Does mining fuel bubbles? An experimental study on cryptocurrency markets

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Abstract

We investigate how key features associated with the Proof-of-Work consensus mechanism of Bitcoin (commonly referred to as mining) affect pricing. In a controlled laboratory experiment, we observe that price bubble formation can be attributed to mining. Moreover, overpricing is more pronounced if the mining capacity is centralized to a small group of individuals. The order book data reveal that miners seem to play a crucial role in bubble formation. Further probing the mechanism in a second study, we find that both mining costs and decisions jointly with the sluggish rate of supply of the asset contribute to the bubble formation. Our results demonstrate that erratic pricing is an inherent feature of cryptocurrencies based on a mining protocol, thus, seriously limiting any prospects for such assets becoming a medium of exchange.

JEL classification: C90; D53; G12.

Keywords: Bitcoin, Bubbles, Cryptocurrency, Financial Market Experiment

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1 Introduction

Speculative bubbles are a major destabilizing factor for the economy and often have 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, the extreme price trajectories in cryptocurrency markets, commonly referred to as bubbles[1], 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.[2] 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.[3] Irresberger et al. (2020) provide an

[1] Of course, when using observational data, bubbles are not well defined as fundamental values are not observable. Precisely for this reason we pursue this topic using a controlled laboratory study that allows to exactly identify the presence of a bubble with the fundamental value being clearly specified.

[2] 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).

[3] Permissionless blockchains are public and decentralized networks with a universal consensus validation. In other words, anyone can join the network and possess a copy of the ledger. Examples of cryptocurrencies that are based on this type of blockchain are Bitcoin and Ether. Permissioned blockchains, on the other hand, are closed networks with

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 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 increases scarcity. In the social psychology literature on influence and manipulation, scarcity has been shown to effectively increase people's valuation of a wide range of products (Cialdini, 2021). 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 individuals to mine bitcoin in a decentralized manner (Alsabah and Capponi, 2020; Ferreira et al., 2019).[4] 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 independently from any other likely sources.[5] However, we are not precluding

limited decentralization. This means that only designated entities or individuals can have access to the blockchain. An example of a permissioned cryptocurrency is Ripple.

[4]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.

[5]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. A hard fork often happens when a subgroup of developers or members of a crypto community grow dissatisfied with functionalities offered by existing blockchain implementations. It is a radical change to a network's protocol that makes previously invalid blocks and transactions valid, or vice-versa. For instance, Bitcoin Satoshi Vision (SV) is a variant of Bitcoin that is much faster and more efficient than the original Bitcoin. But since it is hard forked, the underlying asset is no longer Bitcoin, but Bitcoin SV. 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.

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 pricing 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', is sufficient to ignite overpricing and, thus, may contribute to understanding the commonly observed but otherwise not adequately explained bubble phenomenon 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 of 38 cryptocurrencies and conclude that the computing power (hashrate) and network size (number of miners) influence cryptocurrency prices. Relatedly, Saleh (2021) 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 a counterfactual 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 examine how the PoW consensus mechanism affects pricing in cryptocurrency markets. In this paper, we report the results of two studies. Our first study aims to examine whether key features associated with the Bitcoin mining process discussed above affect mispricing. The second study aims to further understand the underlying mechanisms for bubble formation given the findings in the first study.[6] The experimental method has been successfully employed to test various financial innovations in the past such as the pricing of financial derivatives (e.g., Noussair et al., 2016; Oprea et al., 2009; Porter and Smith, 1995) 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.[7] 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

[6] 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.

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

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 possible redemption values of the asset also include zero. Thus, we allow for the possibility that the asset ends up having no value.

Our first study 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 them at a cost. The cost of mining increases as more units of the asset are mined in total. This is common knowledge for all traders, similar to how prospective miners can easily estimate the cost of mining Bitcoin. There are available estimates of electricity usage for Bitcoin mining[8], which together with a country's electricity prices can allow prospective investors and/or miners to reliably predict and anticipate mining costs. 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

[8] For example: `https://ccaf.io/cbeci/index`.

the mining cost will rise, traders are more eager to purchase the asset early on, albeit at elevated prices. In order to classify bubble markets, we follow the definition proposed by Razen et al. (2017). In particular, we consider our Mining markets to exhibit price bubbles if they significantly differ from the respective Gift treatment (for details, see section 4). We find evidence for bubbles in both Mining-All and Mining-Half. Additionally, we find that in both Mining treatments expenditure on mining activity goes beyond what a social planner would implement (reducing the sum of potential earnings of traders within a market) suggesting that miners further perpetuate mispricing in these markets.

The sluggish supply, or slow introduction of assets that is inherent in the PoW paradigm, means that initially there are only a few assets available in the market of the Mining treatments. The side-effect of assets being slowly introduced in the Mining treatments is that there is an initial difference in the cash-to-asset ratio (CAR) between the Gift and Mining treatments. While in the Gift treatments the CAR is constant, in the Mining treatments it is initially higher and eventually becomes comparable to that in the Gift treatments after a few periods (after some assets have been mined). Thus, it is not entirely clear whether the observed bubble formation in the Mining treatments can be directly attributed to mining costs and mining decisions, or whether the initial difference in the CAR induced from the sluggish supply of assets is already sufficient to ignite bubbles (e.g., Kirchler et al., 2015; Razen et al., 2017). In order to clarify this, in our second study, we conduct two additional treatments called Airdrop-All and Airdrop-Half. In the Airdrop treatments, we remove the act of mining and its associated mining cost but mirror the inflow of assets in an identical way to how it occurs in our Mining treatments. As a result, the new Airdrop treatments closely replicate the CAR trajectories of each session in the Mining treatments. This is operationalized by having each trader in the Airdrop treatments randomly matched with a trader in the Mining treatments. Thus, the assets in the Airdrop treatments are not mined, but instead gifted to traders in every period according to the mining activity of the trader they are matched with.

We find that the magnitudes of the price bubbles in Airdrop-All is virtually indistinguishable to what we find in Mining-All. However, the timing of the peak differs. Since there is no mining cost, prices are not anchored with the mining costs, as in the Mining-All treatment, but immediately spike at the beginning. This confirms our initial conjecture that anchoring plays an important role for the pricing we find in Mining-All. In Airdrop-Half we find that mispricing is of lower magnitude and less frequency in comparison to Mining-Half, though they are statistically not significantly different. Market prices in Airdrop-Half lie between the price trajectories of Mining-Half and Gift-Half. Taken together, our second study suggests that both a high initial CAR (stemming from a sluggish asset supply), as well as mining costs and decisions are joint contributors to the price bubbles observed in Mining-Half.

Overall, the observation that mining and centralization of the mining technology fuel overpricing in a controlled environment is a result of primary importance. The findings of previous studies suggest that extensive effort put into mining of cryptocurrencies may be welfare harming (Biais et al., 2019; Schilling and Uhlig, 2019). 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 ensures the security of the decentralized network. Overall, our results encourage the ongoing search for alternative blockchain consensus mechanisms that are more efficient and less bubble-prone (e.g., Hinzen et al., 2020; Saleh, 2021).

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 of our first study in section 3. In section 4, we present our hypotheses and report our results of the first study in section 5. We then introduce the design and subsequently discuss the results of the second study in section 6. Section 7 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), Biais et al. (2019), and Blackburn et al. (2022).

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. Due to the decentralized nature of the PoW mechanism, this is a welcome development to improve security. Blackburn et al. (2022) note that before BTC reached the $1 landmark, mining in the BTC network was done by only 64 agents. This was risky from a security perspective because these founding miners could theoretically coordinate on a "51% attack" and undermine the credibility of the network. In recent years, the mining difficulty of a large set of cryptocurrencies (which translates into the monetary cost of mining) 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.[9] Our experiment is designed to test whether the defining features of mining enable the erratic pricing patterns observed empirically. Furthermore, our design also tests what further effect the centralization of large professional miners can have on mispricing.

[9]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).

3 Study 1: Experimental Design

3.1 Experimental Asset Market

The basic experimental setup 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. All transactions and asset generation is performed using experimental currency units (ECUs). The exchange rate of ECU to Euro at the end of the experiment is fixed at 560 to 1, i.e., 560 ECU translate to exactly 1 Euro. 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.[10] 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 Gift treatments, or are allowed to mine the asset (i.e. have "access" to the mining technology) 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 in Study 1

		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

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

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. By contrasting Gift-All and Mining-All, we identify the effect of costly mining on asset pricing. Mining operates concurrently with the asset market. The cost of mining is an increasing function of the accumulated units of asset mined (as accumulated expenditure) and this is clearly known by everyone. Traders can decide to spend up to 40 ECUs in each period on mining. The cap on mining expenditure, even when mining is profitable (for example if assets are traded at prices higher than mining cost), ensures that 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.

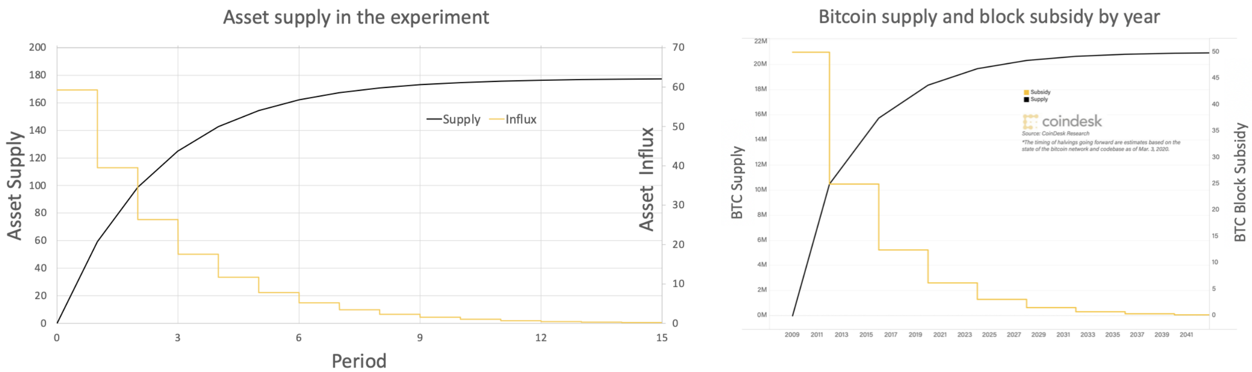
The per unit cost of mining is characterized by the following function:

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

where I denotes the set of traders and $|I| = n$ 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 accumulated expenditure on asset mining 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 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. Participants are clearly informed that mining will become increasingly costly as more units are mined through a graph that depicts the evolution of cost in the long run (see instructions in the appendix). Mining costs adjust discretely at the start of each period. Participants can use a calculator to estimate the short-run future mining cost (the next 4 periods), by inputting their expectation on mining expenditure per trader in the current period. Providing a calculator in our experiment was inspired by the wide-spread online calculators that Bitcoin miners can use to estimate potential costs and effectively profits. 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 approximate the way cryptocurrency mining operates in

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. The left panel shows the evolution of asset supply in our experiment under the assumption that all subjects mine at full capacity in all periods.

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.[11] 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 spend up to 80 ECUs on mining in each period. We double the mining capacity per period to allow for the market to have the same overall potential mining volume as the Mining-All

[11] A stronger form of centralization could have been implemented with only one or two traders having access to the mining technology. This could have likely encouraged bubbles of a larger extent as miners would have almost absolute market power. Such a design would though depend too heavily on individual decisions. For example, what if the randomly determined miner generates very few assets, or even does not at all? With this concern in mind, we choose to implement the current design with a relatively weaker form of mining centralization but which potentially eliminates the dependency on individual decisions.

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

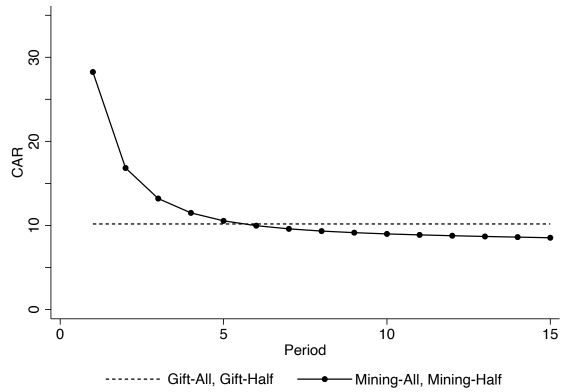
Note: Miners are endowed with more ECUs than non-miners (5900 vs. 5700 & 5540 vs. 5140) to compensate them for the mining cost, which is an increasing function of the accumulated units of asset mined so far. Parameters are calibrated such that the CAR is comparable across treatments. In the Mining treatments, the CAR varies across periods and depends on individual mining decisions. The CAR in the Gift treatments is constant at 10.2. See below for a detailed explanation regarding the comparison of the CAR between the Mining and Gift treatments.

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 onward, the mining cost would exceed the asset fundamental value, thus, risk-neutral agents should refrain from further mining.[12] Analogously, if all role A traders in Mining-Half were to mine using their maximum allowance (80 ECUs) in each of the first five periods, they would reach (approximately) the initial endowment of role A traders in Gift-Half.

It is important to highlight some design choices we make. Firstly, we design the mining process to be deterministic, that is, there is no uncertainty about how many assets a miner will receive for a level of expenditure in a given period. 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

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

Figure 2: Theoretical CAR across trading periods



Note: Assuming mining at full capacity in each period.

in the future are not certain.[13] 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 can be generated in a given period to estimate the mining cost of the next period.[14] 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, modeling miners as having identical costs can 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 take after reading the instructions. The quiz asks about features and parameters of the asset market. All participants have to answer every question correctly before being allowed to move on. We include the quiz questions in appendix F.1. Before initiating the 15 trading periods, participants go through three practice periods of 120

[13]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.

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

seconds each. During these practice periods participants are encouraged to familiarize 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 of all treatments, 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 the related literature (Bossaerts et al., 2019; Bruguier et al., 2010; Corgnet et al., 2022; Hefti et al., 2018). ToM is the ability to infer the intentions of other agents, which is especially important in market environments. The Heider test involves a short film of moving geometric objects (two triangles of different size and one circle). When watching the movie, one could personify the geometric objects as the large triangle bullying the small triangle and the circle trying to intervene. To measure the intensity of ToM, we pause the movie every 5 seconds and ask the 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, which also includes questions regarding 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.[15] 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.[16] 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.[17]

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. We find almost no statistically significant differences at conventional levels of significance in these characteristics in pairwise comparisons across treatments and roles. Overall, our treatments are balanced, in particular with respect to gender (except for between Gift-All and Gift-Half; $p - value = 0.068$), which is important given the findings that gender composition can matter for market efficiency (Eckel and Füllbrunn, 2015). However, more recent evidence suggests that such effects only seem to occur when the gender composition of the market is known (Eckel and Füllbrunn, 2017) and in declining fundamental value regimes (Cueva and Rustichini, 2015; Holt et al., 2017), which should already help alleviate the concerns that gender might influence results in our experiment.

[15] Table A.14 in the appendix summarizes dates and locations of implementation of each of our sessions across all treatments.

[16] 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.

[17] The draws are made without replacement to ensure that all possible asset values are realized.

Table 3: Characteristics of participants across treatments (Study 1)

	Gift-All	Gift-Half		Mining-All	Mining-Half	
		Role A	Role B		Role A	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

Note: There are no statistically significant differences in these characteristics in pairwise comparisons across treatments and roles except for gender (Gift-All vs. Gift-Half, $p - value = 0.068$).
†Crypto experience was elicited using a Likert scale from 1 (none) to 5 (very well).

4 Study 1: Research Hypotheses

Our experimental design allows us to answer a number of research questions. Here, we list three main hypotheses to be evaluated. In order to classify bubble markets, we follow the definition proposed by Razen et al. (2017). In particular, we consider our markets to exhibit price bubbles if the peak average period price (RDMAX), the price run-up (AMPLITUDE), and the price drop (CRASH) are significantly higher in the Mining treatment compared to the respective Gift treatment.

The setup of our baseline treatments, Gift-All and Gift-Half, 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 the established findings in the literature. In the Gift treatments, 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. *Trading in the Gift treatments occurs around the asset's fundamental value.*

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 mining due to the sunk cost fallacy. Second, due to the expenditure cap on mining, the supply of assets 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). In order to identify the presence of a bubble we compare each Mining treatment to its respective Gift treatment and specifically test for a significant difference in each of RDMAX, AMPLITUDE, and CRASH.

Hypothesis 2. *Mining treatments exhibit bubbles.*

The Mining-Half treatment may exhibit a more exacerbated extent of bubbles, as demand could be even stronger when half of the traders can only purchase the asset on the market. Additionally, perhaps only a subset of miners might be initially selling assets that they have mined. This would allow them to enjoy market power and maintain their asks at a relatively higher price level given the limited competition. Lastly, Lugovskyy et al. (2014) explicitly study the effect of initial asset concentration and show that the asset-holdings concentration ratio in initial periods is positively correlated with the magnitude of bubbles. This result has been mirrored by the recent findings of Janssen et al. (2019) and Tucker and Xu (2020). We, thus, anticipate that the extent of bubble formation will be larger in Mining-Half as compared to Mining-All. To operationalize this, we compare the magnitude of bubbles between the two treatments using the bubble measures RAD and RD, among others.

Hypothesis 3. *Bubbles of larger magnitude are realized in Mining-Half compared to Mining-All.*

5 Results: Study 1

5.1 Results on Market Level

Figure 3a depicts the trading prices of the asset across the four treatments in study 1. We calculate the average price per period for each market by weighing each transaction by its volume and report the median volume-weighted average price of the 9 markets of each treatment across periods.[18] 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.

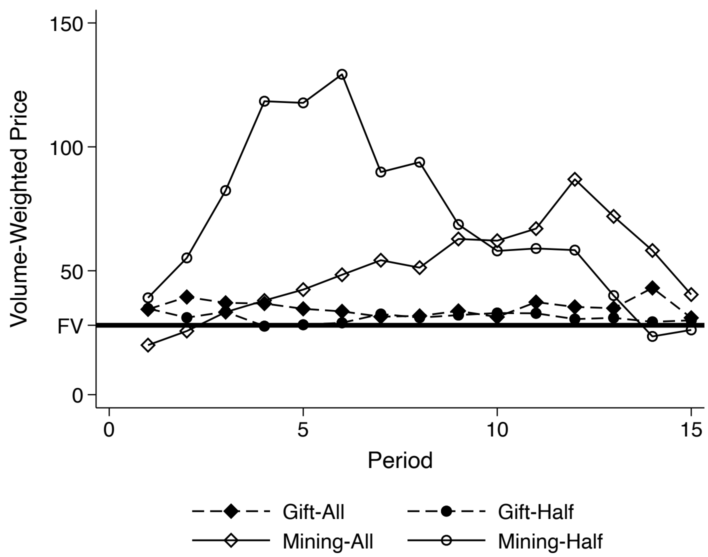
We formalize our analysis using a number of bubble measures, summarized in table 4.[19] These indicators include RD, the relative deviation of prices from fundamental value (normalized at 28) and RAD, the relative absolute deviation of prices from fundamental value (normalized at 28), introduced by Stöckl et al. (2010). RAD measures how closely prices track fundamental value, while RD indicates whether prices on average are above or below fundamental value.

[18]Figure A.2 in the appendix is the equivalent figure depicting averages of volume-weighted average prices, and figure A.3 depicts medians of unweighted prices instead. Both figures offer similar conclusions. Additionally, figures A.11-A.14 depict the price trends separately for each of our 9 individual markets per treatment.

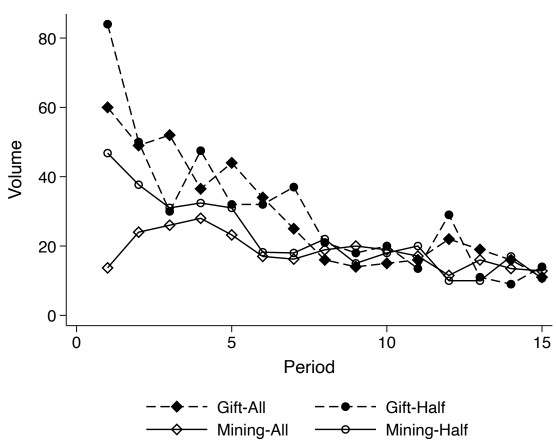
[19]We report the exact formulas of all bubble measures in the appendix. In tables A.7-A.10 in the appendix, we report these measures separately for each market of each treatment.

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

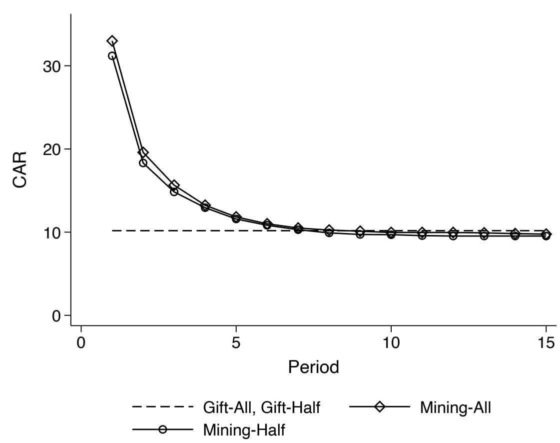


Table 4: Summary statistics of bubble measures by treatment

	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	0.41		0.14		1.05		2.08	
	0.46	(0.47)	0.51	(0.84)	1.93	(1.91)	2.29	(1.54)
RD	0.41		0.14		0.97		1.97	
	0.44	(0.48)	0.49	(0.85)	1.86	(1.91)	2.17	(1.52)
RDMAX	1.04		0.32		3.63		3.62	
	0.92	(0.64)	0.89	(1.38)	7.69	(10.74)	6.11	(5.21)
AMP	0.80		0.32		3.84		3.20	
	0.66	(0.34)	0.65	(0.58)	7.93	(10.73)	5.60	(4.96)
CRASH	-0.46		-0.34		-2.93		-4.03	
	-0.61	(0.58)	-0.65	(0.92)	-7.52	(11.29)	-6.22	(5.41)
TURN	0.21		0.20		0.18		0.20	
	0.21	(0.07)	0.20	(0.07)	0.20	(0.08)	0.23	(0.08)
LQ	0.55		0.98		0.52		0.85	
	0.76	(0.69)	5.53	(13.86)	0.69	(0.57)	5.17	(12.85)
SPREAD	0.22		0.10		0.48		1.21	
	0.27	(0.24)	0.20	(0.28)	1.42	(2.33)	1.50	(1.15)
VOLA	0.21		0.10		0.29		0.44	
	0.31	(0.35)	0.16	(0.13)	0.34	(0.19)	0.47	(0.31)

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. SPREAD measures the gap between buy and sell orders and VOLA measures log-returns of all market prices within a period.

Table 5: Mann-Whitney-U exact 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
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.

In table 4, the median value of RAD and RD in the Gift treatments is between 0.14 and 0.41, suggesting very modest mispricing. Thus, the Gift treatments provide us with a 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.[20] 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 result:

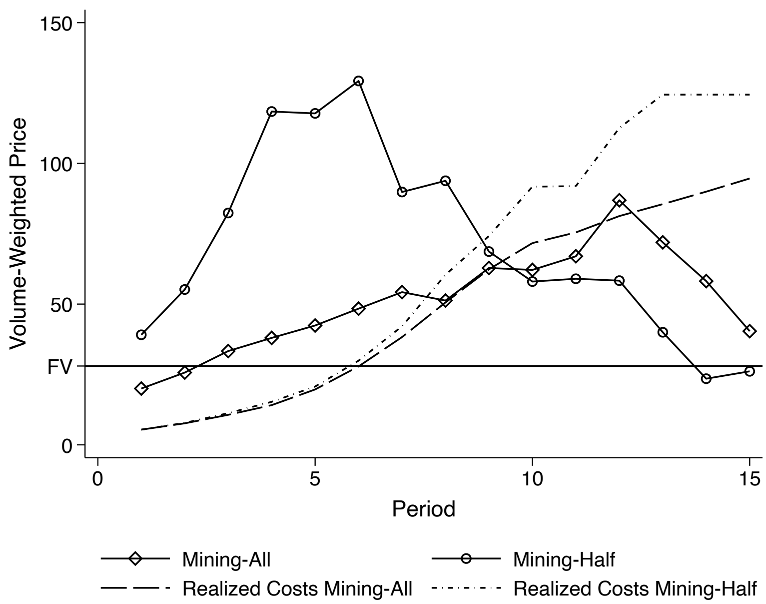
Result 1. *Trading in the Gift treatments occurs around the asset's fundamental value, offering supporting evidence for Hypothesis 1. Furthermore, we find no significant difference in overpricing between Gift-All and Gift-Half treatments. Endowment asymmetry by itself does not ignite a bubble.*

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 are well above fundamental value. Prices seem to decouple from the mining cost already within the

[20] It is ex-ante not clear whether the endowment asymmetry itself may trigger a price bubble in an environment that rarely exhibits bubbles such as ours. Endowment asymmetry, or higher asset concentration, may affect the 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. Lugovskyy et al. (2014) explicitly study the effect of initial asset concentration and show that the asset-holdings concentration ratio in initial periods is positively correlated with the magnitude of bubbles. 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 bubble formation (Palan, 2013).

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.[21] Importantly, our results are not driven by individual traders in the Mining treatments. We observe that the vast majority of traders buy at elevated prices (prices higher than the maximum possible redemption value of 67) in the Mining-All (70.8%) and Mining-Half (77.5%) treatments. Conversely, less than one third of traders do so in Gift-All (31.9%) and Gift-Half (27.9%).

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



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). In order to classify bubble markets, we follow Razen et al. (2017) and consider our markets to exhibit bubbles if the peak average period price (RDMAX), the price run-up (AMPLITUDE), and the price drop (CRASH) are significantly higher in the Mining treatment compared to the respective Gift treatment. Following this definition, we classify the markets in Mining-All and Mining-Half to be bubble markets given the results summarized in table 5.[22] 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

[21]Our median representation is robust to potential outliers; in figure A.4 we replicate figure 3a by systematically removing one of the 9 markets of each treatment with replacement. For each treatment, this results in 9 graphs with 8 (instead of 9) markets each. We report this analysis in figure A.4, where the shaded area indicates the lowest and highest per period price for each treatment. The general price trajectories we report in figures 3a and 4 remain unchanged.

[22]We investigate whether initial market conditions predict overall bubble formation in appendix B.3.

treatments (10.2), thus, ensuring that traders are never cash constrained.[23] 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.

Thus, our second result is:

Result 2. *The Mining treatments exhibit bubbles, thus, we have supporting evidence for Hypothesis 2.*

Table 6: Mann-Whitney-U exact 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.[24] 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 third result:

Result 3. *Generally, the extent of bubbles does not differ between Mining-All and Mining-Half. The price bubble does appear earlier in the Mining-Half markets than in the Mining-All markets. Thus, we partly reject Hypothesis 3.*

It is worth noting that the results that we report are not due to differences in trading volumes across treatments. Figure 3b presents the average trading volume of each treatment across trading periods. No treatment leads to a particularly thin market, albeit there are 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

[23] 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.

[24] 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.

markets. Figure 3c shows the median realized CAR of our treatments across periods.[25] Trading volume across the four treatments is not significantly different once the CAR is similar (from the 6th period onward). This is confirmed using a non-parametric test of comparing average trading volumes of periods 6-15 across the four treatments (Mann-Whitney-U exact test of Mining vs. Gift, $p-value=0.393$; Mann-Whitney-U exact 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; Biais et al., 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 exact 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. We analyze whether the transactions are mostly initiated by buyers or sellers and we separately plot bids and asks proposed by traders. Figure 5 summarizes the results. First, figure 5a shows that approximately three quarters of accepted trades are consistently originating from asks in all four treatments. That is, 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 5b and 5c 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). Bids and asks are significantly higher in the Mining-treatments compared to their respective Gift-treatment. However, the differences occur at different times. Consistently with our earlier analysis, we split the trading periods by first half (1-7) and second half (9-15). We perform Mann-Whitney U exact tests and find significant differences between Mining-All and Gift-All when focusing on later periods (bids: $p-value=0.000$; asks: $p-value=0.000$).

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

Meanwhile, significant differences between Mining-Half and Gift-Half already arise in earlier periods (bids: $p-value = 0.014$; asks: $p-value = 0.000$). The disparity in timing is also reflected in significant differences between the Mining treatments in the first half (bids: $p-value = 0.001$; asks: $p-value = 0.000$). There are no statistically significant differences between Gift-All and Gift-Half in the first half (bids: $p-value = 0.417$; asks: $p-value = 0.112$). Overall, the upward trends in asks in the Mining treatments are clearly steeper than what we observe for bids, which - despite showing some heterogeneity - appear relatively flat. This conclusion is robust to analyzing unweighted bids and asks instead (see figure A.5 in the appendix). 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 5b and 5c 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.

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.[26] 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. 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 6 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 exact test, $p-value = 0.000$). 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 exact test, $p-value = 0.399$).[27]

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 7, 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 exact 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.[28]

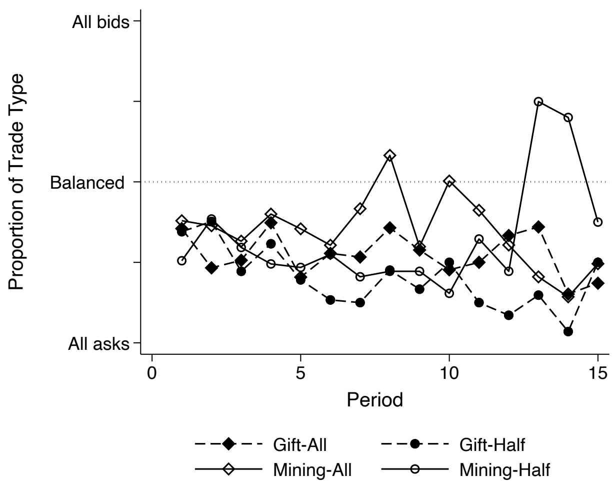
[26] A similar exercise would also be interesting for the Mining-All treatment. However, since everyone can mine (and most do), objectively categorizing participants into miners and non-miners is not possible.

[27] As a bubble forms in early periods in Mining-Half, we repeat the analysis focusing on the first half (i.e., periods 1 to 7) in figure A.6 in the appendix. The overall picture is qualitatively similar. Miners are significantly more likely to act as sellers than non-miners in Mining-Half ($p-value = 0.000$), while "miners" are not more likely to act as sellers than "non-miners" in Gift-Half at a conventional significance level ($p-value = 0.061$).

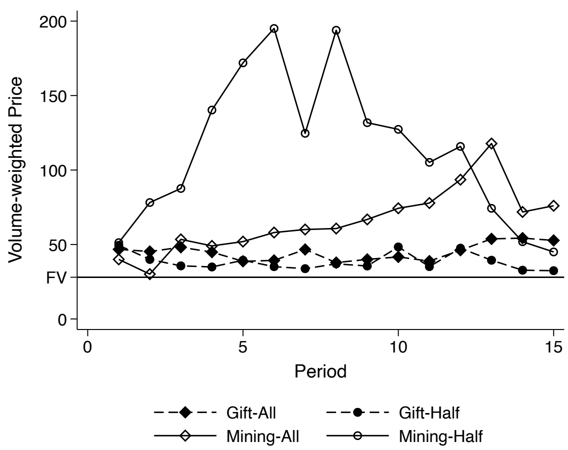
[28] In appendices C.1 - C.3 we provide further analysis at the individual level. In particular, we find that cognitive

Figure 5: Order Book Analysis

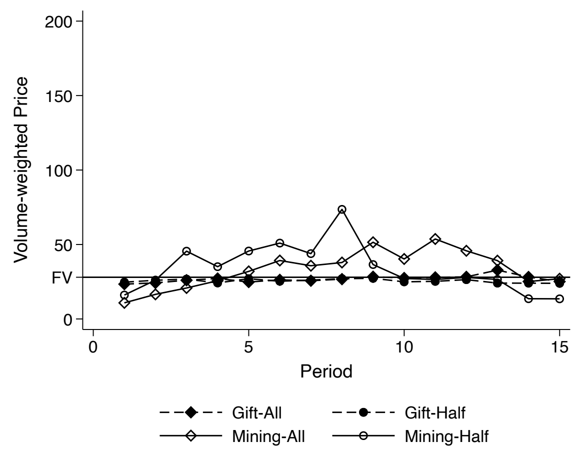
(a) Origin of accepted trades



(b) Asks



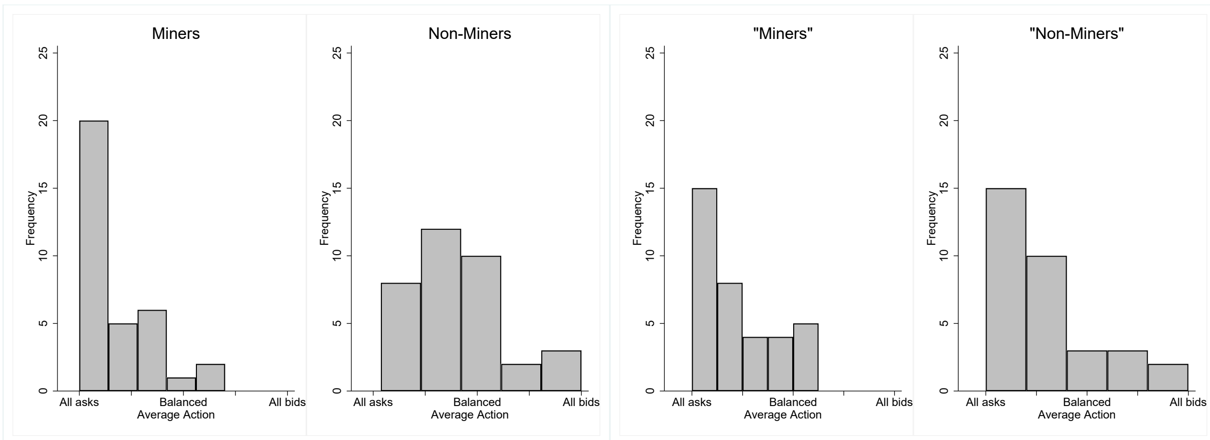
(c) Bids



Note: In panel (a) we report the median ratio of origin of accepted trades per period per treatment. Each node corresponds to the proportion of completed trades that initiated from either bids or asks. In panels (b) and (c) we report asks and bids per treatment. We calculate the volume-weighted average per period for each session, and report the median value of the 9 sessions in each period per treatment.

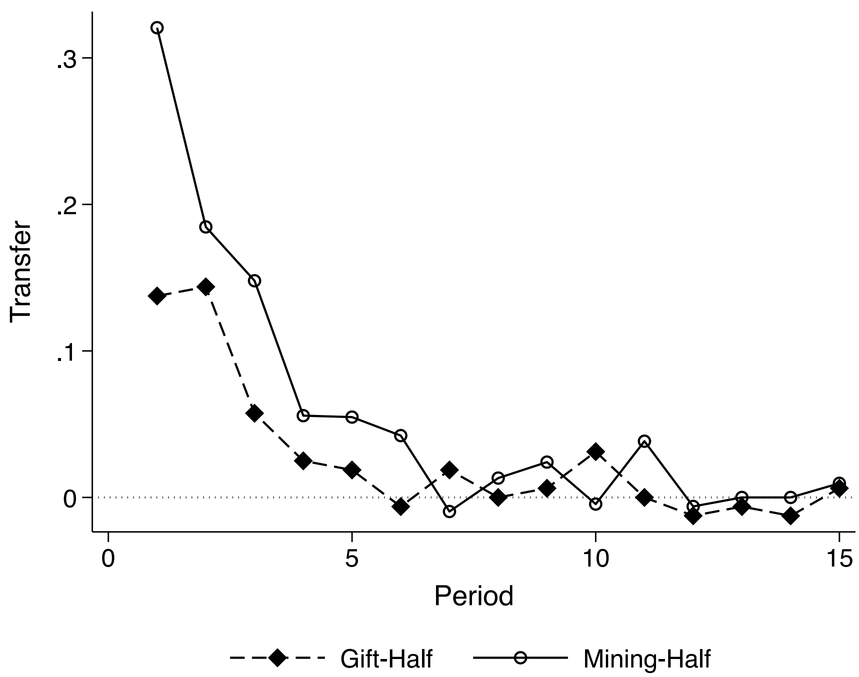
Figure 6: Trader average action by role

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



Note: Histograms present the distribution of trader average action across all periods.

Figure 7: 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.

ability correlates with rational mining, and that both cognitive ability and Theory of Mind are associated with higher earnings.

6 Study 2: Mechanism Behind Bubble Formation

In the first study we find that the Mining treatments exhibit bubbles. One of the important features of the Mining treatments is that the supply of the asset is sluggish, which is operationalized by having an expenditure cap on mining in each period. As a result, the CAR is initially high as there are only a handful of units of the asset in circulation. A high CAR has been shown to be susceptible to bubble formation (e.g., Kirchler et al., 2015; Razen et al., 2017), hence, it is not entirely clear whether the bubbles observed in the Mining treatments can be attributed to mining costs and mining decisions, or whether the dynamic nature of the CAR stemming from the asset's sluggish supply also plays a role. Study 2 aims to disentangle these two possible underlying mechanisms with two new treatments. These treatments match the CAR trajectories of those in the Mining treatments, but do not involve any mining decisions or an associated mining cost.

6.1 Experimental Design: Airdrop Treatments

The second study includes two treatments. The Airdrop-All treatment corresponds to the Mining-All treatment and the Airdrop-Half treatment corresponds to the Mining-Half treatment. These Airdrop treatments are identical to the corresponding Mining treatments, except that assets are supplied to the traders for free according to a pre-determined schedule. In each Airdrop treatment session, we randomly select a market in the corresponding Mining treatment (without replacement) to serve as a matched market. We then pair each trader in the Airdrop treatment session with a randomly chosen trader in the matched market (without replacement) at the start of the market. At the beginning of each period, traders are gifted with the number of assets mined by their matched trader in the corresponding period at no cost.[29]

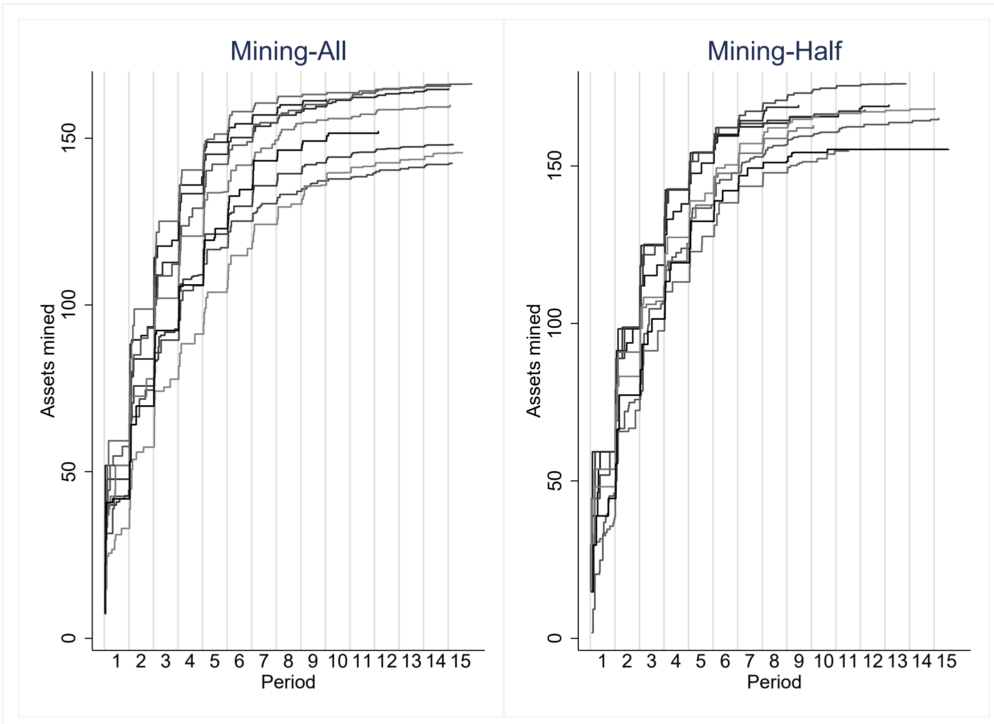
Traders in the Airdrop treatment do not know ex-ante the precise number of units they will receive in each period but they are informed about the maximum possible amount of assets they could receive in future periods. This is calculated by assuming all miners spend the maximum possible amount of cash on mining (as was also described in the instructions of the Mining treatments). After the market starts, traders in the Airdrop treatments have a calculator that can be used to predict the maximum amount of assets they may receive in each of the next four periods (resembling the calculator for the mining cost in the Mining treatments). This calculator takes the realized mining decisions in the current period from the matched trader in the matched market and assumes the matched trader would mine in full capacity in the subsequent 4 periods.

In the Airdrop-All treatment, every trader is endowed with 5,900 ECUs and no assets; identically to the initial endowment in the Mining-All treatment. Traders subsequently receive assets at the start of every trading period according to the matched trader's mining schedule. Assets are gifted to traders at the start of each trading period. This mirrors the mining activity we find in the Mining

[29]For instance, suppose that a trader in the Mining-All treatment mined 2 units of assets in period 1, 1 unit of assets in period 2, 0.5 units of assets in period 3, and 0 units in all subsequent periods. The matched trader in Airdrop-All treatment will also receive the same amount of assets according to this schedule in the beginning of each period.

treatments where most of the mining takes place in the very early stages of trading periods, as seen in figure 8. We inform the traders that they will be randomly assigned one out of 8 pre-determined supply schedules and everyone's schedule is different.

Figure 8: Timing of trades in Mining treatments



Note: Each line depicts the evolution of assets within a given session over time. In most cases, we observe a steep increase in assets (i.e., mining) at the beginning of each period, and a rather flat trajectory till the end of a given period.

In the Airdrop-Half treatment, traders are randomly allocated one of the two roles. Half of the traders assigned Role A (corresponding to Role A, the miners, in Mining-Half). Only Role A traders will receive assets according to a matched mining schedule. The "miners" start with 5,540 ECUs and no asset (identically to the Mining-Half treatment). The other half of the traders are assigned Role B ("non-miners") and are endowed with 6,260 ECUs and no asset (identically to Role B traders in the Mining-Half treatment). Role B traders do not receive any assets from the experimenter at any point. In the instructions, we inform Role A traders that there are four pre-determined supply schedules and that they will be randomly assigned one of these (without replacement).

Importantly, the CAR trajectory in the Airdrop treatments matches the one in the Mining treatments. More specifically, as the traders in the Airdrop treatments will receive the assets at no cost, while the miners in Mining treatments pay up to 40 or 80 ECUs per period (the mining caps of Mining-All and Mining-Half respectively), the CAR is consistently slightly higher in the Airdrop treatments as compared to the Mining treatments (they have the same cash endowment as in the Mining treatments). This difference is very small and negligible, but importantly, the trajectory of the CAR in the Airdrop treatments is exactly parallel to that in the Mining treatments with a small mark-up. We provide an overview of the development of the total amount of ECUs in the market, the total number of assets in circulation, and the CAR by period across treatments in table A.15 in appendix F.

Experiment Implementation Details

A total number of 142 participants took part in our second study. We conducted nine Airdrop-All sessions and 9 Airdrop-Half sessions with the same number of traders as in the matched sessions. Just like in our first study, we conducted the second study in the laboratories of the Universities of Heidelberg and Frankfurt. Table A.14 in the appendix summarizes dates and locations of implementation of each of our sessions for the two treatments. Each market session had 8 participants, except for two where we had 7 participants just like in the first study. Similarly, the software and the randomization procedure are exactly the same as in the first study.

Table 7: Characteristics of participants across treatments (Study 2)

	Airdrop-All	Airdrop-Half	
		Role A	Role B
Avg. Age	23.81	24.14	21.86
Proportion of Females	0.54	0.5	0.39
Avg. Crypto Experience†	1.9	1.72	1.86
Avg. Raven	6.5	7.13	7.42
Avg. Theory of Mind	3.66	3.28	3.58
Avg. Risk Choice	3.61	3.55	3.86

Note: There are no statistically significant differences in these characteristics in pairwise comparisons across treatments and roles except for age (Airdrop-Half, role A vs. role B, $p - value = 0.010$) and average Raven score (Airdrop-Half vs. Gift-Half, vs. Mining-Half, and vs. Airdrop-All (separate tests), $p - values < 0.056$).
†Crypto experience was elicited using a Likert scale from 1 (none) to 5 (very well).

When recruiting subjects, we excluded all subjects who had previously participated in the first study. The average payment was approximately 18 Euros for 90 minutes. We include translated versions of the instructions for the second study in appendix F. Our subject sample for study 2 is balanced in terms of age, gender, and economic preferences, see table 7.[30]

6.2 Results for Airdrop Treatments

Figure 9 depicts the trading prices in the Airdrop treatments. Following study 1, we calculate the volume-weighted average price per period for each market and report the treatment median price

[30]The average Raven score in the Airdrop-All treatment is significantly lower than in other treatments. However, regression analysis of bubble measures show that the variability of Raven scores (and other individual characteristics) across markets does not significantly affect market outcomes in our environment (see table A.3 in appendix B.4).

for each treatment.[31] To facilitate comparison, we also plot the treatment median prices of the Mining treatments on the same figure.

Figure 9: Median of volume-weighted price per period in Airdrop treatments

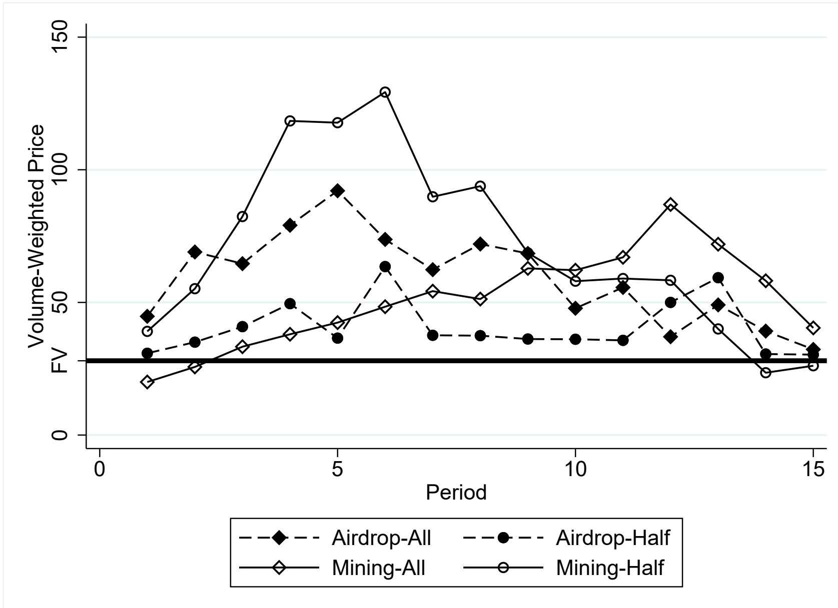


Table 8: Mann-Whitney-U exact tests of bubble measures of Airdrop treatments

	Airdrop-All vs. Gift-All	Airdrop-All vs. Mining-All	Airdrop-Half vs. Gift-Half	Airdrop-Half vs. Mining-Half	Airdrop-Half vs. Airdrop-All
RAD	**0.014**	0.931	0.094	0.258	0.605
RD	**0.019**	0.863	0.190	0.297	0.666
RDMAX	**0.011**	1.000	0.258	0.340	0.387
AMP	**0.001**	0.607	0.497	0.481	0.491
CRASH	**0.006**	0.888	0.114	0.481	0.541
TURN	0.546	0.796	0.297	0.077	0.436
LQ	0.113	0.094	0.605	0.796	1.000
SPREAD	**0.001**	0.258	0.063	0.489	0.489
VOLA	**0.040**	0.063	0.094	0.605	0.387

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

In figure 9, Airdrop-All and Mining-All treatments exhibit similar levels of mispricing. This is also reflected by the bubble measures we estimate and the corresponding statistical tests in table 8. The median value of RAD and RD in the Airdrop treatments is between 0.90 and 1.69, while the

[31]Similar to the analysis for study 1, we also provide the following figures in the appendix: Figure A.7a in the appendix is the equivalent figure depicting the average (instead of the median) of volume-weighted average prices, and figure A.7b depicts medians of unweighted prices. Figure A.8 depicts trading volume per period. Additionally, figures A.15 and A.16 depict the price trends separately for each of our 9 individual markets per treatment.

mean ranges from 1.77 to 2.50.[32] Across all the bubble measures we estimate, we do not find any significant difference between Airdrop-All and Mining-All (second column of table 8). In accordance to the differences we report between Mining-All and Gift-All in the first study, almost all bubble measures in Airdrop-All are significantly higher than those in Gift-All. It is interesting to note that, in the absence of mining costs, prices immediately surge in early periods, instead of closely following the mining cost as we find in the Mining-All treatment. This suggests that the anchoring effect plays an important role in the realized prices we observe in Mining-All.

The price trajectories in Airdrop-Half seem to lie in between Gift-Half (see figure 3a) and Mining-Half in figure 9. Even though the extent of the bubble seems smaller in Airdrop-Half than in Mining-Half from figure 9, the bubble measures are not significantly different between the two treatments. Comparing the price trajectories of Airdrop-Half with Gift-Half suggests that Airdrop-Half exhibits more mispricing, but we do not find any significant difference at conventional significance levels across all bubble measures. Figure A.16 in the appendix indicates that there is quite some variation across sessions in Airdrop-Half. Prices either follow the fundamental value closely or largely deviate from fundamentals. In other words, overpricing does not consistently occur in Airdrop-Half, but if it does, the magnitude is relatively large. By comparing individual sessions across treatments (figures A.12, A.14, and A.16) we find that prices follow the fundamental value closely in seven sessions in Gift-Half, only four sessions in Airdrop-Half, and not a single session in Mining-Half. Putting all this evidence together suggests that the bubble formation in Airdrop-Half lies somewhere between the bubble prone Mining-Half treatment and the more efficient Gift-Half treatment. It should also be noted that statistically, there is no difference between Airdrop-All and Airdrop-Half. This result mirrors the observation Mining-All and Mining-Half are not found to be significantly different overall.[33]

Overall, the results of study 2 show that the dynamic CAR is a contributing factor that encourages mispricing. However, we also see that bubbles occur less consistently in the Airdrop treatments compared to the Mining treatments. Taken together, both the sluggish supply and mining decisions and associated costs are responsible for the large bubbles forming in the Mining treatments of study 1.[34]

7 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

[32] See table A.1 in appendix B.2 for the summary statistics of each bubble measure.

[33] For completeness, in appendix C.4 we report the order book analysis for study 2 performed as we discuss in section 5.3 for study 1. We find similar results for study 2.

[34] We also analyze whether average trader characteristics in our markets relate to bubble measures but find no significant effects, see table A.3 in appendix B.4.

Bitcoin's blockchain technology that are particularly relevant. First, the total supply of the asset is limited. Second, in the 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 erratic price patterns over time. Moreover, our results show that mining centralization places an initial upward pressure on prices which enables prices to decouple from mining cost even earlier, compared to a case where all investors have access to mining. Our implementation of mining centralization is perhaps not as extreme as it is increasingly becoming for Bitcoin; we suspect that with an even stronger form of mining centralization the extent of bubble formation that we report could have been even larger. The result that assets are traded at marginal mining costs with a mark-up for a prolonged period of time in the Mining-All treatment suggests that mining costs may at times serve as a support for prices. This is in line with Hayes (2019) who shows that the marginal cost of Bitcoin production plays an important role in explaining prices. While bubbles may appear, prices tend to revert towards marginal cost of mining when resolved. This suggests that during episodes of bubbles, prices may decouple from mining costs; nevertheless, costs appear to serve as a support for prices when the market crashes. The results are also in line with observational data.[35] Our results, when comparing the Mining-All and Mining-Half treatments, suggest that the centralization of the mining technology creates a further upward pressure on prices through initial excess demand.

The order book analysis shows that market prices are generally set by sellers: the evolution of bids across trading periods is relatively flat in all treatments, whereas the trajectories of asks resemble the price patterns we observe. More specifically, when considering all periods, we find that miners predominantly act as sellers in the market in the Mining-Half treatment. This is not the case in the Gift-Half treatment where comparable roles of "miners" and "non-miners" can be defined. Although in both treatments demand may be stronger due to endowment asymmetry (Lugovskyy et al., 2014; Tucker and Xu, 2020; Weber and Camerer, 1998), it is conceivable that bidding is more aggressive in the Mining-Half treatment. As mining cost projections are clearly communicated to the traders, those who initially do not own the asset might be eager to buy assets

[35]For example, the following website estimates the mining costs and graphs them together with the price of bitcoin: https://en.macromicro.me/charts/29435/bitcoin-production-total-cost. The figure suggests that the Bitcoin price is generally related to mining costs, but at times decouples from these – especially during bubble episodes.

early on in Mining-Half in anticipation that mining would be more costly in the future. Such an anticipation is not reasonable in Gift-Half. This conjecture is supported by the higher initial bids in the Mining-Half treatment compared to the Gift-Half treatment. Taking the evidence together, miners appear to be enabling the bubbles in our markets, as they take advantage of the strong initial demand through setting elevated asks. Another important observation is that in both of our mining treatments, participants choose to mine even after the cost of mining clearly exceeded the fundamental value of the asset, implying that miners may have been speculating on prices.

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 particular, in the trading environment that we implement, with a flat fundamental value and no dividend payments, the steps of reasoning which are necessary to infer the fundamental value of the asset being traded are constant across periods.This suggests that this "end-game effect" that we observe is a good sign as it suggests that traders are not ignorant about the fundamental value of the asset while riding the bubble.

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. 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. More recently, Kopányi-Peuker and Weber (2021) study the role of a fixed ending period on pricing in a call market setting. They vary the length of the horizon and whether the end time is definite or indefinite. The authors find very similar price dynamics with recurring bubbles across all treatments. Future work can investigate further how bubble formation in similar frameworks to our design develops in longer or indefinite trading horizons.

The observation that price trajectories in our Gift-treatments adhere closely to the fundamental value is in line with existing literature. First, a constant fundamental value (instead of a decreasing one) is a simpler asset that may be less likely to create misunderstandings or disagreements in prices among traders (Smith et al., 2000; Kirchler et al., 2012). In the declining fundamental value case, frequent changes of fundamental values to a new level each period may hinder the price discovery process. Second, despite our relatively high cash-to-asset ratio, we do not pay frequent dividends as Noussair et al. (2001) do. The observation that these markets do not exhibit bubbles supports the conjecture that in constant fundamental value settings, a high but constant cash-to-asset ratio is not sufficient to ignite bubbles, while it may affect price levels (Noussair et al., 2001). 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 bubble formation.

The bubbles observed in our Mining treatments deserve further investigation. In particular, due to the sluggish supply feature of the mining algorithm, the cash-to-asset ratio (CAR) is not constant throughout the experiment. Rather, it starts high due to limited asset supply at the outset and gradually decreases over time. The initially high CAR due to the slow introduction of assets to the market may be responsible for bubble formation. Conversely, increasing mining costs may be responsible for the bubbles observed in the Mining treatments. To further investigate the underlying mechanisms for the bubbles observed in the Mining treatments, we conduct two treatments replicating the CAR trajectories of the Mining-All and Mining-Half treatments. The Airdrop-All and Airdrop-Half treatments are otherwise identical to the corresponding Mining treatment, except that assets are gradually endowed (free of charge) to the traders, instead of mined. Our results show that eliminating mining activity alone is not sufficient to remove bubbles completely, though bubbles do seem to be less likely to occur. We conclude that both mining and the CAR dynamic (high initially and decreasing overtime) due to sluggish supply seem to jointly contribute to the bubbles observed in the Mining treatments. Since CAR dynamics are an essential element of the mining process, future work might want to focus on this very specific characteristic of various mining schemes (consensus mechanisms) to better understand their influence on pricing.

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 fails 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 suppressing effect on price levels in the future.

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 it is, by itself, sufficient 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 price volatility to exogenous noise, which could 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 erratic pricing 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 erratic pricing shared by many PoW cryptocurrencies has hindered their potential to become a medium of exchange. Yet, this high volatility seems unavoidable, as it stems 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, 2021). 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. A more flexible token supply can mitigate price volatility for cryptocurrencies with a less rigid supply scheme (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. Under the Proof-of-Work framework, future research may study whether mining costs can serve as a support for prices when the investment horizon is much longer. Given the fact that prices approximately move in lock-step with the mining costs in our Mining-All treatment, it would also be interesting to examine if prices still follow the mining costs when the mining costs initiate at a higher level compared to the fundamental value of the asset. Furthermore, our experimental framework would also allow us to test price stability implications of other consensus mechanisms, such as Proof-of-Stake or Proof-of-Elapsed Time. Take Proof of Stake as an example, while the potentially lower transaction fees and better scalability may reduce price instability, staking itself reduces the amount of coins in circulation, which may apply upward pressures on price in the presence of demand shocks. Our experimental framework offers a test-bed to examine various consensus mechanisms. 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).

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Does mining fuel bubbles?
An experimental study on cryptocurrency markets

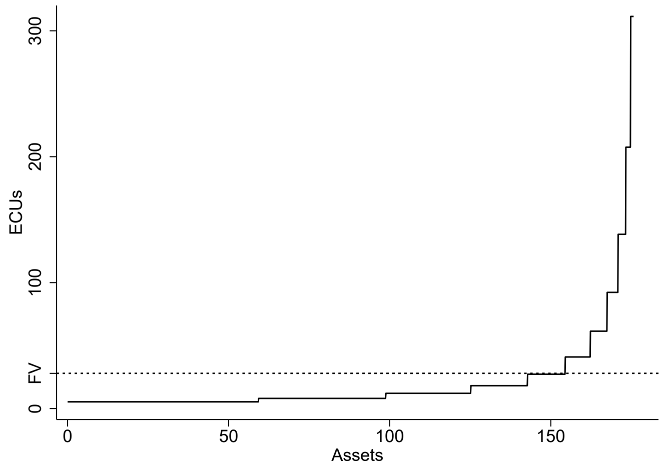
Internet Appendix

November 20, 2023

A Additional Figures

A.1 Study 1

Figure A.1: Asset costs as a function of assets generated in Mining treatments.



Note: Assuming full capacity mining.

Figure A.2: Average volume-weighted average price per period per treatment

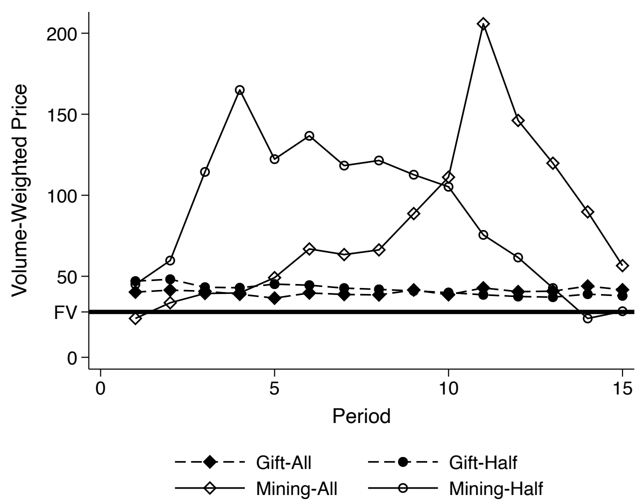


Figure A.3: Median unweighted average price per period per treatment

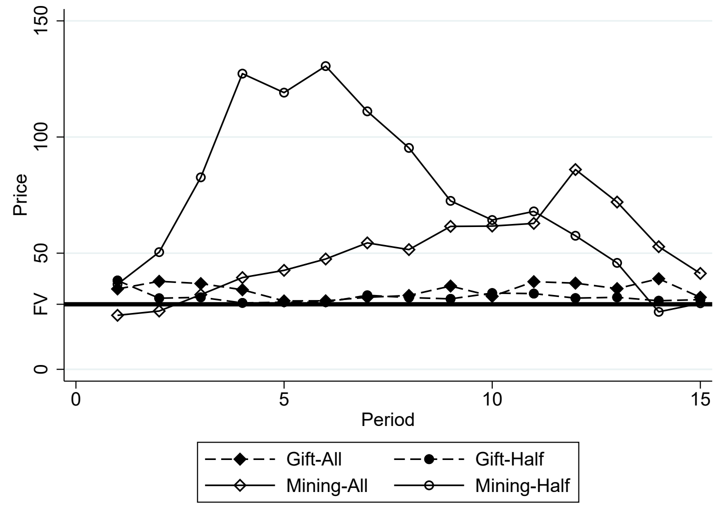
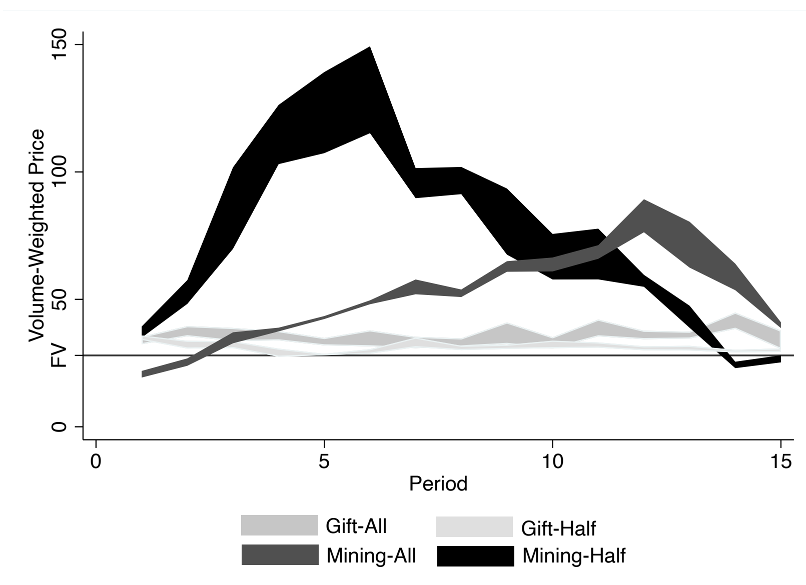


Figure A.4: Range of prices per treatment per period



Note: Range of median volume-weighted price per period across all treatments. We systematically remove one of the 9 sessions of each treatment with replacement, which results in 9 graphs with 8 (instead of 9) sessions each. 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.

Figure A.5: Median unweighted average asks and bids per period per treatment

(a) Asks (b) Bids

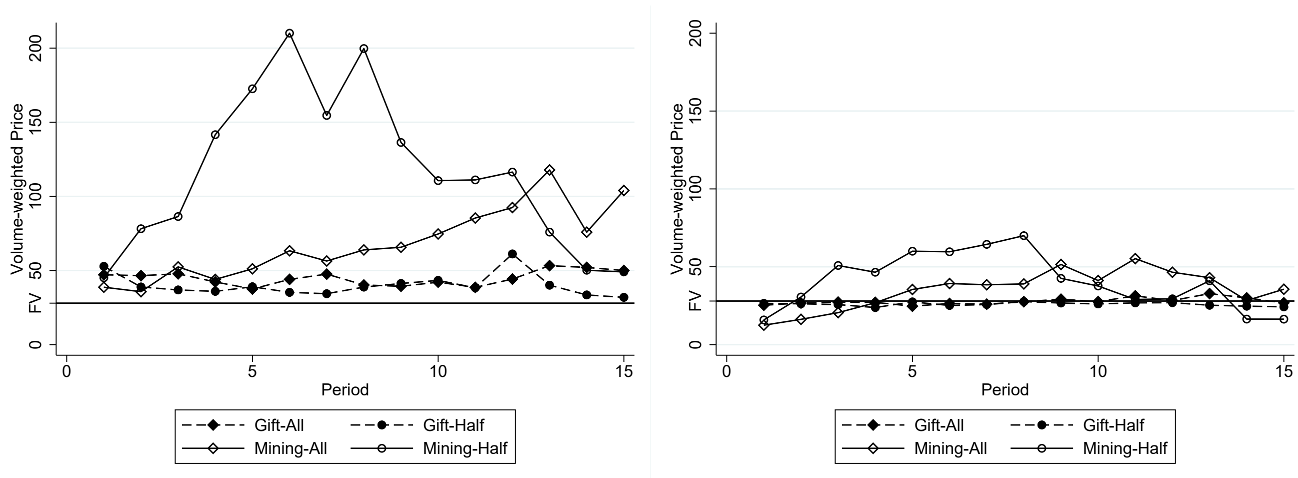
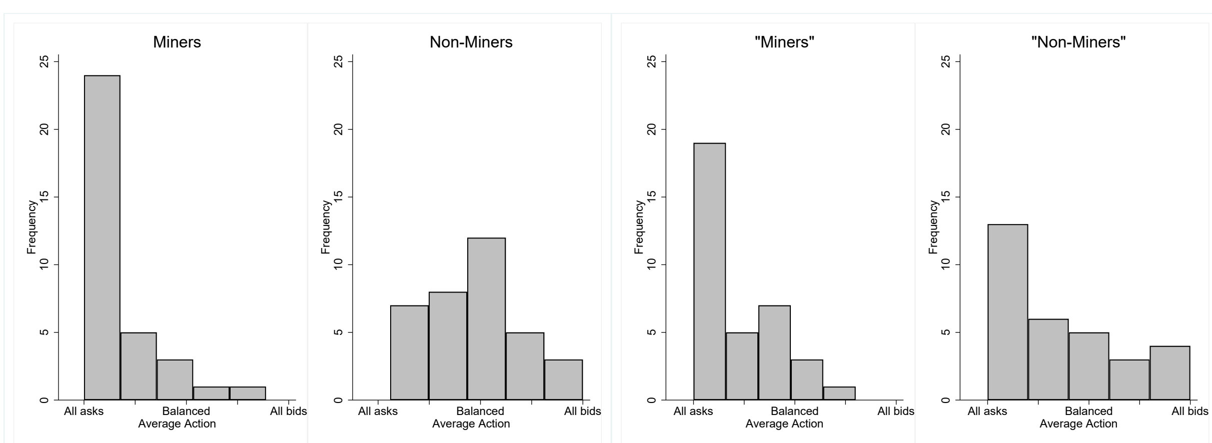


Figure A.6: Trader average action by role

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

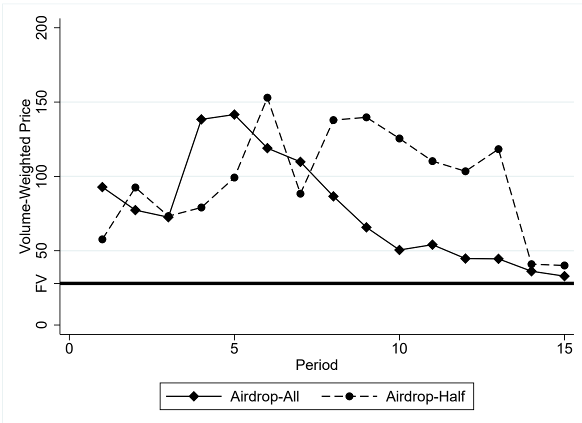


Note: Histograms present the distribution of trader average action across the first half of trading.

A.2 Study 2

Figure A.7: Trading prices and volume in Airdrop treatments

(a) Average volume-weighted average price per period



(b) Median unweighted average price per period

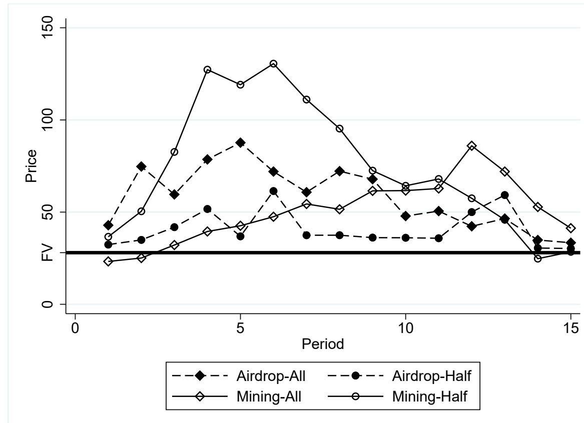
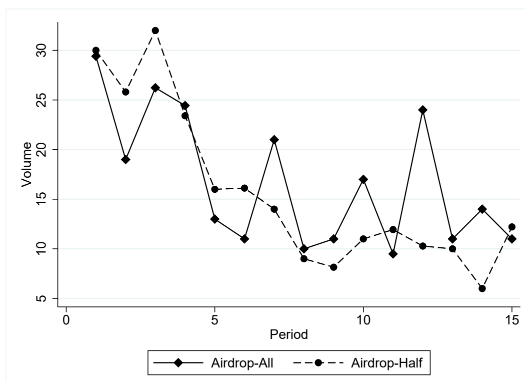


Figure A.8: Session-median trading volume per period



B Bubble Measures

B.1 Bubble measures definitions

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:

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

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

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

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

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

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

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

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

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

B.2 Bubble measures summary statistics

Table A.1: Summary statistics of bubble measures in Study 1 & Study 2

	Gift-All		Gift-Half		Mining-All		Mining-Half		Airdrop-All		Airdrop-Half	
	median mean (std.dev.)		median mean (std.dev.)		median mean (std.dev.)		median mean (std.dev.)		median mean (std.dev.)		median mean (std.dev.)	
RAD	0.41		0.14		1.05		2.08		1.69		0.90	
	0.46	(0.47)	0.51	(0.84)	1.93	(1.91)	2.29	(1.54)	1.81	(1.52)	2.50	(4.04)
RD	0.41		0.14		0.97		1.97		1.69		0.90	
	0.44	(0.48)	0.49	(0.85)	1.86	(1.91)	2.17	(1.52)	1.77	(1.53)	2.45	(4.01)
RDMAX	1.04		0.32		3.63		3.62		4.07		1.69	
	0.92	(0.64)	0.89	(1.38)	7.69	(10.74)	6.11	(5.21)	5.77	(5.35)	6.66	(10.08)
AMP	0.80		0.32		3.84		3.20		2.54		1.18	
	0.66	(0.34)	0.65	(0.58)	7.93	(10.73)	5.60	(4.96)	5.36	(5.69)	7.36	(10.67)
CRASH	-0.46		-0.34		-2.93		-4.03		-3.89		-1.52	
	-0.61	(0.58)	-0.65	(0.92)	-7.52	(11.29)	-6.22	(5.41)	-5.77	(5.45)	-7.13	(10.68)
TURN	0.21		0.20		0.18		0.20		0.18		0.14	
	0.21	(0.07)	0.20	(0.07)	0.20	(0.08)	0.23	(0.08)	0.20	(0.12)	0.16	(0.07)
LQ	0.55		0.98		0.52		0.85		1.16		0.87	
	0.76	(0.69)	5.53	(13.86)	0.69	(0.57)	5.17	(12.85)	2.56	(3.32)	13.23	(36.82)
SPREAD	0.22		0.10		0.48		1.21		1.61		0.39	
	0.27	(0.24)	0.20	(0.28)	1.42	(2.33)	1.50	(1.15)	1.34	(0.75)	2.42	(4.07)
VOLA	0.21		0.10		0.29		0.44		0.46		0.17	
	0.31	(0.35)	0.16	(0.13)	0.34	(0.19)	0.47	(0.31)	0.52	(0.27)	0.40	(0.37)

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. SPREAD measures the gap between buy and sell orders and VOLA measures log-returns of all market prices within a period.

B.3 Bubble measures and initial market conditions

In table A.2, we report Spearman correlations of RD, RAD, RDMAX, AMP, and CRASH with first period volume-weighted average prices, first period trading volumes, and the first period's bid-ask SPREAD in the Mining and Gift treatments. We find that SPREAD in the first period significantly correlates with the bubble measures (at the 5% significance level). Higher SPREAD in the first period is positively correlated with price levels across all trading periods. Note that the average first period SPREAD is larger in the Mining treatments compared to the Gift treatments (0.75 vs 0.64, Mann-Whitney-U exact test $p - value = 0.054$). This result corroborates the order book analysis where we find that the bubbles observed in the Mining treatments are driven by asks. Thus, a higher bid-ask spread in period 1 seems to be responsible for overall price levels observed in the market. We also find that increased trading volume in the first period significantly reduces AMP. There does not seem to be a relationship between first period prices and the overall bubble sizes. This is driven by the fact that prices typically start off below the fundamental value in the Mining-All treatments while starting higher than fundamental value in the Mining-Half treatment, while both treatments exhibit sizable bubbles.

Table A.2: Spearman's correlation coefficients of bubble measures and starting conditions

	RD	RAD	RDMAX	AMP	CRASH
Weighted average price	0.3571	0.2897	0.1956	0.0265	-0.1838
Volume	-0.1215	-0.1636	-0.2356	-0.5141**	0.2736
Spread	0.5674**	0.5297**	0.5380**	0.4381**	-0.5358**

Notes: We include all markets from the Mining and Gift treatments. ** p-value < 0.05.

B.4 Analysis of bubble measures and trader characteristics

We analyze how market outcomes, measured by the bubble measures we define further above, relate to trader cognitive ability, Theory of Mind, and risk preferences while controlling for age, gender, and any self-reported experience with cryptocurrencies. We summarize the results in table A.3. We do not find any significant relationship between any of the bubble measures and market level cognitive ability, Theory of Mind, or risk preferences.

Table A.3: OLS regressions on bubble measures including control variables

	(1) RAD	(2) RD	(3) RDMAX	(4) AMP	(5) CRASH
Gift-Half	0.04	0.04	0.51	1.27	-0.89
	(0.55)	(0.55)	(1.63)	(2.06)	(1.78)
Mining-All	1.28*	1.23*	6.16**	7.28**	-6.54*
	(0.67)	(0.67)	(2.95)	(3.09)	(3.26)
Mining-Half	1.86***	1.77***	6.44***	7.34**	-7.09**
	(0.61)	(0.61)	(2.38)	(2.74)	(2.61)
Airdrop-All	1.70*	1.66	6.70*	7.92	-7.17*
	(0.99)	(0.99)	(3.47)	(4.76)	(3.57)
Airdrop-Half	1.96	1.94	6.54	8.81*	-7.67
	(1.48)	(1.48)	(4.00)	(4.86)	(4.75)
Average Raven	0.24	0.23	1.27	1.93	-1.36
	(0.31)	(0.31)	(1.08)	(1.32)	(1.17)
Average Risk aversion	0.21	0.24	1.22	1.36	-1.60
	(0.46)	(0.46)	(1.75)	(2.12)	(1.83)
Average ToM	-1.19	-1.11	-3.78	-3.77	3.94
	(0.95)	(0.94)	(2.61)	(3.03)	(2.70)
Average Age	0.08	0.08	0.81	1.03	-0.86
	(0.15)	(0.16)	(0.95)	(1.08)	(0.95)
Average Female	0.50	0.45	3.47	5.25	-5.24
	(1.45)	(1.45)	(4.83)	(6.15)	(5.57)
Average Crypto Exp.	-0.69	-0.64	-1.49	-0.72	0.58
	(0.66)	(0.66)	(2.39)	(3.11)	(2.96)
Constant	1.29	0.75	-18.17	-32.40	23.94
	(6.99)	(7.07)	(31.56)	(38.32)	(32.54)
Observations	53	53	53	42	50

Note: OLS regression model. Control variables refer to the average within each session. Robust standard errors in parentheses. * p-value $<$ 0.1, ** p-value $<$ 0.05, *** p-value $<$ 0.01.

C Additional Analysis

C.1 Classification of traders

Following Haruvy and Noussair (2006), we categorize traders into momentum traders, rational speculators, and fundamental value traders. Momentum traders engage in trading activities regardless of the asset's fundamentals. They trade in large volumes when market prices are experiencing rapid changes. These traders are likely to make large purchases at excessively high prices during a booming market. Rational speculators accumulate holdings before prices increase and reduce holdings before prices decrease, while ignoring the difference between prices and fundamentals. Fundamental value traders trade only based on fundamental values, purchasing (selling) when prices are below (above) fundamentals.

More specifically, a trader is classified as a fundamental value trader in period t if they increase (decrease) shareholdings in period t and the average price in period t is lower (higher) than the fundamental value of the asset in period t. A trader is classified as a momentum trader in period t if the difference between the average price in periods $t-1$ and $t-2$ does not have the opposite sign as the change in their holdings in period t. These traders increase (decrease) share holdings in response to an upward (downward) price trend in the recent past. Rational speculators correctly anticipate the next period's price movement and act on it. If the price is moving upwards (downwards), they increase (decrease) their holdings of shares. In other words, they increase (decrease) their holdings in period t if the average price in t is lower (higher) than that in period $t+1$.

However, it should be noted that in our Mining treatments traders can acquire assets not only through trading, but also through mining. This means that shareholding will be influenced by factors outside the market. There are two ways to approach this. One is to ignore the channel through which a subject acquires assets and simply count the number of newly added shares and sold shares in their inventory. The other way is to only focus on trader actions in the market and not count the number of assets mined in each period. We choose to employ the second method because it more directly reflects trader behavior in the market.[1]

Each subject is assigned a score for each of the three types, with the score for each type increasing by 1 with every period in which the net change in his position is consistent with that type. At the end of period 15, we add up the scores for the individual and classify them as an agent of the type for which they have the highest score, provided that the behavior is consistent with that type for the majority of periods. Since we have 15 trading periods in total and classifications may use price information from the past or future, we can observe fundamental trading in all 15 periods, momentum trading in 13 periods, and rational speculation in 14 periods. Thus, the threshold for fundamental trading and rational speculators is reached when we observe this behavior in 8 or more periods, while momentum traders are classified if we observe at least 7 periods of the respective behavior. If a subject has a score lower than the threshold with respect to all three types, the subject is classified as "others", representing none of the three types. Table A.4 reports the share of subjects classified as each type in each treatment. In cases where a score for two types is the same, equals at least 8, and exceeds the score for the remaining type, then the individual is equally split and assigned with a weight of 50% to each type consistently to the procedure in Haruvy and Noussair (2006). Similarly, a trader with an equal score of at least 8 for each of the three types is

[1] To clarify the difference, consider, for example, the definition of a rational speculator as in Haruvy and Noussair (2006). Assume that in period t prices are lower than in period $t+1$. In that situation, rational speculators would act as buyers in the market in period t (which in absence of mining is synonymous with increasing net holdings in period t). If we only focus on net holdings and ignore the channel of acquisition in our mining treatments, we would allow rational speculators to act as sellers in the market in period t if their mining activity exceeds their sales. We consider this to be inconsistent with the original idea of the definition of rational speculators.

assigned with a weight of one third to each type.

Table A.4: Classification of traders by treatment

	Gift-All	Gift-Half	Mining-All	Mining-Half	Airdrop-All	Airdrop-Half
Fundamental Value Trader	0.208	0.111	0.329	0.153	0.243	0.236
Momentum Trader	0.069	0.042	0.086	0.111	0.079	0.049
Rational Speculator	0.139	0.097	0.129	0.111	0.093	0.076
Others	0.583	0.750	0.457	0.625	0.586	0.639

We find no significant differences in the proportion of momentum traders between Mining-All and Gift-All (Mann-Whitney U exact test, $p - value = 0.692$). There seems to be a higher proportion of momentum traders in Mining-Half than in Gift-Half, but the difference is not statistically significant (Mann-Whitney U exact test, $p - value = 0.129$). There is also no difference in the proportion of fundamental value traders, except that the proportion of fundamental value traders in Mining-All is greater than that in Mining-Half (Mann-Whitney U exact test, $p - value = 0.016$). No other significant differences are found between corresponding treatments at the 5% significance level. The absence of significance difference might be due to the imperfect classifications as discussed above.

Next, we examine if there is any correlation between individual cognitive ability (Raven score) and Theory of Mind and being classified as a momentum trader, fundamental value trader, or rational speculator. Table A.5 shows how trading types relate to our cognitive measures. We find that individuals who scored higher with theory of mind are more likely to be a momentum trader. Such individuals appear to be more willing to explore the market trend. We do not find any other significant relationships.

Table A.5: Spearman correlation of trading types and cognitive measures

	Fundamental Value Trading	Momentum Trading	Rational Speculating
Theory of Mind	0.0367	0.1156**	0.0469
Raven Score	-0.0463	-0.0340	0.0359

Notes: ** p-value < 0.05.

C.2 Cognitive ability, theory of mind, and rational miners

In the spirit of Haruvy and Noussair (2006), we also investigate whether being a "rational" miner correlates with cognitive ability and Theory of Mind. We define mining to be rational in period t if the average market price of period t exceeds the mining cost in period t. In periods where this is not the case, we consider it rational not to mine.[2] We count the number of periods a miner behaves rationally and classify subjects as rational miners if they behave rationally in more than half of the periods. Pooling the data from Mining-All and Mining-Half, we find a significant correlation between being classified as a rational miner and cognitive ability (Spearman correlation coefficient

[2] Note that, as most subjects mine at the beginning of a given period, these subjects would need to anticipate or forecast the market prices during the given period. Thus, we choose to condition the mining decision in period t on average market prices in period t rather than on average market prices in period $t + 1$. This is because we consider it rational to mine in period t and potentially sell in period t when prices are higher than the mining cost incurred earlier during period t.

0.3204, $p < 0.05$). However, we do not find a statistically significant relationship between rational mining and Theory of Mind.

C.3 Earnings at Individual Level

Table A.6: 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.

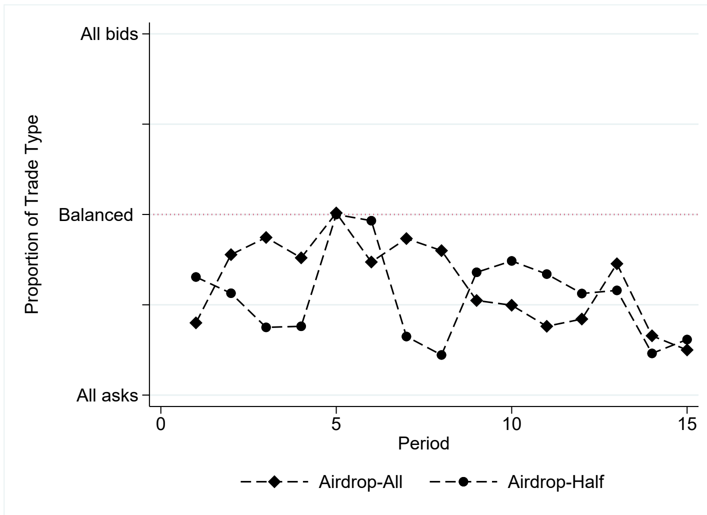
Table A.6 reports the results of a regression analysis on trader earnings based on the data in Study 1. The dependent variable in all specifications is asset market earnings, standardized with respect to their respective treatment. The first column reports the regression results for all participants 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. (2018) and Corgnet et al. (2018), we include an interaction term between Raven and ToM. Overall, we find that both cognitive ability and ToM are associated with higher earnings. These attributes appear to act as substitutes for each other as seen by the negative interaction term which is similar in direction to the findings of Corgnet et al. (2018). Female traders appear to earn less, while in the markets where traders have different roles, those that can only obtain assets through the market are significantly worse off. This may be because their options of acquiring assets are limited.

C.4 Study 2: Order book analysis

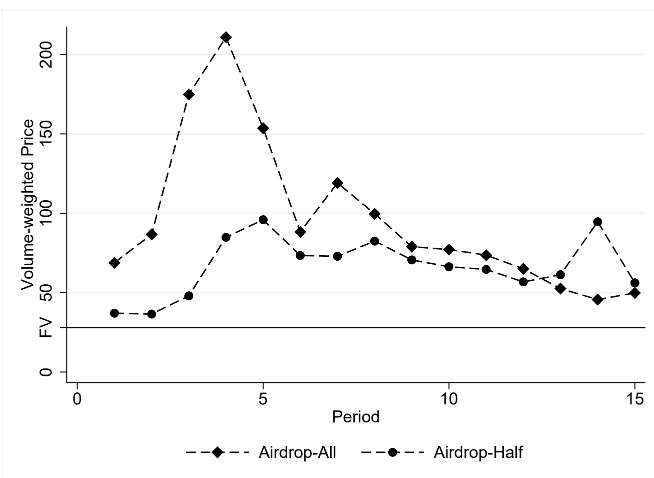
We again perform analysis on the order book to understand whether the observed prices are driven by the demand-side or the supply-side of the market in the Airdrop treatments. Figure A.9 summarizes this analysis.

Figure A.9: Order Book Analysis in Airdrop treatments

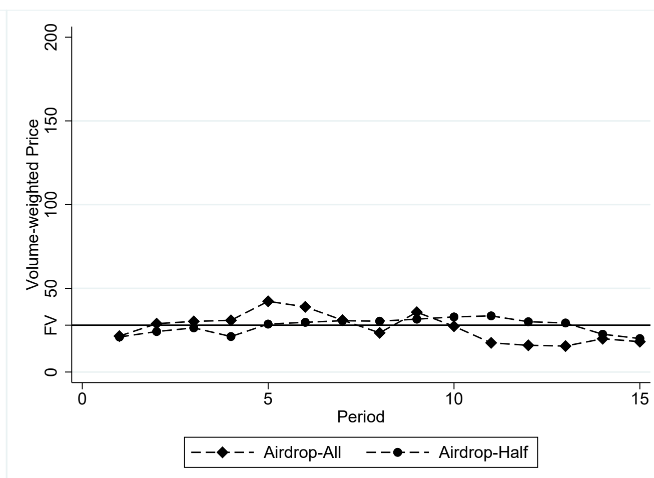
(a) Origin of accepted trades



(b) Asks



(c) Bids



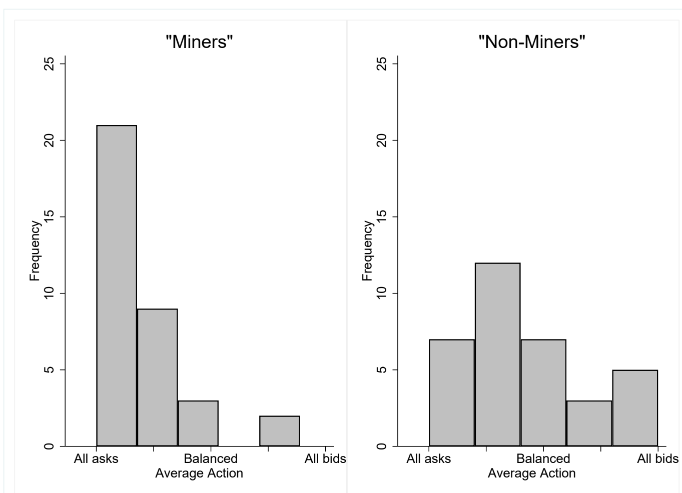
Note: In panel (a) we report the median ratio of origin of accepted trades per period in the Airdrop treatments. Each node corresponds to the proportion of completed trades that initiated from either bids or asks. In panels (b) and (c) we report asks and bids per treatment. We calculate the volume-weighted average per period for each session, and report the median value of the 9 sessions in each period per treatment.

Similarly to study 1, we find that the majority of transactions occur due to traders accepting asks, see A.9a. Once again, sellers appear to have more control over market prices. Asks in the Airdrop treatments have very similar trajectories to the realized price trajectories in the market, as shown in figure A.9b. Finally, bids are relatively flat and much closer to fundamental value during all 15 periods (figure A.9c). We find that in the first seven periods, both bids and asks are significantly higher in Airdrop-All compared to Airdrop-Half (Mann-Whitney U exact test, bids: $p-value = 0.017$; asks: $p-value = 0.004$). In the second half of our markets, however, bids in Airdrop-All are significantly lower than in Airdrop-Half (Mann-Whitney U exact test, $p-value = 0.004$), while we do not find any statistical difference for asks (Mann-Whitney U test, $p-value = 0.524$).

Comparing Airdrop-All to Gift-All, we find higher bids and asks both in the first and in the second half of our Airdrop-All markets (Mann-Whitney U test, bids: $p-value = 0.042$ (first half) and $p-value = 0.000$ (second half); asks: $p-value = 0.000$ (first half) and $p-value = 0.005$ (second half)). Similarly, during the first half of our markets, both bids (Mann-Whitney U exact test, $p-value = 0.033$) and asks (Mann-Whitney U test, $p-value = 0.000$) in Airdrop-All are significantly higher than in Mining-All. However, this picture reverses in the second half, when both bids (Mann-Whitney U exact test, $p-value = 0.000$) and asks (Mann-Whitney U exact test, $p-value = 0.001$) are significantly higher in Mining-All than in Airdrop-All.

Comparing Airdrop-Half to the equivalent treatments in Study 1, we find higher asks in Airdrop-Half compared to Gift-Half throughout (Mann-Whitney U exact test, $p-value = 0.011$ (first half) and $p-value = 0.001$ (second half)). Meanwhile, bids are higher only in the second half (Mann-Whitney U test, $p-value = 0.002$), but not in the first half (Mann-Whitney U exact test, $p-value = 0.254$). The Mining-Half treatment exhibits both higher bids (Mann-Whitney U exact test, $p-value = 0.001$) and asks (Mann-Whitney U exact test, $p-value = 0.017$) than Airdrop-Half during the first seven periods. However, in the last seven periods, bids are higher in Airdrop-Half (Mann-Whitney U exact test, $p-value = 0.065$), while asks are not significantly different (Mann-Whitney U exact test, $p-value = 0.298$). This is in line with our earlier observation that Airdrop-Half lies in between Gift-Half and Mining-Half.

Figure A.10: Trader average action by role in Airdrop-Half



Note: Histograms present the distribution of trader average action in Airdrop-Half across all periods.

Finally, we also look into traders' average action according to the analysis in figure 6 reported for study 1. For each trader, we consider all offers they proposed and calculate on average what mixture of asks and bids they proposed which we report in figure A.10. Clearly, "Miners" (those who receive asset endowment) on average acted as a net seller in the market. "Non-Miners" are more balanced, proposing both bids and asks.

D Individual Sessions/Markets

D.1 Prices by Session/Market

Figures A.11, A.12, A.13, A.14, A.15, and A.16 present the individual markets for each of the six treatments in the two studies. Note that most graphs have a common y-axis, ranging from zero to five times the fundamental value (140). Two markets in Mining-All, four markets in Mining-Half, four markets in Airdrop-All and three markets in Airdrop-Half exhibit particularly high peaks, which makes an adjustment of their y-axis necessary. Trading occurs in all but five specific session periods (period 7 in session 2 of Gift-Half, periods 13 and 14 in session 1 of Mining-Half, period 13 in session 9 of Airdrop-All and period 13 in session 5 of Mining-Half). Consequently, in these periods, we do not provide a volume-weighted price.

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.12, 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.13) 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.14 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.

The individual markets of our Airdrop treatments (figure A.15 and figure A.16) show a remarkable degree of heterogeneity across sessions. Some sessions have a rather flat price trajectory across the 15 trading periods, while others show clear indications for price bubbles. Peak prices are usually reached during the first half of the experimental markets.

Figure A.11: Median volume-weighted prices per period in individual markets of Gift-All

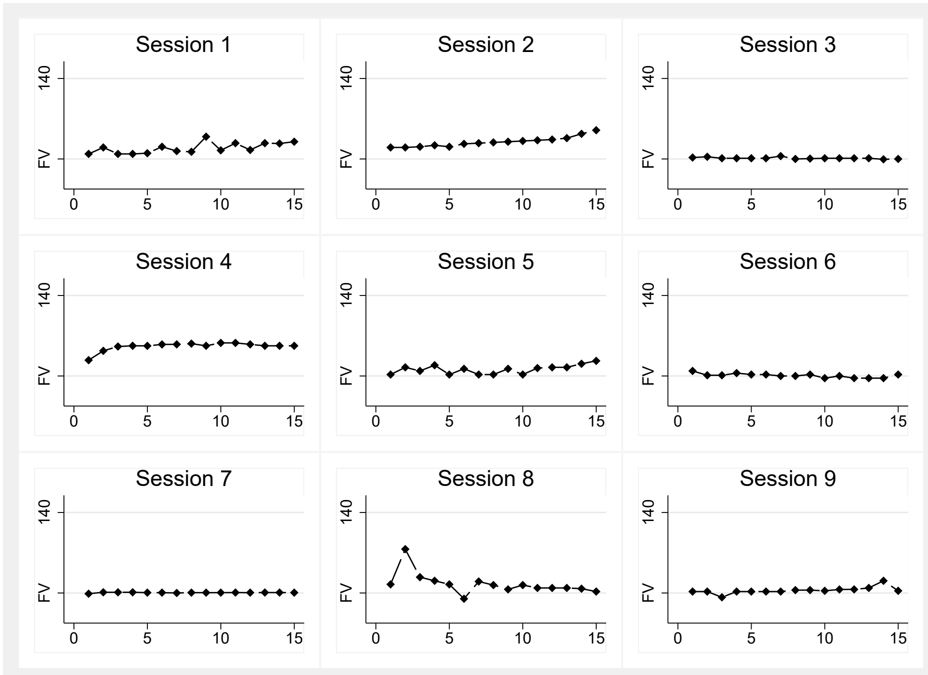


Figure A.12: Median volume-weighted prices per period in individual markets of Gift-Half

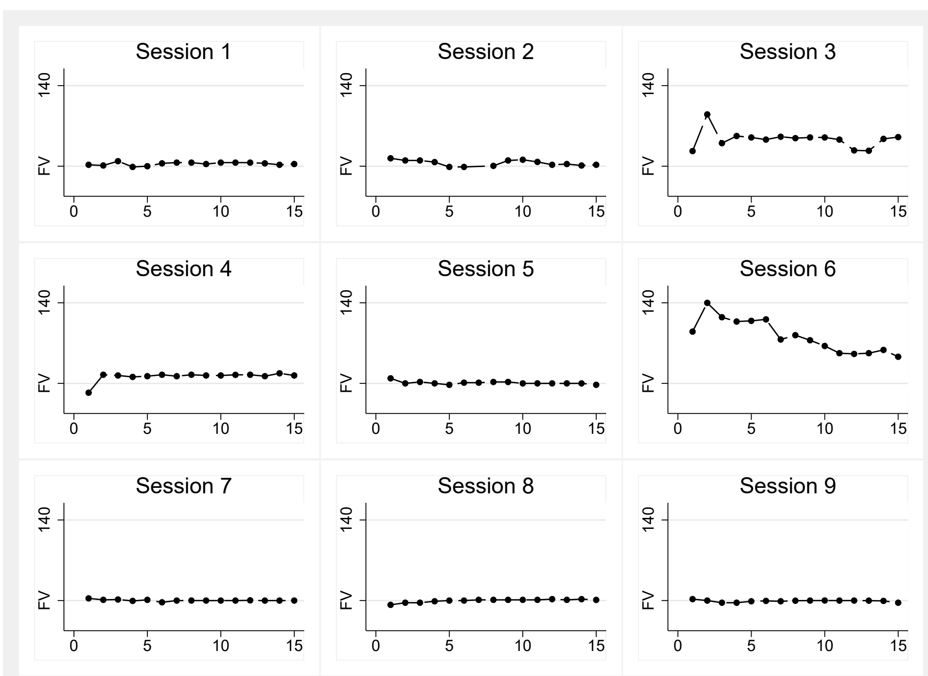


Figure A.13: Median volume-weighted prices per period in individual markets of Mining-All

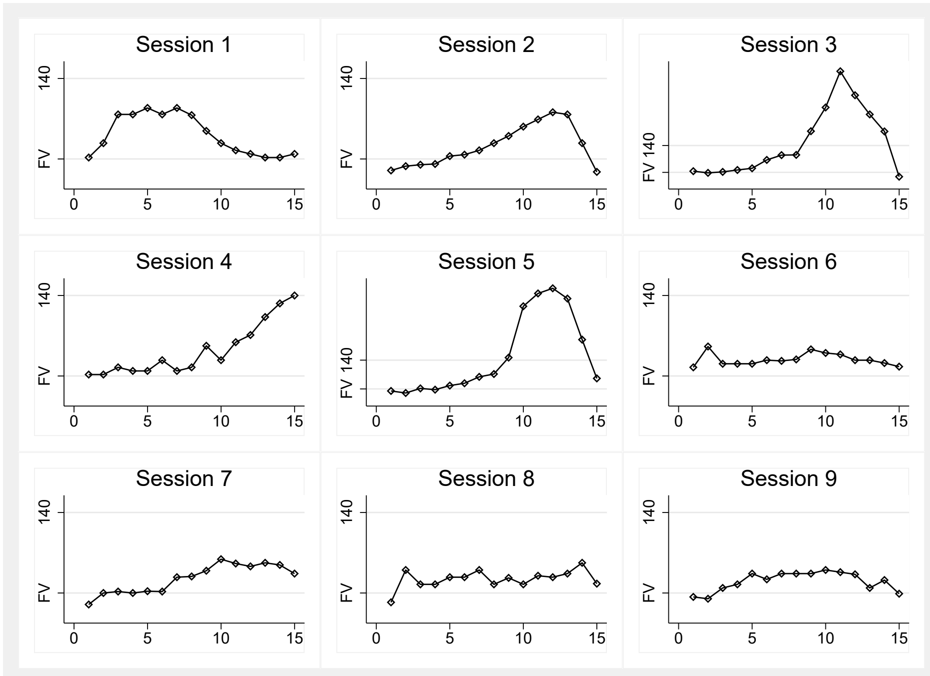


Figure A.14: Median volume-weighted prices per period in individual markets of Mining-Half

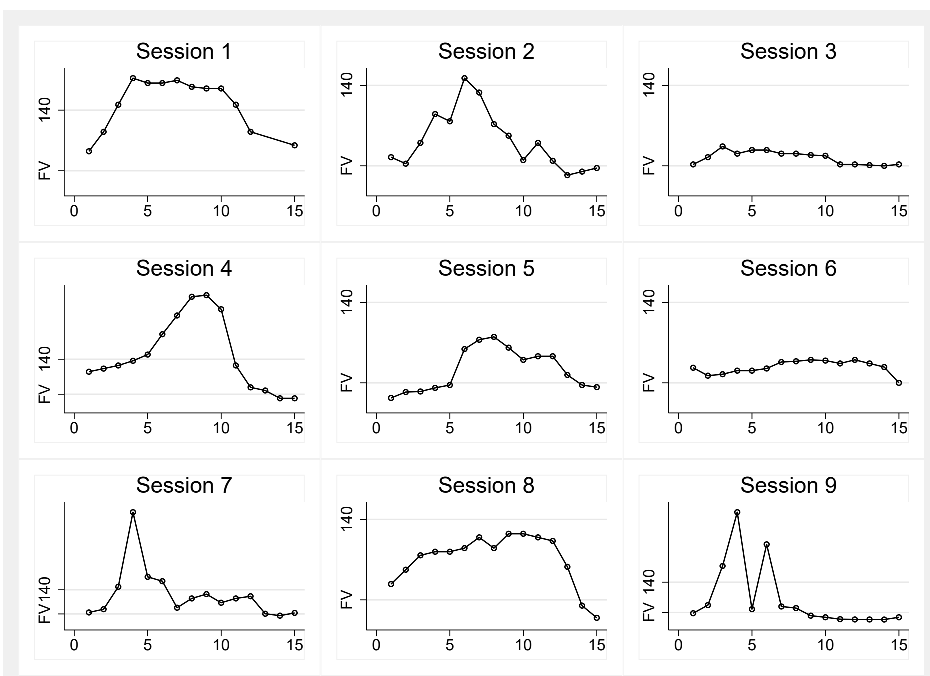


Figure A.15: Median volume-weighted prices per period in individual markets of Airdrop-All

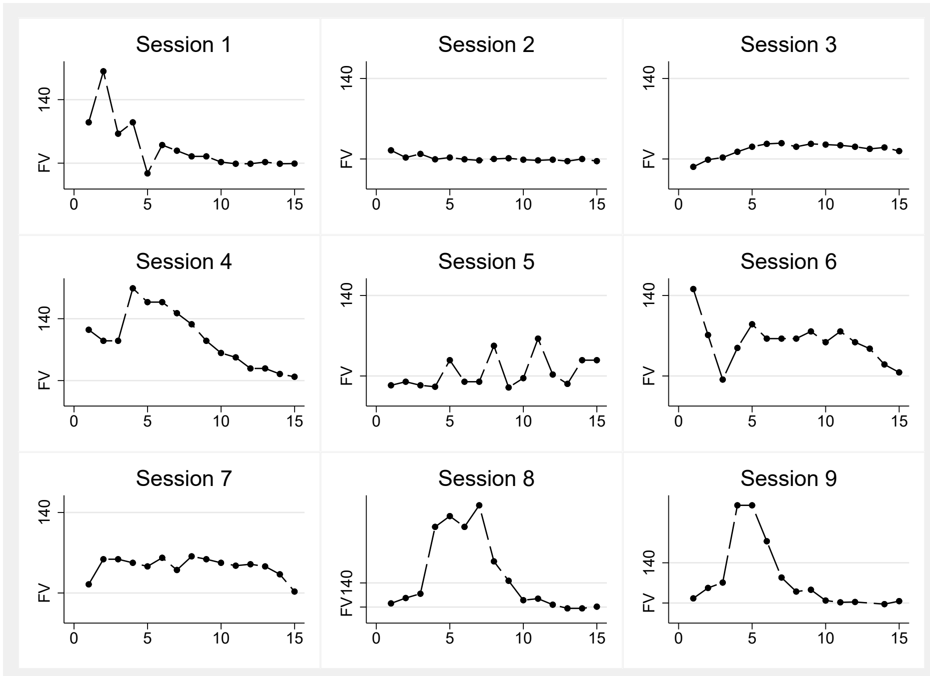
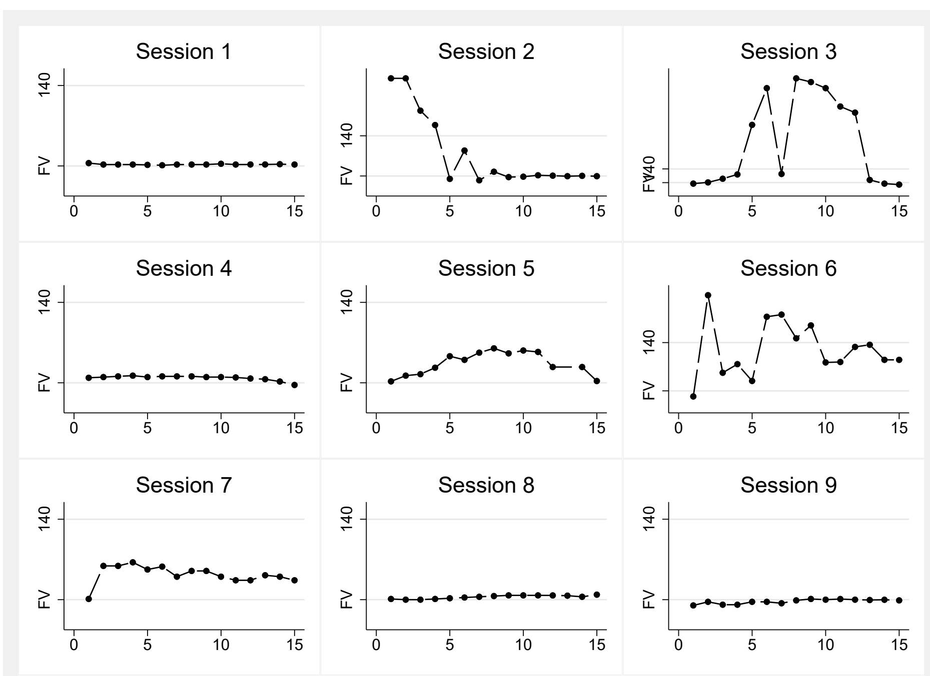


Figure A.16: Median volume-weighted prices per period in individual markets of Airdrop-Half



D.2 Bubble Measures by Session/Market

Tables A.7-A.12 present the different bubble measures for each market separately for our six treatments. As one can clearly see in tables A.8, A.10, and A.12, session 2 in Gift-Half, session 4 in Mining-Half, and session 2 in Airdrop-Half have a puzzling high LIQUIDITY value compared to the other sessions. The interpretation of these values is questionable, as they are based on rather meaningless orders.[3]

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

Table A.7: Bubble measures for the markets in treatment Gift-All

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

Table A.8: Bubble measures for the markets in treatment Gift-Half

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

Table A.9: Bubble measures for the markets in treatment Mining-All

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

Table A.10: Bubble measures for the markets in treatment Mining-Half

Session	RAD	RD	RDMAX	AMP	CRASH	TURN	LQ	SPREAD	VOLA
1	1.71	1.70	11.19	-	-11.22	0.15	6.37	2.34	0.64
2	0.13	0.04	0.54	-	-0.68	0.51	1.50	0.27	0.47
3	0.52	0.47	0.80	1.15	-0.44	0.24	0.44	0.41	0.14
4	2.57	2.57	5.07	2.29	-4.92	0.10	2.14	2.03	0.46
5	0.71	0.59	2.56	2.79	-2.88	0.11	0.49	1.73	1.03
6	1.69	1.69	4.07	-	-3.89	0.22	1.16	1.27	0.82
7	1.27	1.27	1.67	1.07	-1.53	0.15	0.52	0.59	0.33
8	5.16	5.09	15.49	14.68	-15.74	0.18	0.56	1.61	0.38
9	2.56	2.54	10.54	10.16	-10.64	0.18	9.88	1.84	0.41

Table A.11: Bubble measures for the markets in treatment Airdrop-All

Session	RAD	RD	RDMAX	AMP	CRASH	TURN	LQ	SPREAD	VOLA
1	0.09	0.09	0.16	-	-0.13	0.16	0.47	0.07	0.12
2	3.46	3.37	17.75	18.03	-17.71	0.10	111.41	2.71	0.99
3	12.59	12.46	28.46	28.64	-29.01	0.07	1.13	12.56	0.50
4	0.27	0.26	0.35	0.10	-0.43	0.14	0.66	0.13	0.17
5	0.90	0.90	1.69	1.59	-1.60	0.14	0.61	0.39	0.10
6	3.68	3.65	8.82	9.06	-6.64	0.13	2.21	4.25	0.94
7	1.27	1.27	2.31	0.77	-1.43	0.31	0.65	1.42	0.56
8	0.14	0.14	0.36	0.37	-	0.20	1.09	0.11	0.05
9	0.09	-0.08	0.02	0.31	-0.06	0.22	0.87	0.15	0.16

Table A.12: Bubble measures for the markets in treatment Airdrop-Half

E Pre-registration

Table A.13 lists details of our pre-registration, potential deviations from it, and where the corresponding results can be found in our paper.

Table A.13: Details on pre-registration

Pre-registration	Deviation	Reference
The extent to which trading prices deviate from the fundamental value of the asset will be measured through various bubble measures commonly used in the literature. These include RAD, RD, RDMAX, PA, Turnover, Volatility.	We also report CRASH, LQ, and SPREAD. Note that we refer to PA (price amplitude) as AMPLITUDE (AMP).	Tables 4, A.1, A.7-A.12
We will use non-parametric tests to compare the degree of mispricing across the two conditions through bubble measures.	In order to analyze our Mining treatments more closely, we used non-parametric tests separately for the first and second half of our markets. Additional to non-parametric pairwise comparisons, we adopt the definition by Razen et al. (2017) and identify markets to exhibit price bubbles if RDMAX, AMP, and CRASH are significantly higher in the Mining treatment compared to the respective baseline Gift treatment.	Tables 5, 6, 8
We use multivariate analyses to study the role of individual characteristics on trader performance. We also study how cohort level risk preference, cognitive ability and theory of mind measures affect mispricing.		Tables A.3, A.6
	We additionally perform analysis that was not pre-registered, in particular with respect to over-expenditure on mining, analyzing the order book, correlations between bubble measures and initial market conditions, and classification of traders and miners.	Sections 5.2, 5.3, B.3, C.1, C.2, C.4

F Experimental Details & Instructions

Table A.14 below summarizes dates and locations of implementation of each of our sessions across all six treatments. Table A.15 provides an overview of the development of the total amount of ECUs in the market, the total number of assets in circulation, and the CAR by period across treatments. Depending on our treatment, we handed our participants instructions describing the market. We include the translated instructions for Gift-Half, Mining-Half and Airdrop-Half below. Note that the instructions for Gift-All, Mining-All and Airdrop-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 F.1, we include the translated comprehension quiz questions which participants had to answer correctly before the market stage. All but the last two questions refer to the quiz of treatment Mining-Half. The quiz questions of treatments Gift-All, Gift-Half and Mining-All are a subset of these. Note that the correct answers for some questions depend on the treatment. The last two items refer to additional questions which we asked in treatment Airdrop-Half. Figure A.17 shows a fictional result screen similar to those that participants could see in between trading periods of the market stage.

Table A.14: Session Overview

(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	

(e) Airdrop-All

Day	Session	Participants	Location
27/03/2023	1	8	Heidelberg
28/03/2023	2	8	Frankfurt
29/03/2023	5	8	Heidelberg
30/03/2023	6	8	Frankfurt
30/03/2019	7	8	Frankfurt
03/04/2023	3	7	Frankfurt
05/04/2023	8	8	Heidelberg
12/04/2023	9	8	Frankfurt
13/04/2023	4	7	Heidelberg
	Total:	70	

(f) Airdrop-Half

Day	Session	Participants	Location
27/03/2023	2	8	Heidelberg
28/03/2023	3	8	Frankfurt
28/03/2023	4	8	Frankfurt
29/03/2023	5	8	Heidelberg
30/03/2023	6	8	Frankfurt
30/03/2023	7	8	Frankfurt
03/04/2023	8	8	Frankfurt
04/04/2023	9	8	Heidelberg
04/04/2023	1	8	Heidelberg
	Total:	72	

Note: *Session* in our Airdrop treatments refers to the corresponding Mining-session, i.e., the asset supply schedule that was implemented.

Table A.15: Treatment parameters and their developments over time

	Gift			Mining						Airdrop					
	All/Half			All			Half			All			Half		
Period	ECU	Assets	CAR	ECU	Assets	CAR	ECU	Assets	CAR	ECU	Assets	CAR	ECU	Assets	CAR
1	45,600	160	10.2	46,920	48	35.1	46,910	54	31.2	47,200	48	35.3	47,200	54	31.4
2	45,600	160	10.2	46,605	78	21.4	46,620	91	18.3	47,200	78	21.6	47,200	91	18.5
3	45,600	160	10.2	46,367	103	16.1	46,379	112	14.8	47,200	103	16.4	47,200	112	15.1
4	45,600	160	10.2	46,047	121	13.6	46,139	127	12.9	47,200	121	14.0	47,200	127	13.2
5	45,600	160	10.2	45,772	134	12.2	45,849	141	11.6	47,200	134	12.6	47,200	141	11.9
6	45,600	160	10.2	45,607	142	11.4	45,579	150	10.8	47,200	142	11.8	47,200	150	11.2
7	45,600	160	10.2	45,429	149	10.9	45,294	157	10.3	47,200	149	11.3	47,200	157	10.7
8	45,600	160	10.2	45,246	154	10.5	45,132	162	9.9	47,200	154	10.9	47,200	162	10.4
9	45,600	160	10.2	45,159	155	10.4	44,965	165	9.7	47,200	155	10.8	47,200	165	10.2
10	45,600	160	10.2	45,100	156	10.3	44,963	166	9.7	47,200	156	10.8	47,200	166	10.2
11	45,600	160	10.2	45,060	157	10.2	44,803	167	9.6	47,200	157	10.7	47,200	167	10.1
12	45,600	160	10.2	45,020	159	10.1	44,724	167	9.6	47,200	159	10.6	47,200	167	10.1
13	45,600	160	10.2	44,980	159	10.1	44,724	168	9.5	47,200	159	10.6	47,200	168	10.1
14	45,600	160	10.2	44,940	159	10.1	44,724	168	9.5	47,200	159	10.6	47,200	168	10.0
15	45,600	160	10.2	44,900	160	10.0	44,724	168	9.5	47,200	160	10.5	47,200	168	10.0

Note: ECU: the total amount of ECUs in the market. For Gift and Airdrop treatments, this is the total amount of endowed ECUs. For Mining treatments, we report the treatment median for the two Mining treatments for each period. The value changes over time because mining is costly. Assets: the total number of the asset in circulation. CAR: the cash to asset ratio.

Instructions for Gift-Half

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:

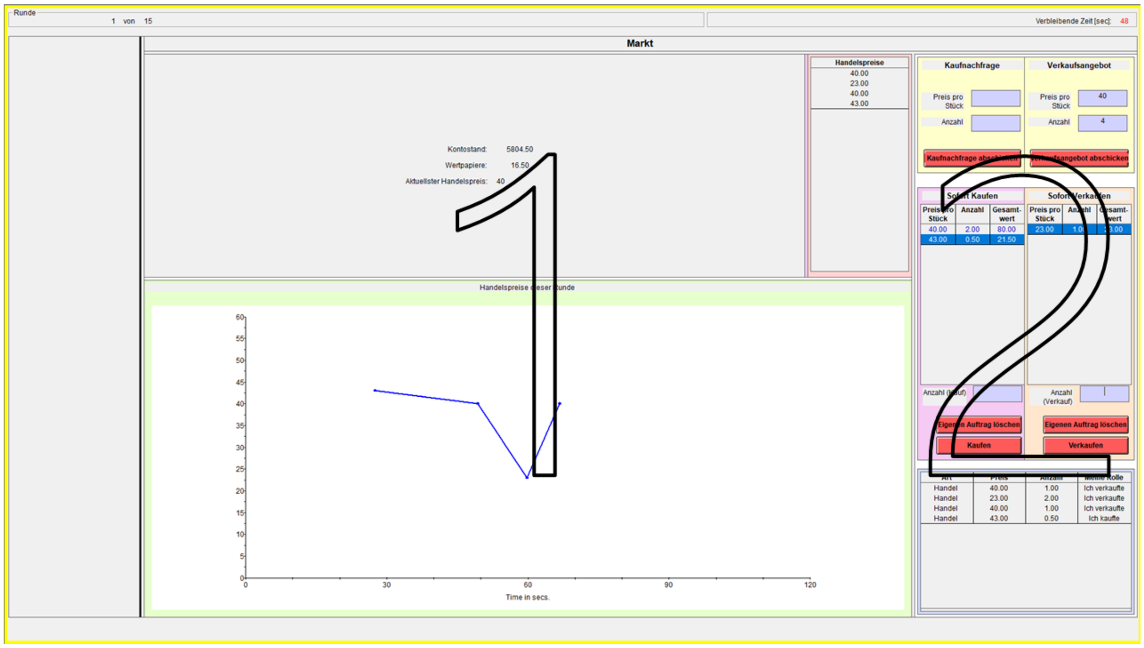


Figure 1: Screen

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.

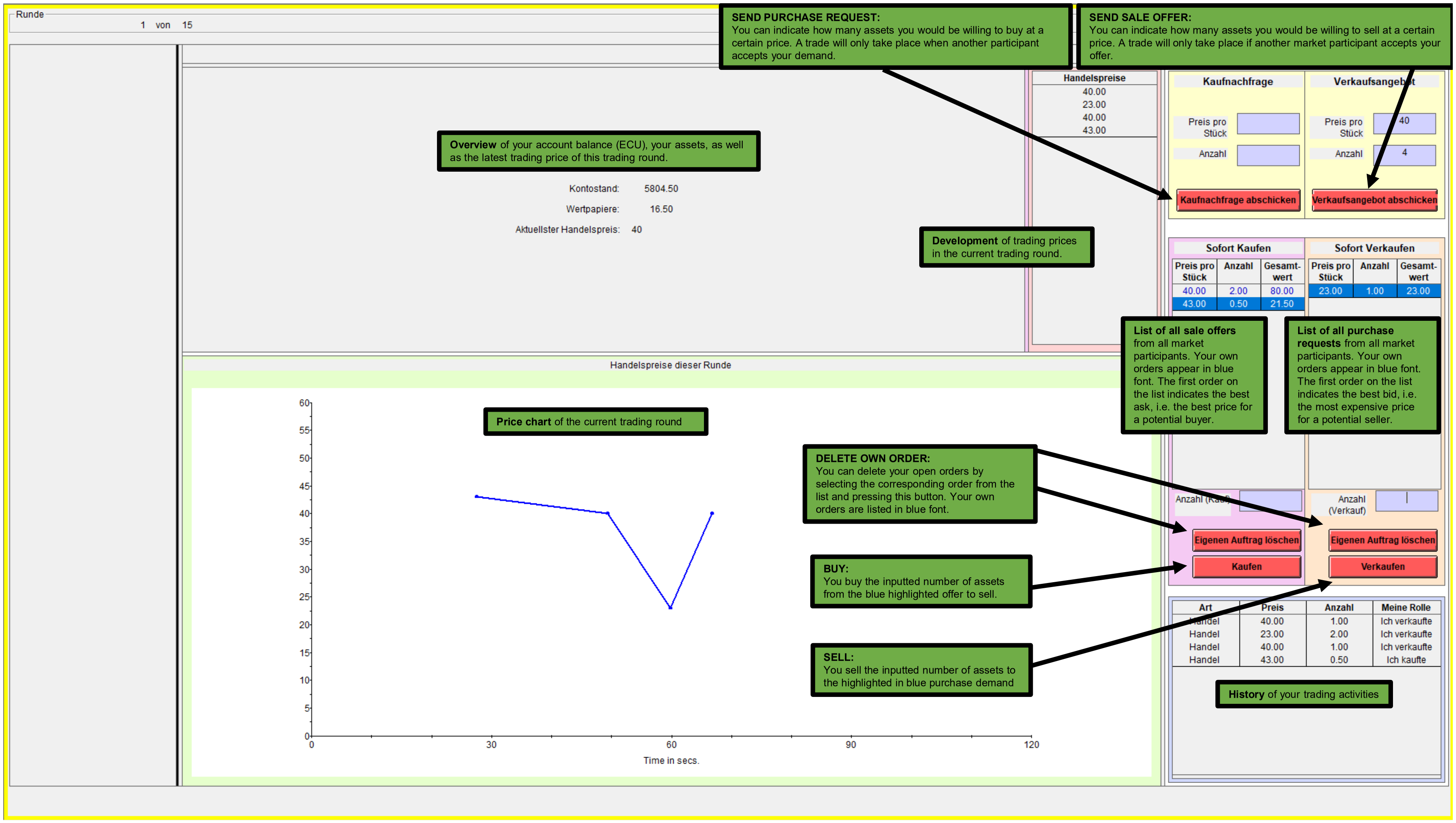
If you want to sell assets, you also have two options:

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 | Gesamtwert
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
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
Time in secs.

Instructions for Mining-Half

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:

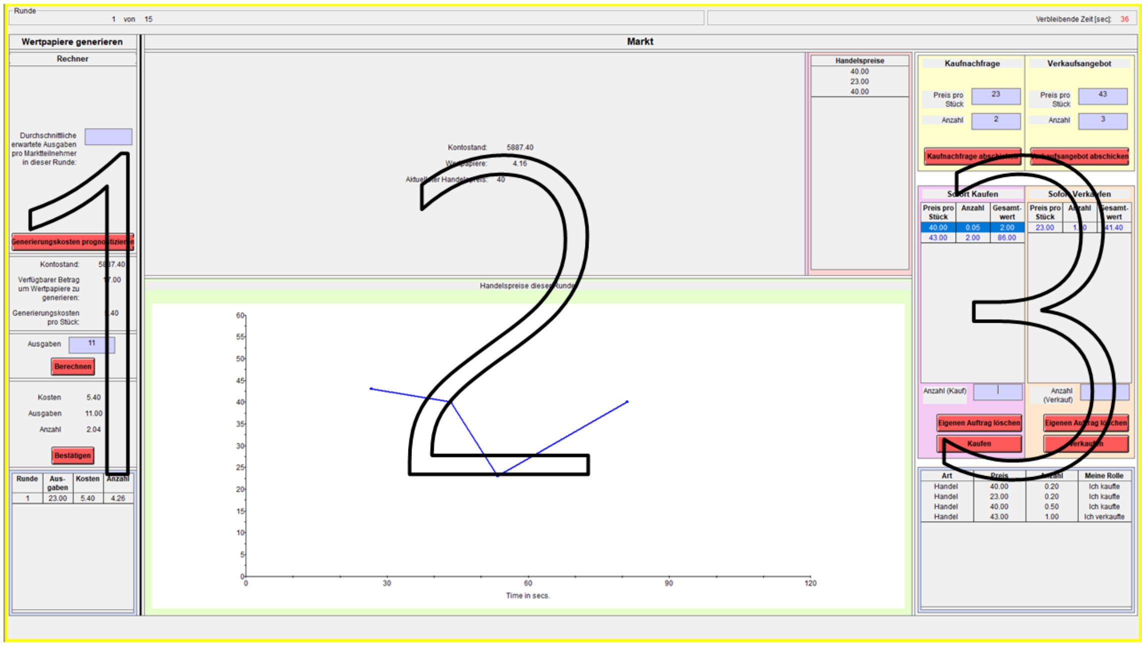


Figure 1: Screen

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.

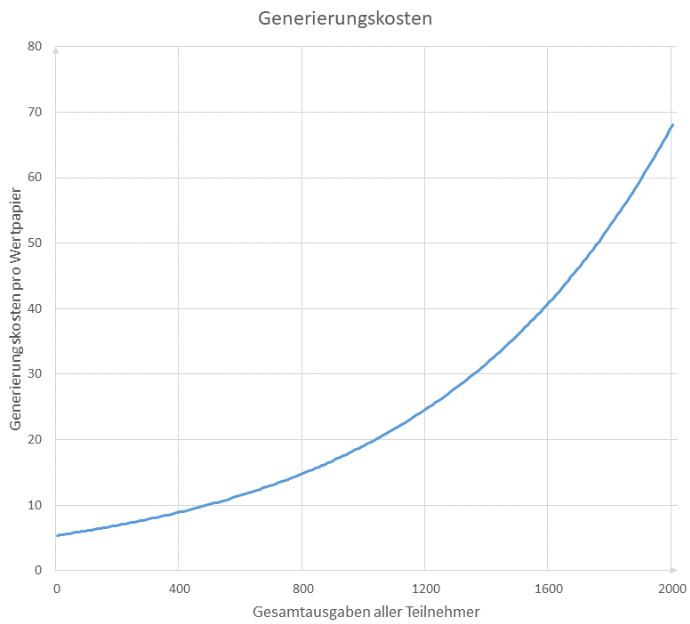


Figure 2: Costs of generating assets

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.

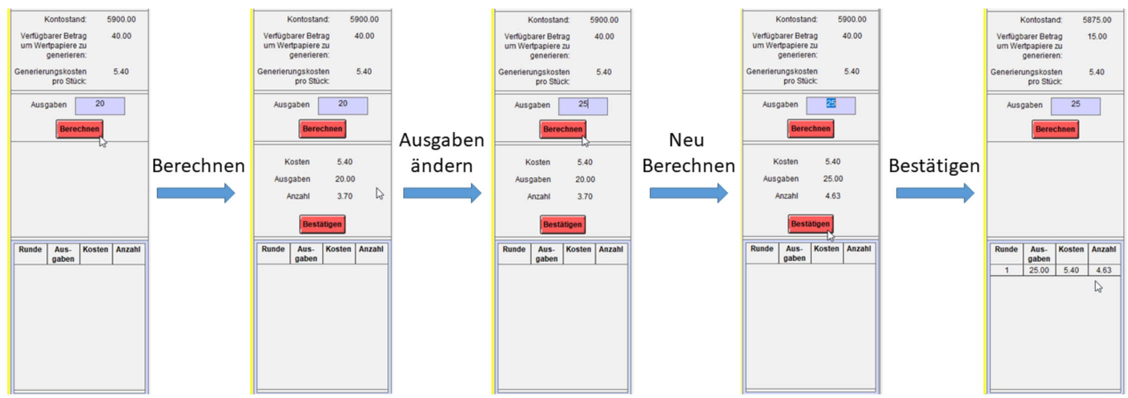


Figure 3: Example for generating assets

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.

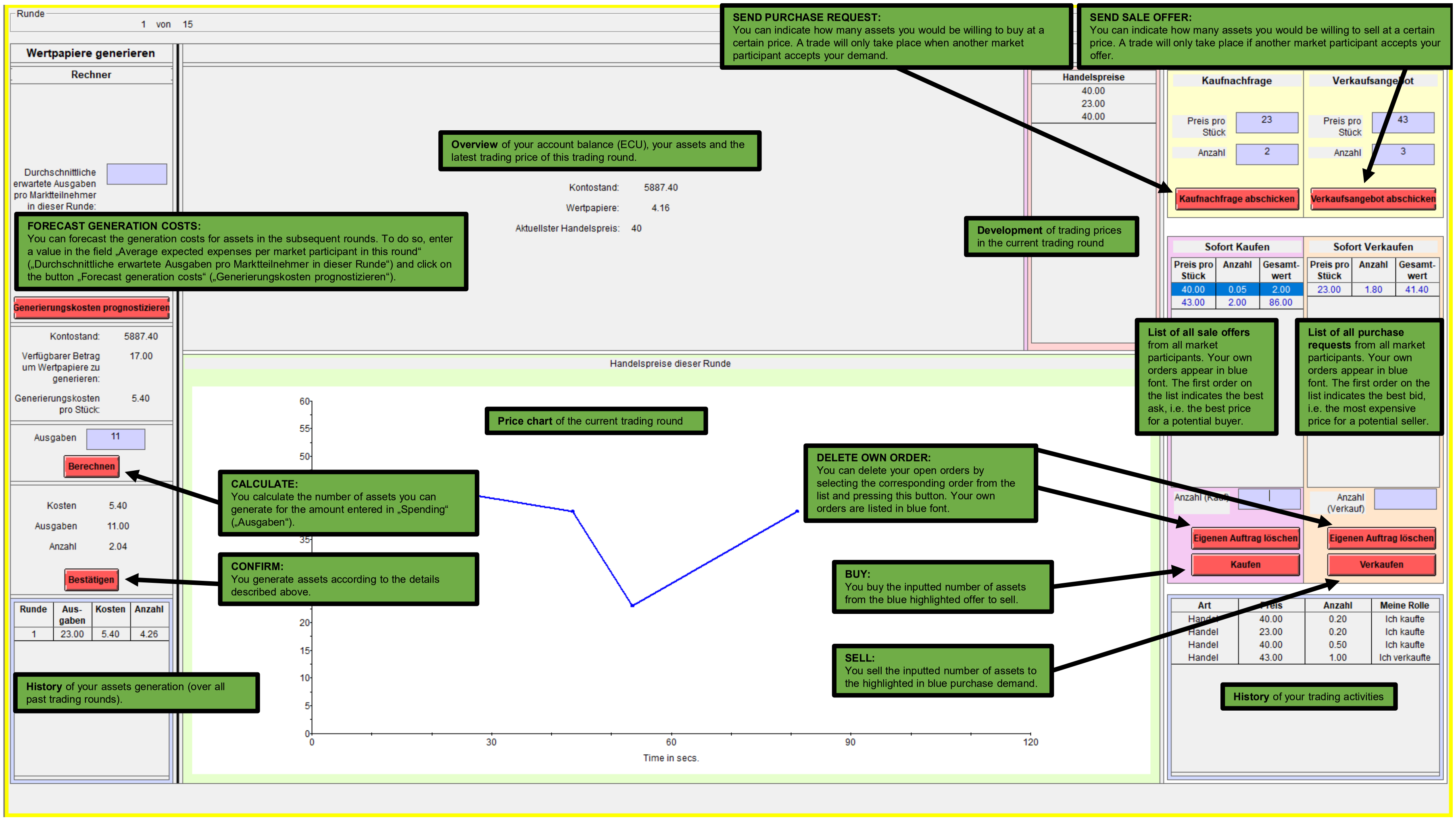
You can withdraw your buy requests and sell offers as long as they have not been accepted by another market participant. To do so, select the corresponding line in the list and then click on "Delete own order" ("Eigenen Auftrag löschen"). You can only delete orders you have submitted yourself. You can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

Instructions for Airdrop-Half

1. General information

The next part of the experiment is about a market for securities. 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 there is a possibility that assets will be credited free of charge at the beginning of a new trading round. Whether assets are credited and how many of them depends on four different delivery schedules specified in advance. These delivery schedules will be further explained in a separate section of these instructions. Participants with role B will receive 6260 ECUs and 0 units of the asset, while also not be credited any securities free of charge. All participants can use their ECUs to buy or sell assets in the market. Your account balance as well as your asset holdings will be transferred from one trading 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 in accordance with the sum of the ECU value of your assets account as well as 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

1. The market and trading rules

Market Rules

You can trade assets in the marketplace. Trading is done in the form of a continuous double auction. This means that everyone 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:

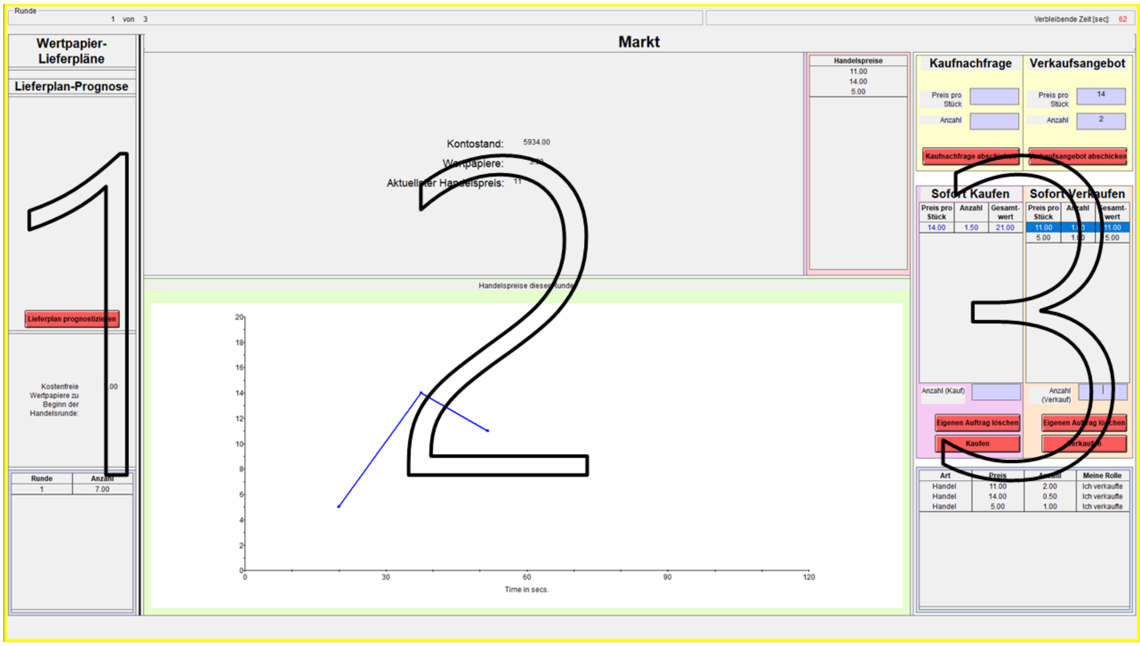


Figure 1: Screen

The screen is split into different segments (see Figure 1). The left segment (1) provides information about the delivery schedules of the assets. In the middle (2) of the screen you 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 list of "Trade Prices" ("Handelspreise") 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 the asset delivery schedules. Then, the functions of the marketplace are described.

Securities delivery schedules

In the three practice rounds, each participant will receive assets according to a standardised "practice delivery schedule". Each participant with role A is given a fixed number of assets for free at the beginning of each round (14 in the first round, 10 in the second round, and 6 in the third round). In the payment-related trading rounds, each participant with role A receives an individual delivery schedule. There is a total of four different delivery schedules which describe whether and how many assets participants with role A receive free of charge during the respective trading rounds. Each of these delivery schedules is randomly assigned to a single participant with role A. Participants with role B do not receive assets for free in any trading round.

You will not know in advance exactly how many assets participants with role A will be credited with in each trading round. However, you will have access to the information on how many assets each participant with role A could be credited with free of charge in the next four trading rounds. A maximum of 14.81 units of the asset can be credited to participants with role A for free in the first trading round. The maximum number of assets that can be credited to participants with role A in the subsequent rounds depends on the credited assets in the first round. Assuming each participant with role A is credited with the maximum assets in the first round, they may be credited with a maximum of 9.88 units in the second trading round, a maximum of 6.58 units in the third trading round, and a maximum of 4.39 units in the fourth round. Otherwise, in case not every participant with role A is credited with the maximum of assets in the first round, the maximum of the following rounds may be adjusted upwards. During the trading rounds, you can access the up-to-date information on how many assets each participant could maximally be credited for free in the next four trading rounds in the upper section of the left section (1) by clicking on "Forecast delivery schedule". In the middle of the left segment (1) you will find information on how many assets have been credited to you for free during the current trading round. In the lower part of the left section (1), your personal delivery history is displayed. Every delivery of assets from the past trading rounds is listed here. In case your delivery history is too extensive for the table's space, 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 so, 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 this price in the "Quantity" ("Anzahl") field (this number 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 sale** 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 unit" ("Preis pro Stück"). Also enter the number of assets you wish to sell at this price in the "Quantity" ("Anzahl") field (this number can be a fraction of a unit). You can submit the offer for sales 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.

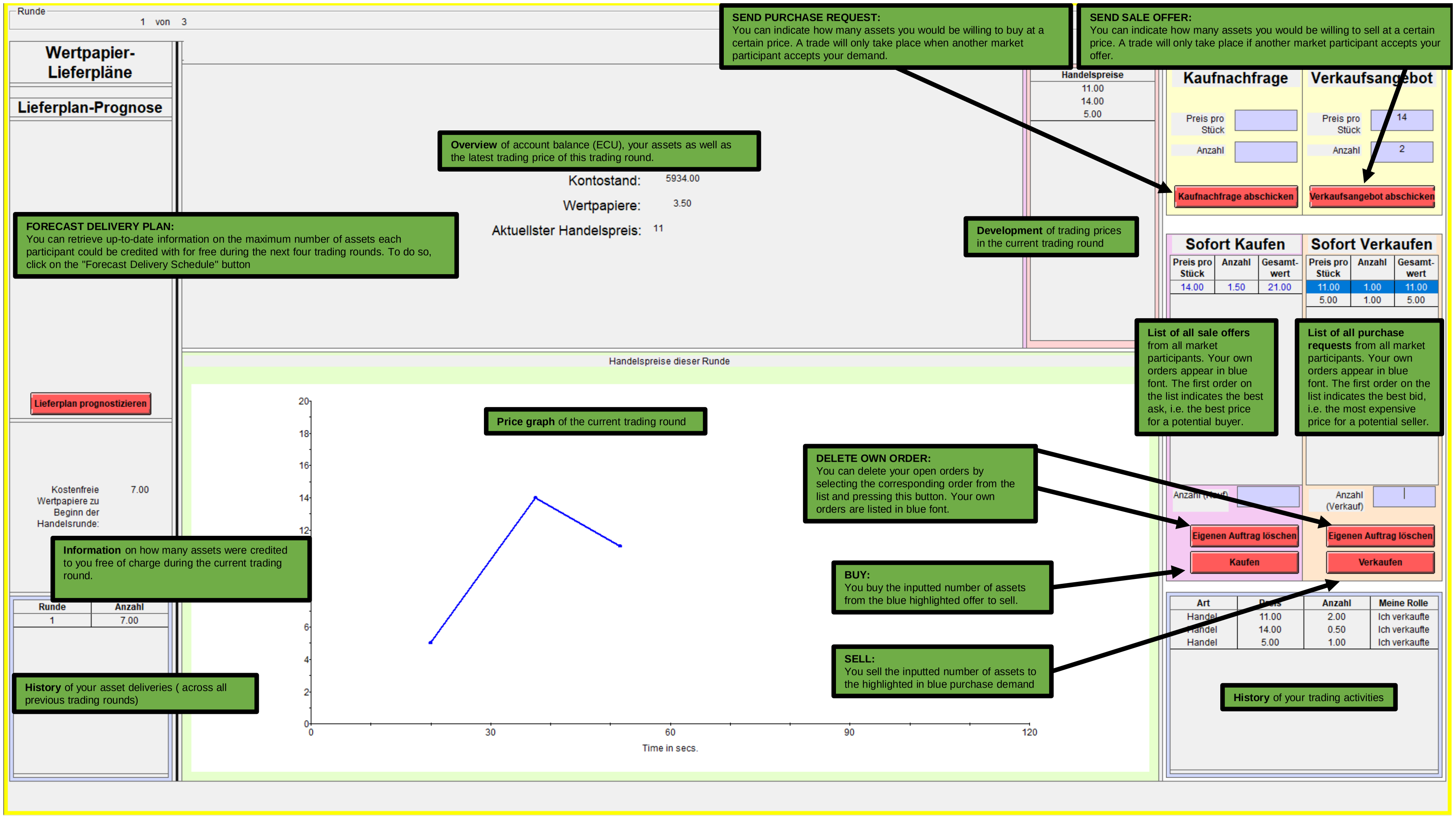
You can withdraw your buy requests and sell offers as long as they have not been accepted by another market participant. To do so, select the corresponding line in the list and then click on "Delete own order" ("Eigenen Auftrag löschen"). You can only delete order you have submitted yourself. You can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

Summary:

- Cash and initial holdings for role A: 5540 ECU, 0 securities
- Cash and initial holdings for role B: 6260 ECU, 0 securities
- Each participant with role A is randomly assigned a pre-determined delivery schedule, which specifies whether and how many assets will be credited free of charge in the respective trading rounds
- 3 practice rounds of 120 seconds each (standardised 'practice delivery schedule' for participants with role A)
- 15 trading rounds of 120 seconds each (individual delivery schedules)
- Account balances are transferred from round to round
- Functions:
    - Forecast delivery schedules
    - Purchase demand
    - Buy now ("Sofort Kaufen")
    - Sales offer
    - Sell now ("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 3
Wertpapier-Lieferpläne
Lieferplan-Prognose
Lieferplan prognostizieren
Kostenfreie Wertpapiere zu Beginn der Handelsrunde: 7.00
Runde | Anzahl
1 | 7.00
Kontostand: 5934.00
Wertpapiere: 3.50
Aktuellster Handelspreis: 11
Handelspreise
11.00
14.00
5.00
Handelspreise dieser Runde
Time in secs.
Kaufnachfrage
Verkaufsangebot
Preis pro Stück
Anzahl
14
2
Kaufnachfrage abschicken
Verkaufsangebot abschicken
Sofort Kaufen
Sofort Verkaufen
Preis pro Stück | Anzahl | Gesamt-wert
14.00 | 1.50 | 21.00
11.00 | 1.00 | 11.00
5.00 | 1.00 | 5.00
Anzahl (Kauf)
Anzahl (Verkauf)
Eigenen Auftrag löschen
Kaufen
Verkaufen
Art | Preis | Anzahl | Meine Rolle
Handel | 11.00 | 2.00 | Ich verkaufte
Handel | 14.00 | 0.50 | Ich verkaufte
Handel | 5.00 | 1.00 | Ich verkaufte
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.
Overview of account balance (ECU), your assets as well as the latest trading price of this trading round.
FORECAST DELIVERY PLAN: You can retrieve up-to-date information on the maximum number of assets each participant could be credited with for free during the next four trading rounds. To do so, click on the "Forecast Delivery Schedule" button
Development of trading prices in the current trading round
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.
Price graph of the current trading round
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.
Information on how many assets were credited to you free of charge during the current trading round.
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
History of your asset deliveries (across all previous trading rounds)
History of your trading activities

F.1 Market stage quiz

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

- Assuming you are a role A player, how many starting assets will you have?
  Correct answer: 0

- Assuming you are a role B player, how many starting assets will you have?
  Correct answer: 0

- How many payment-relevant trading rounds will there be?
  Correct answer: 15

- Assuming you are a role A player, what is the maximum number of ECUs you can spend on asset generation in each trading period?
  Correct answer: 80

- Assuming you are a role B player, what is the maximum number of ECUs you can spend on asset generation in each trading period?
  Correct answer: 0

- Assume that the total expenditure of all participants (including you) on asset generation in previous rounds is approximately 800 ECUs. What would be the approximate cost to generate one unit of the asset (in ECU)?
  Correct answer: 15

- What is the probability that your assets have a redemption value of 67 ECU at the end of all trading periods?
  Correct answer: 25%

- Say you would like to obtain more assets. How can you acquire any?
  Correct answer: buying from the market or generation

- At the end of the market, your asset holdings will be exchanged with:
  Correct answer: ECUs

- If at the end of the market you are holding 5600 ECUs, how much in Euros will you receive?
  Correct answer: 10

- Say you are holding 30 assets at the end of the market and you draw a king. Your asset holdings would be worth a total of (in ECU):
  Correct answer: 900

- Who may be receiving assets free of charge at the beginning of a trading round?
  Correct answer: Role A participants

- Will all role A participants receive the same amount of assets at the beginning of a trading round?
  Correct answer: No

F.2 Summary screen between market periods

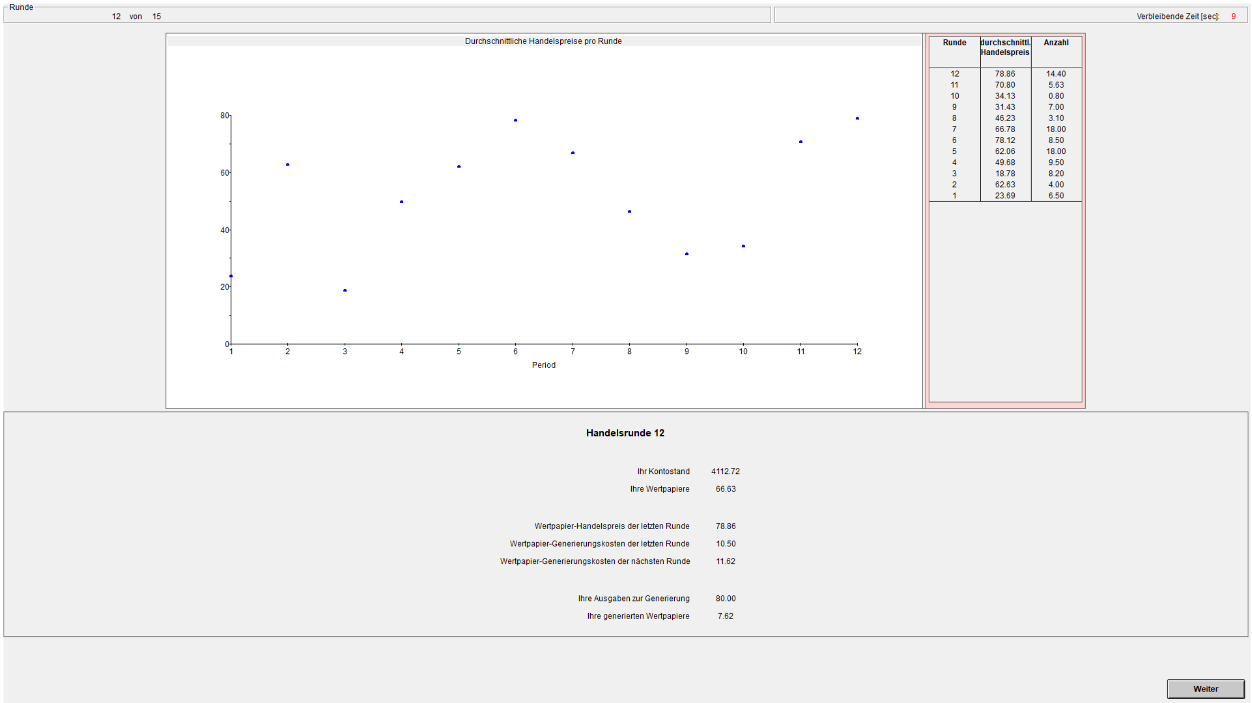


Figure A.17: Price chart and history of previous rounds on the result screen between trading periods. The screen lists average trading prices ("Durchschnittlicher Handelspreis"), volumes ("Anzahl"), periods ("Handelsrunde"), cash balance ("Kontostand"), asset holdings ("Wertpapiere"), the trading price 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").

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