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How Does Passive Investing Effect the Informational Efficiency of Prices?

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Comments

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How Does Passive Investing Effect the Informational Efficiency of Prices?*

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Abstract

We investigate the causal effects of passive investing on informational efficiency and market quality metrics by developing a novel laboratory experiment that introduces Index trackers with exogenous passive investment flows. We find that, while improving liquidity, Index tracking hurts informational efficiency, confirming our main hypothesis. Furthermore, we observe violations of the law of one price, leading to widespread and persistent arbitrage opportunities. Additionally, our research uncovers that Active traders, particularly those with private information about asset values and high cognitive ability, reap benefits from the introduction of Index tracking.

Keywords: Passive Trading, Index Tracking Experimental Markets, Informational Efficiency.

JEL Classification: C92, G12, G14, G41.

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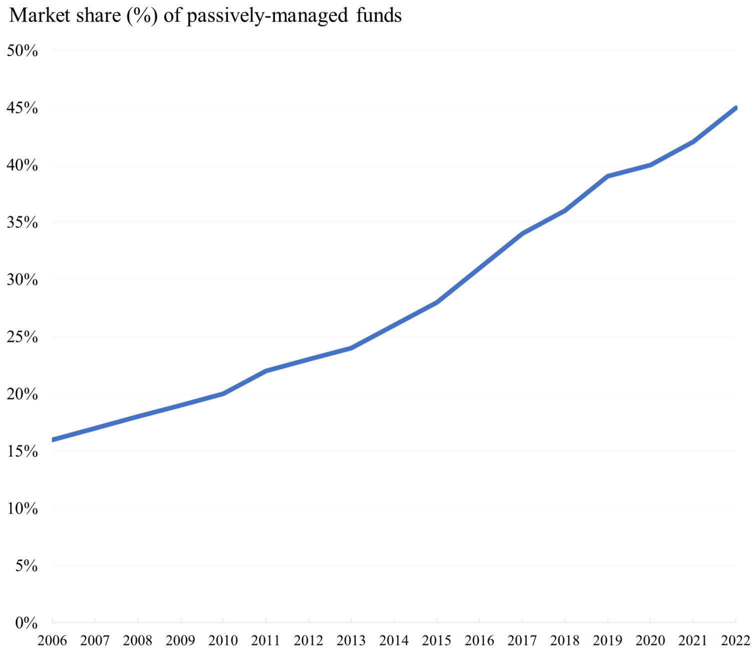
1 Introduction

The passive fund management strategy of index tracking is typically characterized as buying securities that mirror stock market indexes and holding them long-term (Sushko and Turner, 2018). This strategy emerged in the 1970s with the first index funds for individual investors (see Wigglesworth (2021) for a review), responding to the emergence of the Capital Asset Pricing Model (CAPM) (French, 2003; Sharpe, 1964; Lintner, 1965) that shows investors cannot do better than holding the market portfolio. Specifically, in 1976, John C. Bogle, the then-CEO of Vanguard, created the Vanguard 500 Index. This index mirrored the SP 500 and allowed thousands of regular investors to have a stake in the biggest companies in the market without incurring the cost of buying the shares individually. From this humble beginning, the market share of passively managed funds in US equity markets has tripled from 16% in 2006 to 45% in 2022 (see Kerzérho (2018), Kerzérho (2023), and Figure 1(b)).[1] Indeed, the exit from active to passive funds has accelerated since 2013 (Sushko and Turner, 2018), as seen in Figure 1(a).

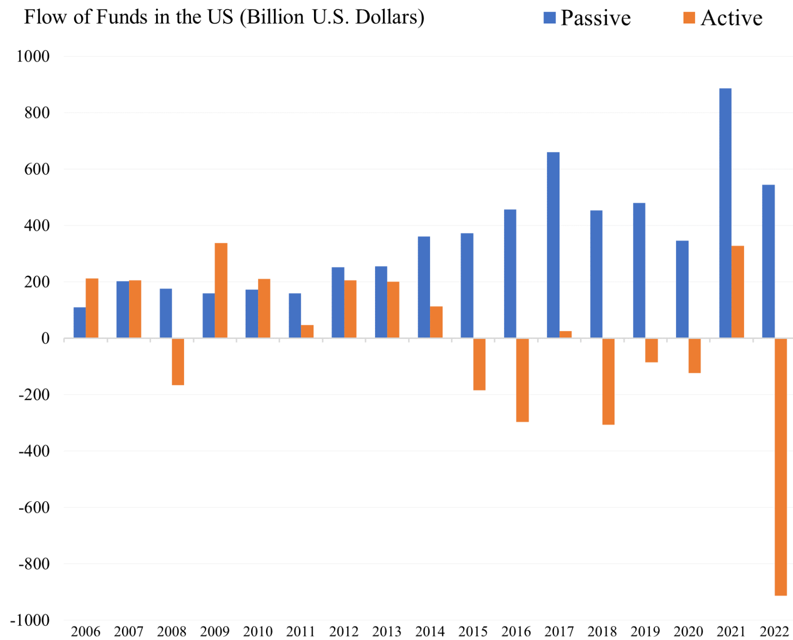
The massive inflow of funds to passive management would be no surprise to Bill Sharpe, who noted in Sharpe (1991) on page 7 that, "after costs, the return on the average actively managed dollar will be less than the return on the average passively managed dollar." Thus, money should find its way to passive funds. Many investors have long touted the buy-and-hold passive strategy of investing. Indeed, an internal performance review of Fidelity accounts between 2003 and 2013 found that the best investors were either dead or inactive, i.e., people who did not trade but just held stock.[2] More recently, Warren Buffett officially won his bet against actively managed funds (Wigglesworth, 2021). The wager asserted that an index fund would outperform a hand-picked portfolio of hedge funds over a 10-year period, taking fees into account. Given the obvious benefits of passive fund management, the natural, and empirically pertinent question is: if everyone places their money in a passive fund, how is price determined? And, does an increase in passive fund management affect price discovery? In a 2022 Wall Street Journal (WSJ) interview with Burton Malkiel, he was asked:

[1]The share of passive investing was only 3% in 1995 (Anadu et al., 2020).

[2]`https://theconservativeincomeinvestor.com/fidelitys-best-investors-are-dead/`.



(a) Percentage of Managed Funds that are Passive



(b) Net Flows into Passive and Active Funds

Figure 1: Increase in the share of passive funds and in the net flows into passive funds between 2006 and 2022 (based on exchange-traded funds and mutual funds data in the US reported in Kerzérho (2018) and Kerzérho (2023))

> *Let's talk about the social cost of indexing. Indexing succeeds by free-riding on the costly research and price-finding activities of active investors. What if everybody did it? Would we even have a stock market? How would we allocate capital? Doesn't indexing reward mediocrity and excellence equally?*

Professor Malkiel responded,

> *We don't have too much indexing; we have too much active management. I think the market could function fine with just 2% or 3% of investors being active and making sure that information was reflected properly in prices.*[3]

Recently, though, academics and practitioners have expressed concerns regarding the unprecedented increase in the share of passive fund management (Wigglesworth, 2022), which is seen as threatening the informational efficiency of markets (Breugem and Buss, 2018; Anadu et al., 2020; Bond and García, 2022; Gârleanu and Pedersen, 2022).[4] Echoing these concerns, our paper asks the following research question: what is the impact of passive fund management, specifically index tracking, on the informational efficiency of markets?

Passively managed funds that track an index impair the informativeness of prices because their transactions are largely insensitive to prices and do not reflect private information. The negative impact of passive fund management on informational efficiency is especially critical because index tracking is motivated by the CAPM, which assumes markets are informationally efficient.[5] Indeed, Biais, Bossaerts, and Spatt (2010) show that indexing is not optimal in a context in which the rational expectations equilibrium only partially reveals private information. This conundrum was highlighted in a series of early publications and recently captured by Shiller (2017): "So people say, 'I'm not going to try to beat the market. The market is all-knowing.' But how in the world can the market be all-knowing, if nobody is trying – well, not as many people – are trying to beat it?"

To tackle this question, we opt for an experimental approach in which we can directly manipulate the share of funds under passive management, precisely track the market portfolio (Roll, 1977) and assess the informational efficiency of asset prices (Frydman et al., 2014). To do this, subjects in the experiment assume the role of either an Index tracker or an Active trader. We compare three treatments that vary the proportion of Index trackers, who are incentivized in the same manner as index fund managers in the field. Specifically, in the

[3] Washington Post article available at `https://rb.gy/fx2it`.

[4] Governance issues related to the concentration of ownership (e.g., Heath et al. (2021)) are also often mentioned. Yet, our focus is on price discovery, which is impacted by passive investing regardless of the structure of ownership of publicly-own companies.

[5] Fama and French (2007) note that in a general CAPM model with informed and misinformed investors, informationally efficient prices ensure that standard CAPM predictions hold.

field these fund managers create portfolios that mirror the makeup of their target index by deploying exogenous inflows such that their portfolio is proportional to that of the index (thus minimizing the needed amount of cash in the fund). Their fees are based on the value of assets under management so they want to buy portfolio assets at the lowest price they can trade. In our experiment, Index trackers are rewarded for each bundle of shares they hold at the end of the period that matches the index portfolio. Thus, they are rewarded for tracking the index, and they want to make as many of these bundles as they can. In our experiment Active traders, who are rewarded solely on the value of their final portfolio, come in two flavors: informed and uninformed. Informed Active traders are endowed with a private signal regarding the true asset value, whereas uninformed Active traders are not. Our Baseline experiments have no Index trackers, reflecting a market structure reminiscent of the 1970s. In our other two treatments, we replace uninformed traders with Index tracking traders. This maintains the volume of private information available in a market, as well as the amount of cash and shares across treatments. In our *4I* treatment, 17% (four of 24) of the traders are Index trackers, while in our *9I* treatment 38% (nine of 24) are in this role.[6] These percentages respectively mirror the market conditions from 15 years ago and those in recent years (see Figure 1(b)).

We find that when the amount of cash and shares devoted to index tracking is sufficiently large (38%), the informational efficiency of the market declines. Specifically, there is no statistical difference in the informational efficiency of the Baseline and the 4I treatment, but the latter is statistically significantly lower than the 9I treatment. We also find that this type of passive trading with positive net flows of cash is inflationary regardless of the asset's true value. Furthermore, we find index tracking leads to violations of the law of one price and to an increase in arbitrage opportunities. However, when viewed through the traditional lens that evaluates informational efficiency using commonly-used proxies, we find that index trading significantly improves market quality. In particular, bid-ask spreads shrink and trading volumes increase, while volatility is not significantly impacted. From an individual trader's perspective, we find that Active traders benefit from the introduction of Index tracking as their trading earnings increase. Furthermore, Active traders who possess accurate private information and high levels of cognitive ability benefit the most from the presence of index tracking funds. This is the case because, as index trading increases, the informational efficiency of prices decreases, leading to an increase in the value of private information and the ability to extract information from noisy prices.

[6] All traders in our experiments are endowed with portfolios of equal expected value, thus the percentage of traders that are Index trackers is equivalent to the percentage of the expected value of the aggregate endowment assigned to the Index trackers.

2 Literature review on passive investing

2.1 Theory

Grossman and Stiglitz (1980) showed that markets cannot be fully efficient in the sense of Fama (1970) whenever information acquisition is costly. This is the case because efficient markets are such that the private return on information acquisition is zero thus not compensating for the cost. In a competitive equilibrium, trading can only occur if markets are not fully efficient so that private information cannot be perfectly inferred from prices (Verrecchia (1982)). This noisy inference characterizes noisy rational expectation equilibria and is a necessary condition for avoiding the no-trade theorem (Milgrom and Stokey (1982)). Baruch and Zhang (2022) developed a conditional CAPM theory in which some investors are passive index traders. They show that asset prices become less informative as more Active traders become passive index traders.

However, passive investors might also increase informational efficiency as they alleviate the no-trade problem and induce a positive return on information acquisition. Indeed, the presence of passive investors who neglect the informational content of prices ensures informed traders will earn a positive return from trading on their private information. In sum, the presence of passive investors can reduce adverse selection issues and increase trading volumes, thus improving informational efficiency. Furthermore, prominent scholars have put forth that even a minimal level of competing active investors would be sufficient to maintain the informational efficiency of markets (Fama and French (2009); Coles, Heath, and Ringgenberg (2022); Malkiel (2022)). As expressed by Fama and French (2009): "If misinformed and uninformed active investors (who make prices less efficient) turn passive, the efficiency of prices improves. If some informed active investors turn passive, prices tend to become less efficient. But the effect can be small if there is sufficient competition among remaining informed active investors." Furthermore, active misinformed and biased investors who turn passive will ultimately improve the informational efficiency of markets (Fama and French (2007)). Extending the model of Grossman and Stiglitz (1980) to introduce passive index investors along with privately- and publicly-informed active investors, Coles, Heath, and Ringgenberg (2022) show that an increase in the proportion of passive investors does not impact informational efficiency. However, Haddad, Huebner, and Loualiche (2021) emphasize that the increased competition among active investors may be insufficient to counter the impact of the increase in passive investing. These diverging predictions reflect the need for an empirical investigation of the impact of passive investing in markets.

Using US stock market data from 2000 to 2016, they estimate that the share of active investors decreased from 78% to 58% leading to a decrease in the price elasticity of demand of 15%. These results suggest markets are not sufficiently competitive to offset the impact of a large increase in Index tracking.

2.2 Empirical methods

2.2.1 Archival studies

To date, empirical studies have used archival data to estimate the impact of passive trading on various market quality metrics. This is no easy task because researchers need to find proxies for passive investing. As pointed out by Wigglesworth (2022), there is no consensus on the exact share of passive investment in markets. The rapid growth of exchange-traded funds (ETF) (Ben-David, Franzoni, and Moussawi (2017); Lettau and Madhavan (2018)) that are characterized by a large variety of strategies including both passive and active investing (Easley et al. (2021); Huang, O'Hara, and Zhong (2021)) has made it increasingly difficult to identify with certainty the magnitude of passive investing. Although experts tend to agree that passive investing has been increasing substantially in the last ten years (Ben-David, Franzoni, and Moussawi (2017); Haddad, Huebner, and Loualiche (2021); Wigglesworth (2022)), estimates can vary in the ratio of one to two (Chinco and Sammon (2022)).[7] It follows that using ETFs ownership of a stock as a proxy for passive investing can be misleading. This might explain why the empirical literature has reported mixed results on the impact of ETF ownership on informational efficiency (see Hasbrouck (2003); Marshall, Nguyen, and Visaltanachoti (2013); Ben-David, Franzoni, and Moussawi (2017); Israeli, Lee, and Sridharan (2017); Glosten, Nallareddy, and Zou (2021)). Relatedly, Boehmer and Kelley (2009) show that institutional ownership improves informational efficiency even when it is associated with passive, liquidity-providing, strategies. In addition to measurement issues, a limitation of the previous literature is that it focuses on correlational evidence and does not assess the causal impact of passive investing.

In the indexing literature, researchers have dealt with causality issues by comparing indexed and non-indexed stocks of similar characteristics. For example, Qin and Singal (2015) use a sample of stocks that are listed on the S&P 500 index and compared with non-S&P 500 stocks with comparable size and turnover ratios. They find that prices are less informationally efficient for listed stocks, where price efficiency is measured by the magnitude of post-earnings-announcement drift or by deviations of prices from a random walk benchmark.

[7] One exception is Easley et al. (2021) who argue that passive investing has increased only slightly.

Recent papers on index investing (e.g., Ben-David, Franzoni, and Moussawi (2018); Ahn and Patatoukas (2022); Coles, Heath, and Ringgenberg (2022)) have also estimated the causal impact of passive investing using FTSE Russell's index reconstitution as a source of exogenous variation in index investing. The Russell Index ranks 4,000 eligible stocks according to market-cap. Companies are ranked in various categories using preset cutoffs (1,000, 2,000 and 3,000) so that stocks ranked around cutoffs points are classified in different Russell indices despite having a similar market-cap. Ahn and Patatoukas (2022) show that micro-cap stocks added to the small-cap index are characterized by increased index investing and a swifter incorporation of public news, which they attribute to increased liquidity. However, they do not report any effect of index investing for larger market-cap stocks in line with Coles, Heath, and Ringgenberg (2022).

The existing empirical literature thus reports mixed effects regarding the impact of passive investing on the informational efficiency of markets. This could be due to persistent methodological issues related to using inaccurate proxies for measuring both the dependent variable (informational efficiency) and the independent variable (passive investing). Although archival data can be used to study price discovery and weak-form price efficiency, assessing strong-form efficiency (Fama (1970)) remains elusive because private information is not directly observed. Furthermore, the joint hypothesis problem (Fama (2014)) implies that market efficiency is always tested along with a model of market equilibrium so that empirical tests cannot falsify the efficient market hypothesis. The study of passive trading using archival data is also constrained by Roll's critique, which highlights the impossibility of observing the market portfolio (Roll (1977)). Finally, despite extensive sensitivity checks, empirical studies of the impact of passive investing are not exempt of potential selection biases given the lack of randomized assignment (see e.g., Wei and Young (forthcoming)).

2.2.2 Experimental approach

A series of papers in the experimental literature has focused on how people allocate money between mutual funds, highlighting numerous anomalies in fund choices such as neglecting differences in volatilities (Ehm, Kaufmann, and Weber (2014); Heuer, Merkle, and Weber (2017)) and fees (Choi, Laibson, and Madrian (2010); Anufriev et al. (2019)). However, these studies focus on individual investment decisions in the absence of financial markets.

The experimental market literature on index investing is remarkably scant. Duffy, Rabanal, and Rud (2021) and Duffy et al. (2022) are the only studies we are aware of that introduce index investing in experimental markets. In Duffy, Rabanal, and Rud (2021), the authors adopt a standard environment in which an asset - there are two assets in their markets - lives for multiple periods, has a declining fundamental value and there is only public information, as introduced by Smith, Suchanek, and Williams (1988). They introduce an index, which is a portfolio composed of one unit of each of the two assets traded in the market. They find that allowing market participants to trade the index tends to lower mispricing while not affecting trading volumes. In Duffy et al. (2022), they consider a collection of Arrow-Debreu state contingent assets and an additional market for an index. There is no asymmetric information, as traders are only informed of the prior distribution of the potential states. One of their treatment variables is the composition of the index, does it include all of the assets or not. This enabled them to demonstrate that included assets trade at a premium. These papers highlight the value of indexing for individual stocks but set aside the question of how indexing impacts the informational efficiency of markets. By contrast, our research question centers on the impact of passive trading on information aggregation.

3 Hypotheses

3.1 Our study

Building on the previous literature, we develop the first study of the impact of index tracking on the informational efficiency of experimental markets. Given our focus on market informational efficiency, we employed a setup in which traders possessed private information about the value of the asset, extending the original Plott and Sunder (1988) design to the case of two assets (X and Y). In this environment, there are only three states of the world, with different asset values in each state. In our baseline treatment, we have informed traders who together hold information that would reveal the true state. Along with these informed traders, there are uninformed traders who only know the prior distribution of states. In our experimental treatments, *4 Index* and *9 Index* (hereafter 4I and 9I), we replace four and nine, respectively, of the uninformed traders in the baseline with index traders who make earnings by creating bundles of units of X and Y based on the outstanding stocks of each asset.

The values of the two assets are perfectly correlated; however, one asset (X) has twice the value of the other (Y) across all states. We chose this design because the information aggregation outcome is clear, and the experiment is easy to understand for subjects. We used the perfect correlation and value differences to allow for clear arbitrage measures across the markets. Perfect correlation across assets' valuation streams also ensures that diversification is ineffective in our setup. This allows us to isolate the impact of passive trading from that of diversification. Charness and Neugebauer (2019) and Neugebauer, Shachat, and Szymczak

(2023) also show that the perfect correlation case is one in which the law of one price holds for average prices. This is an appealing feature for our baseline treatment. We design the incentive structure of Index trackers so that it is insensitive to fundamental asset values, thus capturing an essential feature of passive trading (see Haddad, Huebner, and Loualiche (2021)).[8] This allows us to study the impact of the market activity of Index trackers on the informational efficiency of prices while abstracting away from the institutional features of mutual funds and ETFs.

3.2 Hypothesis development

In our setup, we focus on the impact of passive investing defined as price-insensitive trading (see Haddad, Huebner, and Loualiche (2021)). Index trackers are rewarded for tracking the market portfolio by acquiring shares in proportion to the market weight of each asset. They are not rewarded for speculative gains achieved during training. Therefore, Index trackers have no incentive to use public or private information when posting orders. By neglecting the informational content of prices, they will tend to behave like cursed traders (Eyster, Rabin, and Vayanos (2019)) who have been found to lower informational efficiency (Corgnet, DeSantis, and Porter (2018, 2021)) (see Hypothesis 1(i)). It follows that Index trackers will be less likely to arbitrage away price differences across markets, thus leading to a failure of the law of one price and arbitrage opportunities (see Hypothesis 1(ii)).

Hypothesis 1 (**Informational Efficiency & Arbitrage**). *(i) Index trackers will impair informational efficiency and (ii) produce arbitrage opportunities.*

In the empirical literature, the impact of ETFs and indexing on liquidity is mixed (see Ben-David, Franzoni, and Moussawi (2017) for a review). Conceptually, index tracking can increase turnover by alleviating the no-trade problem (Milgrom and Stokey (1982)). This is the case because Index trackers are largely insensitive to prices, thus being willing to trade with active informed traders and limiting adverse selection. We can also interpret index tracking as producing a divergence in beliefs across traders regarding the valuation of the asset, which, in turn, triggers gains from exchange and promotes trading (Morris (1994). However, passive investing can also produce a crowding-out effect (see Ben-David, Franzoni, and Moussawi (2017)) leading investors to trade the index at the expense of the underlying stocks. This crowding-out effect is absent in our setup so we expect index tracking to increase liquidity (see Hypothesis 2).

[8] An Index trader earns 520 experimental currency units (ECUs) for each bundle assembled, where a bundle consists of 1 unit of X and 2 units of Y (due to there being twice as many outstanding shares of Y as X).

Hypothesis 2 (**Liquidity**)**.** *Index tracking will increase liquidity.*

Regarding the impact of index tracking on volatility, a consensus seems to emerge in the literature that ETFs and indexing tend to increase volatility (see e.g., Basak and Pavlova (2013); Krause, Ehsani, and Lien (2014); Ben-David, Franzoni, and Moussawi (2017, 2018); Coles, Heath, and Ringgenberg (2022); De Rossi and Steliaros (2022),). These findings are consistent with the passive investing model in Haddad, Huebner, and Loualiche (2021) according to which more inelastic markets experience larger price variations due to changing investor demands, and are therefore more volatile (see Hypothesis 3). In sum, as an increasing share of market participants become less sensitive to prices, information is incorporated more irregularly into prices, thereby increasing volatility. Similar predictions are obtained in the model of Bednarek (2023) who calculates that 10% of current market volatility can be attributed to the rise of passive investing.

Hypothesis 3 (**Volatility**)**.** *Index tracking will increase volatility.*

4 Experimental design

4.1 Asset markets and rational expectations equilibrium

The experimental design is based on two simultaneous one-period asset markets. There are three assets: Experimental Currency Units (ECUs or simply C in mathematical expressions henceforth), X and Y. There are three a priori equally likely states of the world: Low (L), Middle (M) and High (H). The assets X and Y have state-dependent valuations, denoted by V_X and V_Y, in which the value of X is always twice the value of Y. Table 1 presents these state-dependent values.

Table 1: States and state-dependent asset values

State (s)	Value of X (V_X)	Value of Y (V_Y)
Low (L)	50	25
Middle (M)	240	120
High (H)	490	245

A market always has 24 traders. Following the design paradigm for informational asymmetry introduced by Plott and Sunder (1988), half of the traders are *Informed* traders. In a market, two states are not realized. Each of these unrealized states is revealed to half of the Informed traders. For example, if the true state is L then 6 of the Informed traders receive the signal 'The state is not M' and the other 6 receive the signal 'The state is not H'. Thus, the union of their signals fully reveals the true state.[9] This structure is mirrored for the other two states. All other traders are *Uninformed*, entering the market with only the prior that the three possible states are equally likely.[10] In addition to this information asymmetry, traders are differentiated in how they value their portfolios.

We differentiate traders by whether they maximize the expected ECU value of their portfolios, *Active traders*, or they maximize the number of index shares they hold, *Index trackers*.[11] An Index tracker derives value by receiving a commission of z (520 ECUs in our experiment) for each index bundle of one unit of X and two units of Y, reflecting the 1:2 ratio of the aggregate endowment of the X and Y assets to be specified shortly. The following Leontief utility function represents the preferences of Index trackers (I).[12]

$$U_{\mathrm{I}}(X_{\mathrm{I}}, Y_{\mathrm{I}}, C_{\mathrm{I}}) = z \cdot \min\left\{X_{\mathrm{I}}, \frac{Y_{\mathrm{I}}}{2}\right\}$$

where X_{I}, Y_{I}, and C_{I} are the X, Y and cash holdings of an Index tracker.[13]

An Active trader (A) only derives value from expected final ECU holdings. At this point, we assume that each Active trader holds common expectations of the X and Y valuations,

[9] We considered using the information structure in Anderson, Bossaerts, and Fattinger (2020), but the aggregation measure was not as direct and used posterior means from two urns. Likewise, we considered the environment in Bloomfield, O'Hara, and Saar (2009) but found the procedure of drawing signals from a uniform interval around the true asset value to be overly complex for the questions we wanted to address with index trading.

[10] An appealing feature of this design is that it introduces both public and private information. Moreover, in single-market studies it has been shown that this design does not lead to fully efficient prices (see, for example, Corgnet, DeSantis, and Porter (2021); Corgnet et al. (2023)). Therefore, there is room for potential positive and negative impacts of Index tracking on informational efficiency and market quality metrics.

[11] One potential critique of the original design of Plott and Sunder (1988) is the absence of gains from trade beyond those driven by differences in risk attitudes across traders. Interestingly, the introduction of Index trackers to the Plott and Sunder (1988) design creates explicit gains from trade, thus alleviating no-trade concerns (Milgrom and Stokey (1982)). This critique is particularly compelling when considering that there is no aggregate uncertainty in this market. In the absence of aggregate uncertainty, risk-averse traders will be discouraged to trade until all private information is revealed, thus preventing risk-sharing transactions to materialize (see Hirshleifer (1978)).

[12] Note, for the case of a fractional bundle we round down to the nearest integer for compensation in the experiment.

[13] Note that Index trackers are not rewarded for cash holdings at the end of the market. They resemble liquidity traders, as introduced in Bloomfield, O'Hara, and Saar (2009), who experience liquidity shocks and need to trade for exogenous reasons while being prevented from speculating.

$E[V_X] = V$ and $E[V_Y] = \frac{V}{2}$. Accordingly, an expected portfolio valuation function is,

$$U_{\mathrm{A}}(X_{\mathrm{A}}, Y_{\mathrm{A}}, C_{\mathrm{A}}) = X_{\mathrm{A}} \cdot V + Y_{\mathrm{A}} \cdot \frac{V}{2} + C_{\mathrm{A}}$$

where X_{A}, Y_{A}, and C_{A} are the X, Y and cash holdings of Active traders.

Our experimental treatment variable is the percentage of the traders that are Index trackers: Baseline (0%), 4I (17%) and 9I (38%). These treatments were designed to match the share of passive investing in US equity markets in the 2000s and in the 2020s (see Kerzérho (2018, 2023) and Figure 1(b). Table 2 specifies individual endowment profiles by trader information and valuation type, and then specifies the number of traders of each type for the three treatments. Note that the expected value of each endowment profile is 2,418 ECUs. There are exactly 12 Informed traders in each treatment, and they have a common endowment. Active but not informed traders, i.e. Uninformed traders, have one of two initial endowments. There are 3 Uninformed traders with the Group 1 endowment in each treatment. There are always 9 traders with the Group 2 endowment profile. The number of Uninformed traders and Index trackers with this Group 2 endowment determines the treatment. In the Baseline, 4I, and 9I treatments the number of Index trackers (who exclusively have the Group 2 endowment) is 0, 4, and 9, respectively. By swapping out the valuation function of those with Group 2 endowments in our experiment, we exogenously control the percentage of the market, as a proportion of the value of the aggregate endowment of shares and cash, that passively trades. Notice we hold the aggregate endowments of assets constant across treatments: 51 units of X, 102 units of Y and 31,512 ECUs. We further hold constant the aggregate number and profile of private signals, as well as the endowments of those who are informed and not informed.

Assigning Index trackers to the Group 2 endowment, and varying the number of Index trackers across treatments links our design to key characteristics of the emergence of Passive trading in security markets. The Group 2 endowment contains a relatively large amount of ECUs but few shares. This renders acquiring bundles the primary tasks of Index trackers, corresponding to the consistent trend of positive cash flows into passive investment vehicles as illustrated in Figure 1(a). The bundles can be viewed as shares of a fund that track a one X-to-two Y index. This ratio is derived from the principle of tracking the market portfolio. The market portfolio in this case contains the supply of Y shares (102) and the supply of X shares (51). This mirrors how an exchange-traded fund (e.g., SPY) benchmarks an index (e.g., S&P 500) to track the return of the index (Wigglesworth (2021)).

Table 2: Trader endowments by treatment

Treatment	Trader Types	Number of Traders	Endowment		
			Cash (ECUs)	X Shares	Y Shares
Baseline	Informed	12	858	3	6
	Uninformed (Group 1)	3	1378	2	4
	Uninformed (Group 2)	9	1898	1	2
	Index tracker	0	-	-	-
4I	Informed	12	858	3	6
	Uninformed (Group 1)	3	1378	2	4
	Uninformed (Group 2)	5	1898	1	2
	Index tracker	4	1898	1	2
9I	Informed	12	858	3	6
	Uninformed (Group 1)	3	1378	2	4
	Uninformed (Group 2)	0	-	-	-
	Index tracker	9	1898	1	2

Solving for the fully revealing rational expectations equilibrium in each treatment is straightforward, conditional on two assumptions. The first assumption is that the law of one price prevails, ergo, no arbitrage. The result of this assumption is that, in equilibrium, the price of X is twice the price of Y, $p^e_X = 2p^e_Y$. The second assumption is that Active traders, both Informed and Uninformed, know the true realized state. To solve for the competitive equilibrium, we solve for the aggregate net demand functions for the Active traders - whose demand is state-dependent - and Index trackers - whose demand is not state-dependent. Then we solve, for both X and Y, the prices that result in zero excess demand for both assets. For an interior equilibrium in which all traders hold strictly positive amounts of both X and Y in their portfolio, the Active traders must be indifferent between holding ECUs, X and Y. This implies that in state s the equilibrium prices satisfy $p^e_X = V_s$ and $p^e_Y = \frac{V_s}{2}$, where V_s is the realized value of asset X when the state is $s \in \{L, M, H\}$.

We do not allow for short sales or leveraged purchases, and this gives rise to potential equilibrium involving corner solutions. This occurs in the L state, in which the equilibrium is a corner solution in which the Index trackers hold all units of X and Y, and the Active traders hold only, and all of, the ECUs. We provide the details of these calculations in Appendix A. Table 3 presents the rational expectation equilibrium prices and the average

Index tracker allocations for the three treatments. We use these equilibrium values as data benchmarks and to provide reference points and further context to the hypotheses presented in the previous section.

Table 3: Fully aggregated rational expectation equilibrium prices and Index tracker portfolios

		4I Treatment		
State	p_X^e	p_Y^e	X_I^e	Y_I^e
Low	80.77	40.39	12.75	25.50
Middle	240.00	120.00	4.95	9.91
High	490.00	245.00	2.94	5.87
		9I Treatment		
State	p_X^e	p_Y^e	X_I^e	Y_I^e
Low	203.36	101.68	5.67	11.33
Middle	240.00	120.00	5.12	10.24
High	490.00	245.00	3.02	6.04

Note: p_X^e and p_Y^e are the fully aggregated rational expectation equilibrium prices, and X_I^e and Y_I^e are the average individual asset holdings of Index trackers under the fully aggregated information equilibrium.

4.2 Experimental market task

The core activity of an experimental session is a sequence of fifteen asset markets adhering to one of our three treatments. Each market in the sequence implements the corresponding parameterisation of the one-period market presented in the previous subsection. Each market in the sequence is a "Groundhog Day" implementation that fixes each participant's trader type and endowment, but there is a new randomization of the state and informative signals. We conducted eight sessions for each of the three treatments. We created a pairing of sessions across treatments that share a common realization of state and informative signal sequences. Eight unidentical sequences of states were pre-drawn independently before the first experimental session was conducted, and each sequence was used for the same session of the Baseline, 4I and 9I treatments.

In each asset market, all participants, whether Active or Index tracking, traded shares of the two different assets (X and Y) and could buy and sell in the same period. Each market period lasted four minutes.[14] Shares of Asset X were traded in the X market, and shares

[14]We initially ran a single session for the Baseline and both treatments. In these first three sessions the first ten periods lasted for four minutes, while the last five periods lasted for three minutes. This design

of Asset Y were traded in the Y market. Markets were organized as continuous double auctions. Participants were able to submit limit orders as well as market orders. Each order was restricted to a single share. Neither borrowing nor short selling was permitted. This design choice was made based on previous findings showing that the law of one price tends to hold even in the absence of short-selling (Fisher and Kelly (2000); Childs and Mestelman (2006)), which was indeed the case in our Baseline treatment. Participants could cancel a limit order provided it was not the best standing order of its type in the order book.

The software's interface is depicted in Figures 2(a) and 2(b). Participants were able to trade shares of Asset X on the left side of the screen and shares of Asset Y on the right side of the screen. Participants could submit limit orders to buy (sell) a single share of the desired asset by entering the amount they were willing to pay (sought to receive) into the Bid (Ask) field and clicking the Submit button. Participants could also submit market orders to buy (sell) a single share at the current lowest ask (highest bid) by clicking the Immediately SELL (BUY) button. The current market period's order book is displayed, and the prices of completed trades are presented graphically as well as in a list. Common information regarding the asset's value as well as the participant's private signal (if the participant received one) is provided in the middle screen. Participants' current holdings of the assets and cash are provided along with their provisional profit should their current holdings remain unchanged. This profit is based upon the realized state for Active traders and the number of bundles held by Index trackers.

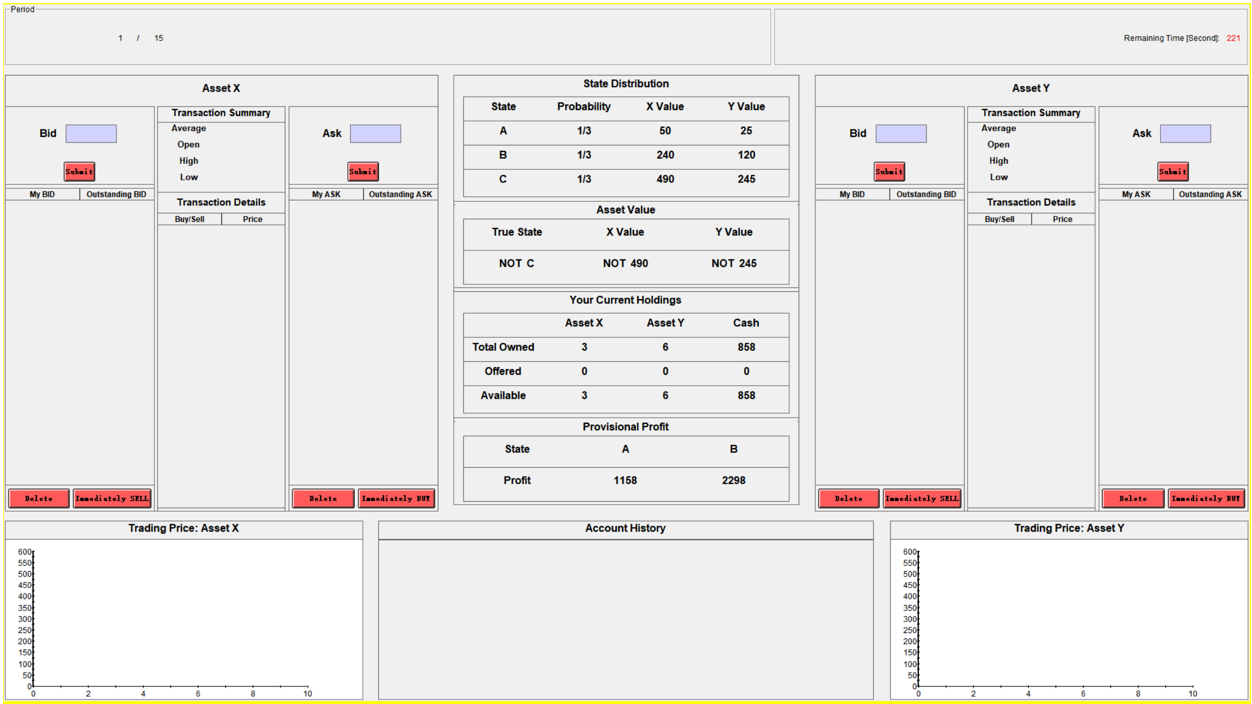
4.3 Experimental methods and protocols

Each session was conducted by seating the 24 participants in cubicles in a computer laboratory. Participants were unable to see the computer screens of other participants and were instructed to communicate with other participants only using the computer. Pre-recorded instructions were played, while participants followed along with hard-copy handouts of the instructions.[15] This lasted 20 minutes. At the end of the instructions, participants were given the opportunity to ask questions after which a brief comprehension quiz was administered, lasting approximately five minutes. Participants earned a 5 CNY bonus payment for correctly answering all questions.[16] Participants were informed of the correct answers for the

choice was made to shorten the overall length of the experiment. However, upon inspection of the data from the first three sessions, it appeared that traders were still actively attempting to complete transactions when the markets closed in the last five periods (e.g., the average number of trades in the last five periods was less than the average number of trades in the first ten periods). Thus, to ensure traders had adequate time to trade, we made all periods last four minutes for the remaining sessions.

[15] English translations of the instructions are provided in Appendix E.

[16] At the time of the experiment, the exchange rate was about 7 CNY = 1 USD.



(a) Interface for an Informed trader

(b) Interface for an Index tracker

Figure 2: The trading interface for Informed traders is presented in subfigure (a), while the interface for Index trackers is depicted in subfigure (b).

quiz and given another opportunity to ask questions. The training phase of the experiment ended with two four-minute practice (non-paid) periods. Upon conclusion of the practice periods, the actual market phase of the experiment began. The experiment ended with participants answering a short survey containing questions related to financial literacy and cognitive ability, in addition to basic demographics. Prior studies have demonstrated that cognitive skills and financial literacy help explain trader behavior (see Grinblatt, Keloharju, and Linnainmaa (2011, 2012); Corgnet et al. (2015); Cueva and Rustichini (2015); Grinblatt et al. (2016); Noussair, Tucker, and Xu (2016); Corgnet, DeSantis, and Porter (2018); Shestakova, Powell, and Gladyrev (2019))). We thus elicited a seven-question version of the Cognitive Reflection Test (CRT, henceforth) (Frederick (2005)) adapted from Toplak, West, and Stanovich (2014). We also measured financial literacy via a short three-question survey taken from Lusardi and Mitchell (2011). Basic demographic information included age, gender, and major. Refer to Appendix D for the actual questions administered in the survey.

The following is a brief summary of the study's protocols. We recruited participants from a pool of approximately 5,000 students at Wuhan University, which is a large university in Central China.[17] No student participated in more than one experimental session. We conducted eight sessions, consisting of exactly 24 participants, for each treatment. The size of our markets was about twice the standard number in experimental markets (Fullbrunn and Haruvy (2022)). Larger markets were adopted to ensure enough competitive pressure among both Index tracking and Active traders, regardless of the treatment. We conducted 24 sessions with a total of 576 participants.

Participants' earnings from each market period were summed, and this sum was converted to CNY at an exchange rate of 1 CNY to 650 ECUs. Participants also received a 20 CNY show-up payment. Thus, their total earnings for the experiment consisted of the bonus comprehension quiz payment (5 CNY), the show-up payment, and their market earnings. On average, participants earned 79 CNY (about 11.8 USD) for the two-hour experiment.

5 Results

5.1 Intra-period prices

Figures 3(a) and 3(b) present the price dynamics within a period. Each period is divided into ten 24-second intervals, and, for a fixed state, prices within each time interval are averaged

[17] This university is part of the 985 Program, which was a Chinese government initiative to elevate 39 selected universities (out of more than 3000 universities) to a world-class level.

across periods and sessions. We report a time series for each treatment. These figures show that average prices in both markets are far from the true asset values when the state is Low or High (see Corgnet, DeSantis, and Porter (2021); Corgnet et al. (2023) for similar results with single-asset markets). Further, there is a strong ordering of asset prices from lowest (Baseline) to highest (9I) by treatment. These observations are supported by the descriptive statistics reported in Table 4.

Table 4: Descriptive Statistics Summary. Sample means (standard deviation) for the Average Price variable.

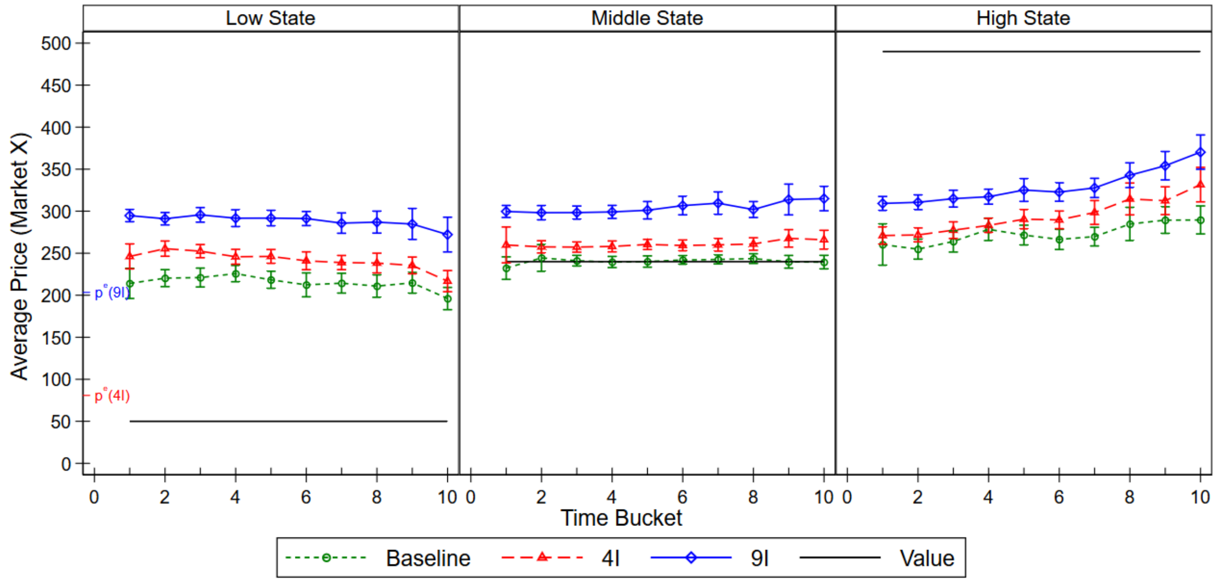
	Treatment	**All States**	**Low State**	**Middle State**	**High State**
Asset Value			50	240	490
Average Price	Baseline	240.44	212.83	238.31	271.01
		(34.50)	(29.72)	(11.82)	(30.11)
	4I	272.29	251.00	265.33	301.45
		(32.16)	(23.80)	(18.98)	(29.59)
	9I	322.01	305.61	318.33	342.71
		(26.86)	(19.02)	(22.41)	(24.93)

Note: Data reported in this table corresponds to the combined Market X and Market Y dataset. *Average Price* used for descriptive statistics is the period-level measure, calculated as (the Average Price in Market X + 2 $\times$ the Average Price in Market Y)/2.

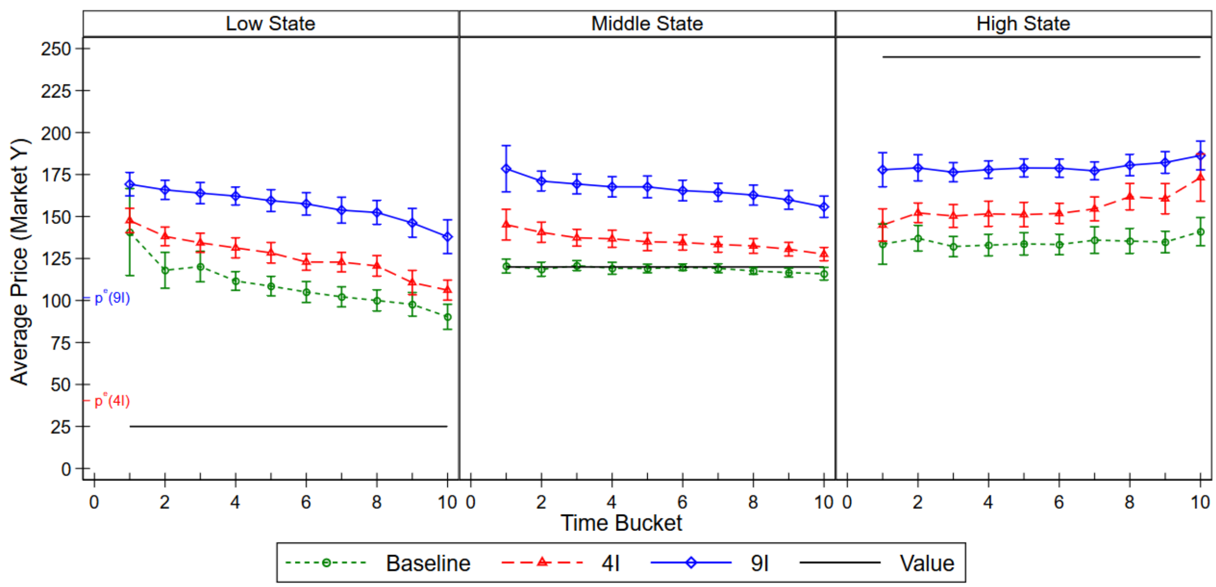
5.2 Hypotheses tests

Testing Hypothesis 1(i) requires studying how market prices respond to states. We thus test Hypothesis 1(i) by conducting regression analyses that assess how sensitive prices are to changes in the asset value. Hypotheses 2 and 3 do not require a state-dependent analysis so we employ a simpler approach using standard non-parametric tests. These tests use measures that are defined at the period-level and averaged across periods to obtain session-level values. This ensures all observations are independent. Treatment-level values are determined by averaging across sessions. Tables 4 and 11 (see Appendix B) provide descriptive statistics for these measures by state, while Tables 5, 6, and 8 provide the results of our analyses.

We obtain similar results when considering Market X and Market Y separately for informational efficiency and market quality measures (see Appendix C). Thus, for clarity of exposition, we combine the data for Markets X and Y and report the results from analyses performed on this consolidated dataset.



(a) Market X



(b) Market Y

Figure 3: For each market the Average Price per 24-second time interval within a period for a particular state is displayed. For each state, this figure plots the average price with 95% confidence intervals in the corresponding time interval across periods and sessions. A time series is provided for each treatment. The true asset value is depicted by a solid horizontal line. The rational expectation equilibrium prices for the Low State are denoted by hash marks on the left vertical axis. Note these prices equal the true asset values in the Middle and High States.

5.2.1 Informational efficiency (Hypothesis 1(i))

The overriding research question is: What impact does increasing passive trading have on the informational efficiency of prices in markets with asymmetric information? To answer this question we consider three different log-linear pricing panel models, within which one individual asset market for each treatment and each session is a cross-section observation (denoted by the subscript Krn), and each market period (denoted by the subscript m) is a time observation.

The following is our basic log-linear pricing model:

$$\ln(p_{Krn,m}) = \beta_0 + \beta_1 \mathbb{1}_{r=4I} + \beta_2 \mathbb{1}_{r=9I} + \beta_3 \mathbb{1}_{K=Y} + \beta_4 \ln(\mathrm{V}_{s(n,m)}) + \mu_{Krn} + \epsilon_{Krn,m} \tag{1}$$

where $K \in \{X, Y\}$ is the asset market, $r \in \{Baseline, 4I, 9I\}$ is the treatment, $n \in \{1, 2, 3, ..., 8\}$ is the session, $m \in \{1, 2, 3, ..., 15\}$ is the market period, $\mathrm{V}_{s(nm)} \in \{50, 240, 490\}$ is the state quantified by the realized value of asset X, μ_{Krn} is the asset market instance specific unobservable factor, and $\epsilon_{Krn,m}$ is an error term with an expected value of zero and uncorrelated with the other factors. A fully revealing rational expectation equilibrium imposes the following constraints on the coefficients of Model (1): when the equilibrium price equals the fundamental value $\beta_0 = 0$, $\beta_4 = 1$, $\exp(\beta_3) = 0.5$ or $\beta_3 \approx -0.69$; and the Low State corner solutions in the passive trader treatments additionally imply $\beta_2 > \beta_1 > 0$.

Figures 3(a) and 3(b) suggest prices do not agree with the fully revealing rational expectations equilibrium in systematic ways. For example, increasing the percentage of passive trading leads to increases in prices independent of the realized asset values. A reasonable conjecture is that positive net inflows into passive investing are inflationary, as the demand from passive traders is detached from the realized dividends of the assets. However, what is not clear is whether there are treatment differences in the correlations between prices and the state. To address these questions we consider the following augmented log-linear pricing model:

$$\begin{aligned} \ln(p_{Krn,m}) = \beta_0 + \beta_1 \mathbb{1}_{r=4I} + \beta_2 \mathbb{1}_{r=9I} + \beta_3 \mathbb{1}_{K=Y} + \beta_4 \ln(\mathrm{V}_{s(n,m)}) \\ + \beta_5 \mathbb{1}_{r=4I} \times \ln(\mathrm{V}_{s(n,m)}) + \beta_6 \mathbb{1}_{r=9I} \times \ln(\mathrm{V}_{s(n,m)}) + \mu_{Krn} + \epsilon_{Krn,m} \end{aligned} \tag{2}$$

In Model (2), informational efficiency treatment effects are captured by the coefficients, β_5 and β_6, for the interaction terms of passive treatments and '$\ln(Value)$'.

To test the robustness of results to learning effects, we consider the following augmented log-linear pricing model with the period trend term:

$$\ln(p_{Krn,m}) = \beta_0 + \beta_1 \mathbb{1}_{r=4I} + \beta_2 \mathbb{1}_{r=9I} + \beta_3 \mathbb{1}_{K=Y} + \beta_4 \ln(\mathrm{V}_{s(n,m)}) \\ + \beta_5 \mathbb{1}_{r=4I} \times \ln(\mathrm{V}_{s(n,m)}) + \beta_6 \mathbb{1}_{r=9I} \times \ln(\mathrm{V}_{s(n,m)}) + \beta_7 \times m + \mu_{Krn} + \epsilon_{Krn,m} \quad (3)$$

In Model (3), learning effects are captured by the coefficient β_7 of the variables 'Periods'.

Columns (1)-(3) of Table 5 report cross-section random effects (μ_{Krn}) regressions where the dependent variable is the average period price.[18] Since Figures 3(a) and 3(b) suggest that prices adjust toward higher efficiency, in columns (4)-(6) we report the same regressions using the average price of the last five transactions in a period.[19] For each dependent variable we report estimation results for Models (1)-(3).

We first consider the results for the average price of all transactions. Model (1) reflects the visual evidence in Figure 3(a), average prices are inconsistent with informational efficiency and a rational expectations equilibrium. The estimated coefficient of '$\ln(Value)$' is significantly less than one (χ^2 test, p-value < 0.001) and the constant term is significant. Further, the estimation is also inconsistent with the law of one price as the coefficient of the 'Market Y' dummy variable, $\hat{\beta}_3$, is -0.65, which is significantly different from -0.69 (χ^2 test, p-value $= 0.010$), implying a mispricing ratio of 0.084. The estimated results of Model (1), in particular the coefficient of the '9I' dummy variable being greater than the positive coefficient of the '4I' dummy variable, i.e. $\hat{\beta}_2 > \hat{\beta}_1 > 0$, also support the conjecture that the impact of exogenous increases in the percentage of passive trading is largely inflationary. The estimates of Model (2) allow us to evaluate differences in information aggregation across treatments while controlling for these inflationary effects. The estimated coefficient for the '9I $\times$ $\ln(Value)$' factor is negative and significant at the 1% level. Compared with Baseline, the elasticity of price relative to value in 9I treatment is reduced by 60%. Thus, sufficiently high passive trading decreases informational efficiency in this setting. Model (3) shows this is robust to learning effects.[20]

When allowing for intra-period learning by considering only the last five transactions of period, columns (4)-(6) of Table 5, we find minimal change in these results. The correlation between price and value increases, as reflected in the larger estimated value of coefficient of

[18] The Breusch-Pagan Lagrange Multiplier tests show that the hypotheses that random effects are not appropriate should be rejected (p-values < 0.001 for regressions of columns (1)-(3) in Table 5).

[19] The Breusch-Pagan Lagrange Multiplier tests show that the hypotheses that random effects are not appropriate should be rejected (p-value = 0.059, 0.046, and 0.044 for regressions of columns (4)-(6) in Table 5, respectively).

[20] Regressions with the period fixed effects based on Model (2) show results similar to those of Model (3).

'ln($Value$)'. Also, inflationary effects remain significant in the 9I treatment, but not in the 4I treatment. The results on differential information efficiency are unchanged. We summarize these observations in our first result.

Table 5: Average period price: Regression analysis

DV: Average period price	Average over all transactions			Average over last five transactions		
	(1)	(2)	(3)	(4)	(5)	(6)
4I	0.13*	0.29*	0.29*	0.14*	0.19	0.19
	(0.02)	(0.11)	(0.11)	(0.02)	(0.16)	(0.16)
9I	0.30*	0.60*	0.60*	0.31*	0.63*	0.63*
	(0.01)	(0.10)	(0.10)	(0.02)	(0.14)	(0.14)
Market Y	-0.65*	-0.65*	-0.65*	-0.71*	-0.71*	-0.71*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln($Value$)	0.07*	0.10*	0.10*	0.15*	0.17*	0.17*
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
4I× ln($Value$)		-0.03	-0.03		-0.01	-0.01
		(0.02)	(0.02)		(0.03)	(0.03)
9I× ln($Value$)		-0.06*	-0.06*		-0.06*	-0.06*
		(0.02)	(0.02)		(0.02)	(0.02)
Periods			-0.00			-0.00
			(0.00)			(0.00)
Constant	5.06*	4.91*	4.93*	4.68*	4.56*	4.58*
	(0.05)	(0.09)	(0.09)	(0.07)	(0.10)	(0.10)
Observations	720	720	720	720	720	720
Clusters	24	24	24	24	24	24
Within Std. Deviation σ_μ	0.04	0.04	0.04	0.03	0.03	0.03
Between Std. Deviation σ_ϵ	0.10	0.10	0.10	0.17	0.17	0.17
Intercluster Correlation ρ	0.14	0.14	0.15	0.03	0.02	0.02
R^2	0.91	0.91	0.91	0.85	0.85	0.85

Note: Regressions with random effect for individual asset market for each treatment and each session, clustered at the experimental session level. Two-sided p-values determine significance: * Significant at the 1% level; † significant at the 5% level.

Result 1 (**Informational Efficiency**). *Treatment 9I reduces the informational efficiency of asset prices. Passive trading treatments (4I and 9I) lead to an increase in prices.*

5.2.2 Arbitrage opportunities (Hypothesis 1(ii))

Based on the experimental design, the prices of asset X should be exactly twice as high as the prices of asset Y. This measure, called the mispricing ratio, is captured by the variable:

$$Mispricing_{rn,m} = \left| \frac{\overline{p}_{Xrn,m}}{\overline{p}_{Yrn,m}} - 2 \right|,$$

where $\overline{p}_{Krn,m}$ is the average price across transactions for asset $K \in \{X, Y\}$ in market period m of treatment r and session n. Note that the law of one price appears to be violated (see Table 6), which should lead to arbitrage opportunities. To assess this, we identify arbitrage opportunities and their magnitudes. Arbitrage opportunities can emerge, alter or extinguish whenever one of the following market events occurs: the market opens, a limit order is submitted or withdrawn, a market order is executed, or the market closes. We measure arbitrage in market period m of treatment r and session n by the variable,

$$TWArb_{rn,m} = \frac{\sum_{j=1}^{J_{rn,m}} Arb_{rn,mj} \times t_{rn,mj}}{T},$$

where $J_{rn,m}$ is the total number of market events for both assets X and Y in market period m of treatment r and session n, and is indexed by j; $Arb_{rn,mj}$ represents the magnitude of the arbitrage opportunity subsequent to event j in market period m of treatment r and session n; and $t_{rn,mj}$ represents the corresponding time duration until the next market event, $j + 1$ in given r, n and m. If there is no arbitrage opportunity after market event j, then $Arb_{rn,mj} = 0$. Otherwise, there is an arbitrage opportunity that takes one of two forms: (i) the sum of the two highest bids in Market Y exceeds the lowest ask in Market X; (ii) the highest bid for asset X exceeds the sum of the two lowest asks in Market Y. In form (i), $Arb_{rn,mj}$ is equal to the revenue one would receive from selling the two units of Y less the cost of purchasing one unit of X. The calculation is similar in form (ii). We multiply the magnitude of each arbitrage opportunity by the length of time it exists, sum these products, and then divide this quantity by the time length of the market period to calculate our time-weighted arbitrage variable, $TWArb$ shown in Figure 4 by period and by treatment.

Table 6 shows that arbitrage opportunities are significantly greater in the 9I treatment than in the 4I treatment or the Baseline (Wilcoxon rank-sum test, WRS henceforth). We do not find a significant difference in arbitrage opportunities between the 4I treatment and the Baseline. Moreover, the average proportion of time that arbitrage opportunities exist in each period is 9% (about 22 seconds), 13% (about 31 seconds) and 55% (about 132 seconds)

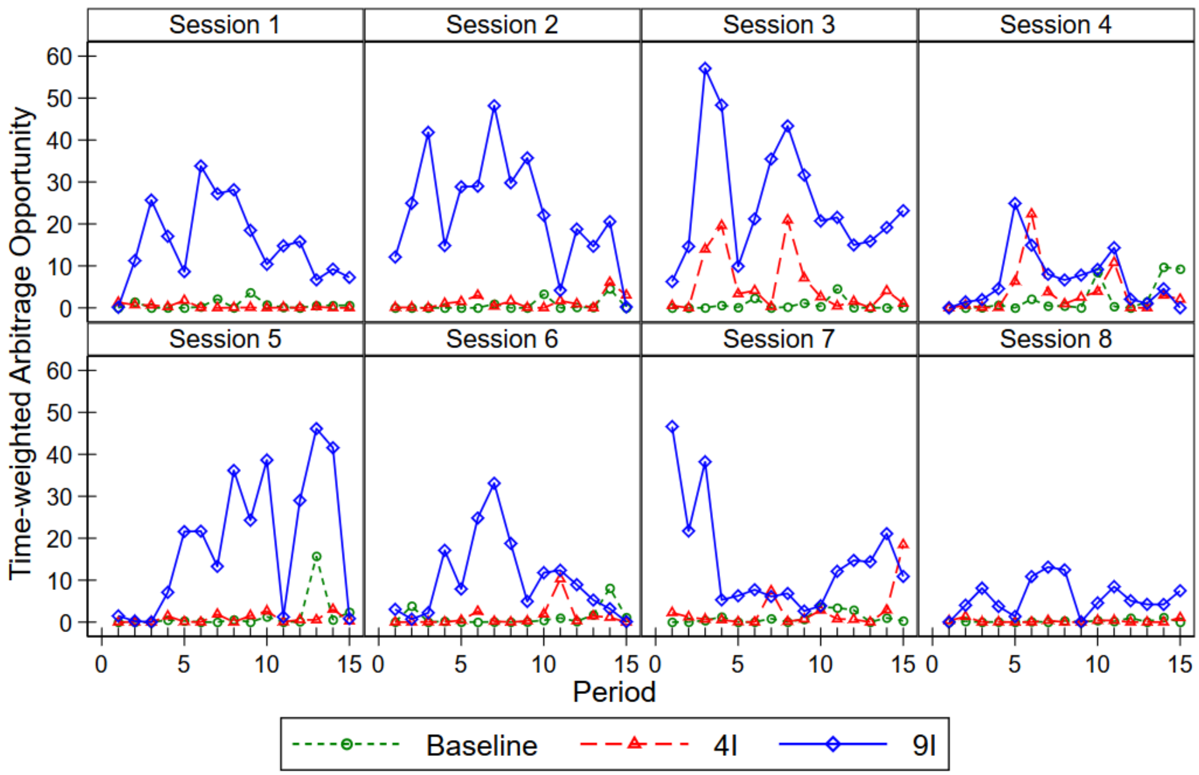


Figure 4: Time-weighted arbitrage opportunities. This figure plots the average Time-weighted Arbitrage variable per period for each session.

Table 6: Descriptive Statistics and Tests. Sample means (standard deviation) for arbitrage measures along with p-values from treatment comparisons across measures using Wilcoxon rank-sum tests <including Holm-Bonferroni corrections>.

Measures	**Treatment**	**Values**	**p-values**	**p-values**
			vs. Baseline	*vs.* 4I
Mispricing Ratio	Baseline	0.17		
		(0.16)		
	4I	0.14	(0.462)	
		(0.13)	<1.000>	
	9I	0.23	(0.021)†	(0.012)†
		(0.13)	<0.146>	<0.100>
TWArb	Baseline	0.98		
		(2.26)		
	4I	1.95	(0.294)	
		(4.11)	<1.000>	
	9I	15.07	(0.001)*	(0.001)*
		(13.15)	<0.012>†	<0.012>†

Note: Two-sided p-values determine significance. The p-values and corrected p-values using the Holm-Bonferroni method are reported in parentheses () and brackets <>. * Significant at the 1% level; † significant at the 5% level.

in the Baseline, 4I, and 9I treatments respectively (WRS, p-values <0.001 when comparing 9I with Baseline and 4I, respectively; p-value = 0.141 when comparing Baseline and 4I).

To evaluate the magnitude of arbitrage opportunities, we also calculate the ratio of the average time-weighted arbitrage opportunity in a period (in ECUs) ($TWArb$) and the combined asset value. This arbitrage ratio was, on average, 1.2% and 1.6% in the Baseline and in the 4I treatment compared to 12.8% in the 9I treatment. The magnitude of arbitrage opportunities, as measured by this arbitrage ratio, in the 9I treatment is significantly greater than in the Baseline and the 4I treatment (WRS, p-values <0.001 for both comparisons), and there is no significant difference between Baseline and the 4I treatment (WRS, p-value = 0.674).

Figure 5 presents the within-period dynamics of the $TWArb$ variable. It is clear that arbitrage opportunities are greater in the 9I treatment than in the 4I treatment or the Baseline. Dividing the period into 10 equal-sized time buckets, we observe that arbitrage opportunities in the 9I treatment start small, grow to be fairly large in the middle of the period, and then taper off at the end of the period.[21] This pattern can be explained by the evolution of the proportion of trades involving Index trackers within a period. In time buckets three through six, the percentage of trades completed by an Active trader selling to an Index tracker exceeds 76%. This percentage falls to approximately 68.5% in the final time bucket, significantly differing from that in buckets three to six (WRS, p-value = 0.021). As Index trackers' incentive is to buy shares in order to form bundles, the only reason for this trading percentage to decline is that Index trackers either ran out of cash to buy shares or shares to buy. Table 7 indicates that Active traders hold a significant number of shares at the end of a given period. If these shares were acquired by Index trackers, then the Index trackers could have formed up to 34 bundles in the 4I treatment and 18 bundles in the 9I treatment. However, the average amount of cash held by Index trackers in the last period was only 286.58 and 269.10 in the 4I and 9I treatments, which is only half of the cash needed to form an additional bundle.[22]

Thus, we find support for Hypothesis 1(ii) because the law of one price breaks down and arbitrage opportunities proliferate when the proportion of Index trackers in a market is high (9I treatment). Yet, it is interesting to note that a low proportion of Index trackers does not impact the law of one price. It seems there is a critical proportion of Index trackers in the market above which arbitrage opportunities surge. Given our design, we estimate this proportion to be between 17% and 38% in terms of market endowment, which is less than current estimates of the proportion of passive trading in US markets (Kerzérho (2023)).

We summarize our findings for Hypothesis 1(ii) below.

Result 2 (**Arbitrage**)**.** *Treatment 9I leads to a substantial violation of the law of one price and more opportunities for arbitrage between the individual markets.*

5.2.3 Market quality (Hypotheses 2 and 3)

We consider three measures of market quality: trading volume, bid-ask spread, and price volatility, which are standard in the literature (see Foucault, Pagano, and Röell (2013)). Trading volume is significantly higher in the 9I treatment than in the 4I treatment or the Baseline (see Table 8). However, there is no significant difference in trading volumes between the 4I treatment and the Baseline.

[21] As noted in Section 4, the last five periods of the first sessions for the Baseline and both treatments lasted for 3 minutes. As a result, the time buckets for these periods in these three sessions were 18 seconds in length. For the rest of the market periods, time buckets were 24 seconds in length.

[22] To form a bundle, an Index tracker needs one share from Market X and two shares from Market Y. Thus, we calculate the cost of forming an additional bundle as the sum of the price in Market X and two times the price in Market Y.

Table 7: Average final cash and asset holdings. This table provides the mean (standard deviation) holdings by treatment and by trader type per market period.

		Cash Holdings [ECUs] by Trader Type					
Treatment	**Index**	**Active**		**Informed**		**Uninformed**	
Baseline	-	1313.00		1038.65		1587.35	
		(762.86)		(789.80)		(624.43)	
4I	286.58	1518.28		1332.25		1797.33	
	(402.53)	(811.67)		(874.50)		(608.76)	
9I	269.10	1939.34		1905.50		2074.69	
	(308.22)	(868.25)		(907.37)		(674.26)	
		Asset Holdings by Trader Type					
Treatment	**Index**	**Active**		**Informed**		**Uninformed**	
	Bundles	X	Y	X	Y	X	Y
Baseline	-	2.13	4.25	2.55	5.32	1.70	3.18
		(1.93)	(3.32)	(2.08)	(3.51)	(1.66)	(2.72)
4I	3.78	1.76	3.50	2.06	4.31	1.30	2.28
	(0.88)	(1.88)	(3.09)	(2.00)	(3.36)	(1.58)	(2.09)
9I	3.30	1.31	2.47	1.38	2.68	1.03	1.65
	(0.76)	(1.71)	(2.69)	(1.76)	(2.82)	(1.45)	(1.88)

Note: Active traders are either informed or uninformed. Average cash and asset holdings are provided for Active traders as a whole group as well as for both subgroups of Active traders. Bundles, X, and Y stand for the average number of bundles, X shares, and Y shares held by a trader in a market period.

Another frequently used measure of market quality is the bid-ask spread. We assess this quality by the time-weighted bid-ask spread,

$$TWSpread_{rn,m} = \frac{1}{2} \sum_{K \in \{X,Y\}} \frac{\sum_{j=1}^{J_{Krn,m}} spread_{Krn,mj} \times t_{Krn,mj}}{\sum_{j=1}^{J_{Krn,m}} t_{Krn,mj} \times \mathbb{1}_{spread_{Krn,mj} \neq \varnothing}}$$

where $J_{Krn,m}$ is the total number of market events for asset K in market period m of treatment r and session n, and is indexed by j; $spread_{Krn,mj}$ represents the bid-ask spread for asset K subsequent to the event j in market period m of treatment r and session n, where $spread_{Krn,mj} = \varnothing$ when the bid-ask spread does not exist[23]; and $t_{Krn,mj}$ represents the time

[23] The bid-ask spread exists 94%, 94% and 96% of the time in the Baseline, 4I and 9I treatments, respectively. There is no significant difference in the amount of time the bid-ask spread exists between the Baseline and the 4I treatment(WRS, p-value = 0.834); however, the amount of time the bid-ask spread exists in the 9I treatment is significantly higher than in the 4I treatment or the Baseline (WRS, p-value = 0.016 and 0.059, respectively).

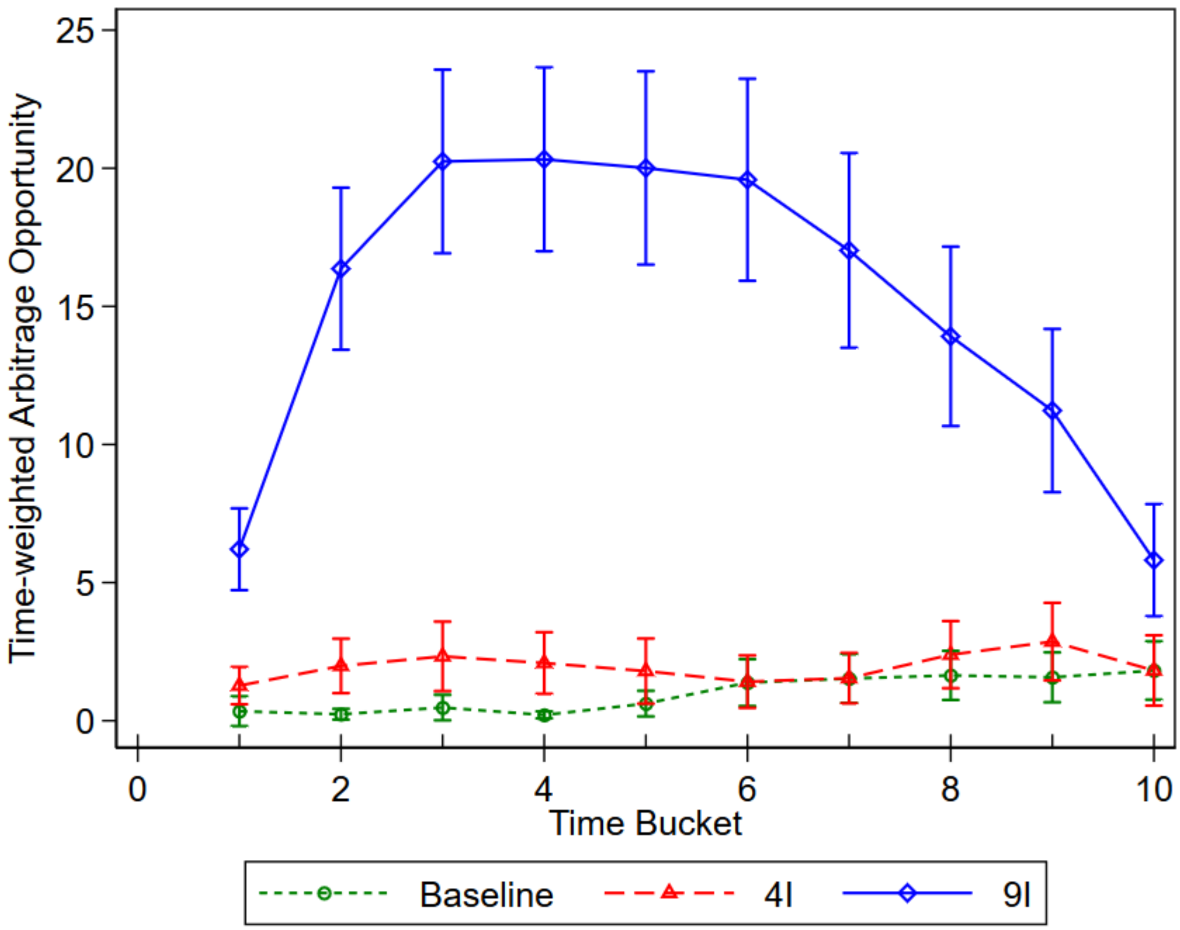


Figure 5: Time-weighted arbitrage opportunities within a period. This figure discretizes periods into ten equal-sized time buckets. The average time-weighted arbitrage opportunity variable is calculated for each time bucket and averaged across periods and then sessions for each treatment. The 95% confidence interval corresponding to each data point is provided.

duration until the next market event, $j+1$, for asset K in given r, n and m. As reported in Table 8, we find that the bid-ask spread narrows as the number of Index trackers increases. Indeed, the *TWSpread* variable in the 9I treatment is significantly smaller than in 4I and the Baseline. Overall, the bid-ask spread is also significantly lower in the 4I treatment than in the Baseline. Hypothesis 2 is thus supported by the data. In particular, once the share of Index trackers in the market is high (9I treatment), liquidity as measured by (high) trading volume and (low) bid-ask spreads is enhanced. Specifically, the trading volume in the 9I treatment surpasses that of the Baseline and the 4I treatment by 37% and 23%, respectively. Moreover, the *TWSpread* variable in the 9I treatment is only 56% and 78% of that observed in the Baseline and the 4I treatment, respectively.

Table 8: Descriptive Statistics and Tests. Sample means (standard deviation) for market quality measures along with p-values from treatment comparisons across measures using Wilcoxon rank-sum tests <including Holm-Bonferroni corrections>.

Measures	**Treatment**	**Values**	**p-values**	**p-values**
			vs. Baseline	*vs.* 4I
Volume	Baseline	33.00		
		(9.19)		
	4I	36.64	(0.207)	
		(5.64)	<1.000>	
	9I	45.22	(0.009)*	(0.001)*
		(4.87)	<0.095>	<0.012>†
TWSpread	Baseline	0.25		
		(0.15)		
	4I	0.18	(0.012)†	
		(0.11)	<0.100>	
	9I	0.14	(0.002)*	(0.009)*
		(0.10)	<0.020>†	<0.087>
Volatility	Baseline	30.88		
		(17.90)		
	4I	30.09	(0.916)	
		(22.27)	<0.916>	
	9I	27.24	(0.462)	(0.141)
		(18.70)	<1.000>	<0.849>

Note: Volume and *Volatility* are reported for the combined data of assets X and Y. Specifically, *Volume* = (Market X Volume + Market Y Volume)/2 and *Volatility* = (Market X Volatility + 2 $\times$ Market Y Volatility)/2. Two-sided p-values determine significance. The p-values and corrected p-values using the Holm-Bonferroni method are reported in parentheses () and brackets <>. * Significant at the 1% level; † significant at the 5% level.

Regarding price volatility, there are no significant differences between treatments (see Table 8). Thus, we do not find support for Hypothesis 3. In sum, when considering frequently-used measures of market quality, the introduction of Index trackers does not harm, and in some cases promotes, market quality. We summarize our findings for Hypotheses 2 and 3 below.

Result 3 (**Market Quality**). *Treatment 9I narrows the bid-ask spread and increases volumes. But, Index tracking treatments (4I and 9I) do not significantly impact price volatility.*

5.3 Individual analyses and trading income

5.3.1 Active traders

Turning the focus to the impact of Index tracking on individual traders, we find Active traders largely benefit from the introduction of Index tracking. This result is to be expected given the compensation mechanism for Index trackers whose only source of earnings is based upon the number of bundles they form in a given market period. Thus, Index trackers' demand is state-independent, which creates earnings opportunities for Active traders. Indeed, as shown in Table 4 average prices in a period increased with the number of Index trackers. These higher prices led to larger earnings for Active traders.

As traders have different endowments of cash and shares, we use trading income to measure an individual trader's performance. For all Active traders and Index trackers, this is defined as their ending portfolio value minus their beginning portfolio value as follows:

$$
\begin{aligned}
TradingIncome_{rnh,m} = & \left(C_{rnh,mf} + X_{rnh,mf} \times V_{s(n,m)} + Y_{rnh,mf} \times \frac{V_{s(n,m)}}{2}\right) \\
& - \left(C_{rnh,mb} + X_{rnh,mb} \times V_{s(n,m)} + Y_{rnh,mb} \times \frac{V_{s(n,m)}}{2}\right),
\end{aligned}
$$

where $C_{rnh,mf}$ is individual trader h's cash balance at the end of a period m in treatment r and session n, $X_{rnh,mi}$ ($Y_{rnh,mi}$) is the number of X (Y) shares held at the beginning ($i = b$) or end ($i = f$) of the corresponding period, and $V_{s(n,m)}$ is the State-dependent realized value of asset X.

This measure accounts for a trader's initial endowment, whereas simply looking at a trader's earnings does not.[24] It allows for a direct comparison in terms of trading performance between trader types. Table 9 summarizes the trading income measure.

When averaging across all states Active traders' trading incomes increase from 0 ECU in the Baseline (our market is a zero-sum game) to 40.61 ECUs in the 4I treatment and 247.49 ECUs in the 9I treatment (WRS, p-values < 0.001 for all pairwise comparisons).[25]

The relationship between Active traders' trading incomes and the number of Index trackers is likely due to the fact that Active traders are net sellers in the 4I and 9I treatments. On average, approximately 51% of trades in a period consisted of an Active trader selling

[24] An Active trader's period earnings equal their ending portfolio value, i.e., $Earnings^{Active}_{rnh,m} = C_{rnh,mf} + X_{rnh,mf} \times V_{s(n,m)} + Y_{rnh,mf} \times \frac{V_{s(n,m)}}{2}$. An Index tracker's period earnings are equal to the bundle commission multiplied by the number of bundles held at the end of the period, i.e., $Earnings^{IndexTracker}_{rnh,m} = 520 \times Bundles_{rnh,mf}$. Participants are paid the sum of their period earnings for all periods multiplied by an exchange rate.

[25] We find qualitatively similar results when considering Active traders' average earnings per period.

Table 9: Average trading income per period by trader type

Treatment	Index	Active	Informed	Uninformed
Baseline	-	0.00	49.99	-49.99
	-	(464.67)	(513.83)	(403.69)
4I	-203.05	40.61	124.12	-84.65
	(999.42)	(519.25)	(572.27)	(396.09)
9I	-412.49	247.49	285.65	94.86
	(873.07)	(703.71)	(737.50)	(521.69)

Note: *Active* traders are either informed or uninformed. Average trading income is provided for *Active* traders as a whole group as well as for both subgroups of *Active* traders. The standard deviation is reported in parentheses.

to an Index tracker in the 4I treatment. This percentage increases to approximately 78% in the 9I treatment and significantly differs from that in the 4I treatment (WRS, p-value $<$ 0.001). In the Baseline, Active traders held an average of 1313 units of cash, 2.13 shares of X, and 4.25 shares of Y at the end of the period. However, in the 4I and 9I treatments, Active traders held more cash (1518.28 and 1939.34, respectively) and fewer shares of X (1.76 and 1.31, respectively) and Y (3.50 and 2.47, respectively) (WRS, p-values < 0.001 for all pairwise comparisons).

5.3.2 Index trackers

Index trackers earn 520 ECUs for each bundle (i.e., one X shares and two Y share) they hold at the end of a period. Thus, as previously noted, Index trackers' demand is state-independent. While it is true that lower transaction prices for Index trackers means they might be able to form even more bundles, any cash held at the end of a period is worthless to the Index tracker. Thus, there is no strong incentive for Index trackers to time their purchase of the asset by waiting for prices to fall. In particular, in the 9I treatment heightened competition between Index trackers forces them to accept higher prices in order to form bundles (their only source of earnings). Not only are there more Index trackers in the 9I treatment than in the 4I treatment, but there are also slightly fewer shares available for purchase (47 X shares and 94 Y shares in the 4I treatment versus 42 X shares and 84 Y shares in the 9I treatment) due to the fewer number of Active traders. Thus, it is not surprising that, on average, an Index tracker's average trading income per period decreased from -203.05 ECUs in the 4I treatment to -412.49 ECUs in the 9I treatment when aggregating data from all states (WRS, p-value < 0.001).[26]

5.3.3 Who benefits from the introduction of Index tracking?

To identify the type of traders who benefit from the presence of Index trackers, we study the impact of individual characteristics and private information. The dataset comprises 576 individual traders as cross-sectional observations and spans 15 market periods, forming the temporal dimension of our panel data. We conducted pooled panel data regressions, controlling for private information and traders' characteristics such as the trader's score on the CRT, age, gender, academic major, and financial literacy. We also control for stock market experience, measured as whether participants had previously traded stocks. Table 10 shows regression results for trading income per period as the dependent variable.

Informed traders

In Table 10 (column (1)), we show that the trading income of Active traders across all states increases with the number of Index trackers. Indeed, the coefficients of the interaction terms 'Baseline×Info', '4I×Info', and '9I×Info' are 110.11 to 180.27 and 338.94, respectively. The differences between these interaction coefficients are all significant (F tests, p-values $<$ 0.001 for all pairwise comparisons). It follows that being informed becomes more profitable when the number of Index trackers in the market increases, which is also when informational efficiency decreases. In informationally inefficient markets, informed traders' private information is not entirely reflected in asset prices allowing them to maintain their informational advantage and boost their earnings. While trading incomes for uninformed Active traders are higher in the 9I treatment compared to the Baseline (see '9I×NoInfo' coefficient in Table 10, column (1)), trading incomes are lower for uninformed Active traders in the 4I treatment. Importantly, informed Active traders benefited more from the introduction of Index trackers than uninformed Active traders. Indeed, the coefficients of '4I×Info' and '9I×Info' in Table 10, column (1) are greater than the coefficients of '4I×NoInfo' and '9I×NoInfo' (180.27 $>$ -33.20; 338.94 $>$ 134.88), respectively (F tests, p-values < 0.001 for both treatments).

Sophisticated traders

In line with prior studies (Breaban and Noussair (2015); Corgnet et al. (2015); Cueva and Rustichini (2015); Noussair, Tucker, and Xu (2016); Corgnet, DeSantis, and Porter (2018); Shestakova, Powell, and Gladyrev (2019)), cognitive ability, as measured with CRT scores,

[26] We find qualitatively similar results when considering Index trackers' average earnings per period. On average, an Index tracker's period earnings decreased from 1964.08 ECUs in the 4I treatment to 1717.93 ECUs in the 9I treatment. This difference is significant at the 5% level (WRS).

Table 10: Individual traders' trading income per period, pooled regressions

	(1)	(2)
DV: Trading Incomes	All States	All States
Baseline × Info	110.11*	108.46*
	(14.43)	(14.86)
4I × NoInfo	−33.21†	-52.88
	(13.25)	(63.28)
4I × Info	180.27*	160.68†
	(15.48)	(67.21)
4I × Index	−53.76	−90.19
	(51.93)	(83.33)
9I × NoInfo	134.88*	72.70
	(16.98)	(40.49)
9I × Info	338.94*	279.75*
	(11.37)	(44.12)
9I × Index	−257.30*	−267.39*
	(38.96)	(47.40)
Act × CRT	15.02*	
	(4.19)	
Index × CRT	−3.29	
	(7.20)	
Baseline × CRT		11.38†
		(4.85)
4I × Act × CRT		14.91
		(9.90)
9I × Act × CRT		21.99*
		(4.67)
4I × Index × CRT		-0.31
		(15.25)
9I × Index × CRT		-5.07
		(7.25)
Age	−4.59	−4.77
	(2.65)	(2.81)
Gender (1 = Male)	17.98	17.79
	(11.97)	(12.46)
Major	7.80	7.45
	(11.26)	(10.83)
Market Experience	41.78*	42.39*
	(11.02)	(10.99)
Financial Literacy	-8.15	-7.90
	(7.86)	(7.92)
Constant	-48.51	-25.25
	(66.21)	(74.49)
State fixed effect	Yes	Yes
Obs.	8640	8640

Note: Robust standard errors clustered at the experimental session level are in parentheses. An observation corresponds to a trader-market pair. Baseline, 4I, and 9I are dummy variables whose values are set to one if the market corresponds to the respective treatment and zero otherwise. CRT reflects the trader's score (0, 1, . . . , 7) on the cognitive reflection test. Info (No Info) is a dummy variable whose value is set to one if the trader is an active informed (uninformed) trader, i.e., received (did not receive) a private signal, and set to zero otherwise. Index (Act) is a dummy variable whose value is set to one if the trader is an index tracker (active trader) and set to zero otherwise. Base category: "Baseline × NoInfo".
Two-sided p-values determine significance. * Significant at the 1% level; † significant at the 5% level.

leads to higher trading incomes for Active traders (see 'Act×CRT' coefficient in Table 10, column (1)). The coefficient of 'Act×CRT' in column (1) is positive and significant suggesting Active traders with higher CRT scores have larger trading incomes. The CRT dummy variable is replaced by five interaction terms in column (2) in Table 10. The coefficients of the interaction terms corresponding to Active traders are positive suggesting higher CRT scores lead to higher trading incomes of Active traders in the Baseline and the two treatments. The coefficients for 'Baseline×CRT' and '9I×Act×CRT' are positive and significant whereas the coefficient '4I×Act×CRT' is not significant. These findings suggest that traders with higher CRT scores can take advantage of Index trackers once the level of Index tracking in the market is high enough. Unsurprisingly, CRT does not help Index trackers as their objective, to create bundles, does not require the ability to engage in statistical inference to extract private information from prices. The previous findings were obtained by controlling for market experience and financial literacy. While financial literacy does not predict earnings in line with Corgnet, DeSantis, and Porter (2018), market experience is associated with higher earnings. Therefore, future research might attempt to isolate the dimensions of market experience that contribute to higher earnings, independent of cognitive ability and financial literacy.

We summarize our findings on the individual analyses of earnings as follows.

Result 4 (**Private information, cognitive ability and earnings**). *Informed traders and those with high cognitive ability benefit the most from the presence of Index trackers.*

6 Conclusion

The surge in passive investing over the past decade has prompted us to examine its effects on various market quality metrics. Our focus on evaluating the causal impact of passive investing on informational efficiency led us to choose an experimental approach, yielding a wealth of insights.

Index tracking enhances liquidity by fostering increased trade volumes and narrower bid-ask spreads. It also had an inflationary impact on asset prices, which echoes the concurrent surge in Index tracking and the boom in US stock prices over the last 15 years, where the correlation between the share of Index tracking as defined in Figure 1(b) and year-end values of the SP500 is 0.97. At the level of individual stocks, empirical evidence shows that companies whose stock is added to a major index increase in value with respect to comparable stocks that are not added to the index (Qin and Singal (2015); Ben-David, Franzoni, and

Moussawi (2018); Ahn and Patatoukas (2022); Coles, Heath, and Ringgenberg (2022); Duffy et al. (2022)).

However, the ultimate gauge of the well-function of markets, namely informational efficiency, is harmed by the presence of passive investing. This is a novel finding that expands upon previous field studies that do not have access to direct measures of informational efficiency.

Ours is the first study that uncovers and quantifies the negative impact of passive investing on the well-functioning of markets. At the core of any well-functioning market is the absence of arbitrage opportunities (Berk and DeMarzo (2019)). Interestingly, arbitrage opportunities were mostly benign in the absence of passive investing as evidenced by our Baseline, which reflects the situation of US markets pre-1995 (Anadu et al. (2020)), and by our 4I treatment, which reflects the situation of US markets at the beginning of the century – before the surge in passive investing. In these two cases, the magnitude of arbitrage opportunities, captured by the arbitrage ratio, was between 1% and 2%. By contrast, the 9I treatment, which reflects current market conditions with passive investing at approximately 38%, led to a dramatic increase in arbitrage opportunities with an arbitrage ratio close to 13%. Our findings thus contradict the claim of Malkiel (2022) that markets can function well with up to 98% of passive investing. Instead, our results suggest that passive investing can threaten the well-functioning of markets when its weight is as low as one-third. Interestingly, despite the surge in passive investing over the last decade (see Figure 1(b)), hedge funds performance on arbitrage strategies has increased substantially (Aurum (2022)). This has been particularly true for the opportunistic arbitrage type considered in our experiment, which involves exploiting price differences across identical assets.

At the individual level, Active traders benefit from the presence of passive investors, especially when they are informed and cognitively sophisticated. In the end, Malkiel (2022) might well be correct that passive investing could be beneficial... to some, but not to the average retail investor.

Despite the decrease in the share of active funds in the market, best-performing funds have done especially well in the last decade. The gap between the top and bottom deciles hedge funds returns has increased from about 20% in 2013 to 40% in 2022 (Aurum (2023)). Furthermore, the gap in net performance between complex high-fee funds and cheaper funds (UCITS) has increased over the last five years. These findings align with our assertion that sophisticated Active traders could capitalize on new arbitrage opportunities arising from the increase in Index tracking.

References

Ahn, B. H., and P. N. Patatoukas. 2022. Identifying the effect of stock indexing: Impetus or impediment to arbitrage and price discovery? *J. Fin. Quant. Anal.* 57:2022–62.

Anadu, K., M. Kruttli, P. McCabe, and E. Osambela. 2020. The shift from active to passive investing: Potential risks to financial stability? *Fin. Econ. Discuss. Ser.* 2020.

Anderson, R., P. L. Bossaerts, and F. Fattinger. 2020. How information structure impacts aggregation of information in markets. *SSRN Electron. J.* .

Anufriev, M., T. Bao, A. Sutan, and J. Tuinstra. 2019. Fee structure and mutual fund choice: An experiment. *J. Econ. Behav. Organ.* 158:449–74.

Aurum. 2022. Arbitrage strategy analytics packs. `https://www.aurum.com/hedge-fund-strategy-definitions`. Accessed: January 2024.

———. 2023. Hedge fund industry deep dive. `https://www.aurum.com/hedge-fund-data/hedge-fund-industry-deep-dive/hedge-fund-industry-performance-deep-dive-h1-2023`. Accessed: January 2024.

Baruch, S., and X. Zhang. 2022. The distortion in prices due to passive investing. *Manage. Sci.* 68:6219–34.

Basak, S., and A. Pavlova. 2013. Asset prices and institutional investors. *Am. Econ. Rev.* 103:1728–58.

Bednarek, P. 2023. Rise of passive investing-effects on price level, market stability, and price informativeness. *Market Stability, and Price Informativeness (August 25, 2023)* .

Ben-David, I., F. Franzoni, and R. Moussawi. 2017. Exchange-traded funds. *Annu. Rev. Fin. Econ.* 9:169–89.

———. 2018. Do ETFs increase volatility? *J. Finance* 73:2471–535.

Berk, J., and P. DeMarzo. 2019. Corporate finance, global ed. *Essex: Person education limited* .

Biais, B., P. Bossaerts, and C. Spatt. 2010. Equilibrium asset pricing and portfolio choice under asymmetric information. *Rev. Financ. Stud.* 23:1503–43.

Bloomfield, R., M. O'Hara, and G. Saar. 2009. How noise trading affects markets: An experimental analysis. *The Review of Financial Studies* 22:2275–302.

Boehmer, E., and E. K. Kelley. 2009. Institutional investors and the informational efficiency of prices. *Rev. Financ. Stud.* 22:3563–94.

Bond, P., and D. García. 2022. The equilibrium consequences of indexing. *Rev. Financ. Stud.* 35:3175–230.

Breaban, A., and C. N. Noussair. 2015. Trader characteristics and fundamental value trajectories in an asset market experiment. *J. Behav. Exp. Finance* 8:1–17.

Breugem, M., and A. Buss. 2018. Institutional investors and information acquisition: Implications for asset prices and informational efficiency. *Rev. Financ. Stud.* 32:2260–301.

Charness, G., and T. Neugebauer. 2019. A test of the Modigliani-Miller invariance theorem and arbitrage in experimental asset markets. *J. Finance* 74:493–529.

Childs, J., and S. Mestelman. 2006. Rate-of-return parity in experimental asset markets. *Review of International Economics* 14:331–47.

Chinco, A., and M. Sammon. 2022. The passive-ownership share is double what you think it is. *SSRN Electron. J.* .

Choi, J. J., D. Laibson, and B. C. Madrian. 2010. Why does the law of one price fail? An experiment on index mutual funds. *Rev. Financ. Stud.* 23:1405–32.

Coles, J. L., D. Heath, and M. C. Ringgenberg. 2022. On index investing. *Journal of Financial Economics* 145:665–83.

Corgnet, B., C. Deck, M. DeSantis, K. Hampton, and E. O. Kimbrough. 2023. When do security markets aggregate dispersed information? *Management Science* 69:3697–729.

Corgnet, B., M. DeSantis, and D. Porter. 2018. What makes a good trader? on the role of intuition and reflection on trader performance. *The Journal of Finance* 73:1113–37.

———. 2021. Information aggregation and the cognitive make-up of market participants. *Eur. Econ. Rev.* 133:103667–.

Corgnet, B., R. Hernán-González, P. Kujal, and D. Porter. 2015. The effect of earned versus house money on price bubble formation in experimental asset markets. *Rev. Financ.* 19:1455–88.

Cueva, C., and A. Rustichini. 2015. Is financial instability male-driven? gender and cognitive skills in experimental asset markets. *J. Econ. Behav. Organ.* 119:330–44.

De Rossi, G., and M. Steliaros. 2022. The shift from active to passive and its effect on intraday stock dynamics. *Journal of Banking & Finance* 143:106595–.

Duffy, J., D. Friedman, J. P. Rabanal, and O. Rud. 2022. The impact of ETF index inclusion on stock prices. *Available at SSRN 4061686* .

Duffy, J., J. P. Rabanal, and O. A. Rud. 2021. The impact of ETFs in secondary asset markets: Experimental evidence. *J. Econ. Behav. Organ.* 188:674–96.

Easley, D., D. Michayluk, M. O'Hara, and T. J. Putniņš. 2021. The active world of passive investing. *Rev. Financ.* 25:1433–71.

Ehm, C., C. Kaufmann, and M. Weber. 2014. Volatility inadaptability: Investors care about risk, but cannot cope with volatility. *Rev. Financ.* 18:1387–423.

Eyster, E., M. Rabin, and D. Vayanos. 2019. Financial markets where traders neglect the informational content of prices. *J. Finance* 74:371–99.

Fama, E. F. 1970. Efficient capital markets: A review of theory and empirical work. *J. Finance* 25:383–.

———. 2014. Two pillars of asset pricing. *Am. Econ. Rev.* 104:1467–85.

Fama, E. F., and K. R. French. 2007. Disagreement, tastes, and asset prices. *Journal of Financial Economics* 83:667–89.

———. 2009. What if everybody indexed? *Dimensional* 17th of September.

Fisher, E. O., and F. S. Kelly. 2000. Experimental foreign exchange markets. *Pacific Economic Review* 5:365–87.

Foucault, T., M. Pagano, and A. Röell. 2013. *Market liquidity: theory, evidence, and policy.* Oxford University Press.

Frederick, S. 2005. Cognitive reflection and decision making. *J. Econ. Perspect.* 19:25–42.

French, C. W. 2003. The treynor capital asset pricing model. *Journal of Investment Management* 1:60–72.

Frydman, C., N. Barberis, C. Camerer, P. Bossaerts, and A. Rangel. 2014. Using neural data to test a theory of investor behavior: An application to realization utility. *The Journal of Finance* 69:907–46.

Fullbrunn, S., and E. Haruvy. 2022. *Handbook of experimental finance.* Edward Elgar Publishing.

Gârleanu, N., and L. H. Pedersen. 2022. Active and passive investing: Understanding Samuelson's dictum. *Rev. Asset Pricing Stud.* 12:389–446.

Glosten, L., S. Nallareddy, and Y. Zou. 2021. ETF activity and informational efficiency of underlying securities. *Management Science* 67:22–47.

Grinblatt, M., S. Ikäheimo, M. Keloharju, and S. Knüpfer. 2016. IQ and mutual fund choice. *Management Science* 62:924–44.

Grinblatt, M., M. Keloharju, and J. Linnainmaa. 2011. IQ and stock market participation. *The Journal of Finance* 66:2121–64.

Grinblatt, M., M. Keloharju, and J. T. Linnainmaa. 2012. IQ, trading behavior, and performance. *Journal of Financial Economics* 104:339–62.

Grossman, S. J., and J. E. Stiglitz. 1980. On the impossibility of informationally efficient markets. *The American Economic Review* 70:393–408.

Haddad, V., P. Huebner, and E. Loualiche. 2021. How competitive is the stock market? theory, evidence from portfolios, and implications for the rise of passive investing. *SSRN Electron. J.* .

Hasbrouck, J. 2003. Intraday price formation in us equity index markets. *The Journal of Finance* 58:2375–400.

Heath, D., D. Macciocchi, R. Michaely, and M. C. Ringgenberg. 2021. Do index funds monitor? *Rev. Financ. Stud.* 35:91–131.

Heuer, J., C. Merkle, and M. Weber. 2017. Fooled by randomness: Investor perception of fund manager skill. *Rev. Financ.* 21:605–35.

Hirshleifer, J. 1978. The private and social value of information and the reward to inventive activity. In *Uncertainty in economics*, 541–56. Elsevier.

Huang, S., M. O'Hara, and Z. Zhong. 2021. Innovation and informed trading: Evidence from industry ETFs. *Rev. Financ. Stud.* 34:1280–316.

Israeli, D., C. M. C. Lee, and S. A. Sridharan. 2017. Is there a dark side to exchange traded funds? an information perspective. *Rev. Acc. Stud.* 22:1048–83.

Kerzérho, R. 2018. The passive vs. active fund monitor. *PWLCAPITAL* .

———. 2023. The passive vs. active fund monitor. *PWLCAPITAL* .

Krause, T., S. Ehsani, and D. Lien. 2014. Exchange-traded funds, liquidity and volatility. *Appl. Fin. Econ.* 24:1617–30.

Lettau, M., and A. Madhavan. 2018. Exchange-traded funds 101 for economists. *J. Econ. Perspect.* 32:135–54.

Lintner, J. 1965. Security prices, risk, and maximal gains from diversification. *The journal of finance* 20:587–615.

Lusardi, A., and O. S. Mitchell. 2011. Financial literacy around the world: an overview. *Journal of pension economics & finance* 10:497–508.

Malkiel, B. 2022. 50 years later, burton malkiel hasn't changed his views on indexing. *Wall Street Journal* 4th of November.

Marshall, B. R., N. H. Nguyen, and N. Visaltanachoti. 2013. Etf arbitrage: Intraday evidence. *Journal of Banking & Finance* 37:3486–98.

Milgrom, P., and N. Stokey. 1982. Information, trade and common knowledge. *Journal of Economic Theory* 26:17–27.

Morris, S. 1994. Trade with heterogeneous prior beliefs and asymmetric information. *Econometrica: Journal of the Econometric Society* 1327–47.

Neugebauer, T., J. Shachat, and W. Szymczak. 2023. A test of the modigliani-miller theorem, dividend policy and algorithmic arbitrage in experimental asset markets. *Journal of Banking & Finance* 106814.

Noussair, C. N., S. Tucker, and Y. Xu. 2016. Futures markets, cognitive ability, and mispricing in experimental asset markets. *Journal of Economic Behavior & Organization* 130:166–79.

Plott, C. R., and S. Sunder. 1988. Rational expectations and the aggregation of diverse information in laboratory security markets. *Econometrica: Journal of the Econometric Society* 1085–118.

Qin, N., and V. Singal. 2015. Indexing and stock price efficiency. *Financial management* 44:875–904.

Roll, R. 1977. A critique of the asset pricing theory's tests part i: On past and potential testability of the theory. *Journal of Financial Economics* 4:129–76.

Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance* 19:425–42.

———. 1991. The arithmetic of active management. *Financial Analysts Journal* 47:7–9.

Shestakova, N., O. Powell, and D. Gladyrev. 2019. Bubbles, experience and success. *Journal of Behavioral and Experimental Finance* 22:206–13.

Shiller, R. J. 2017. Passive investing is a dangerous chaotic system. *CNBC* 14th of November.

Smith, V. L., G. L. Suchanek, and A. W. Williams. 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica: Journal of the Econometric Society* 1119–51.

Sushko, V., and G. Turner. 2018. The implications of passive investing for securities markets. *BIS Quarterly Review, March* .

Toplak, M. E., R. F. West, and K. E. Stanovich. 2014. Assessing miserly information processing: An expansion of the cognitive reflection test. *Thinking & reasoning* 20:147–68.

Verrecchia, R. E. 1982. Information acquisition in a noisy rational expectations economy. *Econometrica: Journal of the Econometric Society* 1415–30.

Wei, W., and A. Young. forthcoming. Selection bias or treatment effect. *Critical Finance Review* 1000:forthcoming–.

Wigglesworth, R. 2021. *Trillions: How a band of wall street renegades invented the index fund and changed finance forever*. Penguin.

———. 2022. How passive are markets, actually? *Financial Times,* 5th of September.

A Appendix: Trader demand functions for assets

Derive the aggregate demand functions for Passive and Active traders. Recall an Index tracker derives value by receiving a commission of z for each index bundle of one unit of X and two units of Y. The following Leontief utility function represents these induced preferences,

$$U_{\mathrm{I}}(X_{\mathrm{I}}, Y_{\mathrm{I}}, C_{\mathrm{I}}) = z \cdot \min\left\{X_{\mathrm{I}}, \frac{Y_{\mathrm{I}}}{2}\right\}.$$

An Active trader solely derives value from his final ECU holdings, i.e. after state-dependent dividends are paid. We assume at this point that each Active trader will hold common expectations of the X and Y valuations, $E[X] = V$ and $E[Y] = \frac{V}{2}$. Accordingly, the expected value of the portfolio $(X_{\mathrm{A}}, Y_{\mathrm{A}}, C_{\mathrm{A}})$ is,

$$U_{\mathrm{A}}(X_{\mathrm{A}}, Y_{\mathrm{A}}, C_{\mathrm{A}}) = X_{\mathrm{A}} \cdot V + Y_{\mathrm{A}} \cdot \frac{V}{2} + C_{\mathrm{A}}.$$

Deriving Competitive Equilibrium by treatment, we start with the two treatments which include Index trackers. First, we impose the no arbitrage condition, $p_X = 2p_Y$. As Index trackers have the same initial endowments, we proceed by defining the aggregate demand functions for the set of Index trackers. Then we can calculate their individual final allocations as the average of their type aggregate final allocations.

A.1 Index tracker demand functions

The aggregate demand functions for Index trackers in the 4I treatment are found by considering the demand quantities satisfying $Y_{\mathrm{I}}^e = 2X_{\mathrm{I}}^e$ and the budget constraint $p_X \cdot X_{\mathrm{I}}^e + p_Y \cdot Y_{\mathrm{I}}^e \leq 4p_X + 8p_Y + 7592$. The resulting demand functions are

$$X_{\mathrm{I}}^e(p_X, p_Y) = \frac{4I_X + 8p_Y + 7592}{p_X + 2p_Y} \text{ and } Y_{\mathrm{I}}^e(p_X, p_Y) = \frac{8p_X + 16p_Y + 15184}{p_X + 2p_Y}.$$

The aggregate demand functions for the 9I treatment are

$$X_{\mathrm{I}}^e(p_X, p_Y) = \frac{9I_X + 18p_Y + 17082}{p_X + 2p_Y} \text{ and } Y_{\mathrm{I}}^e(p_X, p_Y) = \frac{18p_X + 36p_Y + 34164}{p_X + 2p_Y}.$$

Imposing the law of one price, i.e., no arbitrage, along with the index portfolio ratio constraint yields

$$X_{\mathrm{I}}^e(p_X) = 4 + \frac{3796}{p_X} \text{ and } Y_{\mathrm{I}}^e(p_X) = 8 + \frac{7592}{p_X}$$

for the 4I treatment. Solving for X_{I}^e while imposing budget exhaustion leads to the following demand curves

$$p_X \cdot X_I^e + \frac{p_X}{2} \cdot 2X_I^e \leq 4p_X + 8 \cdot \frac{p_X}{2} + 7592.$$

Similar arguments lead to the following aggregate demand curves for the 9I treatment

$$X_{\mathrm{I}}^e(p_X) = 9 + \frac{8541}{p_X} \text{ and } Y_{\mathrm{I}}^e(p_X) = 18 + \frac{17082}{p_X}.$$

A.2 Active trader demand functions

The linear utility of Active traders and the imposition of the law of one price dictates that when prices exceed the value of the assets Active traders will want to sell their endowment of assets and only hold ECUs. When prices are below asset values, Active traders will purchase as many units of the assets as their endowment will allow (and not hold any ECUs). In the 4I treatment, the aggregated budget constraint for the Active traders is

$$p_X \cdot X_{\mathrm{A}} + p_Y \cdot Y_{\mathrm{A}} + C_{\mathrm{A}} = 47p_X + 94p_Y + 23920.$$

The resulting aggregate demand functions are

$$X_{\mathrm{A}}^e(p_X) = \begin{cases} 0, & \text{if } p_X > V \\ [0, 47 + \frac{11960}{p_X}] & \text{if } p_X = V \\ 47 + \frac{11960}{p_X} & \text{if } p_X < V \end{cases} \text{ and } Y_{\mathrm{A}}^e(p_X) = 2X_{\mathrm{A}}^e(p_X).$$

When $p_X = V$, then an Active trader is indifferent between holding p_X units of ECUs, a unit of X and two units of Y. However, the actual quantities demanded in the aggregate portfolio of the Active traders still must satisfy the aggregate budget constraint,

$$p_X^e \cdot X_{\mathrm{A}}^e + 2p_X^e \cdot Y_{\mathrm{A}}^e + C_{\mathrm{A}}^e = 47p_X + 94p_Y + 23920.$$

In the 9I treatment, the aggregated budget constraint for the Active traders is,

$$p_X \cdot X_{\mathrm{A}} + p_Y \cdot Y_{\mathrm{A}} + +C_{\mathrm{A}} = 42p_X + 84p_Y + 14430.$$

The resulting aggregate demand functions are

$$X_{\mathrm{A}}^{e}(p_X) = \begin{cases} 0, & \text{if } p_X > V \\ \left[0, 42 + \dfrac{7215}{p_X}\right], & \text{if } p_X = V \\ 42 + \dfrac{7215}{p_X}, & \text{if } p_X < V \end{cases} \quad \text{and } Y_{\mathrm{A}}^{e}(p_X) = 2X_{\mathrm{A}}^{e}(p_X).$$

The key to identifying the rational expectations equilibrium is to first solve for the unique quantities demanded of assets by the Index trackers for each of the state-dependent values. For values at which the aggregate demand for Index trackers exceeds the aggregate endowments of the whole market, there is a corner solution in which the Index trackers will hold all the units of X and Y. Then the equilibrium price is the one that equates the Index trackers' quantities demanded with the total market endowment of each asset. If we relax the rational expectations assumption to one in which Active traders hold a common expectation on the value, then the competitive equilibrium is calculated in a similar fashion: set the assets' prices to their expected values, calculate the Active traders' quantity demands, and then solve for interior and corner solutions for allocations accordingly.

B Appendix: Descriptive statistics

In this appendix we report statistics for our arbitrage and market quality measures by treatment and by state.

Table 11: Descriptive Statistics Summary. Sample means (standard deviation) for arbitrage and market quality measures.

Measures	**Treatment**	**All States**	**Low State**	**Middle State**	**High State**
Asset Value			50	240	490
		Panel A: The Law of One Price and Arbitrage			
Mispricing Ratio	Baseline	0.17	0.25	0.10	0.15
		(0.16)	(0.23)	(0.08)	(0.11)
	4I	0.14	0.14	0.13	0.15
		(0.13)	(0.16)	(0.10)	(0.13)
	9I	0.23	0.25	0.23	0.22
		(0.13)	(0.13)	(0.15)	(0.11)
TWArb	Baseline	0.98	1.51	0.72	0.71
		(2.26)	(3.19)	(1.53)	(1.61)
	4I	1.95	1.85	1.33	2.70
		(4.11)	(3.46)	(2.47)	(5.77)
	9I	15.07	14.27	16.19	14.71
		(13.15)	(11.73)	(13.89)	(13.95)
		Panel B: Market Quality			
Volume	Baseline	33.00	33.19	34.44	31.28
		(9.19)	(8.40)	(9.15)	(9.94)
	4I	36.64	38.75	38.79	32.21
		(5.64)	(3.67)	(5.63)	(4.75)
	9I	45.22	47.99	46.35	41.18
		(4.87)	(3.92)	(4.12)	(3.80)
TWSpread	Baseline	0.25	0.32	0.20	0.25
		(0.15)	(0.19)	(0.10)	(0.11)
	4I	0.18	0.21	0.16	0.18
		(0.11)	(0.13)	(0.10)	(0.10)
	9I	0.14	0.18	0.12	0.12
		(0.10)	(0.13)	(0.07)	(0.07)
Volatility	Baseline	30.88	33.19	23.22	36.57
		(17.90)	(17.75)	(14.13)	(19.18)
	4I	30.09	29.18	25.59	35.76
		(22.27)	(15.74)	(15.97)	(31.22)
	9I	27.24	27.14	24.32	30.42
		(18.70)	(16.48)	(20.10)	(19.26)

Note: With the exception of the *Mispricing Ratio* and *TWArb*, the data reported in this table corresponds to the combined Market X and Market Y dataset. The variables for this combined dataset were calculated as follows: (i) *Volatility*: (Market X volatility + 2 $\times$ Market Y volatility)/2; (ii) *Volume* and *TWSpread*: (Market X value + Market Y value)/2.

C Appendix: Descriptive statistics and treatment effects of individual markets

In this appendix, we report the results corresponding to individual market analyses.

Table 12: Descriptive Statistics Summary of Market X. This table provides the mean (standard deviation) values for the primary variables of interest.

Measures	Treatment	All States	Low State	Middle State	High State
		Panel A: Informational Efficiency			
Asset Value			50	240	490
Average Price	Baseline	241.80	215.68	239.27	271.26
		(34.43)	(30.12)	(15.73)	(30.08)
	4I	265.44	245.35	260.26	291.50
		(29.34)	(22.57)	(18.34)	(25.83)
	9I	306.96	291.84	302.48	327.16
		(27.73)	(20.46)	(22.26)	(27.85)
		Panel B: Market Quality			
Volume	Baseline	27.37	29.35	28.05	24.62
		(8.75)	(8.67)	(8.61)	(8.52)
	4I	27.77	30.32	28.95	23.92
		(5.30)	(4.38)	(4.65)	(4.70)
	9I	32.73	34.80	33.32	29.97
		(4.44)	(3.85)	(3.80)	(4.31)
TWSpread	Baseline	0.26	0.32	0.19	0.26
		(0.18)	(0.23)	(0.13)	(0.13)
	4I	0.18	0.21	0.16	0.18
		(0.13)	(0.16)	(0.10)	(0.11)
	9I	0.15	0.19	0.12	0.13
		(0.12)	(0.16)	(0.09)	(0.09)
Volatility	Baseline	33.49	33.37	26.13	41.36
		(22.11)	(18.55)	(19.06)	(25.94)
	4I	26.97	24.21	25.71	31.14
		(21.38)	(15.01)	(25.88)	(21.64)
	9I	25.83	23.38	20.88	33.54
		(19.43)	(15.01)	(17.04)	(23.50)

Note: Descriptive statistics for the period-level measures of Asset X.

Table 13: Descriptive Statistics Summary of Market Y. This table provides the mean (standard deviation) values for the primary variables of interest.

Measures	**Treatment**	**All States**	**Low State**	**Middle State**	**High State**
		Panel A: Informational Efficiency			
Asset Value			25	120	245
Average Price	Baseline	119.54	104.99	118.67	135.38
		(19.42)	(18.22)	(6.21)	(17.84)
	4I	139.57	128.32	135.20	155.70
		(19.96)	(16.53)	(12.50)	(19.54)
	9I	168.54	159.69	167.09	179.13
		(18.24)	(15.75)	(17.53)	(16.27)
		Panel B: Market Quality			
Volume	Baseline	38.63	37.02	40.83	37.95
		(12.33)	(11.57)	(12.22)	(13.17)
	4I	45.50	47.17	48.63	40.49
		(7.64)	(5.71)	(7.72)	(6.86)
	9I	57.71	61.17	59.39	52.38
		(6.92)	(5.51)	(5.80)	(6.22)
TWSpread	Baseline	0.25	0.32	0.20	0.23
		(0.14)	(0.16)	(0.12)	(0.12)
	4I	0.19	0.21	0.17	0.18
		(0.11)	(0.12)	(0.11)	(0.11)
	9I	0.13	0.17	0.12	0.10
		(0.10)	(0.13)	(0.10)	(0.06)
Volatility	Baseline	14.13	16.50	10.15	15.89
		(9.84)	(11.31)	(7.18)	(9.56)
	4I	16.61	17.08	12.74	20.19
		(17.85)	(9.26)	(7.32)	(28.70)
	9I	14.33	15.45	13.88	13.65
		(12.45)	(10.15)	(16.08)	(10.27)

Note: Descriptive statistics for the period-level measures of Asset Y.

Table 14: Descriptive Statistics and Tests for Market *X*. Sample means (standard deviation) for market efficiency and quality measures along with p-values from treatment comparisons across measures using Wilcoxon rank-sum tests <including Holm-Bonferroni corrections>.

Measures	**Treatment**	**Values**	**p-values**	**p-values**
			vs. Baseline	*vs.* 4I
		Panel A: Informational Efficiency		
Average Price	Baseline	241.80		
		(34.43)		
	4I	265.44	(0.002)*	
		(29.34)	<0.021>†	
	9I	309.96	(0.001)*	(0.001)*
		(27.73)	<0.009>	<0.009>*
		Panel B: Market Quality		
Volume	Baseline	27.37		
		(8.75)		
	4I	27.77	(0.753)	
		(5.30)	<1.000>	
	9I	32.73	(0.036)†	(0.002)*
		(4.44)	<0.250>	<0.016>†
TWSpread	Baseline	0.26		
		(0.18)		
	4I	0.18	(0.046)†	
		(0.13)	<0.276>	
	9I	0.15	(0.005)*	(0.115)
		(0.12)	<0.037>†	<0.576>
Volatility	Baseline	33.49		
		(22.11)		
	4I	26.97	(0.529)	
		(21.38)	<1.000>	
	9I	25.83	(0.674)	(0.294)
		(19.43)	<1.000>	<1.000>

Note: The p-values and corrected p-values using the Holm-Bonferroni method are reported in parentheses () and brackets <>. * Significant at the 1% level; † significant at the 5% level.

Table 15: Descriptive Statistics and Tests for Market Y. Sample means (standard deviation) for market efficiency and quality measures along with p-values from treatment comparisons across measures using Wilcoxon rank-sum tests <including Holm-Bonferroni corrections>.

Measures	**Treatment**	**Values**	**p-values**	**p-values**
			vs. Baseline	*vs.* 4I
		Pabel A: Informational Efficiency		
Average Price	Baseline	119.54		
		(19.42)		
	4I	139.57	(0.001)*	
		(19.96)	<0.008>*	
	9I	168.54	(0.001)*	(0.001)*
		(18.24)	<0.008>*	<0.008>*
		Panel B: Market Quality		
Volume	Baseline	38.63		
		(12.33)		
	4I	45.50	(0.172)	
		(7.64)	<0.689>	
	9I	57.71	(0.001)*	(0.001)*
		(6.92)	<0.008>*	<0.008>*
TWSpread	Baseline	0.25		
		(0.14)		
	4I	0.19	(0.016)†	
		(0.11)	<0.079>	
	9I	0.13	(0.001)*	(0.001)*
		(0.10)	<0.008>*	<0.008>*
Volatility	Baseline	14.13		
		(9.84)		
	4I	16.61	(0.529)	
		(17.85)	<1.000>	
	9I	14.33	(1.000)	(0.600)
		(12.45)	<1.000>	<1.000>

Note: The p-values and corrected p-values using the Holm-Bonferroni method are reported in parentheses () and brackets <>.
* Significant at the 1% level; † significant at the 5% level.

D Appendix: Post-experiment survey instruments

This appendix provides details of the post-experiment surveys. As is standard practice, these surveys were not incentivized.

D.1 Cognitive reflection test

Participants were given five minutes to complete a seven-question version of the cognitive reflection test. The questions are listed below.

1. A table and a chair cost $150 in total. The table costs 100 dollars more than the chair. How much does the chair cost?

Answer: 25

2. If it takes 10 mechanics 10 hours to fix 10 cars, how long would it take 80 mechanics to fix 80 cars?

Answer: 10

3. A new library is purchasing books for its collection. Every week, the number of books acquired doubles. If it takes 36 weeks to buy all the books they need, how long would it take for the library to buy half of the books they need?

Answer: 35

4. In the zoo, the lions eat one ton of meat every 6 weeks, and the tigers eat another ton of meat every 12 weeks, how long would it take them (lions and tigers) to eat one ton of meat together?

Answer: 4

5. John obtained the 25th fastest mark and the 25th slowest mark in a race. How many people participated in the race?

Answer: 49

6. An art collector acquires a famous painting for 50 million, sells it for 60 million. Some years later, the collector buys it back for 70 million, and sells it finally for 80 million. How much has the collector won in total?

Answer: 20

7. Mary invested $12,000 in the stock market in November 2013. Six months later, on May 2014, the stocks she had purchased were down 50%. Fortunately for Mary, from May 2014 to August 2014, the stocks she had purchased went up 75%. At this point, Mary:

a. has won money

b. has lost money

c. has neither won nor lost money

Answer: b

Table 16: Distribution of CRT scores

CRT Score	% of Subjects
0	0.69
1	1.22
2	6.60
3	6.25
4	10.59
5	15.63
6	21.88
7	37.15
Mean	5.45
Standard Deviation	1.68

D.2 Demographic information

Participants were asked the following five demographic questions. These questions were not timed.

1. How old are you?

____ years

[Average age: 20.98]

2. Are you

male

female

[Percentage of female students: 56.94%]

3. Are you enrolled in an economics-related study programme?

yes

no

[Percentage of students enrolled in an economics-related study programme: 35.94%]

4. Have you ever participated in a market experiment?

yes

no

[Percentage of students who previously participated in a market experiment: 50.17%]

5. How would you rate your knowledge about auctions/financial markets?

expert

basic knowledge

none

[Percentage of students who self-report expert (1.56%); basic (40.80%); none (57.64%) knowledge regarding financial markets.]

D.3 Financial literacy

Participants were asked the following three financial literacy questions. These questions were not timed.

A. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

1. More than $102
2. Exactly $102
3. Less than $102
4. Don't know
5. Refuse to answer

Answer: 1

B. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, with the money in this account, would you be able to buy...

1. More than today
2. Exactly the same as today
3. Less than today
4. Don't know
5. Refuse to answer

Answer: 3

C. Do you think the following statement is true or false? Buying a single company stock usually provides a safer return than a stock mutual fund.

1. True
2. False
3. Don't know

4. Refuse to answer

Answer: 2

Table 17: Distribution of Financial Literacy scores

Financial Literacy Score	**% of Subjects**
0	2.43
1	5.90
2	15.63
3	76.04
Mean	2.65
Standard Deviation	0.70

E Appendix: Instructions

This appendix provides the English translations of the instructions for the 4I treatment.

E.1 Introduction

This is an experiment in the economics of market decision-making. You will be compensated at the end of the experiment based on your decisions. So, it is important that you understand the instructions completely. We will ask you a 7-question quiz at the end of the instructions. If you answer these 7 questions correctly, you will earn an extra bonus of 5 CNYs.

If you have a question during the experiment, please raise your hand, and a monitor will approach you. Otherwise, you should not communicate in any way with anyone else.

In this experiment, you can buy and sell units of two different assets, X and Y. Units of X will be exclusively traded in the X Market, while units of Y will be exclusively traded in the Y Market. The X and Y Markets will operate simultaneously.

The currency in these markets is called Experimental Currency Units (ECUs). At the end of the experiment, your ECUs will be converted into CNY at 1 CNY = 650 ECUs.

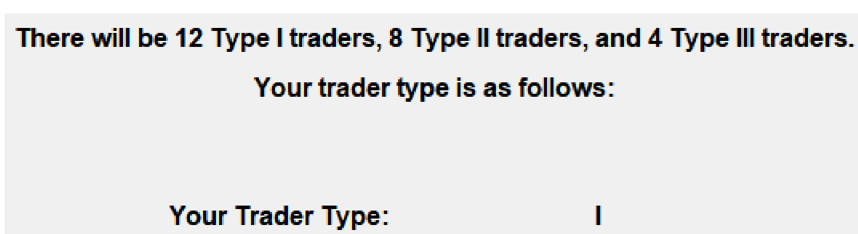
E.2 Trader Types

There are 3 types of traders in this experiment. You will be randomly assigned to one of these trader types, and your type will <u>remain the same</u> for the entire experiment.

The trader types will be identified as I, II, and III.

There will be 12 Type I traders, 8 Type II traders, and 4 Type III traders.

You will be informed of your trader type at the conclusion of the instructions as follows:



The specifics of each trader type will be discussed later in these instructions.

E.3 Traders' Endowments of Cash and Units

The experiment is broken up into a sequence of 15 market periods. Every period will last 4 minutes. The time remaining (in seconds) will be noted in the top right corner of the screen. At the beginning of each market period, traders will be given cash and units:

Type I Traders will be given 858 in Cash, 3 Units of X, and 6 Units of Y.

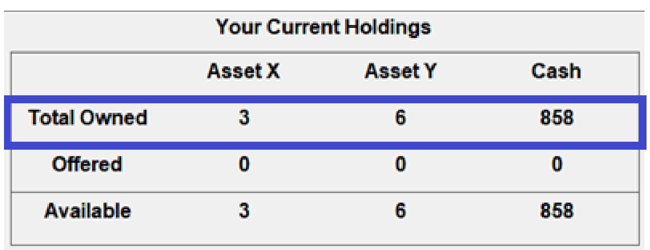
Type II traders will be randomly divided into 2 groups. One group will consist of 3 Type II traders. These traders will be given 1378 in Cash, 2 Units of X, and 4 Units of Y. The other group will consist of 5 Type II Traders. These traders will be given 1898 in Cash, 1 Unit of X, and 2 Unit of Y.

Type III Traders will be given 1898 in Cash, 1 Unit of X, and 2 Unit of Y.

You will start each market period with this same amount of cash and units. That is, your cash and units will not carry over from one period to the next period.

At any point in a market period, you can see the amount of cash and units you hold in the section of the screen called '**Your Current Holdings**'.

For example, if you are a trader of Type I you start the market with 858 in cash, 3 units of Asset X and 6 units of Asset Y. At the beginning of the market period, these values will appear in the row '**Total Owned**' highlighted below.



Your Current Holdings

	Asset X	Asset Y	Cash
Total Owned	3	6	858
Offered	0	0	0
Available	3	6	858

E.4 Asset Values for Type I and Type II Traders

You can trade X units in the X market and Y units in the Y market during each market period. If you are a trader of Type I or II, the amount each unit pays its owner at the end of a market period is based upon the State: A, B or C. Each State occurs with equal chances, that is their probability of occurrence is 1/3. The payoffs for each Asset X or Y across each State (A, B or C) are described in the table below:

State	Probability	X Value	Y Value
A	1/3	50	25
B	1/3	240	120
C	1/3	490	245

So, at the end of each market period, if an X unit is owned by a Type I or Type II trader, then it will pay 50 ECUs if the State is A, 240 ECUs if the State is B, or 490 ECUs if the State is C to that trader. A Y unit will pay 25 ECUs if the State is A, 120 ECUs if the State is B, or 245 ECUs if the State is C to the trader who owns it.

Note that units of X pay the same amount to both Type I and Type II traders. Similarly, units of Y pay the same amount to both Type I and Type II traders.

The State (A, B or C) was randomly determined for each market period before the start of the experiment. This means that the amount units pay in one market period does not provide any information about the amount units will pay in another market period. It also means that the state is equally likely to be A, B, or C in a given market period.

The manner in which Type III Traders earn money is described on later pages.

E.5 Private Signals

At the beginning of each market period, Type I traders will receive a private signal regarding the State (A, B or C) for that period. Type I traders will receive one of the following signals depending on the true state:

1. NOT A
2. NOT B
3. NOT C

Suppose for example that the true state is A, in the '**Asset Value**' section of the screen of a Type I trader indicates that the State is NOT B and that the value of Asset X will not be 240 and Asset Y is Not 120.

Asset Value		
True State	X Value	Y Value
NOT B	NOT 240	NOT 120

Each market period the Type I traders are divided into two groups of six. Each group is given a different signal. For example, when the asset State is A six Type I traders receive the signal "**NOT B**" and the other six Type I traders get the signal "**NOT C**". So in the example above six Type I traders get the screen displayed and the other six Type I traders get the screen below:

Asset Value		
True State	**X Value**	**Y Value**
NOT C	**NOT 490**	**NOT 245**

Type II and Type III traders will not receive a private signal. Thus, they will only know that the asset's value has equal chances of being in state A, B or C. The '**Asset Value**' section of the screen will show question marks '?' for those traders as below as shown below.

Asset Value		
True State	**X Value**	**Y Value**
?	**?**	**?**

E.6 Earnings for Type I and Type II Traders

If you are a Type I or Type II trader, then your earnings for the experiment equal the sum of your earnings from each market period. And, your earnings from a market period equal the cash you have at the end of the market period plus the value of any X and Y units you own at the end of the market period.

$$\text{Period Profit} = \text{Cash} + \text{X value} * \text{X units} + \text{Y value} * \text{Y units}$$

Suppose you have 500 ECUs in cash, 3 X units, and 2 Y units at the end of a market period. Further, suppose the State is A. This means each X unit pays you 50, and each Y unit pays you 25. Then your earnings from this market period are:

$$500 + 3 * 50 + 2 * 25 = 700 \text{ ECUs}$$

During a market period, you can track your provisional profit on your screen. For each State, your provisional profit shows the earnings you would obtain if the market were to close instantaneously. Type I traders will see their provisional profits for the 2 possible states, while Type II traders will see their provisional profits for each possible State (A, B, C). With 500 in cash, 3 X units, and 2 Y units, a Type II trader's provisional profit is:

Provisional Profit			
State	A	B	C
Profit	700	1460	2460

E.7 Earnings for Type III Traders

Similar to Type I and Type II traders, if you are a Type III trader, your earnings for the experiment equal the sum of your earnings from each market period. However, your earnings from a market period are calculated differently from the earnings of Type I and Type II traders.

$$\text{Period Profit} = \text{Bundles} * \text{Commission}$$

Type III traders earn ECUs by creating bundles of units where one bundle is defined as 1 unit of X and 2 units of Y. For each bundle a Type III trader owns at the end of a market period, the Type III trader will be paid a commission of 520 ECUs.

Suppose you have 500 ECUs in cash, 3 X units, and 6 Y units at the end of a market period. Your unit holdings correspond to 3 bundles, each composed of 1 X unit and 2 Y units. Thus, your earnings from this market period are:

$$3 * 520 = 1560 \text{ ECUs}$$

Note that your cash amount of 500 ECUs is not included in your earnings.

Here is another example. Suppose you have 500 ECUs in cash, 4 X units, and 6 Y units at the end of a market period. Even though you hold 1 more unit of X than the previous example, you only have 3 bundles composed of 1 X unit and 2 Y units. Thus, your earnings from this market period are:

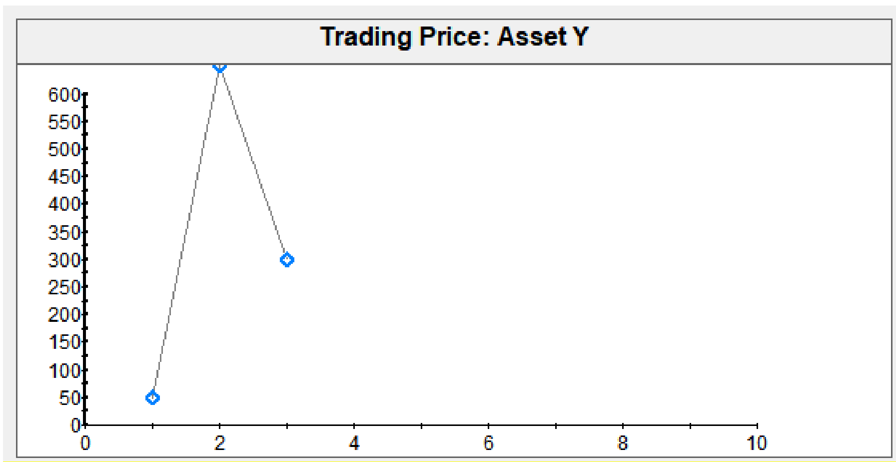
$$3 * 520 = 1560 \text{ ECUs}$$

If you are a trader of Type III, your provisional profit shows the number of bundles you own times the commission. In the example below, your provisional profit is equal to 3 (the number of bundles you have composed) times the commission (520), that is 1560.

Provisional Profit				
Bundles		Commission		Profit
3	x	520	=	1560

E.8 Price Charts

A chart displaying each transaction price for Market X (Market Y) is located on the bottom of the screen to the left (right) of the '**Account History**' table. The x-axis corresponds to the transaction number (e.g., 1, 2, 3, ...), while the y-axis corresponds to the trading price. If there are more than 10 transactions in a period, then the x-axis will automatically rescale to display all transactions. The y-axis will range from 0 to 600. Trading prices greater than 600 ECUs will appear in the Transaction Details section of the screen but not on the chart.



E.9 Account History Table

Regardless of your trader type, at the bottom of the screen (under '**Account History**') you will see a summary of your final position in all prior market periods. Suppose you are currently in market period 2. The image below shows that you ended the first market period with 5 units of Asset X, 4 units of Asset Y, and 130 in cash. The value of X units and Y units was equal to 240 and 120, respectively.

If you are a trader of Type I or II, your earnings would thus be equal to your cash (130) plus the value of your units (5 * 240 + 4 * 120= 1680), that is 1810 ECUs.

Account History

Period	Asset X	Asset Y	X Value	Y Value	Cash	Period Profit(ECU)
1	5	4	240	120	130	1810

If you are a trader of Type III, your earnings would thus be equal to the number of bundles you composed (2) multiplied by the commission of 520, that is 1040 ECUs.

Account History							
Period	Asset X	Asset Y	Bundles	X Value	Y Value	Cash	Period Profit(ECU)
1	5	4	2	240	120	130	1040

E.10 Trading (Offers to Buy)

During a market period, traders can buy or sell Asset X and Asset Y units from one another by making Bids (Offers to Buy) or Asks (Offers to Sell). To create a Bid for Asset X (Asset Y), you have to type in the price you would like to buy in the Bid box on the left side of the trading screen for Asset X (Asset Y). Note that you will not be able to create a Bid with a higher price than your available cash, because you would not have enough money to buy the unit. You may view how much cash you have available for Bids by looking at the Cash amount in the '**Available**' row of the '**Your Current Holdings**' table. The image below shows a case in which you have no cash available to buy units. You have no cash available because the cash you own (500 in the Cash column for '**Total Owned**' in the image below) has already been used to place Bids (see 500 in the Cash column for '**Offered**').

Your Current Holdings			
	Asset X	Asset Y	Cash
Total Owned	3	4	500
Offered	0	1	500
Available	3	3	0

However, this cash has not been spent yet. If you want to increase your cash available, you can delete some of your Bids (identified by blue font and the '***' symbol in the '**My BID**' column next to your bid amount in the '**Outstanding BID**' column) by selecting them and clicking on the '**Delete**' button at the bottom of your screen. You may not delete your bid if it is currently the best (highest) bid in the market.

In the example screen below, a new Bid of 50 ECUs has been entered for Asset X. To confirm the new Bid of **50** ECUs, you have to click on '**Submit**' right below your Bid. The new Bid will then appear in the '**Outstanding BID**' column. Because you submitted this Bid, the symbol '***' appears next to it in the '**My BID**' column. The My BID column is left blank for Bids submitted by other traders.

Another trader can now accept the new Bid of 50 that you have just made by clicking on the '**Immediately SELL**' button at the bottom of the screen. The transaction price will then appear in the middle column '**Transaction Details**' (see image below). Because you bought the asset the Buy/Sell column will indicate '**Buy**' so that you can keep track of what you are buying and selling.

Transaction Details	
Buy/Sell	Price
Buy	50

As a result of the transaction, the Bid will no longer appear in the '**Outstanding Bid**' column.

Because the Bid of 50 has been accepted, you have bought one unit of Asset X at a price of 50 from another trader. Your cash, as shown in '**Your Current Holdings**' will thus go down by 50 and the number of Asset X units you hold will increase by one. The trader who sold the unit to you will increase his or her cash by 50 and hold one unit less of Asset X.

The upper part of the trading screen referred to as '**Transaction Summary**' shows the average value of a transaction for a given asset (X or Y) in a given market period (see

Average) as well as the first transaction price in the period (see **Open**) along with the minimum and maximum transaction prices in the period (see **Low** and **High**).

Note that if you submit a Bid (Offer to Buy) that is greater than the current lowest Ask (Offer to Sell), then you will automatically buy one unit of the asset at the current lowest Ask price.

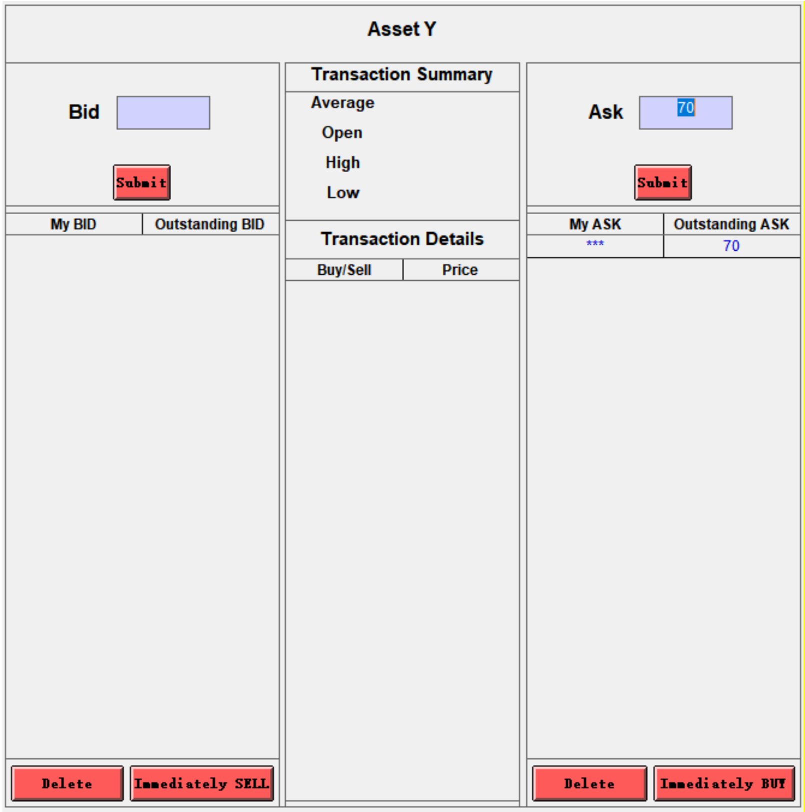
E.11 Trading (Offers to Sell)

Creating a new Ask (Offer to Sell) for a unit works the same way as creating a new Bid, except that you have to place your offers in the Ask box instead of the Bid box. Note that you will not be able to create an Ask for Asset X (Asset Y) if you do not have available units of Asset X (Asset Y). This is the case when the row '**Available**' in the section of the screen called '**Your Current Holdings**' shows a value of 0 for the Asset (X or Y) you want to sell. The image below shows a case in which you have two units of Asset X available for sale but no units of Asset Y available for sale. You have no units of Asset Y available for sale because the only unit of Asset Y that you own (see the Asset Y column for '**Total Owned**' in the image below) has already been offered for sale (see the Asset Y column for '**Offered**' that has a value of 1). However, these offered units have not been sold yet. If you want to increase your units available, you can delete some of your Asks (identified by blue font and the '***' symbol in the '**My ASK**' column next to your ask amount in the '**Outstanding ASK**' column) by selecting them and clicking on the '**Delete**' button at the bottom of your screen. You may not delete your ask if it is currently the best (lowest) ask in the market.

Your Current Holdings

	Asset X	Asset Y	Cash
Total Owned	2	1	850
Offered	0	1	120
Available	2	0	730

In the example screen below, a new Ask of **70** ECUs has been entered for Asset Y. To confirm the new Ask of 70 ECUs, you have to click on '**Submit**' right below your offer. The new Ask will then appear in the '**Outstanding ASK**' column. Because this Ask was submitted by yourself the symbol '***' appears on the '**My ASK**' column. The My ASK column is left blank for Asks submitted by other traders.



Another trader can now accept the new Ask of 70 that you have just made by clicking on the '**Immediately BUY**' button at the bottom of the screen. The transaction price will then appear in the middle column '**Transaction Details**'. Because you sold the asset the Buy/Sell column will indicate '**Sell**' so that you can keep track of what you are buying and selling. As a result of the transaction, the Ask will not be available anymore in the '**Outstanding Ask**' column.

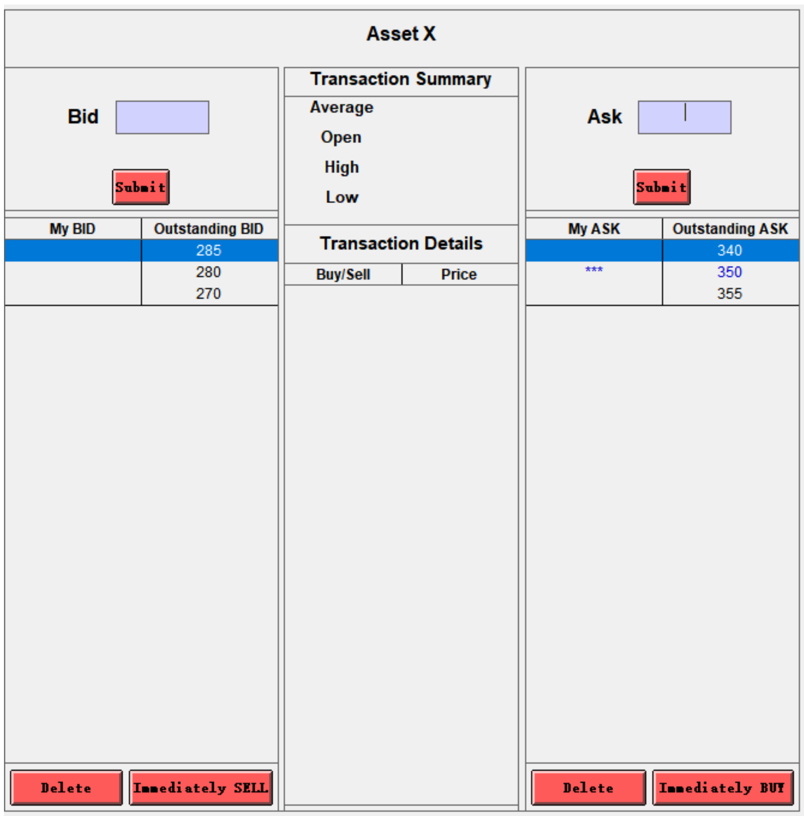
Transaction Details	
Buy/Sell	Price
Sell	70

Because the Ask of 70 has been accepted, you have sold one unit of Asset Y at 70 to another trader. Your cash, as shown in '**Your Current Holdings**' will thus go up by 70 and the number of Asset Y units you hold will decrease by one. The trader who bought the unit from you will decrease his or her cash by 70 and hold one more unit of Asset Y.

Note that if you submit an Ask (Offer to Sell) that is less than the current highest Bid (Offer to Buy), then you will automatically sell one unit of the asset at the current highest Bid price.

E.12 Trading (Order Book)

Several Bids or Asks can be available at the same time for each Asset. In the example screen below, there are three Bids (285, 280, 270) and three Asks (340, 350, 355) available for Asset X. Note that the lowest (best) Ask and the highest (best) Bid appear at the top of the list (Marked in the blue background). The '***' symbol in the '**My ASK**' column indicates you submitted the Ask of 350.

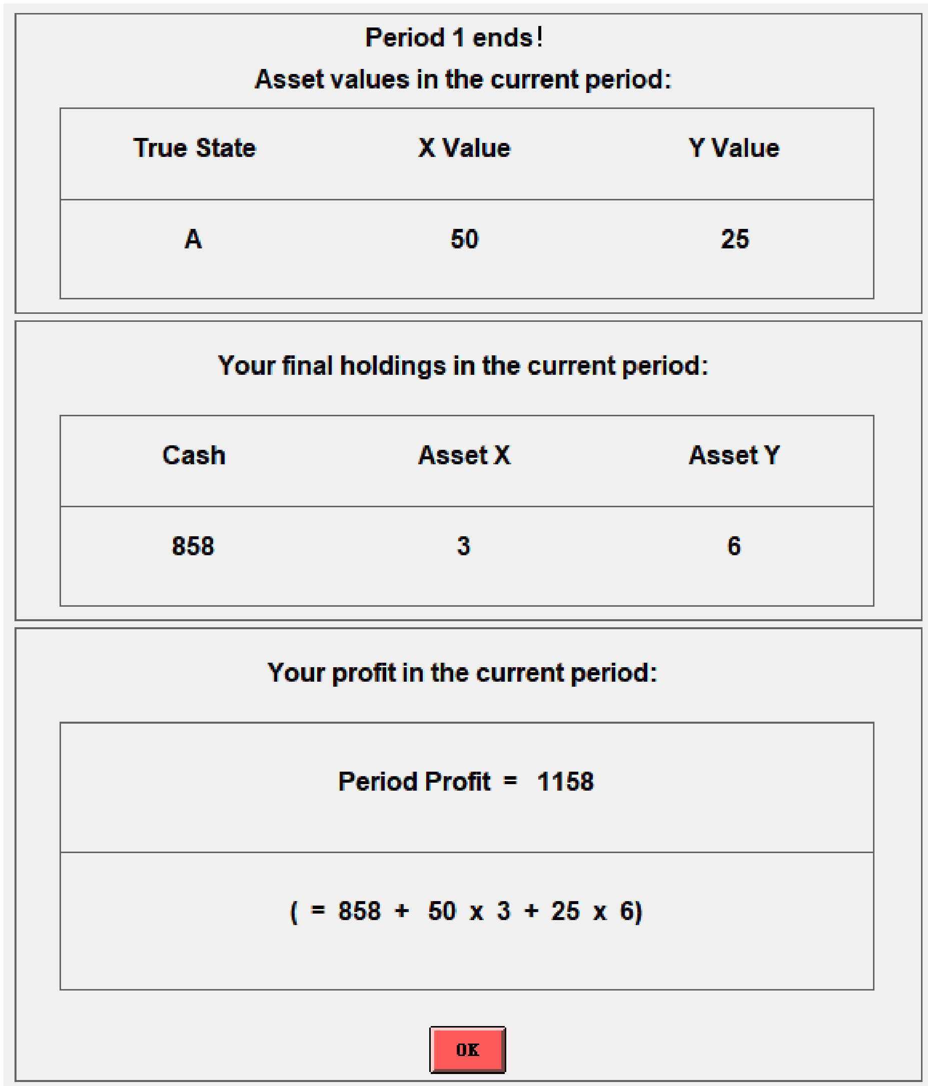


To sell a unit of an asset, click the '**Immediately SELL**' button. This will cause you to sell one unit of the asset at the highest Outstanding BID amount (285 in the above image). To buy a unit of an asset, click the '**Immediately BUY**' button. This will cause you to buy one unit of the asset at the lowest Outstanding ASK amount (340 in the above image).

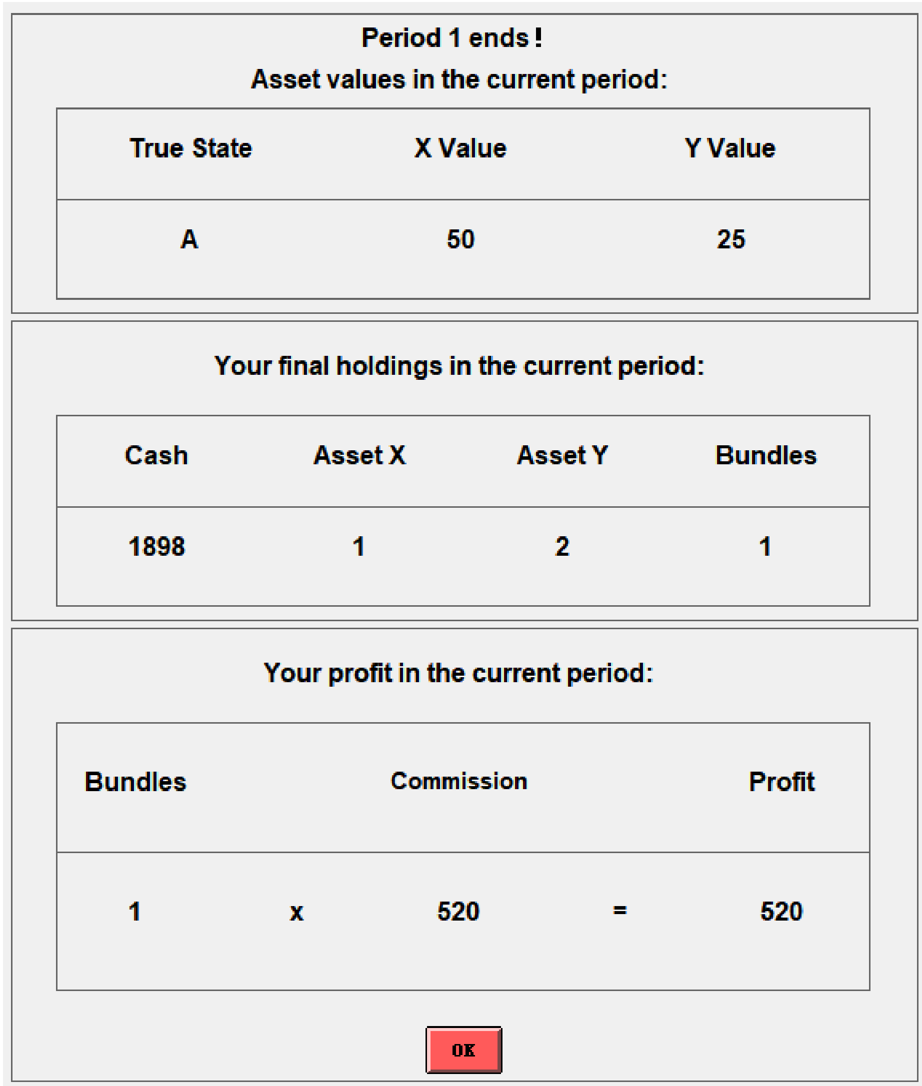
Note that you cannot accept one of your own bids or asks. You will receive an error message if you highlight one of your own bids (asks) and click the '**Immediately SELL**' ('**Immediately BUY**') button.

E.13 End-of-Period Screen

At the end of each market trading period, you will be informed of the true State, the value of X and Y units, your holdings of cash and units, as well as your profit for the period. If you are a Type I or Type II trader, then you will see a screen similar to the following:



If you are a Type III trader, then you will see a screen similar to the following:



E.14 End-of-Experiment Screen

At the end of the experiment you will be shown your earnings from each market period as well as your final earnings for the entire experiment in CNY.

E.15 Summary

1. There will be 15 market periods. Every period will last 4 minutes.

2. You will be given the <u>same amount of cash and units</u> to start <u>each market period</u>.

3. Traders can buy and sell units of two different assets, X and Y. X units will trade in the X market and Y units will trade in the Y market. You can trade in <u>both markets</u>.

4. You can submit Bids and Asks or accept available offers from other traders to trade units.

5. The amount units pay to their owners at the end of a market period is based on the state (A, B, or C) for Type I and Type II as follows. All States are equally likely.

State	Probability	X Value	Y Value
A	1/3	50	25
B	1/3	240	120
C	1/3	490	245

6. There are 12 Type I traders, 8 Type II traders, and 4 Type III traders. The trader type you will be assigned will not change for the entire experiment.

7. At the beginning of a market period, Type I traders will receive a private signal informing them which State will not occur. Type II and Type III traders will not receive a private signal.

8. Market period earnings of Type I and Type II traders are equal to the amount of cash they have at the end of a market period plus the value of their X and Y units.

9. Market period earnings of Type III traders are equal to the number of bundles of units they hold at the end of a market period times a commission of 520. To compose one bundle, Type III traders need to hold 1 unit of Asset X and 2 units of Asset Y.

10. Before starting with the 15 market periods, you will participate in 2 practice periods that will not be paid so that you can get familiar with the software.

11. Your earnings for the experiment equal the sum of your earnings from each market period (converted to CNY at 1 CNY = 650 ECUs) plus a 20 CNY show-up payment.

E.16 Quiz

For each statement, please report whether you think it is true or false. At the end of the experiment, you will receive an extra bonus of 5 CNYs if you answered all 7 questions correctly.

1. At the start of the experiment, you will be assigned one of 3 trader types. And, your trader type will not change for the entire experiment.

a. TRUE.

2. You will start each period with the same amount of cash and units.

a. TRUE.

3. Type I traders are only permitted to trade in the X market, and Type II traders are only permitted to trade in the Y market.

a. FALSE. All traders are permitted to trade in both markets.

4. At the beginning of each period, all the traders will receive a private signal indicating the State.

a. FALSE. Type I traders will receive a private signal indicating which state will NOT occur. Type II and Type III traders will not receive a private signal.

5. The amount a unit of X will pay its owner (if the owner is a Type I or Type II trader) at the end of a market period is equally likely to be 50, 240, or 490.

a. TRUE.

6. The amount a unit of Y will pay its owner (if the owner is a Type I or Type II trader) at the end of a market period is equally likely to be 50 than 240 or 490.

a. FALSE. Units of Y are equally likely to pay their Type I and Type II owners 25, 120, or 245 at the end of a market period.

7. Type III traders earn money by creating bundles of units. To create one bundle, a Type III trader needs to own 2 units of Asset X and 1 unit of Asset Y.

a. FALSE. One bundle is equal to 1 X unit and 2 Y units.