Experiments on Asset Pricing under Delegated Portfolio Management

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Abstract

We study the impact of delegated portfolio management on asset pricing in a large-scale experimental setting. With a few exceptions, models of asset pricing are formulated in terms of the preference functions of final investors. This effectively assumes that adding a layer of management does not affect market equilibrium. In early rounds of our experiments, delegation indeed has no impact on pricing; we replicate CAPM pricing as in earlier experiments without delegation. Choices are also in line with prior evidence. CAPM pricing fails in later rounds, however, and we even observe a negative equity premium. We attribute this to fund flows. Investors tend to increase allocations to managers who performed well in the past (not just the previous period). Moreover, fund flows implicitly reflect a reward for variance. As a result, funds become concentrated with a few managers, and the aggregation of deviations of individual manager demands from mean-variance optimality, needed to ensure CAPM pricing, no longer obtains. Given the predominance of delegated investing in actual equity markets, our results have important implications for asset pricing theory.

JEL Classification: G11, G12

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1 Introduction

The fundamental CAPM papers of Sharpe [1963] and Lintner [1965] that laid the groundwork for modern asset pricing began with the assumption that investors made their own investment decisions. This assumption was motivated, in part, to allow for the derivation of a closed form asset pricing model. However, at the time the CAPM was being developed, the assumption that final investors made investment decisions was not only theoretically useful, it was empirically accurate. That is no longer the case.

To provide some historical perspective, Bogle [2005] notes that as late as in 1950 American households held 91% of all common stocks. French [2008] reports that by 1980 direct holdings by final investors accounted for only 47.9% of the market and by 2007 that figure had fallen to 21.5%. Furthermore, estimates of direct holdings overstate the importance of individual investors because many wealthy individuals are classified as individual investors even though they delegate most of their investment decision making to financial firms or private investment advisers. In addition, less wealthy individual investors often rely on stockbrokers, financial planners, or other advisers, when making investment decisions, even when the investment account is in their name.

Given the dramatic increase in the importance of delegated investing, it is surprising that the impact of delegation on asset pricing has not been more thoroughly investigated. Instead of studying the effect of delegation, efforts to overcome the empirical failures of early asset pricing models have focused on two alternatives. The first is to retain the rational valuation framework, but to build models based on increasingly sophisticated assumptions regarding the stochastic processes of returns and investor preference functions. Contributions in this regard include Breeden [1979], Grossman and Shiller [1981], Hansen and Singleton [1983], Campbell [1996], Constantinides and Duffie [1996] and Campbell and Cochrane [1999], among many others. The second alternative has been to abandon the rational framework and develop "behavioral models" based on various psychological theories. Lacking a specific theoretical framework, a wide variety of behavioral theories have been developed. Fama [1998] provides a critical review of this literature. Barberis and Thaler [2002] offer a more recent, and more favorable, survey. It is somewhat ironic that the behavioral approach largely ignores a central aspect of investment behavior—delegating security selection to professionals.

There are strands of literature that have looked at the problem of delegated investing. The most extensive involves the application of principal-agent theory to study various hypothetical manager-agent contracts. The early seminal paper in that respect is Bhattacharya and Pfleiderer [1985]. Since then, important contributions include Stoughton [1993], Admati and Pfleiderer [1997], Ross [2004] and Dybvig et al. [2004].[1] From the perspective of the current research, this literature has two deficiencies. First, it is largely formal and theoretical and does not tie the models to the actual process of delegated investing observed in the capital market. Second, and more importantly, it does not derive the implications of the delegation process for asset pricing.

There are also papers that analyze the theoretical optimal strategies for individual managers compensated relative to the amount of funds under management, but, again, without considering asset pricing implications. These include Basak, Pavlova, and Shapiro [2007] and Hugonnier and Kaniel [2010].

There is a second smaller literature that does attempt to assess the impact of delegated investing on asset prices. An early contribution is Brennan [1993]. More recently, Cornell and Roll [2005] study how the CAPM is affected when the model is extended to allow for delegated investing. They show that, with no other alterations, introducing delegation has a significant impact on the form of the CAPM that can potentially explain various failings of the original model. Unfortunately, because so little is known about the actual delegation process, papers like Cornell and Roll are forced to rely on stylized assumptions regarding the manner in which delegation occurs.

One approach that has not been tried is to study the impact of delegation in a laboratory setting. This is surprising because experiments could provide useful way to study delegated portfolio management and its effect on asset pricing. Unlike field data, the experimenter can control many of the variables that are crucial for understanding financial markets, such as total supplies, information, contractual agreements, enforcement of contracts, etc. Indeed, it is only under experimental conditions that CAPM pricing has ever been observed (see Bossaerts and Plott [2004]) and that it has been shown why CAPM pricing may obtain even if no-one chooses to hold the market portfolio (see Bossaerts et al. [2007]). This raises the obvious question of whether the CAPM would continue to hold if managers were introduced into the experiments. As experiments allow one to control the exact contract between "investor-subjects" and "manager-subjects," as well as the flow of information be-

[1] Stracca [2005] provides a comprehensive survey of this literature.

tween the two groups, in principle, experiments could also provide important insights about the impact of contracts on asset prices and fund composition.

The present paper provides a first step towards the experimental analysis of delegated portfolio management. It presents the results of a baseline experiment against which general equilibrium effects of incentives (contract design) on performance, prices and choices could be studied. Specifically, it reports on an experiment that was set up in exactly the same way as earlier experiments that have reliably generated CAPM pricing (see earlier references), with one exception: subjects do not trade for their own account, but for the benefit of other subjects. The investor-subjects (the investors) are endowed with assets and cash and allocate those to manager-subjects (the managers). The initial asset allocations to different managers determine the investors' shares in the funds. The managers can then trade the assets allocated to them in an anonymous electronic open-book market within a pre-specified time period and thus rebalance their initial allocations. When trading concludes each investor is paid his share (possibly zero) from the liquidating value of each manager's portfolio, while the managers receive payments for order flow. Basic performance metrics are then reported, investors are given new batches of endowments and invited to allocate them to the managers. This process is repeated eight times in the experiment.

The question we aim to answer is whether adding the layer of delegated management to the economy affects market equilibrium. Two conjectures immediately arise. On the one hand, since our experimental setup is based on the simplest possible management contract design, it is plausible to argue that portfolio delegation should have no effect on asset prices or holdings. All managers have equal information, and, barring unequal trading skill, there is no reason to believe that one manager could outperform the others. Assuming mean-variance preferences for the investors, managers should all choose portfolios on the mean-variance frontier, and the investors should choose to invest in sets of managers as to achieve their optimal portfolios.

On the other hand, we know that the driving force behind the empirical success of the CAPM in earlier experiments (Bossaerts et al. [2007]), where subjects trade for their own account, is the structure of the individual demands. While portfolio holdings are quite erratic, choices reflect demands that deviate from mean-variance optimality only because of a mean-zero error term. Evidently, this error term is independent across subjects and therefore the functional law of large numbers holds, which is why CAPM pricing obtains – provided (by experimental design) there are enough subjects who all have an endowment that is small relative to the market as a whole. In our experiment, however, while the experimenter controls the endowments of the investors, the endowments of the managers are endogenously determined. It is therefore plausible to argue that the erratic nature of portfolio choices could cause some managers to outperform others by pure chance. If investors struggle to decide or are indifferent as to how to allocate their assets and cash across managers, a natural way to resolve their indecisiveness/indifference would be to choose to distribute their endowment among the managers who happen to have the best past performances. This way, investors would also hedge against the possibility that the managers actually outperformed because of skill. But if many investors choose to do so, those managers' funds will be large relative to the market, and their individual demands will eventually influence prices, unless they happen to hold an exact mean-variance optimal portfolio, a rather unlikely event in view of the past evidence. As a result, CAPM pricing would no longer obtain.

To address the research question in general, and the developed conjectures in particular, we design and analyze the experiment with the theoretical benchmark model (that corresponds to our setting but in the absence of delegated investment) in mind. Because the predictions of this model have been experimentally tested and confirmed, our analysis is also a comparison against previous experimental results.

The following provides a succinct description of our findings. Overall, we find that our experimental results depart from the predictions of standard asset pricing models and from the established results in the experimental asset pricing literature. Specifically, in early rounds, investors indeed allocate their shares and cash so that managers effectively receive the same initial endowments. Despite rather erratic holdings at the end of trading, CAPM pricing obtains. After the third round, however, most managers performed poorly (because the market portfolio's payoff was at its lowest realization) except for a few managers who had shorted the market. In subsequent rounds, these successful managers received increasingly large allocations of assets and cash – with funds concentration reaching a peak when four out of the 32 Managers were given 40% of the available assets and cash. In general, we find a correlation of 0.66 between managers' cash distributions back to investors in the previous period and the cash and assets flows back to them in the subsequent period. Managers with large fund flows in a given period are more likely to have large fund flows in the following period as well, a finding that does not disappear when taking into account past performance. Thus, there seems to be "stickiness" in fund flows, a surprising finding provided that mangers' portfolios are "liquidated" after the conclusion of each period and new distributions are made in the next period (thus, unlike the justification for the similar finding in the field, the stickiness cannot be driven by investors keeping funds with a set of managers by default). Moreover, investors do not appear to use mean-variance as a criterion in choosing fund managers. Although they are not given direct information about the expected return and variance of managers' portfolios, investors are given sufficient information to closely approximate those statistics. We find that the fund flows to a manager depend positively (and significantly) on the manager's portfolio variance in the preceding period and negatively (but not significantly) on the portfolio's expected return. As expected from the above described investor behavior, as the funds allocated to a handful of managers grow, so does the mispricing relative to the theoretical benchmark (CAPM). As a matter of fact, the equity premium becomes *negative* as the funds concentration reaches its highest levels. In particular, the market share of the largest manager is significantly positively correlated with the mispricing in the market (as measured by the difference of the Sharpe ratio of the market portfolio from the Sharpe ratio of the mean-variance optimal portfolio). Our results indicate that it is the market share of the largest manager that has a first order effect on the quality of prices while the general segmentation of the markets into large and small funds (as measured by the Gini index) has only marginal effect on prices.

In summary, our results imply that delegation cannot be ignored when attempting to understand market equilibrium and asset pricing, and suggest a reason for the observed discrepancy between the predictions of the standard asset pricing models and the experimental findings, namely, the nature of flows in and out of funds.

The remainder of this paper is organized as follows. Section 2 presents our experimental design. Section 3 presents the empirical results and section 4 concludes.

2 Experimental Setup

The experiment consists of a multi-period main session followed by a one-period concluding session which we call "the end session." The purpose of the end session, described in detail in subsection 2.4, is to eliminate possible end-of-game effects during the main session. In what follows, we outline the design of the main session.

The main session is conducted in a series of six week-long periods, each of which is comprised of three stages, called Asset Allocation (first stage), Trading (second stage), and Information Disclosure (third stage). Individuals who participate in the trading are called *managers*. The 32 managers are the same individuals over all periods. A separate group of participants, called *investors*, are the initial owners of assets and cash. The investors need not be the same individuals each period and their number (equal to 70 on average) can possibly change. Investors receive their endowments in the beginning of each period. Their endowments consist of units of two risky assets, called A and B, and some cash. The assets are risky because their end-of-period liquidating dividends (in US dollars) depend on the realization of a random state variable that can take on three values, called X, Y, and Z. Investors cannot buy, sell or store assets directly, thus in the beginning of each period they must assign all of their initial resources to one or more of the managers to trade on their behalf. The allocations from different investors to one manager constitute this manager's initial (for that period) portfolio. The fraction of this initial portfolio's expected dividend that is due to a single investor is this investor's *share* in the manager's fund. A managers' initial portfolio is the sole determinant of her current period payoff. Specifically, the payoff is equal to 40% of the expected dividend of her initial portfolio. We refer to this payoff as the manager's *fee*.

The allocation of assets from investors to managers constitutes the first stage of a period. Managers (only) then participate in the trading stage that lasts exactly thirty minutes. Trade takes place through a web-based, electronic continuous open-book limit order system called *jMarkets*.[2] A snap shot of the trading screen is provided in Figure 1. During this stage managers may trade their initial portfolio to a new, *final* portfolio. To facilitate borrowing, in addition to trading securities A and B, managers can trade a risk-free security called a "Bond." The Bond pays an end-of-period dividend of $1 in any state of the world and is in zero net supply.

The final portfolio of a manager generates a dividend according to the random realization of a state variable, that becomes known only after the conclusion of trading. The dividend, with the management fee subtracted from it, is distributed to the investors according to their shares in the fund. If this residual dividend is negative, the distribution to the investors is equal to $0.

[2]This open-source trading platform was developed at Caltech and is freely available under the GNU license. See http://jmarkets.ssel.caltech.edu/. The trading interface is simple and intuitive. It avoids jargon such as "book," "bid," "ask," etc. The entire trading process is point-and-click. That is, subjects do not enter numbers (quantities, prices); instead, they merely point and click to submit orders, to trade, or to cancel orders.

The third and final stage of a period is the information disclosure stage. In this stage a series of performance indicators for each manager are published on the experimental webpage[3] and the university newspaper. The details of the information disclosed are presented in subsection 2.3. Except for the information about past periods and the fact that managers are always the same, the weekly periods are otherwise independent events. The timing of the three stages during the week-long period is presented in Table 1

As described in the start of this section, in order to avoid any last-period effects in the managers' behavior, the design includes one concluding period. In this period, instead of being paid 40% of the expected dividend of their initial portfolio, managers are paid 40% of the realized dividend of their final portfolio. The remaining 60% are distributed to the investors according to their shares in the fund.[4]

The following subsections give more detail about payoffs and trading rules, as well as about the disclosed information.

2.1 Trading: Assets and Dividends

Table 2 summarizes the dividends of assets A, B, and the Bond, expressed in US Cents. In each period the three payoff relevant states, X, Y, and Z, are equally likely and this is known to both managers and investors.

According to their initial endowment, there are two types of investors. An investor of type A holds 100 units of asset A, and \$6 of cash, while investor of type B holds 70 units of asset B, and \$9 of cash. The managers do not have initial endowments. The market portfolio is the aggregate endowment of assets A and B. Because the total number of investors as well as the fraction of investors of each type varies from one period to the other, the composition of the (per capita) market portfolio also varies across periods. Table 3 provides period by period details on the distribution of investor types and the corresponding market portfolio composition. Table 4 presents the market portfolio and the corresponding state-dependent aggregate wealth for each of the six periods. As evident from the table, the market portfolio changed

[3]The experimental webpage's URL is http://clef.caltech.edu/exp/dp. In addition to all information disclosures, the webpage contains the experimental instructions for the Managers and the Investors.

[4]The initial design included eight periods followed by the concluding period. While we conducted eight periods, we report the results only of the first six due to an error that caused incorrect reporting in the information disclosure stage. Thus, in effect the concluding period's purpose of eliminating possible last-period effects in the managers' behavior was fulfilled by periods VII and VIII, which are now excluded from the data analysis.

from one period to the next, with changes primarily due to changes in the aggregate supply of security A.

In the asset allocation process, an investor can *only* choose the number of units of his risky asset (A or B, depending on the investor's type) to allocate to each manager. If a manager is allocated a fraction of an investor's risky portfolio, the same fraction of the investor's cash is also allocated to that manager. Investors distribute holdings to managers using a form over the Internet. Before trading starts, each manager knows her initial portfolio but not the portfolios of the other managers.

In the trading stage, in addition to the two risky assets, managers can also trade a risk free security called Bond. Given cash, it is a redundant security. However, managers are allowed to short sell the Bond if they wish. Short sales of the Bond correspond to borrowing. Managers can thus exploit such short sales to acquire assets A or B if they think it is beneficial to do so. Managers are also allowed to short sell the risky securities, in case they think they are overpriced. To avoid bankruptcy (and in accordance with classical general equilibrium theory), our trading software constantly checks subjects' budget constraints. In particular, a bankruptcy rule is used to prevent managers from committing to trades that would imply negative cash holdings in the end of the period. Whenever a manager attempts to submit an order to buy or sell an asset, her cash holdings after dividends are computed for all states of the world, given her current asset holdings and her outstanding orders that are *likely* to trade (an order is considered likely to trade if its price is within 20% of the last transaction price), including the order she is trying to submit. If these hypothetical cash holdings turn out negative for some state of the world, she is not allowed to submit the order. However, in trading sessions where prices change a lot, it is possible that orders that originally passed the bankruptcy check (by not being considered likely to trade) go through while at the same time they no longer guarantee non-negative total payoffs. Thus, some rates of return can be below -100% in volatile periods.

2.2 Payoffs

Below we formalize the payoff functions for the investors and managers in the main experiment.

In the set, I, of investors, let I_A (I_B) be those of type A (B) and let w_A (w_B) and h_A (h_B) denote their individual initial endowments of assets and cash. Let $d_i = (d_i^1, \ldots, d_i^{32})$ denote investor i's distribution of his initial asset endowment among the 32 managers. The initial portfolio of manager j is composed of m_A^j units of asset A, and m_B^j units of asset B, where

$$m_A^j = \sum_{i_A=1}^{I_A} d_{i_A}^j, \qquad m_B^j = \sum_{i_B=1}^{I_B} d_{i_B}^j.$$

Manager j's initial cash holding is

$$h^j = \sum_{i_A=1}^{I_A} \frac{d_{i_A}^j}{w_A} h_A + \sum_{i_B=1}^{I_B} \frac{d_{i_B}^j}{w_B} h_B.$$

Letting $\bar{D}_A$ ($\bar{D}_B$) denote the expected dividend of asset A (B), the expected dividend of manager j's initial portfolio is $\bar{D}^j\left(m_A^j, m_B^j, h^j\right) = \bar{D}_A m_A^j + \bar{D}_B m_B^j + h^j$. **Manager j's payoff** is 40% of the expected dividend of her initial portfolio. That is,

$$Pay^j = 0.4 \times \bar{D}^j\left(m_A^j, m_B^j, h^j\right). \tag{2.1}$$

Also, if $\bar{D}_i^j$ is the expected dividend resulting from investor i's contribution to manager j, then $\bar{D}_i^j = (\bar{D}_{A(B)} + \frac{h_{A(B)}}{w_{A(B)}})d_i^j$ for $i \in I_A(I_B)$. Consequently, investor i's *share* in *fund* j is defined as

$$s_i^j = \frac{\bar{D}_i^j}{\bar{D}^j}. \tag{2.2}$$

Given her initial portfolio $\left(m_A^j, m_B^j, h^j\right)$, manager j can trade to a final portfolio, denoted $\left(\tilde{m}_A^j, \tilde{m}_B^j, \tilde{h}^j\right)$.[5] The final holdings and the realized state of the world, $x \in \{X, Y, Z\}$ determine manager j's realized dividend, Π^j, as follows:

$$\Pi^j\left(\tilde{m}_A^j, \tilde{m}_B^j, \tilde{h}^j; x\right) = D_A(x)\,\tilde{m}_A^j + D_B(x)\,\tilde{m}_B^j + \tilde{h}^j,$$

where $D_g(x)$ denotes the dividend of asset $g \in \{A, B\}$ in state of the world x.

Manager j's *residual* dividend is $\max(\Pi^j - Pay^j, 0)$, i.e. it is the positive part of the realized dividend of manager j after her "fees" (Pay^j) are subtracted from it. Investor i's payoff from manager j equals his share in this manager's residual dividend, i.e., it is equal to $s_i^j \max(\Pi^j - Pay^j, 0)$.

Investor i's total payoff is the sum of his payoffs from all managers, as given

[5] $\tilde{h}^j$ includes both cash and bond holdings (the dividend on the Bond is always \$1).

in the expression below:

$$Pay_i\left(x\right) = \sum_{j=1}^{32} s_i^j \left[\max(\Pi^j\left(\tilde{m}^j, \tilde{h}^j; x\right) - Pay^j, 0)\right]. \tag{2.3}$$

2.3 Disclosure of Information

As pointed out in Table 1, the trading always took place on a Tuesday. Indicators of managers' performance were published online on the following Friday and appeared in the newspaper (*The California Tech*) on the following Monday. To preserve the privacy of the participants in the experiment, all managers were assigned experimental names and all announcements were made under those names. The names were Albite, Alexandrite, Allanite, Alunite, Amazonite, Amblygonite, Amosite, Andalusite, Anthophyllite, Atacamite, Barite, Bassanite, Beidellite, Bementite, Bentonite, Bertrandite, Biotite, Birnessite, Bloedite, Boracite, Calcite, Carnallite, Celestite, Chalcopyrite, Chlorite, Colemanite, Cornadite, Cristobalite, Cryolite, Dolomite, Dumortierite, and Dunite.

In addition to announcing the four performance indicators (specified below) for all managers, we also announced them for the *Dow-tech* Index composed of one unit of asset A, one unit of asset B, and \$1. The following indicators were reported: *Returns, Market Share*[6]*, Residual,* and *Risky Share.* In what follows we describe these indicators in detail.

Given prices $p = (p_A, p_B, 1)$ for assets A, B and the Bond (using the Bond as the numeraire), the *value*, V^j, of manager j's initial portfolio is defined as

$$V^j\left(m^j, h^j; p\right) = p_A m_A^j + p_B m_B^j + h^j.$$

In continuous markets as the one in our trading sessions, assets are traded at many different prices. In computing the valuations V^j, we take p to be the average prices over the last five minutes of trading in a period.

Return. This measure captures the realized rate of return for manager j when the state of the world is x and the average trading price is p. Namely,

$$r^j = \frac{\Pi^j\left(\tilde{m}^j, \tilde{h}^j; x\right) - V^j\left(m^j, h^j; p\right)}{V^j\left(m^j, h^j; p\right)}. \tag{2.4}$$

[6]The Market Share indicator was called Volume in the published reports.

Market Share. This measure is meant to capture the size of mutual fund j. It is equal to the ratio of the expected dividend of manager j's initial portfolio and the expected dividend of the portfolio comprised of all assets and cash available to all investors. Specifically,

$$ms^j = \frac{\bar{D}^j\left(m^j, h^j\right)}{\sum_{k=1}^{32} \bar{D}^k\left(m^k, h^k\right)}. \tag{2.5}$$

Residual. The residual for manager j is the residual dividend as defined in Subsection 2.2,

$$\max(\Pi^j - Pay^j, 0). \tag{2.6}$$

Risky Share. This measure for mutual fund j equals the value of the risky portion of j's final portfolio.

$$\nu^j = \frac{p_A \tilde{m}_A^j + p_B \tilde{m}_B^j}{p_A \tilde{m}_A^j + p_B \tilde{m}_B^j + \tilde{h}^j}, \tag{2.7}$$

where p is again taken to be the average price for the last five minutes of trade in a period.

2.4 End Session

The experiment concluded with an additional pseudo-period. This period was like the periods of the main session in all except the managers' and investors' payoffs. As in the main sessions, investors made their distributions of assets among managers and managers participated in a 30-minutes trading period. However, each manager received a payoff (fee) equal to 40% of the dividend generated by her final portfolio. Investors were paid the sum of their share of each manager's realized dividend after the manager's fee. In other words, manager j's payoff in the *end* session equaled $0.4 \times \Pi^j\left(\tilde{m}^j, \tilde{h}^j; x\right)$ in state x. Investor i's payoff equaled $\sum_{j=1}^{32} s_i^j\left[0.6 \times \Pi^j\left(\tilde{m}^j, \tilde{h}^j; x\right)\right]$.

The end session was implemented to prevent the unraveling of managers' reputation considerations. Namely, in the absence of the end session, in the last period of the main session managers have no reputation reason to perform in a way as to attract more investors into their fund. However, due to a programming error in reporting managers' returns we use only the first six of the original eight periods in the main experiment for our analysis. Thus, in effect the concluding period's purpose of eliminating possible last-period effects in the managers' behavior was fulfilled by periods VII and VIII, which are now excluded from the data analysis.

3 Results

The question we aim to answer is whether adding the layer of delegated management to the economy affects market equilibrium. We approach the problem from two angles. First, we compare our experimental results to the the predictions of the theoretical benchmark model that corresponds to our setting but in the absence of delegated investment. Second, we compare our results to experimental evidence from frameworks analogous to ours in all other respects but the delegation.

The two main indicators we consider are:

1. **State-price probabilities.** According to standard asset pricing with complete markets (see Arrow and Debreu [1954]), the ratios of state prices (the prices of the canonical Arrow-Debreu claims) and state probabilities, called state price-probability ratios, should be inversely related to the aggregate wealth in the corresponding states. This is a weak test of the predictions of equilibrium models of asset prices, and a very useful one since it assumes only that investors be risk averse. The aggregate wealth and the probability of each state are design variables, thus known to the experimenter. Subjects do not trade state securities, but we can infer state prices from the prices of the traded securities because markets are complete.

2. **Sharpe ratio differences.** The Sharpe ratio of a portfolio is the ratio of the mean rate of return of the portfolio in excess of the risk-free rate, divided by the standard deviation of the portfolio return. The Capital Asset Pricing Model (CAPM, see Sharpe [1963], Lintner [1965], Mossin [1966]) predicts that in equilibrium the maximal Sharpe ratio is that of the market portfolio. (A caveat for using CAPM as a theoretical benchmark is that it assumes that the utilities of market participants have a mean-variance form, or are closely approximated by it.[7]) Thus, a commonly used measure of distance between market prices and their theoretical counterpart is the *Sharpe ratio difference*, equal to the difference between the maximal Sharpe ratio under those prices and the Sharpe ratio of the market portfolio. If the CAPM holds, this difference should be zero. The data on the trading prices of the assets and the asset's

[7]Because of the limited amount of risk in the laboratory, the CAPM is a suitable theoretical benchmark. Indeed, the CAPM is universally valid when risks are small, even if some of the assumptions usually made to derive the CAPM (normality; quadratic utility) are violated (Judd and Guu [2001]). Bossaerts et al. [2007] demonstrate that preferences of the mean-variance form provide a good representation of subjects' behavior in market experiments without delegation.

liquidating dividends is used to compute the rate of return and the standard deviation, and therefore the Sharpe ratio, of any portfolio.

The CAPM, and any asset pricing model for that matter, makes strong predictions about equilibrium allocations across states. While in empirical research allocations tend to be ignored, they play a central role in the analysis of experimental data. In experiments without delegation the result is that while the market portfolio is mean-variance optimal, individual investors do not actually hold mean-variance optimal portfolios. Despite erratic behavior of individual traders, in those experiments CAPM is obtained in the aggregate. That is, individual demands are merely perturbations of mean-variance demands, and in the aggregate, investors demand a mean-variance optimal portfolio.

It is against this backdrop that we consider the data from our main experiment.

3.1 Data Description

The data collected during the experiments consists of two parts – one for the investors and one for the managers. For each investor we collect his asset distribution to the 32 managers. For the managers, the data consists of their initial portfolios, all individually posted orders and cancelations along with the resulting transactions and the transaction prices for assets A, B and the Bond. Figure 2 displays the evolution of transaction prices for the three assets in the six main session periods. Time is on the horizontal axis (in seconds). Horizontal lines indicate the expected dividends of the risky assets. Each star is a trade. On average there are 3200 transactions per period, or about 2 transactions per second. Table 5 presents the trading volume and the turnover for each asset in the six trading periods. As apparent from the table, the trading activity in each of the securities increased as the periods advanced, with the increase being more pronounced in security B, which was the security with more stable aggregate supply across periods.

The performance indicators that we report each week (in the university newspaper and on the experimental web page) are readily computed from the data at hand. Table 6 reports the Return indicator values for all managers in all periods. Table 7 reports the Market Share indicator values, table 8 reports the Residual values, while table 9 contains the values of the Risky Share indicator.

3.2 Theoretical Benchmark Comparison

3.2.1 Asset Prices

We first turn to evaluating the pricing quality in the markets across periods. The Arrow-Debreu asset pricing model makes predictions about state prices. Because we have complete markets, given the prices of the traded assets, we can readily compute the state prices (and therefore the ratio of the state prices and the state probabilities). According to the theory, the state price probability ratios should be inversely related to the aggregate wealth in the corresponding state. That is, the state with the lowest aggregate wealth should be the most expensive relative to its probability. In this experiment (as evident from Table 4), the state with the lowest aggregate payoff was always X. Conversely, the state with the highest aggregate wealth should have the lowest state price probability ratio. In all periods the highest payoff state was Y. Thus, the Arrow-Debreu model predicts that in all periods the state price probability ratio for state X should be the highest, followed by that for state Z, and the ratio should be the lowest for state Y.

We compute the state prices every time a transaction occurs (taking the prices for the non-transacted securities to be equal to their last transaction prices). Figure 3 presents the evolution of state price probabilities in each of the periods. As evident from the figure, in the first half of the experiment, the data provide overall support for one of the most fundamental principles of asset pricing, namely, that state price probability ratios should be ranked inversely to aggregate wealth. However, starting from period IV, the ranking of state price probabilities is violated and largely remains such until the end of the experiment. Figure 4 presents the state price probabilities computed at the average prices over the last five minutes of trading (i.e., for each period and each state there is a single state price probability ratio). The average values confirm that indeed in period IV and V there are gross violations in state price probability rankings, with state X carrying the lowest value and state Y carrying the highest.

An alternative way to view the performance of the experimental markets in relation to asset pricing theory (without delegation) is to evaluate the Sharpe ratio differences between the market portfolio and the mean-variance optimal portfolio. In particular, the CAPM predicts that the market portfolio should be mean-variance optimal, or equivalently that the Sharpe ratio of the market portfolio be maximal. In each period, we compute the Sharpe ratio difference every time a transaction occurs. Figure 5 presents the evolution of the market portfolio's Sharpe ratio difference from the Sharpe ratio of the mean-variance optimal portfolio in the six periods of the experiment. The results from the Sharpe ratio evaluation are consistent with the result of the state-price probability ranking, namely that after the third period price quality deteriorates and remains poor until the end of the experiment.

3.2.2 Market Concentration

Here we study how price quality as measured by the ranking of state price probabilities and the Sharpe ratio differences depends on the concentration of funds in the hands of few managers. The deterioration of prices starts after period III, when the realization of the state variable happens to be X (see Table 6 for the period state realizations) and thus the aggregate wealth in the economy is at its lowest. As a result, with the exception of a few funds, the performance of the funds was poor. Those few "fortunate" funds attracted large portions of the investors' inflow in the following period. Thus, our conjecture is that price quality is inversely related to the market concentration.

We use two measures of market concentration. The first is the Gini index of the market according to expected dividends of the initial endowments of managers.[8] For the second measure we rank the managers by the expected dividends of their initial portfolios. Our market concentration measure is then equal to the fraction of the aggregate expected dividend held by the largest manager (according to the above ranking). Table 10 displays the values of the two measures for each of the six periods. The correlation between the two measures is 0.77.

Concentration and trading volume. Market concentration correlates positively with the total trading volume in each period (see Figure 6). When the Gini Index is used, the correlation is equal to 0.7, while it is 0.58 when the market share of the largest manager is used as a proxy for market concentration. In addition, in every period there is a positive correlation between market share of a manager and the number of transactions by this manager. Additional analysis of the data (not included here) indicates that large managers spread their trades across the period, i.e., they do not tend to cluster their trading in the beginning or the end of the trading periods.

[8]The Gini coefficient is based on the Lorenz curve and is defined as the ratio of the area that lies between the line of equality and the Lorenz curve over the total area under the line of equality. The Gini coefficient can range from 0 to 1 with low values indicating a more equal distribution (0 being the complete equality) and high values indicating more unequal distribution (1 being the case that all wealth is in the hands of a single individual).

Concentration and mean-variance efficiency. The correlation between the Gini index and the absolute value of the Sharpe-ratio difference of the market portfolio (computed each period using the average price over the last 5 minutes of trading), while positive (0.2996), is not significant (p-value 0.5641). In comparison, the correlation between the market concentration measured by the size of the largest manager is both positive (0.8194) and significant (p-value 0.0460). Thus, the larger the largest manager (according to the expected dividend of her initial portfolio) the worse the performance of the market as measured by the Sharpe ratio difference. This result indicates that what appears to be important in determining price quality in the marketplace is the size of the largest manager and not simply the fact that the market is polarized between large and small funds.

Since large funds appear endogenously in our experiment (in periods IV and V the largest manager has a market share of 20%), it is important to consider our results in view of the literature on imperfect competition in asset markets. This literature obtains that large traders will affect prices with respect to perfect competition in a profitable way if there is no retrading (Lindenberg [1979]) or if there are significant information asymmetries between large and small traders (e.g., Vayanos [1999], Kyle [1985], and Grinblatt and Ross [1985]; see Pritsker [2002] for a survey of the relevant literature). Our setup falls in neither of those categories, which leads us to conjecture that the large effect of market concentration on asset prices is due to managers' incentives given investor behavior. We turn to these incentives in the following subsection.

Without an appropriate analysis of investor behavior we are tempted to conclude that large managers in our experiment are far from rational, as implied by their final asset holdings. Figure 7 displays the relation between the funds' sizes and their final portfolio's Sharpe ratios. The cross-sectional correlations between the Sharpe ratio of a fund and its current period size are 0.2, -0.37, -0.6, 0.05, -0.09, -0.13 for the six periods of the experiment respectively. The correlations retain their signs and magnitudes after removing the biggest and the smallest 3 funds from the computations.

3.2.3 Investor Behavior

In this section we ask what determines the flows into a fund. The answer to this question will illuminate possible reasons for the findings in the previous subsection. For example, if investors do not reward managers with high Sharpe ratios by allocating more funds to them then managers will rationally respond to investors' demands and choose portfolios that would ensure higher fund flows in subsequent periods. Figure 8 shows the Sharpe ratio difference for each of the managers for all sessions (where the market Sharpe ratio is computed based on the average prices in the last five minutes of trading in each period). As evident from the figure and also confirmed by additional analysis, some managers consistently *outperformed* the market portfolio in that their final holdings had a smaller Sharpe ratio difference than the market portfolio. However, the analysis reveals that the performance of the funds according the their Sharpe ratio does not correlate positively with subsequent flows to the funds. Thus, the funds that grow are not the ones that provide high Sharpe ratios for their final portfolios.[9] In particular, the Market Share of a manager in period t, MS_t, is positively correlated with the standard deviation of the returns on the manager's final portfolio in period $t-1$. The correlation coefficient is 0.207 (p-value 0.006). On the other hand, the correlation between MS and past-period expected return is -0.058 (p-value 0.461). Univariate regressions of MS on each one of these variables (in all of our regressions we adjust the standard errors for clustering by managers) deliver analogous results. That is, there is a negative but not significant coefficient for expected returns and a positive and significant coefficient for variance. When both expected return and standard deviation of last period's portfolio return are included as explanatory variables for the next period's Market Share, the resulting coefficients are -6.098 (p-value 0.009) and 4.421 (p-value < 0.001) correspondingly. This is a clear indication that investors (whether knowingly or not – see footnote 9) were effectively not providing managers with incentives for mean-variance optimization.

In what follows we analyze the relation between fund flows and each of the four indicators of performance provided to the investors at the end of each period. As

[9] We did not give manager Sharpe ratios as part of the information disclosed to investors. Investors had information about the realized state, x, the sum of prices, $p_A + p_B$, and the ratio $\frac{w_A^j D_A(x)+(1-w_A^j)D_B(x)}{w_A^j p_A+(1-w_A^j)p_B}$ for $j = 1, \ldots, 32$, where $w_A^j = \frac{\tilde{m}_A^j}{\tilde{m}_A^j+\tilde{m}_B^j}$ is the fraction of the risky position held in units of asset A. Knowledge of the trading price of one of the risky assets would have sufficed to exactly compute the expectation and variance of managers' returns. In the absence of precise price information, but with the knowledge of $p_A + p_B$, investors could conjecture a price ratio in the vicinity of $\frac{p_A}{p_B} = \frac{\bar{D}_A}{\bar{D}_B}$, which would have led to a very good approximation of the true mean and variance of returns of managers' portfolios and, hence, of their Sharpe ratios. Specifically, in our experiment, $\frac{\bar{D}_A}{\bar{D}_B} = 0.77$, while the values of $\frac{p_A}{p_B}$ for average prices over the last 5 minutes of trade in the experimental periods were, respectively, $0.76, 0.58, 0.72, 0.74, 0.74$, and 0.76. Thus, as long as investors conjectured "reasonable" prices, they could deduce the means, variances and Sharpe ratios of managers' returns on their portfolios.

described in Section 2.3 indicators reported to investors were *Return* (denoted R in the regression reports), *Market Share* (MS), *Risky Share* (Ri), and *Residual* payoff after manager fee (Re). We also construct a variable called Excess Return (ER) that is equal to $R - R_{Dow-Tech}$.

In order to study determinants of investor allocations in any period, we use lagged values of all indicators denoted LR (with $LR_t = R_{t-1}$), LMS, LRi, and LRe correspondingly. We also use the lagged ER variable, denoted LER. In addition, we create variables summarizing the information given in several past periods. The growing average of lagged returns ($GALR$) is the average lagged return of all periods including the current one (equal to the average return of all past periods). For example, $GALR_{III}$ (i.e. the value of $GALR$ in period III) will be the average of the return in periods I and II. A similar average is constructed for the risky share, $GARLi$, as well as for the excess return, $GALER$. In order to differentiate how much weight investors put on last period's indicator vs. the average of this indicator up to the last period, we use lagged value of the growing average variables.

Correlations between all of the above mentioned variables are presented in Table 11. Of particular interest is the strong correlation between the lagged *Residual* variable and the current $Market\ Share$. The *Residual* variable captures both the past return and the size of the manager. Consequently, as the table indicates, there is also strong correlation between the $Market\ Share$ of the managers and their past period return (LR), their cumulative return ($GALR$), and their last period size (LMS). The relatively lower magnitude of the correlation between last period's return and $Market\ Share$ suggest that there is some "stickiness" of fund flows to managers, i.e., even if a manager underperforms in a given period, she is not penalized by investors if her overall performance (as measured by realized returns) has been good. The conclusions from the simple correlations observation are confirmed in a multivariate analysis setup as described below.

The results of several regression specifications with MS as the dependent variable are presented in Table 12. From the univariate regressions, the specification with the highest R-squared is when LRe is used as an independent variable. Other variables with high explanatory power are $GALER$, the growing average of the lagged excess returns and LMS, the lagged market share. On the other end, both LRi or GALRi have insignificant explanatory power as demonstrated by the univariate regression results.

In confirmation of the "stickiness" observation, the coefficient on LMS remains significant even when combined with other variables (with the exception of the regressions that includes LMS and LRe only but this is an obvious result given that those two variables are interdependent).

From the various multivariate regressions included in Table 12, the specification with the highest R-squared is the one including LRe and $GALER$. To further decompose the dependence of current period's fund inflows dependance on past returns, Table 13 presents results of regression specification where lagged values of the growing average variables are included. For example, when both LER and $LGALER$ are included, both slope coefficients are significant, indicating that investor value past performance beyond that of the last period. The significance of $LGALER$ diminishes though if LRe is included, once again indicating that LRe already captures the return information from past periods.

In summary, we find that investors flow their funds to managers with past high realized returns and past risky portfolio choices, and that they do not penalize funds for recent bad performance as long as the funds' overall performance as measured by their average return is good.[10] Those are surprising results. In our experiments the investors have to make allocations each period, i.e., sticking to a fund is not the "default" option as is in the real world. Still, investors act asymmetrically when rewarding and when penalizing funds with cash inflows and outflows correspondingly.

3.3 Experimental Asset Pricing without Delegation

The indicators we presented in section 3.2.1 have been used in numerous experimental studies (see Asparouhova et al. [2003], Bossaerts and Plott [2004], Bossaerts et al. [2007], Bossaerts, Ghirardato, Guarnaschelli, and Zame [2008a], Asparouhova and Bossaerts [2009], and Bossaerts et al. [2008b]) to assess the validity of the basic predictions of the standard asset pricing model. The aforementioned experiments implement designs with complete three- or four-asset markets where a large number (20+) of investors trade for their own benefit during periods of time (usually 6 to 10 such periods) with unchanged market fundamentals in each period (i.e., the market portfolio, the asset payoff distribution, the individual endowments, and the number of participants are identical in each period). A comprehensive review of the

[10] Our investor-subjects' reaction to past returns is in line with empirical evidence (see, e.g., Chevalier and Ellison [1997] and Sirri and Tufano [1998], and see Stracca [2005] for a comprehensive survey of empirical findings). It is well documented that investors react positively to past above-market returns while they have sticky reactions to below-market returns. The experimental setting allows us to also measure fund riskiness and thus directly assess investors' reaction to this variable.

experimental results is provided in Bossaerts [2009].

The general findings are that correct state-price ranking and near-complete mean-variance efficiency are almost always achieved, especially in the later periods of an experiment. That is, pricing is not only consistent with the presence of risk aversion (as expressed in the ranking of state price probabilities), but also with mean-variance preferences. The modal investor holds the market portfolio, thus justifying the mean-variance efficiency of prices (see Bossaerts et al. [2007]). However, individual investors typically do not hold the market portfolio.[11] Figures 9 and 10 give graphical support to the mentioned findings about asset prices.

The findings are *robust* to different dividend structures and market portfolios. In experiments with three states of the world, market portfolios range from ones with little aggregate uncertainty (with the ratio of wealth between the richest and the poorest state being 1.5 in Bossaerts and Plott [2004]) to a large aggregate uncertainty (where the aggregate wealth in the richest state is 43 times the wealth in the poorest state, see Bossaerts, Ghirardato, Guarnaschelli, and Zame [2008a]). The dividend structure of assets ranges from canonical Arrow-Debreu assets, to positively-correlated risky assets, and includes setups where all risky assets have the same expected dividend (see Bossaerts, Ghirardato, Guarnaschelli, and Zame [2008a]).

Thus, it is apparent that our experimental findings depart from the established results in the experimental asset pricing literature. The single design difference between the experiment in the paper and those previously studied is the presence of delegation. Ours is not the first experiment to display asset pricing anomalies. In Bossaerts et al. [2008a], in sessions with ambiguous assets state price probability violate the predictions of the Arrow-Debreu model as well. What the authors find in this case is that the "mispricing" is due to ambiguity aversion and that instead of holding the market portfolio, the modal investor holds an ambiguity-neutral portfolio. We replicate the individual holdings analysis of Bossaerts et al. [2008a]. In our case, however, the modal subject does hold the market portfolio. Thus, it is not the overall distribution of portfolio choices that drives the mispricing in our experiment. Instead, the mispricing appears to be driven by the endogenous incentive mechanism that delegation imposes on managers and the ensuing growth of some funds to a point when they can (adversely) affect asset prices.

[11] For a comprehensive survey of recent experiments on asset pricing see Bossaerts [2009].

4 Conclusions

This paper reports the results of a large scale experiment designed to study the impact of delegation on equilibrium asset prices in competitive financial markets. The experiment (6 periods of the main session and 1 end session) is conducted over 10 weeks with a large group of subjects serving as managers of funds and another large group of subjects serving as investors who can only invest via delegating. In early rounds, all funds receive approximately equal fund flows despite rather erratic holdings at the end of trading, and CAPM pricing obtains. In round III, however, the realized (stochastic) aggregate wealth of the economy was low and as a result all but a handful of funds delivered poor performance. In subsequent rounds, the successful funds received increasingly large allocations of assets and cash. We find that there was a correlation of 0.66 between a manager's funds distributed back to investors in the previous period and the flow to that investor in the next period. Managers with large fund flows were more likely to have large fund flows in the next period as well, a finding that does not disappear when taking account of past returns. Thus, there seems to be "stickiness" in fund flows. Moreover, investors do not appear to use mean-variance as a criterion in choosing the fund managers. We find that next period fund flows depend positively on last period portfolio variance. The size of the largest manager turns out to be significantly positively correlated with the mispricing in the market. When the largest manager held a significant share of the market portfolio (20%), CAPM pricing no longer obtained. In fact, the equity premium became negative. Our results indicate that it is the size of the largest fund more than the segmentation of the markets into large and small funds that matters for explaining the mispricing that occurred in our markets. Most importantly, our results indicate that delegation cannot be ignored when analyzing market equilibrium and asset pricing. This has significant implications for future research.

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Tables and Figures

Table 1: Weekly Calendar

Wed	**Fri**	**Sat**	**Mon**	**Tue**
Investors and managers informed of payoffs	Performance indices published on website	Sign-up announcement for investors	Performance indices published in *Tech*	18.00 Close investor allocation stage
		Restricted sign up for managers	Investors receive access to allocation software	22.00 Opening trading round
				Managers see allocations

Table 2: State-dependent asset dividends in US Cents.

	State		
	X	Y	Z
Asset A	5	80	0
Asset B	0	30	80
Bond	100	100	100

Table 3: Number of participants by type and the corresponding per capita market portfolio composition for each period. The market composition is presented as the average number of units of asset A, asset B and cash per investor.

	Participants		Market Portfolio Composition Per Capita		
Period	Type A	Type B	A	B	Cash
I	30	34	46.9	37.2	\$7.59
II	28	38	42.4	40.3	\$7.73
III	37	34	52.1	33.5	\$7.44
IV	37	35	51.4	34	\$7.46
V	34	33	50.7	34.5	\$7.48
VI	35	35	50	35	\$7.50

Table 4: Market portfolio. The top table gives number of units of each asset that were available in each period. The bottom table gives state-dependent aggregate endowments (in US dollars) in each period.

Asset / Period	I	II	III	IV	V	VI
Asset A	3000	2800	3700	3700	3400	3500
Asset B	2380	2660	2380	2450	2310	2450

State / Period	I	II	III	IV	V	VI
State X	150	140	185	185	170	175
State Y	3114	3038	3674	3695	3413	3535
State Z	1904	2128	1904	1960	1848	1960

Table 5: Trading volume and asset turnover by period.

Trading Volume[a]						
Asset / Period	I	II	III	IV	V	VI
Asset A	1114	1484	1652	1739	1648	1988
Asset B	942	928	1257	1383	1601	1919
Bond	212	135	217	279	349	446

Asset Turnover[b]						
Asset / Period	I	II	III	IV	V	VI
Asset A	0.37	0.53	0.45	0.47	0.48	0.57
Asset B	0.40	0.35	0.53	0.56	0.69	0.78

[a] Trading volume is the number of units of each asset that traded during a period.

[b] Asset turnover is calculated by dividing the trading volume of each asset over a period by the total number of units of this asset outstanding (as presented in Table 4).

Table 6: *Return* (in %) for every manager and every period of the main experimental session. The number reported in the table is $100 \times r^j$, where r^j is as defined in equation (2.4).

	Experimental Period (State Realization)					
	I (Z)	II (Y)	III (X)	IV (Y)	V (Y)	VI (X)
Dow-Tech	20.54	82.99	-77.86	56.99	57.00	-79.70
Mutual Fund:						
Albite	-44.18	396.59	-82.53	124.55	66.00	-190.00
Alexandrite	119.13	113.11	8.04	95.97	-22.00	95.00
Allanite	10.47	49.25	-44.77	183.56	105.00	-5.00
Alunite	38.82	151.01	-92.82	37.93	134.00	-107.00
Amazonite	65.85	90.56	-65.71	140.10	139.00	-125.00
Amblygonite	-134.56	128.56	-151.04	169.80	156.00	-93.00
Amosite	0.72	190.00	-75.85	46.72	8.00	-149.00
Andalusite	-21.88	78.60	-139.44	133.15	50.00	-527.00
Anthophyllite	33.23	79.59	-119.18	45.22	-22.00	-145.00
Atacamite	33.52	99.66	-73.12	11.05	72.00	-96.00
Barite	13.60	42.12	-68.75	-5.77	28.00	-97.00
Bassanite	43.71	103.08	-84.90	180.47	69.00	-119.00
Beidelite	17.53	125.26	-88.90	57.75	9.00	54.00
Bementite	-1.39	256.98	-83.28	65.47	177.00	-13.00
Bentonite	-2.15	160.26	-79.58	34.24	62.00	-109.00
Bertrandite	115.89	-4.83	-79.86	193.54	145.00	93.00
Biotite	10.24	99.33	-65.89	64.34	59.00	-74.00
Birnessite	28.48	-8.78	-68.71	-101.90	-46.00	56.00
Bloedite	-98.78	220.04	-56.92	-50.20	-99.00	-58.00
Boracite	22.92	134.16	-32.08	65.30	66.00	-120.00
Calcite	26.90	143.55	-36.50	-7.17	-17.00	-52.00
Carnallite	-100.51	255.01	-100.67	206.02	206.00	-127.00
Celestite	13.00	38.49	-68.88	58.69	-12.00	3.00
Chalcopyrite	15.59	123.11	-121.49	-3.00	103.00	-60.00
Chlorite	5.94	100.74	-90.37	103.16	71.00	-125.00
Colemanite	-1.19	194.06	42.61	-28.34	52.00	-68.00
Cornadite	23.03	197.94	-69.36	157.00	149.00	-131.00
Cristobalite	33.17	124.76	-74.29	-80.28	2.00	-131.00
Cryolite	67.25	51.22	-100.37	-22.45	37.00	-121.00
Dolomite	-15.93	2.40	-100.54	69.67	-65.00	-74.00
Dumortierite	161.05	98.53	-68.26	49.24	48.00	-90.00
Dunite	-39.27	70.75	-54.42	57.26	-3.00	76.00

Table 7: *Market Share* (in %) indicator for every manager in every period. The number reported in the table is $100 \times v^j$, where v^j is as defined in equation (2.5).

	Experimental Period					
	I	II	III	IV	V	VI
Mutual Fund:						
Albite	2.02	0.34	8.14	4.28	2.42	2.53
Alexandrite	2.38	11.61	10.36	19.95	20.34	8.67
Allanite	2.42	1.96	1.16	2.03	2.91	2.74
Alunite	2.34	2.27	5.69	1.88	1.78	2.21
Amazonite	4.62	6.68	6.19	3.71	5.65	6.80
Amblygonite	5.31	4.38	2.58	6.60	5.48	11.69
Amosite	2.33	0.98	3.89	1.81	0.77	1.29
Andalusite	3.36	0.84	1.22	1.08	2.27	0.85
Anthophyllite	2.78	1.70	0.89	2.03	0.86	0.63
Atacamite	3.38	4.39	2.72	1.25	1.74	0.74
Barite	2.93	2.19	1.12	0.46	0.84	0.57
Bassanite	2.84	3.18	2.11	1.09	5.66	2.68
Beidellite	3.17	1.83	2.06	1.37	0.89	0.74
Bementite	2.96	0.64	4.66	3.20	2.23	5.27
Bentonite	2.31	0.69	1.62	1.12	0.78	0.76
Bertrandite	2.01	10.57	2.98	0.90	4.54	6.27
Biotite	2.48	1.09	1.56	1.19	1.36	1.07
Birnessite	2.47	7.71	0.99	1.04	0.58	0.51
Bloedite	3.44	0.28	3.72	1.86	0.79	0.46
Boracite	3.06	1.44	1.67	3.30	3.77	2.44
Calcite	3.35	1.80	2.90	3.80	1.41	0.71
Carnallite	3.29	0.62	3.90	2.32	6.53	10.80
Celestite	2.78	1.82	1.64	1.23	0.89	0.50
Chalcopyrite	4.41	1.58	1.54	2.94	0.49	2.65
Chlorite	4.42	2.21	2.96	2.67	2.09	1.33
Colemanite	3.52	0.97	2.99	15.66	4.82	6.26
Cornadite	2.74	3.62	6.65	4.42	9.08	13.42
Cristobalite	3.12	1.87	3.07	1.55	2.22	0.69
Cryolite	3.42	6.15	2.82	0.91	1.13	0.70
Dolomite	4.02	12.36	2.28	1.20	1.97	1.18
Dumortierite	2.84	1.53	1.52	1.82	0.91	1.07
Dunite	3.48	0.70	2.38	1.34	2.80	1.77

Table 8: *Residual* (in US Dollars) for manager in every experimental period. The number reported in the table is $\max(\Pi^j - Pay^j, 0)$, as defined in equation (2.6).

	Experimental Period					
	I	II	III	IV	V	VI
Albite	7.41	27.75	0.00	198.71	71.12	0.00
Alexandrite	95.01	398.53	145.59	787.06	177.48	319.36
Allanite	37.85	42.66	2.83	124.41	110.61	35.66
Alunite	51.37	92.75	0.00	46.76	78.94	0.00
Amazonite	131.63	197.72	0.00	187.20	258.46	0.00
Amblygonite	0.00	178.10	0.00	386.10	276.77	0.00
Amosite	31.70	45.57	0.00	49.10	11.98	0.00
Andalusite	28.41	23.16	0.00	52.91	57.78	0.00
Anthophyllite	58.54	44.82	0.00	54.55	7.64	0.00
Atacamite	71.76	142.55	0.00	22.37	52.83	0.00
Barite	48.50	45.34	0.00	6.37	16.88	0.00
Bassanite	66.23	100.13	0.00	65.96	169.05	0.00
Beidellite	53.88	65.45	0.00	40.82	14.38	20.00
Bementite	38.20	36.56	0.00	102.01	122.24	58.24
Bentonite	29.67	27.67	0.00	27.04	22.03	0.00
Bertrandite	77.38	109.82	0.00	57.66	215.50	227.22
Biotite	38.99	33.03	0.00	37.33	37.52	0.00
Birnessite	47.79	73.34	0.00	0.00	1.84	13.95
Bloedite	0.00	15.66	0.00	4.84	-7.15	0.17
Boracite	55.80	51.65	8.82	104.29	109.79	0.00
Calcite	65.03	67.26	12.62	51.06	14.14	1.27
Carnallite	0.00	38.52	0.00	155.34	403.01	0.00
Celestite	45.34	35.75	0.00	37.25	9.66	7.37
Chalcopyrite	76.05	54.24	0.00	42.34	18.37	0.00
Chlorite	64.75	67.77	0.00	109.17	63.70	0.00
Colemanite	46.27	49.33	66.15	126.92	125.06	0.00
Cornadite	51.21	172.12	0.00	241.04	435.21	0.00
Cristobalite	66.14	67.02	0.00	0.00	31.73	0.00
Cryolite	98.90	134.87	0.00	8.88	25.18	0.00
Dolomite	139.73	134.47	0.00	39.79	-2.42	0.00
Dumortierite	39.79	46.54	0.00	50.08	22.95	0.00
Dunite	16.50	15.99	1.12	39.85	37.17	57.17

Table 9: *Risky Share* (in %) for every manager in every experimental period. The number reported in the table is $100 \times \nu^j$, where ν^j is as defined in equation (2.7).

	Experimental Period					
	I	II	III	IV	V	VI
Dow-Tech	86.61	84.75	85.24	86.92	86.92	86.6
Albite	78.88	242.13	93.6	47.98	113.42	197.28
Alexandrite	100.49	100	-10.92	109.86	82.65	-117.53
Allanite	110.26	74.32	57.29	99.36	26.77	-7.2
Alunite	99.75	100	100.76	99.98	99.33	119.57
Amazonite	101.77	96.11	72.49	114.23	76.35	121.52
Amblygonite	99.77	99.99	172.01	89.47	82.67	102.85
Amosite	65.11	112.09	86.3	90.28	113.63	145.98
Andalusite	78.9	120.55	150.07	104.64	120.57	475.63
Anthophyllite	101.64	99.97	127.92	101.73	104.15	159.8
Atacamite	75.97	106.65	80.78	8.47	60.86	101.55
Barite	76.8	62.05	85.09	29.38	39.22	92.17
Bassanite	92.39	99.84	99.75	99.93	96.06	121.64
Beidellite	99.87	111.98	99.68	55.49	11.08	-63.61
Bementite	77.55	106.61	92.29	11.92	54.4	12.15
Bentonite	83	98.58	90.21	77.15	90.66	119.3
Bertrandite	99.84	69.59	98.77	115.29	70.92	-152.87
Biotite	77.81	75.01	77.77	99.6	93.41	79.08
Birnessite	13.33	11.6	75.28	-4.27	7.45	-91.59
Bloedite	57.99	88.08	65.02	-73.78	-174.07	67.24
Boracite	99.62	99.41	34.69	89.15	66.86	128.35
Calcite	70.9	61.12	40.1	4.79	-42.74	30.56
Carnallite	117.61	122.34	123.86	119.12	119.08	155.1
Celestite	45.65	22.71	75.19	98.78	56.31	-18.67
Chalcopyrite	80.66	99.04	135.73	-23.95	-0.49	75.45
Chlorite	37.15	99.55	99.56	90.74	96.46	120.65
Colemanite	0	101.46	-39.2	99.4	77.81	97.51
Cornadite	108.77	120.29	74.92	71.86	114.19	145.84
Cristobalite	87.53	82.17	81.65	30.96	83.43	132.77
Cryolite	99.97	63.35	109.82	101.35	99.74	122.84
Dolomite	71.69	31.31	109.33	-17.45	35.92	78.45
Dumortierite	76.44	96.19	74.98	61.67	93.61	95.43
Dunite	20.89	65.04	58.14	99.38	-2.33	-110.85

Table 10: Gini index given by the market share of each manager. The market share of a manager is the fraction of the market portfolio (value computed with mean dividends) given by her initial allocation.

	Concentration indicator	
Session	Gini index	Market share of largest manager
061017	0.1334	0.0524
061024	0.5039	0.1236
061030	0.3434	0.1032
061107	0.4905	0.1995
061114	0.4978	0.2034
061121	0.5491	0.1342

Table 11: Correlations

	MS[a]	LMS[b]	LR[c]	LRe[d]	LRi[e]	$GALR$[f]	$GALRi$	LER[g]	$GALER$
MS	1	0.5407	0.3648	0.691	0.1065	0.5241	0.1452	0.4313	0.5517
LMS		1	-0.0511	0.652	0.0232	0.2043	0.0079	-0.0604	0.2151
LR			1	0.4629	0.2592	0.7167	0.2747	0.9734	0.6576
LRe				1	0.1303	0.431	0.1711	0.4441	0.4217
LRi					1	0.2361	0.7838	0.3273	0.2369
$GALR$						1	0.3076	0.7601	0.9901
$GALRi$							1	0.3392	0.3208
LER								1	0.7236
$GALER$									1

[a] MS is value of the performance indicator *Market Share*.

[b] LMS is lagged *Market Share*.

[c] LR is lagged *Return*.

[d] LRe is lagged *Residual* (Re).

[e] LRi is lagged *Risky Share* (Ri).

[f] GA stands for *growing average*, meaning that in every period one more observation is added to the computed average.

[g] LER is lagged *ExcessReturn* (ER) over the return of the *Dow Tech*.

Table 12: Regressions of Market Share, periods 2 and on. Numbers in parentheses are t statistics.

Intercept	LMS[a]	LR[b]	LRe[c]	LRi[d]	$GALR$[e]	$GALRi$	LER[f]	$GALER$	R^2
0.012	0.607								0.292
(3.517)	(4.875)								
0.027		0.013							0.133
(6.681)		(6.652)							
0.015			0.00024						0.477
(6.927)			(13.48)						
0.025				0.008					0.011
(3.536)				(1.32)					
0.017					0.043				0.275
(3.579)					(3.439)				
0.016						0.018			0.021
(1.521)						(1.562)			
0.027							0.019		0.186
(6.969)							(6.922)		
0.021								0.047	0.304
(4.789)								(3.336)	
0.007	0.63	0.014							0.447
(2.158)	(5.925)	(7.119)							
0.012	0.176		0.00021						0.492
(5.14)	(1.61)		(7.654)						
0.004	0.508				0.035				0.471
(0.958)	(4.359)				(4.131)				
0.007	0.639						0.02		0.508
(2.326)	(6.335)						(7.061)		
0.007	0.497							0.039	0.491
(2.042)	(4.287)							(3.881)	
0.026		0.013		0.001					0.133
(3.781)		(5.831)		(0.158)					
0.015			0.00022				0.007		0.497
(7.452)			(9.062)				(2.62)		
0.012			0.00019					0.027	0.560
(4.86)			(13.969)					(3.001)	

[a] LMS is lagged *Market Share*.
[b] LR is lagged *Return*.
[c] LRe is lagged *Residual* (Re).
[d] LRi is lagged *Risky Share* (Ri).
[e] GA stands for *growing average*, meaning that in every period one more observation is added to the computed average.
[f] LER is lagged *ExcessReturn* (ER) over the return of the *Dow Tech*.

Table 13: Regressions of Market Share, periods 3 and on. Numbers in parentheses are t statistics.

Intercept	LMS[a]	LR[b]	LRe[c]	LRi[d]	$LGALR$[e]	$GALRi$	LER[f]	$LGALER$	R^2
0.011		0.018			0.039				0.319
(1.98)		(5.603)			(2.51)				
0.003	0.534	0.015			0.015				0.515
(0.974)	(3.968)	(6.114)			(1.655)				
0.008		0.006	0.0002		0.02				0.577
(3.203)		(2.268)	(9.293)		(2.806)				
0.018							0.019	0.034	0.312
(4.454)							(7.255)	(2.035)	
0.008		0.006	0.0002		0.02				0.577
(3.203)		(2.268)	(9.293)		(2.806)				
0.012			0.00019				0.007	0.014	0.562
(6.059)			(9.005)				(2.712)	(1.846)	
0.001	0.186		0.00019					0.004	0.555
(2.741)	(1.445)		(7.853)					(0.51)	

[a] LMS is lagged *Market Share*.
[b] LR is lagged *Return*.
[c] LRe is lagged *Residual* (Re).
[d] LRi is lagged *Risky Share* (Ri).
[e] GA stands or *Growing Average*, meaning that in every period one more observation is added to the computed average. LGA stands for *Lagged Growing Average*.
[f] LER is lagged $ExcessReturn$ (ER) over the return of the *Dow Tech*.

Figure 1: jMarkets Trading Screen

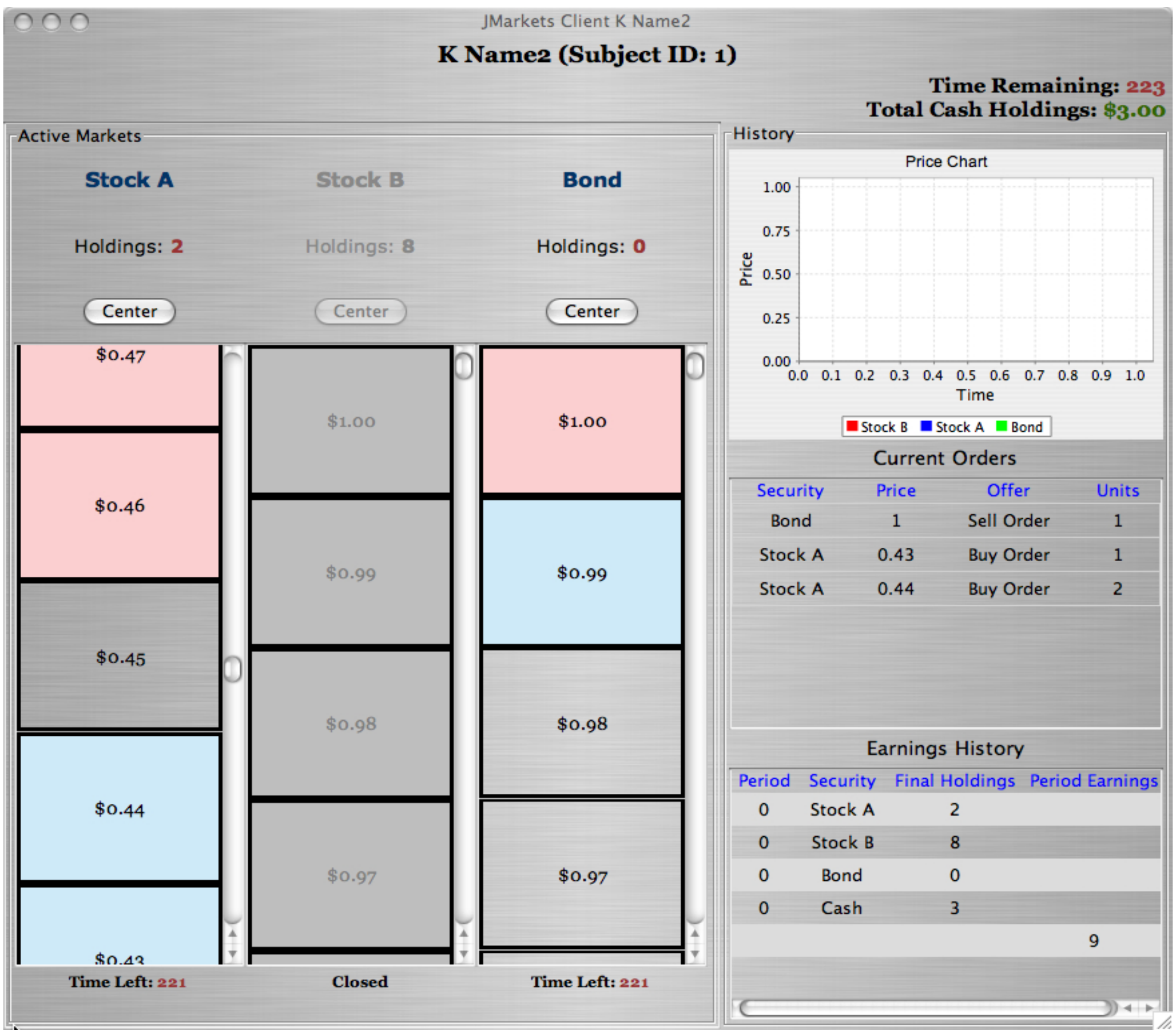

Figure 2: The time series of transaction prices.

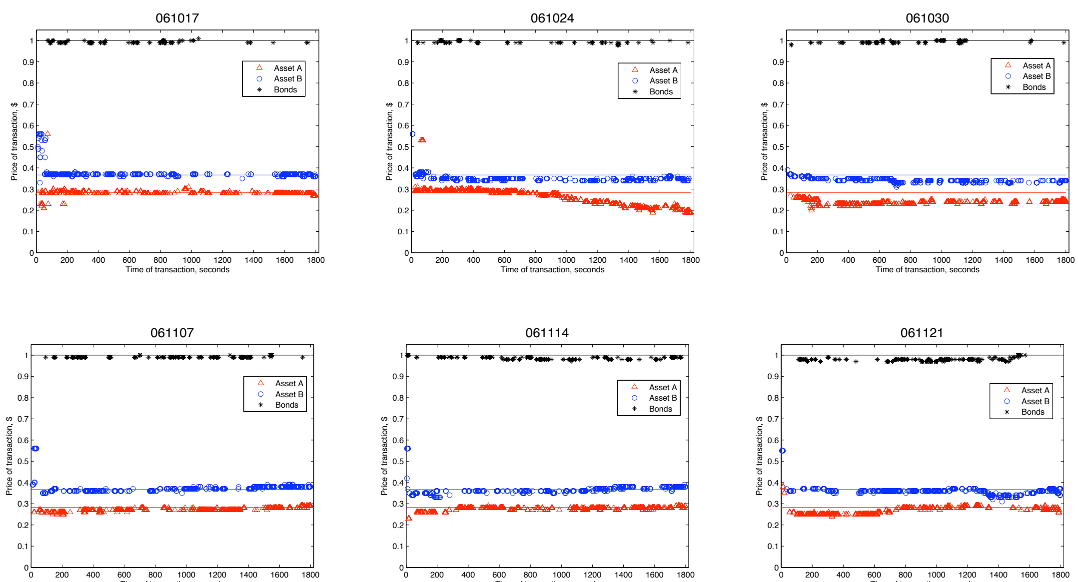

Figure 3: The time series of state-price probabilities.

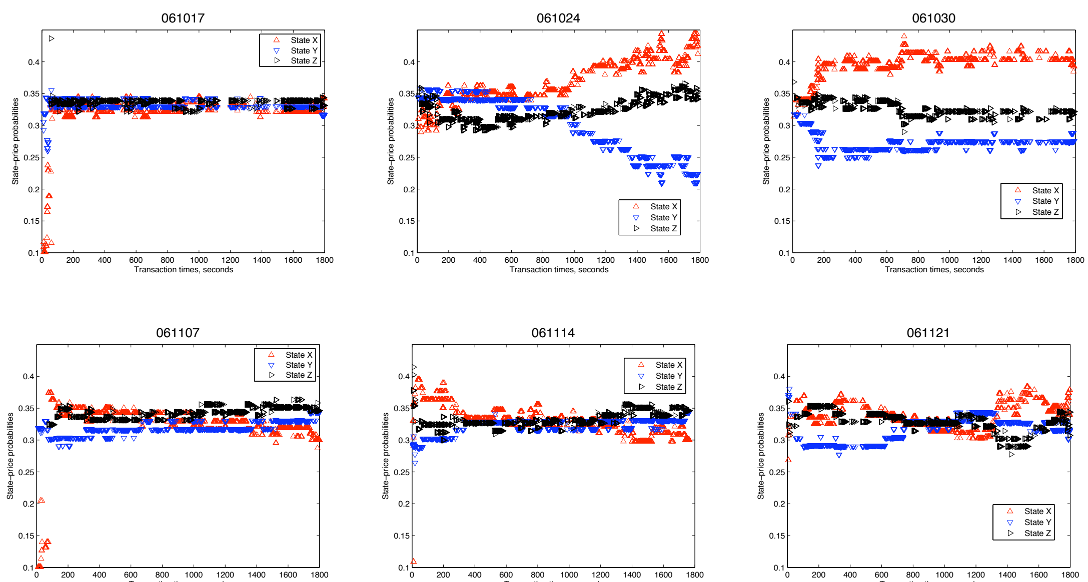

Figure 4: State-price probabilities computed for the average price over the last 5 minutes of trade. All periods.

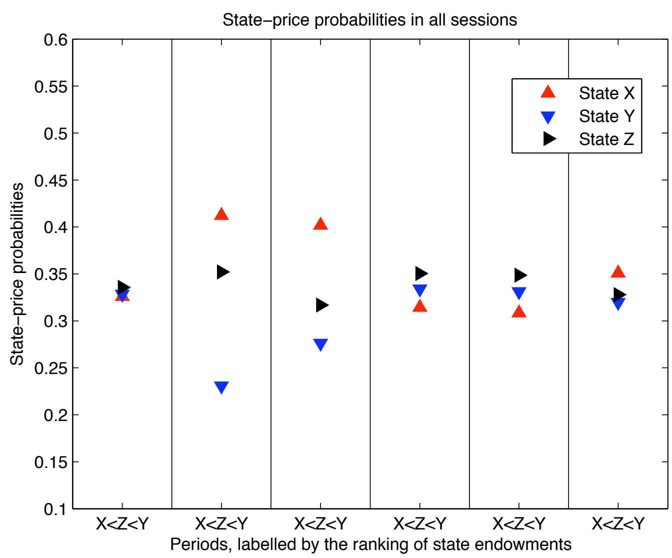

Figure 5: Difference between the Sharpe ratio of the market portfolio and the optimal Sharpe ratio (at current prices) for all trading prices for each period.

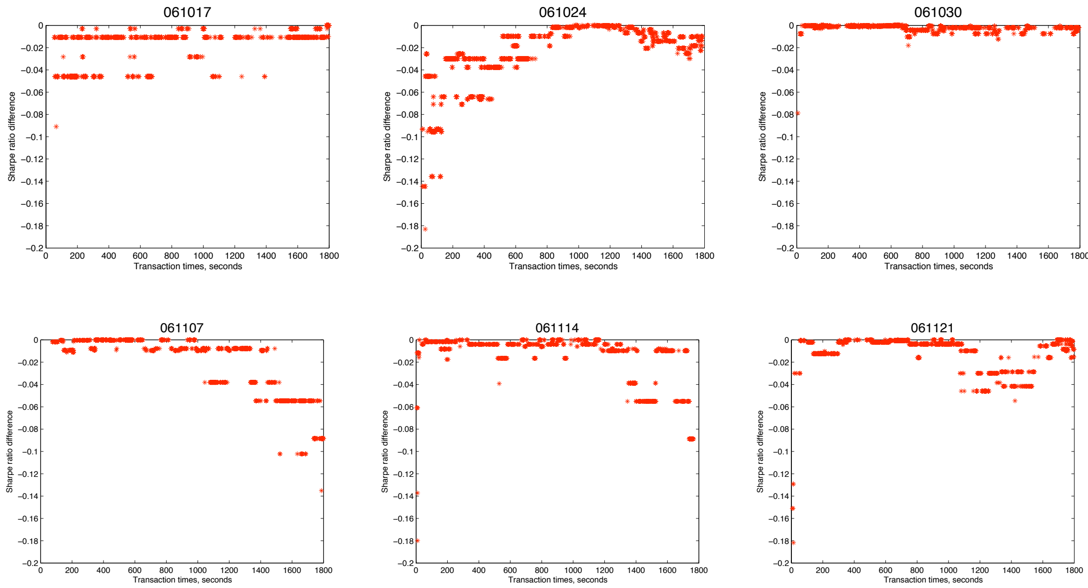

Figure 6: Total trading volume in all assets plotted as a function of market concentration. The blue markers denote market concentration measured as the market share of the largest manager. The black markers denote market concentration measured as the Gini index of manager's initial allocations.

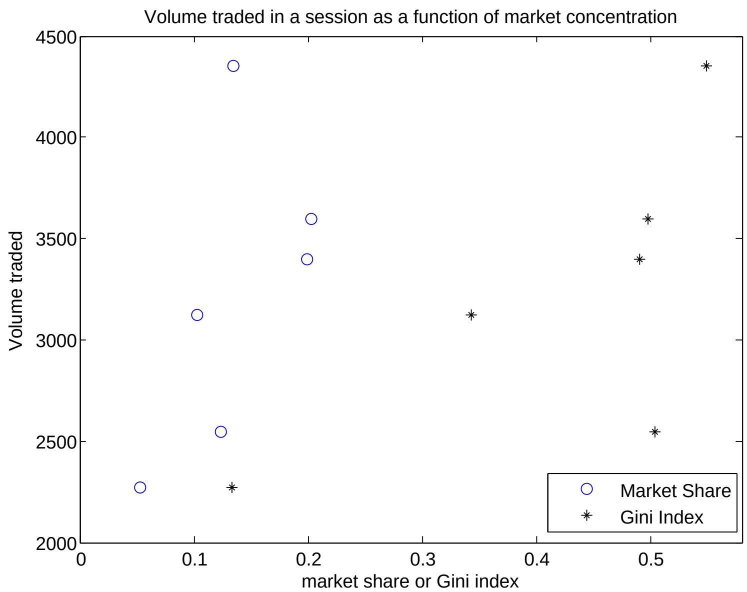

Figure 7: Scatter Plot of The Expected Mean-Standard Deviation Ratio of Final Portfolio as a Function of the Fund's Size.

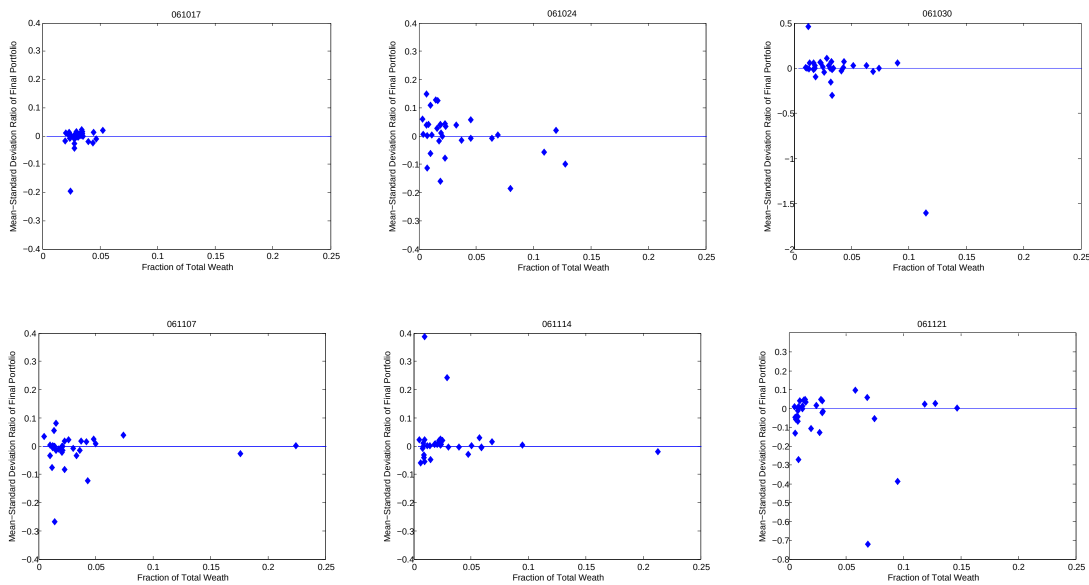

Figure 8: Sharpe ratios for the managers in comparison to the optimal Sharpe ratio (normalized to 0) and the market Sharpe ratio

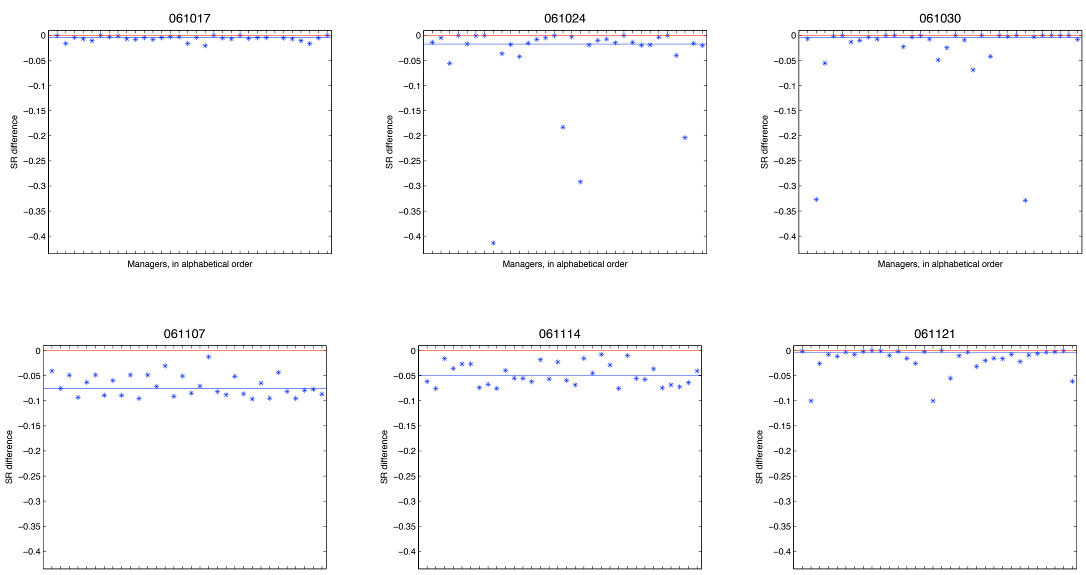

Figure 9: State-price probability ratios in time. From Bossaerts and Plott (2004)

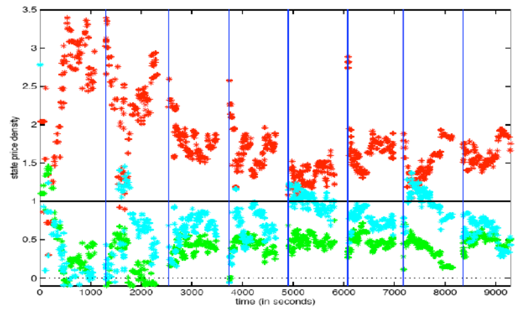

Fig. 4. Corresponding evolution of state price probability ratios (state price density). The Arrow-Debreu model predicts that state price probability ratios should be highest for the state where aggregate wealth is lowest (X; red), and lowest for the state where aggregate wealth is highest (Y; green). ***Adapted from (Bossaerts and Plott, 2004).***

Figure 10: Sharpe ratio differences in time. From Bossaerts, Plott and Zame (2007)

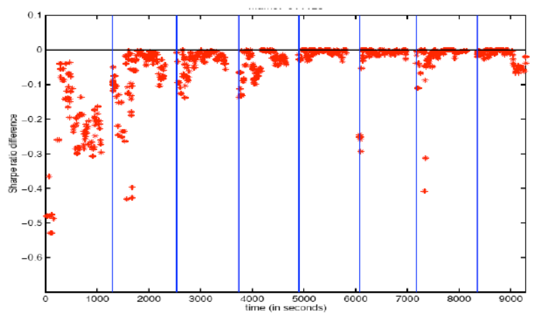

Fig. 3. Corresponding trade-by-trade evolution of the difference between the Sharpe ratio of the market and the maximum Sharpe ratio given latest transaction prices. For the CAPM to hold, this difference should be zero. ***Adapted from (Bossaerts et al., 2007b).***