Ideological Segregation among Online Collaborators: Evidence from Wikipedians*

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Abstract

Do online communities segregate into separate conversations about "contestable knowledge"? We analyze the contributors of biased and slanted content in Wikipedia articles about U.S. politics, and focus on two research questions: (1) Do contributors display tendencies to contribute to topics with similar or opposing bias and slant? (2) Do contributors learn from experience with extreme or neutral content, and does that experience change the slant and bias of their contributions over time? Despite heterogeneity in contributors and their contributions, we find an overall trend towards less segregated conversations. Contributors tend to contribute to articles with slants that are the opposite of their own views, and the slant from experienced contributors becomes less extreme over time. The decline is more pronounced for contributors who have encountered extreme biases. We also find some significant differences between Republicans and Democrats. We discuss the implication of these results for online communities.

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1. Introduction

The growth of virtual communities that blur the boundaries between reader and writer has upended our understanding of processes for generating and consuming online content. These communities generate numerous cooperative and confrontational behaviors. This study examines these behavior around *contested knowledge*—which we define as topics involving subjective, unverifiable, or controversial information. Online communities bring together participants from disparate traditions, with different methods of expression, cultural and historical foundations for their opinions, and, potentially, bases of facts; these diverse perspectives generate conflicts during content creation in online communities (e.g., Arazy et al. 2011). While many studies have examined the processes by which communities resolve conflicts, there is a lack of quantitative research about the how contributors behave in the most challenging situations, as is the case in debates involving contributors with opposing points of view about contested knowledge.

Two extreme poles define two opposite outcomes for conflicts over contested knowledge, a segregated and an unsegregated conversation. In a segregated conversation, like-minded participants self-select into supplying content for others with similar views and read only content from those with whom they already agree. This behavior polarizes information production and consumption (e.g., Mullainathan and Shleifer 2005, Sunstein 2001), creating segregated "small villages" (e.g., Gentzkow and Shapiro 2003, Van Alstyne and Brynjolfsson 2005). An unsegregated conversation looks very different. Here the community engages people with diverse ideas and facilitates a conversation between participants with opposing views (Benkler 2006) until participants reach a consensus about how content combines both views.

Our study measures the micro-behavior that supports or undermines segregated conversations in the presence of contested knowledge. We characterize the tendency of distinct types of contributors to offer slanted contributions to articles that may already contain slanted content. A key novelty of this study is the measurement approach: we characterize both the *slant* and *bias* of contributors and their contributions. In this study we develop a rating of the bias and slant of the *contributors* and how each editor's bias and slant evolves over time.

We examine Wikipedia's articles about US politics. This offers a rich setting for investigating the micro-behavior behind segregated conversations. All revisions are well documented, and plenty of debates in politics involve contested knowledge. In this study we examine 70,305 articles about U.S. political topics, which receive contributions from 2,891,877 unique contributors. As with prior research (e.g., Greenstein and Zhu, 2016, forthcoming), we characterize all articles for bias and slant along a numerical yardstick by adapting the method developed by Gentzkow and Shapiro (2010) for rating newspaper editorials. In these ratings, *slant* denotes degree of opinion along a continuous yardstick, from extreme degrees of red (e.g., Republican) to extreme degrees of blue (e.g., Democrat), and all the shades of purple in between. *Bias* is the absolute value of this yardstick from its zero point, and thus denotes the strength of the opinion.

Wikipedia's importance makes understanding its production interesting in its own right. Most reference information has moved online, and across all developed economies, these online sources have displaced other sources of information. Wikipedia is both a top-twenty site in almost every developed country, and, by far, the most popular and referenced online repository of comprehensive information in the developed world, with the English language version of Wikipedia receiving over 8 billion page views a month at the time we collected the data for this study.[1] Many firms also utilize Wikipedia as an input. Amazon (Alexa), YouTube, and Google (search), among others, use Wikipedia as a free source for neutral "facts" and as an unrestricted source for vocabulary in different languages.[2]

Wikipedia has other advantages as a setting. Wikipedia has been operating since 2001, making it one of the oldest and longest continuously operated communities producing online content. That long life enables research into the evolution of micro-behavior over time, which is novel for studies of bias and slant. Moreover, while the Wikipedia community espouses the ideal that it aspires to achieve a neutral point of view in its content, this is more of a belief about the process than a tested fact. Little is known about whether content arises from segregated or unsegregated communities and, relatedly, whether contributors have a tendency towards EC or not.

The findings demonstrate how contributor behavior moves the site towards less segregated conversation. We find the presence of considerable heterogeneity in contributors and in their behavior. Contributors with every possible bias and slant contribute to articles containing every other possible bias and slant. In spite of that variance, more contributors in Wikipedia exhibit a pattern of behavior consistent with Non-EC than with EC. For example, a slanted contributor is on average 8% more likely to edit an article with the opposite slant than one with the same slant. This tendency is pervasive. For example, we find that the most popular topics display non-EC outcomes while only a few less popular topics display EC. In other words, contributors with different political viewpoints tend to dialogue with each other during their editing of contestable knowledge, and that holds across a wide range of political topics.

Our second finding points in the same direction: Contributors' slant does not persist. Contributors tend to demonstrate less, not more, bias over time. The largest declines are found among contributors who edit or add content to articles that have more biases. Editing articles reduces a contributor's slant, and editing more biased content makes contributors offer less biased contributions later. Together with the first finding, this tendency reduces segregated conversations.

[1] See https://reportcard.wmflabs.org/, accessed January 2017.

[2] See e.g., YouTube may add to the burdens of Humble Wikipedia, https://www.nytimes.com/2018/03/19/business/media/youtube-wikipedia.html.

These findings enhance the understanding of prior work (Greenstein and Zhu 2016, forthcoming), which finds that revisions in Wikipedia tends to lead to more neutrality in its content, but only very slowly. Past work did not measure segregated conversations directly because it did not have a measure of the political slant of contributors. This study characterizes contributor heterogeneity as well as content creation from contributors, and that permits analysis of the speed of adjustment for different types of slants and biases in content. That also enables a general characterization of how adjustment processes differ over time by type of contributor. For example, on average, our estimates suggest it takes extreme Republican content one year longer to reach neutrality than it does for extreme Democrat content. In the study we will trace this distinction to differences in the topics in which Democrats and Republican contributors participate.

In summary, the study permits us to conclude that segregation declines over time *because* contributors have the tendency to both add to content with opposite points of view and moderate their own contributions over time. Because the study focuses on micro-behavior of contributors, it lends itself to tests of alternative explanations, and a battery of tests, which we substantiate that conclusion, and we will present in the text.

1.1. Relationship to Prior Work

The diffusion of the web reduced the costs of assembling the attention of many reviewers and contributors, making it feasible to arrange for a crowd to focus on a single topic. Thus, online organizations gained the capabilities of collective problem solving using community-based knowledge creation or shared knowledge (e.g., Kogut and Zander 1992; Lee and Cole 2003; Hargadon and Bechky 2006; Kuk 2006; Tucci and Villarroel 2007; Faraj et al. 2011; Ransbotham and Kane 2011; Afuah and Tucci 2012; Chen et al. 2012; Pierce 2012; Bassamboo et al. 2015). That does not imply it is feasible for an online aggregator to assemble information on every topic, or garner useful attention from a large crowd. Topics vary in the type of contributors they attract, in the viewpoints of those contributors, and the type of contributions they make. With every topic an aggregator faces numerous challenges aggregating the information from many contributors into text that others find useful, readable, and accessible. That motivated considerable research about how and why users voluntarily participate in online knowledge production (e.g., Kogut and Metiu 2001; Rothaermel and Sugiyama 2001; Yang et al. 2009; Ransbotham et al. 2012; Kane et al. 2014; Gallus forthcoming; among many others). It also motivate considerable innovation in a variety of tasks such as software design, entrepreneurial finance, and engineering (e.g., Kogut and Metiu 2000; Von Krogh and Von Hippel 2006; Chesbrough 2006; Roberts et al. 2006; Ramasubbu and Balan 2012; Xu et al. 2015). Prior research left open questions about how users behave in the present of contested knowledge, where this study is novel.

As with our prior work (Greenstein and Zhu 2012, 2016), we build on many studies of ideological content and contributions on the Internet, and, generally, analysis of segregated conversations (e.g., Sunstein 2001; Carr 2008; Lawrence et al. 2010; Gentzkow and Shapiro 2011; Boxwell et al. 2017). The concern with segregated conversation in prior work has many motivations. Segregation can facilitate radicalization of some individuals and groups (Purdy 2015).[3] The persistence of many segregated conversations also can prevent varying perspectives into a common view, and delay confrontation or a political discourse between contradictory facts and ideas. It also has been held responsible for discouraging interracial friendships, disconnecting different social segments, and stimulating social isolation. Prior work emphasizes different causes, such as the role and design of the social network structure of online communities (e.g., Fan et al. 2005; Ahn et al. 2007), knowledge reuse (Nagaraj forthcoming), and the factors that facilitate contributions in online communities (e.g., Jeppesen and Frederiksen 2006; Chiu et al. 2006; Ma and Agarwal 2007; Xu and Zhang 2009, 2013; Slivko 2014; Slivko et al. 2016; Qiu et al. 2017). None of this prior research focuses was motivated by the challenges shaping contested knowledge, and, thus, none focuses on measuring the micro-behavior behind segregated conversation, as does our study.

Our study also relates to one key behavioral concern of the research on the behavior of crowds. In one line of research a single "right" answer exists and research studies whether (and how) online crowds reach that answer (Page 2007). Several variants on this research topic presume the existence of a single "consensus forecast," and examine whether contributors herd around the consensus or deliberately choose "extreme" positions to influence the consensus (Laster et al. 1999; Zitzowitz 2001). Our study's approach differs in the characterization of motive. Prior literature presumes an extrinsic motive for herding or departing from the consensus, while our study presumes intrinsic motives – i.e., desire to express their opinions.[4] Our measurement strategy differs accordingly. We start with a "fixed" intrinsic viewpoint from each contributor, and then consider a viewpoint that varies over time. In addition, prior work examines online sites that aggregate ratings and whether individuals herd, i.e., follow their predecessors in assigning a rating (Gao et al. 2015; Lee et al. 2015; Kwark et al. 2016; Wang et al. 2017), choosing products (e.g., Salganik et al. 2006), or trigger more future contributions (Aaltonen and Seiler 2015). Research has stressed the role of group thinking (e.g., Janis 1982), decreased communication cost (Rosenblat and Mobius 2004), emotional and social contagion (e.g., Barsade 2002; Sun et al. 2017), and, broadly, the occurrence of homophily in social networks (e.g., McPherson et al. 2001). The closest prior research asks: Does a participant's rating/assessment align with an aggregated report of prior ratings/assessments (e.g., Muchnick

[3] See, for example, http://www.vice.com/read/we-asked-an-expert-how-social-media-can-help-radicalize-terrorists and http://www.rand.org/randeurope/research/projects/internet-and-radicalisation.html, accessed June 2017.

[4] Political bias is one form of bias. Scholars have examined other forms of online bias such as racial and gender bias (e.g., Edelman and Luca 2014; Cui et al. 2016; Carnahan and Greenwood 2017).

et al. 2013)? By comparison, we ask: Does a contributor add to content with a slant which matches his or her own or differs from it, and how does that behavior change over time?

This study also adds to work that focuses on the behavior of segregated online conversations. Gentzkow and Shapiro (2011) focus on online conversations about political content and other topics. Greenstein and Zhu (2012, 2016, forthcoming) focus on measuring and characterizing the evolution of content, while this study focuses on the interactions among online contributors and content. Relatedly, Gentzkow and Shapiro (2010) starts from the premise that there are ideological tendencies that appear in the language of speakers, and it is this insight we borrow for the model of contributors with intrinsic slants. In traditional media, it is found that ideological bias in news content affects political behavior (e.g., DellaVigna and Kaplan 2007; Stone 2009; Chiang and Knight 2011; Durante and Knight 2012). Prior work has also stressed partisanship in online media (e.g., Larcinese et al. 2007), and identified its importance for ideologically segregated conversations among those with different viewpoints (e.g., Carr 2008; Lawrence et al. 2010; Gentzkow and Shapiro 2011; Shore et al. 2016). No prior work measures whether participants change their behavior over time, as in our study. Most other work treats the sources of bias as isolated (e.g., Groseclose and Milyo 2005; Besley and Prat 2006; Reuter and Zitzewitz 2006; Bernhardt et al. 2008) and does not link them to contested knowledge, political discourse or aggregated knowledge, which this study does.

Our findings raise as many questions as they answer about the norms and institutions encouraging unsegregated conversations. While many participants inside Wikipedia believe its principles and processes help its online communities meet the ideals to which the site aspires, little quantitative evidence or controlled experimentation either confirms or refutes this belief. Like other online communities, Wikipedia has adopted explicit rules, norms, policies (Forte et al. 2009; Jemielniak 2014; Schroeder et al. 2012), and quality assurance procedures (Stvilia et al. 2008), which appear to shape behavior. Many online communities have adopted schemes of access privileges that formally define roles in the organization (Arazy et al. 2015; Burke et al. 2008; Collier et al. 2008; Forte et al. 2012), and so has Wikipedia. These lead to a myriad of coordination mechanisms (Kittur et al. 2007a; Kittur and Kraut 2008; Kittur et al. 2007b; Schroeder and Wagner 2012), social interactions (e.g., Halfaker et al. 2011; Forte et al. 2012), and behaviors aimed at conflict resolution (Arazy et al. 2011). In contrast to research about segregated conversations on other platforms (Shore et al. 2016), we find that the most frequent contributors to Wikipedia display more neutral tendencies than the less frequent contributors. Hence, our findings confirm that online conversation can develop mechanisms to overcome tendencies toward segregated conversation. While these findings suggest Wikipedia’s mechanisms are working as desired, they heighten questions about which specific mechanisms or norms are primarily responsible, and which comparable institutions exist in other settings.

2. Measurement and Setting

We begin by defining terms and offering a simple model to motivate our measurement approach. As in Gentzkow and Shapiro (2010) and Greenstein and Zhu (2016, forthcoming), we first define the *slant* of content. This indicates which way a particular piece of content "leans." It takes a numerical value, bounded on the interval [–D, R], D > 0, and R > 0. We normalize a neutral point of view to 0. *Bias* of content is the absolute value of slant. We define the slant and bias of a contributor in an analogous fashion.

2.1. Simple models of Slant in a crowd

One standard model of a crowd presumes a single objective answer, and a platform aggregates contributions from the crowd. In many models the results improve with a larger sample of contributions (Page 2007). We modify this model for a setting in which two groups of contributors with intrinsic political views aspire to improve a controversial topic and do not agree on a single objective answer. Here we develop intuition that guides our empirical approach.

To illustrate the intuition, we build on the simplest models of crowds. In this model, two groups hold opinions along a line on the interval [-D, R], where 2 > R/D > ½.[5] One set of participants holds opinions between [0, R] and the other holds opinions between [-D, 0], and they have an irreconcilable disagreement with one another (except for a tiny set who hold a "neutral" view around zero). These opinions are built on unverifiable facts and subjective information, and views do not change when confronted with one another. Define two sets of opinions as O_D and O_R. O_D includes all potential opinions on the interval [-D, 0] and O_R is on the interval [0, R].[6] The online platform aggregates contributions from a subset of contributors in either or both groups. Define the number of contributions from those who hold opinions within O_R and O_D as N_R and N_D, respectively, and $N = N_R + N_D$.

In this model each contributor has an opinion, o_i, and i indexes the sequence of contributions as 1, 2, 3, …, i, …, N. Define *Slant*, S_i, as an aggregation of the contributions of opinion. For illustrative purposes, we define the function for Slant of a topic in the simplest possible way, as the mean of all contributions to that topic. The process for determining the draw of opinions then determines Slant.

Consider a model of o_i where opinion among potential contributors follows a uniform distribution. In one standard model of crowds the contributions of opinion are *i.i.d.* and drawn equally from any opinion between – D and R. The randomness reflects one of the features we will see in our application, in which a substantial fraction of contributions come from individuals who make one suggestion and no more.

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[5] This latter assumption is for technical purposes only. It says that the most extreme representative of one view is not substantially more biased than the most extreme of the other. This is useful for guaranteeing convergence.

[6] It will be convenient to include a neutral opinion in both sets, though this is not an essential feature of the model.

This model generally does not lead to a neutral outcome. The law of large numbers suggests Slant approaches (R - D)/2 as N becomes large. As N becomes large, the spread around the Slant also will become tight. This outcome is neutral only in the situation when R = D. Otherwise, the slant will equal some arbitrary point in the "interior," and eventually settle into a situation with, at most, only incremental change.[7] This finding easily generalizes to a wide number of distributions. Summarizing, drawing opinions randomly from a crowd does not lead to an aggregation of opinions that is neutral.

Following the herding literature, we next consider two simple situations in which contributions react to aggregated opinions. These illustrations modify the assumption, as in Mullainathan and Shleifer (2005), where contributors have intrinsic motives. In their model contributors prefer to contribute to articles that are consistent with their ideological beliefs. In our setting, contributors with intrinsic ideological slants have a choice over many articles to which they can contribute. The new assumption can take one of two forms in the presence of contested knowledge. In one form contributors prefer to *avoid* contributing to any article that *already* disagrees with their beliefs, so they add only to those with which they *already* agree. In another form contributors prefer to add to articles that *disagree* with their views, so a contribution changes the article, *making it closer* to their beliefs. As a simple model of each will illustrate, one of these will lead to a segregated conversation and the other will lead to an unsegregated conversation.

We use S_i to denote the slant that includes all opinions up to o_i. Define a function f, that defines the relationship between contributed opinion and the prior slant, that is, $o_i = f(S_{i-1})$. Consider a model of segregation. In this model, contributors prefer articles that already slant away from a neutral point of view in a direction consistent with their beliefs, and f follows a rule: *If $S_{i-1} < 0$ then o_i is drawn i.i.d. from O_D, otherwise from O_R.*

In this simple model of segregation, the sign of the slant attracts new random contributions of the same sign. The first draw determines all subsequent contributions. If the first draw is negative, then all subsequent draws are randomly drawn negative opinions between –D and zero. The law of large numbers suggests Slant approaches – D/2 as N_D becomes large.[8] Similarly, if the first draw is positive, then Slant approaches R/2 as N_R becomes large.[9]

Next consider the specification for f where contributors make alterations to articles that disagree with their views. In this case, contributors make alterations to articles that slant away from a neutral point of view in a direction inconsistent with their slant. This leads to a simple model of unsegregated conversation. Here f follows a rule: *If $S_{i-1} > 0$ then o_i is drawn i.i.d. from O_D, otherwise from O_R.*

[7] The distribution around S_i will be $(R+D)^2/(12N_i^{1/2})$, becoming very small as N grows large.
[8] The distribution around S_i will be $D^2/(12N_{Di}^{1/2})$.
[9] The distribution around S_i will be $R^2/(12N_{Ri}^{1/2})$.

In the model of unsegregated conversation, the sign of the slant attracts new contributions of the opposite sign. If the Slant is negative (positive), the next contribution will be positive (negative). In this case it does not matter whether the first draw is negative or positive; contributions will move the Slant towards the center in either case. As N grows large the contribution from each contribution declines, and slant settles near zero.[10]

We keep the model simple to stress the intuition, and we summarize it thusly: First, neutrality cannot emerge from a random draw of opinions. The behavior of contributors is the key factor to consider. Second, reinforcing behavior leads to segregated conversations, i.e., contributions from those with similar slant will appear to be segregated. Third, unsegregated conversations will result from a process that does not reinforce existing slant and draws on opposite opinions. Fourth, segregated conversations are associated with more biased outcomes than unsegregated conversations, and the latter are associated with a comparatively moderate slant near the neutral point of opinion. Finally, slant only settles down in a single place after the number of suggestions reaches a large number. It is an empirical question what "large" means in practice.

2.2. The measurement of segregated conversations

The above theory suggests a measurement approach that focuses on the relations between two key factors – the slant of articles and the slant of contributors. In the application below we will discuss a specific setting in which the underlying distributions are not observable, but the sequence of contributions are, and so are the resulting slants. That leads us to focus on what characterizes contributor behavior – a tendency to edit comment that contains existing slant or different slant.

Our measurement strategy resembles Greenstein and Zhu (2012, 2016, forthcoming), which builds on Gentzkow and Shapiro (2010) and adapts the strategy to Wikipedia. As with the model above, this approach presumes a yardstick for slant, bounded on an interval. There is a key novelty to our measurement strategy: we characterize the tendencies of a contributor to a specific topic – whether a contributor tends to make edits that push the topic in a blue or red direction.[11] Then we analyze two endogenous choices of

[10] If the slant is negative, then the next draw is positive. If the slant is negative again, then again the draw is positive. This continues until the slant is negative. If the slant is positive, then the next draw is negative, and so on. In this way the slant draws new opinions of the opposite sign. As N grows large, the incremental contribution cannot change the result much. At most a new opinion moves the average no more than either R/N or –D/N, which becomes small as N grows. In this way the process will approach zero.

[11] Our measurement strategy uses text-based keywords to measurement slant and bias. This contrasts with citation-based measures of slants, such as Groseclose and Milyo (2005). They count the times that a media outlet cites a list of 200 think tanks in the United States and then compare this with the times that members of Congress cite the same think tanks in their speeches on the floor of the House and Senate. We cannot use this method because our analysis examines individual articles on Wikipedia and most of them do not cite these think tanks.

contributors: whether to contribute to the topic with a slant that is similar to or different from their own and whether to change the slant of their contribution over time.

Some shorthand will be useful for describing empirical regularities below. Echo Chamber, or EC, arises in two ways: When a Democratic contributor edits content with a Democratic slant, or when a Republican contributor edits content with a Republican slant. Non Echo Chamber, or Non-EC, arises in two different types of situations: When a Republican contributor edits Democratic content, or when a Democratic contributor edits Republican content.

If a contributor acts in ways consistent with EC, then additional contributions will reinforce the preexisting slant. If a majority of contributors act in accordance with EC, then segregated conversations will arise. In contrast, if a contributor acts in ways consistent with Non-EC, additional contributions will not reinforce the existing slant, but will reduce the bias of the content.

The discussion so far presumes a contributor retains a fixed slant over his or her lifetime of contributions. A second set of questions arises in a setting with a long history of contributions. Do contributors alter their behavior after contributing to extreme or neutral content? Does experience reduce or increase the bias of their contributions? If so, by how much? These questions have not been a focus of prior research. They arise naturally in this analysis, due to the availability of information about the long-term experience of contributors with (un)segregated conversation. Together, the two questions can flexibly identify the micro-behavior that supports tendencies towards segregated or unsegregated conversations. In one possible extreme, contributors could display EC and not alter the slant of their contributions over time. That would reinforce segregated conversations. If, on the other hand, contributors display Non-EC and alter their contributions over time towards more neutrality, then conversations will tend towards a less segregated conversation. It is also possible that the two micro-behaviors could work in opposite directions, which could result in segregated or unsegregated conversations. In that sense, the approach does not presume anything about the underlying micro-behavior or the outcome.

The foregoing suggest a regression framework for measuring the behavior of contributors. Consider contributors with fixed intrinsic slant. Every contribution is an observation that reveals information about that contributor's tendency to edit content with views that are similar or different, and engage in echo chamber (EC). With a continuous measure of the slant of contributors and articles, and many observations, the following baseline regression model can be estimated:

$$Contributor\ Slant_j = \alpha_0 + \alpha_1 Prior\ Article\ Slant_{it} + \varepsilon_{ijt}\ . \tag{1}$$

In the above baseline model, i indexes articles, j indexes contributors, and t indexes time. The regression estimates whether an article with a slant attracts a contributor with a similar or different slant. In the absence of controls, the coefficient α_1 identifies the correlation between contributor slant and article slant, which reveals whether the contribution follows EC or Non-EC. A negative α_1 arises if contributors edit articles opposite in slant from their own slant, which leads to Non-EC. A positive α_1 arises when contributors edit articles with similar slant, which leads to EC. If there is no systematic behavior shaping the match between contributor and contribution, then α_1 will be zero. The above baseline model also can use a categorical approach (i.e., red, blue), where, again, the statistical model estimates the frequency with which red/blue contributors choose red/blue articles.

As we describe below, EC and Non-EC are identified under weak and plausible assumptions about the exogeneity of existing content's slant/bias to a contributor. We also must consider a range of controls and account for potential issues with the properties of ε_{ijt}.

2.3. *Empirical setting*

Founded in 2001, Wikipedia positions itself as "the free encyclopedia that anyone can edit"—that is, as an online encyclopedia entirely written and edited via user contributions. Topics are divided into unique pages, and users can select any page to revise—expertise plays no explicit role in such revisions. It has become the world's largest "collective intelligence" experiment and one of the largest human projects ever to bring information into one source. The website receives enormous attention, with over eight billion page views per month in the English language, and over 500 million unique visitors per month.[12]

Contributions come from tens of millions of dedicated contributors who participate in an extensive set of formal and informal roles.[13] Some of these roles entail specific responsibilities in editing tasks; however, the Wikimedia Foundation employs a limited set of people and largely does not command its volunteers. Rather it helps develop a number of mechanisms to govern the co-production process by volunteers (Kane and Fichman 2009; Te'eni 2009; Zhang and Zhu 2011, Hill 2017). All these voluntary contributors are considered editors on Wikipedia. The organization relies on contributors to discover and fix passages that do not meet the site's content tenets, but no central authority tells contributors how to allocate editorial time and attention.

The reliance on volunteers has many benefits but comes with many drawbacks. Among the latter, there is a long-standing concern that interested parties attempt to rewrite Wikipedia to serve their own parochial

12 "Wikipedia vs. the small screen". http://www.nytimes.com/2014/02/10/technology/wikipedia-vs-the-small-screen.html?_r=1, assessed June 2016.

13 See https://en.wikipedia.org/wiki/Wikipedia:User_access_levels, accessed June 2017.

interests and views. Despite the persistence of such concerns, there is little systematic evidence pointing in one direction or another. Available evidence on conflicts suggests that contributors who frequently work together do not get into as many conflicts as those who do not, nor do their conflicts last as long (Piskorski and Gorbatâi 2017). Additional evidence suggests a taste for prosocial and reciprocal behavior among contributors also plays an important role in fostering long-lasting cooperation among them (Algan et al. 2013). While such behavior could lead to edits from contributors with different points of view, there is no direct evidence that it leads to more content that finds compromises between opposite viewpoints.

While the Wikipedia community tries to attract a large and diverse community of contributors, there is general recognition that it invites many slanted and biased views. Moreover, the openness of Wikipedia's production model (e.g., allowing anonymous contributions) is subject to sophisticated manipulations of content by interested parties. So there is widespread acceptance of the need for constant vigilance and review.

A key aspiration for all Wikipedia articles is a "neutral point of view" or NPOV (e.g., Majchrzak 2009, Hill 2017). To achieve this goal, "conflicting opinions are presented next to one another, with all significant points of view represented" (Greenstein and Zhu 2012). In practice, when multiple contributors make inconsistent contributions, other contributors devote considerable time and energy debating whether the article's text portrays a topic from a NPOV. Because Wikipedia articles face virtually no limits to their number or size,[14] due to the absence of any significant storage costs or any binding material expense, conflicts can be addressed by adding more points of view to articles, rather than by eliminating them (e.g., Stvila et al. 2008). Like all matters at Wikipedia, contributors have discretion to settle disputes on their own—no command comes from the center of the organization. The organization offers a set of norms for the dispute resolution processes, which today can be quite elaborate, including the three-revert edit war rule, as well as rules for the intervention of arbitration committees and mediation committees. Administrators can also decide to freeze an article under contention.

3. Data and Summary Statistics

A number of statistical challenges arise when measuring micro-behavior of segregated conversations. First, because both contributors and articles may be slanted and biased, we must take both into account when developing a yardstick to compare the contributor to the contribution. That yardstick must enable a

[14] Over time a de facto norm has developed that tends to keep most articles under six to eight thousand words. This arises as editorial teams debate and discuss the length of the article necessary to address the topic of the page. Of course, some articles grow to enormous lengths, and editor contributors tend to reduce their length by splitting them into sub-topics. Prior work (Greenstein and Zhu 2016) finds that the average Wikipedia article is shorter than this norm (just over 4,000 words), but the sample does include a few longer articles (the longest is over 20,000 words).

quantifiable method for studying whether contributors select content with a slant similar to their own slant. Second, the slant and bias of articles changes because contributors revise articles.[15] Thus, we need a method that measures the changes as the content of articles changes. Third, contributors themselves may also change as they gain experience by editing more articles with slants and biases similar to or different from their own. Hence, we need a way to measure the evolution of contributors, as well as their contributions.

Following an approach pioneered in Greenstein and Zhu (2016), we develop a sample of articles from Wikipedia. We focus on broad and inclusive definitions of U.S. political topics, including all Wikipedia articles that include the keywords "Republican" or "Democrat." We start by gathering a list of 111,216 relevant entries from the online edition of Wikipedia on January 16, 2011. Eliminating the irrelevant articles and those concerning events in countries other than the United States[16] reduces our sample to 70,305. Our sample covers topics with many debates over contestable knowledge, ranging from the controversial topics of abortion, gun control, foreign policy, and taxation, to the less disputed ones relating to minor historical and political events and biographies of regional politicians. We next collect the revision history data from Wikipedia on January 16, 2011, which yields 2,891,877 unique contributors.

To mitigate concerns about manipulating statistical procedures, we rely on a modification of an existing method, developed by Gentzkow and Shapiro (2010), for measuring slant and bias in newspapers' political editorials.[17] For example, Gentzkow and Shapiro (2010) find that Democratic representatives are more likely to use phrases such as "war in Iraq," "civil rights," and "trade deficit," while Republican representatives are more likely to use phrases such as "economic growth," "illegal immigration," and "border security."[18] Similarly, we compute an index for the slant of each article from each source, tracking whether articles employ these words or phrases that appears to slant toward either Democrats or Republicans.

Like Gentzkow and Shapiro (2010), we investigate whether Wikipedia articles use words or phrases favored more by Republican or Democratic members of Congress. Gentzkow and Shapiro (2010) select such phrases based on the number of times they appear in the text of the 2005 *Congressional Record*, and

[15] This is a property that Greenstein and Zhu (2012) confirmed in their study of Wikipedia articles.

[16] The words "Democrat" and "Republican" do not appear exclusively in entries about U.S. politics. If a country name shows up in the title or category names, we then check whether the phrase "United States" or "America" shows up in the title or category names. If yes, we keep this article. Otherwise, we search the text for "United States" or "America." We retain articles in which these phrases show up more than three times. This process allows us to keep articles on issues such as "Iraq War," but drop articles related to political parties in non-U.S. countries.

[17] Gentzkow and Shapiro (2010) characterize how newspapers also use such phrases to speak to constituents who lean toward one political approach over another.

[18] Several studies have applied their approach in analyzing political biases in online and offline content (e.g., Greenstein and Zhu 2012; Jelveh et. al. 2014; Shore et al. 2016). In addition, although Budak et al. (2014) use alternative approaches to measure ideological positions of news outlets, their results are consistent with Gentzkow and Shapiro (2010).

apply statistical methods to identify those phrases that separate Democrat and Republican representatives. Their approach rests on the notion that each group uses a distinct "coded" language to speak to its respective constituents.[19] Each phrase is associated with a cardinal value that represents the degree to which each word or phrase is slanted. After offering considerable supporting evidence, Gentzkow and Shapiro (2010) estimate the relationship between the use of each phrase and the ideology of newspapers, using 1,000 words and phrases to identify whether those newspapers' views tend to be more aligned with Democrat or Republican ideologies. As shorthand we refer to these 1000 words and phrases as "code phrases."

This approach has several key strengths in that it has passed many internal validity tests, avoids many subjective elements, and provides a general yardstick for measuring the bias of newspaper articles. The approach is also effective when analyzing information on other online platforms (e.g., Shore et al. 2016) or examining political bias in articles in economic journals (Jelveh et al. 2014), which we believe can be transferred to the context of Internet articles. Wikipedia's contributors are unlikely to have used this yardstick to target these words for editing, though they might have included or excluded them when endeavoring to represent or exclude a specific point of view. The method also leads to a quantifiable measure of "neutral," because the numbers are additive for finding the total slant of an article, and the range of slants can be normalized at the mean. An article is deemed unslanted or unbiased either when it includes no code phrases from many opposing points of view or when its use of Republican and Democrat code phrases equal the same cardinal value.[20]

In general, just as there is no definitive way to measure the "true bias" of a newspaper article in Gentzkow and Shapiro (2010), there is no definitive way to measure the true bias of an online encyclopedia article. Our normalization is valid under the assumption that the underlying differences among the population of contributors do not change over the sample period, and the variance of observed slant around this mean is random. As we illustrate below, because the analysis focuses on the pairing of the slant of contributor/contribution, the inferences will be robust to small changes in the normalization.

3.1. Measures

3.1.1. Dependent variables

Contributor Slant. Every article on Wikipedia has a revision history that, for every edit, records a pre-edit and post-edit version. We compute the slant index for both the pre- and post-edit article versions, take the difference between the two, and use this difference in slant as the *slant change* resulting from this edit. In

[19] See Table I in Gentzkow and Shapiro (2010) for more examples.

[20] Greenstein and Zhu (2016) find no evidence that these two types of unslanted articles differ in their underlying traits. Hence, in this paper we treat them as identical.

this way, we obtain the slant change of every edit. For sequential edits from the same contributor that happened consecutively and without anyone else editing between them, we treat the sequence of edits as one single edit in all our analysis. These consecutive edits tend to be highly correlated, or could be several parts of a complete contribution, such as where the contributors saved their work several times.

Next, we focus on individual contributors as the unit of analysis. For our research purposes, we need to identify the bias and slant of contributors on the basis of their online political ideologies. To do so, we identify and measure the types of changes they make to Wikipedia articles. For every edit in our data, we take the difference between the pre-edit and post-edit versions of the article to determine the slant change of this edit. We assign each edit to each contributor, and assign a slant value for each edit. Under the assumption that every contributor has one fixed type of slant, we compute the *Contributor Slant* as the average value of the slant index of this contributor.

A zero value of *Contributor Slant* means the user's edits either contain a balanced set of Republican/Democratic words (weighted by their cardinal values) or do not include any of the slanted phrases. A negative or positive value of *Contributor Slant* means the contributor is Democrat-leaning or Republican-leaning, respectively. In our sample, 2,678,626 out of 2,891,877 unique contributors (92.6%) have a zero contributor slant, and over 225 thousand contributors make at least one slanted contribution.

Contributor Slant by Year. In our first analysis we will assume contributors have the same slant over their lifetime, and in the second analysis we relax the constraint that contributors maintain the same type of slant over time. In the latter, we divide contributors' edits by year and for each year use the same calculation as for *Contributor Slant*, that is, we compute the average slant change of all the edits a contributor has made within that year. If a contributor's numeric value for slant remains unchanged throughout the years, then his or her *Contributor Slant by Year* equals *Contributor Slant*.[21]

Contributor Category and *Contributor Category by Year*. We create two categorical variables. Based on *Contributor Slant* we create *Contributor Category*, which takes the value of -1, 0, or 1, representing contributors with a slant two standard deviations below mean, in between, and above mean, respectively. *Contributor Category by Year* is the yearly version of *Contributor Category*.

3.1.2. Baseline Explanatory Variable

[21] If a contributor does not make any contribution in a given year, his or her *Contributor Slant by Year* has a missing value in that year.

Prior Article Slant and *Prior Article Category*. *Prior Article Slant* denotes an article's slant before a particular edit. This variable is used as the explanatory variable to analyze the article's relationship with the next contributor's slant. We also create a categorical variable, *Prior Article Category,* by categorizing *Prior Article Slant* into -1, 0, and 1 for articles with slant two standard deviations below mean, in between, and above mean, respectively.

3.1.3. Moderating and Control Variables

We observe the slant of the endogenous and exogenous variables with error. Unobservable features of articles are a central concern, so we add additional measures that may have attracted editors, and otherwise had spurious correlation with the slant or bias of an article.

Contributor Years. For every edit in our sample, this is the number of years the contributor has been on Wikipedia before he or she made this edit. This time variable is used to analyze whether a contributor's slant changes over time.

Average Bias of Articles Edited. Numerically, an article's bias equals the absolute value of its slant. *Average Bias of Articles Edited* is the average bias of all the articles that a contributor has edited. This variable helps measure the contributor's online experiences and helps us identify the role of content bias on a contributor's slant change over time.

Fraction of Extreme Articles Edited. We use this variable to characterize the contents of the articles that contributors interact with during their online experiences. An article is defined as *extreme* if its slant is more than two standard deviations away from the mean. *Fraction of Extreme Articles Edited* equals the ratio between the number of extreme articles that the contributor has edited and the total number of articles the contributor edited. Like *Average Bias of Articles Edited,* the variable, *Fraction of Extreme Articles Edited,* helps identify the role of content bias on contributors' slant change over time.

Prior Article Length and *Prior Refs.* Apart from the article slant, there are some other time-varying article-specific characteristics that may affect the selection of the type of contribution. For instance, articles that are longer may incorporate more viewpoints, which then, in turn, tends to attract more contributors. Also, Wikipedia requires citations from major third-party sources as references for its article content (often listed at the bottom of the page), so articles with more references are also more likely to incorporate more outside arguments or controversial views at the time. Articles with these characteristics may tend to attract certain types of contributors. To control for these influences, we measure the length of the articles using the number of words in an article prior to a certain edit, denoted by *Prior Article Length*, and we measure the number of the article's external references, denoted by *Prior Refs*. These variables are included in the regressions on the relationship between *Contributor Slant* and the *Prior Article Slant* of the article that the contributor chooses to edit.

<u>Number of Edits</u>. As with articles, there are time-varying characteristics of contributors that may affect their slant change over time. One of them is the total number of edits that a contributor has made so far, since people who make more edits may be affected more by the online contents. We use *Number of Edits*, the total number of edits *to date* that the contributor has made on Wikipedia, to control for such influence when analyzing the effect of time on contributor slant changes.

3.2. Descriptive Statistics

Table 1 presents the distribution of types of contributors over ten years. When computing the number of Democratic, Republican, and Neutral contributors to Wikipedia each year, we count each user ID only once—even if the user contributes many times in a year. There are 2,891,877 unique contributors in our sample. As noted above, 92.6% have zero contributor slant. We define a contributor as *core* if his or her total number of edits is distributed in the top 10% of all contributors' total number of edits, which in this case equals a total of no less than three contributions in our sample. Core contributors comprise 10% of contributors, but they make 74% of the contributions in the entire sample. In other words, most of the edits in the sample come from experienced contributors – these are the contributors who we expect to be savvy about reading the existing slant of the articles and responding to that slant. Furthermore, while the number of neutral contributors who contribute each year is more than ten times that of contributors who have a slant, the proportion of core contributors in the neutral slant group (15.9% for the full sample) is much smaller compared to the proportion of core contributors in the other two groups (63.8% and 65.5% for the full sample). In summary, slanted contributors are more core than neutral contributors, and much of the slanted content comes from contributors making many edits.

In Table 2, we provide summary statistics of all variables used in our analysis. The unit of analysis in this table is contributor-edits, and the total number of observations is 10,948,696. Edits from all contributors who have ever contributed to the articles in our sample are included in this table. While in Table 1 we summarize on the level of *contributors*, in Table 2 we focus on all the *edits* made by the contributors within the entire time period. The two tables together help develop a broad understanding of both who contributes and what they contribute to the articles.

In general, the average *Contributor Slant* in our sample is negatively close to zero, while the average *Contributor Category* is positively close to zero. The summary statistics indicate that (1) Democrat-leaning contributors are, on average, more slanted than Republican-leaning contributors, and (2) all article versions in our sample exhibit a Democrat-leaning slant, with similar absolute values of extreme slant on both ends. There is also substantial variation across article versions for each of the three control variable measures, and we use the logarithm of these three control variables in our models since they are highly skewed.

We summarize the distribution of contributors' total number of edits over the ten years in Figure 1. Our sample reflects the well-known skewness of contributions to Wikipedia. More than 75% of the contributors in our sample contributed only once in the entire ten-year period. 97.5% of the contributors contributed fewer than 10 times, averaging to less than one contribution per year. Only 1% of the contributors contributed more than 30 times in our sample. We also show the number of edits, the number of contributors and the average number of edits per contributor by the contributors' years of experience in Figures 2-4, respectively. While contributors with 4 to 5 years of experience comprise the larger part of our sample compared to the rest both in terms of the number of contributors and the total number of edits, the average number of edits per contributor does not vary much with years of experience except for the 0.18% contributors who joined in January 2011.[22]

4. Empirical Results

4.1. Contributors' Participation Pattern on Wikipedia

For every edit in our sample, we estimate the following regression model:

$$Contributor\ Slant_j = \alpha_0 + \alpha_1 Prior\ Article\ Slant_{it} + X_{it}B + \sigma_i + \eta_t + \varepsilon_{it}\ . \qquad (1)$$

The coefficient α_1 identifies whether the average contribution follows EC or Non-EC, as earlier noted. To address concerns about unobservable factors influencing the choice, we include X_{it}, a vector of the article's characteristics and control variables, and σ_i, an article fixed effect to control for any fixed differences among articles (despite many potential changes over many years), and η_t, a year fixed effect to control for any common trend in media/macroeconomic shocks that may differentially affect articles of different years. In an alternative approach described in the text, we also use *Contributor Category* as the dependent variable, with *Prior Article Category* as the explanatory variable, estimating standard models for categorical choice.

[22] Dropping this group of contributors in our analysis does not change our results qualitatively.

In Table 3, we report estimation results of Equation (1) using Ordinary Least Square (OLS) regressions. For the sake of analyzing participant behaviors, we drop the first version of all articles in our sample, since we do not have a prior article slant and cannot observe EC or Non-EC effect for such contributions. This reduces the number of observations in the sample to 10,878,391 and the number of articles to 66,389. Unless pointed out otherwise, this paper uses this analysis sample throughout the paper.

Models (1) through (3) use *Contributor Slant* as the dependent variable. Model (1) includes only *Prior Article Slant* as the explanatory variable. Model (2) adds in control variables *Log (Prior Article Length)* and *Log(Prior Refs)*. Model (3) replicates Equation 1, with article- and year- fixed effects included. The coefficients on *Prior Article Slant* is negative and significant in all three models. This indicates that an increase in the article's slant is associated with a decrease in the slant of its next contributor; namely, when the article is more Republican-leaning, it tends to attract a more Democrat-leaning user as its next contributor. That is consistent with Non-EC behavior.

Models (4)-(6) repeat the analyses in Models (1)-(3) but replace *Contributor Slant* with *Contributor Category* as the dependent variable, and replace *Prior Article Slant* with *Prior Article Category* as the explanatory variable. Again, we find that the coefficients for the categorical explanatory variable *Prior Article Category* is negative and significant in all cases, suggesting that the slant category of the next contributor is significantly negatively correlated with the slant category of the prior article. Results are similar across models and in line with our findings from Models (1)-(3).

We also partition the contributors by their frequency of edits and examine whether core and peripheral contributors behave similarly in our sample. *Core* contributors, as defined earlier, are the top 10% of contributors in terms of each contributor's total number of edits. *Peripheral* contributors are contributors who made only one edit in our sample, here represents 75.5% of all contributors.

Table 4 reports the regression results of Equation 1 based on subsamples of core contributors and peripheral contributors. Again, both types of contributors demonstrate a similar Non-EC pattern in their participation behavior, with peripheral contributors showing greater magnitude of the effect compared to core contributors. The results still hold after controlling for year and article fixed effects in the regressions.[23]

To further illustrate the Non-EC pattern in contributors' online participation, we use multinomial logistic regressions on the relationship between *Contributor Category* and *Prior Article Category*, with control variables and fixed effects similar to the specifications in Equation 1.

[23] Besides core and periperal contributors, there is also a middle group that includes 14.5% of contributors in our sample. Contributors in this middle group demonstrate a similar Non-EC pattern as contributors in the other two groups, with a magnitude of the Non-EC effect inbetween that of the core and the peripheral contributors.

In Table 5, we present the estimation results. Again, Model (1) includes only *Prior Article Category* as the explanatory variable. Model (2) adds in control variables *Log (Prior Article Length)* and *Log(Prior Refs)*. Model (3) includes fixed effects. We can see that the coefficients for *Prior Article Category* are all statistically significant and have opposite signs with the categorical dependent variable. Take the coefficients of *Prior Article Category* in Model (1) as an example. The coefficient for *Prior Article Slant* is 2.10 when the *Contributor Category* is -1, which leads to a 4.0% increase[24] in the probability of attracting a next contributor whose *Contributor Category* equals -1 when the article's prior slant increases by 1. Compared to the baseline coefficient, this result shows that when a prior article's slant moves to a Republican-leaning slant by one category, it is eight times more likely that it will attract a Democrat-leaning user as its next contributor. Similarly, the coefficients in Models (2) and (3) suggest that the increase in the probability of attracting a subsequent contributor with an opposite slant is even higher than it was without control variables or year fixed effects. Overall, the results continue to support our previous findings of a greater Non-EC effect than EC effect in contributors' online participation.

4.2. Do Contributions from Contributors Change Over Time?

In the previous analysis, we have assumed that every contributor's slant is constant over time. We now relax that assumption, and examine how a contributor's slant changes over time. We estimate the following equation:

$$Contributor\ Slant\ by\ Year_{jt} = \beta_0 + \beta_1 Contributor\ Years_{jt} + Z_{it}B + \mu_j + \epsilon_{it}\ . \quad (2)$$

The coefficient β_1 can help identify whether and how the contributor's slant changes over time. Here Z_{it} includes a contributor's characteristics and controls for time-varying differences among contributors, such as *Number of Edits*. μ_j is a contributor fixed effect. Because it is not possible to estimate μ_j, a contributor fixed effect, for contributors who make one contribution, the number of observations that enter the regression with contributor fixed effect becomes smaller. We try estimates with and without this effect.

In Table 6, Models (1)-(4) use the absolute value of *Contributor Slant by Year* as the dependent variable. We take the absolute value to capture how far away the contributor slant is from neutral, regardless of its sign. Model (2) includes contributor fixed effect, and Model (4) includes both contributor fixed effect and contributor characteristics as control variables.

24 $\frac{e^{-5.11+2.07}}{1+e^{-5.11+2.07}+e^{-5.25-2.41}} - \frac{e^{-5.11}}{1+e^{-5.11+2.07}} = 0.0456 - 0.0058 = 0.0398.$

The estimated coefficients of *Contributor Years* in all models are negative and statistically significant. The result means that overall the average Wikipedia contributor slant declines over time. The average contributor slant moves closer to neutral by 0.0002 for every additional year the contributor stays in the community.

Although we observe an overall decline in the bias of contributors over time (e.g., the year 2008 is a notable exception to the trend), one might argue that such a decline arises as an artifact of the dictionary of code phrases we use. We compute the slant measure in 2005, which may become less relevant over time. If this is the case, we would expect to see the contributor slant decline only after 2005. To test this, we exclude all the observations after 2005 from our sample and re-run the above OLS regression to see how the absolute value of *Contributor Slant by Year* changes during these years. Again, the results show a significant negative relationship between contributors' slant and contributor years, indicating that the decline in contributors' slant is not due to deceasing relevance of our slant measure.

In addition to looking at how the average contributor slant changes, we use Markov matrix to illustrate how slant composition of contributors evolves over time. This matrix, reported in Figure 5, is constructed as follows: First, we divide in half every contributor's time that he or she has been on Wikipedia. Then, we divide the direction of this contributor's edits by attaching values (-1, 0, 1) to negative slant, zero slant, and positive slant edits. Based on the sum of these values for the first half and the second half of this contributor's activity, we can categorize the contributor as Democrat, Neutral, or Republican: If the sum of all edits in one half is negative (positive), the contributor is a Democrat (Republican), respectively. And, if the sum of all edits in this half is zero, the contributor is Neutral. We do this for each half of every contributor's activity on Wikipedia and accumulate them to get the overall transition probabilities in the entire community. We find that, for both democratic-leaning and republican-leaning contributors in the first half, there is more than a 70% chance that they will move to Neutral in the second half of their activities. As a result, the community in general has a tendency of moving towards neutral.

Since it is more likely that contributors' slant decline over time instead of remaining constant throughout the years, we next examine whether our findings of Non-EC in contributor participation is still valid under the different contributor slant assumption. We repeat the OLS regressions utilized above by using *Contributor Slant by Year* as the explanatory variable. From the results in Table 7, we can see that, just as in Table 4, the coefficients for *Prior Article Slant* and *Prior Article Category* remain negative and statistically significant ($p < 0.001$). Moreover, compared to those under the constant contributor slant assumption, the magnitudes of the estimated coefficients are actually larger when using *Contributor Slant by Year* as the dependent variable. The results provide further support for our previous findings that there exists a significant Non-EC pattern in contributors' participation in Wikipedia.

4.3. Do Contributors Learn From Their Editing Experiences?

We next investigate how a contributor's prior editing experiences affects the slant of his or her contribution. Equation (3) adds the average bias of prior edited articles for each contributor, *Average Bias of Articles Edited*, and interacts it with *Contributor Years*, yielding:

$$\begin{gathered} \mathit{Contributor\ Slant\ by\ Year}_{jt} = \gamma_0 + \gamma_1 \mathit{Contributor\ Years}_{jt} + \\ \gamma_2 \mathit{Average\ Bias\ of\ Articles\ Edited}_{jt} + \gamma_3 \mathit{Contributor\ Years}_{jt} \times \\ \mathit{Average\ Bias\ of\ Articles\ Edited}_{jt} + Z_{it}B + \mu_j + \tau_{it}\,. \end{gathered} \tag{3}$$

The coefficient γ_3 estimates the moderating effect of extreme contents on contributors' slant change over time. Like Equation (2), Z_{it} refers to *Number of Edits*, which is a contributor characteristics variable controlling for time-varying differences among contributors, and μ_j is a contributor fixed effect to control for any fixed differences among contributors. In an alternative specification we also use *Fraction of Extreme Articles Edited* as an alternative measure for extreme contents, including this variable and its interaction term with *Contributor Years* in Equation (3).

Regression results using each of the two content measures are reported in parallel in Table 8. Model (1) and Model (2) estimate the moderating effect of *Average Bias of Articles Edited*. The coefficients for the interaction terms are negative and statistically significant, which indicates that if a contributor has been interacting with articles that are very biased, his or her own slant becomes neutral more quickly over time. The estimated coefficients show that the average article bias does have a significant influence on contributors' slant change. Models (3)-(4) replace *Average Bias of Articles Edited* with *Fraction of Extreme Articles Edited*. Again, the estimated coefficients of the interaction terms are negative and statistically significant. However, the findings also are mildly mixed because the coefficients for *Contributor Years* are near zero, and change sign with different specifications.

4.4. Rate of Slant Change: How Long Will It Take for Contributors to Become Neutral?

The presence of considerable heterogeneity makes it challenging to characterize the implications of the patterns of these findings. Having observed the tendency of the contributor slant change over time, we next estimate how long it takes for a contributor's slant to gradually converge to neutral if this tendency continues.

We use a Markov Chain Process to simulate the slant convergence. Although a contributor's slant exhibits long-term trend over the years, it fluctuates frequently, and this should be accounted for. We divide slant into different bins and investigate how a contributor's slant changes from one bin to another. *Contributor Slant by Year* is divided into seven bins, divided by the ± 0.5, ± 1.5, and ± 2.5 standard deviations intervals. The middle bin represents a neutral slant; the first and last bins represent extreme slants. We then compute a transition matrix for contributor slant based on our empirical data: For each year, we compute the proportions of contributors whose yearly slant moves from one slant bin to another, and fill the probabilities in the transition matrix for this year. Averaging the transition matrices among all years gives us the final transition matrix we use in our simulation, reported in Figure 6.

In this transition matrix, the rows denote the starting bins and the columns denote the ending slant. Bin 4 represents a neutral slant, defined as a slant index ranging from -0.5 to 0.5 standard deviations away from the mean. We find that: (1) the probabilities on the diagonal are relatively large. As expected, contributors tend to have a higher chance of staying near their original slant; and (2) the farther the end bins are from the start bins, the smaller the probabilities. This indicates that contributor slant change is a gradual and a cumulative process, and it is not likely that the contributor's slant would suddenly jump from one extreme to another.

Next, we use the transition matrix to simulate the contributor slant change process over time (see Table 9). We compute the time it takes for a contributor to have a greater than 50% probability of moving to neutral. As expected, the length of time depends on the contributor's original slant: Extremely slanted contributors spend a longer time moving to neutral than slightly slanted contributors. More surprisingly, we find that on average, it takes one more year for the Republicans to become neutral than for Democrats.

We test for several possible reasons why Republican contributors converge to neutral slant slower than Democratic contributors. First, we consider if Republican contributors in general display more EC behavior than Democratic contributors. Regression results of Equation (1) using the two groups respectively do not support this explanation. In fact, Republican contributors in general show stronger magnitude of Non-EC compared to Democratic contributors.

Second, Republican contributors might choose to edit less extreme articles compared to Democratic contributors, so that they are less influenced during their interaction with online content. However, we find no statistically significant difference between the level of content extremeness for the articles edited by Republicans or Democrats. The distributions contain similar bias and variance.

A third possible reason might stem from the contributors' number of edits – that is, Republican contributors make fewer edits in our sample than Democrats, so their experience has less of an effect on the overall tendency, and may differ in some way. Summary statistics provide evidence for this explanation. In our sample, the total number of edits from Democratic contributors is about 1.5 times that of Republican contributors.

This motivates examining whether the two types of contributors examine different topics, and whether each of these topics display different EC/Non-EC behavior. We characterize the heterogeneity of Non-EC/EC among different topics, using Wikipedia's classification for articles. This exercise is also of independent interest for the potential to derive insight from which topics generate EC for which types.

We create dummy variables for each topic categories and modify Equation (1), adding these dummies and their interactions with $Prior\ Article\ Slant$. We then compute the EC effect for each topic category using the regression results. There are 24 categories of topics in the sample, and these are not mutually exclusive. Articles can speak to one or more topics, and these rarely change over the lifetime of an article. We estimate this modification to Equation (1) for the entire sample, and for two mutually exclusive sub-samples, one consisting of Republican contributors and one for Democrat Contributors. We report the results in Table 10.

Consistent with our overall findings, the majority of topics display Non-EC for contributors from both parties. For example, the four topics with the most edits – Foreign Policy, Government, War and Peace, and Biographies – display an overall pattern of Non-EC. Overall, the general finding about Non-EC is reflected in most subgroups.

The absence of EC is our most striking finding, so its strong presence in any topic is noteworthy. Three topics—Homeland Security, Energy, and Tax—display evidence of a segregated conversation, where both parties engage in EC. These are not in the top ten in terms of the number of edits, so they do not shape the overall patterns very much. In these three topics, however, the EC effect of Republican contributors is much stronger than that of Democrats, indicating that Republicans' edits are the relatively stronger force that contributes to these segregated conversations. This topic also is noteworthy, given later Republican action on taxation. It is harder to interpret on the other two topics.

Since the departures from overall non-EC are rare, even the weak presence of EC is striking. Among the ten topics receiving the most edits, three topics – Budget and Economy, Civil Rights, and Crime – display an interesting pattern: Non-EC overall, with either Democrats displaying EC and Republicans displaying Non-EC, or no significant pattern. This arises because the Democratic contributors resist changing content when Republicans try to insert their points of view. (Yet, it is unclear why these three topics are the focus of Democratic conversation, except for Civil Rights, which is a staple of the Democratic coalition.) A similar but opposite pattern, with Democrats displaying Non-EC and Republicans displaying EC, occurs on only one topic with much fewer edits—Healthcare. (This is noteworthy as a sign of the later passionate views coming from Republicans about US healthcare.)

Overall, Table 10 suggests Republican and Democratic contributors do occasionally have different experiences, selecting among different groups of articles to edit, most frequently those with a different viewpoint. The weight of experience results in Non-EC overall, with Republican editors experiencing (somewhat) segregated conversations less frequently (as a numerical matter). To say it another way, Republicans converge more slowly to neutral because of the proportion of time they find themselves on content of the opposite slant compared to Democrats. The findings again support our primary conclusions that (1) online experiences change contributors' slant and (2) there is a tendency for Wikipedia contributors' slants to converge in the majority of articles.

5. Robustness of Findings and Alternative Explanations

We further corroborate our findings by performing the following robustness tests.

5.1. Is the Measure of Contributor Slant Representative of Ideologies?

First, since the measure of contributors' political ideologies and slant are computed entirely on the basis of data from Wikipedia, one might be concerned about whether such a slant measure is representative of contributors' real-world political ideologies. Also, a neutral article in our sample can either be interpreted as having no slanted words at all or as having equal numbers of very slanted words. These concerns might lead to questioning the external validity of the slant measure.

To address this concern we use an alternative measure of slant and bias of contributors. We match the voting data from the 2004 Presidential Election to locations affiliated with IP addresses of contributors.[25] Because Wikipedia only reveals IP addresses for contributors without user IDs, we restrict our sample to contributors who are not logged in when editing the articles and also drop contributors whose IP addresses indicate that they are located outside the United States. Using OLS regressions, we then test the relationship between the voting record and *Prior Article Slant*. Note that this analyzes the behavior of a different population of contributors than the contributors we have examined thus far.[26] This regression is valid under the assumption that a contributor has – on average – the political tastes of the regions in which they live.

Table 11 presents the results. *RepPerc* denotes the percentage of Republican votes in the contributor's county. As we use positive values in the slant index to indicate Republican-leaning ideologies for Wikipedia users and articles, the negative and statistically significant coefficient of *Prior Article Slant* suggests that a contributor from a county with higher percentage of Republican votes tends to target a Democratic-leaning article when he or she contributes on Wikipedia. The results show a Non-EC pattern in the contributing process and are qualitatively similar to the prior estimates. This also provides support that the measure of contributors' slant reflects contributors' real political ideologies.

[25] The data on geolocation of IP comes from MaxMind. We match on county records.

[26] The identities of contributors are known after they register, and when they edit after logging on. An anonymous edit comes from either an unregistered contributor or from an editor who chose not to logon before editing. Hence, it is possible for the samples to include some of the same contributors, but it is not possible to know what fraction.

We collected talk pages for articles. These are used by contributors to discuss edits in order to achieve consensus. We find that the total size of an article's talk pages has a correlation of 0.22 with the average bias of the article over time, suggesting that our bias measure does capture how contested an article is.

5.2. What Else Could Be Driving the Non-EC behavior?

The effect of Non-EC in contributors' voluntary editing behavior indicates that contributors are more likely to edit articles with the opposite slant. However, apart from the interpretation of contributors being attracted by the article slant, this could also be due to a "correcting" behavior between contributors, which might have little to do with the article's slant. On Wikipedia, we sometimes see edits that are reverted and added back within a short time, which are called "edit wars." Could these edit wars be driving the Non-EC effect? We address this question by including only the initial edits of every contributor when they revise an article for the first time. Doing so rules out edit wars or any possible correcting behavior later in the edits.

We observe from Table 12 that the signs and statistical significance of the estimated coefficients do not change, and the magnitude of the coefficients becomes even larger, indicating an even stronger Non-EC effect than when investigating all edits. The results further strengthen the robustness of the Non-EC effect.

We also conduct several additional robustness checks to make sure the Non-EC effect is not driven by alternative explanations. First, our slant index is measured on the basis of frequently used phrases, or code phrases, favored by party representatives. It may be the case that longer articles tend to contain more code phrases and are therefore more measurable. In this case, long articles could drive our results. To rule out this explanation, we eliminate outlying long articles from our full sample, that is, articles that are more than two standard deviations above the mean article length. We obtain similar results.

Second, since we measure article slant using code phrases, the articles whose titles contain code phrases might tend to show greater biases in our sample simply because these code phrases are more likely to be used repetitively in the article content. To check the robustness of our finding, we exclude from our sample all articles whose title contains code phrases, which is 1.77% of all articles. Again, we find a significant Non-EC effect from the results.

Third, it is possible that certain code phrases are chosen simply because these words do not have other commonly-used synonyms that are neutral or of the opposite slant. In this case, as our measure captures the contributor's choice of words describing the same concept for a given topic, one's contribution may be slanted merely because he or she could not find neutral substitutes of the code phrases to choose from. We rely on the experiences of a legal and copyediting professional to identify these instances in our dictionary and leave only code phrases with natural substitutes. After re-measuring the slant index for articles and contributors, we repeat our analyses and find no significant change in our results. Therefore, the Non-EC effect is not driven by instances where contributors do not have a choice for substitute phrases.

Fourth, because contributors' edits to popular articles tend to have greater impact than those to less popular ones, their political slants measured from these popular articles could carry more weight. Therefore, we use articles' page views as weights when computing the average contribution slant and repeat our analysis using the weighted contributor slant. We continue to find significant Non-EC patterns.

We are also concerned that contributors blocked by Wikipedia administrators may affect our results.[27] These contributors may create extremely biased content initially and drop out of the dataset after being blocked. As a result, contributors overall may become more neutral over time. This problem is mitigated by our approach of assigning missing values to *Contributor Slant by Year* when a contributor makes no edits in a year. As a robustness check, we repeat our analysis after dropping all 56,329 contributors who have ever been blocked (temporarily or permanently) and the associated 480,960 edits from our sample and the results remain unchanged.

Finally, we test if the Non-EC effect is driven only by extremely slanted articles. We eliminate from our full sample articles with slant index two standard deviation points away from the mean. Changing this threshold to articles without slant in the top and bottom 10% does not differ qualitatively in results. The estimated coefficients with subsamples have the same signs but larger absolute values.

5.3. Could There Be Vintage Effects Among Contributors?

Perhaps the average contributor slant declines over years because of the differences among people joining Wikipedia in different years. That is, there may exist some pattern of user vintage effects across the years. For instance, compared to people who contributed later, those who contributed when Wikipedia was still in its early stage may not have been as proficient in editing neutral content as those who entered later. In this case, we may see that contributors who entered earlier are more slanted, and contributors who entered later are more neutral, on average.

We compute the average slant of contributors entering in different years and plot the results in Figure 7. As we can see, there is no obvious inclining or declining pattern in the average contributor slant across the years. Contributors who entered earlier are not systematically more neutral, nor are they more slanted, compared to those who entered later. The figure shows there are no vintage effects influencing the

[27] Blocks are used to prevent damage or disruption to Wikipedia. Contributors may be blocked for reasons such as vandalism and edit warring. See https://en.wikipedia.org/wiki/Wikipedia:Blocking_policy for the detailed policy, accessed August 2017.

contributor slant convergence tendency in our findings. This finding also suggests that the change in slant over time is not caused by entry and exit of contributors exhibiting extreme bias.

6. Conclusion and Discussion

This research shows that Wikipedia has a record of bringing opposing opinions into the same conversation. Our findings point toward patterns that lead contributors to offer content to those with different points of view, avoiding micro-behavior that contributes to EC. We also show that contributors moderate their contribution over time. The change in contributions is especially large for contributors who interact with articles that are more extreme and have greater biases. These effects reinforce the prevalence of unsegregated conversations at Wikipedia over time. We also estimate that this slant convergence process takes one year longer on average for Republicans than for Democrats. In summary, we find that the majority of Wikipedia's contributors do not segregate into a conversation that excludes other viewpoints. Contributors interact with those of opposite viewpoints much more frequently than they silo themselves and participate in echo chambers.

Our study also offers a two-step method for identifying the mechanisms contributing to polarization that distinguishes selection from evolution. Nothing in these methods presumes the results; the method can flexibly measure contributions to (un)segregated conversations in a variety of settings.

These findings have implications for when online communities could be hampered by a crowd's enthusiasm or frenzy. Collective intelligence should be more trustworthy when mechanisms encourage confrontation between distinct viewpoints. It also should adopt processes, as Wikipedia contributors have, which retains contributors who learn to moderate their contributions from their experience.

It is not as if Wikipedia avoids its share of disagreements and confrontations, so the findings also raise a subtle question: How does Wikipedia transform controversial topics into arguments that include many points of view and sustain the community over time? We believe that this success arises from the institutions that help overcome the challenges affiliated with aggregating contested knowledge. For one, the aspiration of achieving NPOV directs attention to specific areas. No side can claim exclusive rights to determine the answer, which allows every contributor to add another paragraph if it diffuses an issue by giving voice to dissent. In addition, miniscule storage and transmission costs reduce the cost of listing another view on a web page. Our results also suggest that the conflict resolution mechanisms and the mix of informal and formal norms at Wikipedia play an essential role in encouraging a community that works towards a neutral point of view. This finding is consistent with theories that articles go through a lifecycle, settle into a consensus, which contributors subsequently "defend" (see e.g., Kane et al, 2014).

These findings also raise questions for the market design literature about other online social media – such as Facebook, Twitter, and Reddit. We speculate that some simple design differences may have profound consequences for (un)segregating conversations. For example, Wikipedia contributors can both add material and remove material or refine the content in myriad ways, whereas contributors on Facebook/Twitter only add additional content on top of what is already there. Allowing for removing or editing anyone's contributions can change how the reader and writer choose to direct the conversations, resulting in contributions from different points of view. Some platforms also aggregate contributions in ways that shape the prevalence of segregation. For example, on Yelp (e.g., rating restaurants) or Rotten Tomatoes (e.g., rating movies) additional material can be added without limit, the platform provides a numerical summary that can direct conversations between readers and reviewers. Our results frame questions about whether a numerical summary motivates others with views that differ from the summary or attracts more reviews from those who agree with it.

These findings also highlight the importance of platform design of algorithms. For example, on Facebook, an algorithm selects content for users, and its design increases the chance that participants read and write contents only in a community of like-minded people. After all, a user often only sees content from his or her friends. Wikipedia contributors have the option to be exposed to different opinions and can freely make the choice of reading and writing any content on the platform. Future work can focus on the heterogeneous effect of online participation on different contributor subgroups—for example, with interest in different political topics, or participation in different types of online platforms, such as resource-sharing platforms versus communities of innovation. In addition, existing literature on open communities investigates the content production more frequently than the contributors themselves. Given the huge number of volunteers on Wikipedia, as well as the enormous attention this community gets from around the globe, we hope to see more research on Wikipedia's online participation and interactions, as well as on the mechanisms behind changes to its content.

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Table 1: Distribution of Different Types of Contributors over Years

Year	Democrat Contributors	Core Democrat Contributors	Republican Contributors	Core Republican Contributors	Neutral Contributors	Core Neutral Contributors	Total # of Contributors Contributed in the Year
2001	26.4%	18.1%	20.0%	12.5%	53.6%	9.9%	800
2002	9.9%	7.5%	9.6%	7.4%	80.4%	17.6%	4,364
2003	8.5%	6.5%	8.8%	6.9%	82.6%	18.3%	14,951
2004	7.8%	5.7%	7.7%	5.9%	84.5%	17.3%	66,867
2005	7.0%	4.7%	6.7%	4.6%	86.3%	15.6%	242,121
2006	5.7%	3.6%	5.7%	3.6%	88.6%	14.7%	584,438
2007	5.3%	3.2%	5.2%	3.3%	89.5%	13.8%	706,195
2008	5.2%	3.1%	5.3%	3.2%	89.5%	13.9%	640,871
2009	4.7%	3.1%	4.7%	3.2%	90.5%	14.1%	526,255
2010	4.2%	2.8%	4.2%	2.9%	91.6%	13.2%	461,663
2011	9.5%	8.5%	10.8%	9.9%	79.6%	19.4%	26,886

Notes: "Democrat/Republican/Neutral contributors" shows the percentage of contributors with negative/zero/positive *Contributor Slant* among all contributors who contribute in that year to the articles in our sample. "Core Democrat/Republican/Neutral contributors" shows the percentage of that year's "Democrat/Republican/Neutral contributors" whose total number of edits is distributed in the top 10% of all contributors' total number of edits. Final year, 2011, is sampled in January, which accounts for the low numbers in that year.

Table 2: Summary Statistics of Variables Used in the Main Analyses

Variable	Mean	Std. dev.	Min	Max
Contributor Slant	-0.0003	0.025	-1.229	0.998
Contributor Category	0.001	0.114	-1	1
Prior Article Slant	-0.057	0.208	-0.605	0.624
Prior Article Category	-0.057	0.264	-1	1
Prior Article Length	4,049.760	3,851.610	0	1,963,441
Prior Refs	33.983	60.904	0	1,636
Contributor Slant by Year	-0.00003	0.024	-1.229	0.998
Contributor Category by Year	0.001	0.121	-1	1
Contributor Years	1.040	1.366	0.003	9.797
Number of Edits	1,175.720	7,567.790	1	122,264
Average Bias of Articles Edited	0.138	0.113	0	0.624
Fraction of Extreme Articles Edited	0.075	0.176	0	1
RepPerc	0.457	0.142	0.093	0.920

Notes: Number of observations in this table is 10,948,696 except for *RepPerc*, which has 2,438,628 observations. For *Contributor Slant by Year*, only the years in which a contributor makes at least one edit are included in the sample.

Table 3: OLS Regressions on the Relationship between Contributor Slant and Prior Article Slant

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Contributor Slant	Contributor Slant	Contributor Slant	Contributor Category	Contributor Category	Contributor Category
Prior Article Slant	-0.0075*** [0.0001]	-0.0074*** [0.0001]	-0.0167*** [0.0004]			
Prior Article Category				-0.0123*** [0.0002]	-0.0124*** [0.0002]	-0.0197*** [0.0009]
Log(Prior Article Length)		0.0005*** [0.0000]	0.0009*** [0.0001]		0.0014*** [0.0000]	0.0017*** [0.0003]
Log(Prior Refs)		-0.0003*** [0.0000]	-0.0009*** [0.0001]		-0.0008*** [0.0000]	-0.0024*** [0.0004]
Observations	10,878,391	10,878,391	10,878,391	10,878,391	10,878,391	10,878,391
Adjusted R-squared	0.005	0.006	0.006	0.001	0.001	0.001
Year FE	No	No	Yes	No	No	Yes
Article FE	No	No	Yes	No	No	Yes
Number of Articles	66,389	66,389	66,389	66,389	66,389	66,389

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%. Observations in this panel are all the edits of the Wikipedia articles in our sample from 2001 to 2011. *Contributor Slant* is defined as the average slant change of all edits a contributor has made on Wikipedia. *Prior Article Slant* is the slant of the article before a particular edit. *Log(Prior Article Length)* is the logarithm of the article's total number of words. *Log(Prior Refs)* is the logarithm of the number of external references in the article plus one.

Table 4: OLS Regressions on the Relationship between Contributor Slant and Prior Article Slant, Core vs. Peripheral Contributors

Sample	Core Contributors	Peripheral Contributors	Core Contributors	Peripheral Contributors	Core Contributors	Peripheral Contributors	Core Contributors	Peripheral Contributors
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Contributor Slant	Contributor Slant	Contributor Slant	Contributor Slant	Contributor Category	Contributor Category	Contributor Category	Contributor Category
Prior Article Slant	-0.0021***	-0.0211***	-0.0056***	-0.0497***				
	[0.0000]	[0.0002]	[0.0002]	[0.0012]				
Prior Article Category					-0.0063***	-0.0237***	-0.0109***	-0.0410***
					[0.0002]	[0.0004]	[0.0006]	[0.0014]
Log(Prior Article Length)			0.0005***	0.0035***			0.0009***	0.0055***
			[0.0000]	[0.0004]			[0.0001]	[0.0017]
Log(Prior Refs)			-0.0004***	-0.0025***			-0.0016***	-0.0043***
			[0.0000]	[0.0003]			[0.0002]	[0.0011]
Observations	8,019,333	2,180,327	8,019,333	2,180,327	8,019,333	2,180,327	8,019,333	2,180,327
Adjusted R-squared	0.001	0.014	0.003	0.016	0.000	0.002	0.001	0.002
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Article FE	No	No	Yes	Yes	No	No	Yes	Yes
Number of Articles	66,313	46,856	66,313	46,856	66,313	46,856	66,313	46,856

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%. "Core Contributors" are contributors whose total number of edits is distributed in the top 10% of all contributors' total number of edits. "Peripheral contributors" are contributors who made only 1 edit in our sample.

Table 5: Logit Regressions on the Relationship between Contributor Category and Prior Article Category

Model	(1)		(2)		(3)	
Dependent Variable	Contributor Category=-1	Contributor Category=1	Contributor Category=-1	Contributor Category=1	Contributor Category=-1	Contributor Category=1
Prior Article Slant	2.0743*** [0.0266]	-2.4063*** [0.0135]	2.0819*** [0.0269]	-2.3404*** [0.0133]	2.1042*** [0.0270]	-2.2918*** [0.0132]
Log(Prior Article Length)			-0.0344 [0.0045]	0.1486*** [0.0052]	-0.0115 [0.0051]	0.1859*** [0.0058]
Log(Prior Refs)			-0.2232*** [0.0032]	-0.3128*** [0.0030]	-0.2851*** [0.0042]	-0.4079*** [0.0040]
Year FE	No		No		Yes	
Article FE	No		No		Yes	
Observations	10,878,391		10,878,391		10,878,391	
Pseudo R-squared	0.021		0.038		0.043	

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Regressions of Contributor Slant Change over the Years

Model	(1)	(2)	(3)	(4)
Dependent Variable	Abs(Contributor Slant by Year)	Abs(Contributor Slant by Year)	Abs(Contributor Slant by Year)	Abs(Contributor Slant by Year)
Contributor Years	-0.0009*** [0.0000]	-0.0002*** [0.0000]	-0.0002*** [0.0000]	-0.0002*** [0.0000]
Log(Number of Edits)			-0.0005*** [0.0000]	-0.0001*** [0.0000]
Observations	10,878,391	10,878,391	10,878,391	10,878,391
R-squared	0.003	0.003	0.004	0.004
Contributor FE	No	Yes	No	Yes

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%. Observations in this panel are the edits made by contributors. The dependent variable *Contributor Slant by Year* denotes the contributor's slant measured on the basis of the edits made within that year. *Contributor Years* denotes the number of years the contributor has been on Wikipedia. *Log(Number of Edits)* is the logarithm of the amount of edits the contributor has made to date.

Table 7: Regressions on the Relationship between Contributor Slant by Year and Prior Article Slant

Models	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Contributor Slant by Year	Contributor Slant by Year	Contributor Slant by Year	Contributor Category by Year	Contributor Category by Year	Contributor Category by Year
Prior Article Slant	-0.0086***	-0.0085***	-0.0188***			
	[0.0001]	[0.0001]	[0.0004]			
Prior Article Category				-0.0147***	-0.0147***	-0.0228***
				[0.0002]	[0.0002]	[0.0008]
Log(Prior Article Length)		0.0006***	0.0010***		0.0015***	0.0021***
		[0.0000]	[0.0001]		[0.0000]	[0.0004]
Log(Prior Refs)		-0.0004***	-0.0009***		-0.0009***	-0.0025***
		[0.0001]	[0.0001]		[0.0000]	[0.0004]
Observations	10,878,391	10,878,391	10,878,391	10,878,391	10,878,391	10,878,391
R-squared	0.006	0.007	0.007	0.001	0.001	0.001
Year FE	No	No	Yes	No	No	Yes
Article FE	No	No	Yes	No	No	Yes
Number of Articles	64,622	64,622	64,622	64,622	64,622	64,622

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Moderating Effect on How Contributor Slant Changes over the Years

Model	(1)	(2)	(3)	(4)
Dependent Variable	Abs(Contributor Slant by Year)	Abs(Contributor Slant by Year)	Abs(Contributor Slant by Year)	Abs(Contributor Slant by Year)
Average Bias of Articles Edited x Contributor Years	-0.0042***	-0.0022***		
	[0.0001]	[0.0004]		
Average Bias of Articles Edited	0.0174***	0.0059***		
	[0.0002]	[0.0008]		
Fraction of Extreme Articles Edited x Contributor Years			-0.0020***	-0.0014***
			[0.0001]	[0.0004]
Fraction of Extreme Articles Edited			0.0088***	0.0037***
			[0.0001]	[0.0006]
Contributor Years	0.0004***	0.0001***	-0.0001***	-0.0001***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Log(Number of Edits)	-0.0005***	-0.0001***	-0.0005***	-0.0001***
	[0.0000]	[0.0000]	[0.0140]	[0.0000]
Observations	10,878,391	10,878,391	10,878,391	10,878,391
R-squared	0.011	0.011	0.009	0.008
Contributor FE	No	Yes	No	Yes

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Time Needed for a Contributor to Have > 50% Probability of Moving to Neutral Slant

Starting Contributor Slant	**Number of Years**
Extremely Democratic	10
Democratic	6
Slightly Democratic	3
Neutral	0
Slightly Republican	4
Republican	7
Extremely Republican	11

Notes: Number of years calculated based on the Markov Chain Process. *Neutral* state includes contributor slant 0.5 standard deviation away from 0. *Slightly Democratic (Republican)* state includes contributor slant between 0.5 and 1.5 standard deviations below (above) 0. *Democratic (Republican)* state includes contributor slant between 1.5 and 2.5 standard deviations below (above) 0. *Extremely Democratic (Republican)* state includes contributor slant more than 2.5 standard deviations below (above) 0. On average, after about 30 years, the probabilities in all articles' end state reach stationary distribution, with the probability of contributor slant moving to *Neutral* being 87.4%.

Table 10: Heterogeneity of EC and Non-EC across Different Article Topics

		All sample		**Republican contributors**		**Democratic contributors**	
Article Topics	No. of Edits	Estimate	Pattern	Estimate	Pattern	Estimate	Pattern
Abortion	30,400	-0.0039*** [0.0012]	Non-EC	-0.0161*** [0.0044]	Non-EC	0.0003 [0.0012]	*n.s.*
Budget & Economy	765,729	-0.0019*** [0.0003]	Non-EC	-0.0125*** [0.0011]	Non-EC	0.0036*** [0.0003]	EC
Civil Rights	902,531	-0.0038*** [0.0002]	Non-EC	-0.0183*** [0.0008]	Non-EC	0.0009*** [0.0002]	EC
Corporations	54,709	-0.0009 [0.0008]	*n.s.*	0.0035 [0.0031]	*n.s.*	-0.0046*** [0.0007]	Non-EC
Crime	957,613	-0.0016*** [0.0002]	Non-EC	-0.0089*** [0.0009]	Non-EC	0.0015*** [0.0003]	EC
Drugs	164,330	-0.0029*** [0.0007]	Non-EC	-0.0163*** [0.0025]	Non-EC	0.0001 [0.0012]	*n.s.*
Education	864,373	-0.0064*** [0.0003]	Non-EC	-0.0270*** [0.0011]	Non-EC	-0.0028*** [0.0003]	Non-EC
Energy	183,598	0.0021*** [0.0004]	EC	0.0103*** [0.0015]	EC	0.0012* [0.0007]	EC
Family	434,980	-0.0013*** [0.0003]	Non-EC	-0.0112*** [0.0014]	Non-EC	0.0020*** [0.0004]	EC
Foreign Policy	1,883,375	-0.0038*** [0.0002]	Non-EC	-0.0079*** [0.0007]	Non-EC	-0.0048*** [0.0004]	Non-EC
Trade	442,561	-0.0038*** [0.0004]	Non-EC	-0.0028*** [0.0010]	Non-EC	-0.0125*** [0.0009]	Non-EC
Government	3,376,993	-0.0039*** [0.0000]	Non-EC	-0.0174*** [0.0004]	Non-EC	-0.0026*** [0.0001]	Non-EC
Gun	62,668	-0.0037*** [0.0009]	Non-EC	-0.0207*** [0.0033]	Non-EC	-0.0003 [0.0012]	*n.s.*
Healthcare	385,659	-0.0004 [0.0004]	*n.s.*	0.0027** [0.0014]	EC	-0.0028*** [0.0006]	Non-EC
Homeland Security	478,796	0.0021*** [0.0004]	EC	0.0045*** [0.0014]	EC	0.0025*** [0.0004]	EC
Immigration	255,461	-0.0035*** [0.0005]	Non-EC	-0.0031* [0.0019]	Non-EC	-0.0047*** [0.0007]	Non-EC
Infrastructure & Tech	920,016	-0.0017*** [0.0003]	Non-EC	-0.0009 [0.0009]	*n.s.*	-0.0034*** [0.0004]	Non-EC

Jobs	693,295	-0.0023*** [0.0003]	Non-EC	-0.0074*** [0.0011]	Non-EC	-0.0031*** [0.0004]	Non-EC
Principles & Values	562,908	-0.0027*** [0.0003]	Non-EC	-0.0017 [0.0012]	*n.s.*	-0.0071*** [0.0004]	Non-EC
Social Security	2,501	-0.0111** [0.0048]	Non-EC	-0.0365* [0.0190]	Non-EC	-0.0138*** [0.0029]	Non-EC
Tax	46,048	0.0058*** [0.0007]	EC	0.0177*** [0.0033]	EC	0.0039*** [0.0007]	EC
War & Peace	1,837,644	-0.0018*** [0.0002]	Non-EC	-0.0030*** [0.0007]	Non-EC	-0.0022*** [0.0003]	Non-EC
Welfare & Poverty	439,851	-0.0031*** [0.0004]	Non-EC	-0.0109*** [0.0014]	Non-EC	-0.0010** [0.0004]	Non-EC
Biographies	1,311,337	-0.0024*** [0.0002]	Non-EC	-0.0014* [0.0008]	Non-EC	-0.0027*** [0.0003]	Non-EC

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%; n.s.: not significant.

Table 11: Regressions on the Relationship between Percentage of Republican in the Area and Prior Article Slant

Model	(1)	(2)
Dependent Variable	RepPerc	RepPerc
Prior Article Slant	-0.0009** [0.0004]	-0.0010** [0.0004]
Log(Prior Article Length)		0.0037*** [0.0001]
Log(Prior Refs)		0.0005*** [0.0001]
Observations	2,438,628	2,438,628
Adjusted R-squared	0.000	0.001

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12: Relationship between Contributor Slant and Prior Article Slant, First Edits Only

Models	(1)	(2)
Dependent Variables	Contributor Slant	Contributor Slant
Prior Article Slant	-0.0092***	-0.0218***
	[0.0001]	[0.0004]
Log(Prior Article Length)	0.0007***	0.0011***
	[0.0000]	[0.0001]
Log(Prior Refs)	-0.0004***	-0.0011***
	[0.0000]	[0.0001]
Observations	7,113,130	7,113,130
R-squared	0.007	0.007
Year FE	No	Yes
Article FE	No	Yes
Number of Articles	66,389	66,389

Notes: Robust standard errors in brackets. *significant at 10%; ** significant at 5%; *** significant at 1%. Observations in this panel only include every contributor's first edit of an article.

Figure 1: Distribution of Each Contributor's Total Number of Edits

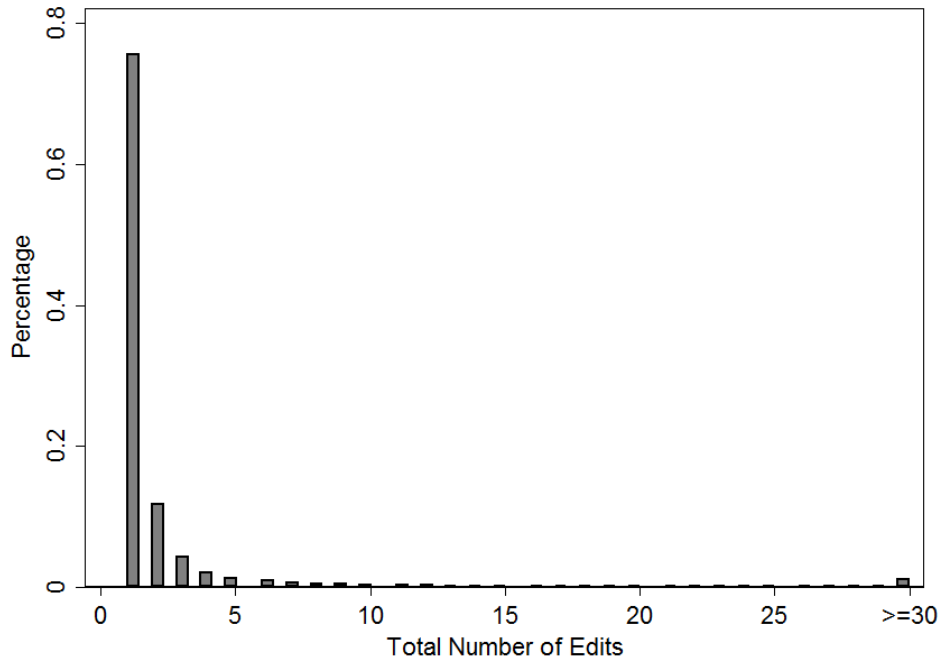

Figure 2: Distribution of All Edits in the Sample by Contributors' Years of Experience

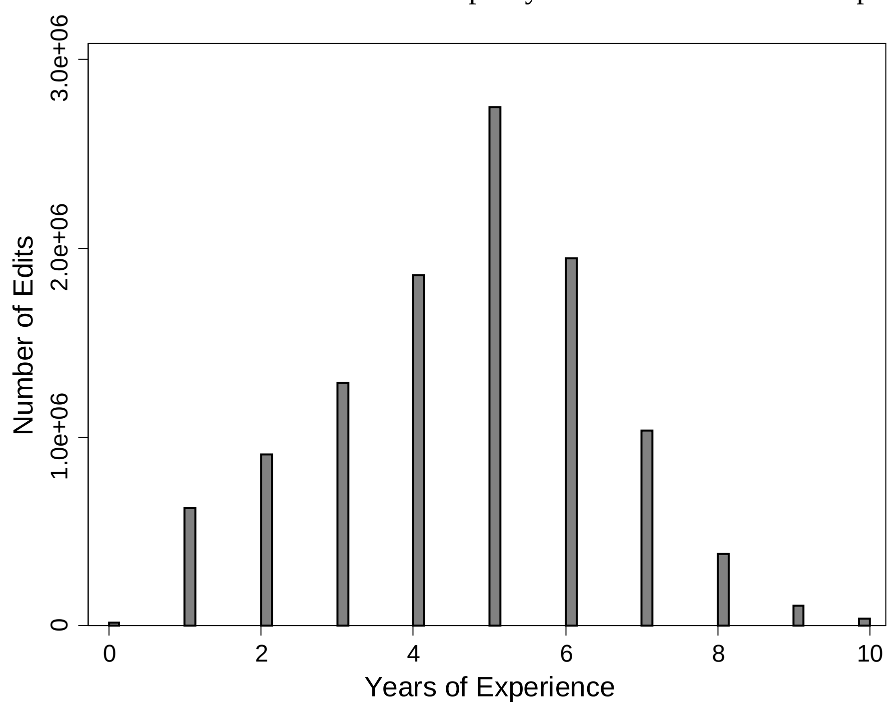

Figure 3: Number of Contributors by Years of Experience

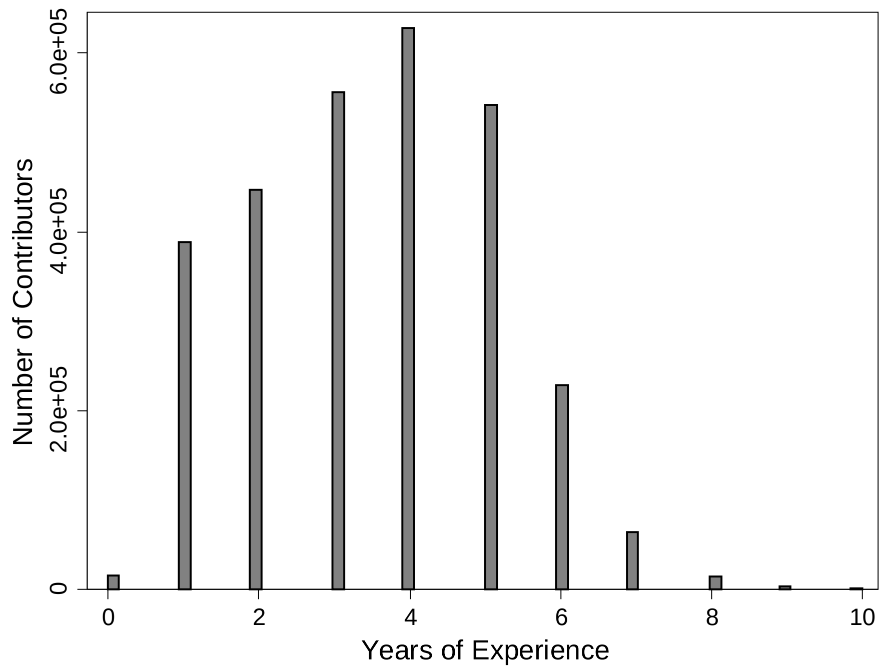

Figure 4: Distribution of Average Number of Edits per Contributor by Years of Experience

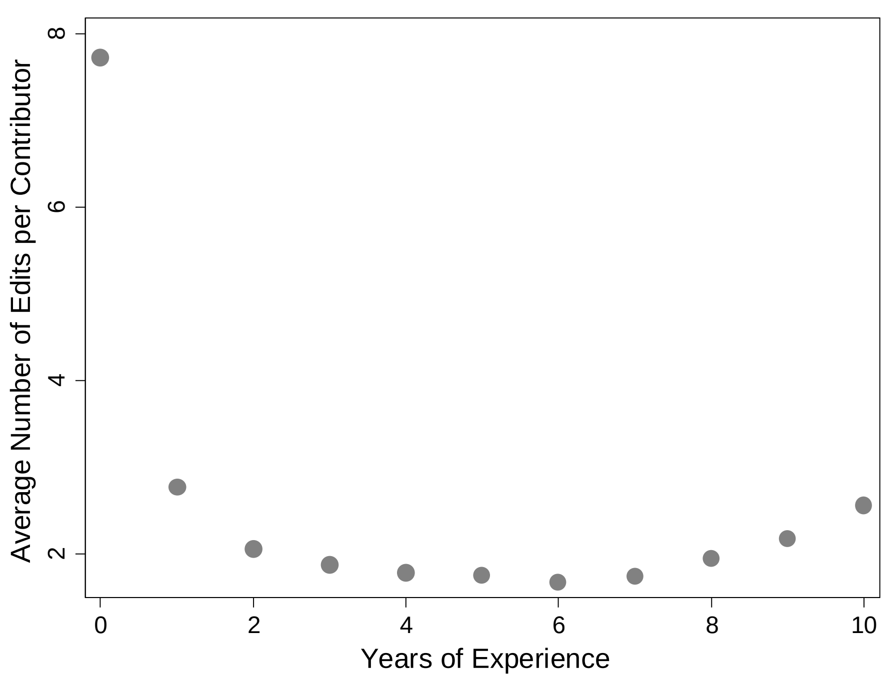

Figure 5: Transition Matrix of Contributor Slant Change in Wikipedia

		First half of activity		
		Democratic Type	Neutral	Republican Type
Second half of activity	Democratic Type	0.1407	0.0328	0.1145
	Neutral	0.7451	0.9333	0.7416
	Republican Type	0.1142	0.0339	0.1439

Notes: The sample is constructed by dividing every contributor's time in half. Then divide the direction of his or her edits, i.e. attach values (-1, 0, 1) to negative, 0, positive slant edits. Sum up the edits' values for the first half and the second half of his or her activity. If the sum of all edits in this half is negative, the contributor is a Democrat Type in this half. If the sum of all edits in this half is zero, the contributor is Neutral in this half. If the sum of all edits in this half is positive, the contributor is Republican Type in this half.

Figure 6: Transition Matrix of Contributor Slant Change over Time

			Start						
			bin1	bin2	bin3	bin4	bin5	bin6	bin7
		Slant Range	[-1.229, -0.059)	[-0.059, -0.035)	[-0.035, -0.012)	[-0.012, 0.012)	[0.012, 0.035)	[0.035, 0.059)	[0.059, 1.000)
End	bin1	[-1.229, -0.059)	0.8298	0.0139	0.0024	0.0011	0.0013	0.0008	0.0015
	bin2	[-0.059, -0.035)	0.0717	0.7242	0.0044	0.0020	0.0103	0.0019	0.0007
	bin3	[-0.035, -0.012)	0.0591	0.1745	0.7438	0.0055	0.0040	0.0149	0.0029
	bin4	[-0.012, 0.012)	0.0323	0.0713	0.2286	0.9795	0.2089	0.0531	0.0277
	bin5	[0.012, 0.035)	0.0036	0.0128	0.0177	0.0060	0.7545	0.1867	0.0624
	bin6	[0.035, 0.059)	0.0008	0.0014	0.0015	0.0033	0.0052	0.7222	0.0757
	bin7	[0.059, 1.000)	0.0028	0.0019	0.0018	0.0025	0.0158	0.0203	0.8291

Note: *Contributor Slant by Year* is split by the ± 0.5, ± 1.5, and ± 2.5 standard deviations intervals. The middle bin represents neutral slant; the first/last bin represents extreme slant.

Figure 7: Vintage Analysis for Contributors Entering in Different Years