Financial Product Differentiation and Fee Competition in the Mutual Fund Industry

Shujing Li
AXA Rosenberg Group
Email: sli@axarosenberg.com
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Comments are welcome.

Abstract: This paper studies how and how much the mutual fund industry increases its fees by differentiating products over the state of nature. To avoid head-to-head competition, mutual fund managers hold different portfolios which yield distinct returns and become star funds alternatively in different market situations. This enables mutual funds to obtain stochastic monopoly power and on average charge higher fees than otherwise. To empirically test this idea, this paper develops a structural model — a multinomial IV logit model with random characteristics. The model is easier to implement than the random coefficient (mixed logit) model, but yields own- and cross-price elasticities for financial products that are as sensible. The paper estimates that, on average, equity mutual funds increase their profits by roughly 30% ($2.2 bn) through this novel form of financial product differentiation. In terms of social welfare, there exists excess entry in the mutual fund industry assuming free-entry with fixed entry costs.

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1 Introduction

Recently, questions on whether mutual fund fees are too high attract tremendous attention in both the academic and popular press\textsuperscript{2}. Given the evidence that active managers cannot outperform passively managed portfolios in most asset classes,\textsuperscript{3} the answers tend to be that fund fees for actively managed portfolios are excessive. Considering that there were more than 13,000 mutual funds competing in the market at the end of 2001,\textsuperscript{4} it is puzzling that profits seem robust and that rents were not dissipated despite the enormous number of competitors in the industry.

Most of the studies on mutual fund fees focus on whether managers can generate higher returns than the index funds in order to justify their much higher fees. The results are generally negative or mixed at best. Even if mutual fund managers do create value, we still need to discuss how much value they pass on to investors. This point can be illustrated by a simple example. Suppose that there are only two mutual funds in the market. If the two funds hold identical portfolios, their gross returns will be exactly the same. Therefore, investors will invest all of their money in the fund charging lower fees. No-arbitrage theory is not much help since it predicts that the two funds coexist in the market only as long as they charge the same fees, in which case it is undetermined how much value can be passed on to the investors. However, if we consider competition, the standard outcome of the Bertrand game will occur. The two funds compete in lowering fees until their fees are equal to their marginal costs. They make zero profits and all of the value created by the funds is passed on to the investors. Therefore, the competition structure affects how much value the investors can receive from the mutual funds. However, few studies have been done to investigate the market structure of the mutual fund industry, despite its vast and growing


\textsuperscript{3}For example, Jensen (1968), Gruber (1996) and Carhart (1997).

\textsuperscript{4}Among them, more than 6,500 held domestic stocks. By the end of 2001, the total number of stocks listed on the NYSE, AMEX, and Nasdaq combined were about 12,000. Normally, multi-class shares are listed as separate mutual funds. The distinct equity portfolios are around 4,000 at the end of 2001. Interested readers can see chapter 3 for the studying of the nonlinear pricing mechanism in the mutual fund industry.
I propose a new approach to the mutual fund industry called “product differentiation over states of nature.” In this special product differentiation model, investors treat equally efficient but imperfectly correlated portfolios as imperfect substitutes because of limitation of investors’ information or knowledge. In this study, investors’ information is limited in the sense that investors do not know mutual fund managers’ talent but believe some managers may have; thus they allocate investment according to some imperfect posterior statistics on talent based on recent past performance.

To illustrate the idea, consider again the duopoly competition example. For simplicity, assume the two fund managers are equally capable. When they hold the same portfolio, as I discussed above, each of them earns zero profits. However, if investors believe mutual funds’ past performance is positively correlated with fund managers’ talent and “chase past performance”, the two funds can actually avoid head-to-head competition by holding different portfolios. Depending on the stochastic outcomes of the two portfolios, one of the two funds will appear to be better than the other in different market situations or different states of nature. Since investors “chase performance”, the fund that appears to be better in the recent period will attract new investments. More important, the “better” fund can charge higher fees and earn non-zero profits in its reigning period since investors’ demand for the fund is relatively inelastic. Therefore, even if the two funds have equal probability of becoming the better fund, the stochastic market power enjoyed

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

6 There are two main reasons for the inefficiency of the investors’ statistics. 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.

7 Theoretically, Ippolito(1992) shows that as long as poor-quality funds exist, an investment algorithm that allocates money according to the latest performance 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 weak 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. However, this study shows that investors put way to much weight in last period returns relative to expenses.
by the winning fund makes it possible that overall, both funds make posi-
tive profits. In this sense, the two equally efficient mutual funds horizontally
differentiate their products over states of nature and become imperfect sub-
stitutes. This results of extra profits from product differentiation hold even
when fees are charged before the random returns are realized.

Based on the above idea, this essay constructs a structural model to em-
pirically analyze financial product differentiation of equity mutual funds and
its effects on fee competition. First, it proposes a multinomial IV logit model
that accommodates stochastic characteristics to estimate the demand system
of mutual funds. I employ the Fama and French (1993) 3-factor model to
decompose mutual funds’ gross returns. I then investigate how investors
respond to the different stochastic components of the returns. I find that
investors not only chase last period’s risk-adjusted returns, but also respond
to the last period’s factor returns (instead of expected factor returns). This
leaves room for the fund managers to load factor returns differently and
horizontally differentiate themselves. Second, the estimated parameters are
used to recover the price-cost margins (PCMs) under Nash-Bertrand com-
petition without observing actual cost data. Third, counterfactual PCMs
are computed under the assumption that fund managers cannot financially
differentiate their products. Finally, by comparing the estimated versus the
counterfactual PCMs, I estimate that, on average, growth-oriented equity
funds improve their annual variable profit levels by about 29% ($2.2 billion
in dollar value) through this mechanism of financial product differentiation.

As far as I know, this special product differentiation and its effect on fee
competition has not been identified and analyzed in the literature. Moreover,
the logic and the empirical framework of this essay are not confined
to the mutual fund industry. They can be easily applied to other indus-
tries where products display stochastic characteristics. One example is the
fashion industry. Since fashion trends are stochastic and unpredictable, in-
stead of betting on the same style, different fashion companies differentiate
themselves by specializing in different styles. Another example is the movie
industry. Since movie-goers’ tastes are stochastic, instead of investing in a

\(^8\)Brown and Goetzman (1997) analyze mutual fund styles using clustering method.
They find that within the “growth” and “growth and income” categories there are different
styles such as “small cap” and “value”.

\(^9\)Laster, Bennett and Geonum (1999) study the strategic behavior of professional fore-
casters. They find that the economists make a range of projection that mimics the true
probability distribution of the forecast variables although they have identical expectations.
portfolio of movies, some movie companies specialize in high-budget movies that are characterized by high risks and high profits, while other companies specialize in low-budget movies with the opposite characteristics.

This essay also contributes to the behavioral finance literature. Since consumer demand can be viewed as an implicit contract to discipline the mutual fund managers, consumer information and knowledge are important in determining the market structure of the mutual fund industry. This justifies the SEC’s decade-long movement to educate investors and to enhance information disclosure\textsuperscript{10}. This chapter quantitatively measures how consumer’s knowledge and information can affect the competition structure and regulation policy of the mutual fund industry.

The remainder of the chapter is organized as follows. Section II reviews literature. Section III constructs the multinomial IV logit model to analyze the spurious financial product differentiation and its implications. Section IV describes the data. Section V estimates the demand parameters. Section VI uses the estimated parameters to compute the profits an equity fund can earn by spurious financial product differentiation. Finally, Section VII concludes the essay.

2 Literature Review

Several papers (e.g. Golec (1992), Tufano and Sevick (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.\textsuperscript{11} Instead, it

\textsuperscript{10}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.

\textsuperscript{11}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 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. Open ended nature of mutual funds makes free-riding problem worse. Furthermore, in cases where the small investors did challenge, most cases terminated in settlements and the
is almost cost-free to transfer money from one fund to another. 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 include Borenstein and Zimmerman (1988), Berkowitz and Kotowitz (1993) and Chevalier and Ellison (1997). However, this study explicitly models and quantifies how the mutual fund managers’ behavior can affect the market power of the mutual funds and how profitable that behavior can be when there is monopolistic competition.

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 similar questions. Massa (2000) argues 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 necessary to span the different dynamic trading strategies of investors. The chapter differs from those two papers in that I 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) study the determinants of mutual fund starts and the market share at the family-of-funds level. However, Khorana and Servaes basically treat financial products as normal commodities without modeling their special properties. Unlike most of the empirical work studying mutual fund industry, this essay develops a structural model instead of reduced form regression model. With a structural model, I can not only demonstrate the mechanism of financial product differentiation, but also do comparative static welfare analysis, e.g. I can compare PCMs of the two equilibria with or without financial product differentiation.

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.

12 The costs of transferring money among mutual funds include loads, realized capital gain taxes and other transaction-related fees.
The most general goals of this study are related to the large literature (e.g. Lazear and Rosen (1981), Ehrenberg and Bognanno (1990) and Meyer and Vickers (1997)) that studies the effects of relative performance evaluation schemes. One of the by-products of the financial market is that the market provides benchmarks to evaluate the performances of the individual firms or mutual funds (Jensen and Murphy (1990), Gibbons and Murphy (1990) and Antle and Smith (1986)). This essay 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 can collect more rent from investors despite the fact that there are large number of players and severe competition in the market.

3 The Empirical Model

The timing and nature of the decision process is a three-stage game as follows: At the first stage, mutual funds choose their service characteristics and investment strategies; at the second stage, mutual funds decide to set their fee levels; at the third stage, the returns of the mutual funds are realized and investors invest their money in the best mutual fund in terms of services and their perception of fund managers’ investment talent. In this model, I assume investors do not know mutual fund managers’ talent but believe some managers may have. They measure fund managers’ talent by some posterior statistics on talent based on recent past performance.

As with most empirical work studying product differentiation, I am interested in the last two stages of the game. I do not model the determination of fund characteristics. Interested readers can see Chapter two for the explicit modelling of the determination of mutual funds’ portfolios. Instead, I treat mutual funds’ characteristics and investment strategies as exogenously given when mutual funds make their decision on fees.

My general estimation strategy goes in the reverse direction from the decision process. I study investors’ demand system first and I am especially

\footnote{I assume that mutual funds set annual expense fees before the outcome of mutual funds’ investments. This is because the change of expense fees must be approved by the shareholders. The existing literature documented that mutual fund fees are not sensitive to recent performances. See Zitzewitz (2003).}
interested in how investors respond to the stochastic characteristics of mutual funds. Then I discuss the possible opportunities for the fund managers to financially differentiate their products and calculate how much the mutual funds can improve their profit margins through financial product differentiation.

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 $\varepsilon_{F_t}$, a $K \times 1$ vector, denote the factor’s excess returns over the riskless rate of interest at time $t$. $R_{jt}$, is the gross excess return of actively managed mutual fund $j$ over the riskless rate of interest. Throughout this article, I assume that the excess gross returns of the mutual fund $j$ are generated by the multi-factor return-generating process of the following form:

$$R_{jt} = \alpha_{0j} + \beta_j \varepsilon_{F_t} + \varepsilon_{jt}. \quad (1)$$

$\beta_j$ is a $1 \times K$ vector of fixed parameters. Its $k$th elements, $\beta_{jk}$, is mutual fund $j$’s loading on the returns of factor-mimicking portfolio $k$. In the closely related style analysis (Sharpe (1992)), the factor loading vector $\beta_j$, determines the “style” of mutual fund $j$. $\alpha_{0j}$ is manager $j$’s ability to outperform the $K$ factor-mimicking portfolios. $\varepsilon_{jt}$, a random variable, is the idiosyncratic risk of mutual fund $j$’s portfolio. The volatility of $\varepsilon_{jt}$, $\sigma^2_{\varepsilon_j}$, measures how consistently fund manager $j$ outperforms or under-performs the $K$ factor-mimicking portfolios. In this study, I assume $\alpha_{0j}$ and $\sigma^2_{\varepsilon_j}$ are exogenously endowed to the fund manager $j$. 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 A Discrete-Choice Framework to Model a Demand System

There are four reasons frequently cited\textsuperscript{14} 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, I employ a discrete-choice framework to model the demand system.

3.2.1 Investors’ Subjective Utility Function

Investor $i$’s subjective utility function of fund $j = 0, ..., J$ at time $t = 1, 2, ..., T$, is:

$$u_{ijt} = X_{jt} b + \text{Index}_{jt}(\varphi, R_{jt}^{t-1}) + \xi_{jt} + \epsilon_{ijt},$$

(2)

where $X_{jt}$ is an $L$-dimensional vector of observable characteristics of fund $j$ which are related to mutual fund $j$’s service and reputation; $b$ is an $L$-dimensional vector of individual-specific taste parameters on those service characteristics. $\xi_{jt}$ is a scalar, which denotes the quality attribute of fund $j$ that is observable to investors but unobservable to econometrician; and $\epsilon_{ijt}$ is a mean-zero stochastic term. $\text{Index}_{jt}(\varphi, R_{jt}^{t-1})$ is a statistics index constructed by investors to evaluate fund manager $j$’s investment talent based on fund $j$’s return history $R_{jt}^{t-1}$; and $\varphi$ are parameters that need to be estimated in the investors’ index function $\text{Index}_{jt}(\varphi, R_{jt}^{t-1})$.

3.2.2 The Index Function

In my model, $\text{Index}_{jt}(\varphi, R_{jt}^{t-1})$ has the flexible function form as below. I assume that investors have commonly applied mean-variance utility functional form. In addition, I assume that investors’ subjective conditional expectation of mutual fund $j$’s return at time $t$ is a linear function of mutual fund $j$’s last period return and investors’ subjective conditional expectation of fund $j$’s return volatility at time $t$ is a linear function of fund $j$’s last period return volatility. Please check Appendix B.1 for discussion of the micro-foundation.

\textsuperscript{14}For example, Gruber (1996) and Chordia (1996).
of the index function:

$$Index_{jt}(\varphi, R_{jt}^{t-1}) = \varphi_0 \cdot \alpha_{0j} + \sum_{k=1}^{K} \varphi_k \cdot (\varepsilon_{F_{kt-1}} \beta_{jk}) - \frac{1}{2} \varphi_{K+1} \cdot Var(R_{jt-1})$$ (3)

where $\varphi_k, k \in \{0, ..., K + 1\}$ are the parameters need to be estimated. They measure how investors respond to different components of mutual fund past returns. $\varepsilon_{F_{kt-1}}$ is the return of factor $k$ at time $t-1$. Mutual fund $j$’s risk-adjusted return, $\alpha_{0j}$ and its style $\beta_{jk} \in \{1, ..., K\}$ are obtained from the decomposition of mutual fund last period gross returns $R_{jt-1}$ by equation 1. $Var(R_{jt-1})$ is the volatility of mutual fund $j$’s last period gross return $R_{jt-1}$.

One special property of mutual funds is that the performance data are noisy across mutual funds and over time. This means it is hard for investors to know fund managers’ talent. However, investors believe that they can evaluate fund managers’ talent according to the above posterior statistics index $Index_{jt}(\varphi, R_{jt}^{t-1})$ based on mutual fund past performance.\(^{15}\)

In my model, I need to estimate parameters $\varphi_k \in \{0, ..., K + 1\}$ to test whether investors’ aforementioned performance chasing behavior is efficient. According to classic asset pricing theories (Ross (1976) and Fama and French (1996)), $\alpha_{0j}$ is the risk-adjusted return which I assume to be the true level of fund manager $j$’s talent in this model. If investors are rational and understand asset pricing theories, they should only respond to $\alpha_{0j}$ but not the first and second moments of fund $j$’s last period returns. If $\exists \varphi_k \in \{1, ..., K + 1\} \neq 0$, investors respond to past factor returns and load some noise in their statistics index.

### 3.2.3 The Ex Post Market Share

Since I have no individual investors’ investment data, I need to integrate out the heterogeneity of the individual investors and obtain the aggregate market share equation. Investors are assumed to invest a fixed amount of money in the fund that gives the highest utility. In the model, investors pick one mutual fund out of a large pool of candidates instead of diversifying among mutual funds. It is worthwhile to discuss the realism of this assumption. One of the main reasons that investors buy mutual funds is that they hold well-diversified portfolios. It is reasonable to assume that investors therefore

\[^{15}\text{Gruber (1996) and Zheng (1999) document that investors chasing past performance can earn extra returns.}\]
hold a single mutual fund. One reason for this 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. This model can also
be viewed as an approximation of the true choice model. Empirical evidence
shows that the median investor holds two funds (Barber, Odean and Zheng
(2000)) and one of them is more likely to be a bond fund (Alexander et al.
(1997)). Since this article studies the demands within one fund category, it
is more likely that investors will want to choose the best fund within the
category.

The set of unobserved stochastic shocks $\epsilon_{ijt}$ that lead to the choice of
fund $j$ is defined by,

$$A_{jt}(X_{jt}, \text{Index}_{jt}, \xi_{jt}; b, \varphi) = \{\epsilon_{ijt} | u_{ijt} \geq u_{il} \forall l = 0, 1, ..., J\}.$$  

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

$$s_{jt} = \int_{A_{jt}} dP(\epsilon_{ijt}).$$

where $P(\cdot)$ is the probability distribution function of the unobserved stochastic shocks $\epsilon_{ijt}$.

If we assume the stochastic shocks $\epsilon_{ijt}$ are distributed i.i.d. with a type I extreme-value distribution, the short-term market share of mutual fund $j$ is equal to,

$$s_{jt} = \frac{\exp(X_{jt}b + \text{Index}_{jt}(\varphi, R_{jt}^{t-1}) + \xi_{jt})}{\sum_{t} \exp(X_{lt}b + \text{Index}_{lt}(\varphi, R_{lt}^{t-1}) + \xi_{lt})}$$  

(4)

After observing mutual fund $j$'s market share, service characteristics at time $t$ and mutual fund last period returns, I can apply the method proposed by Berry (1994) to estimate all the parameters in demand function 4.

3.2.4 The Definition of Financial Product Differentiation

The Equivalent Spatial Competition Model  In the Appendix A.1, I
derive that ex post market share equation 4 is equivalent to a spatial competition model with quadratic “transportation” costs as follows:

$$s_{jt} = \frac{\exp(X_{jt}b + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}) - \frac{1}{2} \varphi_{K+1} \cdot (\beta_{t-1}^j - \beta_j) \psi_{V(t-1)(\beta_{t-1}^{\ast} - \beta_j)} + \xi_{jt})}{\sum_{t} \exp(X_{lt}b + \Psi(\alpha_{lt}, \sigma_{\epsilon_{lt}}) - \frac{1}{2} \varphi_{K+1} \cdot (\beta_{t-1}^l - \beta_l) \psi_{V(t-1)(\beta_{t-1}^{\ast} - \beta_l)} + \xi_{lt})}$$  

(5)
where
\[ \beta_{t-1}^* = (\mathbf{V}_{t-1})^{-1} (\varepsilon_{F_{t-1}} - \varphi_{K+1}), \quad (6) \]

\[ \Psi(\alpha_{jt}, \sigma_{\varepsilon_{jt}}) = \varphi_0 \alpha_{0j} - \frac{1}{2} \varphi_{K+1} \sigma^2_{\varepsilon_{jt}}, \quad (7) \]

\( \varphi \) is the parameter vector \((\varphi_1, ..., \varphi_{K})'\). \( \mathbf{V}_{t-1} \) is the co-variance matrix of the \( K \) factor returns \( \varepsilon_{F} \) during period \( t-1 \). \( \varepsilon_{F_{t-1}} \) is the \( K \times 1 \) vector that denotes the \( K \) factor’s returns at time \( t-1 \). In Appendix A.1, I show that \( \beta_{t-1}^* \) is the “hot” mutual fund style given last period factor returns \( \varepsilon_{F_{t-1}} \). In other words, given last period factor returns \( \varepsilon_{F_{t-1}} \) and other things equal, \( \beta_{t-1}^* \) is the vector of factor loadings giving investors the highest value of \( \text{Index}_{jt}(\varphi, R_{j}^{t-1}) \).

The term \( \Psi(\alpha_{jt}, \sigma_{\varepsilon_{jt}}) \) measures how well fund manager \( j \) can actively manage fund \( j \)'s portfolio. \( \alpha_{0j} \) is manager \( j \)'s ability to outperform the \( K \) factor-mimicking portfolios. The volatility of \( \varepsilon_{jt}, \sigma^2_{\varepsilon_{jt}} \), measures how consistently fund manager \( j \) outperforms or underperforms the \( K \) factor-mimicking portfolios.

It is interesting to compare the above model to the conventional spatial competition model. The hot style \( \beta_{t-1}^* \) is similar to the concept of the position of customers. The loading factor vector \( \beta_{j} \), or the style of fund \( j \), marks mutual fund \( j \)'s position in the state space. \( \frac{1}{2} \varphi_{K+1} (\beta_{t-1}^* - \beta_{j})' \mathbf{V}_{t-1} (\beta_{t-1}^* - \beta_{j}) \) denote the “transaction costs” between fund \( j \)'s portfolio and the hot style \( \beta_{t-1}^* \). From equation 5, we can see that, at time \( t \), the fund with style \( \beta \) equal to \( \beta_{t-1}^* \) has the smallest “transaction costs”.\(^{16}\)

Since I assume that it is cost-free for fund managers to choose the style \( \beta \)s of their portfolios, all the managers want to choose the hot style. However, \( \text{ex ante} \), the hot style \( \beta^* \) is stochastic and unpredictable. We can see this from equation 6. \( \text{ex ante} \), hot style \( \beta^* \) is a linear function of factor returns \( \varepsilon_{F} \) whose outcomes are stochastic and changing from time to time. Thus, if financial firms hold different styles, they become the best hot styles in different states of nature depending on the outcomes of factor returns.

The Definition of Financial Product Differentiation In the market share equation 5, we can see that mutual funds factor loading \( \beta \)s will not

\(^{16}\)In this sense, many of the results of 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. The intuition behind the models is similar.
affect the ex post market share if either investors do not respond to factor returns, i.e. $\varphi_{k \in \{1, ..., K + 1\}}$ are equal to zero, or mutual funds’ styles $\beta$s equal cross-sectionally. However, if $\exists \varphi_{k \in \{1, ..., K + 1\}} > 0$, there are opportunities for fund managers to differentiate their products by holding different factor-loading $\beta$s. Through this, mutual funds can become “hot” in different states depending on the realization of factor returns. For example, when the market is going up, the mutual funds having large positive market-portfolio loadings do particularly well and attract more money. However, in a down market, the mutual fund having less or even negative market-portfolio loadings perform better and obtain a higher market share. If mutual funds hold different $\beta$s, the performance indices $\text{Index}_{jt}$, $j \in \{0, ..., J\}$, look much more different than fund manager’s real ability difference in $\alpha_{jt}$, $j \in \{0, ..., J\}$. I call this form of product differentiation financial product differentiation over the states of nature. I would like to emphasize that mutual funds can horizontally differentiate their products although investors are homogeneous. In this sense, financial product differentiation over states of nature differs from the conventional spatial competition model in a very critical way.

In this model, I assume that the choice of style $\beta_j$ is not correlated with managers’ real ability $\alpha_{jt}$. Hence, the financial product differentiation in the dimensions of factor return loadings is spurious. However, even if for some unknown reason it is useful for investors to chase factor returns, the fund managers can still horizontally differentiate their products, but the financial product differentiation is not spurious any more. Thus, whether investors’ factor returns chasing behavior is rational or not is not a critical assumption and will not affect the main results of this study.

**The Expected Market Share** With financial product differentiation, the market share of fund $j$ is stochastic depending on the realization of factor returns. Thus, ex ante, mutual fund $j$ can only know its expected market share. The expected market share of fund $j$ is:

$$s_{jt}^e = \frac{\int \exp(X_{jt}b + \Psi(\alpha_{jt}, \sigma_{\epsilon_{jt}}) - \frac{1}{2} \varphi_{K+1} \cdot (\beta^*_t - \beta_j) \mathbf{V}_{t-1}(\beta^*_t - \beta_j) + \xi_{jt}) \sum_l \exp(X_{lt}b + \Psi(\alpha_{lt}, \sigma_{\epsilon_{lt}}) - \frac{1}{2} \varphi_{K+1} \cdot (\beta^*_t - \beta_l) \mathbf{V}_{t-1}(\beta^*_t - \beta_l) + \xi_{lt}) dF(\epsilon_{F1}, ..., \epsilon_{FK})}{\sum_l \exp(X_{lt}b + \Psi(\alpha_{lt}, \sigma_{\epsilon_{lt}}) - \frac{1}{2} \varphi_{K+1} \cdot (\beta^*_t - \beta_l) \mathbf{V}_{t-1}(\beta^*_t - \beta_l) + \xi_{lt})},$$

where $F(\epsilon_{F1}, ..., \epsilon_{FK})$ is the probability distribution function (pdf) of factor returns.
**Price Elasticities**  I 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:

$$\eta_j^e = \frac{\partial s_j^e}{\partial p_k} = \begin{cases} \frac{p_j}{s_j} \int b_0 s_{jt}(1 - s_{jt})dF(\varepsilon_{F1}, \ldots, \varepsilon_{FK}) & \text{if } j = k \\ -\frac{p_k}{s_j} \int b_0 s_{jt}s_{kt}dF(\varepsilon_{F1}, \ldots, \varepsilon_{FK}) & \text{if } j \neq k \end{cases}$$

where $b_0$ is the coefficient on fees in investors’ subjective utility function.

It is interesting to compare the above results to the BLP (1995) model with random coefficients. As with the random coefficient model, I 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 in every state. On the other hand, in the BLP (1995) model, the mean price sensitivity is the average of the different price sensitivities of heterogeneous investors. My model also allows for flexible substitution patterns. The products with similar factor loadings have higher cross-price elasticities because their market shares are more highly correlated.

**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.” However, Mamaysky and Spiegel (2001) shows that fund families have incentive to spread out their offerings in strategy space. Laster, Bennett and Geonum (1999) and Zitzewitz (2002) have similar results when they studied the strategic behaviors of professional forecasters. One of the important results of this paper is that mutual fund demand curves become steeper if the mutual funds “walk away” from the competition and differentiate themselves from each other.

**The Effect Coming from a Random Market Share**  If mutual funds differentiate themselves 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 $t$. 

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Then, the price elasticities in this case is:

\[ \eta_{jk} = \begin{cases} b_0 p_j (1 - s_j) & \text{if } j = k \\ -b_0 p_k s_k & \text{if } j \neq k \end{cases} \]

\[ |\eta_{jj}| = \left| \frac{\partial s_j^e p_k}{\partial p_k s_j^e} \right| < |\bar{\eta}_{jj}| \]

**Proof:**

\[ |\eta_{jj}^e| = \left| \frac{\partial s_j^e p_k}{\partial p_k s_j^e} \right| = \left| \beta_0 p_j \int s_j^e (1 - s_j^e) ddF(\varepsilon_{F_1}, ..., \varepsilon_{F_K}) \right| = |\beta_0 p_j (1 - s_j^e - Var(s_j^e)/s_j^e)| < \beta_0 p_j (1 - s_j^e) = |\eta_{jj}| \]

The intuition of the proof is as follows: By holding different \( \beta \)'s, mutual funds become the hot style funds in different states. Thus, different mutual funds attract can in different market situations. When a mutual fund has a lucky year, it enjoys both a higher market share and higher market power since the demand curve of mutual fund is a highly nonlinear function of past performance.\(^{17}\) This means that the year with higher market power has a higher weight. On average, this strategy can cause the demand curves of mutual funds to become steeper.

**Distortion of the Market Share** Furthermore, financial 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 shares are nonlinear functions of product attributes in the model. If the mutual funds hold different portfolios, the market shares will be stochastic. The average of fund \( j \)'s market share is affected not only by the level \( \beta_j \) but also the cross-sectional distribution of \( \beta \). The further a mutual

\(^{17}\)For example, Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998) have documented that the relationship between flow and performance is nonlinear. In this Chapter, I use logit model to estimate the demand function of mutual funds. This may provide a microfoundation for the nonlinearity of the relationship between flow and performance.
fund differs from the average, the more volatile its market share. However, I do not have a closed form solution on how the cross-sectional distribution of $\beta$ affects the average market share. I will study the distortion of the market share empirically.

3.2.5 Supply

Suppose there are $F$ mutual fund families. Each family comprises some subset, $\mathcal{F}_f$, of the $j = 1, \ldots, J$ mutual funds. I assume mutual fund families have full knowledge of investors’ behavior and the characteristics of all the mutual funds in the industry. They are risk neutral and set optimal fee level to maximize their expected profits.

The Mutual Fund’s problem The mutual fund family $f$’s profit maximization problem is as follows:

$$p_j \max \Pi_f = E[\sum_{j \in \mathcal{F}_f} N s_j(p_j)(p_j - mc_j) - C_f]$$

$$= \sum_{j \in \mathcal{F}_f} N s^\epsilon_j(p_j)(p_j - mc_j) - C_f,$$

where $s^\epsilon_j(p_j)$ 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. 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:

$$s^\epsilon_j(p_j) + \sum_{j \in \mathcal{F}_f} (p_r - mc_r) \frac{\partial s^\epsilon_r(p_j)}{\partial p_j} = 0, j = 1, \ldots, J.$$

Define $\Delta$ as a $J \times J$ matrix and its $(j, r)$ item

$$\Delta_{jr} = \{ -\frac{\partial s^\epsilon_r(p)}{\partial p_j}, if (r, j) \subset F_j 0, otherwise. \}

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

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

where $m^e$ is a vector of the markups.
3.2.6 Implications

The Incentive Effect  Assume $\alpha_{0j}$ is the true quality of mutual fund $j$. If investors chase performance index $Index_{jt}(R_{jt}^{t-1})$, mutual fund $j$ with higher $\alpha_{0j}$ is able to capture a higher market share.

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

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 states of nature by holding different factor loading $\beta$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 $s^e_{jt}$, $p^e_{jt}$ and $m^e_{jt}$ 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 $\beta$s and do not differentiate their products. In this case, the counterfactual Nash-equilibrium market share, price and markups of fund $j$ are $s^*_{jt}$, $p^*_j$, and $m^*_j$, respectively.

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

$$m^e_{jt} - m^*_j = (m^e_{jt} - \overline{m}_j) + (\overline{m}_j - m^*_j)$$

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 $s^e_{jt}$ and $p^e_{jt}$ without product differentiation. $\overline{m}_j - m^*_j$ is the change in the markup due to random

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18 According to Berry (1994), there exists $p^*_j\in\{0, 1, ..., J\}$ s.t.

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

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market share effect. From the results of Proposition 1., we have, $m_j^* - m_j^e > 0$ for every $j$ because the own-price elasticities become steeper due to the random market share effect. $m_j^e - m_j^*$ is the markup change due to market share distortion. The sign of the second term $m_j^e - m_j^*$ 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.

4 Data

The sample of funds 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. This dataset is free of survivorship bias\textsuperscript{19}. There are several reasons for examining 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 fund level on the mutual fund family and mutual fund expenses during this period. Furthermore, I 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 general diversified equity funds, which includes the funds in the aggressive growth, long-term growth and growth and income categories in the mutual fund industry. The fund investment strategy is identified by Source Standard and Poor’s Micropal. My sample design is analogous to that of most of the empirical literature on mutual funds, e.g. Carhart (1997) and Zheng (1999). I 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. One remarkable aspect is the tremendous increase in the number of the 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.

In Table 1, I count the multi-class funds as separate funds. Multi-class funds are funds which have the same manager and hold the same portfolio, but with different fee structures (or classes of shares). There are typically

\textsuperscript{19}See Elton, Gruber and Blake (2001) for the limitation of the CRSP dataset.
three classes of funds. Class A fund has high front-load\textsuperscript{20} but low annual expense ratio. Class B fund has no front-load but with high annual expense and high deferred load\textsuperscript{21}. Class B share normally has conversion figure, which means, after several years, the Class B share will change to a Class A share. Class I is for institutional investors. Class I share has neither front-load nor end-load, and the expense ratio is low. However, the initial purchase requirement is high (e.g. $5\text{Million}$). There are other variants. For example, Class C share has relatively lower annual expense and lower deferred load than class B share, but without conversion features. This class share is for the investors who want to stay in a fund less than 5 years. However, the most popular one is the first three types of classes. The regression part of this study covers a total of 1,337 diversified equity funds and 6,132 fund years. If a fund has multi-class shares, I only consider the Class A shares because of the different fee schedules of different classes of funds may generate misleading results.\textsuperscript{22}

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

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

\[
r_{js} = \alpha_j + \beta_{1j} R_{MRFs} + \beta_{2j} S_{MBs} + \beta_{3j} H_{MLs} + e_{js} \quad s = 1, 2, ..., 36
\]

where \( r_{js} \) is the gross return on the portfolio of fund \( j \) in excess of the one-month T-bill return; The three factor-mimicking portfolios, \( R_{MRF} \), \( S_{MB} \), \( H_{ML} \),

\textsuperscript{20}The front load is a one time charge applied at time of purchase. These sale loads have gradually declined from 8.5% in 1960s to an average of 4% to 5% currently.

\textsuperscript{21}The deferred load is also called back-end load or contingent deferred sales charge (CDSC). The deferred load applies when investors leave funds and is commonly levied against the value of the original investment. The fee is contingent in the sense that it decrease periodically in steps and usually disappear after several year.

\textsuperscript{22}Interested readers please see Li and Shoven (2003) for the multi-class funds problem.
and \( HML \) are constructed according to the descriptions in Fama and French (1993). \( RMRF \) 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. \( SMB \) is meant to mimic the returns of the risk factor related to size. It is the returns of a zero-investment portfolio that longs the small-size stocks and shorts the big-size stocks. Similarly, \( HML \) are returns on the value-weighted, zero-investment, factor-mimicking portfolios that longs the high (top 30\%) and shorts the low (bottom 30\%) book-to-market equity stocks. We can also treat these three portfolios as three passive investment strategies available in the market.

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 buy-and-hold investor through period 1992 -1998, 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 proxy are low. The low cross-correlations imply that multicollinearity does not substantially affect the estimated 3-factor model loadings.

In year \( t \), I 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 \( \hat{\alpha}_{j0t} \) and \( \hat{\beta}_{jkt} \). The annual average excess gross return can be decomposed into alpha and factor return loadings based on,

\[
\tau_{jt} \simeq \hat{\alpha}_{j0t} + \hat{\beta}_{j1t}RMRF_t + \hat{\beta}_{j2t}SMB_t + \hat{\beta}_{j3t}HML_t.
\]

\( \tau_{jt} \) is the annual average return of fund \( j \). \( RMRF_t, SMB_t, \) and \( HML_t \) are the annual factor returns at year \( t \). We can interpret that \( \tau_{jt} \) consists of four parts. \( \hat{\beta}_{j1t}RMRF_t, \hat{\beta}_{j2t}SMB_t \) and \( \hat{\beta}_{j3t}HML_t \) indicate the proportions of mean return attributable to the three passive strategies available in the market. Component \( \hat{\alpha}_{j0t} \) measures fund manager \( j \)’s ability to beat the benchmark passive portfolios. Summary statistics of cross-section mutual fund excess returns \( \tau_{jt} \), 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 \( \hat{\alpha}_{j0t} \) and \( \hat{\beta}_{jkt} \) are reported in Table 4 Panel A. The equal weighted average cross-section market portfolio
loading $\hat{\beta}_1$ is almost 1 and slightly declines from 1992 to 1998. The equal weighted average cross-section loadings of size factor is greater than zero, but the loadings of the book-to-market equity factor 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 factors, the cross-section standard deviations of the factor loadings are large and well spread out around the mean levels. This means that the yearly cross-section return variation are attributable to different loadings of the passive benchmark portfolios.

To provide some evidence that mutual fund managers differentiate their products, we compare the cross-section $\hat{\alpha}_{j0t}$ and $\hat{\beta}_{jkt}$ 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 $\hat{\alpha}_{j0t}^h$ and $\hat{\beta}_{jkt}^h$ of the hypothetical mutual fund portfolios. I find 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 $\hat{\alpha}_{j0t}$ and the factor loading $\hat{\beta}_{jkt}$ of mutual funds are more spread out than those of the random strategy funds.

5.2 The Logit and The IV Logit Demand Estimation

5.2.1 Market Share

I estimate the demand functions within three particular investment objectives: aggressive growth, long-term growth, and growth and income as identified by Source Standard and Poor’s Micropal. I define the market share at the objective level for each fund as the total net assets under management by the fund divided by all assets under management in its objective category. I implicitly assume that investors make investment decisions every year. In mutual fund industry, tax and load fees are the transaction costs make this assumption unrealistic. It is interesting to study the effect of transaction

\footnote{A full random coefficient model in the framework of BLP(1995) can also be applied here.}
costs on investors’ demand function. However, more specific individual level data are needed in order to conduct this experiment.

5.2.2 Outside Good

As with most of the logit model, I define an outside “good” to invert the system of equations. If investors decide not to invest in any actively managed portfolios, but instead allocate all income to the passive portfolios (index funds) available in one category, we think investors will invest in mutual fund \( j = 0 \), the “outside fund.” The indirect utility from investing in this outside fund is:

\[
\begin{align*}
    u_{ijt} &= \xi_{0t} + Index_{0t}(\varphi, R_{jt-1}) + X_0b_0 + \epsilon_{0t}.
\end{align*}
\]

As with most empirical work using the discrete-choice model, I normalize \( \xi_{0t} \) to zero. \( X_0b_0 \) not identified separately from the intercept in equation. \( Index_{0t}(\varphi, R_{jt-1}) \) is the mean performance index of the index funds.

5.2.3 Regression Equation

We define \( \zeta_{jt+1} \) as,

\[
\begin{align*}
    \zeta_{jt+1} &= \ln(s_{jt+1}) - \ln(s_{0t+1})
\end{align*}
\]

where \( s_{jt+1} \) is the market share of total net asset of fund \( j \) at year \( t \). \( s_{0t+1} \) is the “outside fund” market share. Hence we obtain the regression function of \( \zeta_{jt+1} \) on price, service characteristics and mutual funds’ temporary performance indices at time \( t \),

\[
\begin{align*}
    \zeta_{jt+1} &= c + \hat{b}_0p_j + \hat{Index}_{jt} - \hat{Index}_{0t} + X_j\hat{b}_6 + \hat{\xi}_{jt},
\end{align*}
\]

where,

\[
\begin{align*}
    \hat{Index}_{jt} &= \hat{b}_1\hat{\alpha}_{j0t} + \hat{b}_2\hat{\beta}_{j1t}RMRF_t + \hat{b}_3\hat{\beta}_{j2t}SMB_t + \hat{b}_4\hat{\beta}_{j3t}HML_t + \hat{b}_5\hat{V arRet}_{jt}
\end{align*}
\]

and,

\[
\begin{align*}
    \hat{Index}_{0t} &= \hat{b}_1\hat{\alpha}_{00t} + \hat{b}_2\hat{\beta}_{01t}RMRF_t + \hat{b}_3\hat{\beta}_{02t}SMB_t + \hat{b}_4\hat{\beta}_{03t}HML_t + \hat{b}_5\hat{V arRet}_{0t}.
\end{align*}
\]

Table 5 summarizes the statistics of variables included in our demand system that are not related to the performance indices. The average fund
size is $673.3$ million. The standard deviation of the fund size is $2656$ million. The average sizes of aggressive growth funds are the smallest. The average sizes of growth and income funds are the biggest. The average gross cash inflow is $95.32$ million per fund. The standard deviation is $316.3$ million. The mean expense ratio is $1.2\%$. Aggressive growth funds charge the most — $1.4\%$, and growth and income funds charge the least — $1.1\%$. The standard 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 $\hat{\xi}_{jt}$ and $p_j$. For example, a mutual fund providing with better services is more likely to charge higher fees. The possible 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 estimates for price elasticities.

### 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 $k$th characteristic of fund $j$ produced by firm $f$. The first order optimal instrumental variables associated with $z_{jk}$ are

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

where $F_f$ is the set of products produced by firm $f$. For example, in my regression, $\hat{\alpha}$ is the characteristic measuring fund manager’s investment ability, which is exogenously endowed to fund manager $j$. Then the $\hat{\alpha}$ of fund $j$, the sum of $\hat{\alpha}$ across the mutual funds in $j$’s family and the sum of $\hat{\alpha}$ across rival fund family’s mutual funds are the three first order optimal instrumental variables associated with $\hat{\alpha}$. Since I include a constant term as one of the characteristics, the number of own-family mutual funds become a natural instruments. If we are sure that $I$ characteristics are 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 $\hat{\xi}_{jt}$ but they affect the fees $p_j$ charged by mutual fund $j$ through competition. Interested readers can
check BLP(1995) for a detailed description of the estimation method.\textsuperscript{24}

In practice, the instruments may have multicollinearity problem. In my regression, I use \( \sum_{r \neq j, r \in \mathcal{F}} \hat{\alpha}_j, \sum_{r \neq j, r \in \mathcal{F}} \hat{\beta}_{j1}, \sum_{r \neq j, r \in \mathcal{F}} \hat{\beta}_{j2} \) and \( \sum_{r \neq j, r \in \mathcal{F}} \hat{\beta}_{j3} \) as the instrumental variables for price additional to the fund characteristics. Using these instrumental variables, I 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 \( \hat{\xi}_{jt} \), 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 6th numerical columns report the estimates from the OLS logit model of the aggressive growth, long-term growth and growth income categories, respectively. I am 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. 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. I 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, investors chase noise factors when they invest. Investors also avoid funds having a high capital gain distribution because of tax considerations. Load funds in general enjoy higher cash inflows compared to nonload funds, probably because brokers’ solicitations are effective. However, within the load fund category, a higher load deters new cash inflows. Being part of a multishare-class common portfolio hurts the market

\textsuperscript{24}The instrumental viables are not legitimate if they correlated with the unobservable quality terms. However, this problem is not serious in my study. The cross-section dispersion of \( \beta_k \) is symmetric around mean, there is no evidence that the lower quality funds will choose larger or smaller beta. Even if the low quality funds are more likely to choose extreme \( \beta_k \)'s, the correlation between \( \beta_k \) and \( \hat{\xi}_{jt} \) is still equal to zero.
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.

5.3.2 Robust Check

In previous estimation, we define the market share using stock data. We implicitly assume that investors make purchase decision every year. The transaction costs, such as sales loads and tax consequences, may put some potential problem on this assumption. For robust check, we define the market share as the market share of the gross cash inflow into the fund.\(^{25}\) However, the gross cash inflow data normally are not available.\(^{26}\) We construct a proxy for the annual gross cash inflow data by adding all the positive monthly net flows over the year\(^{27}\):

\[
\text{GrossInflow} = \sum_{s=1}^{12} \max(\text{Newmoney}_{js}, 0).
\]

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),

\[
\text{Newmoney}_{js} = TNA_{js} - TNA_{js-1} \ast (1 + R_{st}) - MGTNA_{js}.
\]

Then I calculate market share of gross cash inflow at the objective level for each fund as the total gross cash inflow into one fund divided by all assets

---

\(^{25}\)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.

\(^{26}\)Edelen (1999) studies the indirect cost of providing liquidity by using gross cash inflow and outflow data from N-SAR report.

\(^{27}\)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.
under management in its objective category. The demand system estimation using flow data are listed in Table 7. The results are qualitatively the same as the previous one using stock data. Quantitatively, the price elasticity slightly higher in the cash using flow data. The perform chasing behavior are also stronger if we use flow data.

6 The Effect of Spurious Financial Product Differentiation

Assume I obtained consistent estimates of the parameters in the demand system at the previous section. I 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,

$$
\hat{\eta}_j(\cdot) = \frac{\partial s_{jt} p_k}{\partial p_k s_{jt}} = \left\{ \begin{array}{ll}
    -\frac{p_j}{s_{jt}} \hat{b}_0 s_{jt} (1 - s_{jt}) & \text{if } j = k \\
    -\frac{p_k}{s_{jt}} \hat{b}_0 s_{jt} s_{kt} & \text{if } j \neq k
\end{array} \right.
$$

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 bootstrapping method: we draw $12 \times T$ monthly return from empirical distribution; 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

\[28\text{We can also implement the Monte Carlo method.}\]
\( j \) at \( t \):
\[
\hat{\eta}_j^e(\cdot) = \begin{cases} 
-\frac{p^e_j}{s^e_j} \beta_0 1/T \sum_{\tau=1}^T s_{jt}(1 - s_{jt}) & \text{if } j = k \\
-\frac{p^e_j}{s^e_j} \beta_0 1/T \sum_{\tau=1}^T s_{jt}s_{kt} & \text{if } j \neq k 
\end{cases}
\]
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:
\[
\frac{\hat{m}^e}{p^e_j} = \frac{\hat{p}^e - mc}{p^e_j} = \frac{\hat{\Delta} - 1}{s^e_j(p)/p^e_j} = \frac{1}{\hat{\eta}_j^e(\cdot)}.
\]

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 \( \hat{\beta}_{kt} \) are the same cross-sectionally. Let \( s_j^* \) and \( m_j^* \) denote the equilibrium market share and markups of fund \( j \) in this case. I 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. I calculate the counterfactual marginal cost from Equations (*). After we obtain the counterfactual marginal cost, we calculate \( \hat{s}_j^* \), and \( \hat{p}_j^* \) through following equations:
\[
\hat{p}^* = mc_{cont} + \hat{\Delta}^{-1}s^*(\hat{p}^*).
\]
The estimated profit margins without product differentiation over the state space are,
\[
\frac{\hat{m}^*}{p_j^*} = 1/\hat{\eta}_j^*
\]
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. I 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 $9.7 billion. However, without spurious financial product differentiation, the diversified mutual funds can only maintain a profit of $7.5 billion. The mutual fund managers can seek $2.2 billion 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. I 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. I 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. I 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

The following proof shows that the market share equation in this study is equivalent to a spatial competition model with quadratic “transportation” cost.

The above claim is first proved in the framework of a single factor model. It is then generalized to a multi-factor model.

**Single Factor Model**

Suppose the return of mutual fund $j$ $R_j$ is generated by the following one factor model:

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

In addition, suppose the subjective expected utility function of investor $i$ is:

$$E_t(u_{ij}) = b_0 P_j + l = 1 \sum_{l=1}^{L} b_j X_{jt} + E_t(\varphi_i 0 \alpha_0 + \varphi_i (\varepsilon_{R_M} \beta_j) + \varepsilon_j) - \frac{1}{2} \varphi_i 2 Var_t(R_j) + \varepsilon_{ijt}$$

$$= b_0 P_j + l = 1 \sum_{l=1}^{L} b_j X_{jt} + \varphi_i 0 \alpha_0 - \frac{1}{2} \varphi_i 2 \sigma_{ijt}$$

$$+ \left\{ \varphi_{i1} E_t(\varepsilon_{R_M} \beta_j) - \frac{1}{2} \varphi_{i2} Var_t(\beta_j \varepsilon_{R_M}) \right\} + \varepsilon_{ijt}$$

$$= \Psi_i(P_j, X_{jt}, \alpha_{jt}, \sigma_{ijt}) + u_{iM}(\beta_j) + \varepsilon_{ijt}.$$  

where $\Psi_i(P_j, X_{jt}, \alpha_{jt}, \sigma_{ijt}) = b_0 P_j + l = 1 \sum_{l=1}^{L} b_j X_{jt} + \varphi_i 0 \alpha_0 - \frac{1}{2} \varphi_i 2 \sigma_{ijt}$

I can interpret $\Psi_i(P_j, X_{jt}, \alpha_{jt}, \sigma_{ijt})$ as the quality of mutual funds related to mutual fund service and fund manager’s ability to beat the market. $u_{iM}(\beta_j)$ measures how mutual fund $j$’s style $\beta_j$ fits investor $i$.

The best matched style for consumer $i$ is,

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

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

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The utility coming from the best matched style is,

\[ u^*_{iM} = u_{iM}(\beta^*_t) = \frac{1}{2} \varphi_{i2} \left( \frac{\varphi_{i1}}{\varphi_{i2}} V_{mt}^{-1} \cdot \mu_{mt} \right)' V_{mt} \left( \frac{\varphi_{i1}}{\varphi_{i2}} V_{mt}^{-1} \cdot \mu_{mt} \right) \]

\[ = \frac{1}{2} \varphi_{i2} \cdot \beta^*_t V_{mt} \beta^*_t \]

So that,

\[ E_t(u_{ij}) = E_t(u_{ij}) - u^*_{iM} + u^*_{iM} \]

\[ = \Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{jt-1}) - \frac{1}{2} \varphi_{i2}(\beta^*_t - \beta_{jt})' V_{mt}(\beta^*_t - \beta_{jt}) + u^*_{iM} + \varepsilon_{ijt} \]

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

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

\[ \sum_j \exp \left[ \Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{jt-1}) - \frac{1}{2} \varphi_{i2}(\beta^*_t - \beta_{jt})' V_{mt}(\beta^*_t - \beta_{jt}) \right] \]

The ex post market share of fund j is,

\[ s_j = \int d\eta(\varphi_i) \]

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

The expected market share of fund j is,

\[ s^e_j = \int d\eta(\varphi_i) \]

\[ = \int \frac{\exp \left[ \Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{jt-1}) - \frac{1}{2} \varphi_{i2}(\beta^*_t - \beta_{jt})' V_{mt}(\beta^*_t - \beta_{jt}) \right]}{\sum_j \exp \left[ \Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{jt-1}) - \frac{1}{2} \varphi_{i2}(\beta^*_t - \beta_{jt})' V_{mt}(\beta^*_t - \beta_{jt}) \right]} d\varphi_i d\mu_{mt} dV_{mt} \]

**Generalize 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:

\[ R_j = \alpha_0 + \beta'_j \varepsilon_F + \varepsilon_j. \]
\( \beta_j \), a fixed \( K \times 1 \) vector, is mutual fund \( j \)'s loading on the factor returns. \( \alpha_{0j} \) is manager \( j \)'s ability to outperform the \( K \) factors. \( \varepsilon_F \) is the vector of factor returns.

The Investor \( i \)'s subjective expected utility function is:

\[
E_t(u_{ij}) = E_t(u_{ij}) - u_{iM} + u_{iM}^* \]

\[
= \Psi_i(P_j, X_{jt}, \alpha_{jt-1}, \sigma_{\varepsilon_{jt-1}}) - \frac{1}{2} (\beta_i^* - \beta_{jt})'V(\beta_i^* - \beta_{jt}) + u_{iM} + \varepsilon_{ijt}
\]

where

\[
\beta_i^* = (V_t)^{-1} \left( \frac{\varphi_i \cdot \varepsilon_{Ft}}{\varphi_i K + 1} \right).
\]

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

\[
s_{jt+1}^* = \int \sum_j \exp(\delta_{jt+1} + \varphi_i \alpha_{0jt} - \frac{1}{2} \varphi_i K + 1 \sigma_{\varepsilon_{jt}} - \frac{1}{2} \varphi_i K + 1 (\beta_i^* - \beta_{jt})'V_t (\beta_i^* - \beta_{jt})) dP(\varphi_i) dF(\varepsilon_{F_{kt}}, V_t).
\]

**References**


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.

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

*The market returns are the returns on the CRSP value-weighted portfolio of all NYSE, Amex and Nasdaq stocks.
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.

<table>
<thead>
<tr>
<th>Factor Portfolio</th>
<th>Excess Return Std Mean=0</th>
<th>Return Correlation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>t-stat for</td>
<td>RMRF</td>
<td>SMB</td>
</tr>
<tr>
<td>RMRF</td>
<td>1.11</td>
<td>3.58</td>
<td>2.82</td>
</tr>
<tr>
<td>SMB</td>
<td>-.17</td>
<td>2.78</td>
<td>-.55</td>
</tr>
<tr>
<td>HML</td>
<td>.27</td>
<td>2.81</td>
<td>.88</td>
</tr>
</tbody>
</table>
I employ the Fama and French (1993) 3-factor model to decompose mutual funds’ performance, $r_{jt} = \alpha_{jt} + \beta_{j1t}RMRF_t + \beta_{j2t}SMB_t + \beta_{j3t}HML_t$. $RMRF$ is the average difference between CRSP (Center for Research in Security Prices) value-weight stock index and the one-month T-bill return. $SMB$ and $HML$ are the mean of Fama and French’s (1993) factor-mimicking portfolios for size and book-to-market equity. All the data are monthly.

<table>
<thead>
<tr>
<th>Year</th>
<th>$r_{jt}$</th>
<th>$RMRF_t$</th>
<th>$\alpha_{jt}$</th>
<th>$\beta_{j1t}RMRF_t$</th>
<th>$\beta_{j2t}SMB_t$</th>
<th>$\beta_{j3t}HML_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1992</td>
<td>Mean</td>
<td>.00546</td>
<td>.00553</td>
<td>-.00015</td>
<td>.00457</td>
<td>.00139</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>.00891</td>
<td>--</td>
<td>.00513</td>
<td>.00110</td>
<td>.00232</td>
</tr>
<tr>
<td>1993</td>
<td>Mean</td>
<td>.00780</td>
<td>.00606</td>
<td>.00044</td>
<td>.00607</td>
<td>.00141</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>.00893</td>
<td>--</td>
<td>.00477</td>
<td>.00146</td>
<td>.00230</td>
</tr>
<tr>
<td>1994</td>
<td>Mean</td>
<td>-.00437</td>
<td>-.00320</td>
<td>-.00029</td>
<td>-.00312</td>
<td>.00007</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>.00665</td>
<td>--</td>
<td>.00418</td>
<td>.00080</td>
<td>.00021</td>
</tr>
<tr>
<td>1995</td>
<td>Mean</td>
<td>.01853</td>
<td>.02152</td>
<td>-.00055</td>
<td>.02070</td>
<td>-.00114</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>.00921</td>
<td>--</td>
<td>.00479</td>
<td>.00461</td>
<td>.00160</td>
</tr>
<tr>
<td>1996</td>
<td>Mean</td>
<td>.01131</td>
<td>.01268</td>
<td>-.00039</td>
<td>.01164</td>
<td>-.00007</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>.00663</td>
<td>--</td>
<td>.00497</td>
<td>.00251</td>
<td>.00022</td>
</tr>
<tr>
<td>1997</td>
<td>Mean</td>
<td>.01433</td>
<td>.01922</td>
<td>-.00138</td>
<td>.01824</td>
<td>-.00048</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>.00915</td>
<td>--</td>
<td>.00600</td>
<td>.00377</td>
<td>.00078</td>
</tr>
<tr>
<td>1998</td>
<td>Mean</td>
<td>.00971</td>
<td>.01685</td>
<td>-.00131</td>
<td>.01559</td>
<td>-.00537</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>.01740</td>
<td>--</td>
<td>.00721</td>
<td>.00358</td>
<td>.007929</td>
</tr>
</tbody>
</table>
Table 4: Panel A
Cross-Section Alpha and Betas of Mutual Fund Net Returns

I 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.

<table>
<thead>
<tr>
<th>Year</th>
<th>$\hat{\alpha}_{3t}$</th>
<th>Std$\hat{\alpha}_{3t}$</th>
<th>Mean$\hat{\beta}_{1t}$</th>
<th>Std$\hat{\beta}_{1t}$</th>
<th>Mean$\hat{\beta}_{2t}$</th>
<th>Std$\hat{\beta}_{2t}$</th>
<th>Mean$\hat{\beta}_{3t}$</th>
<th>Std$\hat{\beta}_{3t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1992</td>
<td>-.00015</td>
<td>.0051</td>
<td>1.00</td>
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<td>.23</td>
<td>.37</td>
<td>-.07</td>
<td>.28</td>
</tr>
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<td>1993</td>
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<td>.99</td>
<td>.24</td>
<td>.25</td>
<td>.41</td>
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<td>.28</td>
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<td>1994</td>
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<td>.23</td>
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<td>.39</td>
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<td>.31</td>
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<tr>
<td>1995</td>
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<td>.0048</td>
<td>.95</td>
<td>.21</td>
<td>.28</td>
<td>.38</td>
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<td>.31</td>
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<tr>
<td>1996</td>
<td>-.00066</td>
<td>.0051</td>
<td>.93</td>
<td>.18</td>
<td>.24</td>
<td>.42</td>
<td>-.13</td>
<td>.38</td>
</tr>
<tr>
<td>1997</td>
<td>-.0014</td>
<td>.0050</td>
<td>.96</td>
<td>.20</td>
<td>.27</td>
<td>.41</td>
<td>-.10</td>
<td>.35</td>
</tr>
</tbody>
</table>
Panel B  
Cross-Section Alpha and Betas of Simulated Mutual Fund Gross Returns of 1997

The number of portfolio holdings \( n_j \) of each mutual fund \( j \) in year 1997 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.

<table>
<thead>
<tr>
<th>Year 1997</th>
<th>( \hat{\alpha}_3t )</th>
<th>Sd( \hat{\alpha}_3t )</th>
<th>Mn( \beta_{1t} )</th>
<th>Sd( \beta_{1t} )</th>
<th>Mn( \beta_{2t} )</th>
<th>Sd( \beta_{2t} )</th>
<th>Mn( \beta_{3t} )</th>
<th>Sd( \beta_{3t} )</th>
</tr>
</thead>
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<tr>
<td>Hypothetical</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eql Wgt</td>
<td>-.0015</td>
<td>.0047</td>
<td>.86</td>
<td>.14</td>
<td>.85</td>
<td>.16</td>
<td>.14</td>
<td>.23</td>
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<tr>
<td>Cap Wgt</td>
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<td>.99</td>
<td>.10</td>
<td>.20</td>
<td>.09</td>
<td>.18</td>
<td>.18</td>
</tr>
<tr>
<td>Real</td>
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<tr>
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<td>.0050</td>
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<td>.20</td>
<td>.27</td>
<td>.41</td>
<td>-.10</td>
<td>.35</td>
</tr>
<tr>
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<td>.0011</td>
<td>.0068</td>
<td>.97</td>
<td>.26</td>
<td>.68</td>
<td>.34</td>
<td>-.24</td>
<td>.47</td>
</tr>
<tr>
<td>LongTerm</td>
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<td>.0044</td>
<td>.97</td>
<td>.18</td>
<td>.17</td>
<td>.31</td>
<td>-.11</td>
<td>.30</td>
</tr>
<tr>
<td>Income</td>
<td>.0001</td>
<td>.0033</td>
<td>.93</td>
<td>.15</td>
<td>-.02</td>
<td>.20</td>
<td>.06</td>
<td>.19</td>
</tr>
<tr>
<td>( F - test of \sigma^2_{real} &gt; \sigma^2_{hypo} )</td>
<td>2.4</td>
<td>2.5</td>
<td>7.8</td>
<td>3.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Note: For real mutual funds, Alpha is the gross alpha before fees.
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.

<table>
<thead>
<tr>
<th>Market Share</th>
<th>Aggressive Gth</th>
<th>Long-Term Gth</th>
<th>Gth &amp; Income</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
<td>Mean</td>
<td>Std</td>
</tr>
<tr>
<td>TotalNetAsset($M)</td>
<td>380.6</td>
<td>1108</td>
<td>714.6</td>
<td>2881</td>
</tr>
<tr>
<td>GrossInflows ($M)</td>
<td>83.28</td>
<td>245.7</td>
<td>96.30</td>
<td>331.4</td>
</tr>
<tr>
<td>Expense (%)</td>
<td>1.37</td>
<td>.47</td>
<td>1.21</td>
<td>.42</td>
</tr>
<tr>
<td>Age</td>
<td>7.52</td>
<td>9.21</td>
<td>11.45</td>
<td>13.89</td>
</tr>
<tr>
<td>Max_load (%)</td>
<td>1.91</td>
<td>2.44</td>
<td>2.29</td>
<td>2.58</td>
</tr>
<tr>
<td>Cap_Gains (%)</td>
<td>.127</td>
<td>1.06</td>
<td>.089</td>
<td>.465</td>
</tr>
<tr>
<td>Turnover (%)</td>
<td>101.0</td>
<td>143</td>
<td>80.0</td>
<td>75</td>
</tr>
<tr>
<td>imshare</td>
<td>.306</td>
<td>.461</td>
<td>.313</td>
<td>.463</td>
</tr>
<tr>
<td>iload</td>
<td>.494</td>
<td>.500</td>
<td>.527</td>
<td>.499</td>
</tr>
<tr>
<td>N</td>
<td>1847</td>
<td>2670</td>
<td>1615</td>
<td>6132</td>
</tr>
</tbody>
</table>
Table 6: Mutual Fund Demand System Estimates (Stock Data)

<table>
<thead>
<tr>
<th>Market Share</th>
<th>Aggressive Growth</th>
<th>Long-Term Growth</th>
<th>Growth Income</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logit (1)</td>
<td>IV Logit (2)</td>
<td>Logit (3)</td>
</tr>
<tr>
<td>Constant</td>
<td>-.36***</td>
<td>-.26***</td>
<td>-.23***</td>
</tr>
<tr>
<td></td>
<td>(.13)</td>
<td>(.42)</td>
<td>(.16)</td>
</tr>
<tr>
<td>Price</td>
<td>-77.5***</td>
<td>-159.3***</td>
<td>-136.2***</td>
</tr>
<tr>
<td></td>
<td>(3.5)</td>
<td>(34.4)</td>
<td>(7.9)</td>
</tr>
<tr>
<td>Gross_{\alpha_{t-1}}</td>
<td>60.9***</td>
<td>61.3***</td>
<td>166.8***</td>
</tr>
<tr>
<td></td>
<td>(5.4)</td>
<td>(5.6)</td>
<td>(10.0)</td>
</tr>
<tr>
<td>$\beta_{j_{t-1}RM_{t-1}}$</td>
<td>58.5***</td>
<td>49.4***</td>
<td>222.7***</td>
</tr>
<tr>
<td></td>
<td>(9.5)</td>
<td>(10.6)</td>
<td>(15.3)</td>
</tr>
<tr>
<td>$\beta_{j_{t-1}SMB_{t-1}}$</td>
<td>107.8***</td>
<td>107.5***</td>
<td>283.3***</td>
</tr>
<tr>
<td></td>
<td>(12.8)</td>
<td>(13.3)</td>
<td>(37.1)</td>
</tr>
<tr>
<td>$\beta_{j_{t-1}HML_{t-1}}$</td>
<td>7.6</td>
<td>15.8</td>
<td>-8.6</td>
</tr>
<tr>
<td></td>
<td>(11.7)</td>
<td>(12.6)</td>
<td>(25.0)</td>
</tr>
<tr>
<td>VarRet_{t-1}</td>
<td>-127.7***</td>
<td>-98.2***</td>
<td>-227.8***</td>
</tr>
<tr>
<td></td>
<td>(20.2)</td>
<td>(24.3)</td>
<td>(54.0)</td>
</tr>
<tr>
<td>imshare_t</td>
<td>-.36***</td>
<td>-.38***</td>
<td>.85***</td>
</tr>
<tr>
<td></td>
<td>(.08)</td>
<td>(.09)</td>
<td>(.11)</td>
</tr>
<tr>
<td>iload_t</td>
<td>.27***</td>
<td>.44***</td>
<td>.81***</td>
</tr>
<tr>
<td></td>
<td>(.08)</td>
<td>(0.11)</td>
<td>(.10)</td>
</tr>
<tr>
<td>log(age)_t</td>
<td>.75**</td>
<td>.72***</td>
<td>.90***</td>
</tr>
<tr>
<td></td>
<td>(.04)</td>
<td>(.04)</td>
<td>(.04)</td>
</tr>
<tr>
<td>cap_gns_{t-1}</td>
<td>-6.5***</td>
<td>-6.6***</td>
<td>-.03***</td>
</tr>
<tr>
<td></td>
<td>(.62)</td>
<td>(.64)</td>
<td>(.00)</td>
</tr>
<tr>
<td>turnover_{t-1}</td>
<td>.02</td>
<td>.07***</td>
<td>.20***</td>
</tr>
<tr>
<td></td>
<td>(.02)</td>
<td>(.03)</td>
<td>(.05)</td>
</tr>
</tbody>
</table>

\[ N = 1191 \quad 1191 \quad 1771 \quad 1771 \quad 1126 \quad 1126 \]

\[ \text{Adj } R^2 = .43 \quad .38 \quad .47 \quad .45 \quad .49 \quad .47 \]
Table 7:

(Stock Data)

<table>
<thead>
<tr>
<th></th>
<th>Aggressive Growth</th>
<th>Long-Term Growth</th>
<th>Growth Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>1993</td>
<td>.61</td>
<td>.67</td>
<td>.51</td>
</tr>
<tr>
<td>1994</td>
<td>.61</td>
<td>.67</td>
<td>.50</td>
</tr>
<tr>
<td>1995</td>
<td>.62</td>
<td>.66</td>
<td>.51</td>
</tr>
<tr>
<td>1996</td>
<td>.63</td>
<td>.65</td>
<td>.49</td>
</tr>
<tr>
<td>1997</td>
<td>.59</td>
<td>.62</td>
<td>.47</td>
</tr>
<tr>
<td>1998</td>
<td>.61</td>
<td>.69</td>
<td>.56</td>
</tr>
<tr>
<td>Year Ave.</td>
<td>.61</td>
<td>.66</td>
<td>.50</td>
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Panel B: Estimation of the Effect of SPD on Industry Profit Margins in 1998 (Stock Data)

<table>
<thead>
<tr>
<th>Year 1998</th>
<th>Without SPD</th>
<th>With SPD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profit Margins</td>
<td>.53</td>
<td>.66</td>
</tr>
<tr>
<td>In Dollar Value</td>
<td>$12.7billion</td>
<td>$15.9billion</td>
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</table>
Table 8: Mutual Fund Demand System Estimates (Flow Data)

<table>
<thead>
<tr>
<th>Market Share</th>
<th>Aggressive Growth</th>
<th>Long-Term Growth</th>
<th>Growth Income</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logit</td>
<td>IV Logit</td>
<td>Logit</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.2***</td>
<td>-4.4***</td>
<td>-4.2***</td>
</tr>
<tr>
<td></td>
<td>(.24)</td>
<td>(.57)</td>
<td>(.23)</td>
</tr>
<tr>
<td>Price</td>
<td>-112.6***</td>
<td>-181.5***</td>
<td>-183.9***</td>
</tr>
<tr>
<td></td>
<td>(14.4)</td>
<td>(46.4)</td>
<td>(13.1)</td>
</tr>
<tr>
<td>GrossAlpha_{t-1}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>94.1***</td>
<td>95.7***</td>
<td>210.4***</td>
</tr>
<tr>
<td></td>
<td>(15.4)</td>
<td>(15.6)</td>
<td>(18.8)</td>
</tr>
<tr>
<td>\beta_{1t-1}RM_{t-1}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>153.4***</td>
<td>158.0***</td>
<td>300.2***</td>
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<tr>
<td></td>
<td>(21.1)</td>
<td>(22.6)</td>
<td>(36.2)</td>
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<td>\beta_{2t-1}SMB_{t-1}</td>
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<td></td>
<td>29.1**</td>
<td>35.8***</td>
<td>91.5***</td>
</tr>
<tr>
<td></td>
<td>(17.6)</td>
<td>(18.4)</td>
<td>(20.7)</td>
</tr>
<tr>
<td>VarRet_{t-1}</td>
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</tr>
<tr>
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<td>-82.0**</td>
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<tr>
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<td>(17.6)</td>
<td>(39.1)</td>
<td>(54.0)</td>
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<td>-.20</td>
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<td>(.16)</td>
<td>(.13)</td>
</tr>
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<td>.30***</td>
<td>.90***</td>
<td>.71***</td>
</tr>
<tr>
<td></td>
<td>(.06)</td>
<td>(.26)</td>
<td>(.19)</td>
</tr>
<tr>
<td>log(age)_{t}</td>
<td>.30***</td>
<td>.26***</td>
<td>.05</td>
</tr>
<tr>
<td></td>
<td>(.05)</td>
<td>(.05)</td>
<td>(.05)</td>
</tr>
<tr>
<td>max_load_{t}</td>
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</tr>
<tr>
<td></td>
<td>-.05</td>
<td>-.01**</td>
<td>-.11***</td>
</tr>
<tr>
<td></td>
<td>(.04)</td>
<td>(.05)</td>
<td>(.04)</td>
</tr>
<tr>
<td>cap_gns_{t-1}</td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>-.06</td>
<td>-.04</td>
<td>-.125</td>
</tr>
<tr>
<td></td>
<td>(.05)</td>
<td>(.03)</td>
<td>(.09)</td>
</tr>
<tr>
<td>turnover_{t-1}</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>.05*</td>
<td>.08*</td>
<td>.29***</td>
</tr>
<tr>
<td></td>
<td>(.04)</td>
<td>(.04)</td>
<td>(.07)</td>
</tr>
<tr>
<td>\text{N}</td>
<td>1191</td>
<td>1191</td>
<td>1771</td>
</tr>
<tr>
<td>\text{Adj R^2}</td>
<td>.265</td>
<td>.272</td>
<td>.284</td>
</tr>
</tbody>
</table>
Table 9:

(Flow Data)

<table>
<thead>
<tr>
<th>Year</th>
<th>Aggressive Growth</th>
<th></th>
<th>Long-Term Growth</th>
<th></th>
<th>Growth Income</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1992</td>
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<td>.5849</td>
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<td>.4127</td>
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<tr>
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<tr>
<td>1994</td>
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<td>.3897</td>
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<tr>
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<td>.2702</td>
<td>.3405</td>
<td>.3473</td>
<td>.4022</td>
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<tr>
<td>Year Ave.</td>
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<td>.5154</td>
<td>.2688</td>
<td>.3816</td>
<td>.3039</td>
<td>.3467</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Year 1998</th>
<th>Without SPD</th>
<th>With SPD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profit Margins</td>
<td>.32</td>
<td>.42</td>
</tr>
<tr>
<td>In Dollar Value</td>
<td>$7.5billion</td>
<td>$9.7billion</td>
</tr>
</tbody>
</table>