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The Impact of ETFs in Secondary Asset Markets: Experimental Evidence

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Abstract

We examine how exchange traded funds (ETFs) affect asset pricing, and turnover in a laboratory asset market. We focus on behavior in secondary markets with or without ETF assets and whether there is zero or negative correlation in asset dividends. In the latter case, the diversification benefits of ETFs are most salient. We find that when the dividends are negatively correlated, ETFs reduce asset mispricing without decreasing market activity (turnover). When dividends are uncorrelated, the ETF has no impact on these same measures. Thus, our findings suggest that ETFs do not harm, and may in fact improve, price discovery and liquidity in asset markets.

JEL Codes: G11, G12, G14, C92.

Keywords: ETF, index funds, asset pricing, turnover, experimental finance.

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1 Introduction

Exchange traded funds, or ETFs, which were first introduced in 1993, now represent 35% of all equity trades in the United States (Ben-David et al., 2018). The recent, meteoric rise in the popularity of ETFs as an investment vehicle has democratized investing, providing retail investors with access to an investment products that were once available only to institutional investors (Hill, 2016). ETFs are investment products that track a particular market index, and may be one of the most important financial innovations in recent history (Lettau and Madhavan, 2018). The advantages of these investment products are easy to appreciate: (i) they help to diversify market risk by allowing investors to effectively hold a bundle of different assets (as ETFs typically track some market index), (ii) they have lower associated management fees, and (iii) they are traded continuously on an exchange, making them more liquid than mutual funds. In addition, ETFs are appealing to institutional investors who are looking to turn a profit by engaging in arbitrage.

However, the appeal and ubiquity of ETFs might have a destabilizing role in asset markets if demand for ETF assets diverts attention away from price discovery and trade in the assets that underlie those ETF assets or if the market price of the ETF departs from its net asset value (NAV). Such departures may further attract speculators who add even more noise to the price discovery process, or who generate excessive volatility in asset prices. According to Bogle (2016), "Most of today's 1,800 ETFs are less diversified, carry greater risk, and are used largely for rapid-fire trading —speculation, pure and simple."

In this paper we study pricing and trade in secondary asset markets both with and without ETFs. Our approach enables us to provide clear evidence of the impact of ETFs on asset prices and turnover in asset markets that would be difficult to obtain in the field, where ETF assets already coexist with other assets. In the experimental finance literature, there are some studies that examine trading in multiple assets (see Duffy et al., 2021 for a survey) but there are no studies we are aware of that address the impact of composite and tradeable assets on price discovery and market activity.

Although there exists some empirical literature exploring the impact of ETFs on financial markets using field data (as discussed in the next section), we propose a laboratory experiment for several reasons. First, the laboratory provides us with precise control over the fundamental value of the assets so that we can accurately assess the extent to which agents are able to correctly price individual assets as well as composite assets such as ETFs. In the field, knowledge of the fundamental value of assets is much less clear. Second, we consider environments with and without ETF assets in order to clearly identify the impact of ETF assets on asset prices and turnover. In an environment without ETFs, there is no need for Authorised Participants (APs) whose role is to guarantee that ETF shares are always traded close to their NAV. Therefore, to make the clearest possible comparison between the environment without and with ETFs, we exclude APs from our laboratory market and focus only on the *secondary* market (where traders buy/sell existing assets with other traders) which represents about 90% of daily ETF activity (ICI, 2019).[1] Our results show that the omission of APs does not affect the ability of market participants to track the NAV of the ETF asset.[2]

Finally, the control of the laboratory environment allows us to change variables such as the correlation in dividends across assets, in order to emphasize particular characteristics of the ETF asset, such as diversification and/or hedging benefits, and to address whether such differences matter for asset pricing.[3] It is well known that

[1]For a detailed overview of ETFs, see, e.g., Lettau and Madhavan (2018).

[2]Given that we omit the role of APs, the ETF in our environment can be viewed as a closed-end fund.

[3]Varying the correlation in asset returns has been used to explore mispricing behavior, see, e.g.,

ETFs are widely used in markets for hedging and/or diversification purposes. In laboratory markets, this feature of ETFs is challenging to capture given that trade is generally limited to a small number of assets. To overcome this difficulty, we design two distinct environments, one with perfectly negative correlation between asset dividends and another with zero correlation. Perfectly negative correlation allows us to make the diversification and hedging features of the ETF asset more salient to market participants.[4] An alternative interpretation of perfectly negative correlation across asset dividends is that it corresponds to situations where investors hold a portfolio with a long position in one asset and a short position in the other asset, similar to a hedging strategy. Our treatment with zero correlation between asset dividends serves as a control, in which the diversification benefits of ETF assets are less obvious to participants. Alternatively, one could consider a positive correlation environment, but recent evidence suggests that both in the lab and in the field, participants suffer from "correlation neglect" (see, e.g., Ungeheuer and Weber, 2018, Matthies, 2018, and Chinco et al., 2019 for recent applications). Specifically, these studies suggest that subjects react similarly to positive and zero correlation environments. Hence, we restrict our comparison to environments with either zero or negative correlations in asset dividends.

Our laboratory market builds on the seminal design of Smith et al. (1988) (hereafter SSW) and extends it to two assets, A and B. The dividend process for asset A has an expected dividend of zero in every period and a final redemption value, while the dividend process for asset B has a structural break: for the first t periods, it follows the same dividend process as asset A so that the expected dividend is zero, and beginning in period $t+1$, the expected value of the dividend process jumps to one until the terminal period T, where there is a final redemption value for asset B. These two

Charness and Neugebauer (2019), although not in the pressence of a composite asset.

[4] Our experiment is not the first to use negative correlations between asset dividends. For example, Bossaerts and Plott (2004) made a similar assumption.

dividend processes generate either flat or declining paths for the fundamental values of the two assets, which correspond to the two most commonly studied fundamental paths in the experimental asset pricing literature. We further vary whether the asset returns are (i) perfectly negatively correlated, as in our $2N$ treatment, or (ii) have zero correlation, as in our $2Z$ treatment. Our second design innovation concerns the *number* of assets in the market, which may be two or three. Markets with just two assets allow for trading only in assets A and B. In markets with three assets, in addition to assets A and B there is a third, composite ETF asset, referred to as asset C, which can also be traded. This ETF asset is known to be a claim to one unit of asset A and one unit of asset B and so its fundamental value is the equal-weighted fundamental values of assets A and B. In addition to determining and observing the price of the ETF asset C, market participants also learn the net asset value (NAV) of the ETF asset C, equal to sum of the market price of one unit of asset A and one unit of asset B in each period to facilitate arbitrage.[5]

To preview our results, we find that in the negative correlation treatment, mispricing is significantly reduced with the introduction of the ETF asset. Thus, the ETF asset provides an important benchmark to help traders properly price the underlying assets. Indeed, we find that ETF prices are close to the NAV and get even closer with experience in the negative correlation treatment. By contrast, in the zero correlation treatment, we do not find significant differences in mispricing between markets with and without the ETF asset, though the ETF asset continues to closely follow the NAV. In our design, the ETF asset represents 50% of total assets,[6] and yet we do not find any effect from the introduction of the ETF asset on *turnover* (market activity) in the underlying assets in either correlation case. In fact, traders actively participate in mar-

[5]While we refer to our composite assets as ETFs, one can also think of them as similar to mutual funds. The difference is that, unlike mutual funds, ETF shares are not necessarily traded at their NAV at the end of each day.

[6]The supply of assets in our laboratory markets is fixed.

kets for *all* assets across all four of our experimental treatments. Further, our findings suggest that in an environment where there is a high demand for the underlying assets, such as in the negative correlation environment, there will be greater price dispersion with respect to the fundamental values. In such an environment, a composite asset can serve as a useful benchmark to correct mispricing. However, if the actual prices properly reflect the fundamental values, then ETFs may not provide an additional advantage, nor destabilize price discovery, as documented in our paper.

As our experiment represents a first step toward understanding the role of ETFs in asset markets, we consider a simple environment, focusing on the more valued aspects of ETFs — diversification and price discovery. Most of the previous experimental and/or survey papers studying index products and/or mutual funds focus on an individual's portfolio allocation across funds. For example, see Ehm et al. (2014), Heuer et al. (2017), Choi et al. (2010), Anufriev et al. (2019), and Anufriev et al. (2016). In the present paper, we study the impact of index products on asset prices.

2 Related literature

The existing literature on the effects of ETFs on price discovery, volatility and liquidity of the underlying assets is mixed.[7] There is some evidence that ETFs can improve intraday price discovery of securities (Hasbrouck, 2003, Yu, 2005; Chen and Strother, 2008; Fang and Sanger, 2011; Ivanov et al., 2013), particularly if the individual securities are less liquid than the ETF. The improvement in price discovery comes from faster response time to new information on earnings (especially the macro-related component) and the subsequent trading of the lower cost ETFs. The fluctuations in ETF prices

[7] At the macro level, Converse et al. (2020) find that total cross-border equity flows and prices are significantly more sensitive to global financial conditions in countries where ETFs hold a larger share of financial assets.

can help guide the prices of the underlying securities to integrate new information. Hasbrouck (2003) provides some empirical evidence for this phenomenon using index futures. Similar results are also found by Glosten et al. (2021) who document how ETFs positively affect informational efficiency at the individual stock level, in particular with respect to information on earnings. Huang et al. (2021) show similar positive effects for industry level ETFs, while Bhojraj et al. (2020) find a positive effect on efficiency for sector level funds, and a negative effect for non-sector level funds. Agapova and Volkov (2018) determine that when corporate bonds are included in ETFs, the returns are less volatile than for bonds which are not included. Lastly, there is also some evidence that the market liquidity of the underlying assets improves with the introduction of ETFs (Hegde and McDermott, 2004; Holden and Nam, 2019). On the other hand, Hamm (2014) finds that when lower quality individual stocks are included in ETFs, the market can become less liquid as uninformed investors move away from investing in these stocks in favor of the ETF, where asymmetric information problems are mitigated. Since the evidence suggests that ETFs affect the prices of the underlying assets, ETFs may also lead to price volatility and affect market efficiency. For example, a positive change in an asset's fundamental value, perhaps due to favorable news, should lead to an upward price adjustment. However, if that price movement is instead driven by noisy ETF traders, then one would expect a price reversal in the near future, thus increasing the volatility of the underlying assets.

Arbitrage can also transmit pressure to the underlying assets as mispricing of the ETFs is passed through to the basket of individual securities. This can occur due to (i) trades by uninformed investors, and/or (ii) traders who participate in long-short strategies involving other mispriced securities. Ben-David et al. (2018) find that ETF arbitrage activity increases non-fundamental volatility of underlying stocks due to noisy traders. Madhavan and Sobczyk (2016) decompose the price of the ETF relative to its

NAV (ETF premium) into two components, one corresponding to price discovery and the other to transitory liquidity. They find that an ETF-led price discovery following a change in fundamentals can lead to excess volatility when the composite assets are illiquid. Baltussen et al. (2019) also provide evidence of price reversals and noisy shocks to index products.

ETF assets also have some features in common with derivative assets such as futures which track an index. However, unlike futures, ETFs do not have a maturity date, which enhances performance for investors with broader horizons, and ETFs are not derivative assets since they can be directly traded. Noussair and Tucker (2006) studied the impact of futures in an SSW laboratory environment with a single asset and found that a complete set of futures markets, where one matures every period, can correct spot market price bubbles. They also observe widespread mispricing in the futures markets. In a follow-up study, Noussair et al. (2016) constrain the number of futures contracts to one and find that a longer maturity can help reduce mispricing, despite an increase in price volatility observed in some sessions. Porter and Smith (1995) find a very modest mispricing correction in the spot market when the single contract matures half-way through the life of the asset.

The dividend process in our experimental design is based on a large volume of experimental literature, which studied asset pricing using the seminal SSW framework (Smith et al., 1988). These studies have incorporated futures, and analyzed arbitrage conditions using different correlations across dividends and/or varying the structural processes. Indeed, dividend processes similar to those that we use have been examined for a single asset in Noussair et al. (2001), Kirchler et al. (2012), Noussair and Tucker (2016), Noussair and Powell (2010) and Breaban and Noussair (2015). A two-asset SSW market also appears in Fisher and Kelly (2000) and a recent study by Charness and Neugebauer (2019). They find that the law of one price holds when asset dividends have a perfectly positive correlation, and fails to hold when the correlation is zero.

3 The environment

Our experimental design builds upon the seminal work of SSW where market participants trade an asset with a common dividend process and a decreasing fundamental value for a finite number of periods. In the SSW environment, if subjects are risk neutral and have the same endowment, then either there should be no trade or trade will occur only at the fundamental price. Of course, subjects may not be risk neutral and indeed, past studies have shown significant trading in SSW environments (see Palan, 2013 for an overview). Our own econometric analysis of subjects' risk preferences in the present experiment suggests that differences in risk attitudes can provide incentives for asset trade. For instance, risk averse subjects engage in trade in order to diversify their portfolio, while risk tolerant subjects on average hold less balanced portfolios.

In this paper, we extend the original SSW environment to two and three asset markets, where assets are subject to different dividend processes, utilizing a 2×2 experimental design. The first treatment variable concerns the number of assets traded in the market. A market can have either (i) two assets A and B, or (ii) three assets, which includes an ETF asset C, which is a composite asset equal to one share of asset A and one share of asset B. The second treatment variable is the correlation in the dividends earned by the two assets, A and B, which can be either be perfectly negative N or zero Z (no correlation). As mentioned in the introduction, we chose to compare environments with negatively correlated dividends and zero correlation for two reasons: (i) to make the diversification benefits of the ETF asset salient in a market with limited assets, and (ii) to account for "correlation neglect" that is observed in both field and lab studies (see Matthies, 2018, Ungeheuer and Weber, 2018, Chinco et al., 2019 and the references therein). While assets may, on average, exhibit positive correlation[8] subjects, whether in the lab or in the field do not necessarily differentiate between positive and uncorrelated returns.

The fundamental value of a finitely lived asset in any period t, (assuming no discounting), is the expected dividend payments remaining over the life of the asset in periods $T-t+1$, and the asset's terminal value TV, such that $FV_{j,t} = \sum_{s=t}^{T} E_s[D_{j,s}]+TV_j$, where j refers to the asset type. We assume that $T = 15$ and specify the fundamental value of each asset in each period as follows:

$$
\begin{aligned}
&FV_{A,t} = 10 \\
&FV_{B,t} = \begin{cases} 18 & \text{for } t < 8 \\ (T-t+1)+10 & \text{for } t \geq 8 \end{cases} \\
&FV_{C,t} = \begin{cases} 28 & \text{for } t < 8 \\ (T-t+1)+20 & \text{for } t \geq 8. \end{cases}
\end{aligned} \tag{1}
$$

All market participants are endowed with an amount of cash and a portfolio of assets such that the distribution of wealth across players is ex-ante identical. We specify the initial allocation of assets $\Omega = \{A, B, C\}$, and cash for all players in Table 1. In each session, players participate in three separate call markets, each consisting of $T = 15$ trading periods. In every period $t = \{1, \ldots, T\}$, asset A pays a dividend of $D_A \in \{-1, 1\}$, which is decided by a fair coin flip such that the expected dividend $E[D_A] = 0$. Following period T, asset A pays a terminal value, $TV_A = 10$. Thus, the fundamental value of asset A, FV_A, is constant and equal to 10 in all periods.[9]

[8]The average cross-asset correlation for S&P 500 has been determined to be around 30 for the past decade, see https://www.forbes.com/sites/alapshah/2017/07/11/according-to-one-metric-this-could-be-the-best-time-for-stock-picking-in-a-decade/209cb47d78a1.

[9]There is a small probability (equal to 0.059) that $FV_A < 0$ if the realized dividends for asset A

In periods $t = \{1, \ldots, t^*\}$, asset B follows the same dividend structure as asset A, such that $D_B \in \{-1, 1\}$ and $E[D_B] = 0$. For periods $t = \{t^* + 1, \ldots, T\}$, there is a structural break so that $D_B \in \{0, 2\}$, which is decided by a fair coin flip such that the expected dividend $E[D_B] = 1$. Following period T, asset B pays a terminal value $TV_B = 10$. Hence, asset B has a constant fundamental value until period t^*, and a decreasing fundamental value thereafter. In the zero correlation environment the realizations of D_A and D_B are drawn independently of each other. The independence of these realizations and the timing of the structural break in the dividend process for asset B is perfectly known to subjects at the start of each market.

Table 1: Endowment bundles across subjects in all treatments

		3 assets (3N, 3Z)			2 assets (2N, 2Z)	
Subjects	Cash	A	B	C	A	B
1-3	444	8	2	0	8	2
4-6	396	2	8	0	2	8
7-9	280	0	0	10	10	10

Note: we assume an initial total cash-asset ratio of two, and an equal distribution of wealth across participants. The initial fundamental value for assets {A,B,C} is {10,18,28}.

By contrast, in the perfectly negative correlation environment the realizations of D_B are exactly opposite to the realizations of D_A. That is, in the negative correlation environment in periods $t = \{1, \ldots, t^*\}$, when $D_A = -1$, then $D_B = 1$, and when $D_A = 1$, then $D_B = -1$. In periods $t = \{t^* + 1, \ldots, T\}$, when $D_A = -1$, then $D_B = 2$, and when $D_A = 1$, then $D_B = 0$. Again, the timing of the structural break for asset B and the perfect negative correlation in the dividends between assets A and B is perfectly known to subjects at the start of each market.

The fundamental expected values of Assets A, B, and C in each period are provided

are negative for at least 11 of the total 15 periods, given that the terminal value for A is equal to 10. However, in expectation, the value of the dividends is zero and therefore this should not be an issue for forward-looking agents.

to subjects in a table included in the written instructions. A summary of our 2×2 experimental design is provided in Table 2.In the three asset environment, we introduce an ETF asset to the two asset market, which we call asset C. This ETF asset is a composite asset composed of one unit of asset A and one unit of asset B and this structure is perfectly known to subjects.

Table 2: The 2×2 Experimental Design

Assets / Correlation	Zero	Negative
2 (no ETF)	2Z	2N
3 (with ETF)	3Z	3N

Dividend earnings from all assets held by a player in each period are stored in a separate account and are converted into cash earnings at the end of the terminal period T. The number of shares available for trade at any given time is fixed such that $s^A, s^B, s^C = \{30, 30, 30\}$.[10] Since we assume that one share of the ETF asset C, is composed of one share of asset A and one share of asset B, the net asset value (NAV) of the ETF asset C is

$$NAV_{_C} := \frac{s^C_{_A} \times p_{_A} + s^C_{_B} \times p_{_B}}{s_{_C}} = p_{_A} + p_{_B}. \tag{2}$$

Note that the dividends received for holding one share of the ETF asset C follow

$$D_{_C} := \frac{s^C_{_A} \times D_{_A} + s^C_{_B} \times D_{_B}}{s_{_C}} = D_{_A} + D_{_B}. \tag{3}$$

Therefore, for $t = \{1, \ldots, t^*\}$ the ETF asset C pays $\{-2{,}0{,}2\}$ with probability $\{1/4, 1/2, 1/4\}$ when the correlation between the underlying assets is zero, or zero when the correlation between the underlying assets is negative, with certainty. For $t = \{t^* + 1, \ldots, T\}$,

[10]Our ETF environment assumes a fixed supply of assets and is therefore different from an open-ended fund, where shares are created and redeemed in response to market forces. However, given that this is the first paper to study the impact of ETFs on market behavior, we chose to consider a simple environment, focusing on the secondary market.

ETF asset C pays either $\{-1,1,3\}$ with probability $\{1/4, 1/2, 1/4\}$ when the correlation between the underlying assets is zero and one when the correlation between the underlying assets is negative, with certainty.

We assume an initial total cash-asset ratio endowment of two in each experimental session. Moreover, each subject enters the market with the same wealth, though we vary the composition of wealth across subjects. Specifically, subjects 1-3 are endowed with eight shares of asset A and two shares of asset B, subjects 4-6 are endowed with two shares of asset A and eight shares of asset B, and subjects 7-9 are endowed with ten shares of the ETF asset C. In a two-asset market, where only assets A and B are traded, the distribution of shares is the same for the subjects 1-6 and subjects 7-9 now receive ten shares each of assets A and B, which is equivalent to ten shares of the composite ETF asset C. It is important to highlight that the only difference across treatments is the presence of the ETF asset. The distribution of assets and cash is similar across treatments.

3.1 Market format

As a market clearing mechanism, we employ a call market for three reasons: (i) the market setting with three assets is complex and the call market mechanism provides a single, uniform market price for each of the assets traded in each period which enables greater clarity with respect to the differences in prices across assets; (ii) in our call market design, subjects are required to interact in each market, even if they wish to place an order for zero units, and (iii) there is a tradition of using call markets for asset price determination; for some recent examples see Akiyama et al. (2014), Akiyama et al. (2017), and Hanaki et al. (2018).[11] In a three asset environment, subjects can trade

[11] The convergence of asset prices to fundamental values in call markets has been demonstrated by Smith et al. (1982), Cason and Friedman (1997), Plott and Pogorelskiy (2017) and Carlé et al. (2019).

in up to three separate call markets simultaneously, with one market assigned to each asset. Similarly, in the two asset environment, subjects can trade in up to two separate call markets, with one market assigned to each asset.

Each period t, market participants can submit one buy order and/or sell order in each of the three asset markets.[12] Subjects can also choose not to participate in one, two or all three markets. A complete buy order specifies a single bid price and a number of units desired at that price. Similarly, a complete sell order includes a single ask price and a number of units for sale at that price. After all bids and asks are submitted, our computer program sorts the submitted bids in a descending order and asks in an ascending order, to derive the demand and supply schedules for each asset. The intersection of demand and supply (if it exists) results in a single, uniform market price for each asset market (and in the case of a price range, we use the midpoint price). All buyers whose bids are greater than or equal to the market price get to buy the number of units of that asset they specified at the market price, while all sellers whose asks are less than or equal to the market price got to sell the number of units they had specified at the market price. If there were more bids or asks made exactly at the market clearing price, then the rationing rule was that some bids or some asks were randomly selected to clear the market while the remainder did not.

In our environment, participants can only sell assets currently in their portfolio– that is, short-selling is not allowed. Moreover, there is no borrowing, as each participant can only place bid orders which satisfy their budget constraint (current cash available).

At the end of each period, subjects learn the market prices of either two or three assets (p_A, p_B and p_C), depending on the assigned treatment and the net asset value of the ETF asset C or $NAV_C = p_A + p_B$, if appropriate. By design, the NAV_C can

[12] We restricted buy/sell orders to one per period as we use a call market clearing mechanism and the complexity of having three asset markets open at once makes continuous trading throughout a period difficult for subjects (and our software) to handle.

depart from p_C, providing a potential for arbitrage opportunities.

3.2 Hypotheses

Assuming arbitrage activity, ETF prices should not deviate from their net asset values (NAVs), which depend on the market prices of the assets underlying the ETF. It follows that there should be no difference in various market measures, such as mispricing and asset turnover between our three asset market with ETFs and the comparable two asset market without ETFs. We will examine these measures in detail in section 5. We further explore how different risk profiles arising from the two different correlations between asset dividends might affect portfolio holdings.

Hypothesis 1: *A market with ETF assets will exhibit the same level of mispricing as a market without ETF assets, irrespective of the correlations in asset returns.*

The evidence is mixed with regards to how ETFs affect market prices and price discovery. As we noted earlier, some studies suggest an improvement in efficiency, though this is sensitive to scope (sector, industry, etc.), and asset types (greater efficiency gains for bond ETFs, where underlying assets are less liquid). Lastly, experimental evidence suggests that depending on asset return correlations, we should see some evidence of correct relative pricing.

Hypothesis 2: *The turnover of assets in markets with an ETF asset is the same as in a markets without an ETF asset.*

We hypothesize this outcome for two reasons: (i) arbitrage opportunities will ensure active markets in all assets and (ii) although ETFs may be thought of as passive instruments, they are actually actively traded.

Hypothesis 3: *The price of the ETF follows the NAV.*

If the price of the ETF does not follow NAV, then arbitrage between underlying securities and the composite assets will exist.

Hypothesis 4: *Subjects that are more tolerant to risk will hold less balanced portfolios.*

In our environment, holding both assets (A and B) or the ETF reduces portfolio risk. Thus, subjects who are more risk tolerant will have less balanced portfolios compared to subjects who are more risk-adverse. Further, in the perfectly negative correlation, the benefit of holding a balanced portfolio for risk-adverse subject should be more salient compared to the zero correlation treatment.

4 Laboratory Procedures

The experiment was conducted at the Experimental Social Science Laboratory (ESSL) of the University of California, Irvine. Participants included undergraduate students from all fields who were recruited online using the SONA systems software. Subjects were assigned to participate in just one of the four treatments: {*2Z*, *3Z*, *2N*, *3N*}, that is, we use a between-subjects design.[13] In each session, subjects were asked to complete a quiz after reading the instructions. Upon completion, the experimenter checked

[13]The between-subjects design is common in asset markets where participants are required to learn the trading rules in a specific market. Our market includes multiple units, and therefore the participants must also grasp the concept of correlation across them. If the participants are overloaded with a high number of repetitions, it can lead to lack of attention to market dynamics, thus affecting negatively the outcomes of the study.

the answers and if a subject made any incorrect responses, the correct answers were given and explained privately to the individual. Before the market opened for trading, the subjects also completed a risk-elicitation task (Crosetto and Filippin, 2013, implemented in oTree by Holzmeister and Pfurtscheller, 2016).

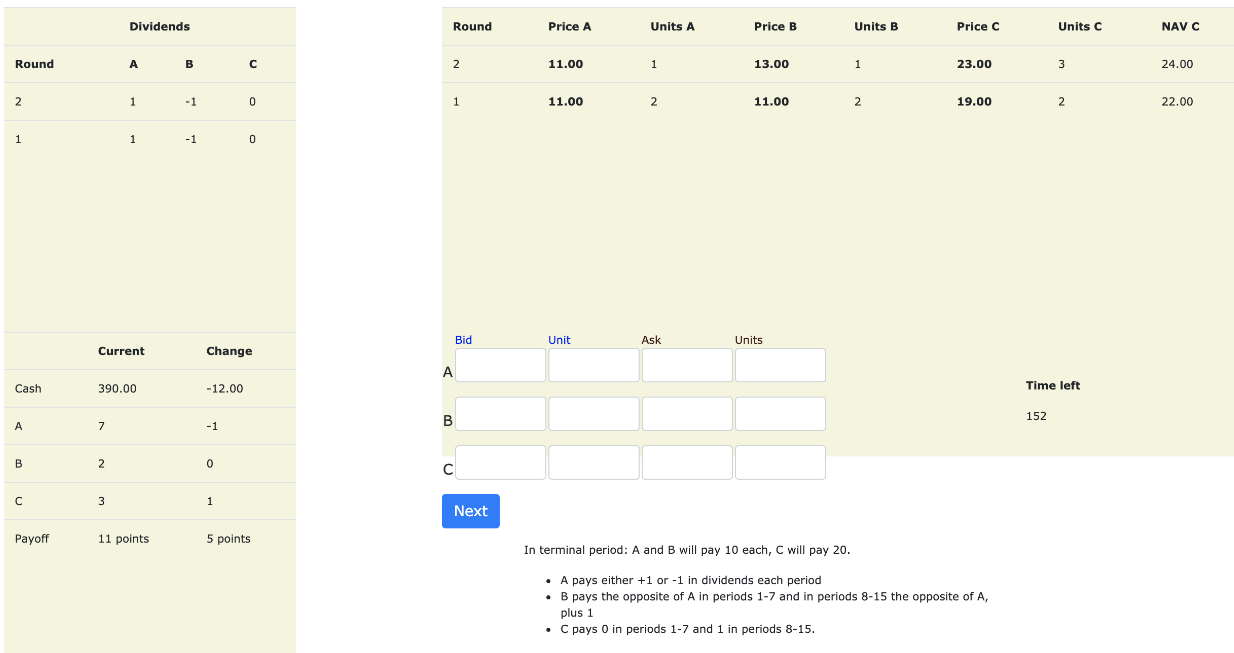


Figure 1: User interface in the $3N$ treatment.

Each session consisted of two 15 period markets. In each period, each subject had the option to input buy and/or sell orders, subject to the constraints that their buy orders did not exceed their endowment and their sell orders were for assets currently in their possession (i.e., no borrowing or short selling was allowed). Once a subject had decided on their order, they had to confirm their order by clicking on a button. For an example of the user-interface, designed in oTree (Chen et al., 2016), please refer to Figure 1.[14]

[14]On the decision screen shown in Figure 1, subjects had to fill in all twelve boxes (0 was always

Among the information provided to the subjects each period was market data (market prices and units transacted) from all previous periods, and the NAV of the ETF asset C (in treatments where there was such an asset). In the case where current price information for either asset A or asset B was not available (because a market clearing price could not be determined), the NAV was computed using the most recently available market price.

Any dividends accrued by subjects over the course of the market were put into a separate account which was converted into cash at the end of the session. The dividend yield was displayed to subjects if and only if she held the relevant asset. Current asset and cash holdings were provided, as well as the previous change in holdings, which appeared as a positive (negative) value for assets that the subject bought (sold), and a negative (positive) value for the cash paid (received). The interface for the two-asset markets, $2N$ and $2Z$, is similar to the one presented in Figure 1, except that all information related to asset C is omitted, including prices, NAV, dividends and buy/sell orders. Subject endowments of cash and assets for all sessions are presented in Table 1.

Table 3: Overview of sessions

Treatment	Sessions	Subjects per session	Payoff (USD, without show-up fee)
$2Z$	5	9	24.64
$3Z$	5	9	24.80
$2N$	5	9	24.64
$3N$	5	9	25.03
Total	20	180	24.78

In total, we conducted 20 sessions, with five sessions per treatment, and nine sub-

an option). The input boxes in the first column were for the per unit bids for assets A, B and C; the boxes in the second column were the number of units the trader was willing buy of assets A, B, and C at his/her bid prices; the boxes in the third column were the per unit asks for assets A, B and C, and the boxes in the fourth column were the number of units the trader was willing to sell of assets A, B, and C. While there was a timer counting down 180 seconds, there was no binding time constraint; market prices were not determined until all 9 subjects had confirmed their orders (completed all 12 boxes and submitted the order).

jects per session. We present an overview of all sessions from our experiment in Table 3. All subjects participated in two, 15-period markets. At the end of the experiment, one of these two markets was randomly selected and subjects' total point earnings from the market were converted into US dollars at the known exchange rate of \$0.04 per point. Subjects' market earnings were equal to the sum of their dividends earned over all 15 rounds from assets held plus their remaining cash balance and the value of their asset position at the end of the 15th round. The latter value was determined by summing together 1) the number of units of asset A held multiplied by 10, 2) the number of units of asset B held multiplied by 10, and 3) (in the three asset markets), the number of units of the ETF asset C held multiplied by 20. On average, each session lasted two hours and the average earnings were \$24.78. In addition, subjects received a show-up fee of \$7, bringing the average total to \$31.78.

5 Results

We begin our analysis by presenting the median market prices, and the fundamental values, of assets A, B and C in Figure 2 across all markets and treatments. The x-axis provides the period number for each of the two markets, with each lasting 15 periods. In the three asset treatments, $3N$ and $3Z$, we also include the NAV which is computed as the sum of the last available prices of assets A and B. In Appendix A we also include the same figures using a subset of data limited to the second market, when subjects have more experience. In all of the statistical analysis that follows, we use data only from the second market to account for subject learning.[15] Overall, the price of asset A closely follows its flat fundamental value across all treatments except $2N$, where we observe a higher level of mispricing. Such behavior is consistent with trading of assets

[15]Our results are qualitatively similar if we use the data from both markets.

with flat fundamental values and a constant cash to asset ratio as shown in Kirchler et al. (2012). The mispricing of asset B increases at the structural break where the fundamental value changes trend, and then decreases by the terminal period. We also observe that the price of the ETF asset C is closer to the NAV than to the fundamental value in the negative correlation treatment.

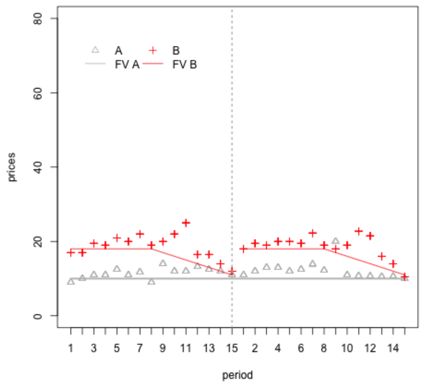
In treatment $3N$ the ETF asset C provides perfect insurance over market outcomes while in treatment $3Z$, the insurance is incomplete. Therefore, if investors are risk-averse, then we need to account for the difference in insurance provided by the different market environments.[16]

Table 4: Summary of results

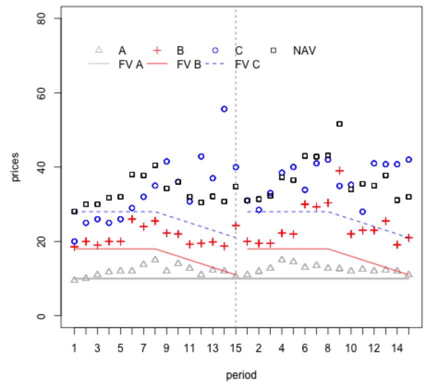
	First market				Second market			
	2Z	3Z	2N	3N	2Z	3Z	2N	3N
Asset A								
Volatility	1.81	3.12	8.88	2.61	2.03	4.13	8.70	3.49
RAD	0.26	0.32	1.01	0.51	0.39	0.70	1.27	0.40
RD	0.22	0.27	0.99	0.45	0.39	0.69	1.21	0.39
Turnover	1.22	1.51	1.45	1.35	1.48	1.48	1.25	1.14
Asset B								
Volatility	3.54	3.31	8.82	5.90	3.65	5.71	7.21	2.25
RAD	0.31	0.47	0.70	0.52	0.34	0.88	0.60	0.36
RD	0.25	0.46	0.62	0.44	0.32	0.87	0.55	0.35
Turnover	1.18	1.33	1.30	1.54	1.19	1.06	0.99	1.11
RAD B/A	0.22	0.33	0.33	0.55	0.17	0.41	0.31	0.15
Asset C								
Volatility	–	7.28	–	3.13	–	3.66	–	5.40
RAD	–	0.55	–	0.45	–	0.59	–	0.47
RD	–	0.43	–	0.48	–	0.52	–	0.47
RAD-NAV	–	0.34	–	0.17	–	0.29	–	0.19
RD-NAV	–	0.04	–	0.08	–	0.09	–	0.10
Turnover	–	1.15	–	0.99	–	0.83	–	0.90

Table 4 presents a summary of our results using averages for each of the four treat-

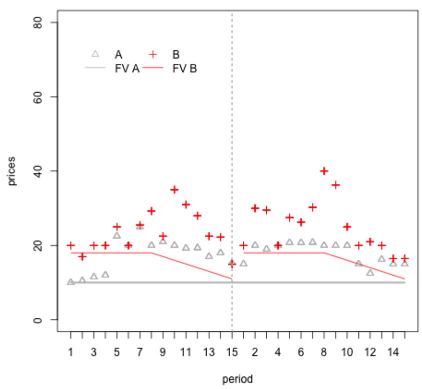
[16]Using a call market, Biais et al. (2017) find that the price of a risky asset is lower in an environment with aggregate risk than in an environment without such risk. In multiple asset markets, a risk-premium also appears under aggregate risk in Bossaerts and Plott (2004) and Bossaerts et al. (2007).



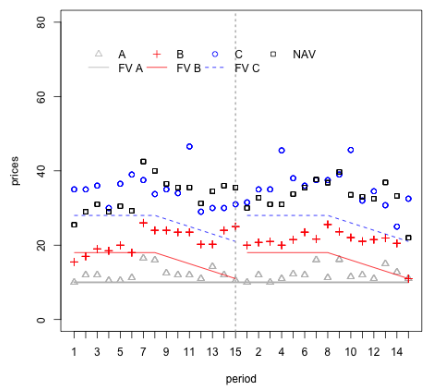
(a) treatment 2Z



(b) treatment 3Z



(c) treatment 2N



(d) treatment 3N

Figure 2: Median asset price per period for each treatment (5 sessions) and fundamental values. Each session contains two markets, each lasting 15 periods.

ments: $2Z$, $3Z$, $2N$, and $3N$.[17] To study market behavior, we employ the following measures: volatility, relative absolute deviation (RAD), relative deviation (RD), relative pricing (RAD B/A), asset turnover, relative absolute deviation from the NAV (RAD-NAV), and relative deviation from the NAV (RD-NAV). To measure the extent of mispricing, or the price deviation from the fundamental value, we follow Charness and Neugebauer (2019), and define the relative absolute deviation of each asset from

[17] Appendix B includes the measures presented in Table 4 for each second market across all sessions.

fundamental value as:

$$\text{RAD-FV}_j := \frac{1}{T}\sum_{t=1}^{T} |P_{j,t}/FV_{j,t} - 1|, \tag{4}$$

where T represents the total number of periods in which assets are transacted.[18] Our results do not significantly change when using a geometric average, as suggested by Powell (2016). We also consider a relative deviation measure, (5) which is same as RAD, but does not take the absolute value of the deviation. RD is useful in tests where the null hypothesis assumes zero differences across variables, and by design the RAD measure is always bounded away from zero.

$$\text{RD-FV}_j := \frac{1}{T}\sum_{t=1}^{T} P_{j,t}/FV_{j,t} - 1, \tag{5}$$

To account for multiple assets, we extend the RAD formula in equation (4) and assign weights according to the number of assets transacted relative to overall number of market transactions. Thus, the total relative absolute deviation is

$$\text{RAD-TOTAL} := \frac{1}{Q}\sum_{j=A}^{C}\sum_{t=1}^{T} |P_{j,t}/FV_{j,t} - 1| \times q_{j,t}, \tag{6}$$

where Q is the total number of market transactions across all assets, and $q_{j,t}$ is the quantity of asset j transacted in time t. If we divide Q by the total supply of assets, which differs across two and three asset markets, then we obtain our measure of asset turnover.

We also present the relative mispricing of assets A and B using a relative RAD B/A, which we define as

[18] We drop the periods in which there are no observations for a given asset from our calculations.

$$\text{RAD-B/A} := \frac{1}{T}\sum_{t=1}^{T}\left|\frac{P_t^B/P_t^A}{FV_t^B/FV_t^A} - 1\right|, \tag{7}$$

where T is the total number of periods with joint transactions of A and B. This is a measure of relative mispricing meant to capture the extent of relative deviation of each asset type relative to the other asset.[19] In the case of the ETF asset C, we measure how far it is priced from the NAV. We follow the definition above, and measure the price deviation with respect to NAV as

$$\text{RAD-NAV} := \frac{1}{T}\sum_{t=1}^{T}|P_t^C/NAV_t - 1|. \tag{8}$$

Similarly, we measure how far the ETF asset C is priced from its NAV using the RD measure (RD-NAV), which does not take the absolute value of the deviation.

Table 4 shows that in the negative correlation treatments, prices are closer to the fundamental value when there is an ETF asset ($3N$) compared to the case without an ETF asset ($2N$). For example, the volatility and RAD of asset B dramatically improves (from 7.21 in $2N$ to 2.25 in $3N$ and from 0.60 in $2N$ to 0.36 in $3N$ respectively, in the second market). On the other hand, in the zero correlation treatment, the introduction of the ETF asset is less helpful in terms of correctly pricing assets A, and B, and reducing volatility.[20]

The observed differences between the zero and negative correlation treatments are intuitive. When the correlation in dividends is negative, there is a greater demand for both assets in the $2N$ setting, in order to eliminate market risk. This increase in the

[19]The first paper that uses a similar relative mispricing measure is Fisher and Kelly (2000).

[20]RAD and volatility both capture dispersion. We favor the analysis of RAD since the call market results in a single market price, and by definition limits the volatility. We believe that the RAD is more relevant, since it evaluates the deviation with respect to the fundamental value. Nevertheless, for completeness we present a nonparametric analysis of volatility in Appendix B, which does not change the conclusions we draw from Table 4.

demand for individual assets moves prices away from their fundamental values. Once an ETF asset is introduced in $3N$, the demand for individual assets decreases. By contrast, in the zero correlation treatment, the role of the ETF asset is less evident for subjects, which explains why its effect is generally not significant in subsequent analysis. The measure of asset turnover, which tells us how active the market is, remains similar across all treatments.

Notice that in Table 4 there is little change in most measures for asset A between markets 1 and 2. However, for the negative correlation treatments, most measures of asset B are considerably lower in the second market relative to the first. Given that asset B is harder to price due to having a decreasing trend in its fundamental value following period eight, we need to allow for subject learning. For this reason, we will focus most of our subsequent analysis on the second market.

Lastly, the improvement in most measures reported in Table 4 for assets A and B, when asset C is introduced in the negative correlation treatment (where diversification is most salient) implies that the price of asset C should follow those of assets A and B. As we discuss further below, we find evidence that the law of one price holds, such that $P_C = NAV$.

In the subsequent paragraphs, with the help of parametric as well as non-parametric tests, we formalize our main findings, using data from the second market to control for possible learning effects. Our first finding, which addresses Hypothesis 1, is the following:

Result 1: *When asset dividends are negatively correlated, the price of asset A, and the relative price of asset B with respect to A are closer to the fundamental value in the market with an ETF asset than in a market without an ETF asset. In the zero correlation case there is no difference.*

For support, we follow equation (4) to compute the RAD for each asset and equation (7) to study the relative price dispersion with respect to fundamentals. The introduction of the ETF asset appears to affect only the asset with a constant fundamental value (A), and only in the negative correlation case where the ETF asset provides perfect diversification of market risk (p-value of 0.056). Similarly, the relative price of asset B with respect to A is closer to the fundamental value (p-value of 0.032) in the environment with negative correlation. There is also improvement in relative pricing B/A in the three asset environment (with an ETF) when the correlation between individual assets is negative, $3N$ versus $3Z$ (p-value of 0.095).

Table 5: Wilcoxon Test: RAD-FV (p-values)

	A			B			B/A			C
Market	2Z	3Z	2N	2Z	3Z	2N	2Z	3Z	2N	3Z
2Z										
3Z	=			=			=			
2N	> (0.056)	=		=	=		=	=		
3N	=	=	< (0.056)	=	=	=	=	< (0.095)	< (0.032)	=

Note: There are five observations per treatment, and we focus on the second market. To interpret the inequality sign, we read row v. column.

Complementary to the non-parametric analysis, we perform OLS regressions using our measures of RAD from equation (4), at the period level for each asset, as the dependent variable. That is, we do not aggregate the absolute deviation across periods in this analysis. Table 6 presents the results. As independent variables we include a set of dummies, Z, $Three$, and $Three \times Z$, which capture marginal effects of the different treatments. The intercept measures the effect of the baseline treatment $2N$.

We define our dummy variables as follows: (i) Z takes the value of one when the correlation of asset dividends is zero, and zero otherwise, and (ii) $Three$ takes the value of one when an ETF asset is traded in the market, and zero otherwise. Hence

Table 6: OLS regressions: RAD

	RAD-FV A		RAD-FV B		RAD-B/A		RAD-FV C	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Intercept	1.26^{***}	1.29^{***}	0.64^{***}	0.37^{*}	0.37^{***}	0.27^{**}	0.44^{***}	0.27
	(0.31)	(0.42)	(0.21)	(0.21)	(0.12)	(0.12)	(0.16)	(0.18)
Z	-0.84^{**}	-0.84^{**}	-0.30	-0.30	-0.21	-0.21	0.36	0.36
	(0.36)	(0.37)	(0.24)	(0.24)	(0.13)	(0.14)	(0.51)	(0.51)
$Three$	-0.82^{**}	-0.82^{**}	-0.25	-0.22	-0.21^{*}	-0.20^{*}	–	–
	(0.37)	(0.37)	(0.25)	(0.24)	(0.12)	(0.12)		
$Three \times Z$	1.12^{*}	1.12^{*}	0.73	0.69	0.41^{**}	0.38^{**}	–	–
	(0.64)	(0.64)	(0.46)	(0.53)	(0.17)	(0.17)		
Period	–	-0.00	–	0.04^{***}	–	0.01^{**}	–	0.02^{*}
		(0.03)		(0.01)		(0.01)		(0.01)
R^2	0.11	0.11	0.09	0.15	0.11	0.15	0.06	0.08
N	240	240	242	242	205	205	103	103

Note: Standard errors are clustered at the session level and computed via bootstrapping.
The number of observations varies across specifications given that each observation is at the period level for the second market. Therefore, a period with no transaction is reported as missing value.
$^{***}p \leq 0.01$, $^{**}p \leq 0.05$, $^{*}p \leq 0.1$

the coefficients Z and $Three$ capture the $2Z$ and $3N$ treatments, respectively. We also include an interaction term $Three \times Z$ which captures the effect of the $3Z$ treatment. To control for group effects, we cluster the standard errors by session, and compute via bootstrapping. The trend variable, $Period$ controls for time and learning.[21] For every asset, we present the specification with and without the time trend. In the last two specifications of Table 6, the interpretation of the intercept is different because the ETF asset C is traded only in the $3N$ and $3Z$ asset markets. Hence, for specifications (VII) and (VIII) the constant captures the baseline $3N$ treatment.

The negative sign on the coefficient of $Three$ in specifications (I)-(VI) indicates that RAD is smaller in $3N$ compared to $2N$. The difference is significant at the 5% level for asset A and at the 10% level for the relative price B/A. Specifically, the RAD for asset A is smaller by 82 percentage points in the $3N$ relative to $2N$.

[21] A time control variable cannot properly identify the effect of the change in fundamentals and learning in the experiment, as both are time dependent. Instead, we include interaction terms using a time trend with the dummies in Table 6 but none of these interactions are significant. For sake of brevity, we omit these interactions terms. Alternatively, we also ran a specification that includes a time dummy that captures the structural break in fundamental value at $t = 8$. The interaction terms of the time dummy with the regressors in Table 6 are also not significant.

We test the effect of the ETF asset on RAD within a zero correlation environment using a Wald test, where the null hypothesis states that the sum of coefficients for the $Three$ and $Three \times Z$ is equal to zero. In all specifications, we cannot reject that the RAD of individual assets in $3Z$ is equal to the RAD in $2Z$. One possible reason for the difference in the impact of the ETF between the zero and negative correlation environments is that in treatment $2N$, asset A is more severely mispriced (has a larger RAD) than in $2Z$ as revealed in Table 3 and in the significance of the Z coefficient in Table 5. (This is also true for a comparison between asset B in the $2N$ versus $2Z$ treatments but that difference is not significant). Thus, it seems that the benefit of the ETF asset in the N treatment is from the correction of mispricing of asset A.

For the ETF asset C, specifications (VII-VIII) do not show any important differences across treatments. The positive time trend coefficient ($Period$) captures the effect of the decreasing trend in the fundamental value of assets B and C, which complicates pricing behavior.

Table 7: Wilcoxon Test: RAD-TOTAL (p-values)

	2Z	3Z	2N
2Z			
3Z	=		
2N	> (0.095)	=	
3N	=	=	< (0.056)

Note: There are five observations per treatment, and we focus on the second market. To interpret the inequality sign, we read row v. column.

To study the overall mispricing relative to fundamentals we refer to equation (6). Consistent with our earlier results, we find that mispricing is smaller in $3N$ than in $2N$, with a p-value of 0.056 as indicated in Table 7. Thus, when the correlation between assets is negative ETFs help reduce the overall level of mispricing.

Result 2: *The ETF asset does not affect market activity, specifically asset turnover.*

To determine whether the ETF asset affects market activity, we compare our two-asset markets (without ETFs) and our three-asset markets (with ETFs) and use asset turnover as an indicator of market activity. The results are reported in Table 15, Appendix B. We define asset turnover as total assets transacted in the market divided by the total supply. Note that in our environment, the ETF asset represents a significant portion of market supply, or 50% of assets. We do not find any difference in the market activity across the two and three asset markets. This result is robust to extending the analysis to the number of bids and asks in the market.

Result 3a: *The price of the ETF asset C closely follows its net asset value.*

We test whether the price of the ETF asset is equal to the NAV using the relative deviation (RD) measure. In this case, RD is a more appropriate measure because RAD is constrained by the lower bound of zero, and thus a test using RAD would fail on the account of the definition of the measure. For each of the treatments, $3N$ and $3Z$, we cannot reject the null (p-value > 0.10) that the price of the ETF asset is equal to the NAV. This suggests that the law of one price holds, which requires that $P_C = NAV$. Further, we do not find any statistically significant difference in the market price of the ETF asset across the $3Z$ and $3N$ treatments.

We also analyze the effect of time and correlation in asset dividends on arbitrage. We look for evidence that price differences from NAV are arbitraged over time by regressing the difference between the price of the ETF asset and its NAV per period on time as well as the correlation between asset dividends in Table 8. The results suggest that in specification (I), there is no difference between the price of the ETF asset and

Table 8: OLS Regressions: P_C-NAV

	P_C-NAV (I)	P_C-NAV (II)
Intercept	3.824	5.178*
	(2.608)	(3.083)
Z	6.836	4.270
	(9.185)	(10.147)
Period	−0.231	−0.418*
	(0.213)	(0.221)
Period × Z	–	0.352
		(0.427)
R^2	0.04	0.07
N	103	103

Notes:
a. Standard errors are clustered at the session level and computed via bootstrapping.
b. Each observation is at the period level for the second market.

$^{***}p \leq 0.01$, $^{**}p \leq 0.05$, $^{*}p \leq 0.1$

its NAV in both the zero and negative correlation treatments. The *Period* variable, while not significant, has a negative sign which would suggest learning. Specification (II) allows further analysis with the addition of the interaction term $Period \times Z$. In this specification, the time trend coefficient, -0.418 is significantly negative (with a p-value of 0.059). This suggests that most of the arbitrage over time occurs in the negative correlation treatment. Thus, we can conclude that the ETF asset serves as an important a benchmark for price discovery.

Result 3b: *The bids across all assets, A, B, and C are more consistent with the no arbitrage condition in treatment $3N$ than in treatment $3Z$.*

We further consider whether there is any inconsistency between the (i) individual bids for the underlying assets, A and B, and the bids for the composite asset C, and (ii) individual asks for the underlying assets, A and B, and the asks for the composite asset C. Recall that the NAV of the ETF is computed as the sum of the prices of the underlying assets, see equation (2) and thus in equilibrium traders should set their bids/asks to follow this condition. We use individual bid data to measure the absolute difference between the sum of the bids (b) for assets A and B and the bids for asset C, as defined by:

$$\text{AD-BIDS} := \frac{1}{T \cdot N} \sum_{i=1}^{N} \sum_{t=1}^{T} |b_{it}^A + b_{it}^B - b_{it}^C|, \tag{9}$$

where T is the number of periods, and N the number of instances with joint bids for all three assets A, B and C. The same approach is used to measure the absolute difference between the sum of the asks for assets A and B and the asks for asset C (AD-ASKS).

Table 9: Bid and ask consistency in ETF markets (second market)

	AD: BIDS		Count (subjects)		AD: ASKS		Count (subjects)		AD: BIDS + ASKS		Count	
Market	3Z	3N	3Z	3N	3Z	3N	3Z	3N	3Z	3N	3Z	3N
I	5.43	4.76	38 (6)	6 (2)	7.13	6.43	12 (3)	7 (4)	5.84	5.66	50	13
II	9.46	3.97	21 (4)	19 (4)	31.5	4.76	5 (4)	27 (5)	13.70	4.43	26	46
III	7.46	3.06	24 (6)	16 (3)	7.56	–	4 (3)	0 (0)	7.47	3.06	28	16
IV	18.35	1.82	13 (6)	47 (6)	23.69	2.77	8 (3)	33 (4)	20.38	2.21	21	80
V	27.67	6.12	6 (3)	39 (3)	18.67	9.01	3 (1)	25 (2)	24.67	7.25	9	64
Mean	13.67	3.95	21 (5.0)	19 (3.6)	17.01	5.74	6.4 (2.8)	18.4 (3)	14.41	4.52	26.8	43.8

Table 9 reports on AD-BIDS, AD-ASKS and AD-BIDS + AD-ASKS along with counts of the number of instances of joint bids or asks for all three assets and the number of subjects making these joint asks or bids (in parentheses). Using a Wilcoxon test, we find that the absolute deviation of bids (left columns), asks (middle columns), and bids and asks (right columns) presented in Table 9, is smaller in the $3N$ treatment relative to the $3Z$ treatment, with a p-value of 0.016, 0.063, 0.016, respectively. Thus, consistent with the results reported in Table 8, arbitrage appears to be stronger in $3N$ than in $3Z$.

Result 4: *Risk averse investors hold more balanced portfolios in the negative correla-*

tion treatment.

We analyze how subjects diversify between assets A and B by constructing a measure of portfolio imbalance as the absolute difference between an individual's holdings of A and B divided by their total holdings of assets A and B.[22] In all markets the supply of asset A equals the supply of asset B (though the total supply of these assets depends on whether there is an ETF in the market), so the market portfolio should hold equal numbers of both assets. Our portfolio imbalance measure helps quantify how far an individual portfolio is from the market portfolio. Since holding a composite asset C is equivalent to holding one A and one B, when a subject adds asset C to her portfolio it increases the denominator in our imbalance measure by a count of two. If a subject does not hold any assets, which accounts for 13% of participants, we drop that subject from the database.[23] When the portfolio imbalance measure is zero, a subject holds the market portfolio, or equal units of assets A and B, while a value of one means that a subject's portfolio only consists of one asset, indicating extreme imbalance.

Table 10 summarizes the regression results of our analysis. All regressions use holdings at the end of the session, and compute the standard errors (clustered at the session level) using bootstrapping. To control for different correlations between asset dividends, we include a dummy variable Z, which takes the value of one when the asset dividends have zero correlation, and the value of zero otherwise. We find that on average the portfolio imbalance is 0.39 and is similar to the initial imbalance of 0.40. This suggests that subjects, on average, do not further diversify their portfolio relative to their initial endowment. The coefficient for Z is positive, but not statistically

[22] Though it may be reasonable to assume that risk averse investors prefer to hold more cash, in our environment cash holdings are affected by trading performance, and initial endowment. For completeness, we regress cash holdings on risk, and find no statistical significance.

[23] There is no significant difference in the number of boxes collected by the dropped players relative to other players in our bomb elicitation task.

significant.[24]

In order to estimate the effect of risk aversion on portfolio imbalance, we regress the individual portfolio imbalance measure on risk attitudes, as measured by the bomb elicitation task Crosetto and Filippin (2013).[25] The mean number of boxes collected is 35.83, which is below the risk-neutral benchmark of 50. The standard deviation of boxes collected is 16. We measure the *Risk* as the maximum number of boxes (100) minus the number of boxes collected. Thus risk aversion range is from 100, maximal risk aversion, to 0, maximal risk tolerance. Specification (II) shows that on average a subject who collects all boxes ($Risk = 0$) will have an imbalance of 0.603, and that risk aversion has a small but positive effect on the portfolio imbalance, at the 5% significance level.

Table 10: OLS Regressions: Portfolio Imbalance

	(I)	(II)	(III)
Intercept	0.385***	0.603***	0.781***
	(0.056)	(0.110)	(0.160)
Z	0.058	–	−0.342
	(0.080)		(0.211)
Risk (100−Boxes)		−0.003**	−0.006***
		(0.002)	(0.002)
Risk × Z		–	0.006**
			(0.003)
R^2	0.01	0.02	0.04
N	156	156	156

Notes:
a. Portfolio imbalance is measured as $|A - B|/(A + B + 2C)$.
b. The data focuses on the second market.
c. Standard errors are clustered at the session level and computed via bootstrapping.
$^{***}p \leq 0.01$, $^{**}p \leq 0.05$, $^{*}p \leq 0.1$

According to specification (III) in Table 10, where the intercept is now 0.781, higher

[24] Recall that subjects 1-6 have an initial imbalance of 0.6, while subjects 7-9 have an initial imbalance of zero, which results in an average imbalance, in a session, of 0.4. We also analyze how the player types change their imbalances, and find that subjects 1-3, who start with a larger endowment of A relative to B, do not change their portfolio imbalance. Subjects 4-6, who start with a larger endowment of B relative to A, improve the diversification of their portfolio by about 25%, which is offset by a higher portfolio imbalance by subjects 7-9, who begin the session with zero imbalance.

[25] We opted for this task for its simplicity, and ability to capture risk-premium.

risk aversion should decrease the imbalance in the negative correlation treatment. On the other hand, risk does not seem to play a role in the zero correlation treatment. The interaction between the Z treatment and the risk measure ($Z \times Risk$) results in a positive but small increase in the imbalance measure.

In Appendix D, we also classify trader behavior according to types (fundamental value trader, momentum trader, and rational speculator) closely following the framework of De Long et al. (1990), Haruvy and Noussair (2006), Haruvy et al. (2013), and Breaban and Noussair (2015). Overall, we find that all three trader types reported in the earlier literature, involving only single assets, are also present in our multiasset markets.

6 Conclusion

Exchange traded funds now comprise 35% of all equity trades in the United States and have been exponentially growing in popularity. Understanding whether and how such assets affect market measures such as prices and volatility is important for policymakers concerned with financial stability. In this paper, we have taken a first, small step toward addressing this question by exploring the trade of composite exchange traded funds in laboratory markets

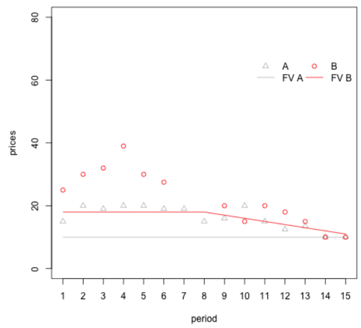
We find that for the most part, ETFs do not foster mispricing, nor reduce market activity. When the incentive for holding an ETF asset is especially salient, as in our negative correlation treatment where it provides perfect hedging, these composite assets actually reduce mispricing, by providing an important benchmark for price discovery. We also find that risk-averse traders prefer more balanced portfolios in our negative correlation treatment, and therefore providing an asset which facilitates holding the market portfolio may result in faster convergence to the largest Sharpe ratio.

We note that the SSW environment we adapt for our experiment is typically used to study asset pricing bubbles, and is known to be a *bubble-prone* environment. Thus, our finding that ETF assets are not destabilizing in the SSW environment suggests, *a fortiori*, that ETFs will not be destabilizing in more realistic, less bubble-prone environments, e.g., those without finite horizons and declining fundamental values.

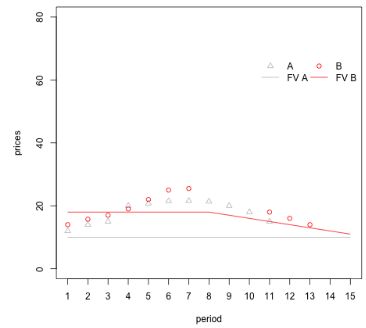
Our experimental design focuses on how participants react to two distinct environments, without and with ETFs. The former offers a counterfactual, which is impossible to observe in field data, while the latter introduces an ETF which covers the market.[26] As our study is the first to examine tradeable composite assets in laboratory asset markets, we have made a number of simplifying assumptions that should be relaxed. For instance, our markets with and without ETF assets make use of a simple call market environment, where the composite asset completely covers the market. In current research we study continuous-time trading, which seems to improve opportunities for arbitrage and we further consider ETFs that do not cover the market or are not representative of market capitalizations. We also study ETFs in a CAPM environment, similar to Bossaerts et al., 2007. These projects, currently in progress, will improve our understanding of how ETFs affect diversification strategies and contribute to a lower market risk premium. Lastly, it is of interest to study the role of Authorized Participants (AP) who facilitate the creation and redemption of ETF assets. As noted, our focus in this paper is on secondary markets, and in the environment without ETFs, there would be no role for APs to play. Thus if we added APs, it would not be so easy to compare the ETF and no ETF environments. Still we plan to address the role of APs in primary markets for ETF assets in future research.

[26]Most of the ETFs in real markets are composed of equities which seek to track large cap indices, sector indices or other indices. According to the *Wall Street Journal*, bond ETFs, have passed 1 trillion in assets in July 2019, a market that did not exist 20 years ago (https://www.wsj.com/articles/bond-exchange-traded-funds-pass-1-trillion-in-assets-11561986396).

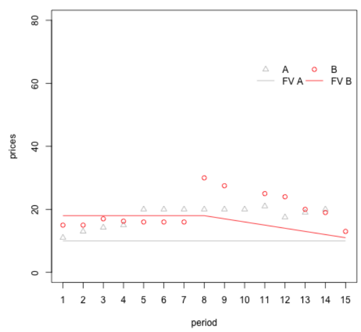
Appendix A: Price plots for each session



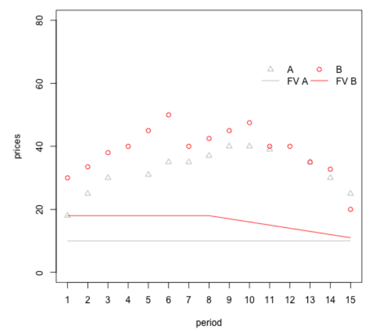
(a) Session 1



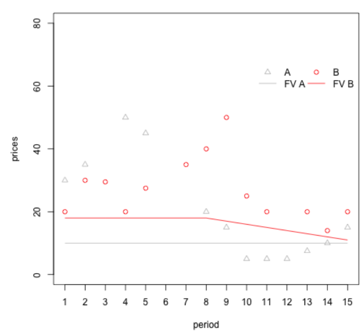
(b) Session 2



(c) Session 3

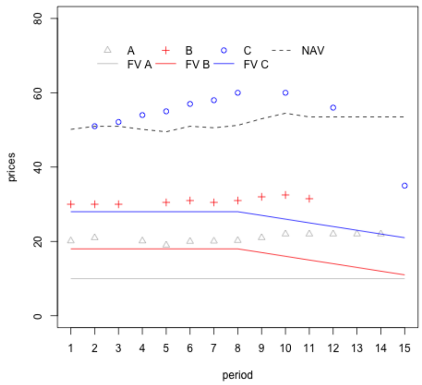


(d) Session 4

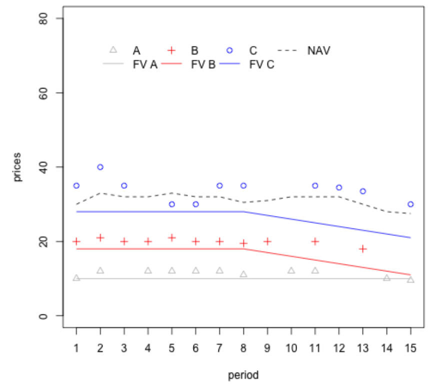


(e) Session 5

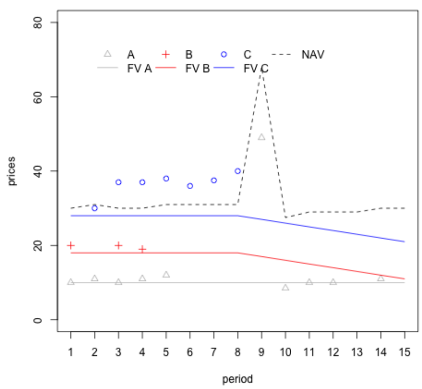
Figure 3: Asset prices and fundamental values per period for treatment $2N$ in the second market.



(a) Session 1



(b) Session 2



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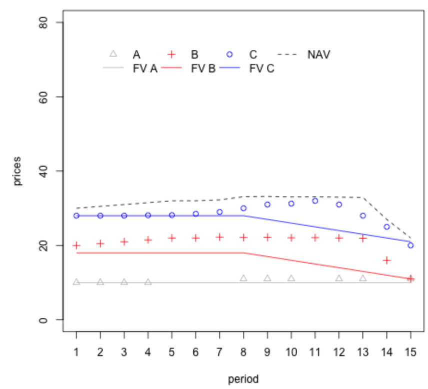
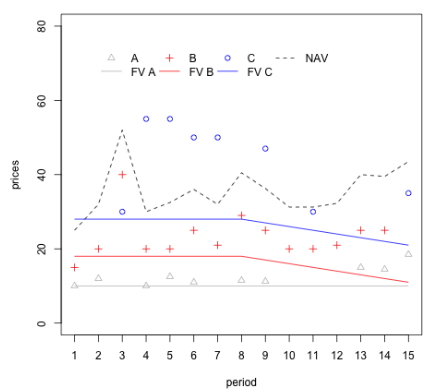
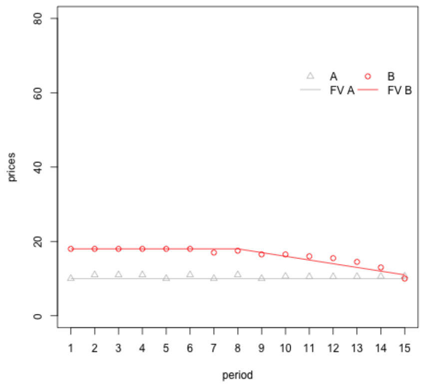


(d) Session 4

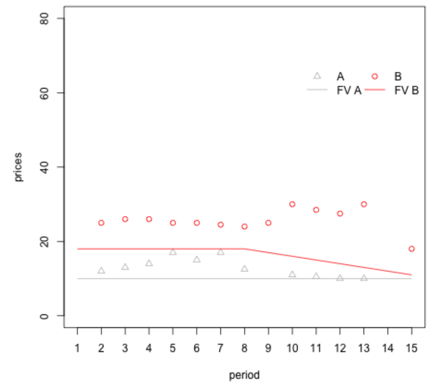


(e) Session 5

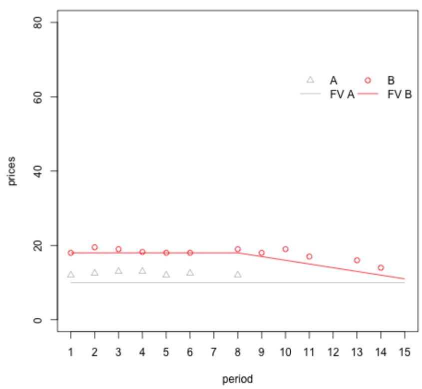
Figure 4: Asset prices and fundamental values per period for treatment 3N in the second market.



(a) Session 1



(b) Session 2



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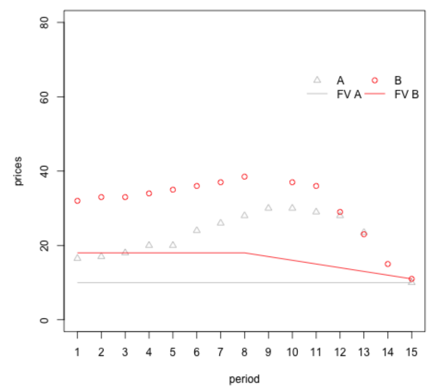
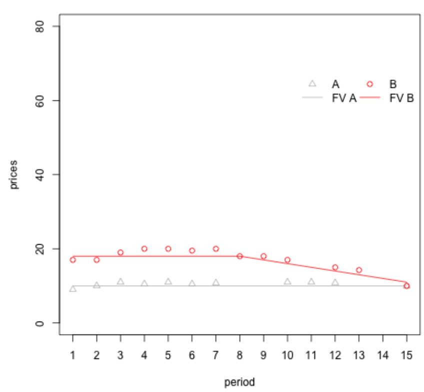
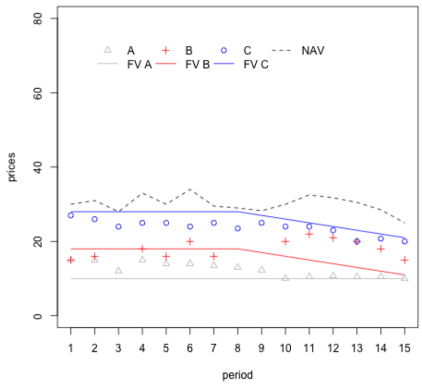


(d) Session 4

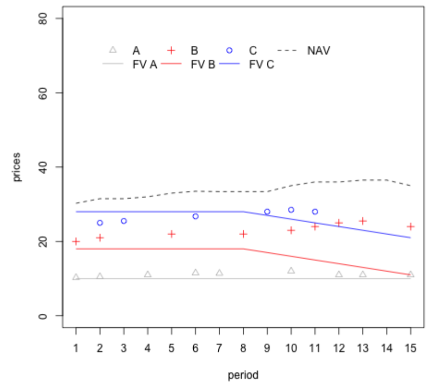


(e) Session 5

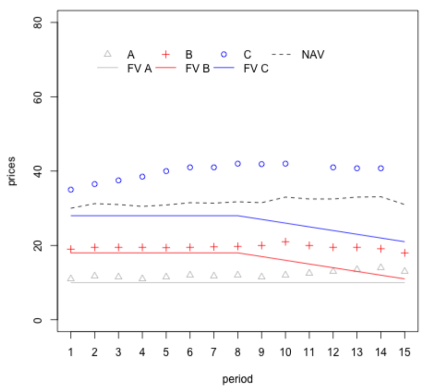
Figure 5: Asset prices and fundamental values per period for treatment 2Z in the second market.



(a) Session 1



(b) Session 2



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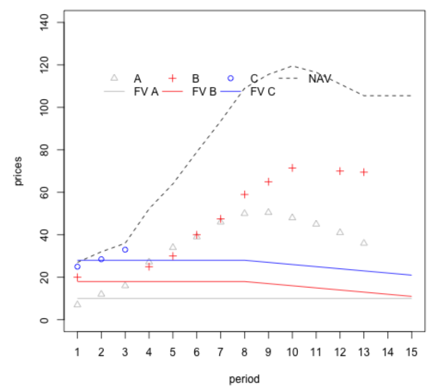
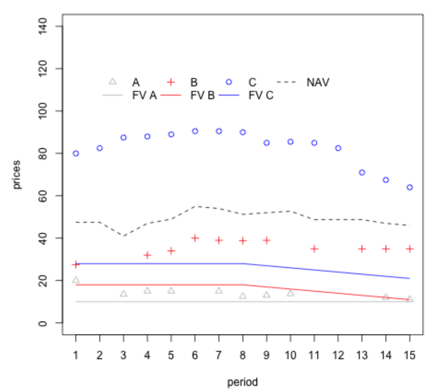


(d) Session 4



(e) Session 5

Figure 6: Asset prices and fundamental values per period for treatment $3Z$ in the second market.

Appendix B: Volatility and Market level data for the second market

Table 11: Wilcoxon Test: volatility (p-values)

	A			B			C
Market	2Z	3Z	2N	2Z	3Z	2N	3Z
2Z							
3Z	=			=			
2N	$>$ (0.056)	$>$ (0.095)		$>$ (0.056)	=		
3N	=	=	$<$ (0.095)	=	=	$<$ (0.032)	=

Note: There are five observations per treatment, and we focus on the second market. To interpret the inequality sign, we read row v. column.

Table 12: RAD A, B and C assets

	A				B				B/A				C	
Market	2Z	3Z	2N	3N	2Z	3Z	2N	3N	2Z	3Z	2N	3N	3Z	3N
I	0.06	0.24	0.63	1.09	0.04	0.27	0.42	0.79	0.06	0.37	0.16	0.13	0.09	1.01
II	0.29	0.11	0.81	0.14	0.61	0.52	0.19	0.17	0.42	0.46	0.36	0.06	0.08	0.30
III	0.24	0.21	0.79	0.46	0.08	0.24	0.34	0.09	0.17	0.09	0.31	0.09	0.51	0.30
IV	1.29	2.52	2.23	.06	0.88	2.09	1.41	0.28	0.14	0.38	0.25	0.22	0.10	0.10
V	0.07	0.41	1.90	0.26	0.07	1.29	0.66	0.46	0.04	0.74	0.81	0.24	2.16	0.65
Mean	0.39	0.70	1.27	0.40	0.34	0.88	0.60	0.36	0.17	0.41	0.30	0.15	0.59	0.47

Note: RAD-FV $:= \frac{1}{T}\sum_{i=1}^{T}|P_i/FV_i - 1|$ and RAD-B/A $:= \frac{1}{T}\sum_{i=1}^{T}|\frac{P_i^B/FV_i^B}{P_i^A/FV_i^A} - 1|$

Table 13: RD A, B and C assets

	A				B				C	
Market	2Z	3Z	2N	3N	2Z	3Z	2N	3N	3Z	3N
I	0.06	0.24	0.63	1.09	0.01	0.19	0.37	0.78	-0.09	1.01
II	0.29	0.11	0.81	0.13	0.61	0.52	0.11	0.17	0.00	0.30
III	0.24	0.21	0.79	0.43	0.08	0.24	0.22	0.09	0.51	0.30
IV	1.29	2.47	2.23	0.06	0.88	2.09	1.41	0.28	0.03	0.09
V	0.05	0.41	1.63	0.26	0.04	1.29	0.66	0.44	2.16	0.65
Mean	0.39	0.69	1.21	0.39	0.32	0.87	0.55	0.35	0.52	0.47

Note: RD-FV $:= \frac{1}{T}\sum_{i=1}^{T} P_i/FV_i - 1$

Table 14: RAD Total Assets

Market	2Z	3Z	2N	3N
I	0.05	0.19	0.62	0.92
II	0.42	0.19	0.53	0.20
III	0.11	0.28	0.55	0.51
IV	1.06	1.62	1.84	0.15
V	0.07	1.42	1.01	0.48
Mean	0.34	0.74	0.91	0.45

Table 15: Turnover A, B and C assets

	A				B				C	
Market	2Z	3Z	2N	3N	2Z	3Z	2N	3N	3Z	3N
I	4.15	3.43	1.97	1.47	2.12	1.77	0.10	1.47	1.63	0.60
II	0.93	0.70	0.97	1.13	1.00	0.40	0.83	0.73	0.47	1.00
III	0.30	1.60	1.63	1.27	0.77	1.70	1.57	0.30	1.07	0.83
IV	1.27	1.23	0.97	137	1.12	0.80	0.77	1.67	0.33	1.47
V	0.73	0.40	0.72	0.47	0.95	0.63	0.75	1.37	0.63	0.60
Mean	1.48	1.48	1.25	1.14	1.19	1.06	0.99	1.11	0.83	0.90

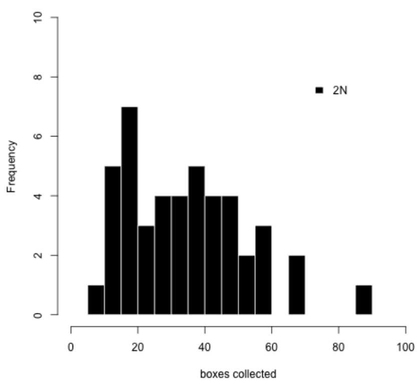
Note: Turnover is measured as total assets transacted divided by the total supply.

Table 16: C - NAV

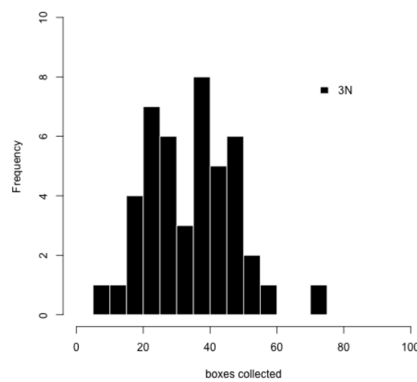
	Amplitude		RAD		RD	
Market	3Z	3N	3Z	3N	3Z	3N
I	0.03	1.10	0.21	0.11	-0.20	0.04
II	0.10	0.40	0.20	0.11	-0.19	0.09
III	0.22	0.40	0.26	0.20	0.26	0.19
IV	0.61	0.07	0.09	0.09	-0.09	-0.09
V	1.14	1.88	0.69	0.43	0.69	0.26
Mean	0.36	0.79	0.29	0.19	0.09	0.10

Appendix C: Risk elicitation responses

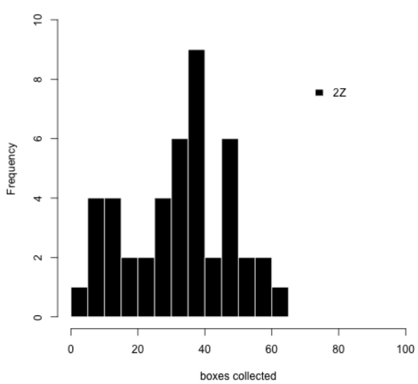
We elicited risk attitudes following the protocol of Crosetto and Filippin (2013) and implemented in oTree (Holzmeister and Pfurtscheller, 2016). The median number of boxes collected in treatments $2Z$, $3Z$, $2N$, and $3N$ are 35, 40, 35 and 36, respectively. Using the Wilcoxon test, we cannot reject that the distribution of boxes collected is equal across treatments, which implies that there are no differences in subjects' risk attitudes across treatments. Figure 7 shows frequency distributions of the number of boxes collected in all four treatments.



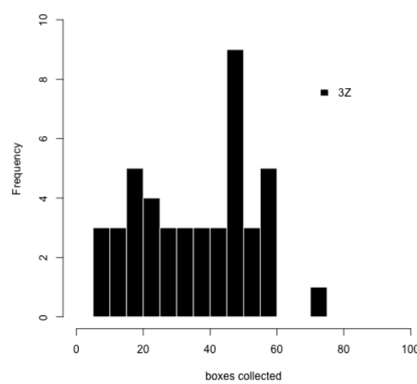
(a) treatment 2N



(b) treatment 3N



(c) treatment 2Z



(d) treatment 3Z

Figure 7: Histogram of the risk elicitation task across treatments.

Appendix D: Trader behavior

We classify trader behavior according to three types, (i) fundamental value trader, (ii) momentum trader, and (iii) rational speculator closely following the framework of Haruvy and Noussair (2006), Haruvy et al. (2013), and Breaban and Noussair (2015). An individual's behavior is defined as consistent with the fundamental value trader type at period t if $s_{i,t} < s_{i,t-1}$ when $p_t > f_t$, where p_t is the price, f is the fundamental value and $s_{i,t}$ is the number of assets that individual i holds in period t. This means that when asset prices rise above the fundamental value, trader i is a net seller. Similarly, if asset prices go below fundamental value, then trader i will be a net buyer. Trader behavior is consistent with being a momentum trader if $s_{i,t} < s_{i,t-1}$ when $p_{t-1} < p_{t-2}$. Similarly, if $p_{t-1} > p_{t-2}$ then $s_{i,t} > s_{i,t-1}$. A momentum trader is a net buyer in period t when there is an increasing price trend over the last two periods, and a net seller when there is a decreasing price trend. Lastly, trader behavior is defined as consistent with the rational speculator trader type if $s_{i,t} < s_{i,t-1}$ when $p_{t+1} < p_t$. Likewise, if $p_{t+1} > p_t$ then $s_{i,t} > s_{i,t-1}$. A rational speculator is assumed to anticipate next period's price in an unbiased manner, and makes positive net purchases when the price is about to increase and positive net sales when the price is about to decrease.

To classify a subject as a type, we first count the number of periods for each asset when subject behavior is consistent with a particular type. We then sum across these counts to determine which trading behavior the subject follows most often per asset. Finally, in order to classify subject behavior according to one of the three aforementioned types, we require that a subject behaves as a particular type for at least two of the three assets.[27] We present these results in Table 17. In the case where there is no dominant behavior, the subject is classified as a combination of two or three types, which we display in the last four rows of Table 17.

[27] This construction allows comparisons across treatments with two and three asset markets.

Table 17: Proportion of trader types

Type	2Z	3Z	2N	3N
Fundamental	0.09	0.22	0.18	0.29
Momentum	0.13	0.13	0.09	0.18
Rational Speculator	0.18	0.38	0.20	0.20
Fundamental & Momentum	0.22	0.00	0.11	0.02
Fundamental & Rational Speculator	0.13	0.07	0.24	0.02
Momentum & Rational Speculator	0.20	0.13	0.11	0.20
All 3 types	0.04	0.07	0.07	0.09

Overall, we find that all three types reported in the earlier literature, involving only single assets, are also present in our multi-asset markets. The frequency of these trading strategies also varies, potentially in response to the environment. For example, the proportion of traders who follow the fundamental strategy for buying and selling is 0.22 in the $3Z$ treatment and 0.29 in the $3N$ treatment.

7 Acknowledgements

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