A Systematic Impact Study for Fuzzer-Found Compiler Bugs

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Despite much recent interest in compiler fuzzing, the practical impact of fuzzer-found miscompilations on real-world applications has barely been assessed. We present the first quantitative and qualitative study of the tangible impact of fuzzer-found compiler bugs. We follow a novel methodology where the impact of a miscompilation bug is evaluated based on (1) whether the bug appears to trigger during compilation; (2) the extent to which generated assembly code changes syntactically due to triggering of the bug; and (3) how likely such changes are to cause runtime divergences during execution. The study is conducted with respect to the compilation of more than 10 million lines of C/C++ code from 309 Debian packages, using 12% of the historical and now fixed miscompilation bugs found by four state-of-the-art fuzzers in the Clang/LLVM compiler, as well as 18 other bugs found by the Alive formal verification tool or human users. The results show that almost half of the fuzzer-found bugs propagate to the generated binaries for some applications, but barely affect their syntax and only cause two failures in total when running their regression test suites. Our manual analysis of a selection of bugs suggests that these bugs cannot trigger on the packages considered in the analysis, and that in general they affect only corner cases which have a low probability of occurring in practice. User-reported and Alive bugs do not exhibit a higher impact, with less frequently triggered bugs and one test failure.

1 INTRODUCTION

Context. Compilers are among the most central components in the software development toolchain. While software developers often rely on compilers with blind confidence, bugs in state-of-the-art compilers are frequent [Sun et al. 2016b]; for example, hundreds of bugs in the Clang/LLVM and GCC compilers are fixed each month. The consequence of a functional compiler bug may be a compile-time crash or a miscompilation, where wrong target code is silently generated. While compiler crashes are spotted as soon as they occur, miscompilations can go unnoticed until the compiled application fails in production, with potentially serious consequences. Automated compiler test generation has been a topic of interest for many years (see e.g. [Boujarwah and Saleh 1997; Hanford 1970; Kossatchev and Posypkin 2005; Purdom 1972; Sauder 1962; Wichmann 1998]), and recent years have seen the development of several compiler fuzzing tools that employ randomised testing to search for bugs in (primarily C) compilers [Le et al. 2014; Nakamura and Ishiura 2016; Yang et al. 2011; Yarpgen 2018].

Problem. Although compiler fuzzers have shown their ability to find hundreds of bugs, including many miscompilations in widely-used compilers, the practical impact of these miscompilations on real applications has barely been evaluated. It is reasonable to question the importance of the bugs found by compiler fuzzers for at least two reasons. First, by their very nature fuzzers detect

\footnote{A recent empirical study of GCC and LLVM compiler bugs [Sun et al. 2016b] provides numerous insights into bug characteristics, but does not address the extent to which bugs found by fuzzers impact on code found in the wild.}
miscompilations via artificial programs, obtained by random generation of code from scratch or random modification of existing code. It is thus unclear whether the code patterns that trigger miscompilations are likely to be exhibited by applications in the wild. Second, there is an argument that a combination of regular testing of the compiler by its developers and its intensive operation by end-users is likely to flag up the most critical miscompilation bugs as they arise. It is thus unclear whether this leaves enough space in practice for fuzzers to find bugs of more than mild severity. The lack of a fine-grained and quantitative study of the real-world impact of compiler bugs means we have little but anecdotal evidence to support or rebut these points.

**Goal and challenge.** Our aim in this work is to investigate how often miscompilation bugs identified by state-of-the-art fuzzers are triggered when compiling a wide range of applications, and the extent to which this impacts the reliability of these applications. Given a fuzzer-found miscompilation bug, our first challenge is to gauge whether the bug is triggered when processing code in a chosen set of real-world applications. Whenever we find an affected application, our second challenge is to estimate whether the compiler bug can actually make the application misbehave in a runtime scenario.

**Approach.** We take advantage of the large number of fuzzer-found bugs in open-source compilers that have been publicly reported and fixed. Given a fixed bug, we analyse the fix and devise a change to the compiler code that emits a warning when the faulty code is reached and a local faulty behaviour triggered. The warnings issued when compiling a set of applications with the modified compiler provide information on whether the bug is triggered at all. In cases where warnings are issued, we compare the application binaries produced by the faulty and the fixed compiler versions (subject to appropriate care to ensure reproducible builds), counting the number of functions that exhibit bug-induced syntactic differences. For applications where such differences are detected, we run the applications’ standard test suites and look for discrepancies caused by these syntactic differences at runtime. In cases where no such discrepancies are detected, we inspect manually some applications’ buggy and fixed binaries and try to craft specific inputs to trigger a runtime divergence when executing the syntactically different sections of these binaries. The frequency of the syntactic differences between the two binaries and their ability to trigger test discrepancies or runtime diversions shed light on the impact of the bug on the application’s reliability.

**Experiments.** Following this three-stage approach, we present what is to our knowledge the first ever study of the real-world impact of fuzzer-found compiler bugs over a large set of diverse applications. In practice, we sample a set of 27 miscompilation bugs detected by four fuzzer families targeting C compilers: Csmith [Chen et al. 2013; Regehr et al. 2012; Yang et al. 2011], EMI [Le et al. 2014, 2015a,b], Orange3/4 [Nagai et al. 2014; Nakamura and Ishiura 2016] and yarpgen [Yarpgen 2018]. We estimate the impact of these bugs when compiling 309 Debian packages, such as Apache, Grep and Samba. Finally, we compare the impact of these fuzzer-found bugs with the impact of a set of 10 bugs reported directly by end users, and 8 bugs found as a by-product of applying the Alive formal verification tool [Lopes et al. 2015].

**Contributions.** Our main contributions are:

(1) A three-stage methodology (detailed in §3) for assessing the impact of a miscompilation bug on a given application (a) during compilation (is the faulty compiler code reached and triggered?), (b) by statically analysing the generated code (how much does the fault impact the assembly syntax of the resulting binary?) and (c) by dynamically probing the produced binary (can the fault lead to application runtime failures?)

(2) The first systematic study on the real-world impact of compiler bugs (presented in §4, §5 and §6), which applies our methodology (a) to evaluate the impact of a sample of 12% of the fixed miscompilation bugs found by four state-of-the-art fuzzers in Clang/LLVM over
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309 diverse Debian packages totalling 10M lines of C/C++, and (b) to compare the impact of these fuzzer-found bugs with 18 bugs found either by users compiling real code or by the Alive tool, over the same Debian packages.

Summary of main findings. Our top-level findings include that the code associated with fuzzer-found bugs is frequently reached when compiling our set of real-world applications, that our conservative bug conditions trigger, and almost half of the bugs result in binary-level differences for some packages. However, these differences only affect a tiny fraction of the functions defined in the application code and they only cause a couple of application test failures, one in SQLite (due to the miscompilation of its test bed) and one in the zsh shell. The impact of the user-reported and Alive-related bugs is even lower: associated compiler code is not always reached, bugs are triggered less frequently, and lead to a single test failure in the leveldb database management system.

Regarding the question in the paper’s title, our results support the argument that bugs in generally high-quality, widely-used production compilers can impact deployed applications, but at a scale which is fairly limited. Furthermore, our study suggests that fuzzer-found compiler bugs appear to have at least as much impact as bugs found via other sources, particularly user-reported bugs.

Companion website. All our experimental data are available online.\(^2\)

2 BACKGROUND

We make precise relevant details of compilation faults and miscompilation failures (§2.1), provide an overview of the compiler validation tools considered in the study (§2.2), provide relevant background on Clang/LLVM, including details of the bug tracker from which we have extracted compiler bug reports (§2.3), and describe the standard framework used to build and test Debian packages (§2.4), which is at the core of the experimental infrastructure deployed for the study.

2.1 Compilation faults and miscompilation failures

We describe the notion of a miscompilation bug using a simple but pragmatic model of how a compiler works. A modern compiler typically converts a source program into an intermediate representation (IR), runs a series of passes that transform this IR, and finally emits target code for a specific architecture. For source program \(P\) and input \(x\), let \(P(x)\) denote the set of results that \(P\) may produce, according to the semantics of the programming language in question. This set may have multiple values if \(P\) can exhibit nondeterminism. Similarly, let \(T(x)\) denote the set of results that target program \(T\) may produce, according to the semantics of the target architecture. For ease of presentation we assume that source and target programs always terminate, so that \(P(x)\) and \(T(x)\) cannot be empty. A compilation \(P \rightarrow T\) is correct with respect to input \(x\) if \(T(x) \subseteq P(x)\). That is, the target program respects the semantics of the source program: any result that the target program may produce is a result that the source program may also produce. Otherwise the compilation exhibits a miscompilation failure with respect to input \(x\). We call a compilation fault any internal compiler operation which is incorrect during a compilation. A miscompilation failure is always caused by a compilation fault, but a compilation can exhibit a fault and no miscompilation failure if, for example, the fault makes the compiler crash or only impacts IR code that will be detected as dead and removed by a later pass. In such a case, the fault is said not to propagate to a miscompilation failure.

\(^2\)https://sites.google.com/view/compiler-bugs-impact/home
2.2 Fuzzers and compiler validation tools studied

Our study focuses on four compiler fuzzing tools (in two cases the “tool” is actually a collection of closely-related tools), chosen because they target compilation of C/C++ programs and have found bugs in recent versions of the Clang/LLVM compiler framework. We also consider some bugs found via application of the Alive tool for verification of LLVM peephole optimisations. We briefly summarise each tool, discussing related work on compiler validation more broadly in Section 7.

Csmith. The Csmith tool [Yang et al. 2011] randomly generates C programs that are guaranteed to be free from undefined and unspecified behaviour. These programs can then be used for differential testing [McKeeman 1998] of multiple compilers that agree on implementation-defined behaviour: discrepancies between compilers indicate that miscompilations have occurred. By November 2013 Csmith had been used to find and report 481 bugs in compilers including LLVM, GCC, CompCert and suncc, out of which about 120 were miscompilations. Many bugs subsequently discovered using Csmith are available from the bug trackers of the targeted compilers.

EMI. The Orion tool [Le et al. 2014] introduced the idea of equivalence modulo inputs (EMI) testing. Given a deterministic C program $P$ (e.g. an existing program or a program generated by Csmith) together with an input $x$ that does not lead to undefined/unspecified behaviour, Orion profiles the program to find those statements that are not covered when the program is executed on input $x$. A set of programs are then generated from $P$ by randomly deleting such statements. While very different from $P$ in general, each such program should behave functionally identically to $P$ when executed on input $x$; discrepancies indicate miscompilations. Follow-on tools, Athena [Le et al. 2015a] and Hermes [Sun et al. 2016a], extend the EMI idea using more advanced profiling and mutation techniques; we refer to the three tools collectively as EMI. To date, the project has enabled the discovery of more than 1,600 bugs in LLVM and GCC, of which about 550 are miscompilations.

Orange3/4. The Orange3 [Nagai et al. 2014] and Orange4 [Nakamura and Ishiura 2016] tools can be used to fuzz C compilers via a subset of the C language, focusing primarily on testing compilation of arithmetic expressions. Orange3 generates a program randomly, keeping track during generation of the precise result that the program should compute. Orange4 instead is based on transforming a test program into equivalent forms that are all guaranteed to generate the same output if compiled correctly. Transformations include adding statements to the program or expanding constants into expressions. The tools have led to the reporting of 60 bugs in LLVM and GCC, out of which about 25 are miscompilations.

Yarpgen. The Intel-developed Yet Another Random Program Generator (Yarpgen) tool [Yarpgen 2018] takes a Csmith-like approach to generating random programs. It accurately detects and avoids undefined behaviour by tracking variable types, alignments and value ranges during program generation. It also incorporates policies that guide random generation so that optimisations are more likely to be applied to the generated programs. It has been used to report more than 150 bugs in LLVM and GCC, out of which 38 are miscompilations.

Alive. The Alive project [Lopes et al. 2015] provides a language to encode formal specifications of LLVM peephole optimisations, together with an SMT-based verifier to either prove them correct or provide counterexamples to correctness. Once an optimisation specification has been proven correct, Alive can generate LLVM-compatible C++ code that implements the optimisation. More

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3https://github.com/csmith-project/csmith/blob/master/BUGS_REPORTED.TXT
4http://web.cs.ucdavis.edu/~su/emi-project
5https://ist.ksc.kwansei.ac.jp/~ishiura/pub/randomtest/index.html
6https://github.com/intel/yarpgen/blob/master/bugs.rst
than 300 optimisations were verified in this way, leading to the discovery of 8 miscompilation bugs in LLVM as a by-product.

2.3 Clang/LLVM framework

The Clang/LLVM framework [Lattner and Adve 2004] is one of the most popular compiler frameworks, used by a large number of research and commercial projects. Written in C++, it supports several source languages (e.g. C, C++, Objective-C and Fortran) and many target architectures (e.g. x86, x86-64, ARM, PowerPC). The bugs discussed in this paper are analysed in the context of compiling C/C++ code to x86 machine code.

The bugs were all reported on the Clang/LLVM online bug tracker.\(^7\) A typical bug report includes a fragment of code that demonstrates the miscompilation, together with the affected Clang/LLVM versions and configurations (target architectures, optimisation levels, etc.). The bug is given a unique ID and classified by severity, being either ranked as an enhancement request, a normal bug or a release blocker. A public discussion usually follows, involving the compiler developers who may end up writing a fix for the bug, if judged necessary. The fix is applied (with attached explanatory comments) directly within the public Clang/LLVM SVN repository.\(^8\) The revision number(s) where the fix was applied is typically provided to close the bug report.

2.4 Build and test framework for Debian packages

Debian is a well-known open-source operating system and software environment. It provides a popular repository for compatible packaged applications,\(^9\) together with a standard framework to facilitate compiling and testing these packages from source. The components of the framework we use in this study are Simple Build,\(^10\) Reproducible Builds\(^11\) and Autopkgtest.\(^12\)

Simple Build provides a standard way to build any package from source in a customised and isolated build environment. The infrastructure provides simple primitives to set up this environment as a tailored Debian installation within a chroot jail,\(^13\) to gather packaged sources for any package and compile them within the environment, and to revert the environment to its initial state after building a package.

Reproducible Builds is an initiative to drive developers towards ensuring that identical binaries are always generated from a given source. This makes it possible to check that no vulnerabilities or backdoors have been introduced during package compilation, by cross-checking the binaries produced for a single source by multiple third parties. The initiative notably provides a list of the packages for which the build process is (or can easily be made) reproducible.

Autopkgtest is the standard interface for Debian developers to embed tests suites in their packages. As soon as the developers provide a test suite in the requested format, Autopkgtest enables running these tests over the package in a Debian environment using a single command. This environment can be the local machine, a distant machine, or a local installation within a chroot jail or emulator.

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\(^7\)https://bugs.llvm.org/
\(^8\)http://llvm.org/viewvc
\(^9\)https://www.debian.org/distrib/packages
\(^10\)https://wiki.debian.org/sbuild
\(^11\)https://wiki.debian.org/ReproducibleBuilds
\(^12\)https://manpages.debian.org/testing/autopkgtest
\(^13\)http://man7.org/linux/man-pages/man2/chroot.2.html
3 METHODOLOGY

Our study focuses solely on miscompilation bugs reported in open source compilers, and for which an associated patch that fixes the bug has been made available. We refer to this patch as the fixing patch for the bug, the version of the compiler just before the patch was applied as the buggy compiler, and the version of the compiler with the patch applied as the fixed compiler.

Given a miscompilation bug and fixing patch, together with a set of applications to compile, we evaluate the practical impact of the bug on each application in three successive stages:

1. **Compile-time analysis.** We check whether the compiler code affected by the fixing patch is reached when the application is compiled with the fixed compiler. If so, we check whether the conditions necessary for the bug to trigger in the buggy compiler hold, indicating that a compilation fault occurred.

2. **Static binary analysis.** We statically check how much the application binaries generated by the buggy and fixed compiler are different. More precisely, we count how many of the functions defined in the produced assembly code have bug-induced syntactic differences. The more of these differently-compiled functions, the higher the chance that the compilation fault might impact the application’s execution.

3. **Dynamic binary analysis.** We probe dynamically whether the syntactic differences spotted at Stage 2 can make the binaries generated by the buggy and fixed compiler diverge semantically at runtime. To do so, we run the application’s test suite twice, once against each binary. If no differences in the test results are detected, we also manually inspect a sample of the spotted syntactic differences for some applications, with the aim of crafting, if they exist, inputs that would trigger a runtime semantic divergence. Based on this manual inspection, we infer a more general qualitative estimation of the likelihood with which syntactic differences induced by the bug might impact the application’s semantics.

We now discuss each of the three stages of our approach in detail, in the process describing the steps we followed to curate a set of bugs with associated compiler versions and fixing patches.

3.1 Stage 1: compile-time analysis

For each bug, the first stage of our approach relies on isolating a fixing patch and preparing appropriate compile-time checks for the conditions under which the compilation fault would occur. We accomplished this by careful manual review of the bug tracker report associated with each miscompilation bug. We limited our attention to bugs where it was clear from discussion between developers in the bug tracker that the fixing patch was incorporated in a single revision (or several contiguous revisions) of the compiler sources and in isolation from any other code modifications.

As a simple running example, the fixing patch for Clang/LLVM bug #26323 (found by one of the EMI fuzzers) is Clang/LLVM revision 258904\(^4\), which makes the following change:

```c
- if (Not.isPowerOf2()) {
+ if (Not.isPowerOf2())
  + && C->getValue().isPowerOf2()
  + && Not != C->getValue()) {
      /* CODE TRANSFORMATION */
```

It is clear from the fixing patch and its explanatory comments on the SVN that the bug is fairly simple and localised, fitting a common bug pattern identified by the Csmith authors [Yang et al.\(^4\), Vol. 1, No. 1, Article . Publication date: April 2019.]

\(^4\)http://llvm.org/viewvc/llvm-project?view=revision&revision=258904
where the precondition associated with a code transformation is incorrect. As a consequence, the transformation can be mistakenly applied, possibly resulting into a miscompilation. The fix simply strengthens the precondition.

We found and discarded a small number of bugs whose fixes were applied together with other code modifications and/or via a series of non-contiguous compiler revisions, except in one case (Clang/LLVM bug #27903, reported by an end-user) where we found it straightforward to determine an independent fixing patch for the bug from the two non-contiguous patches that were used in practice. The first patch, meant as temporary, deactivated the faulty feature triggering the miscompilation, while the second patch permanently fixed this feature and reactivated it. Our independent patch leaves the feature activated and applies the permanent fix of the second patch.

Having identified a fixing patch and understood the conditions under which the compilation fault would possibly trigger, we modify the fixed compiler to print warnings (1) when at least one of the basic blocks affected by the fixing patch is reached during compilation, and (2) when upon reaching the fixing patch, the conditions under which a compilation fault would possibly have occurred had the patch not been applied are triggered. In our running example this involves detecting when \texttt{Not.isPowerOf2()} holds but \texttt{C->getValue().isPowerOf2() \&\& Not != C->getValue()} does not. The fixing patch augmented with warning generation is as follows:

```c
warn("Fixing patch reached");
if (Not.isPowerOf2()) {
    if (!((C->getValue().isPowerOf2())
        \&\& Not != C->getValue())) {
        warn("Fault possibly triggered");
    } else { /* CODE TRANSFORMATION */ } }
```

We sanity-check the correctness of the so crafted \textit{warning-laden compiler} by making sure that the warnings are actually fired when compiling the miscompilation sample provided as a part of the bug tracker report. It is of course possible that the “fixing” patch does not entirely fix the miscompilation, and/or introduces new bugs in the compiler; sometimes bug reports are reopened for just this reason (see Clang/LLVM bug #21903\textsuperscript{15} for an example). We are reasonably confident that the bugs used in our study do not fall into this category: their fixes, accepted by the open source community, have stood the test of time.

For some patches it was tractable to determine precise conditions under which a compilation fault would have occurred in the buggy compiler. However, in other cases it was difficult or impossible to determine such precise conditions, either because the code associated with the patch was so complex that determining the exact conditions under which the patch exhibits erroneous behaviour would require highly-specialized knowledge, or because the occurrence of a fault could not be verified for sure based on available compile-time information only. In these cases we instead settled for \textit{over-approximating conditions}, designed to certainly issue warnings when the fault is triggered, but possibly issuing false positives, i.e. warning that the fault is triggered when it is not. In such cases we worked hard to make the over-approximating conditions precise to the best of our abilities. As an example, Clang/LLVM bug #21242 (reported by the Alive tool) affects an IR code transformation: a multiplication operation between a variable and a power of two, \(x \times 2^n\), is transformed into the shift left operation \(x \ll n\). When \(n = 31\), the transformation is faulty for 32-bit signed integers in case when \(x = 1\), because the overflow semantics of the first operation is not correctly preserved within the second one. As the value \(x\) will hold at runtime is unknown at compile time (and may be different each time the compiled code is executed), we must conservatively issue a fault warning regardless of the value of \(x\).

\textsuperscript{15}https://bugs.llvm.org/show_bug.cgi?id=21903
3.2 Stage 2: static binary analysis

The first stage of our approach provides us with better insight into how the application’s compilation process is affected by the bug, including information on certain (in the case of precise conditions) and potential (in the case of over-approximating conditions) compilation faults. The second stage is focused on the result of a possible faulty compilation: it performs a static comparison of the application binaries produced by the buggy and fixed compilers, to understand how much the possible compilation fault made them differ syntactically.

As a preliminary check, we perform a bitwise comparison of the monolithic application binaries generated by the buggy and fixed compilers. If these monolithic binaries are different, we disassemble them and textually compare the two versions of the assembly code, in order to estimate how many of the defined assembly functions exhibit syntactic differences possibly induced by the compilation fault. Observe that for this approach to be meaningful, we need to make sure that these differences are only caused by the code differences in the two compilers (i.e. by the fixing patch). In practice, this may not always be the case, as the compilation process of some application may not be reproducible. In such cases, we could mistakenly infer that the differences in the two binaries are caused by a compilation fault. We discuss in section 4.2 how we have practically ensured that the applications compiled in our study follow a reproducible build process.

If Stage 1 determines that no fault was triggered during application compilation, the binaries produced by the buggy and fixed compilers are expected to be identical. In such cases, we still perform Stage 2 to sanity-check our approach: if Stage 1 reports no triggered faults but Stage 2 reports differences in generated binaries, it might indicate that something is wrong either with the way the warning-laden compiler has been hand-crafted or with the reproducibility of the application build process. In practice, this careful approach led us to detect that the binaries produced for some applications made use of the revision number of the compiler used to build them. As the buggy and fixed compilers correspond to different revisions, the binaries that they produced for these applications were always different, even when no compilation fault occurred. We solved this problem by removing any mention of the revision number within the compilers that we used.

Finally, observe that when Stage 1 of our approach detects that a fault was triggered during application compilation, the binaries produced by the buggy and fixed compilers might yet be identical. This can be due to a false alarm at Stage 1 resulting from over-approximating conditions, but also to cases where an actual fault is masked at a later stage of compilation.

3.3 Stage 3: dynamic binary analysis

Even if Stage 2 discovers that the binaries produced by the buggy and fixed compilers differ, this does not guarantee that the possible compilation fault detected at Stage 1 propagated to a miscompilation failure. Indeed, Stage 2 only evaluated how much the binaries produced by the buggy and fixed compilers are syntactically different, which does not prevent them from being semantically equivalent. In this case, the differences observed in the binary compiled by the buggy compiler are not the witnesses of a miscompilation, as they cannot trigger any incorrect application behaviour.

The purpose of the third stage of our approach is to understand whether the compilation fault propagated to a miscompilation failure. To study this, we run the default regression test suite of the application once with the binary produced by the buggy compiler, and once with the binary produced by the fixed compiler. If the first binary fails on some tests while the second one does not, it means—modulo some possibly flaky tests [Luo et al. 2014; Marinescu et al. 2014] or some undesirable non-determinism in the application—that the fault can make the application misbehave at runtime and did thus propagate to a failure. If the test results are the same for the two binaries, it
is unknown whether this is because they are semantically equivalent or because the test suite is not comprehensive enough to expose the miscompilation failure.

We note that the effectiveness of Stage 3 is notably impacted by the quality of the application’s test suite, and in particular whether the test suite is deemed thorough enough to act as a proxy for typical real-world usage. Another important point is that if the test suite of a particular application is used in the standard testing process for releases of a compiler, it follows that the application’s test suite will be incapable of triggering bugs that make it into compiler releases: such bugs would be detected pre-release thanks to running the application’s test suite. We would thus get no meaningful information on the potential impact of a fuzzer-found bug by looking for failures in the test suites of applications that are used to regularly test the buggy compiler. We discuss in section 4.2 how we have selected applications in a manner that minimises this risk.

To mitigate the limitations associated with using test suites only, if no differences are observed when running the test suites for a compiler bug, we sample a set of the syntactic differences spotted at Stage 2 in the assembly code of the applications impacted by the bug. Each syntactic difference in the sample is then manually inspected to craft inputs that would make the two binaries diverge at runtime because of this difference. Depending on the complexity of the application, these inputs can either be global inputs to the application leading to a divergence in the application’s behaviour, or inputs local to the function affected by the syntactic difference that trigger a semantic divergence at this local level (such that we do not know—due to the application’s complexity—whether there is an input to the application that would lead to invocation of the function with the local input). Once all the sampled syntactic differences have been investigated, we try to generalise the gained knowledge, complemented by our understanding of the bug and fixing patch’s details on the bug tracker, into a rule of thumb assessing the impact the compiler bug can have over the semantics of any application.

4 EXPERIMENTAL SETUP

We now describe how we chose the bugs (§4.1) and applications (§4.2) considered in the study, and discuss the technical aspects of the chosen experimental process (§4.3).

4.1 Sampling compiler bugs to investigate

Due to the steep learning curve associated with gaining expertise in a production compiler framework, and the intensive manual effort required to prepare warning-laden compilers for each bug we consider, we decided to restrict attention to bugs reported in a single compiler framework. Most publicly-reported compiler fuzzing efforts have been applied to Clang/LLVM and GCC. Either would have been suitable; we chose to focus on Clang/LLVM as this enabled an interesting comparison between bugs found by fuzzers and bugs found as a by-product of formal verification (the Alive tool is not compatible with GCC).

A total of 1,033 Clang/LLVM bugs are listed within the scoreboards of the four C fuzzers and Alive at time of writing. Relevant properties of these bugs are summarised in Table 1.

Our study requires a fixing patch for each bug, and our aim is to study miscompilations. We thus discarded the 799 bugs that remain unfixed or are not miscompilation bugs.

We then removed any of the remaining bugs for which the affected Clang/LLVM versions are too old to be built from source and to compile packages within a Debian 9 installation (with reasonable effort). In practice, this means that we exclude all the bugs affecting Clang/LLVM versions older than 3.1 (which was released more than 6 years ago).

Because the aim of our study is to assess the extent to which miscompilation bugs have high practical impact, we pruned those bugs that only trigger when non-standard compilation settings...
Table 1. Tool-reported Clang/LLVM bugs that we study

| Tool family | Number of Clang/LLVM bugs | Bugs Reported | Miscompilations | Fixed | Cleanup Sample |
|-------------|---------------------------|---------------|-----------------|-------|----------------|
| Csmith      | 164                       | 52            | 10              |       |                |
| EMI         | 783                       | 163           | 10              |       |                |
| Orange      | 12                        | 7             | 5               |       |                |
| yarpgen     | 66                        | 4             | 2               |       |                |
| Alive       | 8                         | 8             | 8               |       |                |
| **TOTAL**   | **1033**                  | **234**       | **35**          |       |                |

are used, e.g. to target old or uncommon architectures or to enable optimisation levels higher than default for Debian packages (-O2).

Finally, we randomly selected 10 bugs (if available) to study per tool, among those bugs for which we were able to isolate an independent fixing patch and write a corresponding warning-laden compiler. This led to a final sample of 35 bugs to analyse, as shown in Table 1. We completed this sample by adding a set of 10 miscompilation bugs reported directly by the Clang/LLVM end-users. These bugs were selected by searching the Clang/LLVM bug tracker for a set of 20 suitable miscompilation bugs not reported by the fuzzers or Alive authors. Then, we picked the first 10 of these bugs for which we could isolate an independent fixing patch and write a corresponding warning-laden compiler.

4.2 Sampling applications to compile

As the set of applications to be compiled, we consider the source packages developed for the last stable release of Debian (version 9). More than 30,000 packages are available. Experimenting with all packages was infeasible in terms of the compute resources available to us. We now describe the process we followed to select a feasible number of packages.

To apply the methodology of §3 to C/C++ compiler bugs in an automated fashion, we required packages that: build in a reproducible fashion (a requirement of stage 2, see §3.2); are not used for exercising Clang/LLVM on a regular basis and come with sufficiently thorough test suites (both requirements of stage 3, see §3.3) that can be executed in a standard fashion (required for automation); and contain more than 1K lines of C/C++ code (a limit that we imposed to filter out uninteresting applications).

For build reproducibility, the Debian Reproducible Builds initiative lists the approximately 23,000 packages for which builds are believed to be deterministic. Regarding availability of test suites, 5,000 packages support the Debian Autopkgtest command as a unified interface for running tests. We thus restricted attention to the 4,000 packages with reproducible builds and Debian Autopkgtest-compatible test suites.

We then filtered out all the packages that contain fewer than 1K lines of C/C++ code, using the cloc tool to count lines of code. This was important in order to filter out trivial applications or applications that are mostly written in another programming language but that include a small C/C++ component.

Of the remaining packages, we removed all packages whose build process fails when compiled using version 3.6 of Clang/LLVM. This is middle-ranged in the timeline of compiler versions used in our study, so we expect it to be among the most representative of the compiler features available across the compiler versions we consider.

To make the running time of our analyses more acceptable (it could take more that one week per compiler bug considering all the remaining packages), we sampled half of these packages.

\[\text{http://cloc.sourceforge.net}\]

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to end up with a set of 309 source packages, consisting of a total of 8,300,478 lines in C source files, 778,662 lines in C++ source files and 1,251,782 lines in C/C++ header files. In more detail, 179 packages consist of between 1K to 10K lines of code in C/C++ source or header files, 109 packages between 10K to 100K, 20 packages between 100K to 1M and one package more than 1M. The sampling was performed first by identifying a set of about 50 popular and 50 limited-audience representatives of a wide variety of application types, such as system utilities (Grep), web servers (Apache), scientific software (Symmetrica), network protocols (Samba) and printer drivers (Epson-inkjet-printer-escpr). Second, we randomly selected other packages to complete the sampling. During package sampling, we also checked that none of the selected packages are part of the extended test suite used by the Clang/LLVM developers. Moreover, we successfully checked that none of the selected packages invoke Clang/LLVM during their standard build process, which is consistent with the fact that GCC is the default compiler within the Debian environment. We thus have a high degree of confidence that the test suites for the packages we consider are unlikely to be immune to bugs in Clang/LLVM releases (which they might be if they were used as part of standard testing for such releases).

To sanity-check reproducibility of builds, we built each selected package twice with the same compiler (an instance of version 3.6 of Clang/LLVM) and verified that bitwise identical binaries are indeed produced.

In order to evaluate test suite thoroughness for the packages to be chosen, we had set out to use the gcov tool to gather statement coverage information for the package test suites. However, integrating gcov within the package build infrastructure presented challenges, e.g. gcov notes files were not always generated during compilation, sometimes coverage data were not generated during test suite runs, and sometimes both were generated but were deemed not to match by gcov. Nevertheless, we were able to gather reliable coverage data for a sample of 39 packages. Across these packages, we found their test suites to achieve a median of 47% and a mean of 46% statement coverage, with lowest and highest coverage rates of 2% and 95%, respectively. About half of the packages—18/39—had test suites achieving at least 50% statement coverage. While statement coverage is a limited metric, these coverage rates were somewhat higher than our team had predicted.

4.3 Experimental process

We now describe the technical aspects of the process we followed to measure the impact of the 45 sampled compiler bugs over the 309 sampled Debian packages, using the three-stage methodology described in §3. We make our experimental infrastructure available at the companion website of this paper. The website also provides an image of the Debian 9 virtual machine used for running the experiments, preloaded with our complete infrastructure and the warning-laden, buggy and fixed compilers for our example bug #26323.

Experiments were performed over six recent Intel servers and ten private cloud instances, except for the test suite runs, which were conducted within virtual machines set up in the cloud, using Amazon Web Services (AWS). Each bug was analysed in one of the Debian 9 virtual machines installed either locally on the servers or remotely in the cloud, while test suite runs necessary for such an analysis were performed over 2 Debian 9 AWS machines specifically created for each bug.

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17We used https://popcon.debian.org to estimate popularity.
18https://llvm.org/docs/TestSuiteGuide.html
19https://gcc.gnu.org/onlinedocs/gcc/Gcov.html
20https://sites.google.com/view/compiler-bugs-impact/home
21https://aws.amazon.com
As a preliminary step, we prepared the list of the 309 packages to analyse in the JSON format (tasks.json), providing the exact package names and versions that allow Simple Build to automatically download the corresponding source packages from the Debian website.

For each package, the analysis starts by running the chroot shell script, which instructs Simple Build to install a fresh local Debian 9 build environment in a chroot jail. The sources of the warning-laden, buggy and fixed compilers are then compiled and installed in this build environment, by running the compiler-llvm shell script provided by the experimental infrastructure. Finally, the steps-llvm shell script iterates over the packages defined in the tasks.json file and performs the three stages detailed in our methodology for each of them.

Stage 1 (§3.1) is performed by setting the warning-laden compiler as the default compiler in the build environment and asking Simple Build to build the package. The resulting build logs are then searched (using grep) for the warning messages. In some cases, Simple Build may fail because the package build process is not compatible with the Clang/LLVM versions affected by the bug. These cases are simply logged and Stages 2 and 3 are not carried out.

Stage 2 (§3.2) is performed by setting successively the buggy and fixed compiler as the default compiler in the build environment and asking Simple Build to build each time the package. The two resulting binaries are then compared bitwise using diff. If the two resulting binaries are different, we disassemble their code sections (using objdump). The functions defined in the two disassembled binaries are then textually compared opcode by opcode and we count the ones that differ. By comparing only the opcodes we aim to achieve a good trade-off between false positives and false negatives. To avoid false positives, we do not consider the differences in the operands, since the differences in the operands, namely addresses, registers and immediate values, may not affect the semantics of the functions. However, aggressively leaving out all the operands may lead us to overlook the compiler bugs that only affect the operands in the binaries produced by the buggy compiler thus cause the problem of false negatives. In practice, we believe that there is no such a bug in our studied sample, but still, we may undercount the number of different assembly functions, making the total number possibly underestimated.

Stage 3 (§3.3) is performed by asking Autopkgtest to execute the package test suite over the two binaries produced at stage 2, if they were different. The two test runs are carried out within the two isolated AWS test environments. The two resulting test logs are then hand-checked and compared. When a difference is spotted, the test runs are repeated several times in fresh test environments to make sure that the results are reproducible and not polluted by flaky tests or non-determinism. For some packages, the testing infrastructure may not be reliable—we log the cases where the infrastructure crashes, making impossible to run the tests. In case no divergences are spotted in the test results, a sample of the differently-compiled functions are randomly selected for each bug and manually inspected. For each function, we use gdbgui\textsuperscript{22} to recover the part of the code that is responsible for the differences. If this code can be easily reached from the executable’s main function and if the program has simple inputs and outputs, we manually try to construct inputs to the program that result in runtime divergences. If the code cannot be easily reached from the main function or if testing the executable as a whole is too complex, we isolate and compile a driver for the C/C++ function that contains the identified code and try to trigger a divergence similarly.

We estimate the total machine time spent to run all the experiments to around 5 months.

5 RESULTS

We now analyise the results obtained for every bug and package pair considered in our study. We discuss the results for the fuzzer-found bugs in detail, covering the three stages of our approach in

\textsuperscript{22}https://gdbgui.com/docs.html
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§5.1—§5.3, and turn to a comparison with bugs found from other sources—user-reported bugs and Alive bugs—in §5.4. We also investigate whether there is a correlation between bug severity and impact (§5.5). We wrap up with a discussion of our overall experimental findings in §5.6. The full set of data for all experiments is available from our companion website.23 For every investigated bug, the downloadable artifacts notably include the warning-laden fixing patch and the build logs produced at Stage 1, the generated binaries and assembly functions (if different) obtained at Stage 2, as well as the testing logs and manual inspection data gathered at Stage 3 (if performed).

Table 2. Impact analysis for 27 Clang/LLVM bugs found by the 4C fuzzers families over 317 Debian packages.

| BUG     | PACKAGES | 1) BUGGY LLVM CODE | 2) BINARY DIFFS | 3) RUNTIME DIFFS |
|---------|----------|--------------------|-----------------|-----------------|
|         | id severity | successful builds | reached | triggered (precise) | packages | functions | test diffs | manual |
| Csmith  |          |                  |        |                      |          |          |            |        |
| 11964   | enhancement | 308              | 307    | 2 (no)               | 2        | 0% [52]  | 0          | low    |
| 11977   | normal     | 308              | 302    | 110 (no)             | 21       | 0% [40]  | 0          | -      |
| 12189   | enhancement | 308              | 298    | 292 (no)             | 46       | 0% [176] | 0          | -      |
| 12885   | enhancement | 306              | 286    | 1 (no)               | 0        | -        | -          | -      |
| 12899   | enhancement | 307              | 144    | 6 (no)               | 0        | -        | -          | -      |
| 12901   | enhancement | 307              | 292    | 287 (no)             | 36       | 0% [52]  | 0          | -      |
| 13326   | enhancement | 305              | 125    | 125 (no)             | 0        | -        | -          | -      |
| 17179   | normal     | 306              | 246    | 3 (no)               | 2        | 0% [7]   | 0          | -      |
| 17473   | release blocker | 308     | 285   | 16 (no)             | 10       | 0% [16]  | 0          | -      |
| 27392   | normal     | 308              | 205    | 205 (yes)            | 202      | 2.7% [5479] | 0      | very low |
| TOTAL   |            | 3071             | 2490   | 1047                 | 319      | 0.4% [5822] | 0      |        |
| EMI     |          |                  |        |                      |          |          |            |        |
| 24516   | normal     | 309              | 132    | 0 (yes)              | 0        | -        | -          | -      |
| 25900   | normal     | 307              | 221    | 4 (no)               | 0        | -        | -          | -      |
| 26266   | normal     | 308              | 302    | 195 (no)             | 0        | -        | -          | -      |
| 26323   | normal     | 305              | 280    | 31 (no)              | 12       | 0% [18]  | 0          | very low |
| 26734   | normal     | 308              | 175    | 5 (no)               | 0        | -        | -          | -      |
| 27968   | normal     | 308              | 122    | 0 (yes)              | 0        | -        | -          | -      |
| 28610   | normal     | 308              | 302    | 297 (no)             | 9        | 0% [15]  | 0          | -      |
| 29031   | normal     | 307              | 297    | 215 (no)             | 127      | 0.3% [680] | 0      | low   |
| 30841   | normal     | 308              | 306    | 191 (no)             | 0        | -        | -          | -      |
| 30935   | normal     | 308              | 3      | 287 (no)             | 37       | 0% [3]   | 0          | low    |
| TOTAL   |            | 3076             | 2424   | 948                  | 151      | 0% [716] | 0          |        |
| Orange  |          |                  |        |                      |          |          |            |        |
| 15940   | normal     | 307              | 158    | 19 (no)              | 0        | -        | -          | -      |
| 15959   | normal     | 307              | 107    | 9 (no)               | 8        | 0% [14]  | 0          | -      |
| 19636   | normal     | 307              | 7      | 7 (no)               | 0        | -        | -          | -      |
| 26407   | normal     | 308              | 4      | 0 (yes)              | 0        | -        | -          | -      |
| 28504   | normal     | 306              | 17     | 0 (no)               | 0        | -        | -          | -      |
| TOTAL   |            | 1535             | 293    | 35                   | 8        | 0% [14]  | 0          |        |
| yarpgen |          |                  |        |                      |          |          |            |        |
| 32830   | enhancement | 308              | 301    | 0 (yes)              | 0        | -        | -          | -      |
| 34381   | enhancement | 308              | 308    | 258 (no)             | 0        | -        | -          | -      |
| TOTAL   |            | 616              | 609    | 258                  | 0        | -        | -          | -      |
| ALL     |            | 8298             | 5816   | 2288                 | 478      | 0.3% [6352] | 0      |        |

5.1 Stage 1: compile-time analysis

Experimental results for the fuzzer-found bugs are presented in Table 2, with Table 3 providing a more condensed view with results aggregated per fuzzer.

23https://sites.google.com/view/compiler-bugs-impact/home
Package build failures. Fewer than 1% of all package builds failed. All but one of the analysed compiler versions failed to build at least one package; the maximum number of packages that a specific compiler version failed to build was four. Across all compiler versions, build failures were associated with 17 particular packages out of 309 packages total. The package with the highest failure rate is the Velvet bioinformatics tool, for which 52% of the builds failed. Manual inspection of build failure logs shows front-end compilation errors, e.g., relating to duplicate declarations and missing header files.

Reachability of fixing patch. For each bug, at least one package caused the associated fixing patch to be reached during compilation; i.e., all the fuzzer-found bugs we studied were related to code that could be reached during compilation of standard packages. Note also that for each of our 309 packages, the compilation process reached the fixing patch of at least one of the bugs that we have studied.

For 19/27 bugs, the proportion of packages for which the patch was reached is above 50% and it remains high for most of the other bugs. The highest proportion is attained with Yarpgen bug #34381, whose patch is reached for 99% of the packages. This bug affects the generation of x86 binary code for additions. The minimal proportion is attained with Orange bug #26407, whose patch is reached for fewer than 2% of the packages. This bug affects the remainder operation for unsigned numbers when it involves a power of two. In general, the proportion of packages where the patch is reached appears to be much lower for the bugs discovered by Orange than by the other tools. A likely explanation is that Orange focuses on bugs affecting potentially complex arithmetic, which does not appear so commonly in real-world code.

Fault triggering. We were able to come up with precise fault-triggering conditions for only 19% of the investigated bugs. The main difficulty in writing such conditions was that the fixing patch for many bugs makes it difficult to identify the precise situations where the buggy version of the code would fail. Indeed, for many patches, it is highly complex to determine how the local changes made by the patch precisely impact the global behaviour of the compiler.

Due to our best efforts to make the imprecise patches as precise as possible only 39% of the builds where a fixing patch is reached lead to the fault conditions triggering. In total, 22/27 compiler bugs and 28% of the package builds generated potential faults. This last number falls at 13% when restricted to the cases where the patch is precise and thus the fault is certain.

5.2 Stage 2: static binary analysis
While Stage 1 returned a 28% possible fault rate, only 6% of the package builds actually led to different binaries being generated by the buggy and fixed compiler. This difference is due mainly to false alarms issued by our fault detectors in the case of imprecise conditions. However, manual inspection revealed that in some cases this can also be caused by the particularities of the package build process. For example, in the context of Csmith bug #27392, there are three packages, namely libffi-platypus-perl, snowball and viennacl where a fault is found to be triggered at Stage 1, but
identical binaries are produced at Stage 2. This is due to the fact the binary for which the fault was triggered is not included as a part of the final packaged binary returned by the build process.

Regarding the aggregated numbers obtained for the Csmith bugs (see Table 2), the buggy compiler code is reached for 81% of the builds and the fault conditions are triggered during 34% of the builds. Similar numbers are obtained for the EMI bugs: 79% and 31% respectively. However, the possible fault rate in terms of packages at Stage 2 decreases almost twice as fast for EMI (5%) as for Csmith (10%), resulting in 4 EMI bugs out of 10 causing binary differences against 7 out of 10 for Csmith. While this trend should be confirmed using a larger number of bugs, a possible explanation is that Csmith was the first tool used to fuzz Clang/LLVM, so it had the privilege to collect some “low-hanging fruit”, i.e. those compiler bugs that trigger more often.

In total, 12/27 fuzzer-reported bugs (44%) lead to differences in the generated monolithic binaries. The compilers affected by bugs Csmith #27392 and EMI #29031 caused 53% of the package builds leading to such differences. These two bugs both affect an optimisation pass, respectively loop unrolling and hoisting of load/store instructions to a dominating code block.

Among the 12 bugs that lead to different binaries, 10 affect only very few (at most 176) of all the assembly functions generated when compiling our 306 packages, accounting for less than 1‰ of them. Noted that three packages, mod-gearman, phyml and samba, are not taken into account because the build process removes some information, e.g. debug symbols, required by our analysis. Bug Csmith #27392 hits a record of 2.7%, while EMI #29031 only affects 0.3% of the generated assembly functions. Notice that the number of assembly functions in the binaries of our 306 packages may vary with the version of Clang/LLVM used to compile them. Indeed, as each version may come with a different implementation of the optimisation passes, the compiler may decide on a different set of function calls to inline. We counted the total number of assembly functions in the binaries produced by the buggy compilers for bugs Csmith #11977, Alive #20189 and Csmith #27392, representing respectively an early, medium and late point in the timeline of the compiler versions used in our study. The average, around 202K, with a standard deviation of 5%, provides an approximate value of the total number of assembly functions generated when compiling our 306 packages.

5.3 Stage 3: dynamic binary analysis

Failed test suite runs. About 13% of the test suite runs could not be carried out because the underlying testing infrastructure was not reliable and crashed. The most common reasons for crashes were missing files or dependencies and failures to compile the testing infrastructure itself.

Differences in test results. Across all bugs and packages, we did not observe any differences in the test results that were obtained; i.e. it would appear that the impact of these compiler bugs is not severe enough to cause failures in the current regression test suites of these packages.

Additional experiments. Given the rather unexpected result that no compiler bug was able to trigger a test failure within our 309 packages, we repeated our analysis over SQLite,24 a large, complex and widely-used application reputed for the thoroughness of its testing process (its free default test suite achieves more than 98% coverage of the application’s 151K statements). SQLite was not part of our selected list of packages because its test suite does not conform to the Autopkgtest format and needed to be executed manually.

This additional analysis did not reveal any difference in the test results, except for Csmith bug #13326,25 where the binary produced by the buggy compiler fails on test case incrblob-2.0.4, while the binary generated by the fixed compiler does not. Interestingly enough, the miscompilation

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24https://www.sqlite.org
25https://bugs.llvm.org/show_bug.cgi?id=13326
responsible for the failure does not affect the SQLite code itself, but the code of the test bed responsible for conducting test incrblob-2.0.4. More precisely, the buggy compiler miscompiles the following line of code, by generating erroneous binary code to compute an 8-bit unsigned integer division part of the remainder evaluation:

\[ zBuf[i] = zSrc[zBuf[i] \% (\text{sizeof}(zSrc) - 1)]; \] // RUNTIME: sizeof(zSrc)=79, zBuf[i]=232

When test incrblob-2.0.4 is then run, the previous code mistakenly returns 254 when computing the remainder of 232 by 78, causing zBuf[i] to take a garbage value zSrc[254]. As the test uses zBuf to exercise a database handled by SQLite, it ends up reporting an error when it detects a value different from the one it expected. Finally, notice that test incrblob-2.0.4 is also miscompiled and fails for the binaries produced by both the buggy and fixed compilers of Clang/LLVM bugs #11964, #11977, #12189 and #12885, as these compiler versions are within the lifetime of bug #13326.

In addition to this analysis of SQLite, we have also run the single stage 3 of our approach over other Debian packages that we had excluded from our package selection, observing a single test failure when compiling the zsh package with the buggy compiler affected by bug EMI #29031.

**Manual inspection.** Given the (nearly) absence of any differences in the test results obtained for all the investigated compiler bugs, we have manually inspected of a sample of the syntactic binary differences detected at Stage 2. We discuss below the most salient results of this inspection.

**CSmith #11964**

- **Bug description:** During the transformation of LLVM IR into x86 assembly code (represented within the compiler’s data structures by directed acyclic graphs (DAG)), the bug causes an IR node representing a decrementation by one for a long integer value to be miscompiled, in case the node has more than one other node using it in the DAG. This miscompilation makes the operation to be possibly performed twice in the x86 code.

- **Manual inspection:** We have reviewed all the syntactically affected functions in the two impacted packages, namely s3ql and simplejson. All the syntactic differences in the functions seem to be related to a memory management macro `Py_DECREF(PyObject * o)`, which is used to keep track of the reference count of a Python object and deallocate the object once the reference count decreases to zero. While we did see internal states corrupted, these corruptions do not impact the global semantics of the packages. For example, the values stored in the x86 RAX register may differ by one at the end of the function `join_list_unicode` of package simplejson, but these values are not used again until the function returns.

- **Generalised impact estimation:** While posing a clear threat of a miscompilation failure, this bug requires specific conditions to be met to trigger, so that it affects a highly limited amount of functions in our packages. For this reason, we rate its impact to low.

**CSmith #27392**

- **Bug description:** The bug affects the loop unrolling optimisation in the case where the loop is unrolled by a given factor at compile-time, but it is not possible to evaluate before runtime whether the total number of times the loop must be executed is a multiple of the loop unrolling factor. To deal with this case, the compiler produces extra target code to find out at runtime how many iterations were possibly left over and execute them. This extra target code evaluates at runtime the number of times the non-unrolled loop must be executed and stores it into an unsigned integer counter variable. However, the case where this number overflows the counter variable is not properly handled, making the loop to be executed a wrong number of times when this case occurs.

- **Manual inspection:** We inspected manually a dozen of the many syntactic binary differences induced by this bug, without being able to trigger any runtime divergence. The main obstacle
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for such a divergence to occur is that the binary difference should affect the loop unrolling management code of a loop able to iterate more times than the largest representable unsigned integer value, which was not the case for any of the affected loops we investigated. For example, the while loop in the main function of the boxes package (boxes.c, line 1661) can be run at most two times, while the for loop in the hash table API of the conntrack-tools package (hash.c, line 45) can be run at most a number of times equal to the largest representable signed integer value:

```
struct hashtable *hashtable_create(int hashsize, ...)
for (i=0; i<hashsize; i++) INIT_LIST_HEAD(&h->members[i]);
```

- **Generalised impact estimation**: This bug causes syntactic binary differences in many packages, because its fixing patch systematically affects the syntax of the loop unrolling management code produced by the compiler, and because such management code will often be generated by the compiler in the expected presence of loops in the package. However, such syntactic differences are typically not the witnesses of miscompilation failures, because it is very unlikely that the application contains loops whose intended behaviour is to iterate more times than largest representable unsigned integer value. As a consequence, we rate the bug impact as very low.

EMI #26323.

- **Bug description**: During one optimisation pass, the compiler may merge a disjunction between two simple integer comparisons into a single comparison. For example, \((n=2 \text{ or } n=3)\) would be merged into \((n \& ~1)==2\). During a later optimisation pass, the compiler may analyse the IR to detect if such a merger has occurred before, in order to undo it and apply another code transformation instead. However, the analysis to locate merger occurrences in the IR is flawed, leading the compiler to trigger the merger undoing process over code where no merger was actually performed, possibly corrupting the code’s semantics.

- **Manual inspection**: Despite the exhaustive manual inspection of several syntactic binary differences induced by the bug, we were not able to trigger any runtime divergence. The syntactic differences are caused by the fact that the buggy compiler applies the merger undoing process to some code, while the fixed compiler does not. However, manual inspection revealed that applying the merger undoing process to the code that we inspected was actually legitimate and would preserve the semantics of the package. For example, the differences spotted in the libdraw (ddraw_common.cpp, line 6308) and art-nextgen-simulation-tools (art_SOLiD.cpp, line 144) packages are caused by the legitimate undoing by the buggy compiler of the two following mergers:

\[
!(\text{id}=308 \text{ or } \text{id}=309) \rightarrow !(\text{id} \& ~1)==308
!(\text{k}=6 \text{ or } \text{k}=7) \rightarrow !(\text{k} \& ~1)==6
\]

- **Generalised impact estimation**: While the bug is caused by a flawed merger locator, the fixing patch replaces this locator by a correct but also overly strict one. As a consequence, the fixed compiler will not apply merger undoing mistakenly any more, but it will also miss many legitimate opportunities to do so which were correctly seized by the buggy compiler. A detailed analysis shows that the fixed compiler applies the following code transformation (where \(c_1\) and \(c_2\) are positive integer constants):

\[
(n \& ~2^{c_1})==2^{c_2} \rightarrow (x==2^{c_2} \text{ or } x==(2^{c_2} \& 2^{c_1})) \text{ where } c_1 \neq c_2
\]

while the buggy compiler has notably the ability to apply the following (more general but still correct) transformation:

\[
(n \& ~2^{c_1})==c_2 \rightarrow (x==c_2 \text{ or } x==(c_2 \& 2^{c_1})) \text{ where } c_1^{th} \text{ bit of } c_2 \text{ is 0}
\]
This situation prevents many syntactic binary differences from affecting the application’s semantics. Considering also the tiny frequency of the syntactic binary differences induced by this bug, we rate the bug impact as very low.

EMI #29031.

- **Bug description**: During one optimisation pass, some operations that use or assign a variable might be hoisted to an earlier point in the code of the current function (referred to as the hoisting point), provided that the candidate operation for hoisting is executed on all execution paths from the hoisting point to a function exit point. The bug is that checking for this last condition to hold may wrongly allow hoisting when the hoisting point is within a loop which contains a path where the candidate operation is not executed before exiting the loop. When this arises, the compiler will produce code that mistakenly execute the candidate operation when this path is executed.

- **Manual inspection**: We were unable to trigger a runtime divergence for this for this bug, despite notably testing different loop execution scenarios in the aragorn package (aragorn1.2.38.c, line 11503). A deeper analysis of the fixing path reveals that it deactivates hoisting as soon as the hoisting point is within a loop and does not live in the same basic block as the candidate operation, even if the candidate operation is always executed within the loop and even if executing this operation during a path where it should have not been executed will not affect the code semantics.

- **Generalised impact estimation**: Given the careful approach taken in the fixing patch, a number of the binary syntactic differences that it triggers will not impact the application’s semantics and thus not be the witnesses of a miscompilation failure. For the binary syntactic differences which cause actual failures, the failure will only impact executions that follow one or some specific paths within the loop. For these reasons, we rate the impact of the bug as low.

EMI #30935

- **Bug description**: During one optimisation pass, the compiler can hoist instructions out of a loop if these instructions are invariant from one loop iteration to another. In case the hoisted instruction is a division, it may occur that the loop entry condition, which was guarding the division execution before hoisting, was preventing the division to be performed with a zero divisor. After hoisting the division out the loop, this division is performed even when the loop entry condition is false, possibly making the program mistakenly crash with a zero divisor error.

- **Manual inspection**: We reviewed each of the three syntactic binary differences induced by this bug. The differences in the nauty (genrang.c) and pixbuf (pixops.c, line 316) packages revealed to be particularly hard to analyse: either there were no clear tracks of a division hoisting in the assembly code, or such tracks were present, but it was totally unclear which statement in the C/C++ source could have been compiled into assembly code involving this division. The hoisting was much more obvious to understand in the infernal package (esl_histogram.c, line 957), but it was also clear that the affected code (detailed below) prevented any division by zero:

```c
if (maxbar > 0) units = ((maxbar-1)/ 58) + 1;
else units = 1;
// The previous definition of "units" prevents it to be 0 at hoisting point
...
// Hoisting point
for (i = h->imin; i <= h->imax; i++)
{ ...
   num = 1+(lowcount-1) / units; // Hoisted division
```
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- **Generalised impact estimation**: The fixing patch for this bug takes a conservative approach and disables hoisting of expressions containing divisions by anything other than non-zero constants. Because of this, some of the syntactic binary differences may be false alarms similar to the one above. However, it appears not unlikely that, in other situations, the affected code would allow the divisor to be zero at loop entrance, while the loop condition would be false, leading to a real miscompilation failure. Nevertheless, considering the tiny frequency of the binary differences induced by this bug, we rate its impact as **low**.

### 5.4 Comparison with other bug sources

Table 4. Impact analysis for the 18 Clang-LLVM bugs found by Alive or end users over 309 Debian packages.

| BUG   | PACKAGES | 1) BUGGY LLVM CODE | 2) BINARY DIFFS | 3) RUNTIME DIFFS |
|-------|----------|--------------------|-----------------|------------------|
|       | id       | SUCCESSFUL BUILDS | REACHED TRIGGERED (PRECISE) | TEST DIFFS | FUNCTIONS | MANUAL |
|       | severity | successful builds | reached | triggered | (precise) | packages | functions | test diffs | manual |
| Alive (8) |          |                    |                |           |          |            |         |            |        |
| 20186 | normal   | 309 | 34 | 0 (yes) | 0 | - | - |
| 20189 | normal   | 309 | 266 | 176 (no) | 122 | 1% [2108] | 0 |
| 21242 | normal   | 309 | 253 | 151 (no) | 51 | 0% [131] | 0 |
| 21243 | normal   | 309 | 55 | 0 (yes) | 0 | - | - |
| 21245 | normal   | 309 | 274 | 0 (yes) | 0 | - | - |
| 21255 | normal   | 309 | 9 | 0 (yes) | 0 | - | - |
| 21256 | normal   | 309 | 167 | 0 (yes) | 0 | - | - |
| 21274 | normal   | 309 | 0 | 0 (yes) | 0 | - | - |
| **TOTAL** | | 2472 | 1058 | 327 | 173 | 0.6% [2239] | 0 |

Table 5. Data of Table 4, aggregated by compiler bug.

| TOOL | BUGS | 1) BUGGY LLVM CODE | 2) BINARY DIFFS | 3) RUNTIME DIFFS |
|------|------|--------------------|-----------------|------------------|
|      |      | REACHED TRIGGERED (PRECISE) | PACKAGES | TEST DIFFS |
| Alive | 8 | 7 | 2 | (0) | 2 | 0 |
| User-reported | 10 | 8 | 4 | (0) | 2 | 0 |

The impact data for the 8 bugs discovered by Alive and our sample of 10 user-reported bugs is reported in Tables 4 and 5.

**Alive bugs.** The average impact of the Alive bugs appears much more limited than the one of the Csmith and EMI bugs. The buggy compiler code is reached twice less often for the Alive bugs, and 6/8 Alive bugs never trigger compared to only 2/20 for Csmith and EMI. The bug impact profile for Alive is actually closer to the one for Orange: Alive bugs trigger in the context of corner cases (typically overflows) of possibly complex arithmetic, which do not appear so often in real-world code. However, two Alive bugs led to binary differences affecting 173 packages and a higher total proportion of functions than the bugs reported by any fuzzer, which, despite the likely limited impact of these bugs in practice (they require the smallest representable integer to be manipulated at runtime), confirm some of the practical interest of Alive.
User-reported bugs. Contrary to fuzzer-reported bugs, user-reported ones were discovered by spotting miscompilations in the code of a real application. Our results tend to show that this does not make user-reported bugs likelier to trigger when compiling other applications. On the contrary, different binaries are only spotted for 2/10 bugs and 2% of the package builds, far below the values of 11/20 and 8% reached by Csmith and EMI. Manual inspection also suggests a low bug impact as both bugs #27903 and #33706 require a very specific interaction between some compiler optimizations to happen for possibly impacting the generated code. This trend should still be confirmed using more than 10 user-reported bugs, but the absence of any impact gap in favour of end-users’ bugs supports the claim that compiler fuzzers are not less relevant because they discover bugs via randomly generated or mutated code. Finally, notice that like for fuzzer-reported bugs, we ran here additional stage 3 experiments with Debian packages that we had excluded, observing a test failure for package leveldb with bug 27903.

5.5 Correlation between bug severity and impact

Table 6 aggregates the impact data by the severity level that bugs were assigned to on the Clang/LLVM bug tracker. We expected a higher impact to be associated with bugs with higher severity, but no clear trend emerged in practice and some numbers are even counter-intuitive: the buggy compiler code is reached almost twice as often at the enhancement level than at the more severe normal level, while different binaries are produced three to six times less often at the release blocker level than at the two lower levels. While the confidence in these results would be increased by bigger samples at the enhancement and release blocker levels, the bug severity appears to be a bad predictor of the practical bug impact.

5.6 Discussion

We now discuss the main results of our study. As with any experimental study, these results are subject to several threats to both internal and external validity, which we detail in Section 6.

Our top-level findings include that the code associated with fuzzer-found bugs is frequently reached when compiling our set of real-world applications, that our conservative bug conditions trigger, and almost half of the bugs result in binary-level differences for some packages. However, these differences only affect a tiny fraction of the functions defined in the code and they only cause a couple of application test failures, on in SQLite (due to the miscompilation of its test bed) and one in the zsh shell. The impact of the user-reported and Alive-related bugs is even lower: associated compiler code is not always reached, bugs are triggered less frequently, and lead to a single failure in the leveldb database management system. Our manual inspection of a sample of the binary-level differences reveals that many of them have no impact over the semantics of the application, because the compiler developers tend to be rather conservative when fixing bugs, e.g. by deactivating many legitimate code transformations as a side-effect of the fix. Our manual inspection suggests that very specific circumstances are typically required to happen at runtime for
the miscompilation to trigger a corruption of the program’s internal state and for this corruption to propagate to the program’s visible outputs. In many cases, these circumstances are very unlikely or simply impossible. For example, bug 11964 affects only 52 functions and after manually analysing all of them, we think none can trigger a runtime failure. Manual inspection also does not reveal any noticeable impact difference between the fuzzer-found and user-reported bugs.

Our major take-aways are that (1) compiler bugs (whether fuzzer-found or not) in a mature compiler platform have an existing but limited impact on real-world code, and (2) fuzzer-found compiler bugs appear to have at least as much impact as bugs found via other sources, particularly user-reported bugs.

In safety-critical software, where avoiding the triggering of any single bug can be the difference between life and death, using a compiler that has been intensively tested with a dedicated fuzzer appears to be a fundamental requirement. Of course, one could argue that in such a case, using a formally verified compiler would be even better. However, such compilers still do not offer the same language and optimization support as traditional compilers, and they are typically not verified end-to-end, enabling fuzzers to find bugs in their non-verified parts [Yang et al. 2011]. In non safety-critical software, where one can tolerate a certain level of unreliability in the application, in exchange for a reduced software development cost, our study supports the claim that fuzzer-found compiler bugs are unlikely to cause a dramatic decrease of the application’s reliability level, at least when using a sufficiently mature compiler platform. We should also mention that any compiler bug could potentially be used by attackers to introduce backdoors in an application [Bauer et al. 2015; Cadar et al. 2015], so from a security perspective, all such bugs should be fixed. However, as demonstrated by the huge list of unfixed compiler bugs in the Clang/LLVM bug repository, developers simply do not have time to resolve all the issues. While these issues seem to be prioritised based solely on the intuition of the developers, our study suggests that this might not be a good indicator of the actual impact for miscompilation bugs, calling for further research on how to better prioritise them quickly.

6 THREATS TO VALIDITY

Threats to internal validity. A first class of threats to the validity of our experimental results arise because the software artefacts that we used, including the shell scripts, warning-laden fixing patch, compilers, package development framework and system tools, could be defective. However, we have crosschecked our results in several ways. The data computed by the shell scripts were verified by hand for a small number of packages and bugs. A sample set of the warning-laden fixing patches were randomly picked and reviewed by a member of the team who had not been involved in producing them. Each warning-laden compiler was tested over the miscompilation samples provided on the bug tracker. Any possible contradiction between the results of Stages 1 and 2, where no potential fault would trigger but the produced binaries would be different, was investigated. A sample of the occurring suspicious behaviours like build failures or triggered bugs leading to similar binaries were investigated for a satisfiable explanation. The test logs were hand-checked and the test runs were repeated several times in clean environments for a dozen of randomly picked bug and package pairs, and also in all the situations where the binaries produced divergent test results or where the test beds crashed. All these sanity checks succeeded.

Another threat is that some of the fixing patches from the Clang/LLVM repository could be incorrect. However, this seems improbable given that all the bug reports from which the patches come from have been closed at least several months and typically several years ago, and they have never been reopened since.

26Around 10,000 bug reports remain open as of April 2019.
Our results might also have been affected by the unrepeatable build process of some Debian packages. However, this is very unlikely as all the used packages were selected among the list of reproducible ones provided by Debian. Moreover, each of the selected packages was built twice and checked for any unrepeatable behaviour. Unrepeateble packages should also have led to contradictions between warning-laden compiler and binary comparison, but none were detected.

Aggressively leaving out all the assembly operands during binary comparison may have lead to undercounting the number of different assembly functions at stage 2, making the total number possibly underestimated. However, our experimental insight of the bugs that we selected suggests that none of them would only affect the operands in the binaries produced by the buggy compiler.

The effectiveness of a part of our dynamic binary analysis is impacted by the thoroughness of the used package’s test suites, and in particular whether these test suites are deemed thorough enough to act as a proxy for typical real-world usage. However, a study of test coverage for a sample of our packages revealed that their test suites do achieve a median 47% statement coverage, peaking at 95%, which appears high enough for not attributing the absence of test suite failures to very poor test coverage. Moreover, we repeated our dynamic binary analysis with the SQLite application, relying on its highly thorough free test suite (more than 98% coverage of SQLite’s 151K statements).

Finally, if some of our packages were used to exercise Clang/LLVM and consequently report bugs in it before one released the versions on which the fuzzer was applied, then the fuzzer would have been prevented to find any bug able to make the packages test suites fail, biasing a part of our dynamic binary analysis results. While this might have anecdotally happened for a limited number of packages and compiler versions, this is unlikely to have affected our results in a systematic way, because we have worked with applications using GCC as their standard compiler and which are not part of the Clang/LLVM’s extended test suite.

**Threats to external validity.** Common to all empirical studies, this one may be of limited generalisability. To reduce this threat, we performed our experiments over 309 diverse applications from the well-known Debian repository, including some very popular ones like Apache and Grep, totalling more than 10 millions lines of code. We have also investigated 45 historical Clang/LLVM bugs. They constitute a sample of about 12% of all the fixed miscompilation bugs reported by the studied fuzzers in the considered compiler. Moreover, our sampling strategy excluded many bugs that are likely to have lower practical impact due to their reliance on specific and uncommon compiler flags.

Our study was performed on Clang/LLVM, which is a mature and widely used compiler platform. Experimenting with less mature compilers, e.g. for emerging languages like Rust, might produce different results, as higher impact bugs may be more likely to be found by fuzzers in such compilers.

### 7 RELATED WORK

**Understanding compiler bugs.** A recent empirical study provides an in-depth analysis of bugs in the GCC and LLVM compilers [Sun et al. 2016b], focusing on aspects such as the distribution of bugs across compiler components, the sizes of triggering test cases associated with bug reports, the lifetime of bug reports from filing to closing, and the developer-assigned priority levels for bugs and how these correlate to compiler components. The study is complementary to ours: beyond a discussion of bug priorities, it is not concerned with the extent to which compiler bugs affect real-world applications, and it does not focus on whether the bugs under analysis are miscompilations, nor whether the bugs were found in the wild or via automated tools such as fuzzers.
Another empirical study [Chen et al. 2016] compares the equivalence modulo inputs and differential testing approaches to compiler testing (see below). A “correcting commits” metric is proposed that helps to identify distinct compiler bugs from failing tests. Otherwise the focus of the study is on understanding the testing techniques themselves, rather than understanding the real-world impact of the bugs they find.

The paper associated with the Csmith tool [Yang et al. 2011] focuses to some degree on understanding compiler bugs, e.g. identifying the most buggy files (according to Csmith-found bugs) in versions of GCC and LLVM at the time. This analysis does distinguish between wrong code bugs and crash bugs, but is simply concerned with whether bugs exist, rather than (as in our study) whether they affect real-world applications. Two projects associated with Csmith, on automatically reducing test cases that trigger fuzzer-found bugs [Regehr et al. 2012], and on ranking reduced test cases in a manner that aims to prioritise distinct bugs [Chen et al. 2013], are important for understanding the root causes of fuzzer-found bugs, but do not directly shed light on how likely such bugs are to be triggered by real applications.

Bauer et al. [Bauer et al. 2015] discuss exploiting compiler bugs to create software backdoors, and show a proof-of-concept backdoor based on a simplified version of an LLVM miscompilation bug found by Csmith. The possibility of code written to maliciously exploit a known miscompilation bug presents a compelling argument that miscompilations matter even though they may not otherwise affect real-world code. An informal online collection of anecdotes about compiler bugs found in the also makes for interesting reading.27

Automated compiler testing. The idea of randomly generating or mutating programs to induce errors in production compilers and interpreters has a long history, with grammar- or mutation-based fuzzers having been designed to test implementations of languages such as COBOL [Sauder 1962], PL/I [Hanford 1970], FORTRAN [Burgess and Saidi 1996], Ada and Pascal [Wichmann 1998], and more recently C [Le et al. 2014, 2015a; Nagai et al. 2014; Nakamura and Ishiura 2016; Sun et al. 2016a; Yang et al. 2011; Yarpgen 2018], JavaScript and PHP [Holler et al. 2012], Java byte-code [Chen et al. 2016], OpenCL [Lidbury et al. 2015], GLSL [Donaldson et al. 2017; Donaldson and Lascu 2016] and C++ [Sun et al. 2016b] (see also two surveys on the topic [Boujarwah and Saleh 1997; Kossatchev and Posypkin 2005]). Related approaches have been used to test other programming language processors, such as static analysers [Cuoq et al. 2012], refactoring engines [Daniel et al. 2007], and symbolic executors [Kapus and Cadar 2017]. Many of these approaches are either geared towards inducing crashes, for which the test oracle problem is easy. Those that can find miscompilation bugs do so either via differential testing [McKeeman 1998], whereby multiple equivalent compilers, interpreters or analysers are compared on random programs, or via metamorphic testing [Chen et al. 1998; Segura et al. 2016], whereby a single tool is compared across equivalent programs, or generating programs with known expected results.

Regarding the fuzzers of our study, Orange3 takes the approach of generating programs with known results [Nagai et al. 2014]; Csmith [Yang et al. 2011] and Yarpgen [Yarpgen 2018] are intended to be applied for differential testing; while the equivalence modulo inputs family of tools [Le et al. 2014, 2015a; Sun et al. 2016a] as well as Orange4 [Nakamura and Ishiura 2016] represent a successful application of metamorphic testing (earlier explored with only limited success [Tao et al. 2010]).

A recent non-fuzzing compiler testing technique involves skeletal program enumeration: exhaustively enumerating all programs (up to $\alpha$-renaming) that have a particular control-flow skeleton [Zhang et al. 2017]. This technique is geared towards finding compiler crashes rather than miscompilations, so the bugs that it finds are not relevant for a study such as ours.

27http://wiki.c2.com/?CompilerBug
Compiler verification. A full discussion of compiler verification is out of scope for this paper, but we mention CompCert [Leroy 2009] as the most notable example of a formally verified compiler. CompCert provides an incomparable level of reliability: intensive fuzzing via Csmith and EMI techniques have not discovered any bugs in verified parts of the code base [Le et al. 2014; Yang et al. 2011] (as should be expected for a formally verified piece of software). One might think that a verified compiler should make the question of whether compiler bugs matter irrelevant by eliminating bugs completely. However, CompCert still faces some major limitations, such as incomplete language support (including no support for C++) and a less mature set of optimizations compared with e.g. GCC or LLVM. A compromise is to verify certain parts of a compiler, an approach taken by Alive [Lopes et al. 2015], whose bugs we have included in this study.

8 CONCLUSION

Compiler fuzzing tools have proven capable of finding hundreds of errors in widely-used compilers such as GCC and LLVM, but very little attention has been paid to the extent to which they affect real-world applications. In this first empirical study investigating these questions, we have shown that almost half of the fuzzer-found bugs in our sample propagate to the compiled binaries of real-world applications, but only affect a very small number of functions and lead to only a tiny number of test suite failures. Our manual analysis of a selection of bugs suggests that these bugs cannot trigger on the packages considered in the analysis, and that in general they affect only corner cases which have a low probability of occurring in practice. At the same time, our study suggests that fuzzer-found compiler bugs appear to have at least as much impact as bugs found via other sources, particularly user-reported bugs.

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