Do Small Code Changes Merge Faster?
A Multi-Language Empirical Investigation

Gunnar Kudrjavets
University of Groningen
Groningen, Netherlands
g.kudrjavets@rug.nl

Nachiappan Nagappan
Meta Platforms, Inc.
Menlo Park, CA, USA
nnachi@fb.com

Ayushi Rastogi
University of Groningen
Groningen, Netherlands
a.rastogi@rug.nl

1 INTRODUCTION

Continuous deployment is a software development methodology that deploys a continuous stream of software updates into the production environment [63, 65]. For engineers working in fast-paced environments, continuous deployment and particularly the speed at which code changes are integrated into the production environment (also referred to as code velocity) are essential [21]. In these environments, since code changes constantly flow to the main branch from multiple sources, frequently fetching from and pushing changes to the main branch prevents merge conflicts and ensures timely deployment. The practice has widespread adoption across high-profile internet and social media companies like Amazon, Facebook, Google, Netflix, and Twitter.

Studies show many factors influence code velocity [9, 12, 32, 37, 39, 55, 64, 77, 78, 80], often referred to and measured as time-to-accept and/or time-to-merge. These include code characteristics (e.g., code churn [37, 77, 78]), project characteristics (e.g., age [77, 78] and the number of open pull requests [77, 78]), and human and social factors (e.g., contributor affiliation [8, 9, 37, 55, 64] and strength of social connection [77, 78]). Notably, only a few of these factors can be controlled by a pull request author to increase code velocity.

Our goal is to explore the practicality of improving code velocity by exploring solutions within the direct control of an engineer. For example, engineers can control the size of a proposed code change but not their reputation. This study investigates two such factors that can be adapted to increase code velocity: pull request size and composition. To investigate whether pull request size and composition can be meaningfully changed to increase code velocity (using time-to-merge as its proxy), we ask three research questions:

RQ1: What characterizes pull request size, composition, and time-to-merge?

The objective of the first research question is to give insights into the characteristics and distribution of the data. This understanding is crucial to identify the scope for improvements (e.g., the extent to which time-to-merge can be decreased) and offer a preliminary understanding (e.g., degree of variability in pull request size) for deeper investigations later.

RQ2: What is the relationship of pull request size and composition to time-to-merge?

The following two questions explore direct (RQ2) and mediated (RQ3) relationships of pull request size and composition to time-to-merge for improving code velocity.
**RQ3:** Does context influence the relationship of pull request size and composition to time-to-merge?

Note that a pull request author cannot control contextual factors in itself; however, they can influence pull request size and composition, potentially influencing the ways to increase code velocity.

We collected information on 100 GitHub repositories: 10 most popular repositories each from the 10 most popular programming languages on GitHub. We report descriptive statistics answering RQ1 and the correlation of pull request size and composition to the time-to-merge (in RQ2) in the presence of confounding factors (RQ3). We confirm our findings by replicating our analysis on smaller datasets from code review platforms Gerrit and Phabricator.

We found that pull request size and its composition do not influence time-to-merge, regardless of the day of the week the pull request is created, programming language, and organizational affiliation. There are no patterns even though:

- code velocity is not the same for industry and non-industry repositories; repositories affiliated with industry have larger pull request sizes, but lower time-to-merge compared to non-industry repositories; and
- expressiveness of programming language influences both pull request size and time-to-merge.

Challenging popular beliefs, our study suggests that neither time-to-accept nor time-to-merge decreases with reduced pull request size or the composition of code changes. Splitting pull requests into smaller and isolated chunks may help with increasing the chances of acceptance [75] or make code changes “reviewable” [59], but it does not decrease the overall time it takes to review or merge them. Likewise, we do not observe that certain types of code changes merge faster than others.

## 2 BACKGROUND AND RELATED WORK

### 2.1 Introduction to Modern Code Review

Most present-day software development organizations and open-source software (OSS) projects have embraced a process known as Modern Code Review (MCR) [64]. The MCR process starts with an engineer proposing a set of changes (insertions, deletions, and modifications) to a source code and submitting the collection of code changes for review. Depending on the organization and context, the collection of code modifications is referred to as “change”, “changelist”, “diff”, “patch” or a “pull request”. For example, Facebook uses “diff”, GitHub uses “pull requests”, Google uses “changelist”, and most of the OSS projects use the term “patch”. Given that the data analysis in this paper is mainly based on GitHub, we use the term pull request. After the changes are submitted for review, the author and reviewer(s) discuss the proposed changes. Code review discussion may result in no critique of the original pull request, changes being outright rejected, or some amount of code churn. Every revision to the pull request will cause the review process to be repeated until a conclusion is achieved. If the changes are approved, the engineer can then propagate the changes to the destination branch, provided the changes pass the required automated validation tests.

A variety of tools are used to conduct MCR. This paper mainly uses the data mined from GitHub and compares our findings with the code review data fetched from Gerrit and Phabricator [23, 53].

Gerrit and Phabricator expose timestamps which enable us to determine when code reviews are approved (accepted). GitHub only added the functionality to explicitly approve changes in 2016, and none of the projects we mined in this study use it consistently [24]. Another conceptual difference between the tools listed above is their default approach to merging approved changes. The policy for Gerrit is to start the merging process automatically. For both GitHub and Phabricator, manual action is required.

### 2.2 Code velocity

Studies show that a wide range of factors influences a pull request’s time-to-merge [9, 12, 32, 37, 39, 55, 64, 77, 78, 80]. These include personal characteristics of the author (e.g., affiliation), project characteristics (e.g., project age), and pull request characteristics (e.g., code churn). See Table 1 for a complete list of factors found to influence the time-to-merge of projects hosted on GitHub [79]. We, on the contrary, explore solution space to increase code velocity by manipulating controllable factors to reduce time-to-merge.

To decrease time-to-merge, one should be able to control and/or manipulate some or all of these factors. By control, we mean something that an engineer proposing the change can influence in a reasonable amount of time. Unfortunately, out of the 29 factors listed in Table 1, only 8 can be controlled by an engineer in a non-trivial manner.

The ability to control or change a characteristic in a reasonable amount of time is important for several reasons. First, a study of five OSS projects reported that more than 80% of developers are newcomers or leavers [22]. This implies that most contributors may not have the time, interest, or ability to become a core member and/or increase their social strength—factors important for improving time-to-merge. Second, factors such as reputation may be within an engineer’s control but take months or years to change. Reputational factors are practically infeasible to optimize for a given pull request. Third, most other remaining factors cannot be controlled by an individual at all. For example, project-related factor, such as the number of open pull requests, depends on various circumstances that an individual cannot easily influence.

Table 1 classifies each factor influencing time-to-merge according to our assessment of controllability. These factors are taken from [31, 79]. Table 1 shows that no known author and project characteristics influencing time-to-merge can be controlled. Some of the factors that can be controlled relate to the size and composition of a pull request (see Section 3.3). Obviously, attributes such as description of code changes can be optimized for grammatical errors and relevance to a change, but the semantic value of these concepts are hard to quantify. We expect that the same factors will also influence code reviews performed using either Gerrit or Phabricator because these code reviewing platforms are semantically similar.

### 2.3 Code size

A study focusing on the Mozilla project finds that developers feel that the size-related factors are the most important for code review time and decision [36]. Another study based on interviews with 10 participants (8 from industry and 2 from OSS community with a median experience of 9.5 years) finds that the smaller the change, the more reviewable it is, but the precise sizes for categories such
Table 1: Factors influencing pull request (PR) time-to-merge.

| Entity | Factor                                      | Controllable |
|--------|---------------------------------------------|--------------|
| Author | Contributor affiliation [37, 55]            | No           |
|        | Core member [12, 39, 77, 78]                | No           |
|        | First pull request [39]                    | No           |
|        | First response time [77, 78]               | No           |
|        | Followers [77, 78]                         | No           |
|        | Integrator affiliation [9, 64]              | No           |
|        | Prev pull requests [37]                    | No           |
|        | Social strength [77, 78]                   | No           |
| Project| Integrator availability [77, 78]            | No           |
|        | Open pull request count [77, 78]            | No           |
|        | Project age [77, 78]                       | No           |
|        | Requester success rate [77]                | No           |
|        | team_size [77, 78]                         | No           |
| PR     | Continuous integration exists [32, 80]      | No           |
|        | Continuous integration latency [77, 78]     | No           |
|        | Continuous integration test passed [77, 78] | No           |
|        | Commits on files touched [77, 78]          | No           |
|        | Friday effect [77, 78]                     | No           |
|        | Number of comments [77, 78]                | No           |
|        | Number of participants [37]                | No           |
|        | Participants in PR/commit comments [37]    | No           |
|        | Test inclusion [78]                        | Yes          |
|        | At tag [77, 78]                            | Yes          |
|        | Hash tag [77, 78]                          | Yes          |
|        | Churn addition [9, 77, 78]                 | Yes          |
|        | Churn deletion [9, 77, 78]                 | Yes          |
|        | Source code churn [37]                     | Yes          |
|        | Number of commits [77, 78, 80]             | Yes          |
|        | Description length [77, 78]                | Yes          |

as extra small, small, medium and large are unknown [59]. In the same study, one of the interviewees states that “for a change to be reviewable it must be at most 250 lines long”.

A study on GitHub finds that pull requests with small commit sizes were more likely to be accepted [73]. However, a large patch size by itself was not a reason for rejecting the code changes. A study examining the patch history of Eclipse and Mozilla found that only 0.3% of the rejections were attributed to the patch size being too large [71]. The need for the patches to be small and concise is affirmed by the study with participants stating that “large patch sets are difficult to review and require a lot of time to read, thus this may delay the acceptance of the patches” and “having small patches is very important for making it easier to revert them” [52].

2.3.1 No consistent relations. The relationship between the speed of patch acceptance and size is not uniformly established. In one of the earliest attempts to investigate the relationship between the patch size and its acceptance speed, the authors found that smaller patches (defined as 15 lines or less for FLAC and 24 lines or less for OpenAFS) have a higher chance of acceptance than average. However, they could not conclusively state that the patch size significantly influenced the acceptance time [75]. Another study researching the patch acceptance in Linux kernel found a link between patch size and time to review the changes, but not the patch integration time [34].

A study on GitHub concludes that “the size of a pull request matters: the shorter it is, the faster it will be reviewed” [77]. A more detailed version of the same study by a subset of the original authors states that “the more succinct a pull-request is, the faster it will be reviewed” [78]. For clarity, we need to point out that though the term “reviewed” is used, the authors of the study use the terms “pull request latency” and “review latency” synonymously. However, those two terms mark different states in a pull request life cycle. Pull request latency is the difference between the pull request closing and creation times. The proposed code changes are considered to be reviewed when another engineer either formally or informally approves the changes or requests additional changes that must be implemented before the pull request can be merged. Changes being reviewed do not mean that a pull request has been merged or closed.

Another study focusing on a single GitHub project (Shopify’s Active Merchant) shows that the size of a pull request had a statistically significant effect on review time [37]. The study consisted of a dataset of 1,475 pull requests. Another study of 97,403 pull requests from 30 projects suggests a relationship between the number of source lines of code (SLOC) modified and pull request lifetime but concludes that there are no means to establish that an increase in SLOC implies a longer pull request lifetime [46].

2.3.2 Size-related recommendations. Reflecting on the assumption that size matters to MCR, industry and OSS projects recommend that pull request size be “small”. The guidance, however, is general and vague. Projects suggest isolated changes of reasonable size. Popular OSS projects such as (i) Linux directs contributors to “Separate each logical change into a separate patch” and suggests that “It cannot be bigger than 100 lines . . .” [40, 41], (ii) LLVM recommends that the patch should be “an isolated change” [42], (iii) Chromium contribution guidelines say that “Patches should be a reasonable size to review” [14], and (iv) PostgreSQL patch submission guidance suggests “Start with submitting a patch that is small and uncontroversial” [56].

What exactly is a small size to submit for a pull request? Challenging the perceptions of developers, a study shows that what engineers think about the size of commits differs from reality by more than an order of magnitude [60]. Even if we consider small as a recommended size, the suggested range differs depending on the source. A study on commits in GNU Compiler Collection codebase classifies the changes based on SLOC into the following categories: (i) extra-small (0–5), (ii) small (6–46), (iii) medium (47–106), (iv) large (107–166), and (v) extra-large (167–203,359) [3].

Guidelines from industry, while also emphasizing small and incremental changes, are likewise vague. (i) Google engineering practices suggest that 100 lines are a reasonable size, and 1,000 lines are considered too large [28], (ii) Phabricator, the code review platform utilized at Facebook, uses “Each commit should be as small as possible, but no smaller” as guidance [54], and (iii) Microsoft’s recommended practices state that “Authors should aim for small, incremental changes that are easier to understand” [43].
2.3.3 Empirical data on code review size. A study on code review practices at Google reported that the median number of lines modified is 24 [64]. At Facebook, each deployed software update (code change reviewed, committed, and then deployed to production) is on average 92 lines [63]. Another investigation covering both industrial and OSS projects found that the median change size for Android and AMD is 44 lines; Apache is 25 lines; Linux is 32 lines; and Chrome is 78 lines [61]. However, the same study also found that for Lucent, the change size was an order of magnitude bigger, with the median being 263 lines. A study exploring the review-then-commit type of changes reported median churn between 11 and 32 lines [62]. One of the first studies that investigated the relationship between patch size and its acceptance time in two OSS projects (FLAC and OpenAFS) noted that for FLAC more than half of the submitted patches change one or two lines of code; for OpenAFS, one-third of the patches change at most two lines [75]. Finally, analysis of many GitHub repositories shows that the median number of lines changed by pull requests is 20 [30].

**Observation 1.** Both industrial and OSS projects recommend "small" or "reasonable" sizes for pull requests, but the guidance is vague. Empirical data shows that actual median code change size differs by orders of magnitude across projects in practice. The lack of concrete guidance may be a driving factor for the wide variance.

2.4 Code composition

When referring to code change size, most studies define code churn as the sum of added and deleted lines [8, 34, 59, 75, 77, 78]. Only two studies classify code changes in detail. One study uses the term change to describe technical contributions with no specific definition [73]. Another study investigating the characteristics of commit sizes separates change types into add, modify, and delete [3].

Most of the data gathered in the above studies are produced by the various diff analysis tools or fetched from GitHub. GitHub uses the output of the `git diff` command (addition and deletion) as one of the attributes describing a pull request. Unfortunately, using only insertions and deletions to estimate the code churn results in an erroneous estimate of the amount of code changed because moves and updates are not accounted for [15].

3 STUDY DESIGN

3.1 Choice of data

We sought data from GitHub repositories that are popular, actively developed, and cover a wide range of programming languages. Our dataset is available here\(^1\) for replication. In the final version, we will also share the scripts, which as of now, contain personally identifiable information.

By analyzing the most popular and actively developed repositories we gain many benefits: (i) a larger dataset populated by a continuous flow of incoming pull requests by a variety of contributors, (ii) a larger number of core developers with permission to approve merges (thus eliminating artificial bottlenecks in the pull request review process), and (iii) an accurate representation of the dynamics of collaboration on GitHub among a diverse set of individuals.

\(^1\)https://figshare.com/s/37af0f90bd2a15f1762

To obtain GitHub data, we considered the following approaches: (i) GHTorrent dataset and tool suite [29], (ii) GH Archive [4], and (iii) GitHub API [25]. We chose the GitHub API to fetch up-to-date information about the state of GitHub directly. GitHub API exposes a set of functionality that enables callers to query and search public repositories and fetch various entities associated with them (e.g., commits, pull requests, and users). The other methods provide only historical snapshots. Utilizing the GitHub API gave us the most flexibility in determining how and what data to collect.

A collection of code review data from various Gerrit projects is available for researchers [76]. The dataset is in the form of a MySQL database and as of July 2nd of 2021, it contains code review data about Eclipse, GerritHub, LibreOffice, and OpenStack. Several major OSS projects also use Phabricator to perform code reviews. We utilize Phabric to mine the publicly accessible code review data for Blender, FreeBSD, LLVM, and Mozilla [15, 16].

3.2 Selection and elimination criteria

To note popularity, GitHub uses the concept of stars. This idea is similar to likes used in social media networks like Facebook, Instagram, and Twitter. Another paradigm used is forks, which allows a user to create their own copy of a repository without affecting the original repository. Forks, stars, and the number of pull requests in a particular repository have all been used as criteria for selecting GitHub projects [11, 32, 46].

Existing studies investigating factors that impact the popularity of GitHub repositories have found a strong positive correlation between stars and forks, making both suitable proxies to measure popularity [11, 51]. Stars, however, have multiple uses in GitHub: as bookmarks, as a way to show appreciation to repository contributors for their work, and as a way to improve GitHub recommendations for similar projects. Contrastingly, when a developer forks their copy of a repository, this act signifies an intent to modify the original code. We find the number of forks as a better selection criterion for active development in a particular repository.

We used GitHub’s report ranking the 10 most popular programming languages for October 2019 through September 2020 [27] to select programming languages. The top 10 languages were: C, C++, C#, Java, JavaScript, PHP, Python, Ruby, Shell, and TypeScript. Our collection covers object-oriented, procedural, and scripting languages.

3.3 Choice of metrics

3.3.1 Code size. The code size is expressed as the number of commits, files, or SLOC included in a pull request. We choose to quantify the size in SLOC because it is a metric easily comprehended, has support in the Gerrit, GitHub, and Phabricator infrastructure, and is already used as a primary numeric value to guide the size of code contributions for various projects [28, 40, 59].

3.3.2 Code composition. We added modified lines as a separate category from insertions and deletions to improve the granularity with which code churn is measured. Modifications are conceptually different from insertions and deletions. With the current metric, one modification is erroneously reported as one insertion and one deletion (e.g., a trivial example of removing an extra semicolon from the end of the line). We believe that differentiating the types
of code changes will enable greater insight into how different types of code changes impact time-to-merge. To analyze code changes in each pull request and extract the number of modifications of each type, we use the diffstat tool.

Below is an example showing the difference between the two approaches for a minor bug fix from the OpenSSL codebase [50]. See code Listing 1.

**Listing 1: Sample OpenSSL code snippet.**

diff --git a/crypto/evp/m_sigver.c b/crypto/evp/m_sigver.c
index bdcac9078..57 c8ce78a 100644
--- a/crypto/evp/m_sigver.c
+++ b/crypto/evp/m_sigver.c
@@ -60,7 +60,7 @@

When using:

git show 5bb888e931b64a132a --shortstat
the result is

1 file changed, 1 insertion(+), 1 deletion(-)

as opposed to the output from diffstat -Cm

1 file changed, 1 modification(!)

The difference in estimating the total changes, even for a trivial example above, is two times. This describes and quantifies the intent behind the choice of code composition metric with greater accuracy. Still, we cannot distinguish actions such as moving chunks of source code from one location to another. This paper uses insertions, deletions, and modifications only.

### 3.3.3 Code velocity

Modern code review systems (such as CodeFlow, Critique, Gerrit, and Phabricator) typically track the amount of time it takes for code changes to be accepted or signed off (i.e., someone other than the author formally decides that the proposed changes can be merged either in their original form or with some modifications). We refer to that point in time as the time-to-accept. However, for our study, we believe that a more relevant metric is the time it takes for code changes to deploy. Code changes are not “real” until they have been merged into a destination branch. The change will be available for building, profiling, testing, and execution in the production or test environments only after it has been merged into the main branch.

We use the term time-to-merge to indicate “...the time since the proposal of a change (…) to the merging in the codebase ...” [33]. Terms like “pull request latency” and “pull request lifetime” have been used synonymously to describe the same concept. However, we will use the term “time-to-merge” as we believe it precisely conveys our intent.

Other reasons justifying our focus on time-to-merge instead of time-to-accept are: (i) even after the formal acceptance of code changes, a non-trivial amount of time may be spent on getting the changes ready to be merged (e.g., applying the code review feedback, resolving merge conflicts, rejecting some of the initial validation, and investigating test case failures in an extended test suite which were not executed during early validation.), (ii) only a few projects on GitHub formally track when the proposed changes were accepted, leaving us, therefore, with a limited dataset for analysis, and (iii) industry experience indicates that time-to-merge is a critical factor to measure. A study about Xen Project’s (hypervisor software) code review experience states that “Xen agreed that [time-to-merge] was the most important parameter to track when considering delays imposed by the review process” [33].

**Observation 2.** The time-to-merge is a more accurate descriptor for code changes being included into a repository than code review acceptance time.

To identify when a particular pull request was created, we used the created_at property of pull requests. To calculate the time-to-merge, we considered two pull request attributes available through GitHub API: closed_at and merged_at. Semantically, merged_at is the better value because we care about when the physical code changes are merged versus when the pull request is marked as closed. The difference between merged_at and created_at represents the time it took for a pull request to be merged.

### 3.4 Data extraction

We deployed a custom tool in C# that uses a GitHub API client library for .NET to gather data about the most forked repositories for each programming language [26]. For each programming language, we retrieved a list of the 100 most forked projects and the number of merged pull requests per project. We ordered the list by the number of merged pull requests in descending order. After manual inspection and elimination of projects not directly related to developing software (e.g., code samples, coding interview study guide, solutions to the programming problems, and storage), we picked 10 projects per language with the most merged pull requests. Finally, we used curl to fetch the contents of code changes included in each pull request and parsed the resulting data locally using diffstat [18].

We obtained 845,316 pull requests in our raw dataset for analysis. After removing entries that did not have any code changes (e.g., changes to the binary files and generally anything not considered text by the diff tools), we ended up with 842,303 pull requests. We removed one pull request with inconsistent timestamp (the time of the merge was set to earlier than its creation time). We also removed all entries that appeared to have zero time-to-merge to ensure that the dataset reflects pull requests that involve meaningful review. Our final sample set contains 826,259 pull requests.

### 3.5 Data preprocessing

During the manual inspection of pull requests, we noticed that several pull requests contain millions of SLOC. To investigate the impact of large pull requests on total code churn, we sorted the pull requests in the descending order of the SLOC modified. We then calculated what percentage of total code churn the outlier values are responsible for. Our analysis shows that 100 pull requests (0.01% of total) are responsible for 23%; 1,000 (0.12% of total) for 53%; and 10,000 (1.21% of total) for 76% of total code churn.

Initial sampling and manual review indicated that these outlier pull requests represent mostly classical merges between branches.
and, for our study, are not representative of the types of pull requests we want to investigate. We applied Tukey $1.5 \times IQR$ fence exclusion criteria to identify outliers to understand their characteristics and whether the merges are a majority of the outliers [74]. We then selected 100 random pull requests from the entries we would potentially remove to avoid distortion of our dataset and categorized them further. The results from the manual classification are shown in Table 2.

Table 2: Distribution of outliers excluded based on SLOC. Random sample of $N = 100$.

| Reason                          | Count |
|---------------------------------|-------|
| New code (feature, scenario)    | 31    |
| Major refactoring (move, rename)| 25    |
| Backporting                     | 12    |
| Dependency update               | 8     |
| Bug fix                         | 7     |
| Documentation update            | 7     |
| Merge between branches          | 6     |
| Dead code removal               | 4     |

In our random sample, most outliers are new code, major refactoring, or backporting existing code. Therefore, we decided not to trim the initial dataset by removing the potential outliers. To ensure the validity of our conclusions, we analyzed the data both with and without the outliers. Without the outliers, the size of our dataset is 613,007 pull requests.

### 3.6 Statistical analysis

To answer RQ1, we report descriptive statistics and visualizations indicating the distribution of pull request size, composition, and time-to-merge in our data. We report statistically significant results at a $p < .001$ and use APA conventions [5]. For RQ2, we compute Spearman rank correlation coefficients [70] of pull request size and composition to time-to-merge. We choose a non-parametric measurement because Shapiro-Wilk tests [67] show that neither the pull request size ($W = 0.031, p < .001$) nor time-to-merge ($W = 0.12, p < .001$) are normally distributed. In addition, Spearman correlation is considered to be robust to outlier values [17].

For RQ3, we examine the influence of three contextual factors: choice of programming language, affiliation (industry versus non-industry), and the day of the week the pull request was created. These factors can potentially influence pull request size and composition, and hence the time-to-merge. For example, existing studies show that the amount of SLOC needed to solve the same problem varies greatly depending upon which programming language is used [48, 57]. A study finds that “Java programs are on average 2.2–2.9 times longer than programs in functional and scripting languages” [48]. Given that we are investigating the relationship between SLOC and time-to-merge, it is essential to differentiate between the various groups of programming languages.

We investigate the influence of contextual factors on pull request size and composition in the case of differences in distribution, we investigate whether it influences the relations of pull request size and composition to time-to-merge. We repeat our analysis on Gerrit and Phabricator (as is feasible), with the addition of time-to-accept.

## 4 RESULTS

**RQ1: What characterizes pull request size, composition, and time-to-merge?**

Earlier, in Section 3.4, we described the method and reasoning behind not removing the outliers. We observe that the presence of outliers has a significant impact on the measures of central tendency. Median values differ by approximately two times, and the mean differs by orders of magnitude (see Table 3).

Table 3: Time-to-merge (hours) and SLOC per pull request before and after removing the outliers using Tukey $1.5 \times IQR$ fence. $N = total\ number, M = mean, Mdn = median, SD = standard\ deviation.$

| Type               | Time-to-merge | SLOC |
|--------------------|---------------|------|
|                    | $N$           | $M$  | $SD$ |  | $M$  | $Mdn$ | $SD$ |
| Before             | 826,259       | 182  | 17   | 860 | 584  | 22    | 17,123 |
| After              | 613,007       | 28   | 9    | 43  | 32   | 12    | 44    |

Given the prevailing guidelines and beliefs surrounding the relationship between the size of a proposed change and the time-to-merge, we expected that both the pull request size and time-to-merge distribution would be skewed towards the smaller values. As expected, Figure 1 and Figure 2 show the size of the pull request and time-to-merge clusters towards smaller values. Both distributions are visually heavily right-skewed.

![Figure 1: A barplot of pull request sizes.](chart1.png)

This finding is consistent with what has been observed in the industry. A study that mined data from 9 million Google code reviews determined that modifications involving a single line account...
for > 10% of changes [64]. In our dataset, single line modifications account for > 11% of changes, and unsurprisingly, the mode value for SLOC changed is 1. Our observation also closely matches what another study has observed after inspecting the code change patterns in a codebase of 2 million SLOC over a decade: “nearly 10 percent of all the changes made during the maintenance of a software under consideration are one-line changes” [58].

This finding raises a question about the link between the guidance and the size of code changes we observe in our dataset. Are the changes small because engineers follow the community guidance about pull request size, or are they small due to the distribution and nature of changes made? For example, does our dataset reflect more bug fixes that tend to be smaller versus larger modifications such as implementing a new feature? Unfortunately, most of the repositories we included in our study do not formally categorize their pull requests based on the issue type (e.g., code defect, feature, refactoring), and we do not have enough data to answer this question.

Existing literature about the distribution of insertions, deletions, and modifications in various codebases is limited. Most studies use only insertions and deletions as code type changes. Existing anecdotal industry experience prompts us to expect engineers to insert or delete more code than they modify. Our dataset shows a similar trend.

**RQ1:** Most pull requests are relatively small (50% ≤ 22 SLOC, 75% ≤ 101 SLOC, and 90% ≤ 381 SLOC). Half of the pull requests get merged in a matter of hours (50% ≤ 18 hrs, 75% ≤ 82 hrs, and 90% ≤ 318 hrs). Insertions outnumber modifications by a 3 : 1 ratio. Deletions outnumber modifications by a 3 : 2 ratio.

**RQ2:** What is the relationship of pull request size and composition to time-to-merge?

In Section 2.3.1, we presented many studies investigating the relations of pull request size to merge speed. These studies have reached contradictory conclusions. When we calculate the Spearman correlation coefficient between pull request size and time-to-merge on our dataset, the strength of the relation is weak ($r_s = 0.26, p < .001$). Our interpretation of correlation coefficients relies on well-accepted guidance used in medicine and psychology [2, 47, 66]. We even looked at the scatter plot of 1,000 randomly selected pull requests from our dataset for other patterns (see Figure 3). Both axes use a logarithmic scale for better display. We observed no patterns and a lack of a strong relationship between pull request size and time-to-merge.

**Figure 2:** A barplot of time-to-merge for pull requests.

**Figure 3:** A scatter plot of pull request sizes and time-to-merge. Random sample of $N = 1,000$ pull requests.

Another factor that we expected to impact the time-to-merge was the ratio of different change types to the total size of a pull request. Intuitively, one can expect that the deletions or modifications of code would be reviewed and merged faster than insertions of new code. Therefore, the pull requests, which mainly consist of insertions, should take longer than those where most of the changes are deletions.

Our study shows that the strength of correlation coefficients between time-to-merge and ratios of different change types is negligible for insertions ($r_s = 0.18, p < .001$), deletions ($r_s = 0.06, p < .001$), and modifications ($r_s = -0.14, p < .001$). One interesting observation is a minor negative correlation between time-to-merge and the modification ratio, which is not present for either insertion or deletion ratios. As the ratio of modifications in a pull request increases, the less time it takes to review that pull request, resulting in a reduced time-to-merge. A possible explanation for this is that given the nature of the modification as a change type (existing code that has already been reviewed), the reviewer assumes that the existing code is correct and gives less scrutiny to the modifications.
We notice that object-oriented and scripting languages such as C and C++ would take longer to review and merge. Mainly because of the amount of meticulous effort required in verifying the correctness of basic frequent and rudimentary operations like handling strings (e.g., checking arguments to `strncpy`), managing heap allocations (e.g., handling either `NULL` returned by `malloc`, or exceptions thrown by `new`), verifying the error handling of return codes, etc. Other languages under review use either built-in string types or utilize garbage collection as a memory management paradigm. These expectations were not confirmed.

### 4.0.2 Affiliation

We explored differences in the time-to-merge per pull request between repositories owned by companies (Apple, Facebook, Microsoft, and Square) and those that are not. We hypothesized that engineers working as employees of those companies have different incentives than volunteer contributors (e.g., adherence to specific deadlines, metrics associated with active pull requests, and organizational pressure to "ship faster"). These differences can cause engineers working in the industry to approach the pull request review process more aggressively.

### Table 5: Spearman correlation coefficient $r_s(p < .001)$ between time-to-merge (hours) and total SLOC. N = total number.

| Language   | N  | $r_s$ |
|------------|----|-------|
| C          | 45,555 | 0.31 |
| C++        | 136,308 | 0.21 |
| C#         | 82,387  | 0.25 |
| Java       | 64,495  | 0.23 |
| JavaScript | 72,510  | 0.23 |
| PHP        | 82,074  | 0.25 |
| Python     | 137,365 | 0.37 |
| Ruby       | 78,814  | 0.34 |
| Shell      | 14,212  | 0.23 |
| TypeScript | 112,539 | 0.20 |
To test our hypothesis, we scanned our projects and identified a total of 12 projects where the GitHub repository is owned by one of the industrial organizations mentioned above, indicating a non-trivial amount of involvement by those companies. The pull request size for GitHub repositories owned by industrial organizations (Mdn = 43) is higher than those that are not (Mdn = 20). A Mann-Whitney U test [44] indicated that this difference was statistically significant \( U(N_{\text{industry}} = 100,000, N_{\text{non-industry}} = 100,000) = 10,923,542,062.5, z = 71.58, p < .001 \). The time-to-merge for GitHub repositories owned by industrial organizations (Mdn = 14.13) is lower than those that are not (Mdn = 17.43). A Mann-Whitney U test indicated that this difference too was statistically significant \( U(N_{\text{industry}} = 100,000, N_{\text{non-industry}} = 100,000) = 9,727,540,456.5, z = -21.11, p < .001 \). However, we do not see any significant difference in the correlation coefficients between time-to-merge and total size of the pull request. For industry projects \( (r = 0.25, p < .001) \) and for non-industry projects \( (r = 0.27, p < .001) \) the ratio of different types of code changes and their relationship to time-to-merge is almost identical.

4.0.3 Day of the week. One potential issue with how we interpreted our data was a failure to account for the weekend. It would be reasonable to assume that most engineers do not constantly work over the weekends for typical industrial projects. Such a practice would systematically introduce longer time-to-merge periods for pull requests submitted on a Friday versus Monday.

However, we would argue that the context on GitHub is different from industrial projects, mitigating the impact of the weekend. Engineers working on a GitHub project may work in their spare time (evenings, holidays, weekends). Contributors are distributed around the world and therefore originate from different time zones. The working week may start and end on different days depending on the country.

Table 6: Spearman correlation coefficient \( r_s(p < .001) \) between time-to-merge in hours and total SLOC in a pull request by pull request creation day. N = total number.

| Day created | N   | \( r_s \) |
|-------------|-----|------------|
| Monday      | 132,488 | 0.26       |
| Tuesday     | 145,908  | 0.27       |
| Wednesday   | 146,326  | 0.27       |
| Thursday    | 143,626  | 0.27       |
| Friday      | 131,587  | 0.27       |
| Saturday    | 65,845   | 0.25       |
| Sunday      | 60,479   | 0.28       |

We decided not to apply any special treatment to the pull requests submitted over the weekend for the above-mentioned reasons. One observation we can make from Table 6 is that the number of pull requests submitted over the weekend significantly drops. Given the nature of the typical workweek, this finding is expected. However, regardless of when a pull request was created [69], we still do not see any relationship between the time-to-merge and pull request size. Given that we consider the same data points repeatedly, the p-values are adjusted using Benjamini–Yekutieli procedure. We also do not observe any significant difference in the ratio of different types of code changes and median size of pull requests between various days of week. This finding suggests no particular period during the week when engineers tend to make changes of a certain type or size.

RQ3: The SLOC and time-to-merge differ between the programming languages. Industry projects tend to have shorter time-to-merge and contain more SLOC per pull request. Day of the week when pull request was created influences the pull request count.

Replication

To determine whether our findings could be replicated across different datasets, we applied a subset of our analysis to projects using Gerrit and Phabricator. Gerrit and Phabricator datasets have the added benefit of being able to track both the time-to Accept and time-to-merge. Though the number of projects in Gerrit and Phabricator datasets is smaller (8 projects with 401,790 code reviews) than we extracted from GitHub, and more homogenous (mainly in C or C++), the results of the analysis are the same: the size of the pull request and its composition has a weak correlation to time-to-accept and time-to-merge (refer to Table 7).

Table 7: Spearman correlation coefficient \( r_s(p < .001) \) for time-to-accept (TTA) and time-to-merge (TTM) in hours versus total changes. N = total number.

| Project       | Review tool | N     | \( r_s \text{TTA} \) | \( r_s \text{TTM} \) |
|---------------|-------------|-------|---------------------|---------------------|
| Eclipse       | Gerrit      | 8,962 | 0.25                | 0.24                |
| GerritHub     | Gerrit      | 31,826 | 0.27               | 0.26                |
| LibreOffice   | Gerrit      | 17,534 | 0.11               | 0.13                |
| OpenStack     | Gerrit      | 151,743 | 0.28              | 0.28                |
| Blender       | Phabricator | 5,224 | 0.26                | 0.26                |
| FreeBSD       | Phabricator | 15,984 | 0.28               | 0.27                |
| LLVM          | Phabricator | 71,082 | 0.32               | 0.30                |
| Mozilla       | Phabricator | 99,435 | 0.28               | 0.30                |

5 DISCUSSION

5.1 Interpretation of our results

Regardless of how the pull requests are partitioned (day of creation, language, and affiliation), the data shows no significant correlation between the size and composition of pull request and time-to-merge. The size of a pull request is not a factor that can be meaningfully changed to speed up code changes. Engineers will need to set realistic expectations about how much of an actual control they have over how fast their changes will be merged. It is possible that social characteristics identified in earlier studies, such as an engineer’s experience or reputation, are more meaningful variables in improving code velocity [30, 73].

One unexpected finding is that no code change type merged faster than others. Intuitively, one would expect that adding new code to the repository should take more time than removing or modifying the existing code. There are many possibilities that can
explain the lack of differences in the time-to-merge (i) reviews of deletions or modifications are accepted faster, but the review process itself represents a minor part in the overall time-to-merge and, therefore, the differences are not noticeable, (ii) reviewers lack sufficient domain knowledge about the history of the codebase and, therefore, require the same amount of time to inspect modifications and deletions as it would take for new code, and (iii) projects based on the repositories we mined do not treat removing obsolete code as a priority.

Our study shows that a programming language matters when it comes to the “verbosity” of changes. We see that more readable and expressive languages such as C#, Java, and TypeScript tend to have bigger pull requests. In contrast, more concise languages such as various dialects of shell scripts have 2–3 times smaller median change size. While not related to time-to-merge, our study highlights the need to account for programming language when measuring an engineer’s productivity [49].

Evidence suggests that changes will be accepted faster on industry projects than non-industry projects and that the median SLOC per pull request is higher for industry projects. This finding seems reasonable because most industrial projects are based on a set of deadlines and are driven by various metrics such as an active bug count, code velocity, and outstanding pull request count. In other words, engineers in the industry are incentivized to merge incoming pull requests faster. We noted in Section 2.3.3 that industry projects generally tend to have a bigger median size for the size of code changes.

5.2 Implications for research and practice

Better understanding of the composition of CI/CD pipelines. Existing studies and recommendations about pull request size and composition are focused on optimizing the code review acceptance time (time-to-accept). However, there is not much publicly available data about the ratio of time-to-accept to time-to-merge. Therefore, it is unknown if focusing on reducing time-to-accept versus other parts of the CI/CD pipeline is the optimal way to reduce the time-to-merge and thus increase the code velocity. Getting more insight into the composition of the CI/CD pipeline will help various organizations to determine what parts of the process may need to be optimized and where the actual bottlenecks are.

Simplify the pull request size related guidance. In Observation 1, we note that the existing guidance is non-specific and varies by project. To avoid misinterpreting subjective quantifiers such as “isolated” and “small”, a project or organization may consider specifying a number. An intriguing suggestion would be a number such as $7 \pm 2$ to ensure optimal cognitive comprehension of code changes under review [45]. Previous research has shown that smaller changes are easier to understand and solicit actionable feedback [6]. Utilizing automatic decomposition of code changes may also help avoid engineers manually partitioning their changes if reviewers consider them “too big” [7].

6THREATS TO VALIDITY

Like any other study, the results we present in our paper are subject to certain categories of threats. In this section we enumerate the threats to construct, internal, and external validity [68].

Using the number of forks as a proxy for the popularity of a GitHub repository creates an issue with construct validity. Like any metric, the number of forks per repository is pliable for manipulation (e.g., forks can be created in an automated manner, a number of forks can be inactive, and a repository is forked with no pull requests). We mitigated these concerns by picking the repositories with the largest number of pull requests and manually verifying that a repository is under active development.

One of the concerns for internal validity is a potential presence of methodological errors in the way analysis and collection of the pull request data is performed. There are various perils associated with mining GitHub for data [35]. We carry the following limitations: we trust GitHub data about the pull request being successfully merged (or not) without manually mining the commits in Git history. We rely on GitHub to adequately summarize all the commits included in the pull request and generate the correct diff describing them.

Threats to external validity are related to the application of our findings in other contexts. We did not analyze the development of widely used OSS projects such as Linux, OpenBSD, and PostgreSQL, where the code reviews are conducted by submitting patches to various mailing lists. However, we confirmed the essence of our findings in Section 4 with a subset of OSS projects where Gerrit or Phabricator code review data was available. Focusing on OSS code versus closed source code is another issue in this category. Though many organizations developing commercial software (e.g., Apple, Facebook, Google, Microsoft, and Twitter) have embraced the GitHub software development model for selected projects, most of their code is still developed in a closed-source model. Therefore, we cannot verify that our findings are valid in a closed-source model.

7 CONCLUSIONS AND FUTURE WORK

This study presents whether the pull request size and composition can be meaningfully changed to increase code velocity. We selected 100 popular, actively developed projects on GitHub to study the relations of pull request size and composition to code velocity measured as time-to-merge. Our analysis shows no relationship of pull request size and composition to the time-to-merge, regardless of how we partition the data: day of the week the pull request was created, affiliation to industry, and programming language. We found no patterns even though pull requests affiliated with the industry are larger and take less time than non-industry equivalents. Our results remain the same on two other platforms: Gerrit and Phabricator, which also offered another indicator of code velocity—time-to-accept.

Our finding that changing size or composition does not influence code velocity prompts new questions. For instance, Influence of personal traits and interpersonal relationships to time-to-merge. Other than pull request size and composition, engineers have limited control over their behavior, communication, and mannerism while interacting with other team members. A study has shown that an engineer’s reputation in the general community and the project is a good predictor for pull request acceptance [8]. Intuitively, it makes sense that engineers who have good communication skills, are well-versed in conflict resolution, and display empathy towards other participants will receive more cooperation.

Influence of personal traits and interpersonal relationships to time-to-merge. Other than pull request size and composition, engineers have limited control over their behavior, communication, and mannerism while interacting with other team members. A study has shown that an engineer’s reputation in the general community and the project is a good predictor for pull request acceptance [8]. Intuitively, it makes sense that engineers who have good communication skills, are well-versed in conflict resolution, and display empathy towards other participants will receive more cooperation.
