

# Quantifying Blockchain Extractable Value: How dark is the forest?

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## Abstract

Permissionless blockchains such as Bitcoin have excelled at financial services. Yet, adversaries extract monetary value from the mesh of decentralized finance (DeFi) smart contracts. Some have characterized the Ethereum peer-to-peer network as a dark forest, wherein broadcast transactions represent prey, which are devoured by generalized trading bots.

While transaction (re)ordering and front-running are known to cause losses to users, we quantify how much value was sourced from blockchain extractable value (BEV). We systematize a transaction ordering taxonomy to quantify the USD extracted from sandwich attacks, liquidations, and decentralized exchange arbitrage. We estimate that over 2 years, those trading activities yielded 28.80M USD in profit, divided among 5,084 unique addresses. While arbitrage and liquidations might appear benign, traders can front-run others, causing financial losses to competitors.

To provide an example of a generalized trading bot, we show a simple yet effective automated transaction replay algorithm capable of replacing unconfirmed transactions without understanding the victim transactions' underlying logic. We estimate that our transaction replay algorithm could have yielded a profit of 51,688.33 ETH (17.60M USD) over 2 years on past blockchain data.

We also find that miners do not broadcast 1.64% of their mined transactions and instead choose to mine them privately. Privately mined transactions cannot be front-run by other traders or miners. We show that the largest Ethereum mining pool performs arbitrage and seemingly tries to cloak its private transaction mining activities. We therefore provide evidence that miners already extract Miner Extractable Value (MEV), which could destabilize the blockchain consensus security, as related work has shown.

## 1 Introduction

With the recent surge of Decentralized Finance protocols, distributed ledgers have shown their strength in mediating trustlessly among financial actors exchanging daily hundreds of millions of USD. Traders rely on immutable smart contracts encoding the rules by which, for instance, decentralized automated market maker (AMM) exchanges [41] operate. The order in which financial transactions execute matters for engaging traders. However, currently deployed permissionless blockchains do not provide a mechanism for traders to guarantee a desired execution order. Transactions are first broadcast, or sent to a miner privately, and then executed based on either a first-come-first-served or transaction fee.

Akin to how Eskandir *et al.* [27] beautifully distill the state of open and decentralized ledgers: we observe a distributed network of transparent dishonesty — once a user broadcasts a profitable transaction, seemingly automated trading-bots attempt to appropriate the trading opportunity by front-running their victim with higher transaction fees [39]. While some characterize the blockchain network as a dark forest full of preys, we aim to shed light on the

practices of those transparently dishonest entities. We capture three sources of BEV, referred to as MEV if extracted by a miner [24] and summarize our main contributions in the following.

**Adversarial Transaction Order Systematization:** We extend a front-running taxonomy [27] to four different transaction ordering strategies allowing mining and non-mining entities to extract value from the blockchain application layer.

**Measurement of State-of-the-Art Value Extraction:** Based on the historical blockchain state of the last 2 years, we quantify the estimated overall extracted value for sandwich attacks, liquidations, and arbitrage. For sandwich attacks, we identify 1,379 independent Ethereum addresses performing attacks on Uniswap v1/v2, Sushiswap, Curve, Swerve, 1inch, and Bancor (representing 82% of the decentralized exchange market) yielding a total profit of 1.51M USD. Those actors pay an average transaction fee of 0.04 ETH, indicating competitive behavior. For fixed spread liquidations protocols, such as Aave, Compound, and dYdX (66% of the DeFi lending market), we find that the past 16,031 liquidations yield an accumulative profit of 20.18M USD over the entire existence of those protocols (19 months). We find that 12.71% of these liquidations back-run the price oracle update transaction, while 87.29% attempt to front-run competing liquidators. For arbitrage, we identify 789 smart contracts performing 51,415 trades, realizing a total profit of 7.11M USD. We further identify 60.08% of the trades as network state arbitrages, which means that the traders are back running market participants' transactions.

**Measuring Blockchain Clogging Events:** We identify 237 blockchain clogging events over 2 years on the Ethereum blockchain. The longest clogging period we find lasts for 5 minutes (24 blocks, corresponding to a cost of 39 ETH), and 93.67% of the clogging periods last less than 2 minutes (10 blocks). Through manual inspection, we find that at least four out of the top 10 clogging events attempt to extract monetary value from gambling protocols.

**Generalized Transaction Replay:** We provide a generic but straightforward transaction replay algorithm to replay on-the-fly profitable transactions discovered on the blockchain network layer. We show how this algorithm operates in real-time by substituting and emulating a transaction in  $0.18 \pm 0.29$  seconds. We estimate that 229,156 transactions could have been replayed over 2 years of the Ethereum blockchain, yielding a profit of over 51,688.33 ETH (17.60M USD).

**Privately Mined Transactions:** To mitigate the negative effects of front-running, we observe an ongoing centralization in the Ethereum network propagation. By monitoring the peer-to-peer (P2P) network layer with a highly connected client (up to 1000 P2P connections), we observe that about 1.64% of the mined transactions were not broadcasted on the public blockchain network. Through manual inspection, we find that e.g., the *Ethermine* mining pool mines 77% of the privately mined transactions in a rather obvious manner at the start of each block. The biggest Ethereum miner, the *Spark Pool* (23.50% hash rate), however, appears to try to conceal its

privately mined transactions with fitting gas prices and seemingly random block order. The Spark pool is issuing its privately mined transactions exclusively to a smart contract which is apparently performing arbitrage. As such we provide evidence that miners already extract MEV.

By capturing generic replay, front-, back-running, clogging, and privately mined transactions, we hope to shed light on the blockchain network practices, which were previously left unquantified.

## 2 Background

An overview of blockchain and decentralized finance follows.

### 2.1 Blockchain and Smart Contracts

Permissionless blockchains are span by a network of globally distributed P2P nodes [37]. If a user wishes to execute a transaction on the blockchain (which in essence is a distributed database), the user broadcasts the transaction to its P2P neighbors. These neighbors then go on to forward that transaction until the transaction eventually reaches a miner. A miner constructs a block to append data to the blockchain and decides how transactions are positioned within the block. A transaction included in at least one blockchain block<sup>1</sup> is considered confirmed (i.e., a one-confirmation) by the network. Different blockchains feature a varying degree of confirmation speeds, ranging from minutes in Bitcoin [37] to seconds in Ethereum [42], and offering different security trade-offs [31]. There is an inherent *time delay*, between the public *broadcast* of a transaction and its execution within a blockchain. Blockchain nodes store unconfirmed transactions within the so-called memory pool, or *mempool*. For a more thorough background on blockchains, we refer the reader to several helpful SoKs [17, 18, 22]. Beyond simple value transfers, smart contract-enabled blockchains [42], allow the construction of decentralized finance protocols. Smart contracts typically execute within a virtual machine, e.g., the Ethereum Virtual Machine (EVM). In this paper, we differentiate among user addresses (i.e., owned by a private key) and smart contract addresses.

### 2.2 Decentralized Finance

DeFi is a subset of finance-focused decentralized protocols that operate autonomously on blockchain-based smart contracts. After excluding the DeFi systems’ endogenous assets, the total value locked in DeFi amounts to 12.5B USD at the time of writing. Relevant DeFi platforms are for instance automated market maker exchanges [33, 41], lending platforms [16, 26, 29, 30] and margin trading systems [14].

**AMM Exchanges:** Contrary to traditional limit order-book-based exchanges (which maintain a list of bids and asks for an asset pair), AMM exchanges maintain a pool of capital (i.e., a liquidity pool) with at least two assets. A smart contract governs the rules by which traders can purchase and sell assets from the liquidity pool. The most common AMM mechanism is a constant product AMM, where the product of an asset  $x$  and asset  $y$  in a pool have to abide by a constant  $k$ . Uniswap, with 1.8B USD total value locked (TVL) the biggest AMM exchange at the time of writing, for instance, follows a constant product AMM model [41].

**Slippage:** When performing a trade on an AMM, the expected execution price may differ from the real execution price. That is because the expected price depends on a past blockchain state, which may change between the transaction creation and its execution — e.g., due to front-running transactions [43]. Therefore, a trader is exposed to an expected slippage (the price increase due to the transaction volume) and an unexpected slippage (the price increase due to unanticipated intermediate blockchain state changes).

**Lending Systems:** Debt is an essential tool in traditional finance [25], and the same applies to DeFi. Because DeFi applications typically operate without Know Your Customer (KYC), the borrower’s debt must be over-collateralized. Hence, a borrower must collateralize, i.e., lock, for instance, 150% of the value that the borrower wishes to lend out. The collateral acts as a security to the lender if the borrower doesn’t pay back the debt. If the collateral value decreases and the collateralization ratio decreases below 150%, the collateral can be freed up for liquidation. Liquidators can then purchase the collateral at a discount to repay the debt. At the time of writing, lending systems on the Ethereum blockchain have accumulated a TVL of 6B USD [16, 26, 29, 30].

## 3 Transaction Ordering Taxonomy

We proceed to extend the front-running taxonomy of Eskandari *et al.* [27] (cf. Figure 1).

### 3.1 System Model

We assume the existence of a trader  $V$  conducting at least one blockchain transaction  $T_V$  (given a public/private key-pair) by e.g., trading assets on AMM exchanges, or interacting with a lending platform. The trader is free to specify its slippage tolerance, transaction fees, and choice of platform. We refer to the trader as victim if the trader is being attacked by other traders (e.g., in a sandwich attack). We further assume the existence of a set of miners that may or may not engage to extract blockchain extractable value. The miners can choose to order transactions according to private policies or may follow the transaction fee distribution.

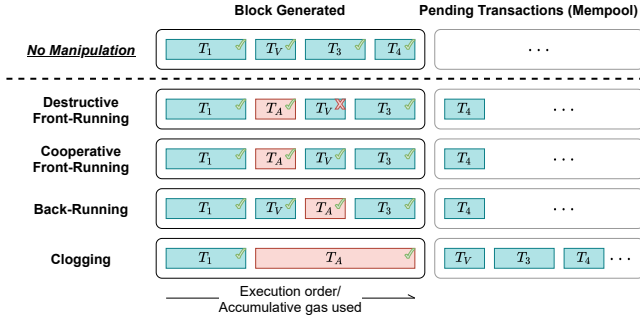
### 3.2 Threat Model

Our threat model captures a financially rational adversary  $\mathcal{A}$  that is well-connected in the network layer to observe unconfirmed transactions in the memory pool.  $\mathcal{A}$  holds at least one private key for a blockchain account from which it can issue an authenticated transaction  $T_A$ . We also assume that  $\mathcal{A}$  owns a sufficient balance of the native cryptocurrency (e.g., ETH on Ethereum) to perform actions required by  $T_A$  e.g., paying transaction fees or trading assets.

### 3.3 Transaction Ordering

The transaction order of blockchains is determined by the miners, which for instance follow the sequence at which transactions arrive on the network layer or in descending transaction fee (gas price) amount. Related work has quantified that in November 2019, about 80% of the Ethereum miners order transactions after the transaction fees [43]. Front-running is the process by which an adversary observes transactions on the network layer and then acts upon this information by, for instance, issuing a *competing transaction*, with the hope that this transaction is mined before a victim transaction (cf. Section 3.4). Related work has, for example, shown how

<sup>1</sup>i.e., the chain with most “Proof of Work”



**Figure 1:** Visualization of the four types of adversarial transaction ordering strategies.  $T_V$  is the victim and  $T_A$  the adversarial transaction. We assume that  $T_1$  to  $T_4$ , are included in the next block in their sequence.

trading bots engage in competitive transaction fee bidding contests [24]. Besides exchange trading, front-running was observed for blockchain-based games, crypto-collectibles, gambling, ICO participation, and name reservation services [27]. Miner Extractable Value, first introduced by Daian *et al.* [24], captures the blockchain extractable value captured by miners. Non-mining traders can also capture BEV by adjusting e.g., their transaction fees, and we treat MEV as a subset of the blockchain extractable value.

### 3.4 Extended Front-Running Taxonomy

We observe the subtle but essential impact of an adversarial front-running transaction on the subsequent victim transaction: either  $T_A$  provokes the victim transaction to fail, or the adversary takes care to avoid that  $T_V$  reverts after front-running. We also explicitly add a fourth category, which captures the act of back-running a transaction [43] (cf. Figure 1).

**Destructive Front-Running:** If  $T_A$  front-runs  $T_V$ , and causes the execution of  $T_V$  to fail (i.e., the EVM reverts the transaction state changes), we classify the act of front-running as destructive. The front-running adversary, therefore, bears no considerations about its impact on subsequent transactions.

**Cooperative Front-Running:** Front-running is cooperative if the adversary ensures that  $T_V$  executes successfully. Cooperative front-running is necessary for, e.g., sandwich attacks [43]. An adversary would not be able to profit from sandwich attacks with destructive front-running.

**Back-Running:** Executing  $T_A$  shortly after  $T_V$  is referred to as back-running, a powerful technique which, for instance, can be applied after, e.g., oracle update transactions [36] and within sandwich attacks [43]. Back-running is, in expectation, cheaper than front-running, as the trader does not engage in a bidding contest.

**Clogging:** An adversary may clog, or jam the blockchain with transactions, to prevent users and bots from issuing transactions (i.e., suppression [27]). Deadline-based smart contracts may create an incentive to clog the blockchain.

Front-running may occur on different blockchain state representations, e.g., we differentiate in this paper between a block state and a mempool or network state (cf. Table 1). A block state corresponds to the last confirmed main-chain head, while the mempool state is a more volatile and local state of a blockchain P2P node. We notice

that sandwich attacks (cf. Section 4.1) and transaction replay (cf. Section 5) can only occur on the network layer (unless a miner were to fork the blockchain).

Use Case	Block State	Mempool/Network State
Sandwich Attack	-	✓
Liquidation	✓	✓ (back-run oracle updates)
Arbitrage	✓	✓
Transaction Replay	-	✓

**Table 1:** Attack surface for a non-mining adversary. While miners always have the option to fork the chain, sandwich attacks and transaction replay must occur on the network layer for non-mining attackers.

## 4 Measuring the Extracted Blockchain Value

In the following, we investigate to what extent traders have extracted financial value from the Ethereum blockchain over a time frame of 2 years. While it is challenging to capture all possible revenue strategies, we do not claim completeness and chose to focus on sandwich attacks, liquidations, and arbitrage trading.

### 4.1 Sandwich Attacks

Sandwich attacks, wherein a trader wraps a victim transaction within two adversarial transactions, is a classic predatory trading strategy [43]. To perform a sandwich, the adversary  $\mathcal{A}$ , which can be a miner or trader, listens on the P2P network for pending transactions. The adversary attacks, if the market price of an asset is expected to rise/fall after the execution of a “large” pending transaction ( $T_V$ ). The attack is then carried out in two-steps: (i)  $\mathcal{A}$  issues  $T_{A1}$  to **cooperatively front-run**  $T_V$ , by purchasing/selling the same asset before  $T_V$  changes the market price; (ii)  $\mathcal{A}$  then issues  $T_{A2}$  to **back-run**  $T_V$  to close the trading position opened by  $T_{A1}$ .  $\mathcal{A}$  must perform cooperative front-running to ensure that  $T_V$ ’s slippage protection does not trigger a transaction revert.

**4.1.1 Heuristics** We apply the following heuristics to identify potentially successful sandwich attacks on AMM exchanges (Uniswap v1/v2, Sushiswap, Curve, Swerve, 1inch, and Bancor).

**Heuristic 1:** The transactions  $T_{A1}$ ,  $T_V$  and  $T_{A2}$  must be included in the same block and in this exact order.

**Heuristic 2:** Every front-running transaction  $T_{A1}$  maps to **one and only one** back-running transaction  $T_{A2}$ . This heuristic is necessary to avoid double counting revenues.

**Heuristic 3:** Both  $T_{A1}$  and  $T_V$  transact from asset  $X$  to  $Y$ .  $T_{A2}$  transacts in the reverse direction from asset  $Y$  to  $X$ .

**Heuristic 4:** Either the same user address sends transactions  $T_{A1}$  and  $T_{A2}$ , or two different user addresses send  $T_{A1}$  and  $T_{A2}$  to the same smart contract.

**Heuristic 5:** The amount of asset sold in  $T_{A2}$  must be within 90% ~ 110% of the amount bought in  $T_{A1}$ . If the sandwich attack is perfectly executed without interference from other market participants, the amount sold in  $T_{A2}$  should be precisely equal to the amount purchased in  $T_{A1}$ . However, according to our empirical data, only 17,741 (84.48%) sandwich attacks we detect are perfect. We therefore relax this constraint to cover  $\pm 10\%$  slippage, thus finding 3,260 (15.52%) imperfect profitable sandwich attacks.



**4.1.2 Empirical Results** We consider a total of 144 cryptocurrency assets and 767 exchanges from block 6803256 (1st December, 2018) to block 11363269 (30th November, 2020) (cf. Table 12 in Appendix). During this period, we identify 1,379 Ethereum user addresses and 455 smart contracts performing 21,001 sandwich attacks on Uniswap v1/v2, Sushiswap, and Bancor, amounting to a total profit of 1.51M USD (cf. Figure 2a). Our heuristics have not found any sandwich attacks on Curve, Swerve, and 1inch. We can explain the lack of attacks on Curve and Swerve with the fact that these exchanges are specialized in correlated, i.e., pegged-coins and the slippage among assets therefore remains limited.

We find that 726 out of the 1,379 user addresses perform sandwich attacks by directly interacting with the AMMs, while the majority of sandwiches we detect (83.93%) operate with a smart contract. The smart contract typically stores the front-running transaction execution status, such that the back-running transaction can decide whether to proceed execution. We also observe that 61.88% of the attacks use different accounts to issue the front and back running transactions. For example, each of the three adversarial smart contracts we find (cf. 0xAfE0..BB32, 0x0000..5832, and 0x0000..7aa2) uses 20 Ethereum user addresses.

**Sandwich Transaction Positions:** We observe that while a sandwich attack adversary will likely try to position its transactions relatively close to the victim transaction, in practice we observe multiple profitable sandwich attacks where the involved transactions are more than 200 block positions apart (cf. Figure 3b).

**Sandwich Gas Prices:** We observe that 87.61% of the back-running transactions ( $T_{A2}$ ) pay only 0 to 1 GWei less than  $T_V$ 's gas price (cf. Table 3). Intuitively, the closer  $T_{A2}$  and  $T_V$  are, the higher the attacks' success rate due to a chance of other transaction interference. For the front-running transaction ( $T_{A1}$ ), the adversary must also consider the competing sandwich attacker. Given a multi-adversary game, Daian *et al.* [24] have outlined two primary gas-bidding adversarial strategies: *reactive counter-bidding* and *blind raising*. Under reactive counter-bidding, an adversary only increases its gas price when another competing transaction pays a higher gas price. In blind raising, the adversary raises the gas price of its transaction in anticipation of a raise of its competitors, without necessarily observing competing transactions yet. Recall that geth only accepts an increase of the gas price by at least 10%.

When assuming that all attackers adopt the reactive counter-bidding strategy, based on the past sandwich attacks, we estimate that at least 24.46% of the sandwiches went through more than five rounds of bidding (cf. Table 2). This is because the first  $T_{A1}$  bid only needs to add 1 Wei to  $T_V$ 's gas price, then each subsequent bid must raise the gas price by 10%. After five rounds of bidding, the adversary needs to pay a gas price of at least  $(110\%)^4 \times (\text{GasPrice}_V + 1)$  Wei. Figure 3a visualizes the number of adversarial sandwich attack smart contracts we detected. In particular, from the 10th to the 11th of August 2020 (Block 10630000-10640000), we identified 49 smart contract addresses attempting to extract value simultaneously.

**Extractable Profit:** Zhou *et al.* [43] estimate that under the optimal setting, the adversary can attack 7,793 Uniswap v1 transactions, and realize 98.15 ETH of revenue from block 8M to 9M. Based on our measurements we estimate that on average only 63.30% (62.13 ETH) of the available extractable value is effectively being extracted.

$r = \frac{\text{GasPrice}_{T_{A1}}}{\text{GasPrice}_{T_V}}$	Count	Percentage	Estimated Bids
$r \leq 1$	23	0.11%	1
$1 < r \leq 1.1$	10752	51.20%	1
$1.1 < r \leq 1.1^2$	2931	13.96%	2
$1.1^2 < r \leq 1.1^3$	1343	6.39%	3
$1.1^3 < r \leq 1.1^4$	816	3.89%	4
$1.1^4 < r$	5136	24.46%	$\geq 5$
total	21001	100.00%	None

**Table 2:** The gas price paid by the adversaries for the front-running sandwich transaction  $T_{A1}$ . A previous study suggests that 79% of the miners (using geth) configure a price bump percentage of 10% to replace an existing transaction from the mempool, while 16% of the miners (using parity) set 12.5% as replacement threshold [43]. Assuming a price bump percentage of 10%, we estimate that at least 24.46% of the attacks experienced more than 5 counter-reactive bids [24].

$d = \text{GasPrice}_{T_V} - \text{GasPrice}_{T_{A2}}$	Count	Percentage
$d < 0$ GWei	28	0.13%
$0 \text{ GWei} \leq d < 1 \text{ GWei}$	18400	87.61%
$1 \text{ GWei} \leq d < 10 \text{ GWei}$	636	3.03%
$10 \text{ GWei} \leq d < 100 \text{ GWei}$	1316	6.27%
$100 \text{ GWei} \leq d$	621	2.96%
Total	21001	100.00%

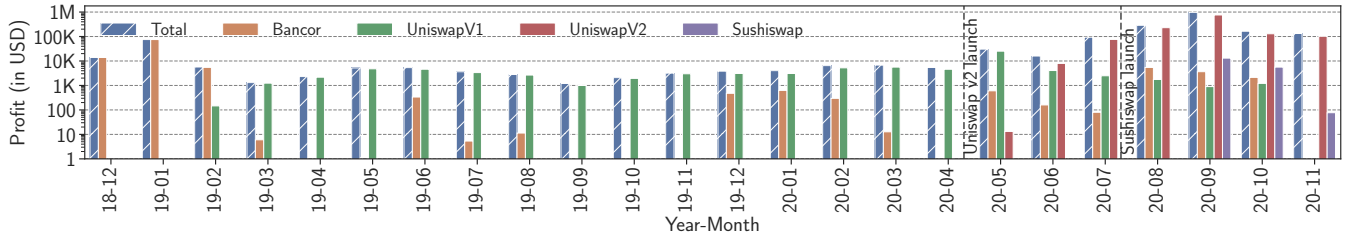
**Table 3:** Adversarial gas prices for the back-running sandwich transaction  $T_{A2}$ . 87.61% of the transactions pay only 0 to 1 GWei less than  $T_V$ .

## 4.2 Fixed Spread Liquidations

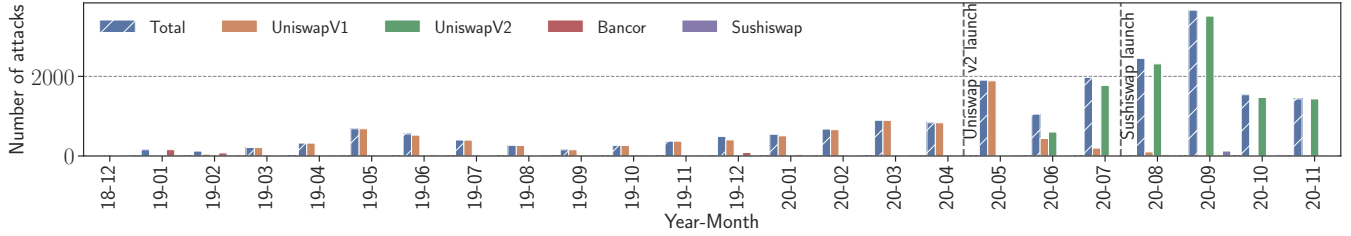
We observe two widely adopted liquidation mechanisms in the current DeFi ecosystem. First, the fixed spread liquidation, used by Compound, Aave, and dYdX, allows a liquidator to purchase collateral at a fixed discount when repaying debt. Second, the auction liquidation, allows a liquidator to start an auction that lasts for a pre-configured period (e.g., 6 hours [30]). Competing liquidators can engage and bid on the collateral price. In this section, we focus on the fixed spread liquidation, which allows to extract value in a single, atomic transaction. To perform a fixed spread liquidation, a liquidator  $\mathcal{A}$  can adopt the following two strategies.

- (1)  $\mathcal{A}$  detects a liquidation opportunity at block  $B_i$  (i.e., after the execution of  $B_i$ ).  $\mathcal{A}$  then issues a liquidation transaction  $T_A$ , which is expected to be mined in the next block  $B_{i+1}$ .  $\mathcal{A}$  attempts to **destructively front-run** other competing liquidators by setting high transaction fee for  $T_A$ .
- (2)  $\mathcal{A}$  observes a transaction  $T_V$ , which will create a liquidation opportunity (e.g., an oracle price update transaction which will render a collateralized debt liquidatable).  $\mathcal{A}$  then **back-runs**  $T_V$  with a liquidation transaction  $T_A$  to avoid the transaction fee bidding competition.

**4.2.1 Empirical Results** We collect all the liquidation events on Aave, Compound, and dYdX from their inception until block 11363269. We observe in total 16,031 liquidations, yielding a collective profit of 20.18M USD over 19 months (cf. Figure 4a). Note that we use the prices provided by the price oracles of the liquidation platforms to convert the profits to USD. As such, our reported prices capture the USD value at the moment of the liquidation. We report the monthly number of liquidation events in Figure 4b.

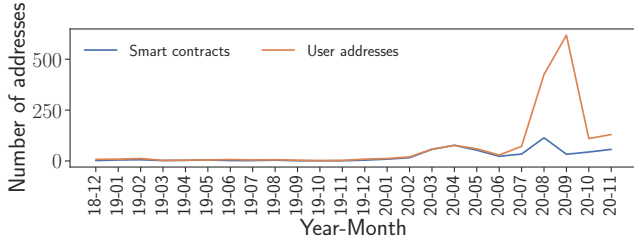


(a) Monthly sandwich attack profit per exchange.

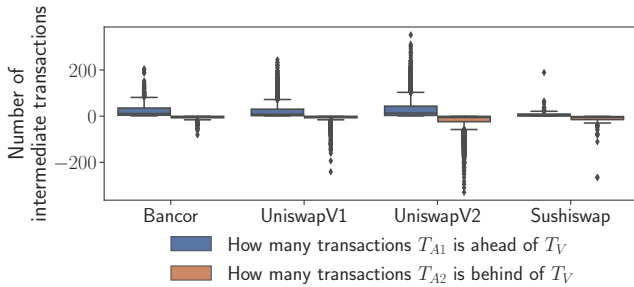


(b) Monthly number of sandwich attacks on 4 exchanges.

**Figure 2:** Extracted sandwich attacks, from block 6803256 (1st December, 2018) to block 11363269 (30th November, 2020).



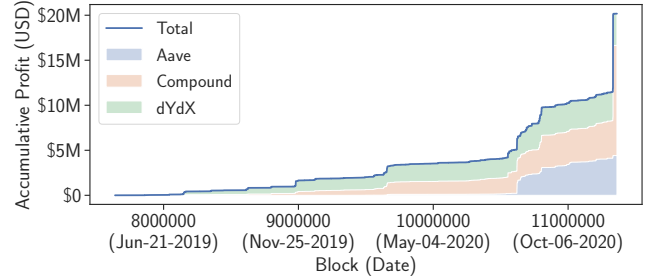
(a) Number of active adversarial sandwich user addresses and smart contracts detected over time.



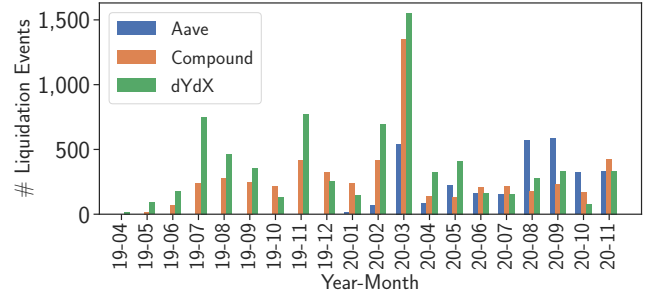
(b) Relative position of sandwich transactions for profitable attacks.

**Figure 3:** Extracted sandwich attacks, from block 6803256 (1st December, 2018) to block 11363269 (30th November, 2020).

**Ordering Strategies:** To classify a liquidation as a front- or back-running liquidation, we observe that a front-running liquidation at block  $B_i$  necessarily requires the collateral to be liquidatable at block  $B_{i-1}$ . If the collateral is not liquidatable at block  $B_{i-1}$ , the liquidator is necessarily acting after a price oracle update in block  $i$ , which corresponds to a back-running liquidation. Therefore, for each of the 16,031 liquidations that we observe on block  $B_i$ , we



(a) Accumulative profit of fixed spread liquidations.



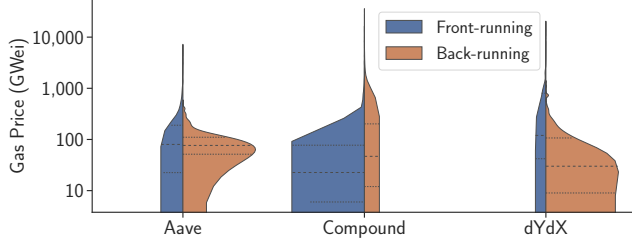
(b) The monthly number of fixed spread liquidation events.

**Figure 4:** We notice that liquidations are frequent when the ETH price collapses in March, 2020. The profit from Compound liquidations increases remarkably in November, 2020, likely due to an irregular oracle price report.

test whether the collateral was liquidatable at block  $B_{i-1}$ . If this test resolves to true, we classify the liquidation as front-running, otherwise as back-running (cf. Table 4). Given 16,031 liquidations, we find that front-running is the dominating strategy accounting for 87.29% of all liquidations. Among the 16,031 liquidations, we

Liquidation Platform	Front-running	Back-running	Total
Aave	2,825	244	3,069
Compound	4,419	1,080	5,499
dYdX	6,750	713	7,463
<b>Total</b>	<b>13,994</b>	<b>2,037</b>	<b>16,031</b>

**Table 4:** Extracting strategies of liquidators. Liquidators either back-run the price oracle updates, or front-run liquidation attempts of other liquidators. Most liquidations apply front-running.



**Figure 5:** Fee distributions of the front- and back-running liquidations.

identify 1,496 unique liquidators identified by their address. We find that 888 liquidators follow the front-running strategy, 328 back-running and the remaining 280 liquidators adopt a mixed strategy.

**Liquidation Gas Prices:** Given the gas price distribution of liquidation transactions (cf. Figure 5), on Aave and dYdX, the front-running liquidations have a higher average gas price than the back-running liquidations. However, to our surprise, we notice that the back-running liquidations have higher gas prices on Compound. We find that this is because Compound allows any participant to update the price oracle with an authenticated message. Hence, some liquidators wrap the price update action and liquidation into one transaction (i.e., back-run in the same transaction). The liquidators issue the wrapped transactions with high gas prices to prevent the internal back-running transaction from being front-run by competitors.

### 4.3 Arbitrage

Arbitrage describes the process of selling/buying an asset in one market and simultaneously buying/selling in another market at a different price. Arbitrage helps to promote market efficiency and is typically considered benign. To perform an arbitrage, DeFi traders/miners monitor new blockchain state changes and execute an arbitrage if the expected revenue of synchronizing the prices on two markets exceeds the expected transaction costs. An arbitrage trader can choose among the following strategies to perform arbitrage:

**Block State Arbitrage:** The arbitrage trader can choose to only listen to confirmed blockchain states. Once a new block  $B_i$  is received, the trader attempts to destructively front-run all other market participants  $B_{i+1}$ .

**Network State Arbitrage:** A trader can listen on the network layer to detect a “large” pending trade, which is likely to raise the price on one exchange. If the trader is not a miner, back-running appears as the optimal strategy. A miner can perform risk-free arbitrage by excluding or delaying all other market participants’ trades in the next block.

**4.3.1 Heuristics** In the following we use  $s$  to denote a swap action which sells  $in(s)$  amount of the input asset  $IN(s)$  to purchase  $out(s)$  amount of the output asset  $OUT(s)$ . We apply the following heuristics to find extracted arbitrages on AMM exchanges (Uniswap v1/v2, Sushiswap, Curve, Swerve, 1inch, and Bancor).

**Heuristic 1:** All swap actions of an arbitrage must be included in a single transaction, implicitly assuming that the arbitrager minimizes its risk through atomic arbitrage.

**Heuristic 2:** An arbitrage must have more than one swap action.

**Heuristic 3:** The  $n$  swap actions  $s_1, \dots, s_n$  of an arbitrage must form a loop. The input asset of any swap action must be the output asset of the previous action, i.e.,  $IN(s_i) = OUT(s_{i-1})$ . The first swap’s input asset must be the same as the last swap action’s output asset, i.e.,  $IN(s_0) = OUT(s_n)$ .

**Heuristic 4:** The input amount of any swap action must be less than or equal to the output amount of the previous action, i.e.,  $in(s_i) \leq out(s_{i-1})$ .

**4.3.2 Empirical Results** We capture 144 assets and 767 exchanges from block 6803256 (1st December, 2018) to block 11363269 (30th November, 2020) (cf. Table 12 in Appendix). We identify 2,705 user addresses and 789 smart contracts performing 51,415 arbitrage trades on Uniswap v1/v2, Sushiswap, Curve, Swerve, 1inch, and Bancor, amounting to a total profit of 7.11M USD. All arbitrage trades we find are executed using smart contracts.

**Arbitrage statistics:** To gain more insights on arbitrage, we classify the transactions according to the number of platforms and markets involved (cf. Table 5). According to our data, most traders prefer simple strategies that only involve 2 or 3 markets (aka. two-point arbitrage and triangular arbitrage). Less than 2% of the transactions execute strategies with more than four markets. We, for example, find that one transaction combines two arbitrage trades into one to save gas costs<sup>2</sup>. Although such optimizations may yield a higher profit, they are also more likely to fail because the more markets an arbitrage involves, the more competitors must be front-run.

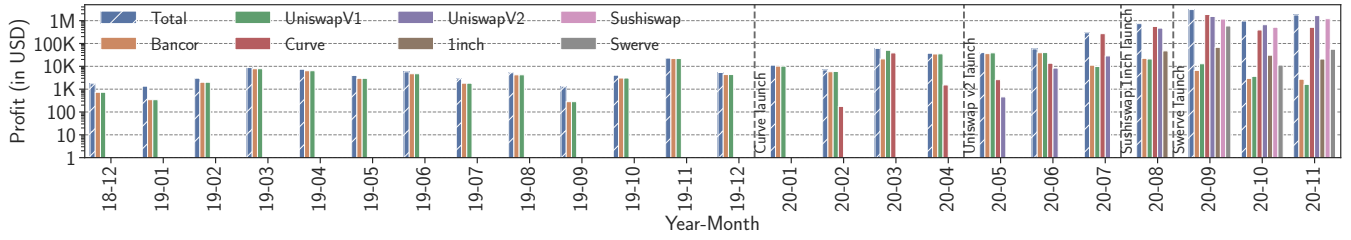
Num. of markets	2	3	4	5	6	Total
Num. of platforms						
1	2,071(4%)	2,944(6%)	122(0%)	29(0%)	3(0%)	5,169(11%)
2	17,843(36%)	25,767(52%)	366(1%)	7(0%)	1(0%)	43,984(90%)
3	N/A	2,163(4%)	88(0%)	3(0%)	N/A	2,254(5%)
4	N/A	N/A	8(0%)	N/A	N/A	8(0%)
<b>Total</b>	<b>19,914(41%)</b>	<b>30,874(63%)</b>	<b>584(1%)</b>	<b>39(0%)</b>	<b>4(0%)</b>	<b>51,415(105%)</b>

**Table 5:** Statistics of the profitable arbitrage trades we detect. 99% synchronize the prices between 2 or 3 markets.

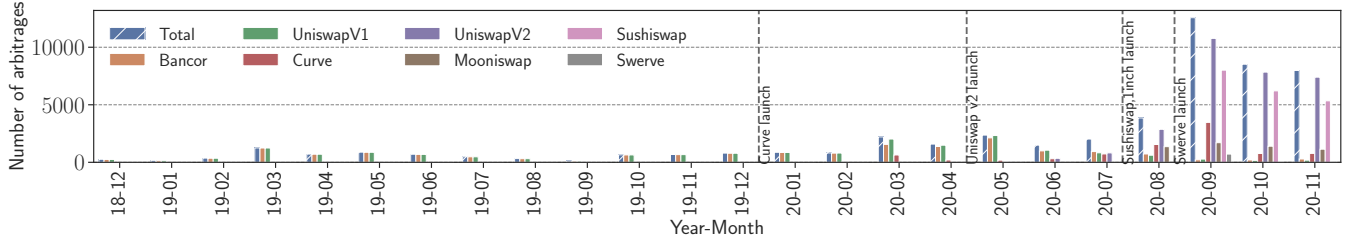
**Arbitrage transaction positions:** By visualizing the arbitrage transaction positions in blocks (cf. Figure 7), we find that a large number of profitable trades are surprisingly positioned at the end. We would have expected that the arbitrage transactions are competitive and perform destructive front-running with higher gas prices. For example, one of the most profitable arbitrage transactions we detect<sup>3</sup> is positioned at index 141 out of 162 transactions in this

<sup>2</sup>In 0x0772.be87, the trader executes the arbitrage in the following order: WETH → BOXT → UNI → USDT → USDN → UNI → WETH. This arbitrage strategy consists of two triangular arbitrages: (i) WETH → BOXT → UNI → WETH; (ii) UNI → USDT → USDN → UNI

<sup>3</sup>In 0x2c79.81a5, the trader first swaps 400 ETH for 1040 COMP on Uniswap v2, then swaps 1040 COMP for 476 ETH on Sushiswap, realizing a revenue of 76 ETH.



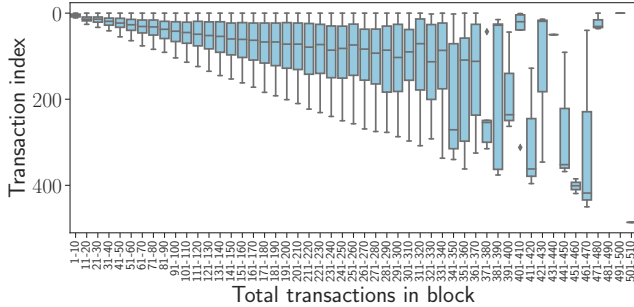
(a) Monthly arbitrage profit.



(b) Monthly number of arbitrages.

**Figure 6:** Extracted arbitrages, from block 6803256 (1st December, 2018) to block 11363269 (30th November, 2020).

block. Our data hence supports the hypothesis that arbitrage is performing back-running on the network layer. To confirm our hypothesis, we re-execute all arbitrage transactions at the top of blocks (i.e., upon the previous block state). If a transaction is a block state arbitrage, then the execution should remain profitable. We find that 60.08% arbitrage transactions are no longer profitable, which indicates that these transactions likely perform back-running.



**Figure 7:** Transaction index distribution of all arbitrages we detect.

#### 4.4 Clogging

Eskandir *et al.* [27] have observed smart contract games which follow the *The War of Attrition* [3, 5]. In such a game, players can bid into a pool of money. Each bid resets a timeout, which, once expired, grants the last bidder the entirety of the amassed money. Economists and evolutionary biologists have studied such games for decades [40], and shown that humans overbid significantly. To participate in such contests, users are likely to construct dedicated bidding bots. Those bots are then configured with a specific budget to pay for transaction fees. If an adversary manages to clog the blockchain, such that those bots run out of funding, the attacker can

win the bidding game. This is what appears to have happened with the infamous Fomo3D game, where an adversary realized a profit of 10,469 ETH by conducting a clogging attack over 66 consecutive blocks (from block 6191962 to 6191896).

The throughput of permissionless blockchains is typically limited to about 7-14 transactions per second, and transaction fee bidding contests have shown to raise the average transaction fees well above 50 USD. A *clogging attack* is, therefore, a malicious attempt to consume block space to prevent the timely inclusion of other transactions. To perform a clogging attack, the adversary needs to find an opportunity (e.g., a liquidation, gambling, etc.) which does not immediately allow to extract monetary value. The adversary then broadcasts transactions with high fees and computational usage to congest the pending transaction queue. Clogging attacks on Ethereum can be successful because 79% of the miners order transactions according to the gas price [43].

##### 4.4.1 Heuristics to identify past clogging period.

**Heuristic 1:** The same address (user/smart contract) consumes more than 80% of the available gas in every block during the clogging period.

**Heuristic 2:** The clogging period lasts for at least five consecutive blocks. Empirical data suggests that the average block time is  $13.5 \pm 0.12$  seconds [20], a clogging period of five blocks, therefore, lasts around 1 minute.

**4.4.2 Empirical Results** From block 6803256 to 11363269, we identify 237 clogging periods, where 16 user addresses and 29 smart contracts are involved (cf. Table 6). While the longest clogging period lasts for 5 minutes (24 blocks), most of the clogging periods (93.67%) account for less than 2 minutes (10 blocks).

**Case Studies:** While our heuristics can successfully detect blockchain clogging, they do explain their motivation and we hence manually inspect the 10 longest clogging periods (cf. Table 7).



Duration	Detected	Avg. Gas Used	Estimated Avg. Cost
5~9 blocks (1~2 mins)	222	43911290	2 ETH (1,763 USD)
10~14 blocks (2~3 mins)	11	87280834	5 ETH (3,504 USD)
15~19 blocks (3~4 mins)	2	111373730	6 ETH (4,472 USD)
20~24 blocks (4~5 mins)	2	187985309	10 ETH (7,548 USD)

**Table 6:** Detected clogging periods, and estimated cost based on the gas and ETH price on the 2nd of January, 2021 (55 GWei/gas, 730 USD/ETH.).

Address	Start Block	Duration (Blocks)	Avg. Gas Consumed	Avg. Gas Price	Cost (ETH)	Usage
0x6670..3A4a	7091122	24	91.22%	31	5.48	Incentivised clogging
0xdAC1..1ec7	10130772	21	96.09%	40	8.05	Mass USDT transfers
0xA869..0AB1	8259506	15	92.59%	26	3.14	ETH CAT Attack
0x67a6..21d2	7788021	15	93.21%	32	3.72	ERD (E) Attack
0xA869..0AB1	8260063	14	94.48%	26	2.98	ETH CAT Attack
0x1056..C268	7073767	12	93.66%	31	2.56	Unknown
0x3fDB..dA11	9786058	12	87.67%	38	3.59	Unknown
0xdAC1..1ec7	8509481	11	89.27%	28	2.27	Mass USDT transfers
0x1056..C268	7048441	11	91.84%	30	2.25	Unknown
0xA869..0AB1	8260051	11	97.28%	26	2.41	ETH CAT Attack

**Table 7:** Top 10 longest clogging periods.

**Incentivised clogging:** The longest clogging event is related to a gambling contract “Lucky Star”, where 203 addresses perform 387 transactions. This game draws the winners, when the cumulative lottery tickets sold exceeds a pre-configured threshold. For every 30,000 ETH of lottery tickets sold, the accumulated prize is split among the last 50 purchasers, the protocol, therefore, incentivizes its users to congest the network at the fictive deadline.

**Attacks on gambling protocols:** We find that the top third, fourth, fifth, and tenth clogging events are related to two FoMo3D games, namely ETH CAT (cf. 0x42ce..0ebb) and ERD (E) (cf. 0x2c58..e769). The rules of these gambling protocols is similar to FoMo3D. If no user address purchases a lottery ticket within a fixed time period, the last participant wins the jackpot. We identify two contracts involved in these four clogging events. To ensure that the winner is not already drawn, both contracts have a function to check the current round’s status in the corresponding gambling smart contract before they start to spam transactions. These two contracts are deployed by the same address (cf. 0xfefe..aa5c).

**Mass USDT transfers:** We find that two clogging events perform a large number of USDT transfers, wherein 2, 462/ 1, 868 Ethereum addresses made 2, 463/ 2, 032 transactions, consuming 96.07%/89.27% of the gas respectively. Although these activities appear abnormal, we cannot seem to figure out the reason for such behavior.

**Unknown:** We classify 3/10 clogging events as unknown, as we cannot determine the reason behind their activity.

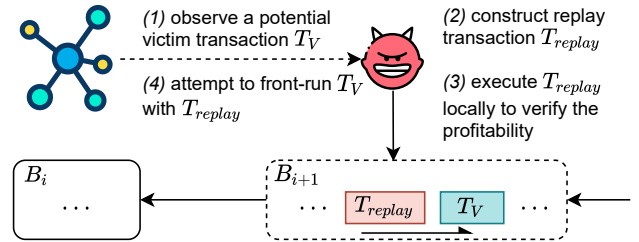
**How expensive is it to clog the blockchain?:** While clogging appears expensive (cf. Table 6), the costs can be written off. Minting *gas tokens* [6] consumes block space, and allows to buffer computation used for clogging, such that later a fraction can be recovered. For example, a gas token costs 20, 000 gas to set an Ethereum storage slot from zero to non-zero ( $G_{sset}$ ). Setting a storage slot from non-zero to zero consumes 5, 000 gas ( $G_{sreset}$ ) but refunds 15, 000 gas ( $R_{sclear}$ ) for freeing the storage [42]. In total, resetting storage back to zero therefore refunds half of the used gas ( $\frac{R_{sclear}-G_{sreset}}{G_{sset}} = 50\%$ ).

## 4.5 Limitations

In the following, we outline the main limitations of our measurements. Notably, as we focus on sandwich attacks, liquidations, and arbitrage, we do not capture all possible sources of BEV. We, however, believe that our methodology can be applied to other BEV sources. Then, for each BEV source, given that we apply custom heuristics, those heuristics have limitations themselves, resulting for instance in false negatives. For instance, Heuristic 1 from the sandwich attacks assumes, that all transactions must be mined in the same block. There may very well exist successful sandwich attacks across multiple blocks, which we do not capture and which may result in false negatives. Also, it could be that by chance two transactions are executing right before and after a supposed victim transaction. Yet, this does not necessarily need to be an attack. As such, heuristics may also introduce false positives into our findings. To reduce the potential inaccuracies of our heuristics, we attempt to tighten the heuristics to avoid double counting revenues. Summarizing, we do not have access to the ground truth, which forces us to present our results as estimates only.

## 5 Generalized Front-running: Transaction Replay

We proceed to present an application-agnostic method, which allows an adversary to extract value by copying and replaying the execution logic of an unconfirmed victim transaction.



**Figure 8:** Overview of the transaction replay attack.

### 5.1 Overview

An adversary  $\mathcal{A}$  attempts the following steps to perform a transaction replay attack (cf. Figure 8).

- (1) observe a potential victim transaction on the network layer;
- (2) construct one or more replay transaction(s) to replay the execution logic of the victim transaction while diverting the generated financial value to an adversary-controlled account;
- (3) perform concrete validation of the constructed replay transaction(s) locally to emulate the execution result;
- (4) if the local execution yields a profit,  $\mathcal{A}$  attempts to **destructive front-run** the victim transaction.

We classify a replay transaction  $T_{replay}$  as profitable, if the native cryptocurrency (e.g., ETH) balance of  $\mathcal{A}$  increases after the execution of  $T_{replay}$ , discounting the transaction fees. To measure profitability, we assume that  $\mathcal{A}$  converts all the received assets (i.e., tokens) within an atomic transaction to the native cryptocurrency following the replay action [38].



```

1  pragma solidity ^0.6.0;
2
3  contract Moneymaker {
4      function TransferRevenueToSender() public {
5          uint profit;
6          // profiting logic omitted for brevity
7          msg.sender.transfer(profit);
8      }
9
10     function SpecifyBeneficiary(address payable
11         beneficiary) public {
12         uint profit;
13         // profiting logic omitted for brevity
14         beneficiary.transfer(profit);
15     }
16 }

```

**Listing 1:** Examples of the transaction replay algorithm patterns.

## 5.2 Algorithm

It appears to be common practice that traders implement profit-generating strategies (e.g., arbitrage) within smart contracts, and then invoke these contracts to extract revenue. This allows the traders to perform complex operations atomically in one transaction, without bearing the risk that the blockchain state is modified intermediately [38]. We show, however, that the following programming patterns, expose a transaction to become exploitable by a replay adversary. Both of these two patterns potentially allow an adversary to replay a victim transaction and reap its revenue.

**Sender Benefits:** The generated revenue is transferred to the transaction sender (cf. `TransferRevenueToSender` in Listing 1).

**Controllable Input:** The transaction input specifies that the sender receives the revenue (cf. `SpecifyBeneficiary` in Listing 1).

**5.2.1 Replay Algorithm** Generally, in a transaction  $T$  on a smart-contract-enabled blockchain (cf. Equation 1), *sender* represents the sender of  $T$ , *value* specifies the amount of native cryptocurrency sent in  $T$ , and *input* are parameters to control the contracts’ execution<sup>4</sup>. *sender* is an authenticated field verified through the signature, and *input* can be amended arbitrarily.

$$T = \{sender, value, input\} \quad (1)$$

We outline the replay logic in Algorithm 1. When observing a previously unknown transaction, the adversary constructs the replay transaction(s) by duplicating all the fields of the potential victim transaction but substitutes the original transaction sender address in the input data field with the adversarial address. The input data of an Ethereum transaction can grow to at most 10 megabytes (cf. geth client) and an address is expressed as a 20-byte array<sup>5</sup>. Substitution is therefore efficient through a string replacement algorithm. The adversary then executes the replay transaction(s) locally upon the currently highest block. If the victim transaction conforms to the applicable patterns (i.e., sender benefits and controllable input), the execution of the replay transaction may yield a positive profit for the adversary, which can then proceed with front-running the victim transaction.

<sup>4</sup>We ignore irrelevant fields (e.g., nonce).

<sup>5</sup>According to the Ethereum contract ABI specification [1], an address in the transaction data is left padded to 32 bytes. However, the adversary is only concerned with the effective 20 bytes when performing the substitution.

---

### Algorithm 1: Transaction Replay Algorithm.

---

**Input:** The current highest block  $B_i$ ; the potential victim transaction  $T_V$ ; the adversarial account address  $\mathcal{A}$ .

**Function** ConstructReplay( $T_V, \mathcal{A}$ ):

```

    T.sender ←  $\mathcal{A}$ 
    T.value ←  $T_V.value$ 
    T.input ← substituting  $T_V.sender$  in  $T_V.input$  with  $\mathcal{A}$ 
    return T

```

**end**

**Algorithm** TransactionReplay( $T_V, \mathcal{A}$ ):

```

    T_replay ← ConstructReplay( $T_V, \mathcal{A}$ )
    Concretely Execute  $T_replay$  upon block  $B_i$ 
    if  $T_replay$  is profitable then
        | Front-run  $T_V$  with  $T_replay$ 
    end

```

**end**

---

**Execution Positions of Replay Transactions:** The execution position of a replay transaction  $T_{replay}$  in block  $B_{i+1}$ , determines the success of the replay attack. As outlined in Algorithm 1,  $\mathcal{A}$  emulates  $T_{replay}$  upon the current highest block  $B_i$  to verify the profitability of  $T_{replay}$ . An adversarial miner can place  $T_{replay}$  at the top of  $B_{i+1}$ , guaranteeing that the execution results of  $T_{replay}$  match the local concrete execution. If  $\mathcal{A}$  is a non-mining entity, the result of a replay attack depend on two factors:

- (1) whether the miner sorts the transactions by gas price;
- (2) whether the transactions positioned before  $T_{replay}$  modify the relevant blockchain states, which may lead to unexpected execution result of  $T_{replay}$  (e.g.,  $T_{replay}$  is reverted).

Because a non-mining replay adversary cannot freely control the transaction execution position, the adversary may potentially be exposed to the risk of being baited by a honeypot. We present the details of the replay honeypot in Appendix C.

## 5.3 Replay Evaluation

We apply Algorithm 1 to all the Ethereum transactions from block 6803256 (1st of December, 2018) to block 11363269 (30th of November, 2020) capturing a total of 568, 776, 169 transactions over 2 years. We execute every constructed replay transaction upon its previous block and verify its profitability. Except for ETH, we consider all ERC20 tokens earned in the replay transactions as revenues. When a replay transaction yields a token revenue, we enforce an exchange transaction that converts the received token to ETH via an on-chain exchange Uniswap v1 or v2 [7]. We, therefore, measure the profitability entirely in ETH without the need for an external price oracle. For simplicity of our analysis, we assume that the adversary pays 1 Wei more than the victim transaction for the gas price of the replay and exchange transaction. When measuring the profitability, we count the replay and exchange transaction fees as cost.

We perform our evaluation on a Ubuntu 20.04.1 LTS machine with AMD Ryzen Threadripper 3990X (64-core, 2.9 GHz), 256 GB of RAM and 4 × 2 TB NVMe SSD in Raid 0 configuration. To execute a replay transaction on a past block, we download the blockchain state from an Ethereum full archive node running on the same machine. On average, generating a replay transaction and verifying its

Required upfront capital $r$ (ETH)	# replay transactions	Average profit (ETH)
$1,000 < r$	1	0.14
$100 < r \leq 1,000$	106	$0.84 \pm 2.23$
$10 < r \leq 100$	1,680	$0.47 \pm 1.46$
$0 < r \leq 10$	26,368	$0.14 \pm 1.89$
$r = 0$	201,001	$0.23 \pm 55.53$

**Table 8:** Required upfront ETH for replay transactions and average profit.

profitability takes  $0.18 \pm 0.29$  seconds (i.e., the time from observing a victim transaction to broadcasting the replay transaction). We remark that an adversary can achieve better performance by running the real-time replay attack inside an Ethereum client without downloading blockchain states from external sources.

**5.3.1 Results** We find 229,156 profitable transactions (0.04%) that could have been replayed, accumulating to an estimated profit of 51,688.33 ETH (17.60M USD<sup>6</sup>). The most profitable replay transaction yields a profit of 16,736.94 ETH. Apart from ETH, there are 798 ERC20 tokens contributing a total revenue of 144,940.78 ETH in 96,943 replay transactions. Note that the ERC20 token revenue is higher than the total profit, because ETH is being used to purchase the ERC20 token (recall that profit equals income minus expenses). Among all replayable transactions, 217,932 transactions follow the *sender benefits* pattern (cf. Section 5.2), while the remaining 11,224 transactions fall into the *controllable input* category (cf. Section 5.2).

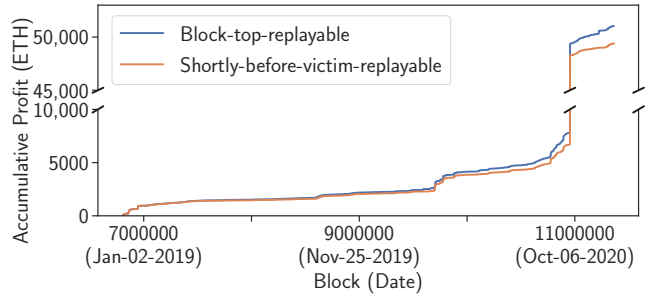
In Table 8, we show the distribution of the upfront ETH capital (i.e., the transaction value) required by the replay transactions, and outline the average profit. We find that 87.71% of the replay transactions do not require upfront ETH, except the transaction fees. We notice that the replay profit is not directly correlated to the transaction value. 967 replay transactions yield a profit of more than one ETH, out of which 483 transactions are of zero-value.

Out of the 229,156 replayable victim transactions, we find that 32,201 transactions are originally reverted in the on-chain history. When the replay transactions are executed at the top of the respective block, we find that the replay transactions of the reverted transactions would execute successfully. However, the replay transaction would be reverted if executed right before the victim transaction, because apparently, earlier transactions modified the relevant blockchain states. Elseways, a non-reverted transaction can be replayed, even if the replay transaction is executed before the victim transaction. In our evaluation, we distinguish among the following two categories of replayable transactions:

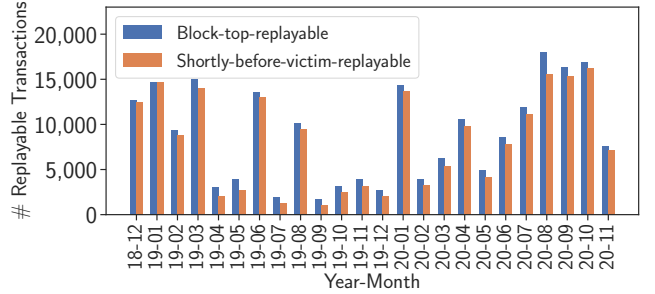
**Shortly-before-victim-replayable:** We consider all the non-reverted replayable transactions as *shortly-before-victim-replayable*.

**Block-top-replayable:** *Block-top-replayable* transactions are a superset of the shortly-before-victim-replayable transactions. Also, reverted transactions can be replayed at the top of the respective block. We find that for a few blocks, there are multiple reverted replayable transactions. To avoid double-counting, we only consider the replay transaction with the highest profit.

<sup>6</sup>Due to the lack of a consistent on-chain price oracle during our evaluation period, we fetch the price of ETH from <https://www.coingecko.com>.



(a) Accumulative profit that can be extracted by replay attacks.



(b) Monthly number of replayable transactions.

**Figure 9:** The profit from block-top-replayable transactions amounts up to 51,030.77 ETH, while the shortly-before-victim-replayable transactions accumulate 49,397.28 ETH. Remarkably, we detect 18,058 block-top-replayable transactions in August, 2020.

Block-top-replayable transactions indicate what a miner could have extracted through replay attacks, while shortly-before-victim-replayable transactions reflect the potential revenue for a non-mining replay adversary following the +1 Wei gas price bidding strategy. We find 215,398 block-top-replayable transactions, which yield a total profit of 51,030.77 ETH. We also discover 196,955 shortly-before-victim-replayable transactions that produce 49,397.28 ETH. We show the accumulative profit of both categories in Figure 9a along with the monthly number of replayable transactions in Figure 9b. Notably, from block 10954411 to 10954419, three transactions, which seem to exploit a smart contract vulnerability [2], generate a total profit of over 41,529 ETH. We also observe a general uptrend in the number of replayable transactions since January, 2020.

#### 5.4 Understanding Replayable Transactions

The replay algorithm may act on any unconfirmed transaction without understanding its logic. To shed light on the nature of the replayable transactions, we cross-compare the 229,156 replayable transactions with the data from Section 4. We detect 188 fixed spread liquidations (cf. Section 4.2) contributing a total profit of 26.57 ETH, and 241 arbitrages (cf. Section 4.3) contributing a total profit of 489.53 ETH. These results suggest that the replay transactions capture a different set of profit-generating transactions than liquidations and arbitrage.

**Case study:** In Table 9, we present the top 17 non-reverted replayable transactions that produce more than 60 ETH and manually classify their motive. We notice 4 replayable transactions associated with two previous DeFi attacks, the Eminence exploit [2]

Transaction hash	Profit (ETH)	Required upfront capital (ETH)	Motive
0x045b..0b2a	16,736.94	0	Eminence exploit [2]
0x3503..8ad8	16,398.34	0	Eminence exploit [2]
0x4f0f..0317	8,393.78	0	Eminence exploit [2]
0x4021..1f89	153.22	2.0	Arbitrage
0xe772..d496	153.17	2.0	Arbitrage
0x475a..cd8f	152.54	0	DSSLeverage
0xfa5f..bb03	144.27	0	DSSLeverage
0x2e27..ce45	136.31	0	DSSLeverage
0xd46c..b091	118.00	5.0	Crypto Fishing [4]
0x6722..a504	92.46	0	DSSLeverage
0xdc1f..a4cd	92.23	0	Arbitrage on Curve/Swerve + dYdX flash loan
0x4d2b..1bb2	78.59	0	DSSLeverage
0xd11e..26b5	78.55	0.0011	Arbitrage on Uniswap, DEX.AG
0xa1af..0205	73.01	0.1	Arbitrage
0xfc52..6ed0	72.14	0	DSSLeverage
0xb5c8..9838	64.97	0	bZx attack [38]
0x30d5..5388	62.98	0	DSSLeverage

**Table 9:** Case studies of the top 17 non-reverted replayable transactions that yield a profit of more than 60 ETH.

and the bZx attack [38]. It appears that the attackers did not consider the threat of replay transactions. We further find 7 replayable transactions that invoke the same *DSSLeverage* smart contract (cf. 0x4c14..bCA2). From the *DSSLeverage* source code, we find that it allows any address to close the contract’s position in MakerDAO and retrieve its balance. This coding pattern matches the *sender benefits* pattern (cf. Section 5.2). We also discover one on-chain game transaction (Crypto Fishing [4]) and five arbitrage transactions. For three of the top 17 replayable transactions, we find that the trader is purchasing ERC20 tokens at a favorable price (i.e., arbitrage), as we convert the gained assets back to ETH for our evaluation.

## 5.5 Replay Protection

We proceed to present two simple methods that protect profitable transactions from being replayed by Algorithm 1.

**(Insecure) Authentication:** Authentication schemes are widely adopted in on-chain asset custody, e.g., when depositing assets into a smart contract wallet that can only be redeemed by an owner. Such schemes can also help to prevent simple replay attacks (cf. *Authentication* in Listing 2, Appendix B). When the authentication-enabled contract is invoked with an unauthorized address, the replay transaction execution is reverted. Note, however, that such authentication method does not remain secure against a potentially more sophisticated replay algorithm.

**Beneficiary Provision:** To avoid a replay, the beneficiary address should not be specified in the transaction input. Instead, the beneficiary address can be stored, for example, in the contract storage (cf. *MoveBeneficiary* in Listing 2, Appendix B).

The aforementioned methods effectively mitigate the simple replay attacks outlined in this section. However, an adversary could go further in locally emulating a victim transaction in an effort to rebuild the execution logic. We leave the specification and evaluation of more complicated replay mechanisms to future work.

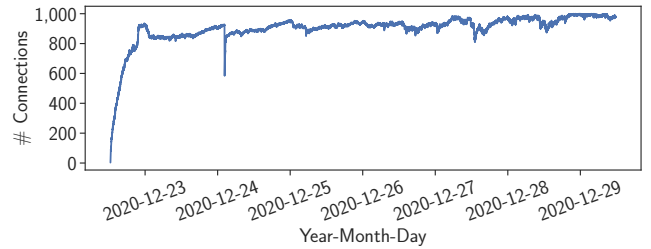
## 6 Privately Mined Transactions

To mine a blockchain transaction, clients typically have to broadcast their transaction, such that it reaches the available miners. A miner can then include the transaction depending on their inclusion policy.

Miners, however, can also include and prioritize their own transactions within blocks. Miners can also reach private agreements e.g., with exchanges or aggregators to mine trader transactions without broadcasting them on the public P2P blockchain network. *1inch*, a decentralized exchange aggregator, provides a “private transaction” service to its users to prevent their transactions from being front-run through sandwich attacks [13, 43]. Note that these transactions are necessarily shown to the miner before being mined.

### 6.1 Identifying Non-Broadcast Transactions

To measure the fraction of transactions that are mined, but not broadcast on the P2P network, we set up a well connected geth client with at most 1000 connections in the Ethereum network (cf. Figure 10) (a default geth client connects to a maximum of 50 peers). The client records any new incoming transaction, before it is added to the memory pool, or written to the blockchain. The number of connections of the Ethereum client are important as in to (i) receive data as early as possible [32] and (ii) to maximize an all encompassing view of the network layer. Once we stored all visible transactions, we compare this network layer dataset with the resulting confirmed blockchain transactions to identify the transactions that were mined, but not broadcast.



**Figure 10:** Number of connections of our modified geth node while listening for transactions on the P2P network. The default geth configuration maintains 50 connections. The more connections a node manages, the earlier this node receives block and transactions from neighboring peers.

### 6.2 Empirical Results

When observing the Ethereum P2P network over 45,669 blocks (1 week) from block 11503300 (Dec-22-2020 12:39:48 PM +UTC) to 11548969 (Dec-29-2020 12:39:58 PM +UTC), the chain recorded 8,285,218 transactions. When comparing those with the transactions we observed on the network layer, we find that 136,143 mined transactions were not broadcast prior to being mined. We hence can conclude that 1.64% of the transactions are being privately. We manually verify 100 transactions at random from our dataset with the data provided by Etherscan [15], and can confirm that our methodology identifies privately mined transactions accurately.

**Private 1inch Trades:** By observing privately mined transactions, we identify with which miners 1inch reached private peering agreements. We for instance found two privately mined 1inch transactions (cf. 0xa026..b15b and 0xaa45..c66f) from the Spark Pool (23.50% hashrate), one (cf. 0xe4d4..86b5) from the Babel Pool (4.83%) and one (cf. 0x4340..aeb5) from the F2Pool (9.59% hashrate).

**Mining Pools Engaging in Private Transactions:** In Table 10 we provide the distribution of miners engaging in mining non-broadcast transactions. Over the course of 45,669 blocks (1 week),

we identified 81 miners, of which 21 (26%) mine transactions privately. We notice that the number of privately mined transactions doesn't necessarily correspond to the hashing power of the miner. The *Ethermine* miner positions private transactions in the beginning of the block with apparent low gas prices. The *SparkPool*, however, mines private transactions while seemingly trying to disguise its transactions as ordinary instances by paying regular gas prices<sup>7</sup>. In particular, we noticed the contract `0x0000..a4c4`, for which all interacting transactions are mined by the SparkPool and not broadcast on the P2P network. Based on the available EVM byte code and engaging transactions, this contract appears to be involved in trading, strongly indicating that the SparkPool is engaging in MEV.

**Private Value Extracting Transactions:** From block `11503300` to `11548969`, we discover 340 liquidation transactions on Aave (both V1 and V2), Compound and dYdX (cf. Section 4.2) out of which we identify 18 private transactions. We also detect 5 private transactions among the 1,067 arbitrage transactions.

**Private Replayable Transactions:** We find that 1,156 of the 8,285,218 transactions are replayable following the methodology of Section 5.3. Out of these replayable transactions, we identify 13 private transactions yielding a profit of 0.59 ETH. Through manually inspection, we find that these 13 transactions are 1inch exchange trades. We recall that private transactions cannot be replayed by non-miners.

Miner address	Private txs	Name	Hashrate
0xEA674fdDe714fd979de3EdF0F56AA9716B89ec8	104,674	Ethermine	20.81 %
0x829BD824B016326A401d083B33D092293333A830	19,560	F2Pool	9.59 %
0x99C85bb64564D9eF9A96621301F22C9993C89E3	5,926	BeePool	2.11 %
0x5A0b54D5dc17e0AadC383d2db43B0a0D3E029e4c	3,256	Spark Pool	23.50 %
0xB3b7874F13387D44a3398D298B075B7A3505D8d4	980	Babel Pool	4.83 %
0xD224cA0c819e8E97ba0136B3b95cF503B79f53	697	UUPool	3.46 %
0x5921c6a53c2cD0987Ae111b59F2E5dDaAF275b60	360	-	0.45 %
0x04668Ec2f57c15c381b461B9fEDaB5D451c87F7	303	zhizhu.top/SpiderPool	7.76 %
0x314653F5933FC25D0A428424F5A645B2bcc37483	142	-	0.11 %
0x52f13E25754D822A3550D0B68FDefe9304D27ae8	59	EthashPool 2	0.1 %
0x3EcE08D0e2DaD803847E052249bb4F8bF2D5bB	59	MiningPoolHub	1.75 %
0xAEE98861388af1D6323B95F78ADF3DDA102a276C	58	-	0.21 %
0x00192Fb10dF37c9FB26829eb2CC623cd1BF599E8	25	2Miners: PPLNS	2.01 %
0xB35c1055aAE02DA8497E9D866e27C86be16CFEF	22	-	0.06 %
0x1aD91ee08f21bE3dE0BA2ba6918E714dA6B45836	7	2Miners: SOLO	4.01 %
0x002e0800acbaE2155Fab7AC0192956499070d	7	Hiveon Pool	0.95 %
0x35F61DFB08ada13cBA64Bf156B80Df3D5B3a738d	4	firepool	0.62 %
0x45a36a8e118C37e4c47eF4Ab827A7C9e579E11E2	1	-	0.11 %
0x8595Dd9e0438640b5E1254f9DF579aC12a86865F	1	EzilPool 2	0.68 %
0xF541C3CD1D2dF407fB9Bb52b3489F2aaeED497E	1	-	0.32 %
0x2A0eE948fBe9bd4B661AdEDb57425753EA0f6	1	-	0.56 %

**Table 10:** Distribution of the number of privately mined transactions per miner coinbase address over 45,669 blocks (1 week). Data measured from the P2P network with a geth client which consistently maintains over 800 P2P connections (cf. Figure 10). We measure the hashrate based on the number of blocks found during measurement by the respective miner. We only report the 21 out of 81 miners which mine transactions privately.

### 6.3 Implications

While transactions mined through private agreements mitigates the threat of predatory front-runners on the network layer, this practice grants unprecedented influence to miners and in our view deteriorates the decentralization of the blockchain network. While miners could also technically exploit private agreements for their own financial gain, e.g., sandwich attacks performed by a miner would likely be visible to any blockchain observer.

<sup>7</sup>We identified for example the following transaction hashes: `0x4e17..29cd`, `0xa67e..4725`

Regarding blockchain consensus security, the biggest danger lies in the willingness of miners to extract and compete over MEV, which would increase the stale block rate and consequently aggravate the risks of double-spending and selfish mining.

## 7 Related Work

We proceed to summarize related work. The study of blockchain security can be structured across the different technical layers, notably, the processing (CPU) layer, the network, consensus and the application or smart contract layer. Within this work we focus on the security challenges of the application layer. Eskandir *et al.* [27] are to the best of our knowledge the first to introduce a front-running taxonomy for permissionless blockchains. While the authors focus on displacement, insertion and suppression front-running, we found that insertions can have an important side effect, namely, whether the subsequent transaction succeeds or fails due to a prior insertion. In our taxonomy we therefore differentiate between destructive or cooperative front-running and explicitly mention back-running for ease of understanding as a particular insertion case. Daian *et al.* [24] follow up with a study on price gas auctions and introducing the concept of Miner Extractable Value. Zhou *et al.* [43] focus on the problem of sandwich attacks on AMM exchanges and quantify the victim transaction value at which an adversary can perform profitable sandwich attacks.

**Blockchain Security and MEV:** Related work captures extensively blockchain security through various models and quantification efforts. The most commonly captured attacks are double-spending [31], selfish mining [28] and bribery attacks [21].

**Preventing Front-Running:** Custodian and centralized exchanges are known to be under the supervision of regulatory bodies which conduct periodic audits [9]. On-chain exchanges are not yet thoroughly regulated, and front-running in the order book is challenging to detect. Exchanges which operate on-chain, however can be transparently inspected [8, 10, 11]. LibSubmarine [12, 23] is a commit-and-reveal proposal to counter front-running of miners. Tesseract proposes a front-running resistant exchange relying on a trusted hardware assumption [19]. CALYPSO [35] enables a blockchain to hold and manage secrets on-chain with the convenient property that it is able to protect against front-running. Kelkar *et al.* propose Aequitas consensus protocols [34], to achieve transaction order-fairness in addition to consistency and liveness.

## 8 Conclusion

In this paper we shed light on the practices of obscure and predatory traders of the Ethereum blockchain. We provide empirical data for the state-of-the-art blockchain value extraction, by notably studying past sandwich attacks and arbitrage on 7 decentralized exchanges as well as liquidations on 3 lending and borrowing platforms. To the best of our knowledge, we are the first to provide a generalized real-time replay trading algorithm, which, according to our estimates could have yielded a profit of 51,688.33 ETH over 2 years of the Ethereum blockchain. By measuring the privately mined transactions of miners, we find first signs of miners exploiting miner extractable value — a worrying, but predicted evolution of open and decentralized ledgers. We hope that our work provides insights into the current practices, which otherwise would remain exclusive to a few profiting entities.



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```

1  pragma solidity ^0.6.0;
2
3  contract ReplayProtections {
4      address owner;
5
6      constructor () {
7          owner = 0x00...33;
8      }
9
10     function Authentication() public {
11         require(msg.sender == owner);
12         uint profit;
13         // profiting logic omitted for brevity
14         msg.sender.transfer(profit);
15     }
16
17     function MoveBeneficiary() public {
18         address beneficiary = 0x01...89;
19         uint profit;
20         // profiting logic omitted for brevity
21         beneficiary.transfer(profit);
22     }
23 }

```

Listing 2: Protection from the transaction replay attack.

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## A Additional empirical data

### A.1 Tokens

Table 12 lists the tokens we consider to measure sandwich attacks and arbitrage trades.

### A.2 Sandwich attack

Table 11 shows the detailed monthly statistics of the sandwich attacks on Ethereum. Compared to the year 2019, we observe an increase in the number of attacks and the number of adversarial addresses (user/smart contract) in 2020. In September 2020, the month with the most active adversarial smart contracts (1665, 24.7%), we find 4604 attacks, of which 97.1% occur on Uniswap V2.

## B Replay Protection

Listing 2 presents the solidity snippets that mitigates the transaction replay attack (cf. Section 5.2).

## C Replay Honeypot

We proceed to show that the non-mining replay adversaries can be baited by a replay honeypot.

### C.1 Extended Threat Model

We extend our threat model in Section 3.2 and assume the existence of a financially rational adversary  $\mathcal{H}$  attempting to bait a transaction replay attacker  $\mathcal{A}$ .  $\mathcal{H}$  owns a sufficient balance of the native cryptocurrency (e.g., ETH) to deploy contracts and issue transactions required by the replay honeypot attack.

	Total	18-12	19-01	19-02	19-03	19-04	19-05	19-06	19-07	19-08	19-09	19-10	19-11	19-12	20-01	20-02	20-03	20-04	20-05	20-06	20-07	20-08	20-09	20-10	20-11
Num. of smart contracts	454	2	5	6	2	3	5	2	2	4	1	1	1	4	9	16	57	77	53	23	34	114	33	44	57
		0.4%	1.1%	1.3%	0.4%	0.7%	1.1%	0.4%	0.4%	0.9%	0.2%	0.2%	0.2%	0.9%	2.0%	3.5%	12.6%	17.0%	11.7%	5.1%	7.5%	25.1%	7.3%	9.7%	12.6%
Num. of user addresses	1379	8	9	12	3	4	5	7	5	6	4	2	3	9	12	20	58	77	60	29	72	425	618	110	130
		0.6%	0.7%	0.9%	0.2%	0.3%	0.4%	0.5%	0.4%	0.4%	0.3%	0.1%	0.2%	0.7%	0.9%	1.5%	4.2%	5.6%	4.4%	2.1%	5.2%	30.8%	44.8%	8.0%	9.4%
Num. of detected attacks	21001	23	158	123	213	324	684	555	401	267	156	266	372	491	545	676	896	835	1904	1052	1974	2451	3662	1539	1434
		0.1%	0.8%	0.6%	1.0%	1.5%	3.3%	2.6%	1.9%	1.3%	0.7%	1.3%	1.8%	2.3%	2.6%	3.2%	4.3%	4.0%	9.1%	5.0%	9.4%	11.7%	17.4%	7.3%	6.8%
Bancor	540	23	158	77	2	0	0	31	2	2	0	0	0	87	39	15	2	0	14	10	3	33	22	20	0
		2.6%	100.0%	100.0%	62.6%	0.9%	0.0%	5.6%	0.5%	0.7%	0.0%	0.0%	0.0%	17.7%	7.2%	2.2%	0.2%	0.0%	0.7%	1.0%	0.2%	1.3%	0.6%	1.3%	0.0%
Uniswap v1	9198	0	0	46	211	324	684	524	399	265	156	266	372	404	506	661	894	835	1888	440	198	104	1	20	0
		43.8%	0.0%	0.0%	37.4%	99.1%	100.0%	100.0%	94.4%	99.5%	99.3%	100.0%	100.0%	82.3%	92.8%	97.8%	99.8%	100.0%	99.2%	41.8%	10.0%	4.2%	0.0%	1.3%	0.0%
Uniswap v2	11107	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	602	1773	2314	3514	1469	1433
		52.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	57.2%	89.8%	94.4%	96.0%	95.5%	99.9%
Sushiswap attacks	156	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	125	30	1
		0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.4%	1.9%	0.1%

**Table 11:** Monthly statistics of the sandwich attacks on Ethereum.

```

1  pragma solidity ^0.6.0;
2
3  contract ReplayHoneyPot {
4      address payable beneficiary;
5
6      function SetBeneficiary(address payable b) public {
7          beneficiary = b;
8      }
9
10     function PayAndExtractValue() public payable {
11         require(msg.value > 0);
12         if (uint160(beneficiary) == 0) {
13             msg.sender.transfer(address(this).balance);
14         } else {
15             beneficiary.transfer(address(this).balance);
16             beneficiary = address(uint160(0));
17         }
18     }
19 }

```

**Listing 3:** HoneyPot contract against transaction replay attacks.

remark that mining replay adversaries are immune to the honeypot attacks, when placing the replay transactions at the top of blocks.

## C.2 Replay HoneyPot

We outline the replay honeypot attack in the following.

- (1)  $\mathcal{H}$  deploys a honeypot contract `ReplayHoneyPot` (cf. Listing 3) and deposits  $x$  ETH.
- (2)  $\mathcal{H}$  issues a tempting replayable transaction  $T_{tempt}$  that pays  $y$  ETH to `ReplayHoneyPot` and invokes `PayAndExtractValue`. The gas price of  $T_{tempt}$  is set to  $g_1$ .  $\mathcal{H}$  also broadcasts a trap transaction  $T_{trap}$  invoking `SetBeneficiary` to set the variable `beneficiary` to an address controlled by  $\mathcal{H}$ .  $T_{trap}$  has a higher gas price  $g_2$  than  $T_{tempt}$  (i.e.,  $g_2 > g_1$ ).
- (3)  $\mathcal{A}$  observes  $T_{tempt}$  and constructs the replay transaction  $T_{replay}$ .  $T_{replay}$  is profitable in the local execution, because the function `PayAndExtractValue` returns the entire ETH balance of `ReplayHoneyPot` (i.e.,  $x + y$  ETH) to the sender (i.e.,  $\mathcal{A}$ ), when the variable `beneficiary` equals to zero.  $\mathcal{A}$  then attempts to front-run  $T_{tempt}$  by broadcasting  $T_{replay}$  with a gas price  $g_3$ , s.t.  $g_3 > g_1$ .
- (4) If the transactions are mined and executed in the order, (i)  $T_{trap}$ , (ii)  $T_{replay}$ , (iii)  $T_{tempt}$  (i.e.,  $T_{replay}$  front-runs  $T_{tempt}$ , but falls behind  $T_{trap}$ , when  $g_2 > g_3 > g_1$ ),  $\mathcal{A}$  loses  $x$  ETH to  $\mathcal{H}$  because `beneficiary` was modified when  $T_{replay}$  is executed.

The primary threat to the non-mining replay adversaries is the state inconsistency between the local and consensus wide execution. We

Name	Address	Symbol	Decimals				
0	Ether	-					
1	0xBitcoin Token	0xb6ed7644c69416d67b522e20bc294a9a9b405b31		ETH	18	72	POA ERC20 on Foundation
2	Aave Interest bearing DAI	0xfc1e690f61efd961294b3e1ce3313fbd8aa4f85d		0xBTC	8	73	QChi
3	Amon	0x737f98ac8ca59f2c68ad658c3c3d8c8963e40a4c		ADAI	18	74	Quant
4	Ampleforth	0xd46ba6d942050d489dbd938a2c909a5d5039a161		AMN	18	75	Quantstamp Token
5	Aragon Network Juror	0xc62b1c403fa761baadfc74c525ce2b51780b184		AMPL	9	77	Raiden Token
6	Aragon Network Token	0x960b236a07cf122663c4303350609a66a7b288e0		ANJ	18	78	Republic Token
7	AirSwap Token	0x27054b13b1b798b345b591a4d2266562d47ea75a		ANT	18	79	renBCH
8	Balancer	0xba100000625a3754423978a60c9317c58a424e3d		AST	4	80	renBTC
9	BandToken	0xba11d00c5f74255f56a5e366f4f77f5a186d7f55		BAL	18	81	renZEC
10	Basic Attention Token	0x0d8775f64830679a709e98d2b0cb6250d2887ef		BAND	18	82	Reputation Augur v1
11	Bloom Token	0x107c4504cd79c5d2696ea0030a8dd4e92601b82e		BAT	18	83	Reputation Augur v2
12	Bancor Network Token	0x1f573d6fb3f13d689ff844b4c37794d79a7ff1c		BLT	18	84	Darwinia Network Native Token
13	PieDAO BTC++	0x03271124233a68efdf1fc402f6c5cb9f7c33fd		BNT	18	85	iEx.ec Network Token
14	bZx Protocol Token	0x5d6811088235f11c8920698a204a5010a788f4b3		BTC++	18	86	Rocket Pool
15	Compound Dai	0x5d3a536e46dbd6114cc1ead3577bab948e3643		BZRX	18	87	Dai Stablecoin v1.0 SAI
16	Celsius	0xaaae6fe4e8e54f431b0c390facfb0b17d094d2d		cDAI	8	88	Salt
17	CelerToken	0x4f9254c83eb525f9fcf346490bb3b2e28a81c667		CEL	4	89	SANtiment network token
18	Chai	0x06af07097e9eb7fd685c692751d5c66d4b9c215		CELR	18	90	Synth sETH
19	Compound	0xc00e94cb662c320282e6f5717214004a7f26888		CHAI	18	91	Shuffle.MONSTER V3
20	Curve DAO Token	0xf533a949740bb3306d119c777fa900ba03ca4d52		COMP	18	92	Status Network Token
21	Compound Dai v1.0 SAI	0xf5dce5f72842d746faf1593d3121fca444dc		CRV	18	93	Synthetic Network Token
22	Compound USD Coin	0x39aa39c021dfbae8fac545936693ac9175d7e563		cSAI	8	94	Unisocks Edition 0
23	Dai Stablecoin	0x6b175474e89094c44da98b954eedea4c95271d0f		cUSDC	8	95	SPANK
24	Streamr DATAcoin	0xc0f0ee63788a0849f5e297f3407f701e122c023		DAI	18	96	Serum
25	DigixDAO	0xe0bf7927c4af23765bc51314a0e0521a9645f0e2a		DATA	18	97	STAKE
26	Digix Gold Token	0x43faee4e5a3f2a6a1a411def7d7fe50e057bf		DGD	9	98	StorjToken
27	Decentralized Insurance Protocol	0xc719d010b63e5bbf2c0551872cd5316ed26ac8d3		DGX	9	99	Synth sUSD
28	Donut	0x0cf9bdf5a5698b6505f643900ffa515ea5df4a9		DIP	18	100	Synth sXAU
29	EURBASE Stablecoin	0x86fadbd80d82f3c3680819e4da99c10232ba0f		DONUT	18	101	Swipe
30	Enjin Coin	0xf629cbcd94d3791c9250152bd8dfbd380e2a3b9c		ENAJ	18	102	TrueAUD
31	SAINT FAME Genesis Shirt	0x06f658cfcbb13a9f37d836fe9708da38ec29b2		ENAB	18	103	TrueCAD
32	FOAM Token	0x4946feca7c692606e8908002e55a582af44c121		FAME	18	104	TrueGBP
33	FunFair	0x1940dd8bd9a5f5e60ae2232d285af190e711b		FOAM	18	105	TrueHKD
34	Flexacoin	0x4a57e687b9126435a9b19e4a802113e266adebde		FUN	8	106	Monolith TKN
35	DAIOstack	0x543ff227f64aa17ea132bf9886cab5db55dcaddf		FEN	18	107	Tellor Tributes
36	Gnosis Token	0x6810e7f6880c02933d47db1b9f0c5908e5386b90		GEN	18	108	Trustcoin
37	GRID Token	0x12b19d3e2ccc14da04f4ac33e63652ce469b3f2fd		GNO	18	109	BitLira
38	Gastoken.io	0x000000000b3f879cb30fc243bd4fee438691c04		GRID	12	110	TrueUSD
39	HedgeTrade	0xf1290473210b2108a85237fbc7f6eb42c654f		GST2	2	111	UniBright
40	HoloToken	0x6c6e5ec31d828de241282b9606c8e98a48526e2		HEDG	18	112	UMA Voting Token v1
41	HUSD	0xdxf574c245e45ef5fcb9a659c229253d111d87e1		HOT	18	113	Uniswap
42	Fulcrum DAI iToken	0x493c57c4763932315a328269e1adad09653b9081		HUSD	8	114	PieDAO USD++
43	IoTeX Network	0x6fb3e0a217407eff7fca062d46c26e5d60a14d69		iDAI	18	115	USDCoin
44	Fulcrum SAI iToken	0x14094949152edbfcd073717200da82fed8dc960		iDAI	18	116	StableUSD
45	KEY	0x4cd988afbad37289baaf53c13e98e2bd46aaeac8c		iSAI	18	117	Tether USD
46	Kyber Network Crystal	0xdd974d5c2e2928dea5f71b9825b8646686b6200		KEY	18	118	dForce
47	EthLend Token	0x80fb784b7ed66730e8b1dbd9820afd29931a0b3		KNC	18	119	Veritaseum
48	ChainLink Token	0x514910771af9ca656af840dff83e8264ecf986ca		LEND	18	120	Wrapped BTC
49	LoomToken	0xa4e83c3e456107ea67d3075bf9e3d3fa75823db0		LINK	18	121	Wrapped CryptoKitties
50	Livepeer Token	0x58b6a8a3302369daec383334672404ee733ab239		LOOM	18	122	Wrapped Ether
51	Liquidity.Network Token	0xd29f0b5b350b07fe9a9511f7d86f4f4bac3f8ca		LPT	18	123	CryptoFranc
52	LoopringCoin V2	0xbbbca6a901e926f240b89eac641d8aec7aeafd		LQD	18	124	XIO Network
53	Decentraland MANA	0x0f5d2fb29bf7d3fcee444a200298f4689080c942		LRC	18	125	0x Protocol Token
54	Matic Token	0x7d1afa7b718f8393db30a3abc0fc608aacfebb0		MANA	18	126	learnDAIv3
55	Marblecoin	0x8888889213dd4da823ebdd1e235b0950633c150		MATIC	18	127	learnUSDv3
56	MachiX Token	0xd15ecdcd5ea683995b2d0527a0ae0a3258302f8		MCX	18	128	learnUSDv3
57	Metronome	0xa3d58c4e56fedcae3a7c43a725aee9a71f0cee4c		MET	18	129	learnTUSD
58	Magnolia Token	0x80f222a749a2e18eb7f676d371f19ad7efeece3b7		MGN	18	130	learnBUSD
59	Maker	0x9f8f72aa9304c8b593d555f12ef6589cc3a579a2		MGR	18	131	ycDAI
60	Melon Token	0xccc67005c4e498ec7f55e092bd1d35cbe47c91892		MLN	18	132	ycUSD
61	Modum Token	0x957c30ab0426e0c93cd8241e2c60392d08c6ac8e		MOD	18	133	ycUSD
62	Meta	0xa3bed4e1c75d00fa6f4e5e6922db7261b5e9acd2		MTA	0	134	BinanceUSD
63	mStable USD	0xe2f2a5c287993345a840db3b0845fbc70f5935a5		mUSD	18	135	Geminidollar
64	Nexo	0xb62132e35a6c13ee1ee0f84dc5d40bad8d815206		NEXO	18	136	Reserve
65	Numeraire	0x1776e1f26f98b1a5df9cd347953a26d3c3b46671		NMR	18	137	USDK
66	Ocean Token	0x7afebbb46fdb47ed17b22ed075cde2447694fb9e		OCEAN	18	138	USDN
67	Orchid	0x575f41308ec1483f3d399aa9a2826d74da13deb		OXT	18	139	LINKUSD
68	Panvala pan	0xd566dc73a4d676646b38ec6d91eb45ce7457c44		PAN	18	140	HuobiBTC
69	PAX	0x8e8704d67f66d095d5be530380d0ec0b388289e1		PAX	18	141	SynthsBTC
70	Paxos Gold	0x45804880e22913d4fe09f4980848ec6ecbaf78		PAXG	18	142	tBTC
71	Pinkion	0x93ed3f3e21207e2e8f2d3c3de6e058b73bc04d		PNK	18	143	3CRV
					18	144	sbtCRV
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