Adoption and Actual Privacy of Decentralized CoinJoin Implementations in Bitcoin

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ABSTRACT

We present a first measurement study on the adoption and actual privacy of two popular decentralized CoinJoin implementations, Wasabi and Samourai, in the broader Bitcoin ecosystem. By applying highly accurate (\(\geq 99\%\)) algorithms we can effectively detect 30,251 Wasabi and 223,597 Samourai transactions within the block range 530,500 to 725,348 (2018-07-05 to 2022-02-28). We also found a steady adoption of these services with a total value of mixed coins of ca. 4.74 B USD and average monthly mixing amounts of ca. 172.93 M USD for Wasabi and ca. 41.72 M USD for Samourai. Furthermore, we could trace ca. 322 M USD directly received by cryptoasset exchanges and ca. 1.16 B USD indirectly received via two hops. Our analysis further shows that the traceability of addresses during the pre-mixing and post-mixing narrows down the anonymity set provided by these coin mixing services. It also shows that the selection of addresses for the CoinJoin transaction can harm anonymity. Overall, this is the first paper to provide a comprehensive picture of the adoption and privacy of distributed CoinJoin transactions. Understanding this picture is particularly interesting in the light of ongoing regulatory efforts that will, on the one hand, affect compliance measures implemented in cryptocurrency ecosystem. Therefore, we would like to examine this area of tension more closely and contribute empirical evidence to the discussion. In particular, this work focuses on

KEYWORDS

Cryptoassets, Mixing, CoinJoin

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1 INTRODUCTION

Privacy in financial transactions and traceability of funds are two inherently contradictory goals in cryptoasset ecosystems like Bitcoin. On the one hand, we observe the increasing adoption of privacy-focused wallets like Wasabi or Samourai to make transactions from several senders unlinkable by combining them into a single transaction using a well-known coin swapping technique called CoinJoin. These wallets fulfill the increasing need for privacy, which is otherwise not given by default in mainstream cryptocurrencies like Bitcoin because it is possible to effectively de-anonymize end-users and trace funds [2, 13, 19].

On the other hand, current regulatory efforts expand the traceability of funds requirement to cryptoassets and impose that obligation on virtual asset service providers, like exchanges. For instance, the Financial Action Task Force (FATF) [6] explicitly identifies mixing and tumbling services as risk factors for money laundering and terrorism financing. It also points out that Virtual Asset Service Providers (VASPs) such as cryptoasset exchanges need to apply preventive measures such as customer due diligence and the obligation to obtain, hold, and transmit originator and beneficiary information (“travel rule”) for transactions above a threshold of USD/EUR 1000. Also, the Council of the European Union recently proposed that this regulation applies for transfers to or from “unhosted wallets” as long as at least one VASP provider is involved [3]. The target of this proposal, which could become part of the broader European Regulation on Markets in Crypto Assets (MiCA) [5], includes transfers between privacy-preserving wallets, like Wasabi or Samourai, and virtual asset providers, such as cryptoasset exchanges.

However, little empirical evidence is available on the adoption and actual privacy guarantees of CoinJoin wallet implementations when considering them part of the broader Bitcoin ecosystem. Therefore, we would like to examine this area of tension more closely and contribute empirical evidence to the discussion. In particular, this work focuses on
the transactions generated by two user-friendly wallet implementations with built-in decentralized CoinJoin functionality, Wasabi and Samourai [7]. While the role of centralized mixing services like JoinMarket, where a trusted third party matches CoinJoin participants, has been studied in the past [16], decentralized wallet implementations have not yet been the focus of a comprehensive measurement study.

Given the current regulatory efforts, we are particularly interested in the extent to which transactions generated by such wallets flow into cryptocurrency exchanges and how this is evolving in light of ongoing regulatory efforts. We also want to better understand the actual privacy of CoinJoin transactions given the information leaked on-chain, thereby helping users assess the anonymity gain of these services, often smaller than the a priori perceived one. However, before answering these questions, we must detect the transactions created by Wasabi and Samourai wallets as accurately as possible. For example, we could use available threshold heuristics proposed by Ficsőr, the creator of Wasabi wallet [27, 28]. However, these heuristics were defined ad-hoc and never evaluated systematically. Therefore, little is known about their accuracy compared to other approaches. In this state of affairs, developing detection methods that can be assessed systematically, preferably using ground-truth data as input, would be interesting.

Our contributions. First, as discussed in Section 3, we propose two highly effective algorithmic methods to detect on-chain CoinJoin transactions. For Wasabi, we show that Ficsőr’s threshold heuristics and a new machine learning approach trained on historical ground-truth data are both highly accurate (99%) and that the choice between them depends on the application area. For Samourai, we introduce a simple deterministic alternative to known heuristics, which traverses the chain starting from genesis mixes and yields Samourai transactions with 100% accuracy. We applied these methods on the Bitcoin blockchain and identified 32,251 Wasabi and 223,597 Samourai transactions within the block range 530,500 (2018-07-05) and 725,345 (2022-02-28), which we make publicly available for other researchers.

Second, we analyzed how the number of transactions and the amount of mixed BTC evolved and found a steady adoption of Wasabi since Nov. 2018 and Samourai since Jan 2020. We also found that the total value of mixed coins is 227,480.84 BTC (ca. 4.74 B USD). Wasabi was used to mix 205,030.21 BTC (ca. 4.02 B USD) and Samourai for 22,450.63 BTC (ca. 715.12 M USD). Recently, the monthly mixing amounts were on average 3527.44 BTC (ca. 172.93 M USD) for Wasabi and 829.25 BTC (ca. 41.72 M USD) for Samourai. Furthermore, we could identify 39,042 Wasabi and 6919 Samourai transactions that were directly accepted by exchange entities and 94,257 and 37,325 transactions that were accepted indirectly via two hops. In terms of mixed coins, this sums up to 13,899 directly received BTC (ca. 322 M USD) and 54,468 indirectly received BTC (ca. 1.16 B USD). These results show that acceptance of CoinJoins by cryptocurrency exchanges is a living practice and not a phenomenon of the unregulated past.

Third, we proposed methods to quantify the gap between the anonymity perceived by users of Wasabi and Samourai wallets and the often smaller anonymity guarantees provided by such services. Unlike in an ideal world where pre- and post-mixed addresses are fresh and unlinkable to any other, the traceability of addresses during the pre-mixing and post-mixing narrows down the anonymity set provided by these coin mixing services. For instance, for the Wasabi wallet, we observe that the ideally possible anonymity set of almost 75K addresses in Jan’21 is largely reduced to less than 25K. Finally, we also observed biases in the selection of addresses for the CoinJoin transactions themselves, also harming anonymity.

Our work has several implications. First, it shows privacy-seeking end-users that third parties can detect CoinJoin transactions generated by Wasabi and Samourai, two popular implementations of decentralized CoinJoin, through relatively simple algorithmic methods. For end-users, this implies that having CoinJoin in the transaction history chain could raise issues when cashing out at cryptocurrency exchanges implementing stringent compliance measures requiring proof of origin of funds. Furthermore, our privacy analysis demonstrates that the anonymity guarantees (i.e., the anonymity set) offered by Wasabi and Samourai is much smaller than expected as effective deanonymization techniques are possible by inspecting pre-mixing and post-mixing transactions.

Our CoinJoin detection algorithms and analytics procedures were implemented in Python 3.7, Apache Spark 3.1.2/Scala 2.12, and R 4.2.0, respectively. We make our scripts along with the collected data available for further research in the following GitHub repository: https://github.com/defconst/wasabi-samourai-analysis

2 BACKGROUND AND RELATED WORK

2.1 Coin Swapping, Mixing Services, and CoinJoin

Swapping coins of different users is a well-known method to disrupt existing de-anonymization methods, such as the multiple-input or co-spent heuristics [14], and complicates the traceability of funds. In the early days of Bitcoin, centralized mixers such as “Bitcoin Fog” or “Bitmixer” offered coin swapping as a service.

CoinJoin is a specific mixing method for combining transactions from multiple senders into one transaction [12], as illustrated in Figure 1. Centralized mixing services or decentralized mixing protocols are possible implementation strategies for CoinJoins. An example implementation for centralized CoinJoin is JoinMarket[1]. Early examples of decentralized mixing protocols making use of the CoinJoin technique include CoinShuffle [22], CoinParty [26], CoinShuffle++ [23], and ValueShuffle [21]. CoinJoin has also become an integral feature of the cryptocurrency Dash [4].

1https://github.com/JoinMarket-Org/joinmarket-clientserver
In a decentralized setting, the challenge lies in coordinating and matching Bitcoin users that want to participate in a CoinJoin transaction and the input and output addresses they want to include. A central coordination server often handles the coordination task and naturally becomes a prime entry point to breach privacy. The users’ privacy can be further improved by splitting the outputs into a fixed set of standard denominations, which obscure the relationship between individual inputs and outputs. CoinJoin is now an integral privacy feature of Bitcoin wallets like Wasabi or Samourai, which are the focus of our investigation.

2.2 Empirical Analysis of Mixing Services

Back in 2013, Möser et al. [17] analyzed transactions of three first-generation, centralized mixing services. They already concluded that enforcement of the KYC principle appears unlikely if mixing services are involved. Later, Möser and Böhme [16] conducted a longitudinal measurement study of JoinMarket, an online market designed to match Bitcoin users wishing to participate in CoinJoin transactions. They [15] also studied second-generation mixing techniques not requiring users to trust in a single entity that might steal their coins. More recently, Pakki et al. [18] explored the Bitcoin mixer ecosystem and analyzed quantitatively how existing mixing services adopt academia’s proposed security features. Finally, Wu et al. [25] proposed a generic model for mixing services and a method for identifying mixing transactions and estimating the profit.

Our work complements this line of research by investigating CoinJoins generated by two second-generation, decentralized CoinJoin implementations. It focuses on two wallets that managed to bring that second-generation mixing technique closer to the end-user: Wasabi\(^2\) and Samourai\(^3\). Both are available as open-source software and backed by an active developer community. Contrary to previous studies, which either relied on a small set of manually created CoinJoin transactions or ad-hoc heuristics with unknown accuracy, we base our analysis on highly accurate CoinJoin transaction detection algorithms. In addition, we systematically evaluated them against a comprehensive ground-truth dataset.

2.3 Wasabi and Samourai CoinJoins

CoinJoin forms the basis for the ZeroLink framework [30], which in turn serves as the foundation for both Wasabi and Samourai wallets. ZeroLink defines three conceptual wallets: a pre-mix wallet for unmixed coins, a post-mix wallet for mixed coins, and a mixing technique that moves coins from the pre-mix into the post-mix wallet. While ZeroLink is compatible with various on-chain mixing protocols, it also defines Chaumian CoinJoin [12] used by both Wasabi and Samourai. It allows participants of these two wallets to construct transactions collaborating with each other and aided by a central coordinator without revealing the links between inputs and outputs.

Wasabi Wallet is an implementation of the Chaumian CoinJoin and supports a mix of multiple denominations in the same CoinJoin transaction, with 0.01 BTC being the lowest possible denomination. A coordinator fee of 0.003 x a, where a is the target anonymity set, is charged for each transaction. Figure 2a illustrates the basic structure of a Wasabi CoinJoin transaction, which can contain n possible inputs, n mix outputs, and n change outputs.

Samourai’s implementation of the Chaumian CoinJoin, Samourai Whirlpool, does not support multi-denomination transactions but instead features four distinct pools with denominations of 0.001 BTC, 0.01 BTC, 0.05 BTC, and 0.5 BTC. As shown in the illustrative example depicted in Figure 2b, each Samourai Whirlpool transaction features exactly five inputs and five outputs. The mixing fees in Samourai are collected in so-called Tx0 transactions, which split selected UTXOs into other UTXOs with the appropriate sizes for the selected pool.

2.4 Known Wasabi and Samourai Transaction Detection Methods

We are aware of two works focusing on detecting transactions generated by Wasabi and Samourai wallets.

First, and most importantly, our approach builds on the work of Ficsor, the creator of Wasabi, who also implemented heuristics to compute various metrics such as transaction volume. He published them in two GitHub repositories [27, 28] intending to compare various statistics for both Wasabi and Samourai, such as the volume of CoinJoin transactions, the number of fresh CoinJoin inputs, the average count of remix inputs, fees paid by users, and estimation of coordinator income.

Detecting Wasabi transactions was straightforward in the early days because Wasabi wallets initially used two static coordinator addresses to collect all fees. This design made their detection relatively simple: a transaction is a Wasabi wallet CoinJoin if one of the static coordinator addresses is in the list of output addresses and if there are at least three indistinguishable outputs with the same value. However, since January 2020, Wasabi wallet has generated new coordinator addresses for every CoinJoin, rendering the original heuristic obsolete. Ficsor, therefore, published a new heuristic that categorizes a transaction t as a Wasabi wallet CoinJoin if it is at least ten equal value outputs, with 0.1 ± 0.02 BTC being the most frequent one, and if it has at least two distinct output values that are unique, and if it features at least as many inputs as occurrences of the most frequent output\(^4\).

Ficsor also proposed a heuristic for detecting Samourai Whirlpool transactions: if the number of inputs and outputs is equal to 5 and all outputs have the same value, which must equal one of the Samourai Whirlpool pool sizes (0.01, 0.05, or 0.5 BTC) ±0.0011 BTC for [27] and ±0.01 BTC for [28], then a transaction can be categorized as Samourai wallet transaction.

\(^2\)https://github.com/zkSNACKs/WalletWasabi
\(^3\)https://code.samourai.io/whirlpool/Whirlpool
\(^4\)https://github.com/noopara73/Dumplings/blob/84ae3747aa52349ab02aad5f6d3bdf0c19d9961/Dumplings/Scanning/Scanner.cs#L129
Figure 1: The basic idea of a CoinJoin transaction based on [12]. A regular Bitcoin transaction (left) represents a relationship between two users (A and B; C and D). A CoinJoin transaction (right) combines inputs signed by several users (A and C). It assigns values to outputs controlled by multiple distinct users (B and D). For a third party, it becomes increasingly difficult to link the various outputs to individual users as the number of participants in a CoinJoin transaction increases.

Figure 2: The basic structure of a Wasabi CoinJoin (a) and a Samourai Whirlpool mix (b) transaction. Note that the number of inputs and outputs and the denomination of the outputs of a Samourai transaction are fixed. In contrast, the number of inputs, outputs, and denominations of mixed outputs may differ for different Wasabi transactions.

The second closely related work is by Wu et al. [25] who consider Wasabi CoinJoin transactions in their study. However, in contrast to analyzing historical transactions on the public ledger, they continuously queried the Wasabi coordinator API to retrieve ongoing CoinJoins. They used these sample transactions as a seed to detect subsequent Wasabi transactions by iterating the outputs of every transaction and checking whether a specific output is referenced by a transaction that features multiple indistinguishable outputs, which is an indicator of being a CoinJoin transaction. However, this approach based on forward-reasoning fails to consider historical transactions, an essential requirement for our study. Moreover, Wu et al. [25] do not detect Samourai CoinJoin transactions.

In summary, we are aware of Fiscór’s heuristic methods for detecting Wasabi and Samourai CoinJoin transactions, and we build on these methods in our study. However, heuristic methods usually rely on manually defined thresholds that are often set without systematic tuning and evaluation. Furthermore, since we aim to study the adoption and actual
privacy of Wasabi and Samourai transactions, we must first ensure that these wallets indeed create considered transactions. Therefore, we first understand the accuracy of possible detection methods and then choose the ones yielding the lowest false-positive rates.

Furthermore, there has been little research on the embedding of CoinJoin transactions in the larger Bitcoin ecosystem, especially their relation to cryptoasset exchanges, which are the focus of current regulatory efforts. In this work, we try to identify which entities conduct CoinJoin transactions either directly or are in the near vicinity of participants. For instance, if entity $A$ sends coins to entity $B$, which then participates in a CoinJoin. If possible, we also try to label these entities as, e.g., exchanges or services. Finally, we also look at the practical anonymity offered by the ZeroLink framework and usage patterns from users of Wasabi and Samourai wallets and investigate whether there are any fundamental weaknesses. To the best of our knowledge, this has not been done before.

## 3 COINJOIN DETECTION METHODS

We now investigate algorithmic methods to detect Wasabi and Samourai CoinJoin transactions and evaluate their accuracy.

### 3.1 Wasabi

We can detect Wasabi CoinJoins with two different approaches: we can apply a simple threshold heuristics as proposed by Ficsó (see Section 2.4), which yields varying accuracy depending on the tuning. Alternatively, we can train a statistical machine learning model, which learns to separate Wasabi from non-Wasabi transactions based on historical ground-truth data. Here, we consider and compare both approaches.

#### 3.1.1 Ground truth dataset.

We received a dataset of in total 28,890 transactions in the date range 2018-07-19 to 2021-12-21 from the Wasabi coordinator service, which is naturally a trust-worthy source for known Wasabi transactions. To establish a balanced ground truth of true and false positives, we considered the corresponding block range 532,600 to 715,100 and randomly sampled of 29,202 negative instances from this block range.

#### 3.1.2 Feature engineering.

Next, we inspected random samples of true and false positive Wasabi transactions and identified the following set of mainly transaction-level features, which may allow the classifier to discriminate between Wasabi and non-Wasabi transactions:

- **numuniqoutputval** number of unique output values.
- **ratiouninputnumoutput** ratio between the number of inputs and outputs.
- **minoutputval** minimum output value.
- **rngoutputval** the range of the output values, i.e., the difference between the maximum and minimum output value.
- **meandecplaces** average number of decimal places of the output values (value in BTC).

#### 3.1.3 Machine learning model.

Predicting the transaction type (Wasabi vs. non-Wasabi) is considered a supervised learning problem. We use a random forest (RF) classifier, an ensemble method that fits several decision trees on various subsamples of the dataset (bagging). The fitted individual trees are aggregated (majority vote for classification tasks) to improve the predictive accuracy and control for over-fitting. RF can account for correlation as well as interactions among predictors. They do not require extensive hyper-parameter tuning and tend to perform usually very well in a default setting [11]. Furthermore, RF provides intrinsic variable importance measures to rank predictors according to their predictive power. We use the RF implementation from the R package ranger [24] within the mlr3 [10] machine learning framework.

For an initial RF model, the dataset was randomly split into 70% training and 30% test set. A completely untuned RF model (500 trees, mtry = 2) immediately yields an out-of-bag prediction error of only 0.029% and a classification error of 0.017% on the test set. On the test set, the model achieves a false positive rate FPR = 0.011 %, and a false negative rate FNR = 0.023 %.

The feature importance scores are depicted in Figure 3 in decreasing order. By far the most important predictor is the indicator for native SegWit transactions (**isnativesegwit**), followed by the number of unique output values (**numuniqoutputval**) and the range of the output values (**rngoutputval**), respectively. Whereas the feature (**numinputreuse**) does not seem to have any predictive power. Only by using the feature **isnativesegwit** as a single predictor on the ground-truth dataset, all positives instances are recognized and only 663 negatives instances are misclassified (FNR = 2.3%).

The robustness and stability of the model were assessed using different resampling techniques. We applied subsampling (5 and 10 repeats) and cross-validation (5 and 10-folds) on the full dataset. Small standard errors (between $10^{-3}$ and $10^{-4}$) indicate relatively stable performance metrics.

#### 3.1.4 Evaluation and Validation.

For validation of the RF model outside of our ground-truth dataset, which we used for training and tuning our machine learning model, we sampled additional 100,443 non-Wasabi transactions in the

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https://github.com/bitcoin/bips/blob/master/bip-0173.mediawiki
considered block range \((532,600 - 715,100)\). Out of these 100,443 transactions, 10 instances were classified as Wasabi transactions (false positives).

Furthermore, using the Wasabi wallet, we manually executed ten Wasabi transactions within the date range 2022-01-14 – 2022-02-02, which is also outside the range of our ground-truth dataset (see Appendix A.2 for a list of transaction hashes). We applied our model and found that all transactions were classified correctly.

Next, we compared the model predictions with Ficsór’s heuristic described in Section 2.4. This heuristic, which we denote as Wasabi CoinJoin Detection Heuristics (WCDH), correctly classifies all 29,202 non-Wasabi transactions in the ground-truth dataset and all 100,443 non-Wasabi transactions in the validation dataset. From the 28,890 Wasabi transactions, 389 are missed (FNR = 1.3%).

A comparison of several performance metrics, which were evaluated on the test dataset for both approaches, is shown in Table 1. It clearly shows that both the heuristics and the statistical machine learning model are highly accurate, and the choice of procedure depends on the application area. For example, to avoid transactions falsely identified as Wasabi, one should choose the heuristic, which yields no false-positive predictions. On the other hand, if one needs even higher accuracy and can live with a few false positives, one should choose the RF model with a better FNR and accuracy.

We want to measure Wasabi transactions and avoid false positives in our subsequent analysis. Therefore, we chose WCDH and, in total, identified 30,251 Wasabi CoinJoin transactions within the block range 530,500 to 725,348 (2018-07-05 to 2022-02-28).

### 3.2 Samourai

To identify Samourai transactions, we can refer to a specific property dictated by Samourai’s architecture. Each pool starts from a so-called genesis mix, and each subsequent transaction features at least one remix address. This means that Samourai transactions form chains that we can traverse deterministically to identify individual transactions.

#### 3.2.1 Ground-Truth Dataset

We rely on data provided by OXT Research\(^6\), which provides a blockchain explorer connected to Samourai Wallet and publishes snapshots of Samourai transaction graphs\(^7\). However, these snapshots only include the first 17 characters of Whirlpool CoinJoin transaction hashes, and they are not guaranteed to be published continually. However, we can use these snapshots to validate further our results as the first 17 chars of a transaction hash are typically unique.

#### 3.2.2 Detection Algorithm

We used a slightly modified version of Ficsór’s heuristic, which can handle different \textit{premix} input denominations, to identify the genesis mix transactions of a particular pool. Interestingly, we identified three distinct genesis mixes for the 0.01 and 0.05 BTC pools, although the vast majority of transactions can be traced to a single one. For the 0.001 and 0.5 BTC pools, we only identified a single genesis mix. The genesis mixes have also been checked and verified against the snapshot data published by OXT Research.

Starting from a set of known, pool-specific genesis mix transactions, our Samourai transaction detection algorithm iterates the Bitcoin blockchain in chronological order and considers a transaction to be a Samourai Whirlpool mix if:

- it follows the structure of a Samourai Whirlpool transaction (5 inputs, 5 outputs), with each output value being equal to the pool denomination.
- at least one of the input transaction hashes has been identified before as a known Samourai Whirlpool transaction.

Conceptually, this detection algorithm can also be thought of as a breadth-first search starting at the genesis mixes. Every child transaction is added to the result set if it matches the structure of Samourai Whirlpool transactions.

#### 3.2.3 Evaluation and Algorithm Validation

We also validated our identified transactions against the data published by OXT Research and found a near-perfect match. The single exception is a transaction listed by OXT Research for the 0.05 BTC pool that is not included in our results with the hash e04e5a5932eb8d42e4ef6d41c836c6d08cd9f05f58ab4f257ca788485a39f0eb2416. This transaction has the same structure as a Genesis mix (there are only \textit{premix} and no \textit{remix} inputs). However, it does not actually start a new chain as only three of the five outputs are used as \textit{remix} inputs for other Whirlpool transactions, all of which feature a second \textit{remix} input that can be traced back to an older Genesis mix.

Finally, we manually conducted five CoinJoin transactions ourselves using Samourai Wallet to verify our results further. We conducted five Toy transactions, one for each of the 0.001, 0.01, and 0.05 BTC pools and one for both the high

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\(^6\)https://oxt.me

\(^7\)https://oxt.me/static/share/whirlpool/whirlpool_mix_txs_001.csv - replace 001 with the denomination of choice
and low 0.001 BTC pools. These Tx0 transactions resulted in 23 premix outputs which were then used in 23 distinct Whirlpool mixing transactions. See Appendix A.3 for the complete list of transaction hashes. In total, we identified 223,597 Samourai Whirlpool transactions within the same block range as for Wasabi.

4 EMPIRICAL ANALYSIS
Building on the CoinJoin detection mechanisms presented in the previous section, we now explore the role of both Wasabi and Samourai in the Bitcoin ecosystem. First, in Section 4.1, we investigate how usage of these services evolved. Next, in Section 4.2, we then analyze the flow of generated CoinJoin transactions to cryptoasset exchanges.

4.1 Longitudinal Analysis
Using our detection mechanisms, we identified 30,251 Wasabi and 223,597 Samourai CoinJoin transactions. For Wasabi, the average number of inputs per transaction is 76, with the average number of outputs being 121. For Samourai, every transaction naturally (see Figure 2b) has exactly five inputs and outputs.

Number of transactions. Figure 4 shows how the number of transactions for both wallets has evolved in our observation period. We can observe that the number of Wasabi transactions has remained relatively stable since Wasabi’s inception in late 2018, with minor changes around new wallet software releases (v1.1.10 in December 2019; v1.1.12 hotfixes around March 2021). This behavior reflects the design of Wasabi’s CoinJoin coordination process, which starts a new round and thus creates a new CoinJoin transaction as soon as 100 peers have registered their coins or after one hour has elapsed since the last round. For Samourai, we can observe adoption since Jan 2020 and a drop in the number of transactions at the beginning of 2021 when the Bitcoin exchange rate exceeded 50K USD. Back then, the minimal possible mixing amount (0.01 pool) suddenly became 500 USD. After introducing the 0.001 pool around March 2021, which made Samourai CoinJoins more affordable, the number of transactions has again risen sharply. In general, as shown in Figure 4 (bottom panel), we can observe higher use of smaller denomination (0.01, 0.001) pools, which is understandable because Samourai wallet users require more small than high denominations for assembling some target value.

Interestingly, while the 0.5 BTC Samourai pool only makes up for 6.35% of Samourai transactions, it is responsible for 64.47% of the total Samourai output. Overall, we can observe a steady adoption of Wasabi since Nov. 2018 and Samourai since Jan 2020. We can also see that software releases and design choices such as coordination interval and pool sizes affect the number of CoinJoin transactions generated by the users of these wallets.

Mixed coins. Next, as shown in Figure 5, we are interested in the value of mixed Wasabi and Samourai coins in the Bitcoin ecosystem; i.e., coins that have been mixed and are not used as remix inputs in subsequent CoinJoins. Figure 5 shows...
(top panel) shows the amount of mixed BTC leaving the Wasabi and Samourai ecosystems. For Wasabi, the mixed amount in BTC is rising steadily until mid-2020, with a large spike in the second half of 2019. This period coincides with several successful law enforcement actions, including the closure of Bestmixer.io, a money-laundering machine that processed several millions of dollars worth of cryptocurrency [1]. That suggests that some users of Bestmixer.io might have turned into Wasabi wallets around that period. From mid-2020 on, we can observe a decline in the mixed amount of BTC and an increase in the amount of mixed USD, which correlates strongly with (monthly aggregated) USD exchange rates (Pearson correlation $\rho = 0.89$). For Samourai, we can also observe a spike in the 0.5 BTC transaction pool, which we cannot explain but increased the amount of mixed BTC and USD. In total, we found that the total value of mixed coins is 227,480.84 BTC (ca. 4.74 B USD$^8$). Wasabi was used to mix 205,030.21 BTC (ca. 4.02 B USD$^8$) and Samourai for 22,450.63 BTC (ca. 715.12 M USD). Within recent months (Sep 2021 – Feb 2022), Wasabi users mixed on average 3527.44 BTC (ca. 172.93 M USD), Samourai users 829.25 BTC (ca. 41.72 M USD) per month.

### 4.2 Relations in the Bitcoin ecosystem

To understand the role of Wasabi and Samourai CoinJoins in the greater Bitcoin ecosystem, we analyzed their connections to cryptoasset exchanges via direct or indirect transaction relationships, as shown in Figure 6. First, we used GraphSense (version 0.5.2) [9], which computes entities using the co-spent heuristic [13], to map all input and output addresses (Level 0) of CoinJoin transactions to entities. Since that heuristic joins addresses based on common input ownership, it merges all input addresses of a CoinJoin transaction into a single entity, which does not represent a single actor but the participants of a CoinJoin. We denote entities that directly forwarded or received values from Wasabi or Samourai CoinJoins as **Level 1** entities and all entities that are sending or receiving coins via two hops as **Level 2** entities. Under the assumption that CoinJoins are filtered out, these entities typically represent clusters of addresses (wallets) controlled by some real-world actor (e.g., an exchange service).

Since large address clusters typically represent services [8] and service-to-service relations are not relevant for our analysis, we introduced the rule-of-thumb assumption that human users typically do not interact manually with more than 100 entities. Technically, we stop traversal at entities with in- or out-degrees of more than $t$ other entities. We considered different threshold values $t$, in particular $t \in \{50, 75, 100\}$. For attributing addresses and categorizing entities, we rely on openly available attribution tags retrieved from walletexplorer.com and manually curated attribution tags, which were collected by interacting with exchanges. In total, we consider 140 distinct cryptoasset exchanges. Since we are aware that our dataset might miss certain exchanges or clusters associated with exchanges, we consider the following findings as lower boundaries and point out that our analysis method is reproducible and easy to repeat with a more comprehensive attribution tag dataset.

**Related exchange entities.** On the output side of CoinJoin transactions, we identified 52,123 distinct entities that forward coins via one hop and 98,314 entities that forwarded coins via two hops ($t = 100$). Interestingly, we found 251 entities associated with cryptoasset exchange services that accepted Wasabi transactions directly and 307 that accepted them via two hops ($t = 100$). For Samourai, we found 187 direct and 253 indirect relations to exchange entities that accepted CoinJoin transactions via two hops ($t = 100$). On the input side, we found that users associated with 155 cryptocurrency exchange entities forwarded their funds from exchange-controlled hot wallets directly to CoinJoin wallets (155 for Wasabi and two for Samourai) or indirectly via two hops from 322 exchange entities (317 for Wasabi and 121 for Samourai; $t = 100$). In summary, we could identify a lower bound of 313 cryptoasset exchange entities that accepted CoinJoin transactions from either Wasabi or Samourai wallets either directly or indirectly via two hops.

**CoinJoin transactions received by exchanges** To understand whether the direct and indirect relations between CoinJoin transactions and entities controlled by cryptoasset exchanges reflect the past or the present, we analyzed their evolution in terms of numbers and amounts of mixed BTC. For each CoinJoin output, we checked the shortest path between the output entity (level 0) to an entity categorized as exchange via one or two hops. The cumulative number of transactions, as well as the cumulative mixed amount of BTC is illustrated in Figure 7. The evolution of the transactions numbers to exchanges shows a nonlinear increase until 2021 for both services and entity levels, respectively, which then turns into almost linear growth. In total, we could pinpoint 39,042 Wasabi and 6919 Samourai transactions that were directly accepted by exchange entities and 94,257 and 37,325 transactions that were accepted indirectly via two hops. In terms of mixed coins, this sums up to 13,899 directly received BTC (ca. 322 M USD) and 54,468 indirectly received BTC (ca. 1.16 B USD).

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$^8$ We converted BTC to USD using historic daily closing exchange rates retrieved from https://api.coindesk.com/v1/bpi/historical/close.json.
5 ANONYMITY ANALYSIS

In this section, we quantify the anonymity perceived by Wasabi and Samourai users and propose methods to quantify how much the real anonymity differs from the perceived one due to the provenance of addresses before and after the mixing. Unlike in an ideal world where pre- and post-mixed addresses are fresh and unlinkable to any other, the traceability of addresses during the pre-mixing and post-mixing allows us to narrow down the anonymity set participating in the mixing. We also observe usage patterns during the mixing itself that harms anonymity.

5.1 Upper Bounding Perceived Anonymity Set

Here, we are interested in the (upper) bound on the number of different transaction outputs of the same denomination that are mixed in Wasabi and Samourai over their lifetime. Intuitively, this study thereby sheds light on the maximum gain in the anonymity set provided by each of the wallets over time. Towards this goal, we first compute the number of bitcoins that are being actively mixed at each point of time (i.e., bitcoins added to the wallet until time $t$ minus the number of bitcoins withdrawn until time $t$). We denote this quantity by $\alpha_t$. Figure 8 (solid line) shows the concrete results for both wallets, while Figure 9 shows the results for each of the pools in Samourai.

Second, since Wasabi and Samourai consider several mixing denominations, we consider the extreme case where all participants use the minimum denomination as we are interested in the upper bound (i.e., the maximum possible number of different outputs, each of them with the minimum denomination, being mixed). In the concrete case of Wasabi, since it supports 0.01 BTC as the minimum mixing denomination $\beta$, we define the upper bound of the number of outputs being mixed at each point of time as $\alpha_t/\beta$. The result is shown in Figure 8 (dashed line). Following the same reasoning as with Wasabi, in Samourai we establish the upper
bound on the number of distinct outputs as $\alpha_c/\beta_{\text{min}}$, where $\beta_{\text{min}}$ is the denomination used in the pool with the minimum denomination.

As mentioned above, these results show the maximum number of outputs being mixed and thus the maximum anonymity set (in an ideal setting where each output belongs to a different user) that each of these wallets has provided over time. These are, however, loose bounds because, e.g., it is likely that a single user owns more than one output, or some of the outputs might be already tainted by an adversary with side information. Therefore, we next study tighter upper bounds on the anonymity set.

### 5.2 Pre- and post-mixing anonymity

The mixing wallets studied in this work improve the anonymity of the addresses within the mixing itself. In other words, assume that a certain address has an anonymity set $s_{\text{init}}$ when first used by the mixing wallet. Then, the mixing wallet’s job is to boost such anonymity set by $s_{\text{boost}}$ so that the address ends up with a bigger anonymity set $s_{\text{final}} := s_{\text{init}} + s_{\text{boost}}$ after the mixing is finished. The ideal scenario would be that $s_{\text{init}}$ is as big as possible so that a small effort (i.e., a small $s_{\text{boost}}$) is required to get a good enough final anonymity set $s_{\text{final}}$. Similarly, whatever is the final anonymity set $s_{\text{final}}$ achieved by an address, the ideal scenario is that such anonymity set stays afterward when the user uses such address outside the mixing (e.g., to pay a merchant).

Unfortunately, the pre- and post-mixing anonymity sets are far from the ideal situation perceived by the users. In the remaining of this section, we show the results of our study on how far are the anonymity sets of current addresses from the ideal scenarios described above.

**Pre-mixing anonymity loss.** The addresses used in the mixing wallets come with a history that is publicly available in the blockchain itself and that effectively reduces their ideal pre-mixing anonymity set. In order to quantify that, we use the entities and their relations as provided by GraphSense (Section 4.2) to compute the provenance of such addresses and quantify the reduction of the pre-mixing anonymity. As an illustrative example, input address 1 in Figure 10 (respectively input addresses 2 and 3) ideally does not have any relation to the other two addresses, therefore having an initial anonymity set $s_{\text{init}}$ of 3. This would correspond to the best case of having three different unrelated entities, and this address could belong to any of the three. However, studying the provenance of these addresses and their corresponding entities, we can observe that all of them belong to the same entity (i.e., entity 1). This pattern that one entity is used to fund different addresses is studied as the star pattern in [20]. In our setting, this appears because a user may use her common Bitcoin wallet to fund the pre-mix wallet of her Wasabi (or Samourai) wallet. In summary, the actual pre-mixing anonymity set of the addresses in this running example is reduced to a single entity, the owner of the entity 1.

Following the logic in this example, we evaluate the actual loss of pre-mixing anonymity by systematically applying the previous approach to the complete set of addresses used as input in Wasabi and Samourai wallets along with the entities provided by GraphSense. The results are shown in Figure 11 (top panel). For Wasabi, we observe that the number of distinct addresses (i.e., ideal anonymity set $s_{\text{init}}$) is significantly narrowed down when clustering them into entities. This implies that the ideally large anonymity set of addresses is significantly reduced if they are not freshly used as input to the Wasabi wallet. For instance, the possible anonymity set of almost 75K addresses in Jan’21 is largely reduced to less than 25K entities. On the other hand, we observe that such a reduction in the anonymity sets for addresses used in Samourai wallet does not occur.

In summary, this exemplifies how the potential anonymity perceived by the users of Wasabi (possibly magnified by the fact that CoinJoin transactions in Wasabi have a larger number of inputs than those from Samourai) is effectively smaller, in fact, even smaller than that of Samourai.

**Post-mixing anonymity loss.** Similar to pre-mixing, the anonymity of the post-mixed addresses can be reduced depending on how they are used after they are mixed. For instance, if multiple post-mixed addresses can be linked to a single entity, the anonymity set gained during the mixing process is reduced. In the simple illustrative example of Figure 10 where only a single CoinJoin transaction is executed, output address 4 (respectively addresses 5 and 6) ideally has a post-mixing anonymity set $s_{\text{final}}$ of 3, meaning the best case of having three different unrelated entities and this address could belong to any of the three. However, as it was the case for pre-mixing, studying the provenance of addresses 4, 5, and 6, we can observe that they belong to the same entity (entity 8). This usage pattern can be quite common in practice because a user might be tempted to collect her mixed coins from the post-mixing wallet in Wasabi or Samourai into her unique Bitcoin wallet to use them further. This usage pattern has been studied as the collector pattern in [20].

In Figure 11 (bottom panel) we show the relation between post-mixed addresses in Wasabi and Samourai (i.e., ideal post-mixing anonymity sets) and the number of entities computed...
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5.3 The Impact of Remix Inputs

The anonymity set of an output increases by having it being an input of other CoinJoin transactions (i.e., a remix input). Conversely, if a CoinJoin exclusively features fresh inputs, i.e., no remix inputs, its anonymity set is only as big as the number of its inputs. The importance of remix inputs is such that the design of Samourai CoinJoin mandates that every CoinJoin features at least one remix input (other than initial Genesis mixes).

However, Wasabi wallet does not require remix inputs. In fact, we detect that 59/30,251 transactions do not feature any remix inputs. This adds to the misperception of anonymity given by Wasabi wallets because these transactions only provide the anonymity of a single mix (instead of the anonymity of several intertwined mixers). This should prompt users that find their addresses in such transactions to remix them as soon as possible.

6 DISCUSSION

Wasabi and Samourai offer users privacy behind the scenes via decentralized CoinJoin and have become, as our results show, an integral part of the Bitcoin ecosystem since Nov 2018. We have shown that it is possible to detect CoinJoin transactions with high accuracy using relatively simple algorithmic methods. We can also trace the flows of funds received by services directly or indirectly. Our analysis also reveals 227,480.84 mixed coins with a total value of ca. 4.74 B USD in the past and a mixing throughput of around 4356.69 BTC or ca. 214.65 M USD within recent months. Furthermore, by attributing services on the input and output side of CoinJoin transactions, we found a lower bound of 313 entities controlled by cryptoasset exchanges and received coins from these wallets via one or two hops. Surprisingly, the amount of accepted CoinJoin transactions and mixed BTC are growing steadily despite increasingly tightening Anti-Money Laundering (AML) regulations. These regulatory efforts demand traceability of funds, which opposes the design goal of decentralized mixing services like Wasabi or Samourai.

The empirical results reported herein should be considered in light of some limitations. First, Ficsór et al. [29] have recently published a generalization of the Chaumian CoinJoin named WabiSabi. WabiSabi serves as the basis...
for Wasabi Wallet 2.0, which has already seen TestNet releases and is expected to be fully released in 2022. It offers, among other features, support for arbitrarily variable CoinJoin amounts. Wasabi 2.0 is expected to limit the effectiveness of the discussed WCDH heuristic severely. Second, we point out that our attribution dataset, which identifies cryptoasset exchanges, is incomplete and that the numbers reported in our ecosystem analysis are, therefore, lower bounds. However, our analysis is easily reproducible with a more comprehensive attribution tag dataset, and it is even possible to name the involved exchanges, which we refrain from for ethical reasons. Therefore, another possible future direction is to run our analysis with a more comprehensive attribution tag dataset to obtain a complete picture of mixing activities in the Bitcoin ecosystem, make informed decisions, and assess compliance with AML regulation.

CoinJoin transactions and software facilitating them are a double-edged sword, and the implications of our work very much depend on the perspective.

For privacy-seeking end users, wallets like Wasabi and Samourai are a practical, low-entry barrier solution to Bitcoin’s anonymity problem. To the best of our knowledge, it is hardly possible to de-mix CoinJoins produced by these wallets. However, users should be aware that a priori perceived anonymity gains of such services is hindered because their transactions are visible on-chain, and cryptoasset tracing and tracking solutions can detect them. Also, pre-mixed and post-mixed addresses can be traced, effectively reducing the anonymity guarantees provided by these mixing wallets. On the other hand, stricter regulations could require users to clearly explain the origin of their coins if they want to cash out coins at an AML-compliant exchange. Of course, this is more difficult to explain when CoinJoins are involved.

For cryptoasset exchanges our findings show that automatically detecting CoinJoin transactions created by two popular wallets is easily possible with relatively simple heuristics. Our results show that the number of transactions and mixed coins accepted is still growing, from which we can infer that acceptance of CoinJoins currently does not yet raise compliance issues, at least for the exchanges in our dataset, 15 of them ranking in the top 20 by 24h trading volume\(^{6}\). However, this may change when the AML compliance rules, which apply to traditional financial service providers, are also enforced in the cryptocurrency area.

For regulatory bodies our results provide insight into the current use of two popular mixing services preventing traceability of funds. One could even imagine applying similar procedures to monitor the adoption of AML compliance in cryptoassets ecosystems without invading users’ privacy. However, we also point out that imposing the traceability-of-funds requirement on cryptoasset exchanges essentially demands CoinJoin not to be part of a coin’s lineage. In the long run, this might discourage users from using tools that protect their fundamental right to privacy in a completely transparent financial ecosystem.

7 CONCLUSIONS

We measured the adoption and privacy guarantees of two popular decentralized CoinJoin implementations: Wasabi and Samourai wallet. We found algorithmic methods that can yield transactions generated by these wallets with high accuracy and constructed a transaction dataset spanning the entire history of these wallets up to the end of our observation period on 2022-02-28. We then quantified the lower-bound volumes of coins mixed by these wallets and showed they have been adopted over time and are not yet affected by current regulatory efforts. However, we also show that the anonymity guarantees are much lower than assumed when considering the flow of funds before the pre-mix and after the post-mix wallets. Overall, our work contributes empirical evidence to a highly controversial discussion in the field of tension between the legitimate right to privacy and the need for transparency and traceability to mitigate the abuse of cryptoassets for illegitimate purposes.

Our work currently focuses on Bitcoin only. Future work could expand our methodology to account-model ledgers like Ethereum and more closely investigate emerging mixing services such as Tornado-Cash. Also, the entire Decentralized Finance (DeFi) ecosystem offers tremendous opportunities for increasing anonymity by tunneling cryptoassets through DeFi protocol compositions, which are currently hardly understood.

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A.2 Manual Wasabi CoinJoin Validation! We conducted the following Wasabi CoinJoin transactions:

- 508e5961f4f442d35a1d9f01972ab4b4aba2e2325d19d0c183a2e02e23df5343ab
- f2426239c02260d202d88f3c2988c0e817f30d6658f426b8cd3243466e839d17
- 6da174f73519a3218ed8989c6e6d4aabc2ac7f7226dd6c598513eef35a56e63cd471c5
- cfe6f8546-c44d4b0409884782f256b56c30ca3e2a9656b3e41883098c
- cb64224eb9c2e22118d4f4d33f955894e9e3c13e099787c3700797a93c17
- 9a5e5bf67f38afef21203c4f51b4dcd6babe0e90e35042c1e943625e549892a0a
- 1307674d47a801d73b3aee33a969fbb9b3658b4636f19f68b7819e19ab09
- ddc54204344f989982875648003b3b7c5b5e6d5ad335ac5ed4b436126e
- 1f6a3288f601c23690ca8a38636174380705c3fc8ee2a24803f916602cb1c43720
- 3a303cfd299b02a2282bf12879363a43926aca8c33b9ada32378ada894b567a4
Figure 12: Monthly amount of fresh BTC entering Wasabi and Samourai (top), as well as by Samourai pools (bottom).

A.3 Manual Samourai CoinJoin Validation

We issued the following Tx0 transactions:

- c6f1526f61745806996ebf61d60924120a90df64dd37f47677c77035ad740e2ce02
- a37f20d22d7d3a7780eb7e4e6e333df86d7f29c91a101d559
- 9b2a64698f9b400b369057b4ef04109ba409d6d8d15b42c00286e56f4155a699
- 2893cf9e37ab64809e9dfbb665b0a4e5d7b857d5b506a2b77d6f1708132b07
- abb227224613a247709b64df12d31f5a0e4d395c7f5e7837c88052df8f093b

The mix outputs of these Tx0 transactions were used in the following Whirlpool CoinJoin transactions:

- 970bca671619bc0c572ca39a3f4f7075e5558d004b6babde1013d4df5256d7c
- e50b71a734227dbf4248699e70b1bece7ed8717516e5a7380e0b73d5833f292e
- 933c2d23abc041571e02790c49f9b50b3a288da11645485e3cd8910e860b54
- c63f1655d5496ed6447dcd613f67f70214385e1b5dd866567e8e8e75106aa
- 0f7c7fe8c68db6c60471f4333232b0499037e27860c947a7a863f1df77cc59
- d27d147e5e8e5e352bcb854d44a883973c9b692d0a37d35313812d6e2a
- 2646d46580c03c63d7e189d0e7a082e630e7a4c50e09b06f1478f2f8f35
- f644a9f728152a31d3eb6b3b3bfa99f7c4ffcf7f9909c21d48c94e9012
- 5348b1534417b6333357f5e26605391800dc0a09ac50e0e1b5ca2b2d21f2
- 7531ee3a77ac40471fa2f22b27729f30335ff8e60d3d52711e00420653010
- 130f1e346ba7ae8d157446a8f4cc41a9f6de09f4bba0a9abb59169559e9
- 20e8630e256833c0db1e478c2c022437442476823c5d0871f2028f8f6cc
- 9abc2b775733b843d24ff7c8b2b506024de5e13147f950e58164375f55
- d2725ec6d6b685c9b8c5c39e9f6b9bf4cc52c43dfca1970dc95080ae9df
- 66d316433513c1ed1c0bab21166a4e27a1f8837b9789ca399256db1db3b105
- 5f8fc2732ab6d6820f6043010f36d5663cf452f7e9fe9acbf3708f8dea0af86