1 A Simple Model of Editing Behavior

To support the empirical analysis, we set up a model of editing behavior in this section. The goal of the model is to outline a simple mechanism of user interaction that leads to consecutive edits of different users influencing each other. In particular, it reflects the type of dynamics we aim to capture in the empirical analysis, which is a positive effect of past contributions on current editing behavior. Note that our aim is not to structurally estimate the model; therefore, the model parameters do not directly map into specific coefficients in the regression framework. The primary aim of the model is to structure our thinking around possible threats to identification in a way that complements the (mostly verbal) exposition in the main text.

We consider the behavior of user \( i \) on article \( j \) in time period \( t \). We assume the content in each article can be represented in a vertical quality space as \( x_{jt} \in [0, \bar{j}] \), where \( \bar{j} \) denotes the article-specific maximum attainable quality level. We also assume users are homogenous with respect to their preferences over content; that is, content translates into a quality metric \( x_{jt} \) that does not vary across users (i.e., no \( i \) subscript exists on the quality level).

When a user visits a particular article \( j \) in time period \( t \), he receives the following utility:

\[
 u_{it} = -\alpha_i (x_{it}^s - x_t),
\]

where \( \alpha_i \geq 0 \) captures how strongly the user feels about the content of the specific article and \( x_{it}^s \) denotes the user’s preferred quality level. All variables are article specific, but for ease of exposition, we suppress the \( j \) subscript. We assume \( x_{it}^s \geq x_t \). Either the consumer is able to improve the article by adding content and his optimal quality level thus lies above the current one, or he has nothing to add and \( x_{it}^s = x_t \). We think of \( x_{it}^s \) as reflecting the user’s preferences as well as his ability to actually make quality improving changes to the content. A low value of \( x_{it}^s \) could be due to two reasons: the consumer is either happy with the current quality level or he finds the quality insufficient but is not able to make any improvements based on his own knowledge of the topic. The utility expression \( u_{it} \) above therefore reflects the disutility incurred by the potential editor from being able to improve quality but not doing so. It does not necessarily reflect the utility from content consumption.

To edit the article, the consumer incurs an editing cost \( c_i \). For simplicity, we assume the cost of editing to be independent of the length of the edit. Given this setup, a consumer will optimally decide to edit the article and reposition it to the optimal quality level \( x_{it}^s \) according to his preferences if
$$\alpha_i(x^*_t - x_t) > c_i$$

If the user decides to contribute, the quality level at the beginning of the next time period is altered: \( x_{t+1} = x^*_t \). If the user does not edit the article, \( x_t \) will remain at its current level.

We assume a user’s optimal quality level is determined by the following relationship:

$$x^*_t = (1 + \gamma_i)x_t + \xi_{it},$$

where \( \xi_{it} \geq 0 \) depends on the knowledge regarding relevant content that the user had before accessing the article and observing the already existing content. In case some of this knowledge is not yet incorporated into the article, this leads to \( \xi_{it} > 0 \). In other words, this component captures editing behavior that is triggered by the user’s inherent knowledge level on the respective topic and that is unaffected by the already existing content. \( \gamma_i \geq 0 \) instead captures that, due to heterogeneity in users’ knowledge, the existing content will make areas for further contributions salient to the user visiting the article. We therefore think of the case in which \( \gamma_i > 0 \) not as creating new knowledge, but allowing the consumer to access existing knowledge more easily. \( \gamma_i \) is the key model component that captures the cumulative nature of the editing process, that is, the extent to which existing content triggers further contributions to the same article.

We assume two types of consumers exist:

Type 1: \( \gamma_i = \gamma > 0 \), \( \xi_{it} = 0 \)

Type 2: \( \gamma_i = 0 \), \( \xi_{it} = \bar{\xi} > 0 \)

Type 1 represents a user that draws inspiration from the current content and will augment it purely based on the knowledge already embedded in the current stock of content. We will refer to this type also as “inspired” users. Type 2 represents a user that brings new information to the article but is not influenced by the existing content. Each time period carries a certain probability of a user of each type arriving. We denote the probability of arrival with \( \lambda_1 \) (\( \lambda_2 \)) for users of type 1 (2).

Based on the equations above, we can derive the edit probability in a given time period as

$$Pr(Edit_t = 1) = \lambda_1 Pr(\gamma x_t > \frac{c_i}{\alpha_i}) + \lambda_2 Pr(\bar{\xi} > \frac{c_i}{\alpha_i})$$

$$= \lambda_1 F(\gamma x_t) + \lambda_2 F(\bar{\xi}),$$

where \( F(\cdot) \) denotes the CDF of \( \frac{\xi}{\alpha} \), the editing cost relative to preferences for the topic, in the user pool. The expression above decomposes the likelihood of an edit into a separate term for each type of user. For each type, the edit probability is equal to the arrival probability
(λ₁ and λ₂) times the probability of editing conditional on arrival. The latter is equal to \( F(\bar{\xi}) \) for type-2 users and independent of current content. For type-1 users instead, the current content level \( x_t \) increases the edit probability. Our main focus in this paper is on estimating the magnitude of the effect of current content on editing behavior, here represented by \( \lambda_1 \frac{\partial F}{\partial x_t} \).

We note that the model entirely ignores social interactions between users and assumes random arrival from a pool of anonymous users. Past contributions influence current editing behavior only through providing inspiration to some subset of arriving users. However, many papers on user interaction on Wikipedia document social interaction between users. For instance, some users explicitly collaborate on an article by coordinating their editing activity. In our model, such dynamics could be captured by an edit increasing the likelihood of a knowledgeable user arriving in the next time period. That is, in the presence of social interactions between users, individual edits can trigger edits by collaborating users in subsequent time periods, which would lead to very similar dynamics in editing behavior and also a positive effect of past contributions on current editing activity. For the sake of simplicity, the version of the model outlined above does not feature such a channel.

**Differences in Article Popularity**

To relate the model to the empirical exercise in a simple way, we assume a uniform distribution for \( F(\cdot) \), which simplifies that edit-probability expression to

\[
Pr(Edit_{jt} = 1) = \lambda_1 \gamma x_{jt} + \lambda_2 j \bar{\xi},
\]

Note that we now reintroduce the so far suppressed article subscript \( j \). One way to think about a regression analog to this expression is a linear probability model based on the relationship above:

\[
Edit_{jt} = \lambda_1 \gamma x_{jt} + \lambda_2 j \bar{\xi} + \varepsilon_{jt},
\]

where \( Edit_{jt} \in \{0, 1\} \) is an indicator for whether an edit happened on article \( j \) in time period (week) \( t \). \( \varepsilon_{jt} \) is the econometric error term, which captures the specific realization of \( \frac{\alpha_i}{\alpha_j} \), which leads to an edit occurring (or not) in any given time period. It reflects the random nature of what type of user (in term of his preferences \( \alpha_i \) and editing costs \( c_i \)) arrives on the article.

To correctly identify the effect of \( x_{jt} \) on the edit probability we need to control for the second term, which drives editing activity in the absence of the inspiration effect. More specifically, if the arrival probability \( \lambda_2 j \) is higher on longer articles, \( x_{jt} \) is correlated with the regression error term if we do not control for article fixed effects. One possible channel for such a correlation to occur is through popularity differences across articles. If more popular articles see more edits and are longer, the implication is that a positive correlation exists between \( x_{jt} \) and \( \lambda_2 j \). To address this issue, we include article fixed effects that control for
across-article differences in $\lambda_{2j}$.

**Platform-level Growth**

Next, we consider the relationship described in the previous section, except we allow the arrival rate of knowledgable users to vary over time (but for the moment not across articles):

$$Edit_{jt} = \lambda_1 \gamma x_{jt} + \lambda_2 \xi + \epsilon_{jt}.$$ 

A similar logic highlights the threat to identification here: if article length $x_{jt}$ is higher in time periods with a higher arrival rate $\lambda_{2t}$, we find (in the absence of time period fixed effects) a correlation of $x_{jt}$ with the error term. Such a correlation is likely due to the general growth trend on the platform as a whole. Articles tend to be longer later in their life, and activity is also higher in later years because of the increase in popularity of Wikipedia. For this reason, we include a full set of week fixed effects.

**Identification with Two-Way Fixed Effects**

Whether we are able to recover the causal effect of article length on editing activity depends critically on our ability to control for differences in user arrival rates across both articles and time. Differences in article popularity as well as an increase in the general user pool over time make arrival rates likely to differ over time and across articles. More generally, we can decompose the article- and time-period-specific arrival rate ($\lambda_{2jt}$) as

$$\lambda_{2jt} = \tilde{\lambda}_{2j} + \tilde{\lambda}_{2t} + \tilde{\lambda}_{2jt},$$

which we can plug into the edit regression above:

$$Edit_{jt} = \lambda_1 \gamma x_{jt} + (\tilde{\lambda}_{2j} + \tilde{\lambda}_{2t} + \tilde{\lambda}_{2jt}) \xi + \epsilon_{jt}.$$ 

The inclusion of article and week fixed effects allows us to control for arrival-rate differences across article ($\tilde{\lambda}_{2j}$) and over time ($\tilde{\lambda}_{2t}$). The key identifying assumption is that any factor that might affect both arrival rates and article length doesn’t vary differentially over time across articles. In other words, article length is uncorrelated with article-specific changes in arrival rates over time: $\text{Corr}(x_{jt}, \tilde{\lambda}_{2jt}) = 0$. Our main robustness checks are all centered around investigating the validity of this assumption.
2 The Evolution of Editing Behavior by User Type

The analysis in this section is an extension of section (5) of the main paper, which describes how edit length per user as well as other aspects of editing behavior change with article length. Table (1) reports all the results described in this section. The top panel replicates Table (5) of the main paper for easier reference, and the middle and bottom panel provide additional regression results.

The Effect of Article Length by Users Type

To dig deeper into the nature of edits being triggered by article-length increases, we analyze the extent to which the triggered edits originate from new users versus users that previously edited the same article. To implement this analysis, we define an edit as belonging to a returning user if an edit was made previously on the same article using the same username. We group the remainder of edits into edits by new users with a registered user account and new users that are only identified by their IP address. The latter case occurs when users make an edit without registering for a user account.

We note that this categorization is not entirely without problems. First, IP address identification is imprecise. For instance, the same user could log on from different computers and therefore have different IP addresses associated with his edits. Second, IP addresses can change over time for the same device. We might therefore miss some returning users that appear under different IP addresses in our data. Our sense is that frequent contributors do usually have a user account, so this issue might not be severe. However, nothing in the data allows us to directly back up this assertion. Third, even a user with a Wikipedia user account could in principle change his username and thus appear as a new user in our data although he previously made edits on the same article. Both issues would lead us to identify a smaller number of returning users than actually exist. We discuss below how this issue affects the interpretation of our results.

We assess the effect on edits by user type in two ways. First, we separately regress the weekly number of each user type on article length and the usual set of controls in columns (1) to (3) of the middle panel in Table (1). Doing so, we find an effect of 0.098 of article length on the number of users with an IP address, as well as an effect of 0.058 and 0.048 on the number of new and returning users, respectively. All effects are statistically significant. Relative to the effect on the total number of users of 0.203, this split implies that about 50% of the triggered edits originate from users with only an IP address. About 25% of edits originate from each of the other two groups. Although this finding illuminates which types of users are making edits when article length increases, it does not describe whether the proportion of user types is systematically different on articles of different length. To shed light on this aspect, we regress the fraction of users of each type on article length (plus controls) separately in columns (4) to (6) of the middle panel. The results of those regressions show article length does not affect the fraction of users with an IP address, but an almost one-to-one substitution

\[1\] We find very few repeat edits from the same IP address on the same article, and therefore do not treat this type of edit as a separate category. Instead, we include those edits in the returning-user category.
exists between new and returning users, with a larger share of edits by returning users on longer articles. We find 10,000 additional characters of article length increase the share of returning users by 1.6 percentage points. Relative to an average share of returning users of 25% and an increase in the share of about 10 percentage points between 2002 and 2009, this effect is relatively modest.

Changes in the Type of Edits by User Type

In a next step, we explore the effect of article length on the type of edits being made separately for each user type. The results in the top panel of Table (1) show that article length does not influence edit distance per user and has only a small effect on the extent of content addition/deletion and the share of reverted edits. As we show in this section, these small and insignificant effects for the average user mask some interesting compositional changes. We find that different types of users change aspects of their editing behavior in opposite directions as article length increases. To analyze the effect of article length by user type, we use the fraction of users of each type (for each article-week) as computed in the previous section and interact the fractions for all three types with article length\(^2\). This approach allows us to trace out how different dimensions of editing behavior change with article length depending on what type of user is making the edit. The regressions, results from which are reported in the bottom panel, mirror the ones in the top panel and decompose the average effects in the top panel by user type.

In terms of edit distance per user, we find this metric increases for returning users but decreases for the other two types. None of the three terms is significantly different from zero. However, the coefficients for IP and new users are both significantly different from the effect on returning users at the 1% and 5% level, respectively. The results are slightly stronger when we use the capped edit-distance measure in column (2). The negative effects for IP address and new users are significantly different from zero now, and the difference relative to returning users is more pronounced. This pattern suggests some reallocation of activity toward returning users on longer articles. Similarly, when decomposing the effect on the addition/deletion metric, we find some interesting differences across types. Here we find that the increase in content deletion relative to content addition originates from new and returning users, but behavior of IP-address users is unchanged. Finally, we find a strong rise in reverted edits for IP-address users solely drives the increase in reverted edits, whereas we actually see a slight decline for the other two types. The increase in edits being reverted for IP-address users is fairly substantial and constitutes about 25% of the standard deviation of the variable.

Overall, the results from these regressions show that the amount of editing activity as well as the impact on article content shifts toward returning users as articles grow. As we saw in the previous subsection, a slight increase occurs in the fraction of returning users. Furthermore, returning users make longer edits and their edits are less likely to be reverted as article length increases. Finally, returning users are more likely than other users to delete content.

\(^2\)When using all three interactions, we cannot include article length on its own as well, because the fractions for all three types add up to one.
on longer articles. Although the effects are not statistically and/or economically strong along all of those dimensions, the results do indicate a stronger influence on content creation by established users on longer articles, which is consistent with the notion of Wikipedia becoming increasingly hostile toward new users, as posited by ?. Also note that because assigning users to the different types is imperfect, we are likely to have included some returning users incorrectly in the other two categories, in which case, we might be underestimating the shift in activity toward returning users.
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tr>
<td>Dependent Variable</td>
<td>Number of IP Users</td>
<td>Number of New Users</td>
<td>Number of Returning Users</td>
<td>Fraction of Edits by IP Users</td>
<td>Fraction of Edits by New Users</td>
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<td>Fraction of Reverted Edits</td>
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Table 1: **Change in Editing Behavior as a Function of Article Length.** The unit of observation is a week-article pair. Standard errors are clustered at the article level. The dependent variable is defined only for article-week combinations with at least one edit in all regressions (except for the first three columns in the middle panel, which are based on the full sample). The number of observations is accordingly smaller than in our baseline regression.