Spillovers in Networks of User Generated Content *

- Evidence from 23 Natural Experiments on Wikipedia

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Abstract

Endogeneity in the formation of networks has been a well known threat to the identification of peer effects, externalities or the role of social networks in generating spillovers. This paper aims at overcoming the usually required, but generally strong, assumptions of exogenous observed characteristics and/or link formation in networks. Identification is based on exploiting exogenous but local shocks or randomized treatments on a relatively small number of nodes in the network. This method also provides identification in small networks, where all nodes are connected.

The method is used to measure how attention to articles spills across links and how additional attention results in new content generation in the German Wikipedia. The effects on neighboring pages are substantial for both attention and content generation. I observe an increase of almost 100 percent in terms of both views and editing activity. However, the activity triggered is small in absolute terms. Aggregated over all neighbors the effects are very large: I find that one click on the treated page translates to one click on one of the neighboring articles.

Keywords: Social Media, Information, Knowledge, Large-scale Networks.

JEL Classification Numbers:

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This paper measures the spillover of attention and contribution effort transmitted through links in German Wikipedia. Understanding how links channel human attention is important for understanding peer production settings, advertisement and public decision making. Although important, endogeneity in the formation of networks has been a constant obstacle for those who try to measure peer effects or the role of social networks in generating spillovers or other externalities. While correlations between nodes' network positions and their outcomes abound, exogenous sources of variation that allow us to pin down causes and distinguish them from effects are usually hard to observe. Consequently, in the absence of an exogenous source of variation in network position, it is rarely possible to create a design that separates cause and effect in a networked setting.

This paper contributes to the literature in two ways. Firstly, I measure spillovers of attention and how they convert to content production in the German Wikipedia, one of the most important citation networks, which is made up of user-generated content items. Previous research in the field of peer production has attempted to analyze 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)). However, the outcome variable is often an important determinant of the network position, thus giving rise to the classic endogeneity problem. Moreover, nodes are likely to be peers (Bramoullé et al. (2009)) and researchers interested in measuring interactions between them face the problems laid out by Manski (1993). This paper attempts to overcome the problems by exploiting local exogenous treatments of single nodes in the article network.

Secondly, to facilitate the analysis of spillover aftershocks I modify the framework of Bramoullé et al. (2009) to allow the incorporation of local and randomized treatments and their spillover effects in a networked setting. I show how it is possible to use exogenous treatments of individual nodes in networks, which are the focus of both Carmi et al. (2012) and this paper, as a new and complementary source of identification beside the network structure (Bramoullé et al. (2009), De Giorgi et al. (2010)). The suggested formalization is quite general and nests not only exogenous treatments of single nodes in networks, but also partial population treatments (Moffitt (2001), Dahl et al. (2012)). The identification strategy is based on the combination of exogenous shocks and an estimator based on comparing differences. After obtaining reduced form estimates based on minimal assumptions, I exploit knowledge of the network structure to back out the structural parameters of the spillover effects. Finally, some of my insights carry over to impact evaluation studies based on a two stage randomization over sub-populations (villages) and then individuals inside sub-populations (Angelucci and De Giorgi (2009), Kuhn et al. (2011), Crépon et al. (2013)). It becomes clear why the reduced form coefficients are boundary estimates if detailed link information is not available. I show under which conditions it is possible to derive not only one bound, but both the upper and the lower bound estimates of the parameter of interest. This second (typically lower) bound is a second contribution to the literature. More details about the formal framework can be found in section 2. How this paper relates to the existing literature is discussed in section 1.

In the application I exploit two sources of variation that trigger substantial changes in the attention that certain pages receive at a known (ex-post) point in time: (i) exogenous and unpredictable large scale media events, such as the outbreak of political upheaval, earthquakes or plane crashes and (ii) articles which are chosen to be featured on Wikipedia's homepage and are thus highly visible for 24 hours. To obtain my dataset I augment the publicly available data dumps provided by the Wikimedia Foundation[1] 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. I identified 23 large scale events and 34 articles that were featured on Wikipedia's main page. Using the revision data of the German Wikipedia, I obtained information on clicks and content generation for the treated pages and their neighbors. That information was extracted 14 days before and after the events and I analyze these two treatments separately. The resulting dataset contains information on almost 13,000 articles and includes more than 750,000 observations. Detailed information about the data is provided in section 3.

For featured articles, I do not find any effects on the pages that were two clicks away, but the effects on neighboring pages are substantial for both attention and content generation. I observe an increase of almost 100 percent in terms of both views and editing activity. For large events, I find substantial spillovers of attention even to pages that are two clicks away from the (originally non-existent) disaster page, but only a relatively modest and not necessarily robust effect on content provision. The rise in the number of clicks on the pages that were in the neighborhood of the shocked area (2 clicks away) amounts to roughly 35 more clicks on average. However, given the small baseline activity, the activity triggered by having a featured article (or even a natural disaster) in the neighborhood is small in absolute terms. Nevertheless, on the aggregate the effects are very large. Over all neighbors I find that one click on the treated page translates to one click on one of the neighbors. Yet, it takes one thousand clicks before an additional revision occurs. In short, my first results suggest that links matter for the attention that a node in a citation network receives, but much less for the content that is generated on such nodes. This may be well justified given the high level of development that the German Wikipedia had achieved by 2007. More results can be found in section 4.

My extension of the framework of Bramoullé et al. (2009) is the first formalization that allows including exogenous treatment of single nodes in networks that I am aware

[1] 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.

of. The model helps to understand how frequently measured reduced form estimates of an ITE can be related to the structural social or spillover effects. It also highlights how to back out the parameter of interest if detailed link information is available or estimate the upper and the lower bounds of the parameter of interest, if it is not. I apply these techniques to my application and obtain an interval estimator for the spillover effect of interest, which suggests that an average increase of ten clicks on the neighboring pages results in an increase of 2.22 to 2.92 clicks on the page in the center. These results suggest that placing links has an effect, but that it is small. For more details please refer to the results in Section 4.

While the strategy of this paper requires a lot from the data[2], recent advances in data handling techniques and the ever increasing availability of data on social interactions are likely to provide further applications where this strategy can be used.

There are two ways of approaching this paper. Readers who are interested in the empirical relationship of links and content generation in Wikipedia might want to skip over Section 2 and focus on Sections 3 and 4. Section 3 discusses the data collection and provides information about the relevant variables. Section 4 describes the results and shows how to relate my reduced form estimation and the structural model. More theoretically oriented readers might be more interested in Section 2, which is dedicated to the reduced form specification, the structural model and the identification strategy. The details of the corresponding derivations are in Appendix B. The relevant literature and details on how this paper contributes to it are discussed in the next section (1). Concluding remarks, limitations and avenues for further research are offered in Section 5. In the Appendix I provide summary statistics, robustness checks and additional figures (Appendix A) together with detailed derivations of Appendix B. Appendix C gives an outlook on the case where the neighbors of the treated observe the treatment and adjust their outcome as a reaction to the mere fact that their neighbor was treated. I briefly illustrate why the spillover parameter can no longer be identified in that case.

1 Literature

This paper builds on two important strands of the literature: firstly the literature on social effects and peer effects or spillovers and secondly that which uses pseudo-treatments to causally identify economic effects.

Social effects, such as peer effects or spillovers in a network, are generally difficult to identify. This is usually because they are frequently confounded with other individual

[2]In the past, a source of exogeneity in networks (e.g. treatment of individuals in groups) could rarely be observed by researchers. Researchers often have the network structure and no exogenous source of information, or exogeneous variation yet no information on the network structure. Data that fulfill my requirements are increasingly generated by field experiments or might be available from online sources

specific characteristics or network dynamics. One quite prominent sub branch of this literature pursues the strategy of investigating the relationship between a node's position in a network and its performance.

A series of papers has focused on the effect of knowledge spillovers on production in social networks. Fershtman and Gandal (2011) investigates indirect and direct knowledge spillovers in the production of open source software and Claussen et al. (2012), pursues a similar question. They use panel data to control for unobserved heterogeneity and look at the electronic gaming industry. Both studies focus on the relationship between developers' network position and the success of the project they are working on. Another very successful improvement has been proposed by Oestreicher-Singer and Sundararajan (2012), who exploit Amazon's link network and show that items that are connected through a visible link influenced each other three times as much, as when the link was invisible. Kummer et al. (2012), borrowing from the approach used by Halatchliyski et al. (2010), who analyze authors' contributions in two related knowledge domains, considers a different network in a similar context, namely the hyperlink network of articles. The strategy in all of the above papers is based on exploiting variations in the link network, be it between or within the nodes of a network, and relating them to the outcome of interest. If this relationship is found to be positive it is taken as prima facie evidence for the existence of spillover effects of knowledge or economic success. However, a common criticism of this strategy is that the variation in the network position might not be exogenous or that it is at least very difficult to identify sources of exogenous variation to a network. The strategy pursued in this paper, like the one by Carmi et al. (2012), approaches the problem from a different vector of attack, because it no longer attempts to measure spillover effects by looking at variation in the link structure. Instead it looks how shocks are transmitted in a given link structure. The underlying reasoning is now based on the observation that pages that happen to be linked to a shocked page receive a spillover, while similar pages that are not linked to a shocked page do not. I will show below under which conditions such an approach can be successful (section 2), but that it might fail in situations where these conditions are not satisfied (cf. Appendix C).

Another well-known and important branch of this literature is dedicated to the identification of peer effects. As has been shown, these are extremely difficult to identify in a setting where both the peers average characteristics and their average performance influence the individual's outcome Manski (1993). One of the most widely known approaches to disentangle these effects is to exogenously vary the composition of peer groups (Sacerdote (2001), Imberman et al. (2009)). Imberman et al. (2009), for example, exploit variation due to a natural disaster in their analysis of the peer-effects of evacuee inflow on Houston and Louisiana's incumbent school children in the aftermath of the hurricanes Katrina and Rita. Their identification strategy is based on the large variation in peer groups and the random allocation of evacuees after the event. They find small peer effects on average, and they also show that an inflow of high-achieving peers has a positive effect on achievement.

Other approaches are based on the structure of networks or, more precisely, on the existence of open triads wherein a peer is connected to two other peers, who themselves are not connected to each other. (De Giorgi et al. (2010) and Bramoullé et al. (2009)) In such a situation the outcome of the peer who is connected to both nodes is instrumented with the performance of one peer before analyzing its influence on the other. This paper extends their framework to allow including exogenous treatments combined with a simple difference-in-difference estimator. I thus use a completely different source of identification to measure the peer effects. Using exogenous sources of variation for identification has the additional advantage of not requiring the existence of open triads in the network structure.[3], which renders the notation compatible with a two-layered setting with randomization across villages, classrooms or other subpopulations and subsequent treatment of randomly selected individuals within the subpopulation. Before discussing this literature, it is worth mentioning some similarities and analogies between this paper and the work of Ballester et al. (2006). I was able to draw upon some of their insights and their formalization of network structure despite the fact that their purpose was different and a centrality measure alone will not overcome the underlying problem that players might be central for a reason.

As far as the second stream of literature on treatment effects is concerned it is well established that social effects play an important, though usually not constructive, role for the causal identification of treatment effects. More precisely, it can be difficult to identify the causal effect of a treatment in the presence of social effects, not least because such effects might lead to a violation of the Stable Unit Treatment Value Assumption (SUTVA) and hence raise doubts about the validity of the control group. (Ferracci et al. (2012)) Since such externalities threaten the identification of treatment effects, researchers have come to understand the importance of adding a second layer of randomization at the level of classrooms, villages, districts etc. (Miguel and Kremer (2003), Angelucci and De Giorgi (2009), Kuhn et al. (2011) and many more). Since such randomization immediately lends itself to computing direct treatment effects many of the mentioned papers put special emphasis on the indirect effects. Crépon et al. (2013) are concerned about the possibility that labor market programs might actually have a negative impact on the non-eligible. They test their hypothesis by not only randomizing over treated populations, but also varying the treatment intensity. There is a very close relationship between the idea of randomizing across subunits and the Partial Population Experiment that Moffitt (2001) suggested as a solution to the Reflection Problem. A prime example of how to use such an "experiment" is the paper by Dahl et al. (2012). They exploit the

[3]Formally open triads are equivalent with linear independence of the adjacency matrix of the graph that represents the network (typically denoted by G) and its own square.

introduction of a new policy that made it easier for some fathers to leave their jobs and spend time at home with their babies and measured how the increased take up of treated fathers impacted the probability that their (old-regime) peers' also decided to stay at home.

This study proposes to use the treatment of *peers in a network* to identify social effects and asks under which circumstances it may be possible to causally identify spillovers or peer effects when treatment of peers can be observed. It is worth emphasizing that the analysis in this paper might be somewhat unusual for readers who are familiar with this literature, because it is not particularly interested in the effect of treatment itself but instead aims at exploiting treatments to identify *the spillover effect*. Hence, it aims to *exploit* the violation of the SUTVA to measure the indirect treatment effects and to identify something else (i.e. the spillover effect). Moreover, in order to identify spillovers in the network I will exploit the fact that exogenous treatment sometimes affects only a single node and use the local network formed by nearby neighbors as an analogue to "villages" over which nature has randomized. Such local treatments are analogous to the partial population treatment coined by Moffitt (2001) and might be dubbed "mini population treatments". This idea is not new; it has been used increasingly often in recent studies. In a widely quoted paper Aral and Walker (2011) develop an approach based on hazard modeling and use randomized treatments of individuals in networks to measure contagion. Most closely related to my approach is a study in the realm of e-commerce. Using the same method as this paper, Carmi et al. (2012) analyze the effect of book recommendations by Oprah Winfrey (as external shocks) on the product network of books on Amazon. They find that the recommendation does not only trigger a spike in sales of the recommended book but also of books that are adjacent to the recommended books in Amazon's recommendation network. They measure demand in terms of the products' sales ranks and, like this paper, use a difference in difference strategy. They obtain a control group by exploiting the fact that Amazon's algorithm chooses different books to highlight in the recommendation network in different points in time. They find a significant and positive effect on the recommended books' neighbors and the neighbors of those neighbors. Their data structure allows a deep analysis into which characteristics of the linked items can predict a higher spillover, which is far beyond the scope of the present paper. Yet, the present paper, although it proposes to apply a similar method to estimate the spillover effects, it contributes in two important ways. Firstly, the paper differs from Carmi et al. (2012) in that it provides a formalization of why this source of exogenous variation ensures identification of the social/spillover parameter and how to relate the reduced form estimators to the structural parameter of interest. Secondly, German Wikipedia is a quite different type of network, since it is a citation network of articles that are created in a peer production process. Also this network is formed by a very large number of links (edges), which is not set to an a priori fixed number of items and which is placed by humans rather than an algorithm. Another difference is that the data structure allows to directly observe the visits of the linked sites (attention) and rather than sales, we can analyze the decision to contribute information on the item. The insights I obtain are hence complementary and my results suggest that more studies of many different types of networks are needed before all underlying phenomena can be understood.

Offline Berge (2011) compares peers of individually treated and non-treated agents in a field experiment to measure information and knowledge spillovers from a business training program in Tanzania. Using in depth interviews he finds that "indirectly-treated" male clients become more "business minded" (i.e. they discuss business more, increase their loans and become more risk averse). Once again we see a close relationship between the work of this paper and randomized treatment of villages or small groups. Hence it is not surprising that an unpublished paper by Banerjee et al. (2012) exploits very detailed information on village networks to analyze the spread of information about microfinance through the villages.

This paper contributes to the literature by providing a simple formalization that allows the inclusion of exogenous local treatments into an existing framework to analyze peer effects in networks Bramoullé et al. (2009). It provides a formalization of why this approach guarantees identifications and it shows how to relate the reduced form estimators to the structural parameter of interest. Like the approach of Bramoullé et al. (2009), local treatments as source of exogenous variation ensure identification of the social parameter even in the famously underidentified model by Manski (1993). Yet, the extension in this paper guarantees identification based on a complementary source of exogeneity. An additional advantage is that the formalization applies to randomized treatment of subpopulations (partial population treatment) in general and all my insights can directly be applied if only one member of the subpopulation (one pupil in a class, one villager in a community) is treated (mini population treatment). Finally, I derive an upper and a lower bound coefficient of interest that can be obtained even without any information on the network structure itself.

On one hand it shows how treatments diffuse across the network if the agents are linked and how average and indirect treatment effects can be linked to a structural parameter that quantifies spillovers. On the other hand it formalizes a relatively new way to identify peer effects and spillovers in networks, one that is based on truly exogenous variation. It can thus contribute to bridging the distance between the experimental and the social network literatures.

Finally, a source of exogenous variation in this paper is natural disasters, accidents and large scale events. Several papers other than the aforementioned paper by Imberman et al. (2009) have been dedicated to natural disasters or other sources of exogenous variations on Wikipedia, or they have exploited treatments similar to the one I use. Ashenfelter and

Greenstone (2002) exploit the effect of a a change in the mandated speed limits on the number of fatal car accidents to estimate the value of a statistical life. The well-known paper by Zhang and Zhu (2011) exploits an exogenous shock that occurred when the Chinese government blocked Wikipedia in mainland China to measure the effect on the incentives to contribute. Keegan et al. (2013) analyze the structure and dynamics of Wikipedia's coverage of breaking news events. They show that the coverage of breaking news events is an increasingly important phenomenon on Wikipedia which makes up an increasing share of edits and, they hypothesize, might become one of Wikipedia's most important sources of new contributors. They contrast the evolution of articles on breaking news events with the genesis of non-breaking news (and "historical" articles) and they find that breaking news articles emerge into well connected collaborations more rapidly than non-breaking news articles.

This paper's application illustrates a new way of looking at content networks such as the one formed by Wikipedia articles. It provides new insights into the dynamics of user activity in the world's largest knowledge repository and shows how users allocate their attention and how attention is converted into contributions.

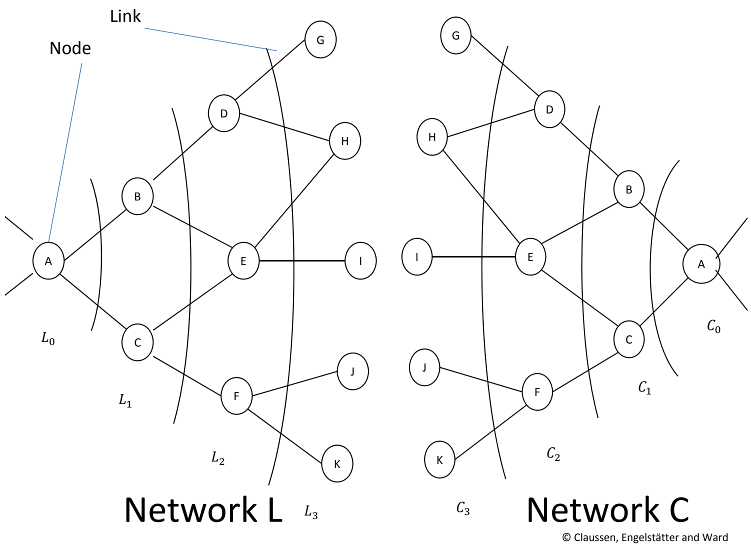
2 The empirical model

In what follows I will discuss the empirical model. I first give a basic and informal intuition of my estimation approach (subsection 2.1) and the assumptions made to identify the effect of the exogenous treatments I use (subsection 2.2). Next I discuss the reduced form estimation used in the regressions (subsection 2.3), before describing the structural model in the last and most extensive subsection (2.4). There I discuss how and under which assumptions the researcher can use the reduced form estimates to identify the parameter that measures spillovers in the structural model if she can observe 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 not apply are situations where the neighbors of the treated nodes/individuals observe the treatment and adjust their outcome as a reaction. An example of such a case would be classmates, that find a certain punishment of their peer unfair and show a reaction of protest. Appendix C shows, how the structural model would have to be extended to include such a possibility. From the insights of that section it quickly gets clear why the spillover parameter can no longer be identified if agents are assumed to react to the mere fact that their neighbor was treated.

2.1 Basic Intuition - A Stone in a Pond

This section is aimed at providing an intuitive idea of the data structure. The schematic representation in Figure 1 gives an idea of how the data is structured. Wikipedia articles are the nodes of the network. They are represented by a circle with a letter inside. Each such circle represents a different article in the German Wikipedia. Articles are connected to each other via links, which are made discernible on Wikipedia through blue highlighting of the word that links to the neighboring article. Clicking on such a word forwards the reader to the next article and these links form the edges of my directed network. In Figure 1 and 2, they are represented by a line between two nodes. Moreover, an important aspect of my identification strategy consists in observing two disconnected subnetworks at the same time. This is represented by showing them as network L and network C facing each other in both figures. I will maintain this notation also in all derivations further below. In what follows I focus on subnetworks around a

Figure 1: Schematic representation of a start node and its direct and indirect neighbors in two subsections of the network.

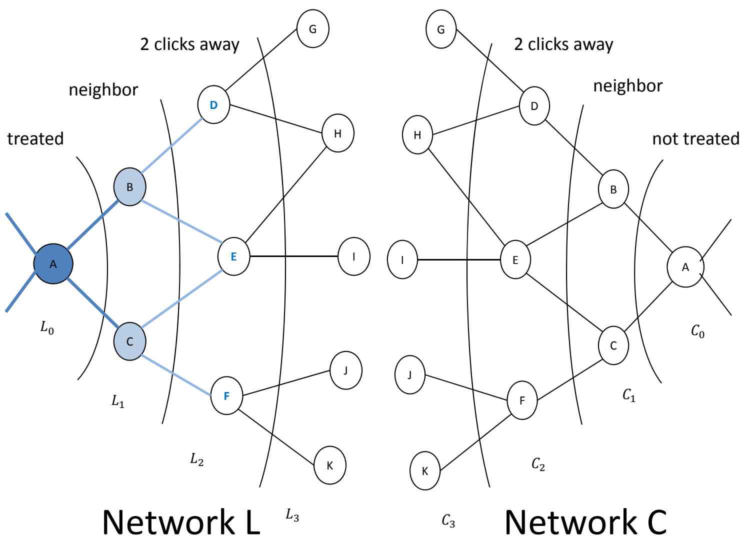


NOTES: The Figure illustrates the structure of the data. Wikipedia articles are the nodes of the network. Each circle with a letter inside represents a different article in the German Wikipedia. Articles are connected to each other via links, which are represented as lines. The left side of the figure draws on a representation in a working paper on network formation by Claussen, Engelstaetter and Ward.

start node. These start nodes are denoted by subscript 0. Hence, the start node of the two networks are denoted by $\ell 0$ and $c0$. 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 $\ell 1$[4]. The set of indirect neighbors[5] in the network L forms L_2 and so on. Analogously the set C_1 is made up of direct neighbors of the start node in network C and C_2 are 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 depend very many correlations and cross influences, but it would be difficult to discern where they originate from or whether they are due to some underlying and unobserved background factors, which merely affect the nodes in similar ways. The basic idea of the research approach can be subsumed under the idea of "throwing stones into a pond and tracing out the shock waves". The design of

Figure 2: 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 effect of 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.

this paper uses the fact that certain nodes were affected by a large increase of attention, that this was exogeneous, and that ex-post it is known to the researcher, when exactly this pseudo-experiment occurred. Moreover, since the link structure is known as well, it is possible to observe what happened in the neighboring nodes and further away from the shocked node. Like in a pond, we would expect the largest effect, in the directly

[4]While the set L_0 consists only of one node ($L_0 = \{\ell 0\}$), the set L_1 typically consists of multiple nodes.

[5]Indirect neighbors are defined as receiving at least one link form a node in set L_1 without themselves being a member of L_1. Hence the shortest path from the start node to an indirect neighbor is via two clicks.

hit node and would expect a decreasing amount of attention, the further away an article is from the epicenter. In the schematic representation of Figure 2, 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 second network from which it is possible to infer what the outcomes would have been if no treatment had taken place. If this is possible, we can use these outcomes for comparing the size of the outcomes layer by layer. More information about how the layers are identified and obtained for obtaining the dataset is provided in Section 3.

2.2 Identifying Assumptions for the Treatment Effects

To better understand the assumptions that are made in the reduced form estimation by layer, they can alternatively be described using the control-treatment notation and the terminology that is commonly used in the impact evaluation literature (cf. Angrist and Pischke (2008)). Doing so serves two purposes: First, it highlights the parallels between the methodology that is based on the ideas similar to the partial population treatment and second I hope it provides a different perspective at the source of identification and and thus a better intuition of the crucial assumptions made. The terminology and notation used to denote counterfactual outcomes and the effect of treatment on nodes/individuals, who are not eligible for treatment is inspired by Kuhn et al. (2011). Readers, who are well familiar with average and indirect treatment effects and the assumptions that underly a difference in difference strategy, might prefer to merely browse the formulas or to skip this section.

A core concept in the evaluation of the effect of treatments is the Average Treatment Effect (cf. Angrist and Pischke (2008). Even though this concept is widely used, I briefly discuss it in the context of my application in the first part of this subsection. Somewhat newer in this literature is the concept of indirect treatment effects as it is analyzed in Kuhn et al. (2011). Revisiting this concept in the present context of a content network with equidistant layers of articles around a shock, somewhat clarifies the assumptions that are being made. This is done in the second part of this subsection. The main insight from this section is, that the reduced form analysis hinges on the assumption that the control observations have a similar rate of change across time as the treated subnetworks, i.e. that they grow at similar rates and that they are affected similarly by any dynamics that affect the entire Wikipedia (weekday dynamics etc.).

2.2.1 Average Effect of Direct Treatment (ATE)

The ATE measures the effect of treatment on the treated, and it is well understood that we would like to compare the (observed) outcome during or after treatment to the (unobservable) outcome of the same individual if we had not treated them. This requires introducing the following notation: Consider node $i \in \{\ell, c\}$ in period t. Let ℓ denote a node in the subnetwork, which is treated in period t and by subscript c the subnetwork that is not. $d_{i,t}$ indicates if node i itself was directly treated or not in period t. Finally, to capture the notion of counterfactual treatments, denote by superscripts 1 the outcome of a treated observation and by superscript 0 the outcome of the untreated counterpart. One of these may typically not be observed and hence be counterfactual. Then $\mathbf{E}[y^0_{\ell 0,t}|d_{\ell 0,t} = 1]$ denotes the (counterfactual) outcome that we would observe for $\ell 0$ in period t, had it not been treated. The object of interest is the treatment effect, i.e.

$$\mathbf{E}[y^1_{\ell 0,t}|d_{\ell 0,t} = 1] - \mathbf{E}[y^0_{\ell 0,t}|d_{\ell 0,t} = 1] \tag{1}$$

The challenge lies in the fact that the second term in this difference cannot be observed. One way to obtain a proxy for the counterfactual observation of the treated is to observe a comparable node/individual, in a period where it is not treated, but which is believed to be affected by treatment in similar ways. In this paper I take two approaches to obtain such an observation: (i) A simple approach is to compare the observation "before and after" the treatment, and to attribute all observed changes in the outcomes to the treatment. This is equivalent to making the assumption that, absent treatment, the node/individual would have the same outcome as in the last period.[6].

Assumption ATE-before-after:

$$\mathbf{E}[y^0_{\ell 0,t}|d_{\ell 0,t} = 1] = \mathbf{E}[y^0_{\ell 0,t-1}|d_{\ell 0,t-1} = 0] \tag{2}$$

The biggest advantage of this counterfactual comes from the fact that the control observation is arguably as close to the treated observation as possible. The biggest drawback, comes from the fact that it will be very difficult to capture any period-specific effects that would have affected all nodes even without any treatment. Any such effects (weekday fluctuations, shocks etc.) will simply be attributed to the treatment. (ii) "Difference in difference" is an alternative well known approach, which makes use of a comparison group that is different from the treated group. This could be individuals in the same populations, which were not eligible for treatment. The (unobservable) counterfactual outcomes of the treated nodes are then assumed to be the treated nodes'/individuals' pre-treatment outcome *plus* the *change* of the non-treated control observation.

[6] 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 ATE-DiD:

$$\text{(3)} \qquad \begin{aligned} \mathbf{E}[y^0_{\ell 0,t}|d_{\ell 0,t}=1] &= \mathbf{E}[y^0_{\ell 0,t-1}|d_{\ell 0,t-1}=0]+ \\ &+ \{\mathbf{E}[y^0_{c0,t}|d_{c0,t}=0]-\mathbf{E}[y^0_{c0,t-1}|d_{c0,t-1}=0]\} \end{aligned}$$

It is worth stressing this fact in the context of Wikipedia articles. The crucial assumption is not that the articles *are* very similar, but merely that they *evolve* in a similar way, i.e. that, on average, they have similar growth in readership and edits, and that they are subject to similar intertemporal fluctuations (such as different activity over weekdays, shutdowns of Wikipedia's servers etc.).

2.2.2 Indirect Treatment Effect (ITE)

While the ATE can be defined on a single group of eligible nodes, the "indirect treatment effect" requires the introduction of at least one additional layer of the population, a group of nodes/individuals, that are not eligible for treatment.[7] The "indirect treatment effect" (ITE) measures the (spillover or external) effect of treatment of eligible objects/individuals on the outcomes of non-eligibles. It may be that treatment of the eligible individuals/nodes also has an effect on the non-eligibles, but, as for the ATE, we cannot observe the outcome of the non-eligibles, had the eligibles not been treated. Well known papers that estimate ITEs are Angelucci and De Giorgi (2009), Kuhn et al. (2011) or Crépon et al. (2013), to name a few.

Since the distance to the epicenter of the treatment is known in my application, we can measure several ITEs and compare the nodes of the subnetwork by layer. ITE_1 then refers to the indirect treatment effects when analyzing direct neighbors of the eligible nodes in a treated subnetwork. Analogously, we can define the ITE_2 to be the effect for nodes that are two steps away, the ITE_3, for three steps away and so on. Miguel and Kremer (2003) is a well known example, where researchers included distance layers in the estimation that incorporate a similar notion of distance to treatment in a real world setup.

Unfortunately this richness in the data will require an even more involved notation, since I have to differentiate along four dimensions (treatment, time, distance and subnetwork). To capture the notion of layers in the estimation, I use $D_{xr,t}$ as shorthand that takes the value 1 if both of the two following conditions are simultaneously satisfied: (i) the subnetwork x was treated and (ii) there exists a treated node that is exactly r steps away[8]. As before, $d_{i,t}$ indicates if node i was directly treated or not in period t. [9] $y^{\mathbf{1}}_{\ell r,t}$ is

[7]A good example would be an intervention to foster the reintegration into the jobmarket after paternity/maternity leave, for which people without children would not be eligible.

[8]An estimation by layers makes sure that the treated node is neither closer nor further away than r steps

[9]Notation has to be more involved here, because it is no longer possible to talk of a single node, as

now the outcome if *a neighbor* in D_{xr} was treated in t, and $y^{\mathbf{0}}_{\ell r,t}$ denotes the outcome if nobody in that set was treated.

The object of interest is the ITE_r, i.e., for direct neighbors we have:

$$ITE_1 = \mathbf{E}[y^{\mathbf{1}}_{\ell 1,t}|D^{\mathbf{1}}_{\ell 1,t}, d^{\mathbf{0}}_{i,t}] - \mathbf{E}[y^{\mathbf{0}}_{\ell 1,t}|D^{\mathbf{1}}_{\ell 1,t}, d^{\mathbf{0}}_{i,t}] \tag{4}$$

and more generally, for any range r[10]

$$ITE_r = \mathbf{E}[y^{\mathbf{1}}_{\ell r,t}|D^{\mathbf{1}}_{\ell r,t}, d^{\mathbf{0}}_{i,t}] - \mathbf{E}[y^{\mathbf{0}}_{\ell r,t}|D^{\mathbf{1}}_{\ell r,t}, d^{\mathbf{0}}_{i,t}] \tag{5}$$

Like for the ATE, also the ITE has to be estimated, since the counterfactual outcome in the absence of treatment cannot be observed. By the same idea as before we can predict the value of the counterfactual outcome by making two different assumptions: (i) a comparison of the same individual before and after treatment and (ii) the counterfactual outcome of the neighbors of the treated can be obtained by computing their pre-treatment outcome *plus* the average change of the neighbors of the eligible node in a non-treated control group.

Assumption ITE_r-before-after:

$$\mathbf{E}[y^{\mathbf{0}}_{\ell r,t}|D^{\mathbf{1}}_{\ell r,t}, d^{\mathbf{0}}_{i,t}] = \mathbf{E}[y^{\mathbf{0}}_{\ell r,t-1}|D^{\mathbf{0}}_{\ell r,t-1}, d^{\mathbf{0}}_{i,t-1}] \tag{6}$$

Estimating an ITE_r from a before-after estimation has the same advantages and drawbacks that applied for the ATE. Analogously, the drawbacks can be accounted for by computing a difference in difference estimator. In the context of an ITE, we need to observe comparable subpopulations (e.g. villages, classrooms, subnetworks), in which we have information about which individuals/nodes are eligible for treatment and which are not (non-eligible). If we also observe some subpopulations where no treatment is administered, the counterfactual can again be approximated. 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 already before the treatment of one takes place. 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.

the treated nodes can have many different neighbors.

[10] Note that this notation includes the ATE as the special case where $r = 0$, i.e. the "ITE_0".

Assumption ITE_r-DiD:

$$(7) \qquad \begin{aligned} \mathbf{E}[y^{\mathbf{0}}_{\ell r,t}|D^{\mathbf{1}}_{\ell r,t}, d^{\mathbf{0}}_{i,t}] &= \mathbf{E}[y^{\mathbf{0}}_{\ell r,t-1}|D^{\mathbf{0}}_{\ell r,t-1}, d^{\mathbf{0}}_{i,t-1}] + \\ &+ \{\mathbf{E}[y^{\mathbf{0}}_{cr,t}|D^{\mathbf{0}}_{cr,t}, d^{\mathbf{0}}_{i,t}] = \mathbf{E}[y^{\mathbf{0}}_{cr,t-1}|D^{\mathbf{0}}_{cr,t-1}, d^{\mathbf{0}}_{i,t-1}]\} \end{aligned}$$

In words, this means that the counterfactual outcome of the neighbors of the treated can be obtained by computing their pre-treatment outcome *plus* the average *change* of the neighbors of the eligible node in a non-treated control group. As before, the crucial assumption is not, that the nodes in the control group *are* very similar to those of the treated subnetwork, but rather that they *grow* similarly and that the way they are affected by Wikipedia-wide fluctuations is the same, as long as no treatment occurs. Before moving on to the econometric specification, I conclude this section by summarizing the identification result in terms of the difference in difference (DiD) estimator:

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

$$(8) \qquad \begin{aligned} ITE_r &= \mathbf{E}[y^{\mathbf{1}}_{\ell r,t}|D^{\mathbf{1}}_{\ell r,t}, d^{\mathbf{0}}_{i,t}] - \{\mathbf{E}[y^{\mathbf{0}}_{\ell r,t-1}|D^{\mathbf{0}}_{\ell r,t-1}, d^{\mathbf{0}}_{i,t-1}] + \\ &+ (\mathbf{E}[y^{\mathbf{0}}_{cr,t}|D^{\mathbf{0}}_{cr,t}, d^{\mathbf{0}}_{i,t}] - \mathbf{E}[y^{\mathbf{0}}_{cr,t-1}|D^{\mathbf{0}}_{cr,t-1}, d^{\mathbf{0}}_{i,t-1}])\} \end{aligned}$$

Note that this conclusion also applies to the ATE, in the case where r is set to 0.

2.3 Reduced Form Analysis

To obtain the ITEs for each layer, it is useful to apply reduced form regressions, which allows to understand 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 main idea is to simply 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,...). I denote all reduced form coefficients by ϕ. Furthermore, I redefine "treatment" for each set of pages accordingly.[11] I let s indicate the day relative to day 0, the day when the treatment is administered. Hence s runs from -14 to 14. λ_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 seperately. So if I focus on the treated nodes, the neighbors and the indirect neighbors, this results in the following system of regression equations, which all are based only on dummy variables:

[11] 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).

L_0.) Diff in Diff specification at level L_0:

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

...$treat_{L0}$: treatment on the very page; $S = \{-14, ..., 14\}$

L_1.) At level L_1 ($treat_{L1}$ featured (in theory) 1 click away):

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

L_2.) At level L_2 ($treat_{L2}$ featured (in theory) 2 clicks away):

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

In words, I run the same difference in difference on three levels (on L_0, L_1 and L_2 (shown only for large events)), but, for the present purpose, change the definition of a treatment: while $treat_{L0,i}$ is an indicator variable for a page that is (going to be) featured on Wikipedia's main page, $treat_{L2,i}$ 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 the value of 0, for an observation in the treated group, this variable will take the value of 1, if the observation that 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 ϕ_2 coefficient that corresponds to day 0 in the regressions above. I look at $\phi_{2,0}^{L_1}$ for the ITE_1, which corresponds to L_1, and analogously for L_0 and L_2.

Note that there is a specificity to the major events condition, which stems from the fact that plane crashes, earthquakes etc. are not anticipated. Consequently, the page of the event itself (the directly shocked node) usually does not exist before the shock. I deal with this fact by specifying the L_1 set as the set of pages that (will) have a reciprocal link from the L_0-page once it is created. Hence, at the time of the shock, these are the pages that are very close at the epicenter. The L_2 group is then defined as before, i.e. as the set of pages that received a link from an L_1-page one week before the shock actually ocurred.

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. 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.

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 even the results from such a reduced form analysis will provide guidance, as to whether attention-spills exist at all, how far they carry over, and whether they result in increased production.

2.4 Structural Form Analysis

Beyond measuring the size of the ITEs, I am interested in quantifying the size of the spillovers of attention that exist between Wikipedia articles on normal days. In this section, I extend the well known linear peer effects model, as it is formulated in Manski (1993), with exogenous shocks. Departing from the version that was used by Bramoullé et al. (2009) to show identification of peer effects in social networks, I show how the availability of exogenous shocks can be exploited to identify spillovers (or the peer effect) in this model, even if the nodes characteristics are endogenous. I other words, the exogeneous shocks are merely used as a focal lense to help identifying the spillovers, which are usually very hard to identify.

Since the derivations involve quite heavy notation, but are otherwise relatively straight forward, the details and derivations can be found in the appendix. Here I only provide the point of departure and the main results. A well known form of the linear model has been formulated in Manski (1993)

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

where y_{it} denotes the outcome of interest in period t and X_{it-1} are i's observed characteristics at the end of period $t-1$.[12] P_{it} is the set of i's peers and $N_{P_{it}}$ represents the number of i's peers. α is the coefficient of interest. In the present context it measures how the clicks on page A are influenced the clicks on the adjacent pages. Bramoullé et al. (2009) suggest a more succinct notation based on vector and matrix notation:

$$\mathbf{y_t} = \alpha \mathbf{G y_t} + \beta \mathbf{X_{t-1}} + \gamma \mathbf{G X_{t-1}} + \mathbf{\epsilon_t} \quad E[\epsilon_t | \mathbf{X_{t-1}}] = 0$$

I augment this model by including a vector of treatments, which, for simplicity, is assumed to take the value of 1 for only one treated node and the value of 0 otherwise.

[12]Note, that I can observe the current state of a Wikipedia article once a day at a fixed time.

This captures the notion of a local treatment condition, under which only one node is exposed to treatment (a “mini population treatment”).

$$\mathbf{y_t} = \alpha\mathbf{G}\mathbf{y_t} + \mathbf{X_{t-1}}\beta + \gamma\mathbf{G}\mathbf{X_{t-1}} + \delta_1\mathbf{D_t} + \epsilon_t \qquad E[\epsilon_t|D_t] = 0 \tag{12}$$

A few remarks concerning this formulation are in order: $\mathbf{G}$ is a NxN matrix. $G_{ij} = \frac{1}{N_{P_i}-1}$ if i receives a link from j and $G_{ij} = 0$ otherwise. For the treated side D_t is a vector consisting of zeros and ones, that indicates who are the treated nodes. In some of the proofs and in my application I will assume a local treatment that affects only one single node. Formally this is written as: $D_t = e_{\ell 0}$; i.e.: a vector with zeros and a unique 1 in the coordinate that corresponds to the treated node. On the untreated subnetwork we have $D_t = \mathbf{0}$, a vector of zeros.

Note that I do not require that the structure of the network (G) is exogenous, but rather which node gets treated has to be exogenous. 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. Also, 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:

$$\mathbf{E}[\mathbf{y_t}|\mathbf{D_t}] = (\mathbf{I} - \alpha\mathbf{G})^{-1}[(\beta + \gamma G)\mathbf{E}[\mathbf{X_{t-1}}|\mathbf{D_t}] + \delta_1\mathbf{D_t}] \tag{13}$$

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

Result 1: Denote the difference in difference estimator as

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

and assume that the treatment affects only the contemporary outcome of the treated node, but not it’s exogeneous characteristics.[13] Then the DiD measures the following quantity:

[13]The independent characteristics X should not be immediately affected by treatment, because this would threaten the identification of the spillover. Note however, that they may adjust over time. As long as we can observe one period where only the outome is affected, but not the characteristics, the result holds.

$$\mathbf{DiD} \quad = \quad \delta_1 \mathbf{D_t}(\mathbf{I} + \alpha\mathbf{G} + \alpha^{\mathbf{2}}\mathbf{G}^{\mathbf{2}} + \alpha^{\mathbf{3}}\mathbf{G}^{\mathbf{3}} + ...) \tag{14}$$

In words, this result means that the node is not only affected by treatment, but also by second and higher order spillovers, the positive feedback loop that ensues as the neighbors increase their performance in sync with their peers. One single instance of a higher order effect[14] are $\alpha^2\delta_1$ in the second round, $\alpha^3\delta_1$ in the third round and so on. The other factor that matters is, the whether and how often spillovers of a given order q arrive, that is it depends on the number of indirect paths of length q that go from the shocked node $\ell 0$ to any focal node j. The proof of this result can be found in Appendix B.3.

My result highlights, that the DiD alone will not directly reveal α, the social parameter of interest, but merely a quantity that is tightly linked to α and δ_1, the parameter that measures the shock. Yet, the result also highlights that computing the parameters is not necessarily feasible, because it involves the knowledge of the complete link structure of the nodes. Luckily, a closer look at the nodes independently reveals that already limited information about the link structure can suffice to acquire additional information about the parameters. In the following two sections I show how to get the point estimate for the peer effects coefficient if the network is known and I show how to derive an upper and a lower bound estimate for the parameter if no information about the network is available.

2.4.1 Estimator of the Peer Effects Parameter if the Network Structure can be Observed.

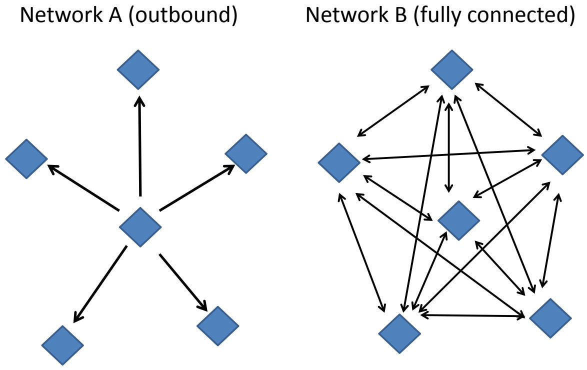
If the network structure can be observed, the peer effects parameter α can be backed out quite easily by computing the higher orders of the network graph (G-matrix). To know how many spills arrive in each round, it suffices to focus on the entries $G_{ij}, G^2_{ij}, G^3_{ij}, ...$ that document the number of paths via 1, 2, 3,... links from the treated node to the neighboring node in question. With this information it is straight forward 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.

2.4.2 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 possible to obtain boundary estimates for the peer effects based merely on the separate comparison of the directly treated nodes and their counterparts (L_0 vs. C_0)in the control group and their neighbors (L_1 vs. C_1). Under quite rigorous, but not uncommon, assumptions it shall thus be able to obtain

[14] Note that I am considering the homogeneous network, so all spillovers have the same magnitude.

Figure 3: 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.

a lower bound estimate for the coefficient α. While randomization and information on the network together are rarely available, a separate comparison of eligible and non-eligible nodes in randomly treated communities or networks is frequently available in empirical settings. In what follows I will briefly show, how to obtain the bounds. The main idea of this derivation is to select two specific "extreme" types of networks which either minimize or maximize second and higher order spillovers. These benchmark networks are schematically represented in Figure 3. I use a directed network with only "outward bound" links emanating from $\ell 0$ to $\ell 1 \in L1$ to obtain the upper bound estimate of the social/spillover parameter α. The opposed benchmark is a fully connected network, where every node is the direct neighbor of every one of its peers, so from there I obtain the lower bound estimate of the social parameter. A more detailed account is provided in Appendix B.4.

If we ignore higher order spillovers[15], we can obtain an upper bound estimate for the ATE ($\overline{\delta_1}$) from applying the the difference in difference estimator on the level of directly treated nodes (L_0) and a suitable comparison group (C_0) . After that we can move on to estimate the upper bound for the parameters for spillovers ($\overline{\alpha}$) based on combining it with a second difference in difference estimator at the neighbor level. Let $DiD_{(\ell a - ca)}$ denote such a difference in difference ($a \in \{0, 1\}$) whether the nodes are in the center of the network (L_0 or C_0) or the neighbors of the start nodes (L_1 vs. C_1):

[15] Or maintain the assumption that we can observe the nodes' performance before any higher order spillovers arrive at the treated node

$$\hat{\bar{\delta}}_1 = \widehat{DiD_{(\ell 0-c0)}} = \Delta\hat{\ell}0 - \Delta\hat{c}0 \tag{15}$$
$$\hat{\bar{\alpha}} = \frac{\widehat{DiD_{(\ell 1-c1)}}}{\widehat{DiD_{(\ell 0-c0)}}} NP_{l1}$$

- $\Delta\hat{\ell}0 := \frac{1}{NP_{\ell 0}} * \sum_i (y_{i,\ell 0,t=1} - y_{i,\ell 0,t=0})$
- $\Delta\hat{c}0 := \frac{1}{NP_{c0}} * \sum_i (y_{i,c0,t=1} - y_{i,c0,t=0})$

with $\widehat{DiD_{(\ell 1-c1)}} = \Delta\hat{\ell}1 - \Delta\hat{c}1$ and the definition of the underlying $\Delta\hat{\ell}1$ and $\Delta\hat{c}1$ paralleling the definition of $\Delta\hat{\ell}0$ and $\Delta\hat{c}0$. In my application's reduced form estimations of last section $DiD_{(\ell 1-c1)}$ corresponds to $\phi^{L_1}_{2,0}$ and $DiD_{(\ell 0-c0)}$ is estimated by $\phi^{L_0}_{2,0}$. This upper bound estimator would be quite suitable under the (potentially quite strong) assumption that higher order spillovers are negligible. In what follows I shall proceed to illustrate 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.

It is also possible to find a lower bound estimate for α and δ_1. This bound can be obtained by imagining that the network is fully connected, i.e. every node links to every other node and assuming that all effects are of the same sign, strictly ordered and (w.l.o.g) positive[16]. Somewhat more involved, but straight forward computations show, that in a network with N nodes, the lower bound of the estimator for α is characterized by the solution to the following quadratic equation:

$$\underline{\alpha}^2 - [\frac{DiD_0}{DiD_1} + (N-1)]\underline{\alpha} + (N-1) = 0 \tag{16}$$

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

$$\underline{\alpha} = \frac{1}{2}[\frac{DiD_0}{DiD_1} + (N-1)] - \sqrt{\frac{1}{4}[\frac{DiD_0}{DiD_1} + (N-1)]^2 - (N-1)} \tag{17}$$

Recall that all the quantities required are readily available from the reduced form estimations. $DiD_{(\ell 1-c1)}$ corresponds to $\phi^{L_1}_{2,0}$ and $DiD_{(\ell 0-c0)}$ is estimated by $\phi^{L_0}_{2,0}$. In Appendix B.4 I provide a proof for my claims and explain how this bound is derived.

[16]The precise assumption is $DiD_0 > DiD_1 > HO^B > 0$, as stated and explained in Lemma 1

3 Data

This section gives detailed information about the dataset. Subsection 3.1 explains how the database was put together and the procedure I used to extract the dataset that I use. Subsection 3.2 describes the dataset itself.

3.1 Preparation of the Data and Definition of the Treated and Control Group

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, we constructed the time-varying graph of the article network, which provides the foundation for how I sample articles in our 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 we use in our analysis, 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 would 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)). This is a novel high-level language which allows to write and efficiently execute queries on nested and ordered collections of data.

To identify major events, we consulted the corresponding page on Wikipedia and selected the 26 events that had the largest impact and for which a site was created after it occurred. For each of these events we identified the page that corresponds to the event, and which are considered to be in the set "L_0" (sometimes also called "start pages"). Note that this page is created after the event occured [17]. We then exploited the data on the link structure to identify the set of pages that shared a reciprocal link with the start page, because this indicates that they were very closely related to the event. After the disaster page existed they were only 1 click away from the event-page (set "L_1"). Next, we identified those pages that received a link from an L_1 page (unidirectional) (2 clicks away set "L_2") Note, that I evaluate the L_2 pages in the network a week before the shock actually occurred to make sure that the results are not driven by endogeneous link formation.[18] Having fixed the set of pages to observe, I extracted daily information

[17] Usually it takes up to two days until the event receives its own page

[18] 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.

about the current 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 base, 14 days before the event occurred (on a neighboring page) and 14 days after the shock (giving a total of 29 observations per page).

The "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^{th} of a month. Similar to the procedure for disasters I identified all the pages that received a direct link (L_1) and an indirect link (L_2) from such a featured article a week before the page was advertised. Since all of these pages existed before treatment, it is possible to design this condition substantially simpler and simply focus on pages that were linked to the treated page more than a week before treatment.

I am most interested in attention-spills and content, which are not directly related to the event but rather a consequence of the peak in interest and the resulting improvements also on the linked pages. Hence, I will not focus on the treated pages directly, but on the set L_1, the pages that are "one click away" from a treated page, in my analysis of the "featured articles"[19] For disasters the shock is very large and the event page usually does not exist at the time of the shock so that I cannot be sure, that the L_1 pages are not actually treated themselves.[20] Hence, it is natural to focus on the pages that received a link from the neighborhood of the event (the indirectly linked set of pages (L_2)) in the analysis below.

The approach I take in this paper hinges on the availability of a valid group for comparison. Thus, I also need to identify a set of observations, against which I can contrast treated pages and their neighbors. To obtain such observations I pursue two distinct strategies. First, I identified pages, which are similar but unlikely to be affected by the treatment. For a first comparison I focus 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). [21] Given such a similar page, I, again, identified

[19]Effects on the pages that are 2 clicks away were to small too be measured.

[20]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 due to the event (e.g. destruction of an important monument) but not merely a consequence of the peak in interest and resulting improvements. Therefore I do not emphasize the change in activity on the pages that are only one click away for disasters. Moreover, to be certain I do not mix up directly and indirectly linked pages, I exclude any pages that were at any later point directly linked to the event page.

[21]This approach is not satisfactory in many ways. In ongoing work I control by using similar events that occur at a different point in time and to reduce the possible overlap. I also plan to select the control groups based on matching procedures. Note however, that my approach is generally quite robust independently of how I specify the control group. Alternatively I tried the following control group: for a region which was affected by an earthquake is compared to a region of similar size and relative importance in a similar, but remote, geographic space or the page of an airline, which lost one of its planes in an air crash is compared to an airline of similar importance but in a different region of the world. Such a

the set of pages which are one click away and which are two clicks away when the event occurs on the treated page. This gives me a set $L2_{control}$ which is both similar in size and also in the characteristics of the sampled pages (before the shock). Yet, since the choice of the start-pages in the comparison group is somewhat arbitrary. To approach this issue I also sampled the treated pages, but now only 42 days before the disaster or event occurred. For this group I simulate a treatment, by setting their $t = 0$ when no actual treatment occurred (I will refer to this group as the "placebo" group ($L2_{placebo}$) and to their treatment as "placebo-treatment"). The obvious advantage of this comparison group over the control group described above stems from the fact, that it consists of the treated articles and their neighbors themselves. This comes at the cost of observing the pages at a different point in time. A third control group of "unrelated" observations results from the combination applying a placebo to the control group. Although this set of observations actually emerged as an artefact from the data extraction it provides yet another group that can be compared to the treated group.

An example of a natural disaster in the dataset is the "Sichuan Earthquake", which took place on May, 12th 2008 in the Province of Sichuan, PRC. The main consequence of this event were more than 60,000 dead and the region also suffered substantial economic loss. Suitable control pages could be pages about similar regions in far away places, or pages about other regions or countries, which were hit by large natural catastrophes, but at a different point in time. The placebo-control would be the same set of pages (on Sichuan and surrounding pages), but evaluated 7 weeks before the event. Table 3 shows which events were included in the data. These include both Natural Disasters as well as technical or economic catastrophes. Since the main focus of this study lies on the pages that are two clicks away. Table 4 also shows the number of observations that are associated with each event, seperated by whether they belong to a time-series with actually treated observations or whether they do not.[22]

A representative "featured article" ("Seite des Tages" might be the page about *Banjo-Kazooie*, which was advertised on Wikipedia's main page on June 10th, 2010. It describes *Banjo-Kazooie*, which appears to be a highly commendable Nintendo-64, *Jump'n'run* video game, which I am admittedly not familiar with. Table 6 shows which featured articles that were chosen by my procedure and were included in the data. In general, the variety of topics that are covered by the articles is much wider than in the other sample. They cover topics as varied as innovations (e.g. the CCD-sensor), places (Helgoland), soccer clubs (Werder Bremen) and art historical topics (Karolingische Buchmalerei - book-illustrations in the carolingian period). For the featured articles treatment the focus of interest lies on the pages that are one click away. Table 7 again shows the

change in the specification of the control group does not affect my results. (available upon request).

[22]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.

number of observations that received a link from the article before it was featured. For one featured article the number of associated observations ranges from a 2,088 to 33,872. Control observations were articles that were featured either later or earlier in time (and neighbors) or, as before, the same set of pages, seven weeks before (after) "featuring".

3.2 A Closer Look at the Dataset

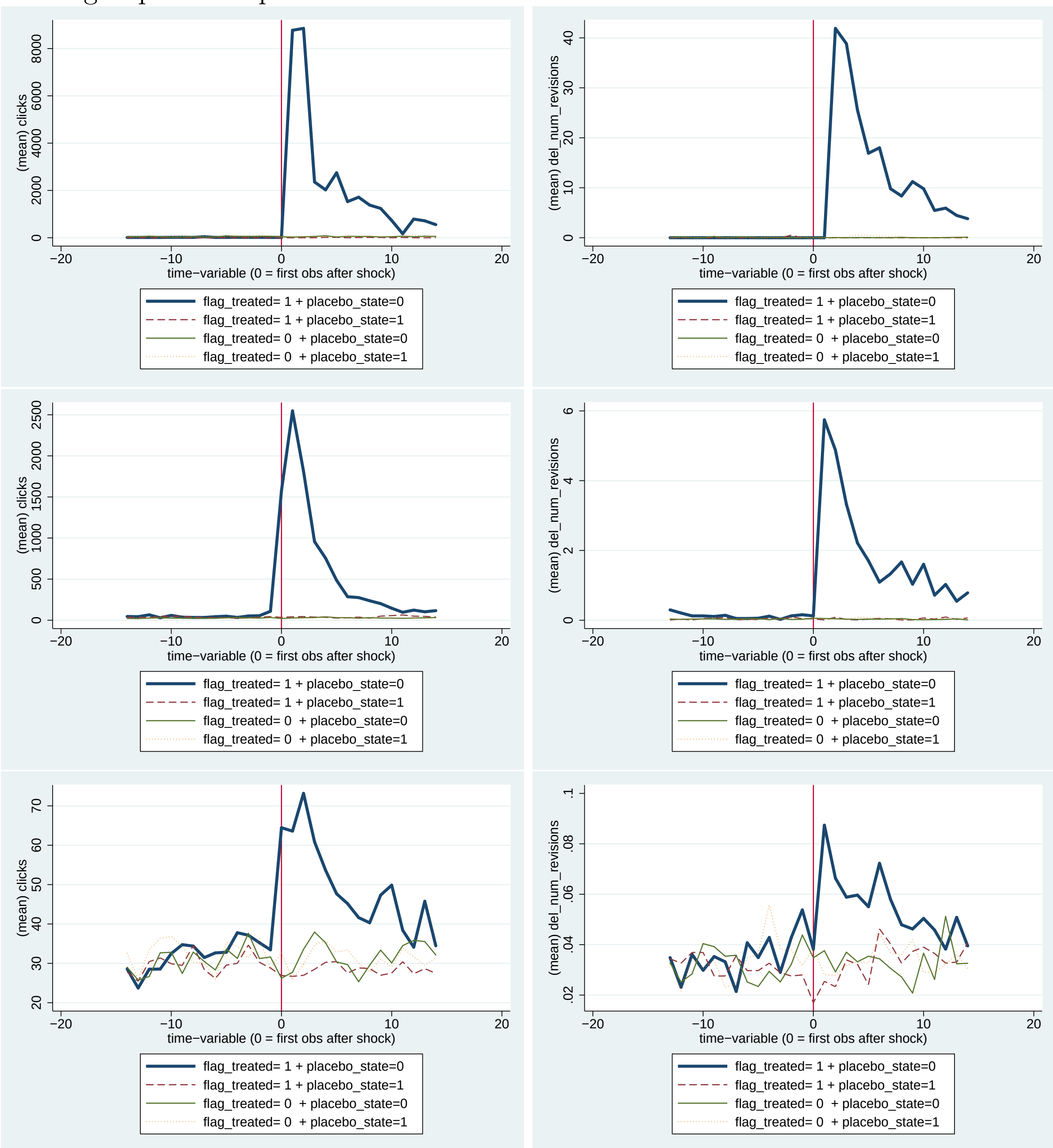
Summary statistics for the data on large events are shown in Table 5. The data contains 425,981 observations from 7,379 pages on the main variables. From the table it can be seen, that the average page contains 5658 bytes of content and has undergone 84 revisions. However, the median is substantially lower (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 to use major events as a focal lense for analyzing activity on Wikipedia.[23], which is confirmed by the visual inspection of the direct and indirect effect of treatments.

In Figure 4 I plot the average clicks (left column) and the average number of added revisions (right columns) for the three groups of pages (zero clicks away (upper row), one click away (middle row) and two clicks away (lower row)). The two lower rows in this figure contains four lines. The first represents the treated group (or it's neighbors) when they were actually treated (hence flag_treated = 1 and placebo_state = 0). The second line represents the same group but during the placebo treatment at an earlier point in time. The third line (flag_treated = 0 and placebo_state = 0) shows the control group at the time when the real shock occurred and the fourth line represents the "unrelated" observations, which are never treated and taken in the placebo period. [24] The upper row contains four lines, showing the control group and the directly treated nodes, 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 few have a have a placebo condition available. The row shows, that the directly affected pages experience a very large spike of 8,500 clicks per day on average. Also the number of additional revisions peaks on the first days of treatment, when the pages are created: an average of almost 40 revisions are added to a page on the first day. Also on the pages that are to share a reciprocal a link from the treated page the effect is quite pronounced: Yet, while the clicks on the average L_1 page increase by 2,500, the absolute value of the average increase in revision activity has decreased to 5. When I look at pages that are two clicks away, the effects are

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

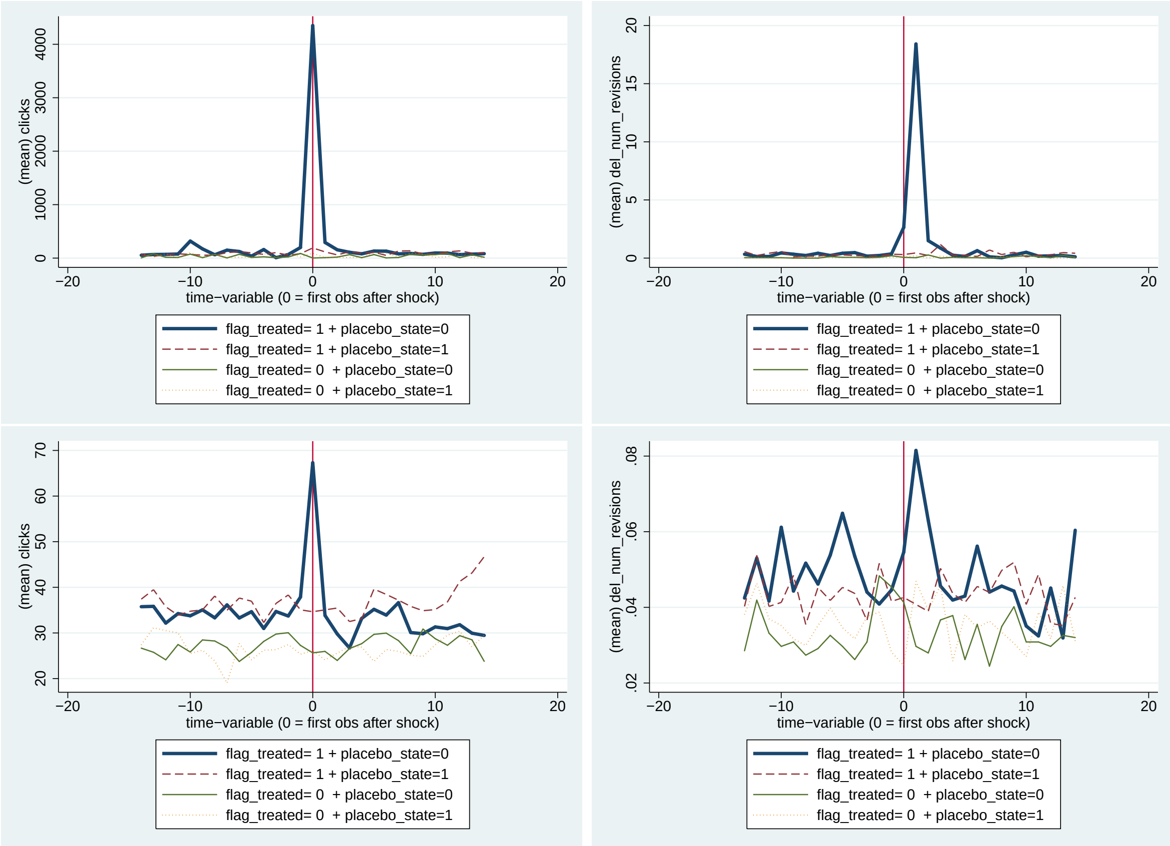
[24]For greater ease of representation I included a graphical representation of only two variables. The summary statistics for these groups before and after treatment are also available as tables upon request.

Figure 4: Contrasting means of clicks vs. number of added revisions over time: looking at all 4 groups in one plot.



NOTES: The upper row shows the average effect on the event pages (which by definition were created after the event), the middle row the directly treated pages (L1, with reciprocal link), and the lower row for the pages that are one click away from L_1. The left column shows the average number of clicks the right column 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.

Figure 5: Page of Day experiment: Contrasting means of clicks vs. number of added revisions over time: looking at all 4 groups in one plot.



NOTES: The upper row 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 left column shows the average number of clicks the right column shows the average number of edits. The outcomes are shown for the treated articles and the control groups separately.

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.

The data from "featured articles" are shown in Table 8. The data contains 317,550 observations from 5,489 pages[25] 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. Also in this sample, the mean is substantially higher (6794 bytes and only 95 revisions). As before, the summary statistics of the first differences show clearly how little activity occurs on a normal day on any given page on Wikipedia.

Figure 5 plots the aggregate dynamics around the day it was shown on Wikipedia's main page and corresponds to Figure 4 for the large event condition. I plot the average

[25]Since pages were observed also in the placebo condition, each page is sampled twice, and hence I observe 10,950 distinct time series.

clicks (left column) and the average number of added revisions (right columns), but now only for the treated pages and the direct neighbors. As before, each of the four figures contains four lines, one for each conditions that can be obtained from 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 the typical levels (below 50 views) to more than 4200 (on average) views, but immediately returns to the old levels the day after treatment was administered. A very similar pattern can be observed for the neighbors where attention is almost twice as high than on a usual day and then falls back to the old levels. A similar pattern can be observed for the number of revisions, but, other than for large events, it can be observed that activity rises already before $t = 0$. Nevertheless, on the day of treatment the spike of activity is pronounced also for the neighbors.

4 Estimation results

In what follows I present estimation results for both groups and discuss their interpretation. Before I proceed with presenting the details of my estimations, it is worth recalling a few important facts. First of all, recall, that the main focus in this paper lies on the estimation of the equation corresponding to equation 11 for large events and 10 for featured articles in section 2.3. This is due to two reasons: first, the two conditions differ in how local the treatment is, that I exploit for estimation. Second, only the "featured articles" exist at treatment, while the page at the center of a large event treatment typically does not yet exist and will only be created during the days to follow.

Moreover, recall that I deal with potentially endogenous link formation that might arise as a result of the treatment by considering only links that had been in place *a week before the treatment*. Moreover, when a page was sampled to lie in both treatment and control group it was excluded from estimation, whenever identifiable. Yet, note that including such pages will bias the estimated coefficients towards zero. Also 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 them. Finally, I use the 7 observations from two weeks before treatment (days -14 through to -8) as the reference group in the estimations and I include only flow variables (clicks, new revisions, new authors etc.) to guarantee that my results are not driven by any anticipation effects.[26]. The following two subsections report the results for both conditions.

[26]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.

4.1 Large Events

For this group the estimation concerns the set of L_2 pages, the 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 very likely directly affected a page that shall 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 was already explained above, this is not the effect I am primarily interested in. Consequently I focused on pages that receive an indirect link, because these are no longer likely to be directly affected by the treatment on the page two clicks away.[27] Moreover, to make sure that also 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 at any later point in time. If this was the case, I concluded the page might have been affected by the shock, despite having been in L_2 before the shock and eliminated it from the sample. Thus I can ensure that only pages that were indirectly linked at the time of the shock and that also never got directly linked enter the sample.

The results for the estimation of the model for L_2 nodes are shown in Table 1.[28] 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). For ease of representation the table only shows the coefficients for the cross terms from 2 periods before the shock until 4 periods after the shock. As was explained before, until the onset of the event (periods -2 to 0), we would effect insignificant effects for the cross terms and after the event has occurred a positive effect would imply that some form of spillover can be measured. Very much in line with the visual evidence, the average increase in click, relative to the control group (column 1), amounts to up 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. This is somewhat different for the number of revisions (as the graphical analysis had already suggested), since the effects are much smaller. A small effect is revealed from the first day after the treatment. This effect is small in absolute terms, since roughly one in 20 to 30 pages gets an additional revision. Yet, given the low levels in average activity on a given page on a given day,

[27] 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.

[28] Non-parametric comparisons of the coefficients of each group taken separately confirm the results from the panel regressions and are thus not reported. They are available upon request.

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			del revisions		
	(1) compare control	(2) compare placebo	(3) compare all	(4) compare control	(5) compare placebo	(6) compare all
t = -2	3.172	3.487	2.065	0.010	0.015	0.008
	(4.709)	(4.545)	(4.431)	(0.009)	(0.010)	(0.008)
t = -1	0.978	3.144	3.450	0.010	0.026***	0.017**
	(3.993)	(3.742)	(3.866)	(0.010)	(0.008)	(0.008)
t = 0	37.391**	36.047**	35.394**	0.003	0.021*	0.004
	(14.421)	(14.386)	(14.287)	(0.011)	(0.011)	(0.010)
t = 1	35.020***	35.397***	36.757***	0.049**	0.062**	0.055**
	(11.098)	(11.113)	(11.082)	(0.024)	(0.023)	(0.023)
t = 2	38.767***	44.730***	42.319***	0.037**	0.043***	0.038***
	(13.650)	(13.589)	(13.523)	(0.014)	(0.012)	(0.012)
t = 3	22.069**	30.895***	25.945***	0.021*	0.025**	0.024**
	(9.168)	(8.730)	(8.448)	(0.011)	(0.011)	(0.010)
t = 4	17.601**	21.918***	19.063***	0.026**	0.028**	0.026**
	(7.065)	(6.917)	(6.838)	(0.012)	(0.013)	(0.012)
Constant	29.900***	29.994***	30.735***	0.033***	0.032***	0.031***
	(1.001)	(1.289)	(0.664)	(0.002)	(0.002)	(0.001)
All cross	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162338	104214	323158	154959	99477	308469
Number of Pages	7379	4737	14689	7379	4737	14689
Adj. R^2	0.003	0.003	0.002	0.001	0.001	0.000

NOTES: The table shows the results of the reduced form regressions to estimate the ITE in the large events condition. Columns (1)-(3) show the results for clicks and Columns (4-6) for new edits to the articles . Specification (1) and (4) contrast treated and comparison group; (2) and (5) show the comparison of treated articles with themselves but seven weeks earlier (placebo treatment). In Columns (3) and (6) I juxtapose the treated subnetworks with all available comparison groups at the same time. 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.

this is still a noteworthy effect. Moreover, when comparing the pages with the placebo treatment, I observe a small increase in editing activity, already before the onset of the event, which is however not confirmed by the comparison with the control group. The size of the effect still more than doubles after day 1, when also the comparison with the control group suggests a drastic increase in editing activity.

4.2 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). This is the relevant group here, because the treatment takes place entirely inside Wikipedia (usually no media coverage or anything of the like) and it is "completely local", in the sense that no two articles can be featured at the same time. Hence, the different nature of the treatment guarantees that 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.

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 also the clustering is implemented on the level of events (like before). The main insight of this table is that it confirms the statistical significant of the effect 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. Also on the revisions (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: Firstly, the effect is very small in absolute terms and corresponds to one additional edit per 30 pages. Secondly however, this is an increase in contribution activity by 80 to 100 per cent.

I tested the robustness of my results by excluding the first third of the "featured articles".[29] Table 9 shows the result of the check and adds a new dependent variable, the change in the number of editors (in columns 5 to 6). In general, results reveal the same pattern as Table 1, but the significance levels might be lower. 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 their neighbor. Yet, while this is a large effect in relative terms it means that only one in 70 articles is edited by a new author.

Another way of understanding the meaning of these point estimates, consists in aggregating the changes in clicks and revisions over all neighboring articles and then averaging over the 34 different featured articles. This is done in figures 6 and 7 in order to summarize and illustrate the insights from the "featured articles" condition. I find that, on

[29]This is clearly not final, but splitting the sample is a common and useful first check to test whether the results are robust.

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

	clicks			del revisions		
	(1) compare control	(2) compare placebo	(3) compare all	(4) compare control	(5) compare placebo	(6) compare all
t = -2	-5.064	-2.629	-3.139	-0.028**	-0.018*	-0.019**
	(4.051)	(3.477)	(3.062)	(0.011)	(0.011)	(0.008)
t = -1	2.149	4.792	3.957	-0.021*	-0.004	-0.007
	(3.082)	(4.187)	(3.242)	(0.012)	(0.008)	(0.007)
t = 0	33.128***	34.638***	34.008***	-0.006	0.004	0.004
	(9.162)	(9.294)	(9.082)	(0.009)	(0.008)	(0.007)
t = 1	-0.158	0.773	0.645	0.032**	0.033**	0.030**
	(2.266)	(3.214)	(2.346)	(0.012)	(0.014)	(0.012)
t = 2	-2.523	-3.700	-3.438	0.015*	0.017	0.014
	(2.965)	(3.144)	(2.758)	(0.008)	(0.011)	(0.009)
t = 3	-8.373**	-3.807	-5.864	-0.011	-0.012	-0.013
	(3.371)	(5.435)	(3.949)	(0.012)	(0.013)	(0.011)
t = 4	-2.557	2.038	0.054	-0.016	-0.009	-0.008
	(2.766)	(5.615)	(3.535)	(0.014)	(0.009)	(0.008)
Constant	31.982***	35.354***	32.534***	0.043***	0.046***	0.042***
	(0.816)	(0.768)	(0.580)	(0.002)	(0.002)	(0.001)
All cross	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120758	166518	240900	115269	158949	229950
Number of Pages	5489	7569	10950	5489	7569	10950
Adj. R^2	0.004	0.003	0.002	0.000	0.000	0.000

NOTES: The table shows the results of the reduced form regressions to estimate the ITE in the 'featured articles' condition. Columns (1)-(3) show the results for clicks and Columns (4-6) for new edits to the articles. Specification (1) and (4) contrast treated and comparison group; (2) and (5) show the comparison of treated articles with themselves but seven weeks earlier (placebo treatment). In Columns (3) and (6) I juxtapose the treated subnetworks with all available comparison groups at the same time. 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.

average, there are 4000 clicks on all neighbors taken together (Figure 6). Given that also the average treated articles received an additional 4000 clicks this corresponds to a one for 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 7) increases from approx. 4.5 to roughly 8.5. This is an additional four changes, which means that the 4000 initial additional clicks are converted in 4000 additional clicks and four new revisions or a ratio of 1000:1000:1.

Finally I report results of an extended analysis, which were omitted here, for reasons of space.[30] I included 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. Moreover I split the sample in well connected articles (many links) and poorly connected ones, but I do not find a significant relationship between this variable and the number of visits. 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. However, when I consider only "stubs", i.e. pages that do not exceed a length of only 1500 bytes, I find a much stronger relative effect in the number of edits. This indicates that the new content that is provided after all, is provided on pages, where the existing content is little.

4.3 Bounds for the Structural Estimator

Unfortunately I cannot compute the precise structural estimator, because the full matrix **G** formed by the German Wikipedia is too large to be computed in memory. Hence I cannot compute the solve for G and higher orders of that matrix.[31] However, it is possible to present an the upper and lower bound estimates of the structural parameters that are discussed in subsection 2.4 and derived formally in Appendix B.

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 quite crude first evaluation, which primarily serves the purpose 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.

To compute the upper bound for the social/spillover parameter α and the shock δ_1 I use equation 38. My preferred estimates are taken from the "featured article" condition and the estimates from the disaster condition are reported in parentheses. $\overline{\delta 1}$ is directly estimated to be 4,200 (2,440 in the disaster condition) The estimate of $\overline{\alpha}$ is 0.292 (34/4,190*N=36) based on "featured articles" (based on disasters: (38/2,440*N=31) =

[30]They are available from the author upon request.

[31]Ongoing work is attempting to solve this issue. If these efforts are fruitful, the results might be included in future versions of this paper.

0.483).

Computing the Lower Bound estimates is slightly more involved since it involves plugging the estimates and the number of nodes into the closed form solution given in formula 44. This gives the point estimator for the lower bound of α, which is estimated to be $\underline{\hat{\alpha}} = 0.222$ for featured articles (and $\underline{\hat{\alpha}} = 0.320$ 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 10, this alone would result in an increase by 2.215 to 2.92 clicks on the page, which all come 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 total clicks on neighbors by 200 (aggregate) is predicted to result in 1.61 additional clicks on the target page.[32] While this absolute effect in clicks is already very small, the conversion to content is even smaller than that, since I have shown that even huge shocks do not generate many revisions. This suggest 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. Future research should investigate if these estimates apply only to mature Wikis or whether the small size of the effects will also pertain on younger wikis with less content.

5 Concluding remarks and further research

In this paper I analyze whether the link network between articles on the German Wikipedia influences how much attention an individual article receives and how much content is provided to it by users. I use observable exogenous shocks, such as large scale media events or natural disasters as a focal lense to analyze the spillovers of user generated content that are mediated through links. I deploy this strategy to find substantial spillovers of attention. While the effects are very large in relative terms they result in a relatively modest impact on content provision in absolute terms. The findings indicate, that the links between nodes seem to be an important medium for attention spillovers in networks that consist of interlinked nodes of user-generated content. The links that point to a node can influence how much attention a node will receive. My structural estimates suggest that an article will receive 30% of the number of average clicks on neighboring articles. Hence, by placing a few links to very frequented nodes and thus increasing the average daily visits (clicks) on the neighbors by ten, it would be possible to obtain three additional daily visits.

[32] As before I use the median number of neighbors for these thought experiments. The quantification is based on the upper bound estimates of α in the “featured article” condition (and would be 3.31 for disasters).

My results indicate also that the spillovers in attention may be to a large extent for the purposes of looking up information. The analysis of the "featured articles" suggests that the average visitor clicks on exactly one of the links. The total number of revisions on the neighboring pages (Figure 7) increases from approx. 4.5 to roughly 8.5. Hence, my estimates suggest that links affect content creation to a much smaller extent, so using the link network is probably a very expensive and possibly inefficient strategy to channel contribution flows.

One of the biggest revolutions of the 21st century will be the creation of a world in which "every single human being can freely share in the sum of all knowledge". This is precisely the vision of the Wikimedia Foundation (2013) and wikis have been a decisive step in that direction by linking articles to create a content network. My results shed light on whether the links forming a content network can be used to manage contribution flows on platforms that rely on user generated content. Hence, it is important for administrators of both new wikis and burgeoning platforms for knowledge documentation, who are concerned with channeling the flows of content contribution. A promising area for further analysis would investigate whether new authors are attracted by the events or whether contributions are made only by authors that previously contributed to the subject. Moreover, future investigations should investigate if these estimates apply only to mature Wikis like the German Wikipedia or whether the small size of the effects will also pertain on younger wikis with less content. This question can only be analyzed via case studies in smaller or younger Wikis, which would be a very promising endeavor. Note that the link network between articles is a citation network. Thus, my findings allow for a more abstract reading when interpreting Wikipedia as a peer produced tool for the documentation of human knowledge, i.e. a setting of peer production, similar to the production of open source software or scientific research. Viewed under this light, it is probably advantageous, that this paper uses data from a mature wiki. My results suggest that the attention to a certain field or project will be more likely, if it receives links from other articles in other areas.

This paper suffers from several limitations. Most importantly, future research should aim at exploiting the heterogeneity in the intensity of direct treatment effects more thoroughly. In particular, I hope to understand whether the attention (that is currently measured as average effect) is evenly distributed across neighbors, or whether users actually herd in only a few of the directly linked pages. Another promising area would be to use the methodology based on exogenous local treatments alongside the methodology that is based on the network structure and the exploitation of open triads (Bramoullé et al. (2009), De Giorgi et al. (2010)). Since the approaches are complementary, research along these lines will result in valuable insights. Finally, the evaluation of the structural parameters of the underlying dynamic with which the clicks on neighboring pages are transmitted to each other is based on several assumptions. Most importantly 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 optimally be included for relating reduced form and structural parameters.

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A Tables and Figures

A.1 Disasters

A.1.1 Descriptive Analysis for Disasters

Table 3: Included disasters and the number of pages that are associated with them (2 clicks away).

name of event	No.
Air-France-Flug_447	102.0
Air-India-Express-Flug_812	369.0
Amoklauf_von_Winnenden	74.0
Bahnunfall_von_Halle_(Belgien)	52.0
British-Airways-Flug_38	144.0
Buschfeuer_in_Victoria_2009	33.0
Deepwater_Horizon	203.0
Erdbeben_in_Haiti_2010	379.0
Erdbeben_in_Sichuan_2008	227.0
Erdbeben_von_LâĂŹAquila_2009	96.0
Flugzeugabsturz_bei_Smolensk	368.0
GrubenunglÃijck_von_San_JosÃľ	149.0
Josef_Fritzl	129.0
Kaukasuskrieg_2008	346.0
KolontÃąr-Dammbruch	99.0
Luftangriff_bei_Kunduz	2,107.0
Northwest-Airlines-Flug_253	1,151.0
Sumatra-Erdbeben_vom_September_2009	116.0
US-Airways-Flug_1549	226.0
UnglÃijck_bei_der_Loveparade_2010	499.0
Versuchter_Anschlag_am_Times_Square	202.0
Wald-_und_TorfbrÃďnde_in_Russland_2010	273.0
ZugunglÃijck_von_Castelldefels	35.0
Total	7,379.0

NOTES: For each event in the data, the table shows the number of pages that are two clicks away from one of the two associated start pages (be it treated or control).

Table 4: Included disasters and the observations that are associated with them (2 clicks away).

name of event	flag_real_treatment 0 No.	1 No.	Total No.
Air-France-Flug_447	4,495.0	1,392.0	5,887.0
Air-India-Express-Flug_812	19,662.0	1,711.0	21,373.0
Amoklauf_von_Winnenden	2,088.0	2,146.0	4,234.0
Bahnunfall_von_Halle_(Belgien)	2,436.0	580.0	3,016.0
British-Airways-Flug_38	6,699.0	1,624.0	8,323.0
Buschfeuer_in_Victoria_2009	928.0	957.0	1,885.0
Deepwater_Horizon	8,178.0	3,596.0	11,774.0
Erdbeben_in_Haiti_2010	15,602.0	6,322.0	21,924.0
Erdbeben_in_Sichuan_2008	11,571.0	1,508.0	13,079.0
Erdbeben_von_LâĂŹAquila_2009	3,654.0	1,885.0	5,539.0
Flugzeugabsturz_bei_Smolensk	12,412.0	8,758.0	21,170.0
GrubenunglÃijck_von_San_JosÃľ	8,033.0	551.0	8,584.0
Josef_Fritzl	6,264.0	1,044.0	7,308.0
Kaukasuskrieg_2008	18,705.0	1,276.0	19,981.0
KolontÃąr-Dammbruch	4,669.0	1,073.0	5,742.0
Luftangriff_bei_Kunduz	113,767.0	7,772.0	121,539.0
Northwest-Airlines-Flug_253	65,279.0	1,276.0	66,555.0
Sumatra-Erdbeben_vom_September_2009	4,002.0	2,726.0	6,728.0
US-Airways-Flug_1549	7,888.0	5,220.0	13,108.0
UnglÃijck_bei_der_Loveparade_2010	15,283.0	13,572.0	28,855.0
Versuchter_Anschlag_am_Times_Square	10,353.0	1,334.0	11,687.0
Wald-_und_TorfbrÃďnde_in_Russland_2010	13,485.0	2,204.0	15,689.0
ZugunglÃijck_von_Castelldefels	1,508.0	493.0	2,001.0
Total	356,961.0	69,020.0	425,981.0

NOTES: For each event, the table shows the number of observations associated with all articles that are two clicks away from a start . Observations associated with actually "featured articles" are shown separately from control observations. Pages included 7,379

Table 5: Summary statistics: indirect neighbors of shocked articles (2 clicks away from the epicenter) in the large events condition

	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
Number of images	1.3	2.4	0	0	0	4	57
Number language links	13	18	0	0	7	37	179
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: Number of images	.00047	.078	-27	0	0	0	20
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 an article 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.

A.2 Page of Day

A.2.1 Descriptive Analysis for Page of Day

Table 6: Included "featured articles" that were advertised on German Wikipedia's start page and the number of articles that are associated with them (1 clicks away).

name of event	No.
Afrikaans	128.0
Alte_Synagoge_(Heilbronn)	52.0
Banjo-Kazooie	125.0
Benno_Elkan	139.0
Bombardier_Canadair_Regional_Jet	92.0
CCD-Sensor	586.0
Charles_Sanders_Peirce	258.0
Das_Kloster_der_Minne	51.0
Deutsche_Bank	343.0
Eishockey	162.0
Ekel	270.0
Fahrbahnmarkierung	44.0
Geschichte_Ostfrieslands	235.0
Geschichte_der_deutschen_Sozialdemokratie	306.0
Glanzstoff_Austria	270.0
Glorious_Revolution	153.0
Granitschale_im_Lustgarten	83.0
Gustav_Hirschfeld	142.0
Hallenhaus	71.0
Helgoland	228.0
Jaroslawl	321.0
Jupiter_und_Antiope_(Watteau)	36.0
Karolingische_Buchmalerei	162.0
Katholische_Liga_(1538)	37.0
Martha_Goldberg	55.0
Naturstoffe	320.0
Paul_Moder	61.0
St._Martin_(Memmingen)	59.0
Stabkirche_Borgund	40.0
Taiwan	167.0
USS_Thresher_(SSN-593)	90.0
Visum	56.0
Wenegnebti	55.0
Werder_Bremen	292.0
Total	5,489.0

NOTES: For all "featured articles", the table shows the number of associated articles that are two clicks away from one of the corresponding start pages (be it treated or control).

Table 7: Included "featured articles" and the number of observations that are associated with them.

name of event	flag_real_treatment		
	0	1	Total
	No.	No.	No.
Afrikaans	5,481.0	1,943.0	7,424.0
Alte_Synagoge_(Heilbronn)	1,885.0	1,131.0	3,016.0
Banjo-Kazooie	5,191.0	2,030.0	7,221.0
Benno_Elkan	5,133.0	2,900.0	8,033.0
Bombardier_Canadair_Regional_Jet	4,205.0	1,073.0	5,278.0
CCD-Sensor	31,001.0	2,871.0	33,872.0
Charles_Sanders_Peirce	11,716.0	3,219.0	14,935.0
Das_Kloster_der_Minne	1,827.0	1,102.0	2,929.0
Deutsche_Bank	10,005.0	9,860.0	19,865.0
Eishockey	4,698.0	4,698.0	9,396.0
Ekel	10,295.0	5,336.0	15,631.0
Fahrbahnmarkierung	1,276.0	1,276.0	2,552.0
Geschichte_Ostfrieslands	7,453.0	6,177.0	13,630.0
Geschichte_der_deutschen_Sozialdemokratie	9,599.0	8,033.0	17,632.0
Glanzstoff_Austria	14,094.0	1,537.0	15,631.0
Glorious_Revolution	6,206.0	2,668.0	8,874.0
Granitschale_im_Lustgarten	3,857.0	928.0	4,785.0
Gustav_Hirschfeld	6,438.0	1,740.0	8,178.0
Hallenhaus	2,117.0	2,001.0	4,118.0
Helgoland	8,120.0	5,104.0	13,224.0
Jaroslawl	12,789.0	5,829.0	18,618.0
Jupiter_und_Antiope_(Watteau)	1,160.0	928.0	2,088.0
Karolingische_Buchmalerei	4,843.0	4,553.0	9,396.0
Katholische_Liga_(1538)	1,682.0	464.0	2,146.0
Martha_Goldberg	1,595.0	1,595.0	3,190.0
Naturstoffe	9,338.0	9,222.0	18,560.0
Paul_Moder	1,798.0	1,682.0	3,480.0
St._Martin_(Memmingen)	1,653.0	1,711.0	3,364.0
Stabkirche_Borgund	1,421.0	899.0	2,320.0
Taiwan	5,017.0	4,669.0	9,686.0
USS_Thresher_(SSN-593)	3,712.0	1,479.0	5,191.0
Visum	1,624.0	1,624.0	3,248.0
Wenegnebti	1,798.0	1,363.0	3,161.0
Werder_Bremen	8,555.0	8,323.0	16,878.0
Total	207,582.0	109,968.0	317,550.0

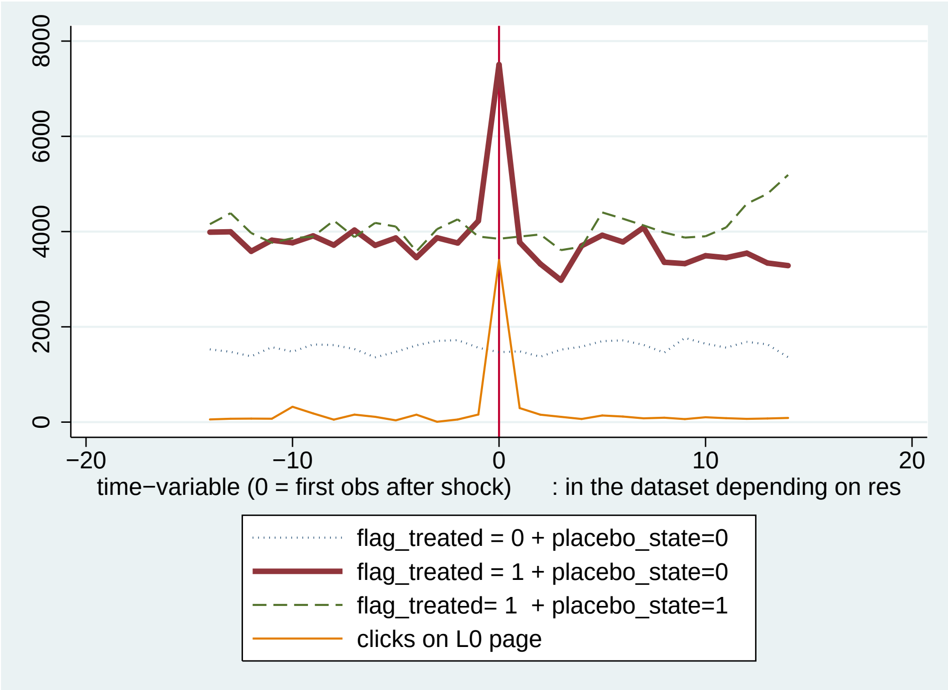
NOTES: For each "featured article", the table shows the number of observations associated with all articles that are one clicks away from a start page. Observations associated with actually "featured articles" are shown separately from control observations. Pages included 5,489.

Table 8: Summary statistics: direct neighbors of shocked articles in the 'featured articles' condition

	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
Number of images	2.3	8.1	0	0	1	5	319
Number language links	13	18	0	0	6	37	180
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: Number of images	.00099	.27	-50	0	0	0	132
Delta: References	.0014	.097	-18	0	0	0	18
Delta: Links further info	.00078	.1	-19	0	0	0	16

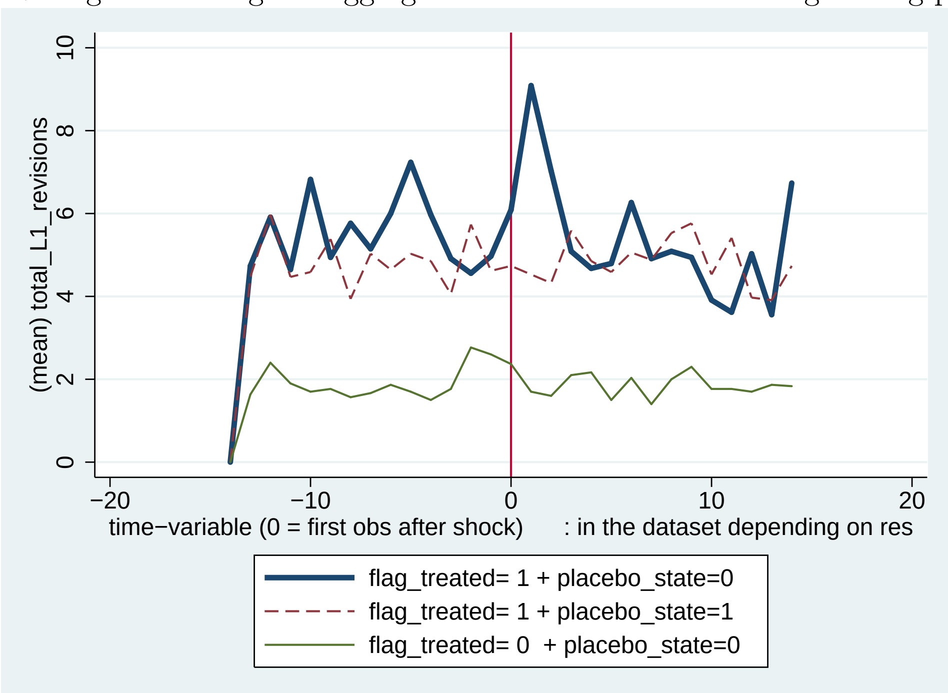
NOTES: The table shows the distribution of the main variables. The unit of observations is the outcome of a page i on day t. The time variable is normalized and runs from -14 to 14.; no. of obs. = 317550; no. of start pages = 63; no. of articles = 5489.

Figure 6: 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 7: 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 9: 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
realtreat_x_period_13	-2.117	4.304	-0.026**	-0.020	-0.014**	-0.009*
	(5.554)	(4.147)	(0.012)	(0.015)	(0.006)	(0.005)
realtreat_x_period_14	2.953	11.074*	-0.012	-0.004	-0.002	-0.005
	(4.448)	(5.974)	(0.013)	(0.011)	(0.005)	(0.004)
realtreat_x_period_15	34.625**	40.149***	-0.013	0.004	-0.006	-0.008
	(13.296)	(13.572)	(0.011)	(0.011)	(0.005)	(0.005)
realtreat_x_period_16	-1.463	2.145	0.037*	0.033	0.015**	0.012
	(2.685)	(4.649)	(0.018)	(0.021)	(0.007)	(0.008)
realtreat_x_period_17	-3.262	-0.427	0.012	0.005	0.002	-0.006
	(4.308)	(4.076)	(0.010)	(0.015)	(0.004)	(0.006)
realtreat_x_period_18	-10.195**	-3.046	-0.009	-0.033*	-0.005	-0.010*
	(4.874)	(4.977)	(0.012)	(0.019)	(0.006)	(0.005)
realtreat_x_period_19	-3.023	5.034	-0.031*	-0.019	-0.009	-0.003
	(4.074)	(3.968)	(0.016)	(0.012)	(0.005)	(0.005)
_cons	30.930***	34.526***	0.047***	0.050***	0.016***	0.016***
	(1.291)	(1.135)	(0.003)	(0.003)	(0.001)	(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^2	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 The empirical model and structural identification of the parameter of interest.

B.1 Introductory remarks

This section presents the structural model and discusses the coefficients we are interested, the usual problems in identifying them and possible avenues that have been suggested by the previous literature.

Recall that the underlying relationship of interest is the role of links in content generation and whether an article is more likely to be improved because of spillovers through links. The mechanism we have in mind, is that attention from article A can be diverted to article B if a link exists and that some of the users who get to see B start to edit it. Thus, the first thing to show is, how much attention spills via links, which 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.

$$y_{it} = \alpha \frac{\sum_{j \in P_{it}} y_{jt}}{N_{P_{it}}} + X_{it-1}\beta + \gamma \frac{\sum_{j \in P_{it}} X_{jt-1}}{N_{P_{it}}} + \epsilon_{it} \tag{18}$$

where 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)[33] P_{it} is the set of i's peers and $N_{P_{it}}$ represents the number of i's peers. α is the coefficient of interest. In the present context it measures how the clicks on page A are influenced the clicks on the adjacent pages.. Bramoullé et al. (2009) suggest a more succinct notation based on vector and matrix notation:

$$\mathbf{y_t} = \alpha \mathbf{G} \mathbf{y_t} + \beta \mathbf{X_{t-1}} + \gamma \mathbf{G} \mathbf{X_{t-1}} + \epsilon_\mathbf{t} \quad E[\epsilon_t | \mathbf{X_{t-1}}] = 0$$

Clearly this model and specifically measuring α is of general interest to a very large literature.

B.2 Setup and Basic Idea

I augment the model in equation 18 by observable treatments (shocks) that are locally applied.

[33] 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).

$$y_{it} = \alpha \frac{\sum_{j \in P_{it}} y_{jt}}{N_{P_{it}}} + X_{i,t-1}\beta + \gamma \frac{\sum_{j \in P_{it}} X_{j,t-1}}{N_{P_{it}}} + \delta_1 D_{it} + \epsilon_{it} \tag{19}$$

...where the interpretation of the new coefficients is as follows:

- δ_1 ... measures the direct treatment 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: $X_{it-1}\beta = \beta_i + \widetilde{X_{i,t-1}}\beta_1 + \beta_2 f(age)$. To see how local treatments can be used as a source of identification, consider two pairs of nodes.

B.2.1 Local application of treatment

First, consider 2 connected nodes, where one is treated ($\ell 0$) in period t and the neighbors are not treated ($l1 \in L1$). Assume for simplicity that $\ell 0$ is the only treated node in l1's neighborhood.

$$\ell 0 :: \boldsymbol{y_{\ell 0t}} = \alpha \frac{\sum_{j \in P_{\ell 0t}} y_{jt}}{N_{P_{\ell 0t}}} + X_{\ell 0t-1}\beta + \gamma \frac{\sum_{j \in P_{\ell 0t}} X_{jt-1}}{N_{P_{\ell 0t}}} + \delta_1 \boldsymbol{1} + \epsilon_{\ell 0t} \tag{20}$$

$$\ell 1 \in L1 :: y_{\ell 1t} = \alpha \frac{\boldsymbol{y_{\ell 0t}} + \sum_{j \in P_{\ell 1t}/\ell 0} y_{jt}}{N_{P_{\ell 1t}}} + X_{\ell 1t-1}\beta + \gamma \frac{\sum_{j \in P_{\ell 1t}} X_{jt-1}}{N_{P_{\ell 1t}}} + \delta_1 0 + \epsilon_{\ell 1t} \tag{21}$$

B.2.2 Controls in remote part of the network around $c0$

Second, take two remote nodes c0 and $c1 \in C1$, where nothing happens (nobody gets treated).

$$c0 :: y_{c0t} = \alpha \frac{\sum_{j \in P_{c0t}} y_{jt}}{N_{P_{c0t}}} + X_{c0t-1}\beta + \gamma \frac{\sum_{j \in P_{c0t}} X_{jt-1}}{N_{P_{c0t}}} + \delta_1 0 + \epsilon_{c0t} \tag{22}$$

$$c1 \in C1 :: y_{c1t} = \alpha \frac{\sum_{j \in P_{c1t}} y_{jt}}{N_{P_{c1t}}} + X_{c1t-1}\beta + \gamma \frac{\sum_{j \in P_{c1t}} X_{jt-1}}{N_{P_{c1t}}} + \delta_1 0 + \epsilon_{c1t} \tag{23}$$

From this equation 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. To formalize this more concretely, I will take a small detour and rewrite the model in the more succinct notation, that was already mentioned above.

B.2.3 Condensed Notation

I use the notation suggested by Bramoullé et al. (2009) and incorporate the newly proposed vector of treatments. The equations above can be written in Matrix notation and X might include a time-dependent component (e.g. a linear function of age) as well:

$$\mathbf{y_t} = \alpha \mathbf{G} \mathbf{y_t} + \mathbf{X_{t-1}} \beta + \gamma \mathbf{G} \mathbf{X_{t-1}} + \delta_1 \mathbf{D_t} + \epsilon_t \qquad E[\epsilon_t | D_t] = 0 \tag{24}$$

A few remarks concerning this formulation are in order.

- $\mathbf{G}$ is NxN
- $G_{ij} = \frac{1}{N_{P_i} - 1}$ if i receives a link from j and $G_{ij} = 0$ otherwise
- treated side: a vector consisting of zeros and ones, that indicates who are the treated nodes. In some of the proofs and in my application I will assume a local treatment that affects only one single node. Formally this is written as: $D_t = e_{\ell 0}$; i.e.: a vector with zeros and a unique 1 in the coordinate that corresponds to the treated node.
- untreated side: $D_t = \mathbf{0}$, a vector of zeros.
- I DO NOT require that the structure of the network (G) is exogenous, but rather which node gets treated has to be exogenous.
- 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. Also, there will be no requirements needed concerning the linear independence of $\mathbf{G}$ and $\mathbf{G^2}$.

B.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. This setting is reasonably close to comparing the evolution of nodes in a very stable network during a post and a pre-treatment stage. 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 $t - S$.[34] 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.

[34]The setting is reasonably close to the "placebo condition" of my application below.

Result 1: The DiD contains the following quantity:

$$\mathbf{DiD} = \delta_1 \mathbf{D_t}(\mathbf{I} + \alpha \mathbf{G} + \alpha^{\mathbf{2}} \mathbf{G}^{\mathbf{2}} + \alpha^{\mathbf{3}} \mathbf{G}^{\mathbf{3}} + ...)$$

Proof.

The reduced form corresponding to equation 24 is given by:

$$\mathbf{y_t} = (\mathbf{I} - \alpha \mathbf{G})^{-1}[\mathbf{X_{t-1}}\beta + \gamma \mathbf{G}\mathbf{X_{t-1}} + \delta_1 \mathbf{D_t} + \epsilon_t] \tag{25}$$

and the expectation conditional on the "treatment" is:

$$\begin{aligned} \mathbf{E}[\mathbf{y_t}|\mathbf{D_t}] &= (\mathbf{I} - \alpha \mathbf{G})^{-1}[(\beta + \gamma G)\mathbf{E}[\mathbf{X_{t-1}}|\mathbf{D_t}] + \delta_1 \mathbf{D_t} + \mathbf{E}[\epsilon_t|D_t]] = \\ &= (\mathbf{I} - \alpha \mathbf{G})^{-1}[(\beta + \gamma G)\mathbf{E}[\mathbf{X_{t-1}}|\mathbf{D_t}] + \delta_1 \mathbf{D_t}] \end{aligned} \tag{26}$$

Clearly, taking the first difference, we obtain a term that depends on the time-dependent component and the effect of any changes in the independent variables.[35]

$$\begin{aligned} \mathbf{\Delta_t E}[\mathbf{y}|\mathbf{D}] = {} & \mathbf{E}[\mathbf{y_t}|\mathbf{D_t}] - \mathbf{E}[\mathbf{y_{t-1}}|\mathbf{D_{t-1}}] = \\ = {} & (\mathbf{I} - \alpha \mathbf{G})^{-1}[(\beta + \gamma G)\{\mathbf{E}[\mathbf{X_{t-1}}|\mathbf{D_t}] - \mathbf{E}[\mathbf{X_{t-2}}|\mathbf{D_{t-1}}]\} + \delta_1 \mathbf{\Delta D_t}] = \\ = {} & (\mathbf{I} - \alpha \mathbf{G})^{-1}[(\beta + \gamma G)\{\mathbf{E}[\mathbf{X_{t-1}}|\mathbf{D_t}] - \mathbf{E}[\mathbf{X_{t-2}}|\mathbf{D_{t-1}}]\} + \delta_1 \mathbf{D_t}] \end{aligned} \tag{27}$$

...where $\mathbf{\Delta D_t} = \mathbf{D_t} - \mathbf{D_{t-1}}$ and the second equality holds, because treatments are assumed to start in period t, but not before.

I use two control groups in this paper: For one, I use a set of nodes that are remote to the treated node and second, I use the same nodes but only several weeks before the shock. Let's start by looking at the control group formed by the same network, but S periods earlier, i.e. in period $t - S$ then we have.

$$\mathbf{y_{t-S}} = \alpha \mathbf{G}\mathbf{y_{t-S}} + \mathbf{X_{t-S-1}}\beta + \gamma \mathbf{G}\mathbf{X_{t-S-1}} + \delta_1 \mathbf{D_{t-S}} + \epsilon_{t-S}$$

Analogously, the first difference of the reduced form's conditional expectations will contain a time-dependent component and the effect of any other changes in the independent variables.[36]

[35] If βX_{it} is modelled to contain an additively separable age-dependent part as in our example above, $\Delta X_{it-S}\beta$ would contain $\frac{df(age)}{dt}$. [which is to be eliminated by taking DiffDiff]

[36] Note that also here $\Delta X_{it-S-1}\beta$ would contain $\frac{df(age_{t-S})}{dt}$, if βX_{it-1} is modelled to contain an

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

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

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

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

$$
\mathbf{DiD} = (\mathbf{I} - \alpha\mathbf{G})^{-1} \quad [(\beta + \gamma G)\{\mathbf{\Delta_t(E[X|D])} - \mathbf{\Delta_{t-S}(E[X|D])}\} + \delta_1\mathbf{D_t}] \tag{28}
$$

which reduces to:

$$
\mathbf{DiD} = (\mathbf{I} - \alpha\mathbf{G})^{-1}\{\delta_1\mathbf{D_t}\} \tag{29}
$$

if the following relatively weak identifying assumptions are satisfied:

- $\mathbf{\Delta_t(E[X|D])} - \mathbf{\Delta_{t-S}(E[X|D])} = 0$, which means that the expected changes of the pages between $t-1$ and t are the same as from $t-S-1$ and $t-S$. 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 $(\mathbf{I} - \alpha\mathbf{G})^{-1} = \sum_{s=0}^{\infty} \alpha^s G^s$ [37] , the general impact of a local treatment is:

$$
\mathbf{DiD} \quad = \quad \delta_1\mathbf{D_t}(\mathbf{I} + \alpha\mathbf{G} + \alpha^{\mathbf{2}}\mathbf{G}^{\mathbf{2}} + \alpha^{\mathbf{3}}\mathbf{G}^{\mathbf{3}} + ...) \tag{30}
$$

where $\mathbf{D_t}$ is a vector which is 1 at the treated nodes (if they are *currently* treated) and 0 otherwise.

---

additively separable age-dependent term.

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

$\blacksquare$

Discussion of the assumptions used: The assumptions I used were

1. $\mathbf{E}[\epsilon_t|D_t]$=0
2. α is smaller than the norm of the inverse of the largest eigenvalue of $\mathbf{G}$. A regularity condition to ensures that the expression $(\mathbf{I}-\alpha\mathbf{G})^{-1}=\sum_{s=0}^{\infty}\ \alpha^s G^s$ is well defined.
3. I assumed the network to be stable over time and used it's 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 can be relaxed to some extent if the following assumption is also adapted.
4. $\mathbf{\Delta_t}(\mathbf{E}[\mathbf{X}|\mathbf{D}])-\mathbf{\Delta_{t-S}}(\mathbf{E}[\mathbf{X}|\mathbf{D}])$, which means that the expected changes of the pages between $t-1$ and t are the same as from $t-S-1$ and $t-S$[38]. This is the analogue of the well known common trend assumption.
5. SUTVA: the non-treated part of the network is not affected by treatment of the treated part, which is undoubtedly satisfied 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 around a similar node.

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 control *network* must "*evolve* in the same way." 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 in order to guarantee that the counterfactual outcome of the treated network can be inferred from its own past and the evolution in the control network.[39]

B.3.1 General Pattern of first and higher order spillovers

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 ℓ. Hence let us recollect that 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:

[38] Particularly, any time trends or other dynamics, is to be eliminated by the Differences in Differences, if $\frac{df(age)}{dt}$ is the same evaluated at t-S and at t.

[39] The derivations require a lot of notational overhead and the resulting conditions are quite unwieldy. They are available from the author upon request.

$$\mathbf{DiD} \;=\; \delta_1 \mathbf{D_t}(\mathbf{I} + \alpha\mathbf{G} + \alpha^{\mathbf{2}}\mathbf{G^2} + \alpha^{\mathbf{3}}\mathbf{G^3} + ...) \tag{31}$$

In words, this means that the node is not only affected by treatment, but also by second and higher order spillovers, the positive feedback loop that ensues as the neighbors increase their performance. One single instance of a higher order effect[40] are $\alpha^2\delta_1$ in the second round, $\alpha^3\delta_1$ in the third round and so on. The other factor that matters is, the whether and how often spillovers of a given order q arrive, that is it depends on the number of indirect paths of length q that go from the shocked node $\ell 0$ to any focal node j.

Clearly, the DID alone will not directly reveal α, the parameter of interest, but merely a quantity that is tightly linked to α and δ_1. Moreover, this result highlights that computing the parameters is not necessarily feasible, e.g. because it involves the knowledge of the complete link structure of the nodes. Luckily, a closer look at each of the nodes independently reveals that already limited information about the link structure can suffice to acquire additional information about the parameters.

B.3.2 Analysis on the Node Level

When taking the analysis back from the level of treated networks and look at the nodes individually it is worth noting that for each focal node j its own row in this set of equations is all that matters. To simplify this analysis I will now begin to use the local treatment assumption, which exploits the fact that only a single node in the network is treated. 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 $D = e_i$, where e_i is an elementary vector with node i being the only treated node.

Node that if only one node is treated, the spillover dynamic is greatly simplified. With $D = e_i$ the only factor to be evaluated for each node is its corresponding ji element in the matrix $\mathbf{G}$, $\mathbf{G^2}$ and it's higher orders.

The information that's contained in the higher orders of the adjacency matrix $\mathbf{G}$ will be 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, and some (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.

[40]note that I am considering the homogeneous network, so all spillovers have the same magnitude.

If only one node in the network is treated, 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:

$$
\begin{aligned}
\ell 0: \ \mathbf{DiD}_{\ell\mathbf{0-c0}} &= \delta_1(1 + 0 + \alpha^2 G_{ii}^2 + \alpha^3 G_{ii}^3 + ...) \\
\ell 1: \ \mathbf{DiD}_{\ell\mathbf{1-c1}} &= \delta_1(0 + \alpha G_{ij} + \alpha^2 G_{ij}^2 + \alpha^3 G_{ij}^3 + ...) \\
\ell 2: \ \mathbf{DiD}_{\ell\mathbf{2-c2}} &= \delta_1(0 + 0 + \alpha^2 G_{ik}^2 + \alpha^3 G_{ik}^3 + ...) \\
&\qquad\qquad\qquad\qquad\qquad\qquad \mathit{etc.}
\end{aligned} \tag{32}
$$

Differentiating 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 α and δ_1. All that is needed is a sequence of reduced form Differences 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.[41]

Also if the researcher lacks information on $\mathbf{G}$ it is possible to compute an upper and a lower bound for the parameters α and δ_1. This is a useful feature, since the precise information on $\mathbf{G}$ is often not easy to obtain or computing its higher orders might confront the researcher with substantial computational challenges. In what follows I proceed to show how the boundary estimates can be computed.

B.4 Estimating Bounds for the Parameters of Interest

As was just pointed out, it will often be the case, that nodes will have a feedback effect on each other, so that the neighbors change in performance (due to the original impulse) will affect the neighbors' neighbours, but also feed back on the treated neighbor. The differences between period 0 and 1 will then also include the second order spillovers. Obviously, the Differences in Differences estimators will then also observe 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.

Clearly to estimate the real spillover coefficient α (and also the treatment effect δ_1) it is actually necessary to observe the exact network structure. However, even if the network

[41] The researcher merely needs to use all the ij values that correspond to each individual focal node j as weights for α, α^2, α^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.

structure is not known to the researcher. In what follows I show that it is possible to back out a lower and an upper bound estimate for α and δ_1, that is only based on the estimated Differences in Differences and the number of nodes. In my proofs I use the local treatment assumption (only one individual in the network is treated), for both ease of notation and understanding. Note that this assumption applies to one of my applications.[42]

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. First, note that the formulas in equation 32 can be rewritten without explicit characterization of the higher order spills:

$$DiD_{(\ell 0 - c0)} = \delta_1 + HO_{\ell 0} \tag{33}$$

$$DiD_{(\ell 1 - c1)} = \frac{\alpha}{NP_{\ell 1}}\delta_1 + HO_{\ell 1} \tag{34}$$

where $HO_{\ell 0} = \delta_1(\alpha^2 G_{ii}^2 + \alpha^3 G_{ii}^3 + ...)$ and $HO_{\ell 1} = \delta_1(\alpha^2 G_{ij}^2 + \alpha^3 G_{ij}^3 + ...)$. As was pointed out extensively, these effects typically depend on the underlying network of peers and need to be characterized from scratch, taking into account the network structure.

I can now 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* $HO^A < HO^B$, $\alpha^{HO^A} > \alpha^{HO^B}$ *and* $\delta_1^{HO^A} > \delta_1^{HO^B}$.[43]

For a proof, please be referred to section B.5.

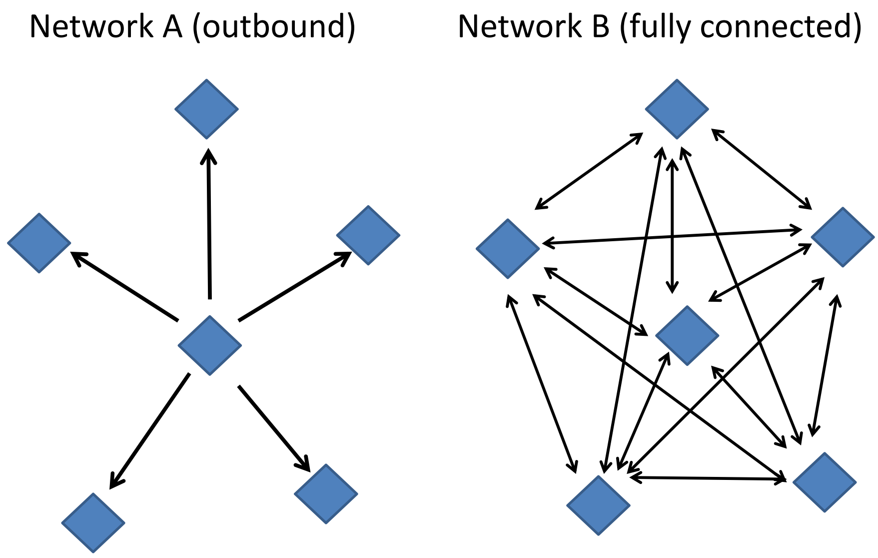
With this lemma in hand we can now proceed to derive benchmarks (upper and lower bound estimates) for the parameters of interest, which can provide useful information on their own. To see how network structure comes in, we can select two 'specific 'extreme" types of networks which either minimize or maximize HO. The network that minimzes higher order spillovers is a directed network with only "outward bound" links emanating from $\ell 0$ to $\ell 1 \in L1$ [44]. This also implies that there are no links between the nodes in $L1$ and will hence serve as benchmark 1.

[42] 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.

[43] 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 ($DiD_0 >> DiD_1$). This is the case in most applications and certainly so in the present one.

[44] and possibly further on to $\ell 2 \in L2$, $\ell 3 \in L3$ and so on.

Figure 8: Schematic representation of the two extreme networks, used to compute the upper and lower bound estimates of the parameters of interest.



The opposite type of network is a network, where every node is the direct neighbor of every one of its peers[45]. Graphically, a fully connected network with 6 nodes is illustrated in figure 8. It is intuitively clear that second and higher order spillover will be greatest in the fully linked structure, when holding α and N fixed. Every node affects every other node via a direct link and hence, it will be possible to estimate the lower bounds of the interesting parameters.

B.4.1 Benchmark 1: A Network without higher order spillovers.

In the "outbound" network higher order spills back to the originating nodes do not exist[46]: $HO_{\ell 0}$ and $HO_{\ell 1}$ would be 0 and a node $\ell 1 \in L1$ would get $\frac{\alpha}{NP_{\ell}1}\delta_1$[47]. In a world where we assume all effects to be of the same sign and by Lemma 1 this is an upper bound of both the coefficients in a setting where $DiD_0 > DiD_1 > HO > 0$.[48]

[45] I will sometimes refer to this network as "classroom" network

[46] Fair enough to point out that, in such a network, endogeneity would not be a problem in the first place.

[47] a node $\ell 2 \in L2$ would get $\frac{\alpha}{NP_{\ell}2} * \frac{\alpha}{NP_{\ell}1}\delta_1$ and so on

[48] A proof is straight forward and provided in the appendix. 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 verified by the researcher. Slightly more involved assumptions will be needed.

By using the "outbound" network, we simply neglect all spillovers of order 2 and higher [49] Consequently all changes in the $\ell 0$ node are attributed to the shock only and all changes in the L1-set are attributed directly to the first order spillovers. In such a network simply set the difference in the shocked node as $\overline{\delta_1}$ and set any differences in the nodes that are two or more clicks away to 0, which is equivalent to assuming:

$$\mathbf{DiD} \stackrel{\mathbf{b.A.}}{=} \overline{\delta_1}\mathbf{D_t}(\mathbf{I} + \overline{\alpha}\mathbf{G} + \mathbf{0} + \mathbf{0} + ...) \tag{35}$$

which is equivalent to having[50]:

$$\begin{aligned} DiD_{(\ell 0-c0)} &= \overline{\delta_1} \qquad for\ treated\ L0-nodes \\ DiD_{(\ell 2-c2)} &= 0 \qquad for\ L2 \\ &\qquad ...analogously\ for\ L3\ and\ higher \end{aligned} \tag{36}$$

This implies, that there are no "multiplication-effects" or "feedback-loops" between the nodes. In the light of the formalization presented here, this is obviously a heroic assumption, yet note that in the impact evaluation literature with fixed and stable classroom sizes or villages, this assumption is implicitely, but very commonly taken. (cf. Angelucci and De Giorgi (2009), Carmi et al. (2012), Dahl et al. (2012), etc. etc.). The Diff in Diff for the neighbors of the treated nodes[51] would simply reduce to:

$$DID_{(\ell 1-c1)} = \frac{\overline{\alpha}}{NP_{l1}}\overline{\delta_1} \tag{37}$$

Given the necessary assumptions, it is obvious that a consistent estimator of $\overline{\delta_1}$ and the observed difference in difference will be enough to estimate $\overline{\alpha}$. Specifically, if we (for now) maintain the assumption that we can observe the nodes' performance before any higher order spillovers arrive at the treated node, we can obtain such an estimate from applying the the Diff in Diff estimator on the level of directly treated nodes and a suitable comparison group and then move on to estimate $\overline{\alpha}$:

[49] Neglecting higher-order spillovers is like implicitely introducing a temporal structure where a spillover takes time to occur and taking a snapshot after the first order effect had just enough time to spill onto it's neighbors, but not yet enough time for any second and higher order spillovers. This is possible if, for example, spillovers are slow and the temporal structure of the available data is fine grained enough. Formalizing these higher order spillovers is quite involved and depends on the specific structure of the network and the nature of the links. Hence, treating them explicitely is tackled in the next section.

[50] $D_{\ell 0}$ denotes the value of D at the central node, that is related to the focal node.

[51] Which corresponds to an Indirect Treatment Effect or an "Externality"

$$(38) \qquad \begin{aligned} \hat{\hat{\delta_1}} &= \widehat{DiD_{(\ell 0 - c0)}} = \Delta\hat{\ell}0 - \Delta\hat{c}0 \\ \hat{\hat{\alpha}} &= \frac{\widehat{DiD_{(\ell 1 - c1)}}}{\widehat{DiD_{(\ell 0 - c0)}}} NP_{l1} \end{aligned}$$

- $\Delta\hat{\ell}0 := \frac{1}{NP_l 0} * \sum_i (y_{i,l0,t=0} - y_{i,l0,t=1})$
- $\Delta\hat{c}0 := \frac{1}{NP_c 0} * \sum_i (y_{i,c0,t=0} - y_{i,c0,t=1})$

with the definition of $\widehat{DiD_{(\ell 1 - c1)}}$ and the underlying $\Delta\hat{\ell}1$ and $\Delta\hat{c}1$ paralleling the definition of $\Delta\hat{\ell}0$ and $\Delta\hat{c}0$. This upper bound estimator would be quite suitable under the (potentially quite strong) assumption that higher order spillovers are negligible. In what follows I shall proceed to illustrate how to compute the lower bound estimates under the assumption of maximal second order spillovers. This will show how to derive an upper bound to the size of the problem that might result from trusting the, easily computed upper bound estimates.

B.4.2 Benchmark 2: A Network with the largest thinkable higher order spillovers.

Considering the fully connected network is useful for two reasons: First, it is intuitively clear, that the fully linked structure implies that second and higher order spillovers are essentially the same for every node of the same type (treated or not). Maybe more importantly, the fully connected network with fixed α and N it is the network with the greatest second and higher order spillovers. Every node affects every other node via a direct link and everybody will get second and higher round spillovers from *every* other node. Hence, it will be possible to derive the lower bounds of the desired coefficient in a closed form solution.

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 basically only two types of nodes. Directly treated nodes and neighbors of directly treated nodes. Finally note that nodes are no longer influenced by only one node ($\ell 0$), but that also the performance of all other neighbors matters for their own. Likewise they exert an influence on their neighbors (the entire network). Finally note that once the primary spillover has occured, *all* direct neighbors have now a higher performance, that is, second order spillovers arrive $(NP_l - 1)$ times at $\ell 1$ and NP_l times at $\ell 0$. Spillovers via three nodes (third order) occur via $(N-1)^2 - (N-1)$ times etc. The number of channels for higher order increases at an almost exponential rate in such a network, which leads to potentially very large effects, that are moderated only by the decrease of the primary effects during transmission.

Formally, consider the matrix $\underline{G}$, that corresponds to a fully connected network:

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

Let us first characterize the higher order spillovers that arrive at the treated node. From equation 32 we know that the spillovers that arrive at a node in L1 are given by:

$$
\ell 0: \; DiD_{(\ell 0 - c0)} = \delta_1 (1 + 0 + \alpha^2 G_{ii}^2 + \alpha^3 G_{ii}^3 + ...)
$$

In words, this simply means that the node is not only affected by treatment, but also by second and higher order spillovers, the positive feedback loop that ensues as the neighbors increase their performance. One single instance of a higher order effect[52] are $\alpha^2 \delta_1$ in the second round, $\alpha^3 \delta_1$ in the third round and so on. Yet, what now matters in the fully connected setting is, the frequency with which spillovers of a given order q arrive, that is it depends on the number of indirect paths of length q that go from node i back to himself. The formula above points out that no spillovers of order 1 arrive at the treated node, since i does not link on to himself.[53] But in a network characterized by $\underline{\mathrm{G}}$, (and maintaining local treatment) the second order spillovers arrive from every neighbor, i.e. $N - 1$ times. Counting the number of channels for third and higher order spillovers is a matter of combinatorics: in general the number of channels for spillovers of order S is given by:

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

The sum of second and higher order spillovers arriving at the treated node himself is then given by:

[52] note that I am considering the homogeneous network, so all spillovers have the same magnitude.

[53] 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.

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

Analogously, all non-treated nodes at $\ell 1$ in such a network can be treated in the same way. We can characterize the number of channels for spillovers of order S from node i to node j in almost[54] the same way:

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

...and again the sum of second and higher order spillovers arriving at the treated node himself is then given by:

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

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.

$$
\begin{aligned}
HO_{ii} &= \sum_{S=2}^{\inf} \delta_1 \frac{\alpha^S}{(N-1)^S} \sum_{s=0}^{S-1} (N-1)^s (-1)^{(S-1)-s} < \\
&< \sum_{S=2}^{\inf} \frac{\alpha^S}{(N-1)^S} (N-1)^{S-1} = \\
&= \frac{1}{(N-1)} \sum_{S=2}^{\inf} \alpha^S = \frac{\alpha^2}{(N-1)} \frac{1}{1-\alpha}
\end{aligned} \tag{40}
$$

Let us call this expression $\overline{HO_{ii}}$. Analogously we obtain $\overline{HO_{ij}} < \frac{\alpha^2}{(N-1)} \frac{1}{1-\alpha}$, and these values can now be used in the equations 33 and 34 from above (and rewritten here for convenience):

[54] Note that s now starts at 0.

$$\begin{aligned} DiD_0 &= \delta_1 + HO_{l0} \\ DiD_1 &= \frac{\alpha}{NP_{l1}}\delta_1 + HO_{l1} \end{aligned}$$

With lemma 1 in hand we can plug in the upper bounds that we derived for HO in a fully connected network to back out the lower bounds of the coefficients α and δ_1, which are characterized by the following two equations.

$$DiD_0 = \underline{\delta_1} + \overline{HO_{l0}} \tag{41}$$

$$DiD_1 = \frac{\alpha}{NP_{l1}}\underline{\delta_1} + \overline{HO_{l1}} \tag{42}$$

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

$$\underline{\alpha}^2 - [\frac{DiD_0}{DiD_1} + (N-1)]\underline{\alpha} + (N-1) = 0 \tag{43}$$

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

$$\underline{\alpha_{1/2}} = \frac{1}{2}[\frac{DiD_0}{DiD_1} + (N-1)] +/- \sqrt{\frac{1}{4}[\frac{DiD_0}{DiD_1} + (N-1)]^2 - (N-1)} \tag{44}$$

It is easy to see that under weak regularity conditions[55] one solution is above 1 and another one between 0 and 1. The latter one is the solution for $\underline{\alpha}$ and it can easily be used to retrieve $\underline{\delta_1}$ from equation 33

Note that this closed form solution is based on nothing, but the number of nodes, and the two estimates from the differences in differences for directly treated nodes and their neighbors. This means, that it can be computed without having any additional information about the network, rather than how many agents and who was treated. It has hence the advantage of being as readily available as the upper bound estimators.

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. The upper bound estimator would be quite suitable if the researcher assumes (potentially quite strong) 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

[55] $DiD_0 > DiD_1$ and $N > 1$

expects the spillover coefficient to be relatively large.[56]

Taken together, the bounds can provide a useful first characterization of the spillover parameters in question. Clearly, one would immediately wish for more, and for some applications the bounds might turn out to be to wide to be actually informative. Also, 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.

B.5 Proof of Lemma

Proof of 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 $HO^A < HO^B$, $\alpha^{HO^A} > \alpha^{HO^B}$ and $\delta_1^{HO^A} > \delta_1^{HO^B}$.[57] **Proof.**

$$\begin{aligned} DiD_{(\ell 0-c0)} &= \delta_1^A + HO^A \qquad vs. \qquad DiD_{(\ell 0-c0)} = \delta_1^B + HO^B \\ DiD_{(\ell 1-c1)} &= \frac{\alpha^A}{NP_{\ell 1}}\delta_1^A + HO^A \qquad vs. \qquad DiD_{(\ell 1-c1)} = \frac{\alpha^B}{NP_{\ell 1}}\delta_1^B + HO^B \end{aligned}$$

$$\delta_1^A = DiD_{(\ell 0-c0)} - HO^A \qquad vs. \qquad \delta_1^B = DiD_{(\ell 0-c0)} - HO^B \tag{45}$$

$$\alpha^A = \frac{(DiD_{(\ell 1-c1)} - HO^A)}{\delta_1^A}NP_{\ell 1} \qquad vs. \qquad \alpha^B = \frac{(DiD_{(\ell 1-c1)} - HO^B)}{\delta_1^B}NP_{\ell 1} \tag{46}$$

From equation 45 it is immediately obvious that $HO^A < HO^B$ implies $\delta_1^{HO^A} > \delta_1^{HO^B}$. For comparing α substitute the corresponding δ_1 from 45 into 46, define $HO^A = HO^B - \varepsilon$ (for $\varepsilon > 0$) and rewrite equation 46 as

$$\alpha^A = \frac{a}{b}NP_{\ell 1} \qquad vs. \qquad \alpha^B = \frac{a-\varepsilon}{b-\varepsilon}NP_{\ell 1} \tag{47}$$

defining $a = (DiD_{(\ell 1-c1)} - HO^A)$ and $b = DiD_{(\ell 0-c0)} - HO^A$. Comparing α^{HO^A} $vs.$ α^{HO^B} is equivalent to comparing $\frac{a}{b}$ $vs.$ $\frac{a-\varepsilon}{b-\varepsilon}$. Since we have $a, b, c > 0$, $c < b$ and $c < a$:

[56] Note that if there is reason to believe that α is greater than 0.5 an analogue of Lemma 1 that relaxes my assumption of $\alpha < 0.5$ is required.

[57] I simplify the proof by assuming that second and higher order spillovers affect treated and neighboring nodes in the same way. This simplifies the proof and it is satisfied in both benchmark cases I use. Furthermore, Recall that the requirement $DiD_1 > HO^B$ has bite, since it implies $\alpha < 0.5$.

$$\begin{aligned}
\frac{a}{b} - \frac{a-\varepsilon}{b-\varepsilon} > 0 \quad &\Leftrightarrow \quad a(b-c) - b(a-c) > 0 \\
&\Leftrightarrow \quad a(b-c) > b(a-c) \\
&\Leftrightarrow \quad -ac > -bc \\
&\Leftrightarrow \quad ac < bc \\
&\Leftrightarrow \quad a < b
\end{aligned}$$

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

C Aside: Reaction to treatment of the neighbor

Everything that was derived above was derived under the assumption that the nodes do not observe or at least do not react to the local treatment of their neighbors. In general however, the subjects of treatment and their neighbors might observe each other and react to these observations.

C.1 Setup with "observing neighbors"

An Example of such a setting could be children in a class at school, who get annoyed or jealous when they observe that their peer was treated in a nice way and they were not. Also economic agents in a village, who observe that their neighbor was refused a social service for failure to comply with the requirement of sending their kids to school, might adapt their behavior in reaction to this observation. Another such situation could be commuters in a city, who observe when their friends got caught after the local transport authority increases the frequency of controls and the punishment for failure to present a valid ticket. In such situations the students/villagers might react to *merely observing* the treatment of their neighbors and they might select a different value for the outcome variable.

To model such a situation we need to further augment the model in equation 19 by both the observable treatments (shocks) that are locally applied, and a term that captures the possible reaction to the treatment of the neighbor.

$$y_{it} = \alpha \frac{\sum_{j \in P_{it}} y_{jt}}{N_{P_{it}}} + X_{it}\beta + \gamma \frac{\sum_{j \in P_{it}} X_{jt}}{N_{P_{it}}} + \delta_1 D_{it} + \delta_2 \frac{\sum_{j \in D_{jt}}}{N_{P_{it}}} + \epsilon_{it} \tag{48}$$

Interpretation of the 2 new coefficients:

- δ_1 ... measures the direct treatment effect if a node(page) is, ITSELF, treated.

- δ_2 ... in general: measures reactions of the node, when it "observes" treatment of one (or several) of its peers.

C.1.1 Local application of treatment

Consider 2 connected nodes, where one is treated ($l0$) in period t and the neighbors are not treated ($l1 \in L1$). Assume for simplicity that l0 is the only treated node in l1's neighborhood.

$$l0 :: y_{l0t} = \alpha \frac{\sum_{j \in P_{l0t}} y_{jt}}{N_{P_{l0t}}} + X_{l0t}\beta + \gamma \frac{\sum_{j \in P_{l0t}} X_{jt}}{N_{P_{l0t}}} + \delta_1 1 + \delta_2 \frac{\sum_{j \in P_{l0t}} 0}{N_{P_{l0t}}} + \epsilon_{l0t} \tag{49}$$

$$l1 \in L1 :: y_{l1t} = \alpha \frac{y_{l0t} + \sum_{j \in P_{l1t}/l0} y_{jt}}{N_{P_{l1t}}} + X_{l1t}\beta + \gamma \frac{\sum_{j \in P_{l1t}} X_{jt}}{N_{P_{l1t}}} + \delta_1 0 + \delta_2 \frac{1 + \sum_{j \in P_{l1t}/l0} D_{jt}}{N_{P_{l1t}}} + \epsilon_{l1t} \tag{50}$$

C.1.2 Assumptions for identification (conjecture)

NOTE: Assuming we have such a local treatment available, we get two types of spillover effects:

- δ_2 ... "behavior change" of the node, when it "observes" treatment of its peer.
- the "pure" spillover α, that we observe, because treatment will affect the outcome of $l0$
- $\rightarrow$ α is only identified if δ_2 is believed to be 0
- $\rightarrow$ otherwise only the total "treatment-of-peer"-effect can be measured. (but that can also be interesting)

C.1.3 Controls in remote part of the network around $c0$

Take two remote nodes c0 and $c1 \in C1$, where nothing happens (nobody gets treated).

$$c0 :: y_{c0t} = \alpha \frac{\sum_{j \in P_{c0t}} y_{jt}}{N_{P_{c0t}}} + X_{c0t}\beta + \gamma \frac{\sum_{j \in P_{c0t}} X_{jt}}{N_{P_{c0t}}} + \delta_1 0 + \delta_2 \frac{\sum_{j \in P_{c0t}} 0}{N_{P_{c0t}}} + \epsilon_{c0t} \tag{51}$$

$$c1 \in C1 :: y_{c1t} = \alpha \frac{\sum_{j \in P_{c1t}} y_{jt}}{N_{P_{c1t}}} + X_{c1t}\beta + \gamma \frac{\sum_{j \in P_{c1t}} X_{jt}}{N_{P_{c1t}}} + \delta_1 0 + \delta_2 \frac{\sum_{j \in P_{c1t}} 0}{N_{P_{c1t}}} + \epsilon_{c1t} \tag{52}$$