The Coevolution of Technology and Prices in Cryptocurrencies*

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Abstract

This paper studies the joint dynamics of cryptocurrency technology, returns, and labor markets for developers. We construct high-frequency measures of GitHub bug reports ("Technology Flaws") and code commits ("Technology Development") for major coins. The main results are twofold. First, a new Technology Flaw predicts a 7 bp drop in next-day returns without future reversals. Second, a 1% decrease in coin valuation leads to a 0.14% decrease in Technology Development labor. These findings suggest that technology is a fundamental factor in cryptocurrency prices, and that prices and technology development coevolve through a bidirectional feedback mechanism.

Keywords: Technology, Cryptocurrency, Cybersecurity, GitHub, Open-Source Labor Market.

JEL Classification: G12, J24, L17, O31

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Abstract

This paper studies the joint dynamics of cryptocurrency technology, returns, and labor markets for developers. We construct high-frequency measures of GitHub bug reports ("Technology Flaws") and code commits ("Technology Development") for major coins. The main results are twofold. First, a new Technology Flaw predicts a 7 bp drop in next-day returns without future reversals. Second, a 1% decrease in coin valuation leads to a 0.14% decrease in Technology Development labor. These findings suggest that technology is a fundamental factor in cryptocurrency prices, and that prices and technology development coevolve through a bidirectional feedback mechanism.

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1. Introduction

As of 2023, hackers have stolen over $6 billion worth of cryptocurrencies by exploiting flaws in their source code, i.e., in the technology underlying cryptocurrencies (see **Table 1**). Therefore, not surprisingly, the importance of cryptocurrencies' underlying technology has attracted significant attention from investors and large asset managers. For example, the largest cryptocurrency ETF, BlackRock's iShares Bitcoin Trust (IBIT), warns its investors in the prospectus:

> *"... flaws in the source code for digital assets have been exposed and exploited, including flaws that disabled some functionality for users, exposed users' personal information and/or resulted in the theft of users' digital assets... any reduction in confidence in the source code or cryptography underlying digital assets generally could negatively affect the demand for digital assets and therefore adversely affect the value of the Shares."*

In this paper, we empirically study the relation between cryptocurrency prices and the development of cryptocurrency technology. In particular, we investigate how cryptocurrency technologies and prices coevolve by studying the joint dynamics of the technology underlying cryptocurrencies, cryptocurrency prices, and the reallocation of development efforts across coins and over time. On the one hand, we investigate whether technological changes predict cryptocurrency returns, consistent with models such as Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2023) that view technology as a fundamental cryptocurrency pricing factor. On the other hand, we investigate whether cryptocurrency prices also influence technology development efforts, consistent with theories such as Pagnotta (2022) that derive cryptocur-

rency technology as an economic outcome of the incentives generated by cryptocurrency valuations.

To investigate these dynamics, we develop two novel high-frequency measures that aim to capture technological changes and development efforts, and vary considerably across cryptocurrencies and over time. The first measure, *Technology Flaws*, is a measure of adverse technological changes in cryptocurrency source code that developers discover and flag. We focus on *Technology Flaws* as a directional change in cryptocurrency technology to predict the sign of subsequent cryptocurrency returns. The second measure, *Technology Development*, is a measure of development efforts in cryptocurrency source code. This measure aims to capture the overall effort of cryptocurrency developers.

To construct these measures, we observe that most cryptocurrencies are open-source projects with public source code housed on GitHub, a platform that allows developers to create, store, manage, and share their code. A public timeline of the versioning history, GH Archive, has terabytes of records, including the evolution of the code-base and all the interactions between developers, with precise second-by-second timestamps. We match 1,414 coins with market capitalization above $1 million to their corresponding GitHub repositories.

We construct *Technology Flaws* based on an important type of interaction, called "issues," which is initiated by anyone who finds a problem with the project, ranging from vague/unclear documentation to bugs in the source code. Issues describe the nature of the bug and are effectively a call for help from other developers to fix the problem. Using a simple dictionary-based approach, we flag issues that identify bugs in the source code. We then count the number of bug-identifying issues for a coin each day or week to form our *Technology Flaws* measure that captures problems in the underlying technology of coins at

the daily or weekly levels, respectively. A significant portion, roughly one-third of the coins in our sample, have had *Technology Flaws* during the sample period.

We construct *Technology Development* based on code commits. A code commit represents an update to the source code of a cryptocurrency project by a developer. We count the number of code commits for each coin each month, capturing the volume of development efforts in the coin's underlying technology. The average volume of monthly development efforts for popular coins such as Bitcoin, Ethereum, and Solana is 321, 620, and 827 code commits per month, originating from 39, 29, and 49 unique monthly developers, respectively.

The first set of results shows that *Technology Flaws* predict future cryptocurrency returns. One new technology flaw in the past day or week predicts a decrease in subsequent daily or weekly returns of 7 or 13 basis points, respectively. More severe flaws have a larger magnitude. The return predictability suggests that cryptocurrency investors understand and follow developments in the underlying technology, as they respond to the occurrence of technology flaws before developers take action to address them. Moreover, these findings indicate that technology is a fundamental factor in cryptocurrency pricing, where prior evidence on fundamental pricing factors is scarce and thus often puzzling.

In subsequent analyses, we consider return reversals. We find that there are no reversals after the initial decrease in returns, either in the short run or in the long run. This finding suggests that the impact of *Technology Flaws* on cryptocurrency returns is permanent, and is less consistent with the view that *Technology Flaws* capture risk exposure that is compensated by higher expected returns. As such, the findings are consistent with recent theory work on equilibrium cryptocurrency pricing that models security risk exposure as a fundamental stochastic process that reduces the future payoffs of cryptocurrencies (Biais et

al., 2023; Pagnotta, 2022). Notably, our measure is different from the construct of traditional firms' exposure to cybersecurity risk, shown to be compensated by a premium in expected returns in recent studies (Florackis, Louca, Michaely, & Weber, 2023; Jiang, Khanna, Yang, & Zhou, 2024).

Given the absence of return reversals, we conjecture that, in the cross-section, cryptocurrencies with high *Technology Flaws* should earn a low return and vice-versa. To test this conjecture, we form a portfolio that longs coins with zero lagged *Technology Flaws* and shorts coins in the top decile based on lagged *Technology Flaws*. On average, coins in the short leg of the portfolio collectively have 20.5 *Technology Flaws* per day. The daily and weekly long-short technology portfolios earn 30 and 88 basis points per period, respectively. Importantly, we do not estimate the profitability of this trading strategy, which will vary with the costs of portfolio rebalancing. Nevertheless, the economically large magnitude of the long-short returns suggests significant return predictability in the cross-section. The non-trivial economic magnitude is lower than, yet still comparable to that of standard portfolios that the literature considered. For example, the weekly market, size, and momentum factors developed by Liu, Tsyvinski, and Wu (2022) earn 167, 353, and 99 basis points, respectively.

The second set of results shows that the relation between cryptocurrency technology and prices is two-way. That is, cryptocurrency prices are not only predicted by technology – they also predict future future technology development efforts. We find that higher prices and market capitalizations over the previous month predict greater *Technology Development* in the subsequent month. We study these effects on a monthly basis (rather than on a daily or weekly basis) since the reallocation of development efforts likely adjusts more slowly. In particular, doubling (i.e., a 100% increase in) the market capitalization or price of a

cryptocurrency leads to a 14% or 17% increase in *Technology Development*, i.e., the number of code commits, in the source code in the following month.

Then, we separate between the intensive and extensive margins. At the intensive margin, we find that the average number of code commits per developer in the subsequent month increases by 9% if the market cap of a cryptocurrency doubles. We also explore specifications at the individual developer level with developer fixed effects, and find that individual developers increase their development efforts in the subsequent month by 3% if the market cap of a cryptocurrency doubles. These findings suggest that the overall increase in *Technology Development* following increases in valuation is driven, at least in part, by existing developers that increase their efforts. At the extensive margin, we find that the number of developers contributing to the coin increases by 15% following the doubling of the market cap of a cryptocurrency.

These findings suggest that changes in coin valuations predict labor reallocation both through the productivity of existing developers and the total number of active developers. A possible interpretation is that cryptocurrency valuations incentivize developers to devote more effort to the underlying technology.[1] As such, this evidence puts forth a novel relation between financial asset valuations and labor market reallocation at a high frequency.

Collectively, the findings suggest a bidirectional feedback mechanism through which cryp-

[1]We propose several non-mutually exclusive mechanisms that can explain these findings. The first is financial incentives, which can come from direct holdings (early contributors often get paid in the token), more funding (higher token value means the foundation/DAO can fund more projects), or transaction fees & dApps (for smart-contract platforms like Ethereum or Solana, developers benefit indirectly if their apps gain users when token prices rise). The second is viability of widespread adoption. Rising prices often signal investor confidence and long-term viability. Developers would prefer to invest time in coins that are less likely to fail and have resources for continued development. A third mechanism is reputation. Higher valuation leads to more visibility, allowing developers to build their reputations and human capital. In other words, developers build a public track record in a more visible ecosystem. A final mechanism can be behavioral. Developers are attracted to hype and excitement, wanting to work on the "next big thing."

tocurrency prices and technologies coevolve. In particular, they imply a mutually reinforcing dynamic whereby technological frictions trigger price declines, which suppress development efforts, further worsening technological frictions in a vicious cycle (and vice versa).

Overall, our paper makes two main contributions to the literature. First, we contribute to the debate about the pricing of cryptocurrencies. Some believe that cryptocurrencies are mere speculative bubbles, that is, that cryptocurrencies do not have an intrinsic value and therefore are irrational bubbles with no return predictability. Others argue that cryptocurrencies are financial assets whose pricing reflects economic fundamentals such as their underlying technology and its adoption (Biais et al., 2023). We demonstrate that flaws in the technology underlying cryptocurrencies predict crypto returns. As such, our results support the view that cryptocurrency returns fundamentally reflect the quality of the underlying blockchain technology.

Second, we document the role of prices in the reallocation of human capital in open-source economies. The estimates show that high-frequency fluctuations in crypto prices correlate with high-frequency reallocation of development efforts across cryptocurrencies. Specifically, the flow of developers and development activities on GitHub increases immediately following an increase in the price or market capitalization of a given cryptocurrency. These findings provide novel estimates of high-frequency labor mobility in response to pricing fluctuations in a labor market where adjustment and reallocation costs are small, contrary to the frictions documented in traditional labor markets (Autor, Dorn, & Hanson, 2013; Jacobson, LaLonde, & Sullivan, 1993; Notowidigdo, 2020).

2. Related Literature

This paper contributes to a growing literature on cryptocurrency return predictability (Bouri, Lau, Lucey, & Roubaud, 2019; Liu & Tsyvinski, 2021; Liu et al., 2022). Many studies justify crypto return predictability with the existence of fundamental value derived from the utility of the token (Cong, Li, & Wang, 2021; Prat, Danos, & Marcassa, 2025; Sockin & Xiong, 2020). Other studies have linked technology to valuations by showing that technological quality affects post-ICO performance (Bourveau, De George, Ellahie, & Macciocchi, 2022; Dittmar & Wu, 2019; Howell, Niessner, & Yermack, 2020; Liu, Sheng, & Wang, 2024). These studies focus on one-time ICO events and do not capture the ongoing technological development of cryptocurrencies after launch. In contrast, we provide a high-frequency measure of technological quality by measuring coin-level cybersecurity exposure. We provide empirical evidence that crypto returns are predicted by the quality of the underlying technology because cybersecurity exposure affects investors' return from holding crypto assets (Biais et al., 2023; Pagnotta, 2022).

We also contribute to the literature on the labor market for cryptocurrencies. There is a large body of work on open-source software development, including the reasons why coders contribute (Conti, Gupta, Guzman, & Roche, 2023; Taylor & Dantu, 2022; Zhou & Mockus, 2012), the value of open-source software (Hoffmann, Nagle, & Zhou, 2024), and the determinants of success in open-source projects (Lee, Kim, & Gupta, 2009; Midha & Palvia, 2012; Subramaniam, Sen, & Nelson, 2009). Recent work such as Trockman, Van Tonder, and Vasilescu (2019) and Petryk, Qiu, and Pathak (2023) study cryptocurrency through the lens of open-source software and find that cryptocurrency prices correlate with GitHub activities.

To the best of our knowledge, we are the first to characterize cryptocurrency technology as a fundamental factor of crypto prices and capture the quality of the technology using developer interactions in GitHub repos.

3. Background and Data

This section describes the data and variable construction. We first provide an overview of GitHub, a developer platform that houses repositories (repos) for open-source projects, including most cryptocurrencies. The computer code underlying each cryptocurrency and the full versioning history of the codebase are stored in these GitHub repositories. Then, we describe how we measure technology flaws that can lead to cybersecurity exposures and development activity in cryptocurrency repos. Lastly, we describe the crypto trading and return data and the sample construction process.

3.1. Open Source Projects and GitHub

Most cryptocurrencies are open-source projects with code repositories housed on GitHub (Reibel, Yousaf, & Meiklejohn, 2018), a platform that stores computer code and facilitates the ongoing development of projects. GitHub is popular among developers due to its transparent versioning system. All changes to the code and interactions between developers since the project's inception are systematically documented and publicly viewable. These interactions are categorized into 17 different event types. In this paper, we focus on three event types – Push Events, Pull Request Events, and Issue Events. We describe these events below, along with a simplified workflow of open-source software development that is relevant to our

study.[2]

The code of an open-source project, for a cryptocurrency or not, evolves over time with new features and bug fixes. There are usually several "branches" of the codebase that serve different purposes. The main branch houses the official code that is live and powers the product (e.g., software, crypto, etc.). Other branches (think of them as additional copies of the code) can be created by developers through a process known as "forking." These branches isolate different development work, such as adding new features and fixing bugs. Specifically, developers update a branch by "pushing" an updated version of the code into the branch history. This action is called a Push Event, and the updated version of the code is called a *commit*. The number of commits is therefore a clean proxy for the throughput of development activities.

After adding new features or fixing bugs, which usually include multiple commits, developers will request that the commits made to the new-feature or bug-fix branches be merged into the main branch. This action is called a Pull Request Event. Once the project administrators approve the pull request, the changes go live in the official codebase. Therefore, the number of pull requests reflects the development activities that passed through the project's governance and review protocols.

Lastly, anyone with a GitHub account can post a thread under a repo (similar to a post on Twitter/Reddit/Facebook) to request new features, report bugs, or even ask questions related to the project. The thread is called an issue, and posting the issue is called an Issue Event. Under the issue, GitHub users (including developers) can answer the question, discuss

[2]See the full list of event types and the detailed descriptions in GitHub's REST API documentation at https://docs.github.com/en/rest/using-the-rest-api/github-event-types.

the problem, and propose solutions. In some cases, a pull request that fixes the reported bug or adds the requested feature will be linked at the end of the issue to show that the issue is resolved.

3.2. Cryptocurrency Technology Flaws and Technology Development

We first construct a Technology Flaw measure based on issues. Not all issues report problems and bugs in the code – some request new features and ask general questions related to the project. To isolate the issues that report bugs, we apply a dictionary-based filter to only count issues that contain keywords in the body of the text that indicate bugs or problems.[3]

Bugs like these have the potential to lead to cybersecurity exposures and result in large-scale cryptocurrency thefts (see a list of major cryptocurrency thefts that resulted in losses of $100 million or more in **Table 1**). For example, a bug in the Wormhole Network allowed the hacker to mint 120,000 wrapped ETH (worth $325 million) out of thin air. While developers identified the bug and pushed the bug fix into one of the branches of the codebase, the bug fix was not merged into the main branch in time before the exploit occurred.[4] We discuss the rationale for and validity of this measure in detail in **Appendix A1**. We use the

[3]The keywords are bug, wrong, mistake, problem, incorrect, issue, bad, flaw, risk, break, breach, compromise, attack, malware, phishing, ransomware, hijack, intrusion, backdoor, and tamper. We check the robustness of different dictionaries that contain either broader keywords such as "bug" and "problem" or more specific keywords such as "malware, phishing, ransomware, hijack, and backdoor". All empirical results remain qualitatively similar with different dictionaries that are a subset of the main dictionary.

[4]See the Solana blockchain record of the hacker minting 120,000 wrapped ETH (WETH) while bypassing the security protocol at https://solscan.io/tx/2zCz2GgSoSS68eNJENWrYB48dMM1zmH8SZkgYneVDv2G4gRsVfwu5rNXtK5BKFxn7fSqX9BvrBc1rdPAeBEcD6Es. See the bug fix in Wormhole Network's code base that would have prevented the exploit at https://github.com/wormhole-foundation/wormhole/commit/7edbbd3677ee6ca681be8722a607bc576a3912c8#diff-0d27d8889edd071b86d3f3299276882d97613ad6ab3b0b6412ae4ebf3ccd6370L92-R101.

count of issues that report bugs to measure technology flaws that could lead to cybersecurity exposures.

We conduct the main analysis of technology flaws and coin returns at the daily and weekly levels because the exploitable bugs are usually short-lived, as hackers and developers often race to identify them. **Table 2a** presents summary statistics. On average, 0.03 and 0.22 bugs are reported for a given coin-day and coin-week, respectively. Technology flaws are highly right-skewed. As expected, issues reporting bugs are rare, as 98% of coin-days and 94% of coin-weeks have zero technology flaws. On the other hand, a significant portion (458, or roughly one-third) of coins have ever had positive technology flaws during the sample period.

Insert **Table 2** About Here

Next, we construct a Technology Development measure of cryptocurrency development activity using the number of commits and pull requests. Since all GitHub events are timestamped at the second level, we can measure development activity at a high frequency over time. The number of commits is a clean proxy for the throughput of development activity because a commit is the smallest, atomic unit of change to a GitHub repo.[5] The number of pull requests is a relatively noisy measure of development activity because an arbitrary number of commits can be bundled into a single pull request to be merged into the main

[5]When a developer runs `git commit`, Git takes what the developer has staged and permanently writes it into the repo's history. Nothing smaller than a commit is ever retained, i.e., there are no partial edits and no individual file changes outside of a commit. Each commit has a SHA-1 hash. Once created, the commit can never be partially modified and can only be "replaced" by new commits in the future.

branch of a repo. However, it has the benefit of reflecting the development activities that are passed through the governance protocols of projects.

We conduct the main analysis of development activity at the monthly level because it takes time for developers to change how hard they work or what project they work on in response to changes in coin valuations. On average, each coin sees approximately 56 new commits from 2 unique developers and 5 new pull requests from 1 developer each month. Popular coins have a much higher development activity. For example, Bitcoin, Ethereum, and Solana have a monthly average commit count of 321, 620, and 827, originating from 39, 29, and 49 unique developers, respectively.

We also provide some context of the development activity at the developer level. We calculate the average development activity from developers with positive productivity per coin per month. On average, they make 5 commits and 1 pull request in each coin-month. Developers tend to stick around – on average, 60% of the crypto projects they work on in a given month overlap with what they worked on in the previous month. In subsequent analyses, we also separate all developers into two subgroups – the top 1% developers in terms of code commits (across all cryptocurrency projects) in the previous month and the rest (which we call grassroots coders). Compared to the sample mean, top coders are way more productive. On average, they make 148 commits per month across all crypto projects. They also exhibit higher stickiness – 82% of the crypto projects they work on in a given month overlap with what they worked on in the previous month.

3.3. Crypto Trading Data and Sample Construction

We obtain cryptocurrency trading data, including trading volume, market capitalization, and price, from CoinGecko for 14,909 coins. We require that a coin enters the sample after having a $1 million market capitalization and never leaves the sample afterward unless its trading stops altogether. We then manually match each coin to its corresponding GitHub repository and discard coins that we could not match. The final sample consists of 1,414 cryptocurrencies from 2014 to 2023. Summary statistics for returns, trading volumes, prices, and market capitalizations are presented in **Table 2b**. The average daily and weekly returns for the sample coins are positive (0.36% and 1.73%), whereas the median daily and weekly returns are negative (-0.15% and -1.33%). This pattern suggests that the majority of cryptocurrencies are in decline, and a small number of cryptocurrencies have high returns. The average and median end-of-month market cap for the sample coins are $197.04 and $5.75 million, suggesting that the crypto market cap is highly right-skewed. As a result, we use the logarithm of market capitalization in all subsequent analyses.

4. Technology Flaws and Cryptocurrency Returns

In this section, we examine the relation between technology flaws in cryptocurrency source code and coin returns. We hypothesize that more technology flaws lead to lower coin returns because more cybersecurity exposure makes the coin more likely to be stolen, reducing its equilibrium price derived from future transactions Biais et al. (2023).

We test this hypothesis by estimating the following equation:

$$\text{Return}_{i,t} = \beta_0 + \beta_1 \text{Technology Flaws}_{i,t-1} + \boldsymbol{\beta} \boldsymbol{X}_{i,t} + \phi_i + \zeta_t + \epsilon_{i,t}, \tag{1}$$

where i indexes coin and t indexes day or week. $\boldsymbol{X}_{i,t}$ is a vector of control variables including the log of trading volume and the log of market cap. ϕ_i is coin fixed effects that sweep out coin-specific time-invariant characteristics, such as how prominent a coin is. ζ_t represents day or week fixed effects that sweep out factors that apply to all coins in the market, such as the overall sentiment in the crypto market. Returns are expressed in percentage points, and technology flaws are the count of issues that report bugs that potentially lead to cybersecurity exposures. **Table 3** reports the results.

Insert **Table 3** About Here

Table 3 shows that technology flaws negatively predict future coin returns. Column 1 in **Table 3a** shows that one additional bug reported on day $t-1$ predicts an 11 basis point reduction in the coin return on day t. Columns 2, 3, and 4 add coin fixed effects, day fixed effects, and coin-day two-way fixed effects and show a consistent pattern. In the most saturated specification in column 4, we see that an additional bug predicts a 7 basis point reduction in coin returns the following day. Table 3b shows a qualitatively similar pattern at the weekly frequency. Under the specification with coin and week fixed effects, an additional bug reported during week $t-1$ predicts a 13 basis point decrease in coin returns in week t. The effect is economically large – an additional bug reported reduces the return in the next

day (week) by 19% (8%) of the unconditional mean return in the sample.

We conduct a series of robustness checks on the return predictability of technology flaws. First, we examine whether the return predictability in crypto returns is only driven by small coins, potentially due to liquidity bias in the inference (Asparouhova, Bessembinder, & Kalcheva, 2010; Chu, Hirshleifer, & Ma, 2020). In **Table A1**, we estimate the relation separately for small and large terciles of coins based on their lagged market cap. The effect is robust across coin sizes and stronger in large coins, suggesting that the return predictability is not driven by liquidity biases. In addition, because of the large fraction of zeros in technology flaws, we also re-estimate the relation only using coin-days and coin-weeks with a positive count of bug reports. **Table A2** shows that the return predictability is robust when we restrict the sample to coin-days and coin-weeks with positive technology flaws.

4.1. Heterogeneity in Technology Flaws

Next, we examine the heterogeneity in the return predictability of technology flaws. We hypothesize that more severe bugs are more likely to lead to cybersecurity exposures and predict a greater reduction in future returns. We identify severe bugs in several ways and then recalculate technology flaws using only these severe bugs. Then, we estimate the relation in Equation 1 using the new technology flaws measures. We expect the return predictability to be stronger when the technology flaw measure only includes severe bugs. Table 4 reports the results.

Insert **Table 4** About Here

Table 4 column 1 replicates the main specification in **Table 3** column 4 for ease of comparison. Panels 4a and 4b report the daily and weekly results, respectively. Column 2 uses technology flaws that only count bugs reported by GitHub issues where the bug was eventually fixed and the fix is documented in the issue.[6] These bugs account for roughly 1/3 of the total bug reports. Compared to bugs reported by issues that are either marked "Closed" without a fix or ignored completely, these bugs are likely more severe as they require a fix (and warrant the explicit documentation of the fix). **Table 4** column 2 shows that the magnitude of the return predictability of bugs that required a fix is roughly 1.4 times that of the baseline results in column 1 in both the daily and weekly results. Though economically meaningful, the difference between the coefficients is not statistically significant ($p = 0.35$ from the chi-square test).

Column 3 uses technology flaws that only count bugs that are heavily discussed under GitHub issues that report them. The rationale is that if a bug report generates a high level of attention and discussion, the bug is likely to be more severe. We only count bugs whose issues have at least 50 comments as of the end of the sample period. For the daily results, the magnitude of the return predictability in column 3 is roughly 6 times that of the baseline result in column 1. The two coefficients are statistically different ($p = 0.02$ from the chi-square test).[7] This pattern also holds true in the weekly results.

Column 4 uses technology flaws that only count bugs reported by top developers, defined as those who have a lifetime commits count in the top 1% as of $t - 1$. These bugs,

[6]For example, issue 28180 in the Bitcoin GitHub repository was eventually fixed by pull request 28505. Both the issue and the pull request link to each other on GitHub. See the issue at https://github.com/bitcoin/bitcoin/issues/28180 and the pull request that fixed the issue at https://github.com/bitcoin/bitcoin/pull/28505

[7]The results are robust to different thresholds for the number of comments. The estimate using a threshold of 10 or 20 comments yields a magnitude that is also greater than the baseline. See **Table A3** for details.

which account for approximately 3% of the total bug reports, are reported by experienced and productive developers and are more likely to result in cybersecurity exposures compared to those reported by regular GitHub users. We see that the magnitude of the return predictability of these bugs is roughly 4 times that of all bugs in the daily result. A chi-square test for whether the coefficients in columns 1 and 4 are statistically different is borderline statistically significant at the 10% level ($p = 0.11$). In weekly results, the magnitude is slightly greater compared to the magnitude of all bugs, but the coefficient is estimated with a large standard error.

To summarize, severe bugs predict a greater reduction in future coin returns. This result suggests that cryptocurrency traders not only pay attention to the underlying technology of cryptocurrencies on GitHub, but they also understand the content and nuances of the technology.

4.2. Return Reversals

Next, we examine return reversals after initial negative responses to technology flaws. There are two possibilities. First, cryptocurrencies may behave similarly to common equities. Specifically, after the initial reduction in return, future long-term returns could be higher because investors demand a higher risk premium for holding a security with greater (cybersecurity) risk. This hypothesis is consistent with recent work on the cybersecurity risk premium in firms by Florackis et al. (2023) and Jiang et al. (2024). On the other hand, cryptocurrencies could behave differently compared to common equities. This is because investors form price expectations based on their beliefs about whether there will be a widespread mar-

ket adoption of the coin in the future (Kogan, Makarov, Niessner, & Schoar, 2024). As a result, the quality of the technology determines the future net transaction benefits, thereby determining the coin price (Biais et al., 2023). Under this scenario, once the information about the quality of the technology is incorporated in coin prices, long-term returns should be uncorrelated with the initial technology flaws.

We examine these two competing hypotheses by empirically estimating the relation between technology flaws and long-term future returns with the following equation:

$$\text{Return}_{i,t+1\to t+j} = \beta \times \text{Technology Flaws}_{i,t-1} + \boldsymbol{X}_{i,t} + \phi_i + \zeta_t + \epsilon_{i,t}, \tag{2}$$

where $\text{Return}_{i,t+1\to t+j}$ is the return for crypto i from day $t+1$ to day $t+j$, i.e., the long-term future return after the initial return predictability on day t. We normalize $\text{Return}_{i,t+1\to t+j}$ to the daily level for ease of interpretation. $\boldsymbol{X}_{i,t}$ is a vector of controls including the log of market cap and trading volume. ϕ_i and ζ_t are coin and date fixed effects. **Table 5** presents the results.

Insert **Table 5** About Here

Column 1 shows that the one-week future return after the initial negative reaction does not correlate with technology flaws. Columns 2 to 4 also show no correlation between technology flaws and longer-term returns over a month, quarter, and year after the initial response. This result supports the hypothesis that cryptocurrency returns behave fundamentally differently compared to common equity because its value is derived from the quality of the

underlying technology (Biais et al., 2023; Kogan et al., 2024). More specifically, combining **Tables 3** and **5**, we see that technology flaws have a permanent effect on cryptocurrency valuations because the initial negative response is not offset by a future reversal. The natural explanation is that cybersecurity exposure, created by bugs in the source code, casts doubt on whether the crypto will become widely adopted in the future due to technology flaws. Our results highlight the importance of the underlying technology on crypto valuations.

4.3. Technology Flaw Long-Short Portfolios

Lastly, we form a long-short portfolio based on the technology flaws in cryptocurrency code-bases. We perform this exercise to understand the magnitude of the return predictability in the cross-section and *not* to devise a profitable trading strategy, as it can be very costly to rebalance many small cryptocurrencies at the daily and weekly frequencies. We form a long-short portfolio in each period based on the technology flaws reported in the previous period. Specifically, we long coins that have no technology flaws reported in the last period and short coins in the top decile based on technology flaws in the last period.[8] On average, coins in the short leg have 10.9 bugs per day. **Table 6** shows the average return of the technology flaw long-short portfolio at daily, weekly, and monthly levels.

Insert **Table 6** About Here

[8]When the 90^{th} percentile of technology flaws is zero for a day or week, there are fewer than 10% of coins with positive bug counts during that period. We handle this situation in two ways. For the results we report in the paper, we skip days and weeks when more than 90% of the coins have zero *Technology Flaws*. Alternatively, in untabulated results, we short coins with zero lagged technology flaws and long coins with positive lagged technology flaws. The results are qualitatively similar.

Table 6 shows that the long-short portfolios based on technology flaws earn significant returns. The portfolio with daily rebalancing earns about 30 basis points per day. With more infrequent rebalancing at the weekly (monthly) level, the long-short portfolio still earns about 11 (9) basis points per day, which translates into an annual return of 40.15% (32.85%). To put it in context, we compare our long-short portfolio based on technology flaws to the cryptocurrency risk factors developed by Liu et al. (2022). Our weekly-rebalanced portfolio earns a cumulative return of roughly 294% from 2017 to 2023. In comparison, the market, size, and momentum factors earn about 544%, 1,149%, and 323% over the same period (see **Figure 1**).[9] Again, we emphasize that even though our long-short portfolio appears highly profitable on paper (with the weekly- and daily-rebalanced portfolios yielding Sharpe ratios of 1.19 and 2.31, respectively), it does not account for potentially very high transaction costs from frequent rebalancing. However, the high profitability on paper does suggest an economically strong return predictability of technology flaws in the cross-section.

Insert **Figure 1** About Here

[9]We thank Yukun Liu for posting the crypto risk factor data on his website. We also show in the appendix that our long-short portfolio earns significant alpha (8 to 14 basis points per day) against the crypto market, size, and momentum factors, depending on the specification. See **Table A4** for details.

5. Cryptocurrency Valuation and Technological Development

In this section, we examine the relation between cryptocurrency valuations and *Technology Development*. A higher valuation may incentivize more development activity for several reasons. First, it is common for the developers of a coin to also hold the coin.[10] As a result, as the coin's valuation increases, developers' incentive to enhance security and add features for the coin becomes stronger, similar to the mining incentive in a proof-of-work network described in Pagnotta (2022). Second, a successful coin with a high valuation may attract more developers because they want to contribute to a success story. The opposite is also true – coins with falling valuations may lose developers who think that their contribution to a failing coin is meaningless. Namely, developers may join (leave) coins with high (low) valuations. We first test the hypothesis that higher coin valuations are associated with higher future development activity. Then, we conduct analyses separately for the intensive margin (whether existing developers work harder) and the extensive margin (whether more developers contribute to the coin).

We begin by examining the relation between coin valuations and future development activity. **Figure 2** plots development activity by quintile based on the past month's coin valuation, measured as the market cap of the cryptocurrency. **Figure 2a** plots the fraction of coins that have positive development activity, measured by commits, in each valuation

[10]For coins launched via an ICO or other pre-mine, project teams and developers almost always receive and hold a portion of the token supply. This practice is called "token vesting," which aims at creating an incentive alignment that ensures the project team's long-term commitment to development and mitigates pump-and-dump risk. For example, the second-largest coin as of 2024, Ethereum (ETH), pre-mined $72 million at launch, of which $9 million was allocated to developers.

quintile. We see a clear monotonic relation – only 14% of the coins in the lowest valuation quintile see developers push commits into the codebase, whereas 36% of the coins in the highest valuation quintile have positive development activity. **Figure 2b** plots the average number of commits conditional on positive development activities. We see a similar monotonic pattern: the mean and median number of commits increase as coin valuation increases. This figure shows clear evidence of a positive relation between coin valuation and future development activity.

Insert **Figure 2** About Here

Next, we examine this relation with the following Poisson regression:

$$\text{Technology Development}_{i,t} = \beta \times \text{Valuation}_{i,t-1} + \phi_i + \zeta_t + \epsilon_{i,t}, \tag{3}$$

where $\text{Technology Development}_{i,t}$ is the count of commits or pull requests for coin i in month t. In addition to the log of market cap, we also use the log of price as a valuation measure for robustness. Using coin prices allows us to isolate the effect from heterogeneity in the way new coins are issued across different types of networks (e.g., proof-of-work mining vs. proof-of-stake minting). ϕ_i is coin fixed effects that control for coin-specific time-invariant unobservables. ζ_t is year-month fixed effects that control for the time trend that applies to all coins, such as the popularity of cryptocurrency among investors. **Table 7** presents the results.

Insert **Table 7** About Here

In **Table 7a**, we present results using the number of commits as the dependent variable. Columns 1 through 4 use the lagged end-of-month log of market cap as the independent variable with different fixed effects. Column 1 shows that a 100% increase in the market cap of a coin is associated with a 35% increase in development activity in the following month. Columns 2, 3, and 4 add year-month fixed effects, coin fixed effects, and both, respectively. In the most saturated specification in column 4, doubling the market cap of a coin is associated with a 14% increase in development activity. Columns 5 through 8 use the lagged end-of-month log of price as the independent variable, which allows us to isolate the effect of valuation from new coin issuance, which can vary significantly across different types of networks (e.g., proof-of-work vs. proof-of-stake). We see a qualitatively similar pattern – higher coin prices are associated with higher levels of development activity. We check the robustness of the results in **Table 7b** using pull requests instead of commits. The count of pull requests is a noisier measure of development activity because developers can bundle an arbitrary number of commits in each pull request. However, it allows us to examine the productivity that passes through the project's governance and approval protocols. Again, we see a qualitatively similar pattern across all specifications. With the most saturated fixed effects, doubling the market cap (price) of the coin increases the next month's pull request count by 12.8% (13.9%). We also conduct additional robustness checks at the weekly level for all these results and show that the pattern remains across different specifications in **Table A5** in the Appendix. In later analyses, we only report results using the number of commits as the dependent variable with the two-way fixed effects for brevity.

5.1. Intensive Margin Channel

We explore the economic channels behind the positive relation between coin valuations and development activity. First, developers who already work on the crypto project may work harder, as they often hold coins as an investment. As the coin becomes more valuable, the developers have a higher incentive to fix bugs or add new features to the coin. To test this hypothesis, which we term the intensive margin channel, we calculate the average commits per developer for each coin month and estimate the following equation:

$$\text{Commits per Developer}_{i,t} = \beta \times \text{Coin Valuation}_{i,t-1} + \phi_i + \zeta_t + \epsilon_{i,t}. \tag{4}$$

ϕ_i and ζ_t are coin and year-month fixed effects. **Table 8** reports the results.

Insert **Table 8** About Here

We see that the average commits per coder increases with higher coin valuations. Columns 1 and 2 show that if a coin doubles in its value, the average commits per developer increase by about 10%. We also separately calculate the average commits per developer for two subsets of developers – those who have a lifetime commits count in the top 1% of the distribution, which we term top developers, and those who do not, which we term grassroots developers. Columns 3 and 4 report results for top developers. The effect of coin valuation on how hard they work is economically smaller and statistically indistinguishable from zero. One possible explanation is that these top developers are members of the development team dedicated to the respective crypto projects. Therefore, they are paid to do the job and clock

in high development activities irrespective of the value of the coin. On the contrary, grassroots developers do respond to the incentive created by coin valuations, as shown in columns 5 and 6. This incentive for development is similar to the incentive for mining in proof-of-work networks characterized by Pagnotta (2022). We also conduct additional robustness checks at the weekly level for these results and show that the pattern remains qualitatively similar in **Table A6** in the appendix.

We also estimate the relation at the developer-coin-month level using the following Poisson regression:

$$\text{Commits}_{i,t,j} = \beta \times \text{Coin Valuation}_{i,t-1} + \phi_i + \zeta_t + \gamma_j + \epsilon_{i,j,t}, \tag{5}$$

where $\text{Commits}_{i,j,t}$ is the number of commits made by developer j to coin i in month t. This specification allows us to add developer fixed effects, γ_j, to account for any potential time-invariant developer-level omitted variables. **Table 9** reports the results and shows a qualitatively similar pattern. Developer-level productivity is positively associated with past coin valuations, and this effect is concentrated among grassroots developers. We also run this analysis at the weekly level and find that the response is muted across all specifications (see **Table A7** in the appendix), which suggests that it takes time for individual coders to adjust their workload in response to changes in coin valuations.

Insert **Table 9** About Here

5.2. Extensive Margin Channel

We also test the extensive margin channel. Developers may gravitate towards coins that have a high valuation and move away from ones that have a low valuation because they do not want their development effort to go to waste in a failing coin. To test this hypothesis, we count the number of unique developers who have contributed to the coin in each month and estimate the following Poisson regression:

$$\text{Number of Coders}_{i,t} = \beta \times \text{Coin Valuation}_{i,t-1} + \phi_i + \zeta_t + \epsilon_{i,t}.$$

Table 10 reports the results.

Insert **Table 10** About Here

Columns 1 and 2 of **Table 10** show that developers flow into coins with rising valuations and flow out of ones with falling valuations. We see that doubling the market cap and price increases the number of developers working on the coin by about 15%. Similar to the results for the intensive margin channel, columns 3 and 4 show that top coders do not respond to valuation changes, consistent with the idea that they are part of the dedicated development team for the project. However, we see that grassroots developers move in and out of projects following valuation changes. This high-frequency labor force flow is unique in this open-source development market, which suggests a high degree of transferability of skills and low barriers and frictions to move between projects. We report additional robustness results at the weekly frequency that are qualitatively similar in **Table A8**.

To summarize, we show that higher coin valuations are associated with a higher level of future development activity. If a coin's valuation increases, existing developers work harder, and more developers join the project. Conversely, if the valuation decreases, existing developers may reduce effort or leave the project altogether. This effect is concentrated in grassroots developers who are likely not members of the dedicated project development team.

6. Conclusion

This paper shows that the technology underlying cryptocurrencies is a fundamental determinant of their value. We provide evidence that newly discovered flaws in source code predict subsequent declines in cryptocurrency prices, with no subsequent reversals. These findings indicate that investors closely monitor technological flaws in cryptocurrency technology and incorporate them into asset prices in real time, consistent with models that view technology as a key pricing factor in cryptocurrency markets. We provide an important dimension of return predictability in an asset class where traditional fundamental factors are often difficult to measure.

We also show that cryptocurrency valuations influence the intensity and allocation of technological development. Rising prices and market capitalizations lead to increases in development activity both along the intensive margin, where existing developers contribute more, and the extensive margin, where new developers join projects. These results suggest that cryptocurrency prices act as incentives that shape the flow of labor and effort in open-source projects. Our findings provide novel evidence of high-frequency labor reallocation

in response to financial valuations, a dynamic less commonly observed in traditional labor markets where mobility is more constrained.

Taken together, our results highlight a two-way feedback loop between technology and prices in cryptocurrency markets. Flaws in the source code trigger price declines, which in turn discourage development efforts. Conversely, rising valuations stimulate development activity, improving technology and sustaining investor confidence. Our study underscores the importance of viewing cryptocurrency markets through the joint lens of both financial valuations and technological fundamentals.

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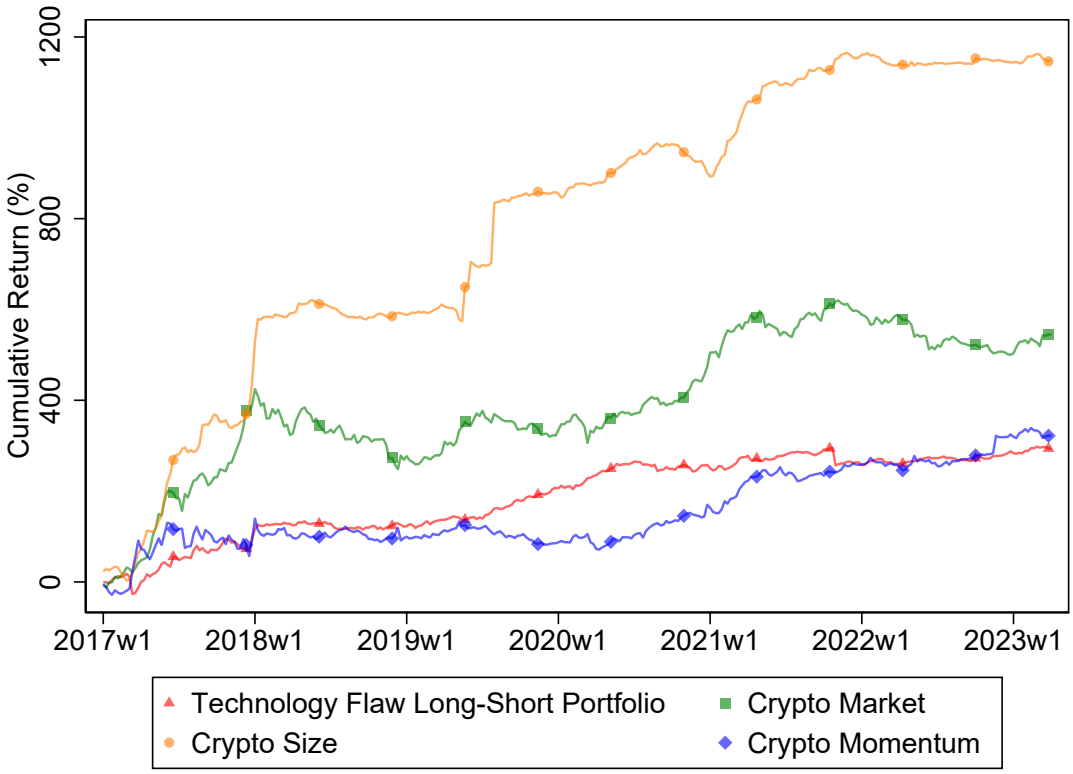
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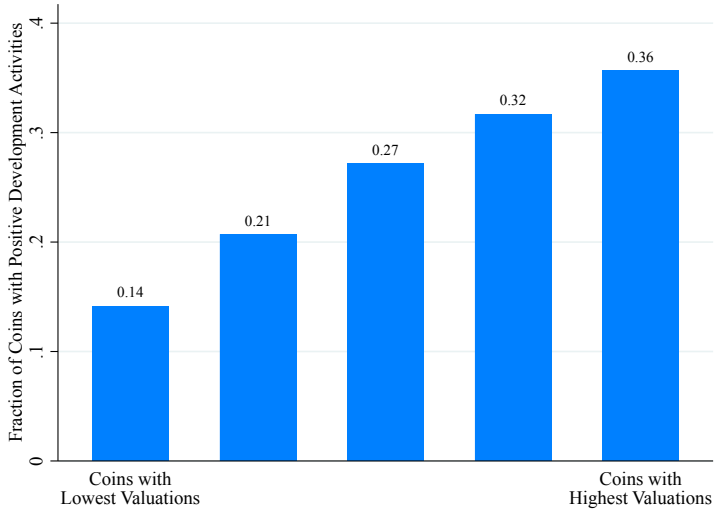
Figure 1. Technology Flaw Long-Short Portfolio Cumulative Return



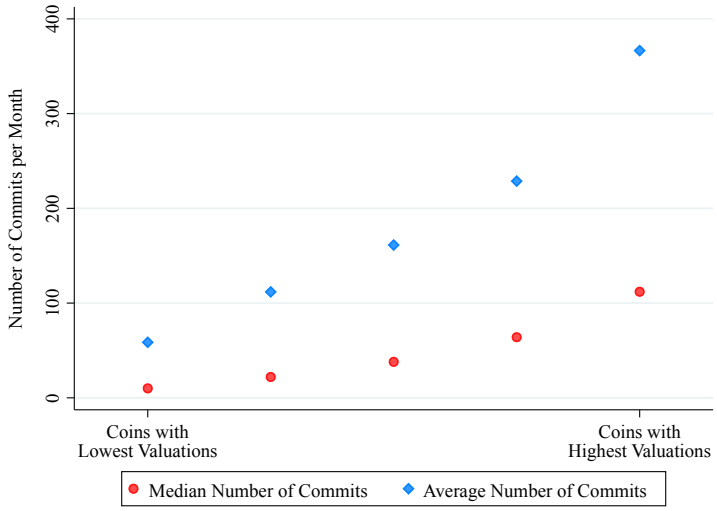
The figure plots the cumulative return (without compounding) of the technology flaw long-short portfolio along with the crypto market, size, and momentum factors from Liu et al. (2022).

Figure 2. Cryptocurrency Development Activity (Commits) by Valuation Quintile

(a) Fraction of Coins with Positive Commits during a Month



(b) Number of Commits during a Month



The figure plots cryptocurrency development activity by prior-month valuation quintiles. **Figure 2a** shows the fraction of coins with at least one commit for each quintile. **Figure 2b** plots the mean and median number of monthly commits for each quintile, conditional on positive commits.

Table 1
List of Crypto Hacks

This table reports all crypto hacks that resulted in $100 million or more stolen from 2014 to 2023. The data is collected from media reports, blockchain transaction records, and announcements from hacked exchanges. The hacked amount is the total dollar value of the crypto stolen by hackers. The recovered amount is the loss recovered through either hackers returning the stolen assets or the platform compensating investors, as of 2023. The cumulative hacked amount does not consider the recovered amount.

Hacks	Date	Hacked Amount ($ Millions)	Cumulative Hacked Amount ($ Millions)	Recovered Amount ($ Millions)
Mt. Gox	Feb 24, 2014	473	473	0
Parity	Nov 08, 2017	155	628	0
Coincheck	Jan 26, 2018	534	1,162	534
BitGrail	Feb 10, 2018	146	1,308	0
Gate.io	Apr 21, 2018	230	1,538	0
KuCoin	Sep 25, 2020	280	1,818	280
Poly Network	Aug 10, 2021	602	2,420	602
Cream Finance	Oct 27, 2021	130	2,550	0
Boy X Highspeed	Oct 30, 2021	139	2,689	0
BitMart Exchange	Dec 04, 2021	196	2,885	0
Vulcan Forged	Dec 12, 2021	140	3,025	0
Wormhole	Feb 02, 2022	326	3,351	326
Ronin	Mar 29, 2022	625	3,976	155
Beanstalk	Apr 18, 2022	181	4,157	0
Maiar DEX	Jun 05, 2022	113	4,270	113
Nomad	Aug 01, 2022	190	4,460	36
Wintermute	Sep 20, 2022	160	4,620	0
BSC Token Hub	Oct 06, 2022	586	5,206	459
BonqDAO	Feb 02, 2023	120	5,326	0
Euler Finance	Mar 13, 2023	196	5,522	177
Atomic Wallet	Jun 04, 2023	115	5,637	1
Multichain	Jul 06, 2023	231	5,868	0
Mixin Network	Sep 23, 2023	142	6,010	0

Table 2
Summary Statistics

This table presents summary statistics of the key variables defined in Sections **3.2** and **3.3**. The sample contains 1,414 unique coins from 2013 to 2023. Panel **2a** includes technology and labor market measures, while Panel **2b** includes return, trading volume, price, and market cap.

(a) Technology

	Mean	StdDev	p10	Median	p90	N
Daily Measures						
Technology Flaws	0.03	0.30	0.00	0.00	0.00	1,605,737
Weekly Measures						
Technology Flaws	0.22	1.54	0.00	0.00	0.00	231,568
Monthly Measures						
# of Commits	55.83	221.95	0.00	0.00	88.00	54,177
# of Pull Requests	5.47	21.08	0.00	0.00	9.00	54,177
# of Coders Making Commits	2.03	5.74	0.00	0.00	6.00	54,177
# of Coders Making Pull Requests	1.08	3.51	0.00	0.00	3.00	54,177
Average # of Commits per Coder	5.09	15.47	0.00	0.00	14.14	54,177
Average # of Pull Requests per Coder	0.83	2.25	0.00	0.00	3.00	54,177

(b) Prices

	Mean	StdDev	p10	Median	p90	N
Daily Measures						
Returns (%)	0.36	10.43	-8.70	-0.15	8.94	1,605,737
Trading Volume ($ millions)	21.76	111.12	0.00	0.13	14.65	1,605,717
Price ($)	234.57	3,366.45	0.00	0.05	3.85	1,605,737
Market Cap ($ millions)	200.54	920.03	0.10	5.98	211.48	1,605,588
Weekly Measures						
Returns (%)	1.73	26.14	-21.55	-1.33	24.65	230,146
Trading Volume ($ millions)	150.99	761.69	0.00	0.97	110.57	231,568
Price ($)	232.47	3,342.10	0.00	0.05	3.80	231568
Market Cap ($ millions)	198.67	915.76	0.09	5.79	208.48	231,558
Monthly Measures						
Returns (%)	7.30	63.11	-42.64	-5.80	62.01	52,762
Trading Volume ($ millions)	645.36	3,228.85	0.01	4.60	505.04	54,177
Price ($)	229.53	3,263.26	0.00	0.05	3.78	54,177
Market Cap ($ millions)	197.04	910.68	0.09	5.75	206.26	54,174

Table 3
Technological Flaws and Cryptocurrency Returns

The table presents the results of the following regression:

$$\text{Return}_{i,t} = \beta \times \text{Technology Flaws}_{i,t-1} + \boldsymbol{X}_{i,t} + \phi_i + \zeta_t + \epsilon_{i,t},$$

where $\text{Return}_{i,t}$ is the return for crypto i on date t in percentage points, $\text{Technology Flaws}_{i,t}$ is the number of bug reports for crypto i on date t, and $\boldsymbol{X}_{i,t}$ is a vector of control variables including the log of trading volume and the log of market cap. ζ and ϕ are time and coin fixed effects, respectively. In the daily (weekly) specification, ζ represents date (week) fixed effects. Panel (a) presents daily results, while panel (b) presents weekly results. Robust standard errors clustered at the coin and date level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Daily

	(1)	(2)	(3)	(4)
Technology Flaws	-0.11***	-0.12***	-0.11***	-0.07***
	(0.02)	(0.03)	(0.02)	(0.03)
ln(Market Cap)	0.02	0.10**	0.01	0.24***
	(0.02)	(0.05)	(0.02)	(0.04)
ln(Volume)	0.01	0.15***	0.01	0.17***
	(0.01)	(0.02)	(0.01)	(0.02)
Coin FE	No	Yes	No	Yes
Date FE	No	No	Yes	Yes
Adjusted R-squared	0.000	0.003	0.124	0.128
Observations	1,492,295	1,492,290	1,492,295	1,492,290

(b) Weekly

	(1)	(2)	(3)	(4)
Technology Flaws	-0.16***	-0.24***	-0.14***	-0.13***
	(0.05)	(0.07)	(0.04)	(0.04)
ln(Market Cap)	0.63***	1.32***	0.57***	1.61***
	(0.11)	(0.26)	(0.07)	(0.17)
ln(Volume)	-0.24***	0.08	-0.25***	0.15*
	(0.08)	(0.12)	(0.06)	(0.08)
Coin FE	No	Yes	No	Yes
Week FE	No	No	Yes	Yes
Adjusted R-squared	0.002	0.008	0.180	0.186
Observations	214,558	214,548	214,558	214,548

Table 4
Heterogeneous Return Predictability of Technology Flaws

The table repeats the analysis in **Table 3** using technology flaws that count only severe bugs. Column 1 replicates the main specification in **Table 3** column 4 for ease of comparison. Column 2 recalculates Technology Flaws$_{i,t}$ by counting only bugs that are fixed by a commit in the future. Column 3 recalculates Technology Flaws$_{i,t}$ by counting only bugs that are heavily discussed in the future, defined as ones that receive more than 50 comments. Column 4 recalculates Technology Flaws$_{i,t}$ by counting only bugs reported by "Top Devs", defined as those who have a lifetime commits count in the top 1% as of $t-1$. $\boldsymbol{X}_{i,t}$ is a vector of control variables including the log of trading volume and the log of market cap (untabulated for brevity). ϕ_i and ζ_t are coin and time fixed effects, respectively. Panel 4a reports the daily results and panel 4b reports the weekly results Robust standard errors clustered at the coin and date level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Daily

		Severe Bugs		
Technology Flaws includes	(1) All Bugs	(2) Bugs that Require Fixes	(3) Bugs that are Heavily Discussed	(4) Bugs Reported by Top Developers
Technology Flaws	-0.07***	-0.10**	-0.41**	-0.28**
	(0.03)	(0.04)	(0.15)	(0.14)
Coin FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.128	0.128	0.128	0.128
Observations	1,492,290	1,492,290	1,492,290	1,492,290

(b) Weekly

		Severe Bugs		
Technology Flaws includes	(1) All Bugs	(2) Bugs that Require Fixes	(3) Bugs that are Heavily Discussed	(4) Bugs Reported by Top Developers
Technology Flaws	-0.13***	-0.18**	-0.67**	-0.14
	(0.04)	(0.08)	(0.28)	(0.32)
Coin FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.186	0.186	0.186	0.186
Observations	214,548	214,548	214,548	214,548

Table 5
Long-Term Return after the Initial Return Predictability of Technology Flaws

The table examines the return reversals after the first day of technology flaws' return predictability by estimating the following equation:

$$\text{Return}_{i,t+1\to t+j} = \beta \times \text{Technology Flaws}_{i,t-1} + \boldsymbol{X}_{i,t} + \phi_i + \zeta_t + \epsilon_{i,t},$$

where $\text{Return}_{i,t+1\to t+j}$ is the return for crypto i from day $t+1$ to day $t+j$. Columns 1 through 4 use future returns from day $t+1$ to next week $(t+7)$, month $(t+30)$, quarter $(t+90)$, and year $(t+365)$, respectively. All returns are normalized to the daily level for ease of comparison. Robust standard errors clustered at the coin and date level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Return Period	1-7	1-30	1-90	1-365
Technology Flaws	-0.01	-0.02	-0.00	0.00
	(0.02)	(0.01)	(0.01)	(0.00)
ln(Market Cap)	-0.27***	-0.21***	-0.17***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.00)
ln(Volume)	-0.03***	-0.02***	-0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Coin FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.250	0.387	0.528	0.708
Observations	1,492,341	1,492,341	1,492,341	1,492,341

Table 6
Long-Short Portfolio by Technology Flaws

This table presents the average portfolio returns for the long leg, short leg, and long-short portfolios. The long leg includes coins that had no bugs (technology flaws = 0) in period $t-1$ (i.e., last day, last week, or last month). The short leg includes coins that were in the top 10th percentile of technology flaws in period $t-1$. We exclude periods where all coins had technology flaws = 0 in period $t-1$. All portfolios are equal-weighted. Portfolio returns are normalized to the daily level and are expressed in percentages. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Long Leg Return	Short Leg Return	Long - Short Return
Rebalance Daily	0.55***	0.25**	0.30***
	(0.08)	(0.10)	(0.05)
Rebalance Weekly	0.34***	0.20*	0.11**
	(0.09)	(0.10)	(0.04)
Rebalance Monthly	0.26**	0.16	0.09**
	(0.11)	(0.12)	(0.04)

Table 7
Cryptocurrency Development and Coin Valuations

The table presents the results of the following Poisson regression:

$$\text{Technology Development}_{i,t} = \beta \times \text{Coin Valuation}_{i,t-1} + \phi_i + \zeta_t + \epsilon_{i,t},$$

where $\text{Development}_{i,t}$ is the number of new commits or the number of new pull requests for coin i in month or week t. $\text{Coin Valuation}_{i,t-1}$ is the log of market cap or the log of price for coin i at the end of month or week $t-1$. ϕ is coin fixed effects and ζ is month or week fixed effects. Panels (a) and (b) report the results at the monthly level, and panels (c) and (d) report the results at the weekly level. Panels (a) and (c) use the number of new commits as the dependent variable, and panels (b) and (d) use the number of new pull requests as the dependent variable. Robust standard errors clustered at the coin and month (or week) level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Commits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Market Cap)	0.352***	0.370***	0.078***	0.139***				
	(0.031)	(0.032)	(0.030)	(0.036)				
ln(Price)					0.155***	0.165***	0.107***	0.166***
					(0.017)	(0.017)	(0.026)	(0.033)
Coin FE	No	No	Yes	Yes	No	No	Yes	Yes
Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	49,311	47,443	35,346	33,634	52,763	50,893	38,013	36,299

(b) Pull Requests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Market Cap)	0.402***	0.419***	0.110***	0.128***				
	(0.035)	(0.036)	(0.032)	(0.031)				
ln(Price)					0.193***	0.204***	0.129***	0.139***
					(0.023)	(0.023)	(0.031)	(0.031)
Coin FE	No	No	Yes	Yes	No	No	Yes	Yes
Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	49,311	47,443	30,803	29,197	52,763	50,893	33,197	31,564

Table 8
Cryptocurrency Development and Coin Valuations, Intensive Margin

The table presents the results of the following Poisson regression:

$$\text{Commits per Developer}_{i,t} = \beta \times \text{Coin Valuation}_{i,t-1} + \phi_i + \zeta_t + \epsilon_{i,t},$$

where Coin Valuation$_{i,t-1}$ is the log of market cap or the log of price for coin i at the end of month $t-1$. The dependent variable in columns 1 and 2 is the average contribution per coder who contributed to coin i's GitHub repository in month t. The average number of contributions per coder in columns 3 and 4 is calculated among only the top coders within the top 1 percentile distribution of lifetime commits. The average number of contributions per coder in columns 5 and 6 is calculated among the rest of the coders who are not in the top 1 percentile in terms of lifetime commits, labeled grassroots coders. ϕ and ζ are coin and month fixed effects, respectively. Robust standard errors clustered at the coin and month level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Commits per Developer for	All Coders		Top Coders		Grassroots Coders	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Market Cap)	0.09***		0.07		0.10***	
	(0.03)		(0.06)		(0.03)	
ln(Price)		0.10***		0.06		0.12***
		(0.03)		(0.06)		(0.03)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,634	36,299	9,037	9,332	33,634	36,299

Table 9
Cryptocurrency Development and Coin Valuations, Individual Coder Productivity

The table presents the results of the following Poisson regression:

$$\text{Commits}_{i,t,j} = \beta \times \text{Coin Valuation}_{i,t-1} + \phi_i + \zeta_t + \gamma_j + \epsilon_{i,j,t},$$

where $\text{Development}_{i,j,t}$ is the number of commits or pull requests made by coder j to coin i in month t. $\text{Coin Valuation}_{i,t-1}$ is either the log of market cap or the log of price for coin i at the end of month $t-1$. Columns 1 and 2 report the results with the full sample, columns 3 and 4 report the results with top coders who have a lifetime contribution in the top 1 percentile, and columns 5 and 6 report the results with the rest of the coders whose lifetime contribution is not in the top 1 percentile, labeled grassroots coders. ϕ, γ, and ζ are coin, coder, and month fixed effects, respectively. Robust standard errors clustered at the coin and month level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Commits from	All Coders		Top Coders		Grassroots Coders	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Market Cap)	0.03**		0.02		0.02**	
	(0.01)		(0.02)		(0.01)	
ln(Price)		0.03**		-0.00		0.04**
		(0.01)		(0.03)		(0.02)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Coder FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	107,581	110,759	3,944	4,074	103,585	106,634

Table 10
Cryptocurrency Development and Coin Valuations, Extensive Margin

The table presents the results of the following Poisson regression:

$$\text{Number of Coders}_{i,t} = \beta \times \text{Coin Valuation}_{i,t-1} + \phi_i + \zeta_t + \epsilon_{i,t},$$

where Coin Valuation$_{i,t-1}$ is the log of market cap or the log of price for coin i at the end of month $t-1$. The dependent variable in columns 1 and 2 is the number of all coders who contributed to coin i's GitHub repository in month t. The number of coders in columns 3 and 4 counts only the top coders within the top 1 percentile distribution of lifetime commits. The number of coders in columns 5 and 6 counts the rest of the coders who are not in the top 1 percentile in terms of lifetime commits, labeled grassroots coders. ϕ and ζ are coin and month fixed effects, respectively. Robust standard errors clustered at the coin and month level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Number of	All Coders		Top Coders		Grassroots Coders	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Market Cap)	0.15***		0.05		0.15***	
	(0.03)		(0.05)		(0.03)	
ln(Price)		0.15***		0.01		0.16***
		(0.03)		(0.04)		(0.03)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,634	36,299	9,037	9,332	33,634	36,299

A1. Discussion of the Technology Flaw Measure

This section provides further discussion of the validity and justification of the technology flaw measure used in the paper. **Section A1.1** provides two examples of GitHub Issues that describe cybersecurity vulnerabilities. **Section A1.2** discusses the credibility of user-reported issues and whether issues can lead to cybersecurity failures.

A1.1. Examples of GitHub Issues and Cybersecurity Exposure

We provide several concrete examples of Issues to demonstrate how technology flaws can lead to cybersecurity vulnerabilities. The following is an Issue initiated by username TippyFlitsUK on the filecoin-project project's lotus repository on November 6, 2020, at 22:59:19 GMT:

> *"I have lost a large amount of money this week primarily as a result of snapshot sync irregularities and deal completion failures. We are very much still in the early stages of Filecoin mainnet and there will obviously be bugs and obstacles to navigate. As early miners we fully accept this but it is also crucial to remember that we are now dealing with real money and livelihoods at a time of great economic instability. I for one am sincerely grateful to the developer team for their considerable efforts and excellent communication in these early days but the fact remains that bugs are an inevitability. I would respectfully like to propose that a contingency fund be established that will allow miners to apply for reimbursement in the unfortunate event of unavoidable financial loss."*[11]

[11] See the original post at https://github.com/filecoin-project/lotus/issues/4759.

This example shows how the crypto community uses Issues as a means to identify problems and call for help. It also highlights that technology flaws can lead to monetary losses.

Issues sometimes provide specific details about bugs in the code even for prominent coins. The following is an Issue initiated by username nopara73 on the Bitcoin project's Bitcoin repository on October 2, 2018, at 00:34:21 GMT:

> *"At the time of writing approximately 86.51% of the Bitcoin network is vulnerable to CVE-20181-7144. It has been two weeks since 0.16.3 was tagged with the vulnerability fix. I believe the occasional breaking of user space is one of the contributing factor to this situation where things can be improved. I believe marking an RPC method deprecated and removing it within a few new release may not be sufficient, since most developers do not code directly against Bitcoin Core, rather I they take an RPC client implementation, written by someone else in their respective programming language. These projects tend to be unmaintained, incomplete, sometimes even buggy. These developers, in such an environment may consider upgrading their Core nodes risky. I know it is hard living together with legacy code and immature API design decisions, but a "never break the user space" policy may result in a more secure and stable environment."*[12]

These examples demonstrate how GitHub Issues capture flaws in cryptocurrencies' underlying technology and how *Technology Flaws* can lead to cybersecurity exposure and monetary losses.

[12]See the original post at https://github.com/bitcoin/bitcoin/issues/14363.

A1.2. Discussion of GitHub Issues and Cybersecurity Exposure

We address two questions concerning the validity of using GitHub Issues to measure technology flaws.

The first concern is whether we should trust the quality of these "bug reports" in GitHub Issues. Are these bug reports really informative considering that people who report the bugs might not have been the ones who wrote the code? We provide two pieces of evidence that these Issues systematically capture technology flaws. First, relying on users to report bugs is widely used by the software development industry to improve software quality and security. For example, Ethereum, the second largest cryptocurrency by market capitalization as of 2023, and Coinbase, the largest US-based crypto exchange as of 2023, have bug bounty programs that incentivize outsiders to find and report bugs.[13] Second, many bugs get fixed later. 30% of the total bug reports result in a future update to the code base that fixes the bug. This number is the lower bound of the response rate because many bugs reported this way can be fixed without explicit documentation. The high response rate suggests that these bug reports have a high quality and are an important mechanism for crypto code to improve over time.

The second concern is whether these bugs lead to serious cybersecurity failures, or are they merely inconveniences for users? Some bugs do lead to serious cybersecurity failures and, eventually, massive monetary loss. For example, in the Wormhole Network exploit, the bug allowed a hacker to "mint" 120,000 wrapped ETH (worth $325 million) out of thin air.

[13] Ethereum's bug bounty program rewards up to $250,000 and can be viewed at https://ethereum.org/en/bug-bounty/. Coinbase's bug bounty program can be viewed at https://hackerone.com/coinbase. See additional background on the inception of Coinbase's bounty program based on outsiders' bug reports at https://www.coinbase.com/blog/retrospective-recent-coinbase-bug-bounty-award.

While the bug was identified and fixed in the code base, it did not go live before the exploit happened.[14] More importantly, it is difficult to assess the severity of most bugs. A bug that looks innocuous can have unexpected grave consequences. For example, an NFT project accidentally locked $34 million worth of ETH in the smart contract simply because the code did not properly add index numbers to the assets in the smart contract, which would seem almost trivial ex-ante.[15] Therefore, the bugs reported in GitHub Issues could lead to serious cybersecurity exposures beyond mere inconvenience.

To summarize, since GitHub Issues report bugs that could lead to cybersecurity exposures and monetary losses, we develop the measure of technology flaws using these Issues and examine whether it predicts crypto returns in subsequent analyses.

[14]See the Solana blockchain record of the hacker "minting" 120,000 wETH at https://solscan.io/tx/2zCz2GgSoSS68eNJENWrYB48dMM1zmH8SZkgYneVDv2G4gRsVfwu5rNXtK5BKFxn7fSqX9BvrBc1rdPAeBEcD6Es. See the bug fix in Wormhole Network's code base that would have prevented the exploit at https://github.com/wormhole-foundation/wormhole/commit/7edbbd3677ee6ca681be8722a607bc576a3912c8#diff-0d27d8889edd071b86d3f3299276882d97613ad6ab3b0b6412ae4ebf3ccd6370L92-R101. See more details about this exploit at https://www.theverge.com/2022/2/3/22916111/wormhole-hack-github-error-325-million-theft-ethereum-solana.

[15]See more for details about the incident of the Aku Ethereum NFT launch at https://decrypt.co/98530/aku-ethereum-nft-launch-ends-with-34m-locked-in-flawed-smart-contract.

A2. Appendix Tables

This section presents additional results that supplement the analyses in the main paper.

Table A1
Technological Flaws and Cryptocurrency Returns, Split on Coin Size

The table repeats the analyses in **Table 3** but estimates the effect in subsamples of terciles based on the lagged coin market cap. Robust standard errors clustered at the coin and date level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Daily

	Small				Large			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Flaws	-0.40***	-0.37**	-0.35	-0.21	-0.13***	-0.12***	-0.12***	-0.06**
	(0.13)	(0.17)	(0.22)	(0.20)	(0.03)	(0.03)	(0.04)	(0.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	No	No	Yes	Yes	No	No	Yes	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R-squared	0.004	0.067	0.010	0.078	0.004	0.302	0.009	0.310
Observations	494,967	494,967	494,948	494,948	498,135	498,134	498,112	498,111

(b) Weekly

	Small				Large			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology Flaws	-0.34***	-0.20	-0.57***	-0.07	-0.18***	-0.18***	-0.27***	-0.13*
	(0.13)	(0.12)	(0.18)	(0.19)	(0.05)	(0.05)	(0.08)	(0.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	No	No	Yes	Yes	No	No	Yes	Yes
Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R-squared	0.014	0.129	0.028	0.147	0.009	0.326	0.019	0.344
Observations	71,636	71,636	71,596	71,596	71,333	71,333	71,292	71,292

Table A2
Technological Flaws and Cryptocurrency Returns, Conditional on Positive Technology Flaws

The table repeats the analyses in **Table 3** but use only coin-days or coin-weeks with positive Technology Flaws$_{t-1}$ for estimation. Robust standard errors clustered at the coin and date level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Daily

	(1)	(2)	(3)	(4)
Technology Flaws	-0.08**	-0.04	-0.14***	-0.10***
	(0.03)	(0.02)	(0.03)	(0.03)
Controls	Yes	Yes	Yes	Yes
Coin FE	No	No	Yes	Yes
Date FE	No	Yes	No	Yes
Adjusted R-squared	0.002	0.306	0.013	0.321
Observations	29,666	29,639	29,568	29,541

(b) Weekly

	(1)	(2)	(3)	(4)
Technology Flaws	-0.08*	-0.05*	-0.20***	-0.16***
	(0.04)	(0.03)	(0.06)	(0.05)
Controls	Yes	Yes	Yes	Yes
Coin FE	No	No	Yes	Yes
Week FE	No	Yes	No	Yes
Adjusted R-squared	0.003	0.321	0.009	0.331
Observations	13,231	13,231	13,132	13,132

Table A3
Heterogeneous Return Predictability of Technology Flaws: Bug Discussions

The table repeats the analyses in **Table 4** column 3 with different thresholds of heavy bug discussion. Column 1 is repeated from **Table 4** for ease of comparison. Robust standard errors clustered at the coin and date level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Daily

Technology Flaws includes	(1) All Bugs	(2) ≥ 10 Comments	(3) ≥ 20 Comments	(4) ≥ 50 Comments
Technology Flaws	-0.07***	-0.18**	-0.40***	-0.41***
	(0.03)	(0.08)	(0.10)	(0.15)
ln(Market Cap)	0.24***	0.24***	0.24***	0.24***
	(0.04)	(0.04)	(0.04)	(0.04)
ln(Volume)	0.17***	0.17***	0.17***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)
Coin FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	1,492,290	1,492,290	1,492,290	1,492,290
Adjusted R-squared	0.128	0.128	0.128	0.128

(b) Weekly

Technology Flaws includes	(1) All Bugs	(2) ≥ 10 Comments	(3) ≥ 20 Comments	(4) ≥ 50 Comments
Technology Flaws	-0.13***	-0.55***	-1.08***	-0.67**
	(0.04)	(0.21)	(0.37)	(0.28)
ln(Market Cap)	1.61***	1.61***	1.61***	1.61***
	(0.17)	(0.17)	(0.17)	(0.17)
ln(Volume)	0.15*	0.15*	0.15*	0.15*
	(0.08)	(0.08)	(0.08)	(0.08)
Coin FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	214,548	214,548	214,548	214,548
Adjusted R-squared	0.186	0.186	0.186	0.186

Table A4
Technology Flaw Long-Short Portfolio and Crypto Market, Size, and Momentum Factors

The table presents the results of the following regression:

$$R_t = \alpha + \beta_1 \text{CryptoMarket}_i t + \beta_2 \text{CryptoSize}_t + \beta_3 \text{CryptoMomentum}_t + \epsilon_t,$$

where R_t is the return of the weekly-rebalancing portfolio that shorts coins with high technology flaws (in top decile) and longs coins with zero technology flaws in week t. CryptoMarket_t, CryptoSize_t, and CryptoMomentum_t are the Liu et al. (2022) crypto market, size, and momentum factors, respectively. All returns are normalized to daily level and expressed in percentage points. Newey West standard errors are estimated with one lag and reported in parentheses.

	(1)	(2)	(3)	(4)
Alpha	0.14***	0.08**	0.12***	0.08**
	(0.04)	(0.04)	(0.04)	(0.04)
Crypto Market	-0.03			-0.05*
	(0.03)			(0.03)
Crypto Size		0.10**		0.11***
		(0.04)		(0.04)
Crypto Momentum			0.04	0.02
			(0.08)	(0.07)
Observations	325	325	325	325

Table A5
Cryptocurrency Development and Coin Valuations, Weekly

This table repeats the analysis of development activities and coin valuations in **Table 7** on weekly level.

(a) Commits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Market Cap)	0.352***	0.371***	0.076***	0.139***				
	(0.030)	(0.032)	(0.028)	(0.036)				
ln(Price)					0.155***	0.166***	0.106***	0.168***
					(0.017)	(0.018)	(0.023)	(0.034)
Coin FE	No	No	Yes	Yes	No	No	Yes	Yes
Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	214,787	206,603	154,955	147,458	230,149	221,960	166,761	159,255

(b) Pull Requests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Market Cap)	0.402***	0.420***	0.109***	0.128***				
	(0.036)	(0.036)	(0.030)	(0.031)				
ln(Price)					0.193***	0.204***	0.128***	0.141***
					(0.023)	(0.024)	(0.028)	(0.032)
Coin FE	No	No	Yes	Yes	No	No	Yes	Yes
Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	214,787	206,603	134,362	127,331	230,149	221,960	144,993	137,843

Table A6
Cryptocurrency Development and Coin Valuations, Intensive Margin, Weekly

This table repeats the analysis of development activities and coin valuations on the intensive margin in **Table** 8 on weekly level.

Commits per coder from	All Coders		Top Coders		Grassroots Coders	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Market Cap)	0.10***		0.07		0.11***	
	(0.03)		(0.04)		(0.03)	
ln(Price)		0.12***		0.06		0.13***
		(0.03)		(0.04)		(0.03)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147,458	159,255	41,731	43,564	147,458	159,255

Table A7
Cryptocurrency Development and Coin Valuations, Individual Coder Productivity, Weekly

This table repeats the analysis of development activities and coin valuations on the intensive margin in **Table 9** on weekly level.

Commits from	All Coders		Top Coders		Grassroots Coders	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Market Cap)	0.02		0.02		0.01	
	(0.01)		(0.02)		(0.01)	
ln(Price)		0.02		0.03		0.01
		(0.01)		(0.02)		(0.01)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Developer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	252,444	259,607	8,144	8,371	244,011	250,943

Table A8
Cryptocurrency Development and Coin Valuations, Extensive Margin, Weekly

This table repeats the analysis of development activities and coin valuations on the extensive margin in **Table 10** on weekly level.

Number of	All Coders		Top Coders		Grassroots Coders	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Market Cap)	0.16***		0.07		0.16***	
	(0.03)		(0.04)		(0.03)	
ln(Price)		0.16***		0.04		0.17***
		(0.03)		(0.04)		(0.03)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147,458	159,255	41,731	43,564	147,458	159,255