_0$ ,  $L_1$  and  $L_2$  (shown only for large events)).  $treat_{L_0,i}$  is an indicator variable for a page that is (going to be) featured on Wikipedia's main page,  $treat_{L_2,i}$  takes the value of 1 for pages that are two clicks away from pages that are (going to be) affected by such a shock. The cross terms correspond to this indicator variable multiplied with the time dummies. Thus, a cross term captures whether treatment has occurred at a given point in time or not. For an observation in the control-group this variable will always take a value of 0, while for an observation in the treated group this variable will take a value of 1 if it corresponds to the event time the time-dummy aims to capture. Hence, if the treatment is effective, the coefficients of the cross terms are expected to be 0 before treatment occurs and positive for the periods after the treatment. The *ITEs* from the previous subsection are captured by the  $\phi_2$  coefficient that corresponds to day 0 in the regressions above. I look at  $\phi_{2,0}^{L_1}$  for the *ITE*<sub>1</sub>, which corresponds to  $L_1$  and analogously at  $\phi_{2,0}^{L_0}$  for  $L_0$  and  $\phi_{2,0}^{L_2}$  for  $L_2$ .

Other than the cross terms I also include page fixed effects and another full set of time dummies (event time) to control for general (e.g. weekday-specific) activity patterns in Wikipedia. This procedure is crude because it does not consider several important factors such as how well neighbors are linked among each other or how large the peak of interest is on the originally shocked page. Yet, it is useful, since the results from the reduced form

---

<sup>21</sup>The specifications I use are fairly standard "regression difference in differences" similar to Jacobson et al. (1993) or as described in Angrist and Pischke (2008).

analysis are based on minimal assumptions and provide guidance as to whether attention spillovers exist at all. They also allow us to see how far they carry over, and whether they result in increased production. Finally, they allow me to provide a lower bound and an upper bound estimate of the aggregate spillover effects to be expected.

### 3.4 Structural Form Analysis and Bounds

Beyond measuring the size of the *ITE*, I am interested in quantifying the size of the spillovers of attention that exist between Wikipedia articles on normal days. In this section, I augment the well known linear-in-means model for peer effects, as formulated in Manski (1993), with exogenous shocks. Departing from the version that was used by Bramoullé et al. (2009),<sup>22</sup> I show how exogenous shocks can be exploited to identify spillovers (or peer effects). This is possible in my modification of the model, even if the nodes characteristics or the network structure are endogenous. In other words, exogenous shocks are used as a focal lens to identify the spillovers, which is usually very challenging. In this section I provide only the point of departure and the main results. The details and derivations can be found in Appendix C.<sup>23</sup>

Recall that the underlying relationship of interest is the role of links.<sup>24</sup> How much attention spills via links can be modeled using the well known linear-in-means model of the type discussed in Manski (1993), who shows that the coefficient of interest is generally very hard to identify. I start from the same form of model.<sup>25</sup>

$$y_{it} = \alpha \frac{\sum_{j \in P_{it}} y_{jt}}{N_{P_{it}}} + X_{it-1} \beta + \gamma \frac{\sum_{j \in P_{it}} X_{jt-1}}{N_{P_{it}}} + \epsilon_{it}$$

$y_{it}$  denotes the outcome of interest in period  $t$  and  $X_{it-1}$  are  $i$ 's observed characteristics at the end of period  $t - 1$ .<sup>26</sup>  $P_{it}$  is the set of  $i$ 's peers and  $N_{P_{it}}$  the number of  $i$ 's peers. The coefficient of interest is  $\alpha$ : It captures the effect of the performance of  $i$ 's peers and in the present context it measures how the views of an article are influenced by the views of the adjacent articles. The coefficient vector  $\beta$  accounts for the impact of  $i$ 's own characteristics and  $\gamma$  measures the effect of the peers' average characteristics on  $i$ 's performance. In the setting of this paper  $\beta$  accounts for how the page's own length or quality might affect how often it is viewed and  $\gamma$  captures how length and quality of neighboring pages affect views of page  $i$ . Bramoullé et al. (2009) suggest a more succinct

---

<sup>22</sup>They show how identification of peer effects can be achieved in social networks, using an IV-strategy.

<sup>23</sup>The derivations involve quite heavy notation, but are otherwise relatively straightforward.

<sup>24</sup>The mechanism we have in mind, is that attention from article A can be diverted to article B if a link exists. This is interesting, since some of the users who get to see B might later start to edit it.

<sup>25</sup>Note that it is easy to add a fixed effect to the model, but that it will be eliminated when taking differences. Consequently, I omit it for ease of notation.

<sup>26</sup>Note, that I can observe the current state of a Wikipedia article once a day at a fixed time.

representation based on vector and matrix notation:

$$\mathbf{y}_t = \alpha \mathbf{G} \mathbf{y}_t + \beta \mathbf{X}_{t-1} + \gamma \mathbf{G} \mathbf{X}_{t-1} + \epsilon_t \quad \mathbf{E}[\epsilon_t | \mathbf{X}_{t-1}] = 0$$

A few remarks:  $\mathbf{G}$  is a  $N \times N$  matrix.  $G_{ij} = \frac{1}{N_{P_i} - 1}$  if  $i$  receives a link from  $j$  and  $G_{ij} = 0$  otherwise. Clearly this model and, specifically, measuring the social parameter  $\alpha$  is of interest to a very large literature. To incorporate exogeneous variation, I augment this model by including a vector of treatments, which for simplicity, is assumed to take the value of 1 for treated nodes and the value of 0 otherwise.

$$(12) \quad \mathbf{y}_t = \alpha \mathbf{G} \mathbf{y}_t + \mathbf{X}_{t-1} \beta + \gamma \mathbf{G} \mathbf{X}_{t-1} + \delta_1 \mathbf{D}_t + \epsilon_t \quad \mathbf{E}[\epsilon_t | \mathbf{D}_t] = 0$$

For the treated side  $\mathbf{D}_t$  is a vector consisting of zeros and ones that indicates which nodes are treated. On the untreated subnetwork we have  $\mathbf{D}_t = \mathbf{0}$ , a vector of zeros. In some of the proofs and in my application I will assume a local treatment that affects only a single node. This captures the notion of a local treatment condition, under which only one node is exposed to treatment (a “mini population treatment”). Formally this is written as  $\mathbf{D}_t = \mathbf{e}_{\ell 0}$ ; that is, a vector of zeros and a unique one in the coordinate that corresponds to the treated node.

Note that I do not require that the structure of the network ( $\mathbf{G}$ ) to be the result of an exogenous network formation process. Rather only the selection which of the eligible node that gets treated must be exogenous.<sup>27</sup> It is worth stressing that my setup is fundamentally different from Bramoullé et al. (2009) because it will use an entirely different source of identification. Moreover, there will be no requirements needed concerning the linear independence of  $\mathbf{G}$  and  $\mathbf{G}^2$ .

In this model, the reduced form expectation conditional on “treatment” is given by:

$$(13) \quad \mathbf{E}[\mathbf{y}_t | \mathbf{D}_t] = (\mathbf{I} - \alpha \mathbf{G})^{-1} [(\beta + \gamma \mathbf{G}) \mathbf{E}[\mathbf{X}_{t-1} | \mathbf{D}_t] + \delta_1 \mathbf{D}_t]$$

Define the set of observations in the subnetwork where treatment occurs in  $t$  by the subscript  $\ell$  and a comparison group in which no node is treated by the subscript  $c$ . If these sets of nodes can also be observed one period earlier, a difference-in-differences estimator can be computed.

**Result 1:** Denote the difference in differences estimator as

$$\text{DiD} := \{\mathbf{E}[\mathbf{y}_{\ell,t} | \mathbf{D}_{\ell,t}] - \mathbf{E}[\mathbf{y}_{\ell,t-1} | \mathbf{D}_{\ell,t-1}]\} - \{\mathbf{E}[\mathbf{y}_{c,t} | \mathbf{D}_{c,t}] - \mathbf{E}[\mathbf{y}_{c,t-1} | \mathbf{D}_{c,t-1}]\}$$

---

<sup>27</sup>In the present application, all “eligible” nodes (featured articles) are equally likely to be treated. They are the nodes in the group  $L_0$ . Neighbors (in  $L_1$ ) are typically not featured. Hence they are not eligible and naturally less likely to be themselves treated.

and assume that the treatment affects only the contemporary outcome of the treated node and not its exogenous characteristics.<sup>28</sup> Then the DiD contains the following quantity:

$$\text{DiD} = \delta_1 \mathbf{D}_t (\mathbf{I} + \alpha \mathbf{G} + \alpha^2 \mathbf{G}^2 + \alpha^3 \mathbf{G}^3 + \dots)$$

**Proof:** For a proof please refer to Appendix C.3.

In words, this result means that the node is affected by both treatment and second and higher order spillovers, the positive feedback loop that ensues as the neighbors increase their performance in sync with their peers. Instances of higher order effects<sup>29</sup> are  $\alpha^2 \delta_1$  in the second round or  $\alpha^3 \delta_1$  in the third round and so on. The other important factor is whether and how often spillovers of a given order  $q$  arrive. This depends on the number of indirect paths of length  $q$  that go from the shocked node  $\ell_0$  to any focal node  $j$ .<sup>30</sup>

Note the close relationship to the Bonacich centrality in the paper by Ballester et al. (2006), who aim at identifying the “key player” of a network. Like in their framework, the *number of channels* for indirect spillovers matters. Yet, for measuring spillovers in a “mini population treatment” we care about the reverse direction, the quantity that spills from the shocked node to any other node.

My result shows that the difference-in-differences approach alone will not directly reveal  $\alpha$ , the social parameter of interest, because nodes might have a feedback effect on each other. The neighbor’s change in performance (due to the original impulse) will affect the neighbors’ neighbors, but also feed back to the originally treated  $\ell_0$ -node. The estimator will observe all the changes in outcome at the end of this process, when all higher order spills have taken place.

In some applications this will be the object of interest to the researcher. However, in the present context, the research is motivated by the desire to know the effect of the link structure and not of the treatment per se. Consequently it is warranted to dig deeper in order to understand the structural parameters.

Computing the parameters is not necessarily feasible, because it requires knowledge of the complete link structure. However, a closer look at the nodes independently reveals that limited information about the link structure suffices to acquire additional information about the parameters. In the following two subsections I show how to get the point estimate for the peer effects coefficient if the network is known and I show how to derive upper and lower bound estimates for the parameter if no information about the network

---

<sup>28</sup>The independent characteristics  $X$  should not be immediately affected by treatment because this would threaten the identification of the spillover. However, they may adjust over time. As long as we can observe one period where only the outcome is affected, but not the characteristics, the result holds.

<sup>29</sup>Note that I am considering the homogeneous network, so all spillovers have the same magnitude.

<sup>30</sup>In the proof I need to assume that the network formation *process* is not affected by the treatment. I checked this assumption in my “today’s featured article application” and verified, that link formation remains on low levels. If anything, there is an increase by 0.2 in-links per article in sync with the peak in edits, but not with clicks. I conclude that this is an acceptably small source of potential bias.

is available.

### 3.4.1 Estimator of the Peer Effects Parameter if the Network Structure can be Observed

If the network structure can be observed, the peer effect parameter  $\alpha$  can be backed out by computing the higher orders of the network graph ( $\mathbf{G}$ -matrix). To know how many spillovers arrive in each round, it suffices to focus on the entries  $\mathbf{G}_{ij}, \mathbf{G}^2_{ij}, \mathbf{G}^3_{ij}, \text{etc.}$  ( $i = \ell_0$ ) that document the number of paths via 1, 2, 3 and more links from the treated node to the neighboring node in question. With this information it is straightforward to compute by how much the observed effect at the node in question has to be discounted and to use this information to compute the true average effect.

### 3.4.2 Upper and Lower Bound Estimates of the Peer Effects Parameter if the Network Structure is Unobserved

If the network structure cannot be observed, it is still possible to obtain boundary estimates for the peer effects based merely on two separate comparisons of (i) the directly treated nodes and their counterparts ( $L_0$  vs.  $C_0$ ) in the control group and (ii) their neighbors ( $L_1$  vs.  $C_1$ ). This is relevant in many empirical settings, because randomization and information on the network *together* are rarely available. In contrast, a separate comparison of eligible and non-eligible nodes in randomly treated communities or networks (without network information) can frequently be observed. Also with this restricted knowledge it is possible to obtain a lower bound estimate for the coefficient  $\alpha$ , if the researcher is willing to make more rigorous, but sensible, assumptions. In what follows I briefly show how to obtain the bounds. The idea behind this derivation is to select two specific “extreme” types of network which either minimize or maximize second and higher order spillovers. These benchmark networks are schematically represented in Figure 2. I use a directed network with only “outward bound” links emanating from  $\ell_0$  to  $\ell_1 \in L_1$  to obtain the upper bound estimate of the social/spillover parameter  $\alpha$ .<sup>31</sup> The opposed benchmark is a fully connected network, where every node is the direct neighbor of every one of its peers. From there I obtain the lower bound estimate of the social parameter. A more detailed account is provided in Appendix C.4.

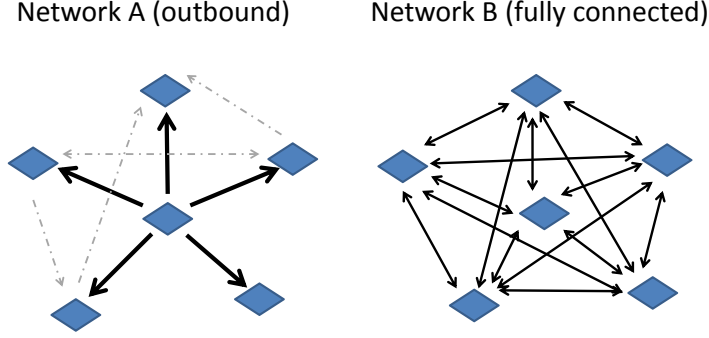
**Upper Bound:** If we ignore higher order spillovers,<sup>32</sup> we can obtain an upper bound estimate for the direct treatment effect ( $\bar{\delta}_1$ ) by applying the difference-in-differences estimator on the level of directly treated nodes ( $L_0$ ) and a suitable comparison group ( $C_0$ ). After that I can move on to estimate the upper bound for the parameters for spillovers ( $\bar{\alpha}$ ) by combining it with a second difference-in-differences estimator at the neighbor level.

<sup>31</sup>For this benchmark we ignore any existing links among  $L_1$  nodes.

<sup>32</sup>Or maintain the assumption that we can observe the nodes’ performance before any higher order spillovers arrive at the treated node



Figure 2: Schematic representation of the two extreme networks, used to compute the upper and lower bound estimates of the parameters of interest.



NOTES: The “outbound network” (left) is used to obtain the upper bound estimate. It is a directed network with only “outward bound” links. This implies ignoring any existing links among  $L_1$  nodes. Holding the number of nodes and the observed ITEs fixed, the social parameter will be estimated to be largest in this type of network. The fully connected network (right), is the benchmark case from which the lower bound of the social parameter can be estimated.

Let  $DiD_{(\ell a-ca)}$  denote such a difference-in-differences, ( $a \in \{0, 1\}$ ), where the nodes are either in the center of the network ( $L_0$  or  $C_0$ ) or are the neighbors of the start nodes ( $L_1$  vs.  $C_1$ ):

$$(14) \quad \begin{aligned} \hat{\delta}_1 &= \widehat{DiD}_0 = \Delta\hat{\ell}0 - \Delta\hat{c}0 \\ \hat{\alpha} &= \frac{\widehat{DiD}_1}{\widehat{DiD}_0} NP_{\ell_1} \end{aligned}$$

- $\Delta\hat{\ell}0 := \frac{1}{NP_{\ell_0}} * \sum_i (y_{i,\ell_0,t=1} - y_{i,\ell_0,t=0})$
- $\Delta\hat{c}0 := \frac{1}{NP_{c_0}} * \sum_i (y_{i,c_0,t=1} - y_{i,c_0,t=0})$

with  $\widehat{DiD}_1 = \Delta\hat{\ell}1 - \Delta\hat{c}1$  and the definitions of  $\Delta\hat{\ell}1$  and  $\Delta\hat{c}1$  paralleling those of  $\Delta\hat{\ell}0$  and  $\Delta\hat{c}0$ . In my application’s reduced form estimations of the previous section  $DiD_1$  corresponds to  $\phi_{2,0}^{L_1}$  and  $DiD_0$  is estimated by  $\phi_{2,0}^{L_0}$ . This upper bound estimator would be suitable under the potentially quite strong assumption that higher order spillovers are negligible. I proceed to show how to compute the lower bound estimates under the assumption of *maximal* second order spillovers. The lower bound gives an idea of the maximal size of the problem that might result from trusting the easily computed upper bound estimates.

**Lower Bound:** It is also possible to compute a lower bound estimate for  $\alpha$  and  $\delta_1$ .

This bound can be obtained by imagining that the network is fully connected, i.e. every node links to every other node, assuming that all effects are of the same sign, strictly ordered and (w.l.o.g) positive.<sup>33</sup> Further computations in Appendix C show that in a network with  $N$  nodes, the lower bound of the estimator for  $\alpha$  is characterized by the solution to the following quadratic equation:

$$(15) \quad \underline{\alpha}^2 - \left[ \frac{DiD_0}{DiD_1} + (N - 1) \right] \underline{\alpha} + (N - 1) = 0$$

This equation has two solutions, one of which lies between 0 and 1. The closed form solution for  $\underline{\alpha}$  is hence given by:

$$(16) \quad \underline{\alpha} = \frac{1}{2} \left[ \frac{DiD_0}{DiD_1} + (N - 1) \right] - \sqrt{\frac{1}{4} \left[ \frac{DiD_0}{DiD_1} + (N - 1) \right]^2 - (N - 1)}$$

Recall that all the quantities required are readily available from the reduced form estimations.  $DiD_1$  corresponds to  $\phi_{2,0}^{L_1}$  and  $DiD_0$  is estimated by  $\phi_{2,0}^{L_0}$ . In Appendix C.4 I provide a proof for my claims and explain how this bound is derived. Which of the estimates is more accurate will depend on the size of the spillover effect, but to a very large extent also on the real network structure and the number of nodes.

A closer examination of Result 1 reveals that the upper bound estimator would be quite suitable if the researcher has reasons to make the (potentially quite strong) assumption that higher order spillovers are negligible. It would also be appropriate in networks with very sparse connections among its members. The lower bound estimator might be more suitable if the researcher believes the network to be highly connected and expects the spillover coefficient to be relatively large.<sup>34</sup> The bounds have several limitations (cf. Appendix C.4) and for some applications the bounds might turn out to be too wide to be actually informative. Still, taken together, the bounds can provide a useful first characterization of the spillover parameters in question.

## 4 Data

This section briefly surveys the data collection procedure in Subsection 4.1, and describes the datasets used both for disasters (large events) and “today’s featured article” (Subsection 4.2). A more detailed description of how the underlying database was put together and the procedure I used to extract the dataset is provided in Appendix B.

---

<sup>33</sup>The precise assumption is  $DiD_0 > DiD_1 > HO^B > 0$ , as stated and explained in Lemma 1

<sup>34</sup>So large that  $\alpha^2$  and  $\alpha^3$  are still sizeable.

## 4.1 Data Preparation - Treated and Control Group

To obtain my dataset I augment the publicly available data dumps provided by the Wikimedia Foundation<sup>35</sup> with data on the link structure between articles, data on the download frequency of pages and information on major media events which occurred during our period of observation. The data I use are based on 153 weeks of the entire German Wikipedia’s revision history between December 2007 and December 2010.<sup>36</sup>

I will now briefly provide relevant background information about the two conditions and Wikipedia’s tools that allow selecting candidate pages, before describing how the comparison groups for estimation the counterfactual were chosen.

### 4.1.1 Preparation - Background Information of Treatments

I use 23 large-scale events, 34 featured articles that were advertised on Wikipedia’s main page, and all their respective network neighbors. “Featured” is a quality status that the top rated articles in Wikipedia receive, if they cover all the relevant information in a particularly well written and structured way. The status is awarded by the community of Wikipedia editors in a structured procedure that involved a nomination and a review period. Altogether, the German Wikipedia had a few thousand featured articles in the period of observation. Of those “featured” articles, every day one is selected to be advertised on the start page and thereby becomes “Today’s featured article.” The featured articles in the dataset and their corresponding date of advertisement on the start page were found by consulting the German Wikipedia’s archive of pages that were selected to be advertised on Wikipedia’s main page (“Seite des Tages”).

To identify major events, I consulted the corresponding page on Wikipedia. The most important feature of major events is that they are arguably exogenous to Wikipedia and unpredictable to Wikipedians. However, “unpredictability” is threatened for events that take several days to build up (e.g. floods, hurricanes or ash clouds produced by volcanos) and are hence predictable in the sense that experts might foresee the disastrous event before it is in the media. To avoid this problem, I focus on 26 large events with spontaneous onset, e.g. earthquakes and accidents. I focus on the content provision that results from attention spillovers and which is a consequence of the spike in interest and the resulting improvements to the linked pages. Hence, I will not focus on the treated pages where content generation might be related to the events directly. Instead I obtained data on the direct and indirect network neighbors.

---

<sup>35</sup>I have access to a database that was put together in a joint effort of the University of Tübingen, the IWM Tübingen and the ZEW Mannheim. It is based on data from the German project, which currently has roughly 1.4M articles and thus provides us with a very large number of articles to observe.

<sup>36</sup>The data were stored in a relational database (disk-based) and queried using Database Supported Haskell (DSH) (Giorgidze et al. (2010)).

### 4.1.2 Choice of Control Group

For each primary shock I obtain two sets of control observations. The first set is based on pages which are similar but unlikely to be affected by the treatment. To find a control observation for “Today’s featured articles” it is important to keep in mind, that, by being featured, they are clearly different (longer, better linked, etc.) from a randomly selected article. To find a good match I selected other featured articles, which were advertised either later or earlier in time (“last year’s featured article”). These articles fulfill the same requirements for “featuring”. Furthermore they are equally eligible for treatment, as proven by the fact that they actually *were* treated, but at a different point in time. Finally, note that the focus of the estimation is on the *neighbors* of such articles. Neighbors are typically not themselves featured and are usually much less different from a randomly chosen article, than the treated featured article itself. Thus selecting neighbors of featured articles that were advertised at a different point in time, gives me a set  $C1_{control}$  which is similar in size, network structure and characteristics to the sampled pages (before the shock). The second set is obtained by extracting the data based on treated pages a second time, but 42 days before the actual shock occurred. I refer to the articles in this “placebo-treatment” as  $C1_{placebo}$ .

The resulting dataset contains information on views and content generation of almost 13,000 articles, 14 days before and after the events (more than 750,000 observations). Table 8 shows which events were included in the “today’s featured article” dataset and the associated number of observations for each of the conditions. Column 1 shows the number of articles that belong to each featured article. Columns 2-4 show the corresponding number of observations, separated by treatment status.<sup>37</sup> Table 9 shows the information for the data on large events which includes both natural disasters as well as technical or economic catastrophes. More details about the data preparation and selection of the events are provided in Appendix B.

## 4.2 A Closer Look at the Datasets

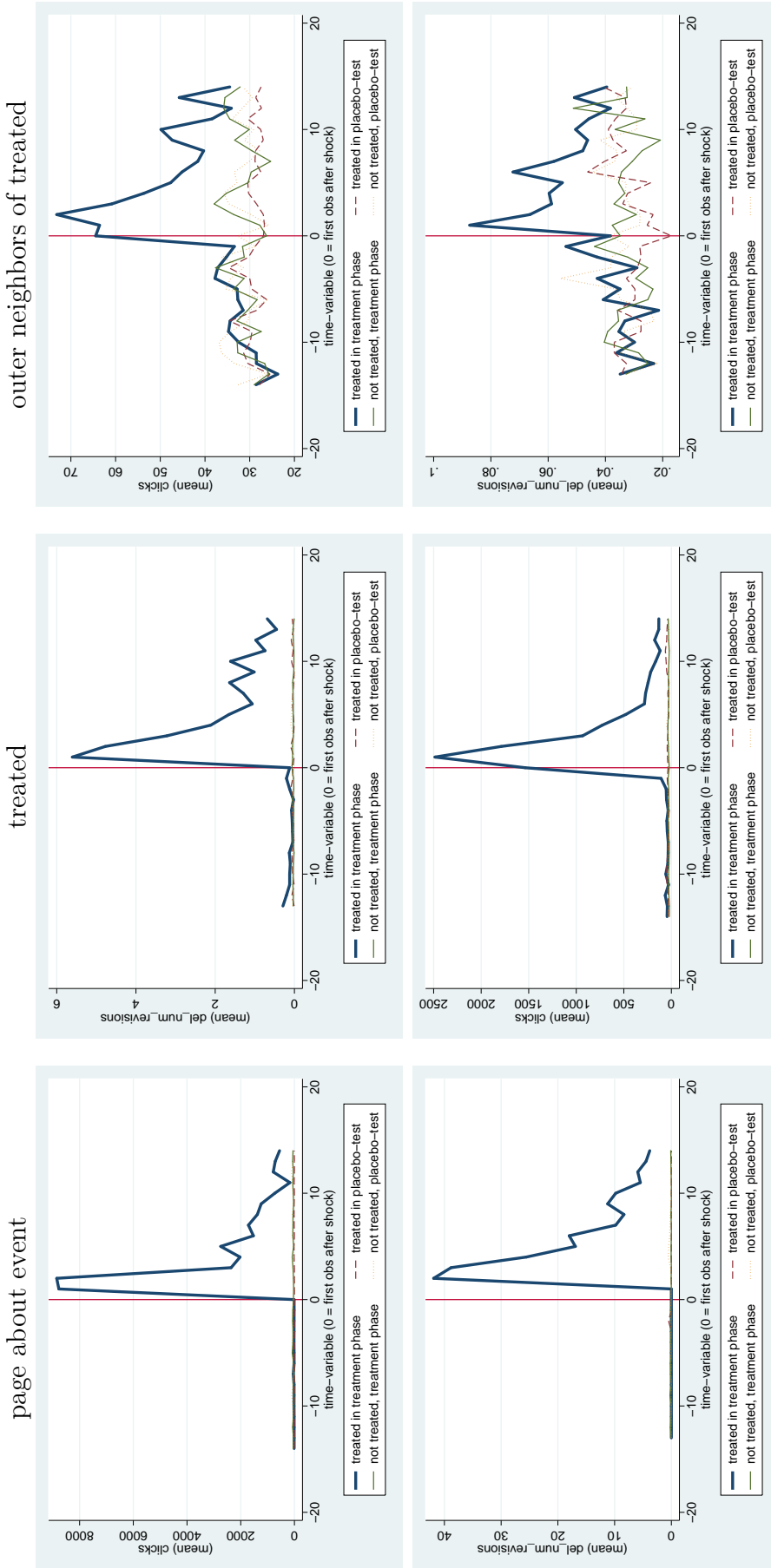
Summary statistics for the data on large events are shown in Table 7. The data contains 425,981 observations from 7,379. From the table it can be seen that the average page contains 5658 bytes of content and has undergone 84 revisions. However, the median is substantially lower at 3885 bytes and only 40 revisions. Also, the summary statistics of the first differences (variables starting with “Delta:”) reveal that on a typical day nothing happens on a given page on Wikipedia. This highlights the necessity of using major events as a focal lens for analyzing activity on Wikipedia,<sup>38</sup> which is confirmed

---

<sup>37</sup>Observations range from 2,088 to 33,872, covering various topics such as innovations (CCD-sensor), art history (Carolingian book illustrations) or soccer clubs (Werder Bremen).

<sup>38</sup>Further descriptive analyses that compare treated and control groups before and during treatment show that the groups are very similar in their activity levels before the shocks occurred and that the

Figure 3: Catastrophes: Comparing average clicks (new edits) of treated pages (and neighbors) to three comparison groups.



NOTES: The figure shows the results for natural disasters and large accidents. The left column shows the average effect on the pages about the disaster (“event pages” - by definition, they were created after the event), the middle column the directly treated pages, that users turn to, until the event gets a page of its own (“L1”, with reciprocal link to the future event page), and the right column for the pages that are one click away from  $L_1$ . The upper row shows the average number of clicks the lower row shows the average number of edits. The outcomes are shown for the treated articles and the control groups separately. Directly hit pages received up to 8,500 additional clicks and up to 40 new revisions on average. Pages that will have a reciprocal link received up to approx. 2,500 clicks and up to 5 additional revisions. However, not only the treated pages, but also their neighbors received 35 additional clicks and up to 0.04 additional revisions on average.

by the visual inspection of the direct and indirect effect of treatments.

In Figure 3 I plot the average clicks (top row) and the average number of added revisions (bottom) for the three groups of pages zero clicks away (left column), one click away (middle column) and two clicks away (right column). Each of the plots features four lines. The bold blue line represents the treated group or its neighbors when they were actually treated, hence “treated in treatment phase”. The dashed red line represents the same group but during the placebo treatment at an earlier point in time. The thin green line (“not treated, treatment phase”) shows the control group at the time when the real shock occurred and the thin dotted yellow line represents the “unrelated” observations, which are never treated and observed in the placebo period.<sup>39</sup> The left column shows the control group and the article about the incident (“event page”;  $L_0$ ), which are created only after the onset of the event. Most of these 23 pages did not exist at all before the onset of the event and therefore only a few have a placebo condition available. The upper row shows that the directly affected pages experience a very large spike of 8,500 clicks per day on average. The number of additional revisions peaks on the first days of treatment, when the pages are created: an average of almost forty revisions are added to a page on the first day. On the pages that are to share a reciprocal a link from the treated page the effect is quite large: while the clicks on the average  $L_1$  page increase by 2,500, the absolute value of the average increase in revision activity is only five. When I look at pages that are two clicks away, the effects are much smaller, especially for revisions, but quite pronounced. The clicks on the average adjacent page go up by 35 and the absolute value of the average increase in revision activity is already no more than 0.04.

A summary of the data from “featured articles” are shown in Table 6. The data contains 317,550 observations from 5,489 pages<sup>40</sup> on the main variables. Note that this corresponds to a much smaller number of pages per treatment, which is due to the fact that I focus on the directly linked pages in this condition. The table shows that the median page contains 4833 bytes of content and has undergone 48 revisions. In this sample, the mean is substantially higher at 6794 bytes and 95 revisions. As before, the summary statistics of the first differences show how little activity occurs on a normal day on any given page on Wikipedia.

Figure 4 plots the aggregate dynamics around the day when the start node was shown on Wikipedia’s main page and corresponds to Figure 3 for the large event condition. I plot the average clicks (left column) and the average number of added revisions (right columns), but now only for the treated pages and direct neighbors. As before, each

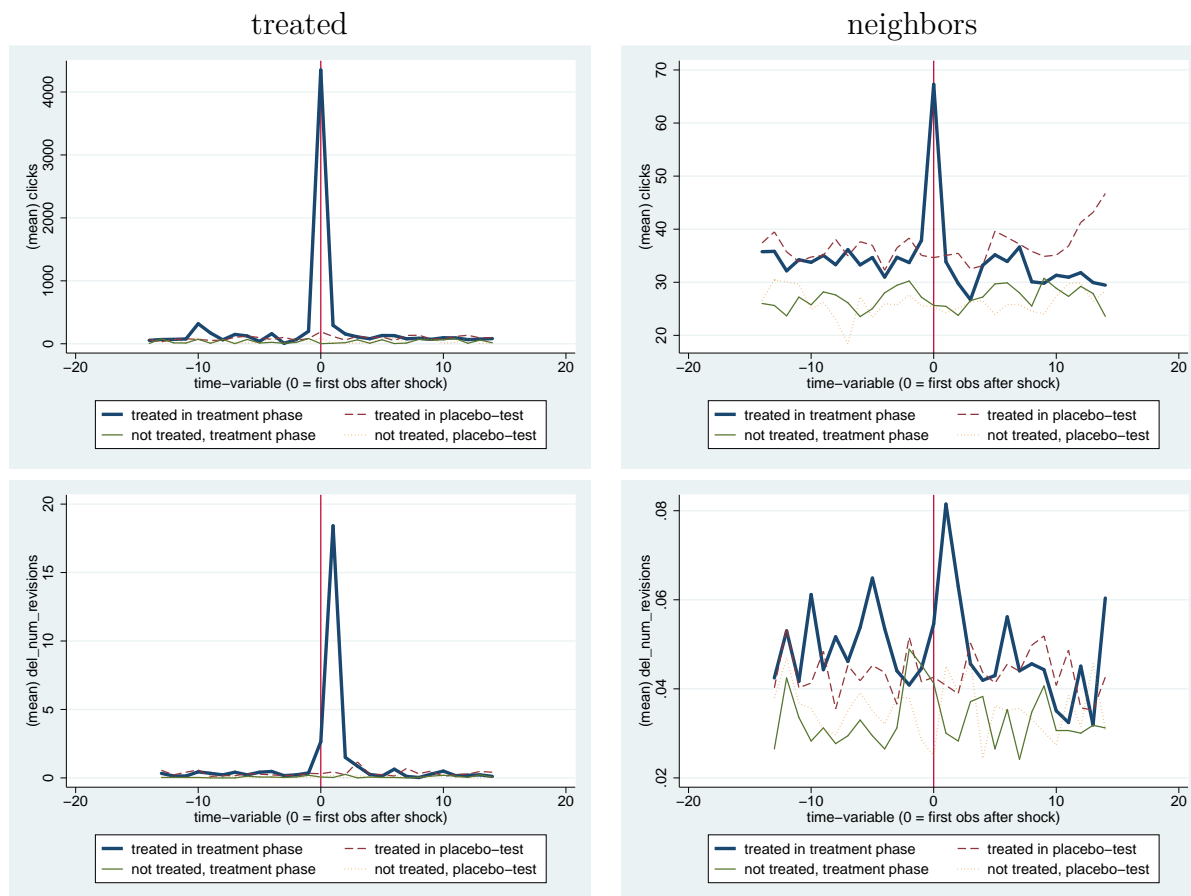
---

control group did not change its behavior during treatment. These tables and their description were omitted for reasons of brevity. They are available from the author upon request.

<sup>39</sup>For greater ease of representation I included a graphical representation of only two variables. The summary statistics for these groups before and after treatment are also available as tables upon request.

<sup>40</sup>Since pages were observed also in the placebo condition, each page is sampled twice, and hence I observe 10,950 distinct time series.

Figure 4: “Today’s featured articles”: Comparing average clicks (new edits) of treated pages (and neighbors) to three comparison groups.



NOTES: The figure shows the results for featured articles that were advertised for a full day on Wikipedia’s main page. The left column shows the average outcome on the directly treated pages (set “ $L_0$ ” containing 63 pages total), the lower row for the pages one click away (set “ $L_1$ ”, which contains 5,489 pages). The upper row shows the average number of clicks the lower row shows the average number of edits.

of the four figures contains four lines, one for each condition that can be obtained by combining treatment (yes/no) and placebo (yes/no). The major difference to the large events condition is the brevity of the treatment. Attention rises from typical levels, below 50 views, to more than 4200 views on average, but immediately returns to the old levels the day after treatment is administered. A very similar pattern can be observed for the neighbors where attention is almost twice as high as on a usual day and then falls back to the old levels. A similar pattern can be observed for the number of revisions. Excepting large events, activity rises already before  $t = 0$ . Nevertheless, on the day of treatment the spike of activity is also pronounced for the neighbors.<sup>41</sup>

<sup>41</sup>Note that I cannot cleanly estimate the direct treatment effect if the treatment drastically increased the number of links. (cf. Comola and Prina (2013)). This may be a minor issue for disasters and, if important, introduces noise in the quantification of the conversion rates. I checked this for “today’s featured articles” and found that it is a minor issue. Link formation increases by 0.2 new in-links over 120 in-links per article on average on the day after treatment. It moves in sync with the peak in edits,

## 5 Estimation Results

In what follows I present my estimation results and discuss their interpretation. Before I proceed with the details of my estimations, it is worth recalling a few important facts. The point of departure of the estimations in this paper is estimating Equation 11 (Section 3.3) for large events and Equation 10 for “featured articles”. This is due to two reasons: first, the two conditions differ in how local the treatments are. Second, only the “featured articles” exist at the time of treatment, while the page at the center of a large event treatment typically does not exist and will instead be created in the following days.

Moreover, I avoid potentially endogenous link formation during treatment by considering only links that had been in place *a week before the treatment*. When a page is found to lie in both the treatment and control groups it is excluded from the estimation, because including such pages will bias the estimated coefficients towards zero. Extremely broad pages with a very large number of links (e.g. pages that correspond to years) were excluded from estimation to avoid biases from oversampling. Finally, I use the seven observations from two weeks before treatment (days -14 through to -8) as the reference group in the estimations and I include only flow variables such as views, new revisions, new authors etc. to guarantee that my results are not driven by any anticipation effects.<sup>42</sup> The following two subsections report the results for both conditions.

### 5.1 Large Events

For this group the estimation concerns the set of  $L_2$  pages that are two clicks away from the epicenter: the future page about the disaster. This is not because closer pages are uninteresting, but because the shock of the analyzed events is very big and likely to directly affect pages that will eventually be directly and bidirectionally linked. If, for example, a city in the province under consideration was hit by the earthquake, the added content on that page might simply cover this very fact. In such a case, this is not an improvement that arose from the increased attention that results from the adjacent event, but a change that is directly caused by the treatment. As explained above, this is not the effect I am primarily interested in. Consequently I focus on pages that were indirectly linked at the time of the shock and that never became directly linked. These articles are

---

but not with clicks. This is a small source of potential bias resulting from the edit activity, but is unlikely to affect viewership. Hence, the result from “today’s featured articles” are my preferred estimates.

<sup>42</sup>Anticipation effects are impossible for disasters but cannot be entirely ruled out in the “featured articles” condition, where sophisticated users, who can obtain the information about pages that are going to be presented soon. In fact the editors of the daily featured article, have to edit the article in the week before it is advertised, to make sure it fits into the corresponding box on Wikipedia’s main page. This alone results in increased activity during the week before treatment. After carefully studying this process, I am not very concerned about this feature of the data, because the magnitude of the day-0 effect suggests that the vast majority of attention influx is due to readers who do not anticipate which page is to be advertised.



Table 1: Relationship of clicks/added revisions and time dummies for indirect neighbors of shocked articles (2 clicks away from epicenter) in the large events condition.

	clicks			new edits		
	(1) before after	(2) compare control	(3) compare placebo	(4) before after	(5) compare control	(6) compare placebo
t = -2	4.442 (4.372)	3.172 (4.709)	3.487 (4.545)	0.011 (0.008)	0.010 (0.009)	0.015 (0.010)
t = -1	2.639 (3.040)	0.978 (3.993)	3.144 (3.742)	0.022*** (0.007)	0.010 (0.010)	0.026*** (0.008)
t = 0	33.661** (14.471)	37.391** (14.421)	36.047** (14.386)	0.006 (0.010)	0.003 (0.011)	0.021* (0.011)
t = 1	32.794*** (11.075)	35.020*** (11.098)	35.397*** (11.113)	0.055** (0.023)	0.049** (0.024)	0.062** (0.023)
t = 2	42.375*** (13.671)	38.767*** (13.650)	44.730*** (13.589)	0.034*** (0.012)	0.037** (0.014)	0.043*** (0.012)
t = 3	30.066*** (8.283)	22.069** (9.168)	30.895*** (8.730)	0.027*** (0.009)	0.021* (0.011)	0.025** (0.011)
t = 4	22.871*** (6.850)	17.601** (7.065)	21.918*** (6.917)	0.027** (0.012)	0.026** (0.012)	0.028** (0.013)
Constant	30.795*** (2.296)	29.900*** (1.001)	29.994*** (1.289)	0.032*** (0.004)	0.033*** (0.002)	0.032*** (0.002)
All cross	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	No	Yes	Yes	No	Yes	Yes
Observations	52360	162338	104214	49980	154959	99477
Number of Pages	2380	7379	4737	2380	7379	4737
Adj. R <sup>2</sup>	0.003	0.003	0.003	0.002	0.001	0.001

NOTES: The table shows the results of the reduced form regressions estimating the ITE. Columns (1)-(3) show the results for clicks and Columns (4-6) for new edits to the articles. Specification (1) and (4) show a simple 'before and after'; (2) and (5) contrast treated and comparison group; Columns (3) and (6) show the comparison of treated articles with themselves but seven weeks earlier (placebo treatment). Fixed Effects Panel-Regressions with heteroscedasticity robust standard errors. The unit of observations is the outcome of a page  $i$  on day  $t$ . The time variable is normalized and runs from -14 to 14.; Only crossterms closer to treatment are shown, but all were included. Reference group t-14 to t-5; standard errors in parentheses: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; no. of obs. = 323158; no. of clusters = 44; no. of articles = 7379.

no longer likely to be directly affected by the treatment on the page two clicks away.<sup>43</sup> Moreover, to ensure that my  $L_2$  pages are not directly related to the event I checked whether a page that was in  $L_2$  when I evaluated the network a week before the shock was going to be linked to the page of the disaster later. Since this indicates a potential direct relationship, I eliminated such pages from the sample.

The results of the estimation of the model for  $L_2$  nodes are shown in Table 1. The table shows the results for clicks in the first three columns and the results for the number of added revisions in Columns 4,5 and 6. All the specifications are OLS panel regressions which include a fixed effect for the page and standard errors are clustered on the event level (23 clusters). Column (1) and (4) shows the results of a simple before and after.

<sup>43</sup>The results for the  $L_1$  group are included in the appendix. The effects are very large and statistically significant. The estimated coefficients for the  $L_0$  group (not reported) are close to 4,500 for clicks and between 20 and 25 for revisions. However, due to the lack of sufficient observations, even these very large coefficient estimates are not statistically different from zero.

Columns 2, 3, 5 and 6 show the contrast in the difference-in-differences. Note that I run each regression twice to take advantage of my two comparison groups: first I contrast the treated pages against the control group and then I contrast it with the placebo treatment, i.e. with the treated articles themselves, but simulating a (placebo) treatment 42 days (i.e. 7 weeks) before the real shock.

For ease of representation the table only shows the coefficients for the cross terms from two periods before the shock until four periods after the shock. Until the onset of the event (periods -2 to -1), we would expect insignificant effects for the cross terms and after the event has occurred a positive effect would imply that some form of spillover is present. As in the visual evidence, the average increase in clicks relative to the control group (Column 1) amounts to 35-38.7 more clicks on average. For the placebo treatment (Column 2) this effect is almost equal, but a bit larger from the second day onwards.

Does the spillover in attention also translate to additional content generation? Obviously, this question matters for the relevance of the spillovers I find in this paper. If it does, spillovers of attention have far-reaching implications for other peer production settings.<sup>44</sup> Generally, the effects are somewhat different for the number of revisions (in line with the graphical analysis), since the effects are much smaller. An effect is consistently revealed from the first day after the treatment. It is small in absolute terms, since roughly one in twenty-five pages gets an additional revision. Yet, given the low levels in average activity on a given page and day, this is still a noteworthy effect. Comparing the pages with the placebo treatment I observe a small increase in editing activity before the onset of the event, which is however not confirmed by comparison with the control group. The size of the effect still more than doubles after day 1, at which point the comparison with the control group suggests a drastic increase in editing activity.<sup>45</sup>

## 5.2 Neighbors of Featured Articles

Table 2 shows the results for the “featured articles”. For this reduced form estimation I consider the model for  $L_1$  nodes (Equation 10) in Section 3.3. This is the relevant group here because the treatment takes place entirely inside Wikipedia<sup>46</sup> and it is “completely

---

<sup>44</sup>If more attention leads to better or more contributions, the importance of link networks for channeling attention would have important implications for open source software, research activities and innovation.

<sup>45</sup>I verified that the result is not driven by running a robustness check, where I exclude four events: the event which was associated to most pages in my dataset, Tunisia and those where the starting date or the most important page of the event was most difficult to identify: the bankruptcy of Lehman, the eruption of Eyjafjallajökull and the plane crash in Smolensk. In this specification, the results are confirmed. The most notable difference is the increased magnitude of the effect in the clicks, as for the remaining events, the average increase is close to 15 additional clicks. Despite the fact, that there are still more than 6,000 pages included in both comparisons, the effects for the number of revisions are no longer significantly different from zero, except in the fourth period of one specification.

<sup>46</sup>Unlike in the disaster case, when an article is advertised on German Wikipedia’s start page this is usually not covered by media or anything of the like.

local” since no two articles can be featured simultaneously. Hence, only the treated page is directly affected and any variation in the neighbors is almost certainly a result of the processes that take place inside Wikipedia.

Table 2: Relationship of clicks/added revisions and time dummies for direct neighbors of shocked articles in the ‘featured articles’ condition.

	clicks			new edits		
	(1) before after	(2) compare control	(3) compare placebo	(4) before after	(5) compare control	(6) compare placebo
t = -2	-0.709 (2.644)	-5.064 (4.051)	-2.629 (3.477)	-0.010 (0.007)	-0.028** (0.011)	-0.018* (0.011)
t = -1	3.454 (2.668)	2.149 (3.082)	4.792 (4.187)	-0.006 (0.006)	-0.021* (0.012)	-0.004 (0.008)
t = 0	32.888*** (9.073)	33.128*** (9.162)	34.638*** (9.294)	0.004 (0.006)	-0.006 (0.009)	0.004 (0.008)
t = 1	-0.572 (1.799)	-0.158 (2.266)	0.773 (3.214)	0.030** (0.011)	0.032** (0.012)	0.033** (0.014)
t = 2	-4.639* (2.511)	-2.523 (2.965)	-3.700 (3.144)	0.012 (0.008)	0.015* (0.008)	0.017 (0.011)
t = 3	-7.705** (3.114)	-8.373** (3.371)	-3.807 (5.435)	-0.005 (0.008)	-0.011 (0.012)	-0.012 (0.013)
t = 4	-1.225 (2.178)	-2.557 (2.766)	2.038 (5.615)	-0.009 (0.007)	-0.016 (0.014)	-0.009 (0.009)
Constant	34.421*** (1.060)	31.982*** (0.816)	35.354*** (0.768)	0.051*** (0.003)	0.043*** (0.002)	0.046*** (0.002)
All cross	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	No	Yes	Yes	No	Yes	Yes
Observations	83424	120758	166518	79632	115269	158949
Number of Pages	3792	5489	7569	3792	5489	7569
Adj. R <sup>2</sup>	0.005	0.004	0.003	0.000	0.000	0.000

NOTES: The table shows the results of the reduced form regressions estimating the ITE. Columns (1)-(3) show the results for clicks and Columns (4-6) for new edits to the articles. Specification (1) and (4) show a simple ‘before and after’; (2) and (5) contrast treated and comparison group; Columns (3) and (6) show the comparison of treated articles with themselves but seven weeks earlier (placebo treatment). Fixed Effects Panel-Regressions with heteroscedasticity robust standard errors. The unit of observations is the outcome of a page  $i$  on day  $t$ . The time variable is normalized and runs from -14 to 14.; Only crossterms closer to treatment are shown, but all were included. Reference group t-14 to t-5; standard errors in parentheses: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; no. of obs. = 240900; no. of clusters = 63; no. of articles = 5489.

The first three columns of the table show the results with clicks as the dependent variable. The estimation is the same as in Table 1 and the clustering is implemented on the level of events as before. The main insight of this table is that it confirms the statistical significance of the effect in the graphical analysis and provides a quantification of its size. The size of the effect is estimated to be 33.1 to 34.6 additional clicks on the average neighbor page on the day of treatment. In Columns 4-6, I observe an important effect of about 0.032 additional revisions one day after the treatment of the neighbor page. Note two things here: First, the effect is very small in absolute terms and corresponds to one additional edit per thirty pages. Second however, this is an increase in contribution activity of eighty to one hundred per cent.

Table 3: Spillover of views and translation to edits.

	epicenter (L0)		direct neighbors (L1)		
	(1) clicks	(2) clicks	(3) clicks	(4) new edits	(5) new authors
t = -2	-32.686 (59.224)	-25.611 (58.298)	-0.709 (2.644)	-0.010 (0.007)	-0.005** (0.002)
t = -1	36.002 (85.090)	76.750 (78.919)	3.454 (2.668)	-0.006 (0.006)	-0.003 (0.002)
t = 0	4269.573*** (1421.399)	4121.472*** (1422.301)	32.888*** (9.073)	0.004 (0.006)	-0.000 (0.003)
t = 1	206.540* (118.136)	138.306 (132.641)	-0.572 (1.799)	0.030** (0.011)	0.013*** (0.005)
t = 2	58.453 (68.899)	56.972 (68.261)	-4.639* (2.511)	0.012 (0.008)	0.002 (0.003)
t = 3	-31.991 (58.213)	-50.944 (54.872)	-7.705** (3.114)	-0.005 (0.008)	-0.005* (0.002)
t = 4	-7.338 (59.781)	-49.194 (63.384)	-1.225 (2.178)	-0.009 (0.007)	-0.003 (0.003)
Constant	80.235* (41.869)	93.085** (39.295)	34.421*** (1.060)	0.051*** (0.003)	0.018*** (0.001)
All cross	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	No	No	No
Observations	1474	1584	83424	79632	79632
Number of Pages	67	72	3792	3792	3792
Adj. R <sup>2</sup>	0.182	0.182	0.005	0.000	0.000

NOTES: The table summarizes the results of the reduced form regressions to estimate the spillovers in clicks and edits. Columns (1)-(2) show the results for the direct effect of treatment on clicks (ATE) and Columns (3) the spillover to direct neighbors of the articles (ITE), and Columns (4) show the conversion of the spillover in clicks to new edits at the direct neighbors and Column (5) shows the number of new author's that contributed to the articles (at the neighbors). All Specifications are a simple before-after comparison. Fixed Effects Panel-Regressions with heteroscedasticity robust standard errors. The unit of observations is the outcome of a page  $i$  on day  $t$ . The time variable is normalized and runs from -14 to 14.; Only crossterms closer to treatment are shown, but all were included. Reference group t-14 to t-5; standard errors in parentheses: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ;

Table 3 summarizes the results in view of the spillover. The first two columns show the results of the difference-in-differences in views for the treated article in the epicenter. Columns 3 and 4 repeat the before-after estimates from Columns 1 and 4 in Table 2 for the change in views and edits of the neighbors. In Column 5 I add a new dependent variable, the change in the number of editors. This serves as a robustness check of whether the shock's effects on edits are some sort of artifact or whether this actually brings in new knowledge. As can be seen in the first two columns, the estimated direct effect of treatment is approximately 4200 views depending on the comparison group. The number of authors, shown in Column 5, experiences a spike paralleling the one for edits (Column 4). Usually less than 1 in 50 articles (on average) is edited by an author, who never edited the article before. During treatment 1 in 30 of the neighbors are edited by a new author (a 72% increase).

I further test the robustness of my difference-in-differences results by excluding the first third of the “featured articles”. Results are shown in Table 10 and reveal the same patterns as Table 1, but at lower significance levels.<sup>47</sup> The number of authors moves largely in parallel with the number of revisions, indicating that twice as many new authors as usual edit the article due to the treatment of its neighbor. On the one hand this is a large effect in relative terms, on the other hand it means that only one in seventy articles is edited by a new author. More robustness checks included regressing against all comparison groups simultaneously and using different samples or resolutions. They do not convey additional insight and are available in the online appendix.<sup>48</sup>

### 5.3 Bounds for the Structural Estimator

Unfortunately I cannot compute the precise structural estimator because the full matrix  $\mathbf{G}$  formed by the German Wikipedia is too large to be computed in memory. Hence I cannot solve for  $\mathbf{G}^2$  and higher orders of the link matrix.<sup>49</sup> However, it is possible to present upper and lower bound estimates of the structural parameters that are discussed in Subsection 3.4 and derived formally in Appendix C.

To compute these values the researcher has to decide where to evaluate the number of peers. I choose to evaluate the coefficients at the median which is 31 for indirect neighbors of disaster pages and 36 for neighbors of “featured articles”. This is a crude first evaluation which primarily serves to highlight how easy it is to retrieve the structural parameters once this decision is made. The rest reduces to a back of the envelope calculation for the upper bound of the social/spillover parameter  $\alpha$  and the shock  $\delta_1$ . I use Equation 38:  $\bar{\delta}_1$  is directly estimated to be 4,190 (2,440 in the disaster condition). The estimate of  $\bar{\alpha}$  is 0.292 based on “featured articles” (and based on disasters, 0.483).<sup>50</sup>

Computing the lower bound estimates is not much more involved: It suffices to plug the estimates and the number of nodes into the closed form solution given in Equation 44. This gives the point estimator for the lower bound of  $\alpha$ , which is estimated to be  $\hat{\alpha} = 0.222$  for “featured articles” and  $\hat{\alpha} = 0.320$  for disasters.

To conclude this section I attempt to quantify the meaning of these results: literally they mean that if the average clicks on the neighboring pages are increased by ten, this alone would result in an increase of 2.215 to 2.92 clicks on the page, which all come

---

<sup>47</sup>The coefficients are not significant for the placebo-condition, but note that I apply extremely rigorous clustering and further note that all surrounding point estimates are negative, while the one at  $t = 1$  is positive.

<sup>48</sup><https://sites.google.com/site/kummersworkingpapers/spilloveronlineappendix>

<sup>49</sup>Ongoing work is attempting to solve this issue. If these efforts are fruitful, the results might be included in a revised version of this paper.

<sup>50</sup>I briefly illustrate how simple this computation is: merely divide the estimated effect on the neighbors (34) by the estimated effect on the treated (4,190) and multiply by the median in-degrees (36). For disasters the analogous computation is  $(38/2,440 * N=31)$ .

from the neighbors. Even though caution is needed to make the following claim, the results suggest that placing links has an effect, but that it is small. Provided this out of equilibrium thought experiment is warranted, creating additional links from neighbors that increase aggregate viewership of the neighbors by 200 is predicted to result in 1.61 additional views on the target page.<sup>51</sup> While this absolute effect in clicks is very small, the conversion to content is even smaller than that since even huge shocks did not generate many revisions on neighboring articles. This suggests that placing links strategically will only generate large effects if the pages that link out are very frequented. However, for the normal traffic on a typical Wikipedia page we would expect very small effects.

## 5.4 Aggregate Effects and Heterogeneities in the Spillover.

In this subsection I first discuss the aggregate spillover effects. Second, I offer the results of a first analysis of how article and network characteristics mediate the spillovers of attention and the associated conversion into content generation. This serves as a test of the assumption that attention spillovers are homogeneous, as is assumed in my model. Moreover, it is interesting for understanding the factors that mediate how attention spills across links and also how attention is converted into content.

First I aggregate the changes in clicks and revisions over all neighboring articles and then average over the 34 different “featured article” clusters. This is done in Figures 5 and 6 in order to summarize and illustrate the insights from the “featured articles” condition. I find that on average there are 4000 clicks on all neighbors taken together (Figure 5). Given that the average treated articles received an additional 4000 clicks this corresponds to a one to one conversion of clicks on the treated page to clicks on one of the neighbors. In other words, the average visitor clicks on exactly one of the links. The total number of revisions on the neighboring pages (Figure 6) increases approximately from 4.5 to 8.5. This means that the 4000 initial additional clicks are converted into 4000 additional clicks on neighbors and four new revisions or a ratio of 1000:1000:1. On the level of the individual article, where usually one in 30 gets an edit, it is still only one in 15 on the day of treatment. Note that these findings are in line with the average “facebook-engagement rate”, which is typically just below 0.01.<sup>52</sup>

Second, I analyze how article characteristics influence the spillovers. I add additional control variables that account for differences in the articles’ characteristics. The results of this analysis are shown in the first three columns of Table 4, where I added variables that account for an article’s length, how well it is generally linked and how closely they are

---

<sup>51</sup>As before I use the median number of neighbors for these thought experiments. Consequently 200 aggregate view correspond to five more views on average. The quantification is based on the upper bound estimates of  $\alpha$  in the “featured article” condition (and would be 3.31 for disasters).

<sup>52</sup><http://www.michaelleander.me/blog/facebook-engagement-rate-benchmark/>. The benchmark measures, how many of a user’s friends and followers react to their posts.

Table 4: Clicks/added revisions over time, when including article heterogeneity.

	joint estimation			short articles only		
	(1) clicks	(2) revisions	(3) length	(4) clicks	(5) revisions	(6) length
t = -2	-5.064 (4.051)	-0.028** (0.011)	-2.484 (3.012)	-2.241 (1.564)	0.004 (0.006)	-0.105 (0.202)
t = -1	2.177 (3.278)	-0.022* (0.012)	7.659 (6.390)	5.178* (3.014)	0.006 (0.005)	0.204 (0.283)
t = 0	38.770*** (11.776)	-0.017* (0.009)	0.419 (2.756)	35.748*** (12.929)	0.002 (0.007)	0.009 (0.197)
t = 1	-0.675 (2.781)	0.041** (0.018)	1.972 (1.681)	1.559 (2.571)	0.017* (0.010)	1.151 (1.210)
t = 2	-2.523 (2.965)	0.015* (0.008)	6.698* (3.957)	-0.134 (2.136)	0.003 (0.002)	-0.089 (0.198)
t = 3	-8.373** (3.371)	-0.011 (0.012)	-2.057 (1.370)	-0.813 (2.258)	0.005 (0.009)	-0.744 (0.541)
t = 4	-2.557 (2.766)	-0.016 (0.014)	-2.308 (1.722)	7.067 (4.435)	-0.005 (0.007)	0.927 (1.027)
short article on t = 0	-2.631 (5.745)	0.003 (0.008)	-1.386 (2.343)			
short article on t = 1	-0.962 (2.726)	-0.037** (0.017)	-0.159 (1.029)			
many L1 links article on t = 0	24.027 (19.759)	0.009 (0.025)	19.834 (18.849)			
many L1 links article on t = 1	-6.963 (7.463)	-0.020 (0.024)	-3.385 (2.825)			
long article on t = 0	-8.770 (10.807)	-0.001 (0.016)	-4.732 (3.983)			
long article on t = 1	3.164 (4.333)	-0.000 (0.029)	10.428 (6.505)			
well linked article on t = 0	-15.565 (14.763)	0.030** (0.014)	2.261 (5.132)			
well linked article on t = 1	1.484 (4.648)	-0.003 (0.023)	-3.044 (4.871)			
Constant	31.982*** (0.823)	0.043*** (0.002)	2.959*** (0.524)	10.297*** (0.994)	0.003*** (0.001)	0.137* (0.071)
All cross	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120758	115269	115269	19932	19026	19026
Number of Pages	5489	5489	5489	906	906	906

NOTES: The table shows the results of the reduced form regressions estimating the ITE for neighbors. Columns (1)-(3) show additional control variables that provide a deeper characterization of the articles to analyze if spillovers vary across these groups. Columns (4-6) analyze the reduced sample that only contains articles that were shorter than 1500 bytes ("stubs"). Specification (1) and (4) show the results for clicks, (2) and (5) for new edits, and Columns (3) and (6) show added content. All estimations contrast the treated with both comparison groups (based on other featured articles and the same articles but seven weeks earlier (placebo treatment)). Fixed Effects Panel-Regressions with heteroscedasticity robust standard errors. The unit of observations is the outcome of a page  $i$  on day  $t$ . The time variable is normalized and runs from -14 to 14.; Only crossterms closer to treatment are shown, but all were included. Reference group t-14 to t-5; standard errors in parentheses: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ; no. of obs. = 120758; no. of clusters = 63; no. of articles = 5489.

linked to the shocked articles (by counting closed triads with other neighbors). Columns 4-6 show the results of an analysis that considers short articles (“stubs”) separately. A word of caution is in place here: The explanatory variables at hand are subject to many unobserved influences, such as relevance, challenging topics, etc. Hence, these regressions might introduce endogeneity problems. Nevertheless these questions deserve to be studied further, so I report the results with the caveat that they are correlations that they cannot necessarily afford a causal interpretation.

Splitting the sample into well-connected articles with many links and poorly connected ones with few, I do not find a significant difference between the two groups. The same is true for a variable that captures whether a page is very long or not. I get a positive but insignificant point estimate for page views. By the same token, there is no statistically significant effect for nodes that show high clustering relative to the shocked node (neighbors, that get many links also from other neighbors). The point estimate seems to indicate a higher click-through rate onto those articles, but these clicks might be indirect click-throughs (forwarded from neighbors of the shocked node). Generally, no effect on clicks in Column 1 is statistically significant which indicates that the spillovers do not vary systematically by the four mentioned properties.

An interesting pattern emerges, when I consider only “stubs”, i.e. pages that do not exceed a length of 1500 bytes. I find that the increase is the same as on average, but that attention is less likely to convert into edits (Columns 4-6 of Table 4). Short articles are viewed 32 times more often than on an average day, but in absolute terms the increase in edits is smaller (.017 vs. .034, in separate estimation). A remark is in order: Since stubs generally have a much lower probability to be viewed or edited, these increases are *larger in relative terms* than for normal articles.<sup>53</sup> Finally I report results of an extended analysis which is omitted here, for reasons of brevity.<sup>54</sup> I include the number of clicks on the treated page in the regression and, as expected, the number of links on the neighboring pages is positively related to that value.

It is exciting to contrast my findings for the contribution of content with the donations of money during Wikipedia’s annual campaign for donations.<sup>55</sup> I do so in Table 5, which shows my main results for content contributions and contrasts them with the click-through rates during the campaign. When doing so I find a striking similarity in the size of the click-through rates between content items and the click-through to the donation banners during the campaign. In other words, it turns out that the spillover of attention is almost the same between articles and from articles to the donations-banner. However, the

---

<sup>53</sup>The probability of being viewed increases by 300% (vis a vis 100%) for the average neighbor. The chances for an edit increases by 500% vis a vis an 80% increase over baseline levels. This much stronger relative effect in the number of edits indicates that contributors do make a greater effort (in comparative terms) to contribute to pages where the existing content is limited.

<sup>54</sup>Available online at <https://sites.google.com/site/kummersworkingpapers/spilloveronlineappendix>.

<sup>55</sup>Available at [http://de.wikipedia.org/wiki/Wikipedia:Fundraiser\\_2011/Tests](http://de.wikipedia.org/wiki/Wikipedia:Fundraiser_2011/Tests) (last: Feb. 27, 2014)



Table 5: Conversion of attention to action: Content vs. money contributions.

	donations		contributions	
	donations high	donations low	all articles	short articles
click-through	0.024	0.002	0.008	0.008
conversion to action	0.124	0.004	0.001	0.0005

NOTES: As the click-through rate for donations I used the “Banner-Klick pro Impressions”-statistic, which measures the ratio of how often the banner was shown, vs. how often it was clicked on. As analogue to the conversion to an edit (action) I used “Anzahl pro Banner Klick”, which measures the ratio of actually completed donations to banner-clicks. I report the minimum (25% quartile attention: 0.004, action: 0.01) and the maximum (75% quartile attention: 0.009, action: 0.019) of the 2011 campaign. Source: 2011 Wikipedia campaign tests and own calculations.

conversion into action, once on the donating page, is even higher for monetary donations than for making an edit on the new page. Even though the intention behind clicking on a banner is certainly different from the one behind clicking on any link, this fact gives an idea of just how costly it is for most visitors to make an edit.

## 6 Limitations and Further Research

While my findings highlight the importance of citation networks for channeling human attention, they also suggest that using the link network is an expensive and inefficient strategy for channeling contribution flows. My results also indicate that many users only look up information. I cannot say whether the low levels of conversion from attention to an action are the same for Wikipedia (editing) and adverts (purchase), but the similarities of the click-through rates to donations are striking. Further research could study if similar dynamics can be found on young wikis with less content.

There are some limitations to the presented approach. Most importantly, the strategy of exploiting local exogenous treatments will not allow the identification of the social spillover parameter if neighbors of the treated nodes observe the treatment and adjust their outcome as a reaction to the mere fact that their neighbor was treated. An example would be a teacher who selectively punishes or favors a single student: if other pupils react to the special treatment, e.g. by changing their motivation to study for the subject, then their performance change reflects the sum of the spillover and their behavioral adjustment. In Appendix D, I outline such a case and illustrate formally why the spillover parameter can no longer be identified. Another limitation is the assumption that the network formation *process* is not affected by the treatment. This assumption is warranted for Wikipedia’s “today’s featured article” but less so for disasters. Generally, if the process is affected by treatment all estimates of indirect treatment effects will reflect a sum of the treatment on the existing network and new spillovers due to the changes in the link network which might lead to upward biases (cf. Comola and Prina (2013)).

A promising area for further analysis would investigate whether the new contribu-

tions, especially the ones by new authors, add substantive knowledge or rather focus on improving small details. Future research should also exploit the heterogeneity in intensity of direct treatment effects more thoroughly. In particular, it would be interesting to analyze how attention, here measured as average effect, is distributed across neighbors. Is it evenly distributed or do users herd to only a few of the linked pages? Another promising area would use the methodology based on exogenous local treatments alongside that based on the network structure and the exploitation of open triads (Bramoullé et al. (2009), De Giorgi et al. (2010)). The approaches are complementary; research along these lines will result in valuable insights. Finally, it was not yet possible to surmount the computational hurdle of exploiting the detailed network information when obtaining the structural estimates. Future research should include this information and investigate which population parameter should be optimally included for relating reduced form and structural parameters.

## 7 Conclusions

This paper investigates how the network of links between articles on the German Wikipedia influences the attention and subsequent content generation individual articles receive. To the best of my knowledge my results are the first to provide a causal quantification of how the link network influences users' contributions in an important online network of content pages. By studying exogenous short term shocks to attention I can measure attention spillovers. I find substantial spillovers in terms of both views and editing activity. Articles in the neighborhood of shocked articles received 35 more visits on average - an increase of almost 100 percent.

Moreover, I am able to isolate the effect of attention from other determinants of public good contribution such as reputation, social image and altruism. I find that on average 1000 views are needed before additional content (an edit) is generated. I also find that this rate is lower than the conversion rate from clicks on funding campaign banners to donations, indicating that it is less costly to donate money than to contribute content.

Although my design allows a causal interpretation of the reduced form estimates of the spillover, I set up a simple empirical model of the underlying dynamics with which views are transmitted between neighboring pages: I augment the workhorse model for estimating peer effects (or spillovers) in networks (Bramoullé et al. (2009)), by incorporating exogenous treatments of individual nodes. Exogenous treatments can serve as complementary source of identification of the structural spillover effect, which does not depend on assuming an exogenous network structure. The model I suggest also nests two-layered randomized control settings that rely on exogenous variation over subpopulations.<sup>56</sup>

---

<sup>56</sup>Moffitt (2001), Angelucci and De Giorgi (2009), Kuhn et al. (2011), Crépon et al. (2013) etc.

My structural estimates suggest that an article will receive 30 percent of the average views on neighboring articles. Placing links to oft frequented nodes and thus increasing the average daily views on their neighbors by ten, one could obtain three additional daily visits to an article. I show that upper and lower bounds for the structural parameters can be computed even if the underlying network structure is unknown. The bounds are easily computed for settings where only one node is treated in each subpopulation. I conjecture that they can easily be generalized to treatments that affect more than one node. It is thus no longer necessary to neglect the network structure in an experiment that aims at identifying social effects, merely because the information on links is not available. Finally, the modeling approach of exploiting open triads in the network structure is formally similar to spatial Durbin models in spatial econometrics (cf. LeSage (2008)).

So what do we learn for advertising on the web, setting up a firm wiki or for realizing the Wikimedia Foundation’s vision?<sup>57</sup> Additional views translate one for one into additional views on a neighbor. The significance of this result deserves emphasis: On average, *every* visitor of “today’s featured article” clicks on one of the links to acquire further information. The click-through rates I find are very similar to the clicks-throughs to the donation banner. Moreover, the spillover does not depend on the targets’ characteristics - all contents have a fair chance of getting some attention. However, what happens once the attention is there *does* depend on the items’ characteristics - much less content is generated *shorter* pages.

Taken together, my findings suggest that (i) making an edit is very costly and (ii) that contributions due to attention alone will ensure sufficient provision of public goods only, whenever large amounts of traffic are available, which can be the case online. They also confirm earlier research which suggested that offline or with platforms that lack many visitors, other drivers of public goods contributions, such as social image and altruism may be needed (e.g. Carpenter and Myers (2010)): Contributions due to attention alone occur at a rate that is unlikely to ensure sufficient provision of public goods in small offline communities. Online, however, whenever modularity of tasks, strong enough leadership *and large amounts of traffic* are available, the “miracle of Wikipedia” awaits repetition.

## References

- Angelucci, Manuela and Giacomo De Giorgi**, “Indirect Effects of an Aid program: How do Cash Transfers Affect Ineligibles’ Consumption?,” *The American Economic Review*, 2009, 99 (1), 486–508.
- Angrist, Joshua D and Jörn-Steffen Pischke**, *Mostly Harmless Econometrics: An Empiricist’s Companion*, Princeton University Press, 2008.
- Aral, Sinan and Dylan Walker**, “Creating Social Contagion through Viral Product Design: A Randomized Trial of Peer Influence in Networks,” *Management Science*, 2011, 57 (9), 1623–39.
- Ashenfelter, Orley and Michael Greenstone**, “Using Mandated Speed Limits to Measure the Value of a Statistical Life,” *Journal of Political Economy*, 2004, 112 (S1), S226–S267.
- Ballester, Coralio, Antoni Calvo-Armengol, and Yves Zenou**, “Who’s Who in Networks. Wanted: The Key Player,” *Econometrica*, 09 2006, 74 (5), 1403–17.

---

<sup>57</sup>A world where all “can freely share in the sum of all knowledge” (Wikimedia-Foundation (2013))

- Banerjee, Abhijit, Arun G Chandrasekhar, Esther Dufo, and Matthew O Jackson**, “The Diffusion of Microfinance,” Technical Report, National Bureau of Economic Research 2012.
- Barber, Brad M and Terrance Odean**, “All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors,” *Review of Financial Studies*, 2008, 21 (2), 785–818.
- Benkler, Y.**, “Coase’s Penguin, or, Linux and “The Nature of the Firm”,” *Yale Law Journal*, 2002, pp. 369–446.
- , *The wealth of networks: How social production transforms markets and freedom*, Yale Univ Pr, 2006.
- and **H. Nissenbaum**, “Commons-based Peer Production and Virtue\*,” *Journal of Political Philosophy*, 2006, 14 (4), 394–419.
- Berger, Jonah, Alan T Sorensen, and Scott J Rasmussen**, “Positive effects of negative publicity: When negative reviews increase sales,” *Marketing Science*, 2010, 29 (5), 815–827.
- Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin**, “Identification of Peer Effects through Social Networks,” *Journal of Econometrics*, 2009, 150 (1), 41–55.
- Carmi, Eyal, Gal Oestreicher-Singer, and Arun Sundararajan**, “Is Oprah Contagious? Identifying Demand Spillovers in Online Networks,” *NET Institute Working Paper.*, 2012, No. 10-18., Available at SSRN: <http://ssrn.com/abstract=1694308> or <http://dx.doi.org/10.2139/ssrn.1694308> (August 3, 2012).
- Carpenter, Jeffrey and Caitlin Knowles Myers**, “Why volunteer? Evidence on the role of altruism, image, and incentives,” *Journal of Public Economics*, 2010, 94 (11), 911–920.
- Claussen, J., O. Falck, and T. Grohsjean**, “The Strength of Direct Ties: Evidence from the Electronic Game Industry,” *International Journal of Industrial Organization*, 2012, 30 (2), 223–30.
- Coase, Ronald H**, “The nature of the firm,” *economica*, 1937, 4 (16), 386–405.
- Comola, Margherita and Silvia Prina**, “The Impact of Exogenous Interventions on Networks: A Dynamic Peer Effect Model,” 2013.
- Crépon, Bruno, Esther Dufo, Marc Gurgand, Roland Rathelot, and Philippe Zamora**, “Do Labor Market Policies have Displacement Effects? Evidence from a Clustered Randomized Experiment,” *The Quarterly Journal of Economics*, 2013, 128 (2), 531–80.
- Dahl, Gordon B, Katrine V Løken, and Magne Mogstad**, “Peer Effects in Program Participation,” Technical Report, National Bureau of Economic Research 2012.
- Ferracci, Marc, Grégory Jolivet, and G. J. van den Berg**, “Evidence of Treatment Spillovers within Markets,” online 2012. last retrieved on Nov. 11, 2013 at [http://www.efm.bris.ac.uk/ecgrjeval\\_resubmit.pdf](http://www.efm.bris.ac.uk/ecgrjeval_resubmit.pdf).
- Fershtman, C. and N. Gandal**, “Direct and Indirect Knowledge Spillovers: The “Social Network” of Open-source Projects,” *RAND Journal of Economics*, 2011, 42 (1), 70–91.
- Giorgi, Giacomo De, Michele Pellizzari, and Silvia Redaelli**, “Identification of Social Interactions through Partially Overlapping Peer Groups,” *American Economic Journal: Applied Economics*, 2010, 2 (2), 241–75.
- Giorgidze, G., T. Grust, T. Schreiber, and J. Weijers**, “Haskell Boards the Ferry: Database-supported Program Execution for Haskell,” in “Revised selected papers of the 22nd international symposium on Implementation and Application of Functional Languages, Alphen aan den Rijn, Netherlands,” Vol. 6647 of *Lecture Notes in Computer Science* Springer 2010. Peter Landin Prize for the best paper at IFL 2010.
- Hinz, Oliver, Bernd Skiera, Christian Barrot, and Jan U Becker**, “Seeding strategies for viral marketing: an empirical comparison,” *Journal of Marketing*, 2011, 75 (6), 55–71.
- Ho, Jason YC and Melanie Dempsey**, “Viral marketing: Motivations to forward online content,” *Journal of Business Research*, 2010, 63 (9), 1000–1006.
- Hoffman, Andrew J and William Ocasio**, “Not all events are attended equally: Toward a middle-range theory of industry attention to external events,” *Organization Science*, 2001, 12 (4), 414–434.
- Hu, Nan, Yi Dong, Ling Liu, and Lee J Yao**, “Not all that glitters is gold: the effect of attention and blogs on investors’ investing behaviors,” *Journal of Accounting, Auditing & Finance*, 2013, 28 (1), 4–19.
- Huberman, Bernardo A, Daniel M Romero, and Fang Wu**, “Crowdsourcing, attention and productivity,” *Journal of Information Science*, 2009, 35 (6), 758–765.
- Imberman, Scott, Adriana D Kugler, and Bruce Sacerdote**, “Katrina’s Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees,” Technical Report, National Bureau of Economic Research 2009.
- Jacobson, Louis S, Robert John LaLonde, and Daniel G Sullivan**, “Earnings Losses of Displaced Workers,” *American Economic Review*, 1993, 83 (4), 685–709.
- Keegan, Brian, Darren Gergle, and Noshir Contractor**, “Hot Off the Wiki Structures and Dynamics of Wikipedia’s Coverage of Breaking News Events,” *American Behavioral Scientist*, 2013, 57 (5), 595–622.
- Kuhn, Peter, Peter Kooreman, Adriaan Soetevent, and Arie Kapteyn**, “The Effects of Lottery Prizes on Winners and their Neighbors: Evidence from the Dutch Postcode Lottery,” *The American Economic Review*, 2011, 101 (5), 2226–47.
- Kummer, Michael E, Marianne Saam, Iassen Halatchliyski, and George Giorgidze**, “Centrality and Content Creation in Networks – The Case of German Wikipedia,” *ZEW-Centre for European Economic Research Discussion Paper*, 2012, (12-053).
- Lerner, J. and J. Tirole**, “Some Simple Economics of Open Source,” *Journal of Industrial Economics*, 2002,

pp. 197–234.

- LeSage, James P**, “An introduction to spatial econometrics,” *Revue d’économie industrielle*, 2008, (3), 19–44.
- Manski, Charles F**, “Identification of Endogenous Social Effects: The Reflection Problem,” *The Review of Economic Studies*, 1993, 60 (3), 531–42.
- Miguel, Edward and Michael Kremer**, “Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities,” *Econometrica*, 2003, 72 (1), 159–217.
- Moffitt, Robert A**, “Policy Interventions, Low-level Equilibria, and Social Interactions,” *Social Dynamics*, 2001, pp. 45–82.
- Sacerdote, Bruce**, “Peer Effects with Random Assignment: Results for Dartmouth Roommates,” *The Quarterly Journal of Economics*, 2001, 116 (2), 681–704.
- Shang, Jen and Rachel Croson**, “A field experiment in charitable contribution: The impact of social information on the voluntary provision of public goods,” *The Economic Journal*, 2009, 119 (540), 1422–1439.
- Wikimedia-Foundation**, “Frequently Asked Questions,” online 2013. last retrieved on Sept. 9, 2013 at <http://wikimediafoundation.org/wiki/FAQ/en>.
- Wu, Fang and Bernardo A Huberman**, “Novelty and collective attention,” *Proceedings of the National Academy of Sciences*, 2007, 104 (45), 17599–17601.
- Zhang, X. and F. Zhu**, “Group Size and Incentives to Contribute: A Natural Experiment at Chinese Wikipedia,” *The American Economic Review*, 2011, 101, 1601–15.

# A Data-Appendix

Table 6: Summary statistics: direct neighbors of shocked 'featured articles'

	mean	sd	min	p10	p50	p90	max
Length of page (in bytes)	6794	6784	17	51	4833	15262	81585
Number of authors	33	35	1	2	21	77	324
Clicks	33	131	0	0	0	77	20384
Number of Revisions	95	130	1	3	48	237	1382
Links from Wikipedia	118	301	0	6	36	286	9484
Dummy: literature section	.3	.46	0	0	0	1	1
References (footnotes)	1.3	4.5	0	0	0	4	182
Links to further info	2.3	4.2	0	0	1	6	155
time variable (normalized)	0	8.4	-14	-12	0	12	14
Delta: Number of Revisions	.042	.39	0	0	0	0	42
Delta: Length of page	2.1	159	-31473	0	0	0	31462
Delta: Number of authors	.015	.13	0	0	0	0	9
Delta: Links from Wikipedia	.054	1.1	-90	0	0	0	438
Delta: References	.0014	.097	-18	0	0	0	18
Delta: Links further info	.00078	.1	-19	0	0	0	16

NOTES: The table shows the distribution of the main variables. The unit of observations is the outcome of a page  $i$  on day  $t$ . The time variable is normalized and runs from -14 to 14.; no. of obs. = 317550; no. of start pages = 63; no. of articles = 5489.

Table 7: Indirect neighbors of shocked 'large events articles' (2 clicks away)

	mean	sd	min	p10	p50	p90	max
Length of page (in bytes)	5658	6287	16	33	3885	13210	76176
Number of authors	29	34	1	1	18	71	435
Clicks	33	174	0	0	0	70	29865
Number of Revisions	84	133	1	2	40	211	2083
Links from Wikipedia	123	447	0	5	31	269	27611
Dummy: literature section	.2	.4	0	0	0	1	1
References (footnotes)	1.3	4.2	0	0	0	4	150
Links to further info	2.7	5.1	0	0	1	7	130
time variable (normalized)	0	8.4	-14	-12	0	12	14
Delta: Number of Revisions	.035	.35	0	0	0	0	44
Delta: Length of page	1.8	106	-22416	0	0	0	27500
Delta: Number of authors	.013	.12	0	0	0	0	11
Delta: Links from Wikipedia	.049	2.5	-1148	0	0	0	216
Delta: References	.0014	.13	-32	0	0	0	29
Delta: Links further info	.0011	.12	-15	0	0	0	31

NOTES: The table shows the distribution of the main variables. The unit of observations is the outcome of a page  $i$  on day  $t$ . The time variable is normalized and runs from -14 to 14.; no. of obs. = 425981; no. of start pages = 44; no. of articles = 7379.

Table 8: Included “featured articles” that were advertised on German Wikipedia’s start page and the number of associated articles and observations (1 clicks away).

name of event	pages no.	observations		
		control	treated	Total
Afrikaans	128.0	5,481.0	1,943.0	7,424.0
Alte_Synagoge_(Heilbronn)	52.0	1,885.0	1,131.0	3,016.0
Banjo-Kazooie	125.0	5,191.0	2,030.0	7,221.0
Benno_Elkan	139.0	5,133.0	2,900.0	8,033.0
Bombardier_Canadair_Regional_Jet	92.0	4,205.0	1,073.0	5,278.0
CCD-Sensor	586.0	31,001.0	2,871.0	33,872.0
Charles_Sanders_Peirce	258.0	11,716.0	3,219.0	14,935.0
Das_Kloster_der_Minne	51.0	1,827.0	1,102.0	2,929.0
Deutsche_Bank	343.0	10,005.0	9,860.0	19,865.0
Eishockey	162.0	4,698.0	4,698.0	9,396.0
Ekel	270.0	10,295.0	5,336.0	15,631.0
Fahrbahnmarkierung	44.0	1,276.0	1,276.0	2,552.0
Geschichte_Ostfrieslands	235.0	7,453.0	6,177.0	13,630.0
Geschichte_der_deutschen_Sozialdemokratie	306.0	9,599.0	8,033.0	17,632.0
Glanzstoff_Austria	270.0	14,094.0	1,537.0	15,631.0
Glorious_Revolution	153.0	6,206.0	2,668.0	8,874.0
Granitschale_im_Lustgarten	83.0	3,857.0	928.0	4,785.0
Gustav_Hirschfeld	142.0	6,438.0	1,740.0	8,178.0
Hallenhaus	71.0	2,117.0	2,001.0	4,118.0
Helgoland	228.0	8,120.0	5,104.0	13,224.0
Jaroslawl	321.0	12,789.0	5,829.0	18,618.0
Jupiter_und_Antiope_(Watteau)	36.0	1,160.0	928.0	2,088.0
Karolingische_Buchmalerei	162.0	4,843.0	4,553.0	9,396.0
Katholische_Liga_(1538)	37.0	1,682.0	464.0	2,146.0
Martha_Goldberg	55.0	1,595.0	1,595.0	3,190.0
Naturstoffe	320.0	9,338.0	9,222.0	18,560.0
Paul_Moder	61.0	1,798.0	1,682.0	3,480.0
St._Martin_(Memmingen)	59.0	1,653.0	1,711.0	3,364.0
Stabkirche_Borgund	40.0	1,421.0	899.0	2,320.0
Taiwan	167.0	5,017.0	4,669.0	9,686.0
USS_Thresher_(SSN-593)	90.0	3,712.0	1,479.0	5,191.0
Visum	56.0	1,624.0	1,624.0	3,248.0
Wenegnebti	55.0	1,798.0	1,363.0	3,161.0
Werder_Bremen	292.0	8,555.0	8,323.0	16,878.0
Total	5,489.0	207,582.0	109,968.0	317,550.0

NOTES: The table shows the “featured articles” in the dataset. Column 1 shows the number of associated articles that are one click away from one of the corresponding start pages (be it treated or control). Columns 2-4 show the number of observations. Observations associated with actually treated articles are shown separately from control observations. Pages can be accessed by pasting the title behind the last slash in: <http://de.wikipedia.org/wiki/>

Table 9: Included disasters, associated observations and number of pages (2 clicks away).

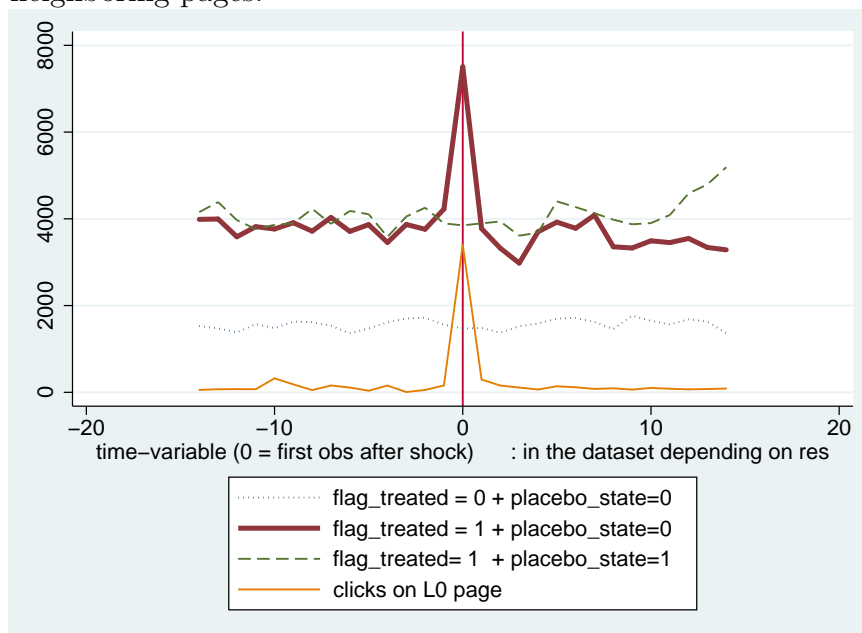
name of event	pages No.	observations		
		control	treated	Total
Air-France-Flug_447	102.0	4,495.0	1,392.0	5,887.0
Air-India-Express-Flug_812	369.0	19,662.0	1,711.0	21,373.0
Amoklauf_von_Winnenden	74.0	2,088.0	2,146.0	4,234.0
Bahnunfall_von_Halle_(Belgien)	52.0	2,436.0	580.0	3,016.0
British-Airways-Flug_38	144.0	6,699.0	1,624.0	8,323.0
Buschfeuer_in_Victoria_2009	33.0	928.0	957.0	1,885.0
Deepwater_Horizon	203.0	8,178.0	3,596.0	11,774.0
Erdbeben_in_Haiti_2010	379.0	15,602.0	6,322.0	21,924.0
Erdbeben_in_Sichuan_2008	227.0	11,571.0	1,508.0	13,079.0
Erdbeben_von_L'Aquila_2009	96.0	3,654.0	1,885.0	5,539.0
Flugzeugabsturz_bei_Smolensk	368.0	12,412.0	8,758.0	21,170.0
Grubenunglück_von_San_Jose	149.0	8,033.0	551.0	8,584.0
Josef_Fritzl	129.0	6,264.0	1,044.0	7,308.0
Kaukasuskrieg_2008	346.0	18,705.0	1,276.0	19,981.0
Kolontár-Dammbruch	99.0	4,669.0	1,073.0	5,742.0
Luftangriff_bei_Kunduz	2,107.0	113,767.0	7,772.0	121,539.0
Northwest-Airlines-Flug_253	1,151.0	65,279.0	1,276.0	66,555.0
Sumatra-Erdbeben_vom_September_2009	116.0	4,002.0	2,726.0	6,728.0
US-Airways-Flug_1549	226.0	7,888.0	5,220.0	13,108.0
Unglück_bei_der_Loveparade_2010	499.0	15,283.0	13,572.0	28,855.0
Versuchter_Anschlag_am_Times_Square	202.0	10,353.0	1,334.0	11,687.0
Wald-_und_Torfbrände_in_Russland_2010	273.0	13,485.0	2,204.0	15,689.0
Zugunglück_von_Castelldefels	35.0	1,508.0	493.0	2,001.0
Total	7,379.0	356,961.0	69,020.0	425,981.0

NOTES: The table shows the events in the dataset. Column 1 shows the number of pages that are two clicks away from one of the two associated start pages (be it treated or control). Columns 2-4 show the number observations associated with the articles. Observations associated with actually treated articles are shown separately from control observations. Pages can be accessed by pasting the title behind the last slash in: <http://de.wikipedia.org/wiki/>



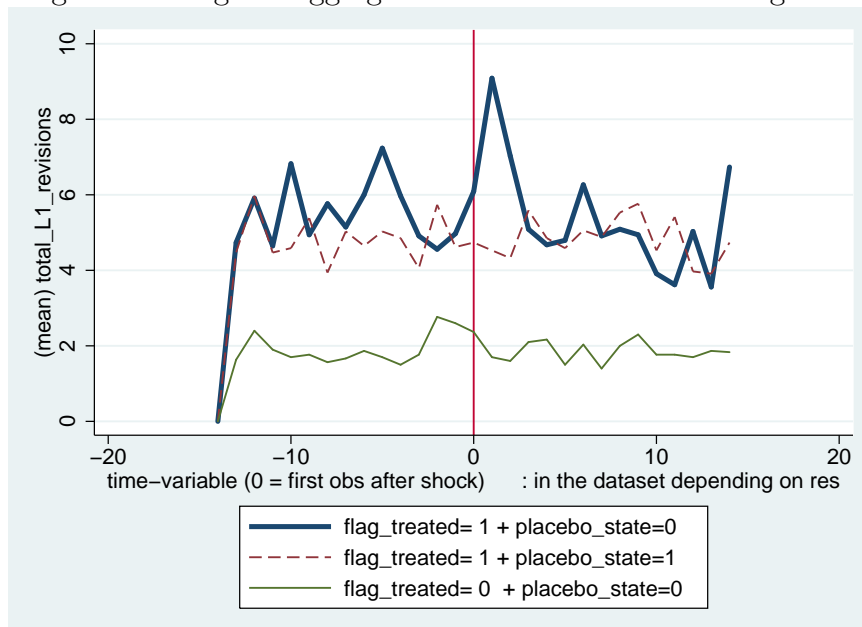
## A.1 Additional Regression and Figures

Figure 5: Figure contrasting the mean of clicks on featured articles, with the aggregated clicks on all neighboring pages.



NOTES: The figure shows the aggregated effect on the pages that are one click away. The average treated page received up to 4000 additional clicks, all neighbors together received approx. the same number of additional clicks

Figure 6: Figure showing the aggregated new revisions on all neighboring pages.



NOTES: The figure shows the aggregated effect on the pages that are one click away. All neighbors of treated articles together received approx. four additional revisions.

Table 10: Robustness Check: Relationship of clicks/added revisions and time dummies for direct neighbors of shocked articles in the 'featured articles' condition for only a reduced number of events.

	clicks		del revisions		del authors	
	(1) compare control	(2) compare placebo	(3) compare control	(4) compare placebo	(5) compare control	(6) compare placebo
t = -2	-2.117 (5.554)	4.304 (4.147)	-0.026** (0.012)	-0.020 (0.015)	-0.014** (0.006)	-0.009* (0.005)
t = -1	2.953 (4.448)	11.074* (5.974)	-0.012 (0.013)	-0.004 (0.011)	-0.002 (0.005)	-0.005 (0.004)
t = 0	34.625** (13.296)	40.149** (13.572)	-0.013 (0.011)	0.004 (0.011)	-0.006 (0.005)	-0.008 (0.005)
t = 1	-1.463 (2.685)	2.145 (4.649)	0.037* (0.018)	0.033 (0.021)	0.015** (0.007)	0.012 (0.008)
t = 2	-3.262 (4.308)	-0.427 (4.076)	0.012 (0.010)	0.005 (0.015)	0.002 (0.004)	-0.006 (0.006)
t = 3	-10.195** (4.874)	-3.046 (4.977)	-0.009 (0.012)	-0.033* (0.019)	-0.005 (0.006)	-0.010* (0.005)
t = 4	-3.023 (4.074)	5.034 (3.968)	-0.031* (0.016)	-0.019 (0.012)	-0.009 (0.005)	-0.003 (0.005)
Constant	30.930*** (1.291)	34.526*** (1.135)	0.047*** (0.003)	0.050*** (0.003)	0.016*** (0.001)	0.016*** (0.001)
All cross	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73084	98252	69762	93786	69762	93786
Number of Pages	3322	4466	3322	4466	3322	4466
Adj. R <sup>2</sup>	0.004	0.003	0.000	0.000	0.001	0.001

Standard errors in parentheses

Fixed Effects Panel-Regressions with heteroscedasticity robust standard errors.

Only crossterms closer to treatment are shown, but all were included. Reference group t-14 to t-5

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

## B Details about Data Preparation, the Treated and the Control Groups

This section gives detailed information about the preparation and storage of the dataset. The subsequent subsections explain how the database was put together and the procedure I used to extract the dataset that I use.

### B.1 Preparation and Extraction

The dataset is based on a full-text dump of the German Wikipedia from the Wikimedia toolserver. To construct the history of the articles' hyperlink network for the entire encyclopedia, it was necessary to parse the data and identify the links. From the resulting tables, I constructed a time-varying graph of the article network, which provided the foundation for how I sample articles in my analysis. Furthermore, information about the articles, such as the number of authors who contributed up to a particular point in time or the existence of a section with literature references was added. Hence, the data I use are based on 153 weeks of the the entire German Wikipedia's revision history between December 2007 and December 2010. Since the data are in the order of magnitude of terabytes, it was not be possible to conduct the data analysis using only in-memory processing. We therefore stored the data in a relational database (disk-based) and queried the data using Database Supported Haskell (DSH) (Giorgidze et al. (2010)).<sup>58</sup>

### B.2 Choice of Treated Articles and Neighborhood

“Featured articles” were found by consulting the German Wikipedia's archive of pages that were selected to be advertised on Wikipedia's main page (“Seite des Tages”) between December 2007 and December 2010. To reduce the computational burden and to avoid the risk of temporal overlaps of different treatments, I focus on pages that were selected on the 10<sup>th</sup> of a month. I identified all the pages that received a direct link ( $L_1$ ) or an indirect link ( $L_2$ ) from such a featured article more than a week before treatment. I evaluated links with this time gap before the shock actually occurred to make sure that the results are not driven by endogeneous link formation.<sup>59</sup> Having fixed the set of pages to observe, I extracted daily information on the contemporary state of the articles (page visits, number of revisions, number of distinct authors that contributed, page length, number of external links etc.). I determine these variables on a daily basis, 14 days before the event occurred (on a neighboring page) and 14 days after the shock (giving a total of 29 observations per page).

To identify major events, I consulted the corresponding page on Wikipedia and selected the 26 largest events with spontaneous onset. For each of these events we identified the page that corresponds to the event, which are considered to be in the set “ $L_0$ ” (sometimes also called “start pages”). Note that this page is typically created *after the event* occurred<sup>60</sup>, which obliges me to identify the pages, that user will most likely turn to until the disaster's page is in place. To achieve this, I used the link data to identify the set of pages that later shared a reciprocal link with the start page. Such a reciprocal link indicates that they were closely related to the event. After the event page came in to existence they were only one click away (set “ $L_1$ ”). Next, we identified those pages that received a link from an  $L_1$  page (unidirectional) (2 clicks away set “ $L_2$ ”).

I am most interested in attention spillovers and content provision, which are not directly related to the events but rather a consequence of the spike in interest and the resulting improvements to the linked pages. Hence, I will not focus on the treated pages directly, but on the set  $L_1$  that are “one click away”, in my analysis of the “featured articles”.<sup>61</sup> For disasters the shock is very large and the event page usually does not exist at the time of the shock, so the  $L_1$  pages

---

<sup>58</sup>This is a novel high-level language allowing the writing and efficient execution of queries on nested and ordered collections of data.

<sup>59</sup>I thus only include pages that had a link before it was known that the start page will be hit. I furthermore exclude pages that receive their indirect ( $L_2$ ) link via a page that has more than 100 links, since such pages are very likely either pure “link pages” very general pages (such as pages about a year), that bare only a very weak relationship to the shocked site.

<sup>60</sup>Usually it takes up to two days until the event receives its own page.

<sup>61</sup>Effects on the pages that are 2 clicks away were to small too be measured.

might have been treated themselves.<sup>62</sup> Hence, I focus on the indirectly linked set of pages ( $L_2$ ) in the analysis below.

### B.3 Choice of Control Group Articles and Neighborhood

The approach I take in this paper hinges on the availability of a valid control group. To obtain such observations I pursue two distinct strategies. The first approach uses pages which are similar but unlikely to be affected by the treatment. For a first comparison I selected other featured articles and neighbors thereof that were advertised featured either later or earlier in time. Given such a similar page, I identified their direct and indirect neighbors when the event occurred on the treated page. This gives me a set  $C1_{control}$  which is similar in both size and characteristics to the sampled pages (before the shock). Yet, the choice of the start pages in the comparison group is somewhat arbitrary.<sup>63</sup> I address this issue by simulating a treatment on the treated pages 42 days before the disaster or event occurred. I refer to the articles in this “placebo-treatment” as  $C1_{placebo}$ , because for them  $t = 0$  when no actual treatment occurred. By design, this comparison group consists of the same set of articles (treated and their neighbors). This comes at the cost of observing the articles at a different point in time. A third control group of “unrelated” observations results from applying a placebo to the control group.<sup>64</sup>

Table 8 (in the data appendix) shows which featured articles were chosen by my procedure and included in the data. In general, they cover various topics such as innovations (e.g. the CCD-sensor), places (Helgoland), soccer clubs (Werder Bremen) or art history topics (Carolingian book illustrations). The first column of the table shows the number of articles that belong to each featured article. The last three columns show the number of observations that received a link from an article before it was advertised featured, separated by whether or not they belong to a time-series with actually treated observations.<sup>65</sup> The numbers range from 2,088 to 33,872.

For disasters I proceeded along similar lines. I focused on the network around older catastrophes that occurred at a different point in time and were not from exactly the same domain, to avoid overlaps in the link network ( $C_{control}$ ). Alternatively, I observe the same set of pages seven weeks before the disaster ( $C_{placebo}$ ). Table 9 shows which events were included in the data and shows the associated number of observations for each of them. The dataset includes both natural disasters as well as technical or economic catastrophes.

## C The empirical model and structural identification of the parameter of interest.

This section presents the structural model and discusses the parameters of interest, the challenges in identifying them and the approach taken to tackle them.

---

<sup>62</sup>Some of the consequences of major events, such as earthquakes, might change the state of the world and thus trigger a change in content, which is merely *due to the event* (e.g. destruction of an important monument). Consequently, I do not emphasize the change in activity on the pages that are only one click away for disasters. I also exclude pages if they were later directly linked to the event page.

<sup>63</sup>Ideally the selection of comparison pages should be based on matching procedures, which is unfortunately not possible without computing the characteristics of all the 1,000,000 nodes. My approach is however quite robust independently of how I specify the control group. I also compared to the neighbors around articles of similar size and relative importance, about similar topics, but in a remote geographic space or technical domain. Such a change in the specification of the control group does not affect my results. (available upon request).

<sup>64</sup>This set of observations actually emerged as an artifact from the data extraction. Nevertheless it provides yet another group that can be compared to the treated group.

<sup>65</sup>Note, that each page shows up 29 times in the raw data and was sampled twice (placebo and real treatment), so that the number of corresponding pages (treatment or control) can be inferred by dividing the number of observations by 58.

## C.1 Introductory remarks

I depart from the well known linear-in-means model as formulated by Manski (1993).<sup>66</sup>

$$(17) \quad y_{it} = \alpha \frac{\sum_{j \in P_{it}} y_{jt}}{N_{P_{it}}} + X_{it-1} \beta + \gamma \frac{\sum_{j \in P_{it}} X_{jt-1}}{N_{P_{it}}} + \epsilon_{it}$$

$y_{it}$  denotes the outcome of interest in period  $t$  and  $X_{it-1}$  are  $i$ 's observed characteristics at the end of period  $t-1$  (beginning of period  $t$ ).<sup>67</sup>  $P_{it}$  is the set of  $i$ 's peers and  $N_{P_{it}}$  represents the number of  $i$ 's peers.  $\beta$  measures the effect of  $i$ 's own characteristics and  $\gamma$  accounts for how  $i$ 's performance is affected by the peers' average characteristics. The coefficient of interest is  $\alpha$ . In the present context it measures how the clicks on page  $i$  are influenced the clicks on the adjacent pages. Bramoullé et al. (2009) suggest a more succinct notation based on vector and matrix notation:

$$\mathbf{y}_t = \alpha \mathbf{G} \mathbf{y}_t + \beta \mathbf{X}_{t-1} + \gamma \mathbf{G} \mathbf{X}_{t-1} + \epsilon_t \quad \mathbf{E}[\epsilon_t | \mathbf{X}_{t-1}] = \mathbf{0}$$

Note that the linear in means model provides the weakest basis for identification. I conjecture that the insights carry over to other linear models and less weakly identified non-linear models.

## C.2 Setup and Basic Intuition

Augment the model (eq. 17) by observable and locally applied treatments (shocks):

$$(18) \quad y_{it} = \alpha \frac{\sum_{j \in P_{it}} y_{jt}}{N_{P_{it}}} + X_{i,t-1} \beta + \gamma \frac{\sum_{j \in P_{it}} X_{j,t-1}}{N_{P_{it}}} + \delta_1 D_{it} + \epsilon_{it}$$

where the new coefficient  $\delta_1$  measures the direct effect if a node(page) is treated.

Note that  $X_{it-1} \beta$  may contain an individual fixed effect and an additively separable age-dependent part:  $X_{it-1} \beta = \beta_i + \widetilde{X_{i,t-1}} \beta_1 + \beta_2 f(\text{age})$ . To see how local treatments can be used as a source of identification, consider two pairs of nodes.

**Local application of treatment:** First, consider two connected nodes, where one is treated ( $\ell 0$ ) in period  $t$  and the neighbors are not treated ( $\ell 1 \in L1$ ). Assume for simplicity that  $\ell 0$  is the only treated node in  $\ell 1$ 's neighborhood.

$$(19) \quad \ell 0 :: \mathbf{y}_{\ell 0 t} = \alpha \frac{\sum_{j \in P_{\ell 0 t}} y_{jt}}{N_{P_{\ell 0 t}}} + X_{\ell 0 t-1} \beta + \gamma \frac{\sum_{j \in P_{\ell 0 t}} X_{jt-1}}{N_{P_{\ell 0 t}}} + \delta_1 \mathbf{1} + \epsilon_{\ell 0 t}$$

$$(20) \quad \ell 1 \in L1 :: y_{\ell 1 t} = \alpha \frac{\mathbf{y}_{\ell 0 t} + \sum_{j \in P_{\ell 1 t} / \ell 0} y_{jt}}{N_{P_{\ell 1 t}}} + X_{\ell 1 t-1} \beta + \gamma \frac{\sum_{j \in P_{\ell 1 t}} X_{jt-1}}{N_{P_{\ell 1 t}}} + \delta_1 \mathbf{0} + \epsilon_{\ell 1 t}$$

If we now consider a comparison group of two connected nodes ( $c0$  and  $c1$ ) where nobody gets treated,  $D_t$  would take the value 0 for both  $c0$  and  $c1$ . The newly introduced term would simply drop out. It can easily be seen, how the local treatment will allow to measure the spillover or peer effect. This will be possible despite the richness in other sources of variation, provided (i) the shocks are large enough and (ii) the ‘‘control network’’ allows to credibly infer the dynamics in the ‘‘treated network’’, had no treatment taken place.

<sup>66</sup>Note that it is easy to add a fixed effect to the model, but that it will be eliminated when taking differences. Consequently, I omit it for ease of notation.

<sup>67</sup>The choice of the temporal structure depends on the application that the researcher has in mind. In the present application many independent variables are stock variables (articles' characteristics such as page length), while the dependent variables are typically flows (clicks or new revisions).

**Condensed Notation:** I use the matrix notation suggested by Bramoullé et al. (2009) and incorporate the newly proposed vector of treatments<sup>68</sup>:

$$(21) \quad \mathbf{y}_t = \alpha \mathbf{G} \mathbf{y}_t + \mathbf{X}_{t-1} \beta + \gamma \mathbf{G} \mathbf{X}_{t-1} + \delta_1 \mathbf{D}_t + \epsilon_t \quad \mathbf{E}[\epsilon_t | \mathbf{D}_t] = \mathbf{0}$$

$\mathbf{G}$  is a  $N \times N$  matrix, which captures the link structure in the network.  $G_{ij} = \frac{1}{N_{P_i} - 1}$  if  $i$  receives a link from  $j$  and  $G_{ij} = 0$  otherwise. Note that I do not require  $\mathbf{G}$  to be exogenously given, but only  $\mathbf{D}_t$ , a vector which is 1 at the treated nodes (if they are *currently* treated) and 0 otherwise. In some of the proofs and in my application I will assume a local treatment that affects only a single node. Formally this is written as an elementary vector  $\mathbf{D}_t = \mathbf{e}_{i0}$  with the 1 in the coordinate that corresponds to the treated node. On the untreated subnetwork we have  $\mathbf{D}_t = \mathbf{0}$ , a vector of zeros.

Unlike Bramoullé et al. (2009), I do not look for an instrument for  $\mathbf{G} \mathbf{y}$ . Since I rather use exogenous shocks that affect only one part of the network, there will be no requirements on the linear independence of  $\mathbf{G}$  and  $\mathbf{G}^2$ .

### C.3 Proof of Result 1

I shall now proceed to provide the formal argument for Result 1. To increase the readability I will make a few assumptions to keep things simple. Most importantly I assume the network  $\mathbf{G}$  to be stable over time but I allow  $\mathbf{X}_t$  to change dynamically. I set the comparison group (which was indexed by  $c$ ) to be the group itself  $S$  periods earlier, which results in an  $S$ -period difference-in-differences.<sup>69</sup>

**Result 1:** A difference-in-differences estimator contains the following quantity:

$$\text{DiD} = \delta_1 \mathbf{D}_t (\mathbf{I} + \alpha \mathbf{G} + \alpha^2 \mathbf{G}^2 + \alpha^3 \mathbf{G}^3 + \dots)$$

**Proof.**

The reduced form corresponding to equation 21 is given by:

$$(22) \quad \mathbf{y}_t = (\mathbf{I} - \alpha \mathbf{G})^{-1} [\mathbf{X}_{t-1} \beta + \gamma \mathbf{G} \mathbf{X}_{t-1} + \delta_1 \mathbf{D}_t + \epsilon_t]$$

and the expectation conditional on the “treatment” is:

$$(23) \quad \begin{aligned} \mathbf{E}[\mathbf{y}_t | \mathbf{D}_t] &= (\mathbf{I} - \alpha \mathbf{G})^{-1} [(\beta + \gamma \mathbf{G}) \mathbf{E}[\mathbf{X}_{t-1} | \mathbf{D}_t] + \delta_1 \mathbf{D}_t + \mathbf{E}[\epsilon_t | \mathbf{D}_t]] \stackrel{b.A.}{=} \\ &\stackrel{b.A.}{=} (\mathbf{I} - \alpha \mathbf{G})^{-1} [(\beta + \gamma \mathbf{G}) \mathbf{E}[\mathbf{X}_{t-1} | \mathbf{D}_t] + \delta_1 \mathbf{D}_t] \end{aligned}$$

Taking the first difference, we obtain:

$$(24) \quad \begin{aligned} \Delta_t \mathbf{E}[\mathbf{y} | \mathbf{D}] &= \mathbf{E}[\mathbf{y}_t | \mathbf{D}_t] - \mathbf{E}[\mathbf{y}_{t-1} | \mathbf{D}_{t-1}] = \\ &= (\mathbf{I} - \alpha \mathbf{G})^{-1} [(\beta + \gamma \mathbf{G}) \{ \mathbf{E}[\mathbf{X}_{t-1} | \mathbf{D}_t] - \mathbf{E}[\mathbf{X}_{t-2} | \mathbf{D}_{t-1}] \} + \delta_1 \Delta \mathbf{D}_t] = \\ &= (\mathbf{I} - \alpha \mathbf{G})^{-1} [(\beta + \gamma \mathbf{G}) \{ \mathbf{E}[\mathbf{X}_{t-1} | \mathbf{D}_t] - \mathbf{E}[\mathbf{X}_{t-2} | \mathbf{D}_{t-1}] \} + \delta_1 \mathbf{D}_t] \end{aligned}$$

...where  $\Delta \mathbf{D}_t = \mathbf{D}_t - \mathbf{D}_{t-1}$  and the second equality holds, because treatments are assumed to start in period  $t$ , but not before.<sup>70</sup>

Now consider the control group formed by the same network, but  $S$  periods earlier:

$$\mathbf{y}_{t-S} = \alpha \mathbf{G} \mathbf{y}_{t-S} + \mathbf{X}_{t-S-1} \beta + \gamma \mathbf{G} \mathbf{X}_{t-S-1} + \delta_1 \mathbf{D}_{t-S} + \epsilon_{t-S}$$

<sup>68</sup> $\mathbf{X}$  might include a time-dependent component (e.g. a linear function of age) as well.

<sup>69</sup>Importantly the nodes in the network have to be observed over time and have to evolve in a stable fashion, to ensure that the first differences are the same at  $t$  and  $t - S$ . This setting corresponds to comparing the evolution of nodes in a very stable network during a post and a pre-treatment stage. It is also reasonably close to the “placebo condition” of my application below. At the end of the formal derivations I will discuss the consequences of relaxing the requirement of a stable network or the consequences of adding the assumption that  $\mathbf{X}_t$  does not change between the periods of observation.

<sup>70</sup>That difference contains the time-dependent component and the effect of any changes in the independent variables. If  $\beta X_{it}$  is modeled to contain an additively separable age-dependent part as in our example above,  $\Delta X_{it-S} \beta$  would contain  $\frac{df(\text{age})}{dt}$  (to be eliminated by taking the Difference in Differences).

The first difference of the reduced form's conditional expectations are:

$$\begin{aligned}\Delta_{t-S}\mathbf{E}[y|\mathbf{D}] &= \mathbf{E}[y_{t-S}|\mathbf{D}_{t-S}] - \mathbf{E}[y_{t-S-1}|\mathbf{D}_{t-S-1}] = \\ &= (\mathbf{I} - \alpha\mathbf{G})^{-1}[(\beta + \gamma\mathbf{G})\{\mathbf{E}[\mathbf{X}_{t-S-1}|\mathbf{D}_{t-S}] - \mathbf{E}[\mathbf{X}_{t-S-2}|\mathbf{D}_{t-S-1}]\} + \delta_1\Delta\mathbf{D}_{t-S}] = \\ &= (\mathbf{I} - \alpha\mathbf{G})^{-1}[(\beta + \gamma\mathbf{G})\{\mathbf{E}[\mathbf{X}_{t-S-1}|\mathbf{D}_{t-S}] - \mathbf{E}[\mathbf{X}_{t-S-2}|\mathbf{D}_{t-S-1}]\} + 0]\end{aligned}$$

with  $\Delta\mathbf{D}_{t-S} = 0$ , since treatments are assumed to start in period  $t$ , but not earlier. Proceeding to take the Difference in Differences, we obtain:

$$\begin{aligned}\text{DiD} &:= \Delta_{y_t}\mathbf{E}[y|\mathbf{D}] - \Delta_{y_{t-S}}\mathbf{E}[y|\mathbf{D}] = \\ &= (\mathbf{I} - \alpha\mathbf{G})^{-1} [(\beta + \gamma\mathbf{G})\{\mathbf{E}[\mathbf{X}_{t-1}|\mathbf{D}_t] - \mathbf{E}[\mathbf{X}_{t-2}|\mathbf{D}_{t-1}]\} + \delta_1\mathbf{D}_t] - \\ &\quad - (\beta + \gamma\mathbf{G})\{\mathbf{E}[\mathbf{X}_{t-S-1}|\mathbf{D}_{t-S}] - \mathbf{E}[\mathbf{X}_{t-S-2}|\mathbf{D}_{t-S-1}]\}\end{aligned}$$

Denoting the change in the expectation of  $\mathbf{X}_{t-1}$  conditional on  $\mathbf{D}_t$  more concisely by  $\{\mathbf{E}[\mathbf{X}_{t-1}|\mathbf{D}_t] - \mathbf{E}[\mathbf{X}_{t-2}|\mathbf{D}_{t-1}]\} = \Delta_t(\mathbf{E}[\mathbf{X}|\mathbf{D}])$  and rearranging gives:

$$(25) \quad \text{DiD} = (\mathbf{I} - \alpha\mathbf{G})^{-1} [(\beta + \gamma\mathbf{G})\{\Delta_t(\mathbf{E}[\mathbf{X}|\mathbf{D}]) - \Delta_{t-S}(\mathbf{E}[\mathbf{X}|\mathbf{D}])\} + \delta_1\mathbf{D}_t]$$

which reduces to:

$$(26) \quad \text{DiD} = (\mathbf{I} - \alpha\mathbf{G})^{-1}\{\delta_1\mathbf{D}_t\}$$

if  $\Delta_t(\mathbf{E}[\mathbf{X}|\mathbf{D}]) = \Delta_{t-S}(\mathbf{E}[\mathbf{X}|\mathbf{D}])$ . Thus, the identifying assumption is that the expected changes of the pages between  $t-1$  and  $t$  are the same as from  $t-S-1$  and  $t-S$ . This is satisfied if  $\Delta X_t|D_t$  is stationary of order one.

Provided  $(\mathbf{I} - \alpha\mathbf{G})^{-1}$  is invertible we can use the property that  $(\mathbf{I} - \alpha\mathbf{G})^{-1} = \sum_{s=0}^{\infty} \alpha^s \mathbf{G}^s$ <sup>71</sup>, the general impact of a local treatment is:

$$(27) \quad \text{DiD} = \delta_1\mathbf{D}_t(\mathbf{I} + \alpha\mathbf{G} + \alpha^2\mathbf{G}^2 + \alpha^3\mathbf{G}^3 + \dots)$$

which completes the proof. ■

### Discussion of the assumptions used:

1.  $\mathbf{E}[\epsilon_t|\mathbf{D}_t] = \mathbf{0}$
2.  $\alpha$  is smaller than the norm of the inverse of the largest eigenvalue of  $\mathbf{G}$ . A regularity condition to ensure that the expression  $(\mathbf{I} - \alpha\mathbf{G})^{-1} = \sum_{s=0}^{\infty} \alpha^s \mathbf{G}^s$  is well defined.
3. I assumed the network to be stable over time and used its earlier state as control observation. Formally this is written as  $\mathbf{G}_{\ell,t} = \mathbf{G}_{\ell,t-1} = \mathbf{G}$  and  $\mathbf{G}_{c,t} = \mathbf{G}_{\ell,t-S} = \mathbf{G}$ . This assumption could be relaxed, but only at the expense of strengthening the following assumption.
4.  $\Delta_t(\mathbf{E}[\mathbf{X}|\mathbf{D}]) - \Delta_{t-S}(\mathbf{E}[\mathbf{X}|\mathbf{D}])$ , which means that the expected changes of the pages between  $t-1$  and  $t$  are the same as from  $t-S-1$  and  $t-S$ <sup>72</sup>. This is the analogue of the well known common trends assumption.
5. SUTVA on the level of subnetworks: the non-treated subnetwork is not affected by treatment of the treated subnetwork. In the present context SUTVA holds for my placebo condition and, given the size of the Wikipedia network, it is also plausibly satisfied for the control group formed by a remote part of the network.

The proof for the control group consisting of remote nodes is analogous. It relaxes the third assumption and requires a more general formulation of the fourth. The qualitative meaning of the generalized assumption will be the same: Absent treatment the treated *network* and the

<sup>71</sup> $\mathbf{G}$  is invertible if  $\alpha < 1$  (Bramoullé et al. (2009)) and the infinite sum is well defined if  $\alpha$  is smaller than the norm of the inverse of the largest eigenvalue of  $\mathbf{G}$  (Ballester et al. (2006)).

<sup>72</sup>Particularly, any time trends or other dynamics, is to be eliminated by the Differences in Differences, if  $\frac{df(\text{age})}{dt}$  is the same evaluated at  $t-S$  and at  $t$ .

control *network* must “*evolve* in the same way.”<sup>73</sup> However, I have to maintain the assumption that the network formation *process* is not affected by the treatment.<sup>74</sup> I do not consider this assumption warranted for disasters and I checked this assumption in my “today’s featured article application”: Link formation remains on low levels. On normal days, articles’ degree grows steadily by about 0.1 links per day, with total in-links averaging at 120. There is a short increase by 0.2 in-links per article (or 0.2% of the link stock). Yet, first this is in sync with the peak in edits, but not with the peak in clicks, and second, like for edits, the peak is large in relative, but small in absolute terms. I conclude that this is an acceptably small source of potential bias.

### C.3.1 Estimating $\alpha$ : Analysis on the Node Level

Above we have shown what is measured by the difference-in-differences. From now on I shall refer to a node in the control condition by  $c$  and to a node in the treated condition by  $\ell$ . If  $\mathbf{D}_t$  denotes the vector of treatments which is 1 at the treated nodes and 0 otherwise, estimation of the difference-in-differences identifies:

$$(28) \quad \mathbf{DiD} = \delta_1 \mathbf{D}_t (\mathbf{I} + \alpha \mathbf{G} + \alpha^2 \mathbf{G}^2 + \alpha^3 \mathbf{G}^3 + \dots)$$

When we take the analysis back from the level of treated networks and look at the nodes individually, all that matters for each focal node  $j$  is its own row in this set of equations. To simplify this analysis I now introduce the local treatment assumption, exploiting the fact that only a single node in my network is treated each day. This is like a partial population treatment Moffitt (2001) with only one single node (a mini population) being treated.

**Local Treatment Assumption:** *Under the local treatment assumption  $\mathbf{D}_t = \mathbf{e}_i$ , where  $\mathbf{e}_i$  is an elementary vector with node  $i$  being the only treated node.*

If only one node is treated, the spillover dynamic is greatly simplified. With  $\mathbf{D} = \mathbf{e}_i$ , the only factor to be evaluated for each node is its corresponding  $ji$  element in the matrix  $\mathbf{G}$ ,  $\mathbf{G}^2$  and its higher orders.<sup>75</sup> We distinguish a shocked node  $\ell 0 \in L0$ , a neighbor  $\ell 1 \in L1$  and the indirect neighbors (2 clicks away, 3 clicks away etc.) as follows:

$$(29) \quad \begin{aligned} \ell 0 : \mathbf{DiD}_0 &= \delta_1 (1 + \mathbf{0} + \alpha^2 G_{ii}^2 + \alpha^3 G_{ii}^3 + \dots) \\ \ell 1 : \mathbf{DiD}_1 &= \delta_1 (\mathbf{0} + \alpha G_{ij} + \alpha^2 G_{ij}^2 + \alpha^3 G_{ij}^3 + \dots) \\ \ell 2 : \mathbf{DiD}_2 &= \delta_1 (\mathbf{0} + \mathbf{0} + \alpha^2 G_{ik}^2 + \alpha^3 G_{ik}^3 + \dots) \\ &\quad \text{etc.} \end{aligned}$$

Sorting the nodes with respect to their distance from  $\ell 0$  and estimating these strata separately results in as many estimation equations as can reasonably be traced and two parameters to be estimated. This fact is the basic idea of this paper, because it enables the researcher to back out the estimates for the structural parameters  $\alpha$  and  $\delta_1$ . All that is needed is a sequence of reduced form difference-in-differences estimates for increasingly large link distances. If the precise information on  $\mathbf{G}$  and its higher orders is available the parameters can be directly estimated.<sup>76</sup>

<sup>73</sup>To be more precise, the link formation and the way in which the characteristics of the nodes change over time have to be the same (common trends) in both networks. This guarantees that the counterfactual outcome of the treated network can be inferred from its own past and the evolution in the control network. The derivations require a lot of notational overhead and the resulting conditions are quite unwieldy. Assumption 4 would refer not only to  $\Delta \mathbf{X}$ , but to  $\Delta \mathbf{G} \mathbf{X}$  to allow for relaxing Assumption 3.

<sup>74</sup>If this is the case, all estimates of indirect treatment effects, will reflect a sum of the treatment on the existing network and new spillovers due to the changes in the link network (cf. Comola and Prina (2013)), which will lead to upward biases if not accounted for.

<sup>75</sup>The information in the higher orders of the adjacency matrix  $\mathbf{G}$  is the same as the information from the sampling strategy in combination with knowing who was affected by the local treatment. Some nodes (L0) are known to be directly treated. Neighbors (L1) have a direct link so that the entry in  $\mathbf{G}$  that links them to the treated node is positive. However, for those who only have an indirect link, the corresponding entry in  $\mathbf{G}$  takes the value 0 and only the relevant element of  $\mathbf{G}^2$  will be greater than 0.

<sup>76</sup>To do this use all the  $ij$  values that correspond to each individual focal node  $j$  as weights for  $\alpha$ ,  $\alpha^2$ ,  $\alpha^3$ , etc. and minimize a quadratic loss function. Unfortunately I cannot show this here, because the full matrix  $\mathbf{G}$  formed by the German Wikipedia is too large to be computed in memory.



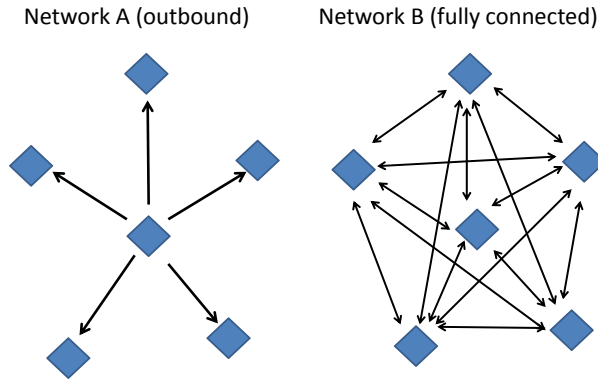
If not, it is possible to compute an upper and a lower bound for the parameters  $\alpha$  and  $\delta_1$ . In the next subsection I proceed to show how the boundary estimates can be computed.

## C.4 Estimating Bounds for the Parameters of Interest

If the researcher lacks information on  $\mathbf{G}$  it is possible to compute an upper and a lower bound for the social parameter  $\alpha$  and the treatment effect  $\delta_1$ . The goal in this section is to back out a lower and an upper bound estimate for  $\alpha$  and  $\delta_1$ , that is based only on the estimated  $DiD$ 's and the number of nodes. This is useful, since the precise information on  $\mathbf{G}$  is often not easy to obtain.<sup>77</sup> In my proofs I use the local treatment assumption (only one individual in the network is treated), for both ease of notation and understanding. It applies to “today’s featured articles”.<sup>78</sup>

In what follows I will show how to obtain these bounds. In Subsection C.4.1, I will give an intuitive account of the underlying ideas. In Subsection C.4.2, I will set up the preliminaries, including a Lemma that will be used. Subsection C.4.3 obtains the upper bound and Subsection C.4.4, finally, provides the proof for the lower bound.

Figure 7: Schematic representation of the two extreme networks, used to compute the upper and lower bound estimates of the parameters of interest.



NOTES: The “outbound network” (left) is used to obtain the upper bound estimate. It is a directed network with only “outward bound” links. Holding the number of nodes and the observed ITEs fixed, the social parameter will be estimated to be largest in this type of network. The fully connected network (right), is the benchmark case from which the lower bound of the social parameter can be estimated.

### C.4.1 Intuition for obtaining Bounds

To see why we can bound the parameter, even without knowing the details of the network structure, we can select two ‘specific ‘extreme’’ types of networks which either minimize or maximize the higher order effects. For greater convenience, I repeat the illustration of such networks in Figure 7.

The network that minimizes higher order spillovers is a directed network with only “outward bound” links from  $\ell_0$  to  $\ell_1 \in L_1$ <sup>79</sup>. This implies no links between the nodes in  $L_1$  and will serve as upper bound. The opposite type of network is a network, where every node is the direct neighbor of every one of its peers.<sup>80</sup> The fully connected network simplifies the analysis, because

<sup>77</sup>The information might either not be available, or so big that computing its higher orders might confront the researcher with substantial computational challenges.

<sup>78</sup>I conjecture that extending the proof to partial population or randomized treatments will be straight forward. It merely means taking into account that more than one node gets treated and that the effects from the treated can also spill to the other treated, which will render the formulas quite unwieldy.

<sup>79</sup>and possibly further on to  $\ell_2 \in L_2$ ,  $\ell_3 \in L_3$  and so on.

<sup>80</sup>I will sometimes refer to this network as “classroom” network.

it has only two types of nodes (treated or not). Higher order spillovers are the same for every node of the same type. Moreover, given  $\alpha$  and  $N$ , the fully connected network has the greatest second and higher order spillovers.<sup>81</sup> This allows to derive a closed form solution for the lower bounds of the relevant parameters.

### C.4.2 Preliminaries

Before I proceed to characterize the bounds of the coefficient, it is useful to point out a fact that will be important in the argument that follows. Start by rewriting the formulas in equation 29 without explicit characterization of the higher order spills:

$$(30) \quad DiD_0 = \delta_1 + HO_{\ell 0}$$

$$(31) \quad DiD_1 = \frac{\alpha}{NP_{\ell 1}}\delta_1 + HO_{\ell 1}$$

where  $HO_{\ell 0} = \delta_1(\alpha^2 G_{ii}^2 + \alpha^3 G_{ii}^3 + \dots)$  and  $HO_{\ell 1} = \delta_1(\alpha^2 G_{ij}^2 + \alpha^3 G_{ij}^3 + \dots)$ . These effects are typically not trivial. They depend on the underlying network of peers and need to take into account the network structure. However, I can use a simple insight concerning the size of the higher order effects.

**Lemma 1** *Given the total effect, larger higher order effects, imply smaller coefficients, i.e. for  $DiD_0 > DiD_1 > HO^B > HO^A \geq 0$ : for any  $HO^A < HO^B$ ,  $\alpha^A > \alpha^B$  and  $\delta_1^A > \delta_1^B$ .<sup>82</sup>*

**Proof.** We have to make the following two comparisons:

$$\begin{aligned} DiD_0 = \delta_1^A + HO^A & \quad vs. \quad DiD_0 = \delta_1^B + HO^B \\ DiD_1 = \frac{\alpha^A}{NP_{\ell 1}}\delta_1^A + HO^A & \quad vs. \quad DiD_1 = \frac{\alpha^B}{NP_{\ell 1}}\delta_1^B + HO^B \end{aligned}$$

This can be transformed as follows:

$$(32) \quad \delta_1^A = DiD_0 - HO^A \quad vs. \quad \delta_1^B = DiD_0 - HO^B$$

$$(33) \quad \alpha^A = \frac{(DiD_1 - HO^A)}{\delta_1^A} NP_{\ell 1} \quad vs. \quad \alpha^B = \frac{(DiD_1 - HO^B)}{\delta_1^B} NP_{\ell 1}$$

From equation 32 it is immediately obvious that  $HO^A < HO^B$  implies  $\delta_1^A > \delta_1^B$ . For comparing  $\alpha$  substitute the corresponding  $\delta_1$  from 32 into 33, define  $HO^A := HO^B - \varepsilon$  (for  $\varepsilon > 0$ ) and rewrite equation 33 as

$$(34) \quad \alpha^A = \frac{a}{b} NP_{\ell 1} \quad vs. \quad \alpha^B = \frac{a - \varepsilon}{b - \varepsilon} NP_{\ell 1}$$

where  $a = (DiD_1 - HO^A)$  and  $b = DiD_0 - HO^A$ . Comparing  $\alpha^A$  vs.  $\alpha^B$  is equivalent to comparing  $\frac{a}{b}$  vs.  $\frac{a - \varepsilon}{b - \varepsilon}$ . Since we have  $a, b, \varepsilon > 0$ ,  $\varepsilon < b$  and  $\varepsilon < a$ :

$$\begin{aligned} \frac{a}{b} - \frac{a - \varepsilon}{b - \varepsilon} > 0 & \quad \Leftrightarrow \quad a(b - \varepsilon) - b(a - \varepsilon) > 0 \\ & \quad \Leftrightarrow \quad a\varepsilon < b\varepsilon \\ & \quad \Leftrightarrow^{b.A.} \quad a < b \end{aligned}$$

The last inequality holds by the initial assumptions, which completes the proof. ■

With this lemma in hand we can now proceed to derive benchmarks (upper and lower bound estimates) for the parameters of interest.

<sup>81</sup>Every node affects every other node via a direct link and everybody will get second and higher round spillovers from *every* other node.

<sup>82</sup>Note that the requirement  $DiD_1 > HO^B$  has bite, since it implies  $\alpha < 0.5$ . This assumption need not be satisfied in all applications, but it applies well to settings where the spills dissipate quickly and to settings where the direct effect on the treated is much larger than on the neighbors ( $DiD_0 \gg DiD_1$ ). This is the case in most applications and certainly so in the present one.

### C.4.3 Upper Bound: Network without higher order spillovers.

In the “outbound” network higher order spills back to the originating nodes do not exist<sup>83</sup>:  $HO_{\ell_0}$  and  $HO_{\ell_1}$  would be 0. This is equivalent to assuming:

$$(35) \quad \mathbf{DiD} = \mathbf{b.A.} \bar{\delta}_1 \mathbf{D}_t (\mathbf{I} + \bar{\alpha} \mathbf{G} + \mathbf{0} + \mathbf{0} + \dots)$$

which is equivalent to having<sup>84</sup>:

$$(36) \quad \begin{aligned} DiD_0 &= \bar{\delta}_1 && \text{for treated } L0 - \text{nodes} \\ DiD_2 &= 0 && \text{for } L2 \\ &&& \dots \text{analogously for } L3 \text{ and higher} \end{aligned}$$

By Lemma 1 this assumption leads to an upper bound of both coefficients. If all effects are of the same sign and  $DiD_0 > DiD_1 > HO > 0$ <sup>85</sup>, the difference-in-differences for a node  $\ell_1 \in L1$ <sup>86</sup> would simply reduce to:

$$(37) \quad DID_1 = \frac{\bar{\alpha}}{NP_{\ell_1}} \bar{\delta}_1$$

A consistent estimator of  $\bar{\delta}_1$  and the observed difference-in-differences will be enough to estimate  $\bar{\alpha}$ . In the “outbound network”, I apply difference-in-differences on the level of directly treated nodes to obtain such an estimate. Then I move on to estimate  $\bar{\alpha}$ :

$$(38) \quad \begin{aligned} \hat{\delta}_1 &= \widehat{DiD_0} = \hat{\Delta\ell_0} - \hat{\Delta c_0} \\ \hat{\alpha} &= \frac{\widehat{DiD_1}}{\widehat{DiD_0}} NP_{\ell_1} \end{aligned}$$

with  $\hat{\Delta\ell_0} := \frac{1}{NP_{\ell_0}} * \sum_i (y_{i,\ell_0,t=0} - y_{i,\ell_0,t=1})$ ,  $\hat{\Delta c_0} := \frac{1}{NP_{c_0}} * \sum_i (y_{i,c_0,t=0} - y_{i,c_0,t=1})$ . The definition of  $\hat{\Delta\ell_1}$  and  $\hat{\Delta c_1}$  for the  $\widehat{DiD_1}$  parallels the definition of  $\hat{\Delta\ell_0}$  and  $\hat{\Delta c_0}$ .

**Discussion:** The assumption in equation 35 implies no “multiplication-effects” or “feedback-loops” between the nodes.<sup>87</sup> In the light of the formalization presented here, this is a strong assumption. However, in the impact evaluation literature with fixed and stable classroom sizes or villages, this assumption is almost taken implicitly, whenever the researchers report merely the ATE and ITEs. (cf. Angelucci and De Giorgi (2009), Carmi et al. (2012), Dahl et al. (2012), etc. etc.).

Having said that, the upper bound estimator is quite suitable if higher order spillovers are negligible. In what follows I compute the lower bound estimates under the assumption of maximal higher order spillovers. This will give a sense of the maximal size of the bias that might result from assuming away the higher order complexities of a network.

<sup>83</sup>Admittedly, in such a network, endogeneity would not be a problem in the first place.

<sup>84</sup> $D_{\ell_0}$  denotes the value of D at the central node, that is related to the focal node.

<sup>85</sup> $DiD_0$  ( $DiD_1$ ) denotes the difference-in-differences for treated nodes (neighbors). For the reverse relationships ( $DiD_0 < DiD_1 < HO < 0$ ) the estimate based on assuming an “outward bound” network gives a lower bound, if the effects go in opposite directions, my claims do not necessarily hold and will have to be verified by the researcher. Slightly more involved assumptions will be needed.

<sup>86</sup>Which corresponds to an Indirect Treatment Effect or an “Externality”

<sup>87</sup>Neglecting higher-order spillovers is like implicitly introducing a temporal structure where a spillover takes time to occur and taking a snapshot after the first order effect. This is possible if, for example, spillovers are slow or if the temporal structure of the available data is fine grained enough.

#### C.4.4 Lower Bound: Network with maximum higher order spillovers.

In this subsection I derive the lower bound estimates under the assumption of a fully connected network. Formally, consider the matrix  $\underline{\mathbf{G}}$ , that corresponds to a fully connected network:

$$\underline{\mathbf{G}} = \begin{pmatrix} 0 & \frac{1}{N-1} & \frac{1}{N-1} & \cdots & \frac{1}{N-1} \\ \frac{1}{N-1} & 0 & \frac{1}{N-1} & \cdots & \frac{1}{N-1} \\ \frac{1}{N-1} & \frac{1}{N-1} & 0 & \cdots & \frac{1}{N-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{1}{N-1} & \frac{1}{N-1} & \frac{1}{N-1} & \cdots & 0 \end{pmatrix}$$

First, observe that all nodes are direct neighbors, i.e.  $NP_{\ell 0} = NP_{\ell 1} = NP_{\ell} = N - 1$ . Next, note that there are only two types of nodes: Directly treated nodes and neighbors. Let us now characterize the higher order spillovers that arrive at the treated node. From equation 29 we know that the spillovers that arrive at a node in L0 are given by:

$$\ell 0 : DiD_0 = \delta_1(1 + \mathbf{0} + \alpha^2 G_{ii}^2 + \alpha^3 G_{ii}^3 + \dots)$$

The formula above points out that no spillovers of order 1 arrive at the treated node, since  $i$  does not link on to himself.<sup>88</sup> But in a network characterized by  $\underline{\mathbf{G}}$ , (and maintaining local treatment) the second order spillovers arrive from *every* neighbor, i.e.  $NP_{\ell}$  times, third order spillovers arrive  $(N - 1)^2 - (N - 1)$  times etc.<sup>89</sup> The number of channels for spillovers of order  $S$  is given by:

$$\begin{aligned} \#channels_{ii,S} &= (N - 1)^{S-1} - (N - 1)^{S-2} + (N - 1)^{S-3} + \dots \\ &= \sum_{s=1}^{S-1} (N - 1)^s (-1)^{(S-1)-s} \quad S \geq 2 \end{aligned}$$

The sum of second and higher order spillovers arriving at the treated node is:

$$\begin{aligned} HO_{ii} &= \sum_{S=2}^{\inf} \delta_1 \frac{\alpha^S}{(N - 1)^S} \#channels_{ii,S} \\ &= \sum_{S=2}^{\inf} \delta_1 \frac{\alpha^S}{(N - 1)^S} \sum_{s=1}^{S-1} (N - 1)^s (-1)^{(S-1)-s} \end{aligned}$$

All non-treated neighbors are the same and the number of channels for spillovers of order  $S$  from node  $i$  to node  $j$  is computed almost<sup>90</sup> in the same way:

$$\begin{aligned} \#channels_{ij,S} &= (N - 1)^{S-1} - (N - 1)^{S-2} + (N - 1)^{S-3} + \dots \\ &= \sum_{s=0}^{S-1} (N - 1)^s (-1)^{(S-1)-s} \quad S \geq 2 \end{aligned}$$

Again the sum of second and higher order spillovers at the neighboring nodes is:

$$(39) \quad \begin{aligned} HO_{ij} &= \sum_{S=2}^{\inf} \delta_1 \frac{\alpha^S}{(N - 1)^S} \#channels_{ij,S} \\ &= \sum_{S=2}^{\inf} \delta_1 \frac{\alpha^S}{(N - 1)^S} \sum_{s=0}^{S-1} (N - 1)^s (-1)^{(S-1)-s} \end{aligned}$$

<sup>88</sup>Note that this is precisely the point where the local treatment assumption is most useful, because had we treated  $T > 1$  nodes, then we would have to count  $T-1$  direct spillovers that arrive at  $i$ , which obviously would render the following considerations less tractable.

<sup>89</sup>Counting the number of channels for third and higher order spillovers is a matter of combinatorics: The number of channels for higher order increases at an almost exponential rate, leading to potentially very large effects, that are moderated only by the decrease of the primary effects during transmission.

<sup>90</sup> $s$  now starts at 0.

Before we can move on to derive the lower bound estimates, note that we have  $\sum_{s=1}^{S-1} (N-1)^s (-1)^{(S-1)-s} < (N-1)^{S-1}$  which will be a convenient fact for simplifying the estimation of the lower bound.

$$\begin{aligned}
(40) \quad HO_{ii} &= \sum_{S=2}^{\inf} \delta_1 \frac{\alpha^S}{(N-1)^S} \sum_{s=1}^{S-1} (N-1)^s (-1)^{(S-1)-s} < \\
&< \sum_{S=2}^{\inf} \frac{\alpha^S}{(N-1)^S} (N-1)^{S-1} = \\
&= \frac{1}{(N-1)} \sum_{S=2}^{\inf} \alpha^S = \frac{\alpha^2}{(N-1)} \frac{1}{1-\alpha}
\end{aligned}$$

Let us call this expression  $\overline{HO}_{ii}$ . Analogously we obtain  $\overline{HO}_{ij} = \frac{\alpha^2}{(N-1)} \frac{1}{1-\alpha}$ . Plug these values into the equations 30 and 31 from above. With Lemma 1 at our disposal, we can use  $\overline{HO}_{ii}$  and  $\overline{HO}_{ij}$  to back out the lower bounds of the coefficients  $\alpha$  and  $\delta_1$ :

$$(41) \quad DiD_0 = \widehat{\delta}_1 + \overline{HO}_{\ell 0}$$

$$(42) \quad DiD_1 = \frac{\widehat{\alpha}}{NP_{\ell 1}} \widehat{\delta}_1 + \overline{HO}_{\ell 1}$$

It is somewhat tedious, but straight forward to show, that solving this system of equations results in a quadratic equation for  $\widehat{\alpha}$ :

$$(43) \quad \widehat{\alpha}^2 - \left[ \frac{DiD_0}{DiD_1} + (N-1) \right] \widehat{\alpha} + (N-1) = 0$$

The closed form solution for  $\widehat{\alpha}$  is hence given by:

$$(44) \quad \widehat{\alpha}_{1/2} = \frac{1}{2} \left[ \frac{DiD_0}{DiD_1} + (N-1) \right] + / - \sqrt{\frac{1}{4} \left[ \frac{DiD_0}{DiD_1} + (N-1) \right]^2 - (N-1)}$$

Under weak regularity conditions<sup>91</sup> one solution is above 1 and another one between 0 and 1. The latter one is the solution for  $\widehat{\alpha}$  and it can easily be used to retrieve  $\widehat{\delta}_1$  from equation 30

**Discussion:** Note that this closed form solution requires only the number of nodes, and the two estimates from the difference-in-differences (for treated nodes and neighbors). It can be computed when nothing is known about the network, except how many agents and who was treated. It is thus as readily available as the upper bound estimators.

Clearly, one would immediately wish for more.<sup>92</sup> Having more information about the network structure or even the link strength between nodes is certainly desirable and, generally, will allow for more interesting additional results. Finally, while the proof here advantageously uses the local treatment assumption, I conjecture, that it is straightforward to extend it to treatments of more than one node.

## D Aside: Reaction to treatment of the neighbor

Everything above was derived under the assumption that nodes do not observe or at least do not react to the local treatment of their neighbors. This is appropriate for neighbors of Wikipedia articles that get advertised on the start page.<sup>93</sup> In general however, subjects might observe treatment of their neighbors and react to the fact.

<sup>91</sup>  $DiD_0 > DiD_1$ , which is to be expected for most treatments and follows from  $\alpha < 0.5$  and  $N > 1$

<sup>92</sup> Note that if there is reason to believe that  $\alpha$  is greater than 0.5 an analogue of Lemma 1 that relaxes my assumption of  $\alpha < 0.5$  is required.

<sup>93</sup> For two reasons: (i) Wikipedia articles cannot react and (ii) the advertisement is not associated with any changes in the real world, so there is no reason for any updates.

An example are children at school, who get annoyed or jealous when their peer was treated in a nice way and they were not.<sup>94</sup> In such situations the students/villagers might react to *merely observing* the treatment of their neighbors by selecting a different value for the outcome variable. To model such a situation we need to further augment the model in equation 18 by both the observable treatments (shocks) that are locally applied, and a term that captures the possible reaction to the treatment of the neighbor.

$$(45) \quad y_{it} = \alpha \frac{\sum_{j \in P_{it}} y_{jt}}{N_{P_{it}}} + X_{it}\beta + \gamma \frac{\sum_{j \in P_{it}} X_{jt}}{N_{P_{it}}} + \delta_1 D_{it} + \delta_2 \frac{\sum_{j \in P_{it}} D_{jt}}{N_{P_{it}}} + \epsilon_{it}$$

Where  $\delta_1$  measures the direct treatment effect and the new coefficient  $\delta_2$  measures reactions of the node, when it “observes” treatment of one (or several) of its peers. Consider again two connected nodes, where one is treated ( $\ell 0$ ) in period  $t$  and the neighbors are not treated ( $\ell 1 \in L1$ ). Assume for simplicity that  $\ell 0$  is the only treated node in  $\ell 1$ ’s neighborhood. Similarly, but different, we have:

$$(46) \quad \ell 0 :: y_{\ell 0 t} = \alpha \frac{\sum_{j \in P_{\ell 0 t}} y_{jt}}{N_{P_{\ell 0 t}}} + X_{\ell 0 t}\beta + \gamma \frac{\sum_{j \in P_{\ell 0 t}} X_{jt}}{N_{P_{\ell 0 t}}} + \delta_1 \mathbf{1} + \delta_2 \frac{\sum_{j \in P_{\ell 0 t}} \mathbf{0}}{N_{P_{\ell 0 t}}} + \epsilon_{\ell 0 t}$$

$$(47) \quad \ell 1 \in L1 :: y_{\ell 1 t} = \alpha \frac{y_{\ell 0 t} + \sum_{j \in P_{\ell 1 t}/\ell 0} y_{jt}}{N_{P_{\ell 1 t}}} + X_{\ell 1 t}\beta + \gamma \frac{\sum_{j \in P_{\ell 1 t}} X_{jt}}{N_{P_{\ell 1 t}}} + \delta_1 \mathbf{0} + \delta_2 \frac{\mathbf{1} + \sum_{j \in P_{\ell 1 t}/\ell 0} D_{jt}}{N_{P_{\ell 1 t}}} + \epsilon_{\ell 1 t}$$

Now we get two types of spillover effects in this model: First the “pure spillover”  $\alpha$ , due to the effect of treatment on the outcome of  $\ell 0$ . But second, also the “behavior change” of the node,  $\delta_2$ , when it “observes” treatment of its peer kicks in.

Applying a Difference in Differences strategy alone will measure the joint effect of these two “spillovers”. It will not identify  $\alpha$  separately, unless  $\delta_2$  is believed to be 0. If this assumption is not warranted only the total “treatment-of-peer”-effect can be measured. Depending on the application we might care about the effect of treatments, in which case this aggregate effect will be interesting. It is simply important to be aware that it is not possible to identify the pure spillover effect in such a setting.

---

<sup>94</sup>Other examples entail economic agents in a village, who observe that their neighbor was refused a social service for failure to comply with a requirement (e.g. sending their kids to school) or commuters in a city, who observe when their friends got caught (after the local transport authority increased the frequency of controls and the punishment for failure to present a valid ticket).