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Does mining fuel bubbles?
An experimental study on cryptocurrency markets

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Abstract

Recent years have seen an emergence of decentralized cryptocurrencies that were initially devised as a payment system, but are increasingly being recognized as investment instruments. The price trajectories of cryptocurrencies have raised questions among economists and policy-makers, especially since such markets can have spillover effects on the real economy. We focus on two key properties of cryptocurrencies that may contribute to their pricing. In a controlled lab setting, we test whether pricing is influenced by costly mining, as well as entry barriers to the mining technology. Our mining design resembles the proof-of-work mechanism employed by the vast majority of permissionless cryptocurrencies, such as Bitcoin. In our second condition, half of the traders have access to the mining technology, while the other half can only participate in the market. This is designed to model high concentration in cryptocurrency mining. In the absence of mining, no bubbles or crashes occur. When costly mining is introduced, assets are traded at prices more than 200% higher than fundamental value and the bubble peaks relatively late in the trading periods. When only half of the traders can mine, prices surge much earlier and reach values of almost 400% higher than the fundamental value at the peak of the market. Overall, the proof-of-work mechanism seems to fuel overpricing, which is further intensified by concentration in mining.

JEL classification: C90; D53; G12.

Keywords: Bitcoin, Bubbles, Cryptocurrency, Financial Market Experiment

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1 Introduction

Speculative bubbles are a major destabilizing factor for the economy and often have long-lasting real consequences.¹ There are many episodes of bubbles and crashes in history such as the tulip bubble, the South Sea bubble and the Mississippi bubble. However, bubbles observed in cryptocurrency markets dwarf any major historical bubbles in terms of magnitude and have been far more protracted (Cheah and Fry, 2015; Bianchetti et al., 2018).

Originally, cryptocurrencies and the Blockchain technology were devised as a communication protocol that facilitates decentralized electronic payments (Böhme et al., 2015) but are increasingly recognized as an investment vehicle (Glaser et al., 2014). Take Bitcoin as an example, it constituted a market capitalization of \$238 billion at its peak price in 2017.² Yet, the fundamental value of such assets is difficult to measure, since no income such as dividends or interest will be paid while holding them, as is common when holding traditional fixed-income or equity securities. It is also difficult to treat them simply as conventional commodities, because they are intangible and have no actual usage in producing other products. It is perhaps best to recognize them as a completely novel asset class (Kristoufek, 2015; Burniske and White, 2017; Hong, 2017). Nowadays, the majority of holders of cryptocurrencies are not holding them as a substitute for cash (Baur et al., 2018), but rather for speculative purposes (Yermack, 2015). As more investors hold cryptocurrencies in their portfolios, the risk of speculative bubbles in cryptocurrency markets may spread to other financial markets and ultimately to the real economy (Guo et al., 2011; Manaa et al., 2019). Thus, policy makers and financial institutions need to better understand the functioning of the cryptocurrency markets in order to design regulation and help contain potential systemic risks.

Cryptocurrencies are gaining popularity mostly due to the successful introduction of Bitcoin, which is the first and most prominent cryptocurrency. The concept of Bitcoin was developed by Nakamoto (2008) as a decentralized peer-to-peer (P2P) electronic cash system. Traditionally, electronic payment is only possible with a trusted third party who records and verifies each transaction, such as a commercial bank. With the new P2P system, this trusted third party is purposely eliminated from the network and thus a new solution is required to keep a ledger of transactions that is accepted by everyone. The solution offered by Nakamoto (2008) for Bitcoin is called the Blockchain, which essentially is a trusted public ledger that contains all Bitcoin transactions since its inception. Copies of the ledger are stored on multiple devices of a cryptographically secured P2P network. Since there is no central administrator to record transactions, a consensus mechanism is required to determine who can add new information to the Blockchain. To date, the most widely used consensus mechanism for cryptocurrencies is called the Proof-of-Work (PoW).³

Under the PoW mechanism, a new block can only be added to the Blockchain if its creator has successfully solved a very computationally intensive cryptographic puzzle (finding the required hash). The process of solving this math problem is what is commonly called ‘mining’. To compensate participants for their contribution of computational power, the payment network rewards the miners with certain units of Bitcoin, which is the only way of introducing new Bitcoins into the market. The level of the reward is set by the Bitcoin white paper and is halved approximately every 4 years (Nakamoto, 2008). Thus, the amount of new Bitcoins supplied to the market is decreasing geometrically over time. As a result, the total number of Bitcoins supplied to the market in the long run will reach a predetermined limit of 21 million coins.

Importantly, Nakamoto’s white paper also makes sure that this 21 million coins will be supplied over a fixed number of years up until the year 2140. This is achieved by adjusting the difficulty

¹See Brunnermeier and Schnabel (2016) for a comprehensive review.

²<https://www.statista.com/statistics/377382/Bitcoin-market-capitalization/>

³A more detailed description can be found in Gervais et al. (2016) or Biais et al. (2019) among others.

of the mathematical problem for the PoW. In particular, “the [PoW] difficulty is determined by a moving average, targeting an average number of blocks per hour [roughly 6 blocks per hour].” (Nakamoto, 2008, p.3). This ensures a smooth (sticky) supply of Bitcoins in the short-run. When mining intensifies (diminishes), the PoW difficulty increases (decreases). The increase in mining difficulty is also a protective measure for the Blockchain to ensure more security against attacks. A comprehensive description of PoW and Bitcoin mining can be found in Auer (2019).

As Bitcoin and other PoW cryptocurrencies gain popularity, the number of computers participating in its P2P network increases. With more computing power, the so-called hash-power of the entire network increases. Accordingly, the mining difficulty increases over time to keep its target block time, while miners compete against each other for the limited block reward. In recent years, the mining difficulty of a large set of cryptocurrencies (which translates into monetary costs) has become prohibitively high for individual miners, fostering the rise of professional miners. Professional miners have dedicated equipment (ASICs) to efficiently mine cryptocurrencies, while individual investors can typically only purchase Bitcoins on the cryptocurrency exchanges to include them in their portfolios. This concentration of large professional miners could be applying further upward pressures on price.

These key properties of PoW discussed above are unique to Bitcoin and other similar cryptocurrencies and are not shared by other conventional asset classes.⁴ We are interested in how the hard-wired supply smoothing feature and the mining concentration affect asset prices.⁵ The naturally occurring financial data often suffers from an absence of counterfactuals and it is typically difficult to disentangle the effect of mining from other (unobservable) factors that may also influence prices due to endogeneity. It is important to note that we are not attempting to exhaust all potential reasons why cryptocurrency bubbles are observed. For instance, Shiller (2019) attributes Bitcoin bubbles to a successful narrative. Alternatively, Foley et al. (2019) suggest that Bitcoin prices are largely related to the darknet marketplace criminal activities. Here, we focus on arguably more fundamental reasons that are hard-wired in cryptocurrency protocols and examine if they are related to the tremendous price surge observed in cryptocurrency markets.

This paper, using a controlled laboratory setting, aims to test whether the PoW mechanism and its implied properties, discussed above, fuel bubbles in cryptocurrency markets. Our experimental setup follows Smith et al. (2000) where market participants can trade an asset with a random redemption value. There are several advantages of using this design. First, as there is no intermediate dividend payments but only a redemption value, the fundamental value of the asset is constant and flat. It has been shown that such environments are not prone to bubble and thus are suitable to use as a baseline (for example: Noussair et al., 2001; Kirchner et al., 2012; Cueva and Rustichini, 2015). Second, we employ an asset that can be valuable with some degree of uncertainty, capturing the idea that cryptocurrency evangelists envision cryptocurrencies being widely adopted as a payment method. This would in turn warrant some intrinsic value for these currencies. Meanwhile, it also captures the idea that beliefs regarding the specific value of the cryptocurrency may differ.

Our experiment features a 2×2 design. The first dimension that we vary is the way traders acquire the asset: either as a gift endowment or mining. In one condition, traders receive assets as a gift and are also endowed with experimental cash, as is standard practice in the experimental finance literature. In the mining condition, traders do not receive any assets at the outset, but only experimental cash. To acquire assets, they need to spend some money on “mining” the asset

⁴While the property of costly mining arguably shares similarities to natural resource extraction, it is worth noting that cryptocurrencies do not depreciate after usage, and the speed of extraction does not depend on the miners themselves.

⁵In practice, PoW includes transaction costs which are paid in Bitcoin. As we want to focus on the effect of asset creation over transfers between agents we abstract away from transaction costs in our design.

at a cost. The cost of mining increases as more assets are mined. The second dimension that we vary aims to capture the mining concentration observed in cryptocurrencies. That is, how not all interested miners can indeed efficiently mine. Specifically, in the mining condition, we vary if all or only half of the traders have access to the mining facility.

To the best of our knowledge, we are the first to design a controlled laboratory environment to study how the PoW protocol affects pricing in cryptocurrency markets. Not surprisingly, given the importance of these markets, there has been some recent work attempting to study cryptocurrencies but none have done so in a controlled laboratory setting. For example, Krafft et al. (2018) conduct an online experiment by inducing buy activity in cryptocurrency markets through bots that trade for less than a penny. Their results highlight the potential impact of peer influence on buying activities in these markets.

Our main results suggest that the PoW mechanism fuels bubbles. In the absence of mining, there is no indication of bubbles. Price trajectories remain relatively flat and close to fundamental value throughout the entire life of the asset. Once costly mining is introduced we observe trading at prices of more than 200% higher than the fundamental value when all traders have access to mining, while prices of almost 400% above fundamental value when only half of the traders can mine. With mining concentration we also find that prices surge earlier resulting in a more protracted deflation of the market.

Overall, the observation that mining and concentration of access to the mining technology in a controlled environment fuel overpricing is a highly important result. Any effort put into mining of cryptocurrencies is by design inefficient (see Schilling and Uhlig (2019) for a detailed argument). Furthermore, Auer (2019) explores what the future might hold for cryptocurrencies and concludes that limitations of proof-of-work will ultimately slow down transactions significantly. Similarly, Huberman et al. (2017) and Easley et al. (2019) highlight the potential for inefficiencies and instabilities due to mining. Our results support the ongoing search for alternative consensus mechanisms (Basu et al., 2020; Hinzen et al., 2020; Saleh, forthcoming).

The remainder of the paper is structured as follows. In section 2, we describe the experimental design of our study, in section 3 we present our hypotheses and report our results in section 4. Section 5 concludes. In the appendix we report some additional analysis and further experimental details including the translated experimental instructions.

2 Experimental Design

2.1 Experimental Asset Market

We employ the Smith et al. (1988) and Smith et al. (2000) paradigm, where participants use experimental currency units (ECU) to trade an asset with a common dividend process. Trading is done over 15 trading periods. The asset they trade only pays out a random redemption value of either 0, 15, 30, or 67 ECUs with equal chance at the end of the life of the asset. Thus, the fundamental value of the asset is flat at 28 ECUs. The flat but uncertain fundamental value captures the plausibly divergent views on how cryptocurrencies are valued by different investors. After the final trading period, the asset becomes worthless. Thus, the only source of value of the asset is the redemption value, which is clearly communicated to the participants. Trading is performed using an open book continuous double auction (Smith, 1962; Plott and Gray, 1990), which is the trading institution used in all our experimental markets. Traders can freely post their own bids and asks or accept others' proposals. We do not allow for short selling or cash borrowing for purchases. Trades can be made in whole units or fractions (up to two decimals) of assets. Furthermore, there are no transaction costs for trades nor interest payments for cash holdings.

We employ a 2×2 factorial design to examine the effects of the PoW mechanism and the restricted access to mining facilities, summarized in table 1. We vary how traders receive assets to trade: participants are either endowed with assets at the outset of the market, as a gift, or they start only with experimental cash and can mine assets at a cost. The costly mining incorporates the sticky and limited supply features of the PoW mechanism, employed by the vast majority of cryptocurrencies. Note that costly mining implies that the cash-to-asset ratio (CAR) in our mining treatments varies over time. We elaborate further on how we control the CAR across treatments below. Additionally, we vary if all or only half of the traders are endowed with the asset in the Gift treatments, or are allowed to mine the asset in the Mining treatments. We conduct 9 market sessions for each of the four resulting treatments: Gift-All, Gift-Half, Mining-All, and Mining-Half.

Table 1: Summary of treatments

		<i>Concentration</i>	
		<i>All</i>	<i>Half</i>
<i>Asset Influx</i>	<i>Gift Mining</i>	Gift-All Mining-All	Gift-Half Mining-Half

The Gift-All treatment is our baseline treatment in which all traders are endowed with an equal amount of experimental cash and assets: 5700 ECUs and 20 units of the asset, following Weitzel et al. (2019). This is a standard experimental asset market environment similar to market A1 in Smith et al. (2000). Since each unit of asset has a fundamental value of 28 ECUs, the CAR, calculated as the total amount of money in the market over the product of shares outstanding and the fundamental value, is 10.2. This ensures that traders will not be cash constrained if they are willing to pay more to acquire the asset from the market.

The Mining-All treatment is identical to the baseline, except that traders are endowed with only experimental cash, but no assets at the outset. If traders want to acquire assets, they can either mine the asset at a cost, or buy the asset directly from the market, provided that some units have already been mined. The cost of mining is an increasing function of the cumulated amount of assets mined (as cumulative expenditure). The sticky and limited supply features identified earlier are incorporated into the cost function for mining. Even when mining is potentially profitable (for example if assets are traded at prices higher than mining costs), there is a cap on how many assets traders can mine per period. The cap is set at 40 ECUs as expenditure allowance on mining per period. Mining operates concurrently with the asset market. By contrasting Gift-All and Mining-All, we separate the effect of costly mining on asset pricing. To compensate for mining costs and to control the CAR across treatments (see details below), traders are endowed with slightly more experimental cash as compared to the Gift-All treatment. Specifically, traders are endowed with 5900 ECUs but no assets.

The cost of mining is characterised by the following function.

$$C \left(\sum_{i \in I, t < \hat{t}} x_{i,t} \right) = C(\chi_{\hat{t}}) = 5.4 \cdot 1.5^{\frac{\chi_{\hat{t}}}{40n}} \quad (1)$$

where n denotes the number of traders in the market, \hat{t} denotes the current period, and $x_{i,t}$ the mining expenditure of subject i in period t . Mining costs start at 5.4 ECUs per asset and increase by approximately 50% in every period, assuming that mining takes place at full capacity in each

period.⁶ Participants can use a calculator to estimate the mining cost for the next 4 periods by inputting their expectation on mining expenditure per trader in the current round. Figure 1a presents the evolution of the asset supply in our mining treatments over time. As a comparison, figure 1b presents the equivalent trend for Bitcoin – very similar trends are found in many other cryptocurrencies.⁷ Notice how both figures exhibit an exponentially decreasing supply over time. Assuming all traders mine at full capacity, the cost function is calibrated to result in mining costs at approximately the asset’s fundamental value at the fifth trading period.

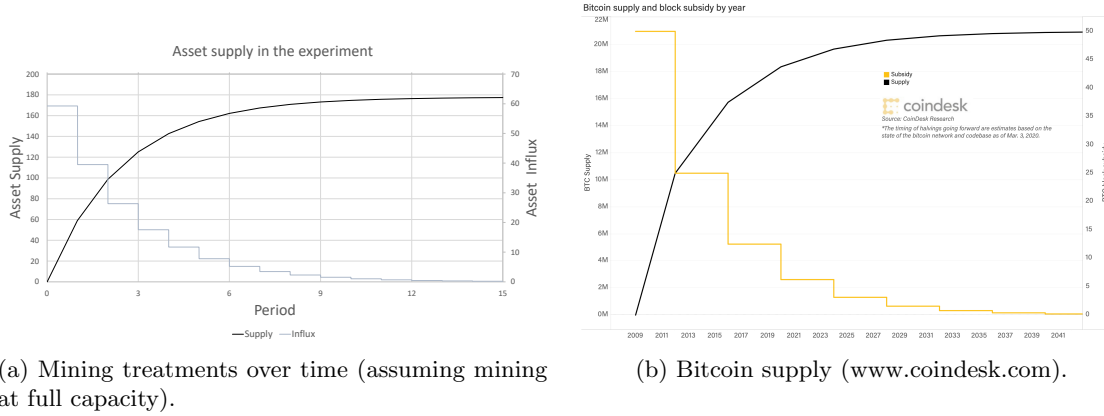


Figure 1: Contrasting asset supply between experimental PoW implementation and Bitcoin.

Condition Mining-Half is designed to capture the way cryptocurrency mining operates in the real world. For most cryptocurrencies, mining requires a large number of dedicated devices which are costly to acquire and utilize. This implies that many investors have no option to efficiently mine coins and are thus constrained to only obtaining them through trading in the market. We study whether and how asset pricing is affected when only half of the traders have the possibility to mine for assets, while the other half is restricted to acquiring assets only from the market. With this treatment, we can identify how concentration of access to the mining technology influences the asset pricing over and above mining itself. However, the effect may also be attributed to asymmetry in holdings rather than the mining (PoW) protocol alone. In order to control for this, we also implement the Gift-Half treatment where we randomly assign half of the traders to be endowed with both assets and ECUs, while the other half do not receive any assets from the outset, but only experimental cash.

In the Gift-Half and Mining-Half treatments, how traders are initially endowed depends on their randomly assigned role. Half of the traders are assigned role A and the other half role B. In Gift-Half, role A traders are endowed with 5140 ECUs and 40 assets at the outset, while role B traders are endowed with 6260 ECUs but no assets. Note that, given the expected redemption value of 28, the initial portfolios of traders in Gift-Half are equivalent to those of traders in Gift-All in terms of expected dividend value for both roles. In Mining-Half, role A traders have a starting endowment

⁶We choose to update costs as a function of total expenditure, as we consider it simpler for participants to comprehend. Traders have a maximum amount of cash that they are allowed to spend on mining in each period. Thus, this allows immediate interpretation of asset costs over time (i.e., an increase by 50% in every period when people mine at full capacity). Interpreting costs as a function of assets would make it necessary to calculate how many assets are actually affordable to see what the cost of the next period is. Although the exact functional form is not communicated to subjects, they are clearly informed that mining will become increasingly costly as more units are mined. Figure A.1 in the appendix depicts costs as a function of assets in our experiment.

⁷Asset influx in figure 1b is denoted as asset subsidy. This wording is commonly used to highlight that new Bitcoins are introduced as block rewards to successful miners.

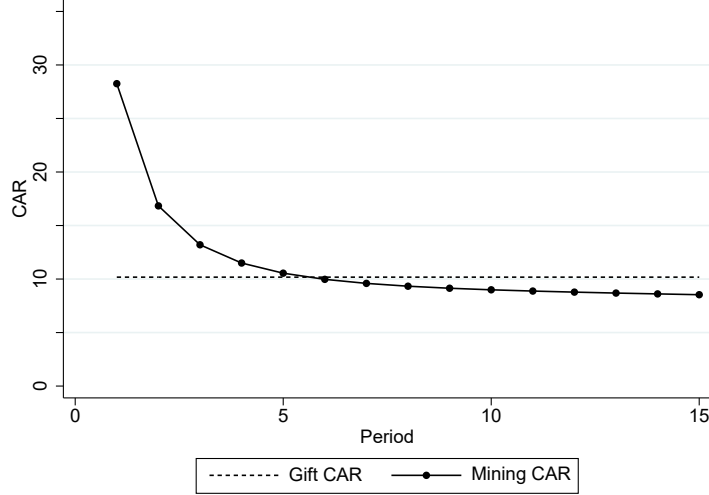


Figure 2: Theoretical CAR across trading periods, assuming mining at maximum capacity in each period.

of 5540 ECUs and zero assets and are allowed access to the mining technology. Role A traders can potentially spend up to 80 ECUs on mining in each period. We double their mining capacity per period to allow for the market to have the same potential mining volume as the Mining-All treatment. In the Mining-half treatment, role B traders are endowed with 6260 ECUs but no assets and have no access to the mining technology. Table 2 offers an overview of the parameters for each treatment.

Table 2: Overview of parameters across treatments

		All	Half	
			Role A	Role B
Gift	ECUs	5700	5140	6260
	Assets	20	40	0
Mining	ECUs	5900	5540	6260
	Assets	0	0	0
	Cap per Period	40	80	0

Special attention has been given to the calibration of the experimental parameters to make our treatments comparable. While the CAR in Gift-All and Gift-Half is constant throughout the trading periods, it varies over time in the Mining treatments (it is strictly decreasing whenever mining takes place). We calibrate the parameters in a way that the CAR of Gift and Mining treatments are similar – in figure 2 we depict the theoretical expectation of the CAR development. Assuming every trader in Mining-All spends the maximum amount possible (40 ECUs) in mining during each of the first five trading periods and if no other transactions take place in the meantime, their holdings would be 5700 ECUs and approximately 20 units of asset in period 5. This is approximately the initial endowment of traders in the Gift-All treatment. Since the cost of mining is lower than the fundamental value of the asset during these first five periods, the assumption of traders mining at full capacity seems reasonable. From period 6 onwards, the mining cost would

exceed the asset fundamental value, thus, risk-neutral agents should refrain from further mining.⁸ Analogously, if all role A traders in Mining-Half were to mine using their maximum allowance (80 ECUs) in each of the first five periods, they would reach (approximately) the initial endowment of role A traders in Gift-Half.

All subjects receive printed instructions to read at their own pace.⁹ We administer a quiz which every participant has to pass after reading the instructions. The quiz asks about features and parameters of the asset market to ensure comprehension of the task. Before the beginning of the 15 trading periods, participants are able to practice for three periods of 120 seconds each. During these practice periods participants are encouraged to familiarise themselves with the various functionalities of the platform. For example, they are encouraged to try out asset generation and the corresponding calculator (if applicable) as well as placing ask/buy orders and completing trades. The asset and ECU holdings are reset after these practice periods (practice periods do not count towards final earnings). The 15 trading periods also have a duration of 120 seconds each. In Gift-Half and Mining-Half, the roles of traders were randomly determined before the practice periods and were preserved for the trading periods.

The basic asset market experiment design was pre-registered at the AsPredicted platform of the Penn Wharton Credibility Lab. The pre-registration is found at <https://aspredicted.org/8hx2k.pdf> and <https://aspredicted.org/4w4hz.pdf>.

2.2 Additional Controls

Before implementing our experimental asset market, in all sessions, we elicit a number of individual traits and characteristics to be used as controls in the analysis.

Participants complete a short version of the Raven Advanced Progressive Matrices (APM) test. The Raven test is a non-verbal test commonly used to measure fluid intelligence, which is the capacity to solve problems in novel situations, independent of acquired knowledge. In order to shorten the duration of this test, we follow Bors and Stokes (1998) in using 12 from the total of 36 matrices from Set II of the APM. Matrices from Set II of the APM are appropriate for adults and adolescents of higher average intelligence. Participants are allowed a maximum of 10 minutes. Initially, participants are shown an example of a matrix with the correct answer provided below for 30 seconds. For each question, a 3×3 matrix of images is displayed on the subjects' screen; the image in the bottom right corner is missing. The subjects are then asked to complete the pattern choosing one out of 8 possible choices presented on the screen. The 12 matrices are presented in the order of progressive difficulty as they are sequenced in Set II of the APM. Participants are allowed to switch back and forth through the 12 matrices during the 10 minutes and change their answers. They are rewarded with 1 Euro per correct answer from a random choice of two out of the total of 12 matrices.

We elicit Theory of Mind (ToM) using the Heider test (Heider and Simmel, 1944), following Bruguier et al. (2010) and Bossaerts et al. (2019). ToM is the ability to infer the intentions of other agents, which is especially important in market environments. The Heider test involves a short film of moving geometric objects (two triangles of different size and one circle). When watching the movie, one could personify the geometric objects as the large triangle bullying the small triangle and the circle trying to intervene. To measure the intensity of ToM, we pause the movie every 5 seconds and ask the subject to forecast whether the two triangles are going to be further apart or closer together 5 seconds later. People who are better able to imagine a bullying scene are more capable in forecasting the future distance between the triangles (Bossaerts et al., 2019). The test

⁸In this example, mining costs would increase from 27.3 to 41 ECUs per asset from the 5th period to the 6th.

⁹Translated versions of these are included in the appendix.

results in a score of 0 up to 6 depending on how many of the 6 predictions participants are correct about. For each correct prediction participants are rewarded with 50 cents.

Finally, we elicit risk preferences using an incentivized Eckel and Grossman (2008) task. Once the asset market was completed, we administer a questionnaire for general demographics, comprehension of the expected value of the asset traded and previous experience with cryptocurrencies.

2.3 Experiment Implementation Details

A total number of 286 subjects participated in our experiment. We conducted 36 sessions in total, with 9 sessions per treatment.¹⁰ Each market session had 8 participants, except for two where we had 7 participants due to no-shows. The whole experiment was implemented using z-Tree (Fischbacher, 2007) and the trading platform within z-Tree was implemented using the technical toolbox GIMS developed by Palan (2015). To determine the redemption value of our assets, we implemented a transparent randomization process which guaranteed that each of the four buyback values would be assigned to exactly two participants.¹¹ This was done by having each trader physically draw from a deck of cards. The deck of cards had 4 pairs of cards. Each pair corresponded to one of the 4 buyback values. The cards were drawn privately without replacement by each of the 8 traders.

Our experimental sessions took place in the economics lab facilities in Heidelberg University and Frankfurt University. Participants were mostly undergraduate students from a variety of majors. Subjects were recruited using ORSEE (Greiner, 2015) in Frankfurt and SONA (www.sona-systems.com) in Heidelberg. The average payment was approximately 18 Euros for 90 minutes.

We summarize participant characteristics by treatment and role in table 3. Overall, our treatments are balanced, in particular with respect to gender, which is important given the recent finding that gender composition matters for market efficiency (Eckel and Füllbrunn, 2015).

Table 3: Characteristics of participants across treatments

	Gift-All	Gift-Half		Mining-All	Mining-Half	
		A	B		A	B
Avg. Age	23.54	22.28	24.94	24.21	21.75	22.72
Proportion of Females	0.58	0.39	0.47	0.47	0.58	0.47
Avg. Crypto Experience [†]	1.72	1.94	1.81	1.73	1.67	1.92
Avg. Raven	8.22	7.78	7.83	8.11	7.61	7.78
Avg. Theory of Mind	3.36	3.50	3.56	3.61	3.58	3.56
Avg. Risk Choice	3.54	3.54	3.31	3.51	3.42	3.81

[†]Crypto experience was elicited using a Likert scale from 1 (none) to 5 (very well).

¹⁰Table A.5 in the appendix summarizes dates and locations of implementation of each of our sessions across all four treatments.

¹¹In the two sessions with only seven participants, one of the buyback values was assigned to only one participant and which of the values would be assigned only once was part of the random procedure.

3 Research Hypotheses

Our experimental design allows us to answer a number of interesting questions. Here, we list four main hypotheses to be evaluated. As our basic market setup is close to market A1 of Smith et al. (2000), where an asset with a flat fundamental is traded, we can make a few hypotheses based on the established findings in the experimental finance literature.

For the baseline treatment, Gift-All, we do not expect to observe bubbles and crashes given the similarities of the market setup with Smith et al. (2000). In this treatment, if traders are on average risk neutral, we should observe no trade, or trade only at around the fundamental value (Palan, 2015). Moreover, this design does not have frequent dividend payments as in Smith et al. (1988) with decreasing fundamentals or as Bostian et al. (2005) with a flat fundamental in which bubbles are commonly observed (see also the discussion in Noussair and Tucker, 2016). Smith et al. (2000) report little price deviation from the fundamental value and no sign of bubbles and crashes. However, prices may not track fundamental values perfectly, as our CAR is 10.2. Higher CARs have been shown to induce greater mispricing (Caginalp et al., 1998, 2001, 2002; Haruvy and Noussair, 2006; Noussair and Tucker, 2016; Angerer and Szymczak, 2019). In particular, Caginalp et al. (2001) estimate that each dollar per share of additional cash results in a maximum price that is \$1 per share higher.

Hypothesis 1. *Prices in Gift-All do not exhibit a pattern of bubbles and crashes.*

We next examine the treatment Gift-Half where only half of the traders are endowed with both experimental cash and assets, while the other half are only endowed with experimental cash. This endowment asymmetry may affect traders' willingness to pay for the asset. Weber and Camerer (1998) have suggested that traders tend to achieve a balanced portfolio, implying that those starting with only cash may want to hold some assets as well. More recently, Janssen et al. (2019) and Tucker and Xu (2020) find that bubbles are larger and more common when traders start with an asymmetric endowment. However, it should be noted that both studies adopt the Smith et al. (1988) framework, which is prone to bubbles. It is ex-ante not clear whether the endowment asymmetry itself may elevate the prices in an environment that is not prone to bubble, such as ours.

Hypothesis 2. *Prices in Gift-Half are higher than prices in Gift-All.*

When mining is introduced, there are a number of behavioral reasons why prices may decouple from the fundamental value leading us to observe bubbles and crashes. First, the cost function implies that mining will be more costly in the future when more units of assets are mined, creating an expectation of a rising cost. Thus, the mining cost may serve as a price anchor at different points in time. Additionally, it may also serve as a support of prices in that traders may feel reluctant to sell the asset below the cost of acquisition. Second, due to the expenditure cap on mining, the supply is sluggish. This means that when the demand is high in a given period, the supply of the asset cannot accommodate the demand in a reasonably short period of time, thus, applying upward pressure on the price (Saleh, 2019; Hinzen et al., 2020).

Hypothesis 3. *Prices in Mining treatments are higher than prices in Gift treatments, exhibiting a pattern of bubbles and crashes.*

The Mining-Half treatment may further exacerbate this issue, as demand could be even stronger when half of the traders can only purchase the asset on the market. Again, relating to the recent findings of Janssen et al. (2019) and Tucker and Xu (2020) we anticipate that the potential bubbles will be larger in Mining-Half as compared to Mining-All,

Hypothesis 4. *Prices in Mining-Half are higher than prices in Mining-All.*

4 Results

4.1 Results on Market Level

Figure 3a depicts the trading prices of the asset across our four treatments. We report the median price of each treatment based on volume weighted average prices from each market.¹² In both Gift treatments, trading prices follow the asset fundamental value relatively well across all trading periods. In other words, under neither of our Gift treatments do we observe a pattern of bubbles and crashes.

Result 1. *Prices in Gift-All treatment do not exhibit any pattern of bubbles and crashes, offering supporting evidence for Hypothesis 1.*

In Mining-All, prices initially start below fundamental value but above mining cost. Pricing then follows an upward trend parallel to the mining cost with a clearly identifiable mark-up (see figure 4 where we depict trading prices only for the two mining treatments together with their respective mining cost trends). Overall, prices continue rising for 12 periods and crash in the last three. Similarly, in treatment Mining-Half, prices go well above and beyond fundamental value. As seen in figure 3a, the peak price of the median prices in the Mining-All and Mining-Half treatments are more than 200% and close to 400% above fundamental value, respectively. Our median representation is robust to potential outliers. Figure 5 replicates figure 3a by systematically removing one of the 9 markets with replacement. The general tendencies and conclusions we make according to figures 3a and 4 remain.

We formalize our analysis using a number of bubble measures, summarized in table 4.¹³ These indicators include RD, the relative deviation of prices to fundamentals (normalized at the fundamental value of 28) and RAD, the relative absolute deviation of prices to fundamentals (normalized at the fundamental value of 28), both of which were introduced by Stöckl et al. (2010). RAD measures how closely prices track fundamental value, while RD indicates whether prices on average are above or below fundamental value. Furthermore we include RDMAX, measuring the overpricing of the peak period. AMPLITUDE captures the relative difference of the pre-peak minimum price and the peak price in terms of magnitudes of the fundamental value and CRASH compares the peak price to the minimum price post-peak (Razen et al., 2017). We further compute the indicators TURNOVER, LIQUIDITY, SR (submission rate), SPREAD and VOLA (volatility) commonly analysed in the literature. TURNOVER measures the volume of trade. LIQUIDITY describes the volume quantities of open orders at the end of each period, while SR is defined as the number of limit orders posted divided by the sum of limit and market orders posted in a period. SPREAD measures the gap between buy and sell orders, and VOLA measures log-returns of all market prices within a period.¹⁴

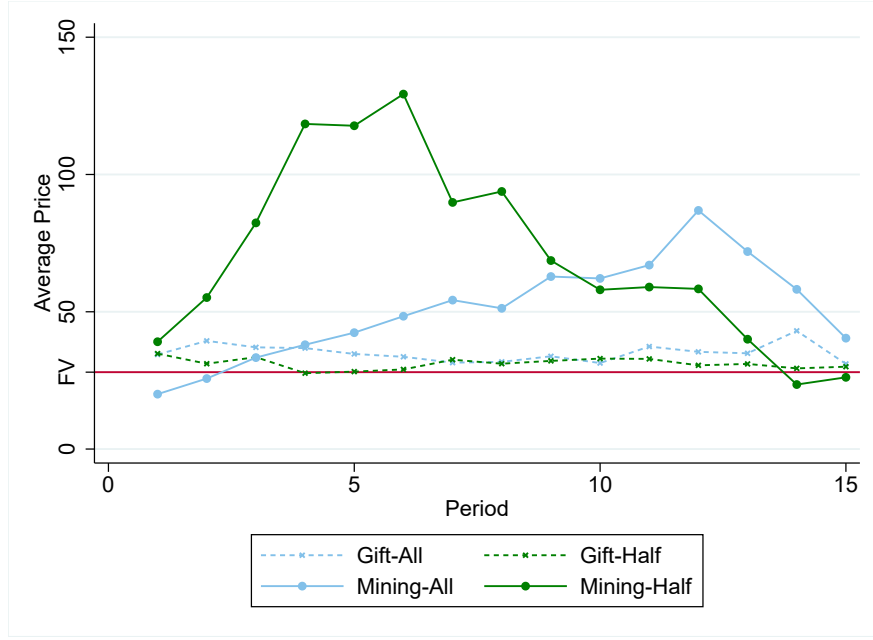
The conclusions drawn from figure 3a remain. Gift-All and Gift-Half are characterized by moderately sized bubble measures. In table 5, we find no significant difference when comparing the bubble measures of the two Gift treatments. This implies that endowment asymmetry by itself does not ignite a bubble.

Result 2. *We find no significant difference in overpricing between Gift-All and Gift-Half treatments. Endowment asymmetry by itself does not ignite a bubble, thus, we reject Hypothesis 2.*

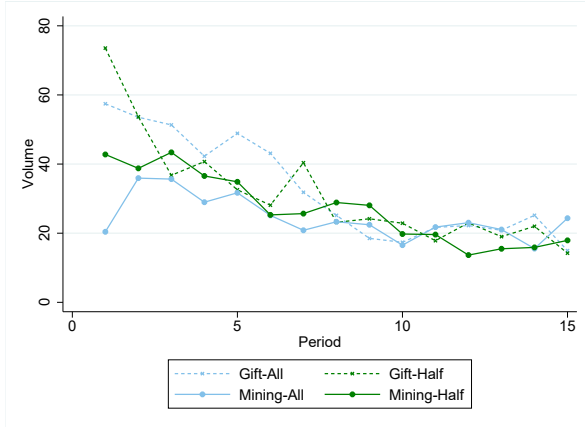
¹²Figure A.2 in the appendix is the equivalent figure depicting average prices instead of median prices, offering similar conclusions. Additionally, figures A.3-A.6 depict the price trends separately for each of our 9 individual markets per treatment.

¹³We report these measures separately for each market of each treatment in tables A.1-A.4 in the appendix.

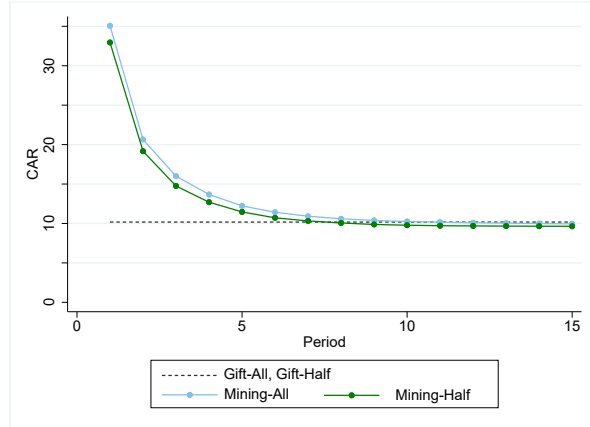
¹⁴We report the exact formulas of all bubble measures in the appendix.



(a) Median weighted average price per period



(b) Average trading volume per period



(c) Realised average CAR

Figure 3: Trading prices, volumes and cash-to-asset ratio in all treatments.

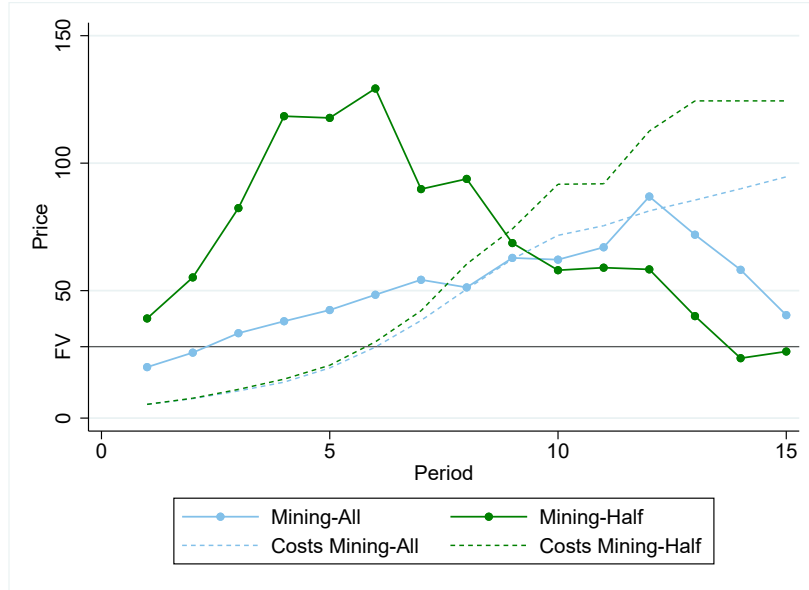


Figure 4: Median weighted average price and mining cost per period in Mining treatments

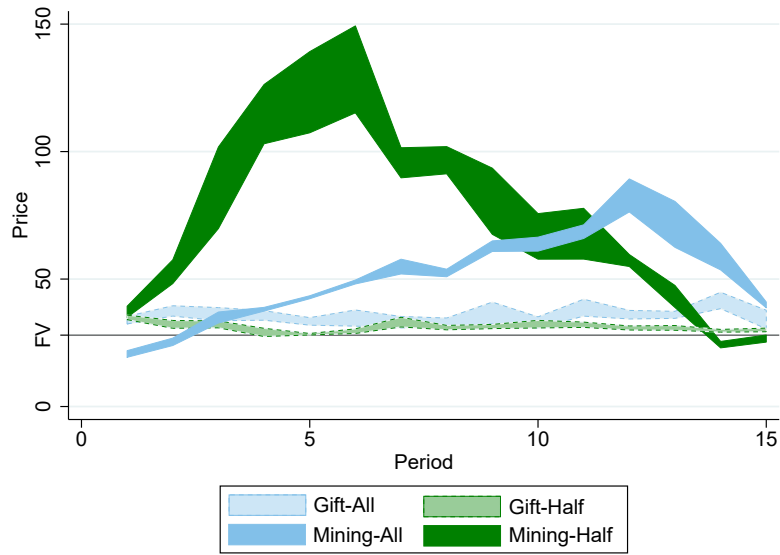


Figure 5: Robustness check: Median weighted average price per period of all but one session in all treatments, which yields eight graphs per treatment. We shade the area between the highest and lowest period prices per treatment, i.e. all eight graphs of a treatment lie within the shaded area of the respective treatment.

Table 4: Summary statistics of bubble measures by treatment

	Gift-All		Gift-Half		Mining-All		Mining-Half	
	median		median		median		median	
	mean	(std.dev.)	mean	(std.dev.)	mean	(std.dev.)	mean	(std.dev.)
RAD	0.4		0.1		1.0		2.1	
	0.5	(0.5)	0.5	(0.8)	1.9	(1.9)	2.3	(1.5)
RD	0.4		0.1		1.0		2.0	
	0.4	(0.5)	0.5	(0.9)	1.9	(1.9)	2.2	(1.5)
RDMAX	1.0		0.3		3.6		3.6	
	0.9	(0.6)	0.9	(1.4)	7.7	(10.7)	6.1	(5.2)
AMP	0.8		0.3		3.8		3.2	
	0.7	(0.3)	0.6	(0.6)	7.9	(10.7)	5.6	(5.0)
CRASH	-0.5		-0.3		-2.9		-4.0	
	-0.6	(0.6)	-0.7	(0.9)	-7.5	(11.3)	-6.2	(5.4)
TURN	0.2		0.2		0.2		0.2	
	0.2	(0.1)	0.2	(0.1)	0.2	(0.1)	0.2	(0.1)
LQ	0.6		1.0		0.5		0.8	
	0.8	(0.7)	5.5	(13.9)	0.7	(0.6)	5.2	(12.8)
SR	20.9		19.3		17.1		22.1	
	20.4	(4.4)	21.1	(4.9)	16.3	(3.5)	21.9	(3.5)
SPREAD	0.2		0.1		0.5		1.2	
	0.3	(0.2)	0.2	(0.3)	1.4	(2.3)	1.5	(1.2)
VOLA	0.2		0.1		0.3		0.4	
	0.3	(0.3)	0.2	(0.1)	0.3	(0.2)	0.5	(0.3)

When comparing the bubble measures of the Mining treatments to their respective Gift treatment (Gift-All vs. Mining-All & Gift-Half vs. Mining-Half), we do find significant differences. Specifically, price deviations from fundamental value are significantly more pronounced in the Mining treatments as compared to the Gift treatments. It is worth emphasizing that this result should not be plainly attributed to the differences in CAR at the outset of the market. The cash endowment in the Mining treatments is only around 4% higher than in the Gift treatments. Additionally, the CAR is already quite high in the Gift treatments (10.2), thus, ensuring that traders are never cash constrained. Furthermore, the bubble observed in the Mining-All treatment peaks in the second half of trading periods, by which point the CAR is already lower compared to the CAR in Gift-All.

Result 3. *Overpricing in the Mining treatments is significantly greater than in the Gift treatments, thus, we have supporting evidence for Hypothesis 3.*

We are interested in identifying what effect concentration of access to the mining technology might have on asset pricing. To this end, we now focus on contrasting our two Mining treatments. We find no significant difference when comparing the bubble measures of Mining-All to Mining-Half when taking all periods into consideration (Table 5). However, figure 4 suggests that there is a difference in the timing of the bubble occurrence between the Mining-All and Mining-Half treatments. In the latter, prices seem to decouple from the mining cost already within the first few periods and peak even higher. Table 6 compares our Mining treatments, by splitting the trading periods in two halves. We refer to periods 1 – 7 as the first half and periods 9 – 15 as the second half. The bubble measures RAD and RD of our mining treatments show a statistically significant difference in the first half of trading periods.¹⁵ The peak price comes much earlier in treatment Mining-Half compared to Mining-All and the bubble persists for a number of periods before prices crash to fundamental value.

Result 4. *The degree of overpricing of Mining-All and Mining-Half does not differ overall, but Mining-Half markets bubble earlier than Mining-All markets. Thus, we partly reject Hypothesis 4.*

Regarding the results we report, it is relevant to compare trading volumes across our treatments. Figure 3b presents the average trading volume of each treatment across trading periods. From this figure it is evident that our results are not due to differences in trading volumes. This is not surprising, as given our experimental calibration, these should not differ across our treatments. The Gift treatments appear to initially trade at higher volumes but this difference eventually disappears. A plausible explanation for the initial difference may be the fact that in the first few periods there are substantially fewer assets available to trade in the Mining treatment markets. Figure 3c shows the average realised CAR of our treatments across periods.¹⁶ Trading volumes across our four treatments are not significantly different once the CAR is similar (from the 6th period onwards). This is confirmed using a non-parametric test of comparing average trading volumes of periods 6-15 across the four treatments (Wilcoxon rank-sum test of Mining vs. Gift, $p = 0.39$; Wilcoxon rank-sum test of All vs. Half, $p = 0.80$).

4.2 Results at Individual Level

For the last part of our analysis, we study the characteristics of individual traders and how these influence their earnings in the experimental asset market. Table 7 reports the results of a regression

¹⁵Note that the bubble measures RDMAX, AMPLITUDE and CRASH are calculated with respect to the peak period and therefore cannot be calculated when the sessions are split in half.

¹⁶The figure reports the average realised CAR over the 9 markets implemented for each of the four treatments.

Table 5: P-values of exact Mann-Whitney-U tests comparing bubble measures of different treatments (pairwise)

	Gift-All vs. Gift-Half	Gift-All vs. Mining-All	Gift-Half vs. Mining-Half	Mining-All vs. Mining-Half
RAD	0.546	0.004***	0.003***	0.666
RD	0.387	0.006***	0.004***	0.605
RDMAX	0.387	0.001***	0.002***	0.931
AMPLITUDE	1.079	0.002***	0.036**	1.000
CRASH	0.673	0.005***	0.001***	0.606
TURN	0.863	0.931	0.387	0.546
LQ	0.340	1.000	1.000	0.297
SR	1.000	0.050*	0.666	0.006***
SPREAD	0.340	0.006***	0.000***	0.136
VOLA	0.222	0.161	0.014	0.436

Table 6: Exact Mann-Whitney-U tests of bubble measure RAD, comparing first half and second half of mining treatments

		Mining-All	Mining-Half	Mining-All vs. Mining-Half (M-W-U test)
RAD	First half	0.60	2.20	p=0.011
	Second half	1.33	0.81	p=0.436
RD	First half	0.47	2.20	p=0.008
	Second half	1.33	0.81	p=0.340

Table 7: Multivariate analysis on traders' (normalized) earnings

Standardized earnings (Euro)	All (1)	All (2)	Mining-All, Mining-Half (3)	Gift-Half, Mining-Half (4)
Raven	0.277** (0.088)	0.247** (0.099)	0.311** (0.105)	0.281*** (0.077)
ToM	0.383* (0.183)	0.344 (0.206)	0.451** (0.159)	0.512** (0.170)
Raven X ToM	-0.458* (0.022)	-0.040 (0.025)	-0.063** (0.022)	-0.055** (0.018)
Controls				
Risk choice		0.064 (0.039)	0.022 (0.067)	0.058 (0.049)
Age		0.001 (0.098)	-0.012 (0.012)	0.005 (0.007)
Gender		-0.240* (0.111)	-0.472** (0.204)	-0.168 (0.187)
Crypto Exp.		0.040 (0.087)	-0.053 (0.084)	0.018 (0.060)
Role in Market				-0.371** (0.158)
Constant	-2.270** (0.687)	-2.261*** (0.646)	-1.759** (0.728)	-2.583** (0.868)
R^2	0.074	0.113	0.146	0.123
Observations	278	278	142	144

Notes: Robust standard errors reported in parentheses, clustered at the session level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

analysis on traders' earnings. The dependent variable in all specifications is asset market earnings, standardized with respect to their respective treatment.¹⁷ The first column reports the regression results without controls, while the second column includes control variables. In column 3, we report the regression results estimated only for our Mining treatments, to examine whether and how individual characteristics affect performance in a bubble-prone environment. Finally, in column 4, we also control for the role of traders in the treatments Gift-Half and Mining-Half to identify what (if any) advantage these roles might offer. Following Hefti et al. (2016) and Corgnet et al. (2018), we include an interaction term between Raven and ToM. Overall, we find that both cognitive ability and ToM are associated with higher earnings. These attributes appear to act as substitutes for each other as seen by the negative interaction term which is similar in direction to the findings of Corgnet et al. (2018). Female traders appear to earn less, while in the markets where traders have different roles, those that can only obtain assets through the market are significantly worse off. This might be because their options of acquiring assets are limited.

¹⁷We standardize the earnings by subtracting treatment average earnings and dividing by the standard deviation of earnings in the respective treatment.

5 Concluding Remarks

This paper aims to understand whether the features associated with the proof-of-work consensus mechanism help fuel bubbles. More specifically, we are interested in understanding if the (by design) sticky supply of cryptocurrencies together with entry barriers to the mining technology lead to the large price fluctuations observed in cryptocurrency markets.

We design a laboratory experiment to examine the effect of mining and access to mining technology on cryptocurrency pricing. Our results show a remarkable degree of overpricing; traders trade assets at significantly higher prices than fundamental value when mining is introduced. While risk seeking preferences might explain slight overpricing, we, nevertheless, observe prices frequently double the maximum possible redemption value of the asset. These findings indicate that the proof-of-work mechanism contributes to overpricing and enables significant volatility of pricing over time. Moreover, our results show that mining concentration further pushes prices upwards and makes the prices decouple from mining costs earlier, compared to a case where all have access to mining. These results in our mining conditions suggest that mining costs may serve as a support for prices in the early periods, while concentration of the mining technology creates a further upwards pressure on prices through initial excess demand. It is conceivable that demand would be stronger in markets with asymmetric endowment, given the results of Tucker and Xu (2020), who show that endowment asymmetry seems to be responsible for bubbles. Traders who initially do not own the asset might be eager to buy the asset at an early stage of the market, knowing that mining costs may get higher in the future. This might explain how Bitcoin surged from a few cents to the \$1 milestone. In the early days only few computer science aficionados had access to the mining technology (and the knowledge to run it). Potential investors who envisioned Bitcoin to be more valuable in the future but had no access to mining facilities could only buy from the market and thus apply upward pressure on prices. Our results show that both the mining protocol as well as the exclusive access to mining technology (concentration) might be crucial to understand the magnitude and duration of cryptocurrency bubbles.

The fact that the prices trajectory in our Gift-treatments adheres more closely to the fundamental value is in line with existing literature. First, a constant fundamental value (instead of a decreasing one) is a simpler asset that may be less likely to create misunderstandings or disagreements in prices among traders (Smith et al., 2000; Kirchler et al., 2012). In the declining fundamental value case, frequent changes of fundamental values to a new level each period may hinder the price discovery process. Second, despite our relatively high cash-to-asset ratio, we do not pay frequent dividends as Noussair et al. (2001). The observation that these markets do not bubble supports the conjecture in Noussair et al. (2001) that in constant fundamental value settings, a high cash-to-asset ratio is not sufficient to ignite bubbles (while it may affect price levels). We are sympathetic to this conjecture and do not anticipate that increasing the (already high) cash-to-asset ratio in the Gift treatments would result in any bubbles occurring. Consequently, we conjecture that the bubbles we find in the Mining treatments cannot be simply attributed to the (initially) higher cash-to-asset ratio but rather to the specific features of the PoW mechanism we study.

The fundamental value of cryptocurrencies is a much-debated issue (Cheah and Fry, 2015; Biais et al., 2018; Hayes, 2019; Schilling and Uhlig, 2019). We concede that our implementation in this aspect is potentially an over-simplification of this as a first step in understanding cryptocurrency pricing. However, the focus of our study is on the effects of mining protocols on overpricing. We anticipate that the effects of mining we identify would persist in situations where the fundamental value would be uncertain and skewed. This would be an interesting avenue for future research.

Clearly, many other aspects that are left out in this study may also influence how cryptocur-

rencies are priced. For example, since ambiguity has been found to be relevant in financial decision making (e.g. Chen and Epstein, 2002; Ju and Miao, 2012), it would be interesting to study its implications on cryptocurrency markets. Füllbrunn et al. (2014) do not find effects in market experiments comparing ambiguity and risk, while Corgnet et al. (2020) observe that bubbles are less pronounced and do not crash when assets’ fundamentals are ambiguous. The specific context of cryptocurrency markets has so far not been investigated. Oechssler et al. (2011) study markets with asymmetric information and find that the mere possibility that some traders are better informed than others can create bubbles. It is conceivable that traders succumb to such biases in cryptocurrency markets, especially given their apparent prohibitive complexity to an outsider. Further plausible explanations that have been suggested as contributors to the price volatility of cryptocurrency also include the hype surrounding these novel assets as well as the likely fear of missing out (FOMO) from entering the market too late. These are certainly interesting avenues that the present framework could be extended towards.

In a broader picture, our results can inform economists and policy makers in their efforts to develop more stable alternative cryptocurrencies as well as other consensus mechanisms. The high price volatilities shared by many PoW cryptocurrencies hinder their potential to become a mainstream method of payment. Yet, these high volatilities seem unavoidable, as they stem from the properties of the PoW mechanism as an equilibrium outcome (Alsabah and Capponi, 2019; Saleh, 2019; Hinzen et al., 2020). Our findings lend support to the widely documented concerns on the drawbacks of the PoW mechanism, and the ongoing search for better consensus mechanisms and incentive structures (Basu et al., 2020; Hinzen et al., 2020; Saleh, forthcoming). If central banks around the world have the ambition to issue their own digital currencies (known as CBDCs), the need for a more stable mechanism is clearly evident (Raskin and Yermack, 2018; Dell’Erba, 2019; Camera, 2020).

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Appendices

A Asset Costs in our Mining Treatments

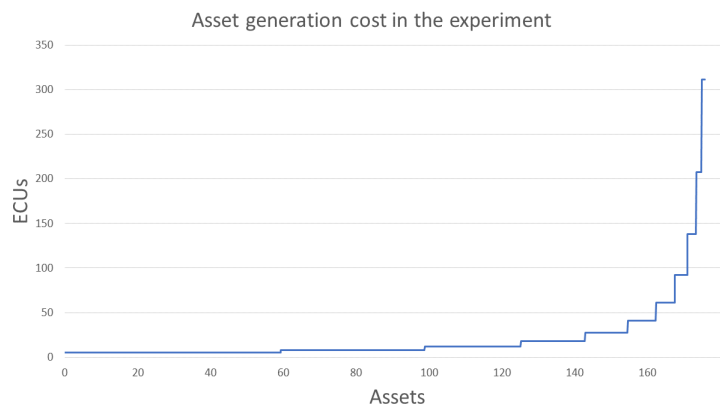


Figure A.1: Asset costs as a function of assets in our mining treatments (assuming maximum mining).

B Average Prices

Figure A.2 reports the average of the nine weighted average prices of a treatment.

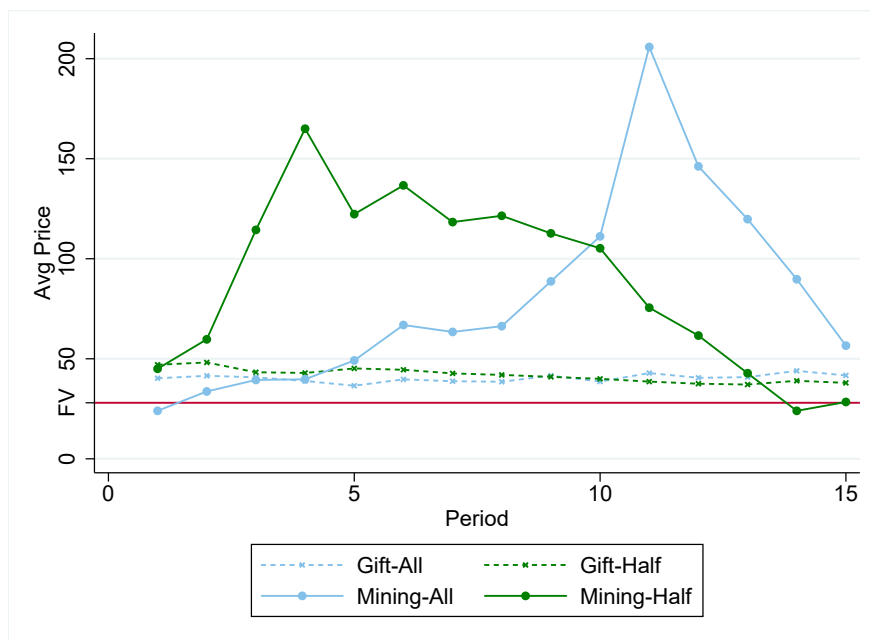


Figure A.2: Weighted average price per period of all sessions in every treatment

C Individual Sessions/Markets

Figures A.3, A.4, A.5 and A.6 present the individual markets for each of the four treatments. Note that the scale on the y-axis had to be adjusted for about one third of the markets, while the others have a common y-axis, ranging from one to three times the fundamental value. This adjustment was necessary for only one of the gift markets (i.e. Session 6 in Gift-Half), five markets in treatment Mining-All and six markets in treatment Mining-Half. Price trajectories of treatment Gift-All markets are flat in general. Sessions 1 and 2 show a slight upward tendency over time. Session 8 started on a high price level initially, but experienced a downward correction after three periods and stayed flat afterwards. The analysis of the price charts of treatment Gift-Half, Figure A.4, leads to similar conclusions. Most markets have very stable pricing across periods, while session 6 seems to be an exception. In this session, prices started surprisingly high and decreased over time.

The individual markets of treatment Mining-All (Figure A.5) show a different overall pattern than the Gift sessions. Only session 6 shows a flat price trajectory, while all other markets follow an upward trend in the first periods. Session 4 keeps this trend throughout all periods, the highest price is reached in the last period. The other seven markets reach a peak price (session 1 and session 9 do so in early periods, sessions 2,3,5,7 and 8 in later periods) and afterwards experience a drop of prices towards the fundamental value of the asset. The magnitude of these peaks and drops differs from market to market. In Figure A.6 of treatment Mining-Half most markets show a similar trajectory, but again the magnitude differs quite notably. It is noteworthy that most markets reach their peak price in the earlier periods - none of the sessions had their peak price after period 10.

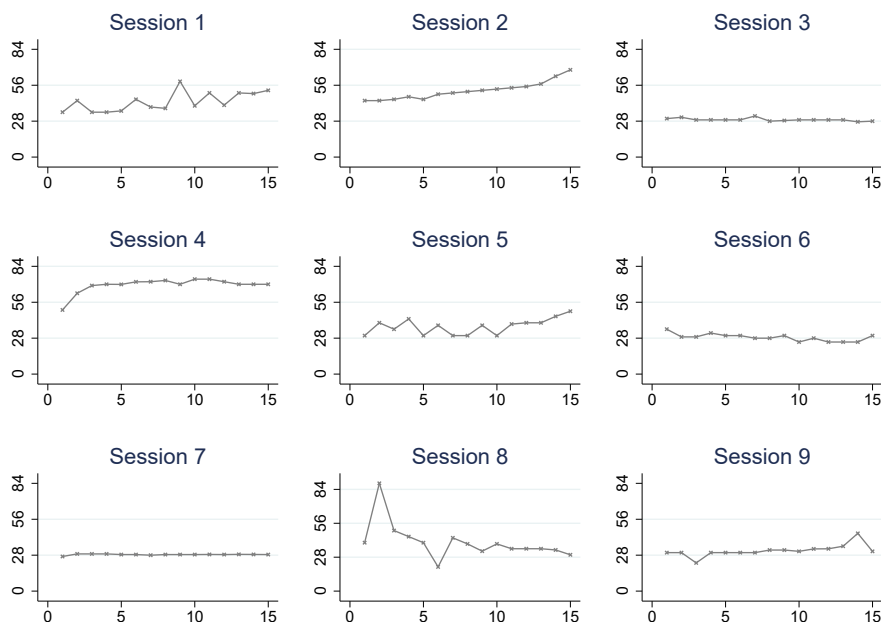


Figure A.3: Median Prices per period in the individual markets of treatment Gift-All

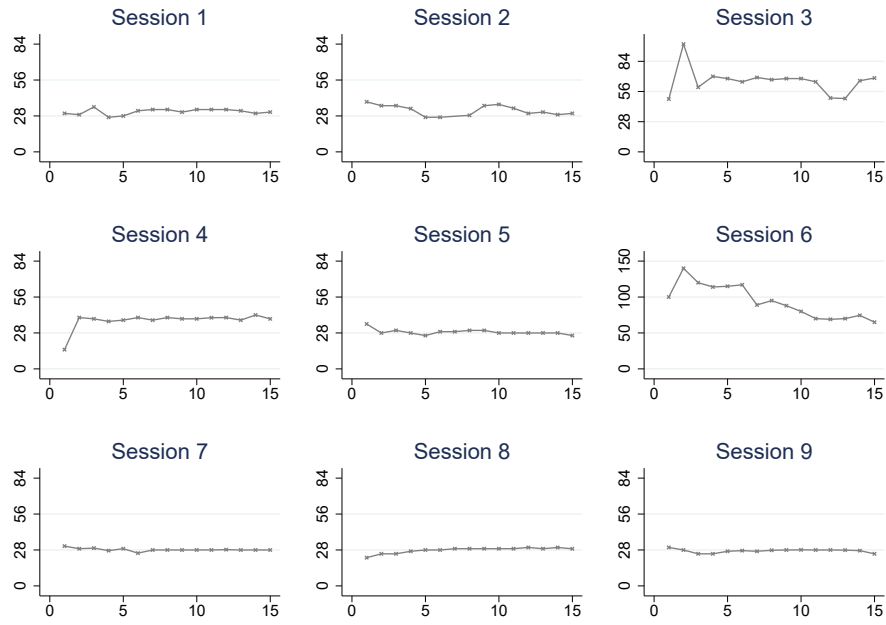


Figure A.4: Median Prices per period in the individual markets of treatment Gift-Half

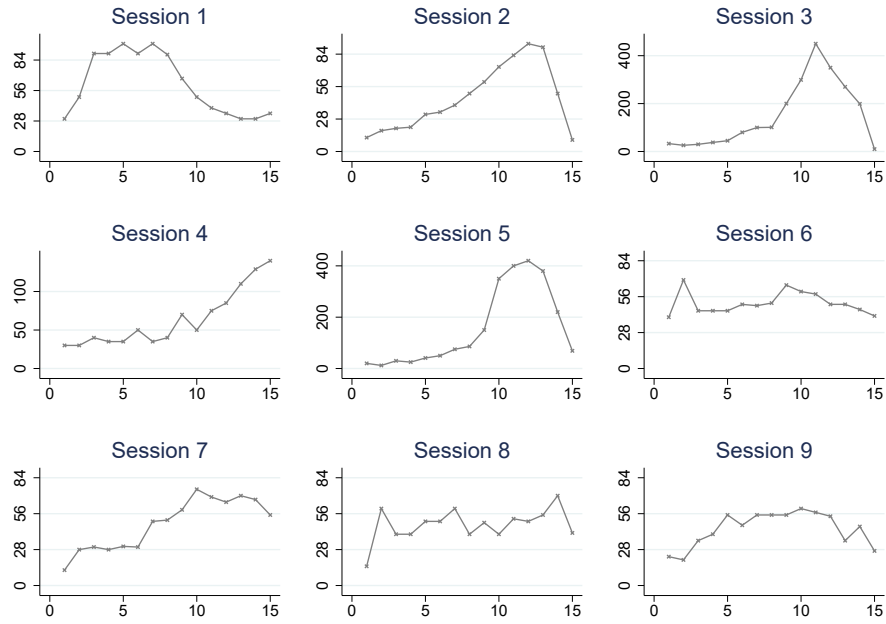


Figure A.5: Median Prices per period in the individual markets of treatment Mining-All

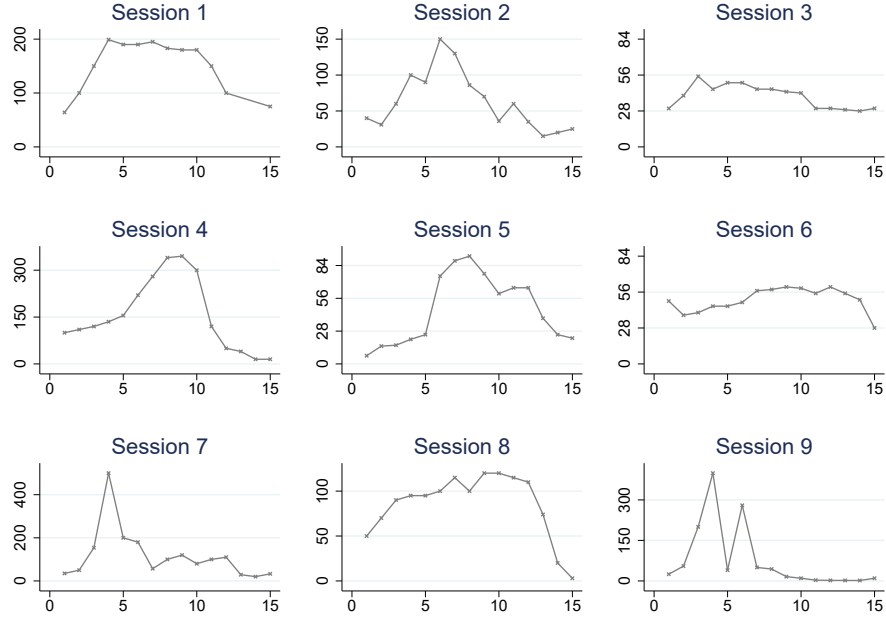


Figure A.6: Median Prices per period in the individual markets of treatment Mining-Half

D Bubble Measures

This section provides the formulas to calculate the bubble measures we use for our analysis. To fix notation, denote:

- T the total number of periods,
- FV_t the fundamental value in period t ,
- N_t the total number of trades in period t ,
- t^* the period with the highest volume-weighted mean price,
- \bar{P}_t the volume-weighted mean price in period t ,
- LO_t the number of shares offered to trade in period t ,
- MO_t the number of shares traded based on accepted orders posted by other subjects in period t ,
- $R_{t,j}$ the log-return of a trade, i.e. $R_{t,j} = \ln(P_{t,j}/P_{t,j-1})$,
- $\bar{R}_{t,j}$ the average log-return in period t ,
- $S_{\hat{t},j}$ the price of sell order j at the end of period t ,
- $B_{\hat{t},j}$ the price of buy order j at the end of period t ,
- $O_{\hat{t}}$ the number of open orders at the end of period t ,
- O_o^j the quantity offered in order o .

Now, define the following bubble measures:

$$\begin{aligned}
RAD &= \sum_{t=1}^T \left| \frac{\bar{P}_t - FV_t}{FV_t} \right| \\
RD &= \sum_{t=1}^T \frac{\bar{P}_t - FV_t}{FV_t} \\
RDMAX &= \max_t \left\{ \frac{\bar{P}_t - FV_t}{FV_t} \right\} = \frac{\bar{P}_{t^*} - FV_{t^*}}{FV_{t^*}} \\
AMPLITUDE &= \frac{\bar{P}_{t^*} - FV_{t^*}}{FV_{t^*}} - \min_{0 \leq k < t^*} \left\{ \frac{\bar{P}_{t^*-k} - FV_{t^*-k}}{FV_{t^*-k}} \right\} \\
CRASH &= \min_{0 \leq l \leq T-t^*} \left\{ \frac{\bar{P}_{t^*+l} - FV_{t^*+l}}{FV_{t^*+l}} \right\} - \frac{\bar{P}_{t^*} - FV_{t^*}}{FV_{t^*}} \\
SPREAD &= \sum_{t=1}^T \frac{1}{FV_t} \frac{1}{T} \left[\min_{j \in N_t} \{S_{\hat{t},j}\} - \max_{j \in N_t} \{B_{\hat{t},j}\} \right] \\
VOLA &= \sum_{t=1}^T \frac{1}{T} \sqrt{\frac{1}{N_t} \sum_{j=1}^{N_t} (R_{t,j} - \bar{R}_t)^2} \\
TURNOVER &= \sum_{t=1}^T \frac{1}{T} \frac{VOL_t}{TSO} \\
SR &= \sum_{t=1}^T \sum_{j=1}^{N_t} \frac{1}{T} \frac{LO_{j,t}}{LO_{j,t} + MO_{j,t}} \\
LIQUIDITY &= \frac{1}{TSO} \sum_{t=1}^T \sum_{o=1}^{O_{\hat{t}}} \frac{1}{T} O_o^j
\end{aligned}$$

D.1 Bubble Measures by Session/Market

Tables A.1-A.4 present the different bubble measures for each market separately for our four treatments. As one can clearly see in Tables A.2 and A.4, session 2 in Gift-Half and session 4 in Mining-Half have a puzzling high LIQUIDITY value compared to the other sessions. The interpretation of those values is questionable, as they are based on rather meaningless orders.¹⁸

Session	RAD	RD	RDMAX	AMP	CRASH	TURN	LQ	SR	SPREAD	VOLA
1	0.53	0.53	1.07	0.81	-0.48	0.21	1.09	16.52	0.23	0.23
2	0.82	0.82	1.34	0.93	-	0.30	0.19	21.79	0.22	0.14
3	0.04	0.03	0.12	0.15	-0.16	0.12	0.41	18.55	0.05	0.08
4	1.47	1.47	1.65	0.71	-0.22	0.18	0.55	25.55	0.15	0.10
5	0.41	0.41	1.04	0.98	-0.97	0.28	0.20	24.31	0.51	0.46
6	0.13	0.06	0.67	0.79	-0.81	0.12	0.78	19.65	0.11	0.23
7	0.02	0.01	0.02	0.10	-0.01	0.15	0.29	20.88	0.07	0.14
8	0.56	0.56	1.85	-	-1.79	0.27	2.38	24.53	0.79	1.18
9	0.16	0.08	0.54	0.82	-0.43	0.23	0.93	11.72	0.26	0.21

Table A.1: Bubble measures for the markets in treatment Gift-All

Session	RAD	RD	RDMAX	AMP	CRASH	TURN	LQ	SR	SPREAD	VOLA
1	0.15	0.14	0.32	-	-0.35	0.29	1.09	19.31	0.10	0.16
2	0.14	0.14	0.37	-	-0.39	0.06	42.46	13.95	0.18	0.05
3	1.27	1.27	2.06	1.31	-1.32	0.14	0.46	18.05	0.31	0.10
4	0.38	0.38	0.50	0.31	-0.10	0.20	0.49	18.27	0.16	0.27
5	0.06	0.00	0.24	-	-0.34	0.20	0.36	19.60	-0.02	0.24
6	2.48	2.48	4.20	-	-2.89	0.21	0.98	27.55	0.88	0.42
7	0.03	0.02	0.19	-	-0.26	0.20	1.72	26.93	0.02	0.04
8	0.06	-0.01	0.07	0.32	-0.04	0.30	1.98	27.33	0.05	0.07
9	0.04	-0.02	0.10	-	-0.21	0.18	0.23	19.02	0.09	0.06

Table A.2: Bubble measures for the markets in treatment Gift-Half

¹⁸For example, in session 4 in treatment Mining-Half, one trader offered to buy 100000 assets for a price of 0.01 ECU each.

Session	RAD	RD	RDMAX	AMP	CRASH	TURN	LQ	SR	SPREAD	VOLA
1	1.13	1.11	2.39	2.53	-2.32	0.36	2.06	20.72	0.48	0.28
2	0.87	0.63	2.27	2.84	-2.65	0.21	0.54	17.41	0.35	0.29
3	5.62	5.61	34.31	34.40	-34.28	0.18	0.24	12.20	7.57	0.70
4	1.29	1.26	3.63	3.84	-	0.11	0.22	10.18	0.85	0.31
5	4.91	4.78	14.11	14.59	-10.60	0.28	0.64	17.97	1.43	0.30
6	0.79	0.79	1.24	0.71	-0.76	0.25	1.08	19.92	0.32	0.18
7	0.77	0.71	1.57	2.05	-0.62	0.13	0.52	14.26	0.48	0.11
8	0.92	0.86	3.65	4.12	-3.21	0.17	0.43	17.13	0.84	0.61
9	1.05	0.97	6.02	6.33	-5.70	0.14	0.47	16.96	0.48	0.28

Table A.3: Bubble measures for the markets in treatment Mining-All

Session	RAD	RD	RDMAX	AMP	CRASH	TURN	LQ	SR	SPREAD	VOLA
1	3.76	3.76	6.27	4.76	-4.59	0.11	0.30	22.11	1.21	0.22
2	1.49	1.37	3.62	3.20	-4.03	0.31	0.84	25.05	1.76	0.60
3	0.40	0.40	0.81	0.76	-0.83	0.20	1.93	17.37	0.34	0.12
4	4.83	4.72	11.38	8.87	-11.84	0.24	39.40	22.36	1.02	0.08
5	0.94	0.85	2.20	2.80	-2.27	0.34	1.22	20.36	0.96	0.65
6	0.75	0.75	1.07	0.89	-0.99	0.20	0.85	17.86	0.66	0.35
7	3.52	3.49	14.74	14.67	-14.94	0.20	0.40	19.49	1.93	0.87
8	2.08	1.97	3.23	2.83	-3.87	0.33	0.37	23.92	1.32	0.44
9	2.87	2.23	11.69	11.59	-12.62	0.14	1.22	28.16	4.28	0.93

Table A.4: Bubble measures for the markets in treatment Mining-Half

E Experimental Details & Instructions

Table A.5 below summarises dates and locations of implementation of each of our sessions across all four treatments. Depending on our treatment, we handed our subjects instructions describing the market. We include the translated instructions for Gift-half and Mining-half below. Note that the instructions for Gift-All and Mining-All are identical to the respective half versions, except for the endowment parameters (which are the same for every participant in our All-treatments, i.e. no different roles exist). In subsection E.1, we include the translated comprehension quiz questions which participants had to respond to before the market stage of treatment Gift-Half.¹⁹ Subsection E.2 shows a fictional result screen similar to those that participants could see in between periods of the market stage.

Table A.5: Dates of Sessions

(a) Gift-All				(b) Gift-Half			
Date	Session	Subjects	Location	Day	Session	Subjects	Location
30/09/2019	1	8	Heidelberg	22/10/2019	1	8	Heidelberg
01/10/2019	2	8	Heidelberg	24/10/2019	2	8	Frankfurt
04/10/2019	3	8	Heidelberg	25/10/2019	3	8	Frankfurt
09/10/2019	4	8	Heidelberg	25/10/2019	4	8	Frankfurt
15/10/2019	5	8	Frankfurt	07/11/2019	5	8	Heidelberg
15/10/2019	6	8	Frankfurt	14/11/2019	6	8	Frankfurt
18/10/2019	7	8	Frankfurt	14/11/2019	7	8	Frankfurt
18/10/2019	8	8	Frankfurt	18/11/2019	8	8	Heidelberg
24/10/2019	9	8	Frankfurt	22/11/2019	9	8	Heidelberg
Total:		72		Total:		72	
(c) Mining-All				(d) Mining-Half			
Day	Session	Subjects	Location	Day	Session	Subjects	Location
30/09/2019	1	8	Heidelberg	24/10/2019	1	8	Frankfurt
01/10/2019	2	8	Heidelberg	25/10/2019	2	8	Frankfurt
04/10/2019	3	7	Heidelberg	28/10/2019	3	8	Heidelberg
09/10/2019	4	7	Heidelberg	05/11/2019	4	8	Frankfurt
15/10/2019	5	8	Frankfurt	07/11/2019	5	8	Heidelberg
15/10/2019	6	8	Frankfurt	14/11/2019	6	8	Frankfurt
18/10/2019	7	8	Frankfurt	14/11/2019	7	8	Frankfurt
18/10/2019	8	8	Frankfurt	18/11/2019	8	8	Heidelberg
24/10/2019	9	8	Frankfurt	22/11/2019	9	8	Heidelberg
Total:		70		Total:		72	

¹⁹The quiz questions of our other treatments are a subset of these. Note that the correct answers for some questions depend on the treatment.

1. General information

The next part of the experiment is about a market for assets. Please read these instructions carefully. Your decisions will influence your payment at the end of the experiment. You should therefore make sure that you have fully understood the functions of the trading platform.

First, you will go through three practice rounds in which you can learn and try out the functions of the interface. These practice rounds will not affect your payment. Each of the practice rounds will last 120 seconds. After that there will be 15 trading rounds that will count towards your final earnings. Each of these trading rounds will also last 120 seconds. You will have the opportunity to buy and sell assets in a market. The currency in this market is called ECU (Experimental Currency Unit). All trading and earnings are in ECUs. At the beginning of the experiment, half of the participants are randomly assigned **role A**, while the other half are assigned **role B**. Participants with role A receive 5540 ECUs and 0 units of the asset, and the opportunity to generate assets. Participants with role B receive 6260 ECUs and 0 units of the asset and have no possibility to generate assets. All participants can use their ECUs to buy or sell assets in the market. How participants with role A can generate assets is explained below. Your account balance and asset holdings are transferred from one round to the next.

At the end of the experiment, the value of your assets is determined randomly for all participants. For this purpose, 8 playing cards are used: Two Aces, two Kings, two Queens and two Jacks. Each card corresponds to a different value for the assets:

<u>Playing card</u>	<u>Value of one asset</u>
Ace	67 ECU
King	30 ECU
Queen	15 ECU
Jack	0 ECU

Each participant will draw one card in turn so that all playing cards are distributed. This guarantees that exactly two participants draw an ace, exactly two participants draw a king, exactly two participants draw a queen and exactly two participants draw a jack.

After the value of your assets has been determined, you are paid out. You will receive Euros according to the sum of the ECU value of your assets account and your ECU account balance. The more ECUs you earn, the more Euros you will receive. Your ECUs will be converted into Euros at the following rate:

$$560 \text{ ECUs} = 1 \text{ Euro}$$

2. Generation of assets, the market and trading rules

Market Rules

You can trade assets with others on the marketplace. Trading is done in the form of a continuous double auction. This means that anyone can buy and sell assets.

If you buy some units of the asset, your ECU account balance will be reduced by the amount of money due (price times quantity) whereas your stock of assets will increase by the quantity purchased. If you sell assets, your ECU account balance will increase by the amount of money due (price times quantity) and your stock of assets will decrease by the quantity sold. Please note that you can only buy or sell as many assets as covered by your account.

During the experiment you will see a screen like the following:

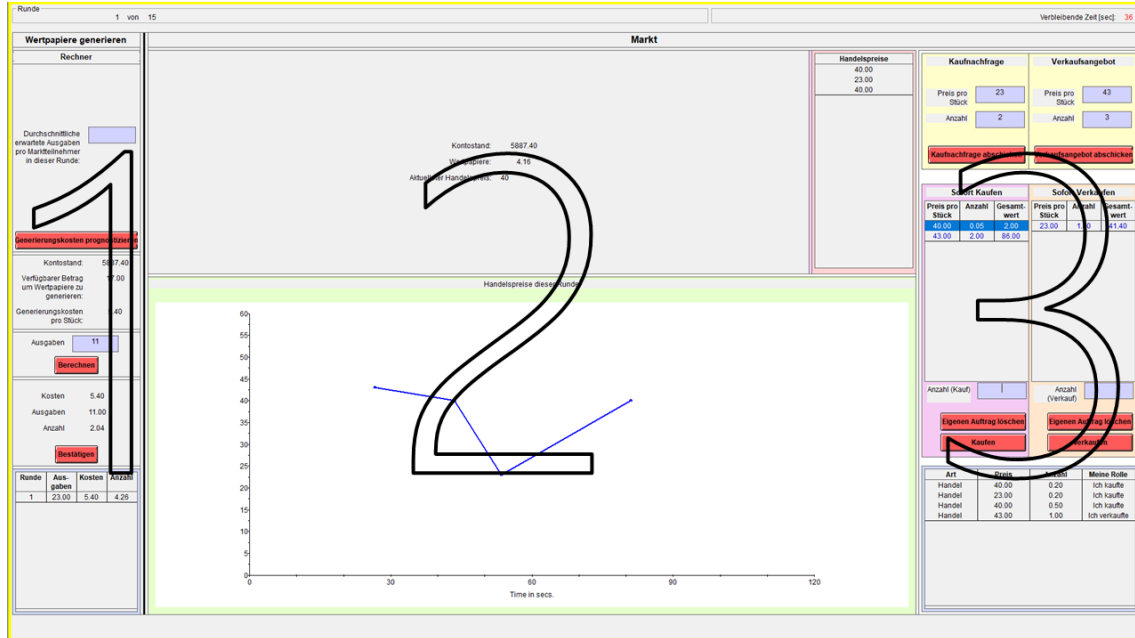


Figure 1: Screen

The screen is divided into different segments (see Figure 1). The left segment (1) is for the generation of assets. In the middle (2) of the screen you will see information about your current account balance and assets, as well as a price list for the current trading round. When a new trade takes place, this information will appear in the "Trade prices" ("Handelspreise") list and as a new marker in the price chart below.

In the right segment (3) of the screen you will find a user interface where you can trade assets with others.

The following section first explains how to generate a asset. Then the functions of the marketplace are described.

Generate assets

In the left area (1) you can decide in each trading round if you want to spend some of your ECUs to generate assets. Note that you can spend a maximum of 80 ECUs to generate assets in each round, provided you have been assigned role A. If you are assigned role B, you can spend 0 ECUs to generate assets. The cost of generating assets varies over time. The cost remains constant in each round but is recalculated at the beginning of each round. The cost of generation depends on how many ECUs have been spent by all market participants in all previous rounds. Figure 2 shows how the costs depend on the total expenditure for the generation of assets. The vertical axis shows the generation cost per asset, the horizontal axis shows the total expenditure (all expenditure over all previous rounds of all participants added together). Note that the cost of generation can only increase, it will never decrease.

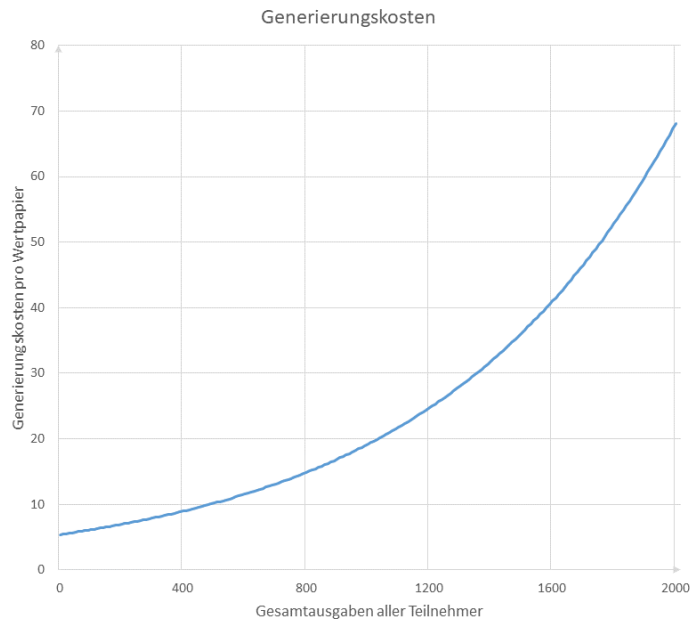


Figure 2: Costs of generating assets

The screen for generating assets (segment 1) consists of three parts. At the top is a calculator that helps you to calculate the cost of generation in the following rounds. In the field "Average expected expenses per market participant in this round" ("Durchschnittliche erwartete Ausgaben pro Marktteilnehmer in dieser Runde") you can enter a number that you think the participants will spend on average in the current round. If you click on "Forecast generation costs" ("Generierungskosten prognostizieren"), a table will appear showing how the generation costs will develop in the next four rounds (assuming that the others spend as much as you have indicated in each round). In the middle of the left segment (1) you can generate assets. There you will find information about the ECUs you have in total and the number of ECUs you have left available to generate assets (this value is reset to 80 ECUs at the beginning of each round, if you have been assigned role A). You will also find the current cost of generating a asset. At the beginning of each new round, the costs are calculated as shown in the figure above. The costs always refer to exactly one asset. However, it is also possible to generate parts of a asset. To generate, enter the number of ECUs you want to spend in the "Spend" ("Ausgaben") field. If you then click on the "Calculate" ("Berechnen") button, you will see how many assets you can generate with these expenses. If you want to continue the generation, you can do so by clicking on "Confirm" ("Bestätigen"). If you want to change the amount of the expenses, you can simply change the number in the "Expenses" ("Ausgaben") field and click "Calculate" ("Berechnen") again. You can see an example of this procedure in figure 3. If you confirm your generation, your account balance will be updated immediately, the corresponding ECUs will be deducted from your account and your assets balance will be increased.



Figure 3: Example for generating assets

In the lower part of the left area (1) your personal generation history is listed. Every generation of assets you complete is listed here. If your history is too large for the space of the table, you can scroll through it.

Marketplace

If you wish to purchase assets, you can do so in two ways:

1. You can create a **buy request** in the "Buy Request" ("Kaufnachfrage") box, which can then be accepted by another participant who wants to sell to you. To do this, enter the price you are willing to pay for one unit of the asset in the "Price per unit" ("Preis pro Stück") field. Also enter the number of assets you wish to buy at that price in the "Quantity" ("Anzahl") field (this can also be a fraction of a unit). You can submit your purchase request by clicking on "Submit purchase request" ("Kaufnachfrage abschicken").
2. You can **buy immediately** by selecting an offer to sell from the list in the "Buy Now" ("Sofort Kaufen") box and entering the number of units you wish to buy at the specified price in the "Quantity (Buy)" ("Anzahl (Kauf)") field and then clicking "Buy" ("Kaufen"). The list shows all the offers for sale sorted by price, so the lowest price is at the top.

If you want to sell assets, you also have two options:

1. You can create an **offer to sell** in the "Offer to sell" ("Verkaufsangebot") box, which can then be accepted by another participant who wants to buy from you. To do this, enter the price at which you are willing to sell one unit of the asset in the "Price per unit" ("Preis pro Stück") box. Also enter the number of assets you wish to sell at this price in the "Number" ("Anzahl") field (this can be a fraction of a unit be). You can submit the offer for sale by clicking on "Submit offer for sale" ("Verkaufsangebot abschicken").

-
2. You can **sell immediately** by selecting a purchase request from the list in the "Sell immediately" ("Sofort Verkaufen") box, entering the quantity you wish to sell at the price indicated in the "Quantity (Sale)" ("Anzahl (Verkauf)") field and then clicking on "Sell" ("Verkaufen"). The list will show all purchase requests sorted by price, so the highest price is at the top.

You can withdraw your buy requests and sell offers as long as they have not been accepted by another market participant. To do so, select the corresponding line in the list and then click on "Delete own order" ("Eigenen Auftrag löschen"). You can only delete orders you have submitted yourself. You can recognize your orders by their colour. Your own orders will be in blue font, those of others in black font.

At the bottom right (2) of the screen you will see a list of all the actions you have been involved in. If this history becomes larger than the table, you have the option to scroll so that you can browse the entire history.

At the end of each round, a summary screen will be displayed, showing your current ECU account balance and assets position, as well as generation information. You will also find a graph and a list of average trading prices from previous rounds.

Summary:

- Cash and initial holdings for role A: 5540 ECU, 0 assets
- Cash and initial holdings for role B: 6260 ECU, 0 assets
- 3 practice rounds of 120 seconds each
- 15 trading rounds of 120 seconds each
- Account balances are transferred from round to round
- Functions:
 - Assets generation
 - Purchase demand
 - Buy now ("Sofort Kaufen")
 - Sales offer
 - Sell immediately ("Sofort Verkaufen")
- Generation limit role A: 80 ECU
- Generation limit role B: 0 ECU
- Generation costs increase at the beginning of each round as long as the total expenditure of all participants increases
- Own orders in blue font, other orders in black font
- At the end of the market:
 - Assets = 0/15/30/67 ECU
 - 560 ECU = 1 EUR



1. General information

The next part of the experiment is about a market for assets. Please read these instructions carefully. Your decisions will influence your payment at the end of the experiment. You should therefore make sure that you have fully understood the functions of the trading platform.

First, you will go through three practice rounds in which you can learn and try out the functions of the interface. These practice rounds will not affect your payment. Each of the practice rounds will last 120 seconds. After that there will be 15 trading rounds that will count towards your final earnings. Each of these trading rounds will also last 120 seconds. You will have the opportunity to buy and sell assets in a market. The currency in this market is called ECU (Experimental Currency Unit). All trading and earnings are in ECUs. At the beginning of the experiment, half of the participants are randomly assigned **role A**, while the other half are assigned **role B**. Participants with role A receive 5540 ECUs and 0 units of the asset, and the opportunity to generate assets. Participants with role B receive 6260 ECUs and 0 units of the asset and have no possibility to generate assets. All participants can use their ECUs to buy or sell assets in the market. How participants with role A can generate assets is explained below. Your account balance and asset holdings are transferred from one round to the next.

At the end of the experiment, the value of your assets is determined randomly for all participants. For this purpose, 8 playing cards are used: Two Aces, two Kings, two Queens and two Jacks. Each card corresponds to a different value for the assets:

Playing card	Value of one asset
Ace	67 ECU
King	30 ECU
Queen	15 ECU
Jack	0 ECU

Each participant will draw one card in turn so that all playing cards are distributed. This guarantees that exactly two participants draw an ace, exactly two participants draw a king, exactly two participants draw a queen and exactly two participants draw a jack.

After the value of your assets has been determined, you are paid out. You will receive Euros according to the sum of the ECU value of your assets account and your ECU account balance. The more ECUs you earn, the more Euros you will receive. Your ECUs will be converted into Euros at the following rate:

$$560 \text{ ECUs} = 1 \text{ Euro}$$

2. Generation of assets, the market and trading rules

Market Rules

You can trade assets with others on the marketplace. Trading is done in the form of a continuous double auction. This means that anyone can buy and sell assets.

If you buy some units of the asset, your ECU account balance will be reduced by the amount of money due (price times quantity) whereas your stock of assets will increase by the quantity purchased. If you sell assets, your ECU account balance will increase by the amount of money due (price times quantity) and your stock of assets will decrease by the quantity sold. Please note that you can only buy or sell as many assets as covered by your account.

During the experiment you will see a screen like the following:

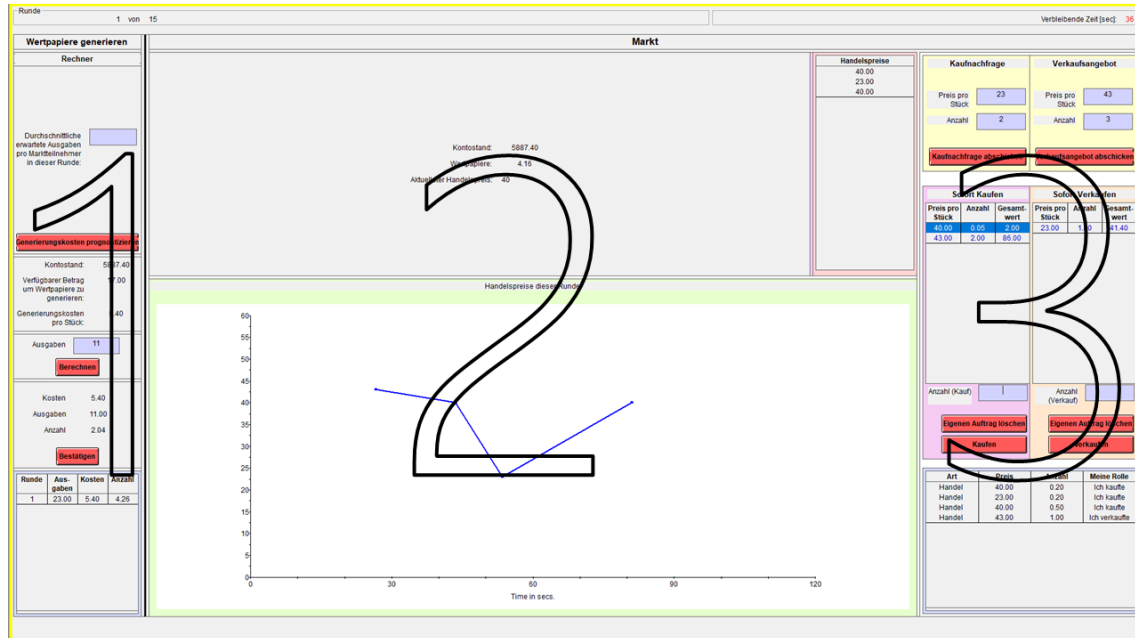


Figure 1: Screen

The screen is divided into different segments (see Figure 1). The left segment (1) is for the generation of assets. In the middle (2) of the screen you will see information about your current account balance and assets, as well as a price list for the current trading round. When a new trade takes place, this information will appear in the "Trade prices" ("Handelspreise") list and as a new marker in the price chart below.

In the right segment (3) of the screen you will find a user interface where you can trade assets with others.

The following section first explains how to generate a asset. Then the functions of the marketplace are described.

Generate assets

In the left area (1) you can decide in each trading round if you want to spend some of your ECUs to generate assets. Note that you can spend a maximum of 80 ECUs to generate assets in each round, provided you have been assigned role A. If you are assigned role B, you can spend 0 ECUs to generate assets. The cost of generating assets varies over time. The cost remains constant in each round but is recalculated at the beginning of each round. The cost of generation depends on how many ECUs have been spent by all market participants in all previous rounds. Figure 2 shows how the costs depend on the total expenditure for the generation of assets. The vertical axis shows the generation cost per asset, the horizontal axis shows the total expenditure (all expenditure over all previous rounds of all participants added together). Note that the cost of generation can only increase, it will never decrease.

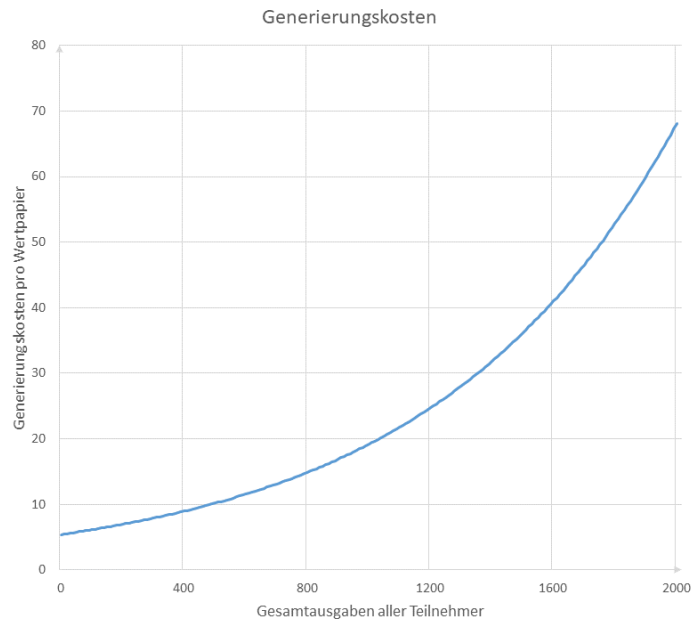


Figure 2: Costs of generating assets

The screen for generating assets (segment 1) consists of three parts. At the top is a calculator that helps you to calculate the cost of generation in the following rounds. In the field "Average expected expenses per market participant in this round" ("Durchschnittliche erwartete Ausgaben pro Marktteilnehmer in dieser Runde") you can enter a number that you think the participants will spend on average in the current round. If you click on "Forecast generation costs" ("Generierungskosten prognostizieren"), a table will appear showing how the generation costs will develop in the next four rounds (assuming that the others spend as much as you have indicated in each round). In the middle of the left segment (1) you can generate assets. There you will find information about the ECUs you have in total and the number of ECUs you have left available to generate assets (this value is reset to 80 ECUs at the beginning of each round, if you have been assigned role A). You will also find the current cost of generating a asset. At the beginning of each new round, the costs are calculated as shown in the figure above. The costs always refer to exactly one asset. However, it is also possible to generate parts of a asset. To generate, enter the number of ECUs you want to spend in the "Spend" ("Ausgaben") field. If you then click on the "Calculate" ("Berechnen") button, you will see how many assets you can generate with these expenses. If you want to continue the generation, you can do so by clicking on "Confirm" ("Bestätigen"). If you want to change the amount of the expenses, you can simply change the number in the "Expenses" ("Ausgaben") field and click "Calculate" ("Berechnen") again. You can see an example of this procedure in figure 3. If you confirm your generation, your account balance will be updated immediately, the corresponding ECUs will be deducted from your account and your assets balance will be increased.

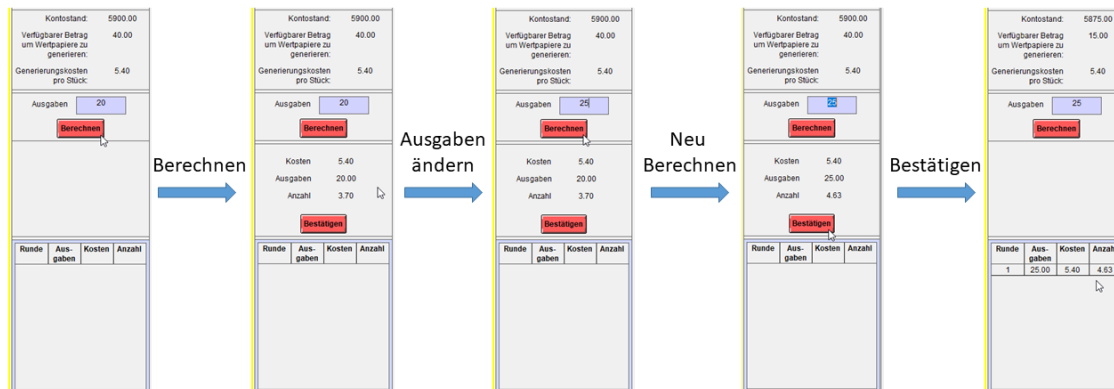


Figure 3: Example for generating assets

In the lower part of the left area (1) your personal generation history is listed. Every generation of assets you complete is listed here. If your history is too large for the space of the table, you can scroll through it.

Marketplace

If you wish to purchase assets, you can do so in two ways:

1. You can create a **buy request** in the "Buy Request" ("Kaufnachfrage") box, which can then be accepted by another participant who wants to sell to you. To do this, enter the price you are willing to pay for one unit of the asset in the "Price per unit" ("Preis pro Stück") field. Also enter the number of assets you wish to buy at that price in the "Quantity" ("Anzahl") field (this can also be a fraction of a unit). You can submit your purchase request by clicking on "Submit purchase request" ("Kaufnachfrage abschicken").
2. You can **buy immediately** by selecting an offer to sell from the list in the "Buy Now" ("Sofort Kaufen") box and entering the number of units you wish to buy at the specified price in the "Quantity (Buy)" ("Anzahl (Kauf)") field and then clicking "Buy" ("Kaufen"). The list shows all the offers for sale sorted by price, so the lowest price is at the top.

If you want to sell assets, you also have two options:

1. You can create an **offer to sell** in the "Offer to sell" ("Verkaufsangebot") box, which can then be accepted by another participant who wants to buy from you. To do this, enter the price at which you are willing to sell one unit of the asset in the "Price per unit" ("Preis pro Stück") box. Also enter the number of assets you wish to sell at this price in the "Number" ("Anzahl") field (this can be a fraction of a unit be). You can submit the offer for sale by clicking on "Submit offer for sale" ("Verkaufsangebot abschicken").

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2. You can **sell immediately** by selecting a purchase request from the list in the "Sell immediately" ("Sofort Verkaufen") box, entering the quantity you wish to sell at the price indicated in the "Quantity (Sale)" ("Anzahl (Verkauf)") field and then clicking on "Sell" ("Verkaufen"). The list will show all purchase requests sorted by price, so the highest price is at the top.

You can withdraw your buy requests and sell offers as long as they have not been accepted by another market participant. To do so, select the corresponding line in the list and then click on "Delete own order" ("Eigenen Auftrag löschen"). You can only delete orders you have submitted yourself. You can recognize your orders by their colour. Your own orders will be in blue font, those of others in black font.

At the bottom right (2) of the screen you will see a list of all the actions you have been involved in. If this history becomes larger than the table, you have the option to scroll so that you can browse the entire history.

At the end of each round, a summary screen will be displayed, showing your current ECU account balance and assets position, as well as generation information. You will also find a graph and a list of average trading prices from previous rounds.

Summary:

- Cash and initial holdings for role A: 5540 ECU, 0 assets
- Cash and initial holdings for role B: 6260 ECU, 0 assets
- 3 practice rounds of 120 seconds each
- 15 trading rounds of 120 seconds each
- Account balances are transferred from round to round
- Functions:
 - Assets generation
 - Purchase demand
 - Buy now ("Sofort Kaufen")
 - Sales offer
 - Sell immediately ("Sofort Verkaufen")
- Generation limit role A: 80 ECU
- Generation limit role B: 0 ECU
- Generation costs increase at the beginning of each round as long as the total expenditure of all participants increases
- Own orders in blue font, other orders in black font
- At the end of the market:
 - Assets = 0/15/30/67 ECU
 - 560 ECU = 1 EUR

E.1 Market stage quiz

You will now have to respond to some questions regarding the next stage of the experiment. Please use the instructions to assist you.

- Assuming you are a role A player, how many starting assets will you have?
Correct answer: 0
- Assuming you are a role B player, how many starting assets will you have?
Correct answer: 0
- How many payment-relevant trading rounds will there be?
Correct answer: 15
- Assuming you are a role A player, what is the maximum number of ECUs you can spend on asset generation in each trading period?
Correct answer: 80
- Assuming you are a role B player, what is the maximum number of ECUs you can spend on asset generation in each trading period?
Correct answer: 0
- Assume that the total expenditure of all participants (including you) on asset generation in previous rounds is approximately 800 ECUs. What would be the approximate cost to generate one unit of the asset (in ECU)?
Correct answer: 15
- What is the probability that your assets have a redemption value of 67 ECU at the end of all trading periods?
Correct answer: 25%
- Say you would like to obtain more assets. How can you acquire any?
Correct answer: buying from the market or generation
- At the end of the market, your asset holdings will be exchanged with:
Correct answer: ECUs
- If at the end of the market you are holding 5600 ECUs, how much in Euros will you receive?
Correct answer: 10
- Say you are holding 30 assets at the end of the market and you draw a king. Your asset holdings would be worth a total of (in ECU):
Correct answer: 900

E.2 Summary screen between market periods

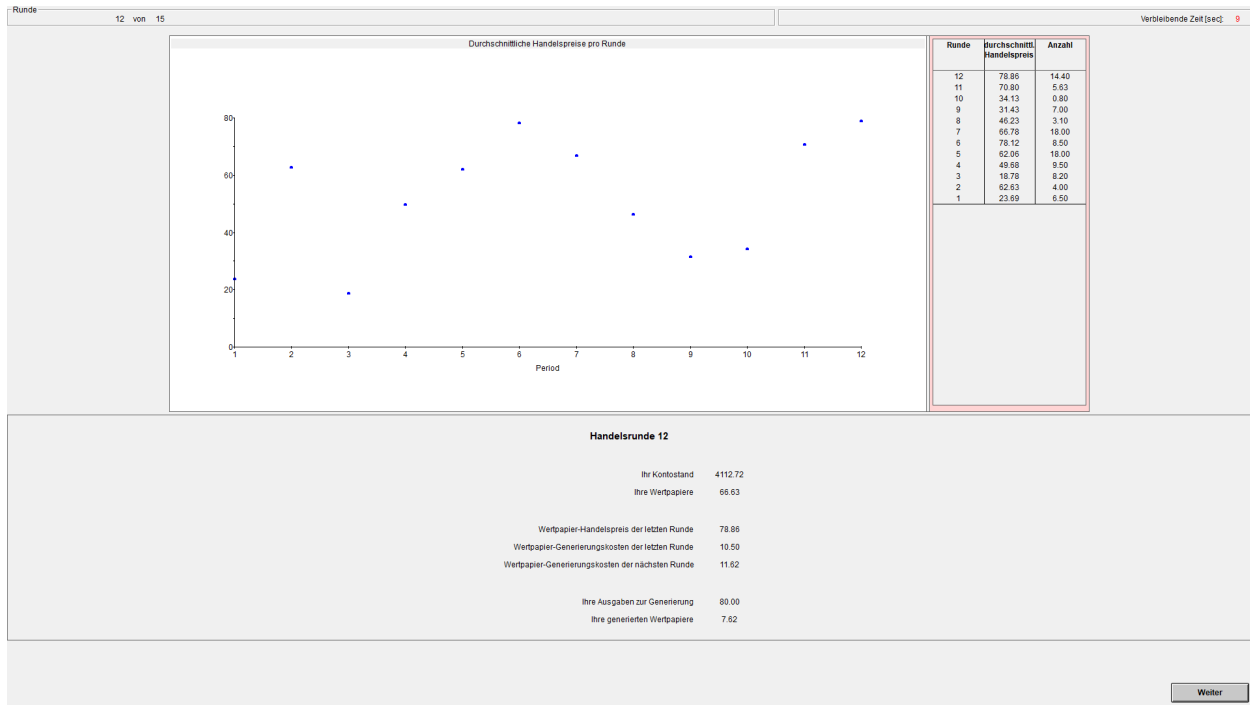


Figure A.7: Price chart and history of previous rounds on the result screen between trading periods. The screen lists average trading prices (“Durchschnittlicher Handelspreis”), volumes (“Anzahl”), periods (“Handelsrunde”), cash balance (“Kontostand”), asset holdings (“Wertpapiere”), the trading price of the last period (“Wertpapier-Handelspreis der letzten Runde”), asset generation price of the last/next period (“Wertpapier-Generierungskosten der letzten/nchsten Runde”), own expenditure on asset generation (“Ihre Ausgaben zur Generierung”) and the number of assets generated (“Ihre generierten Wertpapiere”).