

# The Bitcoin Backbone Protocol Against Quantum Adversaries

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**Abstract.** Bitcoin and its underlying blockchain protocol have received recently significant attention in the context of building distributed systems as well as from the perspective of the foundations of the consensus problem. At the same time, the rapid development of quantum technology brings the possibility of quantum computing devices from a theoretical concept to an emerging technology. Motivated by this, in this work we revisit the formal security of the core of the Bitcoin protocol, called the Bitcoin backbone, in the presence of an adversary that has access to a scalable quantum computer. We prove that the protocol’s essential properties stand in the post-quantum setting assuming a general quantum adversary with suitably bounded number of queries in the Quantum Random Oracle (QRO) model. In order to achieve this, we investigate and bound the quantum complexity of a Chain-of-Proofs-of-Work search problem which is at the core of the blockchain protocol. Our results imply that security can be shown by bounding the quantum queries so that each quantum query is worth  $O(p^{-1/2})$  classical ones and that the wait time for safe settlement is expanded by a multiplicative factor of  $O(p^{-1/6})$ , where  $p$  is the probability of success of a single classical query to the protocol’s underlying hash function.

## 1 Introduction

Bitcoin [35] and its underlying blockchain protocol structure have received substantial attention in recent years both due to its potential for various applications as well as to the possibility of using it to solve fundamental distributed computing questions in alternative and novel threat models. In [21], an abstraction of Bitcoin’s underlying protocol, termed the “Bitcoin backbone”, was presented and analyzed assuming a fixed (albeit unknown) number of parties (“miners”), a fraction of which may behave arbitrarily as controlled by an adversary. This was followed by [36, 22, 6], refining the model and the security analysis.

At a high level, the protocol relies on a concept known as a *proof of work* (PoW) [18], which, intuitively, enables a party to convince others that he has invested some effort for solving a task—specifically, finding a value (“witness”)

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such that a hash function (SHA-256) applied to that value together with (the hash of) the last block and new transactions yields an output that is less than a target value. A party who successfully produces a PoW gets to add a new block to the blockchain (and is rewarded). In the abstraction, the hash function is modelled as a random oracle (RO) [9], and it assumes a uniform configuration, meaning that parties are endowed with the same computational power, as measured by the allowed number of queries to the RO per round.

A number of desired properties for the blockchain thus constructed—such as *common prefix* and *chain quality* [21]—were introduced and shown sufficient for the realization of applications, notably a robust public transaction ledger (a.k.a. “Nakamoto consensus”), assuming an honest majority of computational power (or equivalently, in the uniform configuration setting mentioned above, that the number of honest parties exceed the number of malicious ones).

In the model of [21] as well as those in subsequent papers [36, 22, 6] follow [24, 15], parties are “classical” and modelled as polynomially bounded Interactive Turing Machines (ITMs), and protocol properties such as the ones above can be expressed as predicates over random variables quantifying over all possible adversaries.

In summary, the above works put forth elegant modeling and analyses and constitute an important step forward in our understanding of the capabilities of this emerging technology, but quantum computing, which equips attackers with unprecedented power and is changing the landscape of cryptography, “is coming,” with the known devastating consequences: Shor’s quantum algorithm [41] solves factorization and discrete logarithm efficiently, and hence breaks the popular public-key cryptosystems based on them. Further, the mere capability of collecting side information in a quantum register sometimes compromises information-theoretically secure schemes, such as randomness extractors for privacy amplification [23]. In fact, the unique features of quantum information, such as intrinsic randomness and no-cloning, render many classical security analyses obsolete (e.g., rewinding [46, 48]), and even the right *modeling* of security in the presence of quantum attacks can be elusive [47, 20, 43, 44, 26, 11, 2, 3].

As mentioned above, a core ingredient of the Bitcoin blockchain is proofs of work (PoW) [17], and the dynamic construction of a blockchain can be seen as sequential compositions of PoWs. Most existing analyses critically rely on generic properties of cryptographic hash functions, modeled as a random oracle (RO) [8] and only given oracle access. When quantum attackers are present, however, Boneh *et al.* [10] argued the need for granting the attackers the ability to query the random oracle in *quantum-superposition*, giving rise to the *quantum random oracle* (QRO) model.

Quantum superposition attacks turn out to be devastating to symmetric-key cryptosystems also which are usually considered less vulnerable to quantum attacks; for example, several practical authentication schemes using block ciphers are broken in this strong attack model [30, 38]. Roughly speaking, the PoW problem used in blockchain protocols corresponds to solving some search problem by making quantum-superposition queries to a (random) hash function, which

at first sight is reminiscent of some standard problems studied in quantum query complexity. However, existing results and techniques for proving quantum query lower bounds do not immediately translate to the cryptographic setting. This is because in cryptography we are interested in *average-case* complexity as opposed to the typical *worst-case* complexity; also, standard quantum query lower bounds usually apply to quantum algorithms with high success probability only, whereas an attacker with small but noticeable chance of breaking a scheme is still relevant. The abstract search problem, namely, that of chain of PoWs with bounded total resources, is clearly not related in a straightforward way to any of the known quantum complexity results.

Motivated by the above, the main open question we set out to answer in this work is characterizing the security of Nakamoto consensus in the post-quantum setting. Specifically, we ask what will happen when a quantum adversary emerges in the context of Bitcoin (and other similar PoW-based blockchain protocols). Does the protocol break or it remains secure? And in the latter case, what are the restrictions that need to be imposed on the quantum adversary?

*Our contributions.* We set out to answer the main open question by analyzing the Bitcoin backbone protocol [21] under the assumption that the adversary has access to devices able to perform universal quantum computing. As mentioned above, the two main properties that are required in [21] are *common prefix* (honest parties always agree on truncated local chains) and *chain quality* (expressing the ratio of honest/adversarial blocks and guaranteeing that at least a certain fraction of the blocks are generated by honest parties). As a result of our analysis, we are able to ensure that the common prefix and chain quality properties can still be satisfied against quantum attackers, provided some bounds on the quantum computational hashing power hold. The “honest majority” condition<sup>1</sup> we get is that the total number of quantum queries  $Q$  of the attacker has to be less than the total number of classical queries of all the honest parties divided by an extra  $O(p^{-1/2})$  factor, where  $p$  is the probability of success of a single query and, informally, represents the difficulty level of the PoW. This extra factor is the main difference from the classical analysis and, as we will prove, stems from a quadratic quantum speed-up in a search problem related to chained PoWs.

The common prefix and chain quality properties hold except with negligible probability, and this negligible probability is achieved after a number of rounds  $s$ . Our analysis indicates that to achieve the same negligible probability against a quantum attacker, the required number of rounds needs to be multiplied by an extra  $O(p^{-1/6})$  factor compared to the classical setting. This has the implication that, for post-quantum security, the number of “block confirmations” necessary for a transaction to be accepted has to be increased accordingly in order to protect against double-spending.

Having proven that the common prefix and chain quality properties hold against quantum attackers, we can build applications (such as consensus [a.k.a.

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<sup>1</sup> Necessary (and sufficient) for the properties to be satisfied in [21]’s uniform configuration with respect to hashing power.

Byzantine agreement [31]) and a public transaction ledger [i.e., Bitcoin]) as exactly shown in [21]. Now, these applications require digital signatures and it is well known that a quantum attacker can compromise some of the digital signature schemes (including ECDSA, used in Bitcoin). Therefore, in order for our analysis of the Bitcoin backbone protocol to carry over to the above applications we need to ensure that a post-quantum secure digital signature scheme is used (see also [1] where different post-quantum signature schemes were compared for their suitability for Bitcoin).

*Overview of our results.* Our contributions can be summarized as follows:

- We model quantum attackers in the context of Nakamoto consensus and the Bitcoin backbone protocol.
- *En route* to our main result, we introduce new search problems—namely, *Bag-of-PoWs* and *Chain-of-PoWs*—and bound their quantum complexity. For the analysis of the former we derive a new concentration theorem (specifically, a generalized version of Azuma’s inequality) for martingales, which might be of independent interest. We then apply our analysis to the latter, to obtain bounds on the expected number of PoWs that *any* quantum adversary can solve within a given number of rounds, which we then use to obtain an “honest majority” condition.
- Finally, using our new concentration result, we complete the analysis of the Bitcoin backbone protocol, giving a tight characterization of the overwhelming probabilities that the protocol’s properties hold with.

In Section 6, we give the exact bounds obtained for a general quantum adversary and the comparison to the classical adversaries.

A technical overview of our results follows. In our setting (see Section 2 for more details) we model the computational power of honest parties as a number of  $q$  queries per party to a random oracle (RO). In the classical setting, the adversary is assumed to benefit from the joint computational effort of the parties under his control. Accordingly, we assume that there is a quantum adversary with a total computational power of  $Q$  queries per round—to a Quantum Random Oracle (QRO) [10].

To ensure that Bitcoin remains secure against a quantum adversary, one needs to bound the probability of such adversary of being able to generate a “long” chain of PoWs. If the adversary outperforms the honest parties in this task, it would allow him to create a fork in the blockchain that affects blocks in the ledger that are already “established.” We therefore start by abstractly defining this problem as a generalized search problem, namely, the problem of achieving a maximum “chain of PoWs,” given  $N$  queries to the QRO and with at least some probability  $\delta$ . We obtain the following bounds on the Chain-of-PoWs search, which constitutes our main result:

**Theorem 3 (Main Theorem – Informal).** *Any quantum adversary having  $N$  queries to the QRO, can obtain a chain of PoWs of length at most  $M_A(N, p) = O(\sqrt{p} \cdot N)$ , with probability  $p_A(N, p) = O(\exp(-p^{2/3} \cdot N))$  or less, where  $p$  is the probability of a successful PoW with a single query.*

To prove the theorem, we first consider a simpler problem (for the adversary), which we call *Bag-of-PoWs*, which relaxes the requirement that the PoWs need to form a chain. Intuitively, bounding the adversary’s performance in the simpler problem, also provides a bound for the Chain-of-PoWs problem. To achieve this we need to (i) bound the expected number of PoWs and (ii) give tight expressions for the tails of the distributions.

We first show that it suffices to consider a more restricted adversary that uses his QRO queries *sequentially*, attempting to solve one PoW and conditioned on the outcome of the search, adapting his plan on how to spend the remaining queries suitably. This results into variables (successful PoWs) that are correlated and whose formal modelling involves martingales. We proceed to derive the optimal expectation  $E = \sqrt{cp}N$  (that can be obtained considering independent variables as shown in subsection 4.2.1). Next, we derive a new concentration theorem for martingales, Theorem 6 (which may be of independent interest), and use it to bound the tails of the distribution by  $\exp(-O(p^{1/6}E))$  from the expected value  $E$ . Combining these results gives Theorem 3.

We then turn to the security analysis of the Bitcoin backbone protocol. From [21] we extract two conditions (Lemma 8, Lemma 10) between the adversary’s and honest parties’ variables, that essentially suffice to satisfy the backbone’s essential properties (common prefix and chain quality) ensuring the security of the protocol. This, together with the bounds on the Chain-of-PoWs that we derived earlier, completes the analysis. We get an “honest majority” condition (relation between honest and adversarial hashing power), that roughly counts each quantum query as  $\frac{1}{\sqrt{cp}}$  classical queries. And, finally, we get an increased “relaxation time” (number of block confirmations before protecting against double spending) by a factor of  $\sim p^{-1/6}$ . Importantly, we note that our work, apart from the different parameter values we obtain, directly inherits all the generality of the analysis of [21], which includes strategies correlated with honest-parties’ actions as well as long-term attacks (such as selfish mining).

*Related work.* An important first step in understanding Bitcoin’s vulnerabilities against quantum attacks was taken by [1], who investigated the quantum threats to Bitcoin, taking into account detailed resource estimations (e.g., quantum error correction) and the prospect of the physical implementation of quantum computers. They asserted the imminent vulnerability of the elliptic-curve-based signature scheme used in Bitcoin, but on the other hand, they observed that the stand-alone search problem induced by PoW is relatively resistant to near-term quantum computations due to their slow clock speed and large overhead of quantum error correction. However, no complete analysis or explicit bounds were presented, leaving the full security analysis of the protocol as open question.

The Bitcoin protocol in a setting where honest parties are also quantum was considered in [32, 40]. While these papers offer interesting insights, including attacks not directly foreseen, they stop short of offering concrete security guarantees quantifying over all possible adversaries, as the work of [21] does for the classical setting.

On top of the challenges against superposition attacks, the quantum random oracle model has proven arduous to deal with. Many proof techniques in classical RO become ill-formed in QRO. Thankfully, many have been salvaged (at least partially) in QRO over the years. We can simulate a quantum random oracle [49, 51, 42], program it under a variety of circumstances [19, 45], establish generic security of hash functions [29, 7, 27, 33], and even paradoxically *record* quantum queries by Zhandry’s recent work [52]. These developments enable proving quantum security of many cryptographic schemes in QRO, such as CCA-secure public-key encryption and the general Fiat-Shamir approach to constructing digital signatures [28, 37, 4, 34, 16].

*Organization of the paper.* The rest of the paper is organized as follows. In Section 2 we present our security model and some background information regarding the Bitcoin Backbone protocol. In Section 3 we describe the Chain-Of-PoWs problem, and present our main result regarding bounding the quantum complexity for this problem. In Section 4 we prove our central result: We firstly describe a related problem called Bag-of-PoWs Problem, we show how solutions for the two problems are connected and we formalize the most general quantum strategies (SMS) for the Bag-of-PoWs Problem in Subsection 4.1. In Section 4.2 we perform the analysis for the SMS strategies. We derive the maximum expectation length of a solution (Section 4.2.2). We model the most general quantum strategies using martingales in Section 4.2.4 and to bound the tails of the corresponding distribution we derive new (stronger for our case) Azuma-type concentration inequalities in Section 4.2.6. Using them we bound the tails for the quantum adversaries in Section 4.2.7. Finally, we combine all these and complete the proof in Section 4.3.

In Section 5.1 we extract the essential results from [21] reducing the security analysis of the Bitcoin backbone protocol to essentially two conditions that the (quantum) adversary’s power should respect. In Section 5.2 we apply our results about quantum strategies for Chain-Of-PoWs problem with these conditions, to complete the security analysis of the Backbone against general quantum attackers. We conclude in Section 6 with a comparison between quantum and classical adversaries against the Bitcoin backbone protocol, and giving future directions.

## 2 Model and Definitions

We will analyze our post-quantum version of the Bitcoin backbone protocol in the network model considered in [21], namely, a synchronous communication network which is based on Canetti’s formulation of “real world” execution for multi-party cryptographic protocols [13, 14]). As such, the protocol execution proceeds in rounds with inputs provided by an environment program denoted by  $\mathcal{Z}$  to parties that execute the protocol. The execution is assumed to have a polynomial time bound. Message delivery is provided by a “diffusion” mechanism that is guaranteed to deliver all messages, without however preserving their order

and allowing the adversary to arbitrarily inject its own messages. Importantly, the parties are not guaranteed to have the same view of the messages delivered in each round, except for the fact that all honest messages from the previous round are delivered. Furthermore, we have a single adversary, which has quantum computing power and is formally defined later and is allowed to change the source information on every message (i.e., communication is not authenticated).

*The Bitcoin backbone protocol.* First, we introduce some blockchain notation, following [21]. A *block* is any triple of the form  $B = \langle s, x, ctr \rangle$  where  $s \in \{0, 1\}^\kappa$ ,  $x \in \{0, 1\}^*$ ,  $ctr \in \mathbb{N}$  are such that satisfy predicate  $\text{validblock}_q^D(B)$  defined as

$$(H(ctr, G(s, x)) < D) \wedge (ctr \leq q), \quad (2.1)$$

where  $H, G$  are cryptographic hash functions (e.g., SHA-256) modelled as random oracles. The parameter  $D \in \mathbb{N}$  is also called the block’s *difficulty level*. We then define  $p = D/2^\kappa$  to be the probability that a single classical query solves a PoW. The parameter  $q \in \mathbb{N}$  is a bound that in the Bitcoin implementation determines the size of the register  $ctr$ ; in our treatment we allow this to be arbitrary, and use it to denote the maximum allowed number of hash queries performed by the (classical) parties in a round.

A *blockchain*, or simply a *chain* is a sequence of *blocks*. The rightmost block is the *head* of the chain, denoted  $\text{head}(\mathcal{C})$ . Note that the empty string  $\varepsilon$  is also a chain; by convention we set  $\text{head}(\varepsilon) = \varepsilon$ . A chain  $\mathcal{C}$  with  $\text{head}(\mathcal{C}) = \langle s', x', ctr' \rangle$  can be extended to a longer chain by appending a valid block  $B = \langle s, x, ctr \rangle$  that satisfies  $s = H(ctr', G(s', x'))$ . In case  $\mathcal{C} = \varepsilon$ , by convention any valid block of the form  $\langle s, x, ctr \rangle$  may extend it. In either case we have an extended chain  $\mathcal{C}_{\text{new}} = \mathcal{C}B$  that satisfies  $\text{head}(\mathcal{C}_{\text{new}}) = B$ . Consider a chain  $\mathcal{C}$  of length  $m$  (written as  $\text{len}(\mathcal{C}) = m$ ) and any nonnegative integer  $k$ . We denote by  $\mathcal{C}^{\lceil k}$  the chain resulting from the “pruning” of the  $k$  rightmost blocks. Note that for  $k \geq \text{len}(\mathcal{C})$ ,  $\mathcal{C}^{\lceil k} = \varepsilon$ . If  $\mathcal{C}_1$  is a prefix of  $\mathcal{C}_2$  we write  $\mathcal{C}_1 \preceq \mathcal{C}_2$ .

The Bitcoin backbone protocol is executed by an arbitrary number of parties over an unauthenticated network, as described above. It is assumed in [21] that the number of parties running the protocol is fixed however, parties need not be aware of this number when they execute the protocol. In our analysis we will have  $n$  honest parties and a single quantum adversary. Also as mentioned above, communication over the network is achieved by utilizing a send-to-all DIFFUSE functionality that is available to all parties (and may be abused by the adversary in the sense of delivering different messages to different parties).

Each party maintains a blockchain, as defined above, starting from the empty chain and mining a block that contains the value  $s = 0$  (by convention this is the “genesis block”). If in a given round, a party is successful in generating a PoW (i.e. satisfying conjunction 2.1), it diffuses it to the network. At each round, each party chooses the longest chain amongst the one he received, and tries to extend it by computing (mining) another block. In such a process, each party’s chain may be different, but under certain well-defined conditions, it is shown in [21] that the chains of honest parties will share a large common prefix (see below).

In the backbone protocol, the type of values that parties try to insert in the chain is intentionally left unspecified, as well as the type of chain validation they perform (beyond checking for its structural properties with respect to the hash functions  $G(\cdot), H(\cdot)$ ), and the way they interpret the chain. Instead, these actions are abstracted by the external functions  $V(\cdot)$  (the *content validation predicate*),  $I(\cdot)$  (the *input contribution function*), and  $R(\cdot)$  (the *chain reading function*), which are specified by the application that runs “on top” of the backbone protocol (e.g., a transaction ledger).

*Basic security properties of the blockchain.* It is shown in [21] that the blockchain data structure built by the Bitcoin backbone protocol satisfies a number of basic properties. At a high level, the first property, called *common prefix*, has to do with the existence, as well as persistence in time, of a common prefix of blocks among the chains of honest parties.

**Definition 1 (Common Prefix).** *The common prefix property with parameter  $k \in \mathbb{N}$ , states that for any pair of honest players  $P_1, P_2$  adopting chains  $\mathcal{C}_1, \mathcal{C}_2$  at rounds  $r_1 \leq r_2$ , it holds that  $\mathcal{C}_1^k \preceq \mathcal{C}_2$  (the chain resulting from pruning the  $k$  rightmost blocks of  $\mathcal{C}_1$  is a prefix of  $\mathcal{C}_2$ ).*

The next property relates to the proportion of honest blocks in any portion of some honest party's chain.

**Definition 2 (Chain Quality).** *The chain quality property with parameters  $\mu \in \mathbb{R}$  and  $l \in \mathbb{N}$ , states that for any honest party  $P$  with chain  $\mathcal{C}$ , it holds that for any  $l$  consecutive blocks of  $\mathcal{C}$ , the ratio of blocks created by honest players is at least  $\mu$ .*

*Relevant random variables.* Following [21], we use the following two random variables:  $X_i$ : if at round  $i$  an honest party obtains a PoW, then  $X_i = 1$ , otherwise  $X_i = 0$ ;  $Y_i$ : if at round  $i$  exactly one honest party obtains a PoW, then  $Y_i = 1$ , otherwise  $Y_i = 0$ . For a set of consecutive rounds  $S$  of size  $s$ , we denote  $X(s) = \sum_{i \in S} X_i$ ,  $Y(s) = \sum_{i \in S} Y_i$ . Additionally, we denote by  $Z(s)$  the number of PoWs obtained by a (quantum in our case) adversary within  $s$  consecutive rounds. The security of the Bitcoin backbone protocol can be reduced to certain relations among these variables (see Section 5.1).

$n$ : number of honest parties	$q$ : # honest classical queries per round
$Q$ : number of adversarial quantum queries per round	$f$ : prob. at least one honest party finds a PoW in a round
$\epsilon$ : concentration quality of random variables	$\kappa$ : security parameter
$k$ : number blocks for common prefix	$\mu$ : chain quality parameter
$s$ : number of rounds	$p$ : prob of success of a single classical query
$X(s)$ : no of honest PoWs within $s$ rounds	$Z(s)$ : no of adversarial PoWs within $s$ rounds
$Y(s)$ : number of honest 'unique' PoWs within $s$ rounds	

**Table 1.** Parameters used for our analysis

A list of parameters and variables specific to the Bitcoin backbone protocol and to our analysis can be found in Table 1. More specifically, we let  $f = \mathbb{E}[X_i]$ , a parameter with respect to which all the other quantities are expressed (in the Bitcoin system,  $f$  is about 2 – 3%) and  $\epsilon$  denote the quality of concentration of random variables. We require  $3(f + \epsilon) < 1$ , implying that  $f, \epsilon < \frac{1}{3}$ . Following [21], we have the following bounds on these quantities:  $(1 - f)pqn < f < pqn$  and  $\mathbb{E}[Y_i] = pqn \cdot (1 - p)^{q(n-1)} > pqn(1 - pqn) \geq f(1 - f)$ . Which then give us the following concentration results for the random variables  $X(s)$  and  $Y(s)$ :

**Lemma 1 ([21]).** *For any  $s \geq 2/f$  rounds, we have that with probability  $1 - e^{-\Omega(\epsilon^2 sf)}$ , the following hold:*

$$\begin{aligned} (1 - \epsilon)fs &< X(s) < (1 + \epsilon)fs \\ (1 - \epsilon)\mathbb{E}[Y(s)] &< Y(s) \\ (1 - \epsilon)f(1 - f)s &< Y(s) \end{aligned} \tag{2.2}$$

*The quantum adversary model.* We will assume that the quantum adversary has a number  $Q$  of quantum queries to  $H$  per round. The adversary can access the cryptographic hash functions in a general quantum state (superposition) and receive the corresponding quantum output. This is modeled with  $Q$  queries per round to a Quantum Random Oracle (QRO) [10]. As in the classical case, the adversary cannot carry over the queries to a different round (attempting to solve a block at a later stage with more queries). What the adversary can do though is to transfer a quantum state that is the output of queries to the QRO of one round, to the next round. This possibility, on the one hand, enables the adversary to continue amplifying his probability of success (with the corresponding quantum speed-up) for more queries than those within one round. On the other hand, the transfer of quantum states makes the analysis more complicated since we can no longer assume that queries in different rounds are independent.

Further, for a quantum adversary even to define a classical random variable (such as  $Z(s)$ ) is not straightforward, since strictly speaking we can do this only once a measurement is performed. In other words, the quantum state received from the QRO after one query does not give any classical information unless a measurement is performed. In the general case the QRO is used to amplify the probability, multiple queries are used before a single measurement is performed, making hard to even know the number of classical random variables.

We define  $N = sQ$  to be the total number of queries to the QRO in  $s$  rounds;  $K_i$  the number of queries to the QRO used for the  $i$ th measurement (i.e. the quantum state measured in the  $i$ th round has passed  $K_i$ -times from the QRO);  $P_{K_i}$  the corresponding probability of success of the  $i$ th measurement, and  $w_i$  the  $i$ th measurement outcome (1 if a block is created, 0 otherwise).

*Randomized quantum search.* Our analysis relies on a tight quantum query bound for solving a randomized search problem.

**Theorem 1 ([29]).** *Let  $F : \{0, 1\}^\kappa \rightarrow \{0, 1\}$  be a function such that for any  $x \in \{0, 1\}^\kappa$ ,  $F(x) = 1$  with probability  $\lambda$ . Then, for any quantum algorithm  $\mathcal{A}$ ,*

the probability to find a solution for  $F$  using  $q$  quantum queries is upper bounded by:

$$\Pr_F[F(x) = 1 \mid x \leftarrow \mathcal{A}^F()] \leq 8\lambda(q+1)^2 \quad (2.3)$$

This bound is tight due to Grover’s quantum search algorithm.

**Theorem 2 ([25, 12]).** *Let  $F : \mathcal{X} \rightarrow \{0,1\}$  be an oracle function and let  $\mathcal{X}_F = \{x \in \mathcal{X} : F(x) = 1\}$ . Then there is a quantum algorithm with  $q$  queries that finds an  $x \in \mathcal{X}_F$  with success probability  $\Omega(q^2 \frac{|\mathcal{X}_F|}{|\mathcal{X}|})$ .*

In our analysis, we assume that the optimal success probability to solve a PoW using  $K$  queries to the QRO is determined by the expression:

$$P_K = cpK^2, \text{ where } c \text{ is a constant.} \quad (2.4)$$

*Concentration bounds.* Our analysis also uses (and extends) some standard concentration results, which can be found in Appendix A.

### 3 Quantum Complexity of Chain-of-PoWs Search

The basic problem that a (quantum) adversary tries to solve in the Backbone is to produce a chain of blocks that is longer than the honest chain. In order to bound the probability of such event, we need to be able to bound the maximum length of a chain that the adversary can produce (up to some small probability determined by the security level of the protocol). Abstractly, this problem translates to a search problem where the desired output is a chain of hashes (the output of one hash is fed as input to the next hash). We will call this problem the *Chain-of-PoWs* search problem, denote it by  $\Pi_G$  and we formalise it here:

PROBLEM  $\Pi_G$ : CHAIN-OF-POWS

**Given:**  $N, x_0 \in X, \delta$  and  $h_0, \dots, h_{N-1}$  as (quantum) random oracles, where each  $h_i : X \times Y \rightarrow X$  is independently sampled.

**Goal:** Using  $N$  total queries find a sequence  $y_0, \dots, y_{k-1}$  such that  $x_{i+1} := h_i(x_i, y_i)$  and  $x_{i+1} \leq D \forall i \in \{0, \dots, k-1\}$  such that the length of the sequence  $k \leq N$  is the maximum that can be achieved with success probability at least  $\delta$ .  $D$  is a fixed positive integer.

Note here that the output of this problem is the maximum length  $k$  and the corresponding sequence  $(y_0, \dots, y_{k-1})$ . For notational simplicity we will omit  $h_0, \dots, h_{N-1}$  from the input of  $\Pi_G$ .

**Definition 3 (PoW).** *We define a PoW to be any pair  $(x, y)$  s.t.  $h(x, y) \leq D$ .*

The stringent correlation between the consecutive output values makes this search problem difficult to analyze. A direct approach would require establishing a particular composition theorem, which appears beyond the scope of existing results and techniques in quantum query complexity. Instead, by a series of reductions, we are able to bound the maximum length that can be achieved for this problem.

**Theorem 3 (Main Theorem).** *We are given  $\Pi_G(N, x_0, \delta)$ , and let  $p := \frac{D}{2^\kappa}$  be the probability of success of a single query to the random oracles and  $c$  the corresponding constant in Theorem 2. The maximum length  $k$  of a solution of  $\Pi_G(N, x_0, \delta)$ , that any quantum algorithm can achieve, for any  $\delta \geq p_A = \exp(-f_0(c, p, \epsilon) \cdot N)$  is bounded by  $M_A = \left( \frac{(1+\epsilon)\sqrt{cp}}{1-(1+\epsilon)\sqrt{cp}} \right) \cdot N$ , where  $f_0(c, p, \epsilon) = (cp)^{\frac{2}{3}} \cdot \frac{1}{1-(1+\epsilon)\sqrt{cp}} \frac{\epsilon^{1/3}(7\epsilon-1)}{32}$  and  $\frac{1}{7} < \epsilon \leq \frac{1}{3}$  is a constant.*

It is worth noting that  $p \ll 1$  and the expressions (approximately) simplify to  $k \lesssim O(p^{1/2} \cdot N)$ , while the probability  $\delta \gtrsim \exp(-O(p^{2/3} \cdot N))$ . This probability decays exponentially with  $N$ , which means that the bound for  $k$  that we give (which scales linearly with  $N$ ) becomes impossible to achieve as  $N$  grows. We will see that, in the bitcoin context, this means that by running sufficient rounds and imposing certain constraints on the relative hashing power of honest parties and the quantum adversary, we should be confident that the adversary cannot create a large fork in the blockchain.

*Proof Sketch.* To derive this bound, we need a number of steps, namely:

1. In Section 4.1 we define a simpler problem Bag-of-PoWs (denoted  $\Pi'_G(N, \delta)$ ) and prove a relation that bounds the maximum sequence length of  $\Pi_G$  with the maximum cardinality of  $\Pi'_G$  (Lemma 2).
2. Given a fixed number of queries, and a relation between the maximum cardinality of Bag-of-PoWs and the corresponding success probability, we bound the maximum length of  $\Pi_G$  and maximum cardinality of  $\Pi'_G$  (Lemma 3).
3. We define a family of algorithms which we call Sequential Measurement Strategy (SMS) (Definition 4) and prove it is optimal for solving  $\Pi'_G$  i.e. finds a solution with maximum cardinality (Lemma 4).
4. For the SMS adversaries, we obtain a relation between the maximum cardinality of Bag-of-PoWs and the corresponding maximum success probability, which completes the proof given steps 1-3 above. To derive this relation, in Subsection 4.2 we first consider a restricted class of SMS adversaries that is called Non-Adaptive, where the algorithm has a predetermined (fixed) number of queries assigned to each oracle. This class is considered only as a step towards proving the general case as they achieve the optimal expectation value for the maximum cardinality. This is then combined with a newly derived concentration theorem for non-independent variables (Theorem 6) in order to prove the relation for the general SMS adversaries (Theorem 7).

□

## 4 Proof of Main Theorem and the Bag-of-PoWs Problem

To show our main result, we first introduce the simplified problem  $\Pi'_G$  that aims to find the maximum cardinality of Bag-of-PoWs that an algorithm can solve given a fixed number  $N$  of total quantum queries and a minimum success probability  $\delta$ . This problem is also of separate interest.

## 4.1 The Bag-of-PoWs Problem

PROBLEM  $\Pi'_G$ : BAG-OF-POWS

**Given:**  $N, \delta$  and  $h_0, \dots, h_{N-1}$  as oracles, where each  $h_i : X \times Y \rightarrow X$  is independently sampled.

**Goal:** Using  $N$  total number of queries find a set of pairs  $\{(x_{i_1}, y_{i_1})_1, \dots, (x_{i_k}, y_{i_k})_k\}$  so that  $h_{i_l}(x_{i_l}, y_{i_l}) \leq D$ , for all  $l \in \{1, \dots, k\}$ , such that the cardinality  $k \leq N$  of the set of pairs is the maximum that can be achieved with success probability at least  $\delta$ . Note that in the set, each pair should correspond to different oracle.  $D$  is a fixed positive integer.

This problem differs from  $\Pi_G$  in that the blocks are neither sequential nor chained since the condition that  $x_{i+1} = h_i(x_i, y_i)$  that exists in  $\Pi_G$  is removed. For the same reason, a hardness result on  $\Pi'_G$  readily implies the hardness of  $\Pi_G$ , which we make formal below.

**Lemma 2.** *The maximum sequence length  $k$  of  $\Pi_G(N, x_0, \delta)$  is at most the maximum cardinality of the set of pairs  $k'$  of  $\Pi'_G(N + k, \delta)$ .*

*Proof.* We prove this by contradiction, assuming that  $k' < k$ . We are given an algorithm  $\mathcal{A}$  for  $\Pi_G(N, x_0, \delta)$  returns a solution  $y_0, \dots, y_{k-1}$ . Then we are able to construct an algorithm  $\mathcal{A}'$  to solve  $\Pi'_G(N + k, \delta)$ .

$\mathcal{A}'$  first samples at random an element  $x_0$  (from the domain of any oracle  $h_i$ ). Then it runs  $\mathcal{A}$  the algorithm solving  $\Pi_G$  on input  $(N, x_0, \delta)$  to obtain the sequence  $y_0, \dots, y_{k-1}$  with probability  $\delta$  spending  $N$  queries. Then starting from  $y_0$ , computes  $x_i = h_i(x_{i-1}, y_{i-1})$  (which is guaranteed to hold from the setting of problem  $\Pi_G$ ) spending one extra query per element of the sequence, i.e. extra  $k$  queries. Then the algorithm outputs the pairs  $(x_0, y_0), (x_1, y_1), \dots, (x_{k-1}, y_{k-1})$  having used  $N + k$  queries and will succeed with probability  $\delta$ . This is a solution to  $\Pi'_G(N + k, \delta)$  with cardinality  $k$  contradicting the assumption that the maximum cardinality solving the problem is  $k' < k$ .  $\square$

**Lemma 3.** *Assume that for any quantum algorithm  $\mathcal{A}$  having  $N + M_A$  quantum queries, the probability of giving a set of pairs  $\{(x_{i_1}, y_{i_1})_1, \dots, (x_{i_{k'}}, y_{i_{k'}})_{k'}\}$  of cardinality  $k' < M_A$ , satisfying  $h_{i_l}(x_{i_l}, y_{i_l}) \leq D \forall i_l$ , is at least  $1 - p_A$ . Then the maximum sequence length  $k$  of a solution of  $\Pi_G(N, x_0, p_A + \epsilon')$ , where  $\epsilon'$  is a positive constant, is at most  $M_A$ .*

*Proof.* From our assumption we have that:

$$\Pr[\mathcal{A}(N + M_A) = (x_{i_1}, y_{i_1}), \dots, (x_{i_{k'}}, y_{i_{k'}}) \text{ such that } k' < M_A] \geq 1 - p_A \quad \forall \mathcal{A} \quad (4.1)$$

which is equivalent to:

$$\Pr[\mathcal{A}(N + M_A) = (x_{i_1}, y_{i_1}), \dots, (x_{i_{k'}}, y_{i_{k'}}) \text{ such that } k' \geq M_A] \leq p_A \quad \forall \mathcal{A} \quad (4.2)$$

Any solution for the problem  $\Pi'_G(N + M_A, \delta)$ , where  $\delta = p_A + \epsilon' > p_A$ , has the maximum cardinality  $k' < M_A$ . Then by using Lemma 2, we conclude that the maximum length  $k$  for  $\Pi_G(N, x_0, p_A + \epsilon')$  satisfies  $k \leq k' < M_A$ .  $\square$

In Section 4.2.6 we get such bounds for the probability of giving a set of such pairs with cardinality  $k' < M_A$  is at least  $1 - p_A$ .

**Definition 4 (Sequential Measurements Strategy).** *We define SMS adversary to be an adversary that tries to solve Bag-of-PoWs, given a fixed total number of quantum queries  $N$ , in a sequential way (following one order), i.e. starting with the oracle  $h_{i_1}$ . The number of queries  $K_j$  spent at each oracle ( $i$ ) satisfy  $\sum_{i=1}^N K_i = N$  and (ii) depend on the remaining queries ( $N - \sum_{i=1}^{j-1} K_i$ ) and on the previous outcomes of the searches  $[w_1, \dots, w_{j-1}]$  where  $w_i$  represents whether a PoW was solved using the  $i$ th oracle.*

We then prove that the Sequential Measurements Strategies are optimal for the Bag-of-PoWs  $\Pi'_G$  problem:

**Lemma 4.** *For any adversary for the  $\Pi'_G(N, x_0, \delta)$  problem, there is an SMS adversary that achieves the same maximum cardinality with the same probability.*

*Proof.* To prove the optimality of SMS adversaries it suffices to show that any general adversary to this problem can be re-written as an SMS adversary with unchanged probability.

Any adversary trying to solve  $\Pi'_G$ , can be modelled by a party providing an attempted PoW for each of the oracles. If successful, returns one, if unsuccessful returns zero, and if the adversary did not attempt to solve it (c.f. spent no queries) is also denoted with zero. This means that every run can be modelled by a  $N$ -bit string. For a given strategy, every such string has some probability, e.g.  $Pr[\text{PoW}_1 = \text{yes}, \text{PoW}_2 = \text{no}, \dots, \text{PoW}_N = \text{yes}] = Pr[10, \dots, 1]$ . To compute the probability of having at least  $k$  PoWs, one simply sums the probabilities of all strings with Hamming weight  $k$  or more.

Each oracle is independent and the inputs also are not correlated, therefore the probability to find a PoW for each oracle, is bounded (closely to optimally) by the standard quantum search bounds, namely  $cpK^2$  for  $K$  queries. However the variables corresponding to attempting to solve different PoWs are not independent. What makes them correlated, is the choice of  $K_i$ . It depends on the queries allocated to other oracles (bounded total number of queries), but also it could depend on other, classical but non-fixed, parameters such as measurement outcomes on states that have information about other oracles.

In general,  $K_{i_i}$  are classical variables and thus may depend on other classical variables, and the only such variables are measurement outcomes. We can define a (partial) order between the  $K_{i_i}$ 's, which captures the causal order that effects happen. We then find any total (temporal) order that is consistent with this partial order  $T(\{i_1, \dots, i_N\}) = \{t(i_1), \dots, t(i_N)\}$  which is essentially a permutation of the indices.

We can assume that we are making a single guess/measurement for each oracle<sup>2</sup>. Therefore, if the queries of oracle  $t(j)$  are to the future of those of oracle

<sup>2</sup> In general, it is allowed to try to solve the same PoW after a failed attempt. However, in terms of success probability, the adversary would be equally successful if after a failed attempt he tried to find a PoW at a fresh oracle.

$t(i)$ , the measurement of qubits having information on oracle  $t(j)$  are also to the future of oracle  $t(i)$  (and thus do not effect it). We then permute the order of the oracles according to the above temporal order. Finally, we express the probabilities using (iteratively) Bayes rule:

$$Pr[\text{PoW}_{t(1)}, \text{PoW}_{t(2)}, \dots, \text{PoW}_{t(N)}] = Pr[\text{PoW}_{t(1)}]Pr[\text{PoW}_{t(2)}, \dots, \text{PoW}_{t(N)}|\text{PoW}_{t(1)}]$$

where PoW takes values  $\{0, 1\}$ , the first term depends on  $K_{t(1)}$  only and is fixed, while the remaining terms depend also on the first measurement outcome. This expression can be realised with a Sequential-Measurement Strategy: adversary fixes  $K_{t(1)}$ , with probability  $cpK_{t(1)}^2$  solves it, and then the next oracle has up to  $N - K_{t(1)}$  queries, and it may follow different strategy depending on the value of  $\text{PoW}_{t(1)}$ , which coincides with the measurement outcome of the “first search”, and then proceeds iteratively.  $\square$

## 4.2 General Adversaries for Bag-of-PoWs

We have proved that for Bag-of-PoWs problem the most general adversaries are equivalent with the SMS adversaries. From here on, we call *general* the SMS adversaries. These adversaries can decide how many queries to use on each oracle, depending on how successful they were in previous attempts to generate PoWs. This “adaptivity” makes the analysis considerably more complex. Instead, it turns out it is much simpler to bound the expected maximum cardinality, rather than bound directly the maximum cardinality given an error threshold (see Section 4.2.2). However, having bound the expectation, it suffices to bound the tails of the distribution too, in order to solve the problem  $\Pi'_G$  (Section 4.3).

We start with a simpler subclass of SMS adversaries, which we call “Non-Adaptive”. Interestingly, these restricted strategies, can achieve the best (greatest) cardinality of PoWs *on average*, as we prove in Theorem 4. These adversaries do not take into account the history of successes, meaning that the number of queries  $K_i$  used on each oracle before the corresponding measurement, are independent of the previous measurement outcomes. We assume that the adversary decides in advance how to split his  $N$  total queries between the oracles.

In the following sections, we will denote the Non-Adaptive family of strategies by  $\mathcal{A}_{\text{nonad}}$  while the general as  $\mathcal{A}_{\text{qu}}$ . We denote by  $Z_{\mathcal{A}_{\text{nonad}}}$  the random variable corresponding to the cardinality of a Bag-of-PoWs solution for Non-Adaptive strategy. Similarly, we denote by  $Z_{\mathcal{A}_{\text{qu}}}$  the random variable corresponding to the cardinality of a Bag-of-PoWs solution for general strategy <sup>3</sup>.

### 4.2.1 Non-Adaptive Expectation is Optimal

<sup>3</sup> When we refer to  $\mathcal{A}_{\text{qu}}$  or  $\mathcal{A}_{\text{nonad}}$ , in general we need to also specify how many queries they have as input, e.g.  $\mathcal{A}_{\text{qu}}(N)$ , but for simplicity, in our entire analysis, when we write  $Z_{\mathcal{A}_{\text{qu}}}$  we implicitly assume that  $\mathcal{A}_{\text{qu}}$  has  $N$ (variable) queries available.

As the total number of available queries is  $N$ , we consider that there are  $N$  variables corresponding to measurements performed by the adversary, with  $K_i$  queries per measurement  $\sum_{i=1}^N K_i = N$ , where if the actual number of measurements is  $t$  we define  $K_i = 0 \forall i > t$ .

Let  $P_{\mathcal{A}_{\text{nonad}}}(i)$  be the probability of solving  $i$  PoWs for Non-Adaptive adversaries, then the expected number of PoWs can be computed as:

$$P_{\mathcal{A}_{\text{nonad}}}(i) = \sum_{I \subseteq \{1, 2, \dots, N\}, |I|=i} \left[ \prod_{j \in I} P_{K_j} \right] \cdot \left[ \prod_{l \in \{1, 2, \dots, N\} - I} (1 - P_{K_l}) \right] \text{ for } 1 \leq i \leq N$$

$$\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] = \sum_{i=1}^N P_{\mathcal{A}_{\text{nonad}}}(i) \cdot i \quad (4.3)$$

**Theorem 4.** *The Non-Adaptive adversaries are optimal with respect to the expected length of the solution for the Bag-of-PoWs problem.*

*Proof.* Suppose the optimal general strategy  $\mathcal{A}_{\text{qu}}$ . According to Definition 4,  $\mathcal{A}_{\text{qu}}$  initially decides the first chunk size  $K_1$  for the first measurement, where this decision (size of  $K_1$ ) is fixed since it does not depend on any measurement outcome. Then, for the remaining measurements, the chunk-sizes  $K_i$  are determined as a function  $\zeta$  of the remaining queries and the history of successes/failures in obtaining a PoW (measurement outcomes  $[w_1, \dots, w_{i-1}]$ ):  $K_i = \zeta(N - (K_1 + \dots + K_{i-1}), [w_1, \dots, w_{i-1}])$ . Hence,  $\mathcal{A}_{\text{qu}}$  can be described as follows:

$$\mathcal{A}_{\text{qu}} = (K_1, \zeta(N - K_1, [w_1]), \dots, \zeta(N - (K_1 + \dots + K_{i-1}), [w_1, \dots, w_{i-1}]), \dots) \quad (4.4)$$

In particular, the size of  $K_2$  depends on the first measurement outcome  $w_1$  only. To each of the two measurement outcomes corresponds an adversarial strategy with  $w_1$  is fixed (here  $K_2$  is also fixed). These two strategies are denoted  $\mathcal{A}^{w_1=1}$  and  $\mathcal{A}^{w_1=0}$ . Then, we compute the following two values:

$$e_1 = \mathbb{E}[Z_{\mathcal{A}_{\text{qu}}} | w_1 = 1] - 1 \quad ; \quad e_0 = \mathbb{E}[Z_{\mathcal{A}_{\text{qu}}} | w_1 = 0] \quad (4.5)$$

This value expresses which of the two strategies  $\mathcal{A}^{w_1=1}, \mathcal{A}^{w_1=0}$  have greater expectation value in the *remaining* measurements (i.e. excluding the first measurement outcome). Let  $\bar{w}_1$  be the outcome for which the above is maximised (i.e.  $\bar{w}_1 = 1$  if  $e_1 \geq e_0$  while  $\bar{w}_1 = 0$  if  $e_1 < e_0$ ). We define  $\mathcal{A}_2$  to be a new strategy that has the same  $K_1$  as our initial strategy, but then the remaining strategy is fixed as if the first measurement outcome was  $\bar{w}_1$  irrespective of the actual measurement outcome. Then, for this strategy  $\mathcal{A}_2$ , we have:

$$\mathcal{A}_2 = (K_1, K_2 := \zeta(N - K_1, [\bar{w}_1]), \zeta(N - (K_1 + K_2), [\bar{w}_1, w_2]), \dots, \zeta(N - (K_1 + \dots + K_{i-1}), [\bar{w}_1, \dots, w_{i-1}]), \dots) \quad (4.6)$$

It is clear that for  $\mathcal{A}_2$ , both chunks  $K_1$  and  $K_2$  are fixed, (while the rest are picked adaptively but having fixed the dependency on the first measurement outcome). By construction, the expected number of adversarial blocks is at least as big as

the expected number of adversarial blocks of the initial strategy  $\mathcal{A}_{qu}$ , since we chose  $\bar{w}_1$  to be the measurement outcome that maximises the expectation of the remaining  $N - K_1$  strategies.

We then proceed iteratively in the same manner until we construct a strategy  $\mathcal{A}_N$ , such that all  $N$  measurement chunks are fixed,  $\mathcal{A}_N = (K_1, \dots, K_N)$ . But, then  $\mathcal{A}_N$  is a Non-Adaptive strategy with expected number of adversarial blocks at least as large as  $\mathcal{A}_{qu}$ 's value, which concludes the proof.  $\square$

#### 4.2.2 Maximum Expectation

Having established that Non-Adaptive strategies achieve the maximum expectation for general adversaries, we now obtain that maximum value.

**Theorem 5.** *For any SMS quantum adversary  $\mathcal{A}_{nonad}$ , the maximum expected number of PoWs, given any number of queries  $N \geq \frac{1}{\sqrt{cp}}$ , is:*

$$E := \max \mathbb{E}[Z_{\mathcal{A}_{qu}}] = \max \mathbb{E}[Z_{\mathcal{A}_{nonad}}] = \sqrt{cp} \cdot N, \text{ for any } N \geq \frac{1}{\sqrt{cp}} \quad (4.7)$$

*Proof.* First, let us define  $K_{max}$  as the number of quantum queries required to create a block with probability one:

$$cpK_{max}^2 = 1 \quad ; \quad K_{max} = \frac{1}{\sqrt{cp}} \quad (4.8)$$

This implies that for each measurement we also have  $K_i \leq K_{max} = \frac{1}{\sqrt{cp}}$  (as an optimal adversary would not waste more than  $K_{max}$  queries per measurement) and hence we can rewrite  $K_i$  as:

$$K_i = \xi_i K_{max}, \text{ where } 0 \leq \xi_i \leq 1 \quad \forall i \in \{1, \dots, N\} \quad (4.9)$$

Therefore, to compute the optimal expected number of adversarial blocks, we need to determine the variables  $\xi_i$  which maximize  $\mathbb{E}[Z_{\mathcal{A}_{nonad}}]$ . Then, by using Theorem 2, the success probability per each measurement  $i$  becomes:

$$P_{K_i} = cpK_i^2 = cp(\xi_i K_{max})^2 = cp\xi_i^2 \frac{1}{cp} = \xi_i^2 \quad \forall i \in \{1, \dots, N\} \quad (4.10)$$

Then, using Eq. (4.3), we can compute the expected number of blocks created during  $s$  consecutive rounds  $\mathcal{A}_{nonad}$  as:

$$\mathbb{E}[Z_{\mathcal{A}_{nonad}}] = \sum_{i=1}^N P_{\mathcal{A}_{nonad}}(i) \cdot i = \sum_{i=1}^N i \cdot \left( \sum_{\substack{I \subseteq \{1, 2, \dots, N\} \\ |I|=i}} \prod_{j \in I} \xi_j^2 \cdot \prod_{l \in \{1, \dots, N\} - I} (1 - \xi_l^2) \right) \quad (4.11)$$

Which, as we showed in Eq. (H.3) and Eq. (H.4), can be rewritten as:

$$\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] = \sum_{i=1}^N \xi_i^2 \quad (4.12)$$

From the total number of queries condition  $\sum_{i=1}^N K_i = N$ , we also have  $\sum_{i=1}^N \xi_i = \frac{N}{K_{\text{max}}} = \sqrt{cp} \cdot N$ . Therefore, we want to maximize  $\sum_{i=1}^N \xi_i^2$  subject to the constraint  $\sum_{i=1}^N \xi_i = \sqrt{cp} \cdot N$  and  $0 \leq \xi_i \leq 1$ . However we have  $\xi_i^2 \leq \xi_i \leq 1$  which leads to:

$$\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] = \sum_{i=1}^N \xi_i^2 \leq \sum_{i=1}^N \xi_i = \sqrt{cp} \cdot N \quad (4.13)$$

We can also easily see that there exists an optimal Non-Adaptive strategy which achieves this maximum value  $E = \sqrt{cp} \cdot N$ . We define a Non-Adaptive strategy which uses  $\frac{N}{K_{\text{max}}}$  measurements and for each of these measurement use the same number of  $K_i = K_{\text{max}}$  queries, while there are no queries for the remaining variables. For this strategy, using Eq. (4.9) we have  $\xi_i = 1 \forall i \leq \frac{N}{K_{\text{max}}}$  and  $\xi_j = 0 \forall j > \frac{N}{K_{\text{max}}}$ . Then, by using Eq. (4.12) we get:  $\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] = \frac{N}{K_{\text{max}}} = N\sqrt{cp}$ . This concludes the proof that  $E = \sqrt{cp} \cdot N$  is the maximum expected number of adversarial blocks, achieved by Non-Adaptive strategies and is in fact achieved when the adversary spends enough queries per measurement to deterministically solve a PoW.  $\square$

The analysis for Non-Adaptive adversaries when the total number of queries is sufficiently small (less than  $\frac{1}{\sqrt{cp}}$ ) is presented in Appendix C.

### 4.2.3 From Non-Adaptive to General Adversaries

So far we have examined Non-Adaptive strategies, who choose how to split the queries independently from the outcomes of previous measurements. A general strategy is not of this type. Instead, a general strategy adaptively decides how to use the remaining queries depending on how successful the previous attempts (to solve a PoW) were. Because of Theorem 4 we know that in terms of expectation, the Non-Adaptive strategies are optimal. However, this does not mean that these strategies are better always as we will illustrate with two examples.

*Example 1:* Imagine a scenario that the expected cardinality of solutions of a strategy is longer than that of the Non-Adaptive strategy. The strategy that maximises the expected cardinality of the Non-Adaptive solution is deterministic, since as proven earlier, the algorithm runs quantum search until he is (w.h.p.) certain that he will solve the PoW. This strategy has zero probability of getting more (or less) than the expected number (is a very concentrated distribution). It is therefore obvious that any other strategy (preferably with longer tails), Non-Adaptive or adaptive, that is non-deterministic should be better.

*Example 2:* Assume that there is an Non-Adaptive strategy aiming to generate a solution for the Bag-of-PoWs problem of cardinality at least  $M$ , by separating the  $N$  queries to chunks of  $N/M$ . This strategy will only succeed if all  $M$  searches are successful, meaning that a single failed search makes the strategy unsuccessful and the remaining queries wasted. It is evident that an adaptive strategy can do better. An adversary can start with the same strategy measuring after  $N/M$  queries, as long as the searches are successful. In case one search is unsuccessful, any strategy that has one more measurement than the Non-Adaptive (which now would have failed) would be more promising.

The point here is that both the cardinality but also the shape of the tails of the distribution can be different for, non-optimal in terms of expectation, adaptive strategies. Therefore, to bound the probabilities of the tails in the most general adaptive strategy we need to be more careful. We will model the corresponding random variables using martingales. Unfortunately, the standard concentration results (Azuma) for our setting provide very weak bounds on the probabilities. This leads to an unreasonable large  $N$  required to achieve the same probability of concentration with that of classical or Non-Adaptive strategies. In the remaining section we will demonstrate this issue, derive some novel concentration inequalities suitable for our purpose and get much improved bounds.

#### 4.2.4 A Martingale Modelling of General Adversaries

In the general strategies scenario, we cannot assume the independence of the variables corresponding to different measurements, and thus we cannot use Chernoff inequalities to bound the tails of the distribution as was done in the classical case. To bound the observed number of adversarial PoWs using the maximal expectation value we need to use an alternative concentration theorem.

We will then define the number of successful PoWs (cardinality of the solution of Bag-of-PoWs problem) as a *martingale*. This would then allows us to get a concentration result by applying the Azuma-Hoeffding Inequality. The first step is to use the *Doob Martingale* construction.

We start from the sequence of random variables  $\{W_i\}_i$  - where  $W_i = 1$  if the  $i$ -th measurement after using  $K_i$  queries was successful and  $W_i = 0$  otherwise. We consider the total number of variables  $W_i$  to be  $N$ , denoting that there are at most  $N$  measurements, and if in the actual strategy there are less measurements, let's say  $m$  measurements, then  $K_{m+1} = \dots = K_N = 0$  and consequently  $W_{m+1} = \dots = W_N = 0$  (as in Definition 4 of SMS adversaries). As seen in Definition 7, we need to define a function  $\Phi$ , which in our case will be  $\Phi(W_1, W_2, \dots, W_N) = W_1 + \dots + W_N$ , i.e. the number of successful measurements using the chunk splits  $K_1, \dots, K_N$ . Then, we have the following martingale sequence:

$$V_i = \mathbb{E}[\Phi(W_1, W_2, \dots, W_N) \mid W_1, W_2, \dots, W_i] \quad (4.14)$$

In order to apply the Azuma inequality (Lemma 11), we must first upper bound the difference (determine  $c_i$  such that):

$$|D_i| = |V_i - V_{i-1}| = |\mathbb{E}[\Phi \mid W_1, W_2, \dots, W_i] - \mathbb{E}[\Phi \mid W_1, W_2, \dots, W_{i-1}]| \leq c_i \quad (4.15)$$

### 4.2.5 Bounds from the Standard Azuma Inequality

As each measurement cannot change the expected cardinality of Bag-of-PoWs solution by more than 1, we get directly that  $|D_i| \leq 1$ . Using Lemma 11, we get:

$$\Pr(V_N - V_0 \geq \alpha N) \leq \exp\left(-\frac{\alpha^2 N^2}{2 \sum_{i=1}^N D_i^2}\right) \quad (4.16)$$

For any  $\alpha > 0$ . Noting that

$$\begin{aligned} V_N &= \mathbb{E}[\Phi(W_1, W_2, \dots, W_N) | W_1, \dots, W_N] = \Phi(W_1, W_2, \dots, W_N), \\ V_0 &= \mathbb{E}[\Phi(W_1, W_2, \dots, W_N)] \end{aligned} \quad (4.17)$$

we get the following concentration result:

**Lemma 5 (Concentration from Standard Azuma).** *For any quantum strategy  $\mathcal{A}_{qu}$  having  $N$  quantum queries and for any  $\alpha \geq 0$ , we have:*

$$\Pr(Z_{\mathcal{A}_{qu}} - \mathbb{E}[Z_{\mathcal{A}_{qu}}] \geq \alpha N) \leq \exp\left(-\frac{\alpha^2 N}{2}\right) \quad (4.18)$$

We want a concentration result which bounds the difference  $Z_{\mathcal{A}_{qu}} - \mathbb{E}[Z_{\mathcal{A}_{qu}}]$  by  $\epsilon \mathbb{E}[Z_{\mathcal{A}_{qu}}]$ , so we choose  $\alpha = \frac{\epsilon}{N} \max \mathbb{E}[Z_{\mathcal{A}_{qu}}] = \epsilon \sqrt{cp}$ , which leads to:

$$\Pr(Z_{\mathcal{A}_{qu}} - \mathbb{E}[Z_{\mathcal{A}_{qu}}] \geq \epsilon \mathbb{E}[Z_{\mathcal{A}_{qu}}]) \leq \exp\left(-\frac{\epsilon^2 cp N}{2}\right) \quad (4.19)$$

If we keep  $N$  as a variable, and we use the upper bound for  $\mathbb{E}[Z_{\mathcal{A}_{qu}}] \leq N/K_{max} = N\sqrt{cp}$ , we obtain:

$$Z_{\mathcal{A}_{qu}} \leq (1 + \epsilon) \mathbb{E}[Z_{\mathcal{A}_{qu}}] \quad (4.20)$$

with probability at least  $1 - \exp\left(-\frac{\epsilon^2}{2} N \sqrt{cp} \cdot \frac{1}{K_{max}}\right)$ . Here we can immediately see that this is very similar with the classical with the crucial difference that in the exponent of the tail of the distribution, there is a  $\frac{1}{K_{max}}$  factor. Given that  $K_{max} \gg 1$  this means that this probability becomes small for large  $N$ , when the expected cardinality of Bag-of-PoWs exceed  $K_{max} \sim 1/p^{1/2}$ . The mathematical reason for this weak bound, is that while the difference  $D_i$  is bounded by one, “expected” difference is very small, something that cannot be captured unless the variance of the variables also is included. Trying to use other known versions of Azuma’s inequality such as the one defined in [39] also give equally weak bound (see Appendix D).

We therefore seek for a tighter bound, not only for theoretical interest, but also because this particular bound when applied to the Bitcoin Backbone Protocol, results to totally impractical security parameters. Instead, we derive our own version of Azuma’s inequality that when applied to the Bag-of-PoWs problem (and subsequently to the Bitcoin Backbone) gives a much tighter bound.

#### 4.2.6 An Azuma Generalization

Following up to a point steps of the proof from [39], we derive our own version of Azuma's inequality, and apply it to our problem. We begin by introducing the random variable  $\sigma_i$  (which will use the quantum problem-specific bounds), defined as:  $\sigma_i^2 := \mathbb{E}[(V_i - V_{i-1})^2 | W_1, \dots, W_{i-1}]$ .

Consider two non-negative constants  $\gamma_1 < \gamma_2$ . Now, let us consider that for  $N_1$  of the  $i$ 's we have  $\sigma_i^2 \leq \gamma_1$  and for the remaining  $N_2 = N - N_1$  the variance is larger but smaller than  $\gamma_2$ , i.e.  $\gamma_1 < \sigma_i^2 \leq \gamma_2$ , and we denote  $\Gamma_1$  the set of indices that have smaller variance and  $\Gamma_2$  the set of indices that have greater variance. Note, that in [39] a unique number  $\sigma$  was used to bound all the variances, while we split the variances to two set: one with very small variance and one with larger variance. We can now derive the following concentration result:

**Theorem 6 (Alternative concentration inequality).** *Let  $\{V_i\}_{i=0}^N$  be a martingale with respect to the sequence  $W_1, W_2, \dots, W_N$  such that  $|V_i - V_{i-1}| \leq 1$ . Consider  $\sigma_i^2 := \mathbb{E}[(V_i - V_{i-1})^2 | W_1, \dots, W_{i-1}]$  and assume for some constants  $0 < \gamma_1 < \gamma_2$ , the following hold:  $\sigma_i^2 \leq \gamma_1 \forall i \in \Gamma_1$  where  $|\Gamma_1| = N_1$  and  $\gamma_1 < \sigma_j^2 \leq \gamma_2 \forall j \in \Gamma_2$  where  $|\Gamma_2| = N - N_1$ . Then for any  $t > 0$ ,  $\alpha > 0$ , we have:*

$$\Pr[|V_N - V_0| \geq \alpha \cdot N] \leq e^{-\alpha N t} \cdot \left( \frac{\exp(-t\gamma_1) + \gamma_1 \exp(t)}{1 + \gamma_1} \right)^{N_1} \cdot \left( \frac{\exp(-t\gamma_2) + \gamma_2 \exp(t)}{1 + \gamma_2} \right)^{N - N_1} \quad (4.21)$$

Note that this gives a bound for this probability for any choice of  $t$ . In principle, given other constraints (regarding the values of  $\gamma_1, \gamma_2$  and the cardinalities of the sets  $\Gamma_1, \Gamma_2$ ), one can find the suitable/optimal choice of  $t$  that minimises the tail in this inequality. The proof is similar to the first steps of [39], and we give the details in Appendix E.

#### 4.2.7 A Stronger Bound from Alternative Concentration Inequality

Having obtained this new concentration inequality of Eq. (4.21), we return to the analysis of SMS strategies trying to bound the tails of the distribution of the variable  $Z_{\mathcal{A}_{qu}}$ . Using the martingale defined in the beginning of the section, we see that  $D_i^2 \leq 1$ , and also  $\sigma_i^2 = \mathbb{E}[D_i^2 | W_1, \dots, W_{i-1}] \leq 1$ . Therefore, we can choose  $\gamma_2 = 1$  and use the notation  $\gamma := \gamma_1$  and use Eq. (4.21).

**Lemma 6 (Concentration from alternative inequality).** *For any general quantum adversary  $\mathcal{A}_{qu}$  and for any  $t > 0$ ,  $\alpha \geq 0$  and  $1 \geq \gamma \geq 0$ , we have:*

$$\Pr[Z_{\mathcal{A}_{qu}} - \mathbb{E}[Z_{\mathcal{A}_{qu}}] \geq \alpha \cdot N] \leq A^{N_1} \cdot B^{N - N_1} \text{ where,} \quad (4.22)$$

$$A := \frac{\gamma \exp(t(1 - \alpha)) + \exp(-t(\gamma + \alpha))}{1 + \gamma} ; \quad B := \frac{\exp(t(1 - \alpha)) + \exp(-t(1 + \alpha))}{2} \quad (4.23)$$

To get a good bound, we need to make some choices for the various parameters in Eq. (4.22). The most important choice is the relation between the value  $\gamma$  of “small-variance” variable and the size of the corresponding set  $|I_1| = N_1$ . It is not hard to see that the bigger the set  $I_1$ , the better the bound, since variables with smaller variance contribute less in the tail of the distribution. Therefore we would like to lower bound the value of  $N_1$ .

**Lemma 7.** *For all SMS adversaries, the number of individual random variables that have variance greater than  $\gamma$  is bounded by  $\frac{N}{K_{max}\sqrt{\gamma}}$ , i.e.*

$$N - N_1 \leq \frac{N}{K_{max}\sqrt{\gamma}} \quad ; \quad N_1 \geq N \left( 1 - \frac{1}{K_{max}\sqrt{\gamma}} \right) \quad (4.24)$$

*Proof.* For Bernoulli variables, the variance  $\sigma_i^2$  is bounded by the average probability  $p_i$ . We want to obtain (a bound on) the maximum number of variables that can have variance greater than  $\gamma$ . Therefore  $\sigma_i^2 \geq \gamma$  implies  $p_i \geq \gamma$ . However,  $p_i = \frac{K_i^2}{K_{max}^2}$  since this is a quantum strategy also means that for every variable  $i$  that belongs to  $I_2$ , the corresponding queries to the QRO are at least  $K_i \geq K_{max}\sqrt{\gamma} \forall i \in I_2$ . Given that the total number of queries is  $N = \sum_i K_i$ , the set  $I_2$  can have no more than  $\frac{N}{K_{max}\sqrt{\gamma}}$  elements.  $\square$

Using the optimality of the Non-Adaptive strategies with respect to the expectation (Theorem 4), and their maximum expectation value (Theorem 5)  $E = \sqrt{cp} \cdot N$ , leads to the following main result regarding general adversaries:

**Theorem 7.** *Given the choice of parameters:  $\gamma = \alpha^{2/3}$  and  $t = \frac{\alpha^{1/3}}{4}$ ,  $\alpha = \frac{\epsilon}{K_{max}}$  where  $0 < \epsilon \leq 1/3$ , for any quantum adversarial strategy, we have the concentration result:*

$$Pr(Z_{A_{qu}} - \mathbb{E}[Z_{A_{qu}}] \geq \epsilon E) \lesssim \exp\left(-\frac{E}{K_{max}^{1/3}} \cdot g_2(\epsilon)\right) \quad (4.25)$$

or equivalently:

$$Pr(Z_{A_{qu}} \geq (1 + \epsilon)\sqrt{cp}N) \lesssim \exp\left(-(\epsilon)^{\frac{2}{3}} N \cdot g_2(\epsilon)\right) \quad (4.26)$$

where  $g_2(\epsilon) = \frac{\epsilon^{1/3}}{32} (7\epsilon - 1)$ .

*Proof Sketch (full proof in Appendix F).* Assuming that all parameters  $\gamma, t, \alpha \ll 1$  are small, Eq. (4.23) becomes:

$$A \lesssim \exp\left(\frac{\gamma t^2}{2} - \alpha t\right) \quad ; \quad B \leq \exp\left(t\left(\frac{t}{2} - \alpha\right)\right) \quad (4.27)$$

which using  $\gamma = \alpha^{2/3}, t = \frac{\alpha^{1/3}}{4}$  is:

$$A \lesssim \exp\left(-\frac{7\alpha^{4/3}}{32}\right) \quad ; \quad B \leq \exp\left(\frac{\alpha^{2/3}}{4} \left(\frac{1}{8} - \alpha^{2/3}\right)\right) \quad (4.28)$$

Using the lower bound on  $N_1$  from Eq. (4.24) and plugging these into Eq. (4.22):

$$Pr(Z_{\mathcal{A}_{\text{qu}}} - \mathbb{E}[Z_{\mathcal{A}_{\text{qu}}}] \geq \alpha N) \lesssim \exp\left(-\frac{7\alpha^{4/3}}{32}N + \frac{\alpha^{1/3}}{32} \frac{N}{K_{\text{max}}}\right) \quad (4.29)$$

By choosing  $\alpha = \frac{\epsilon}{K_{\text{max}}}$  and noting that  $E \leq \frac{N}{K_{\text{max}}}$  we get:

$$\begin{aligned} Pr(Z_{\mathcal{A}_{\text{qu}}} - \mathbb{E}[Z_{\mathcal{A}_{\text{qu}}}] \geq \epsilon \frac{N}{K_{\text{max}}}) &\lesssim \exp\left(-\frac{N}{K_{\text{max}}^{4/3}} \cdot \frac{\epsilon^{1/3}}{32} (7\epsilon - 1)\right) \\ Pr(Z_{\mathcal{A}_{\text{qu}}} - \mathbb{E}[Z_{\mathcal{A}_{\text{qu}}}] \geq \epsilon E) &\lesssim \exp\left(-\frac{E}{K_{\text{max}}^{1/3}} \cdot \frac{\epsilon^{1/3}}{32} (7\epsilon - 1)\right) \end{aligned} \quad (4.30)$$

□

We can see immediately that this is a much better bound than the ones obtained from Lemma 5 and Lemma 14, since on these lemmas the exponential decay was divided by a term  $K_{\text{max}}$ , while here is divided by  $K_{\text{max}}^{1/3}$ . Moreover, the choices of the parameters in Theorem 7 lead to a bound, that is not only much better than the results using Azuma inequalities, but is also very close to the optimal bound obtained with this approach (see Appendix G).

Of separate interest may also be the similar concentration results we obtained, for certain restricted types of adversaries (Non-Adaptive and “Noisy Quantum Storage”) which can be found in Appendix H (Theorem 10).

### 4.3 Bounds on Quantum Strategies for Chain-of-PoWs

Finally, we can determine upper bounds on the best quantum strategies against the Chain-of-PoWs Problem, and essentially completing the proof of Theorem 3. To do so, we combine the concentration result of the most general type of SMS strategies against Bag-of-PoWs Problem (Theorem 7, Eq. 4.26) together with the relation between best strategies against Bag-of-PoWs Problem and Chain-of-PoWs Problem stated in Lemma 3.

*Proof of Theorem 3.* From Eq. 4.26 we know that: From  $N+x$  queries we obtain an upper bound of  $M_B(N+x) = (1+\epsilon)\sqrt{cp}(N+x)$  queries with probability  $p_B(N+x) = \exp\left(-(N+x) \cdot (cp)^{\frac{2}{3}} \cdot g_3(\epsilon)\right)$ .

To map it to the setting of Lemma 3 we need to find  $x$  such that:  $M_B(N+x) = x$ , which will give us our new bound  $M_A$  for the Chained Problem. This is equivalent to:  $x = N \cdot \frac{(1+\epsilon)\sqrt{cp}}{1-(1+\epsilon)\sqrt{cp}}$ , leading to:

$$M_A = N \cdot \frac{(1+\epsilon)\sqrt{cp}}{1-(1+\epsilon)\sqrt{cp}}$$

Now to compute  $p_A$  for the Chained Problem, as seen in Lemma 3, we just need to compute  $p_B(N + M_A)$ , which gives us:

$$p_A = \exp\left(-N \cdot (cp)^{\frac{2}{3}} \cdot \frac{g_2(\epsilon)}{1 - (1 + \epsilon)\sqrt{cp}}\right)$$

By replacing the function  $g_2$  we get:

$$p_A = \exp\left(-N \cdot (cp)^{\frac{2}{3}} \cdot \frac{1}{1 - (1 + \epsilon)\sqrt{cp}} \frac{\epsilon^{1/3}}{32} (7\epsilon - 1)\right)$$

And by introducing the notation  $f_0(c, p, \epsilon) = (cp)^{\frac{2}{3}} \cdot \frac{1}{1 - (1 + \epsilon)\sqrt{cp}} \frac{\epsilon^{1/3}}{32} (7\epsilon - 1)$ :

$$p_A = \exp(-f_0(c, p, \epsilon) \cdot N) \tag{4.31}$$

which concludes the proof of Theorem 3.  $\square$

## 5 Quantum Analysis of the Backbone Protocol

In this section we first introduce some further background about the Backbone protocol, together with a series of restrictions, relating the honest and adversarial variables (Lemma 8, Lemma 10) that jointly suffice to ensure the security of the protocol. Then, in the following subsection, we combine these restrictions with our main result (Theorem 3), to obtain: (i) bounds on the adversarial quantum hashing power required to guarantee that the security of the Backbone protocol holds in the presence of quantum adversary and (ii) the probabilities that the two properties of the Backbone hold quantifying the wait time for safe settlement.

### 5.1 The Backbone Protocol Properties, Revisited

To ensure the two main properties common prefix and chain quality hold as in the classical adversary scenario [21], we need to satisfy two conditions. In [21] these conditions are referred to as requirements of a “typical execution”. The first condition requires that some events regarding the hash function  $H$  occur with exponentially small probability. Specifically, these events are defined as follows: An *insertion* occurs when, given a chain  $C$  with two consecutive blocks  $B$  and  $B'$ , a block  $B^*$  created after  $B'$  is such that  $B, B^*, B'$  form three consecutive blocks of a valid chain. A *copy* occurs if the same block exists in two different positions. A *prediction* occurs when a block extends one which was computed at a later round.

As proven in [21] (Theorem 10), these events imply finding a collision for the hash function  $H$ . However, for the collision finding problem, it is known that the best quantum algorithms require  $O(2^{\frac{n}{3}})$  queries (which is optimal as proven in [50]) compared to the  $O(2^{\frac{n}{2}})$  in the classical case. Therefore, the same analysis

showing that these events hold with negligible probability in the quantum adversary case is sufficient.

The second condition refers to bounding the number of adversarial PoWs within a number  $s$  of consecutive rounds. More specifically, to ensure that the common prefix property holds with the same parameter as in the classical adversary scenario, [21], for any type of adversary, it is sufficient to impose two restrictions on  $Z(s)$ : with respect to  $X(s)$  and  $Y(s)$ , respectively. These restrictions, will then imply upper bounds on the quantum adversarial hasing power  $Q$ , which in turn will also give us the parameter of the chain quality property.

From now on in this section and in the remaining of the paper, as for the first condition, the probabilities of the  $H$ -related events is negligible in the security parameter  $\kappa$ , we will focus only on the probabilities for which the number of adversarial blocks  $Z(s)$  is bounded, and will denote these latter probabilities as the ones under which the security (the two main properties) of the Bitcoin backbone protocol hold.

**Lemma 8.** *The common prefix property of the Bitcoin backbone protocol holds with parameter  $k \geq 2sf$ , for any  $s \geq \frac{2}{f}$  consecutive rounds, against any quantum adversary  $\mathcal{A}$  if the following condition holds:*

$$\frac{Z_{\mathcal{A}}(s)}{s} < (1 - \epsilon)f(1 - f) \quad (5.1)$$

*Proof.* Following exactly the lines of the proofs from [21], we must first ensure that: any  $k \geq 2fs \geq 4$  consecutive blocks of a chain have been computed in  $s \geq \frac{k}{2f}$  consecutive rounds.

Which by following the proof by contradiction of Lemma 13 ([21]), imposes the condition: For any quantum adversary  $\mathcal{A}$  and for any  $s \geq \frac{2}{f}$ , we have:

$$X(s) + Z_{\mathcal{A}}(s) < 2fs \quad (5.2)$$

Secondly, the condition between  $Z_{\mathcal{A}}(s)$  and  $Y(s)$  comes from the proof of the following result, which then implies the common prefix property:

**Lemma 9 (GKL15).** *Consider two chains  $\mathcal{C}_1$  and  $\mathcal{C}_2$ . If  $\mathcal{C}_1$  is adopted by an honest player at round  $r$  and  $\mathcal{C}_2$  is either adopted by an honest party at round  $r$  or diffused at round  $r$  and has  $\text{len}(\mathcal{C}_2) \geq \text{len}(\mathcal{C}_1)$ , then  $\mathcal{C}_1^{[k]} \preceq \mathcal{C}_2$  and  $\mathcal{C}_2^{[k]} \preceq \mathcal{C}_1$  for  $k \geq 2fs$  and  $s \geq \frac{2}{f}$ .*

For the proof of this lemma, what we must guarantee is that for any quantum adversary  $\mathcal{A}$  and for  $s \geq \frac{2}{f}$ , we have:  $Z_{\mathcal{A}}(s) < Y(s)$ . Therefore, in order to prove that the common prefix property holds with parameter  $k \geq 2sf$ , it is sufficient to impose on the quantum adversary the following two conditions for any  $s \geq \frac{2}{f}$  consecutive rounds:

$$X(s) + Z(s) < 2fs \quad ; \quad Z(s) < Y(s) \quad (5.3)$$

Which using the bounds on the honest players variables  $X(s)$  and  $Y(s)$  from Lemma 1, the sufficient conditions become:

$$\frac{Z(s)}{s} < (1 - \epsilon)f \ ; \ \frac{Z(s)}{s} < (1 - \epsilon)f(1 - f) \quad (5.4)$$

Which given that  $\min\{(1 - \epsilon)f(1 - f), (1 - \epsilon)f\} = (1 - \epsilon)f(1 - f)$  leads to:

$$\frac{Z(s)}{s} < (1 - \epsilon)f(1 - f) \quad (5.5)$$

□

**Lemma 10.** *The chain quality property of the Bitcoin backbone protocol holds with parameter  $l \geq 2sf$  and ratio of honest blocks  $\mu$ , where  $\mu$  is determined by the condition:*

$$Z(s) < (1 - \mu)X(s) \quad (5.6)$$

*Proof.* Follows directly from the proof of chain quality in Theorem 16 ([21]). □

Moreover, if we ensure  $\mu > 0$ , then this proves that for any  $s \geq \frac{2}{f}$ :

**Corollary 1 (GKL15).** *Any  $2sf$  consecutive blocks in the chain of an honest party contain at least one honest block.*

Crucially, besides obtaining restrictions on  $Q$ , we must specify with what probability the common prefix property holds, which is the reason we seeked for the tightest concentration result possible.

## 5.2 Backbone Protocol Analysis against Quantum Strategies

Finally, we determine the conditions on the hashing power of the quantum adversary such that the properties of the Bitcoin backbone protocol are satisfied. We can apply Theorem 3 to bound the adversarial variable  $Z(s)$ , where the available queries are  $N = sQ$ , i.e. the number of rounds, multiplied by the quantum queries per round.

**Theorem 8.** *The common prefix property is satisfied with parameter  $k \geq 2sf$ , for any  $s \geq \frac{2}{f}$  consecutive rounds against any quantum adversary, with probability  $1 - \exp(-f_0(c, p, \epsilon) \cdot Q \cdot s)$ , as long as:*

$$Q < \frac{(1 - \epsilon)f(1 - f) (1 - (1 + \epsilon)\sqrt{cp})}{(1 + \epsilon)\sqrt{cp}} \approx \frac{(1 - \epsilon)f(1 - f)}{(1 + \epsilon)\sqrt{cp}} \quad (5.7)$$

where the approximation holds for  $p \ll 1$ .

*Proof.* Using Lemma 8 and the concentration result from Theorem 3, the condition of the adversary's hashing power  $Q$  becomes:

$$\frac{(1 + \epsilon)\sqrt{cp}}{1 - (1 + \epsilon)\sqrt{cp}} \cdot Q < (1 - \epsilon)f(1 - f) \quad (5.8)$$

The proof follows from the above and Theorem 3, where  $f_0(c, p, \epsilon) = (cp)^{\frac{2}{3}} \cdot \frac{1}{1 - (1 + \epsilon)\sqrt{cp}} \cdot \frac{\epsilon^{1/3}}{32} (7\epsilon - 1) \approx (cp)^{\frac{2}{3}} \cdot \frac{\epsilon^{1/3}}{32} (7\epsilon - 1)$  for  $p \ll 1$ . □

**Theorem 9.** *The chain quality property is satisfied with parameter  $l \geq 2sf$ , and  $\mu = f$  for any  $s \geq \frac{2}{f}$  consecutive rounds against any quantum adversary, with probability  $1 - \exp(-f_0(c, p, \epsilon) \cdot Q \cdot s)$ .*

*Proof.* Follows from Lemma 10 and concentration result in Theorem 3.  $\square$

**Corollary 2.** *Under the above restrictions on  $Q$ , the probability under which the common prefix and chain quality are satisfied becomes:*

$$P_{qu} = 1 - \exp\left(-g_3(\epsilon) \cdot f(1-f) \cdot (cp)^{\frac{1}{6}} \cdot s\right) \quad (5.9)$$

where  $g_3(\epsilon) = g_2(\epsilon) \cdot \frac{1-\epsilon}{1+\epsilon}$ .

*Proof.* Follows directly from Theorem 8 and Theorem 9.  $\square$

Additionally, we have performed similar analysis of the Backbone Protocol against restricted types of adversaries (Non-Adaptive and Noisy Quantum Storage) which can be found in Appendix I.

## 6 Summary and Future Directions

We can now provide a comparison between the analysis of the Bitcoin backbone protocol against classical adversaries of [21] and our analysis against a general quantum adversary. In Table 2 and in the following we compare four aspects:

- “Honest Majority” which expresses the relation between the honest hashing power and the (classical or quantum) adversary’s hashing power.
- The expected number of adversarial blocks within a sufficiently large number of consecutive rounds.
- The probability of a “typical execution,” referring to the probability that the required bounds on the number of adversarial queries hold.
- The number of rounds required to reach the same level of security.

	$\mathcal{A}_{cl}$	$\mathcal{A}_{qu}$
Honest Majority	$\frac{t}{n-t} < 1 - 3(f + \epsilon)$	$Q < \frac{1-\epsilon}{1+\epsilon} \cdot \frac{f(1-f)}{\sqrt{cp}}$
Maximum Expectation Adversarial PoWs	$pqt \cdot s$	$\sqrt{cp} \cdot Q \cdot s$
Probability of Concentration	$P_{cl} = 1 - e^{-\Omega(\epsilon^2 fs)}$	$P_{qu} = 1 - e^{-g_3(\epsilon) f(1-f)(cp)^{\frac{1}{6}} s}$
Number of Rounds	$s_{cl}$	$s_{qu} = g_4(\epsilon) \cdot \frac{1}{1-f} \cdot p^{-1/6} s_{cl}$

**Table 2.** Comparison between adversaries

where  $g_1(\epsilon) = \frac{1-\epsilon}{1+\epsilon} \cdot \frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)}$  and  $g_3(\epsilon) = \frac{1-\epsilon}{1+\epsilon} \cdot \frac{\epsilon^{\frac{1}{3}}(7\epsilon-1)}{32}$  and  $g_4(\epsilon) = \frac{\epsilon^2 \cdot c^{-1/6}}{g_3(\epsilon)}$ . Note that for the bound on  $Q$  for  $\mathcal{A}_{qu}$  we have used an approximation that  $p \ll 1$ , while the exact bound can be found in Theorem 8.

The expressions in Table 2 use the parameter  $f$  that denotes the probability that at least one honest party computes a PoW at round  $i$ . To directly relate the hashing power of the honest players  $qn$  with the hashing power of the adversary  $Q$ , we use  $f = 1 - (1 - p)^{qn}$ .

For  $\mathcal{A}_{\text{qu}}$ , applying the Bernoulli inequality, and approximating  $\frac{1-pqn}{1+pqn}$  with 1, we obtain the condition  $Q \leq qnO(\sqrt{p})$ , indicating that for general quantum adversaries, the quantum adversarial hashing power must be of order the honest hashing power multiplied by the square root of the probability of success of a single query. Again we can see that there is a quantum speed-up that leads to requiring stronger constraints on the adversarial hashing power. One, naively, could imagine that the speed-up and the separation between classical and quantum power (being quadratic) would keep growing with the number of queries (and thus rounds). This is not what happens, since the quadratic speed-up reaches a maximum, when one uses sufficient queries such that the probability of solving a PoW becomes unity. This happens when one uses  $K_{\text{max}} = (cp)^{-1/2}$  queries. Hence, the overall quantum speed-up means that the honest classical hashing power should be  $K_{\text{max}}$  times greater than the adversarial quantum hashing power.

Finally, from relating the probabilities  $P_{\text{cl}}$ , and  $P_{\text{qu}}$ , under which the properties of the backbone Protocol hold (common prefix and chain quality) we can relate the number of rounds required to achieve same accuracy. We denote  $s_{\text{cl}}$  the number of necessary rounds in the analysis against classical adversaries to achieve a given accuracy (determined by the security parameter) and similarly,  $s_{\text{qu}}$  are the corresponding rounds for general quantum adversaries. In the limit  $p \ll 1$ , we get  $s_{\text{qu}} = s_{\text{cl}} \cdot O(p^{-1/6})$ . This indicates that for the most general quantum adversary to achieve the same negligible probability for a non-typical execution, we need more rounds but this extra overhead is relatively small as it scales with the sixth root of  $p^{-1}$ .

*Future Directions:* Regarding directions for future work, there are a few generalizations of our analysis that one can consider. Our analysis of the backbone protocol considers a model with a fixed number of parties and difficulty. The first generalization to consider is the Bitcoin backbone protocol with variable difficulty [22]. The second is to consider multiple quantum adversaries. Having multiple classical adversaries that are controlled by a single party, is relatively straight forward, as we can assume that the single party has access to the sum of the individual queries. This assumption is not easy to make in the quantum case. Having more parallel quantum computation power is not the same as having sequential, and to obtain the quantum search speed-up, the queries need to be applied sequentially (since the output quantum state of the one query from the QRO needs to be fed back to the next query). Therefore a more accurate modelling would be required to truly capture the scenario of multiple quantum attackers. The third generalization would be to consider the possibility of hybrid classical-quantum adversaries. i.e. adversaries having a number of classical queries and on top of this a number of quantum queries too (the quantum queries can always be used as classical queries but not the converse). Finally, a fourth and potentially the more substantial generalization to the analysis of the Bitcoin

backbone protocol in the quantum era, is to allow (at least some of the) honest parties to have quantum hashing power.

## References

1. D. Aggarwal, G. Brennen, T. Lee, M. Santha, and M. Tomamichel. Quantum attacks on bitcoin, and how to protect against them. *Ledger*, 3(0), 2018.
2. G. Alagic, A. Broadbent, B. Fefferman, T. Gagliardoni, C. Schaffner, and M. S. Jules. Computational security of quantum encryption. In *International Conference on Information Theoretic Security*, pages 47–71. Springer, 2016.
3. G. Alagic, T. Gagliardoni, and C. Majenz. Unforgeable quantum encryption. In *Advances in Cryptology – EUROCRYPT 2018*, pages 489–519. Springer, 2018.
4. A. Ambainis, M. Hamburg, and D. Unruh. Quantum security proofs using semi-classical oracles. In *Advances in Cryptology – CRYPTO 2019*, pages 269–295. Springer, 2019.
5. K. Azuma. Weighted sums of certain dependent random variables. *Tohoku Math. J. (2)*, 19(3):357–367, 1967.
6. C. Badertscher, U. Maurer, D. Tschudi, and V. Zikas. Bitcoin as a transaction ledger: A composable treatment. In J. Katz and H. Shacham, editors, *Advances in Cryptology – CRYPTO 2017*, pages 324–356, Cham, 2017. Springer International Publishing.
7. M. Balogh, E. Eaton, and F. Song. Quantum collision-finding in non-uniform random functions. In *Post-Quantum Cryptography - 9th International Conference, PQCrypto 2018*, pages 467–486, 2018.
8. M. Bellare and P. Rogaway. Random oracles are practical: A paradigm for designing efficient protocols. In *CCS '93*, pages 62–73, 1993.
9. M. Bellare and P. Rogaway. The exact security of digital signatures-how to sign with rsa and rabin. In *International Conference on the Theory and Applications of Cryptographic Techniques*, pages 399–416. Springer, 1996.
10. D. Boneh, Ö. Dagdelen, M. Fischlin, A. Lehmann, C. Schaffner, and M. Zhandry. Random oracles in a quantum world. In *Advances in Cryptology – ASIACRYPT 2011*, pages 41–69. Springer, 2011.
11. D. Boneh and M. Zhandry. Quantum-secure message authentication codes. In *Advances in Cryptology – EUROCRYPT 2013*, pages 592–608. Springer, 2013.
12. M. Boyer, G. Brassard, P. Høyer, and A. Tapp. Tight bounds on quantum searching. *arXiv:quant-ph/9605034*, 1996.
13. R. Canetti. Security and composition of multiparty cryptographic protocols. *J. Cryptology*, 13(1):143–202, 2000.
14. R. Canetti. Universally composable security: A new paradigm for cryptographic protocols. *IACR Cryptology ePrint Archive*, 2000:67, 2000.
15. R. Canetti. Universally composable security: A new paradigm for cryptographic protocols. In *42nd Annual Symposium on Foundations of Computer Science, FOCS 2001, 14-17 October 2001, Las Vegas, Nevada, USA*, pages 136–145. IEEE Computer Society, 2001.
16. J. Don, S. Fehr, C. Majenz, and C. Schaffner. Security of the fiat-shamir transformation in the quantum random-oracle model. In *Advances in Cryptology – CRYPTO 2019*, pages 356–383. Springer, 2019.
17. C. Dwork and M. Naor. Pricing via processing or combatting junk mail. In E. F. Brickell, editor, *CRYPTO*, volume 740 of *Lecture Notes in Computer Science*, pages 139–147. Springer, 1992.

18. C. Dwork and M. Naor. Pricing via processing or combatting junk mail. CRYPTO '92, pages 139–147, London, UK, UK, 1993. Springer-Verlag.
19. E. Eaton and F. Song. Making existential-unforgeable signatures strongly unforgeable in the quantum random-oracle model. In *10th Conference on the Theory of Quantum Computation, Communication and Cryptography, TQC 2015*, volume 44 of *LIPICs*, pages 147–162. Schloss Dagstuhl, 2015.
20. S. Fehr and C. Schaffner. Composing quantum protocols in a classical environment. In *Theory of Cryptography Conference*, pages 350–367. Springer, 2009.
21. J. A. Garay, A. Kiayias, and N. Leonardos. The Bitcoin Backbone Protocol: Analysis and Applications. In *Advances in Cryptology - EUROCRYPT 2015*, 2015.
22. J. A. Garay, A. Kiayias, and N. Leonardos. The bitcoin backbone protocol with chains of variable difficulty. In *CRYPTO*, pages 291–323. Springer, 2017.
23. D. Gavinsky, J. Kempe, I. Kerenidis, R. Raz, and R. De Wolf. Exponential separations for one-way quantum communication complexity, with applications to cryptography. In *Proceedings of the thirty-ninth annual ACM symposium on Theory of computing*, pages 516–525. ACM, 2007.
24. O. Goldreich. *The Foundations of Cryptography - Volume 1, Basic Techniques*. Cambridge University Press, 2001.
25. L. K. Grover. A fast quantum mechanical algorithm for database search. In *Proceedings of the twenty-eighth annual ACM symposium on Theory of computing*, pages 212–219. ACM, 1996.
26. S. Hallgren, A. Smith, and F. Song. Classical cryptographic protocols in a quantum world. *International Journal of Quantum Information*, 13(04):1550028, 2015. Preliminary version in Crypto'11.
27. B. Hamlin and F. Song. Quantum security of hash functions and property-preservation of iterated hashing. In *10th International Conference on Post-Quantum Cryptography (PQCrypto 2019)*. Springer, 2019.
28. D. Hofheinz, K. Hövelmanns, and E. Kiltz. A modular analysis of the fujisaki-okamoto transformation. In *Theory of Cryptography Conference*, pages 341–371. Springer, 2017.
29. A. Hülsing, J. Rijneveld, and F. Song. Mitigating multi-target attacks in hash-based signatures. In *Proceedings, Part I, of the 19th IACR International Conference on Public-Key Cryptography — PKC 2016 - Volume 9614*, pages 387–416, Berlin, Heidelberg, 2016. Springer-Verlag.
30. M. Kaplan, G. Leurent, A. Leverrier, and M. Naya-Plasencia. Breaking symmetric cryptosystems using quantum period finding. In *Advances in Cryptology - CRYPTO 2016*, pages 207–237. Springer, 2016.
31. L. Lamport, R. E. Shostak, and M. C. Pease. The byzantine generals problem. *ACM Trans. Program. Lang. Syst.*, 4(3):382–401, 1982.
32. T. Lee, M. Ray, and M. Santha. Strategies for Quantum Races. In A. Blum, editor, *10th Innovations in Theoretical Computer Science Conference (ITCS 2019)*, volume 124 of *Leibniz International Proceedings in Informatics (LIPIcs)*, pages 51:1–51:21, 2018.
33. Q. Liu and M. Zhandry. On finding quantum multi-collisions. In *Advances in Cryptology - EUROCRYPT 2019*, pages 189–218. Springer, 2019.
34. Q. Liu and M. Zhandry. Revisiting post-quantum fiat-shamir. In *Advances in Cryptology - CRYPTO 2019*, pages 326–355. Springer, 2019.
35. S. Nakamoto. Bitcoin open source implementation of p2p currency. <http://p2pfoundation.ning.com/forum/topics/bitcoin-open-source>, February 2009.

36. R. Pass, L. Seeman, and A. Shelat. Analysis of the blockchain protocol in asynchronous networks. In J. Coron and J. B. Nielsen, editors, *Advances in Cryptology - EUROCRYPT 2017*, volume 10211 of *Lecture Notes in Computer Science*, 2017.
37. T. Saito, K. Xagawa, and T. Yamakawa. Tightly-secure key-encapsulation mechanism in the quantum random oracle model. In *Advances in Cryptography - EUROCRYPT 2018*, pages 520–551. Springer, 2018.
38. T. Santoli and C. Schaffner. Using simon’s algorithm to attack symmetric-key cryptographic primitives. *Quantum Information and Computation*, 17(1&2):65–78, 2017.
39. I. Sason. On refined versions of the Azuma-Hoeffding inequality with applications in information theory, 2011. arXiv:1111.1977.
40. O. Sattath. On the insecurity of quantum bitcoin mining. *arXiv preprint arXiv:1804.08118*, 2018.
41. P. W. Shor. Polynomial-time algorithms for prime factorization and discrete logarithms on a quantum computer. *SIAM Journal on Computing*, 26(5):1484–1509, 1997.
42. F. Song and A. Yun. Quantum security of NMAC and related constructions - PRF domain extension against quantum attacks. In *Advances in Cryptology - CRYPTO 2017*, pages 283–309. Springer, 2017.
43. D. Unruh. Universally composable quantum multi-party computation. In *Advances in Cryptology - EUROCRYPT 2010*, pages 486–505. Springer, 2010.
44. D. Unruh. Quantum proofs of knowledge. In *Advances in Cryptology - EUROCRYPT 2012*, pages 135–152. Springer, 2012.
45. D. Unruh. Non-interactive zero-knowledge proofs in the quantum random oracle model. In *Advances in Cryptology - EUROCRYPT 2015*, pages 755–784. Springer, 2015.
46. J. van de Graaf. Towards a formal definition of security for quantum protocols. PhD thesis, Universit’e de Montr’eal, 1997.
47. J. Watrous. Limits on the power of quantum statistical zero-knowledge. In *The 43rd Annual IEEE Symposium on Foundations of Computer Science, 2002. Proceedings.*, pages 459–468. IEEE, 2002.
48. J. Watrous. Zero-knowledge against quantum attacks. *SIAM Journal on Computing*, 39(1):25–58, 2009.
49. M. Zhandry. How to construct quantum random functions. In *2012 IEEE 53rd Annual Symposium on Foundations of Computer Science*, pages 679–687. IEEE, 2012.
50. M. Zhandry. A note on the quantum collision and set equality problems. *Quantum Info. Comput.*, 15(7-8):557–567, May 2015.
51. M. Zhandry. Secure identity-based encryption in the quantum random oracle model. *International Journal of Quantum Information*, 13(4), 2015.
52. M. Zhandry. How to record quantum queries, and applications to quantum indistinguishability. In *Advances in Cryptology - CRYPTO 2019*, pages 239–268. Springer, 2019.

# Appendices

## A Preliminaries Probability Theory

**Definition 5 (Chernoff Bounds).** Consider  $\{X_i\}_i$  a sequence of independent random variables and let  $X = \sum_{i=1}^n X_i$ , such that  $X_i = 1$  with probability  $p_i$  and  $X_i = 0$  with probability  $1 - p_i$ . Let  $\mu = \mathbb{E}(X)$ . Then, we have:

$$\text{Upper Tail: } Pr[X \leq (1 + \epsilon)\mu] \geq 1 - e^{-\frac{\epsilon^2}{2+\epsilon}\mu} \text{ for all } \epsilon > 0 \quad (\text{A.1})$$

$$\text{Lower Tail: } Pr[X \geq (1 - \epsilon)\mu] \geq 1 - e^{-\frac{\epsilon^2}{2}\mu} \text{ for all } 0 < \epsilon < 1 \quad (\text{A.2})$$

**Definition 6 (Martingale).** A Martingale is a sequence of random variables  $V_1, V_2, \dots$  such that for any  $n$ , we have:

$$\mathbb{E}[V_{n+1} | V_1, \dots, V_n] = V_n \quad (\text{A.3})$$

**Definition 7 (Doob Martingale).** Consider any sequence of variables  $U = (U_1, \dots, U_n) \in A^n$  and a function  $\Phi : A^n \rightarrow \mathcal{R}$ .

Then the following sequence  $V_i$  is a martingale:

$$V_i = \mathbb{E}[\Phi(U_1, U_2, \dots, U_n) | U_1, U_2, \dots, U_i] \quad (\text{A.4})$$

**Lemma 11 (Azuma's inequality [5]).** If  $V$  is a martingale, then the following holds:

- If  $|V_k - V_{k-1}| < c_k$  for any  $k$ ,
- Then for any  $N$  and any  $\alpha > 0$ , we have:

$$Pr[V_N - V_0 \geq \alpha N] \leq \exp\left(\frac{-\alpha^2 N^2}{2 \sum_{i=1}^N c_i^2}\right) \quad (\text{A.5})$$

**Lemma 12 (Refined Azuma's inequality [39]).** Let  $\{V_i\}_{i=0}^N$  be a martingale with respect to the sequence  $W_1, W_2, \dots$ . Assume for some constants  $d, \sigma > 0$ , the following hold:

$$\begin{aligned} |V_i - V_{i-1}| &\leq d \\ \text{Var}(V_i | W_1, \dots, W_{i-1}) &= \mathbb{E}[(V_i - V_{i-1})^2 | W_1, \dots, W_{i-1}] \leq \sigma^2 \end{aligned} \quad (\text{A.6})$$

Then for every  $\alpha \geq 0$ , we have:

$$Pr[V_N - V_0 \geq \alpha N] \leq \exp\left(-N \cdot D\left(\frac{\delta + \gamma}{1 + \gamma} \parallel \frac{\gamma}{1 + \gamma}\right)\right) \quad (\text{A.7})$$

where:

$$\begin{aligned} \gamma &= \frac{\sigma^2}{d^2}, \quad \delta = \frac{\alpha}{d} \\ D(p \parallel q) &= p \ln \frac{p}{q} + (1 - p) \ln \frac{1 - p}{1 - q} \quad \forall p, q \in [0, 1] \end{aligned} \quad (\text{A.8})$$

## B Refined Chernoff Bound : Proof of Lemma 15

*Proof.* We separate in 2 possible cases:

If  $\mathbb{E}[X] \geq \frac{M}{2}$ , then in this case, we can apply Multiplicative Chernoff bound (Definition 5) and we get for any  $\epsilon > 0$ :

$$Pr[X > (1 + \epsilon)\mathbb{E}[X]] \leq \exp\left(-\frac{\epsilon^2}{2 + \epsilon} \cdot \mathbb{E}[X]\right) \leq \exp\left(-\frac{\epsilon^2}{2 + \epsilon} \cdot \frac{M}{2}\right) \quad (\text{B.1})$$

If instead  $\mathbb{E}[X] < \frac{M}{2}$ , then we follow the next steps. As  $X_i$  are independent random variables, using the generic Chernoff bound, we obtain that for any  $t > 0$  and any  $a > 0$ , we have:

$$Pr[X \geq a] \leq e^{-ta} \cdot \mathbb{E}\left[\prod_{i=1}^n e^{tX_i}\right] = e^{-ta} \cdot \prod_{i=1}^n \mathbb{E}[e^{tX_i}] \quad (\text{B.2})$$

where for the last equality we used the independence of the variables  $X_i$ .

Now, given that we want to compare  $X$  with the maximum expectation  $M$ , we are choosing  $a = (1 + \epsilon)M$ , which gives us:

$$Pr[X > (1 + \epsilon)M] \leq e^{-t(1+\epsilon)M} \cdot \prod_{i=1}^n \mathbb{E}[e^{tX_i}] \quad (\text{B.3})$$

Now, using the notation  $Pr[X_i = 1] = p_i$  and thus  $Pr[X_i = 0] = 1 - p_i$ , we have that  $e^{tX_i}$  is equal to  $e^t$  with probability  $p_i$  and equal to 1 with probability  $1 - p_i$ , which leads to:  $\mathbb{E}[e^{tX_i}] = p_i \cdot e^t + (1 - p_i) \cdot 1$ . Therefore, the above equation can be rewritten as:

$$Pr[X > (1 + \epsilon)M] \leq e^{-t(1+\epsilon)M} \cdot \prod_{i=1}^n [p_i(e^t - 1) + 1] \quad (\text{B.4})$$

Using the inequality:  $1 + x \leq e^x$  for  $x = p_i(e^t - 1)$ , implies:

$$Pr[X > (1 + \epsilon)M] \leq e^{-t(1+\epsilon)M} \cdot \prod_{i=1}^n e^{p_i(e^t - 1)} = e^{-t(1+\epsilon)M} \cdot e^{(e^t - 1) \sum_{i=1}^n p_i} \quad (\text{B.5})$$

But  $\sum_{i=1}^n p_i = \mathbb{E}[X]$ , which leads us to:

$$Pr[X > (1 + \epsilon)M] \leq e^{-t(1+\epsilon)M} \cdot e^{(e^t - 1) \cdot \mathbb{E}[X]} \quad (\text{B.6})$$

Using the condition  $\mathbb{E}[X] < \frac{M}{2}$ , we obtain:

$$Pr[X > (1 + \epsilon)M] < e^{-t(1+\epsilon)M} \cdot e^{(e^t - 1) \cdot \frac{M}{2}} \quad (\text{B.7})$$

Now, we can choose  $t = \ln(1 + \epsilon) > 0$ :

$$Pr[X > (1 + \epsilon)M] < \frac{e^{\epsilon \cdot \frac{M}{2}}}{(1 + \epsilon)^{(1+\epsilon)M}} = \left[ \frac{e^{\frac{\epsilon}{2}}}{(1 + \epsilon)^{1+\epsilon}} \right]^M \quad (\text{B.8})$$

Then, using the inequality:  $\frac{2\epsilon}{2+\epsilon} \leq \ln(1+\epsilon)$ , it can be shown that:

$$\frac{e^{\frac{\epsilon}{2}}}{(1+\epsilon)^{1+\epsilon}} \leq \exp\left(-\frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)}\right) \quad (\text{B.9})$$

which leads to the final result:

$$\Pr[X > (1+\epsilon)M] < \exp\left(-\frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)} \cdot M\right) \quad (\text{B.10})$$

To complete the proof we need to find the minimum probability between the 2 probabilities we determined for the cases  $\mathbb{E}[X] \geq \frac{M}{2}$  and  $\mathbb{E}[X] < \frac{M}{2}$ :

$$\exp\left(-\frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)} \cdot M\right) < \exp\left(-\frac{\epsilon^2}{2+\epsilon} \cdot \frac{M}{2}\right) \quad (\text{B.11})$$

Therefore, we have obtained the final result:

$$\Pr[X > (1+\epsilon)M] < \exp\left(-\frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)} \cdot M\right) \quad (\text{B.12})$$

□

## C Optimal Non-Adaptive for Queries Number $N \leq \frac{1}{\sqrt{cp}}$

**Lemma 13.** *For any Non-Adaptive quantum adversary  $\mathcal{A}_{\text{nonad}}$ , the maximum expected number of PoWs obtained by  $\mathcal{A}_{\text{nonad}}$ , for any number of queries  $N \leq \frac{1}{\sqrt{cp}}$  is:*

$$e := \max \mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] = cp \cdot N^2, \text{ for any } N \leq \frac{1}{\sqrt{cp}} \quad (\text{C.1})$$

*Proof.* Firstly we can rewrite the expected number of PoWs as:

$$\begin{aligned} \mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] &= \sum_{i=1}^t P_{\mathcal{A}_{\text{nonad}}}(i) \cdot i = \\ &= \sum_{i=1}^t i \cdot \left( \sum_{I_i \subseteq I_t, |I_i|=i} \left[ \prod_{j \in I_i} cp \cdot K_j^2 \right] \cdot \left[ \prod_{l \in I_t - I_i} (1 - cp \cdot K_l^2) \right] \right) \end{aligned} \quad (\text{C.2})$$

If for all  $i$ , we have  $0 \leq P_{K_i} \leq 1$ , in other words when  $K_i^2 \leq N^2 \leq \frac{1}{cp}$ , or equivalently  $N < \frac{1}{\sqrt{cp}}$ , we can compute  $\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}]$  as:

$$\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] = cp \cdot (K_1^2 + K_2^2 + \dots + K_t^2), \text{ when } N \leq \frac{1}{\sqrt{cp}} \quad (\text{C.3})$$

Then, by maximizing  $\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}]$  over all  $t$  and all  $K_1, \dots, K_t$  subject to the constraint  $K_1 + \dots + K_t = N$ , we obtain that the maximum value is obtained for:  $t = 1$  and  $K_1 = N$ . Which leads to:

$$\max \mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] = cp \cdot N^2 = e, \text{ when } N \leq \frac{1}{\sqrt{cp}} \quad (\text{C.4})$$

□

## D Concentration from Stronger Azuma of [39]

In order to improve the bound of Eq. (4.19), we try to use the stronger version of Azuma's inequality, defined in Lemma 12, that explicitly has the variance in the expressions. Firstly, one can easily see that we can choose<sup>4</sup>  $d = \sigma = 1$ . We can therefore use  $\gamma = 1$  and  $\delta = \alpha$  in Lemma 12. We will choose  $\alpha = \epsilon/K_{max} = \epsilon\sqrt{cp} \ll 1$  and thus we get:

**Lemma 14 (Concentration from Stronger Azuma).** *For any general quantum adversary  $\mathcal{A}_{qu}$  and for any  $\alpha \geq 0$ , we have:*

$$\Pr(Z_{\mathcal{A}_{qu}} - \mathbb{E}[Z_{\mathcal{A}_{qu}}] \geq \alpha N) \leq \exp\left(-N \cdot \left(\frac{1+\alpha}{2} \ln(1+\alpha) + \frac{1-\alpha}{2} \ln(1-\alpha)\right)\right) \quad (\text{D.1})$$

Then, as the maximum expected number of adversarial blocks is:  $\max \mathbb{E}[Z_{\mathcal{A}_{qu}}] = E = N\sqrt{cp}$ , we get:

$$\Pr[Z_{\mathcal{A}_{qu}} \geq (1+\epsilon)\mathbb{E}[Z_{\mathcal{A}_{qu}}]] \leq \exp\left(-N \cdot \left(\frac{1+\epsilon\sqrt{cp}}{2} \ln(1+\epsilon\sqrt{cp}) + \frac{1-\epsilon\sqrt{cp}}{2} \ln(1-\epsilon\sqrt{cp})\right)\right) \quad (\text{D.2})$$

which is also a weak bound. Specifically, it is no better than the standard Azuma, as one can see noting that  $\sqrt{cp} = \frac{1}{K_{max}} \ll 1$  and by expanding the logarithms of the r.h.s. the bound becomes:  $\exp(-N\epsilon^2/K_{max}^2) = \exp(-\epsilon^2 N\sqrt{cp} \cdot \frac{1}{K_{max}})$  giving the exact same result as that obtained from standard Azuma at Eq. (4.19).

## E Proof of Theorem 6

The proof, up to some point, follows [39], and the reader is referred to that reference for more details in the first steps. Since in our case the difference  $D_i$  of the martingale is bounded by unit, in our theorem we have restricted attention to that case (in [39] notation we set  $d = 1$ ). It is not hard to generalise for different values of the difference.

We note that

$$\sigma_i^2 = \mathbb{E}[(V_i - V_{i-1})^2 | W_1, \dots, W_{i-1}]. \quad (\text{E.1})$$

Then, we can first prove that:

$$\text{Var}(D_i | W_1, \dots, W_{i-1}) = \sigma_i^2 \quad (\text{E.2})$$

---

<sup>4</sup> Note that choosing  $\sigma = 1$  seems to be very big. In any reasonable adversarial strategy (using multiple queries for measurements) the majority of the  $N$  variables will actually have zero variance zero, since their corresponding probability will also be zero.

To prove that we first show that:

$$\mathbb{E}[D_i | W_1, \dots, W_{i-1}] = 0 \quad (\text{E.3})$$

Then, we have that for any  $t \geq 0$ :

$$\mathbb{E} \left[ \exp \left( t \cdot \sum_{i=1}^N D_i \right) \right] = \mathbb{E} \left[ \exp \left( t \cdot \sum_{i=1}^{N-1} D_i \right) \cdot \mathbb{E}[\exp(t \cdot D_N) | W_1, \dots, W_{N-1}] \right] \quad (\text{E.4})$$

Using Bennett Inequality: if  $X$  is a random variable, and let  $\bar{x} = \mathbb{E}[X]$  such that:  $\mathbb{E}[(X - \bar{x})^2] \leq \sigma^2$  and  $X \leq b$ . then for any  $t \geq 0$ , we have:

$$\mathbb{E}[e^{tX}] \leq \frac{e^{t\bar{x}}[(b - \bar{x})^2 e^{-\frac{t\sigma^2}{b-\bar{x}}} + \sigma^2 e^{t(b-\bar{x})}]}{(b - \bar{x})^2 + \sigma^2} \quad (\text{E.5})$$

where for our case we have  $X = D_i | W_1, \dots, W_{i-1}$ , and thus,  $\bar{x} = 0$  and  $b = 1$ , we therefore obtain:

$$\mathbb{E}[e^{t \cdot D_i} | W_1, \dots, W_{i-1}] \leq \frac{\exp(-t \cdot \sigma_i^2) + \sigma_i^2 \cdot \exp(t)}{1 + \sigma_i^2} \quad (\text{E.6})$$

By combining Eq. (E.4) and Eq. (E.6) for  $i = N$ , we then get:

$$\mathbb{E} \left[ \exp \left( t \cdot \sum_{i=1}^N D_i \right) \right] \leq \frac{\exp(-t \cdot \sigma_N^2) + \sigma_N^2 \cdot \exp(t)}{1 + \sigma_N^2} \cdot \mathbb{E} \left[ \exp \left( t \cdot \sum_{i=1}^{N-1} D_i \right) \right] \quad (\text{E.7})$$

And then by recursively applying this inequality, we obtain:

$$\mathbb{E} \left[ \exp \left( t \cdot \sum_{i=1}^N D_i \right) \right] \leq \frac{\exp(-t \cdot \sigma_N^2) + \sigma_N^2 \cdot \exp(t)}{1 + \sigma_N^2} \dots \frac{\exp(-t \cdot \sigma_1^2) + \sigma_1^2 \cdot \exp(t)}{1 + \sigma_1^2} \quad (\text{E.8})$$

Now, to relate to the quantity we are interested in:  $V_N - V_0 = W_1 + \dots + W_N - \mathbb{E}[W_1 + \dots + W_N] = Z_{\mathcal{A}_{\text{qu}}}(s) - \mathbb{E}[Z_{\mathcal{A}_{\text{qu}}}(s)]$ , we apply Chernoff inequality, which gives us for any  $\alpha > 0$ :

$$\Pr[V_N - V_0 \geq \alpha N] \leq \exp(-\alpha N t) \cdot \mathbb{E} \left[ \exp \left( t \cdot \sum_{i=1}^N D_i \right) \right] \quad (\text{E.9})$$

Using Eq. (E.8), we get the following concentration result for any  $\alpha > 0$ :

$$\Pr[V_N - V_0] \geq \alpha \cdot N \leq \exp(-\alpha N t) \cdot \prod_{i=1}^N \left( \frac{\exp(-t \cdot \sigma_i^2) + \sigma_i^2 \exp(t)}{1 + \sigma_i^2} \right) \quad (\text{E.10})$$

Now, we can use the upper bounds on  $\sigma_i$  specified in Theorem 6:

$$\begin{aligned}\sigma_i^2 &\leq \gamma_1 \quad \forall i \in \Gamma_1 \text{ where } |\Gamma_1| = N_1 \\ \gamma_1 &< \sigma_j^2 \leq \gamma_2 \quad \forall j \in \Gamma_2 \text{ where } |\Gamma_2| = N - N_1\end{aligned}\tag{E.11}$$

Using the fact that the function  $g(x) = \frac{x \exp(t) + \exp(-tx)}{1+x}$  is an increasing function for  $x > 0$ , the concentration result in Eq. (E.10) becomes:

$$\begin{aligned}Pr[V_N - V_0] \geq \alpha \cdot N] &\leq \\ \exp(-\alpha N t) \cdot \left( \frac{\exp(-t\gamma_1) + \gamma_1 \exp(t)}{1 + \gamma_1} \right)^{N_1} &\cdot \left( \frac{\exp(-t\gamma_2) + \gamma_2 \exp(t)}{1 + \gamma_2} \right)^{N - N_1}\end{aligned}\tag{E.12}$$

for all values of  $t \geq 0$  and  $\alpha \geq 0$ .

## F Proof of Theorem 7

First we obtain simpler form for  $A, B$ . Using the inequality:  $e^x + e^{-x} \leq 2e^{x^2/2}$ , leads to:

$$B \leq \exp\left(-\alpha t + \frac{t^2}{2}\right) = \exp\left(t\left(\frac{t}{2} - \alpha\right)\right)\tag{F.1}$$

Similarly we can simplify the  $A$  term. In our analysis, we will have  $0 \leq t \ll 1$  (and the same for  $\gamma$ ) and we can therefore use Taylor expansion of the exponentials to get:

$$\begin{aligned}A &\leq \frac{\exp(-\alpha t)}{1 + \gamma} \left( \gamma(1 + t + t^2/2 + \gamma \frac{t^3}{3!}) + (1 - t\gamma + (\gamma t)^2/2 - \gamma^3 \frac{t^3}{3!} + O(t^4)) \right) \\ &\leq \frac{\exp(-\alpha t)}{1 + \gamma} \left( (\gamma + 1) + \frac{\gamma t^2}{2}(1 + \gamma) + \frac{\gamma t^3}{3!}(1 - \gamma^2) + O(t^4) \right) \\ &\lesssim \left( 1 + \frac{\gamma t^2}{2} \right) \exp(-\alpha t)\end{aligned}\tag{F.2}$$

where in the last step we omitted terms involving  $\gamma t^3$  and higher. Then using, the inequality  $1 + x \leq e^x$  for any real  $x$ , we obtain:

$$A \leq \exp\left(\frac{\gamma t^2}{2} - \alpha t\right)\tag{F.3}$$

Plugging these into Eq. (4.22), we deduce the following bound on the concentration result:

$$Pr[Z_A - \mathbb{E}[Z_A] \geq \alpha \cdot N] \leq \exp\left(N_1\left(\frac{\gamma t^2}{2} - \alpha t\right) + (N - N_1)t\left(\frac{t}{2} - \alpha\right)\right)\tag{F.4}$$

Equivalent to:

$$Pr[Z_{\mathcal{A}} - \mathbb{E}[Z_{\mathcal{A}}] \geq \alpha \cdot N] \leq \exp\left(\frac{(N - (1 - \gamma)N_1)}{2}t^2 - \alpha Nt\right) \quad (\text{F.5})$$

By further replacing  $N_1$  from Eq. (4.24), we get:

$$Pr[Z_{\mathcal{A}} - \mathbb{E}[Z_{\mathcal{A}}] \geq \alpha \cdot N] \leq \exp\left(\left(\frac{\gamma}{2} + \frac{1 - \gamma}{2K_{max}\sqrt{\gamma}}\right)Nt^2 - \alpha Nt\right) \quad (\text{F.6})$$

From Theorem 7 we use:

$$\gamma = \alpha^{2/3} \quad \text{and} \quad t = \frac{\alpha^{1/3}}{4} \quad (\text{F.7})$$

and Eq. (F.2) becomes:

$$\begin{aligned} A &\leq \exp\left(-\frac{\alpha^{4/3}}{4}\right) \left(1 + \frac{\alpha^{4/3}}{32}\right) \\ &\lesssim \exp\left(-\frac{7\alpha^{4/3}}{32}\right) \end{aligned} \quad (\text{F.8})$$

We can see that this converges to zero (if raised to a sufficiently high power). Similarly, Eq. (F.1) becomes:

$$B \leq \exp\left(\frac{\alpha^{2/3}}{4} \left(\frac{1}{8} - \alpha^{2/3}\right)\right) \quad (\text{F.9})$$

This term, actually, diverges when raised to high enough power. It is essential to show that the product of these two terms converges to zero for our parameters choices.

We also note that with  $\gamma = \alpha^{2/3}$  Eq. (4.24) becomes

$$N_1 = N \left(1 - \frac{1}{K_{max}\alpha^{1/3}}\right) \quad (\text{F.10})$$

Now, we revisit Eq. (4.22) and using Eqs. (F.8,F.9,F.10) we obtain

$$\begin{aligned} Pr[Z_{\mathcal{A}} - \mathbb{E}[Z_{\mathcal{A}}] \geq \alpha N] &\leq \\ &\exp\left(-\frac{7\alpha^{4/3}}{32}N \left(1 - \frac{1}{K_{max}\alpha^{1/3}}\right) + \frac{\alpha^{2/3}}{4} \left(\frac{1}{8} - \alpha^{2/3}\right) \frac{N}{K_{max}\alpha^{1/3}}\right) \\ &\lesssim \exp\left(-\frac{7\alpha^{4/3}}{32}N + \frac{\alpha^{1/3}}{32} \frac{N}{K_{max}}\right) \end{aligned} \quad (\text{F.11})$$

where we kept the leading orders from each of the two terms. Setting  $\alpha = \frac{\epsilon}{K_{max}}$  where  $0 < \epsilon \leq 1/3$  is the concentration parameter we get:

$$Pr\left(Z_{\mathcal{A}} - \mathbb{E}[Z_{\mathcal{A}}] \geq \epsilon \frac{N}{K_{max}}\right) \lesssim \exp\left(-\frac{N}{K_{max}^{4/3}} \frac{\epsilon^{1/3}}{32} (7\epsilon - 1)\right) \quad (\text{F.12})$$

which clearly converges to zero if  $\epsilon > 1/7$ . The proof is concluded by noting that  $E := \max \mathbb{E}[Z_{\mathcal{A}}] = N/K_{max}$ .

## G Optimality of Generalised Azuma Concentration

In Section 4.2.6 we made certain choices for  $\gamma, t, \alpha$  and we got a concentration result that is (much) better than the earlier attempts using existing concentration results (Azuma and stronger version). In this appendix we give a heuristic argument why those choices not only are asymptotically optimal, but also get a concentration result that is very close to the one we expect to be the best (including the constants in the exponential decay of the expression).

We will fix  $\alpha = \frac{\epsilon}{K_{max}}$  as in the main text (but for now we keep it as  $\alpha$ ). We want to find the value of  $t$  that minimises Eq. (4.22) given the minimum  $N_1$  allowed by Eq. (4.24). Once we do this for any  $\gamma$  we find also the choice of  $\gamma$  that minimises this further (note that the chosen  $N_1$  also is a function of  $\gamma$ ). We make a heuristic analysis, where using the assumptions that  $\gamma, \alpha, t \ll 1$ , we expand the expressions for  $A, B$  keeping only the leading terms with respect all the (small) variables. We then get:

$$A \sim 1 - \alpha t + \frac{(\gamma + \alpha^2)t^2}{2} + O(\text{higher}).$$

and

$$B \sim 1 + \frac{t^2}{2}(1 + \alpha) - \alpha t + O(\text{higher})$$

Also we use  $N - N_1 = \frac{N}{K_{max}\sqrt{\gamma}}$  and since  $\frac{1}{K_{max}\sqrt{\gamma}} \ll 1$  we can approximate  $N_1 \sim N$  so that Eq. (4.22) becomes:

$$\begin{aligned} A^{N_1} B^{N-N_1} &\lesssim \left(1 - \alpha N t + \frac{\gamma t^2}{2} N\right) \left(1 + \frac{t^2}{2} \frac{N}{K_{max}\sqrt{\gamma}} - \alpha t \frac{N}{K_{max}\sqrt{\gamma}}\right) \quad (\text{G.1}) \\ &\lesssim 1 + N \left(-\alpha t \left(1 + \frac{1}{K_{max}\gamma^{1/2}}\right) + \frac{\gamma t^2}{2} \left(1 + \frac{1}{K_{max}\gamma^{3/2}}\right) + O(\text{higher})\right) \end{aligned}$$

The optimal choice of  $t$  for this expression can be found to be approximately:

$$t = \frac{\alpha}{\gamma} \cdot \frac{1 + \frac{1}{K_{max}\gamma^{1/2}}}{1 + \frac{1}{K_{max}\gamma^{3/2}}} = \alpha \cdot \frac{1 + K_{max}\gamma^{1/2}}{1 + K_{max}\gamma^{3/2}}$$

To obtain this, we dropped higher terms and then fixed all variables except  $t$ , took the derivative of the truncated expression w.r.t.  $t$  and got the above value.

We therefore know that for this value of  $t$  we have the tightest bound irrespective of the value of  $\gamma$ . The bound becomes:

$$A^{N_1} B^{N-N_1} \lesssim 1 - N \cdot \frac{\alpha^2}{2} \cdot \left( \frac{K_{max} \gamma^{1/2} + 1}{K_{max} \gamma^{3/2} + 1} \right)$$

Assuming  $K_{max} \gg 1$ , we can find the minimum of the above expression (taking derivative w.r.t.  $\gamma$  this time) that occurs for  $\gamma \approx \frac{1}{(2K_{max})^{2/3}}$ .

This means:

$$\gamma = \left( \frac{\alpha}{2\epsilon} \right)^{2/3} = \left( \frac{1}{2K_{max}} \right)^{2/3}$$

By plugging this value of  $\gamma$  to the above expression for  $t$  gives us:

$$t = (2K_{max})^{2/3} \left( \frac{\alpha}{3} \right) = \frac{(2\epsilon)^{2/3}}{3} \alpha^{1/3} = \left( \frac{(2)^{2/3} \epsilon}{3} \right) \frac{1}{K_{max}^{1/3}}$$

In other words, the optimal bound could be obtained with the following choices:

$$\gamma = \left( \frac{\alpha}{2\epsilon} \right)^{2/3} \quad ; \quad t = \frac{(2\epsilon)^{2/3}}{3} \alpha^{1/3} \tag{G.2}$$

It is worth to note, that these choices are extremely close with the ones used in our analysis in the main paper. As far as the dependency on  $\alpha$  is concerned, for both  $\gamma, t$  we have the same functional dependency. The constants that actually are required to achieve the best bound, depend on  $\epsilon$  in general. The values we chose are close to optimal for some choices of  $\epsilon$ .

The final optimal bound with the approximations made (that holds for all the allowed  $\epsilon$ 's), after plugging the expressions for  $\gamma, t$  we obtained and some more calculations turns out to be:

$$A^{N_1} B^{N-N_1} \lesssim \exp \left( -\frac{N}{K_{max}^{4/3}} \cdot \frac{\epsilon^2}{3} \cdot \left( \frac{1}{2} \right)^{1/3} \right) \approx \exp \left( -\frac{N}{K_{max}^{4/3}} \cdot \frac{\epsilon^2}{4} \right)$$

For example, for the choice  $\epsilon = 2/7$  the above expression gives a coefficient of  $1/49$  which is marginally better than the  $0.02$  that we get with the same  $\epsilon$  from Eq. (4.25).

This section demonstrates that our choices (that might have appeared random in the main text) not only give a good bound that is asymptotically the best, but they also give a bound that even the constants of the exponential decay are close to the optimal ones.

## H Concentration Results for Restricted Strategies: Noisy Quantum Storage and Non-Adaptive

In this section we study 2 restricted types of strategies against the Bag-of-PoWs Problem: Noisy Quantum Storage Adversaries and Non-Adaptive Adversaries.

Then the main concentration results for these two families of strategies can be described as follows;

**Theorem 10.** *For the problem Bag-of-PoWs Problem we have the following concentrations:*

1. *For any Noisy Quantum Storage adversary having  $N$  quantum queries and being forced to measure once every  $Q$  quantum queries, we have that the maximum length is at least  $M_B = (1 + \epsilon)cpNQ$  with probability at most  $p_B = \exp(-\frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)}cpNQ)$ .*
2. *For Non-Adaptive adversaries having  $N$  quantum queries, we have that the maximum length is at least  $M_N = (1 + \epsilon)\sqrt{cp}N$  with probability at most  $p_N = \exp(-\frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)}\sqrt{cp}N)$ .*

In the following subsections we describe and motivate these families of strategies and prove their concentrations described in Theorem 10.

## H.1 Noisy Quantum Storage Adversaries

In the Noisy Quantum Storage model the adversary's quantum memory is degrading in time and after a fixed amount of time needs to be reset. This constrained model implies that the adversary cannot continue the Grover iterations as long as it wants, and instead it is forced to make a measurement after a fixed number of queries  $Q$ . For simplicity, we will assume that the total number of queries  $N$  is a multiple of  $Q$ . We will denote this adversary as  $\mathcal{A}_{\text{noisy}}$ .

### H.1.1 Maximum Expectation of Noisy Quantum Storage Strategies

**Theorem 11.** *For any Noisy Quantum Storage adversary  $\mathcal{A}_{\text{noisy}}$ , the maximum expected number of PoWs, given any number of rounds  $s$ , is:*

$$B := \max \mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}}] = cp \cdot N \cdot Q \quad (\text{H.1})$$

*Proof.* We start with a simplifying scenario, where we assume that  $\mathcal{A}_{\text{noisy}}$  performs a single measurement after each  $Q$  queries. Using Theorem 2, the expected number of adversarial blocks created after every  $Q$  queries (probability that the single PoW is solved) can be bounded by  $\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}(Q)}] \leq cpQ^2$ . In this model we then have  $N/Q$  measurements and we can compute  $\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}}]$  as:

$$\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}}] = \sum_{i=1}^{N/Q} \mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}(Q)}] = \frac{N}{Q} \cdot \mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}}] \leq cpNQ \quad (\text{H.2})$$

However, while the adversary because of the noisy memory, is obliged to make a measurement at the end of  $Q$  queries, he could decide still to split the  $Q$  queries he has into multiple measurements, either attempting to solve multiple different PoWs (to, in principle, extend his solution, by more than one pair  $(x_{i_j}, y_{i_j})$  or

he may wish to try solving the same PoW (if he fails in earlier attempts). We generalize, and consider that  $\mathcal{A}_{\text{noisy}}$  can perform in each block of  $Q$  queries a variable number of measurements  $t$ , and for each measurement uses  $K_i$  queries before performing the corresponding measurement ( $\sum_{i=1}^t K_i = Q$ ). We can make the convention that the number of measurements is  $t = Q$ , where since there are  $Q$  queries in total,  $t = Q$  is the maximum possible within a block of  $Q$  queries, and we can always consider that the last chunk sizes are 0 (e.g. if adversary performs  $m_1 < Q$  measurements, we will have  $K_{m_2} = 0 \forall m_2 > m_1$ ).

We can assume that the adversary, in the first measurement, is trying to solve one particular PoW. If successful, the second measurement tries to solve a new PoW. If he was unsuccessful, the adversary in his second measurement, tries to solve again the same problem.

Then, if we denote by  $P_{\mathcal{A}_{\text{noisy}}}(i)$  the probability of obtaining  $i$  PoWs (out of  $Q$  possible PoWs), the expected number of adversarial blocks obtained by  $\mathcal{A}_{\text{noisy}}$  within any block of  $Q$  queries, can be described as:

$$\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}(Q)}] = \sum_{i=1}^Q i \cdot P_{\mathcal{A}_{\text{noisy}}}(i) = \sum_{i=1}^Q i \cdot \left( \sum_{\substack{I \subseteq \{1, 2, \dots, Q\} \\ |I|=i}} \left[ \prod_{j \in I} cp \cdot K_j^2 \right] \cdot \left[ \prod_{l \in \{1, \dots, Q\} - I} (1 - cp \cdot K_l^2) \right] \right) \quad (\text{H.3})$$

However, we notice that  $Z_{\mathcal{A}_{\text{noisy}}(Q)}$  is defined as the number of successes in a sequence of  $Q$  independent measurements with outcome success or failure, each of the measurements having success probability  $P_{K_1}, P_{K_2}, \dots, P_{K_Q}$ , then  $Z_{\mathcal{A}_{\text{noisy}}}$  is a *Poisson Binomial* distribution. Therefore, as  $Z_{\mathcal{A}_{\text{noisy}}(Q)}$  is a Poisson Binomial distribution, its mean is equal to the sum of the  $Q$  Bernoulli distributions:

$$\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}(Q)}] = \sum_{i=1}^Q P_{K_i} = cp \cdot \sum_{i=1}^Q K_i^2 \quad (\text{H.4})$$

Then, we need to find the maximum of  $\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}(Q)}]$  over all possible  $K_1, \dots, K_Q \in \{0, 1, \dots, Q\}$  subject to the constraint  $\sum_{i=1}^Q K_i = Q$ . As each  $K_i \leq Q$ , we can rewrite the chunk sizes as:  $K_i = \chi_i Q$ , where  $\chi_i \in [0, 1]$ . The constraint  $\sum_{i=1}^Q K_i = Q$  becomes  $\sum_{i=1}^Q \chi_i = 1$ . The expectation value can be rewritten as:

$$\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}(Q)}] = cpQ^2 \cdot \sum_{i=1}^Q \chi_i^2 \quad (\text{H.5})$$

Since  $\chi_i \in [0, 1]$ , we have  $\chi_i^2 \leq \chi_i$ , which leads to:

$$\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}(Q)}] = cpQ^2 \cdot \sum_{i=1}^Q \chi_i^2 \leq cpQ^2 \cdot \sum_{i=1}^Q \chi_i = cpQ^2 \quad (\text{H.6})$$

Therefore, we have determined that the maximum value on the expected number of blocks obtained by  $\mathcal{A}_{\text{noisy}}$  is

$$\max \mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}(Q)}] = cpQ^2 = B. \quad (\text{H.7})$$

We can also observe that this maximum value is obtained when the adversary uses a single measurement with all  $Q$  queries:  $K_1 = Q$ ,  $K_i = 0 \forall i \neq 1$  since  $\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}}] = cp(Q^2 + 0 + \dots + 0) = cpQ^2 = B$ . This indicates, that it is optimal (w.r.t. the average number of adversarial blocks) for  $\mathcal{A}_{\text{noisy}}$  to perform a single measurement (within  $Q$  queries).  $\square$

### H.1.2 Concentration Result of Noisy Quantum Storage Adversaries

To complete the analysis, it is not sufficient to know what is the maximum number of PoWs the adversary achieves *on average*, but we also need to know how concentrated around this average value are the actual maximum solution lengths for those type of adversaries. In this first simplified analysis, since the best expectation is achieved with a single measurement, we assume that the adversary sticks with this and makes a single measurement in each block of  $Q$  queries.

With these assumptions, for  $\mathcal{A}_{\text{noisy}}$  adversary, it is not hard to obtain a concentration result, since  $Z_i$ 's - corresponding to number of PoWs obtained during blocks of  $Q$  queries, are independent random variables. Since  $Z_{\mathcal{A}_{\text{noisy}}} = \sum_{i=1}^{N/Q} Z_i$ , we could apply either Chernoff or Hoeffding inequalities, however the former cannot be directly applied since we can only bound the maximum expectation of  $Z_{\mathcal{A}_{\text{noisy}}}$ , while the former gives a very weak bound (see the problem with Azuma inequality in Section 4.2.5).

Instead, we derive our own bound on the probability of  $Z_{\mathcal{A}_{\text{noisy}}}$  that involves the value  $B$  (and not  $\mathbb{E}[Z_{\mathcal{A}_{\text{noisy}}}]$ ). This newly derived Chernoff-type of inequality, proved in Appendix B, is stated as below:

**Lemma 15.** *Let  $X_1, \dots, X_n$  be  $n$  independent random variables, taking values 0 or 1. Let  $X = X_1 + \dots + X_n$ . Then, for any  $M > 0$ , such that  $\mathbb{E}[X] \leq M$  and for any  $\epsilon > 0$ , we have:*

$$\Pr[X > (1 + \epsilon)M] < \exp\left(-\frac{\epsilon(3\epsilon + 2)}{2(2 + \epsilon)} \cdot M\right) \quad (\text{H.8})$$

In our setting, we use  $n = s$ ,  $X_i = w_i$  (where  $w_i = 1$  if  $i$ -th measurement succeeded, and 0 otherwise),  $X = Z_{\mathcal{A}_{\text{noisy}}}(s)$ ,  $M = B$ . Hence, we obtain:

$$\Pr[Z_{\mathcal{A}_{\text{noisy}}} > (1 + \epsilon)B] < \exp\left(-\frac{\epsilon(3\epsilon + 2)}{2(2 + \epsilon)} \cdot B\right) \forall \epsilon > 0 \quad (\text{H.9})$$

Combining this concentration result together with Theorem 11, gives us the following bound on the number of adversarial PoWs:

**Theorem 12.** *For any Noisy Quantum Storage adversary  $\mathcal{A}_{\text{noisy}}$ , with probability  $1 - \exp(-\frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)}cpNQ)$  and for any  $\epsilon > 0$ , it holds that:*

$$Z_{\mathcal{A}_{\text{noisy}}} < (1 + \epsilon)cpNQ \quad (\text{H.10})$$

## H.2 Concentration Result of Non-Adaptive Adversaries

Non-Adaptive strategies represent a very important mathematical tool used for our analysis of the most general adversaries against the Bag-of-PoWs problem. As we have proven in Theorem 4, these are the optimal strategies with respect to the maximum expected length of the solution of the Bag-of-PoWs problem. More specifically, from Theorem 5, we have that:  $E := \max \mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] = \sqrt{cp} \cdot N$ .

We now turn on the issue of how concentrated around the average value is the number of actual measured adversarial blocks. For the Non-Adaptive adversary, we have an independent search problem after each measurement, which has outcome  $w_i$  0 or 1, irrespective of how many solutions have been found earlier. We can therefore use Chernoff bounds to approximate the number of adversarial blocks using the expectation value:

$$\Pr[Z_{\mathcal{A}_{\text{nonad}}} < (1 + \epsilon)\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}] \geq 1 - e^{-\frac{\epsilon^2}{2+\epsilon} \cdot \mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}]}$$
 (H.11)

Unfortunately, as we only know the maximum value  $E$  that the expectation can achieve, we cannot use directly the Chernoff inequality (again using Hoeffding inequality would give a much weaker bound). Instead, we need to derive our own bound on the probability of  $Z_{\mathcal{A}_{\text{nonad}}}$  to exceed the value  $E$ , probability which can be expressed as a function of  $E$  (and not  $\mathbb{E}[Z_{\mathcal{A}_{\text{nonad}}}]$ ). In order to use this new derived Chernoff type of inequality, stated in Lemma 15 (and proved in Appendix B), we make the following choice of variables:  $n = N$ ,  $X_i = w_i$  (where  $w_i = 1$  if  $i$ -th measurement succeeded, and 0 otherwise),  $X = Z_{\mathcal{A}_{\text{nonad}}}$ ,  $M = E$ . This gives us the following concentration result:

$$\Pr[Z_{\mathcal{A}_{\text{nonad}}} > (1 + \epsilon)E] < \exp\left(-\frac{\epsilon(3\epsilon + 2)}{2(2 + \epsilon)} \cdot E\right) \forall \epsilon > 0$$
 (H.12)

Combining this concentration result together with Theorem 5, gives us the following bound on the number of adversarial PoWs:

**Theorem 13.** *For any Non-Adaptive adversary  $\mathcal{A}_{\text{nonad}}$ , with probability  $1 - \exp(-\frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)}\sqrt{cp}N)$  and for any  $N \geq \frac{1}{\sqrt{cp}}$  and any  $\epsilon > 0$ , it holds that:*

$$Z_{\mathcal{A}_{\text{nonad}}} < (1 + \epsilon)\sqrt{cp} \cdot N$$
 (H.13)

## I Backbone Protocol Analysis against Restricted Quantum Strategies

In this section we study the two restricted SMS adversaries, Noisy Quantum Storage and Non-Adaptive against the Backbone protocol.

### I.1 Backbone Protocol Analysis for Noisy Quantum Storage

As explained in Subsection 5.1, we now need to determine the conditions on the hashing power of the adversary such that the properties of the Bitcoin backbone protocol are satisfied.

**Theorem 14.** *The common prefix property is satisfied with parameter  $k \geq 2sf$ , for any  $s \geq \frac{2}{f}$  consecutive rounds against any Noisy Quantum Storage adversary, with probability  $1 - \exp(-g_0(\epsilon)cpQ^2s)$ , as long as:*

$$Q < \sqrt{\frac{1-\epsilon}{1+\epsilon} \cdot \frac{f(1-f)}{cp}} \quad (\text{I.1})$$

*Proof.* Using Lemma 8 and the concentration result from Theorem 12, the condition of the adversary's hashing power  $Q$  becomes:

$$(1+\epsilon)cpQ^2 < (1-\epsilon)f(1-f) \quad (\text{I.2})$$

The proof follows from Eq. (I.2) and Theorem 12, where  $g_0(\epsilon) := \frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)}$ .  $\square$

**Theorem 15.** *The chain quality property is satisfied with parameter  $l \geq 2sf$ , and  $\mu = f$  for any  $s \geq \frac{2}{f}$  consecutive rounds against any Noisy Quantum Storage adversary, with probability  $1 - \exp(-g_0(\epsilon)cpQ^2s)$ .*

**Corollary 3.** *Under the above restrictions on  $Q$ , the probability under which the common prefix and chain quality are satisfied becomes:*

$$P_{noisy} = 1 - \exp(-g_1(\epsilon) \cdot f(1-f) \cdot s) \quad (\text{I.3})$$

where  $g_1(\epsilon) = g_0(\epsilon) \cdot \frac{1-\epsilon}{1+\epsilon}$ .

### I.2 Backbone Protocol Analysis for Non-Adaptive Strategies

Now we need to determine the conditions on the hashing power of the adversary such that the properties of the Bitcoin backbone protocol are satisfied.

**Theorem 16.** *The common prefix property is satisfied with parameter  $k \geq 2sf$ , for any  $s \geq \frac{2}{f}$  consecutive rounds against any Non-Adaptive adversary, with probability  $1 - \exp(-g_0(\epsilon)\sqrt{cp}Qs)$ , as long as:*

$$Q < \frac{1-\epsilon}{1+\epsilon} \cdot \frac{f(1-f)}{\sqrt{cp}} \quad (\text{I.4})$$

*Proof.* Using Lemma 8 and the concentration result from Theorem 13, the condition of the adversary's hashing power  $Q$  becomes:

$$(1+\epsilon)\sqrt{cp}Q < (1-\epsilon)f(1-f) \quad (\text{I.5})$$

The proof follows from the above and Theorem 13, where  $g_0(\epsilon) = \frac{\epsilon(3\epsilon+2)}{2(2+\epsilon)}$ .  $\square$

**Theorem 17.** *The chain quality property is satisfied with parameter  $l \geq 2sf$ , and  $\mu = f$  for any  $s \geq \frac{2}{f}$  consecutive rounds against any Non-Adaptive adversary, with probability  $1 - \exp(-g_0(\epsilon)\sqrt{cp}Qs)$ .*

**Corollary 4.** *Under the above restrictions on  $Q$ , the probability under which the common prefix and chain quality are satisfied becomes:*

$$P_{nonad} = P_{noisy} = 1 - \exp(-g_1(\epsilon) \cdot f(1-f) \cdot s) \quad (\text{I.6})$$