Mutual fund competition and stock market liquidity.

Massimo Massa*

INSEAD

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Abstract

We study how competition in the mutual fund industry affects the stock market and its liquidity. We argue that mutual fund families operate as multi-product firms, jointly choosing fees, performance and number of funds. We show that competition between fund families distorts the incentives to collect information and induces the families to trade off performance and number of funds. An increase in the cost of information reduces the amount of information that families collect and the fees they charge and increases the number of funds they offer. The presence of more and relatively less informed funds impacts the market, increasing liquidity and reducing volatility and prices. This allows us to use observable equilibrium conditions in the mutual fund market (i.e., fees, number of funds, performance, cost of information, investor demand) to proxy for the unobservable level of information and to relate it to stock market conditions. We test our theory using the universe of the US equity funds in the past 20 years. We identify the fund characteristics and relate them to the volatility, liquidity, cross-correlation and prices of the stocks that are held by them. We show that the fund characteristics do affect stocks in the way predicted by the model.

JEL classification: **G11, G12, G14.**

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*Corresponding author: M. Massa, Finance Department, INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France. Tel: (33)1 60 72 44 81 Fax: (33)1 60 72 40 45. Email: massimo.massa@insead.edu. I thank for helpful comments and discussions P.Balduzzi, M.Blume, B.Dumas, W.Ferson, X.Gabaix, N.Garleanu, C.Gezcy, W.Goetzmann, H.Hau, L.Hodrick, R.Kihlstrom, T.Moskowitz, V.Nanda, J.Pontiff, S.Ross, M.Suominen, J.Wang, J.P. Zigrand and the participants at the LSE Conference on Liquidity (London) and the seminar at Boston College. All the remaining errors are mine.

1 Introduction

Traditionally, the finance literature has devoted scarce attention to the development of the mutual fund industry and, in particular, to the *impact that the competition among mutual fund families has on the stock market*. Mutual funds have been considered as portfolios of assets and not as products sold by companies competing with each other. The standard models (Admati and Pfleiderer, 1986, 1988, 1990) assume away the market structure of the mutual fund industry or postulate it to be monopolistic, with no effective competition between mutual fund providers. Mutual funds are identified as "information collection mechanisms" that provide the service of specialized investment and information collection in return for the payment of fees (Berk and Green, 2002). An increase in the number of mutual funds should, under these conditions, imply more information collected at equilibrium and greater market liquidity. Indeed, it is a widely held folk theorem that the introduction of mutual funds informationally improves financial markets, reduces stock price volatility and enhances market liquidity. This mantra, that has percolated in the financial press and has shaped the official position of the mutual fund industry, implies a positive relationship between number of funds and information.

However, if we move the perspective to the level of the mutual fund family and we assume that fund families operate as multi-product firms, jointly choosing fees, performance and number of funds, a different view emerges. *Competition between mutual fund families distorts the incentives to collect information and induces the fund families to trade off performance and number of funds.* In particular, there is an implicit trade-off between the number of funds that the family sets up and the amount of information that the family collects. An increase in the cost of generating information reduces the amount of information that is provided and the level of the fees that are charged and increases the number of competing funds. That is, fund proliferation becomes the optimal reaction of the mutual fund family if the cost of information rises. This induces a negative correlation between the number of existing funds and the amount of information that each of them collects at equilibrium.

This intuition provides several important insights. First, it gives a new way of looking at one of the most glaring stylized facts in finance: the rise in the number of funds. Mutual funds have experienced an exponential growth in the last decade. Over the period 1990-2000 the number of US mutual funds has grown from 3,081 to 8,171, more than the total number of stocks traded on NYSE and AMEX added together. This growth has almost entirely taken the form of an increase in the number of mutual funds, while the number of fund families has stayed more or less the same (it slightly increased, from 361 to 431). The intuition we propose is that the mutual fund families, faced either with an increase in the cost of generating

information or with a reduction in the cost of setting up new funds, have optimally chosen to reduce the purchase of information and increased, instead, the number of funds.

Second, our intuition has also profound implications in terms of the relation between the competition among mutual funds and the equilibrium in the stock market. Mutual funds, being in general big players, directly impact the market. Standard intuition (Kyle, 1985, Wang, 1993) suggests that the more informed the funds are, the higher the asymmetry with the other traders (market makers), the greater the funds' market impact and the lower the liquidity. Therefore, the amount of information available to the funds becomes one of the main determinants of market liquidity. If we assume that information is the very product mutual funds sell, or at least one of the dimensions along which they compete, the amount of information - and therefore market liquidity - must be directly related to the way families compete (i.e., the fees they charge, the demand they face, their cost of generating information, the number of their competitors). This implies that the main factors that characterize competition in the mutual fund industry should also be directly linked to the equilibrium in the stock market. Indeed, not only are informational shocks of the mutual fund managers amplified (reduced) by the fund characteristics, but also exogenously driven changes to these characteristics should impact the stock market.[1]

We will provide a model that supports this intuition and creates the link between information and (fully and partially) observable mutual fund characteristics (number of funds, level of fees, fund's informativeness, fund's demand, cost of information). We will then show how these observable fund characteristics should be related to the equilibrium in the stock market (stock volatility, liquidity, price and cross-stock correlations). In particular, we will describe how competition within the mutual fund industry generates a trade-off between information and number of funds. If the cost of information rises, less information is collected and more funds are established. The presence of more and relatively less informed funds affects market makers's behavior, reducing volatility and prices and increasing liquidity.

We will test the empirical restrictions of our approach using the universe of the US equity funds in the past 20 years. We will identify the observable fund characteristics that are related to the way fund families compete with each other, such as the fees they charge, the performance they provide (i.e., the information they collect), their cost of information, the demand they face, as well as the number of funds themselves. We will then directly relate price, volatility, liquidity and cross-

[1]For example, a change in the fees charged, being linked to the amount of information that is generated by the fund, directly impacts the value of stocks that the fund holds.

correlation of the stocks to the characteristics of the mutual funds that are holding them. We will provide evidence that these fund characteristics do indeed affect stocks, directly impacting prices, volatility and liquidity and inducing stocks held by funds with analogous characteristics to be more closely correlated. Moreover, we will show that fund-based characteristics aggregate at the overall market level, induce co-movements in liquidity and generate priced factors.

Our results shed new light on the determinants of market liquidity and on the reason why some stocks co-move more than others. This provides a "rational" explanation to stock behaviors and other anomalies that had, up to now, been mostly explained in behavioral terms.

The paper is structured as follows. In Section 2, we relate to the existing literature and describe our contribution. In Section 3, we lay out the model and in Section 4 we derive the main testable restrictions. In Section 5, we describe the data and the methodology we use. In Section 6, we reports the empirical tests and discuss the findings. A brief conclusion follows.

2 Relation to the existing literature.

We relate and contribute to three strands of literature. The first analyzes the mutual fund industry and studies its development. The second focuses on the impact of mutual funds on the stock market. The third studies market liquidity.

Surprisingly few attempts have been made to model the mutual fund industry. Massa (1998) argues that market segmentation and fund proliferation can be seen as marketing strategies used by the fund families to exploit investors' heterogeneity. Market segmentation is justified in terms of the positive "spill-over" that having a "star" fund provides to all the funds belonging to the same family. Nanda *et al.* (2000) study the fee setting decision of the mutual funds, showing how management fees and load fees are jointly endogenously determined in a competitive setting. They argue that heterogeneity in managerial skills induce differences in fees. Mamaysky and Spiegel (2001) consider mutual funds as "trading devices", set up by investors who cannot remain in the market to trade at all times. Mutual funds exist to overcome investors' hedging needs. Christoffersen and Musto (2002) study the fee structure and how it affects investor welfare, by influencing the portfolio selection incentives of the adviser and the risk-sharing between adviser and investor.

On the empirical side, also, few have directly analyzed the mutual fund industry from an industrial organization perspective. Khorana and Servaes (1999, 2001) study the determinants of mutual fund starts, Khorana (2003) focuses on the takeovers and

mergers within the mutual fund industry and Massa (2003) analyzes the performance implications of the mutual fund market structure. The role of the fund family has also been analyzed by Ivzkovich (2002) and by Nanda *et al.* (2003) who study the performance spill-overs within the mutual funds families. However, all these contributions, the empirical as well as the theoretical, do not make the additional step of linking mutual fund behavior to stock market equilibrium nor do they try to use the competition in the mutual fund industry to explain the stock market.

The second strand of literature focuses on the impact of financial intermediation on the stock market. While mutual funds are not explicitly considered,[2] there are two potential channels through which mutual funds may impact the market. The first relies on the information dimension and builds on the earlier results of Admati and Pfleiderer (1986, 1988, 1990). The introduction of a mutual funds, just like any financial innovation, should increase the informational completeness of the market. The second channel relies on market frictions. Limits of arbitrage and inelastic stock supply (Shleifer, 1986, Wurgler and Zhuraskaya, 2000, Barberis and Shleifer, 2002) or transaction cost (Petajisto, 2003) explain why mutual funds may play a role in amplifying market fluctuations.

Indirect empirical evidence on the role of mutual and index funds has been collected by the event studies that focus on the compositional changes in the S&P500 index (Garry and Goetzmann, 1986, Harris and Gurel, 1986, Shleifer, 1986, Beniesh and Whaley, 1996 and Lynch and Mendenhall, 1997). The direct evidence is scarcer and often contradictory, not able to resolve the issue of reverse causality between mutual funds and stock market. Warther (1995), Zheng (1999), Edelen and Warner (1999) and Goetzmann and Massa (2002) and Teo and Woo (2003) argue that demand pressure from mutual funds directly impacts stock prices. All these findings are predicated upon some forms of market frictions that have not yet been explicitly modelled. We will provide an explanation based on information and product competition among mutual funds.

Finally, we relate to the literature on liquidity. There is now a consolidated bulk of evidence that relates stock prices to liquidity costs, both theoretically (Amihud and Mendelson, 1986, Constantinides, 1986, Grossman and Miller, 1988, Vayanos, 1998, Vayanos and Vila, 1999) and empirically (Brennan and Subrahmanyan, 1996, Brennan, *et al.* 1998, Amihud, 2002). Illiquid stocks should earn a higher rate of return to compensate investors for the cost/risk of illiquidity. This can be seen as a transaction cost or as a common factor inducing co-movement across stocks (Chordia and Roll, 2000, Chordia and Subrahmanyam, 2001, Chordia *et. al.*, 2001, Huberman and Halka 2001) and priced in equilibrium (Pastor and Stambaugh, 2003

[2]The only noticeable exception is Petajvisto (2003).

and Acharya and Pedersen, 2003). However, as O'Hara (2002) points out, we do not know what really generates commonality and how the process of price discovery and trading impact prices and affect liquidity. We follow an approach in line with O'Hara (2002), but we directly focus on the main actors in the markets: the mutual funds. Mutual funds are interesting investors to consider, as they compete in two markets: the financial markets, where they invest and generate performance for their clients and the mutual fund market where they compete with each others on the basis of the service they provide and the price they charge. Nobody has, until now, considered their dual dimension.

Our contribution to the aforesaid literature is three-fold. First, we model the link between mutual funds and stock characteristics (price, volatility, liquidity, stock cross-correlation), directly analyzing *the role of competition between mutual funds on the equilibrium conditions of the financial markets where they operate.* We show that, if we properly account for this "product competition", the behavior of the funds and their market impact may differ from the way it has always been portrayed, with important implications for the equilibrium conditions of the financial markets where the funds operate.

Second, we provide testable implications of the role of mutual funds. We construct proxies ("fund characteristics") for unobservable shocks to the mutual fund industry and to their ability and willingness to generate information. This is the first attempt to directly quantify the informational impact of mutual funds by using micro-funded proxies.

Third, we test our restrictions on the US mutual fund industry. We directly investigate the relationship between the stocks held by the mutual funds and the characteristics of the funds who are holdings them. This is, to our knowledge, the first study that deals with the way the characteristics of the stocks (price, volatility, liquidity, cross-stock correlations) are related to the characteristics of the mutual funds (fees, number of funds, quality and cost of information of the funds and investor demand) that hold them, by using data disaggregated at the level of fund stock-holdings. Indeed, we complement the existing literature on mutual funds, (Grinblatt and Titman, 1995, Wermers, 2002) by using mutual funds holdings to investigate the determinants of the stock market.

3 The model

The economy.

We consider an economy with two classes of investors: ordinary investors and

mutual fund families. Families offer investment vehicles (i.e., mutual funds) that manage money on investors' behalf. Mutual funds compete to attract investors' money. The investors can either trade on their own accounts or invest in the mutual funds.

There are three periods. At time 1, the families set up the mutual funds and choose the investment in the information technology as well as the fees they charge for each fund. At time 2, the market opens and stocks are traded. Investors choose whether to invest in mutual funds or directly in stocks. Mutual funds invest the money they receive from the investors. The world ends at time 3, when the terminal payoff is realized.

The technology.

There are two assets: a risky asset and a riskless asset. The risky asset (stock) has a terminal value in period 3 equal to V. The price of the stock in period 2 is p_2. The riskless asset is in infinitely elastic supply and has a price in period 2 equal to p_B, which we normalize to 1. For simplicity and with no loss of generality we assume the riskless rate to be equal to 0.

There are M mutual fund families ($j = 1 : M$). Each mutual fund family (henceforth "family") offers several mutual funds. Mutual funds differ in terms of the information they have as well as of the fees they charge. Information can be represented in terms of the precision of the signal on the future value of the risky asset. Each mutual fund f [3] observes a signal $S_f = V + s_f$, where s_f is the noise of the signal. We assume that all the variables are normally distributed and independent of each other. In particular, $V \sim (0, \sigma_V^2)$ and $s_f \sim (0, \sigma_{s_f}^2)$, so that $S_f \sim (0, \sigma_V^2 + \sigma_{s_f}^2)$. We define $h_f = (\sigma_{s_f}^2)^{-1}$ the precision of the information available to the *fth* mutual fund. It represents the quality of the fund, or, alternatively, its performance, while θ_f is the fee it charges. In Period 2, the mutual fund invests on behalf of its clients, exploiting its superior information advantage (F_f) due to the investment in information. Both the mutual funds and the investors have mean-variance utility and, when investing in the stock market, submit market orders to risk neutral market makers who set the price. [4] We abstract from agency issues.

[3] *Fund f belongs to family j. We omit the subscript j to keep the notation simple. We will return to this point in the next section.*

[4] This modelization is similar to Hong and Stein (1999). Using a CARA utility, they derive a similar demand function of the form: $F_t = A + \phi \Delta P_{t-1}$, where ΔP_{t-1} represents the information set of the investors. In our case, we are implicitly standardizing around a previous price equal to zero. Given assumption of joint normality and zero mean of the payoff and signal variables, this amounts to a rescaling.

Proposition 1. *The mutual fund's investment in the stock is equal to:* $x_f = \frac{E\left[V|F_f\right]}{\rho Var\left[V|F_f\right]}$, *(see Appendix).*

Alternatively, we can define the investment of the fund directly in terms of its signal and its precision:

$$x_f = \frac{E\left[V|F_f\right]}{\rho Var\left[V|F_f\right]} = \frac{\left[V + s_f\right] h_f}{\rho}, \tag{1}$$

where ρ is the risk aversion of the investors in the fund. All the investors are assumed to have the same degree of risk aversion. The fund takes the clients' risk profile (ρ). This can be seen as the implementation of the "Best Execution Rule" that requires fund managers to suggest investments that are in line with investors' preferences and riskiness. Alternatively, this is the optimal response of the fund to investors' riskiness. The more risk averse the investors are, the more likely they are to redeem their units. This implies that the fund has to keep a fraction of its portfolio in liquid assets just to meet early redemptions (Edelen, 1999).

The investors' choice: delegation versus direct investment.

There is a continuum (of mass equal to 1) of small investors with identical degree of risk aversion (ρ). In period 2 each investor is endowed with a level of wealth that we normalize to 1. He chooses the investment in the *fth* mutual fund (ω_f) depending on the quality of the fund (h_f) and the fees it charges (θ_f). The investor can also directly invest in the stock. This corresponds to investing in a mutual fund that has the same information as the investor (h_0) and faces the investor's cost of generating such information (θ_0). Each investor maximizes a mean-variance function (Das and Sundaram, 1998):

$$Max\left\{E[W_3] - 0.5\rho Var[W_3]\right\}, \tag{2}$$

where W_3 is equal to:

$$W_3 = 1 + \sum_f \omega_f x_f V - \sum_f \omega_f \theta_f, \tag{3}$$

where x_f is defined as in equation 1. We can derive the optimal investment in mutual funds.

Proposition 2. *The investor invests in the fth fund according to:*

$$\omega_f = \frac{1}{\sigma_V^2\left[1 + \frac{2\sigma_V^2}{\rho} h_f\right]} \left[\frac{\sigma_V^2}{\rho} - \frac{\theta_f}{h_f} - \frac{2\sigma_V^4}{\rho} \sum_{i \neq f} \omega_i h_i\right], \tag{4}$$

where i represents all the other fund competing with the fth fund (see Appendix).

The investor trades-off the fees against the quality of the fund. The sensitivity to fees is related to the quality of the fund: as the precision of the signal grows, the demand becomes less sensitive to the fees. It is worth noting that a risk-averse investor will not invest in only one fund, but will purchase many funds as this allows him to diversify away his risk. That is, "a single fund manager would not offer diversification against the risk attendant in relying on his one signal" (Ross, 1998). This implies that the investors construct portfolios of funds diversifying away the signals.

The investment in the fund is also affected by the standard parameters - the volatility of the fundamentals (σ_V) - as well as some "competition parameters" - the quality of information of the competitors weighted by their demand ($\sum_{i \neq f} \omega_i h_i$). Given that each fund suffers the competition of the other existing funds, the demand for each fund is negatively related to the demand of the competitors as well as to the quality of the information they offer. That is, the more precise the signals of the competing funds, the lower the demand of the fund.

The mutual funds' strategies.

Let's now consider the mutual funds' strategies in more detail. For simplicity, we assume that the funds the family offers are carbon copies of each other - i.e., they charge the same fees and face the same start-up costs. We will use the subscript j to define the *jth* family. The profits of the family (Π_j) are determined by the number of funds the family offers, the fees it charges and the investment it makes in the information technology:

$$\Pi_j = N_j \omega_j \theta_j - c_j h_j - N_j K_j, \tag{5}$$

where N_j is the number of funds offered by the *jth* family, c_j is the cost to generate information, h_j is the amount of information generated (precision of the signal), θ_j the fee charged and K_j is a fixed cost incurred to start-up a fund.

Specification 5 is based on some underlying assumptions. First, the mutual fund family can be seen as a group of managers that get together and share the cost of the common research department. Each manager pays its own cost to access the market (K) and shares with the other managers the common costs of the research department (c). Alternatively, it can be seen as a centralized family that optimally chooses how many managers to hire. The family pays a fixed cost to recruit each manager (K) and faces a variable cost that is related to the size of the research department (c). In the standard literature on information (Admati, 1985, Admati

and Pfleiderer, 1988), these two variables can be interpreted as a fixed cost to access the information market (K) and a variable cost that is related to the amount of information purchased (c). The existence of the mutual fund family allows managers to share the variable costs.

Investors by buying several funds diversify across the signals. The family could provide the diversification service by offering only one fund that exploits the signals of all its managers/funds. That is, instead of offering new funds, the family can simply recruit new managers that endow the single fund with their signal. This strategy would not save the investors the payment of the Ks as these represent the remuneration for the managers to generate the signals. So investors would be indifferent between a single big fund with many managers and many funds run by a single manager. However, it would not be in the interest of the mutual fund managers. There are many reasons why managers do not want to be merged into one fund. Maybe the most important one is the desire to build a personal track record. Each fund manager has his own track record that depends on the quality of his past performance. This is something that allows the manager to market himself should he decide to leave the company. Merging the managers into one single funds would deny the managers such externally verifiable track record and would subject them to be "held-up" by the mutual fund family. Also, it would not be the same for the family as a big fund would face higher transaction costs related to its market impact.[5] We therefore rule out such possibility and focus on strategies where multiple funds are offered and the number of funds is endogenously chosen.

Also, equation 5 assumes that the investment in information is centralized at the family level. We can think of this as the research generated within the research department of the management company (e.g., Fidelity Asset Management) that benefits all the funds belonging to the same company. While funds run by different fund managers have access to different signals, the common research department gives the same precision to the signals. This captures the reality of the mutual funds families where the different managers have different abilities, but share a common information source - the research department of the family - that refines their signals.

The family is risk neutral and maximizes equation 5, solving for the optimal levels of funds, fees and information. At time 1, the family chooses the number of funds it sets up (N_j), the fees it charges (θ_j) and the investment in information (h_j). The latter can be interpreted as choice of the size of the research department

[5]Evidence of this is the increasing number of fund closures (from nil in the 1980s to 31 in 1996 alone). Some famous examples include Fidelity Magellan Fund, the largest mutual in the U.S., that was closed in 1997 and Turner Micro Cap Growth Fund and that was closed in 2000.

of the family.[6] We consider a competitive equilibrium, where each family does not consider its impact on either the mutual fund market or the stock market, but properly accounts for how its control variables (i.e., N_j, θ_j and h_j) affect investors' demand in the fund.[7]

At time 2, each fund receives a certain inflow of money to manage that is proportional to the fraction of investors who decide to invest in the fund according to the demand 4 and invests it. At time 3, the fund realizes the profits. We start at time 1 and determining the family's choice of quality of information, fees and number of funds.

Proposition 3. *The jth family chooses a level of investment in the information technology equal to* $h_j = \frac{2\rho}{\sigma_V^2}\Xi_j$*, sets the fees equal to* $\theta_j = \Psi_j h_j$*, and establishes a number of funds equal to* $N_j = \frac{c_j\rho\left(1-2\sigma_V^2\Theta_j\right)}{\sigma_V^2 K_j\left[1-8\rho K_j-4\sigma_V^2\Theta_j+4\sigma_V^4\Theta_j^2\right]}\Xi_j$*, where* $\Psi_j = \sigma_V^2\frac{\left(1-2\sigma_V^2\Theta_j\right)}{2\rho}$, $\Xi_j = \frac{2\rho K_j}{\left[1-8\rho K_j-4\sigma_V^2\Theta_j+4\sigma_V^4\Theta_j^2\right]}$ *and* $\Theta_j = \sum_{g\neq j}\omega_g h_g$ *(see Appendix).*

Fees and the investment in information are related through the parameter Ψ_j that captures the role played by the competition between funds. It is a function of the equilibrium number of funds in the industry, of the number of families, as well as of the volatility of the fundamentals. The Ψ_j term places a wedge between the investment in information and the fees that are charged.

It is interesting to compare this to the model of Berk and Green (2002). There, the assumption is that free competition in the mutual fund market equalizes fees to the fund performance (i.e., information of the fund). Here, there is a spread between performance and fees that is a function of the type of competition in the mutual fund industry. In particular, Ψ_j increases as investors invest less in the competing families (Θ_j). That is, the spread between the performance of the fund

[6] An alternative approach would be to consider a sequential decision process. The family first choose the number of funds to set up. Then, depending on the number of funds, the family decides the investment in information. Finally, conditional on the funds and the quality of information, it chooses the fee it charges. In this case, we work by backward induction: first we define the optimal level of fees that each family chooses, conditional on (i.e., parametric) the number of funds and the investment in information technology. Then, we solve for the investment in information technology conditional on the optimal number of funds and finally we solve for the optimal number of funds. This approach is more similar to the industrial organization literature (Anderson, de Palma and Thisse, 1994). Also, is consistent with the observation that funds change the fees and design the size of their research departments discretely over time, while they continuously reallocate their portfolios. Given that both the sequential and the simultaneous approach deliver similar results, we report only the ones based on the simultaneous approach. The others are available upon request.

[7] The assumption of competive mutual fund market is justified by the recent studies on fee setting in the mutual fund market (Christophersen *et al.*, 2000).

and the fees it charges increases with the market share of the family. At the limit, if investors just invest in the *jth* family (i.e., $\Theta_j \to 0$), then $\Psi_j = \sigma_V^2/2\rho$. That is, the *jth* family has the maximum market power and sets the fees as a function of the level of uncertainty (volatility of fundamentals) per unit of risk aversion. The higher the uncertainty, the more the family can charge for a unit of performance. This is consistent with standard theory that suggests that the value of information is higher in very uncertain states.[8]

This is a partial equilibrium result, as Θ_j is still a function of the behavior of the other families. We therefore now proceed to solve for the symmetric equilibrium. We assume that all the families have access to the same technology. That is, $c_j = c_g = c$, and $K_j = K_g = K$, for each $g \neq j$. Given the assumption of a common cost technology, we can find a symmetric equilibrium, where $\theta_j = \theta_g = \theta$, $h_j = h_g = h$, and $N_j = N_g = N$ for each $g \neq j$.

Proposition 4. *There exists a symmetric equilibrium in the mutual fund market that defines the solution* $\{\theta, h$ and $N\}$ *(see Appendix).*

The equilibrium in the mutual fund industry is defined in terms of the level of fees (θ), the investment in the information technology (h) and the number of funds (N). At equilibrium the number of funds will be a function of the cost structure of the mutual fund industry (c and K), of the number of families (M) and of the fundamentals (σ_V). We will carry out the comparative statics in the following section. We now concentrate on the specification of the equilibrium in the stock market.

Equilibrium in the stock market.

In period 2 fund managers, as well as the investors who invest directly, submit their bids to a risk-neutral market maker. The total order flow to the market maker is:

$$F = A + BV + C\overline{s}, \tag{6}$$

where F is the total demand of the stock, $\overline{s}$ is the aggregate noise of the signal of

[8]It is also interesting to note that both the investment in information and the fee charged are not a *direct* function of the cost of information, while the number of funds is. That is, the optimal reaction function of the family to an increase in the cost of information is an increase in the number of funds it offers. This however, does not mean that the amount of information and the fees are not *indirectly* related to the cost of information. Indeed, in equilibrium, an increase in the cost of information, inducing an increase in the number of funds and, therefore an increase in Θ_j, also reduces the investment in information. To explore this issue we have to solve for equilibrium.

the mutual funds[9] and A, B and C are coefficients defined in the Appendix. These coefficients are a function of the equilibrium parameters in the mutual fund market (θ, h and N). The market maker observes the order flow and sets the price equal to the expected value of the asset. That is,

$$p_2 = E[V|F] = \mu_p + \lambda F, \tag{7}$$

where $\lambda = \frac{\sigma_V^2}{B\sigma_V^2 + C\sigma_s^2}$ and $\mu_p = \frac{V_1(\sigma_V^2+\sigma_s^2)-\sigma_V^2(A+BV_1)}{\sigma_V^2+\sigma_s^2}$. We can therefore determine the equilibrium in the stock market.

Proposition 5. *The equilibrium stock price is $p_2 = \mu_p + \lambda F$, volatility is $\sigma_{p_2} = \lambda\sqrt{B^2\sigma_V^2 + C^2\sigma_s^2}$, trading volume is $T_{p_2} = 2\sqrt{\frac{2}{\pi}}\left(|B|\,\sigma_V^2 + |C|\,\sigma_s^2\right)$ and market depth is $D_{p_2} = \frac{B^2\sigma_V^2+C^2\sigma_s^2}{B\sigma_V^2}$ (see Appendix).*

Our goal is to link the empirical restrictions that link stock characteristics to mutual fund characteristics. We will therefore not dwell on the welfare implications of the model. However, there is one interesting point worth stressing. Given that investors are relatively less informed than the mutual funds, they are expected to lose when they trade with the market makers. Indeed, the market makers compensate the losses from trading with more informed funds with the gains from trading with less informed investors. At equilibrium investors either pay a fee to invest into the fund or face a loss by directly trading. Therefore, mutual funds can be seen as a device that allows investors to overcome their informational disadvantage and the fees they charge are directly related to the total cost of direct trading.

4 Main testable restrictions

We now carry out some comparative statics to see how the equilibrium conditions of the mutual fund industry (fees, cost of and investment in information, investors' demand of the fund, number of funds) are related to the equilibrium conditions of the stock market (stock price, volatility, volume and market depth). In order to do this, we refer to Figures 1-2. Each Figure represents a set of comparative statics for a change of either the cost of information (Figure 1) or the cost of setting up a new fund (Figure 2). The graphs stacked on the left side of the figure describe the amount of information purchased, the fees charged and the number of funds offered

[9] We have a discrete number of mutual funds so, while s_f approaches 0 as the number increases, this is not necessarily the case in a limited sample.

by each family and the investment in mutual funds. The graphs stacked on the right side represent stock volatility, trading volume, market depth and stock price.[10]

We immediately see the trade-off between number of funds and information. An increase in the cost of generating information reduces the amount of information and increases the number of funds. Conversely, an increase in the cost of adding new funds reduces the number of funds and raises the investment in information. Fees are linked to the investment in information: they decrease as the cost of information rises and increase as the cost of setting up new funds increases. The intuition is that fees are directly related to the services the fund provides. If performance is lower (due to lower information), funds have to make it up for it with lower fees. In both cases (i.e., a change in the cost of setting up a fund as well as the cost of generating information), there is a *negative correlation between the amount of information that is generated in equilibrium and the number of funds.*

Let's now consider the equilibrium in the stock market. First, less information (due to either an increase in the cost of generating it, or a reduction in the cost of setting up new funds) increases the investment in mutual funds (last graph in the first column of Figures 1-2) and, consequently, the investment in stocks of the mutual funds. This unexpected result is due to the trade-off that mutual fund families have between number of funds and performance. Lower quality information induces the investors to reduce their investment in each individual fund and to diversify across many funds. Families cater to this desire by setting up more funds. At the aggregate level, this implies a greater investment in the mutual fund industry as a whole. Therefore, as information drops, more demand accrues to the mutual funds. This raises the investment in the market of relatively less informed mutual funds.

What is the market impact? *A higher demand from relatively less informed investors reduces the informational disadvantage of the market makers.* This lowers volatility and prices and increases market depth. This is straightforward from Kyle's intuition. The market impact (λ) of the trades placed by the mutual funds is lower the lower the quality of their information or, alternatively, the higher their learning errors.[11] Moreover, this also implies a negative correlation between information and trading volume.

It is interesting to consider the effects in terms of informational efficiency. More information (due to either a lower cost of information production or a higher cost of setting up new funds) increases price informativeness. However, this higher in-

[10]These results are qualitatively invariant to changes in the fundamental value of the risky asset.

[11]Note that here the learning error of the mutual funds (or the noise of their signal s) plays the role of "noise trading" in the standard Kyle model.

formational efficiency is not enough to offset the higher informational asymmetry between funds and market makers. This explains the higher volatility and lower liquidity.

Therefore, *an increase in the cost of generating information, or a reduction in the cost of setting up a new fund reduce the amount of information, increase the investment in mutual funds and funds' investment in stocks. Mutual fund families reduce fees and increase the number of funds offered. The net effect is a reduction in volatility and prices and an increase in market liquidity (market depth and trade).*

This implies also a set of restrictions on stock prices.[12] An increase of the cost of information (or reduction in the cost of setting up a fund) lowers the amount of information and reduces prices. If stock prices decrease with the cost of information, there is a positive correlation between prices and the level of fees the funds charge and their degree of informativeness and a negative correlation between prices and the number of funds and the demand facing them.

The model is a single asset framework. However, in the case of many assets, the same parameters affecting price and volatility would also determine the correlations across stocks. For example, if two stocks are held by funds with fees relatively higher than average, we would expect that they would also be more cross-correlated. Therefore, we expect the absolute level of cross-stock correlation to be directly affected by the fund characteristics.

We now have available a way of directly investigating the channel through which mutual funds affect stocks. The intuition in the literature has always been that a reduction in the cost of information production lowers volatility, increases stock prices and liquidity. However, there is no direct data available about the amount of information. Our simplified model provides testable restriction in terms of (fully and partially) observable variables: level of fees, funds' performance/informativeness, number of funds, investors' demand of funds and cost of producing information. *Fees,* and the level of *information of the fund* should be positively related to stock price, volatility and cross-stock correlation and negatively related to liquidity. *The*

[12]From equation 7 it appears that stock prices are affected by the cost of information, the cost of setting up a fund and the degree of risk aversion of the investors and fund managers. The results depend on the values of the market prior of the true value of the asset and on the true value of the asset (V). It can be shown that an increase in the cost of information (or reduction in the cost of setting up a fund) amplifies market sentiment. That is, if the market prior on the value of the asset is higher than the true value, an increase in the cost of information (and therefore an increase in the number of funds) raises prices. Viceversa, if the market prior on the value of the asset is lower than the true value, an increase in the cost of information lowers prices. We consider a benchmark case where market prior coincides with the value of the asset and where the number of mutual funds is high.

number of funds, investors' demand of the fund and the *cost of information* should be negatively related to stock price, volatility and cross-stock correlation and positively related to liquidity. These restrictions are summarized in Table 1.

Table 1: Impact of Fund Characteristics and Stock Characteristics.

Stock Characteristics	Fund Characteristics				
	Fees	Info	N.Funds	Demand	Info Cost
Prices	+	+	-	-	-
Volatility	+	+	-	-	-
Liquidity	-	-	+	+	+
Correlation	+	+	+	+	+

What are the proxies for these variables? The level of fees and the number of funds are easily available. In the case of the number of funds, we are in fact proxying for the information that is generated in the sub-segment of the mutual fund industry that invests in the specific stock. Indeed, our model assumes the cost of generating information as well as the cost of setting up a new fund (hiring a manager) to be the same for all the families *investing in the same stock*. That is, the stock and the segment coincide. However, funds tend to operate in different market segments (i.e., style or investment objective) and the cost technology varies across segments. The ideal proxy would therefore be the number of funds per market segment. The higher the number of funds in such a market, the less information is generated. Given that we do not have a good definition of market segment[13], we use the number of funds as a proxy for it.

Unlike the style literature, our variable is directly related to the information generated in that segment, and not just to the generic effect of belonging to a "style" (Barberis and Shleifer, 2002 and Teo and Woo, 2003). In order to test for pure "style effects" (Barberis and Shleifer, 2002 and Teo and Woo, 2003), we also construct categories based on the objective of the mutual fund. Mutual funds are classified into 25 categories based on their objective as given by the ICDI_OBJ field in the CRSP annual summary data file. In this case, given that this field has no significance before 1992, we restrict our analysis to the period 1992 onwards a file generated based on integration with morning star database is used. The results with this classification do not turn out to be significant.

The information of the fund is directly related to its performance. It can therefore be proxied by fund's performance. Investors' demand of a fund can be represented

[13]The Weisember classification contains 27 styles, the one based on ICDI number 25, the classification based on styles-objectives contains 173. If we focus only on funds that hold stocks, the number drops to 40.

by the total amount invested in the fund.[14] The variable for which is more difficult to find a direct proxy is the cost of information. We consider two alternative variables: the standard deviation of funds' returns and the standard deviation of investors' flows. The rationale is the following. Regarding the volatility of returns, we appeal to the standard literature on information economics that relates the value of information to the riskiness of the payoff. When volatility is high, information that reveals it is more valuable. Therefore, we expect that also its cost should be higher. This suggests a positive correlation between the volatility of returns and the cost of information.

Regarding the volatility of investors' flows, the intuition is related to the cost of liquidity. It has been shown that mutual funds have to pay a liquidity cost due to the need to meet redemptions (Edelen, 1999). Therefore, the higher the probability of redemptions, the more expensive it would be to generate performance as some money has to be tied up in liquid assets. The higher the volatility of investors' flows, the higher the probability of redemptions and therefore the higher the cost. This implies that there is a positive correlation between the volatility of investors' flows and the cost of information/performance.

Two points are worth stressing. First, it may be argued that more redemptions flows change the mix of informed versus uninformed trade. For example, a fund with more redemptions may be induced to rebalance his portfolio on a pure uninformative basis more often, just in order to invest the flows. This would make a fund with higher volatility of flows a less informed investor. In this case, as Table 1 shows, the restrictions would be the same. That is, we expect high volatility of flows to be negatively related to volatility either because a high-volatility flows has higher cost of information (last column) or because is less informed (second column). Second, all our empirical tests will be based on classifications of funds defined in terms of their "historical" characteristics. For example, a fund is defined as "high volatility" if it has had a volatility higher than the volatility of the other funds *in the previous* 12 months. This prevents any "circularity" in our reasoning and spurious correlation in the regressions.

The main testable restriction of our model is the link between the characteristics of the funds (i.e., fees, information, number of funds, investor demand of the fund and cost of information) and the equilibrium conditions of the stocks they hold (i.e., stock price, volatility, liquidity and cross-sectional correlation). To investigate it,

[14]Given that investors can, at any time, redeem their shares in the fund, the actual demand is the total amount invested in the funds as opposed to the mere fund inflows. These just represent a change of demand. Therefore, the correct measure of investors' demand for a mutual fund are its total net assets. This directly corresponds to the demand ω_f in the model.

we proceed in two steps: fund categorization and testing. First we categorize funds in terms of their characteristics. That is, for each fund characteristic, (e.g., level of fees), we group funds in 10 categories on the basis of the "intensity" of such a characteristics (e.g., level of fees). Then, we link stocks to the holdings of the funds belonging to each category. As a second step, we construct portfolios of stocks on the basis of these characteristics and we test whether these portfolios display significant differences in terms of prices, volatility, liquidity and cross-correlations and whether these differences can be explained in terms of the holdings of the mutual funds.

5 Methodology and data

5.1 Fund categorization

The process of fund categorization involves grouping mutual funds in 7 categories on the basis of their characteristics as outlined in the model (i.e., fees, fund informativeness, number of funds, investor demand of the fund, and three alternative measures of the cost of information). Stocks are then assigned to each category on the basis of the characteristics of the funds who hold them. We proceed as follows. First, each quarter, we identify the characteristics of each mutual fund for that quarter (e.g., fees). We then rank the funds on ascending level of that characteristic and group them in ten deciles. Once funds are divided into deciles, for each stock we compute the holdings of the funds belonging to each decile. For example, in the case of IBM, we determine how many shares of IBM are held by all the funds that belong to the lowest decile of fees, to the next to the lowest decile, and so on. This delivers, for each stock, 10 time series of holdings, each one corresponding to a different decile, with 92 quarterly observations, from January 1978 to December 2000. We also adopt a second approach where we attribute each stock to one single category. That is, each quarter, for each stock, we identify the decile whose funds own the highest number of shares of the stock and we *uniquely* attribute the stock to such a decile, setting to zero the holdings in the other deciles. We will refer to the first approach as Classification I and the second as Classification II.

The categorization based on fees uses the total expense ratio. This is constructed as in the literature, adding 1/7 of the load fees to the expense ratio.[15] It represents the percentage of the assets under management that is paid by the fund-holder to the mutual fund and is the broadest measure of fees (θ). Funds are divided into ten deciles: funds with the lowest fees come in category 1; the ones with the next to the lowest fees come in category 2 and so on.

[15]It assumes that investors in the fund have an investment horizon of 7 years.

The categorization based on fund informativeness uses performance (Sharpe ratio)[16] in the previous 12 months, while the categorization based on investors' demand of the fund uses the total net assets of the fund. The funds with the lowest performance (demand) are in the first decile, the funds with the next to the lowest performance (demand) are in the second decile and so on. Then, for each stock we calculate the holdings of the funds belonging to each decile. This delivers for each stock ten times series with 92 quarterly observations, from January 1978 to December 2000.

The categories based on cost of information are constructed as follows. Cost of information is defined in terms of the standard deviation of the fund flows (i.e., higher standard deviation corresponds to higher cost of information) as well as the standard deviation of performance. We use both the level of flows as well as the relative flows (i.e., standardized by the total net assets at the beginning of the period where flows are computed). Funds are categorized on the basis of the standard deviation of flows (performance) in the previous 12 months and sorted according to it. The funds with the lowest standard deviation of flows (performance) are in the first decile, the funds with the next to the lowest standard deviation of flows (performance) are in the second decile and so on. Then, for each stock we construct the holdings of the funds belonging to each category.

The categorization based on the number of funds that hold a stock is different, as it relies on a characteristic (i.e., the number of funds) that is defined at the stock level. One possibility would be to use as a variable the number of funds for each stock. This however, would not exploit the information contained in the holdings. We therefore adopt a different approach. Each quarter, stocks are divided into ten deciles: the stocks held by the lowest number of funds are in the first decile, the stocks with the next to the lowest number of funds come in second decile and so on. This generates 10 deciles. The affiliation of a stock with a decile is based on the number of funds holding the stock. Then, for each stock, we assign all the fund holdings to the decile it belongs to. For example, if IBM ranks second in terms of the number of funds holding it, IBM will have all the holdings in the second decile. In other words, IBM is held by a fictitious fund that, in terms of the characteristic "number of funds", ranked second from the bottom. This also implies that for the categorization based on the number of funds, both Classification I and II will coincide.

[16]The Sharpe ratio may also reflect the style. To control for it we will use as control variables the book-to-market ratio, market capitalization (size) and number of share outstanding of the stocks under consideration.

5.2 Proxies for liquidity

In line with the literature, we consider different proxies for liquidity. The main proxy we focus on is Amihud's illiquidity ratio (2002). The daily illiquidity ratio of Amihud (2002) is constructed as:

$$IR_{it} = \frac{\mid R_{it} \mid}{T_{it} * P_{it}},$$

where R_{id} is the return on day t on stock i, T_{it} is the number of shares traded of stock i for day t and P_{id} is the stock price. What we define as illiquidity ratio is the monthly average of the daily illiquidity ratios. This variable represents the total cost associated with trading a given number of shares. It is based upon Kyle's intuition that illiquidity is the relationship between price change and the associated order flow. It can be shown that this variable is positively related to the high-frequency measures of price impact and fixed trading costs (Cooper *et al.*, 1985 and Khan and Baker, 1993). This measure has been used by Amihud *et al.* (1997) and Berkman and Elsewarapu (1998) and, more recently, by Acharya and Pedersen (2002). Hasbrouck (2002) has shown that it is a good proxy of Kyle's lambda derived by using micro-structure data.

In addition to this measure, we construct other measures of liquidity commonly used in the literature: the number of shares traded, dollar volume, turnover and bid-ask spread. Dollar volume, defined as the number of shares traded times price, has been used by Brennan *et al.* (1998). Turnover is constructed as the ratio of the number of shares traded and the number of shares outstanding. It has been originally proposed by Amihud and Mendelson (1986). It is negatively related to illiquidity costs, under the assumption that "the more illiquid costs are allocated to investors with lower trading frequency who amortize the illiquidity cost over a longer period, thus mitigating the loss due to the asset's illiquidity costs."

Bid-ask spread is defined as the difference of daily bid and ask prices standardized by the price. For standard-size transactions, the bid-ask spread is a good proxy of the market impact of each trade (Kraus and Stoll, 1972 and Keim and Madhavan, 1996). As such it is linked to measures of inside information (Easley and O'Hara, 1987). However, this measures suffers from the quality of the data as contained in CRSP. We therefore use this measure mostly as a robustness check. Both the illiquidity ratio and the bid-ask spread are negatively related to the level of liquidity, while turnover, dollar volume and number of shares traded are positively related to it.

5.3 The data

We focus on the US equity market and US equity mutual funds. We use three datasets: CRSP Stocks, CRSP Mutual Funds and SPECTRUM Mutual Funds. The CRSP Mutual Funds Files contain detailed information on the mutual funds (i.e., performance, total net asset values, fees, family affiliation, and other characteristics). For each fund we extract information about the fees (expense ratio and load fees), monthly returns and flows in the fund. The volatility of the flows (returns) over a year is calculated as the standard deviation of the flows (returns) over the respective twelve months. The flows are calculated using the total net assets file and the returns as: $FLOW_t = TNA_t - TNA_{t-1} - TNA_{t-1} * Ret_t$,where TNA_t and Ret_t are, respectively, the total net asset value and the returns of the fund. Alternatively, we consider the relative flows, that is, the flows standardized by funds' total net asset value at the beginning of the period. This allows us to consider two measures of volatility of flows: the volatility of the absolute level flows and the volatility of the relative flows.

We use the daily CRSP Stocks Files to calculate the monthly stock returns, traded volumes, turnover, volatility and bid-ask spreads. The SPECTRUM Mutual Funds data contain informations on the mutual funds' holdings of stocks traded in NYSE, AMEX and NASDAQ. All registered mutual funds filing shareholder reports with SEC are included. From the SPECTRUM dataset we derive the stock holdings of the funds.

All the three datasets sets have information that dates back to the 70s. This allows a proper analysis of the long term relationship between stocks and funds. However, as of now, few have exploited such information in its entirety, due to the problem of merging the three datasets. Partial use of it has been done by Wermers (2000) and Cheng *et al.* (2003). For a detailed description of the procedure used we refer to the Appendix. For the purpose of this paper, we eliminate the index funds as their economics is very different from the other mutual funds. Indeed, index funds merely replicate the return on aggregated indexes and therefore we do not expect them to generate information.

6 Empirical relationship between stock and fund characteristics

We now proceed to test the relationships contained in Table 1. It is important to emphasize the scope of our search. Table 1 provides a series of restrictions that come from a model where there is a clearly defined causality from the mutual funds

to the stock market. We plan to use the plurality of restrictions to assess whether mutual funds affect the stock market. If the causality were from stock market to funds, there is no reason to expect *all* these restrictions to be *simultaneously* met. In additions, the way we define the variables allows us to control for reverse causality, as we construct our fund-based characteristics relying on classifications that use previous (12 months) data.

6.1 Volatility and liquidity

We start by looking at the relationship between stock volatility and liquidity and mutual fund characteristics. We defer the discussion on correlations and returns to the following sections. We consider the restrictions summarized in Table 1. For consistency with the literature, we adopt a methodology analogous to the one employed by Gompers and Metrick (2000) and by Coval and Moskowitz (2000 and 2002).[17] We estimate:

$$S_{it} = \alpha + \beta F_{it} + \gamma C_{it} + \varepsilon_{it}, \tag{8}$$

where S_{it} is the stock characteristic (alternatively volatility and liquidity) of the *ith* stock at time *t,* F_{it} is the proxy that captures fund characteristics and C_{it} is a vector of control variables. The control variables include the stock market capitalization, the number of shares outstanding and the book-to-market ratio of the stock. We also use a dummy that proxies for the exchange where the stock is listed. These variables are similar to the ones already employed by Gompers and Metrick (2000) and are standard in the literature.

The variable that proxies for the fund-specific characteristics (F_{it}) is constructed using the mutual funds' stock holdings we defined before. For each stock and quarter we define the holdings of "High" and "Low" funds. The High funds are the funds belonging to the top 3 deciles and the Low funds are the ones belonging to the bottom 3 deciles. The top 3 deciles and the bottom 3 deciles constitute the "High" and "Low" groups.[18]

Then, for each stock and quarter we construct 2 proxies of fund characteristics. The first is the difference between the number of shares of the stock held by the High funds and the number of shares of the stock held by the Low funds. The second is based on the standardized difference. That is, the difference between the number of shares held by the High funds and the number of shares held by the

[17] As a robustness check we also estimated a panel specification. The results are consistent with the ones reported.

[18] The only exception is the categorization based on fees. Given that the CRSP dataset is not very precise in reporting the case of zero load fees, we use as bottom deciles the 2nd, 3th and 4th.

Low funds is divided by the sum of the number of shares of both High and Low funds. The results based on the first proxy are reported in Specification I, while the results based on the second proxy are reported in Specification II. The estimations are based on a Fama-MacBeth procedure with correction for autocorrelation. As we mentioned before, we consider two alternative ways of defining the holdings of the funds. The first reports, for each stock, the holdings of all the funds belonging to the 10 deciles within each category (Classification I). The second classification, instead, only reports the holdings of the main decile (Classification II).[19]

The results are displayed in Table 2, Panel A for Classification I and Panel B for Classification II. We report the average values of the cross-sectional coefficients as well as the *t-statistic* for β, for the different measures of liquidity and volatility. The results are strikingly supportive of our hypothesis and are robust across specifications. In almost all the specifications, stocks that display higher volatility and lower liquidity are the ones held by funds either more informed, or charging higher fees or with lower cost of information. In contrast, stocks held by more funds or funds facing higher demand have lower volatility and higher liquidity. These results show that mutual funds do indeed affect the stocks they hold.

It is interesting to note that the results are not predicated on the fact that a generic mutual fund hold the stocks, but on the fact that *funds with specific characteristics* hold them. In both classifications (I and II), the factor that proxies for mutual fund characteristics is either based on the difference of holdings or on the *standardized* holdings. That is, the absolute amount of holdings *per se* is not the key determinant. This sets this paper aside from previous contributions to the literature (Warther, 1995, Starks *et al.*, 1998, Zheng, 2000). Moreover, it differentiates our contribution in terms of the literature on limited arbitrage as the impact of mutual funds on stocks is redefined in terms of the characteristics of the fund.

These results link stock volatility and liquidity to the characteristics of the mutual funds holding them. These can be considered a stock-specific characteristics. However, as Brennan *et al.* (2000) have shown, there is a commonality in liquidity. That is, there are common factors that drive stock liquidity and induce stock liquidity to co-move. In our model, the common factor is represented by the mutual fund stockholdings. It is therefore possible that fund-based characteristics aggregate at the market level, inducing common movements across stocks. That is, we may expect stock volatility and liquidity to be affected by the *aggregate* difference between the holdings of 'High' and 'Low' funds. For example, the more stocks are held by high fee funds, the lower the liquidity and the higher the volatility.

[19]In the case of the standardized specifiication, this effectively corresponds to a dummy taking a value of +1 or -1. This allows us to control for potential spurious correlation on quantities.

In order to test this, we construct common fund-based factors and relate them to stock volatility and liquidity. The factors are constructed as follows. For each stock we calculate the standardized difference between the number of shares held by the top 3 deciles and the bottom 3 deciles within each category. These ratios are then aggregated across all the stocks, for each quarter. Then, we estimate:

$$S_{it} = \alpha + \beta F_t + \gamma C_{it} + \varepsilon_{it}, \tag{9}$$

where F_t represents the mutual fund factor. As in the previous case, we consider two different classifications, one based on the holdings of all the funds in the specific category (Classification I) and one based on the holdings of just the main category (Classification II). We estimate three specifications: one based on the contemporaneous value of the F_t and two based on lagged (one and two period lagged) values of F_t. That is, for each quarter in which we define the holdings, we construct our fund-based factors and then we relate them to volatility and liquidity in the same month and one and two months ahead. The purpose is to determine the stickiness in the reaction of such variables to the common fund-based factor. Equation 9 is estimated as a pooled cross-section with consistent-White corrected variance covariance matrix.

The results are reported in Table 2, Panel C. They mostly confirm the previous results, even if in some cases (cost of information) the results are not significant. The impact seems to fade away with time.

6.2 Cross-stock correlations

We now consider the stock cross-correlations and see whether we can explain them in terms of the fund characteristics. We argued that the very fact that stocks are held by mutual funds with similar characteristics (i.e., fees, fund informativeness, number of funds, investor demand of the fund and fund cost of information) should make them move more in sync. That is, for each characteristics, stocks should covary more with other stocks held by funds belonging to the same decile. For example, the stocks held by funds belonging to the 1st decile in terms of fees (i.e., lowest fee) should covary more with the other stocks held by funds belonging to the 1st decile.

We can test this hypothesis in two ways. First, for each stock we can calculate the relationship between its (absolute) correlation with the other stocks belonging to the same category/decile and the fund-based characteristics of such a category/decile. Alternatively, for each stock we can construct the difference between its (absolute) correlation with the other stocks belonging to the same category/decile and the (absolute) correlation with the stocks belonging to an 'opposite' decile within the

same category. For example, in the case of fees, we can calculate the difference between the correlation of stock i with all the other stocks belonging to the 1st decile (i.e., lowest fees) and the correlation of stock i with all the stocks belonging to the 10th decile (i.e., highest fees). Then, we can relate these differences in cross-correlations to the difference in fund-based characteristics of the two deciles.

6.2.1 A measure of cross-stock correlations

What is the measure of cross-correlation? For each mutual fund characteristics (i.e., fees, informativeness, number of funds, investor demand of the fund and cost of information) we construct a measure of stock cross-correlation. We proceed as follows. First, for each fund characteristics (e.g. fees) we rank the funds into deciles as defined above. Then, within each decile, we calculate the average stock cross-correlation for all the stocks held by the funds belonging to such a decile. The calculation of the correlations uses the daily return data from CRSP Stock Files. The daily returns of each stock in each category are correlated with those of the other stocks in that particular decile. Given that we have information on the holdings only at a quarterly frequency, we construct quarterly time series.

As before, we consider two classifications: one based on the holdings of all the funds in the specific decile (Classification I) and one based on the holdings of just the main decile (Classification II). In the first case, we consider the correlation between all the stocks for which there is at least a fund with the specific decile/characteristic (i.e., 1st decile in terms of fees) that holds the stocks. In the second classification we consider the correlation between all the stocks for which the main holders are the funds with the specific decile/characteristic. Given that we want to focus only on the stocks that are more affected by the specific fund characteristics, we limit ourselves only to the top 25% of stocks within each decile. That is, we divide the holdings by the number of shares outstanding to obtain homogeneous ratios, we rank stocks according to these ratios and then we select the top 25% and construct the cross-correlation of each of these stocks with the other stocks within the same decile/category.[20]

One possible criticism of this approach is the fact that high cross-stock correlation may be due to similar stock-specific factors as opposed to fund-specific ones. The company size or its book-to-market ratio would be an example of it. In order to address this issue, we also consider an alternative way of construction of the correlations based on the book-to-market characteristics of the stock. This second criterion

[20]This procedure also has the advantage of being less computational intensive. Indeed, the computation of the cross-correlation for all the stocks within a category is very time-consuming, requiring the calculation of all the combinatorial possibilities of stocks' cross-correlations.

is based on a pre-classification of stocks on the basis of the book-to-market criterion. That is, within each category, the stocks are first ranked in terms of the BE/ME ratio into top, medium and bottom classes, using the BE/ME [21] methodology proposed by Fama and French (1992,1993).[22] Then, we compute the cross-correlation of each of these stocks with the other stocks belonging to the same decile/category. We will define this second way of constructing correlations as "Adjusted" and the former one as "Unadjusted".

6.2.2 The specification and the findings

Our tests are based on the following specification:

$$\Psi_{it} = \alpha + \beta F_{it} + \gamma C_{it} + \varepsilon_{it}, \tag{10}$$

where Ψ_{it} is one of the two measures of stock cross-correlation we mentioned before. In the first case, it is the difference between the absolute value of the correlation of the *ith* stock with the other stocks within the same decile/category at time t and the absolute value of the correlation of the *ith* stock with the other stocks belonging to the opposite decile within the same category at time *t*. In the second case, it is the absolute value of the correlation of the *ith* stock with the other stocks within the same category at time *t*. We will define the first specification as "Differential Specification" and the second as "Level Specification". F_{it} is the proxy that captures the characteristics of the funds holdings the *ith* stock and C_{it} is a vector of control variables defined as in the previous section. F_{it} has been constructed, as in the previous section, as a standardized difference of holdings. As before, we consider two classifications one based on the holdings of all the funds in the specific category (Classification I) and one based on the holdings of just the main category (Classification II). Also, as a robustness check we consider both the "Unadjusted" correlations (Specifications I and II) or the "Adjusted" ones (Specifications III and IV). We define as top and bottom percentile, either the 3 top deciles and the 3 bottom deciles (Specification I and III) or the 5 top deciles and the 5 bottom deciles (Specification II and IV).

The estimations are done using the Fama-MacBeth procedure with correction for autocorrelation. The results are in Table 3, Panel A for the differential specification

[21] Book Equity (BE) is equal to Stockholder's Equity + Balance Sheet Deferred Taxes + Investment Tax Credit, or Compustat (216)+Compustat(35)-Compustat(56), while Market Equity (BE) is equal to Closing Price x Common Shares outstanding, or Compustat (199) xCompustat(25).

[22] That is, the value of the BE/ME for every stock is compared with the closest value in the percentile information and the stock is categorized using the break points defined by Fama and French (see K. French's web page). We consider as top the percentile >= 18, medim the percentile such that 11 >= Percentile >= 9 and bottom the percentile <=2.

and Panel B for the level specification.[23] We report the value of the coefficient β and its *t-statistic*. The results support our working hypotheses. For all the fund characteristics there is a positive and statistically significant correlation between fund-based characteristics and stock cross-correlations. These results hold across all the specifications and are robust to the change of the criterion of classification as well as for both the level and differential specifications.

Similarly to the previous section, we also consider the relationship between stock cross-correlations and a common factor constructed on the basis of fund characteristics. The common factor is based on aggregated measures of fund characteristics defined as in the previous section. The dependent variable is, for each stock, the difference between the stock's (absolute) correlation with the other stocks belonging to the same decile/category and the stock's (absolute) correlation with the stocks belonging to an 'opposite' decile within the same category. We estimate the specification both as a pooled GLS (with White correction) and as a panel fixed-effect. As before, we consider two classifications one based on the holdings of all the funds in the specific category (Classification I) and one based on the holdings of just the main category (Classification II). Also, as a robustness check we consider both the "Unadjusted" correlations (Specifications I and II) or the "Adjusted" ones (Specifications III and IV). As before, we define as top and bottom percentile, either the 3 top deciles and the 3 bottom deciles (Specification I and III) or the 5 top deciles and the 5 bottom deciles (Specification II and IV). For brevity we report only the results based on the first classification (Classification I).

The results are reported in Table 3, Panel C. They confirm the previous findings, suggesting that fund characteristics directly impact the level of stock cross-correlation. These results are robust across specifications and for different classifications. Fund characteristics not only affect the stocks directly held by the funds, but they also aggregate at the market level generating co-movement. These findings show that fund-specific characteristics, *unrelated to the stocks as well as to the terminal investors themselves*, may affect stock volatility, liquidity and cross-correlations. Moreover, the fact that the results hold also after having controlled for book-to-market and size, provides additional strength to our results.

It is interesting to compare these results to the existing literature. Barberis and Shleifer (2002), have argued that investors have a tendency to classify risky assets into different styles. This implies that "news about one style can affect the prices of other apparently unrelated styles. Assets belonging in the same style will co-move more than assets in different styles." More recently, Barberis *et al.* (2003) show how the inclusion in the S&P 500 index increases the correlation of the new stock with all

[23]For brevity, we report only the ones based on the Unadjusted correlations.

the other stocks belonging to the same index. This avenue of impact from mutual funds to stock returns is entirely "demand driven", based on the irrationality of investors' behavior (i.e., tendency to classify) and on their tendency to evaluate the assets on the basis of relative performance. Our story is "supply driven", that is, it is the industrial organization of the mutual fund industry that affects the liquidity, volatilities, and cross-correlations of the stocks held by the funds. The structure of the mutual fund industry (information cost, cost of setting up new funds,...) acts as an amplifying device. We now move on to analyze the impact on prices.

6.3 Prices

We now move on to the relationship between stock prices and fund characteristics. We refer to Table 1 for the main restrictions. As we pointed it out, the impact of mutual funds should increase the price of some stocks and reduce the price of others, depending on fund characteristics. We therefore directly focus on fund-specific characteristics and see whether they allow us to "forecast" future stock prices. Then, relying on the previous findings on co-movement, we push further and we adopt a standard "pricing test", a la Fama and French (1993) to see whether the fund-based characteristics are priced factors.

6.3.1 Trading strategies based on fund-characteristics

A way of assessing whether fund-based characteristics affect stock prices consists of studying if it is possible to design strategies that rely on such fund-characteristics and deliver significantly higher returns than strategies based on the standard market factors. We adopt the standard methodology (Coval and Moskowitz, 2001, Gompers *et. al.*, 2003) and construct portfolios based on such characteristics. In particular, each quarter we construct High and Low funds portfolios by averaging the returns of the stocks belonging to the top and bottom percentile in terms of fund characteristics. We consider both the top and bottom decile and the top and bottom quintile. We then estimate:

$$R^d_{it} = \alpha + \boldsymbol{\beta}\mathbf{R}_{mt} + \varepsilon_{it}, \tag{11}$$

where R^d_{it} is the difference between High and Low portfolios and $\mathbf{R}_{mt}$ is the vector of factors proxying for market conditions. We consider two alternative specifications: a three factor and a four factor specification. The three factor specification contains the three Fama and French factors (Market, SMB and HML) and a constant. The four factor specification also includes a "momentum factor". This is an important control, as the difference in returns in some categories (for example

informativeness/performance) may be actually due to momentum. Indeed, the difference between the returns of the portfolios of the best performing funds and the returns of the portfolios of the worst performing ones may persist simply because of the presence of momentum.

The coefficient α represents the extra-returns of such a portfolio and captures the economic relevance of the gain (Gompers *et. al.*, 2003). It is the gain that accrues from rebalancing the portfolio every quarter on the basis of the information contained in the mutual funds' characteristics, as opposed to a strategy based on investing in a portfolio based on the (3 or 4) market factors. For brevity we report the results where the stocks are ranked into portfolios on the basis of their standardized differences in holdings. The estimation is based on monthly frequency for the period 1978-2000.[24]

The results are reported in Table. In the first three columns we report the raw returns for the top and bottom portfolios as well as their difference. In the next columns we report the risk-adjusted returns (3 factors and 4 factors). They show that a strategy based on fund-characteristics can deliver significant positive returns. In particular, this is the case if we consider the categorizations based on fees, informativeness of the funds, number of funds, investor demand of the fund and cost of information. These extra-returns are statistically as well as economically significant. If we interpret the Fama and French factors as proxies for fundamental uncertainty (Liew and Vassalou, 2000), these results quantify the extra-return that compensate investors to hold the mutual-fund induced risk.

How do the signs of the premia compare with our working hypothesis? They are mostly consistent with it. In particular, strategies based on stocks held by more informed mutual funds, or funds with lower information costs or by more funds outperform those based on stocks held by less informed funds, funds with higher information costs or by fewer funds. The only case where the results are conflicting with the working hypothesis is the case of the level of fees. Stocks held by funds charging lower fees outperform stocks with held by funds charging higher fees. The classification based on demand does not turn out significant.

These results are robust across specifications and for different control (3 and 4 factors). Moreover, it is worth remembering that in the case of the categorization based on the degree of informativeness of the funds, the categorization relies on Sharpe ratios as opposed to mere returns. It is therefore difficult to attribute these

[24]While the information on stock returns is available at a monthly frequency, the holdings are available only every quarter. If we use quarterly frequency, we have more accurate information about the holdings, but we lose in terms of the sample size. If we use the monthly frequency, the information about the holdings may be stale. We use monthly information. Each quarter we define the holdings and then we consider the following month returns.

findings to a statistical artifact or spurious correlation. The results indicate that mutual funds directly affect the market and their impact is economically significant. However, they are suggestive of the existence of a relationship between fund and stock characteristics, *at the individual stock level*. The next step is to consider if mutual funds' behavior impacts the market so much to be priced.

6.3.2 Evidence of pricing

In a previous section we found evidence that mutual funds, not only affect volatility and liquidity, but also induce them to co-move. This suggests that mutual fund-based characteristics should also induce co-movements in prices. That is, they should act as factors that explain stock returns.[25] If our "fund-based" factors turn out to be significant, then they should directly affect the market as a whole and not just be stock-specific (Brennan *et al.*, 1998, Daniel *et al.*, 2001). To investigate the evidence of pricing, we construct portfolios based on the characteristics of the funds and test the explanatory power of such portfolios against standard factors that explain returns. The test is based on the standard Fama and French (1993) methodology. We group stocks into 20 portfolios[26] and then we estimate:

$$R_{it} = \alpha + \boldsymbol{\beta}\mathbf{R}_{mt} + \gamma R_{ft} + \varepsilon_{it}, \tag{12}$$

where R_{it} is the return on the *ith* portfolio and $\mathbf{R}_{mt}$ is the vector of factors containing the three Fama and French factors (Market, SMB and HML) and the momentum factor. R_{ft} is the fund-based factor. This is constructed as follows. For each stock and for each quarter, we identify the number of shares held by the funds belonging to each category and we define the "High" and "Low" funds as described before. Then, we rank the stocks on the basis of the standardized[27] difference between the number of shares held by the High funds and the number of shares held by the Low funds. Finally, using such ranking we group the stocks in deciles (quintiles) and construct two portfolios made of the returns of the stocks within the top and bottom decile

[25] We refer to Table 1 and consider the *ex-post* returns that we define as the difference between prior prices and current equilibrium prices.

[26] We consider two sets of portfolios: randomly drawn portfolios and liquidity based portfolios. The first are constructed by dividing the number of shares existing in each month into 20 equal-sized portfolios, sorted by PERMNO number. The second are constructed by dividing the number of shares existing in each month into 20 equal-sized portfolios, sorted by the level of liquidity. Given that the results are consistent, we report only the former, less subject to potential selection bias (Ferson, 1999).

[27] That is, the difference between the number of shares held by the top funds and the number of shares hedl by the bottom funds is divided by the sum of the number of shares held by bottom and top funds.

(or quintile). The difference in the returns of such portfolios represents the Fund Factor. The estimation is based on monthly frequency for the period 1978-2000.[28]

As before, we define the holdings of the funds in two alternative ways. The first is based on the holdings of all the funds in the specific decile (Classification I) and the second is based on the holdings of just the main decile (Classification II). We consider two specifications: one defines the top and bottom portfolios as, respectively, the 1st and 10th decile. The second defines the top and bottom portfolios as, respectively, the 1st and 5th quintile.

The results are described in Table 5. In Panels A and B we report the results for Classification I, in Panels C and D we report the results for Classification II, in Panels A and C we report the results for the Specification I and in Panels B and D we report the results for Specification II. We display the value of the coefficients of the fund-factor (γ) and their robust *t-statistic*. The results consistently show an impact of the mutual fund market on stock returns. Indeed, the fund-based factors are significant in most categorizations and for most portfolios.[29] The results are also robust across different classifications and specifications and suggest that mutual funds impact stock risk premia. We can interpret as evidence that (information) shocks to the fund managers get amplified and transmitted to the market according to the market structure of the mutual fund industry.

7 Conclusion

We studied how the market structure of the mutual fund industry affects the stock market. We showed that competition between mutual fund families affect funds' incentives to collect information and therefore impacts stock prices. We identified a trade-off for the mutual fund family between the number of funds it offers and the performance it provides - i.e., the level of information it generates. We argued that an increase in the cost of generating information reduces the amount of information collected and the level of the fees charged *and* increases the number of competing funds. The presence of more and relatively less informed funds affects the stock market, increasing liquidity and stock cross-correlations and reducing volatility and prices.

[28] While the information on stock returns is available at a monthly frequency, the holdings are available only every quarter. If we use quarterly frequency, we have more accurate information about the holdings, but we lose in terms of the sample size. If we use the monthly frequency, the information about the holdings may be stale. We use monthly information. Each quarter we define the holdings and then we consider the following month returns.

[29] In particulat, they are always significant for the classifications that were significant in specification 11 (i.e., fees, fund informativeness, demand, number of funds and managers' risk tolerance).

We empirically tested our model using the universe of the US equity funds in the past 30 years. We identified the characteristics of the mutual funds that are related to their market structure and family competition (i.e., fees, demand, attitude towards risk, number of funds) and related them to stock characteristics (volatility, liquidity, cross-correlation and prices). We provided evidence that fund characteristics affect stocks characteristics and seem to aggregate at the overall market level as priced factors.

These results provide a new stimulating view about the role of the mutual fund industry. Further research may study whether issues such as momentum, anomalies, over(under) reactions, can be explained in terms of the industrial organization side of the markets. Alternative rational and behavioral stories have been brought forward to explain them, but a simpler answer may be found by directly inspecting the structure of the market where the funds operate and the way they compete.

As it is now industrial organization and finance have coexisted without really interacting, except in the microstructure literature. The asset pricing literature has not considered the implications of the market structure of the main financial players. The literature on limits to arbitrage has shown the limitations of the standard frictionless market model, without replacing it with an alternative theory. We believe that the study of the type and modality of competition of the main players in the financial markets will provide useful insights in such a direction. This paper represent a first step in this direction.

8 Appendix

8.1 Proof of propositions

Proof of Proposition 1

The mutual fund invests on behalf of its clients, using a mean-variance objective function and exploiting its superior information advantage ($\boldsymbol{F}_f$). The mutual fund submits market orders:

$$x_f = \frac{E\left[V|\boldsymbol{F}_f\right]}{\rho Var\left[V|\boldsymbol{F}_f\right]}, \tag{13}$$

where x_f is the number of units invested in the risky asset and ρ is the mutual fund's degree of risk aversion. Alternatively, we can think that the mutual fund behaves as in Hong and Stein (1999), submitting market orders and not knowing the price at which these orders will be executed. This induces it to forecast the price as well as the terminal value. In this case, we could write equation 13 as $x_f = \frac{E\left[(V-p_2)|\boldsymbol{F}_f\right]}{\rho Var\left[(V-p_2)|\boldsymbol{F}_f\right]}$.

The two specifications coincide if we consider V as the net (of price) gain/loss on the stock. Using the definition of the signal provided in the text, we can rewrite equation 13 as:

$$x_f = \frac{V + s_f}{\rho \sigma^2_{s_f}}. \tag{14}$$

Proof of Proposition 2

Investors maximize a mean-variance function equal to:

$$Max \left\{ E[W_3] - 0.5\rho Var[W_3] \right\}, \tag{15}$$

where W_3 is the terminal wealth. The investor decides how many units of the *fth* mutual fund to buy (ω_f), depending on the expected performance of the fund (i.e., the investor knows the precision of the fund's signal h_f) and the fees it charges (θ_f). Given equation equation 14, the total amount indirectly invested in the stock is: $\omega_f x_f$. In particular, the indirect investment in the stock is:

$$\omega_f x_f = \omega_f \frac{E\left[V|\boldsymbol{F}_f\right]}{\rho Var\left[V|\boldsymbol{F}_f\right]} = \omega_f \frac{V + s_f}{\rho \sigma^2_{s_f}}. \tag{16}$$

We can therefore write the investor's wealth in period 3 as:

$$W_3 = 1 + \sum_f \omega_f x_f V - \sum_f \omega_f \theta_f = 1 + \frac{V^2}{\rho} \sum_f \frac{\omega_f}{\sigma^2_{s_f}} + \frac{V}{\rho} \sum_f \frac{\omega_f}{\sigma^2_{s_f}} s_f - \sum_f \omega_f \theta_f. \tag{17}$$

From the investor' s standpoint (i.e., on the basis of his information set), W_3 is a function of two random variables: V and s_f. Let us define a variable X equal to $X = \sum_f \frac{\omega_f}{\sigma^2_{s_f}} s_f$. Under the aforesaid distributional assumptions $X \sim (0, \Omega)$ with $\Omega = \sum_f \frac{\omega_f^2}{\sigma^2_{s_f}}$. This allows us to write:

$$W_3 = \alpha_{VV} V^2 + VX\alpha_{VX} + \alpha_0, \tag{18}$$

where $\alpha_{VV} = \frac{1}{\rho} \sum_j \frac{\omega_f}{\sigma^2_{s_f}}$, $\alpha_{VX} = \frac{1}{\rho}$, and $\alpha_0 = 1 - \sum_f \omega_f \theta_f$. This is the value of W_3 that is the argument of the optimization 15 (see Ross, 1998). That is, the investor calculates the expected value ($E[W_3]$) and its variance ($Var[W_3]$).

The investor chooses how much to invest in the different funds by maximizing 15, conditional on his information set and on the basis of the distributional assumptions on V and X we mentioned before. Under these assumptions, we have:

$$Max_{\omega_f} \left\{ 1 + \frac{\sigma_V^2}{\rho} \sum_f \omega_f h_f - \sum_f \omega_f \theta_f - 0.5\rho \left[\frac{2\sigma_V^4}{\rho^2} (\sum_f \omega_f h_f)^2 + \sum_f \frac{\omega_f^2}{\sigma^2_{s_f}} \frac{\sigma_V^2}{\rho} \right] \right\}, \tag{19}$$

The first order conditions, after some manipulations, and redefining everything in terms of the precision of the signal ($h_f = \frac{1}{\sigma^2_{s_f}}$), deliver the optimal investment in the fth fund. This is:

$$\omega_f = \frac{1}{\sigma_V^2\left[1+\frac{2\sigma_V^2}{\rho}h_f\right]}\left[\frac{\sigma_V^2}{\rho} - \frac{\theta_f}{h_f} - \frac{2\sigma_V^4}{\rho}\sum_{i\neq f}\omega_i h_i\right], \tag{20}$$

where i represents all the other fund competing with the *fth* fund.

Proof of Proposition 3

The *jth* family maximizes profits, defined as:

$$\Pi_j = N_j\omega_j\theta_j - c_j h_j - N_j K_j, \tag{21}$$

choosing the number of funds (N_j), the investment in information technology (h_j) and fees to charge (θ_j). We optimize equation 21 with respect to the three control valiables (N_j, h_j, θ_j). The level of fees is:

$$\theta_j = \frac{(1-2\sigma_V^2\Theta_j)}{2\rho}\sigma_V^2 h_j, \tag{22}$$

where $\Theta_j = \sum_{g\neq j}\omega_g h_g$, for all the other *gs* family different from the *jth* one.The optimal investment in the information technology is:

$$h_j = \frac{2\rho}{\sigma_V^2}\frac{2\rho K_j}{\left[1-8\rho K_j - 4\sigma_V^2\Theta_j + 4\sigma_V^4\Theta_j^2\right]} = \frac{2\rho}{\sigma_V^2}\Xi_j, \tag{23}$$

where $\Xi_j = \frac{2\rho K_j}{\left[1-8\rho K_j - 4\sigma_V^2\Theta_j + 4\sigma_V^4\Theta_j^2\right]}$. The number of funds the family chooses is:

$$N_j = \frac{c_j\rho\,(1-2\sigma_V^2\Theta_j)}{\sigma_V^2 K_j\left[1-8\rho K_j - 4\sigma_V^2\Theta_j + 4\sigma_V^4\Theta_j^2\right]}\Xi_j. \tag{24}$$

Proof of Proposition 4

We now proceed to define a symmetric equilibrium, where families have identical cost technology (i.e., $c_j = c$ and $K_j = K$). We therefore substitute in equations 22, 23 and 24 the common cost (c and K). The results are now parametric in terms of Θ. The solution for a symmetric equilibrium requires us to replace Θ with $\sum_{g\neq j}\omega h = N(M-1)\omega h$. This implies solving a high order equation. We select the real root that provides positive prices. The results are plotted in Figures 1 and 2.

Proof of Proposition 5

Let us now consider the equilibrium in the stock market. This can be defined in terms of the fundamental parameters as well as of the equilibrium in the mutual fund market $\{\theta,\ h,\ N\}$. The solution in the mutual fund market determines the equilibrium value of Θ. We define this as $\widehat{\Theta}$. Mutual funds and the investors submit their bids to a risk-neutral market maker who sets prices equal to the expected value of the terminal payoff (Kyle, 1985). That is, the market maker observes the order flow and sets:

$$p_2 = E[V|F], \tag{25}$$

where: $F = \sum x_j + I$. The terms x_j and I are, respectively, the indirect and direct investment in stocks. We can solve the model in two ways. In the first one, we explicitly consider the direct investment. In this case, we exploit the fact that equation 4 also represents the direct investment in stocks, given investors' cost and quality of information (θ_0 and h_0), so that the direct investment in stocks is: $I = \sqrt{\frac{c\left[a-\frac{\theta_0}{h_0}-h2\sigma_V^4/\rho(M-1)N\right]}{a^3\rho^3 N}}$. The lower the quality of the information of the investors (i.e., as $h_0 \to 0$), the more the direct investment will shrink in favor of the investment in mutual funds [30] In this case case, the solution depends upon the chosen value of $\frac{\theta_0}{h_0}$. We simulate the model for different values of $\frac{\theta_0}{h_0}$.[31] Alternatively, we consider a situation of restricted market participation (Basak and Cuoco, 1998), where investors can only invest in mutual funds and not in stocks. Both approaches deliver qualitatively similar results. In both cases, we can rewrite F in terms of the main state variables as:

$$F = A + BV + C\overline{s}, \tag{26}$$

where $\overline{s}$ is the aggregate noise of the signals of the mutual funds and A, B, and C are, respectively:

$$A = A_{01} + A_{02},$$

$$A_{01} = \frac{4a^2c\rho M\omega\left(a - b\widehat{\Theta}\right)^2}{a\rho\sigma_V^2 E}V_0,$$

$$A_{02} = \frac{\left(a - \frac{\theta_0}{h_0}\right)E - (M-1)\left(a - b\widehat{\Theta}\right)8ab\rho cK}{a\rho E},$$

[30] Technically, if $h_0 \to 0$, $i \to -\infty$. However, if investors are subject to short sale constraint, we have that $i \to -0$.

[31] The results are robust to a change in the value of θ_0/h_0. The results displayed on Figures 1 and 2 use a value of θ_0/h_0 equal to 0.01.

$$B = C = \frac{64a^3\rho^3 cK^2 M\omega\left(a - b\widehat{\Theta}\right)^2}{E^2},$$
$$E = \left[a^2 - 2ab\widehat{\Theta} + b\left(b\widehat{\Theta}^2 - 4K\right)\right]^2,$$

where $a = \sigma_V^2/\rho$ and $2\sigma_V^4/\rho$. We can then apply the standard projection theorem and have:

$$p_2 = E[V|F] = \mu_p + \lambda F, \tag{27}$$

where

$$\mu_p = V_0 - \frac{\sigma_V^2(A + BV_1)}{B\sigma_V^2 + C\sigma_s^2} \text{ and } \lambda = \frac{\sigma_V^2}{B\sigma_V^2 + C\sigma_s^2}. \tag{28}$$

Stock volatility and trading volume are therefore defined as:

$$\sigma_{p_2} = \lambda\sqrt{B^2\sigma_V^2 + C^2\sigma_s^2} \text{ and } T_{p_2} = 2\sqrt{\frac{2}{\pi}}\left(|B|\,\sigma_V^2 + |C|\,\sigma_s^2\right),$$

(Wang, 1994, Pages 162-163).

8.2 The merge of the datasets

The main problem in merging the CRSP Mutual Funds and SPECTRUM Mutual Fund Files is the fact that they use different identifiers in order to uniquely identify each mutual fund. The CRSP ICDI_NO is a five character alpha-numeric identifier. The SPECTRUM identifier is a five digit number called the Fundnumber. The task is complicated by the fact that the names of the funds have different extensions. SPECTRUM uses 25 characters for its FundName whereas CRSP uses a 50 character text field to represent the name of the fund.

We therefore proceeded as follows.[32] First, we performed a merge based on the ticker. The ticker is the five-digit code that is used to represent a stock or a mutual fund. A ticker is an unofficial way of representing a mutual fund and there are no guarantees about it being unique. However, we found it to be reasonably consistent and hence we used it as the first step in generating the match between CRSP and SPECTRUM. The ticker merge may thus be considered as the first phase in the merger.[33]

However, ticker data is available in SPECTRUM only for three years, 1999, 2000 and 2001. This allowed us to match the years 1999-2001. Then, the ticker matches

[32]The procedure is similar to the one proposed by Wermers (2000).

[33]The ticker in CRSP comes from the annual summary data file. The column called ticker has the NASDAQ ticker symbol as a five-character field. In SPECTRUM, the ticker comes from the file 8, the Fund Ticker Information file. The fund ticker symbol here is also a five-character symbol.

that were found in 1999 were extrapolated for the prior years. It should, however, be noted that some funds' tickers were changed during the course of time. Some funds had died and their tickers had been reused. Thus, the reliability of the ticker merge weakens as we move behind in time before 1999.

We therefore, considered a second criterion. The other characteristic more suitable to match fund after the ticker is the name of the fund. Unfortunately, CRSP database uses a 50-character text field for the name, while SPECTRUM uses a 25-character field for the name of the fund. Thus, the names are abbreviated differently in both the databases. We used a "name recognition" code written in Delphi to match the names. This code was based on the idea of matching two strings. The names of the two databases were arranged beside each other and each name was compared with every name in the other database.

Certain assumptions were made about the way the fund names were abbreviated in SPECTRUM based on observation.[34] After applying these reductions, we are left with two strings that can be compared using the name matching algorithm. A match of 90 percent or more on the two reduced strings is considered to be a match and is accepted. This match has lower priority than the ticker merge. This means that if there is a conflict in the merge between the name merge and the ticker merge, the conflict is resolved by considering the ticker merge as valid.

Finally, for all the other cases as well as the ones that seemed to be dubious, we performed a "eye match". That is, the funds have been manually compared against each other. A SAS program later combines the name match and the eye match to produce a final match.

The process of matching from CRSP to SPECTRUM and vice versa is then performed in the following way. First, we sort all the funds by their ICDI number, extract from all the data pertaining to the particular year (and quarter if the year is 2000) [35] and merge them. Then, we sort based on the basis of the fundnumber and merge it with one of the files from SPECTRUM for the same quarter. In the merging we accept only the entries that are present in both. This allows us to be sure that the funds that are used are definitely present in both datasets. As a final step, we proceeded to remove the index funds.

[34]For example, for in each name of the fund, the word fund is dropped in SPECTRUM, company is abbreviated as Co.

[35]This is done using the annual summary data file (ANNSUM). This contains information on the the calendar year to which the data applies, the objective of the fund, its total net asset, net asset value, total load fees, expenses, ...

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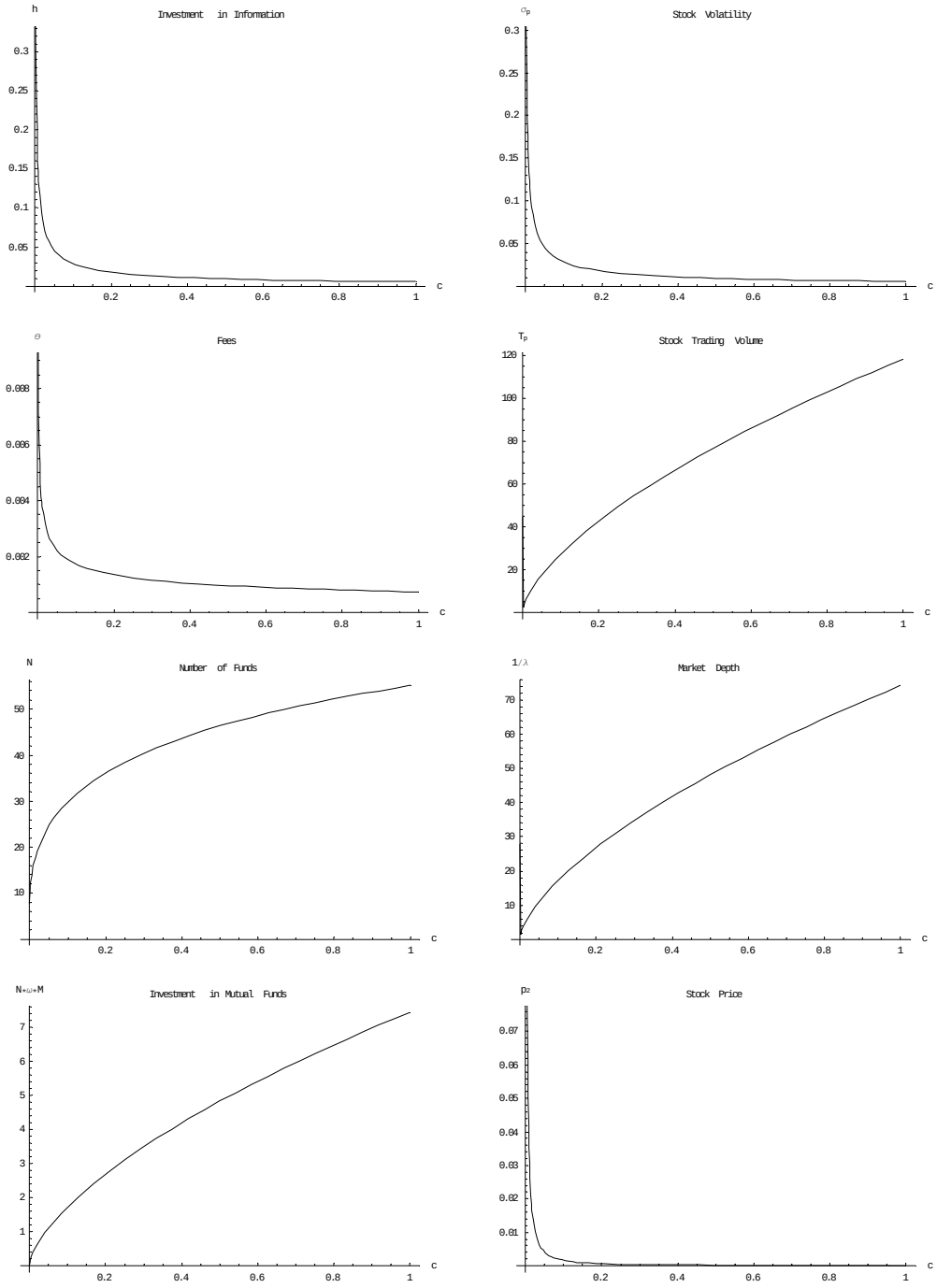

Figure 1: Mutual Fund and Stock Characteristics for different values of the cost of information (c). The parameters are V_2= 0, V_3= 1, $S = 1$, $\mu_v = 0$, σ_V= 1, $K = 0.001$,and $\rho = 1$.

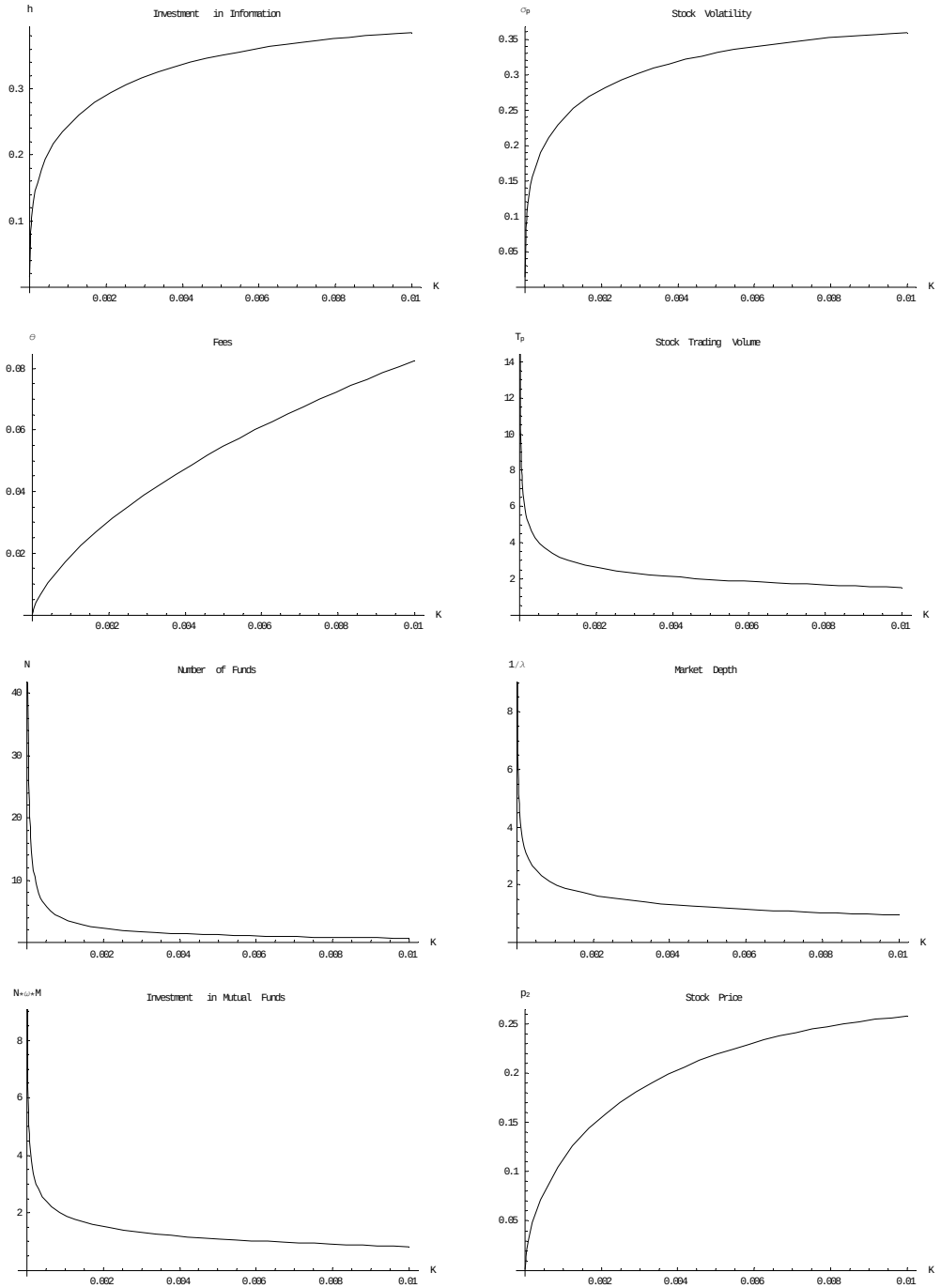

Figure 2: Mutual Fund and Stock Characteristics for different values of the cost of establishing a fund (K). The parameters are V_2= 0, V_3= 1, $S = 1$, $\mu_v = 0$, σ_V= 1, $c = 0.01$,and $\rho = 1$.

Table 2: Stock Volatility, Liquidity and Fund Characteristics

In Panel A and B, we report the results of a Fama-MacBeth procedure to estimate the relationship between volatility and different measures of liquidity and our fund-based characteristics. The measures of liquidity are: Amihud's illiquidity ratio (2002), the number of shares traded, dollar volume, turnover and bid-ask spread. Dollar volume is defined as the number of shares traded times price. Turnover is constructed as the ratio of the number of shares traded and the number of shares outstanding. Bid-ask spread is defined as the difference of daily bid and ask prices standardized by the price. Both the illiquidity ratio and the bid-ask spread are negatively related to the level of liquidity, while turnover, dollar volume and number of shares traded are positively related to it. The control variables the stock market capitalization, the number of shares outstanding, the book-to-market ratio of the stock and a dummy that proxies for the exchange where the stock is listed. The variable that proxies for the fund characteristics is constructed using the mutual funds' stock holdings. The characteristics are: fees (total expense ratio), number of funds, fund informativeness ("Info") based on fund performance in the previous 12 months, investors' demand of the fund (based on the total net assets) and the cost of information. The latter is defined in terms of the standard deviation of the level of fund flows ("Info Cost 1"), of the standard deviation of the relative level of fund flows ("Info Cost 2") and the standard deviation of returns ("Info Cost 3"). For each stock and quarter we define the holdings of "High" and "Low" funds. The High funds are the funds belonging to the top 3 deciles and the Low funds are the ones belonging to the bottom 3 deciles. For the categorization based on the number of funds, we refer to the main text. The top 3 deciles and the bottom 3 deciles constitute the "High" and "Low" groups. We consider 2 proxies for fund characteristics. The first is the difference between the number of shares of the stock held by the High funds and the number of shares of the stock held by the Low funds. The second is based on their standardized difference. That is, the difference between the number of shares held in the stock by the High funds and the number of shares of the stock held by the Low funds is divided by the sum of the number of shares of both High and Low funds. The results based on the first proxy are reported in Specification I, while the results based on the second Fund Factor are reported in Specification II. We also consider two alternative ways of defining the holdings of the funds. The first reports, for each stock, the holdings of all the funds belonging to the 10 deciles within each category (Classification I). The second classification, instead, only reports the holdings of the main decile (Classification II). The estimations are based on a Fama-MacBeth procedure with correction for autocorrelation. We report the average values of the cross-sectional coefficients linking the different measures of stock liquidity and volatility to fund characteristics. The period is 1st January 1978 - 31 December 2000. In Panel C, we report the result of a pooled consistent-White corrected estimation where all the separate cross-sections are stacked together. The factor based on fund characteristics is the aggregation of the individual fund specific characteristics across all the funds. The factors are constructed as follows. For each stock we construct the standardized difference between the number of shares held by the top 3 deciles and the bottom 3 deciles within each category. These ratios are then aggregated across all the stocks, for each quarter. We report three specifications: one based on the contemporaneous value of the factor and two based on lagged (one and two month lagged) values of it.

Panel A: Stock Characteristics and Funds Characteristics (Classification I)

Fund Characteristics

Stock Characteristics	*Fees*		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Specification I														
Volatility	0.09	(4.22)	0.06	(1.95)	-0.09	(-13.90)	-0.14	(-12.40)	-0.11	(-5.45)	-0.13	(-13.20)	-0.07	(-2.20)
# Trades	-0.40	(-3.78)	-0.60	(-4.94)	0.48	(21.40)	0.71	(22.40)	0.98	(21.40)	0.73	(22.90)	0.30	(2.28)
Turnover	-0.11	(-1.17)	-0.88	(-6.43)	0.56	(19.40)	0.81	(18.40)	1.48	(14.50)	0.85	(19.80)	1.40	(8.02)
Volume	-0.16	(-2.64)	-0.17	(-1.95)	0.19	(9.74)	0.28	(13.90)	0.39	(7.44)	0.29	(12.60)	0.05	(0.78)
Illiquidity Ratio	0.07	(2.66)	0.11	(4.22)	-0.08	(-9.44)	-0.12	(-9.82)	-0.18	(-9.57)	-0.13	(-9.34)	-0.12	(-3.62)
Bid-Ask Spread	0.17	(2.45)	0.18	(1.51)	-0.14	(-7.41)	-0.27	(-7.99)	-0.47	(-4.92)	-0.28	(-7.85)	-0.52	(-3.36)
Specification II														
Volatility	0.08	(3.79)	0.05	(1.58)	-0.07	(-10.36)	-0.11	(-9.97)	-0.08	(-4.52)	-0.11	(-10.62)	-0.08	(-2.76)
# Trades	-0.39	(-4.05)	-0.55	(-5.14)	0.37	(17.83)	0.57	(16.50)	0.83	(22.89)	0.58	(17.37)	0.40	(2.97)
Turnover	-0.11	(-1.20)	-0.78	(-5.94)	0.43	(13.97)	0.66	(14.27)	1.28	(12.02)	0.69	(15.04)	1.43	(8.74)
Volume	-0.16	(-2.94)	-0.16	(-2.31)	0.14	(11.97)	0.22	(11.59)	0.32	(11.81)	0.22	(11.78)	0.10	(1.33)
Illiquidity Ratio	0.06	(2.50)	0.09	(3.83)	-0.06	(-8.94)	-0.10	(-9.30)	-0.15	(-8.69)	-0.10	(-8.87)	-0.13	(-4.09)
Bid-Ask Spread	0.15	(2.25)	0.15	(1.30)	-0.10	(-6.41)	-0.22	(-7.24)	-0.42	(-4.46)	-0.23	(-7.16)	-0.52	(-3.53)

Panel B: Stock Characteristics and Funds Characteristics (Classification II)

Fund Characteristics

Stock Characteristics	*Fees*		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Specification I														
Volatility	0.07	(3.61)	0.07	(2.10)	-0.09	(-13.89)	-0.16	(-11.88)	-0.11	(-4.54)	-0.15	(-12.95)	-0.06	(-1.43)
# Trades	-0.46	(-5.42)	-0.65	(-5.32)	0.48	(21.41)	0.81	(21.29)	1.18	(23.52)	0.85	(23.66)	0.22	(1.80)
Turnover	-0.30	(-3.59)	-1.05	(-6.63)	0.56	(19.40)	0.89	(15.79)	1.93	(15.01)	0.96	(18.65)	1.59	(8.44)
Volume	-0.19	(-3.74)	-0.18	(-2.12)	0.19	(9.74)	0.32	(16.38)	0.46	(10.80)	0.34	(16.03)	-0.01	(-0.11)
Illiquidity Ratio	0.10	(3.75)	0.15	(4.60)	-0.08	(-9.44)	-0.14	(-9.61)	-0.25	(-9.16)	-0.15	(-8.58)	-0.14	(-3.65)
Bid-Ask Spread	0.22	(3.05)	0.25	(1.60)	-0.14	(-7.41)	-0.32	(-7.82)	-0.70	(-4.44)	-0.32	(-7.83)	-0.71	(-3.36)
Specification II														
Volatility	0.07	(3.41)	0.06	(1.89)	-0.07	(-10.36)	-0.14	(-9.87)	-0.10	(-4.06)	-0.13	(-10.98)	-0.07	(-1.74)
# Trades	-0.45	(-5.51)	-0.62	(-5.62)	0.37	(17.83)	0.66	(14.43)	1.02	(22.92)	0.70	(16.46)	0.33	(2.77)
Turnover	-0.29	(-3.59)	-0.97	(-6.28)	0.43	(13.97)	0.76	(12.92)	1.75	(13.02)	0.81	(15.04)	1.61	(8.95)
Volume	-0.18	(-3.82)	-0.18	(-2.59)	0.14	(11.97)	0.25	(10.32)	0.39	(11.51)	0.27	(10.94)	0.05	(0.79)
Illiquidity Ratio	0.09	(3.71)	0.13	(4.41)	-0.06	(-8.94)	-0.11	(-9.04)	-0.22	(-8.64)	-0.12	(-8.17)	-0.15	(-3.95)
Bid-Ask Spread	0.21	(2.97)	0.23	(1.48)	-0.10	(-6.40)	-0.27	(-7.14)	-0.65	(-4.19)	-0.27	(-7.32)	-0.71	(-3.45)

Panel C: Stock Characteristics and Funds Aggregated Characteristics

Stock Characteristics	Fund Characteristics													
	Fees		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Classification I														
Contemporaneous Specification														
Volatility	1.19	(3.13)	1.12	(12.90)	-3.84	(-7.34)	-72.39	(-28.71)	-3.02	(-7.84)	-0.09	(-2.78)	-2.10	(-10.92)
# Trades	-0.11	(-10.26)	-0.07	(-17.01)	0.73	(11.81)	2.45	(3.29)	0.01	(2.67)	-0.04	(-0.47)	0.06	(1.69)
Illiquidity Ratio	0.21	(3.21)	0.01	(3.27)	-0.01	(-2.59)	-0.19	(-7.87)	-0.01	(-4.67)	0.02	(1.12)	-0.02	(-8.08)
One-period ahead Specification														
Volatility	2.02	(18.24)	2.49	(11.51)	-16.21	(-3.01)	-61.27	(-12.19)	-2.98	(-11.74)	-1.13	(-4.74)	-2.14	(-1.88)
Volume	-0.06	(-2.30)	-0.07	(-3.83)	0.31	(3.24)	1.16	(4.78)	-0.01	(-0.98)	0.02	(2.34)	0.03	(7.43)
Illiquidity Ratio	0.18	(4.92)	0.03	(2.32)	-0.08	(-2.16)	-0.27	(-6.47)	-0.04	(-7.20)	-0.01	(-3.21)	-0.02	(-1.16)
Two-period ahead Specification														
Volatility	-0.12	(-0.48)	1.31	(1.90)	2.94	(7.32)	-23.10	(-9.66)	-0.46	(-4.19)	1.75	(6.92)	4.88	(2.39)
# Trades	-0.09	(-1.93)	-0.02	(-1.31)	0.21	(2.87)	2.32	(6.34)	-0.01	(-0.84)	-0.01	(-0.74)	0.01	(0.32)
Illiquidity Ratio	0.08	(0.96)	0.01	(1.18)	-0.05	(-1.98)	-0.47	(-9.19)	0.01	(1.31)	0.04	(1.14)	0.01	(0.49)
Classification II														
Contemporaneous Specification														
Volatility	1.23	(2.76)	1.17	(11.90)	-3.84	(-7.34)	-68.34	(-21.13)	-3.13	(-2.31)	-0.08	(-1.21)	-1.99	(-4.76)
# Trades	-0.17	(-8.31)	-0.09	(-14.02)	0.73	(11.81)	3.33	(2.79)	0.01	(1.95)	-0.02	(-0.43)	-0.03	(-1.24)
Illiquidity Ratio	0.41	(1.21)	0.03	(2.87)	-0.01	(-2.59)	-0.12	(-2.37)	-0.01	(-2.88)	0.02	(1.61)	-0.01	(-7.53)
One-period ahead Specification														
Volatility	2.00	(11.38)	2.22	(7.56)	-16.21	(-3.01)	-66.21	(-11.00)	-2.76	(-8.79)	-1.89	(-4.60)	-2.22	(-1.98)
# Trades	-0.05	(-1.46)	-0.01	(-2.99)	0.31	(3.24)	1.08	(3.21)	-0.01	(-1.42)	0.01	(2.44)	0.01	(2.31)
Illiquidity Ratio	0.13	(2.10)	0.02	(2.16)	-0.08	(-2.16)	-0.01	(-8.94)	-0.07	(-8.26)	-0.01	(-1.76)	-0.01	(-0.98)
Two-period ahead Specification														
Volatility	-0.67	(-1.88)	0.67	(0.84)	2.94	(7.32)	-22.10	(-11.23)	-0.45	(-3.78)	1.88	(3.12)	2.85	(4.30)
# Trades	0.13	(-1.12)	-0.01	(-1.66)	0.21	(2.87)	1.78	(8.45)	0.01	(0.62)	-0.01	(-1.63)	-0.01	(-0.27)
Illiquidity Ratio	-0.01	(-0.74)	0.01	(1.01)	-0.05	(-1.98)	0.07	(0.99)	0.02	(0.83)	0.01	(1.22)	-0.01	(-0.23)

Table 3: Stock Cross-Correlations and Fund Characteristics

In Panel A and B, we report the results of the regression of stock cross-correlations on fund-based characteristics and control variables. We use two measures of stock cross-correlation. The first is the difference between the absolute value of the correlation of the *ith* stock with the other stocks within the same decile/category at time *t* and the absolute value of the correlation of the *ith* stock with the other stocks belonging to the opposite decile within the same category at time *t* ("Differential Specification"). The second measure is the absolute value of the correlation of the *ith* stock with the other stocks within the same category at time *t* ("Level Specification"). The fund fund-based characteristics are the characteristics of the funds holdings the *ith* stock and are defined as in Table 2. The control variables are defined as in Table 2. We consider two classifications one based on the holdings of all the funds in the specific category (Classification I) and one based on the holdings of just the main category (Classification II). We also consider an alternative way of construction of the correlations based on the book-to-market characteristics of the stock. This second criterion is based on a pre-classification of stocks on the basis of the book-to-market criterion. That is, within each category, the stocks are first ranked in terms of the BE/ME ratio into top, medium and bottom classes, using the BE/ME methodology proposed by Fama and French (1992,1993). The value of the BE/ME for every stock is compared with the closest value in the percentile information and the stock is categorized using the break points defined by Fama and French (see K. French's web page). We consider as top the percentile >= 18, medim the percentile such that 11 >= Percentile >= 9 and bottom the percentile <=2. Then, we compute the cross-correlation of each of these stocks with the other stocks belonging to the same decile/category. We define this second way of constructing correlations as "Adjusted". We report the "Unadjusted" correlations in Specifications I and II and the "Adjusted" ones in Specifications III and IV. The estimations are done using the Fama-MacBeth procedure with correction for autocorrelation. In Panel C, we report the results of a pooled consistent White-corrected regression of a measure of stock cross-correlation and a common factor based on fund characteristics. The measure of stock cross-correlation is the difference between the stock's (absolute) correlation with the other stocks belonging to the same decile/category and the stock's (absolute) correlation with the stocks belonging to an 'opposite' decile within the same category. The common factor is based on aggregated measures of fund characteristics defined as in the previous section. We define as top and bottom percentile, either the 3 top deciles and the 3 bottom deciles (Specification I and III) or the 5 top deciles and the 5 bottom deciles (Specification II and IV).

Panel A: Cross-Correlations and Fund Characteristics (Differential Specification)

Stock Characteristics	Fund Characteristics													
	Fees		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Type 1 (Classification I)														
Specification I	0.59	(4.66)	0.19	(4.12)	0.50	(5.54)	0.17	(3.00)	0.92	(3.86)	0.20	(3.31)	0.73	(4.50)
Specification II	0.33	(4.35)	0.24	(5.12)	0.54	(5.38)	0.11	(2.68)	0.35	(3.41)	0.09	(2.56)	0.22	(3.95)
Specification III	0.35	(4.27)	0.22	(4.73)	0.11	(3.27)	0.13	(3.45)	0.11	(2.95)	0.10	(3.13)	0.25	(4.57)
Specification IV	0.16	(4.20)	0.11	(4.18)	0.12	(3.26)	0.10	(3.41)	0.08	(3.02)	0.09	(3.11)	0.10	(3.69)
Type 2 (Classification II)														
Specification I	0.51	(4.61)	0.16	(4.84)	0.50	(5.54)	0.20	(3.14)	1.17	(4.01)	0.22	(3.41)	0.91	(4.37)
Specification II	0.25	(4.23)	0.21	(5.19)	0.54	(5.38)	0.15	(2.85)	0.53	(3.92)	0.10	(2.70)	0.27	(3.88)
Specification III	0.36	(4.11)	0.29	(4.15)	0.11	(3.27)	0.16	(3.71)	0.12	(2.98)	0.12	(3.41)	0.27	(4.38)
Specification IV	0.13	(4.13)	0.18	(4.10)	0.12	(3.26)	0.13	(3.74)	0.13	(3.51)	0.11	(3.38)	0.12	(3.31)

Panel B: Cross-Correlations and Fund Characteristics
(Level Specification)

Fund Characteristics

Stock Characteristics	*Fees*		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Type 1 (Classification I)														
Specification I	2.12	(5.31)	1.73	(3.97)	0.38	(5.13)	0.87	(5.13)	1.30	(4.21)	0.80	(4.84)	1.82	(4.92)
Specification II	0.45	(3.91)	0.28	(2.51)	0.07	(2.71)	0.16	(3.15)	0.10	(2.08)	0.13	(2.82)	0.26	(3.49)
Type 2 (Classification II)														
Specification I	1.85	(5.17)	1.78	(4.00)	0.38	(5.13)	1.04	(5.14)	1.53	(4.38)	0.94	(5.04)	1.99	(4.50)
Specification II	0.48	(3.89)	0.29	(2.54)	0.07	(2.71)	0.20	(3.48)	0.10	(2.15)	0.16	(3.17)	0.25	(3.18)

Panel C: Cross-Correlations and Fund Aggregated Characteristics
(Differential Specification)

Fund Characteristics

Stock Characteristics	*Fees*		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*
Specification I	0.01	(3.72)	0.04	(15.04)	0.03	(17.73)	0.03	(1.85)	0.01	(0.89)	0.03	(3.02)	0.01	(10.81)
Specification II	0.07	(4.09)	0.48	(20.21)	0.78	(53.22)	0.25	(3.16)	0.95	(11.75)	0.38	(6.56)	0.12	(16.26)
Specification III	0.00	(1.33)	0.02	(7.42)	0.02	(5.32)	0.03	(2.40)	0.00	(0.60)	0.05	(4.82)	0.02	(10.32)
Specification IV	0.11	(2.90)	0.51	(12.21)	0.40	(7.78)	0.35	(2.52)	0.88	(9.47)	0.63	(5.13)	0.30	(13.72)

Table 4 : Profitability of fund-based trading strategies

The table reports the profits from a strategy based on the fund-based factors. In the first three columns we report the raw returns for the top and bottom portfolios as well as their difference. In the next columns we report the risk-adjusted returns (3 factors and 4 factors). Risk adjustment is done according to Fama and French (1993). For each quarter we construct High and Low fund portfolios by averaging the returns of the stocks belonging to the top and bottom percentile in terms of fund characteristics. We consider both the top and bottom decile and quintile. We then regress the difference between High and Low portfolios on either three or four market factors and a costant. The three factor specification contains the three Fama and French factors (Market, SMB and HML) and a constant. The four factor specification also includes a "momentum factor". The estimation is based on monthly frequency for the period 1978-2000. We report the value of the coefficient (intercept) and its t-statistic.

Classification I (1st and 10th decile)

	Raw Returns			Risk Adjusted			
	Top	*Bottom*	*Difference*	*3 Factors*		*4 Factors*	
Fees	1.30%	1.32%	-0.01%	-0.55	(-2.51)	-0.55	(-2.51)
Info	1.71%	1.14%	0.57%	1.23	(2.12)	0.75	(1.45)
Number of Funds	1.38%	1.34%	0.04%	-0.93	(-2.08)	-0.87	(-1.93)
Demand	1.25%	1.45%	-0.19%	0.09	(0.39)	0.11	(0.47)
Info Cost 1	1.23%	1.54%	-0.31%	-1.27	(-3.10)	-1.19	(-2.89)
Info Cost 2	1.38%	1.38%	-0.00%	0.05	(0.16)	0.06	(0.21)
Info Cost 3	1.28%	1.36%	-0.07%	-0.52	(-1.63)	-0.49	(-1.53)

Classification I (1st and 5th quintile)

Fees	1.37%	1.32%	0.05%	-0.42	(-2.31)	-0.44	(-2.41)
Info	1.68%	1.21%	0.47%	1.38	(2.72)	0.98	(2.13)
Number of Funds	1.39%	1.42%	-0.03%	-0.94	(-2.41)	-0.89	(-2.26)
Demand	1.33%	1.52%	-0.19%	0.06	(0.28)	0.08	(0.34)
Info Cost 1	1.26%	1.58%	-0.32%	-1.23	(-3.36)	-1.16	(-3.15)
Info Cost 2	1.39%	1.48%	-0.09%	-0.02	(-0.10)	-0.01	(-0.04)
Info Cost 3	1.39%	1.44%	-0.05%	-0.23	(-0.86)	-0.24	(-0.89)

Classification II (1st and 10th decile)

Fees	1.33%	1.39%	-0.06%	-0.44	(-2.24)	-0.46	(-2.30)
Info	1.73%	1.18%	0.56%	1.21	(2.57)	0.81	(1.94)
Number of Funds	1.38%	1.34%	0.04%	-0.93	(-2.09)	-0.87	(-1.94)
Demand	1.35%	1.47%	-0.12%	-0.41	(-1.17)	-0.34	(-0.99)
Info Cost 1	1.30%	1.54%	-0.24%	-0.78	(-2.35)	-0.77	(-2.30)
Info Cost 2	1.37%	1.40%	-0.03%	-0.42	(-1.23)	-0.37	(-1.09)
Info Cost 3	1.27%	1.44%	-0.17%	0.01	(0.02)	-0.03	(-0.07)

Classification II (1st and 5th quintile)

Fees	1.39%	1.38%	0.00%	-0.11	(-0.74)	-0.15	(-0.96)
Info	1.67%	1.26%	0.41%	1.09	(2.78)	0.75	(2.17)
Number of Funds	1.39%	1.42%	-0.03%	-0.95	(-2.42)	-0.89	(-2.26)
Demand	1.36%	1.52%	-0.17%	-0.67	(-1.95)	-0.61	(-1.77)
Info Cost 1	1.32%	1.57%	-0.26%	-0.85	(-2.87)	-0.85	(-2.85)
Info Cost 2	1.38%	1.48%	-0.10%	-0.60	(-1.79)	-0.55	(-1.63)
Info Cost 3	1.36%	1.43%	-0.07%	0.25	(0.90)	0.21	(0.75)

Table 5: Evidence of Pricing

The table reports the results of time series regressions in line with Fama and French (1993). We group stocks into 20 portfolios constructed by dividing the number of shares existing in each month into 20 equal-sized portfolios, sorted by Permno number. Then, we regress the portfolios on the 3 Fama and French factors, a momentum factor, a costant and a fund-based factor. This is constructed as follows. For each stock and for each quarter, we identify the number of shares held by the funds belonging to each category as described before. Then, we rank the stocks on the basis of the standardized difference between the number of shares held by the High funds and the shares held by the Low funds (Specification I) and construct two portfolios made of the returns of the stocks within the top and bottom decile (or quintile). The difference in the returns of such portfolios represents the Fund Factor. The estimation is based on monthly frequency for the period 1978-2000. We consider two classifications. The first reports, for each stock, the holdings of all the funds belonging to the 10 deciles within each category (Classification I). The second instead, only reports the holdings of the main decile (Classification II). We consider two specifications: one defines the top and bottom portfolio as, respectively, the 1st and 10th decile. The second defines the top and bottom portfolio as, respectively, the 1st and 5th quintile. The frequency is monthly. The period is 1st January 1978 - 31 December 2000. We report for the 20 portfolios the value and the *t-statitic* of the coefficient that relates returns to the fund-based factors.

Panel A: Classification I (1st and 10th decile)

	Fees		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors
Portfolio 1	-0.69	-0.68	-0.60	-0.51	-0.80	-0.82	-0.63	-0.65	-0.56	-0.58	-0.55	-0.56	-0.62	-0.63
	(-9.07)	(-9.59)	(-24.76)	(-20.82)	(-23.99)	(-27.42)	(-8.62)	(-9.54)	(-15.84)	(-17.95)	(-9.00)	(-9.89)	(-12.80)	(-14.48)
Portfolio 2	-0.73	-0.73	-0.51	-0.45	-0.68	-0.69	-0.56	-0.57	-0.67	-0.70	-0.48	-0.49	-0.71	-0.73
	(-9.28)	(-9.80)	(-20.41)	(-16.68)	(-24.21)	(-27.68)	(-7.13)	(-7.41)	(-18.07)	(-20.11)	(-7.40)	(-7.66)	(-13.05)	(-14.03)
Portfolio 3	-0.38	-0.38	-0.40	-0.32	-0.57	-0.59	-0.33	-0.34	-0.59	-0.62	-0.33	-0.34	-0.48	-0.49
	(-5.30)	(-5.80)	(-13.13)	(-9.78)	(-17.09)	(-19.21)	(-3.45)	(-3.66)	(-13.63)	(-15.32)	(-4.36)	(-4.55)	(-7.59)	(-8.10)
Portfolio 4	-0.22	-0.22	-0.31	-0.22	-0.46	-0.48	-0.44	-0.46	-0.59	-0.61	-0.28	-0.29	-0.46	-0.47
	(-3.50)	(-3.62)	(-9.47)	(-6.39)	(-14.18)	(-15.50)	(-4.44)	(-4.71)	(-12.86)	(-13.68)	(-3.45)	(-3.58)	(-7.51)	(-8.11)
Portfolio 5	-0.15	-0.15	-0.17	-0.11	-0.41	-0.43	-0.37	-0.38	-0.41	-0.43	-0.34	-0.34	-0.18	-0.20
	(-2.40)	(-2.47)	(-4.85)	(-2.85)	(-13.27)	(-14.90)	(-3.93)	(-4.04)	(-9.52)	(-10.71)	(-4.26)	(-4.37)	(-2.94)	(-3.41)
Portfolio 6	-0.27	-0.26	-0.12	-0.05	-0.53	-0.54	-0.35	-0.37	-0.38	-0.40	-0.29	-0.30	-0.12	-0.14
	(-3.30)	(-3.60)	(-3.53)	(-1.24)	(-17.48)	(-18.55)	(-4.03)	(-4.44)	(-8.68)	(-9.44)	(-3.86)	(-4.06)	(-2.18)	(-2.58)
Portfolio 7	-0.28	-0.28	0.02	0.09	-0.43	-0.45	-0.54	-0.55	-0.44	-0.46	-0.38	-0.39	-0.12	-0.13
	(-3.80)	(-3.95)	(0.59)	(2.70)	(-11.53)	(-13.37)	(-7.03)	(-7.47)	(-9.12)	(-9.83)	(-5.64)	(-5.89)	(-2.09)	(-2.41)
Portfolio 8	-0.29	-0.29	0.05	0.13	-0.50	-0.52	-0.50	-0.52	-0.41	-0.44	-0.41	-0.42	-0.15	-0.16
	(-3.09)	(-3.15)	(1.52)	(3.49)	(-16.63)	(-17.85)	(-5.95)	(-6.47)	(-9.39)	(-10.10)	(-5.64)	(-6.02)	(-2.54)	(-2.92)
Portfolio 9	-0.32	-0.32	0.04	0.12	-0.46	-0.47	-0.52	-0.53	-0.47	-0.50	-0.42	-0.43	-0.02	-0.03
	(-3.35)	(-3.39)	(0.97)	(2.93)	(-14.65)	(-16.19)	(-6.91)	(-7.25)	(-11.27)	(-12.28)	(-6.71)	(-7.11)	(-0.26)	(-0.48)
Portfolio 10	-0.22	-0.22	-0.02	0.07	-0.52	-0.54	-0.57	-0.58	-0.48	-0.51	-0.38	-0.39	-0.05	-0.07
	(-1.99)	(-1.97)	(-0.44)	(1.75)	(-16.91)	(-18.68)	(-7.80)	(-8.52)	(-12.50)	(-14.02)	(-6.11)	(-6.45)	(-0.89)	(-1.14)
Portfolio 11	-0.29	-0.29	0.02	0.11	-0.47	-0.49	-0.39	-0.41	-0.40	-0.43	-0.31	-0.32	-0.07	-0.08
	(-2.59)	(-2.60)	(0.53)	(2.51)	(-13.09)	(-15.07)	(-6.17)	(-6.98)	(-10.66)	(-12.00)	(-5.57)	(-5.96)	(-1.10)	(-1.34)
Portfolio 12	-0.48	-0.48	0.01	0.10	-0.52	-0.54	-0.41	-0.43	-0.44	-0.46	-0.28	-0.29	-0.19	-0.20
	(-4.18)	(-4.19)	(0.24)	(2.19)	(-13.65)	(-15.63)	(-6.67)	(-7.32)	(-10.85)	(-12.03)	(-5.57)	(-6.00)	(-3.16)	(-3.46)
Portfolio 13	-0.28	-0.28	0.07	0.15	-0.44	-0.46	-0.23	-0.24	-0.33	-0.36	-0.21	-0.22	-0.11	-0.12
	(-2.47)	(-2.49)	(1.71)	(3.70)	(-13.93)	(-14.99)	(-3.97)	(-4.63)	(-9.26)	(-11.79)	(-4.23)	(-4.80)	(-1.71)	(-1.84)
Portfolio 14	-0.34	-0.34	0.04	0.11	-0.25	-0.27	-0.25	-0.27	-0.29	-0.32	-0.10	-0.11	-0.18	-0.20
	(-3.66)	(-3.68)	(0.95)	(2.61)	(-7.58)	(-8.32)	(-4.37)	(-4.74)	(-7.86)	(-9.41)	(-1.97)	(-2.37)	(-2.65)	(-2.96)
Portfolio 15	-0.26	-0.26	0.11	0.17	-0.18	-0.19	-0.01	-0.02	-0.13	-0.16	0.03	0.02	-0.29	-0.31
	(-3.05)	(-3.06)	(3.05)	(4.38)	(-4.73)	(-5.24)	(-0.17)	(-0.47)	(-3.57)	(-4.83)	(0.59)	(0.48)	(-4.20)	(-4.45)
Portfolio 16	-0.33	-0.33	0.21	0.29	-0.10	-0.11	0.03	0.02	-0.06	-0.09	-0.07	-0.07	-0.17	-0.18
	(-4.08)	(-4.10)	(6.28)	(7.91)	(-2.66)	(-3.18)	(0.50)	(0.27)	(-1.76)	(-2.67)	(-1.10)	(-1.28)	(-2.34)	(-2.46)
Portfolio 17	-0.05	-0.05	0.35	0.44	0.09	0.07	0.21	0.19	0.04	0.01	-0.03	-0.04	-0.08	-0.09
	(-0.67)	(-0.64)	(10.02)	(11.93)	(2.68)	(2.36)	(2.50)	(2.39)	(1.25)	(0.44)	(-0.46)	(-0.58)	(-1.16)	(-1.31)
Portfolio 18	-0.01	0.00	0.33	0.41	0.29	0.28	0.22	0.21	0.18	0.15	0.05	0.04	0.05	0.04
	(-0.12)	(-0.05)	(11.03)	(12.78)	(9.09)	(9.41)	(2.32)	(2.21)	(5.15)	(4.77)	(0.59)	(0.51)	(0.78)	(0.63)
Portfolio 19	0.35	0.36	0.44	0.53	0.31	0.29	0.37	0.36	0.35	0.32	0.43	0.42	0.28	0.26
	(5.11)	(5.63)	(17.79)	(20.78)	(9.65)	(10.26)	(4.81)	(4.77)	(11.04)	(11.28)	(6.33)	(6.40)	(6.09)	(6.19)
Portfolio 20	0.23	0.23	0.45	0.51	0.22	0.20	0.44	0.43	0.42	0.40	0.53	0.52	0.40	0.38
	(2.58)	(2.76)	(19.35)	(20.88)	(8.59)	(9.14)	(6.24)	(6.36)	(12.27)	(12.55)	(9.11)	(9.63)	(6.85)	(7.04)

Panel B: Classification I (1st and 5th quintile)

	Fees		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors
Portfolio 1	-0.85	-0.82	-0.65	-0.54	-0.87	-0.90	-0.62	-0.63	-0.62	-0.65	-0.64	-0.65	-0.55	-0.55
	(-9.43)	(-9.56)	(-21.55)	(-17.99)	(-21.23)	(-23.86)	(-7.87)	(-8.63)	(-15.81)	(-17.89)	(-7.86)	(-8.68)	(-8.84)	(-9.25)
Portfolio 2	-0.81	-0.77	-0.59	-0.51	-0.74	-0.76	-0.57	-0.58	-0.77	-0.79	-0.56	-0.57	-0.64	-0.63
	(-8.24)	(-8.29)	(-20.22)	(-16.70)	(-21.37)	(-24.03)	(-6.87)	(-7.11)	(-18.62)	(-20.77)	(-6.64)	(-6.90)	(-8.96)	(-9.14)
Portfolio 3	-0.76	-0.72	-0.50	-0.42	-0.67	-0.69	-0.69	-0.70	-0.78	-0.81	-0.69	-0.70	-0.69	-0.68
	(-9.63)	(-10.22)	(-15.19)	(-11.93)	(-18.31)	(-20.84)	(-7.32)	(-7.61)	(-18.49)	(-21.47)	(-7.59)	(-7.93)	(-9.97)	(-10.20)
Portfolio 4	-0.64	-0.62	-0.40	-0.31	-0.57	-0.59	-0.78	-0.79	-0.77	-0.79	-0.71	-0.72	-0.76	-0.75
	(-9.47)	(-9.60)	(-11.30)	(-8.35)	(-16.33)	(-18.08)	(-7.96)	(-8.33)	(-16.84)	(-18.11)	(-7.22)	(-7.47)	(-12.18)	(-12.65)
Portfolio 5	-0.21	-0.18	-0.22	-0.16	-0.45	-0.47	-0.59	-0.60	-0.49	-0.52	-0.51	-0.52	-0.39	-0.38
	(-2.76)	(-2.54)	(-5.40)	(-3.51)	(-12.22)	(-13.69)	(-6.19)	(-6.31)	(-10.62)	(-11.97)	(-5.11)	(-5.27)	(-5.79)	(-6.03)
Portfolio 6	-0.27	-0.22	-0.17	-0.09	-0.60	-0.61	-0.52	-0.54	-0.47	-0.49	-0.53	-0.54	-0.33	-0.32
	(-2.73)	(-2.51)	(-4.12)	(-1.97)	(-16.88)	(-17.91)	(-5.80)	(-6.27)	(-9.89)	(-10.75)	(-5.70)	(-6.01)	(-5.09)	(-5.27)
Portfolio 7	-0.30	-0.27	0.01	0.09	-0.47	-0.49	-0.68	-0.70	-0.56	-0.59	-0.67	-0.68	-0.30	-0.30
	(-3.39)	(-3.21)	(0.42)	(2.40)	(-10.77)	(-12.48)	(-8.88)	(-9.39)	(-11.01)	(-11.88)	(-8.24)	(-8.66)	(-4.64)	(-4.72)
Portfolio 8	-0.31	-0.28	0.06	0.14	-0.56	-0.57	-0.71	-0.72	-0.52	-0.55	-0.74	-0.76	-0.25	-0.25
	(-2.69)	(-2.49)	(1.44)	(3.30)	(-15.80)	(-16.95)	(-8.52)	(-9.18)	(-11.09)	(-11.95)	(-8.48)	(-9.13)	(-3.78)	(-3.86)
Portfolio 9	-0.23	-0.20	0.03	0.12	-0.50	-0.52	-0.66	-0.67	-0.58	-0.61	-0.70	-0.71	0.01	0.01
	(-1.96)	(-1.76)	(0.80)	(2.65)	(-13.81)	(-15.24)	(-8.85)	(-9.23)	(-12.87)	(-14.07)	(-9.24)	(-9.88)	(0.09)	(0.17)
Portfolio 10	-0.21	-0.20	-0.02	0.08	-0.59	-0.61	-0.71	-0.73	-0.58	-0.61	-0.72	-0.73	0.02	0.03
	(-1.53)	(-1.46)	(-0.50)	(1.60)	(-16.57)	(-18.34)	(-9.82)	(-10.70)	(-14.10)	(-15.92)	(-9.77)	(-10.41)	(0.32)	(0.42)
Portfolio 11	-0.27	-0.24	0.03	0.13	-0.52	-0.54	-0.47	-0.49	-0.48	-0.51	-0.55	-0.56	-0.03	-0.02
	(-1.95)	(-1.78)	(0.72)	(2.64)	(-12.43)	(-14.30)	(-7.23)	(-8.11)	(-11.68)	(-13.18)	(-8.15)	(-8.80)	(-0.41)	(-0.35)
Portfolio 12	-0.48	-0.46	0.01	0.10	-0.56	-0.59	-0.49	-0.50	-0.51	-0.54	-0.42	-0.43	-0.13	-0.12
	(-3.44)	(-3.32)	(0.12)	(1.96)	(-12.57)	(-14.34)	(-7.70)	(-8.39)	(-11.42)	(-12.66)	(-6.64)	(-7.21)	(-1.81)	(-1.78)
Portfolio 13	-0.31	-0.28	0.07	0.17	-0.49	-0.50	-0.29	-0.31	-0.37	-0.41	-0.29	-0.31	0.00	0.00
	(-2.24)	(-2.04)	(1.69)	(3.58)	(-13.20)	(-14.21)	(-5.00)	(-5.71)	(-9.48)	(-12.06)	(-4.70)	(-5.40)	(-0.06)	(-0.01)
Portfolio 14	-0.27	-0.25	0.05	0.14	-0.27	-0.28	-0.29	-0.30	-0.32	-0.35	-0.13	-0.15	-0.11	-0.10
	(-2.38)	(-2.23)	(1.20)	(2.84)	(-6.90)	(-7.60)	(-4.72)	(-5.07)	(-7.66)	(-9.16)	(-1.91)	(-2.37)	(-1.33)	(-1.29)
Portfolio 15	0.04	0.06	0.13	0.20	-0.16	-0.18	-0.09	-0.10	-0.13	-0.16	0.10	0.09	-0.17	-0.17
	(0.36)	(0.57)	(3.15)	(4.43)	(-3.72)	(-4.19)	(-1.57)	(-1.93)	(-3.12)	(-4.30)	(1.54)	(1.43)	(-2.04)	(-2.01)
Portfolio 16	0.06	0.08	0.25	0.33	-0.06	-0.08	0.04	0.03	-0.07	-0.10	0.03	0.02	0.04	0.05
	(0.60)	(0.76)	(6.56)	(8.15)	(-1.51)	(-1.97)	(0.69)	(0.53)	(-1.76)	(-2.66)	(0.40)	(0.24)	(0.48)	(0.52)
Portfolio 17	0.49	0.51	0.46	0.57	0.16	0.14	0.42	0.41	0.08	0.05	0.22	0.21	0.22	0.22
	(5.52)	(5.97)	(12.30)	(14.84)	(4.50)	(4.30)	(4.91)	(4.91)	(2.07)	(1.37)	(2.49)	(2.42)	(2.85)	(2.94)
Portfolio 18	0.26	0.29	0.42	0.51	0.38	0.36	0.35	0.33	0.23	0.20	0.22	0.21	0.37	0.37
	(3.69)	(4.52)	(12.87)	(15.03)	(10.70)	(11.20)	(3.48)	(3.42)	(6.13)	(5.82)	(2.23)	(2.16)	(5.38)	(5.57)
Portfolio 19	0.13	0.16	0.49	0.58	0.36	0.34	0.20	0.19	0.35	0.32	0.38	0.37	0.34	0.34
	(1.48)	(2.03)	(16.68)	(18.89)	(10.16)	(10.82)	(2.40)	(2.32)	(9.33)	(9.37)	(4.23)	(4.21)	(6.41)	(7.07)
Portfolio 20	0.06	0.10	0.49	0.55	0.24	0.22	0.40	0.38	0.41	0.38	0.57	0.55	0.45	0.45
	(0.60)	(0.95)	(17.70)	(18.55)	(8.35)	(8.82)	(5.15)	(5.26)	(9.91)	(9.94)	(7.36)	(7.65)	(6.52)	(7.25)

Panel C: Classification II (1st and 10th decile)

	Fees		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors
Portfolio 1	-0.62	-0.59	-0.73	-0.63	-0.80	-0.82	-0.68	-0.71	-0.61	-0.61	-0.64	-0.68	-0.55	-0.54
	(-8.34)	(-9.36)	(-24.21)	(-19.91)	(-24.04)	(-27.47)	(-15.02)	(-18.22)	(-15.10)	(-15.98)	(-13.81)	(-16.98)	(-14.04)	(-14.88)
Portfolio 2	-0.61	-0.59	-0.51	-0.45	-0.68	-0.69	-0.70	-0.72	-0.66	-0.66	-0.66	-0.67	-0.52	-0.51
	(-8.90)	(-9.52)	(-18.06)	(-14.41)	(-24.14)	(-27.61)	(-21.84)	(-24.46)	(-16.95)	(-18.90)	(-18.97)	(-20.33)	(-13.57)	(-14.36)
Portfolio 3	-0.30	-0.29	-0.33	-0.23	-0.57	-0.59	-0.70	-0.73	-0.65	-0.66	-0.66	-0.68	-0.29	-0.28
	(-3.61)	(-3.60)	(-9.79)	(-6.32)	(-17.16)	(-19.29)	(-15.37)	(-17.08)	(-14.26)	(-15.27)	(-13.86)	(-15.17)	(-7.50)	(-7.85)
Portfolio 4	0.11	0.13	-0.26	-0.14	-0.46	-0.48	-0.71	-0.74	-0.62	-0.62	-0.66	-0.68	-0.16	-0.15
	(1.40)	(1.63)	(-6.99)	(-3.62)	(-14.19)	(-15.52)	(-13.87)	(-15.58)	(-12.37)	(-12.94)	(-12.74)	(-13.92)	(-4.27)	(-4.24)
Portfolio 5	0.00	0.02	-0.17	-0.06	-0.41	-0.43	-0.72	-0.74	-0.56	-0.57	-0.64	-0.66	-0.14	-0.13
	(-0.01)	(0.20)	(-4.46)	(-1.44)	(-13.30)	(-14.94)	(-16.62)	(-17.44)	(-12.93)	(-13.57)	(-13.75)	(-14.47)	(-3.36)	(-3.26)
Portfolio 6	0.04	0.06	-0.01	0.12	-0.53	-0.54	-0.67	-0.70	-0.64	-0.64	-0.67	-0.69	0.05	0.06
	(0.46)	(0.64)	(-0.17)	(2.76)	(-17.52)	(-18.58)	(-13.64)	(-15.96)	(-13.50)	(-14.70)	(-13.72)	(-15.17)	(1.38)	(1.75)
Portfolio 7	0.11	0.12	-0.03	0.11	-0.43	-0.45	-0.69	-0.72	-0.58	-0.58	-0.70	-0.72	0.14	0.15
	(1.16)	(1.32)	(-0.69)	(2.53)	(-11.53)	(-13.37)	(-14.24)	(-15.97)	(-13.42)	(-14.22)	(-13.66)	(-15.26)	(3.04)	(3.24)
Portfolio 8	0.16	0.18	0.03	0.16	-0.50	-0.52	-0.78	-0.81	-0.66	-0.67	-0.71	-0.73	0.16	0.17
	(1.73)	(2.01)	(0.73)	(3.66)	(-16.64)	(-17.87)	(-15.03)	(-16.47)	(-12.62)	(-14.09)	(-14.04)	(-15.21)	(2.73)	(2.98)
Portfolio 9	0.13	0.14	0.13	0.23	-0.46	-0.47	-0.76	-0.78	-0.62	-0.62	-0.82	-0.85	0.22	0.23
	(1.29)	(1.39)	(3.57)	(5.70)	(-14.65)	(-16.21)	(-15.33)	(-16.44)	(-13.42)	(-14.18)	(-15.05)	(-16.33)	(4.01)	(4.26)
Portfolio 10	0.17	0.19	0.08	0.20	-0.52	-0.54	-0.67	-0.69	-0.59	-0.59	-0.75	-0.77	0.09	0.11
	(1.78)	(2.01)	(1.81)	(4.39)	(-16.94)	(-18.71)	(-15.15)	(-16.55)	(-9.88)	(-10.28)	(-16.09)	(-17.43)	(1.74)	(2.00)
Portfolio 11	0.17	0.19	0.13	0.26	-0.47	-0.49	-0.55	-0.57	-0.65	-0.65	-0.60	-0.61	0.12	0.13
	(1.70)	(1.89)	(2.85)	(5.36)	(-13.10)	(-15.08)	(-13.24)	(-14.79)	(-12.20)	(-12.59)	(-15.60)	(-16.42)	(2.73)	(3.06)
Portfolio 12	0.05	0.07	0.10	0.20	-0.52	-0.54	-0.50	-0.53	-0.66	-0.66	-0.55	-0.57	0.10	0.11
	(0.53)	(0.68)	(2.35)	(4.50)	(-13.69)	(-15.67)	(-12.20)	(-13.75)	(-12.67)	(-13.66)	(-12.02)	(-13.24)	(1.97)	(2.25)
Portfolio 13	0.04	0.06	0.08	0.18	-0.44	-0.46	-0.39	-0.42	-0.47	-0.47	-0.45	-0.47	0.15	0.16
	(0.37)	(0.57)	(1.81)	(3.82)	(-13.93)	(-14.99)	(-9.48)	(-10.97)	(-9.64)	(-10.08)	(-9.65)	(-10.47)	(3.03)	(3.35)
Portfolio 14	0.12	0.13	0.07	0.17	-0.26	-0.27	-0.33	-0.35	-0.45	-0.45	-0.28	-0.29	0.12	0.13
	(1.24)	(1.48)	(1.73)	(3.81)	(-7.60)	(-8.33)	(-8.15)	(-9.13)	(-9.92)	(-10.51)	(-6.91)	(-8.00)	(2.41)	(2.65)
Portfolio 15	0.11	0.12	0.10	0.23	-0.18	-0.19	-0.11	-0.13	-0.29	-0.29	-0.12	-0.14	0.20	0.21
	(1.19)	(1.35)	(2.25)	(4.76)	(-4.72)	(-5.24)	(-2.92)	(-3.75)	(-6.90)	(-7.40)	(-3.16)	(-3.85)	(3.98)	(4.29)
Portfolio 16	0.09	0.10	0.17	0.27	-0.10	-0.11	0.00	-0.03	-0.19	-0.20	-0.02	-0.04	0.12	0.13
	(0.93)	(1.10)	(4.11)	(6.12)	(-2.69)	(-3.20)	(-0.11)	(-0.86)	(-4.57)	(-5.08)	(-0.51)	(-1.10)	(2.40)	(2.71)
Portfolio 17	0.03	0.03	0.25	0.34	0.09	0.07	0.12	0.08	-0.05	-0.05	0.16	0.14	0.10	0.11
	(0.29)	(0.37)	(6.79)	(8.31)	(2.67)	(2.35)	(2.99)	(2.50)	(-1.07)	(-1.24)	(4.07)	(3.88)	(2.06)	(2.29)
Portfolio 18	0.20	0.22	0.29	0.37	0.30	0.28	0.27	0.24	0.08	0.08	0.30	0.27	0.14	0.16
	(2.55)	(2.84)	(8.94)	(10.45)	(9.11)	(9.44)	(7.09)	(7.08)	(2.18)	(2.22)	(7.32)	(7.65)	(2.95)	(3.30)
Portfolio 19	0.47	0.49	0.40	0.50	0.30	0.29	0.36	0.33	0.37	0.36	0.39	0.37	0.49	0.50
	(7.02)	(8.31)	(13.40)	(16.22)	(9.63)	(10.23)	(9.19)	(9.62)	(10.49)	(11.39)	(9.69)	(10.32)	(11.74)	(12.52)
Portfolio 20	0.31	0.33	0.37	0.43	0.22	0.20	0.26	0.24	0.36	0.36	0.30	0.28	0.44	0.46
	(3.73)	(4.48)	(12.99)	(13.51)	(8.59)	(9.14)	(8.48)	(8.87)	(8.87)	(9.39)	(8.77)	(9.24)	(11.36)	(13.17)

Panel D: Classification II (1st and 5th quintile)

	Fees		*Info*		*Number of Funds*		*Demand*		*Info Cost 1*		*Info Cost 2*		*Info Cost 3*	
	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors	3 Factor	4 Factors
Portfolio 1	-0.91	-0.81	-0.84	-0.72	-0.87	-0.90	-0.63	-0.67	-0.67	-0.67	-0.62	-0.65	-0.61	-0.58
	(-9.87)	(-10.09)	(-21.29)	(-17.12)	(-21.25)	(-23.89)	(-13.31)	(-15.79)	(-14.48)	(-15.16)	(-12.67)	(-15.59)	(-10.13)	(-10.27)
Portfolio 2	-0.79	-0.72	-0.63	-0.56	-0.74	-0.76	-0.68	-0.70	-0.74	-0.74	-0.62	-0.64	-0.62	-0.59
	(-8.97)	(-8.78)	(-19.16)	(-15.41)	(-21.31)	(-23.96)	(-19.89)	(-21.91)	(-16.47)	(-18.08)	(-16.62)	(-17.79)	(-10.86)	(-11.07)
Portfolio 3	-0.63	-0.56	-0.49	-0.39	-0.67	-0.69	-0.80	-0.83	-0.85	-0.85	-0.76	-0.78	-0.43	-0.40
	(-5.96)	(-5.54)	(-13.48)	(-9.97)	(-18.36)	(-20.90)	(-20.34)	(-23.23)	(-18.73)	(-20.27)	(-17.49)	(-19.70)	(-8.03)	(-8.19)
Portfolio 4	-0.19	-0.14	-0.42	-0.31	-0.57	-0.59	-0.82	-0.85	-0.84	-0.84	-0.77	-0.80	-0.24	-0.22
	(-1.84)	(-1.35)	(-10.25)	(-6.99)	(-16.31)	(-18.07)	(-18.09)	(-20.82)	(-17.04)	(-17.93)	(-16.60)	(-18.65)	(-4.66)	(-4.47)
Portfolio 5	-0.02	0.05	-0.26	-0.14	-0.45	-0.47	-0.76	-0.77	-0.66	-0.66	-0.67	-0.69	-0.12	-0.10
	(-0.21)	(0.45)	(-5.74)	(-2.83)	(-12.23)	(-13.71)	(-18.39)	(-19.32)	(-13.73)	(-14.33)	(-14.47)	(-15.34)	(-2.11)	(-1.82)
Portfolio 6	0.11	0.17	-0.06	0.08	-0.60	-0.61	-0.71	-0.74	-0.73	-0.73	-0.70	-0.73	0.13	0.16
	(0.91)	(1.46)	(-1.18)	(1.55)	(-16.88)	(-17.91)	(-15.02)	(-17.69)	(-13.83)	(-14.91)	(-14.86)	(-16.69)	(2.51)	(3.13)
Portfolio 7	0.24	0.30	-0.07	0.08	-0.47	-0.49	-0.72	-0.75	-0.68	-0.68	-0.72	-0.75	0.32	0.33
	(1.99)	(2.48)	(-1.47)	(1.59)	(-10.76)	(-12.48)	(-15.14)	(-16.99)	(-14.31)	(-15.07)	(-14.27)	(-16.15)	(5.21)	(5.59)
Portfolio 8	0.45	0.54	0.01	0.16	-0.56	-0.57	-0.84	-0.87	-0.79	-0.79	-0.75	-0.77	0.37	0.39
	(3.74)	(4.65)	(0.29)	(3.13)	(-15.78)	(-16.95)	(-17.04)	(-18.78)	(-13.84)	(-15.37)	(-15.39)	(-16.90)	(4.85)	(5.30)
Portfolio 9	0.43	0.47	0.14	0.26	-0.50	-0.52	-0.84	-0.86	-0.73	-0.73	-0.87	-0.90	0.50	0.52
	(3.27)	(3.62)	(3.10)	(5.12)	(-13.81)	(-15.26)	(-18.36)	(-19.85)	(-14.49)	(-15.22)	(-16.38)	(-18.02)	(6.94)	(7.43)
Portfolio 10	0.34	0.41	0.07	0.22	-0.59	-0.61	-0.72	-0.74	-0.74	-0.74	-0.80	-0.82	0.33	0.36
	(2.75)	(3.42)	(1.43)	(3.93)	(-16.59)	(-18.34)	(-17.01)	(-18.67)	(-11.50)	(-11.92)	(-17.96)	(-19.79)	(4.59)	(5.11)
Portfolio 11	0.46	0.53	0.12	0.26	-0.52	-0.54	-0.56	-0.58	-0.80	-0.80	-0.62	-0.64	0.29	0.31
	(3.56)	(4.19)	(2.13)	(4.46)	(-12.42)	(-14.30)	(-13.58)	(-15.13)	(-14.14)	(-14.54)	(-16.57)	(-17.59)	(4.93)	(5.52)
Portfolio 12	0.26	0.32	0.09	0.22	-0.56	-0.59	-0.51	-0.53	-0.77	-0.77	-0.56	-0.59	0.28	0.31
	(1.96)	(2.48)	(1.88)	(3.92)	(-12.58)	(-14.36)	(-12.28)	(-13.79)	(-13.26)	(-14.19)	(-12.30)	(-13.68)	(4.11)	(4.62)
Portfolio 13	0.15	0.23	0.07	0.19	-0.49	-0.50	-0.39	-0.42	-0.55	-0.55	-0.48	-0.50	0.35	0.37
	(1.11)	(1.75)	(1.41)	(3.35)	(-13.20)	(-14.20)	(-9.55)	(-11.00)	(-9.96)	(-10.33)	(-10.26)	(-11.24)	(5.39)	(5.98)
Portfolio 14	0.27	0.35	0.07	0.18	-0.27	-0.28	-0.31	-0.33	-0.48	-0.48	-0.28	-0.30	0.33	0.35
	(2.28)	(3.01)	(1.28)	(3.27)	(-6.90)	(-7.60)	(-7.41)	(-8.27)	(-9.10)	(-9.53)	(-6.89)	(-8.08)	(5.02)	(5.46)
Portfolio 15	0.24	0.29	0.11	0.26	-0.16	-0.18	-0.10	-0.12	-0.30	-0.30	-0.11	-0.13	0.43	0.45
	(1.96)	(2.46)	(2.03)	(4.51)	(-3.71)	(-4.19)	(-2.57)	(-3.33)	(-6.38)	(-6.74)	(-2.83)	(-3.56)	(6.48)	(7.06)
Portfolio 16	0.20	0.25	0.21	0.34	-0.07	-0.08	0.02	0.00	-0.17	-0.17	0.00	-0.03	0.32	0.35
	(1.69)	(2.19)	(4.36)	(6.46)	(-1.53)	(-1.99)	(0.71)	(0.08)	(-3.60)	(-3.91)	(-0.09)	(-0.72)	(5.05)	(5.65)
Portfolio 17	0.54	0.57	0.39	0.52	0.16	0.14	0.17	0.14	0.05	0.05	0.22	0.20	0.37	0.38
	(4.67)	(5.00)	(9.34)	(11.68)	(4.50)	(4.30)	(4.55)	(4.32)	(0.97)	(1.01)	(5.65)	(5.53)	(5.96)	(6.45)
Portfolio 18	0.60	0.67	0.42	0.54	0.38	0.36	0.31	0.28	0.16	0.16	0.34	0.31	0.42	0.45
	(6.19)	(7.25)	(11.77)	(14.28)	(10.72)	(11.23)	(8.13)	(8.30)	(3.80)	(4.02)	(8.62)	(9.04)	(6.67)	(7.41)
Portfolio 19	0.34	0.43	0.43	0.55	0.36	0.34	0.36	0.33	0.37	0.37	0.39	0.36	0.75	0.78
	(3.68)	(5.17)	(11.50)	(13.57)	(10.16)	(10.81)	(9.00)	(9.45)	(9.01)	(9.83)	(9.30)	(9.72)	(14.15)	(15.50)
Portfolio 20	-0.01	0.09	0.37	0.42	0.24	0.22	0.24	0.22	0.33	0.33	0.29	0.27	0.56	0.60
	(-0.06)	(0.89)	(9.99)	(10.01)	(8.36)	(8.82)	(7.71)	(8.01)	(6.79)	(7.21)	(8.27)	(8.53)	(10.22)	(12.11)