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Too Many Mutual Funds? – Financial Product Differentiation Over the State Space

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Too Many Mutual Funds?[1]
– Financial Product Differentiation Over The State Space

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Comments are welcome.

Abstract: This paper identifies in the mutual fund industry a novel form of product differentiation – financial product differentiation over the state space. On the one hand, it is a well-documented fact that investors chase past performances of the mutual funds. On the other hand, the mutual funds' performances are determined not only by fund managers' abilities, but also by stochastic noise factors. In such a context, to avoid head-to-head competition created by holding the same portfolio, the mutual fund managers could gain higher profits by holding different portfolios which yield distinct returns at varying states. In other words, different funds win and attract cash in different periods and thus obtain market power alternatively.

To empirically test this idea, this paper rigorously developed a structural model – a multinomial IV logit model with random characteristics. Similar to BLP (1995), this model produces meaningful own-price and cross-price elasticities for financial products. It estimates that, on average, equity mutual funds can increase their profits by roughly 30% ($2.2 bn) through financial product differentiation over the state space. It concludes that from the social welfare point of view, there exists excess entry in the mutual fund industry if we assume free-entry and the entry incurs fixed costs.

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1. Introduction

At least 13,000 open-end mutual funds were in the market vying for investors' money by the end of 2001, among which more than 6,500 held domestic stocks.[2] This fact alone could prompt great interest from economists of both finance and industrial organization. First, the traditional finance models, such as CAPM and multifactor asset pricing models, predict that a few risk factors can span the market and account for most of the cross-section return variations of financial assets. In other words, there should exist only a few mutual funds in the market representing those few factor-mimicking portfolios. Therefore, it is puzzling to see that mutual funds numbered in the thousands. In the finance literature, few attempts have been made to explain the puzzle and no explanation is widely considered convincing so far.

Second, as the mutual fund industry expands, competition becomes a more and more significant force in disciplining the fund managers and affecting investors' wealth. Hence, it is increasingly important to study and understand the demand, supply and market structure of the industry. However, market structure is not a usual topic of finance. Many finance theories can only predict the relationships of prices in the equilibrium but are silent on which equilibrium should prevail in the market. We can illustrate this point through a simple example. One may argue that the large number of mutual funds are redundant assets in the market, thus their existence does not violate the no-arbitrage theory. However, no redundant assets can exist in the market if we consider competition. Suppose there are only two mutual funds in the market. If the two funds hold the same portfolio, their gross returns will be exactly the same. Therefore, investors will invest all their money in the fund charging lower fees. The no-arbitrage theory predicts that the two mutual funds can coexist in the market as long as they charge the same fees. However, if we consider competition, the standard outcome of the Bertrand game will occur: the two mutual funds can only make zero profits – they cannot charge fees higher than their marginal costs. If there is a minimum level of fixed costs required to establish a mutual fund, no mutual fund can survive. Nonetheless, few studies have been done to investigate the market structure of the mutual fund industry, despite its vast and growing size and its importance to our daily life.[3]

[2] By the end of 2001, the total number of stocks listed on the NYSE, AMEX, and Nasdaq combined were about 12,000.

[3] At the end of 2001, there were approximately 250 million mutual fund accounts and $7 trillion of assets managed by mutal funds; The industry employed half a million people.

Therefore, this paper partially fills the gap by implementing a structural model to analyze the demand, supply, and market structure of the mutual fund industry. In particular, it identifies in the mutual fund industry a novel form of product differentiation – product differentiation over the state space, as a response to the performance-chasing behavior of investors. As far as I know, this particular kind of firm behavior has never been studied in the literature. It is different from other forms of product differentiation, particularly because the quality of the financial products are highly stochastic and hard to measure.

In the case of the mutual fund industry, the basic idea is as follows. First, investors' demands for the portfolio of a particular mutual fund is positively correlated with the mutual fund's last period performance index, which is a function of the mutual fund's return history. In practice, this kind of performance-chasing behavior is well-documented in the literature.[4] Second, the performance index of the mutual funds referred to by investors may not be able to measure fund managers' qualities perfectly.[5] As a result, the performance index depends not only on the mutual fund manager's ability (in case we want to assume that there are indeed hot hands), but also on some noise factors.

As a simple example, consider the case of the oligopoly competition. Suppose there are two equally capable fund managers in the market. If they apply exactly the same investment strategy, they are in the Bertrand game situation as we mentioned before: each fund has one half of the market share and earns zero profit. However, as long as the investors' performance index loads in some noise factors, in order to avoid such a head-to-head competition, the two funds can "walk away" from each other by holding different portfolios. Hence, in different market situations (states), one fund's performance becomes better than the other's from time to time. Since consumers invest in the mutual fund that does better in the last period, the two funds alternatively become the cash attracting one.

[4] Theoretically, Ippolito(1992) shows that as long as poor-quality funds exist, an investment algorithm that allocates more money to the latest best performer is a rational investor behavior. Empirically, Roston (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998) and others report performance chasing behavior. Carhart (1997), Brown and Goetzmann (1995), Elton, Gruber and Blake (1996), and Grinblatt and Titman (1994) suggest performance persistence. Gruber (1996) and Zheng (1999) provide evidence that the return on new cash flows is better than the average return for all investors in the mutual funds.

[5] There are two main reasons for the inefficiency of the investors' indices. First, it is reasonable to assume that mutual fund managers have an information advantage over investors. Second, investors may not have enough training in investment and choose mutual funds according to some simple rule of thumb. They may be confused about the concept of the return and the risk-adjusted return, the alpha, or even the one realization of the return and the expected return.

In the period when a fund is winning, the fund possesses market power because investors can tolerate the higher fees charged by the top fund. Although each fund still has one half of the market share on average, the demands for mutual funds become relatively inelastic to fees. As a result, the mutual funds can charge higher fees and maintain non-zero profits although there is severe competition in the market. The two portfolios do not make any "real" difference to the investors because they care about the true quality of the mutual funds, which we assume are equal in this example. We call this special form of product differentiation spurious financial product differentiation over the state space.[6]

Based on the above idea, this paper constructs a structural model to empirically analyze the idea and its implications. First, it proposes a multinomial IV logit model to estimate the demand system of mutual funds, which accommodate stochastic and unobserved quality characteristics. Particularly, it employs the Fama and French (1993) 3-factor model to decompose mutual funds' gross returns, based on which it investigates whether and how investors respond to the different stochastic components. We find that investors not only chase last period risk-adjusted returns, the alphas, but also respond to the last period factor returns (instead of expected factor returns), which are irrelevant to fund managers' abilities. This leaves room for the fund managers to load factor returns differently and spuriously differentiate their products. Second, the estimated parameters are used to recover the price-cost margins (PCMs) under Nash-Bertrand competition without observing actual cost data. Third, the counterfactual PCMs are computed under the assumption that fund managers cannot financially differentiate their products. Finally, by comparing the estimated versus the counterfactual PCMs, we estimate that, on average, the growth-oriented equity funds improve their variable profit levels by about 30% ($2.2 billion in dollar value) through financial product differentiation.

[6] The logic can be applied beyond the financial product sector to other products which have stochastic characteristics and highly volatile market share. For example, it does not make any sense for two supermarkets to be on sales simultaneously if the total demands are constant. Instead, the two supermarkets may follow some random strategy. This special case has be demonstrated by Varian (1980). The movie industry is another good example. Instead of investing in a portfolio of movies, some companies specialized in high-budget movies which are characterized by high risks and high profits, but some companies specialized in low-budget movies. In the apparel and toy industry, the trends of fashion are unpredictable. Instead of betting on the same style, different companies try to differentiate from each other. The reason that they want to do this is in case one company catches the trend; then that firm will obtain its monopoly power in its lucky year.

The empirical framework derived in this study can be applied to other products which have stochastic characteristics and highly volatile market shares. Although the multinomial IV logit model with random characteristics is easier to implement than the BLP (1995) random coefficient (mixed logit) model, it produces meaningful own-price and cross-price elasticities for financial products.

In some sense, this paper has an additional contribution to the behavior finance literature. Since consumer demands can be viewed as an implicit contract to discipline the mutual fund managers, consumers' knowledge and information have become important factors for determining the market structure of the mutual fund industry. In fact, the implication of this work justifies the decade-long movement of the SEC to strengthen the disclosure requirement and investors' education program.[7] This paper is an attempt to quantitatively measure how the consumer's knowledge and information structure can affect the industry structure and regulation policy.

The remainder of the paper is organized as follows. We review the related literature in Section II. In Section III, we construct the structure model to analyze the financial product differentiation idea and its implications. In Section IV, we describe the data used for the estimation. Demand parameters are estimated in Section V. In Section VI, we use the estimated parameters to compute how much the diversified equity funds can improve their profit through financial product differentiation. Finally, Section VII summarizes our conclusions.

2. Literature Review

Several papers (e.g. Golec (1992), Tufano (1997) and Deli (2002)) discuss the advisory contract in the mutual fund industry from a principle-agent perspective. However, considering the large number of investors and mutual funds, it is very costly to write and enforce any contract.[8] Instead, it is almost cost-free to transfer

[7] Also on December 30th, 2002, in the settlement agreed upon among ten Wall Street firms and regulators, the firms will provide $85m to be spent on educating investors. See the *Economist*, January 4th-10th 2003, pp.59.

[8] Within the framework of federal securities law, mutual fund organizations are perhaps the most strictly regulated business entities. The major federal regulatory statues for this industry are the Investment Company Act of 1940 and the Investment Company Amendments Act of 1970. In addition, some new regulatory measures were initiated recently to tighten governmental and judiciary controls.

Theoretically speaking, the small shareholders can mobilize a challenge to the undesirable actions of management. In practice, however, both academic research and recent studies called

money from one fund to another.[9] In essence, open-end funds provide a strong form of the "voting with the feet" mechanism. It is reasonable to believe that market competition is the most important force for disciplining the fund managers.

Previous papers that have investigated market demand as an implicit incentive scheme (like this one) include Borenstein and Zimmerman (1988), Berkowitz and Kotowitz (1993) ,and Chevalier and Ellison (1997). However, my paper explicitly models and quantifies how the mutual fund managers' behavior can affect the market power of the mutual funds and how profitable that behaviors can be when there is monopolistic competition. Whereas my work studies the information game among mutual fund managers, the methodological framework can be generalized to study other financial markets in which market competition is a form of the governance method.

There is increasing interest in studying the financial industry from the industrial organization point of view. As far as I know, there are two theoretical models addressing the similar questions. Massa (2000) argue that the brand proliferation in mutual fund industry is the marketing strategy used by the managing companies to exploit investors' heterogeneity and the reputation of the top performing fund. The closest paper to this study is Mamaysky and Spiegel (2001). They treat mutual funds as financial market intermediaries to take orders from their investors. The large number of mutual funds are to span the different dynamic trading strategies of the investors'. The story of this paper differs from those two in that this paper argue that the fund proliferation is a product differentiation strategy used by fund managers to maintain higher profit-cost margins. On the empirical side, Khorana and Servaes (1997, 2001) studies the determinants of mutual fund starts and the market share at the family level. However, it basically treats the financial products as normal commodities without modeling the special properties of financial products. Unlike most of the empirical work studying mutual fund industry, this paper develops a structural model instead of reduced form

by the Congress and the SEC indicated that small shareholders had little incentive to challenge a fund manager's decision because of the free-rider problem. Furthermore, in cases where the small investors did challenge, most cases terminated in settlements and the plaintiffs were almost never successful. For instance, as of 1987, fifty-five litigation cases were generated under the 1970 Amendments. Among these fifty-five cases, most were settled, six were decided for dependants and four were decided for plaintiffs. In general, although the two Acts provided the weapons with which the small investors could fight, they were ineffective in actually helping the investors to solve the problems.

[9] The costs of transfering money among mutual funds include loads, realized capital gain taxes and other transaction-related fees.

regression model. With a structural model, we can demonstrate the mechanism of financial product differentiation and better understand the assumptions that we need to consistently estimate the model.

The most general goals of this study are related to the large literature that studies the effects of relative performance evaluation schemes. It is well known that one of the functions of the financial market is that the market provides benchmarks to evaluate the performances of the individual firms or mutual funds. This paper provides an empirical framework to qualitatively and quantitatively study the effect of relative performance evaluation schemes when there are a large number of contestants. My work demonstrates that, as long as the measures of quality are not perfect, the mutual fund managers can make the benchmark ineffective by differentiating from each other and seek more rent from investors despite the fact that there is severe competition in the market. (Incomplete)

3. The Empirical Model

3.1. Mutual Fund Returns

The assumption that returns are linear functions of a set of observable or unobservable factors is an important building block in the finance literature. Assume there are a set of K factor-mimicking portfolios (also known as passive benchmark assets) and J actively managed mutual funds available in the market. Let $\boldsymbol{\varepsilon}_{\mathbf{F}_t}$, a $K \times 1$ vector, denote the factor's excess returns over the riskless rate of interest at time t. R_t, a $J \times 1$ vector, is the gross excess return vector of actively managed mutual funds over the riskless rate of interest. Throughout this article, we assume that the excess gross returns of the mutual funds are generated by the multi-factor return-generating process of the following form:

$$\mathbf{R}_t = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}\boldsymbol{\varepsilon}_{\mathbf{F}_t} + \boldsymbol{\varepsilon}_t.$$

$\boldsymbol{\beta}_{jk}$, a fixed parameter, is mutual fund j's loading on the returns of factor-mimicking portfolio k. $\boldsymbol{\alpha}_{0j}$ is manager j's ability to outperform the K factor-mimicking portfolios. $\boldsymbol{\alpha}_{0j}$ is exogeneously endowed to the fund manager j and independent of the choices of $\boldsymbol{\beta}_{jk}$. $\boldsymbol{\varepsilon}_{jt}$, a random variable, is the idiosyncratic risk of mutual fund j's portfolio. The K-factor model is consistent with a model of market equilibrium with K-risk factors. Alternately, it may be interpreted as a performance attribution model, in which the coefficients and premiums on the factor-mimicking portfolios indicate the proportion of mean return attributable to the K elementary passive strategies available in the market.

3.2. The Empirical Model

Our general strategy is as follows: first, we propose a multinomial IV logit model with stochastic characteristics to estimate the demand system of mutual funds. We are especially interested in whether and how investors respond to some stochastic characteristics of mutual funds. Then we discuss the possible opportunities for the fund managers to financially differentiate their products and the conceivable effects on the price-cost margins (PCMs). After demand parameters are estimated, we use them to recover the PCMs and compute the counterfactual PCMs under the assumption that investors cannot financially differentiate their products. Finally, we calculate how much the mutual funds can improve their profit margins through financial product differentiation.

3.2.1. A Discrete-Choice Framework to Model a Demand System

There are four reasons frequently cited[10] for the appeal of mutual funds: customer services, low transaction costs, diversification and professional management (security selection). When investors are faced with the decision of choosing a mutual fund, they need to choose among a large number of closely related products that vary according to the aforementioned attributes. To circumvent the dimensionality problem, we employ the discrete-choice framework to model the demand system. This approach provides a parsimonious model to represent consumer preferences over products as a function of the product attributes.

Demand

A Behavioral Investment Choice Model Investor i's subjective expected utility function of fund $j = 0, ..., J$ at time $t = 0, 1, 2, ..., T$, is:

$$u_{ijt} = X_{jt} b_i + Index_{ijt}(\varphi_i, R_j^t) + \xi_{jt} + \epsilon_{ijt},$$

where X_{jt} is an L-dimensional vector of observable characteristics of fund j which are unrelated to mutual fund j's portfolio performance; $Index_{ijt}(\varphi_i, R_j^t)$ is an index constructed by investor i to evaluate mutual fund j's return performance based on fund i's return history R_j^t; ξ_{jt} is a scalar, which denotes the unobservable quality attribute of fund j; and ϵ_{ijt} is a mean-zero stochastic term. b_i are L

[10] For example, Gruber (1996).

individual-specific coefficients and φ_i are parameters that need to be estimated in the investors' index function $Index_{ijt}(\varphi_i, R_j^t)$.

One special property of the financial products in the mutual fund industry is that the performance data are noisy across mutual funds over time. Ippolito (1992) shows that as long as poor-quality funds exist, an investment algorithm that allocates more money to the latest best performer is a rational investor behavior.[11] Given that investors are not sure about the qualities of mutual funds and respond to their short-term performances, we have a performance index $Index_{ijt}(\varphi_i, R_j^t)$ in the investors' subjective expected utility function.

The Index function The performance index $Index_{ijt}(\varphi_i, R_j^t)$ of fund j is constructed by investors i according to their own preferences, endowment, income shocks, information set or other factors. If the investors' information set is not perfect, $Index_{ijt}(\varphi_i, R_j^t)$ depends not only on the true quality of mutual fund j but also on some noise signal, either unbiased or biased. To make performance-chasing a rational behavior, we require that $Index_{ijt}(\varphi_i, R_j^t)$ positively correlate with the true quality of mutual fund j. Such a performance index can be the alphas calculated from the CAPM, Fama-French 3-factor model or the 4-factor model used by Carhart (1997). It can also be the Bayesian inference according to fund j's historic returns, or even the Mornigstar rankings. Although our model can analyze very complicated function forms of $Index_{ijt}(\varphi_i, R_j^t)$, we construct it based on the commonly applied mean-variance utility function form:

$$\begin{aligned}
Index_{ijt}(\varphi_i, R_j^t) &= E_t\left[\varphi_{i0}\boldsymbol{\alpha}_{0j} + \sum_{k=1}^{K}\varphi_{ik}(\varepsilon_{F_k}\boldsymbol{\beta}_{jk}) + \varepsilon_j\right] - \frac{1}{2}\varphi_{iK+1}Var_t(R_j) \\
&= \left\{\varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}}\right\} + \left\{\sum_{k=1}^{K}\varphi_{ik}\varepsilon_{F_{kt}}\boldsymbol{\beta}_{jk} - \frac{1}{2}\varphi_{iK+1}\boldsymbol{\beta}_j^{'}V_t\boldsymbol{\beta}_j\right\} \\
&= \Psi_i(\alpha_{jt}, \sigma_{\epsilon_{jt}}; \varphi_{i0}, \varphi_{iK+1}) + \Phi_i(\varepsilon_{F_{kt}}, V_t, \boldsymbol{\beta}_j; \varphi_{ik\in\{1,\ldots,K\}})
\end{aligned}$$

where $\boldsymbol{\beta}_j$ is fund j's factor loadings; $\boldsymbol{\alpha}_{0jt}$ and $\sigma_{\varepsilon_{jt}}$ denote the investors' subjective conditional expectation of $\boldsymbol{\alpha}_{0j}$ and the variance of mutual fund j's idiosyncratic risk at time t, respectively; $\varepsilon_{F_{kt}}$ is the conditional expectation of the return ε_{F_k} of factor k at time t; V_t is the conditional co-variance matrix of the K factor returns.

[11] Also see Gruber (1996), Zheng (1997) and Shleifer and Vishny (2002).

We assume that $\boldsymbol{\alpha}_{0jt}$ and $\sigma_{\varepsilon_{jt}}$ are exogenously endowed to fund manager j and are independant of his choice of $\boldsymbol{\beta}_j$.

The above index function are otherwise similar to the standard mean-variance utility function, except that φ_{ik}, $k \in \{1, ..., K+1\}$ may have different values. φ_{ik}, $k \in \{1, ..., K+1\}$ models investor's sensitivity to factor k. Given an expected return and a given set of $\boldsymbol{\beta}_{jk}$, $k \in \{1, ..., K+1\}$ the above index function exhibited Rothschild and Stiglitz risk aversion. Therefore, this function is a special case of the utility function used by Elton and Gruber (1992) and Fama (1996) when they analyzed the multifactor asset pricing problem.

In the above utility function, we allow the coefficients b_i and φ_{ik}, $k \in \{1, ..., K+1\}$ are different for different investors i. However, the main purpose of this article is to demonstrate that there is product differentiation over the state space even if the investors have the same preference parameters. To simplify our demonstration of the main idea and also maintain the model in a manageable level, we assume that the contributions of various product attributes to investors' utility levels are the same and investors are checking the same index. We will discuss how to incorporate the heterogenous coefficients at the end of this section. In the empirical part, we solve the possible problem of heterogenous preference by studying the mutual fund demand within every category. We assume that investors have the same risk preference parameters within every category. Hence we can drop the subscription i of all coefficients in the subjective expected utility funciton:

$$\begin{aligned} u_{ijt} &= X_{jt}b + Index_{jt}(\varphi, R_j^t) + \xi_{jt} + \epsilon_{ijt} \\ &= \delta_{jt} + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}; \varphi_0, \varphi_{K+1}) + \Phi(\varepsilon_{F_{kt}}, V_t, \boldsymbol{\beta}_j; \varphi_{k\in\{1,...,K\}}) + \epsilon_{ijt}, \end{aligned}$$

where δ_{jt} is value of fund services not related to fund performance; $\Phi(\boldsymbol{\beta}_j)$ evaluates how well the loading $\boldsymbol{\beta}_j$ of portfolio j matches investors' needs; $\Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}})$ measures how well fund manager j can actively manage fund j's portfolio.

The Ex Post Market Share Investors are assumed to invest one unit of their money in the fund that gives the highest utility. Since investors picking one mutual fund out of a large pool of candidates instead of diversifying is a key assumption of this study, it is worthwhile to discuss its reality. One of the main reasons that investors buy mutual funds is that they can hold well-diversified portfolios. It is not reasonable to assume that investors use multiple mutual funds to diversify their risk. The second reason is transaction costs. If it is costly for investors to follow two mutual funds, investors will sacrifice the benefit of holding both to save the transaction costs. If one still is not convinced, this model can be viewed as

an approximation of the true choice model. Empirical evidence shows that the median investor holds two funds; one of them is more likely to be a bond fund. Especially, this article studies the demands within one category. It is more likely that investors will want to choose one best fund within one category.

The set of unobserved variables that lead to the choice of good j is defined by,

$$A_{jt+1}(\delta_{.t+1}, Index_{.t}; b, \varphi) = \{\epsilon_{it} | u_{ijt} \geq u_{ilt} \ \forall l = 0, 1, ..., J\}.$$

Then, mutual fund j's market share at time $t+1$ is:

$$s_{jt+1} = \int_{A_{jt+1}} dP(\epsilon_{it})$$

Assume the stochastic shocks ϵ_{it} are distributed i.i.d. with a type I extreme-value distribution. The the short-term market share is equal to,

$$\begin{aligned} s_{jt+1} &= \frac{\exp(\delta_{jt+1} + \varphi_0 \boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{K+1}\sigma_{\varepsilon_{jt}} + \sum_{k=1}^{K} \varphi_k \varepsilon_{F_{kt}} \boldsymbol{\beta}_{jk} - \frac{1}{2}\varphi_{K+1}\boldsymbol{\beta}_j' V_t \boldsymbol{\beta}_j)}{\sum_j \exp(\delta_{jt+1} + \varphi_0 \boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{K+1}\sigma_{\varepsilon_{jt}} + \sum_{k=1}^{K} \varphi_k \varepsilon_{F_{kt}} \boldsymbol{\beta}_{jk} - \frac{1}{2}\varphi_{K+1}\boldsymbol{\beta}_j' V_t \boldsymbol{\beta}_j)} \\ &= \frac{\exp\left\{\delta_{jt} + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}; \varphi_0, \varphi_{K+1}) + \Phi(\varepsilon_{F_{kt}}, V_t, \boldsymbol{\beta}_j; \varphi_{k\in\{1,...,K\}})\right\}}{\sum_j \exp\left\{\delta_{jt} + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}; \varphi_0, \varphi_{K+1}) + \Phi(\varepsilon_{F_{kt}}, V_t, \boldsymbol{\beta}_j; \varphi_{k\in\{1,...,K\}})\right\}}. \end{aligned}$$

After observing mutual fund j's market share and return histroy at time t, we can apply the method proposed by Berry (1994) to estimate all the parameters in the demand system.

3.2.2. The Definition of the Spurious Financial Product Differentiation

The Equivalent Spatial Competition Model In the appendix, we derive that the above ex post market share equation is equivalent to a spatial competition model with quadratic "transportation" costs as follows:

$$s_{jt+1} = \int \frac{\exp(\delta_{jt+1} + \varphi_0 \boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{K+1}\sigma_{\varepsilon_{jt}} - \frac{1}{2}\varphi_{K+1}(\boldsymbol{\beta}_t^* - \boldsymbol{\beta}_{jt})' V_t (\boldsymbol{\beta}_t^* - \boldsymbol{\beta}_{jt}))}{\sum_j \exp(\delta_{jt+1} + \varphi_0 \boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{K+1}\sigma_{\varepsilon_{jt}} - \frac{1}{2}\varphi_{K+1}(\boldsymbol{\beta}_t^* - \boldsymbol{\beta}_{jt})' V_t (\boldsymbol{\beta}_t^* - \boldsymbol{\beta}_{jt}))}$$

where

$$\boldsymbol{\beta}_t^* = (V_t)^{-1} (\frac{1}{\varphi_{K+1}} \boldsymbol{\varphi} \cdot \boldsymbol{\varepsilon}_{\mathbf{F_t}}).$$

$\boldsymbol{\beta}_t^*$ is the vector of the factor loadings best matched to investor i without considering other attributes.

It is interesting to compare the above model to the conventional spatial competition model. $\boldsymbol{\beta}_t^*$ is similar to the concept of the position of customers. The factor loading vector $\boldsymbol{\beta}_{jt}$ of fund j marks mutual fund j's position in the state space. $\frac{1}{2}\varphi_{K+1}(\boldsymbol{\beta}_t^* - \boldsymbol{\beta}_{jt})' V_t (\boldsymbol{\beta}_t^* - \boldsymbol{\beta}_{jt})$ denote the "transaction costs" between fund j's portfolio and investors $i's$ best style $\boldsymbol{\beta}_t^*$. In this sense, many intuitions and results of the spatial competition models, such as Hotelling (1929), and many of the models discussed in Anderson, De Palma, and Thisse (1992) and Goettler and Shachar (2001), are valid here.

However, the spatial competition in the state space is different from the convential spatial competition model. In this model, investors are homogeneous and their optimal position $\boldsymbol{\beta}_t^*$ depends on the common conditional first moments, $\boldsymbol{\varepsilon}_{F_{kt}}$, and the second moments, V_t, of the factor returns. However, the optimal position of $\boldsymbol{\beta}_t^*$ is stochastic and changing from time to time. Thus, financial firms have incentive to differentiate their products to bet on the best position $\boldsymbol{\beta}_t^*$ although investors are homogeneous.

The Definition of Spurious Financial Product Differentiation From the above market share equation, we find that, if $\exists \varphi_{k\in\{1,\ldots,K+1\}} > 0$, there are opportunities for fund managers to differentiate their products by holding different factor-loading $\boldsymbol{\beta}_k s$. Through this, mutual fund performance indices $Index_{.t}$ respond differently to the factor return moments, $\varepsilon_{F_{kt}}$, and V_t, although $\varepsilon_{F_{kt}}$, and V_t are common to all the mutual funds**.** For example, when the market is going up, the mutual funds having large positive market-portfolio loadings have their moments and attract more money. However, in a depression market, the mutual funds having less or even negative market-portfolio loadings have better returns and obtain more market shares. We call this form of product differentiation **financial product differentiation over the state space**. Since investors have the same risk preference and the choice of $\boldsymbol{\beta}_k$ is not correlated with managers' real ability $\boldsymbol{\alpha}_{0jt}$ and $\sigma_{\varepsilon_{jt}}$, the product differentiation is **spurious**. If mutual funds hold different $\boldsymbol{\beta}_{.k}$, the performance indices $Index_{.t}$ as well as the market share of fund j is stochastic. Thus, ex ante, mutual funds can only know their expected market share.

The Expected Market Share The expected market share of fund j is:

$$s_{jt+1}^{e} = \frac{\exp\left\{\delta_{jt} + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}; \varphi_0, \varphi_{K+1}) + \Phi(\varepsilon_{F_{kt}}, V_t, \boldsymbol{\beta}_j; \varphi_{k\in\{1,...,K\}})\right\}}{\sum_j \exp\left\{\delta_{jt} + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}; \varphi_0, \varphi_{K+1}) + \Phi(\varepsilon_{F_{kt}}, V_t, \boldsymbol{\beta}_j; \varphi_{k\in\{1,...,K\}})\right\}} dF(\boldsymbol{\varepsilon}_{F_{kt}}, V_t).$$

Price Elasticities We model the demand system of mutual funds by a multinomial IV logit model. However, the above model is in essence a mix-logit model (BLP (1995), McFadden & Train (2000)). The average own and cross-price elasticities of fund j are:

$$\eta_j^e = \frac{\partial s_j^e p_k}{\partial p_k s_j^e} = \begin{cases} \frac{p_j}{s_j} \int b_0 s_{jt}(1 - s_{jt}) dF(\varepsilon_{F_1}, ..., \varepsilon_{F_K}; V_t) & if\ j = k \\ -\frac{p_k}{s_j} \int b_0 s_{jt} s_{kt} dF(\varepsilon_{F_1}, ..., \varepsilon_{F_K}; V_t) & if\ j \neq k \end{cases}.$$

It is interesting to compare the above results to the BLP (1995) model with random coefficients. Similar to the random coefficient model, we find the multi-logit model with random characteristics can produce reasonable own-price elasticity and cross-price elasticities. The own-price and cross-price elasticities will no longer be determined by a single parameter, b_0 and market share. In each state, the mutual fund will have a different price sensitivity. The mean price sensitivity will be the average of the different price sensitivities at *every state*. Instead, in the BLP (1995) model, the mean price sensitivity is the average of the different price sensitivities of *heterogenous investors*. The model also allows for flexible substitution patterns. The products with similar factor loadings have higher cross-price elasticities because their market shares have higher correlations.

The Demand Curves Become Steeper Scharfstein and Stein (1990) and Zwiebel (1995) present models in which optimal performance evaluation gives managers an incentive to "herd." My paper shows that, ex ante, the mutual fund managers have incentives to "walk way" from each other. One of the important results of this paper is that the mutual fund demand curves become steeper if the mutual funds differentiate from each other.

The Effect Coming from a Random Market Share If mutual funds differentiate from each other, their market shares s_{jt} are stochastic. Let s_j^e denote the average market share of mutual fund j. For comparison, consider a hypothetical case such that the mutual fund shares are not stochastic, but fixed at their

average level, i.e. $s_{jt} = \overline{s_j} = s_j^e$ for all t.[12] Then, define the price elasticities in this case as:

$$\overline{\eta}_{jk} = \begin{cases} \frac{\beta_0}{1-\lambda} p_j (1 - s_j^e) & if\ j = k \\ -\frac{\beta_0}{1-\lambda} p_k s_k^e & if\ j \neq k \end{cases}.$$

Proposition 3.1. $|\eta_{jj}^e| = |\frac{\partial s_j^e p_k}{\partial p_k s_j^e}| < |\overline{\eta}_{jj}|$

Proof:

$$\begin{aligned} \left|\eta_{jj}^e\right| &= \left|\frac{\partial s_j^e p_k}{\partial p_k s_j^e}\right| \\ &= \left|\beta_0 \frac{p_j}{s_j} \int s_{jt}(1 - s_{jt}) dF(\boldsymbol{\omega}_1, ..., \boldsymbol{\omega}_K)\right| \\ &= \left|\beta_0 p_j (1 - s_j^e - Var(s_j^e)/s_j^e)\right| \\ &< \beta_0 p_j (1 - s_j^e) \\ &= |\overline{\eta}_{jj}| \end{aligned}$$

If $\exists \varphi_{ik \in \{1,...,K+1\}} > 0$, by holding different $\boldsymbol{\beta}_{jk}$, mutual funds' performances will respond to common factor return moments, $\varepsilon_{F_{kt}}$ and V_t differently. Thus, instead of competing state-by-state, mutual funds become top performing funds alternatively (in different situations or states). When a mutual fund has a superior return in one year, it enjoys both a higher market share and higher market power. On average, this strategy can cause the demand curves to become steeper**.**

Distortion of the Market Share Furthermore, this form of product differentiation also distorts the distribution of the average market shares which in turn affects the price elasticities. Because of the monopolistic competition, the market share are nonlinear functions of product attributes in our model. If the mutual funds hold different portfolios, the market shares will be stochastic. The average of the market shares will be affected by both the level $\boldsymbol{\beta}_{jk}$ and the distribution of $\boldsymbol{\beta}_{.k}$. The more a mutual fund differs from the average, the more volatile its market

[12] According to Berry (1994), there exists α_{jt}^e and $\sigma_{\epsilon_{jt}}^e$ s.t.

$$\frac{\exp(\delta_j + \Psi(\alpha_{jt}^e, \sigma_{\epsilon_{jt}}^e; \varphi_0, \varphi_{K+1}))}{1 + \sum_j \exp(\delta_j + \Psi(\alpha_{jt}^e, \sigma_{\epsilon_{jt}}^e; \varphi_0, \varphi_{K+1}))} = s_j^e \ for\ all\ j = 0, 1, ..., J$$

share is. Although we have no closed form solution, we can study the distortion of the average market shares empirically. The overall change of price elasticities is the combination of the random effect documented in the previous section and the effect originating from the distortion of market shares.

3.2.3. Supply

Suppose there are F mutual fund families. Each family comprises some subset, $\mathcal{F}_f$, of the $j = 1, ..., J$ mutual funds.

The Mutual Fund's problem The mutual fund family f maximizes its profits:

$$\begin{aligned} \underset{p_j}{Max}\ \Pi_f &= E[\sum_{j \in \mathcal{F}_f,} N s_j(p_j)(p_j - mc_j) - C_f] \\ &= \sum_{j \in \mathcal{F}_f,} N s_j^e(p_j)(p_j - mc_j) - C_f, \end{aligned}$$

where $s_j^e(p_j)$ is the expected market share of mutual fund j; N is the size of the market, and C_f is the fixed cost of production.

As most of the literature does, the characteristics are taken as given. At least, we think they are determined in the first-stage game. Assuming the existence of a pure-strategy Bertrand-Nash equilibrium in prices, the price, p_j, satisfies the first-order conditions:

$$s_j^e(p) + \sum_{r \in \mathcal{F}_f,} (p_r - mc_r) \frac{\partial s_r^e(p)}{\partial p_j} = 0,\ j = 1, ..., J.$$

Define

$$\Delta_{jr} = \begin{cases} -\frac{\partial s_r^e(p)}{\partial p_j}, & if\ (r, j) \subset \mathcal{F}_f \\ 0 \end{cases}.$$

In vector notation, the first order conditions can then be written as

$$\mathbf{m}^e = p - mc = \Delta^{-1} s^e(p),$$

where $\mathbf{m}^e$ is a vector of the markups.

3.2.4. Implications

The Incentive Effect Assume α_{0j} is the true quality of mutual fund j. If investors chase performance index $Index_{jt}(R_j^t)$, mutual fund j with higher α_{0j} is able to capture a higher market share.

Lemma 3.2.

$$\frac{\partial s_j^e}{\partial \alpha_{0j}} = \int \varphi_0 s_{jt}(1 - s_{jt}) dF(\varepsilon_{F_1}, ..., \varepsilon_{F_K}; V_t) > 0$$

This provides the incentives for the fund managers to generate a higher alpha.

The Effect on Mutual Fund Profits As we discussed in the previous section, if $\exists \varphi_{ik \in \{1,...,K+1\}} > 0$, fund managers can differentiate their products over the state space by holding different factor loading $\boldsymbol{\beta}_k s$. This form of product differentiation has two effects: (1) a decrease in the own-price elasticity (in absolute value) because of stochastic market shares; (2) the distortion of average market shares. It is interesting to check how those two effects impact mutual fund profits.

Let s_j^e, p_j^e and m_j^e denote the Nash-equilibrium expected market share, price and expected markups of fund j if there is spurious financial product differentiation. Consider a hypothetical case in which mutual funds hold the same $\boldsymbol{\beta}_k s$ and do not differentiate their products. In this case, the counterfactual Nash-equilibrium market share, price and markups of fund j are s_j^*, p_j^*[13] and m_j^*, respectively.

Then, the difference in markups between the case with and without spurious financial product differentiation is as follows:

$$m_j^e - m_j^* = (m_j^e - \overline{m_j}) + (\overline{m_j} - m_j^*)$$

where $\overline{m_j}$ is the markups of the intermediate case in which mutual fund j maintains its market share and price at the level of s_j^e and p_j^e without product differentiation. $\overline{m_j} - m_j^*$ is the change in the markup due to random market share effect. From the results of Proposition 2.1., we have, $\overline{m_j} - m_j^* > 0$ for every j because the own-price

[13] According to Berry (1994), there exists $p^*_{j \in \{0,1,...,J\}}$ s.t.

$$\frac{\exp(\delta_j + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}; \varphi_0, \varphi_{K+1}))}{1 + \sum_j \exp(\delta_j + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}; \varphi_0, \varphi_{K+1}))} = s_j^* \ for\ all \text{ j=0,1,...,J}$$

elasticities become steeper due to the random market share effect. $m_j^e - \overline{m_j}$ is the markup change due to market share distortion. The sign of the second term $m_j^e - \overline{m_j}$ is ambiguous. The main task of this paper is to correctly estimate the demand system and then calculate whether the whole industry's profit actually improved with the spurious financial product differentiation documented in this paper.

3.3. Discussion: The Mixed Coefficient Model

So far we assume the risk preference parameters φ_{ik}, $k \in \{1, ..., K+1\}$ are the same for different investors i within every category. It is easy to extend our framework to accomodate heterogenous coefficients φ_{ik}, $k \in \{1, ..., K+1\}$.

3.3.1. The Ex Post Market Share

If we allow investors' risk preference parameters φ_{ik}, $k \in \{1, ..., K+1\}$ to be hetergenous, the set of unobserved variables that lead to the choice of good j is defined by,

$$A_{jt+1}(\delta_{.t+1}, Index_{.t}, \varphi; b) = \{\boldsymbol{\varphi}_i, \epsilon_{it} | u_{ijt} \geq u_{ilt} \ \forall l = 0, 1, ..., J\}.$$

Then, mutual fund j's market share at time $t+1$ is:

$$s_{jt+1} = \int_{A_{jt+1}} dP(\epsilon_{it}) dP(\boldsymbol{\varphi}_i)$$

Assume the stochastic shocks ϵ_{it} are distributed i.i.d. with a type I extreme-value distribution. The the short-term market share is equal to,

$$s_{jt+1} = \int \frac{\exp(\delta_{jt+1} + \varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}} + \sum_{k=1}^{K} \varphi_{ik}\varepsilon_{F_{kt}}\boldsymbol{\beta}_{jk} - \frac{1}{2}\varphi_{iK+1}\boldsymbol{\beta}_j' V_t \boldsymbol{\beta}_j)}{\sum_j \exp(\delta_{jt+1} + \varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}} + \sum_{k=1}^{K} \varphi_{ik}\varepsilon_{F_{kt}}\boldsymbol{\beta}_{jk} - \frac{1}{2}\varphi_{iK+1}\boldsymbol{\beta}_j' V_t \boldsymbol{\beta}_j)} dP(\boldsymbol{\varphi}_i)$$

3.3.2. The Equivalent Spatial Competition Model

The above ex post market share equation is equivalent to a spatial competition model with quadratic "transportation" costs as follows:

$$s_{jt+1} = \int \frac{\exp(\delta_{jt+1} + \varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}} - \frac{1}{2}\varphi_{iK+1}(\boldsymbol{\beta}_t^{i*} - \boldsymbol{\beta}_{jt})' V_t (\boldsymbol{\beta}_t^{i*} - \boldsymbol{\beta}_{jt}))}{\sum_j \exp(\delta_{jt+1} + \varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}} - \frac{1}{2}\varphi_{iK+1}(\boldsymbol{\beta}_t^{i*} - \boldsymbol{\beta}_{jt})' V_t (\boldsymbol{\beta}_t^{i*} - \boldsymbol{\beta}_{jt}))}$$

$$dP(\boldsymbol{\varphi}_i).$$

where

$$\boldsymbol{\beta}_t^{i*} = (V_t)^{-1}\,(\frac{\boldsymbol{\varphi}_i \cdot \boldsymbol{\varepsilon}_{F_t}}{\varphi_{iK+1}}).$$

$\boldsymbol{\beta}_t^{i*}$ is the vector of the factor loadings best matched to investor i without considering other non-portfolio attributes.

Then, investor i's optimal position $\boldsymbol{\beta}_t^{i*}$ depends not only on the conditional first moments, $\boldsymbol{\varepsilon}_{F_{kt}}$, and the second moments, V_t, of the factor returns, but also on investor i's preference parameters $\boldsymbol{\varphi}_i$. Thus, the financial firms differentiate their products is affected by both the preference parameters and the stochastic components.

3.3.3. The Expected Market Share

Since the performance measures $Index_{.t}$ are not perfect measures of fund managers' abilities, they are stochastic *ex ante*. The expected market share of fund j is:

$$s_{jt+1}^e = Es_{jt+1} = \int \frac{\exp(\delta_{jt+1} + \varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}} + \sum_{k=1}^{K} \varphi_{ik}\varepsilon_{F_{kt}}\boldsymbol{\beta}_{jk} - \frac{1}{2}\varphi_{iK+1}\boldsymbol{\beta}_j^{'}V_t\boldsymbol{\beta}_j)}{\sum_j \exp(\delta_{jt+1} + \varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}} + \sum_{k=1}^{K} \varphi_{ik}\varepsilon_{F_{kt}}\boldsymbol{\beta}_{jk} - \frac{1}{2}\varphi_{iK+1}\boldsymbol{\beta}_j^{'}V_t\boldsymbol{\beta}_j)}$$
$$dP(\boldsymbol{\varphi}_i)dF(\boldsymbol{\varepsilon}_{F_{kt}}, V_t).$$

After observing mutual fund j's market share and return histroy at time t, we can estimate all the parameters of demand system with aggregate market share data using the method proposed by Berry, Levinsohn, and Pakes (1995) (BLP (1995)).

4. Data

The sample funds we examined are the open-end diversified equity mutual funds from 1992 until 1998 at the Center for Research in Security Prices (CRSP) Mutual Fund Database which is free of survivorship bias. There are several reasons for covering the 1992-1998 period. First, the industry experienced rapid growth during this period. Second, the CRSP Supplementary Annual Data File provides relatively complete information at the individual level on the mutual fund family

and mutual fund fees during this period. Furthermore, we supplement the above information with data on distribution channels and other detailed fund characteristics from the Morningstar Principia CDs, which are available from 1992 onwards.

Table 1 provides the descriptive statistics of the growth-oriented diversified equity funds, which includes the funds in the aggressive growth, long-term growth and growth and income categories in the mutual fund industry.[14] One remarkable aspect is the tremendous increase in the number of the funds. If we count the multi-class funds as separate funds, there were around 779 funds in 1992, while in 1998 there were 2,943 funds. However, the number of management companies increased only from 444 to 542. Obviously, the management companies adopted a multiple products strategy to compete. Our study covered a total of 1,337 diversified equity funds and 6,132 fund years. If a fund has multi-class shares, we only consider the Class A shares because of the nonlinear pricing structure of the mutual funds.[15]

The individual stock and the factor-mimicking portfolio returns that we used to decompose the mutual fund returns were obtained from the CRSP US Stock and Indices Data database. The market capitalization data of individual stocks came from Standard and Poor's Compustat database.

5. Estimation

5.1. Return Decomposition

We employ the Fama and French (1993) 3-factor model to decompose the performance of mutual funds:

$$r_{js} = \alpha_{j0t} + \beta_{j1t} RMRF_s + \beta_{j2t} SMB_s + \beta_{j3t} HML_s + e_{js} \qquad s = 1, 2, ..., 36$$

where r_{js} is the gross return on the portfolio of fund j in excess of the one-month T-bill return; RMRF is the difference between the return on the CRSP value-weighted portfolio of all NYSE, Amex and Nasdaq stocks and one-month T-bill yields; and SMB and HML are returns on value-weighted, zero-investment, factor-mimicking portfolios for size and book-to-market equity in stock returns. RMRF,

[14] Our sample design is analogous to that of most of the empirical literature on APT. We omit sector funds, international funds, and balanced funds for testing purposes. Such funds contain other factors not covered in these studies. However, all the methodology is easy to implement in other categories.

[15] Interested readers please see Li and Shoven (2003) for the multi-class funds problem.

SMB, and HML are constructed according to the descriptions in Fama and French (1993).

Summary statistics of the factor portfolios are reported in Table 2. The 3-factor model can explain considerable variation in returns. First, note the relative low mean returns of the SMB, HML zero-investment portfolios. This means for a long-term portfolo holder, the mean contribution coming from this two factors are almost zero. Second, the variance of the SMB, HML zero-investment portfolios are high. This suggests that the 3-factor model can explain sizeable time-series variations. Third, the correlations between these two factors and between these two factors and the market proxie are low. The low cross-correlations imply that mulitcollinearity does not substantially affect the estimated 3-factor model loadings.

In year t, we run the monthly gross excess return r_{js} of mutual fund j in the past three years on $RMRF$, SMB and HML to obtain the estimates $\widehat{\alpha}_{j0t}$ and $\widehat{\beta}_{jkt}$. Then we calculate the annual average return $\overline{r}_{jt}$ of fund j, and the annual factor returns $\overline{RMRF}_t, \overline{SMB}_t$ and $\overline{HML}_t$ at year t. The annual average excess gross return can be decomposed into factor return loadings based on,

$$\overline{r}_{jt} \simeq \widehat{\alpha}_{j0t} + \widehat{\beta}_{j1t}\overline{RMRF}_t + \widehat{\beta}_{j2t}\overline{SMB}_t + \widehat{\beta}_{j3t}\overline{HML}_t.$$

Summary statistics of cross-section mutual fund excess returns $\overline{r}_{jt}$, and factor return loadings are reported in Table 3. Each year, alphas and the three factor return loadings account for much cross-sectional variation in the annual mean return on stock portfolios.

Summary statistics of cross-section mutual fund $\widehat{\alpha}_{j0t}$ and $\widehat{\beta}_{jkt}$ are reported in Table 4 Panel A. The equal weighted average cross-section market portfolio loading $\widehat{\beta}_1$ is almost 1 and slightly declines from 1992 to 1998. The equal weighted average cross-section common size factor is greater than zero, but the common book-to-market equity factor loading is smaller than zero. This reflects the fact that mutual funds tended to hold small and growth-oriented stocks during this period. However, we find, for all the three $\widehat{\beta}s$, the cross-section standard deviation is large and well spread out around the mean levels, which means the indices are variate cross-sectionally.

To provide some evidence that mutual fund managers differentiate their products, we compare the cross-section $\widehat{\alpha}_{j0t}$ and $\widehat{\beta}_{jkt}$ of mutual fund return processes to those simulated mutual funds that choose stocks randomly. First, we obtain the number of equity holdings of each of the mutual funds in our sample in year 1998. Second, we assume that the fund managers choose publicly traded stock

randomly from the stock universe, i.e. throw a dart at the stock list board to make a choice. Then we calculate the $\widehat{\alpha}^h_{j0t}$ and $\widehat{\beta}^h_{jkt}$ of the hypothetical mutual fund portfolios. We find the interesting result that the cross-section distribution of factor loadings of real mutual fund portfolios are much more fat-tailed than those of the hypothetically simulated mutual funds. In Table 4 panel B, the F test shows that both the manager's ability measure $\widehat{\alpha}_{.0t}$ and the factor loading $\widehat{\beta}_{.kt}$ of mutual funds are more spread out than those of the random strategy funds.

5.2. The Logit and The IV Logit[16]

5.2.1. The Gross Cash Inflow

We define the market share as the market share of the gross cash inflow into the fund.[17] However, the gross cash inflow data normally are not available. We construct the annual gross cash inflow data by adding all the positive monthly net flows over the year[18]:

$$GrossInflow = \sum_{s=1}^{12} \max(Newmoney_{js}, 0).$$

The monthly new money or cash flow is defined as the dollar change in total net assets (TNA) minus the appreciation in the fund assets and the increase in total assets due to merger (MGTNA),

$$Newmoney_{js} = TNA_{js} - TNA_{js-1} * (1 + R_{st}) - MGTNA_{js}.$$

[16] A full random coefficient model in the framework of BLP(1995) can also be applied here.

[17] There are three reasons for using gross cash inflows instead of total net assets managed by mutual funds: 1) In typical demand systems, purchases are flows of goods. New flows into the fund, rather than the asset stock of the fund, are closer to this traditional definition. 2) Survey studies report that fund managers are most concerned about the new money they make. The fund managers compete for floating money in the market. 3) Empirical work, such as Sirri and Tufano (1998), documented that the relationship of the relative performance and growth is option-like. The market share function in the logit model is a good approximation of the relationship between performance and growth.

[18] Since any within-month redemption will cancel out an equal amount of purchases in that month, the true gross flows are higher than the value we estimated. However, we observe that each year, the absolute amounts of cash inflow and outflow tend to be negatively correlated. Therefore, our estimations of gross cash inflows are reasonable measures of the true value.

5.2.2. Outside Good

As with most of the logit model, we define an outside "good" to simplify the regression. If investors decide not to invest in any of the growth-oriented mutual funds studied in this paper, but instead allocate all income to other funds, we think investors will invest in mutual fund $j = 0$, the "outside fund." The indirect utility from investing in this outside fund is:

$$u_{ijt} = \xi_{0t} + Index_{i0t}(\varphi_i, R_{jt-1}) + \epsilon_{i0t}.$$

As with most empirical work using the discrete-choice model, I normalize ξ_{0t} to zero. $Index_{i0t}(\varphi_i, R_{jt-1})$ are not identified separately from the intercept in equation.[19]

5.2.3. Regression Equation

We define ζ_{jt+1} as,

$$\zeta_{jt+1} = \ln(s_{jt+1}) - \ln(s_{0t+1})$$

where s_{jt+1} is the market share of gross cash inflow of fund j at year t. s_{0t+1} is the outside fund market share. Hence we obtain the regression function of ζ_{jt+1} on price, service characteristics and mutual funds' temporary performance indices at time t,

$$\zeta_{jt+1} = c + \widehat{b}_0 p_j + \widehat{b}_1 \cdot \widehat{\alpha}_{j0t} + \widehat{b}_2 \cdot \widehat{\beta}_{j1t} \overline{RMRF_t} + \widehat{b}_3 \cdot \widehat{\beta}_{j2t} \overline{SMB_t} + \widehat{b}_4 \cdot \widehat{\beta}_{j3t} \overline{HML_t} + \widehat{b}_5 \cdot Var\,\mathrm{Re}\,t_{jt} + \mathbf{X}_j \widehat{\mathbf{b}}_6 + \widehat{\xi}_{jt}.$$

Table 5 summarizes the statistics of variables included in our demand system that are not related to the performance indices. The average gross cash inflow is \$95.32 million per fund. The standard deviation is \$316.3 million which is large. The mean expense ration is 1.2%. Aggressive growth funds charge the most — 1.4%, and growth and income funds charge the least – 1.1%. The sample deviation of the expense ration is 0.45%.

We can use the OLS method to estimate the above logit model. However, the OLS estimation can under-estimate the demand elasticities to fees because of the correlation between the unobservable quality term $\widehat{\xi}_{jt}$ and p_j. For example, a mutual fund with a better relationship with investors is more likely to charge higher fees. The probably correlation between price and the unobserved attribute will tend to bias the price coefficient upwards. We need to instrument for price in order to obtain consistent estimation for price elasticities.

[19] Another way to define the outside goods is to define $Index_{i0t}(\varphi_i, R_{jt-1})$ as a mean index level of other funds in this category.

5.2.4. Instruments

The instrumental variables used are basically the demand-side instrumental variables discussed in Berry (1994) and BLP (1995). Let z_{jk} denote the kth characteristic of product j produced by firm f. The instrumental variables associated with z_{jk} are

$$z_{jk}, \quad \sum_{r \neq j, r \in F_f} z_{rk}\,, \quad \sum_{r = j, r \in F_f} z_{rk}$$

where F_f is the set of products produced by firm f. If we are sure that I characteristics are not exogenous, we have $3I$ instrumental variables for each regression. The reason that those variables can be used as instrumental variables is because they are not correlated with the unobservable quality variable $\widehat{\xi}_{jt}$ but they affect the fees p_j charged by mutual fund j through competition. Insterested readers can check Berry, Levinsohn and Pakes (1995) for a detailed description of the estimation method. Using these instrumental variables, we run the above logit regression using two-stage least squares. For comparison, we report both the results based on the simplest logit without instrumenting for the unobservable component $\widehat{\xi}_{jt}$, and IV logit specification for the utility function.

5.3. Results

5.3.1. The Demand System

The estimated results of the demand system are shown in Table 6. The 2nd, 4th and 5th numerical columns report the estimates from the OLS logit model of the aggressive growth, long-term growth and growth income categories, respectively. We are most interested in investors' sensitivity to the price (fees) and their response to past performance. The price coefficients are negative and significantly different from zero. The price coefficient of the aggressive growth category is lower than those of the other two categories. The 3rd, 5th and 7th columns in Table 6 report the estimates from the two-stage least square estimation. After we instrument for price, the estimated demand becomes more elastic. The most interesting results are that investors do respond to historic performance. They not only respond to gross alphas but also to different factor returns. The coefficients of the factor terms are positive and significantly different from zero. We also find that investors do not like funds with higher return volatility. According to "the rule of thumb," investors should adjust the factor risks and chase only alphas. In this sense, the investors chase noise factors when they invest.

Investors also avoid funds having a high capital gain distribution because of tax considerations. The load funds in general enjoy higher cash inflows compared to nonload funds, probably because of brokers' effective solicitations. However, within the load fund category, a higher load deters new cash inflows. Being part of a multishare-class common portfolio hurts the market shares of funds. The overall effect of multishare-class is unclear. The 2SLS coefficients of the attributes other than price remain quantitatively similar to the OLS results.

6. The Effect of Spurious Financial Product Differentiation

After obtaining consistent estimates of the parameters in the demand system, we can study how financial product differentiation over the state space affects the demand elasticities and the profit margins of the mutual funds.

6.1. Ex Post Price Elasticities

The **ex post** own-price and cross-price elasticities of fund j can be calculated by,

$$\widehat{\eta}_j(\cdot) = \frac{\partial s_{jt} p_k}{\partial p_k s_{jt}} = \begin{cases} -\frac{p_j}{s_{jt}} \widehat{b}_0 s_{jt}(1 - s_{jt}) & if\ j = k \\ -\frac{p_k}{s_{jt}} \widehat{b}_0 s_{jt} s_{kt} & if\ j \neq k \end{cases} .$$

The estimated individual fund ex post price elasticities are available upon request.

6.2. Ex Ante Expected Price Elasticities

For calculating the expected own-price and cross-price elasticities at ex ante, we need to simulate the results. When we decomposed the fund returns, we obtained the factor loadings of fund j at time t. Then we simulated the T observations of the K factor returns by the bootstraping method: we draw $12 \times T$ monthly return from empirical distribution;[20] then we generate T observations of the yearly conditional first and second moments of the K factor returns. Then, we can calculate the expected price elasticities of fund j at t:

$$\widehat{\eta}_j^e(\cdot) = \begin{cases} -\frac{p_j}{\widehat{s}_j^e} \widehat{\beta}_0 1/T \sum_{\tau=1}^{T} s_{j\tau}(1 - s_{j\tau}) & if\ j = k \\ -\frac{p_k}{\widehat{s}_j^e} \widehat{\beta}_0 1/T \sum_{\tau=1}^{T} s_{j\tau} s_{k\tau} & if\ j \neq k \end{cases} .$$

[20] We can also implement the Monte Carlo method.

The estimated individual fund expected price elasticities are available upon request.

6.3. Estimated Variable Profit Margins With Spurious Financial Product Differentiation

Assuming that a mutual fund maximizes its own profits, the estimated profit margins are:

$$\begin{aligned} \widehat{m}^e/p_j^e &= (\widehat{p^e - mc})/p_j^e = \widehat{\Delta}^{-1} s^e(p)/p_j^e \\ &= 1/\widehat{\eta}_j^e(\cdot). \qquad (*) \end{aligned}$$

The individual fund markup estimations with the product differentiation over the state space are available upon request.

6.4. Estimated Variable Profit Margins Without Spurious Financial Differentiation

Suppose mutual fund managers do not financially differentiate their product, i.e. the factor loadings $\widehat{\beta}_{.kt}$ are the same cross-sectionally. Let s_j^* and m_j^* denote the equilibrium market share and markups of fund j in this case. We have already estimated the parameters in the demand system. However, we need to know the marginal cost information to calculate the new Nash equilibrium. Since I have no data on the marginal cost, we estimate the marginal cost by assuming that Equations (*) give the correct functions for the mutual fund managers to make their decisions. We calculate the conterfactual marginal cost from Equations (*). After we obtain the conterfactual marginal cost, we calculate $\widehat{s}_j^*$, and $\widehat{p}_j^*$ through following equations:

$$\widehat{p}^* = mc_{cont} + \widehat{\Delta}^{-1}\widehat{s}^*(\widehat{p}^*).$$

The estimated profit margins without product differentiation over the state space are,

$$\widehat{m}^*/p_j^* = 1/\widehat{\eta}_j^*$$

The estimated individual fund profit margins without spurious product differentiation are available upon request.

6.5. Industry Profit Margin Improvement through Spurious Financial Differentiation

The whole industry's average profit margins with and without spurious financial product differentiation, $\sum_{j=1}^{J} s_j m_j^e / p_j^e$ and $s_j^* m_j^* / p_j^*$ respectively, are listed in Table 7. We find that the aggressive growth category has the highest profit margin, on average more than 50%. Every year, the total industry profit margins with spurious product differentiation are higher than without it in each category. On average, we find that the mutual fund industry improved its profits by 29% through the spurious product differentiation in 1998.

$$\frac{\sum_{j=1}^{J} s_j m_j^e / p_j^e - s_j^* m_j^* / p_j^*}{\sum_{j=1}^{J} s_j^* m_j^* / p_j^*} = 29\%.$$

In dollar value, with spurious financial product differentiation, the diversified equity funds can maintain a profit of \$9.7billion. However, without spurious financial product differentiation, the diversified mutual funds can only maintain a profit of \$7.5billion. The mutual fund managers can seek \$2.2billion more rent from investors through spuriously differentiating their products.

7. Conclusion

This study shows that one of the key factors for driving brand proliferation in the mutual fund industry is a special form of spurious financial product differentiation over the state space, which is caused by investors' performance-chasing behavior. Through this kind of financial product differentiation, mutual funds can become top funds and obtain market power alternatively in different market situations to avoid competing head-to-head (state by state). Since investors can tolerate higher fees charged by top funds, on average, mutual funds can lower their own price elasticities (absolute value) and maintain higher profits.

To measure the market power that the mutual funds can obtain through spurious financial product differentiation, we propose a multinomial IV logit discrete-choice model, which accommodates both stochastic and unobservable quality characteristics, to study the demand system of the growth-oriented equity funds. We

estimate the parameters of how investors respond to mutual fund fees. In particular, we find that investors not only chase last period risk-adjusted returns, the alphas, which we treat as the real quality measures of the mutual funds, but also respond to the last period factor returns (instead of expected factor returns), which are not relevant to the quality of mutual funds'. This leaves room for the fund managers to load factor returns differently and spuriously differentiate their products. We estimated the brand-level price elasticities under the assumptions, with or without the aforementioned spurious financial product differentiation. Then the estimated elasticities are used to compute the price-cost margins under Nash-Bertrand price competition. We estimate that the average variable profit margin of growth-oriented equity funds was 42% in 1998. Nonetheless, the calculated average variable profit margin without spurious financial product differentiation was 32%. The mutual fund industry improves its profit level by about 30% ($2.2 billion in dollar value) through spuriously differentiating their products.

An immediate application of the result of this study is to analyze the values of the mutual fund ranking service companies, e.g. the Morningstar, Inc. From investors' point of view, better informed investment behavior can improve the competition of mutual funds and lower the industry expense ratio about 25%. From a social welfare standpoint, first, the investor can avoid the welfare loss because of the fund managers' deviations from the optimal style to the investors; second, if we assume free-entry and there are fixed costs to start a new fund, there is excess entry in the mutual fund industry. However, more sensible tests require more detailed mutual fund cost data.

The structural model and method of this paper can be applied to analyze the welfare effect of the regulation policies, such as the risk disclosure requirements and the SEC's decade-long investor education program. All these analyses rely on estimates of demand and assumptions about pre- and post- policy equilibrium to predict the effects of such policies. This paper pointed out a special and important dimension to consider when estimating the demand system of financial products, whose quality characteristics are highly stochastic and difficult to measure.

Although we study fee competition in the mutual fund industry instead of asset-pricing, we provide suggestive evidence that the state prices discussed by most asset-pricing models are also determined by market competition structure. Similar to the spatial competition concept, where the mutual fund companies allocate their assets over the state space affects their market share and their ability to charge fees. In summary, better understanding the demand, supply and price competition in the financial industry is important and much more work

needs to be done.

Appendix

We derive that the market share equation in this study is equivalent to a spatial competition model with quadratic "transportation" cost.

Proof.

For demonstration, we first prove the above claim in the framework of single-index model. It is straight forward to generate the proof to multi-factor model.

Single Factor Model

Suppose the mutual fund j's return R_j is generated by the following one factor model:

$$R_j = \alpha_j + \beta_j \varepsilon_{R_M} + \epsilon_j$$

The investor i's subjective expected utility function is:

$$\begin{aligned}
E_t(u_{ij}) &= b_0 P_j + \sum_{l=1}^{L} b_j X_{jt} + E_t(\varphi_{i0}\alpha_{0j} + \varphi_{i1}(\varepsilon_{R_M}\beta_j) + \epsilon_j) - \frac{1}{2}\varphi_{i2} Var_t(R_j) + \varepsilon_{ijt} \\
&= b_0 P_j + \sum_{l=1}^{L} b_j X_{jt} + \varphi_{i0}\alpha_{0jt} - \frac{1}{2}\varphi_{i2}\sigma_{\epsilon_{jt}} \\
&\quad + \left\{ \varphi_{i1} E_t(\varepsilon_{R_M}\beta_j) - \frac{1}{2}\varphi_{i2} Var_t(\beta_j \varepsilon_{R_M}) \right\} + \varepsilon_{ijt} \\
&= \Psi_i(P_j, X_{jt}, \alpha_{jt}, \sigma_{\epsilon_{jt}}) + u_{iM}(\beta_j) + \varepsilon_{ijt}.
\end{aligned}$$

where $\begin{array}{l} \Psi_i(P_j, X_{jt}, \alpha_{jt}, \sigma_{\epsilon_{jt}}) = b_0 P_j + \sum_{l=1}^{L} b_j X_{jt} + \varphi_{i0}\alpha_{0jt} - \frac{1}{2}\varphi_{i2}\sigma_{\epsilon_{jt}} \\ u_{iMt}(\beta_j) = \varphi_{i1} E_t(\varepsilon_{R_M}\beta_j) - \frac{1}{2}\varphi_{i2} Var_t(\beta_j \varepsilon_{R_M}). \end{array}$ We can interpret $\Psi_i(P_j, X_{jt}, \alpha_{jt}, \sigma_{\epsilon_{jt}})$ as the quality of mutual funds related to mutual fund service and fund manager's ability to beat the market. $u_{iMt}(\beta_j)$ measures how mutual fund j's style.β_j fits investor i.

The best matched style for consumer i is,

$$\beta_t^{*i} = \left(\frac{\varphi_{i1}}{\varphi_{i2}}\right) V_{mt}^{-1} \cdot \mu_{mt}$$

where $V_{mt} = Var_t(\varepsilon_{R_M})$ and $\mu_{mt} = E_t(\varepsilon_{R_M})$.

The utility coming from the best matched style is,

$$\begin{aligned} u_{iM}^{*} &= u_{iM}(\beta_t^{*i}) = \frac{1}{2}\varphi_{i2}(\frac{\varphi_{i1}}{\varphi_{i2}}V_{mt}^{-1}\cdot\mu_{mt})'V_{mt}(\frac{\varphi_{i1}}{\varphi_{i2}}V_{mt}^{-1}\cdot\mu_{mt}) \\ &= \frac{1}{2}\varphi_{i2}\cdot\beta_t^{*i\prime}V_{mt}\beta_t^{*i} \end{aligned}$$

So that,

$$\begin{aligned} E_t(u_{ij}) &= E_t(u_{ij}) - u_{iM}^{*} + u_{iM}^{*} \\ &= \Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\epsilon_{jt-1}}) - \frac{1}{2}\varphi_{i2}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})'V_{mt}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt}) + u_{iM}^{*} + \varepsilon_{ijt} \end{aligned}$$

For consumer i, the measure of choosing fund j is,

$$d\eta(\varphi_i) = \frac{\exp\left[\Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\epsilon_{jt-1}}) - \frac{1}{2}\varphi_{i2}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})'V_{mt}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})\right]}{\sum_j \exp\left[\Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\epsilon_{jt-1}}) - \frac{1}{2}\varphi_{i2}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})'V_{mt}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})\right]}$$

The ex post market share of fund j is,

$$\begin{aligned} s_j &= \int d\eta(\varphi_i) \\ &= \int \frac{\exp\left[\Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\epsilon_{jt-1}}) - \frac{1}{2}\varphi_{i2}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})'V_{mt}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})\right]}{\sum_j \exp\left[\Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\epsilon_{jt-1}}) - \frac{1}{2}\varphi_{i2}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})'V_{mt}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})\right]} \\ & d\varphi_i \end{aligned}$$

The expected market share of fund j is,

$$\begin{aligned} s_j^e &= \int d\eta(\varphi_i) \\ &= \int \frac{\exp\left[\Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\epsilon_{jt-1}}) - \frac{1}{2}\varphi_{i2}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})'V_{mt}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})\right]}{\sum_j \exp\left[\Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\epsilon_{jt-1}}) - \frac{1}{2}\varphi_{i2}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})'V_{mt}(\boldsymbol{\beta}_t^{*i} - \boldsymbol{\beta}_{jt})\right]} \\ & d\varphi_i d\mu_{mt} dV_{mt} \end{aligned}$$

Generate to Multifactor Model

Assume that the excess gross returns of the mutual funds are generated by the multi-factor return-generating process of the following form:

$$R_j = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}_j'\boldsymbol{\varepsilon}_{\mathbf{F}} + \varepsilon_j.$$

$\boldsymbol{\beta}_j$, a fixed $K \times 1$ vector, is mutual fund j's loading on the factor returns. $\boldsymbol{\alpha}_{0j}$ is manager j's ability to outperform the K factors. $\boldsymbol{\varepsilon}_{\mathbf{F}}$ is the vector of factor returns.

The Investor i's subjective expected utility function is:

$$\begin{aligned} E_t(u_{ij}) &= E_t(u_{ij}) - u^*_{iM} + u^*_{iM} \\ &= \Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\epsilon_{jt-1}}) - \frac{1}{2}(\boldsymbol{\beta}^{*i}_t - \boldsymbol{\beta}_{jt})' V (\boldsymbol{\beta}^{*i}_t - \boldsymbol{\beta}_{jt}) + u^*_{iM} + \varepsilon_{ijt} \end{aligned}$$

where

$$\boldsymbol{\beta}^{i*}_t = (V_t)^{-1} (\frac{\boldsymbol{\varphi}_i \cdot \boldsymbol{\varepsilon}_{F_t}}{\varphi_{iK+1}}).$$

Thus, we can obtain the expected market share of fund j as follows,

$$\begin{aligned} s^e_{jt+1} &= \int \frac{\exp(\delta_{jt+1} + \varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}} - \frac{1}{2}\varphi_{iK+1}(\boldsymbol{\beta}^{i*}_t - \boldsymbol{\beta}_{jt})' V_t (\boldsymbol{\beta}^{i*}_t - \boldsymbol{\beta}_{jt}))}{\sum_j \exp(\delta_{jt+1} + \varphi_{i0}\boldsymbol{\alpha}_{0jt} - \frac{1}{2}\varphi_{iK+1}\sigma_{\varepsilon_{jt}} - \frac{1}{2}\varphi_{iK+1}(\boldsymbol{\beta}^{i*}_t - \boldsymbol{\beta}_{jt})' V_t (\boldsymbol{\beta}^{i*}_t - \boldsymbol{\beta}_{jt}))} \\ &\quad dP(\boldsymbol{\varphi}_i) dF(\boldsymbol{\varepsilon}_{F_{kt}}, V_t). \end{aligned}$$

■

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Table 1 Statistics of the Growth-Oriented Funds 1992-1998

Sample includes growth-oriented diversified equity funds in the aggressive growth, long-term growth and growth and income categories reported in CRSP Dataset. The multi-class funds count as separate funds. The mutual fund annual net returns are the annual after expense return and the market return is the annual CRSP (Center for Research in Security Prices) value-weight stock index.

Year	No. of Funds	Mutual Fund Net Return	Market Return	Average Size ($M)	No. of Mgmt. Company.	No. of New Fund	No. of Dead Fund
1992	779	0.09	0.09	429.6	444	198	41
1993	996	0.12	0.10	469.9	464	217	43
1994	1261	−0.02	0.01	405.8	491	256	46
1995	1582	0.31	0.32	495.8	496	321	75
1996	1912	0.19	0.20	560.5	512	330	75
1997	2431	0.23	0.28	604.7	533	519	90
1998	2943	0.14	0.25	612.1	542	512	130

Table 2: Performance Measurement Model Summary Statistics, January 1992 to December 1998

RMRF is the difference between CRSP (Center for Research in Security Prices) value-weight stock index and the one-month T-bill return. SMB and HML are Fama and French's (1993) factor-mimicking portfolios for size and book-to-market equity. All the return data are monthly.

Factor	Excess		t-stat for	Return Correlation			
Portfolio	Return	Std	Mean=0	PR1YR	RMRF	SMB	HML
RMRF	1.11	3.58	2.82	1.00			
SMB	−.17	2.78	−.55	.368	1.00		
HML	.27	2.81	.88	−.534	−.299	1.00	

Table 3: Cross-Section Excess Return and Factor loading Summary Statistics, January 1992 to December 1998

We employ the Fama and French (1993) 3-factor model to decompose mutual funds' performance, $\overline{r}_{js} = \widehat{\alpha_{j0t}} + \widehat{\beta_{j1t}}\overline{RMRF}_s + \widehat{\beta_{j2t}}\overline{SMB}_s + \widehat{\beta_{j3t}}\overline{HML}_s$. $\overline{RMRF}$ is the average difference between CRSP (Center for Research in Security Prices) value-weight stock index and the one-month T-bill return. $\overline{SMB}$ and $\overline{HML}$ are the mean of Fama and French's (1993) factor-mimicking portfolios for size and book-to-market equity. All the data are monthly.

Year		$\overline{r}_{jt}$	$\overline{RMRF}_t$	$\widehat{Alpha}_{3t}$	$\widehat{\beta}_{j1t}\overline{RMRF}_t$	$\widehat{\beta}_{j2t}\overline{SMB}_t$	$\widehat{\beta}_{j3t}\overline{HML}_t$
1992	*Mean*	.00546	.00553	−.00015	.00457	.00139	−.00122
	StdDev	.00891	−−	.00513	.00110	.00232	.004592
1993	*Mean*	.00780	.00606	.00044	.00607	.00141	−.00094
	StdDev	.00893	−−	.00477	.00146	.00230	.00319
1994	*Mean*	−.00437	−.00320	−.00029	−.00312	.00007	.00005
	StdDev	.00665	−−	.00418	.00080	.00021	.00023
1995	*Mean*	.01853	.02152	−.00055	.02070	−.00114	.00028
	StdDev	.00921	−−	.00479	.00461	.00160	.00076
1996	*Mean*	.01131	.01268	−.00039	.01164	−.00007	.00009
	StdDev	.00663	−−	.00497	.00251	.00022	.00027
1997	*Mean*	.01433	.01922	−.00138	.01824	−.00048	−.00048
	StdDev	.00915	−−	.00600	.00377	.00078	.00268
1998	*Mean*	.00971	.01685	−.00131	.01559	−.00537	.00012
	StdDev	.01740	−−	.00721	.00358	.007929	.00524

Table 4:
Panel A
Cross-Section Alpha and Betas of Mutual Fund Net Returns

We employ the Fama and French (1993) 3-factor model to decompose mutual funds' net returns, $r_{js} = \alpha_{j0t} + \beta_{j1t} RMRF_s + \beta_{j2t} SMB_s + \beta_{j3t} HML_s + e_{js}$, s=1,2,...,36. RMRF is the difference between CRSP (Center for Research in Security Prices) value-weight stock index and the one-month T-bill return. SMB and HML are Fama and French's (1993) factor-mimicking portfolios for size and book-to-market equity.

Year	$\widehat{Alpha}_{3t}$	**Std**$\widehat{Alpha}_{3t}$	Mean $\widehat{\beta}_{.1t}$	**Std** $\widehat{\beta}_{.1t}$	Mean $\widehat{\beta}_{.2t}$	**Std** $\widehat{\beta}_{.2t}$	Mean $\widehat{\beta}_{.3t}$	**Std** $\widehat{\beta}_{.3t}$
1992	-.00015	**.0051**	1.00	**.24**	.23	**.37**	-.07	**.28**
1993	.00045	**.0048**	.99	**.24**	.25	**.41**	-.08	**.28**
1994	-.00029	**.0042**	.99	**.23**	.27	**.39**	-.07	**.31**
1995	-.00055	**.0048**	.95	**.21**	.28	**.38**	-.12	**.31**
1996	-.00039	**.0050**	.92	**.20**	.24	**.42**	-.12	**.38**
1997	-.0014	**.0060**	.92	**.19**	.28	**.43**	-.07	**.40**
1998	-.0013	**.0072**	.94	**.22**	.30	**.45**	-.01	**.45**

Panel B
Cross-Section Alpha and Betas of Simulated Mutual Fund Gross Returns of 1998

The number of portfolio holdings n_j of each mutual fund j in year 1998 are obtained from Morningstar Procinpia Plus. The hypothetical portfolios of mutual fund j consist of n_j equally weighted stocks which are randomly picked from the stocks listed in NYSE, Amex and NASDAQ. Then we decompose the gross returns of the hypothetical portfolios and calculate the alphas and betas of the hypothetical portfolio.

Year 1998	$\widehat{Alpha}_{3t}$	**Std** $\widehat{Alpha}_{3t}$	Mn $\widehat{\beta}_{.1t}$	**Std** $\widehat{\beta}_{.1t}$	Mn $\widehat{\beta}_{.2t}$	**Std** $\widehat{\beta}_{.2t}$	Mn $\widehat{\beta}_{.3t}$	**Std** $\widehat{\beta}_{.3t}$
Hypothetical	-.0015	**.0047**	.86	**.14**	.85	**.16**	.14	**.23**
Real Portfolios	-.0013	**.0072**	.95	**.22**	.30	**.45**	-.01	**.45**
$F-test\ of$ $\sigma^2_{\cdot\text{real}} > \sigma^2_{\cdot Hypo}$		**2.4**		**2.5**		**7.8**		**3.7**

Table 5: Descriptive Statistics

Note: Sample limited to the funds that at least have 12 month return data in CRSP dataset. The sample only includes Class A fund if one fund has multi-class shares.

Market Share	Aggressive Growth		Long-Term Growth		Growth and Income		Total	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
GrossInflows ($M)	83.28	245.7	96.30	331.4	107.50	359.33	95.32	316.3
Expense (%)	1.37	.47	1.21	.42	1.11	.44	1.23	.45
Age	7.52	9.21	11.45	13.89	15.27	20.47	11.2	15.1
Max_load (%)	1.91	2.44	2.29	2.58	2.21	2.57	2.15	2.54
Cap_Gains ($)	.787	1.82	1.01	3.61	.891	1.68	.915	2.72
Turnover (%)	100	143	80	75	59	57	81	76
imshare	.306	.461	.313	.463	.309	.462	.310	.463
iload	.494	.500	.527	.499	.536	.499	.519	.500
N	1847		2670		1615		6132	

Table 6: Mutual Fund Demand System Estimates

Market Share	Aggressive Growth		Long-Term Growth		Growth Income	
	Logit	**IV Logit**	Logit	**IV Logit**	Logit	**IV Logit**
Constant	-5.4***	-5.2***	-4.2***	-3.7***	-3.9***	-3.1***
	(.24)	(0.48)	(.26)	(.57)	(.26)	(.56)
Price	-104.3***	-125.4***	-186.3***	-244.2***	-216.2***	-307.22***
	(11.0)	(42.27)	(13.1)	(51.8)	(13.4)	(57.5)
GrossAlpha_{t-1}	128.9***	129.0***	188.4***	190.2***	190.5***	186.8***
	(10.1)	(10.1)	(14.2)	(14.4)	(21.5)	(22.1)
$\beta_{j1t}\overline{RM_{t-1}}$	83.3***	82.5***	227.5***	224.7***	247.0***	228.4***
	(14.3)	(14.5)	(18.6)	(18.9)	(22.6)	(25.7)
$\beta_{j2t}\overline{SMB_{t-1}}$	142.5***	144.5***	259.2***	264.7***	110.6	139.8*
	(21.7)	(22.1)	(37.5)	(38.1)	(77.0)	(80.5)
$\beta_{j3t}\overline{HML_{t-1}}$	37.4**	40.2**	62.4***	66.5***	139.0***	133.8***
	(17.6)	(18.5)	(23.2)	(23.7)	(37.4)	(38.3)
imshare_t	-.19	-.17	-.09	-.12	-.09	-.10
	(.13)	(.15)	(.12)	(.13)	(.14)	(.14)
iload_t	.48***	.57***	.56***	.77***	.53***	1.04***
	(.17)	(.26)	(.19)	(.19)	(.20)	(.37)
$\log(\text{age})_t$	.35***	.35***	.10**	-.04	.09	.09
	(.05)	(0.05)	(.04)	(.08)	(.14)	(.14)
max_load_t	-.05	-.07	-.07*	-.11**	-.08**	-.14***
	(.04)	(.05)	(.04)	(.05)	(.03)	(.06)
cap_gns_t	-.08***	-.08***	-.07***	-.07***	-.09***	-.09***
	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
turnover_t	.07**	.08**	.29***	.34***	-.01	.06
	(.03)	(.04)	(.07)	(.08)	(.09)	(.10)
VarRet_{t-1}	-88.0***	-80.3***	-145.1***	-129.1***	-113.0**	-111.6***
	(32.8)	(36.3)	(42.2)	(44.1)	(55.1)	(56.1)
N	1320	1320	1897	1897	1192	1192
Adj R^2	.274	.272	.298	.291	.346	.320

Table 7:

Panel A: Estimated Variable Profit Margins From 1992 to 1998

	Aggressive Growth		Long-Term Growth		Growth Income	
	Without	**With**	**Without**	**With**	**Without**	**With**
1992	.4295	.5849	.3329	.4127	.4067	.3767
1993	.4397	.4626	.2644	.3303	.2972	.3479
1994	.3315	.3592	.2494	.4814	.2421	.3091
1995	.3655	.5884	.2433	.3808	.2462	.3355
1996	.3563	.4434	.2536	.3897	.2898	.3054
1997	.3681	.5817	.2680	.3354	.2981	.3499
1998	.3919	.5875	.2702	.3405	.3473	.4022
Year Ave.	.3832	.5154	.2688	.3816	.3039	.3467

Panel B: Estimation of the Effect of SPD on Industry Profit Margins in 1998

Year 1998	**Without SPD**	**With SPD**
Profit Margins	.32	.42
In Dollar Value	$7.5billion	$9.7billion