The Rise and Fall of Cryptocurrencies

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Abstract

Since Bitcoin's introduction in 2009, interest in cryptocurrencies has soared. One manifestation of this interest has been the explosion of newly created coins. This paper examines the dynamics of coin creation, competition and destruction in the cryptocurrency industry. In order to conduct the analysis, we develop a methodology to identify peaks in prices and trade volume, as well as when coins are abandoned and subsequently "resurrected". We study trading activity associated with 1 082 coins over a nearly five-year period. We present evidence that the more frequently traded coins experience the biggest price rises. They are also much less likely to be abandoned, that is, to experience a drop in average trading volume to below 1% of a prior peak value. Overall, we find that 44% of publicly-traded coins are abandoned, at least temporarily. 71% of abandoned coins are later resurrected, leaving 18% of coins to fail permanently. We then examine the association between entry and exit and other key variables such as price, volume, and market capitalization in order to analyze and provide intuition underpinning the fundamentals in this market. We conclude by examining the bursting of the Bitcoin bubble in December 2017. Unlike the end of the 2013 bubble, some alternative cryptocurrencies continue to flourish after the fall of Bitcoin.

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1 Introduction

Over the past three years, the market capitalization for cryptocurrencies has exploded: soaring from $12 Billion in February 2014 all the way up to $414 Billion in February 2018. Furthermore, the number of coins has increased ten fold in the same period.

In this paper, we analyze the dynamics of this burgeoning industry. Here, we restrict our attention to coins, that is, entities with their own distributed ledger. We do not consider tokens, which are entities built on top of coins.

We develop a methodology in order to define volume peaks, price peaks, coin abandonment, and coin "resurrections." We then examine the association between entry and exit and other key variables such as price, volume, and market capitalization in order to analyze and provide intuition underpinning the fundamentals in this market. Importantly, we also examine the after-effects of two periods in which bitcoin prices rose steeply and then fell steeply.

Our main results are as follows:

- We find that 44% of publicly traded coins are subsequently abandoned, 18% permanently. Furthermore, 85% of announced coins fail before being traded publicly.
- Most coins are not traded much, and these coins are more likely to be abandoned than their larger counterparts.
- Several of the indicators we examine suggest that many of the entrants and resurrected coins are riding "the wave" created by the huge increase in the cryptocurrency market.
- We analyze two Bitcoin price bubbles and identify the effects on the other coins. Following the bursting of the 2014 bubble, other major cryptocurrencies fell by more than Bitcoin did. Following the recent bubble, many of the popular cryptocurrencies including leaders like Ethereum and Ripple (as well as others) fell only slightly. This may represent a potentially game-changing period, in which other cryptocurrencies challenge Bitcoin's leadership.

It is important to examine the dynamics in the cryptocurrency industry, in addition to the meteoric growth. One reason why is that the potential for fraud in such an unregulated marketplace is significant, from actors deliberately manipulating prices to their own benefit to hucksters creating new coins promising benefits that deceive investors. This is not merely a theoretical risk. Gandal et al. have shown that the massive rise in the bitcoin price in 2013 from approximately $150 to more than $1 000 in one three month period was likely due to price manipulation in the market [14]. At the beginning of 2014, the "bubble" burst and the price of bitcoin fell dramatically.

The price of bitcoin has exploded again in 2017, jumping from approximately $1 000 in early 2017 to more than $19 000 in December 2017 and back down to $7 000 at the time of writing (early February 2018). The percent increase in 2017 (approximately 1 900 percent) is even greater than the percent increase that bitcoin experienced during 2013 (approximately 500 percent). Concern abounds that price manipulation exists in this industry today [22]—.

Another reason to study the market dynamics is because Bitcoin's dominance of the industry is being challenged by other coins. Currently Bitcoin has 35 percent of the market, while Ethereum has 20 percent and Ripple has another 10 percent. Ethereum has been able to challenge Bitcoin based on its extensibility – 19 of the top 20 tokens are built on top of Ethereum. Ripple, created by the same creator as the now-defunct Bitcoin exchange, Mt. Gox, has been able to attract over 100 banks as well as Western Union to its platform [21]. This is a stark comparison to the earlier days of Bitcoin: from its inception through 2016, Bitcoin had more than 90 percent of the market.

2 Background

History of the Cryptocurrency Market Bitcoin (BTC), the first cryptocurrency, was founded in 2009. While the market took off slowly, a massive spike in the price of bitcoin in late 2013 led to wider interest in what had been until then a niche industry. The value of Bitcoin increased from around \$150 in mid 2013 to over \$1 000 in late 2013. The fall was dramatic as well and by 2016, one bitcoin was worth approximately \$200. Despite the bursting of the bubble, cryptocurrencies were on the map and massive entry (as well as non-trivial exit) has occurred in the industry during the last four years.

While Bitcoin dominated the market through most of the 2009-2016 period, in 2013, a few other cryptocurrencies competed with Bitcoin. These coins began appreciating much more quickly than Bitcoin during the price rise.

Gandal and Halaburda analyzed how network effects affected competition in the cryptocurrency market during the price spike and subsequent fall in the price of bitcoin [13] in . Their analysis suggests that there were strong network effects and winner-take-all dynamics following the fall in the price of bitcoin in early 2014. From July 2014 to February 2016, bitcoin's value was essentially constant against the USD, while the other currencies depreciated dramatically against the USD. Litecoin, the number two coin in the market, declined by 70% in value, while other "main" coins declined by more than 90% in value. In early 2016, Bitcoin accounted for 94% of the total market capitalization, while Litecoin (the number two cryptocurrency) accounted for 2%. Despite its shortcomings, Bitcoin had emerged at that point as the clear winner and beneficiary of network effects.

In 2017, things changed dramatically. Bitcoin began rising again and by early 2017, the value of bitcoin was again more than \$1 000. It had taken more than three years for the value of bitcoin to return to the 2013 peak level, but that was only the beginning.

The market capitalization of cryptocurrency grew stunningly in the past few years. In February 2014, the market capitalization of all cryptocurrencies was approximately \$14 Billion. As of February 2018, the total market capitalization was approximately \$414 Billion. That is more than a ten-fold increase. Currently, there are more than 300 cryptocurrencies with market capitalization between \$1 Million and \$100 Million. In January 2014, there were less than 30 coins with market capitalization between \$1 million and \$100 million. This has raised concerns of price manipulation.

Related Work Our paper straddles two literatures. The first is an economics literature on emerging industries. A common theme in the theoretical literature on the topic is that both "learning by doing" (supply side) and "learning by using" (demand side) play a key role in the evolution of new industries.[1] There is also a theoretical literature on the dynamics in industries with network effects. See Gandal for a selective review [12].

In addition to the theoretical literature, there is also a large empirical literature in Economics on the dynamics of entry and exit.[2] One particular focus in this literature is on the post-entry performance of firms. These studies typically examine the entry and exit rates over time, the number of firms in the industry over time, the survival rate of new firms, and the evolution of firm size over time.[3] One particularly robust finding in this literature is that entry into new markets generally occurs in waves. This seems to be the case in the cryptocurrency industry as well, as we show in our analysis. The empirical literature in economics has also examined and measured the strength of network effects. A key question is whether first-mover advantages and large networks can be overcome by improvements in quality by late entrants. Our analysis suggests that quality advantages of later entrants may eventually overcome bitcoin's first-mover advantages in the cryptocurrency market.

Our paper also adds to a nascent literature on cryptocurrencies and the financial sector.[4] Within the finance literature, there is growing interest in discovering what drives a "valueless" currency. Li and Wang investigate the bitcoin exchange rate in an effort to expand our understanding of the motivation behind the rise and fall of cryptocurrency values [19]. Corbet et al. expanded upon that, finding that shocks to traditional financial assets did not affect cryptocurrencies [10]. However the shocks to the price of the three cryptocurrencies they studied (Bitcoin, Ripple, and Litecoin) did affect each other. Xie et al. analyze the effects of social activity on the Bitcoin forum on the price of Bitcoin [26]. They find that during periods of time when users are highly connected, the price of Bitcoin is highly likely to rise. Bolt and van Oordt build a theoretical model to examine the exchange rate of virtual currencies [9]. Additionally, Hayes constructs a model for determining the value of a "bitcoin-like" cryptocurrency by calculating its cost of production.

There are others that have researched the altcoin and initial coin offering (ICO) ecosystem. Huang et al. looked at the profitability of mining alternative cryptocurrencies [17]. They compare potential profits earned by mining a currency or speculating on the same currency and claim that miners can earn more and that mining is less risky. Adhami et al. looked at token sales [1]. They took a survey of ICOs and found that most of the token sales were successful and that the secondary market was quite liquid. Amsden and Schweizer studied features that caused tokens to trade on currency exchanges [3], finding that features like quality token operators increased the likelihood of trading. Krafft et al. did an experimental study of 271 "penny cryptocurrencies" (similar to penny stocks) using the currency exchange, Cryptsy [18]. They found that when their bots bought a "penny cryptocurrency," the result was a two percentage point increase in buying activity from others. Bian et al. designed a system to identify scam ICOs by analyzing their whitepapers, websites, and other aspects of tokens [6]. Bacina and Kassra analyzed token sales through the lens of Australian law [5]. They divided tokens into three categories: "protocol tokens," "asset-backed tokens,"

[1]Rob developed a theoretical model that shows that under uncertainty regarding the size of the market, entry will occur in waves [23]. Vettas obtained similar results in an extension of the Rob model to a setting with uncertainty on both sides of the market [25].

[2]For a good summary of early work, see the Audretsch and Mataon the post-entry performance of firms [4].

[3]See Geroski and the references cited within for a survey of the literature [15].

[4]For an in-depth overview of how the Bitcoin ecosystem works, see Böhme et al. [7].

and “access tokens.” In our analysis, we only consider coins, that is, entities with their own distributed ledger. In the terminology of Bacina and Kassra, we are examining protocol tokens. These value of these entities are based on their trading value, and are not tied to any asset or any network. This focus makes sense, since we are interested in competition between coins in the cryptocurrency industry.

Finally, this work is relevant to literature in cybersecurity and finance investigating fraud. Currently, cryptocurrency markets are largely unregulated. As such, they are highly susceptible to price manipulation: by small scale traders, such as Krafft et al. trading penny cryptocurrencies [18], by wayward insiders, such as the bots run by the operators of the Mt. Gox exchange [14], or by hucksters running Ponzi schemes [24]. Financially motivated actors have been shown to manipulate over-the-counter stock markets [2] and use email spam to tout pump-and-dump stock schemes [8, 11, 16]. Also, we analyze currency abandonment, analogous to the Bitcoin exchange closures that have wreaked havoc on the ecosystem [20]. Note that in this work, we do not try to investigate the motives behind the market dynamics and identify fraudulent activity. Rather, we expect that our contribution of characterizing peaks, abandonments, and the overall dynamics of the market might spur further investigations in this vein.

3 Methodology

We first describe the data sources used to investigate cryptocurrencies. Next, we describe how we identify peaks in trading volume and price, as well as when coins are abandoned and resurrected.

Data Sources To examine the dynamics in the cryptocurrency industry, we gather publicly available data on coins from `coinmarketcap.com`. The website lists all cryptocurrencies that reports pricing and 24-hour trading volume via a public API.[5] Such transparent and easy-to-achieve criteria has enabled the website to become the most comprehensive public repository of cryptocurrency trading information. The available data for each cryptocurrency includes daily summary values for the open, high, low, and close prices, trading volume, exchanges, and market capitalization. All monetary values reported by `coninmarketcap.com` are given in USD. We collected data on 1 082 currencies on 2018-02-07, which yielded 662 837 daily observations, starting from February 2013 up to February 2018. This is, of course, an unbalanced panel.

Because currencies appearing on `coinmarketcap.com` are already being traded, this data excludes coins that have been announced but not yet traded. We also want to identify when coins fail prior to public launch, so we gather supplemental data from the altcoin announcements forum on `bitcointalk.org`. We crawl the forum and consider all announcements which had the term “coin” in them and did not reference a token platform such as Bitcoin, Waves, or Ethereum. We also throw out posts referring to coins that appear on the token section of coinmarketcap. We semi-automatically parse out the name of the coin and consider the timestamp of the first post for a given coin as the announcement date.

[5]This is true as long as at least one such API reports positive trade volume.

Identifying Peaks, Abandonments, and Resurrections In order to say something about exits, we need to identify peaks in volume. This is because trade in marginal cryptocurrencies can be dormant for many months only to increase again when investment surges in the industry. We are also interested in identifying price peaks since they indicate the potential profits or losses that may result from trading.

We begin by identifying "candidate" price and volume peaks for each cryptocurrency. We define a candidate peak as a day in which the 7-day rolling average value is greater than any value 30 days before or after. In order to identify only those peaks with sudden jumps in value, we define a candidate as a peak that satisfies two additional criteria:

- The candidate peak value must be greater than or equal 50% of the minimum value in the 30 days prior to the candidate peak.
- The candidate peak value must be at least 5% as large as the currency's maximum peak.

We then use our resulting peak data to define cryptocurrency abandonment. We compare each of the peak values to all of the succeeding daily volume values for each cryptocurrency. We define abandonment as follows:

- If the daily average volume for a given month is less than or equal to 1% of the peak volume, the currency is considered *abandoned*.

Unlike other industries, where exit is a "one-way road," currencies don't necessarily stay "dead" when they are abandoned. If the average daily trading volume for a month following a peak is greater than ten percent of the peak value and that currency is currently abandoned, then its status changes to *resurrected*.

Two examples of currency abandonment and then resurrection are shown in Figure 1. VeriCoin was established in mid-2014, reached an early peak volume of $1.5 million, but then was promptly abandoned within a few months. Nearly two years later, in mid-2016, volume jumped slightly, but to less than 10% of the prior peak value. Then, in the spring of 2017, the currency was resurrected, eventually reaching a trading volume more than 15 times greater than its first peak volume of $1.6 million.

MaxCoin began trading in early 2014 and quickly reached a peak volume of $2.7 million before becoming abandoned less than four months later. The cryptocurrency was resurrected during the 2017 period of massive growth before once again becoming abandoned in October of 2017. During this period peak trading volume did not reach its initial peak value, however, it came close at $1.8 million at its highest point. The last abandonment of the currency appears to be a permanent abandonment as it has not yet been resurrected in 2018.

4 Results

In Section 4.1, we discuss summary measures of peaks, abandonment and resurrection. We then analyze market dynamics in Section 4.2, including how coin creation and abandonment is correlated with Bitcoin's popularity. In Section 4.3, we compare the bursting of two bubbles in cryptocurrency prices – and show that first-mover advantages appear to have declined over time.

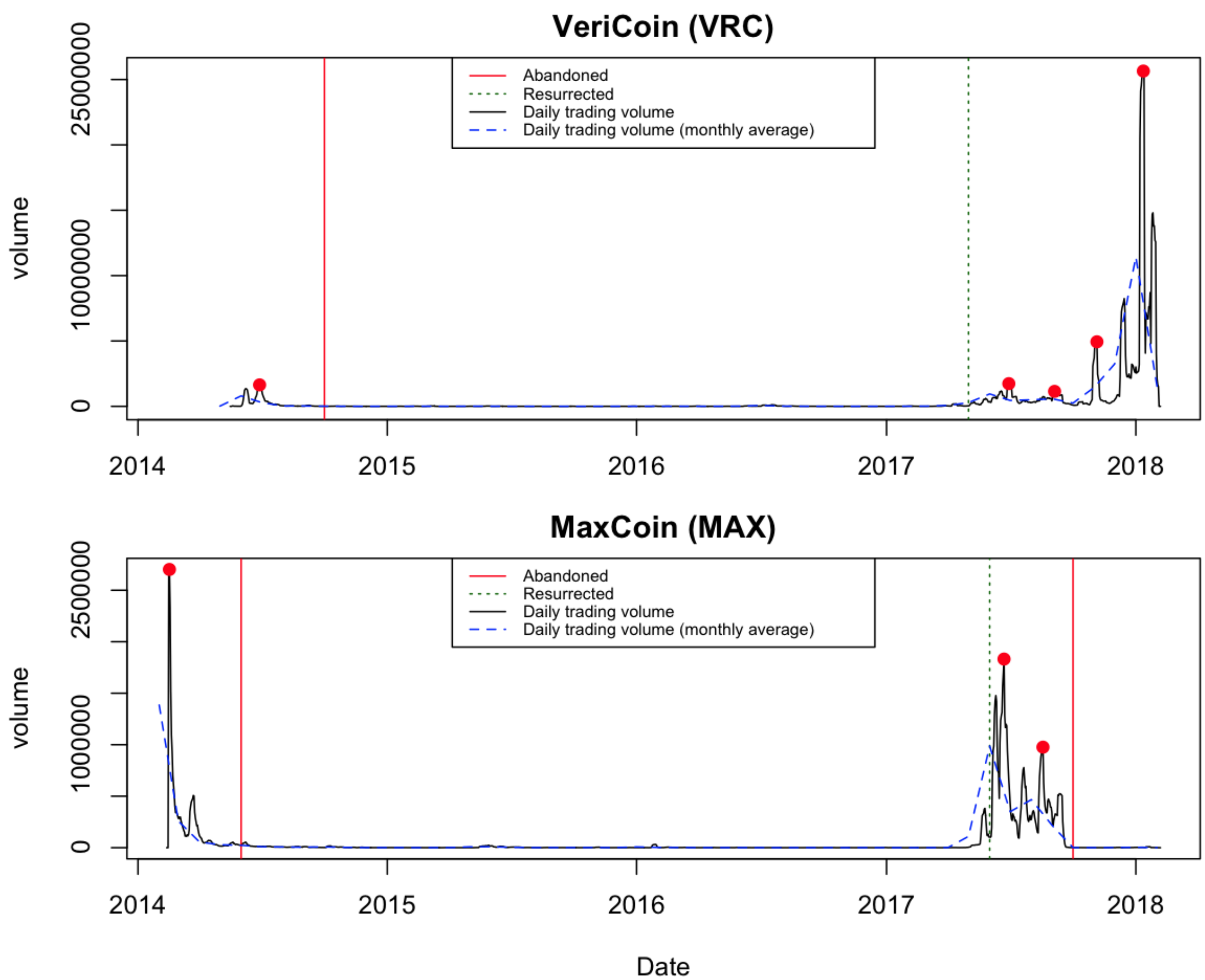

Figure 1: Volume plot showing currency abandonment. Red dots indicate peaks.

4.1 Peaks, Abandonment and Resurrection

Peaks Nearly all currencies had at least one price and volume peak. 1 068 (out of 1 082 total) currencies had price peaks, yielding a total of 3 508 peaks across all currencies. Furthermore, 1 076 (out of 1 082 total) currencies experienced volume peaks, yielding a total 3 828 total peaks across all currencies.

In a constantly-expanding environment with more than 1 000 coins, it is no surprise that only a small number attract large numbers of transactions, while many never catch on. In order to study characteristics of the entire ecosystem while recognizing vast differences in popularity, we binned the coins into different size groups based on total transaction volume.

Table 1 reports summary statistics on many key measures reported throughout this section, listing both overall measures and figures split by these size groups. In the first row, we can see that just 57 coins report total transaction volume exceeding \$1 billion. Most coins are much less popular: 374 have traded less than \$1 million total, while another 344 have traded between \$1–\$10 million. In other words, two thirds of coins report less than \$10 million in total trading volume.

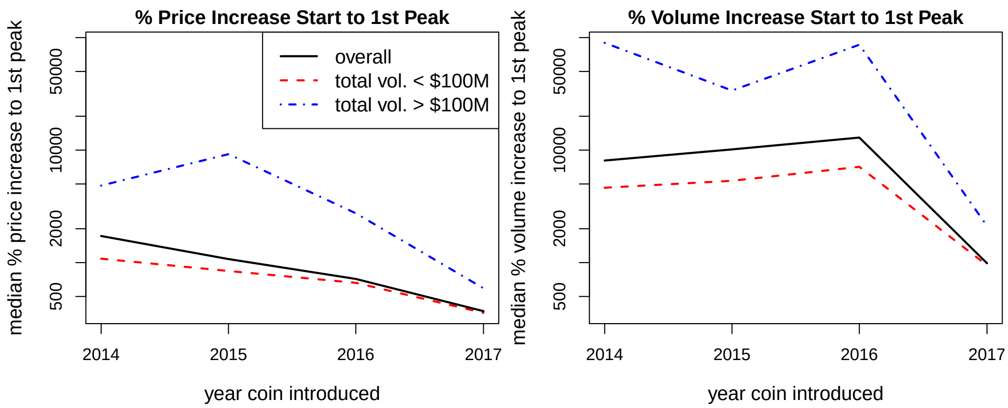

Figure 2: Percentage price and volume increase from a coin's launch to first peak, based on the year in which the coin is launched and its size. (Note: the vertical axis is logarithmic.)

Unsurprisingly, these smaller coins account for the majority of observed price and volume peaks, as indicated in the table. However, the number of volume and price peaks per coin is quite consistent regardless of coin size. The median number of price and volume peaks is each 3, and this number varies only between 2 and 4 for each size category.

What more can we say about these peaks? The first peak after launching is important because it represents what early backers of coins stand to gain by getting behind the coins before the general public can participate. The median time to the first peak in trade volume is just 40 days, and the median increase in trade volume from the first trading day to the first peak is 3 714%. For price peaks, the median jump in price from a coin's launch to the first peak is 749%. This means that half of coin backers see at least a seven-fold rise in price by the time the first peak is reached.

Breaking down the initial price and volume peaks by coin size is quite telling. Smaller coins experience a much smaller price and volume rise than larger coins. For coins under $1 million total trade volume, the median price jump is "only" 418%. For the 57 coins with eventual trading volume of more than $1 bilion, the median price rise for the first peak is 3 441%! The median jumps in volume are even more extreme, with a 90 530% rise for the biggest coins compared to 917% for the smallest coins. We of course recognize that the biggest coins are more likely to also be the ones with the bigger jumps, these figures do quantify just how extreme these differences are. It also points to the possibility that investors may be attracted to coins experiencing bigger initial increases.

Figure 2 examines the relationship between when a coin is launched and the magnitude of the initial peak after launch. The left graph plots the median percent price rise based on the coin's launch year. Overall, coins launched in 2015 enjoyed a median initial price jump of over 1 700%. This fell steadily, to 1 075% in 2015 and 370% for coins launched in 2017. Coins with higher transaction volume fared even better, with the median initial price rise peaking at over 9 000% in 2016.

The initial volume jumps shown in Figure 2 (right) show a slightly different story. Median percentage jumps for the first volume peak were consistently higher than for prices, but stayed relatively level for coins launched in 2014–16. The median initial volume rise fell sharply in 2017, however. Taken together, these figures indicate that jumps in trading volume are very

	overall	<$1M	$1–10M	$10–100M	$100M-1B	>$1B
# coins	1 082	374	344	183	124	57
# price peaks (total)	3 508	1 426	1 022	531	376	153
# price peaks (median)	3	4	3	2	3	3
% price increase 1st peak (median)	749	418	583	999	1 936	3 441
# volume peaks (total)	3 828	1 734	1 064	468	406	156
# volume peaks (median)	3	4	2	2	3	3
% volume increase 1st peak (median)	3 714	917	1 561	6 915	24 992	90 530
# coins abandoned	475	239	154	50	32	0
% coins abandoned	44	64	45	27	26	0
# abandonments	642	347	192	62	41	0
days abandoned (median)	182	153	184	242	426	—
# coins resurrected	336	183	103	25	25	—
% coins resurrected	71	38	27	13	19	—
# resurrections	452	261	135	30	26	—
months to resurrection (median)	6	5	6	10	19	—
# coins permanently abandoned	190	86	57	32	15	0
% coins permanently abandoned	18	23	17	17	12	0

Table 1: Summary statistics on coin peaks, abandonment and resurrection, broken down by total trading volume per coin.

high, while initial price peaks have moderated somewhat.

We now more closely examine the distribution of the size of both the rise and fall surrounding all peaks. Recall from our definition that a peak must be at least 50% of the minimum value of the 30 days prior to the peak. We now consider just how big those rises tend to be, as well as the magnitude of the resulting fall after the peak.

Figure 3 (top left) plots the 10th to 90th percentiles of the peak's percent price increase relative to the smallest price in the month prior.[6] The percentiles are further divided by coin size. For example, we can see that the median price rise during peaks ranges from 200 to 300%. While this is lower than those reported for the initial price rise in Table 1, this can be attributed to the fact that here we are computing the rise over just 30 days prior to the peak. The top 10% of price rises range from 1 100% for coins traded between $100M-$1B to nearly 3 000% for coins with $1-10M in trading volume. In fact, this trend is consistent

[6]For this analysis we exclude any price or volume rises from peaks occurring in the first week of a coin's operation, as well as any falls within the last week of its operation. This is to deal with edge effects from the 7-day rolling average used to compute peaks.

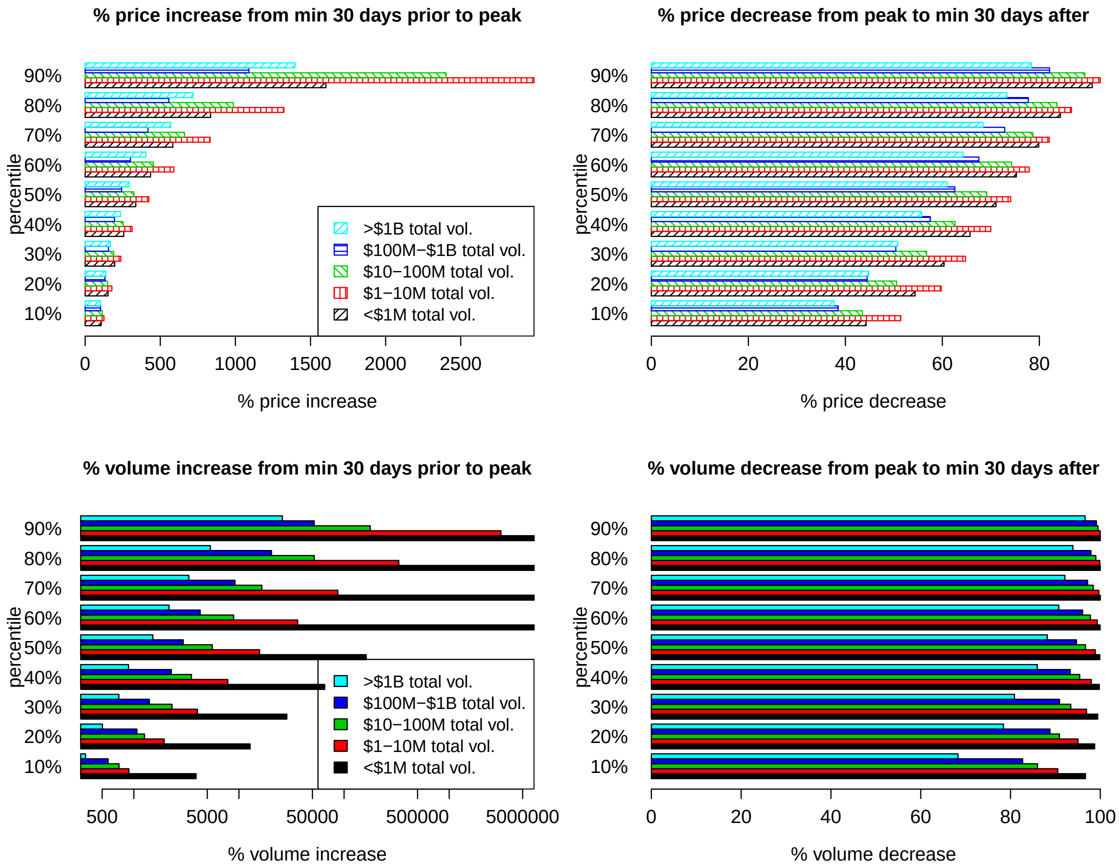

Figure 3: Deciles of percent price and volume rises from the smallest value in the month prior to a peak to the peak itself (left graphs); deciles of percent price and volume falls from the peak to the smallest value in the month following the peak (right graphs).

throughout, with the second-smallest category rising fastest and the second-largest category rising slowest.

Figure 3 (top right), meanwhile, examines what happens after the peak. Since by definition the price must go down during the entire 30 days following the peak, we can quantify just how far prices fall. While there are differences across coin size (smaller coins fall farther), the most striking result is just how deep the falls are across the board. 9 out of 10 coins lose at least 40–50% of their value in the month following a peak. Half lose at least 60-75%. Even 10% of the biggest coins lose around 80% of their value within a month of reaching a peak.

The bottom two graphs in Figure 3 look at the distribution of the rises associated with peaks in trading volume. The bottom left graph clearly indicates that smaller currencies experience consistently bigger percentage increases in trading volume around peaks. This is unsurprising, given the lower starting base of trading volume in these smaller coins. Nonetheless the percentage increases are quite staggering. Note that the graph uses a logarithmic scale. The median volume jump ranges from around 1 500% for the most frequently traded coins to more than 100 times that for the coins with the lowest trading volume. For the coins with less than $1 million in total trading volume, more than 30% of the time, there

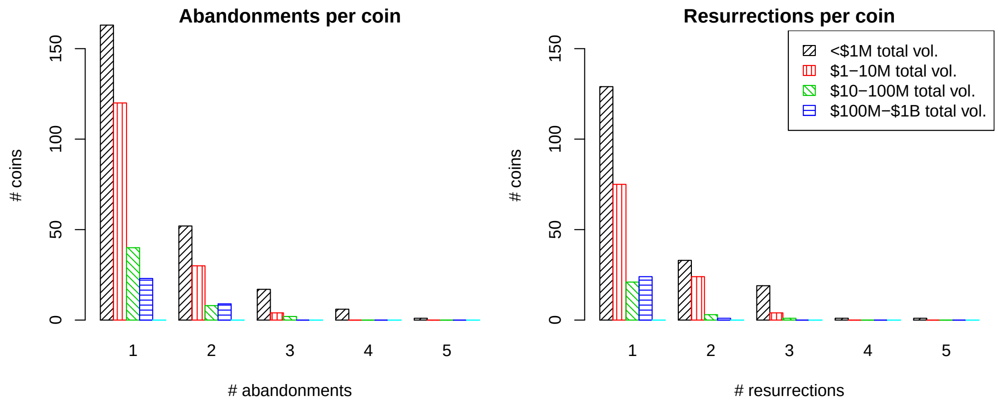

Figure 4: Abandonments (left) and resurrections (right) per coin, split by total trading volume.

were days with zero trading within a month of hitting a new peak volume level.

Finally, the decrease in volume after a peak is extreme. For all but the biggest coins, trading volume regularly falls more than 90% in the month following a peak.

Abandonment and Resurrection Despite huge price and volume rises, interest in many coins is not sustained. As shown in Table 1, we found that 475 cryptocurrencies, or 44% of all coins listed on `coinmarketcap.com`, were abandoned at least once according to our definition of average daily trading volume falling below 1% of the coin's peak level in a given month. Of those 475 coins, 336 were "resurrected", that is, a previously abandoned currency's average daily trading volume rises to 10% of a prior peak value.

There were a total of 642 cases of currencies being abandoned and 452 resurrections. That is, some currencies were abandoned or resurrected more than once. Figure 4 shows the number of abandonments (left) and resurrections (right) per coin based on trading volume. Most coins are abandoned just once, but a few are abandoned more often. Most multiple resurrections occur with smaller coins.

A coin's total trading volume is associated with its potential for abandonment. As shown in Table 1, 65% of coins with less than $1 million trading volume are subsequently abandoned, compared to just 26% for those coins with trading volume between $100 million and $1 billion. Notably, no coins with total trading volume in excess of $1 billion have been abandoned. Similar trends follow for resurrection. Lower-volume coins are more likely to be resurrected than higher-volume ones.

On average, abandoned coins disappear within 7.5 months of reaching their first peak (4 month median). So when coins fail, it can happen quickly. Resurrection takes a bit longer, with a 6 month median overall. In addition to being less likely to resurrect, higher volume coins take longer to do so. The median time to resurrection for coins with more than $100 million in trading volume is 19 months.

For a closer look at the time to abandonment and resurrection, we compute survival probabilities using Kaplan Meier estimators, as shown in Figure 5. This enables us to empirically estimate the time from launch to abandonment using the duration of all coins, even those that have not been abandoned. Overall, the median time to abandonment for coins is 547

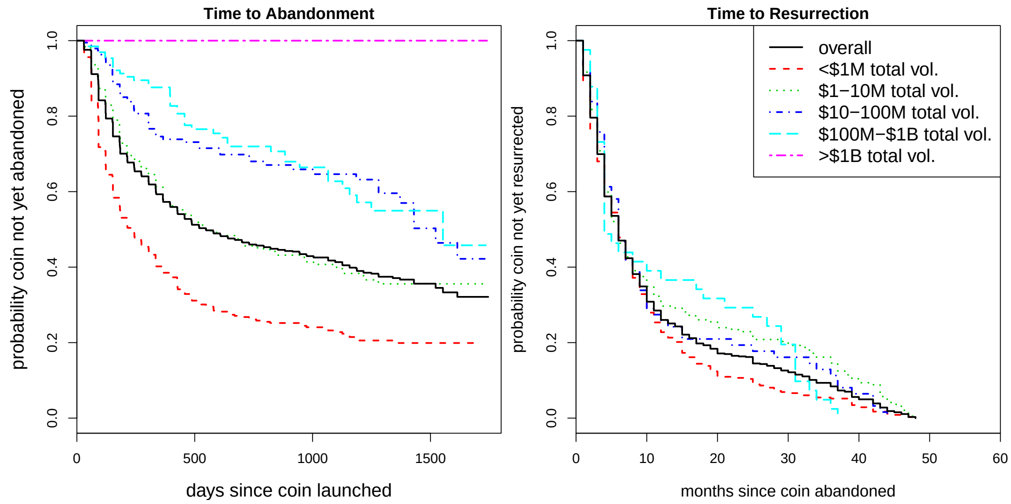

Figure 5: Survival probabilities for the time to abandonment (left) and time to resurrection (right).

days. The time to abandonment varies considerably with the coin's total trading volume. For lightly-traded coins under $1 million, the median time from launch to abandonment is just 242 days. By contrast, for coins traded between $100 million and $1 billion, the median time to abandonment is 1 249 days, or around 3.5 years. Note, once again, that no coins with trading volume in excess of $1 billion have been abandoned.

The right graph in Figure 5 shows the estimated time to resurrection. A few trends are apparent. First, the time to resurrection is shorter than the time to abandonment. Overall, the median time from abandonment to resurrection is 6 months. While there is variation between coin sizes, these differences are smaller in magnitude and not statistically significant.

Ultimately, 190 coins (18% of all coins on `coinmarketcap.com`) remain abandoned at the end of our inspection period. This 18% permanent abandonment rate understates considerably the true rate of failure. This is because some cryptocurrencies fail to list themselves on an exchange after they first launch. This can happen for a variety of reasons, ranging from purposely operating as a short-lived scam to not having the resources to put the coin together as the founders intended.

After crawling 12 794 posts on bitcointalk, we find 2 361 different cryptocurrencies announced on the altcoin announcements section from January 2014 through September 2017. Of these currencies, only 346 later appeared on `coinmarketcap.com`. While 18% of listed currencies later become permanently abandoned, a whopping 85% of announced currencies on bitcointalk fail before ever becoming publicly traded. Figure 6 shows this trend over time. Many new currencies were introduced on the Bitcoin forums during 2014, however most never made it to be publicly traded. Note that in 2014, it was easy to create your own alternative currency using the now-defunct `coingen.io`. This service, which was less than $100, created clones of Bitcoin's code with a few changed parameters. However, as many of these currencies failed to trade publicly, this fad died off.

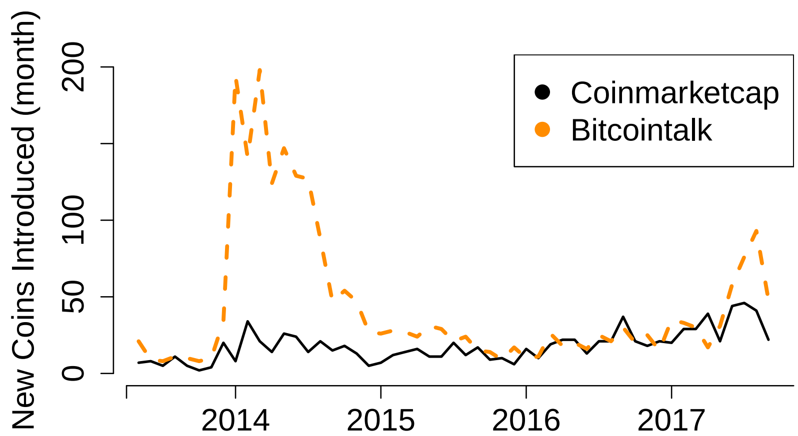

Figure 6: New currencies announced on the Bitcoin Forums each month (orange) compared to new currencies traded each month (black).

4.2 Relationships between Key Variables

During 2017 the combined market cap of all cryptocurrencies increased very significantly due to the meteoric rise in the prices of virtually all cryptocurrencies, as shown in Figure 7. During this meteoric rise, others have tried profiting off the increased interest in cryptocurrencies by issuing their own coins. Some improved existing protocol's deficiencies as they saw them (such as the Turing-complete Ethereum and the anonymous ZCash), while others simply tried to "ride the wave" of its success, providing an entrance to the ecosystem. This has led to an explosion of new currencies being minted. Furthermore, interest in altcoins (as measured by coin price and trading volume) also fluctuates with broader interest in Bitcoin.

This trend picks up when there is a significant increase in the price of Bitcoin and other major cryptocurrencies. This is most visible during the price hike of bitcoin at the end of 2013, when it reached more than $1 000. When prices went back down, the pace of coins being added and invested in went down with it. The same is true for the bull market in 2017 which continues until Bitcoin's peak of more than $19,000 in December 2017: prices, trading volume and the rate of new coins increased substantially.

Figure 8 plots the number (top) and proportion (bottom) of active coins (i.e., those not abandoned) that experience a price or volume peak each month over time. Unsurprisingly, the graph shows significant correlation between the number of price and volume peaks. In any given month between 2014 and 2016, 10–20% of coins reported a peak in volume or price. In 2017, the trend accelerated significantly, with 60% of coins reaching a peak in June 2017, and over 90% of coins peaking in January 2018.

The relationships between bitcoin price, coin creation, abandonment and resurrection are visible in Figure 9. Using the heuristics we develop on coin abandonment and resurrection, we examine market dynamics in this ecosystem.

Intuitively, during a period of rapid price hikes, more competing currencies are being minted. Benefiting from traders' exuberance, they enter circulation in noticeable volumes.

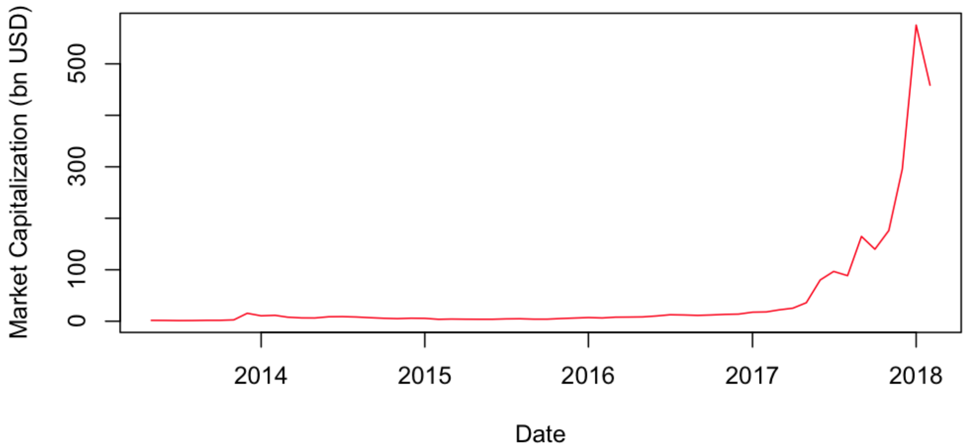

Figure 7: Average monthly market capitalization of all cryptocurrencies traded (in Billions of dollars).

However, when markets calm and prices fall, some currencies are abandoned.

Taking this to the data, we would expect the share of altcoins being abandoned would lag the trend in prices. Well-established currencies such as Bitcoin might endure the volatility of cryptocurrency markets (and indeed we have found that no currencies with more than $1 billion in trading volume has been abandoned). However, a new currency which doesn't yet have a substantial number of users holding it will likely suffer from the network effects that push activity towards bigger, more widely accepted, cryptocurrencies. This might lead to an increase in the number of coins entering the market as well as the number of coins being abandoned.

What do the data actually show? The top graph in Figure 9 illustrates the churn, with the number of newly introduced and abandoned coins per month. In early 2014, many coins were introduced, followed by a spike in abandonments later that year. The rate of both introduction and abandonment stayed relatively constant in 2015 and early 2016, before rising markedly in 2017. The next graph looks at resurrection and the daily transaction volume over time. Here, there is a fairly strong correlation: rates of resurrection are flat through 2015, slowly picking up in 2016 before accelerating rapidly in early and late 2017. As more people trade cryptocurrencies, it makes sense that more people would seek an opportunity to invest in previously abandoned coins.

The next two graphs in Figure 9 show how the rate of introduction and abandonment impact the overall number of coin offerings over time. The solid black line in the third graph plots the number of coins currently active in a given month, while the dashed line plots the number of presently abandoned coins in a given month. The trend shows a steadily increasing number of active coins, and a lesser number of abandoned coins with a spike in late 2017. To see the impact of the spike, look at the next graph plotting the fraction of coins each month that are currently abandoned. In early 2015, nearly 40% of coins were marked as abandoned. That proportion has steadily declined in the time since, with considerable fluctuation. By January 2018, following 2017's build-up of interest in cryptocurrencies, only around 20% of coins were still abandoned.

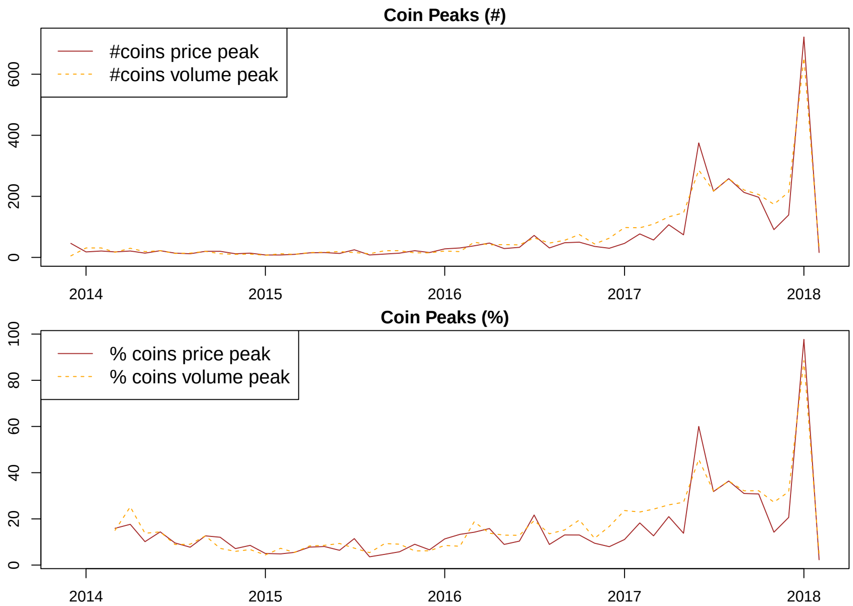

Figure 8: Number (top) and percentage of active (bottom) coins experiencing price and volume peaks over time.

The last graph plots the BTC-USD price on a logarithmic scale. Notably, spikes in activity in the graphs above frequently coincide with peaks in the BTC-USD price.

	# Coins Abandoned	# Coins Resurrected	# Coins Created	Trade Volume	log_{10}(Average BTC Price)	# Price Peaks	# Volume Peaks
# Abandoned	1						
# Resurrected	0.2080	1					
# Created	0.6107	0.3858	1				
Trade Volume	0.0695	0.7512	0.0959	1			
log_{10}(Average BTC Price)	0.5321	0.7078	0.5053	0.7996	1		
# Price Peaks	0.2756	0.8504	0.4515	0.6524	0.6798	1	
# Volume Peaks	0.3795	0.9007	0.5013	0.7072	0.7756	0.9721	1

Table 2: Monthly correlations between key variables in the ecosystem.

To dig a bit deeper, in Table 2 we provide correlations between the key variables in the ecosystem using our monthly data. These correlations reveal two key trends in the market.

- As expected, resurrection is highly correlated with the number of price and volume peaks (0.85 and 0.90 respectively). This suggests that many of the resurrected coins are riding “the wave” created by the huge increase in the cryptocurrency market. Additionally, trade volume (0.75) and the log-transformed BTC-USD price (0.71) are both positively correlated with resurrection (0.75)[7].

[7]See Figure 9 for a graphic representation of the latter correlation.

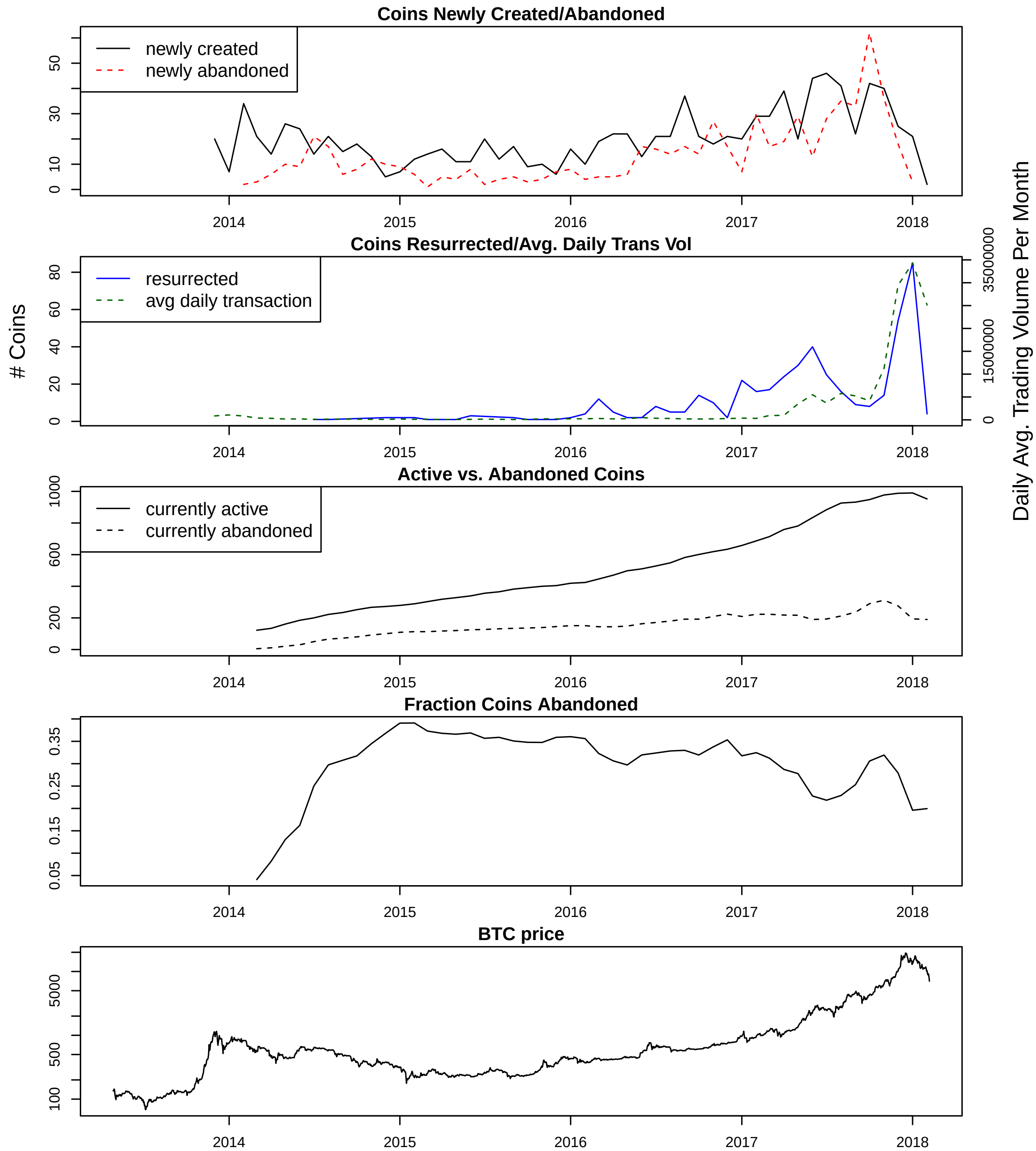

Figure 9: Cryptocurrency summary statistics including abandonment, resurrection, creation, and daily average trading volume.

- There is a high positive correlation (0.61) between the number of coins abandoned and the number of new coins created, suggesting that new coins are created to fill gaps left by coin abandonment. Thus, despite the general upward trend in prices, volume, there appears to be some competition between coins. This also suggests that there is substitutability among some of the coins. Thus, it is not the case that a "rising tide" is lifting all cryptocurrencies.

Figure 9 illustrates these effects visually. The top plot shows that coin abandonment and creation have similar trends over time. The second from the top plot shows the coin resurrection trend. We can see that coins start to be resurrected after there are sufficient dead coins. After that point, resurrection tracks the rest of the other trend lines. What seems to explain all of the currency trends is shown on the bottom plot – the bitcoin/USD trading price over time. Bitcoin is the market leader and still sets the trend for all of the other coins. This is supported by the relatively high correlation values among all variables and the log transformed BTC-USD price.

4.3 Bursting of bubbles and the changing of the guard

During the steep decline is Bitcoin prices in 2014, Gandal and Halaburda found that the trading prices of other cryptocurrencies fell when the price of Bitcoin fell [13]. Particularly, when Bitcoin fell from \$1 151 on December 4, 2013 to \$448 on April 30, 2014, Litecoin, the second most popular cryptocurrency at the time, fell from to \$44.73 to \$10.90. While the drop in Bitcoin was steep (-61%), Litecoin fell by 76%. From April 2014 through February 2016, the price of Bitcoin stayed virtually constant (it fell by 2%), while the prices of all the other top cryptocurrencies declined significantly in USD, with the declines ranging between 69% and 94%.

In the recent rise and fall of Bitcoin, the currency reached a peak value of \$19 498 on December 17, 2017. In the fifty-two days following the peak (to February 6, 2018), Bitcoin declined to \$6 955, which is a decline of 64%. In the 52 days preceding the peak, Bitcoin rose from \$5 905 to \$19 498.

Unlike the previous "rise and fall" at the end of 2013/beginning of 2014, other currencies behaved differently. Ethereum, for example, did not fall at all during the period in which Bitcoin fell by 64 percent. Similarly, Ripple fell by just 6%.

Some currencies declined steeply, similar to the same magnitude as Bitcoin. As Table 3 shows, of the top 14 coins, eight (including Bitcoin) declined steeply after Bitcoin's peak. Three coins declined slightly. In addition to Ripple, and Ethereum, Cardana declined by less than 20%. Two coins in the top-10, NEO and XLM, continued to rise even after the Bitcoin peak.

This is very different behavior compared to early 2014. In large part, this appears to be due to innovations by late entrant cryptocurrencies, which has led to a changing playing field. The changes show that Bitcoin's network effect and first-mover advantage may not be able to compensate for the fact that Ripple and Ethereum's platform have built complementary products onto the platform. Ethereum, for example, has applications outside of simply financial transactions, something that Bitcoin does not really have.

Furthermore, Ethereum used its own token, Ether, to create a decentralized marketplace for computing power and other services. Ripple focuses on sending global payments quickly (a few seconds per transaction) and cheaply.

These two platforms have cut deeply into Bitcoin's market share. At the beginning of 2017, Bitcoin's market share was above 80%. As of early February 2018, Bitcoin's share of the total cryptocurrency market had fallen to just 34 percent. Ethereum's market share is now 20 percent, while Ripples market cap is now 10 percent. And it is not just Ethereum and Ripple who are challenging Bitcoin: many other late entrant cryptocurrencies are creating

	Percent change during each time period			Percent change in 12/17 bubble		
Coin	10/16 - 10/17	10/16-12/17	10/16-2/18	52 days prior	52 days following	all 104 days
Bitcoin (BTC)	774	2 861	972	239	**-64**	23
Ethereum (ETH)	2 519	6 018	6 119	134	**2**	137
Ripple (XRP)	2 201	8 389	7 837	269	**-6**	245
Bitcoin Cash (BCH)				446	**-51**	168
Cardano (ADA)				1 311	**-14**	1 108
Litecoin (LTC)	1 344	7 618	3 161	434	**-58**	126
NEO (NEO)	20 887	36 554	61 853	75	**69**	195
Stellar (XLM)	1 395	9 852	14 181	566	**43**	855
NEM (XEM)	5 162	16 692	11 564	219	**-31**	122
IOTA (MIOTA)				723	**-59**	234
Dash (DASH)	2 978	10 704	4 737	251	**-55**	57
Monero (XMR)	1 348	5 287	2 870	272	**-45**	105
Lisk (LSK)	2 686	5 553	8 075	103	**45**	193
Ethereum Classic (ETC)	941	3 310	1 542	227	**-52**	58
Qtum (QTUM)				174	**-28**	96
Bitcoin Gold (BTG)				117	**-71**	-38
Nano (XRB)				2 079	**269**	7 947
Zcash (ZEC)				117	**-35**	41
Steem (STEEM)	470	1 106	1 803	111	**58**	234
Bytecoin (BCN)	2 402	6 566	6 139	166	**-6**	149
Verge (XVG)	20 215	160 350	166 215	690	**4**	719
Siacoin (SC)	761	2 792	3 948	236	**40**	370
Stratis (STRAT)	12 465	26 702	15 328	113	**-42**	23
BitShares (BTS)	1 072	9 959	4 398	758	**-55**	284
Waves (WAVES)	948	3 673	1 179	260	**-66**	22
Dogecoin (DOGE)	382	2 602	1 518	461	**-40**	236
Decred (DCR)	3 941	9 609	6 779	140	**-29**	70
Hshare (HSR)				130	**-64**	-17
Ardor (ARDR)	1 518	7 350	2 908	360	**-60**	86
Komodo (KMD)				138	**-27**	74
Ark (ARK)				94	**-36**	24
DigiByte (DGB)	2 673	9 210	7 869	236	**-14**	187
PIVX (PIVX)	96 865	196 640	133 964	103	**-32**	38
ZClassic (ZCL)				137	**1 683**	4 134
Bitcore (BTX)				136	**1**	137
Syscoin (SYS)	2 451	5 217	4 165	108	**-20**	67
GXShares (GXS)				156	**-16**	116
MonaCoin (MONA)	12 268	44 501	10 345	261	**-77**	-16
Factom (FCT)	491	1 110	724	105	**-32**	39
ZCoin (XZC)	259	1 677	1 092	395	**-33**	232
ReddCoin (RDD)	2 152	5 824	10 889	163	**86**	388
Nxt (NXT)	747	9 446	2 075	1 027	**-77**	157
Neblio (NEBL)				-18	**110**	72
Vertcoin (VTC)	8 140	22 740	6 100	177	**-73**	-25
DigitalNote (XDN)	569	2 078	5 549	226	**159**	745
ZenCash (ZEN)				34	**-10**	20
Achain (ACT)				376	**-14**	307
Asch (XAS)				58	**-35**	4
Einsteinium (EMC2)	4 919	135 317	19 688	2 598	**-85**	294
Metaverse ETP (ETP)				-16	**-64**	-70
LBRY Credits (LBC)	223	783	527	174	**-29**	94
BitConnect (BCC)				122	**-99**	-98
Voxels (VOX)	73	1 484	486	814	**-63**	238
Steem Dollars (SBD)	9	1 069	198	972	**-75**	173
Elastic (XEL)				50	**-45**	-18
Rise (RISE)	4854	13 004	2 816	165	**-78**	-41
ATBCoin (ATB)				-44	**-58**	-76
Internet of People (IOP)				120	**-65**	-24
Regalcoin (REC)				-74	**-97**	-99
ATMCoin (ATMC)				0	**27**	27
Tezos (Pre-Launch) (XTZ)				237		
SegWit2x (B2X)				-80	**-96**	-99
InfChain (INF)				172	**-59**	12

Table 3: Currency movement during different influential time periods.

platforms for the exchange of digital goods. We may be indeed witnessing a changing of the guard.

4.4 Further analysis of the "returns" top 80 coins

We then examined in more detail the returns from the top 80 coins (in terms of trading volume) produced during the following three (52 day) periods, where returns are measured price changes in percentage terms.[8]

- Period I: From October 26, 2017 – Dec 17, 2017 (December 17 was Bitcoin's peak)
- Period II: From Dec 17, 2017 – Feb 6, 2018
- Period III: From Feb 6, 2018 – March 31, 2018

In period one (the euphoric period), we find that the median return was 174%. Nevertheless, during this period, 25% of the top 80 coins lost 18% or more. On the flip side, 25% of the coins earned a median return greater than 376%. The variance of the returns was extremely large. The highest return during this period was 2 600 percent! Bitcoin itself rose from $5,748 to $19,475.

In period two, when Bitcoin declined significantly (from its peak to $7 051), the median return was -32% and more than 75% of the coins had declines in value. Further, 25% of the coins lost more than 60% of their value. Nevertheless, 10% of the coins increased in value by 58% or more. The variance of the returns was an order of magnitude smaller than period one. The highest return during this period was 1 683%.

In period three, when Bitcoin remained virtually unchanged, the median return was -36%. More than 75% of the coins declined in value. 25% of the coins lost more than 60% of their value. More than 95% of the valuations fell. The variance was two orders of magnitude smaller than the variance in the second period. The highest return during this period was "only" 17%.

There is virtually no correlation between period I and period II returns, while the correlation between periods II and III is -0.41. This suggests that those coins that did not decline in the second period did so in the third period, and vice versa.

Total volume and market capitalization of the coins (as of May 15, 2018) are uncorrelated with first and second period returns. Total volume and market capitalization are, however, positively correlated with third period returns.

When we split these 80 coins into two groups (large trade volume vs. small trade volume and large market capitalization vs. small market capitalization), we find the following: the correlation between period III returns and volume/market cap is much higher for the more important coins, i.e., those with higher trading volume and market capitalization. The analysis suggests that investors/speculators became somewhat more selective in the third period.

[8]We chose 52 day periods in order to have three periods to analyze: the rise, the fall, and the aftermath.

5 Conclusion

In this paper, we provided a preliminary analysis of the dynamics in the cryptocurrency market. We have devised methods to identify peaks in trading volume and prices for over 1 000 coins. We find that lower-volume coins face greater risk of abandonment, but they are also more likely to rise again. We find that many of the entrants and resurrected coins are riding "the wave" created by the huge increase in the cryptocurrency market. Nevertheless, the high correlation between resurrection and exit suggests that there is increasing competition among coins.

Another piece of evidence consistent with increasing competition is that unlike the bursting of Bitcoin's first bubble in early 2014 (when nearly all altcoins followed Bitcoin down), in early 2018 there appears to be a divergence. Some coins' fate are indeed tied to Bitcoin, but this time there are clear exceptions to that rule, suggesting a changing of the guard. While our results are preliminary, they have identified key themes that we will investigate moving forward.

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Appendix A: Sensitivity Analysis of Peak Detection

	% of max peak	% price jump for peak 25	50	100	200
Volume (median)	10	2	2	2	2
	5	3	3	3	3
	0	7	7	7	6
Volume (total)	10	3 482	3 452	3 377	3 241
	5	4 185	4 148	4 054	3 867
	0	9 746	9 643	9 381	8 677
Price (median)	10	3	2	2	2
	5	3	3	2	2
	0	5	5	4	2
Price (total)	10	3 384	3 064	2 549	1 991
	5	4 078	3 650	2 963	2 227
	0	7 459	6 260	4 593	3 046

Table 4: Sensitivity Analysis of Peak Definition Algorithm

The algorithm used to discover peaks in the dataset utilizes several values that, when increased or decreased, change the number of peaks returned. The three main variables whose values can be modified easily are: the window size on each side of the data point, the minimum value increase for peak, and threshold for minimum peak size. The values accepted for each are days (30 day default), percent (50% default), and percent (5% default) respectively.

Table 4 displays the results from modifying the values. The cells shaded blue show the numbers obtained from the algorithm configuration used in the paper. Reducing the minimum required price jump has no effect on the median number of peaks found per currency, but it increases the total number of peaks discovered. Additionally, removing the restriction on the minimum peak value compared to the maximum peak found essentially doubles the number of peaks found for all currencies. This is concerning as most small peaks are within the domain of normal trading and do not lead us to believe they are result of anomalous trading activity.

The number shown in the tables associated with Appendix A and B are higher than the numbers reported earlier in the paper due to the fact that an updated dataset was used for the sensitivity analysis. However, these results are consistent with the numbers generated with the earlier dataset.

Appendix B: Sensitivity Analysis of Abandonment and Resurrection Detection

The abandonment and resurrection algorithm, like the peak algorithm, utilizes two threshold values to determine if a coin/token is abandoned and resurrected. The first variable, used to detect abandonment, uses a default value of 10%. If the price following a peak drops below 10% of the peak value the currency is considered to be abandoned. The second variable, used to detect resurrection following a period of abandonment, uses a default value of 1%. If the price following abandonment increases to or above 1% of the abandonment value then the currency is said to be resurrected.

To examine how modifications would alter the results we tested a multitude of different values for both abandonment and resurrection. These values can be seen in Tables 5, 6, and 7.

The values chosen for our analysis find a reasonable balance between too many and not enough abandonments.

	resurrection threshold (%)					
abandonment threshold (%)	1.0	2.0	5.0	10.0	20.0	30.0
0.0	109	108	105	104	104	103
0.1	335	328	316	305	299	294
1.0	818	773	697	645	608	591
2.0	1 121	1 036	898	819	757	730
5.0	1 696	1 541	1 232	1 081	962	911
10.0	2 192	2 021	1 631	1 373	1 186	1 096

Table 5: Total Number of Abandonments (Sensitivity Analysis)

	resurrection threshold (%)					
abandonment threshold (%)	1.0	2.0	5.0	10.0	20.0	30.0
0.0	273	336	366	425	456.5	488
0.1	151	183	228.5	276	365	366
1.0	62	92	153	184	215	243
2.0	31	62	122	153	184	212
5.0	31	31	92	123	153	184
10.0	31	31	61	92	151	153

Table 6: Median Number of Abandonments (Sensitivity Analysis)

	resurrection threshold (%)					
abandonment threshold (%)	1.0	2.0	5.0	10.0	20.0	30.0
0.0	38 033	41 913	45 491	49 940	53 966	56 564
0.1	98 898	113 732	124 156	134 987	145 062	149 344
1.0	137 793	174 138	202 585	221 512	238 413	245 693
2.0	141 652	185 281	225 671	247 349	264 658	272 882
5.0	146 169	197 586	248 743	280 190	303 058	314 647
10.0	153 929	203 780	264 042	301 590	327 755	340 271

Table 7: Total Duration of Abandonments (Sensitivity Analysis)