HEIDELBERG UNIVERSITY
DEPARTMENT OF ECONOMICS

UNIVERSITÄT HEIDELBERG
ZUKUNFT SEIT 1386

Does mining fuel bubbles? An experimental study on cryptocurrency markets

Marco Lambrecht

Andis Sofianos

Yilong Xu

AWI DISCUSSION PAPER SERIES NO. 703
May 2021

Does mining fuel bubbles? An experimental study on cryptocurrency markets

Marco Lambrecht* Andis Sofianos† Yilong Xu‡

May 28, 2021

Abstract

The massive price bubbles of decentralized cryptocurrencies, such as Bitcoin, have created a puzzle for economists. How can a non-revenue-generating asset exhibit such extreme price dynamics, forming multiple episodes of bubbles and crashes since its creation? The answer is not straightforward, since cryptocurrencies differ in several important aspects from other conventional assets. In this paper, we investigate how key features associated with the Proof-of-Work consensus mechanism affect pricing. In a controlled laboratory experiment, we observe that the formation of price bubbles can be causally attributed to mining. Moreover, bubbles are more pronounced if the mining capacity is centralized to a small group of individuals. Analysis of the order book data reveals that miners seem to play a crucial role in bubble formation. The results demonstrate that high price volatility is an inherent feature of cryptocurrencies based on a mining protocol, which seriously limits any prospects for such assets truly becoming a medium of exchange.

JEL classification: C90; D53; G12.
Keywords: Bitcoin, Bubbles, Cryptocurrency, Financial Market Experiment

*Hanken School of Economics; email: marco.lambrecht@hanken.fi
†University of Heidelberg; email: andis.sofianos@uni-heidelberg.de
‡University of Heidelberg; email: yilong.xu@awi.uni-heidelberg.de

We thank Peter Bossaerts, Gabriele Camera, William Cong, Peter Duersch, Kose John, Nobuyuki Hanaki, Juergen Huber, Yaron Lahav, Tibor Neugebauer, David Schindler, Joerg Oechssler, Luba Petersen, Vernon Smith, Stefan Trautmann, Steve Tucker, Harald Uhlig, Christoph Vanberg, Matthias Weber, and the seminar and conference participants at University of Konstanz, University of Birmingham, Radboud University, University of Regensburg, Helsinki GSE and CAL2020, HeiKaMaXY, ESA Global 2020, WEAI Virtual International Conference, for their constructive comments and suggestions on this paper. We are grateful for research assistance from Katrin Weiß. The funding provided by the University of Heidelberg is gratefully acknowledged.

1 Introduction

Speculative bubbles are a major destabilizing factor for the economy and often have persistent real consequences (e.g. Brunnermeier and Schnabel, 2016; Brunnermeier et al., 2020; Gao et al., 2020). Perhaps one of the most well-known examples is the long-lasting economic stagnation in Japan during 1991 to 2001 ("the lost decade") after the burst of its stock market bubble (Hoshi and Kashyap, 2004). There are many episodes of bubbles and crashes in economic history such as the Dutch Tulip Mania, the Mississippi Bubble and the South Sea Bubble (Garber, 2001), or the more recent Dot-com and U.S. housing bubbles (Shiller, 2015). However, bubbles observed in cryptocurrency markets dwarf any major historical bubbles in terms of magnitude and have been far more protracted (Bianchetti et al., 2018; Cheah and Fry, 2015).

Although cryptocurrencies were originally devised as a communication protocol that facilitates decentralized electronic payments (Böhme et al., 2015), they are increasingly recognized as an investment vehicle (Glaser et al., 2014). The first and perhaps most prominent cryptocurrency is Bitcoin. Bitcoin alone constituted a market capitalization of over $1 trillion at its peak price in 2021, which is comparable to the market capitalization of all companies in the German DAX index. Choi and Jarrow (2020) carefully study the prevalence of bubbles in cryptocurrency markets.[1] Out of the eight most popular cryptocurrencies, five clearly exhibit bubbles, including Bitcoin. It is puzzling why Bitcoin exhibits such extreme bubbles since it does not generate any income such as dividends or interest. Furthermore, it is different from commodities as it is intangible and has no potential in being incorporated in the production of any further products in the way, for example, gold does. Therefore, the conventional economic valuation measures cannot be directly applied to cryptocurrencies (Burniske and White, 2017; Hong, 2017; Kristoufek, 2015). Nowadays, the majority of individuals who own 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 spreading to other financial markets and ultimately to the real economy is increasingly likely (Guo et al., 2011; Manaa et al., 2019).

What separates decentralized cryptocurrencies from conventional assets is the underlying blockchain technology. Blockchain is a public ledger that records coin ownership, but many permissionless cryptocurrencies such as Bitcoin require a consensus mechanism to determine who has the right to add new information to the blockchain. Irresberger et al. (2020) provide an extensive overview of the public blockchain ecosystem and find that although there are hundreds of blockchains, only a few are of economic relevance. They show that Bitcoin is by far the most adopted blockchain in terms of active users and that it is one of the most relevant blockchains from an economic welfare perspective. Bitcoin's blockchain technology relies on the Proof-of-Work (PoW) consensus mechanism, commonly known as mining, which is the most common consensus mechanism in cryptocurrencies (Gervais et al., 2016). Bitcoin mining can be very costly as miners are required to solve a computationally

[1] In order to determine bubbles, the authors apply the local martingale theory of bubbles, where the fundamental value of a cryptocurrency can be interpreted as the currency's liquidation value at the model's horizon (the buy and hold value).

intensive problem but only those who succeed are allowed to add new information to the blockchain. To encourage participation, the algorithm rewards miners with newly created coins, which is also purposefully designed to be the only way to supply new coins to the market. We offer a more detailed background on Bitcoin and its blockchain technology in section 2.

We identify three defining features associated with the Bitcoin mining process that may affect pricing. First, the reward of mining decreases over time such that in the long run, the total supply of Bitcoin is limited by design. This is achieved by repeatedly halving a miner's reward at given intervals, which creates an increasing perception of scarcity. Second, the rate at which new blocks are added to the blockchain is fixed (on average one block per 10 minutes). This implies that the supply is smoothed and cannot instantly respond to demand shocks. Third, as Bitcoin gains popularity, competition for the reward of mining increases (Alsabah and Capponi, 2020; Cong et al., 2021a). As more processing power joins the mining network, the blockchain's algorithm automatically increases the mining difficulty, making mining more costly. Moreover, exceedingly high computational power requirements for mining will disadvantage small individual miners, making it increasingly infeasible for such individuals to mine bitcoins in a decentralized manner (Alsabah and Capponi, 2020; Ferreira et al., 2019).[2] This can further apply upward pressure on prices as the channel through which individuals can acquire the asset becomes more exclusive as compared to when mining is less centralized.

In this study, we analyze whether these key properties of Bitcoin mining can help explain its extreme price patterns.[3] However, we are not precluding that other channels could be causally related to pricing. Earlier studies have attributed Bitcoin bubbles on a successful narrative (Shiller, 2019), or on darknet marketplace criminal activities (Foley et al., 2019). More recently, Cong et al. (2021b) explain how the price volatility of cryptocurrencies may be causally related to endogenous user adoption. We instead focus on arguably more fundamental reasons related to PoW based cryptocurrencies. In particular, we aim to test whether the blockchain technology and supply scheme of Bitcoin, that we collectively refer to as 'mining', contribute to explaining the commonly observed but otherwise not adequately explained bubble phenomenon observed in cryptocurrency markets. Given the abundant availability of naturally occurring financial data, there has been some effort in the literature to understand the link between mining costs and prices of cryptocurrencies using empirical studies. For instance, Bhambhwani et al. (2019) perform a multi factor analysis

[2]The hash power small individual miners have is negligible compared to the global hash rate, thus, making the expected reward proportionally smaller. This gives rise to mining pools for the purpose of risk-sharing (Cong et al., 2021a). But even within such pools, the reward (net of fees) can be negligible for an average individual miner as it is based on their individual hash power. Overall, the arms-race of mining technology makes it infeasible for small individual actors to obtain Bitcoin through mining, who instead have to rely on trading platforms.

[3]While we focus on the case of Bitcoin, our analysis extends to cryptocurrencies relying on the PoW mechanism such as hard forked variants of Bitcoin (Cash, Gold, Satoshi's Vision), Ethereum Classic (ETC), Dash, Litecoin, and Zcash. Our results do not apply to cryptocurrencies that adopt alternative consensus mechanisms or without a supply limit such as Binance Coin, EOS, Ether, Monero (XMR), Ripple (XRP), Stellar, and Tron (TRX). See Cong and Xiao (2020) for a comprehensive overview of the various categories of cryptocurrencies.

of 38 cryptocurrencies and conclude that the computing power (hashrate) and network size (number of miners) influence cryptocurrency prices. Relatedly, Saleh (forthcoming) theoretically studies the relationship between computing power and electricity consumption, which is the main expense when mining. Hayes (2017, 2019) and Xiong et al. (2020) empirically show that production costs, especially electricity cost, play an important role in explaining cryptocurrency prices. However, such financial data and empirical studies suffer from an absence of counterfactuals and it can be difficult to disentangle the effect of mining from other (unobservable) factors that may also influence prices. Thus, we study mining and mining centralization in a controlled laboratory environment, which allows us to identify their causal effect on prices.

We are the first to design a controlled laboratory environment to study how the PoW consensus mechanism affects pricing in cryptocurrency markets.[4] The experimental method has been successfully employed to test various financial innovations in the past such as the pricing of financial derivatives (e.g., Oprea et al., 2009; Porter and Smith, 1995a; Noussair et al., 2016) and algorithmic trading (Aldrich and López Vargas, 2020; Angerer et al., 2019). Our experimental framework follows Smith et al. (2000) where market participants can trade an asset with a random redemption value.[5] In our setting, asset holders receive 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 are, thus, suitable to use as a baseline (e.g., Cueva and Rustichini, 2015; Kirchler et al., 2012; Noussair et al., 2001). There is no consensus how one should model the fundamental value of a cryptocurrency, which is a much-debated issue in the literature and has not yet been settled. For instance, Cheah and Fry (2015) and Shiller (2019) consider Bitcoin worthless, as it is not a dividend-paying asset, while Biais et al. (2020) and Cong et al. (2021b) suggest that Bitcoin (and other cryptocurrencies) has value because of the transactional benefits it provides. These include acting as an alternative to fiat money when the national currency and the banking system are in disarray or avoiding capital control. Given the lack of consensus on evaluating the fundamental value of a cryptocurrency, we follow the experimental finance literature and model our asset as a non-dividend paying asset with a flat fundamental value that is not far from zero. This allows us to anticipate the price dynamics of our baseline environment from the literature, thus, allowing us to study the effect of mining in a controlled setting.

The 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 (Gift vs. Mining). In the gift condition, traders receive assets as a gift and are also endowed with cash. In the mining condition, traders do not receive any assets at the outset, but only cash. To acquire assets, they need to spend some cash on 'mining' such that the asset can be generated for

[4]To the best of our knowledge, there has not been any experimental study on cryptocurrency pricing in a controlled laboratory environment. Perhaps the closest study to a controlled setting is Krafft et al. (2018), who conduct an online field experiment and examine the effect of peer buying activity in cryptocurrency markets on market liquidity. The authors deploy bot traders who initiate thousands of trades for less than a penny for each of the 217 cryptocurrencies in their sample. Their results highlight the potential impact of peer influence on liquidity in these markets.

[5]A random redemption value is not crucial for bubble formation as shown by Porter and Smith (1995b) who replace four point random payoffs by the expected value.

them at a cost. The cost of mining increases as more units of the asset are mined in total. The second dimension that we vary aims to capture the mining centralization, commonly observed in permissionless cryptocurrencies where not all miners can mine cost effectively. Specifically, along the mining condition, we vary if all or only half of the traders have access to the mining facility (All vs. Half).

Our main results demonstrate that mining fuels bubbles. In the baseline treatment, where mining is absent, there is no indication of bubbles. Price trajectories remain relatively flat and close to fundamental value throughout the entire life of the asset, which is in line with our conjecture based on the existing literature. Once mining is introduced, we observe trading at prices of more than 200% above the fundamental value when all traders have access to mining. More specifically, prices typically start below the fundamental value but above the mining cost at the outset, then follow the mining cost for about 9 periods (i.e. more than half of the trading periods) with some mark-up, before they peak and subsequently crash. The mining costs seem to play a prominent role in determining prices in periods where prices are hiking up. In the presence of mining centralization, our data shows even more extreme patterns of bubbles and crashes. In particular, prices typically trade already above fundamental value from the outset and soon after surge to a level of almost 400% above fundamental value, resulting in a more protracted deflation of the market. Prices decouple from both the fundamental value and mining cost at an early stage. We observe that when half of the traders can only acquire the asset through the market while there is a shared expectation that the mining cost will rise, traders are more eager to purchase the asset early on, albeit at elevated prices. In both Mining treatments, we find that mining activity goes beyond the social optimum suggesting that miners further perpetuate mispricing in these markets.

Overall, the observation that mining and centralization of the mining technology fuel overpricing in a controlled environment is a highly important result. Any effort put into mining of cryptocurrencies is by design welfare harming (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 versions of the blockchain technology which require costly mining will ultimately slow transactions down significantly. Similarly, Easley et al. (2019) highlight the potential for inefficiencies and instabilities due to mining. Relatedly, Huberman et al. (forthcoming) discuss various inefficiencies of the Bitcoin transaction process that stem from its mining protocol and propose alternatives that alleviate these. On the other hand, it has been widely argued among popular media that mining will become cheaper and faster with technological progress. However, as long as the price of the cryptocurrency is attractive, miners will keep competing with each other and increase their effort, leading to an unavoidable arms-race between miners (Alsabah and Capponi, 2020). The PoW algorithm adapts the mining difficulty according to mining effort ensuring that the rate of block creation is stabilized at a predetermined level. Thus, even if only the most cost efficient miners remain active, the mining cost would be sustained at high levels due to the competition among miners. After all, competition is the only way to secure the decentralized network. Overall, our results encourage the ongoing search for alternative blockchain consensus mechanisms that are more efficient (e.g., Hinzen et al., 2020; Saleh, forthcoming).

The remainder of the paper is structured as follows. In section 2, we provide more detail about the blockchain technology as employed by Bitcoin which is similar for many cryptocurrencies. We then describe our experimental design in section 3. In section 4, we present our hypotheses and report our results in section 5. Section 6 discusses the implications of our results and concludes. In the appendix, we report some additional analysis and further experimental details, including the translated experimental instructions.

2 Background on Bitcoin & the blockchain technology

Against the backdrop of the 2008 financial crisis and deteriorated trust on the financial system, the concept of Bitcoin was developed by Nakamoto (2008) as a decentralized peer-to-peer (P2P) electronic cash system that is free from any entity's control. The rules of the money supply of Bitcoin are predetermined and fixed, which brings more monetary discipline to the Bitcoin ecosystem. The information about the coin ownership of all participants is recorded in a cryptographically secured public ledger, known as blockchain. It contains all Bitcoin transactions since its inception. However, due to the absence of a central administrator to manage the blockchain, a consensus mechanism is required to determine who is allowed to add new information to the blockchain. The solution offered by Nakamoto (2008) is called Proof-of-Work (PoW), which is widely used in other permissionless cryptocurrencies. We focus here on the pertinent characteristics of PoW in the context of Bitcoin for our purposes, for a comprehensive description of PoW and Bitcoin mining see Gervais et al. (2016), Auer (2019) and Biais et al. (2019).

Under the PoW consensus mechanism, a new block can only be added to the blockchain if its creator has successfully solved a computationally intensive cryptographic puzzle (i.e., finding a hash value that meets certain conditions). The process of solving this mathematical problem is commonly referred to as 'mining'. To compensate participants for their contribution of computational power, the payment network rewards miners with certain units of Bitcoin, which at the same time is the only way of introducing new coins to the Bitcoin ecosystem. The level of the reward is set by the Bitcoin white paper and is halved approximately every 4 years. Thus, the amount of new coins supplied to the market is decreasing geometrically over time. As a result, the total number of Bitcoin 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 these 21 million coins will be supplied over a fixed number of years up until the year 2140. This is achieved by adjusting the difficulty of the cryptographic puzzle 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 supply of Bitcoin in the short-run. When mining activities intensify (diminish), the PoW difficulty increases (decreases) accordingly. The increase in mining difficulty is also a protective measure for the blockchain to ensure more security against attacks.

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 (Application-Specific Integrated Circuits, ASICs) to efficiently mine cryptocurrencies, while individual investors can typically only purchase Bitcoin on the cryptocurrency exchanges to include them in their portfolios.

These key properties of PoW discussed above are unique to Bitcoin and other similar cryptocurrencies and are not shared by other conventional asset classes.[6] Our experiment is designed to test whether the defining features of mining cause the price volatility observed empirically. Furthermore, our design also tests what further effect the centralization of large professional miners can have on mispricing.

3 Experimental Design

3.1 Experimental Asset Market

Our basic experimental set up is close to Smith et al. (2000), which is similar to Smith et al. (1988) but without intermediate dividends payment. Trading is done over 15 trading periods. The asset that subjects 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, hence, 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 organized using an open book continuous double auction (Smith, 1962; Plott and Gray, 1990), which is the trading institution used in all our experimental markets.[7] Traders can freely post their own bids and asks or accept others' proposals. We do not allow for short selling or purchasing on margin. 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 mining and the centralization of mining, summarized in table 1. We vary the nature of the asset influx to the market: 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. Mining implies that the cash-to-asset ratio (CAR) in our mining treatments varies over time. We elaborate further on the specific implementation of the mining process as well as 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

[6] While the property of costly mining arguably shares similarities to natural resource extraction, cryptocurrencies do not depreciate after usage and the speed of extraction does not depend on the miners themselves (unlike, for instance, in the case of gold extraction, where it does depend on mining effort).

[7] This type of trading organization is also commonly used in Bitcoin trading, see for example www.bitcoin.de.

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

		Centralization	
		All	*Half*
Asset Influx	*Gift*	Gift-All	Gift-Half
	Mining	Mining-All	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 the 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 fundamental value, is 10.2. This ensures that traders will not be cash constrained if they are willing to pay elevated prices to acquire the asset from the market.

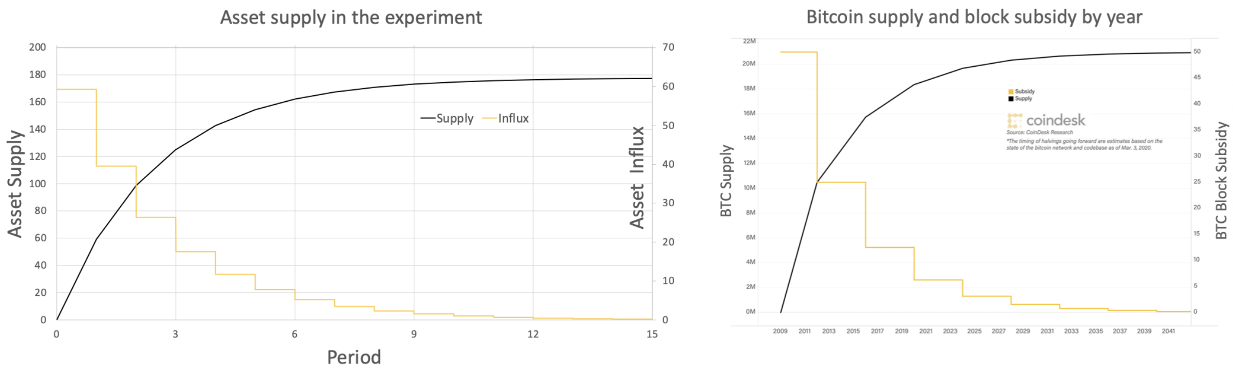
The Mining-All treatment is identical to the baseline, except that traders are endowed with only experimental cash, but no assets at the outset. If traders want to acquire assets, they can either mine the asset at a cost, or buy the asset directly from the market, provided that some units have already been mined. Mining operates concurrently with the asset market. By contrasting Gift-All and Mining-All, we identify the effect of costly mining on asset pricing. The cost of mining is an increasing function of the cumulated units of asset mined (as cumulative expenditure). Traders can decide to spend up to 40 ECUs in each period on mining. The mining cost per unit of asset is clearly known by everyone. Due to the 40 ECU cap on mining expenditure, even when mining is profitable (for example if assets are traded at prices higher than mining costs), there is a limit on how many assets traders can mine per period. Thus, the smooth and limited supply features identified earlier are proxied in the asset generation process. 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 characterized by the following function:

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

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

Figure 1: Experimental implementation of asset supply vs. real-world supply schedule



Note: For both figures, the left vertical axis corresponds to aggregate asset supply, while the right vertical axis corresponds to asset influx. The term *asset subsidy* in the right figure is commonly used to highlight that new coins are introduced as a reward to successful miners.

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. The exact functional form is not communicated to participants, but they are clearly informed that mining will become increasingly costly as more units are mined (see instructions in the appendix). Mining costs adjust discretely at the start of each period. 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 period. The left panel of figure 1 presents the asset supply evolution in our mining treatments over time. As a comparison, the right panel of figure 1 presents the equivalent trend for Bitcoin. Notice how both figures exhibit an exponentially decreasing supply over time.

Treatment Mining-Half is designed to capture the way cryptocurrency mining operates in the real-world. For most cryptocurrencies, cost efficient mining requires a large number of dedicated devices which are costly to acquire and utilize. This implies that many investors have no option to cost effectively mine coins and, hence, are 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 centralization of 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 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 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 overall 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
	Mining Cap per Period (in ECUs)	40	80	0

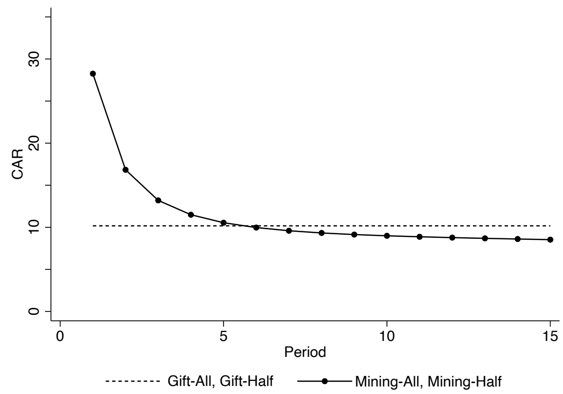
Miners are endowed with more ECUs than non-miners (5900 vs. 5700 & 5540 vs. 5140) to compensate them for the mining cost, which is an increasing function of the cumulated units of asset mined so far. These parameters are calbirated such that the CARs are comparable across treatments. See below for a detailed description.

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 (recall that the mining cost starts from 5.4 ECU in period 1, this will increase to 27.3 ECU in period 5 if everyone mines at full capacity). This is essentially 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

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

five periods, they would reach (approximately) the initial endowment of role A traders in Gift-Half.

Figure 2: Theoretical CAR across trading periods



Note: Assuming mining at full capacity in each period.

It is important to highlight some design choices we make. Firstly, we design the mining process to be deterministic. Thus, we abstract away from uncertainty in the mining process as miners can directly generate assets using ECUs. At any given point in time, the difficulty of mining Bitcoin is public knowledge, while the direction, size and timing of any difficulty updates in the future are not certain.[9] Furthermore, miners can reduce the uncertainty of successful mining through joining a mining pool (Cong et al., 2021a). These pools share rewards of successful mining among all contributors, thus, reducing significantly any uncertainty over reward of their costly effort. Similarly, in our design, subjects do not face uncertainty about mining costs of the current period, but they can only estimate the mining costs of future periods. This also helps to not overly burden our subjects with increased complexity and uncertainty. Secondly, we choose to update costs as a function of total expenditure. This allows for the natural interpretation of asset mining costs over time: an increase by 50% in every period where mining is at full capacity. Updating costs as a function of assets would require calculating how many assets are affordable to estimate the mining cost.[10] Finally, our mining cost implementation assumes identical costs for all miners. In doing so, we abstract away from varying cost efficiency across miners around the world. As we have already argued, irrespective of how cost efficient miners are, the adaptive difficulty algorithm behind the PoW mechanism will always ensure that the rate of new block creation and asset influx are both fixed at a predetermined speed. Thus, the critical characteristic of PoW is this nature of a predetermined rate of asset influx which is what we focus our design on. Additionally, modelling miners as having identical costs can

[9]The difficulty level of mining is updated with every 2016 blocks added to the blockchain. The direction of the difficulty update depends on the joint effort of all miners. The presence or absence of other miners influences the difficulty level in the future. This is both through the exact timing of the next update, as well as, through the new difficulty level after the update.

[10]Figure A.1 in the appendix depicts costs as a function of total assets generated in our experiment.

be seen as an approximation of a long-run environment where the less efficient miners are crowded out.

All participants receive printed instructions to read at their own pace. We administer a comprehension quiz which every participant has to pass after reading the instructions. The quiz asks about features and parameters of the asset market.[11] Before initiating the 15 trading periods, participants go through three practice 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 (and 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 for the All treatments with and without mining can be found at `https://aspredicted.org/8hx2k.pdf` and for the Half treatments with and without mining can be found at `https://aspredicted.org/4w4hz.pdf`.

3.2 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, they 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 participants' screen; the image in the bottom right corner is missing. The participants 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

[11] We include the quiz questions in appendix E.

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 participant 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 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.

3.3 Experiment Implementation Details

A total number of 286 participants took part in our experiment. We conducted 36 sessions in total, with 9 sessions per treatment.[12] 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.[13] 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 possible redemption 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 the University of Heidelberg and Frankfurt University. Participants were mostly undergraduate students from a variety of majors. Participants 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 include translated versions of the experiment instructions in the appendix.

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).

4 Research Hypotheses

Our experimental design allows us to answer a number of research questions. Here, we list four main hypotheses to be evaluated.

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

[13]In 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.

Table 3: Characteristics of participants across treatments

	Gift-All	Gift-Half Role A	Gift-Half Role B	Mining-All	Mining-Half Role A	Mining-Half Role B
Avg. Age	23.54	22.98	24.84	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	3.5	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).
Note: There are no statistically significant differences in these characteristics in pairwise comparisons across treatments and roles (corrected for multiple testing using Bonferroni-Holm correction).

The setup of our baseline treatment, Gift-All, is closely related with market A1 of Smith et al. (2000), where an asset with a flat fundamental is traded. Thus, we can formulate hypotheses following from the established findings in the literature. In the Gift-All treatment, we do not expect to observe bubbles and crashes given the results of Smith et al. (2000). If traders are on average risk neutral, we should observe no trade, or trade only at around the fundamental value (Palan, 2013). Moreover, our experimental design does not entail frequent dividend payments as in Smith et al. (1988) with decreasing fundamentals, or in Bostian et al. (2005) with a flat fundamental, where 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 be elevated and not track fundamental values perfectly, as the CAR is relatively high at 10.2. Higher CARs have been shown to induce greater mispricing (Angerer and Szymczak, 2019; Caginalp et al., 1998, 2001, 2002; Haruvy and Noussair, 2006; Noussair and Tucker, 2016). 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 has been shown consistently in the literature that it is prone to bubbles (Palan, 2013). It is ex-ante not clear whether the endowment asymmetry itself may trigger a price bubble in an environment that rarely bubbles 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 as 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 due to the sunk cost fallacy. Second, due to the expenditure cap on mining, the supply is sluggish. This means that when 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. Furthermore, initially, there may just be a subset of miners who are selling assets that they mined. This may make it easier for them to enjoy market power and maintain their asks at a relatively higher price level given the limited competition. Lastly, 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.*

5 Results

5.1 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 prices from each market.[14] We first examine our Gift treatments. The price trajectories in figure 3a show that prices follow the fundamental value relatively well across all trading periods regardless of endowment centralization.

We formalize our analysis using a number of bubble measures, summarized in table 4.[15] These indicators include RD, the relative deviation of prices from fundamental value (normalized at 28) and RAD, the relative absolute deviation of prices from fundamental value (normalized at 28), 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.

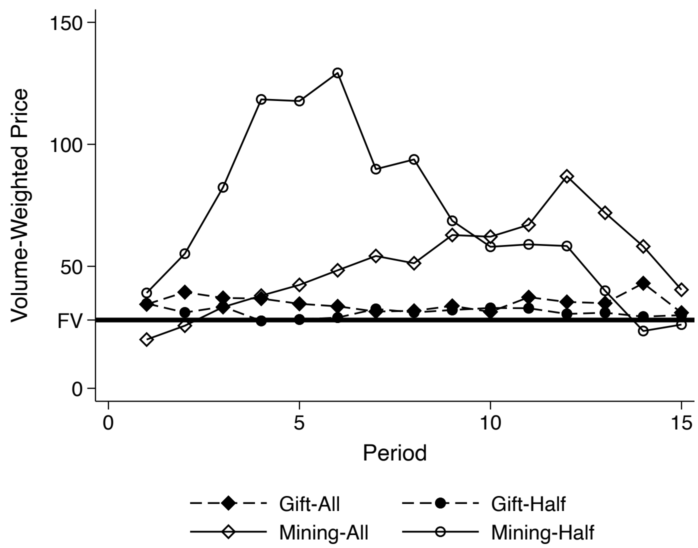
In table 4, the median value of RAD and RD in the Gift treatments is between 0.1 and 0.4, suggesting very modest mispricing. Thus, the Gift treatments provide us with a

[14]Figure 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.

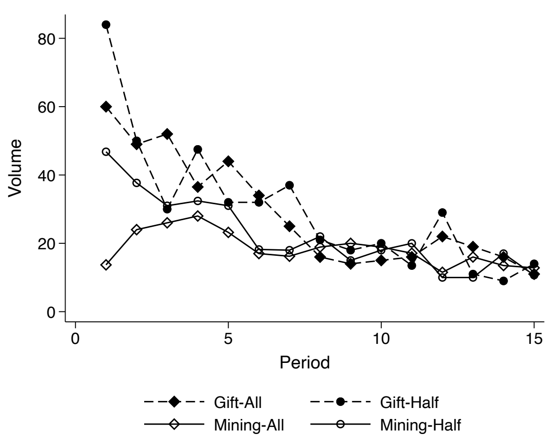
[15]We report the exact formulas of all bubble measures in the appendix. In tables A.1-A.4 in the appendix, we report these measures separately for each market of each treatment.

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

(a) Median of volume-weighted price per period



(b) Session-median trading volume per period



(c) Realized session-median CAR

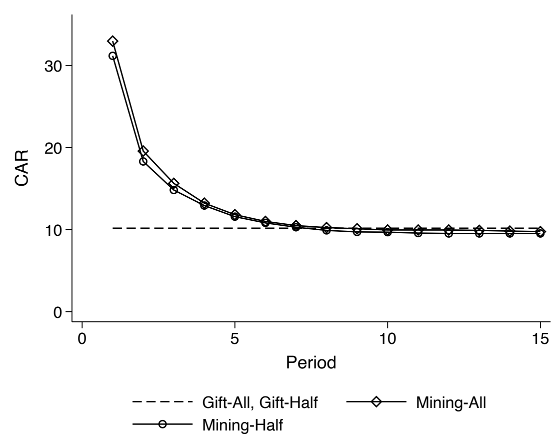


Table 4: Summary statistics of bubble measures by treatment

	Gift-All median mean (std.dev.)		Gift-Half median mean (std.dev.)		Mining-All median mean (std.dev.)		Mining-Half median 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)

Notes: RD: relative deviation of prices from fundamentals (normalized at the fundamental value of 28); RAD: the relative absolute deviation of prices from fundamentals (normalized at the fundamental value of 28); RDMAX measures 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). 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.

Table 5: Exact Mann-Whitney-U tests comparing bubble measures across treatments

	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

Note: We report the p-values for each test; we report in bold font whenever p-value ≤ 0.050.

good benchmark to study the effect of mining, with or without mining centralization. In table 5, we report p-values of the Mann-Whitney U exact test to detect potential treatment effects. We find no statistically significant differences in any of the bubble measures when contrasting Gift-All and Gift-Half. This implies that endowment asymmetry by itself does not ignite a bubble. Indeed, as observed in figure 3a, in neither of our Gift treatments do we observe a pattern of bubbles and crashes. These observations lead to our first two results:

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

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.*

We next examine the Mining treatments. Figure 4 depicts trading prices only for the two mining treatments together with their respective mining cost trends. In Mining-All, prices initially start below fundamental value but above mining cost. The trajectory follows an upward trend clearly parallel to the mining cost with a distinguishable mark-up. Overall, prices continue rising for 12 periods before they crash in the last three periods. Similarly, in treatment Mining-Half, prices go well above and beyond fundamental value. Prices seem to decouple from the mining cost already within the first few periods and peak at even higher levels. As seen in figures 3a and 4, 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; in figure 5 we replicate figure 3a by systematically removing one of the 9 markets of each treatment

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

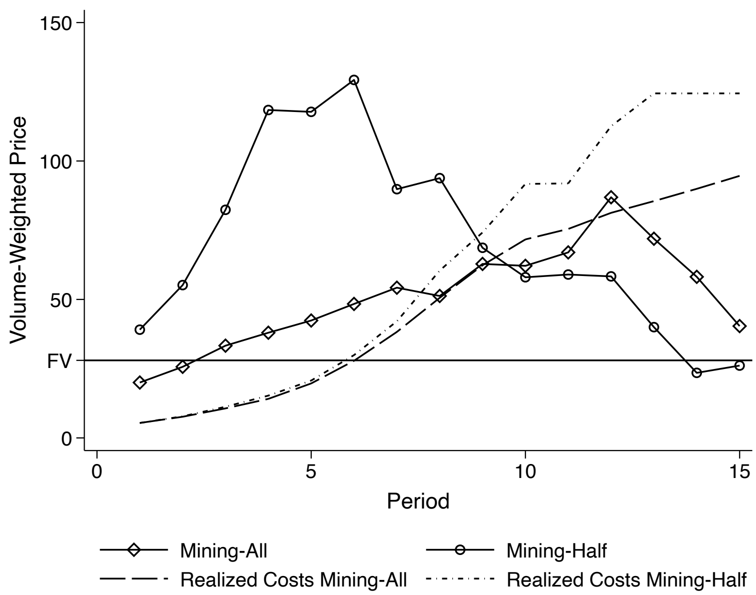
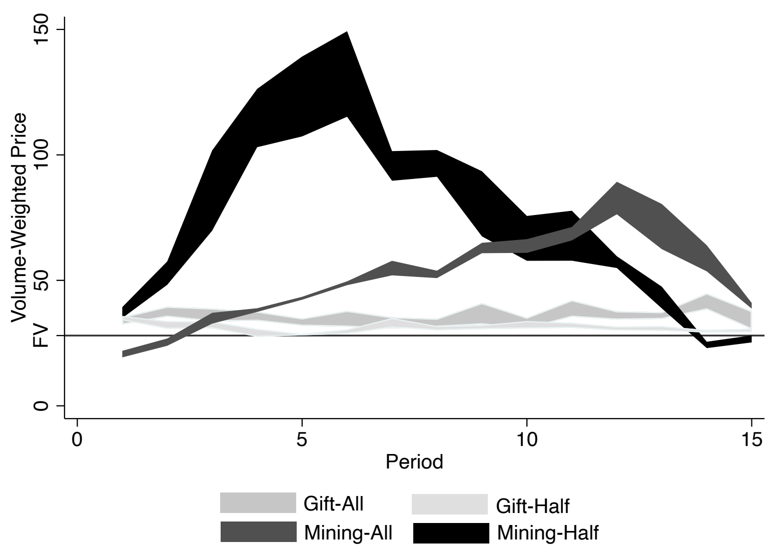


Figure 5: Range of prices per treatment per period



Note: Median volume-weighted 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.

with replacement. The general price trajectories per treatment we report in figures 3a and 4 remain unchanged.

In table 5, 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 find statistically significant differences (second and third columns). Specifically, mispricing is significantly more pronounced in the Mining treatments as compared to the Gift treatments. It is worth emphasizing that this result should not be solely attributed to the difference in the 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.[16] Furthermore, the bubble observed in the Mining-All treatment peaks in the second half of the trading periods, by which point the CAR is already lower compared to the CAR in the Gift treatments.

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

Table 6: Exact Mann-Whitney-U test in first and second half of trading

		Mining-All	Mining-Half	p-values
RAD	First half	0.60	2.20	0.011
	Second half	1.33	0.81	0.436
RD	First half	0.47	2.20	0.008
	Second half	1.33	0.81	0.340

Finally, we are interested in identifying what effect centralization of 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 (fourth column of 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. 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.[17] The market peaks earlier in treatment Mining-Half compared to Mining-All and the bubble persists for a number of periods before prices crash to fundamental value. This leads to our fourth result:

[16]In fact, only 3 out of 144 traders in the Gift treatments are ever cash-constrained; two in Gift-Half and one in Gift-All. These three traders used up approximately 95% of their ECU endowment in the first three periods by purchasing at high prices and selling at low prices.

[17]Since the bubble measures RDMAX, AMPLITUDE and CRASH are calculated with respect to the peak period, they cannot be calculated when the trading periods are split in two.

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

It is worth noting that the results that we report are not due to differences in trading volumes across treatments. No treatment leads to a particularly thin market. Figure 3b presents the average trading volume of each treatment across trading periods, albeit with small differences in the initial periods. The Gift treatments appear to initially trade at higher volumes but this difference quickly 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 median realized CAR of our treatments across periods.[18] Trading volume across the four treatments is not significantly different once the CAR is similar (from 6th period onwards). This is confirmed using a non-parametric test of comparing average trading volumes of periods 6-15 across the four treatments (Mann-Whitney-U test of Mining vs. Gift, $p-value = 0.393$; Mann-Whitney-U test of All vs. Half, $p - value = 0.800$).

5.2 Over-expenditure on Mining

Given the discussion in the literature on how effort spent on mining can have harmful implications on overall welfare (e.g. Auer, 2019; Schilling and Uhlig, 2019), we want to understand if mining expenditure is executed optimally in the Mining treatments. From figure 4, given the rising mining costs, it can be inferred that mining expenditure is not halted once costs exceed the fundamental value of the asset. At the individual level, such behavior can be rationalized since market price exceeds mining cost. However, from a social planner's perspective, mining at a cost above fundamental value is detrimental to overall welfare. We find spending on mining is more than the social optimum, with market over-expenditure on mining across different sessions ranging from 25% to about 133% in the Mining treatments (median session over-expenditure in Mining-All and Mining-Half is 53.5% and 55.0%, respectively). However, there is no statistically significant difference in over-expenditure on mining between the Mining-All and Mining-Half treatments (Mann-Whitney-U test, $p - value = 0.474$).

5.3 Additional insights from the order book

To gain some insight into what leads to the bubbles we observe, we now focus on analyzing the order book. We want to identify whether trades are mostly driven by the demand-side or the supply-side of the market and in particular, whether the bubbles appear to be supply- or demand-driven. To this end, we analyze whether the transactions are mostly initiated by buyers or sellers and we separately plot bids and asks proposed by traders. Figure 6 summarizes the results. First, figure 6a shows that approximately three quarters of accepted trades are consistently originating from asks in all four treatments. That is,

[18]The figure reports the median realized CAR over the 9 markets implemented for each of the four treatments.

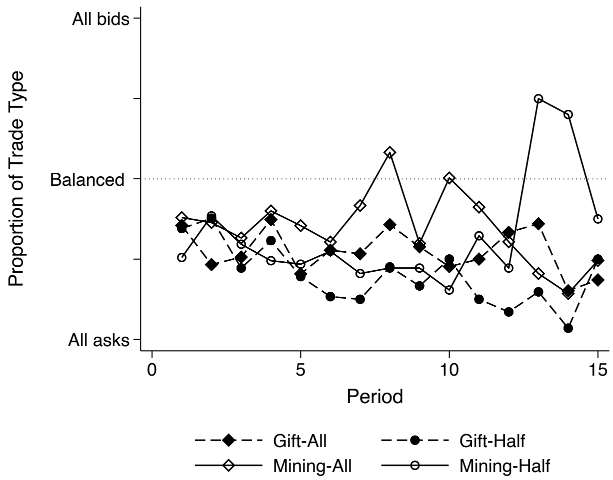
trades are mostly driven by the supply-side and sellers appear to have more control over market prices because buyers' bids are mostly not taken. Comparing and contrasting figures 6b and 6c makes it quite clear that the bubbles we observe are supply-side driven. Asks in the Gift treatments are relatively flat and slightly above fundamental value, while asks in the Mining treatments have very similar trajectories to the realized price trajectories in the market (as seen in figure 3a). A starkly different picture is observed when focusing on bids in figure 6c. In all four treatments, bids are relatively flat, albeit somewhat with an upward trend in the Mining treatments. In table 5, we report that the SPREAD is significantly different between respective Gift and Mining treatments. The ask/bid trajectories we see in figures 6b and 6c shed some light in explaining why this is the case. With bids remaining relatively flat, asks have a steep upward trend, especially for the Mining-Half treatment. Putting this evidence together, it appears that sellers are responsible for the bubbles that we observe.

A natural question that follows immediately from this observation is who are the sellers in the Mining treatments. Are miners selling their assets in the market or are non-miners buying in early periods and look for reducing their holdings in later periods? To shed some light on this question, we focus on the markets of the Mining-Half treatment. In this treatment we can clearly distinguish the miners (role A traders) from the non-miners (role B traders) in the market.[19] For each trader, we consider all offers they proposed and calculate on average what mixture of asks and bids they proposed. We compare this average action score across miners and non-miners in the Mining-Half treatment. Since by design, miners are more likely to be a seller in earlier periods, we analyze offers only for later periods of the market. Specifically, we look at average action from period 7 onwards, during which mining cost is above fundamental value. We contrast this analysis with a similar exercise in the Gift-Half treatment where roles of traders are also clearly defined: they are either endowed with the asset at the outset (role A, i.e. "miners") or not (role B, i.e. "non-miners"). We present the distribution of trader average action in figure 7 separately for each role. In the Mining-Half treatment, we find that miners are significantly more likely to act as sellers than non-miners (Mann-Whitney U test, $p-value = 0.020$). This is not the case in the Gift-Half treatment where traders who are initially endowed with assets are not significantly more likely to act as sellers (Mann-Whitney U test, $p - value = 0.215$). Additionally, we construct a measure to gauge relative amount of asset transfers from miners to non-miners. This is calculated using the total volume of transfer from miners to non-miners divided by the amount of outstanding assets in a given period. In figure 8, we compare the relative transfers of assets from miners to non-miners by period in Mining-Half to those from "miners" to "non-miners" in Gift-Half. We observe that in the first six periods during which bubbles are forming, the average transfers between the two roles are significantly larger in Mining-Half than in Gift-Half (Mann-Whitney U test, $p - value = 0.030$). The analysis in this subsection leads us to conclude that miners predominantly act as sellers in the Mining-Half treatment and, thus, are responsible for the bubbles we observe.

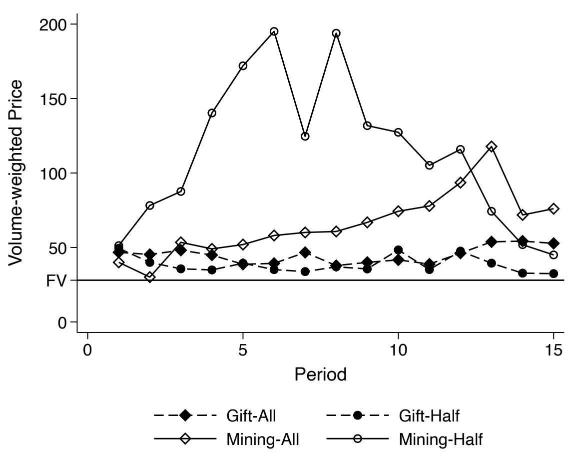
[19] A similar exercise would be interesting to conduct for the Mining-All treatment also. However, since everyone can mine (and indeed most do), categorizing participants into miners and non-miners is not possible.

Figure 6: Order Book Analysis

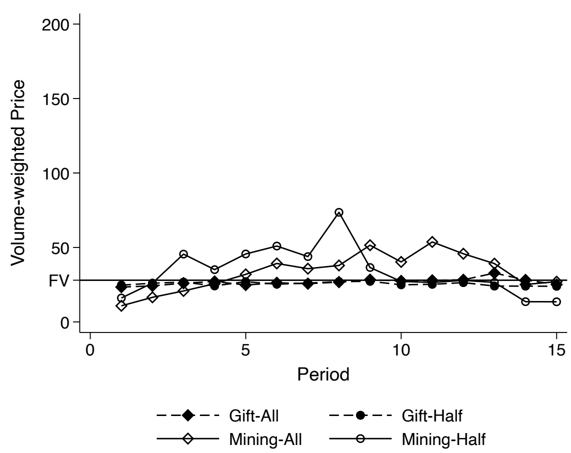
(a) Origin of accepted trades



(b) Asks



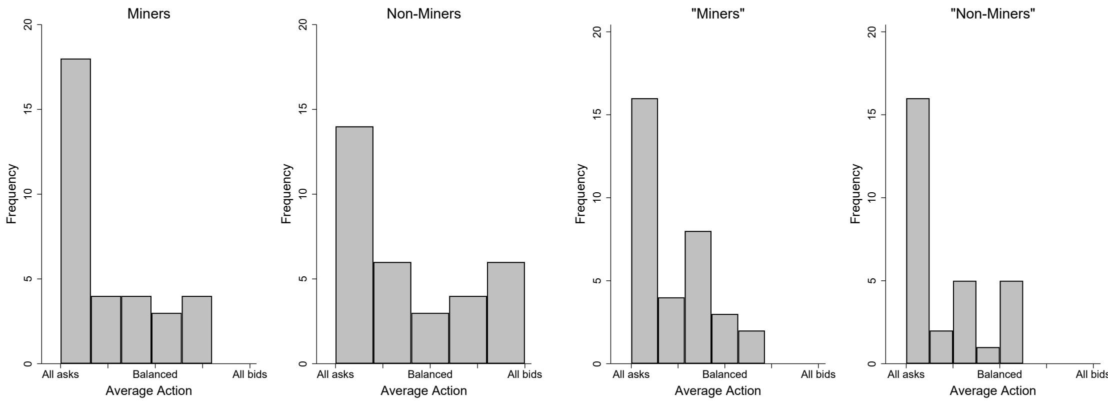
(c) Bids



Note: In panel (a) we report the median ratio of origin of accepted trades per period per treatment. That is, each node corresponds to the proportion of completed trades that initiated from either bids or asks. In panels (b) and (c) we report the median volume-weighted asks and bids per period per treatment respectively.

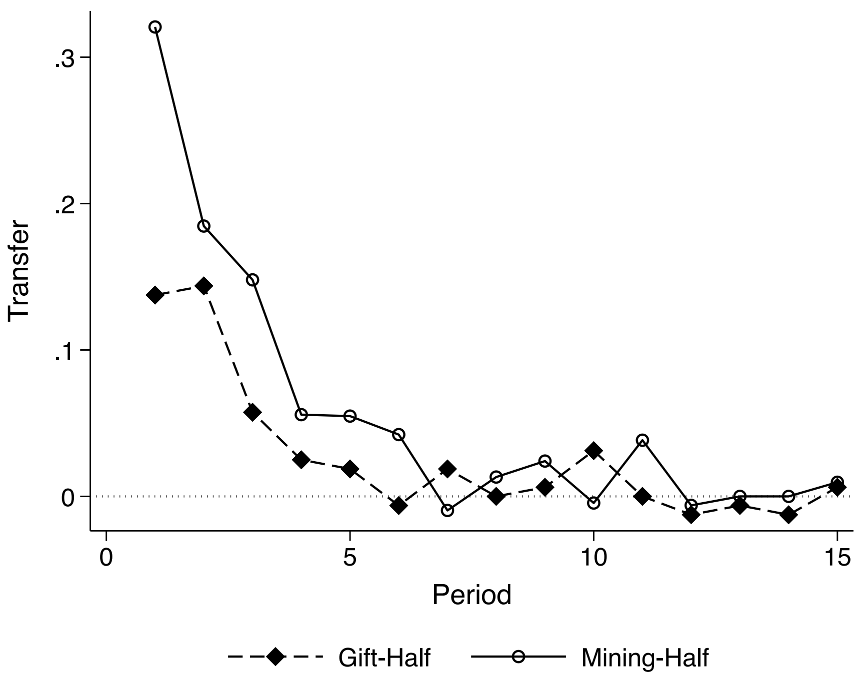
Figure 7: Trader average action by role

(a) Mining-Half (b) Gift-Half



Note: Histograms present the distribution of trader average action. We consider the average offer a trader made from period 7 onwards.

Figure 8: Transfers from miners to non-miners in Half-treatments



Note: Median proportion of transfers from miners to non-miners in Mining-Half (and “miners” to “non-miners” in Gift-Half) relative to the outstanding assets in the market per period. This proportion can range from -1, if all assets are transferred from non-miners to miners, to 1, if all assets are transferred from miners to non-miners.

Table 7: Regression analysis on trader (normalized) earnings

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

Notes: OLS regression model. Standard errors reported in parentheses, clustered at the session level. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

5.4 Earnings 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 analysis on trader earnings. The dependent variable in all specifications is asset market earnings, standardized with respect to their respective treatment.[20] The first column reports the regression results for all participants across all treatments. In the second column, 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 the third column, 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

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

where traders have different roles, those that can only obtain assets through the market are significantly worse off. This may be because their options of acquiring assets are limited.

6 Concluding Remarks

The first decentralized cryptocurrency, Bitcoin, was introduced by Satoshi Nakamoto in 2008. Although originally devised as a prospective medium of exchange, Bitcoin failed to present itself as a stable currency, but has instead exhibited many episodes of bubbles and crashes. In this paper, we identify unique features associated with its PoW consensus mechanism and blockchain technology that might have contributed to these bubbles. There are three implications of the Bitcoin's blockchain technology that are particularly relevant. First, the total supply of the asset is limited. Second, in short run, the rate of supply of the asset is fixed such that supply cannot rapidly respond to demand shocks. Third, the mining cost is increasing over time, which will crowd out small miners and lead to mining centralization, as individual mining is increasingly infeasible (Alsabah and Capponi, 2020; Ferreira et al., 2019; Hinzen et al., 2020). This means that individual investors will have to increasingly rely on the market to obtain Bitcoin. However, note that even if the mining equipment is centralized and controlled by large firms (often the manufacturers of this equipment), this does not undermine the decentralization of the Blockchain (Cong et al., 2021a).

We are the first to study the link between these specific features of the Bitcoin technology and bubble formation in a controlled laboratory setting. Our results show a remarkable degree of overpricing. Assets are traded at significantly higher prices than fundamental value when mining is introduced. While risk seeking preferences might explain slight overpricing, nevertheless, we observe prices frequently double the maximum possible redemption value of the asset. These findings indicate that mining contributes to bubble formation and enables significant volatility of pricing over time. Moreover, our results show that mining centralization further pushes prices upwards and makes the prices decouple from mining costs even earlier, compared to a case where all investors 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 centralization 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, expecting that mining costs may get higher in the future. The order book analysis we report shows that market prices are generally determined by sellers. Going further, in the Mining-Half treatment, where miners can be clearly defined, we find that miners predominantly act as sellers in the market. Another important observation is that in both of our mining treatments, participants choose to mine even after the cost of mining exceeded the fundamental value of the asset, implying that miners perpetuate price bubbles.

For both of our Mining treatments, prices crash towards the fundamental value in the end. It has been well-documented that prices in experimental asset markets that follow the Smith et al. (1988) design crash towards fundamental value in the last three periods.

In fact, this "end-game effect" is a good sign as it suggests that traders are aware of the fundamental values of the asset while riding the bubbles.

The literature has offered some insights of what might happen to the markets if trading is implemented with a longer horizon. Lahav (2011) conduct an asset market experiment with 200 periods and find several recurrent bubbles, instead of one big bubble that crashes towards the end. More recently, Hoshihata et al. (2017) conduct an experiment with 100 periods and find that it is more often the case that markets exhibit only one bubble and one crash, rather than multiple bubbles and crashes. Both of these papers suggest that the bubbles we observe in our markets burst because of the limited number of trading periods. Future work should investigate further how bubble formation in similar frameworks to our design develops in longer horizons.

The observation that price trajectories in our Gift-treatments adheres 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 in 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. Thus, it is unlikely that bubbles observed in the Mining treatments is merely due to the (initially) higher cash-to-asset ratio, but rather due to the specific features of the PoW mechanism we study.

Our results also speak to the literature on monetary policy and inflation. Our experimental setup can be readily interpreted as a monetary framework where the asset can be viewed as a currency and miners decide the currency supply. In the Mining treatments, the creation of new 'money' should stop when the mining cost exceeds the fundamental value of the currency in period 6. However, the money supply continues to grow because prices at the moment are much greater than the fundamental value. Potentially such over-provision could eventually devalue the currency and erode the real value of the currency. This would echo results in recent experimental work by Bigoni et al. (2020) who show that fiat money that has no intrinsic value facilitates trade when the money supply is strictly limited. Economic agents in their environment spontaneously learn to use the fiat money for trade, even if it carries no value. However, when there is a lack of discipline in printing the fiat money, the institution of monetary trade failes to emerge spontaneously, and the monetary system collapses. Indeed, it is tempting for central bankers to provide extra liquidity to the market when it seems beneficial to do so in the short-run (in Bigoni et al. (2020)'s environment, it may facilitate trade), but this may come at a cost of currency devaluation. Similarly, Galí et al. (2020) show that while an expansionary monetary policy makes bubbles more pronounced in the short run, it has a suppresing effect on price levels in the future.

Perhaps the single most innovative idea behind Bitcoin is the blockchain technology and how it creatively solves the consensus and consistency problems using the PoW consensus mechanism. As miners depend on rewards in the form of newly minted coins (or transaction fees) to cover their mining expenses (see Easley et al. (2019) for a detailed discussion), it seemed a natural first step to study the link between cryptocurrency pricing and mining cost. However, it is important to highlight that we are not claiming that costly mining is a necessary condition for cryptocurrency bubbles, but rather that costly mining appears to be a sufficient condition for bubble formation. Some recent theoretical work provides insights into alternative explanations for Bitcoin's erratic pricing other than mining costs. For instance, Schilling and Uhlig (2019) set up a model where a cryptocurrency competes with traditional fiat currency as mediums of exchange. The cryptocurrency has fixed supply with a deterministic supply schedule while the fiat money has an inflation target set by the central bank. The model generates a wide range of equilibria, including one where prices exhibit high volatility (see their Appendix E.2). Relatedly, Biais et al. (2020) consider an overlapping generations model that ascribes the price volatility to exogenous noise. In particular, for risk neutral agents in their model, an equilibrium price sequence multiplied by extrinsic noise (with an expectated value of one) will also be an equilibrium. The magnitude of exogenous noise, although bounded by the endowment of younger generations, can explain the large price volatility observed in the cryptocurrency market.

Many other aspects that are left out in this study may also influence how cryptocurrencies 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. Indeed, the high price volatilities shared by many PoW cryptocurrencies have hindered their potential to become a medium of exchange. Yet, these high volatilities seem unavoidable, as they stem from the properties of the equilibrium outcome of the PoW mechanism (Alsabah and Capponi, 2020; 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). Cryptocurrencies, both present and future ones, may differ fundamentally from each other. In order to understand which of them are prone to bubble due to their specific supply scheme, a case-by-case examination would be necessary to identify those that share the key properties of Bitcoin we identify in this study. For cryptocurrencies featuring a less rigid supply scheme, flexbible adjustments in token supply can mitigate price volatility (Cong et al., 2021b). The experimental framework that we develop is highly flexible and allows for future research in examining the price stability of other (digital) currency designs. 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; Chiu et al., 2020).

References

ALDRICH, E. M. AND K. LÓPEZ VARGAS (2020): "Experiments in high-frequency trading: comparing two market institutions," *Experimental Economics*, 23, 322–352.

ALSABAH, H. AND A. CAPPONI (2020): "Pitfalls of Bitcoin's Proof-of-Work: R&D Arms race and mining centralization," *Available at SSRN 3273982*.

ANGERER, M., T. NEUGEBAUER, AND J. SHACHAT (2019): "Arbitrage bots in experimental asset markets," *Working Paper*.

ANGERER, M. AND W. SZYMCZAK (2019): "The impact of endogenous and exogenous cash inflows in experimental asset markets," *Journal of Economic Behavior & Organization*, 166, 216–238.

AUER, R. (2019): "Beyond the doomsday economics of 'proof-of-work' in cryptocurrencies," *BIS Working Papers No. 765*.

BASU, S., D. EASLEY, M. O'HARA, AND G. SIRER (2020): "StableFees: A Predictable Fee Market for Cryptocurrencies," *Working Paper*.

BAUR, D. G., K. HONG, AND A. D. LEE (2018): "Bitcoin: Medium of exchange or speculative assets?" *Journal of International Financial Markets, Institutions and Money*, 54, 177–189.

BHAMBHWANI, S., S. DELIKOURAS, AND G. M. KORNIOTIS (2019): "Do fundamentals drive cryptocurrency prices?" *Available at SSRN 3342842*.

BIAIS, B., C. BISIERE, M. BOUVARD, AND C. CASAMATTA (2019): "The Blockchain Folk Theorem," *The Review of Financial Studies*, 32, 1662–1715.

BIAIS, B., C. BISIERE, M. BOUVARD, C. CASAMATTA, AND A. J. MENKVELD (2020): "Equilibrium Bitcoin Pricing," *EconPol Working Papers 48*.

BIANCHETTI, M., C. RICCI, AND M. SCARINGI (2018): "Are cryptocurrencies real financial bubbles? Evidence from quantitative analyses," *Working Paper*.

BIGONI, M., G. CAMERA, AND M. CASARI (2020): "Money is more than memory," *Journal of Monetary Economics*, 110, 99–115.

BÖHME, R., N. CHRISTIN, B. EDELMAN, AND T. MOORE (2015): "Bitcoin: Economics, technology, and governance," *Journal of Economic Perspectives*, 29, 213–38.

BORS, D. A. AND T. L. STOKES (1998): "Raven's advanced progressive matrices: Norms for first-year university students and the development of a short form," *Educational and Psychological Measurement*, 58, 382–398.

BOSSAERTS, P., S. SUZUKI, AND J. P. O'DOHERTY (2019): "Perception of intentionality in investor attitudes towards financial risks," *Journal of Behavioral and Experimental Finance*, 23, 189–197.

Bostian, A., J. Goeree, and C. A. Holt (2005): "Price bubbles in asset market experiments with a flat fundamental value," in *Draft for the Experimental Finance Conference, Federal Reserve Bank of Atlanta September*, vol. 23.

Bruguier, A. J., S. R. Quartz, and P. Bossaerts (2010): "Exploring the Nature of Trader Intuition," *The Journal of Finance*, 65, 1703–1723.

Brunnermeier, M., S. Rother, and I. Schnabel (2020): "Asset Price Bubbles and Systemic Risk," *The Review of Financial Studies*, 33, 4272–4317.

Brunnermeier, M. K. and I. Schnabel (2016): "Bubbles and Central Banks," in *Central Banks at a Crossroads: What Can We Learn from History?*, ed. by M. D. Bordo, Ø. Eitrheim, M. Flandreau, and J. F. Qvigstad, Cambridge University Press, 493–562.

Burniske, C. and A. White (2017): "Bitcoin: Ringing the bell for a new asset class," *Ark Invest (January 2017).*

Caginalp, G., V. Ilieva, D. Porter, and V. Smith (2002): "Do Speculative Stocks Lower Prices and Increase Volatility of Value Stocks?" *Journal of Psychology and Financial Markets*, 3, 118–132.

Caginalp, G., D. Porter, and V. Smith (1998): "Initial cash/asset ratio and asset prices: An experimental study," *Proceedings of the National Academy of Sciences*, 95, 756–761.

——— (2001): "Financial Bubbles: Excess Cash, Momentum, and Incomplete Information," *Journal of Psychology and Financial Markets*, 2, 80–99.

Camera, G. (2020): "Introducing a CBDC: evidence from laboratory data," *Working Paper*.

Cheah, E.-T. and J. Fry (2015): "Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin," *Economics Letters*, 130, 32–36.

Chen, Z. and L. Epstein (2002): "Ambiguity, risk, and asset returns in continuous time," *Econometrica*, 70, 1403–1443.

Chiu, J., S. M. R. Davoodalhosseini, J. H. Jiang, and Y. Zhu (2020): "Bank Market Power and Central Bank Digital Currency: Theory and Quantitative Assessment," *Staff Working Papers.*

Choi, S. H. and R. A. Jarrow (2020): "Testing the Local Martingale Theory of Bubbles using Cryptocurrencies," *Available at SSRN 3701960.*

Cong, L. W., Z. He, and J. Li (2021a): "Decentralized Mining in Centralized Pools," *The Review of Financial Studies*, 34, 1191–1235.

Cong, L. W., Y. Li, and N. Wang (2021b): "Tokenomics: Dynamic Adoption and Valuation," *The Review of Financial Studies*, 34, 1105–1155.

Cong, L. W. and Y. Xiao (2020): "Categories and Functions of Crypto-Tokens," *Available at SSRN 3814499.*

Corgnet, B., M. Desantis, and D. Porter (2018): "What makes a good trader? On the role of intuition and reflection on trader performance," *The Journal of Finance*, 73, 1113–1137.

Corgnet, B., R. Hernán-González, and P. Kujal (2020): "On booms that never bust: Ambiguity in experimental asset markets with bubbles," *Journal of Economic Dynamics and Control*, 110, 103754.

Cueva, C. and A. Rustichini (2015): "Is financial instability male-driven? Gender and cognitive skills in experimental asset markets," *Journal of Economic Behavior & Organization*, 119, 330–344.

Dell'Erba, M. (2019): "Stablecoins in Cryptoeconomics. From Initial Coin Offerings (ICOs) to Central Bank Digital Currencies (CBDCs)," *New York University Journal of Legislation and Public Policy.*

Easley, D., M. O'Hara, and S. Basu (2019): "From mining to markets: The evolution of bitcoin transaction fees," *Journal of Financial Economics*, 134, 91–109.

Eckel, C. C. and S. C. Füllbrunn (2015): "Thar she blows? Gender, competition, and bubbles in experimental asset markets," *American Economic Review*, 105, 906–20.

Eckel, C. C. and P. J. Grossman (2008): "Men, women and risk aversion: Experimental evidence," *Handbook of Experimental Economics Results*, 1, 1061–1073.

Ferreira, D., J. Li, and R. Nikolowa (2019): "Corporate capture of blockchain governance," *European Corporate Governance Institute (ECGI)-Finance Working Paper.*

Fischbacher, U. (2007): "z-Tree: Zurich toolbox for ready-made economic experiments," *Experimental Economics*, 10, 171–178.

Foley, S., J. R. Karlsen, and T. J. Putnins (2019): "Sex, Drugs, and Bitcoin: How Much Illegal Activity Is Financed through Cryptocurrencies?" *Review of Financial Studies*, 32, 1798–1853.

Füllbrunn, S., H. A. Rau, and U. Weitzel (2014): "Does ambiguity aversion survive in experimental asset markets?" *Journal of Economic Behavior & Organization*, 107, 810–826.

Galí, J., G. Giusti, C. N. Noussair, et al. (2020): "Monetary policy and asset price bubbles: a laboratory experiment," *Barcelona GSE Working Paper Series No.1184.*

Gao, Z., M. Sockin, and W. Xiong (2020): "Economic Consequences of Housing Speculation," *The Review of Financial Studies.*

Garber, P. M. (2001): *Famous first bubbles: The fundamentals of early manias*, MIT Press.

Gervais, A., G. O. Karame, K. Wüst, V. Glykantzis, H. Ritzdorf, and S. Capkun (2016): "On the security and performance of proof of work blockchains," in *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, 3–16.

Glaser, F., K. Zimmermann, M. Haferkorn, M. C. Weber, and M. Siering (2014): "Bitcoin-asset or currency? revealing users' hidden intentions," *Revealing Users' Hidden Intentions (April 15, 2014). ECIS.*

Greiner, B. (2015): "Subject pool recruitment procedures: organizing experiments with ORSEE," *Journal of the Economic Science Association*, 1, 114–125.

Guo, F., C. R. Chen, and Y. S. Huang (2011): "Markets contagion during financial crisis: A regime-switching approach," *International Review of Economics & Finance*, 20, 95–109.

Haruvy, E. and C. N. Noussair (2006): "The effect of short selling on bubbles and crashes in experimental spot asset markets," *The Journal of Finance*, 61, 1119–1157.

Hayes, A. S. (2017): "Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin," *Telematics and Informatics*, 34, 1308–1321.

——— (2019): "Bitcoin price and its marginal cost of production: support for a fundamental value," *Applied Economics Letters*, 26, 554–560.

Hefti, A., S. Heinke, and F. Schneider (2016): "Mental capabilities, trading styles, and asset market bubbles: theory and experiment," Tech. rep.

Heider, F. and M. Simmel (1944): "An experimental study of apparent behavior," *The American Journal of Psychology*, 57, 243–259.

Hinzen, F. J., K. John, and F. Saleh (2020): "Bitcoin's Fatal Flaw: The Limited Adoption Problem," *NYU Stern School of Business.*

Hong, K. (2017): "Bitcoin as an alternative investment vehicle," *Information Technology and Management*, 18, 265–275.

Hoshi, T. and A. K. Kashyap (2004): "Japan's Financial Crisis and Economic Stagnation," *Journal of Economic Perspectives*, 18, 3–26.

Hoshihata, T., R. Ishikawa, N. Hanaki, and E. Akiyama (2017): "Flat bubbles in longhorizon experiments: Results from two market conditions," *GREDEG Working Papers Series.*

Huberman, G., J. Leshno, and C. C. Moallemi (forthcoming): "Monopoly without a monopolist: An economic analysis of the bitcoin payment system," *The Review of Economic Studies*.

Irresberger, F., K. John, and F. Saleh (2020): "The public blockchain ecosystem: An empirical analysis," *NYU Stern School of Business*.

Janssen, D. J., S. Füllbrunn, and U. Weitzel (2019): "Individual speculative behavior and overpricing in experimental asset markets," *Experimental Economics*, 22, 653–675.

Ju, N. and J. Miao (2012): "Ambiguity, learning, and asset returns," *Econometrica*, 80, 559–591.

Kirchler, M., J. Huber, and T. Stöckl (2012): "Thar she bursts: Reducing confusion reduces bubbles," *American Economic Review*, 102, 865–83.

Krafft, P. M., N. Della Penna, and A. S. Pentland (2018): "An experimental study of cryptocurrency market dynamics," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–13.

Kristoufek, L. (2015): "What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis," *PloS One*, 10, e0123923.

Lahav, Y. (2011): "Price patterns in experimental asset markets with long horizon," *Journal of Behavioral Finance*, 12, 20–28.

Manaa, M., M. T. Chimienti, M. M. Adachi, P. Athanassiou, I. Balteanu, A. Calza, C. Devaney, E. Diaz Fernandez, F. Eser, I. Ganoulis, et al. (2019): "Crypto-Assets: Implications for financial stability, monetary policy, and payments and market infrastructures," *ECB Occasional Paper*, No. 223.

Nakamoto, S. (2008): "Bitcoin: A peer-to-peer electronic cash system," .

Noussair, C., S. Robin, and B. Ruffieux (2001): "Price bubbles in laboratory asset markets with constant fundamental values," *Experimental Economics*, 4, 87–105.

Noussair, C. N. and S. Tucker (2016): "Cash inflows and bubbles in asset markets with constant fundamental values," *Economic Inquiry*, 54, 1596–1606.

Noussair, C. N., S. Tucker, and Y. Xu (2016): "Futures markets, cognitive ability, and mispricing in experimental asset markets," *Journal of Economic Behavior & Organization*, 130, 166–179.

Oechssler, J., C. Schmidt, and W. Schnedler (2011): "On the ingredients for bubble formation: informed traders and communication," *Journal of Economic Dynamics and Control*, 35, 1831–1851.

Oprea, R., D. Friedman, and S. T. Anderson (2009): "Learning to Wait: A Laboratory Investigation," *The Review of Economic Studies*, 76, 1103–1124.

Palan, S. (2013): "A review of bubbles and crashes in experimental asset markets," *Journal of Economic Surveys*, 27, 570–588.

——— (2015): "GIMS - Software for asset market experiments," *Journal of Behavioral and Experimental Finance*, 5, 1–14.

Plott, C. R. and P. Gray (1990): "The multiple unit double auction," *Journal of Economic Behavior and Organization*, 13, 245–258.

Porter, D. and V. Smith (1995a): "Futures Contracting and Dividend Uncertainty in Experimental Asset Markets," *The Journal of Business*, 68, 509–41.

Porter, D. P. and V. L. Smith (1995b): "Futures contracting and dividend uncertainty in experimental asset markets," *Journal of Business*, 509–541.

Raskin, M. and D. Yermack (2018): *Digital currencies, decentralized ledgers and the future of central banking*, Cheltenham, UK: Edward Elgar Publishing.

Razen, M., J. Huber, and M. Kirchler (2017): "Cash inflow and trading horizon in asset markets," *European Economic Review*, 92, 359–384.

Saleh, F. (2019): "Volatility and welfare in a crypto economy," *Available at SSRN 3235467.*

——— (forthcoming): "Blockchain without Waste: Proof-of-Stake," *Review of Financial Studies.*

Schilling, L. and H. Uhlig (2019): "Some simple bitcoin economics," *Journal of Monetary Economics*, 106, 16–26.

Shiller, R. J. (2015): *Irrational Exuberance: Revised and Expanded Third Edition*, Princeton University Press, rev - revised, 3 ed.

——— (2019): *Narrative economics: How stories go viral and drive major economic events*, Princeton University Press.

Smith, V. L. (1962): "An Experimental Study of Competitive Market Behavior," *Journal of Political Economy*, 70, 322–323.

Smith, V. L., G. L. Suchanek, and A. W. Williams (1988): "Bubbles, crashes, and endogenous expectations in experimental spot asset markets," *Econometrica*, 1119–1151.

Smith, V. L., M. Van Boening, and C. P. Wellford (2000): "Dividend timing and behavior in laboratory asset markets," *Economic Theory*, 16, 567–583.

Stöckl, T., J. Huber, and M. Kirchler (2010): "Bubble measures in experimental asset markets," *Experimental Economics*, 13, 284–298.

Tucker, S. and Y. Xu (2020): "Nonspeculative Bubbles Revisited: Speculation Does Matter," *Working Paper*.

Weber, M. and C. F. Camerer (1998): "The disposition effect in securities trading: An experimental analysis," *Journal of Economic Behavior and Organization*, 33, 167–184.

Weitzel, U., C. Huber, J. Huber, M. Kirchler, F. Lindner, and J. Rose (2019): "Bubbles and Financial Professionals," *The Review of Financial Studies*, 33, 2659–2696.

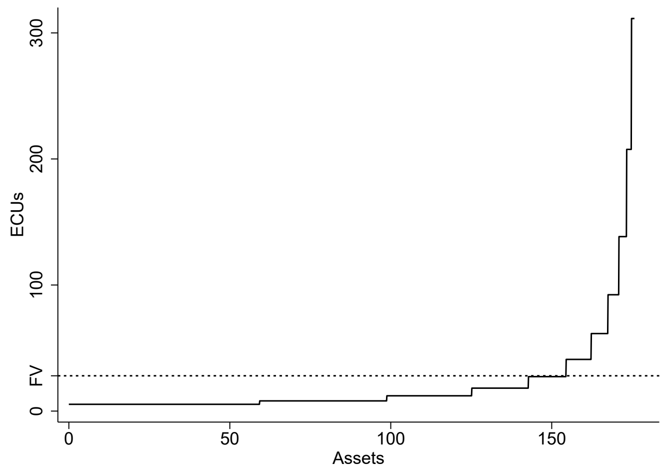
Xiong, J., Q. Liu, and L. Zhao (2020): "A new method to verify Bitcoin bubbles: Based on the production cost," *North American Journal of Economics and Finance*, 51, 101095.

Yermack, D. (2015): "Chapter 2 - Is Bitcoin a Real Currency? An Economic Appraisal," in *Handbook of Digital Currency*, ed. by D. Lee Kuo Chuen, San Diego: Academic Press, 31 – 43.

Appendix

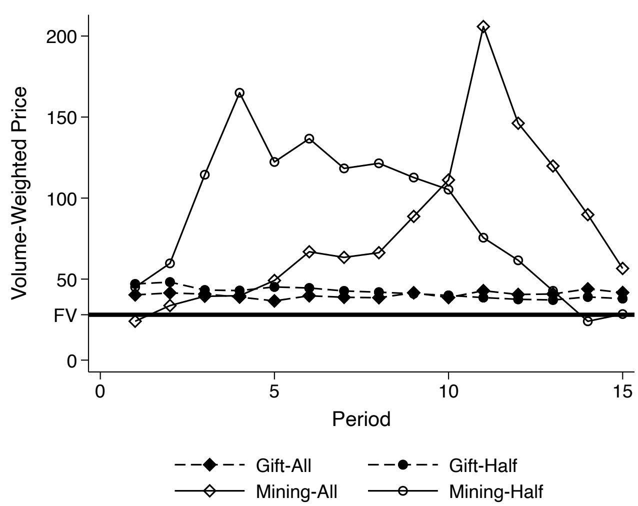
A Asset Costs in our Mining Treatments

Figure A.1: Asset costs as a function of assets generated in Mining treatments (assuming full capacity mining).



B Average Prices

Figure A.2: Average volume-weighted average price per period per 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 most graphs have a common y-axis, ranging from zero to five times the fundamental value (140). Two markets in treatment Mining-All and four markets in treatment Mining-Half exhibit particularly high peaks, which makes an adjustment of their y-axis necessary.

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 volume-weighted prices per period in individual markets of Gift-All

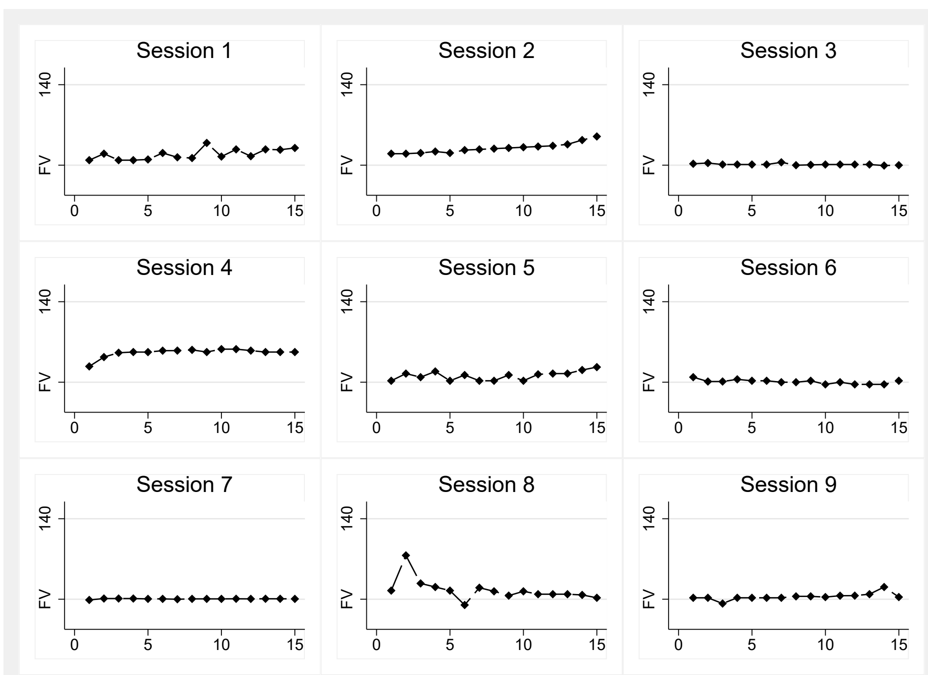


Figure A.4: Median volume-weighted prices per period in individual markets of Gift-Half

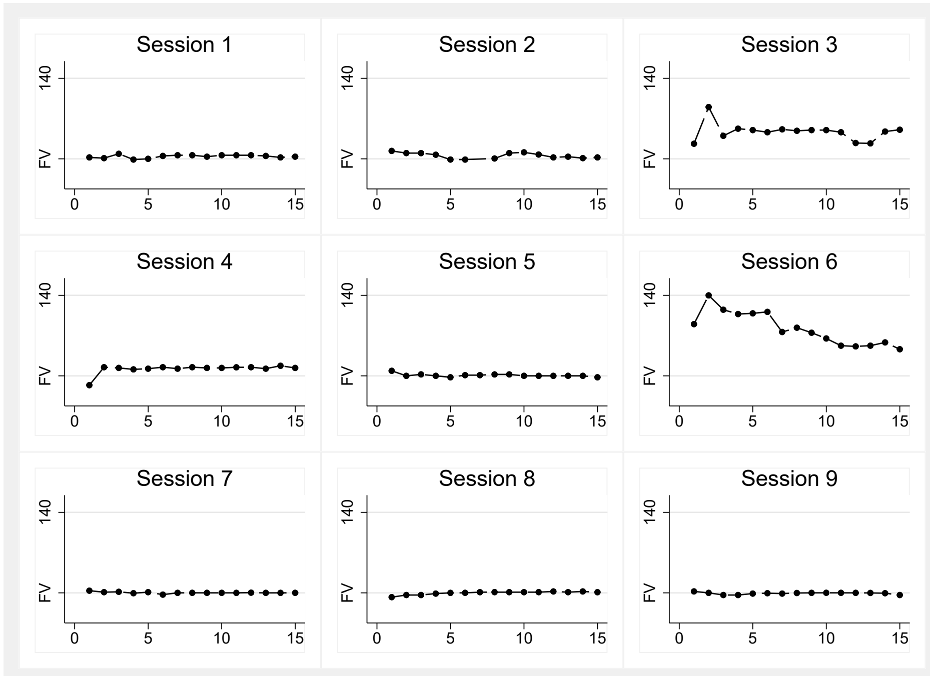


Figure A.5: Median volume-weighted prices per period in individual markets of Mining-All

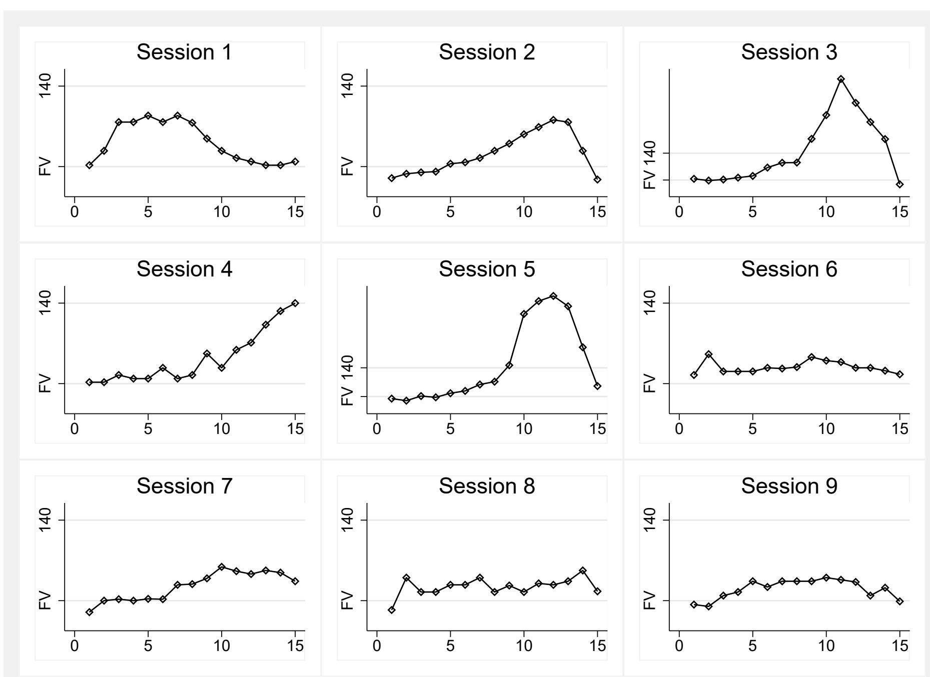
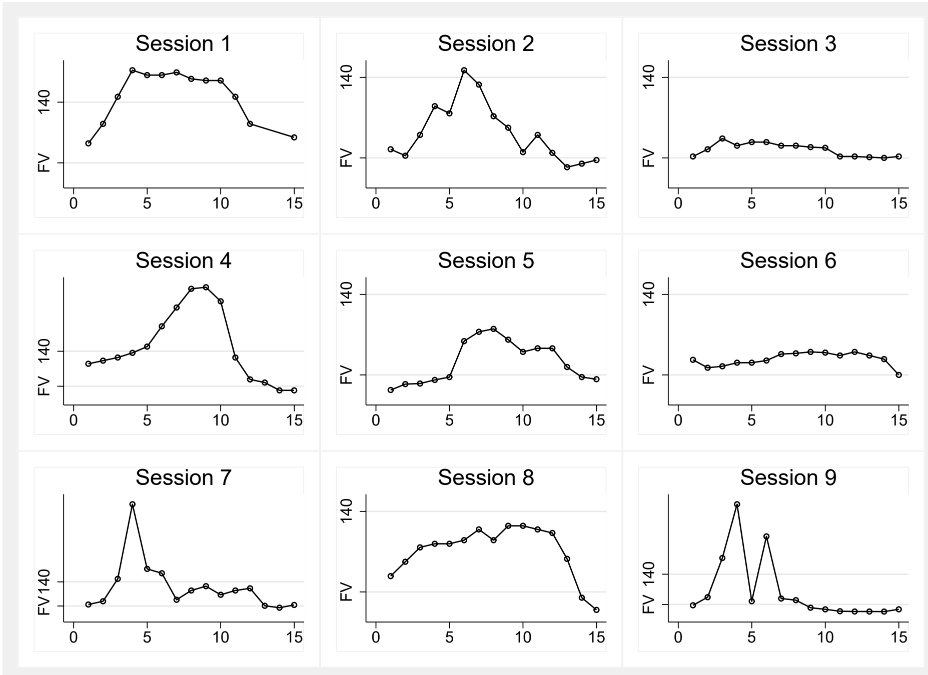


Figure A.6: Median volume-weighted prices per period in individual markets of Mining-Half



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,
- $\overline{P}_t$ 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 participants in period t,
- $R_{t,j}$ the log-return of a trade, i.e. $R_{t,j} = \ln(P_{t,j}/P_{t,j-1})$,
- $\overline{R}_{t,j}$ 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:

$$RAD = \sum_{t=1}^{T} \frac{\mid \frac{\overline{P}_t - FV_t}{FV_t} \mid}{T}$$

$$RD = \sum_{t=1}^{T} \frac{\frac{\overline{P}_t - FV_t}{FV_t}}{T}$$

$$RDMAX = \max_t \left\{ \frac{\overline{P}_t - FV_t}{FV_t} \right\} = \frac{\overline{P}_{t^*} - FV_{t^*}}{FV_{t^*}}$$

$$AMPLITUDE = \frac{\overline{P}_{t^*} - FV_{t^*}}{FV_{t^*}} - \min_{0 \le k < t^*} \left\{ \frac{\overline{P}_{t^*-k} - FV_{t^*-k}}{FV_{t^*-k}} \right\}$$

$$CRASH = \min_{0 \le l \le T - t^*} \left\{ \frac{\overline{P}_{t^*+l} - FV_{t^*+l}}{FV_{t^*+l}} \right\} - \frac{\overline{P}_{t^*} - FV_{t^*}}{FV_{t^*}}$$

$$SPREAD = \sum_{t=1}^{T} \frac{1}{FV_t} \frac{1}{T} \left[\min_{j \in N_t} \left\{ S_{\hat{t},j} \right\} - \max_{j \in N_t} \left\{ B_{\hat{t},j} \right\} \right]$$

$$VOLA = \sum_{t=1}^{T} \frac{1}{T} \sqrt{\frac{1}{N_t} \sum_{j=1}^{N_t} (R_{t,j} - \overline{R}_t)^2}$$

$$TURNOVER = \sum_{t=1}^{T} \frac{1}{T} \frac{VOL_t}{TSO}$$

$$SR = \sum_{t=1}^{T} \sum_{j=1}^{N_t} \frac{1}{T} \frac{LO_{j,t}}{LO_{j,t} + MO_{j,t}}$$

$$LIQUIDITY = \frac{1}{TSO} \sum_{t=1}^{T} \sum_{o=1}^{O_{\hat{t}}} \frac{1}{T} O_o^j$$

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.[21]

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

[21] For 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 summarizes dates and locations of implementation of each of our sessions across all four treatments. Depending on our treatment, we handed our participants 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, we include the translated comprehension quiz questions which participants had to respond to before the market stage of treatment Gift-Half.[22] Subsection E 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

Date	Session	Participants	Location
30/09/2019	1	8	Heidelberg
01/10/2019	2	8	Heidelberg
04/10/2019	3	8	Heidelberg
09/10/2019	4	8	Heidelberg
15/10/2019	5	8	Frankfurt
15/10/2019	6	8	Frankfurt
18/10/2019	7	8	Frankfurt
18/10/2019	8	8	Frankfurt
24/10/2019	9	8	Frankfurt
	Total:	72	

(b) Gift-Half

Day	Session	Participants	Location
22/10/2019	1	8	Heidelberg
24/10/2019	2	8	Frankfurt
25/10/2019	3	8	Frankfurt
25/10/2019	4	8	Frankfurt
07/11/2019	5	8	Heidelberg
14/11/2019	6	8	Frankfurt
14/11/2019	7	8	Frankfurt
18/11/2019	8	8	Heidelberg
22/11/2019	9	8	Heidelberg
	Total:	72	

(c) Mining-All

Day	Session	Participants	Location
30/09/2019	1	8	Heidelberg
01/10/2019	2	8	Heidelberg
04/10/2019	3	7	Heidelberg
09/10/2019	4	7	Heidelberg
15/10/2019	5	8	Frankfurt
15/10/2019	6	8	Frankfurt
18/10/2019	7	8	Frankfurt
18/10/2019	8	8	Frankfurt
24/10/2019	9	8	Frankfurt
	Total:	70	

(d) Mining-Half

Day	Session	Participants	Location
24/10/2019	1	8	Frankfurt
25/10/2019	2	8	Frankfurt
28/10/2019	3	8	Heidelberg
05/11/2019	4	8	Frankfurt
07/11/2019	5	8	Heidelberg
14/11/2019	6	8	Frankfurt
14/11/2019	7	8	Frankfurt
18/11/2019	8	8	Heidelberg
22/11/2019	9	8	Heidelberg
	Total:	72	

[22]The 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 test 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 5140 ECUs and 40 units of the asset. Participants with role B receive 6260 ECUs and 0 units of the asset. All participants can use their ECUs to buy or sell assets in the market. 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 ECUs = 1 Euro

2. 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:

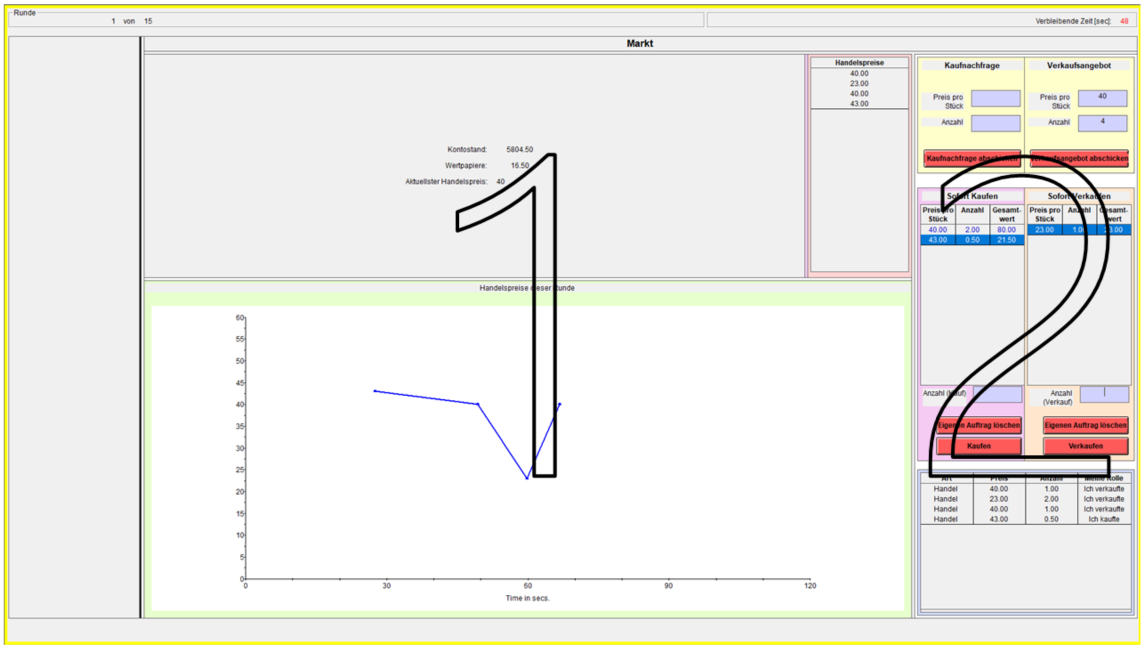


Figure 1: Screen

In the middle (1) of the screen (see Figure 1) you will see information about your current account balance and assets, as well as a price list for the current round of trading. 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 (2) of the screen (see Figure 1) you will find a user interface where you can trade assets with others.

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 so, enter the price you are willing to pay for one unit of the asset in the "Price per unit" (“Preis pro Stück”) box. Also enter the number of assets you wish to buy at this 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 field "Price per piece" (“Preis pro

Stück”). Also enter the number of assets you wish to sell at this price in the "Quantity" (“Anzahl”) field (this can also be a fraction of a unit). You can submit the offer to sell by clicking on "Submit offer to sell" (“Verkaufsangebot abschicken”).

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

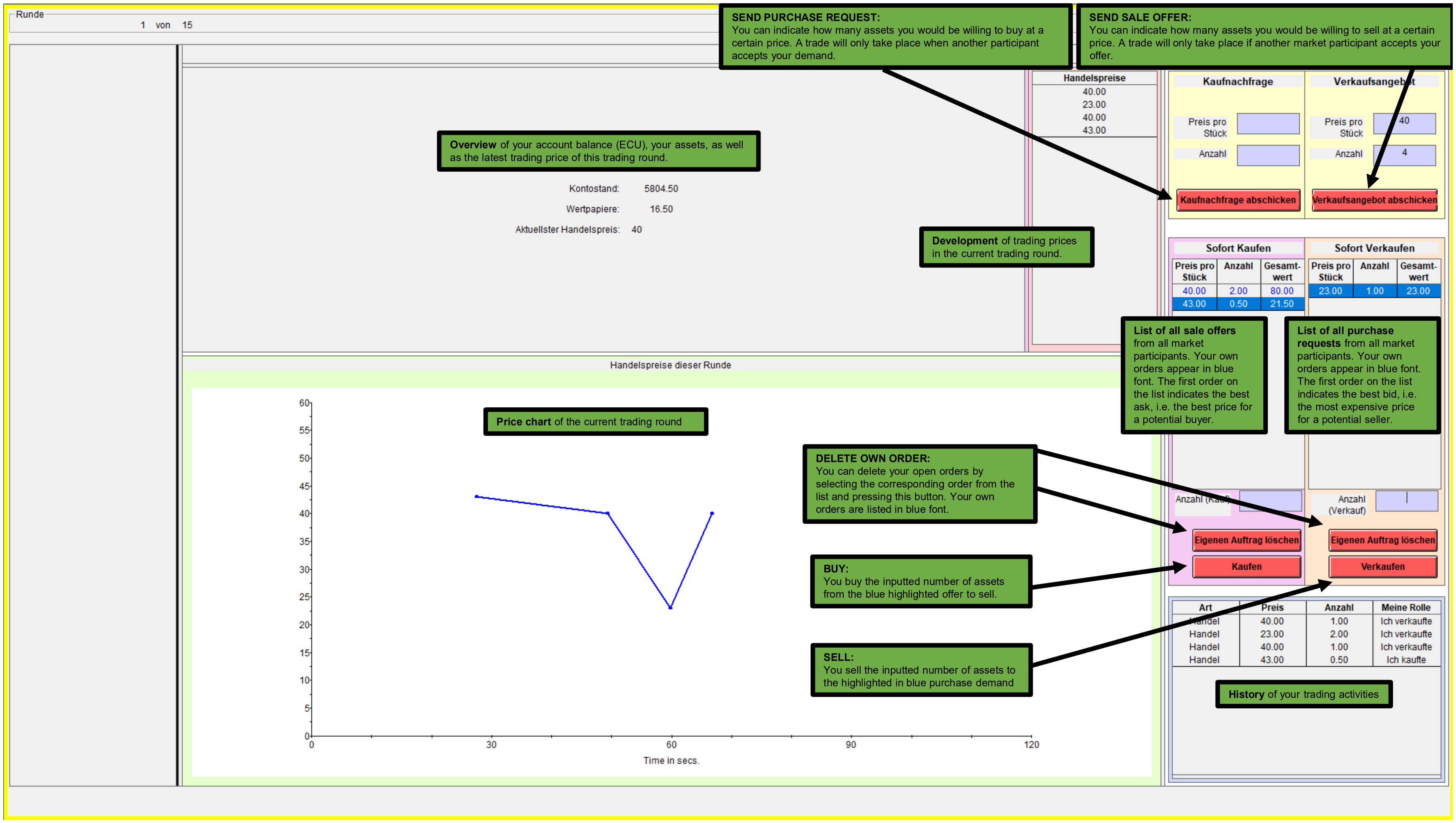
You can withdraw your buy requests and sell offers as long as they have not been accepted by another market participant. To do so, select the corresponding line in the list and then click on "Delete own order" ("Eigenen Auftrag löschen"). You can only delete orders you have submitted yourself. You can 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. You will also find a graph and a list of average trading prices from previous rounds.

Summary:

- Cash and initial holdings for role A: 5140 ECU, 40 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:
  - Purchase demand
  - Buy now (“Sofort Kaufen”)
  - Sales offer
  - Sell immediately (“Sofort Verkaufen”)
- 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


Runde
1 von 15
SEND PURCHASE REQUEST:
You can indicate how many assets you would be willing to buy at a certain price. A trade will only take place when another participant accepts your demand.
SEND SALE OFFER:
You can indicate how many assets you would be willing to sell at a certain price. A trade will only take place if another market participant accepts your offer.
Overview of your account balance (ECU), your assets, as well as the latest trading price of this trading round.
Kontostand: 5804.50
Wertpapiere: 16.50
Aktuellster Handelspreis: 40
Handelspreise
40.00
23.00
40.00
43.00
Development of trading prices in the current trading round.
Kaufnachfrage
Verkaufsangebot
Preis pro Stück
Anzahl
40
4
Kaufnachfrage abschicken
Verkaufsangebot abschicken
Sofort Kaufen
Sofort Verkaufen
Preis pro Stück | Anzahl | Gesamt-wert
40.00 | 2.00 | 80.00
43.00 | 0.50 | 21.50
23.00 | 1.00 | 23.00
List of all sale offers from all market participants. Your own orders appear in blue font. The first order on the list indicates the best ask, i.e. the best price for a potential buyer.
List of all purchase requests from all market participants. Your own orders appear in blue font. The first order on the list indicates the best bid, i.e. the most expensive price for a potential seller.
Handelspreise dieser Runde
Price chart of the current trading round
Time in secs.
DELETE OWN ORDER:
You can delete your open orders by selecting the corresponding order from the list and pressing this button. Your own orders are listed in blue font.
BUY:
You buy the inputted number of assets from the blue highlighted offer to sell.
SELL:
You sell the inputted number of assets to the highlighted in blue purchase demand
Anzahl (Verkauf)
Eigenen Auftrag löschen
Kaufen
Verkaufen
Art | Preis | Anzahl | Meine Rolle
Handel | 40.00 | 1.00 | Ich verkaufte
Handel | 23.00 | 2.00 | Ich verkaufte
Handel | 40.00 | 1.00 | Ich verkaufte
Handel | 43.00 | 0.50 | Ich kaufte
History of your trading activities

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 ECUs = 1 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:

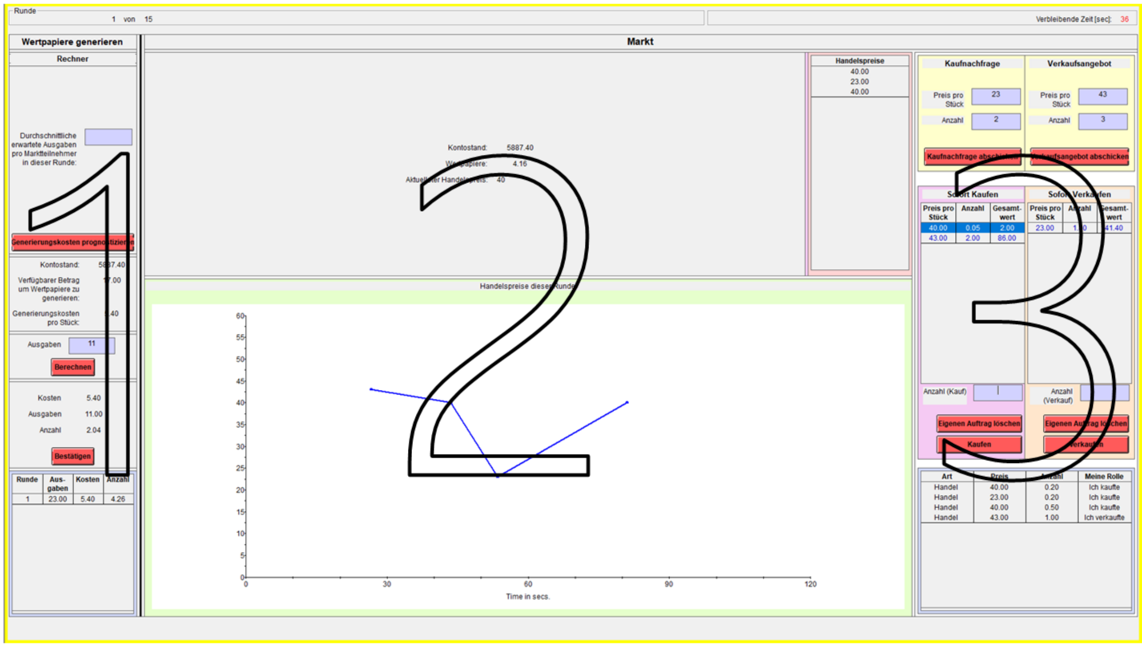


Figure 1: Screen

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.

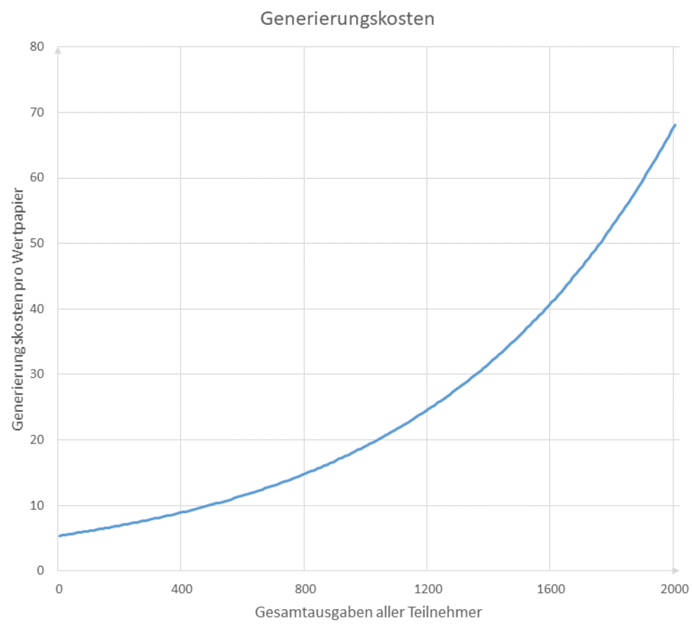


Figure 2: Costs of generating assets

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.

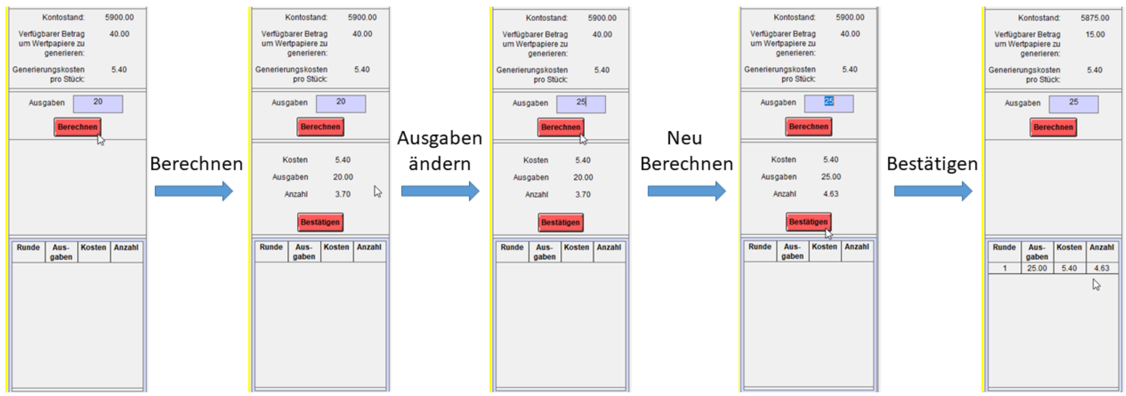


Figure 3: Example for generating assets

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.

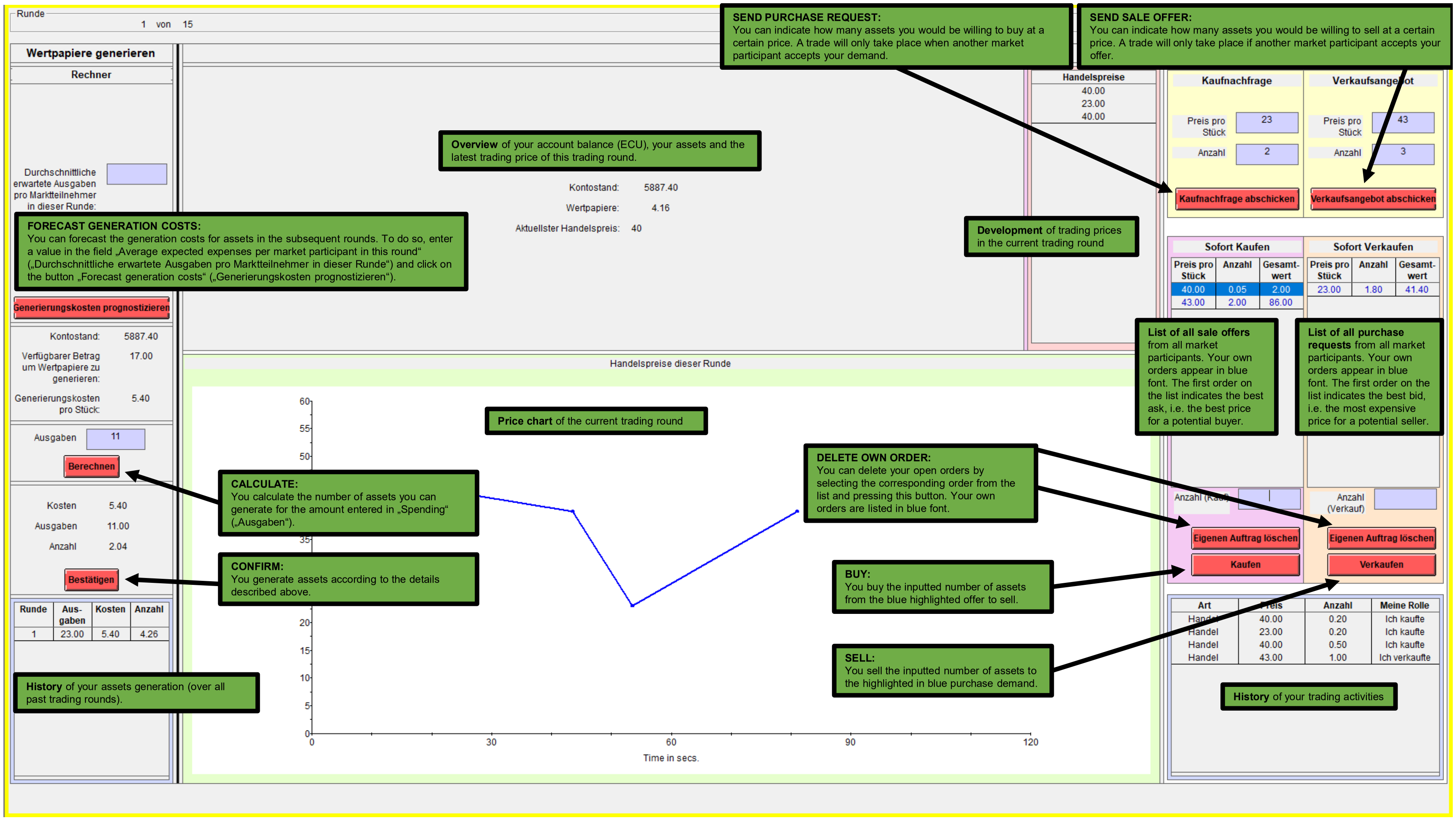
You can withdraw your buy requests and sell offers as long as they have not been accepted by another market participant. To do so, select the corresponding line in the list and then click on "Delete own order" ("Eigenen Auftrag löschen"). You can only delete orders you have submitted yourself. You can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


Runde
1 von 15
Wertpapiere generieren
Rechner
Durchschnittliche erwartete Ausgaben pro Marktteilnehmer in dieser Runde:
FORECAST GENERATION COSTS:
You can forecast the generation costs for assets in the subsequent rounds. To do so, enter a value in the field „Average expected expenses per market participant in this round" („Durchschnittliche erwartete Ausgaben pro Marktteilnehmer in dieser Runde") and click on the button „Forecast generation costs" („Generierungskosten prognostizieren").
Generierungskosten prognostizieren
Kontostand: 5887.40
Verfügbarer Betrag um Wertpapiere zu generieren: 17.00
Generierungskosten pro Stück: 5.40
Ausgaben 11
Berechnen
Kosten 5.40
Ausgaben 11.00
Anzahl 2.04
Bestätigen
Runde | Aus-gaben | Kosten | Anzahl
1 | 23.00 | 5.40 | 4.26
History of your assets generation (over all past trading rounds).
CALCULATE:
You calculate the number of assets you can generate for the amount entered in „Spending" („Ausgaben").
CONFIRM:
You generate assets according to the details described above.
Overview of your account balance (ECU), your assets and the latest trading price of this trading round.
Kontostand: 5887.40
Wertpapiere: 4.16
Aktuellster Handelspreis: 40
SEND PURCHASE REQUEST:
You can indicate how many assets you would be willing to buy at a certain price. A trade will only take place when another market participant accepts your demand.
SEND SALE OFFER:
You can indicate how many assets you would be willing to sell at a certain price. A trade will only take place if another market participant accepts your offer.
Handelspreise
40.00
23.00
40.00
Development of trading prices in the current trading round
Kaufnachfrage
Preis pro Stück 23
Anzahl 2
Kaufnachfrage abschicken
Verkaufsangebot
Preis pro Stück 43
Anzahl 3
Verkaufsangebot abschicken
Sofort Kaufen
Preis pro Stück | Anzahl | Gesamt-wert
40.00 | 0.05 | 2.00
43.00 | 2.00 | 86.00
Sofort Verkaufen
Preis pro Stück | Anzahl | Gesamt-wert
23.00 | 1.80 | 41.40
List of all sale offers from all market participants. Your own orders appear in blue font. The first order on the list indicates the best ask, i.e. the best price for a potential buyer.
List of all purchase requests from all market participants. Your own orders appear in blue font. The first order on the list indicates the best bid, i.e. the most expensive price for a potential seller.
Handelspreise dieser Runde
Price chart of the current trading round
60
55
50
35
20
15
10
5
0
0
30
60
90
120
Time in secs.
DELETE OWN ORDER:
You can delete your open orders by selecting the corresponding order from the list and pressing this button. Your own orders are listed in blue font.
Anzahl (Verkauf)
Eigenen Auftrag löschen
Kaufen
Eigenen Auftrag löschen
Verkaufen
BUY:
You buy the inputted number of assets from the blue highlighted offer to sell.
SELL:
You sell the inputted number of assets to the highlighted in blue purchase demand.
Art | Anzahl | Meine Rolle
Handel | 40.00 | 0.20 | Ich kaufte
Handel | 23.00 | 0.20 | Ich kaufte
Handel | 40.00 | 0.50 | Ich kaufte
Handel | 43.00 | 1.00 | Ich verkaufte
History of your trading activities

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

Summary screen between market periods

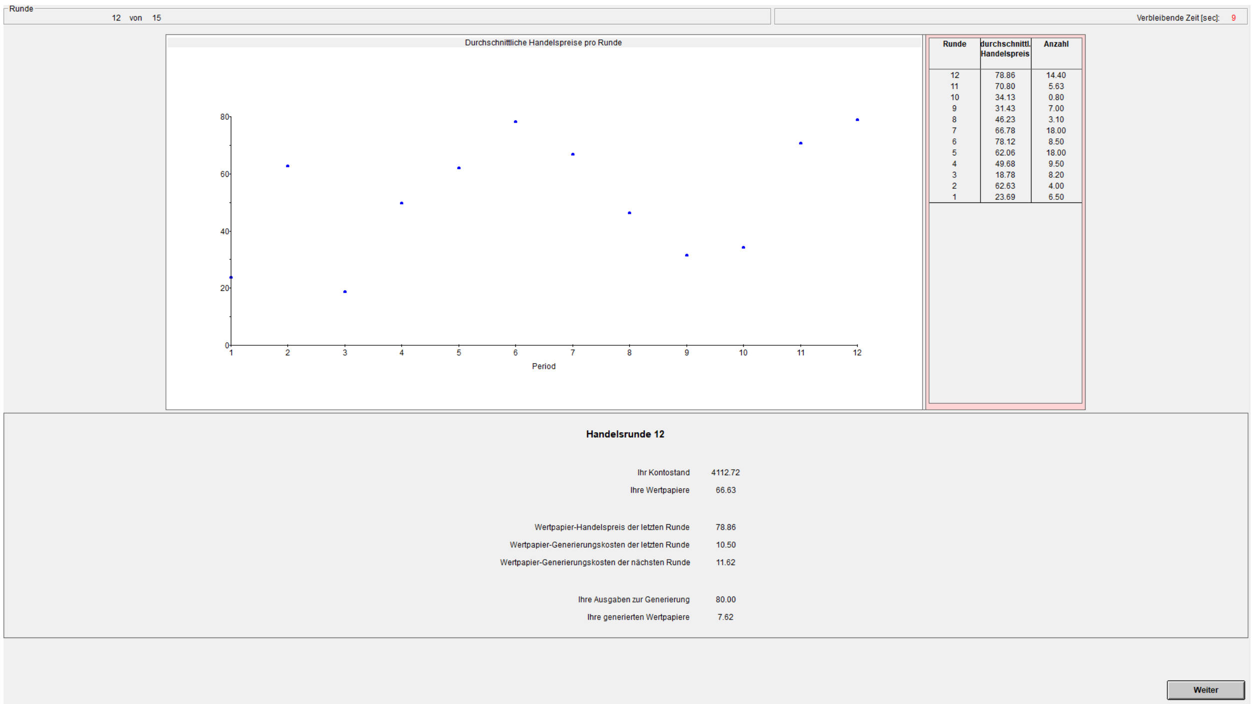


Figure A.7: Price chart and history of previous rounds on the result screen between trading periods. The screen lists average trading prices ("Durchschnittlicher Handelspreis"), volumes ("Anzahl"), periods ("Handelsrunde"), cash balance ("Kontostand"), asset holdings ("Wertpapiere"), the trading price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