Individuals and Windfall Income in the Form of Equity: A Case Study in Decentralized Finance

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1 Executive Summary

In this paper, we investigate one of the first instances of a growing trend in cryptocurrency: giving away tokens that represent ownership of a protocol to past users. We gather some of the abundant blockchain data to investigate how recipients responded to this sudden unexpected influx of wealth (whose market value started at around $1200 USD) and how that differed with the individual's net worth. Overall, there were many issues that may have rendered this policy ineffective as a way of positioning the protocol for success.

We find similarities with one of the few historical parallels: the "voucher privatization" of the early post-Soviet years in Russia. In both cases, large numbers of ordinary people were gifted equity and most ended up selling it for very unfavourable prices while a small savvy group accumulated more. We conjecture that this can be attributed to poor information and risk aversion and that it may be a general fact that when people are placed in such a scenario, they tend to sell the equity. This would contrast with work on the "house money effect" which says that individuals tend to take more risk with money they just won. We also conjecture that flat transaction costs and decision-making simplicity led most to sell their entire "airdrop" instead of keeping some, which would have turned out to be very lucrative.

Given the sheer number of accounts that claimed very quickly and proceeded to transfer their airdrop away, the airdrop does not seem like it succeeded at decentralizing the ownership of the protocol and incentivizing past users to support and improve the protocol. Instead, it may have simply acted as a wealth transfer. Transferring it away generally means that it is being sold or someone with multiple accounts is aggregating their airdrops to their main account, neither of which are desirable. Furthermore, we find some evidence that suggests that people may have anticipated the airdrop and created many accounts to obtain a large number of airdrops.

As for how people reacted differently based on their net worth, due to time and data constraints, we were unable to carry out a full analysis of this issue. We do propose a model to investigate how a change in the net worth of an individual will affect the probability of them selling their airdrop but there are some significant challenges in carrying out the analysis.

2 Introduction

On September 16th 2020, a prominent Decentralized Exchange protocol on the cryptocurrency platform Ethereum called Uniswap launched its token with a total supply of 1 Billion UNI tokens and "airdropped" a portion of the supply to past users. Anyone who had used (or even attempted to use) the exchange prior to September 2020 (UTC) was eligible to claim at least 400 UNI tokens. Part of the reason to do this was to distribute the ownership of the protocol widely, keeping with the ethos of the Decentralized Finance movement. The initial price was over $3 USD and reached over $7 USD a few days later, making the airdrop a substantial sum of money, especially for those who may live in developing countries. Our goal is to examine how recipients reacted to this windfall income and how this differed based on their wealth.

Since all transactions on Ethereum are public, substantial data is available to analyze their choices. We collect some of the available data ourselves to analyze this issue. However, there is a significant potential problem: we cannot link Ethereum accounts to individuals and individuals may have multiple accounts (the so-called "Sybil problem"). This also means that we have to use the account's balance of Ether (the native token of Ethereum which is necessary to pay for transactions) as a proxy for the individual's net worth. This necessarily introduces significant measurement error and this may be "nonclassical" measurement error in that it is correlated with the variable e.g. wealthier individuals have a smaller fraction of their net worth in Ether.

Some of these issues can be ameliorated with a more careful analysis of the blockchain. For example, if a relatively poor account regularly makes substantial transfers to another account, we have good reason to suspect that they are in fact owned by the same individual. With the growth of airdrops, this is even more common now to "hunt" for airdrops as the distributions usually try to be more equal but the Sybil problem creates these perverse incentives. However, due to data and time constraints, we were not able to obtain the necessary information to do a complete analysis.

The results from this complete analysis would have interesting implications. Firstly, if we assume that individuals have to sell their tokens to consume using the wealth (not necessarily true given lending platforms), our results can give an upper bound on the Marginal Propensity to Consume and how that changes with wealth. These results can also potentially be useful to evaluate the consequences of wide-ranging stimulus programs such as the stimulus payments in the US during COVID-19 and "helicopter money" from the central bank. They may also be very relevant for those trying to understand the dynamics of the crypto markets because they can point to how a significant subset of crypto market participants make investment decisions. Also airdrops have only grown in popularity since this one and our results suggest they may not be effective at widely distributing protocol ownership. Finally, our paper highlights the abundant rich data available about economic decisions on public blockchains which is of great relevance to economic researchers.

3 Literature Review

Economists have tried to understand consumption behaviour for a long time as it is key to understanding the economy. To test these theories, it is useful to consider what consumers do with "windfall income" i.e. an unexpected one-time source of income. For example, one could win the lottery. Milton Friedman's permanent income hypothesis predicts that consumption is primarily determined by expected lifetime income. Thus consumers will not spend much of a small windfall - they prefer to smooth consumption over time. (Of course, large lottery wins may substantially increase expected lifetime income). The evidence is mixed but Jappelli and Pistaferri (2010) review the literature and conclude that consumption does respond much more strongly to permanent shocks compared to transitory shocks.

Our natural experiment combines windfall income with issues of risk as the income was given in the form of tokens which are essentially equity. Perhaps the most analogous situation to this one was the "voucher privatization" of state-owned enterprises soon after the collapse of the Soviet Union. The reformist government decided to privatize the inefficient state controlled enterprises left over from the Soviet Union. One of the ways this was achieved was by distributing cash-denominated vouchers (for free) to the population which could be exchanged for shares in the firms to be privatized. However, according to Appel (1997), since many were ill-informed and/or poor, anecdotal evidence suggests that a significant fraction of recipients sold these vouchers in the market for far below fair value. Many even sold for much less than the face value! In the end, a small group controlled most of the shares in these companies, leading to a very negative public perception of the program.

For more on the interaction of windfall income and risk taking, Briggs et al. (2021) find that lottery wins increase stock market participation among prior nonparticipants but by substantially less than standard life cycle models would predict. They argue that much of this is due to overly pessimistic beliefs about equity returns. Hsu and Chow (2013) investigate the house money effect proposed by Thaler and Johnson in 1990 which leads to investors taking increased risk after a successful investment. Individuals take more risk with the newly gained money because it's "the house's money". Using data from the Taiwan stock exchange, they find strong evidence for this effect. Our experiment is in some sense the opposite of these. The windfall income comes in the form of equity instead of cash and so the decision is to reduce risk instead of increase it.

4 Model and Data

We obtained our data set from the public blockchain records of Ethereum. A Node.js program was written that pulled data from APIs. In this way, we obtained information on all Ethereum addresses which interacted with the airdrop distributor contract prior to Oct 2021 (UTC). As the airdrop claim could be triggered by any address, we then created a list of actual airdrop recipients. Using this list, we were then able to examine these accounts' transaction history to see what they subsequently did with their UNI airdrop. To be precise, we obtained all logs of transfers of the UNI token involving the address in question and ran through them in chronological order until the recipient transferred away all their airdrop tokens or there were no more logs. We excluded recipients which had abnormally large numbers of transfers of UNI tokens (over 10000 transfers from or to the address - this was technically convenient), recipients which were actually smart contracts themselves, and recipients who unusually received and sent UNI in the same block. Importantly, we also collected data on how much Ether each account possessed at the time the airdrop contract was deployed, which marked the start of the airdrop but was before the official announcement.

Future research can build substantially on this work. Careful analysis of the blockchain will be able to pin down many of the variables we have used more precisely. For example, we can get a better measure of an account's net worth by looking at everything they own, not just Ether. We would be able to cleanly classify most transactions e.g. are you selling your UNI or just transferring it to your main account? We would also be able to expand the number of variables we have. By closely examining the blockchain, we would be able to construct a rich set of controls to perform regression analyses. We would also be able to identify accounts that likely belong to the same individual.

$$S_\tau = \alpha W + X\beta + \epsilon \tag{1}$$

1: Our Model

Given more data with a set of rich controls, we propose to use a linear probability model to analyze how the probability of selling the airdrop changes with net worth, where S is an indicator for having sold the entire airdrop within a certain time frame τ. We choose this binary outcome variable because the summary statistics show that when people did sell, mostly they sold the entire amount. X are controls, such as airdrop size, account activity, account age, type of account activity etc. W represents the log of our measure of the individual's net worth which will depend on the available data. For example, we could have the total value of the account's assets. α then represents the parameter of interest.

Of course, the net worth variable is likely to be endogenous for at least two different reasons. The first is that it may be correlated with unobservables that affect the probability of selling the airdrop. Perhaps more wealthy individuals are less impulsive on average so that these individuals would have a lower probability of selling the airdrop even if they weren't wealthy. The second is that we measure the individual's net worth imperfectly. Even if we had an accurate measure of the individual's crypto wealth, this is a noisy measure of their true total net worth. Moreover, this is what is called "nonclassical" measurement error where the error may be correlated with the level of the variable. For example, we can easily imagine this may be true in this situation. Perhaps wealthier individuals have a smaller fraction of their total wealth in crypto.

$$W = \kappa G + X\gamma + u \tag{2}$$

$$G = \frac{1}{N}\sum_{t}^{N} \frac{G_t}{G_{median}} \tag{3}$$

2: First Stage where t runs over all transactions in the one year period prior to the airdrop, N is the total amount of these transactions, G_t is the gas price of the transaction t, and G_{median} is the median gas price at the time of transaction t

To correct for these issues, we propose to use an Instrumental Variables approach, using a measure of the account's relative gas price preferences to instrument for net worth. For every transaction on Ethereum, one must set a gas price which is how much Ether one is willing to pay for one unit of computation (gas). The gas price fluctuates according to demand with supply mostly fixed. A higher gas price ensures that one's transaction will be officially included faster. We propose to construct an instrument that measures how the gas price set by that account compares to the median at the time for their transactions for a year before the airdrop. Of course we want our instrument to be exogenous so we will not use transactions after the airdrop. We limit the time frame to a year to account for the fact that net worth can change significantly over time (especially in crypto).

We argue that this instrument is valid. Certainly it seems likely that transaction confirmation speed is a normal good so that this instrument is relevant. On the other hand, it does not seem like a change in willingness to pay for faster transactions will affect the probability of selling the airdrop except through its correlation with net worth, so it satisfies the exclusion restriction. Similarly, it will be exogeneous. However, one could argue that it is not valid because it is correlated with impatience/impulsiveness. More impatient people will set higher gas prices and they will also be more likely to sell their airdrop quickly. Since we cannot observe impatience directly, our instrument is not valid. A potential solution to this is to attempt to construct a measure of impatience from blockchain data so that we can explicitly control for it.

This approach can solve the first endogeneity problem but will struggle with the second since the error is correlated with the true value of the variable. Two solutions come to mind. The first would be to obtain more data to link individuals with accounts and gain a relatively accurate measure of their net worth but this may be very difficult and would likely limit our sample significantly. The second would be to just interpret the net worth regressor differently. Our α is then the causal effect of an increase in the crypto net worth of an individual by 1 percent on the probability that they will sell their entire airdrop within a specified time frame τ multiplied by one hundred.

In terms of testing, we can perform a Hausman test to determine if the net worth regressor is endogenous, assuming our instrument is valid. We should also make sure our first stage is strong so that our instrument is not too weak. Since we only have one instrument, our model is just identified so we cannot perform an overidentifying Sargan test.

5 Empirical Results

We find a remarkably similar outcome as to the voucher privatization in the early post-Soviet years in Russia discussed in the literature review. Most airdrop recipients claimed very soon after the announcement and disposed of the tokens immediately. A small number of recipients accumulated more. If one of the goals of the airdrop was to decentralize the ownership of the protocol, it does not seem like it succeeded, merely serving as a wealth transfer. We also find some evidence that the airdrop was anticipated and Sybil attacked despite being one of the first. In addition, questions can be raised about whether the majority were truly behaving optimally, given that the price of UNI climbed steeply afterwards, reaching a high of over $40 USD just over half a year later. It seems unlikely that recipients would sell (at least not all of) their tokens if they knew for certain that the token would go up so much in less than a year. The likely suspects are poor information and risk aversion. Participants in the crypto market are notoriously uninformed - just see the number of scams and hyped projects that fizzle out. Especially for those poor living in developing countries, they may also be very risk averse when handed free assets that are volatile. The initial sum of money may have been extremely valuable for them already so they want it in fiat as soon as possible. Given the similarity between this outcome and the outcome of voucher privatization, we conjecture that in general individuals are very likely to sell when given assets for free.

Our data set consisted of 214 982 addresses with 6 having been dropped due to abnormally high numbers of UNI transfers. After excluding those who we mentioned we would exclude above, we had 211 305 left. About 22 000 addresses received additional UNI before selling their airdrop. (This includes those who did not sell at all). It is important to remember that UNI would go up 10 times in price less than eight months later. These accounts likely fall into one of two categories: they were either well-informed investors buying more tokens or they were aggregating airdrops from their other accounts. Consistent with this description, these accounts had significantly more Ether before the airdrop than the other accounts. The three quartiles for them was 0.0453, 0.331, 2.22 Ether while for the others, it was just 0.003, 0.0477, 0.373. (The price of Ether at this time was about $375 USD). A more sophisticated blockchain analysis would be able to distinguish these two cases. We then remove these addresses from our sample.

More than half (53.2%) of the remaining addresses transferred their UNI to another address which was not a contract (a so-called Externally Owned Account (EOA)). Only 11.5% of these transferred less than their total airdrop amount. There are two main explanations for this: either they sent their airdrop to a (centralized) exchange to sell or this was one of their many accounts and they were aggregating all their airdrops to a single main address. Again a more advanced blockchain analysis would be able to classify these well.

The most striking observation is that most airdrop recipients claimed very soon after the airdrop announcement and moved it (usually selling) immediately after. 25% claimed within ten hours, 50% claimed within nineteen hours and 75% claimed within two days. These times can also be considered too large by two hours since they count from the first claim which happened prior to the official announcement when the floodgates really opened! To illustrate how quickly individuals moved their airdrop, we determine how many "blocks" elapsed from the block the airdrop was claimed until the last time airdrop tokens were moved. For most, this was just the one transaction they made. Excluding those who never moved their UNI, 81% moved their entire airdrop at once. 25% finished transacting with their airdrop after only about 15 minutes. Half did so in an hour and 75% in about a day. The quartiles of the time that individuals finished transacting with their airdrop are what one might expect after these statistics. 25% finished ten hours after the airdrop announcement, half after a day, and 75% after ten days. Notably, the price of UNI had not yet risen to its post-airdrop local high of over $7 USD before half had already moved their tokens. In fact, it appears that it had just reached around $4 at that point, having stayed around $3 for most of the first day. So we see that even if the intent was to hold for a short period of time, many sold too early, missing out on the chance to double their airdrop value.

We also created a list of the top destination addresses for those moving their airdrops and manually identified the top ten addresses which were Decentralized Exchanges. We can then identify those as likely sales. However, this is not perfect because some of these transactions may have been providing liquidity to the exchange. Again a more detailed blockchain analysis would distinguish between these scenarios.

Conditioning on a recipient having sent some of their airdrop to one of these addresses (which represents 47% of our sample), we can examine these variables again. Only 72.5% moved their entire airdrop at once in contrast to before. This makes sense because those aggregating their airdrops or sending their airdrop onto a centralized exchange so they can sell more conveniently and without potentially high gas fees would send their entire airdrop, biasing our previous statistic upwards. Still, this is a significant fraction who took a move that seems unwise in retrospect, again given the incredible surge that would follow. In economic terms, we conjecture that a combination of flat transaction costs (a swap on Ethereum costs roughly the same gas regardless of amount) and decision-making simplicity led to most individuals choosing this "corner solution". However, note that a swap was only around $10-15 USD at this time.

The quartiles of time elapsed from claim to last transaction was also larger once we condition on this. The first quartile was still around 15 minutes while the median moved from an hour to ninety minutes and the third quartile was about 3 days from a day. The quartiles of the time accounts finished transacting was also increased. The first quartile shifted up by about an hour to eleven hours, the median shifted up by about eight hours to thirty two hours and the third quartile shifted significantly from ten days to three weeks. Still these represent a very short holding period and an obvious desire to exit the risky equity position they were entered into quickly.

In multiple areas of the data, there is a striking pattern where those accounts with very little Ether and a lot of Ether appear to be grouped together. In Figure 1, we see the log of the Ether balance plotted against the time the airdrop was claimed. We see a clear pattern where the accounts that claimed later than most had Ether balances closer to the middle. In Figure 2, we see the log of the Ether balance plotted against the number of failed claiming transactions from that account. Again we see a clear pattern where those with more errors tend to be in the middle of the distribution in terms of their Ether balance. In both cases, these variables are associated with less familiarity and awareness of crypto. Since these are characteristics of the individual controlling these accounts, it seems likely that many of these accounts with extremely low amounts of Ether are in fact owned by wealthy or at least well-informed people.

Along the same lines, Figure 3 shows a striking pattern. We plot the percent of airdrop moved against the log of the Ether balance of these accounts. We see multiple horizontal lines corresponding to multiples of 50 UNI as most received the minimum airdrop amount of 400 UNI. But what is most striking is that almost every account with a minuscule amount of Ether ("dust") proceeded to transfer the airdrop away. Figure 4 shows the same graph but only counting transfers to decentralized exchanges. This is similar but shows that many dust accounts did not transfer to decentralized exchanges.

This raises suspicions of anticipation and Sybil attacking the airdrop. Almost 36 000 airdrop recipients had an Ether balance of less than e^{-10} or about 1.7 US cents. It would've been immensely profitable to move some Ether into a new account, perform a swap on Uniswap, and then move the funds out. This would probably cost $20 USD or less and ten minutes per account while the airdrop was worth $1200 USD even at launch and only rose from there. Clearly, someone executing this scheme would want to leave only minimal Ether in each address to lower the cost of carrying it out, though it is not immediately clear why they would leave any. A more sophisticated blockchain analysis would be able to determine with a higher degree of certainty exactly how much Sybil attacking took place. Obviously, protocols do not want their airdrops to be exploited in this way.

6 Conclusion

To conclude, we have looked at the Uniswap airdrop and what followed, which represented a very interesting natural experiment. What we have seen suggests that even though they have only grown in popularity since then, airdrops may not be an efficient way to grow the protocol and put it in a position to ultimately succeed. In a striking parallel to the experience of "voucher privatization" in the early post-Soviet years in Russia, recipients are easily exploited by the relatively wealthy and well-informed, selling their airdrop almost immediately for dirt-cheap. The airdrop then amounts to a small wealth transfer to prior users. Not only that but airdrops incentivize people to pose as many different people to obtain more than their fair share of those wealth transfers which is even more undesirable.

As for consumer behaviour, we have proposed a model to investigate how people differentially react to the airdrop based on their net worth, though there are some hurdles that need to be tackled to conduct the analysis. We have conjectured that consumers sell at unfavourable prices because of information asymmetries and risk aversion and that this phenomenon is in fact characteristic of such a scenario where consumers are given free equity. An interesting place this could be investigated is with Robinhood data, as they have had an offer where they gift new users free stock, though the value is generally quite a bit smaller. As for the decision of consumers to sell the totality of their airdrop instead of some smaller portion, we conjecture that flat transaction costs and decision-making simplicity may have contributed to most choosing to do so. All in all, though it may not have been as successful as the Uniswap team may have hoped, the Uniswap airdrop was undoubtedly a very interesting experiment, both in crypto and in economics, and points to the abundant potential research that can be done with airdrops and crypto in general.

7 References

Appel, Hilary. 1997. "Voucher Privatisation in Russia: Structural Consequences and Mass Response in the Second Period of Reform." Europe-Asia Studies 49 (8): 1433–49. https://doi.org/10.1080/09668139708412508.

Briggs, Joseph, David Cesarini, Erik Lindqvist, and Robert Östling. 2021. "Windfall Gains and Stock Market Participation." Journal of Financial Economics 139 (1): 57–83. https://doi.org/10.1016/j.jfineco.2020.07.014.

Hsu, Yuan-Lin, and Edward H Chow. 2013. "The House Money Effect on Investment Risk Taking: Evidence from Taiwan." Pacific-Basin Finance Journal 21 (1): 1102–15. https://doi.org/10.1016/j.pacfin.2012.08.005.

Jappelli, Tullio, and Luigi Pistaferri. 2010. "The Consumption Response to Income Changes." Annual Review of Economics 2 (1): 479–506. https://doi.org/10.1146/annurev.economics.050708.142933.

8 Figures

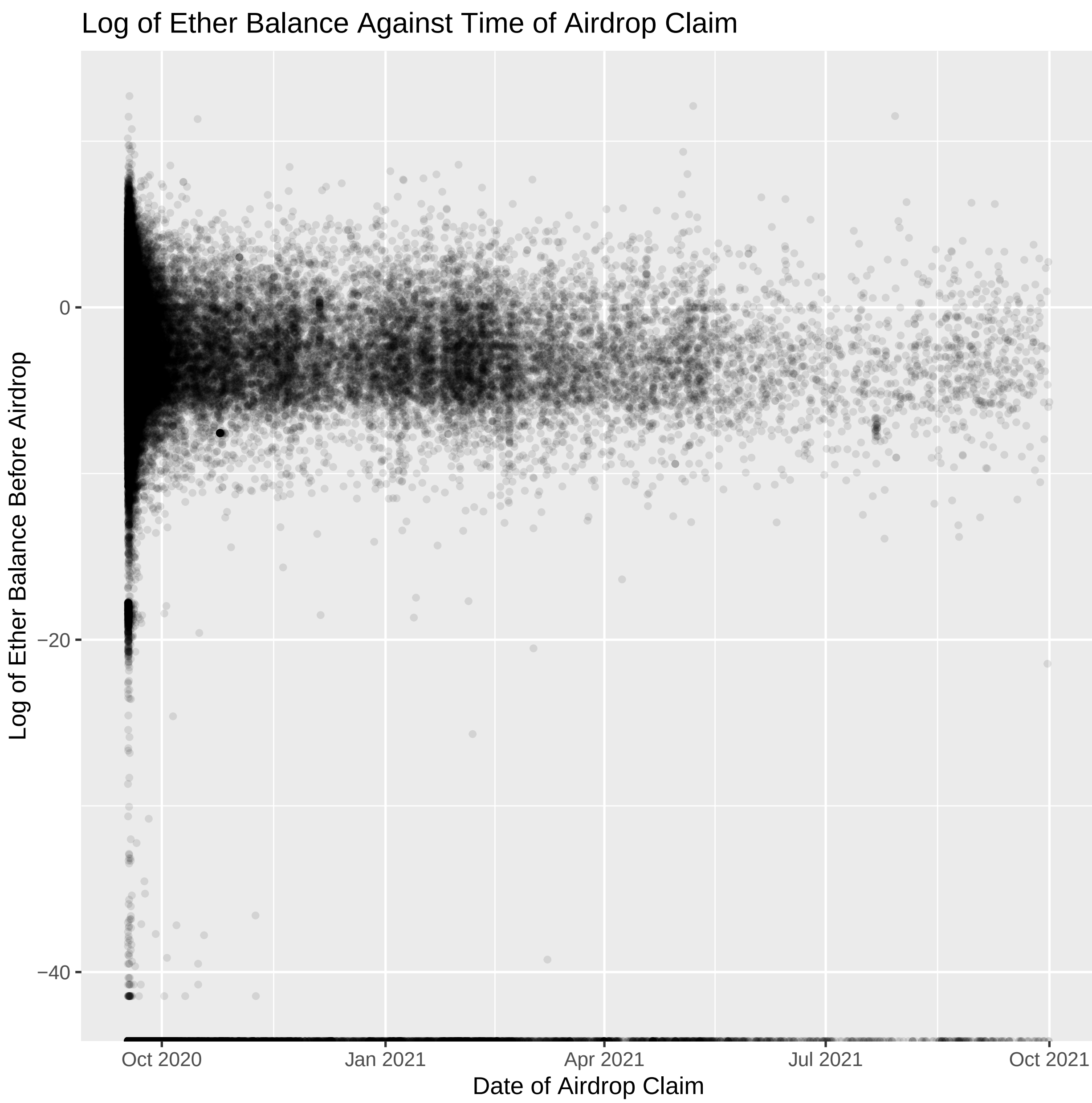


Figure 1

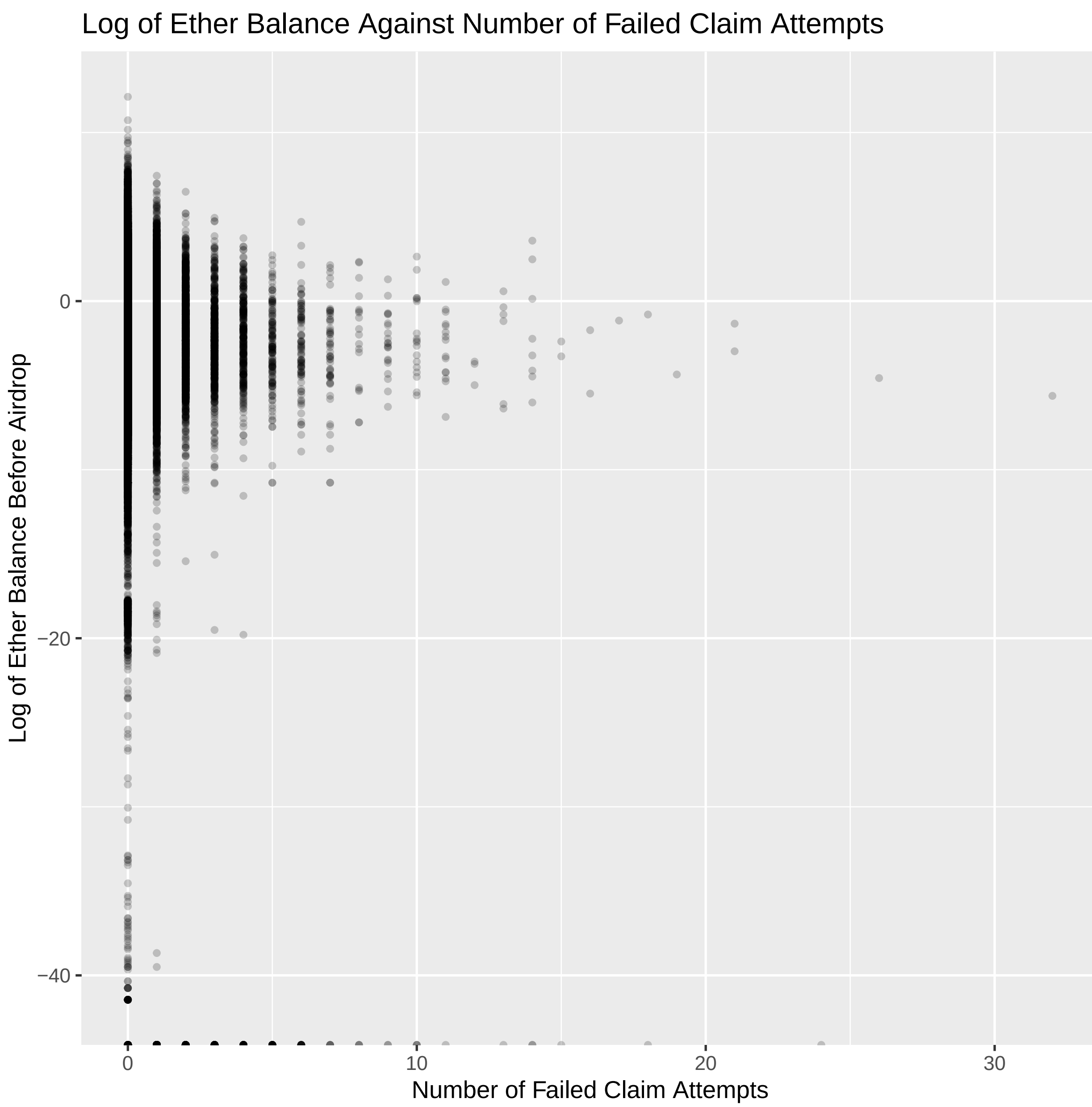

Log of Ether Balance Against Number of Failed Claim Attempts
Log of Ether Balance Before Airdrop
0
−20
−40
0
10
20
30
Number of Failed Claim Attempts

Figure 2

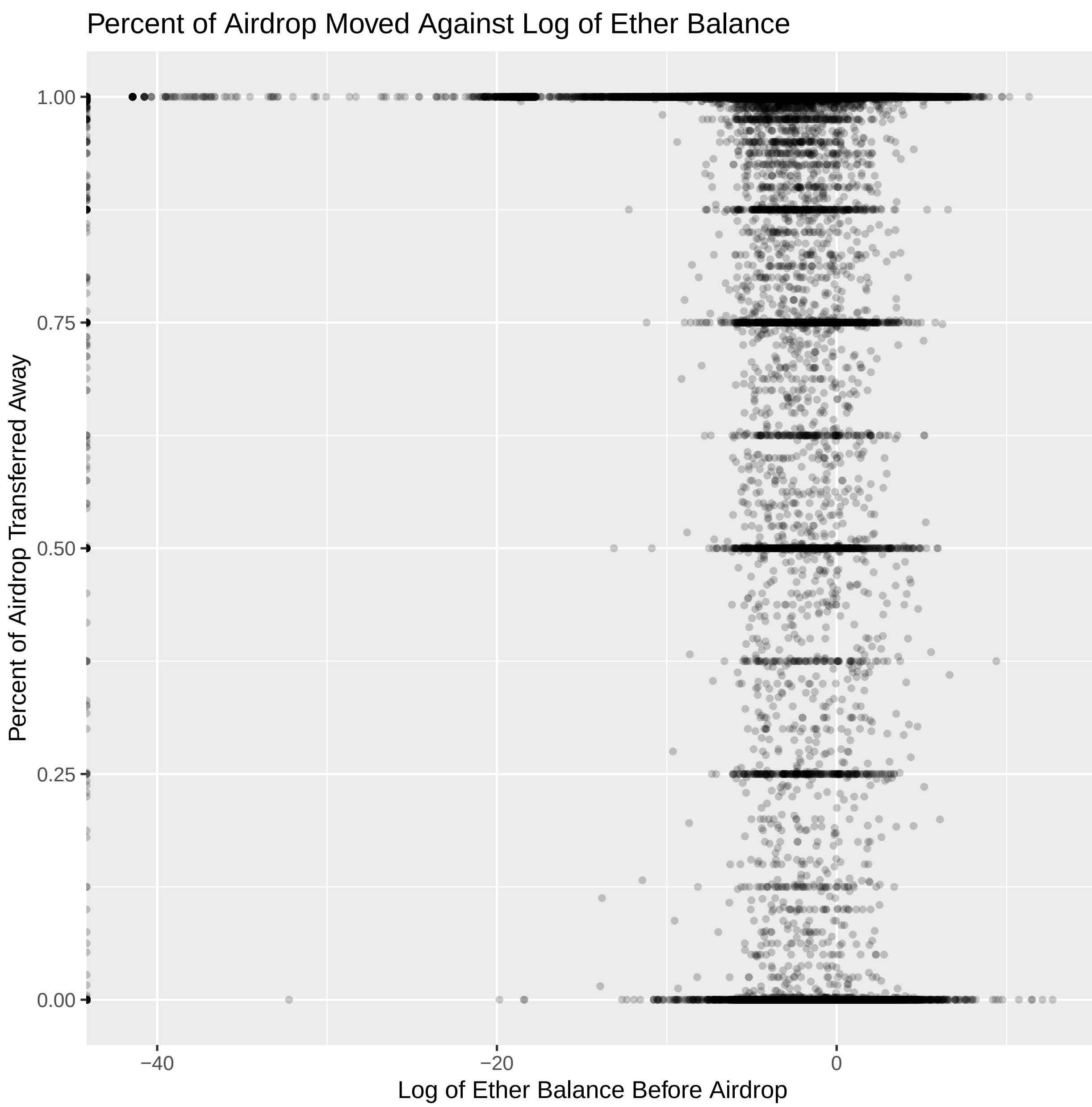
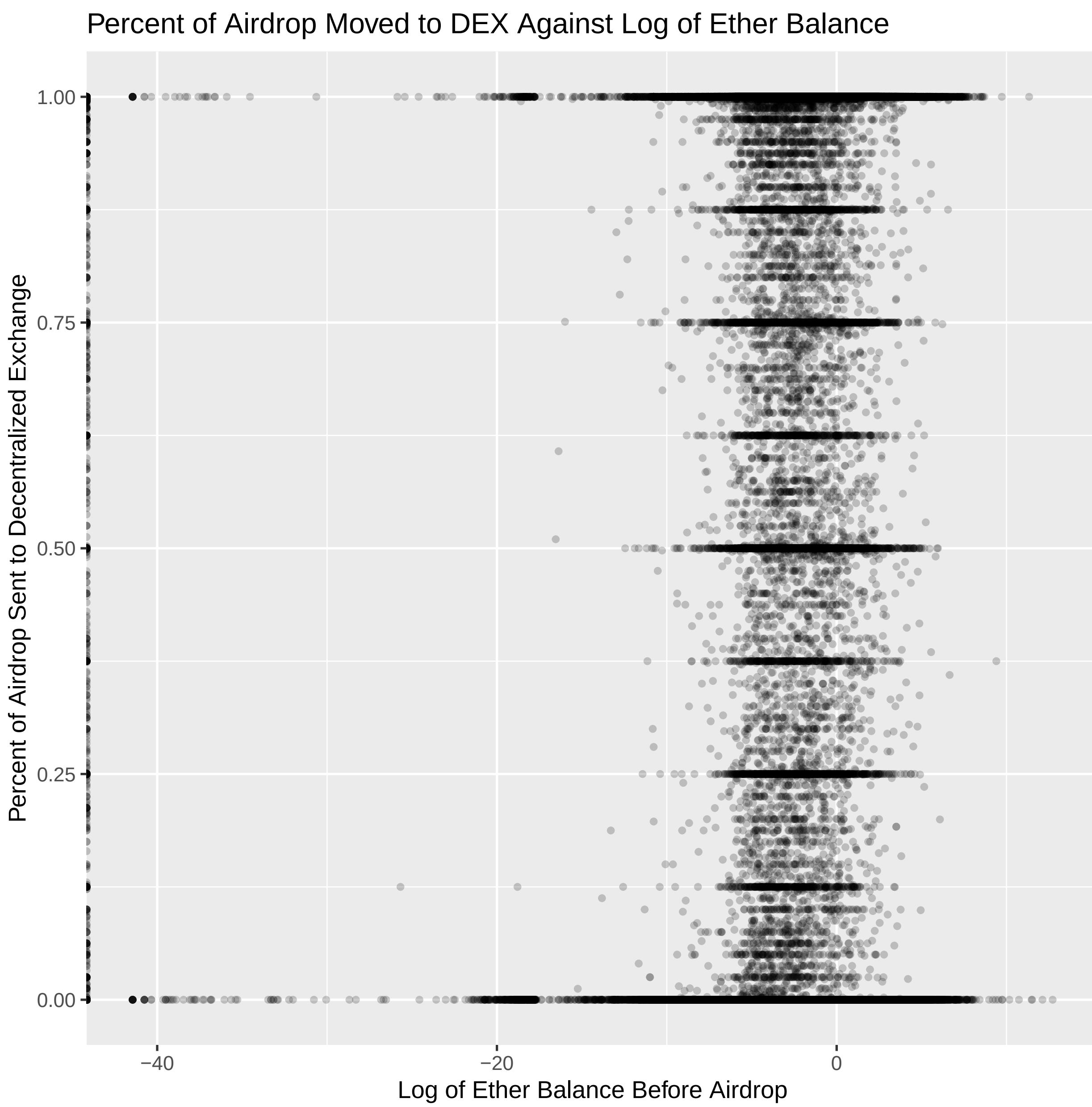

Percent of Airdrop Moved Against Log of Ether Balance
Percent of Airdrop Transferred Away
1.00
0.75
0.50
0.25
0.00
−40
−20
0
Log of Ether Balance Before Airdrop

Figure 3



Percent of Airdrop Moved to DEX Against Log of Ether Balance
Percent of Airdrop Sent to Decentralized Exchange
1.00
0.75
0.50
0.25
0.00
−40
−20
0
Log of Ether Balance Before Airdrop

Figure 4

9 R Code

```
library("jsonlite")
library("janitor")
library("dplyr")
library(ggplot2)
options(digits=18)

data <- fromJSON(txt="C:/Users/Jeffrey/Desktop/ECO1400/Paper/data.json
    ")
data <- as.data.frame(data)
data <- row_to_names(dat=data,row_number=1)
data <- clean_names(data)
data$claim_block_number <- strtoi(data$claim_block_number)
data$airdrop_amount <- as.double(data$airdrop_amount)
data$claim_tx_index <- strtoi(data$claim_tx_index)
data$claimer_recipient <- data$claimer_recipient == "TRUE"
data$recipient_eoa <- data$recipient_eoa == "TRUE"
data$ether_balance <- as.double(data$ether_balance)
data$other_uni_received <- data$other_uni_received == "TRUE"
data$both_transfer_and_received_in_a_single_block <-
    data$both_transfer_and_received_in_a_single_block == "TRUE"
data$transferred_to_eoa <- data$transferred_to_eoa == "TRUE"
data$completely_sold_in_one_transaction <-
    data$completely_sold_in_one_transaction == "TRUE"
data$completely_sold <- data$completely_sold == "TRUE"
data$total_uni_sold <- as.double(data$total_uni_sold)
data$number_of_sales <- as.numeric(data$number_of_sales)
data$number_of_transfers_away <- as.numeric(
    data$number_of_transfers_away)
data$number_of_transfers_received <- as.numeric(
    data$number_of_transfers_received)
data$index_of_transfers_away <- as.numeric(data$index_of_transfers_away
    )
data$index_of_transfers_received <- as.numeric(
    data$index_of_transfers_received)
data$block_number_of_last_sale <- as.numeric(
    data$block_number_of_last_sale)
data$claim_timestamp <- as.numeric(data$claim_timestamp)
```

```r
data$claim_nonce <- as.numeric(data$claim_nonce)
data$claim_gas_price <- as.numeric(data$claim_gas_price)
data$claim_error <- as.numeric(data$claim_error)
data$number_of_claim_errors <- as.numeric(data$number_of_claim_errors)
data$amount_transferred_to_eo_as <- as.double(
   data$amount_transferred_to_eo_as)
data$amount_swapped <- as.double(data$amount_swapped)
data$date <- as.POSIXct(data$claim_timestamp,origin="1970-01-01",tz="
   UCT")
data$delta <- data$block_number_of_last_sale - data$claim_block_number
data$percent_sold <- data$total_uni_sold / data$airdrop_amount
data$percent_swapped <- data$amount_swapped / data$airdrop_amount

summary(data$recipient_eoa)
summary(data$both_transfer_and_received_in_a_single_block)

data$percent_eoa <- data$amount_transferred_to_eo_as /
   data$airdrop_amount

filtered <- filter(data,recipient_eoa &
                       !both_transfer_and_received_in_a_single_block)

summary(filtered$other_uni_received)
summary(subset(filtered,other_uni_received,select=ether_balance))
summary(subset(filtered,!other_uni_received,select=ether_balance))

filtered <- filter(filtered,!other_uni_received)
same_claim <- filter(filtered, claimer_recipient)

summary(filtered$transferred_to_eoa)

summary(subset(filtered,transferred_to_eoa,select=percent_eoa))
summary(filtered$percent_eoa > 0 & filtered$percent_eoa < 1)

summary(filtered$claim_block_number)

sold <- filter(filtered, block_number_of_last_sale > 0)
summary(sold$completely_sold_in_one_transaction)
summary(sold$delta)
```

```
summary(sold$block_number_of_last_sale)

swapped <- filter(filtered, amount_swapped > 0)
summary(swapped$completely_sold_in_one_transaction)
summary(swapped$delta)
summary(swapped$block_number_of_last_sale)

summary(subset(filtered,log(ether_balance) < -10))

pdf('eth_percent.pdf')
ggplot(filtered,aes(x=log(ether_balance),y=percent_sold)) + geom_point(
    size=1,alpha=1/5) +
  labs(x = "Log of Ether Balance Before Airdrop",
       y = "Percent of Airdrop Transferred Away",
       title = "Percent of Airdrop Moved Against Log of Ether Balance")
dev.off()

pdf('eth_percent_swapped.pdf')
ggplot(filtered,aes(x=log(ether_balance),y=percent_swapped)) +
    geom_point(size=1,alpha=1/5) +
  labs(x = "Log of Ether Balance Before Airdrop",
       y = "Percent of Airdrop Sent to Decentralized Exchange",
       title = "Percent of Airdrop Moved to DEX Against Log of Ether
          Balance")
dev.off()

pdf('eth_time.pdf')
ggplot(filtered,aes(x=date,y=log(ether_balance))) + geom_point(size=1,
    alpha=1/10) +
labs(x = "Date of Airdrop Claim") +
labs(y = "Log of Ether Balance Before Airdrop") +
labs(title = "Log of Ether Balance Against Time of Airdrop Claim")
dev.off()

pdf('eth_error.pdf')
ggplot(same_claim,aes(x=number_of_claim_errors,y=log(ether_balance))) +
     geom_point(size=1,alpha=1/5) +
  labs(x = "Number of Failed Claim Attempts",
       y = "Log of Ether Balance Before Airdrop",
```

```
        title = "Log of Ether Balance Against Number of Failed Claim
            Attempts")
dev.off()
```