Website Changes and User Behavior: Using Panjiva Data to Examine Code Changes

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Abstract

Most software developers implicitly believe that change tends to improve a website. However, the story seems far more complicated. This paper examines how code changes affect user behavior on the internet by analyzing a particular website, `http://www.panjiva.com` and its database of activity logs. The paper identifies some factors which affect how code changes influence user activity levels and finds patterns in how users respond to change. Users tend to increase their repeat usage when code changes are of high quality. Users respond more negatively to changes in areas of the website they already frequent than to changes in areas that they do not know as well. A massive volume of code change, in general, does not necessarily lead to higher user activity on a website and in fact may negatively impact the user experience.

Contents

1 Introduction

Silicon Valley has historically been built on constant change. Indeed, one of the tenets of technology companies and web-based startups is the idea of change. For example, Facebook's official motto is "Move fast and break things." However, few people have examined the effects of website and product changes on user activity and a number of questions still inger. For instance, do users tend to respond favorably to website changes? Moreover, how do users react to different types of changes? Can different characteristics of users change how users respond to certain changes?

All of these questions are crucial and allow developers to create better websites and tools for their users. This paper examines the effects of code changes on user activity. In particular, the paper focuses on the short term effects of everyday changes to a website. The paper exploits a unique dataset and examines how short-term user activity (both overall on the entire website and on a more granular, per-user level) are affected by code changes. The unique dataset comes from Panjiva, Inc., which provided the author access to its entire database.

2 Dataset Explanation

The proprietary dataset used in this paper comes from the back-end databases collected by Panjiva, Inc. Panjiva's website `http://www.panjiva.com` acts as a medium for buyers and suppliers of manufactured goods. The site provides a communication platform so that bulk buyers of a particular good can search and obtain unbiased information on factories and suppliers of that good. These two parties can then communicate and send messages over Panjiva's interface, attempting to strike a deal.

Panjiva's competitive advantage rests in its ability to parse government import and export data in order to obtain unbiased information about suppliers. Panjiva determines a supplier reliability score and also provides recent history of a supplier's shipments, and allows buyers to search and aggregate this information easily. Most firms that use Panjiva are large to medium size buyers of components. For example, a department store would use Panjiva to search for suppliers of shirts or clothing, or a home improvement store would search for suppliers of socket wrenches. In addition, Panjiva provides data on trends in global manufacturing and shipping by leveraging the government data it already mines for individual supplier information.

The dataset used in this paper comes from the event and activity logs of Panjiva's website. Each time a user performs some significant event or activity on the Panjiva website, an entry will be created in either the event or activity log. If the user has a registered account with Panjiva, the action will be recorded in the activity logs. All activities, regardless of whether a user has an account, are recorded in the event logs. All nontrivial features of the website, including supplier search, U.S. import and export search, and profiles views, are accounted for and stored in a SQL database.

The data in the event and activity logs are organized so that one can trace the exact user or subscribed account for which the entry corresponds to. In particular, the logs contain information on the ip address of the user, the time the activity was performed, the webpage the activity occurred on, and extra data depending on the type of activity performed.

The enormous quantity and granularity of this data enable the analysis of user-level interactions. The event logs contain about 124 million entries while the activity logs contain about 13 million entries. Moreover, the data in each of these logs extends for multiple years, allowing one to analyze the growth of Panjiva as a company and the effect of different changes to the website.

2.1 Summary Statistics

Summary statistics providing an overview of Panjiva's business and website are provided in table 1. Panjiva was incorporated in 2008 and has since developed a customer base composed mostly of buyers of manufactured goods. The website provides free services (a limited number of searches) for free users, and provides many more services to subscribers (there are multiple levels of subscription).[1]

Table 1: Panjiva Overview

Total Registered Users	121,653
Subscribing Users	2,985
Monthly Site Visits	903,426
Monthly Unique Visitors	762,723
Average Pages per Visit	1.99
Average Visit Duration	1 min 18 sec

"Commits" can be thought of as changes to the code. In each commit, a software developer will introduce new code or delete old code which will then be launched to the production website. Typically a single developer at Panjiva will commit a couple of times throughout the workday. Figure 1 shows a histogram of the number of commits throughout a 52 week period ending on 11/24/2012. Commit activity varies depending on the season and the week. In particular, commits during the summer spike upwards and there will be one or two weeks each quarter when commits fall to low levels. The second phenomenon is due to the fact that Panjiva holds a quarterly retreat where engineers reflect upon the work done over the quarter. Typically the amount of code written decreases during these weeks.

Figure 1: 52-Week Commit Activity

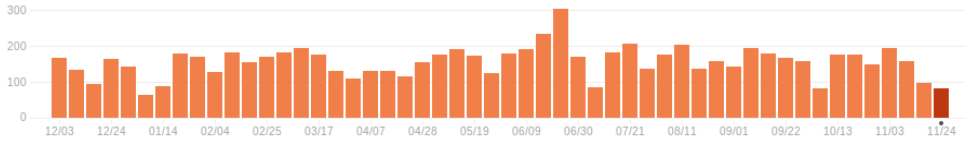


Table 2 shows statistics on a snapshot of the commit repository made on 11/25/2012. The table shows an enormous number of changes throughout the history of the website.

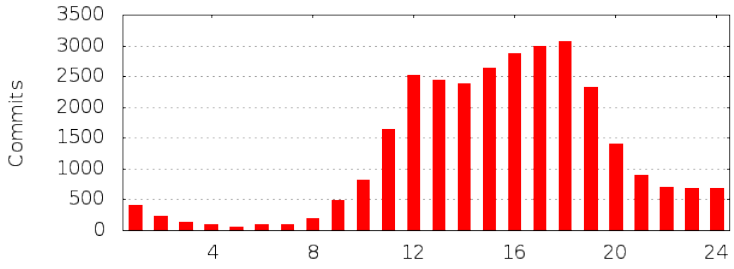
Table 2: Overall Commit Statistics - 11/25/2012

Active Days (at least 1 commit)	1,983
Total Current Files	20,901
Total Lines of Code	1,313,235
Total Lines of Code Added	3,989,295
Total Lines of Code Removed	2,676,060
Total Commits	29,924
Total Authors/Developers	33

Examining commits in more detail, one can see that the majority of commits occur during working hours (from 11am to 6pm EST). Moreover, each day is fairly regular in the number of commits that occur. Commits are at a high level throughout the work day, and fall off to a low, relatively constant level throughout the night. Figure 2 shows the times of day during which commits happen the most frequently.

[1]Note that although there exists data for multiple years, due to time constraints, this paper only examines data in the range from 7/24/2011 to 11/25/2012. The summary statistics, however, provide data for all years of operation.

Figure 2: Commit Frequency by Time of Day



Finally, note that almost no commits occur on weekends. Only 5% of the commits happen on either Saturday or Sunday.

3 Macro-Level Results

This section examines how code changes affect the total amount of user activity across the entire website (macro-level effects). In particular, this section analyzes the change in a number of metrics of user activity controlling for the amount of code changed in a particular day. The regression specification used will be as follows:

$$y_{t+x} - y_t = c_0 + \bar{\gamma}^T \bar{M}_t + \bar{\beta}^T \bar{\chi}_t + \epsilon_t \tag{1}$$

Where t indexes day, y_t corresponds to some metric of total user activity occuring only on day t (*activitylog_count* or *eventlog_count* are examples of y_t), $\bar{M}_t$ corresponds to a vector of covariates that represent changes in the code, $\bar{\chi}_t$ is a vector of controls, and ϵ_t is an error term. We will use a number of different metrics for user activity and the specification will be run with each of them.[2] The x term is the number of days ahead for which the difference in user activity is taken. For the regression in table 3, $x = 5$ so that the dependent variable represents the change in user activity over 5 days.

3.1 Daily Effects of Code Changes

Table 3 displays the results from using the total action count, total distinct user count, and average actions per user as metrics for user activity. The regressions in table 3 attempt to find the effect of different changes in the code base on different measures of user activity. A commit can be measured by the number of files it changes, or the number of lines of code it changes. Changes in lines of code can be either insertions or deletions. Each of these measures is percentilized (see the data appendix for details). The regressions below are performed on aggregated statistics per day, with a dummy variable equal to 1 on the weekends and 0 otherwise.

The table shows the effect of commits on same day user activity. In general, changes to the code have minor and insignificant effects on metrics derived from the event logs. There are only significant effects for the *eventlog_count*. However, code changes have a stronger effect on metrics derived from the activity logs. Notice that for *activitylog_count*, the *insertions_percentile* variable is significant.

Using the *avg_user_activity* variable as the regressor, one can get a better idea at the per user changes associated with code changes. It seems that deletions significantly increase

[2]See the data appendix for the definition of the variables used in the macro-level dataset.

Table 3: Effect of Commits on User Activity

	(1) activitylog_count	(2) eventlog_count	(3) actionlog distinct_user_count	(4) eventlog distinct_user_count	(5) avg_user_activity	(6) avg_user_events
	Note: All dependent variables are 5 day differences ($y_{t+5} - y_t$)					
fileschanged_percentile	-1139.3	16056.9	-375.8	-511.2	-8.922	-69.79
	(-0.34)	(0.43)	(-0.43)	(-0.63)	(-1.85)	(-0.56)
insertions_percentile	-6333.7*	-59671.7*	-663.8	-346.9	4.644	19.89
	(-2.37)	(-2.02)	(-0.95)	(-0.54)	(1.20)	(0.20)
deletions_percentile	1416.0	-11747.8	-361.8	-190.4	10.53**	94.35
	(0.56)	(-0.42)	(-0.55)	(-0.31)	(2.91)	(1.01)
weekend	16314.2***	82665.9***	560.6*	392.5	2.637	-333.7***
	(15.76)	(7.22)	(2.06)	(1.57)	(1.77)	(-8.62)
_cons	-1658.0	4165.8	533.6	403.9	-3.673*	72.05
	(-1.59)	(0.36)	(1.95)	(1.61)	(-2.45)	(1.85)
N	469	470	469	470	469	470

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table provides regression estimates of how different measures of user actions vary with changes in the codebase. The table was created by aggregated data from the Panjiva activity and event logs over the period from 7/14/2011 to 11/24/2012. There is a single observation per day.

The *activitylog_count* and *eventlog_count* variables aggregate the total number of records seen per day in the activity and event logs respectively, while *activitylog_distinct_user_count* and *eventlog_distinct_user_count* aggregate the number of distinct users that have performed an action in either the activity or event logs respectively. Finally, *avg_user_activity* and *avg_user_events* divide the total number of records by the total number of distinct users per day to arrive at an average number of actions per day.

The *weekend* dummy variable is equal to 1 if the day is a Saturday or Sunday and 0 otherwise. The other covariates are percentilized by sorting and taking the rank (see data appendix). Files changed, insertions, and deletions are obtained from commit history and are aggregated over each day. Insertions and deletions are the total number of lines of code inserted or deleted, respectively.

average user activity. The magnitude of this change (a difference of 10.5 actions per user when moving up a percentile) is incredibly high when noting that thoughout the dataset the average user activity was 30 actions per user, with a range between 2 and 79. The coefficient is statistically significant to the 0.01 level, which provides evidence that this effect is strong and not engendered by chance.

Increasing the number of insertions tends to decrease user activity while increasing the number of deletions tends to increase user activity. Although this result seems perplexing, there are a number of possible explanations. First, it is possible that the commits which delete lines tend to be higher quality commits (fixing old old). If a commit increases the lines of code, there is a higher likelihood that this commit would introduce a bug or contain low quality changes.

Another, though possibly less satisfying explanation, is that code changes hurt average user activity in general. Since average user activity provides a measure of the organic growth of the website, it may be a better measure for the effects of code changes. Note that increasing total user count could result from a large number of new distinct user performing one or two actions each on the website. Although this could be construed as an increase in activity, each user could leave quickly, which would negatively affect long term traffic. Thus, one can think of the negative coefficient on the fileschangedpercentile variable as decreasing the long-term user activity with more code changes.

However, the second explanation seems unlikely because of the fact that code changes are constantly occurring. The regression is measuring the marginal effect of commits. Each additional insertion could provide a negative effect due to diminishing returns. Thus, one could have a negative coefficient on *insertions_percentile* even when increasing the *lineschanged_percentile* at very low levels would increase user activity.

Also, notice that commits have no significant effect on the total number of distinct users. This is unsurprising since it is likely that it takes a significant period of time to increase the number of distinct users. Changes to the website will probably not spill over to other users during short time spans (like a day). Users do not have the time yet to share their new experiences on the site, so each user can be thought of as independent of others during these short time periods. Therefore, it is unsurprising that code changes fail to increase the total number of distinct users on the website.

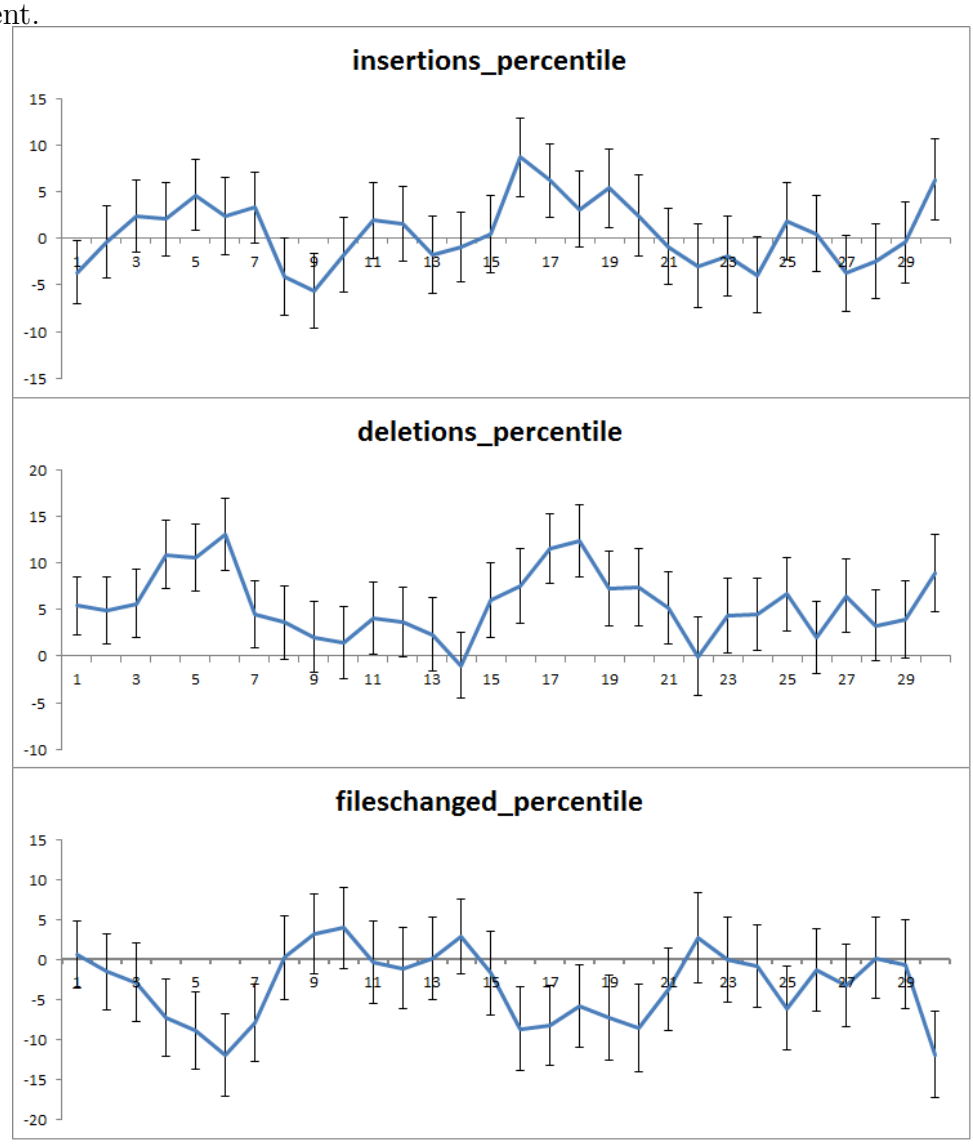
3.2 Lagged Effects of Code Changes

It is instructive to examine the results of the above regression for difference time lags. For instance, what if one accounts for the changes induced by commits over a single day, or possible over a month? In this section, results are presented for the above regression specification with lags of $x \in [1, 30]$. The plots in figure 3 provide the coefficients on $fileschanged\_percentile$, *insertions_percentile*, and *deletions_percentile* for lags x ranging from 1 to 30 days. The x-axis represents the lag and the y-axis plots the coefficient of the regression. The error bars present standard errors.

The results from the previous section seem to be reinforced by these plots. In particular, *deletions_percentile* has a positive and statistically significant coefficient for the majority of different time lags. Moreover, it never has a negative coefficient for any time lag. This is informative, and shows that in fact, there are strong and lasting increases in user activity associated with deletions in code. The effects seem to be strongest 2-5 days after a commit, although they do again increase 15-20 days after the commit.

The magnitude of the effect of deletions is large. Since average user activity per day over the entire dataset is about 30, coefficients ranging between 5 and 15 represent a nontrivial amount of change. Moving a percentile in the number of deletions will increase average user activity

Figure 3: Coefficients with Varying Lags. The lags $x \in [1, 30]$ are given on the x-axis while coefficients from the macro-level regression specification are plotted on the y-axis. An x day lag corresponds to using $y_{t+x} - y_t$ as the dependent variable in the specification, where y is *avg_user_activities*. For example, the coefficient on *fileschanged_percentile* for a lag of $x = 5$ would be found in the last graph at the point where $x = 5$. Error bars give the standard errors of each coefficient.



by about 20-50% depending on the time lag used. Note, however, that an entire percentile is non-trivial and represents moving from the lowest number of deletions to the highest number of deletions in a day in the period from 7/14/2011 to 11/25/2012. Nevertheless, the strong and significant coefficients across time provide evidence that code deletions strongly increase average user activity.

The coefficient on *insertions_percentile* has much more variance and is infrequently statistically significant. The coefficient is significant and negative as often as it is significant and positive, and there seems to be little pattern to its up and down jumps. Although one could attempt to attribute the patterns seen in the second graph of figure 3 to different short-term and medium term effects, these hypotheses would have no support without further analysis.

The coefficient on *fileschanged_percentile* tends to be negative. In fact, it is never pos-

itive and significant, but there are numerous time lags (between 3-7 and 15-21 days of lag) for which it is negative and statistically significant. Notice that the time lags of statistical significance correspond almost exactly to the time lags when *deletions_percentile* are statistically significant. This could imply that these are time time lags for which commits have the most effect. It also provides evidence that the results for both $fileschanged\_percentile$ and *deletions_percentile* during these periods are not flukes. The negativity of the coefficient on $fileschanged\_percentile$ could imply that commits which changed fewer files tend to increase user activity. One hypothesis, mentioned in the previous section, would be that commits touching fewer files tend to be higher quality commits since presumably the developer spent more time editing only a single file. The other possibility is that commits with a large number of files are large changes to the code-base which will tend to have more bugs simply because of how large the feature is.

These findings seems to imply that removing code tends to be better than adding code. Although this hypothesis was reached on macro-level data, it is still an interesting idea. Perhaps removing code is correlated with making better code, and inserting new code usually happens with a new, possibly buggy feature being added. If this is the case, then it seems that users respond better to clean, non-buggy code. To investigate this further, regressions are performed on a more granular level.

4 Micro-Level Results

Although the macro-level regressions provided some insight into how code changes affect user activity, they really could not provide anything more than correlations. Complex factors could have been governing the relationship between code changes and user activity, and only weekend dummies were included in the regressions. Thus, the macro-level results must be taken with a grain of salt since the correlations observed could be brought through completely different mechanisms than the ones suggested.

However, the micro-level dataset can be much more powerful in its results. The dataset used in this section exclusively uses the activity logs, and exploits the fact that each recorded activity comes with a unique user identification tag and timestamp. Therefore, it is possible to know exactly when a user was visiting a given page.

Even better, most of the code changes made throughout the day can be thought of as exogeneous shocks. This arises from the fact that almost none of the releases made by developers are announced to the user base beforehand. Even if the changes are announced, few users would be notified and aware of the change because Panjiva typically advertises such changes through its blog. Less than 1% of Panjiva's total pageviews come from its blog, so it is safe to assume that most users are unaware of any planned changes to the website. Since these code changes can be thought of as exogeneous with a high degree of accuracy, one can develop an empirical approach that examines the shock induced by each code change.

4.1 Search Controller

The search page has always been Panjiva's most trafficked page. Possibly due to this, it has received a number of code changes, both in terms of back-end structure and also in terms of the user interface. There is, correspondingly a large amount of variation in the number of lines of code changed and the times at which code was changed on the search page. To exploit this variation, this section will examine user activity before and after a code change.

In particular, this section limits the activity log dataset to only users who have seen the search page both two days before and after a particular change. Thus, for each code change in the search page, the users that had recently seen the unchanged page and also the changed

page were examined. Any users seeing the search page over two days before the change were dropped, as were users who saw the search page over two days after the change. User activity was measured with the *num_views_day_later* variable. For a particular user page view, the *num_views_day_later* variable is equal to the number of views by that user of that particular page in the 24 hours after the original view.[3]

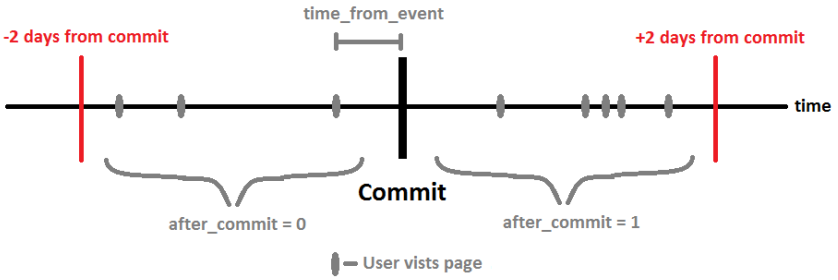
Since the dataset was confined to only users who saw both the original website and the changed website, one can take the difference between the number of views before and after the change as the effect of the change (assuming that commits are exogeneous). Another refinement made to the dataset is that only commits to the search controller were examined.[4] This choice was made because a significant portion of the user interface code is antiquated and left in the code-base. Therefore, large changes to the user interface code could spuriously affect parts of the code that no longer are seen on the production website.

The time period from 7/14/2011 until 11/25/2012 was examined (to confine the dataset to more recent changes). A total of 294 changes occurred during this time, ranging from small one line changes to larger changes in hundreds or thousands of lines. The following regression specification was used:

$$num\_views\_day\_later_{it} = c_0 + \beta_0 \mu_{it} + \beta_1 hour\_dummies_{it} + \epsilon_{it} \tag{2}$$

Where i indexes the commit and t indexes the distinct views of any user seeing the commit. Here μ_{it} is either a dummy variable $after\_commit$ which is equal to 1 if the view of the search page occurred after the commit and 0 otherwsie, or it is equal to $time\_from\_event$ which is the number of seconds since the commit. Therefore, if a view of the search controller occured at time T_1 and the commit occurred at time T_2, then $time\_from\_event = T_1 - T_2$.

Figure 4: Regression Specification for Micro-Level Analysis



To understand the above specification, a diagram is provided in figure 4. Each grey dot represents a page view by user j. The regression takes all of the grey dots surrounding a given commit (for all users) and uses *num_views_day_later* as the dependent variable. This is done for all commits on a particular page.

There are about 2.3 million observations in this refined dataset and table 4 shows the regression results of the specification defined above. The table shows that actions recorded after the commit occurs have a significantly higher number of views. Moreover, the positive coefficient on the $time\_from\_event$ variable shows that as one gets further away from the commit time, the number of views of the search page increases. Thus, the number of views that occur after the commit is greater than the number of views before the commit (since

[3]See the data appendix for more explanation.

[4]A controller in a Model-View-Controller web framework is typically the piece of the code that manages the data and sends it along to the user interface. For Panjiva, almost all of the heavy-lifting is done in the controller (this includes data processing and the search algorithm itself).

Table 4: Search Controller Micro-Level Results

	Dependent Variable: num_views_day_later			
	(1)	(2)	(3)	(4)
after_commit	5.541***		3.378***	
	(17.91)		(11.20)	
time_from_event		0.0000737***		0.000110***
		(43.76)		(66.60)
created_at_hour dummies?	No	No	Yes	Yes
_cons	156.9***	159.9***	138.3***	139.7***
	(731.32)	(1033.47)	(127.71)	(130.50)
N	2345617	2345617	2345617	2345617

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Regression using micro-level dataset. Confined only to users who saw the search page both before commit i and after commit i inside of a 4 day window surrounding the time of the commit. The *num_views_day_later* variable contains the number of views of the search page for each user one day after the record was created. Commits are confined only to changes in the search controller.

$time\_from\_event$ is negative before a commit and positive afterwards). The coefficients on $after\_commit$ and $time\_from\_event$ are strongly statistically significant (much higher than normal levels), which suggests that commits have a large positive effect on user actiivty.

The statistical significance remains even when hour dummies are included (a set of 24 dummy variables where $created\_at\_hour\_i = 1$ if the activity record was created in the ith hour of the day and 0 otherwise). This provides strong evidence that code changes in the search controller significantly affect user behavior. Since commits are most likely exogeneous, user activity seems to increase significantly due to the changes in the search controller.

4.2 Insertions and Deletions

However, it is still unclear from these regressions why user activity increases. To examine this in more detail, a regression with the following specification was conducted:

$$\begin{aligned} num\_views\_day\_later_{it} &= \beta_0 after\_commit_{it} + \beta_1 insertions\_percentile_{it} \\ &+ \beta_2 deletions\_percentile_{it} \\ &+ \beta_3 insertions\_percentile_{it} * after\_commit_{it} \\ &+ \beta_4 deletions\_percentile_{it} * after\_commit_{it} \\ &+ \beta_5 hour\_dummies_{it} + c_0 + \epsilon_{it} \end{aligned} \tag{3}$$

Here, the specification uses interaction terms between the $after\_commit$ dummy variable and the insertion and deletion percentile variables. Using the interaction coefficients, one can determine the additive effect of insertion an extra line of code on the change in the number of views after the commit. Looking on the β_3 and β_4 coefficients in the above specification will tell one how much additive effect on the number of views there is when a commit increases the insertion or deletion percentile (respectively) by 1 after a commit. In essence, it measures the effect of inserting or deleting lines of code on how users will respond to a change.

Table 5 displays the results of the above specification with and without the hour dummies, and also with different sets of controllers. The regressions in columns 1 and 2 of table 5 use observations confined to users who saw changes in the search controller. Columns 3 and 4 use the same specification, but include observations from seven other controllers as well. These controllers are the communication, customs, my_panjiva, profile, project, us_exports, and us_imports controllers. Each of these controllers corresponds to a different landing page on the Panjiva website.

Including all of the controllers almost doubles the number of observations available to 3.8 million. However, the results with different controllers mirror the results found just in the search controller. In particular, the interaction term coefficients (β_3 and β_4 from the specification) tend to be similar across all the regressions. More insertions in the codebase increase the positive effect of a code change on user activity. One sees that β_3, which corresponds to the coefficient on the interaction between an increase in the *insertions_percentile* and the $after\_commit$ variable, is large, positive, and highly statistically significant.

This implies that insertions in the code tend to increase the number of views a user will have on a particular page p of the site, with respect to how much that user viewed p before the code change. Deletions in the code tend to have the opposite effect, though this seems to depend on the controller affect. Although the negativitiy of β_4 is highly statistically significant on only the search controller, it loses its significance once all controllers are included in the regression in columns 3 and 4. However, one can say that deletions in the code, at least in the search controller, have a significant negative effect on the number of pages a user will view in the future.

4.3 Differential Controller Effects

One might also want to examine how users change their behaviors depending on the controller for which a change is made. Perhaps users react differently to changes in different controllers. For example, the search controller is the most heavily used and is the controller that is most frequently a "return controller" (a page that a user will repeatedly visit). However, other controllers tend to be visited less often and tend not to be repeatedly visited. One would expect that changes in different types of controllers would have different affects on user activity on those controllers.

Thus, the following regression specification was used to determine the effects of each controller:

$$\begin{aligned} num\_views\_day\_later_{it} &= \beta_0 after\_commit_{it} + \bar{\beta}_1 \overline{controllers}_{it} \\ &+ \bar{\beta}_2 \overline{controllers}_{it}^{T} \times \overline{after\_commit}_{it} \\ &+ \beta_3 hour\_dummies_{it} + \epsilon_{it} \end{aligned} \tag{4}$$

Where $\overline{controllers}$ is a vector of dummies of possible controllers. For example, if the current observation corresponds to an activity on the search controller then $\overline{controllers}_{search} = 1$ while $\overline{controllers}_j = 0$ for all $j \neq search$. However, there is no coefficient in this regression that guages the impact of controller k on the user activity after a commit. Notice that before a commit, after_commit = 0 and the interaction terms for the $\bar{\beta}_2$ coefficient are all zero. However, one controller dummy variable, namely the controller dummy corresponding to the kth controller is equal to 1. After the commit on controller k, the after_commit variable will be equal to 1, as will the interaction term corresponding to controller k. Thus, in order to find the difference between these two effects, one needs to take $\beta_{2k} + \beta_{1k} + \beta_0 - \beta_{1k} = \beta_{2k} + \beta_0$.

Thus, to find the difference in the number of views due to a code change in controller k, one has to examine the sum $\Gamma_k = \beta_{2k} + \beta_0$. Note that for significance testing, one uses the

Table 5: Types of Commits and User Responses to Code Changes

	(1) num_views_day_later	(2) num_views_day_later	(3) num_views_day_later	(4) num_views_day_later
after_commit	-10.86***	-13.79***	-325.5***	-305.9***
	(-16.90)	(-22.03)	(-154.63)	(-149.28)
insertions_percentile	-50.97***	-50.76***	-650.6***	-609.5***
	(-54.12)	(-55.34)	(-218.09)	(-209.88)
deletions_percentile	66.31***	63.35***	251.5***	230.8***
	(70.67)	(69.34)	(84.73)	(79.94)
insertions_percentile * after_commit	57.00***	58.05***	393.0***	365.1***
	(41.21)	(43.09)	(89.07)	(85.01)
deletions_percentile * after_commit	-24.16***	-23.64***	2.306	3.295
	(-17.65)	(-17.74)	(0.53)	(0.77)
created_at_hour dummies?	No	Yes	No	Yes
Controllers Used	Search	Search	All	All
_cons	150.1***	133.2***	606.5***	491.0***
	(336.67)	(116.37)	(420.98)	(130.17)
N	2345617	2345617	3858943	3858943

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Set of regressions which examine the effect of insertions and deletions in the code on the number of views that a user will have on page p in the one day time span after viewing page p. The $after\_commit$ variable is equal to if the current observation occurs after the commit that it corresponds to. All observations are within a four day window of the commit (2 days before and 2 days after) and contain only users who have seen page p both before the commit and after the commit.

The variables *insertions_percentile* and *deletions_percentile* are calculated as the percentile rank of the number of insertions and deletions for the current commit, respectively. The *created_at_hour* dummies correspond to dummies equaling 1 if the hour is equal to i and 0 otherwise for $i \in [1, 24]$.

The dataset is either confined to the search controller, or uses all the controllers in the following list: communication, customs, my_panjiva, profile, project, us_exports, and us_imports controller.

null hypothesis $H_0 : \beta_{2k} + \beta_0 = 0$, and standard errors can be calculated with the formula:

$$SE_{sum} = \sqrt{SE^2_{controller_{2k}} + SE^2_{after\_commit} + 2Cov(controller_{2k}, after\_commit)} \quad (5)$$

These differential controller effects Γ_k are given in table 6. It is clear that each controller has a different effect. In particular, one can see why the effects for all the controllers in table 5 differ from the effects found for just the search controller in table 4. Both the My_Panjiva controllers and the Project controllers have negative and significant Γ coefficients.

Table 6: Differential Controller Effects on After Commit User Activity

	(1)	(2)
	No Hour Controls	With Hour Controls
Communication	-2.673	5.111
	(-0.50)	(0.98)
My_Panjiva	-41.718*	-54.530***
	(-1.98)	(-2.68)
Profile	-8.167	-6.339
	(-1.30)	(-1.04)
Project	-410.438***	-388.496***
	(-235.55)	(-228.27)
Search	5.541***	1.516
	(4.37)	(1.23)
US_Exports	10.318	-28.946
	(0.28)	(-0.80)
US_Imports	-12.487	-8.73
	(-0.82)	(-0.59)
N	3858943	3858943

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Examining the differential effects, one can see that there is no significant effect to user behavior when there are changes in most of the controllers. There is a significant and negative effect for the My_Panjiva and Project controllers, and a positive effect for the Search controller. Moreover, the magnitude of the coefficients differ greatly accross controllers. The magnitude of the Project controller's Γ is much larger than the Γ for the search controller.

Therefore, it seems that there is significant variation in user responses across different controller types. Interestingly, the My_Panjiva and Project controllers do not tend to be repeatedly used, unlike the Search controller which has many repeat views. One hypothesis could be that code changes have a positive effect on user activity only on pages which users repeatedly use. However, one could also notice that controllers with more repeated views are more likely in general to have a higher number of views on any given day. Thus, the difference in the number of views after a commit could be due solely to the fact that a viewer visits a certain page more often.

Thus, to determine the effect of commits on controllers with different frequencies of use, one must include another variable that controls for how often a controller is usually viewed. A new variable, *num_controller_views* will be created for each observation. The variable will be equal to the total number of times the current user views the current controller (minus the

num_views_day_later variable so as to not introduce explicit multicollinearity).[5]

The new regression specification will now contain the *num_controller_views* variable and also an interaction term between *num_controller_views* and $after\_commit$ to see how the number of controller views affects the success of a commit. Results are shown in table 7.

Table 7: Controller Popularity Effects

	(1) num_views_day_later	(2) num_views_day_later
after_commit	-13.79***	-9.618***
	(-9.02)	(-6.40)
insertions_percentile	-108.8***	-104.9***
	(-52.39)	(-51.40)
deletions_percentile	-5.528**	-6.231**
	(-2.70)	(-3.10)
insertions_percentile * after_commit	63.96***	54.02***
	(20.91)	(17.96)
deletions_percentile * after_commit	67.98***	67.61***
	(22.53)	(22.79)
num_controller_views	0.0475***	0.0469***
	(1780.26)	(1751.65)
num_controller_views * after_commit	-0.0138***	-0.0134***
	(-333.01)	(-328.18)
Hour Dummies?	No	Yes
_cons	-47.43***	-69.41***
	(-44.85)	(-26.29)
N	3858943	3858943

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From the table, one can see that both insertions and deletions increase the effectiveness of a commit (their interaction term coefficients with $after\_commit$ are positive and statistically significant). This falls in line with previous results from the micro-level dataset. Interestingly, controllers with higher number of views tend to respond poorly to commits, ceteris paribus.

The coefficient on the $num\_controller\_views * after\_commit$ interaction term provides the change in slope after the commit. Past regression specifications did not account for the fact that already popular pages would have more views after a commit simply because of its past popularity. This specification, however, examines how commits change the number of views depending on the previous popularity of a page.

The negative and significant interaction term coefficient implies that in fact, controlling for previous popularity, controllers which already have a high number of views tend to be adversely affected by commits. This might occur because users require adjustment time, especially for pages that they use frequently. Another explanation is that changes to infrequently used pages tend to increase user behavior more than changes to frequently used pages since users have less familiarity with the workflows of the former.

One must take these results with caution however, since multicollinearity could be lurking. Its possible that the number of controller views is correlated with the number of views the day after an observation, even though explicit dependency has been removed. Thus, further research needs to be done in order to support this hypothesis fully.

[5]See data appendix for a more thorough explanation.

5 Conclusion

This paper examined the effect of code changes on user activity. Total user activity tended to decrease when the total number of code insertions increased. However, both total and average user activity tended to increase with more deletions. This phenomenon most likely occurs because of the high volume of code changes on Panjiva's website. Thus, it seems likely that users respond positively to higher quality code, or alternatively, that users respond negatively to low quality code.

Exploiting the granularity of Panjiva's dataset, the paper found that code changes on particular website pages, such as the Search page, resulted in a higher number of repeat views. The micro-level dataset also reinforced the hypothesis that user activity tends to increase with an increase in the number of lines of code, ceteris paribus. Finally, the paper found that code changes tended to have negative affects on popular pages, possibly because of the time required to adjust to these changes.

Code changes seem to have an ambiguous effect on user activity in general. They can be successful only with a confluence of factors. In particular, high quality changes tend to have a better chance of positively influencing users. Also, changes to highly trafficked pages can have negative effects on user behavior. Thus, it seems that change by itself does not tend to be a good strategy in general. Changes need to be targetted and of high quality in order for them to be successful.

A Data Appendix

The original event and activity log datasets are tables in a PostgreSQL database. Panjiva uses a Ruby on Rails framework for its entire website, and stores ruby objects in the PostgreSql database. The activity and event logs each contain certain attributes that can be queried for. The attributes are listed below:

Table 8: Activity Log Attributes

Attribute Name	Attribute Type	Comment
id	*integer*	Unique id for each record
user_account_id	*integer*	Id of the associated user account
controller	*string*(255)	Controller viewed
action	*string*(255)	Specific action of the controller viewed
model_id	*integer*	Id of the database model
status	*string*(255)	Status of completion of request
created_at	*datetime*	Time the record was created
ip_address	*string*	
session_id	*integer*	Id of the browser session

The event log attributes are very similar except there is less informative data. In particular, the event logs do not have data on the controller or actions viewed by a given user. Note that activity logs only record actions performed by users who have registered with Panjiva and have sigend into the website. Event logs tracks actions performed both both registered users and by those who have not logged in. Consequently, the event log is much larger, but has less informative data.

The event logs contain about 124 million records, while the action logs contain 13 million records. The data in the PostgreSql database was parsed into macro level and micro level datasets.

A.1 Macro-Level Dataset

The macro-level dataset contains aggregated count statistics for each active day after 7/14/2011. The dataset was created by making a SQL query to find the total count of actions on the event and activity logs, as well as the total distinct users. This populated the *activitylog_count*, *activitylog_distinct_user_count*, *eventlog_count*, and *eventlog_distinct_user_count* variables (since these were broken down by day, the *date* and ay_of_week variables were also created).

To get information about commits, such as the insertions, deletions, and files changed for a given day, the version control system used by Panjiva was mined. Panjiva uses git and Github to store and track changes in its source code. In order to find the total number of lines and files changed in a given day, the master git repository (the version of the code which is public and launched to production) was programmatically scraped for information. Note that the variable *lineschanged* counts every line that was changed, whether an insertion or deletion, and is simply equal to $insertions + deletions$. The variable $fileschanged$ is the number of distinct files for which at least one line was inserted or deleted.

The percentile variables were created by sorting the base variable and dividing the index by the number of days. For example, if the number of lines changed was $[10, 5, 2, 3, 12]$ for days 0 through 4 respectively, then the list would first be sorted to $[2, 3, 5, 10, 12]$ and the day corresponding to two lines changed would have a percentile of $0/5 = 0$, while the day corresponding to three would have a percentile of $1/5 = 0.2$. This would continue upwards until the last day with a percentile of $4/5 = 0.8$. Thus, the percentiles for days 0 through 4 would be $[3/5, 2/5, 0/5, 1/5, 4/5]$.

Table 9: Variables used in the Macro-Level Dataset

Attribute Name	Attribute Type	Comment
date	*date*	Date of the record
day_of_week	*integer*	Sunday = 0 and Saturday = 6
lineschanged	*integer*	Total number of lines changed
fileschanged	*integer*	Total number of files chanegd
insertions	*integer*	Number of lines changed that were insertions
deletions	*integer*	Number of lines changed that were deletions
fileschanged_percentile	*float*	See description below
insertions_percentile	*float*	See description below
deletions_percentile	*float*	See description below
activitylog_count	*integer*	Count of all activity log actions in the current day
eventlog_count	*integer*	Count of all event log actions in the current day
activitylog_distinct_user_count	*integer*	Number of distinct users that appeared in the activity logs in the current day
eventlog_distinct_user_count	*integer*	Number of distinct users that appeared in the event logs in the current day
avg_user_activities	*float*	Average number of actions per distinct user in the activity logs
avg_user_events	*float*	Average number of actions per distinct user in the event logs

The percentile variables are simply the ranked percentile of a given observation in comparison to the entire distribution. In essence, one can think of the percentile transformation as mapping an arbitrary distribution to a uniform distribution. The transformation was done for fileschanged, deletions, and insertions.

A.2 Micro-Level Dataset

The micro-level dataset was obtained in a similar manner, however, much more attention was paid to each commit. First, the git repository was searched for all commits in the period from 7/14/2011 until 11/26/2012 concerning a given page of the site. Each of these commits had a timestamp, the exact lines of code changed, and the author of the change. For each commit, the timestamp was examined, and the activity logs were searched for all actions that occurred within two days of the commit's timestamp (a four day window corresponding to two days before and two days after) and occurred on a page changed by the commit. For each of these observations, the number of total views of the page in the twenty four hours following the observation's date were recorded in *num_views_day_later*. Dummies for the controller were created for each observation. A dummy $after\_commit$ was also created for observations that occurred after a commit (1 if after and 0 otherwise.

For each commit, the number of files changed, insertions, and deletions was also calculated (and percentilized by the method used above). The final list of variables for the micro-level dataset is given below:

The total number of controller views was also calculated for each user and incorporated into the dataset in the form of the *num_controller_views* varaible. The variable contains a count of the total number of times a user performed an action in the given controller across the time period from 7/14/2011 to 11/25/2012 (corrected for *num_views_day_later*).

For instance, suppose user i viewed the search controller page 53 times between 7/14/2011 and 11/25/2012. Say that for some commit occurring on 10/1/2012, he had 5 views of the search controlling in the two days preceding the commit and 10 views in the two days after the commit. Each of these views would be instantiated as an observation in the micro-level

Table 10: Variables used in the Micro-Level Dataset

Attribute Name	Attribute Type	Comment
user_account_id	*long*	ID of the user which performed the action
controller	*string*	Controller on which the action occurred (later processed into individual dummy variables)
created_at	*datetime*	Time and date at which the action was performed
session_id	*long*	ID which identifies the browser session of the user
time_from_event	*float*	Seconds elapsed between the commit and the action (negative when action occurred before the commit)
num_controller_views	*integer*	Total number of times the current user viewed the controller all the logs
after_commit	*boolean*	Dummy variable equal to 1 if action occured after the commit and 0 otherwise
num_views_day_later	*integer*	Number of views of the controller in the day after the action
commit_date	*datetime*	Date at which the commit occurred
fileschanged	*integer*	Total number of files chanegd
insertions	*integer*	Number of lines changed that were insertions
deletions	*integer*	Number of lines changed that were deletions
fileschanged_percentile	*float*	See description below
insertions_percentile	*float*	See description below
deletions_percentile	*float*	See description below

regression, where $num\_controller\_views = 53 - num\_views\_day\_later$. Note that the subtraction occurs so that multi-collinearity is not introduced into the regression. The variable *num_views_day_later* is calculated as the total number of views in the 24 hours after each of the 15 views that user i has had on the search controller.