Asset management and investment banking

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Abstract

We find evidence that conflicts of interest are pervasive in the asset management business owned by investment banks. Using data from 1990 to 2008, we compare the alphas of mutual funds, hedge funds, and institutional funds operated by investment banks and non-bank conglomerates. We find that, while no difference exists in performance by fund type, being owned by an investment bank reduces alphas by 46 basis points per year in our baseline model. Making lead loans increases alphas, but the dispersion of fees across portfolios decreases alphas. The economic loss is $4.9 billion per year.

JEL classification: G21, G24
Keywords: Investment banks, Institutional funds, Hedge funds, Mutual funds, Performance evaluation

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1. Introduction

The critical issue for financial economists studying conflicts of interest in financial institutions is the balance between the value added of an institution and the potential harm arising from conflicts of interest. A conflict of interest is defined as a situation in which a party to the transaction can gain at the expense of another party. Its occurrence does not necessarily mean that, in equilibrium, it results in an economic loss. As discussed in Mehran and Stultz (2007), the many potential conflicts of interest for investment banks are typically accompanied by a variety of mechanisms that control the impact of conflicts of interest. Bolton, Freixas and Shapiro (2007) develop a theory that models the interplay between conflicts of interest and their impact. The model predicts that, when profit margins are equal across products, conflicts will have less of an impact for the clients of an integrated financial institution than of a specialized institution. The question of whether the mechanisms control conflicts is ultimately an empirical one. We examine this question by testing whether diversification of activities within financial institutions adds value to assets under management due to information links or subtracts value due to conflicts of interest. The literature has ignored the large portfolios of publicly traded assets operated by investment banks with the exception of Massa and Rehman (2008) and Ritter and Zhang (2007), both of whom focus on bank operated mutual funds. This is surprising given that investment banking is highly regulated and, now, publicly supported. To fill the gap, we compare asset management services offered by investment banks with the same services offered by specialized firms, which do not engage in the range of activities of an investment bank.

Because investment banks operate many types of portfolios, any study of investment banking and portfolio management inevitably requires an examination of the economics of investment contracts. Investors who do not directly invest their money must choose not only the type of organization that manages their investments but also the type of contract that governs the relationship with the manager. The efficiency of the contract form is clearly important for researchers in evaluating whether investment banks add or subtract value compared with other organizations. Existing studies of contract form such as Ackerman, McEnally, and Ravenscraft (1999) and Cici, Gibson, and Moussawi (2010) compare mutual funds only with hedge funds and, with the exception of the side-by-side comparison in Cici, Gibson, and Moussawi (2010), they do not control for differences in the companies that offer these portfolios. Variation in assets under management, centralization of information gathering and trading, economies of scale, transactions costs levels, and risk control can create risk-return differences across portfolio type. A distinguishing feature of this study is the comparison of the investment performance of three types of delegated portfolios: mutual funds, hedge funds, and institutional funds. We compare portfolios owned by investment banks versus those owned by nonbank financial services groups, which we simply call financial conglomerates. Our sample consists of all financial groups, both investment banks and financial conglomerates that managed all three types of portfolios for at least one year during 1990–2008 and reported their performance data to widely available databases. There are 23 investment banks and 48 non-investment banks in our data. We examine the impact of investment banks (and the investor contract form) on the alphas of all portfolios that these financial groups operated during the time period. We compare investment banks only with other financial groups to control for the effect of omitted variables. Comparing investment bank–operated portfolios with portfolios not in a financial group is likely to increase the effect of omitted variables because comprehensive investment organizations centralize services that portfolio managers commonly demand.

To examine the risk-return differences, we estimate alphas on unsmoothed returns using the moving average process developed by Getmansky, Lo, and Makarov (2004) to account for differences in portfolio exposure to various risk factors. We use a seven-factor model with time-varying alphas similar to Agarwal and Naik (2004).We test the hypothesis that investment banks produce different alphas relative to nonbank conglomerates by examining the cross-sectional regression of fund alphas on control variables and type of organization. Our tests show that the form of the contract offered to investors does not matter once the control variables are included. While the contract form is occasionally significant in year-by-year regressions, competition equalizes the impact of the three contract forms across time. It is clear that the control variables are a critical part of explaining the difference between types of contracts. However, when the data are confined to a single contract, these organizations appear to be optimized for institutional clients because the control variables do not matter for institutional funds. For hedge funds and mutual funds, the control variables are significant.

Our findings show that the organizational ownership structure matters. On average, investors experience a lower alpha of 46 basis points per year when an investment bank operates a fund. The harm is largely borne by mutual fund investors and depends on the fee dispersion across portfolios offered by the investment bank and the participation of the investment bank in lead loans during the year. It does not depend on equity or debt underwriting business. The greater the fee dispersion, the more the harm; the more the participation in lead loans, the lower the harm. The effect of investment bank ownership is material amounting to at least $93 billion loss over the 19-year sample, but the dollar loss is time-varying. For 14 years of the 19-year sample, the costs of being owned by a bank were higher than the benefits. There were only five years, 1993–

1994 and 2001–2003, when the benefits of being owned by an investment bank outweighed the costs.

The paper proceeds as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 presents the sample collection process and introduces descriptive statistics. Section 4 discusses our procedures for correcting selection biases in our sample and the methodology for testing our hypotheses. Section 5 discusses results and Section 6 concludes.

2. Hypotheses

We proceed by outlining theory papers that examine conflicts of interest for investment banks.

2.1 Conflicts of interests for investment banking

The Bolton, Freixas, and Shapiro (2007) model predicts that an integrated financial institution is more capable of offering an appropriate product for a customer simply because it has more products than a specialized financial firm. However, this also gives the integrated firm more opportunities to offer inappropriate products. In the model, the financial institution maximizes profits net of the reputation cost of lying to customers. If the reputation cost is sufficiently high, then there is no conflict of interest. However, Mehran and Stulz (2007) argue that reputation costs are likely not high enough to eliminate conflict of interest, and Bolton, Freixas, and Shapiro carefully examine the case in which reputation costs are lower than profits. They show (in Proposition 2) that all conflicts are eliminated if the gross margins are the same across products. Equal gross margins for products eliminates the incentive to misdirect the customer into inappropriate but profitable products. Mehran and Stulz (2007) observe that, in a perfectly competitive market for asset management services, products have the same profit margins. Cabral and Santos (2001) use a model with a different focus and develop the incomplete contracting between the client and the financial institution. Their financial institution is better informed, which creates a moral hazard problem. By exploiting its superior information to take advantage of a relationship with a client, the financial institution takes the risk of jeopardizing future transactions with that client. If selling multiple products increases the likelihood and number of future transactions, a financial institution selling multiple products bears a reputation cost of engaging in a conflict of interest. Both theories suggest that multiproduct firms both have more potential conflicts of interest and more incentives than specialized firms to reduce the costs of their conflicts of interest. These theories motivate our focus on comparing investment banks, which are multiproduct financial institutions, with specialized asset managers.

The benefits of a fund being affiliated with a multiproduct firm is generally described by Mehran and Stultz (2007) as the "re-usability" of information. Here the information generated by one product line (e.g., lending, analysts, underwriting) is employed by another product line (e.g., asset management) to generate value. The literature has evidence that the re-usability occurs with bank loans (Massa and Rehman, 2008), initial public offerings (Ritter and Zhang, 2007), and analysts (Irvine, Lipson, and Puckett, 2007). In each case, the costs of re-usability arise from conflicts of interest that are poorly controlled. Whether the multiproduct investment bank provides more net benefit to investors than a specialized firm is reflected in the relative net return after all fees and transactions costs.

2.2. Portfolio type

Two questions arise concerning types of portfolios: (1) Which contract form is likely to benefit or lose from an association with investment banks? (2) Which, if any, contract form is superior? Each contract specifies different cash flow claims and ownership rights for investors that reduce the agency costs between managers and clients. The portfolio manager is the agent who has more information about securities than the client who is the principal. Bhattacharya and Pfleiderer (1985) prove that if the preferences of managers can be observed, then a contract can be designed that forces managers to reveal their information eliminating agency costs. In practice, it is probably impossible for such a contract to be written. As a consequence, the investment business has evolved into three major segments with common contract features that attempt to control agency costs for the clients in those segments.

Existing studies of contract form suggest that four mechanisms help align these interests: incentive contracts, ownership structure, market forces, and government. The studies are mixed in their conclusions. Cici, Gibson, and Moussawi (2010) examine a sample of managers that manage side-by-side mutual funds and hedge funds, finding evidence that side-by-side managers strategically transfer performance from mutual funds to hedge funds. Ackermann, McEnally, and Ravenscraft (1999) examine a sample of hedge fund data and find that the hedge funds industry consistently outperforms the mutual fund industry in terms of Sharpe ratios but do not beat standard market indices. They attribute some of the higher performance to incentive fees but, after finding that incentive fees cannot account for increased risk, they explain hedge fund superiority by the regulatory differences between mutual funds and hedge funds.

None of the preceding studies controls for differences in the companies that offer these portfolios. Variations in assets under management, centralization of information gathering, economies of scale, transactions costs levels, and risk control can create risk-return differences across portfolio type. Our paper extends the current literature by offering a cross-industry performance comparison within a multifactor risk adjustment setting while controlling for conglomerate effects on fund performance. It is the first study to examine portfolios across the three managed fund industries. The examination of the effect of investment banks necessitates our study of the differences between the risk and return relation that investors earn due to the form of the contract between managers and investors.

2.3. Hypotheses

Our study examines the differences in the risk and return relation that an investor can expect by investing in one of the three fund types, which we refer to as portfolio hypotheses, and whether these differences depend on ownership by an investment bank, which we refer to as investment banking hypotheses.

Our baseline investment banking hypothesis is whether being owned by an investment bank adds value to the portfolios under management over being owned by a financial conglomerate. The hypothesis is strongly suggested by the theories of Bolton, Freixas, and Shapiro (2007) and Cabral and Santos (2001). The theoretical literature on conflicts of interest suggests that competitive multiproduct firms have fewer conflicts than specialized firms if profit margins are equal, such as when the market is perfectly competitive. When the market profit margins are equal the multiproduct firm matches the product to the needs of the clients because a multiproduct firm has more products than a single product firm. In addition, multiproduct firms are more interested in long-term relationships. These studies imply that the sign of an investment banking dummy variable indicates value added or subtracted in a regression mode, in which a portfolio alpha is a function of the portfolio and organization characteristics.[1]

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[1] The empirical studies find that banks have sources of information that enable asset managers to choose better securities. See the empirical work of Massa and Rehman (2008) and Ritter and Zhang (2007), as an example.

We add to the baseline hypothesis by considering that the market for investment banking services might not be competitive enough to resolve all conflicts. Relying on the model of Bolton, Freixas, and Shapiro (2007), the dispersion in gross margins on financial products indicates the degree of conflicts of interest for a financial institution. They define gross margins as the fees paid by investors less all costs of operating the fund. Unfortunately, we cannot observe the economic gross margins on managed portfolios, but we believe fees of a fund are a reasonable proxy. First, the largest component of total fees is the management fee. For some funds this could precisely measure the economic gross margins, but for others the accounting numbers do not necessarily measure the economic concept. However, it is well recognized that the management fee is independent of the costs of operating a fund and is strategically determined.[2] Second, the excess of total fee over management fee is not related to performance of a fund but to its size and the number of clients—at least for the small number of mutual funds in our sample in which we can observe this difference. While we can observe the management fee for some mutual funds, we cannot for pension funds and hedge funds. The management fee is not reported separately from the total fee for these funds, and the management fee is likely to be almost equal to the total fee because hedge funds and institutional funds do not have the costs of retail mutual funds serving many small clients. Third, the fund families with publicly traded equity, such as Blackrock (in our sample) and T. Rowe Price (not in our sample), have revenues that are highly correlated with profits over time.[3] Revenues are largely, even solely, dependent

[2] A central feature of the Berk and Green (2004) model is that managers increase their fees to the point where expected returns to investors are competitive. Similarly, Gil-Bazo and Ruiz-Verdu (2009) argue that fees are strategically set and that many high fee funds have low gross performance.

[3] Over the past ten years, the correlation between T. Rowe Price revenue and income was 94%, and for Blackrock it was 98%. Three other firms in our sample are publicly traded, single product, companies: Franklin Resources, which had a 99% correlation; Diamond Hill Investment, which had a 47% correlation; and Calamos Asset Management, which had a -21% correlation. The negative correlation is due to charges from a subsidiary that is not an asset management firm.

on fees times assets under management. These reasons suggest that fees are a reasonable proxy for the economic profit—the focus of the Bolton, Freixas, and Shapiro model.

We use dispersion of fees to test our second investment banking hypotheses that multiproduct firms – investment banks with higher conflicts of interest should have a lower alpha to investors. The dispersion of fees in a year for a financial institution is a proxy for conflicts of interest. We expect that the cross-sectional dispersion of fees in year *t* for financial institution *i* will be negatively related to alphas for multiproduct firms – investment banks.

We define portfolio hypotheses as hypotheses that explain differences in abnormal returns due to contract type. Our first portfolio hypothesis is the management alignment hypothesis. Specifically, the greater the alignment of interests between management and clients, the higher the return. If interests are better aligned, agency costs are reduced in two ways. First, management reveals the information (by actively trading securities) that adds value to the portfolio. Second, management charges lower expenses for the value-adding information and reduces hidden expenses such as soft dollars. Thus, we expect that the risk and return relation differs between the organizational forms (proxied by portfolio type), reflecting the variations in the degree of alignment.[4]

Our second portfolio hypothesis is the flexibility hypothesis, that is, as the fewer restrictions on the manager, the higher the return to clients. If fewer restrictions exist, management is better able to achieve an optimal return for the risk taken in an efficient market and better able to use the information that they have if they receive information that is not already reflected in the price of the security. Ceteris paribus, we expect hedge funds and institutional funds to perform better than mutual funds, which are restricted to liquid securities

[4] See the Ackerman, McEnally, and Ravenscraft (1999) discussion on how the principal-agent theoretical arguments by Holmstrom (1979) and Starks (1987) apply to the asset management.

and diversified portfolios. Hedge fund managers invest their own funds, receive high bonus fees, can choose long and short positions in any asset, and can follow a wide range of investment strategies. Institutional funds are also subject to much less regulation than mutual funds, but their clients allow them less flexibility than hedge funds.

The alternative to these two portfolio hypotheses is the theoretical model of Berk and Green (2004), who argue that managers capture the wealth created by each portfolio in a competitive market. They assume that investors observe the skill of managers and place assets in portfolios until the marginal benefit equals the marginal cost. The assumption that the asset flow is in response to manager skill implies that the contract between manager and client fully reveals the information of the manager. Under this hypothesis, we should observe no difference in performance across organizational forms. In other words, mutual funds should exhibit similar performance to hedge funds and institutional funds.

2.4. Control variables

With the exception Cici, Gibson, and Moussawi (2010), the previous studies comparing performance across portfolio types do not control for differences that have an effect on performance but that are not related to portfolio type. We suggest that when these investment segments are all owned by the same company the effect of omitted variables is mitigated. Investment conglomerates and banks provide a variety of services that are centralized and tend to reduce differences in the segments unrelated to the contract, namely, partially or fully centralized information collection, a common resource base to pay for information, risk control over all managed portfolios, common reporting and monitoring to reduce the risk of fraud and blowup risk, and economies of scale in costs (legal cost, transactions costs). Grossman and Stiglitz (1980) argue that the more expenditures on manager skill and information, the higher the return.

Because these large financial organizations vary widely in their revenue, we introduce several control variables that proxy for the Grossman and Stiglitz effect. We include the assets under management by the fund and the conglomerate to control for differences in size. In addition, we control for the concentration of the type of funds because the information and skill could have some economies of scope across fund type. Some conglomerates and investment banks have mostly mutual funds under management, while others have concentrations of hedge funds and institutional funds.

Many hedge funds are younger and more active than mutual funds and institutional funds, yet this difference has nothing to do with being a hedge fund. Younger and more active mutual funds could have exactly the same risk-return characteristics. Transactions costs per share are probably lower for the more active and larger portfolios. Institutional portfolios are often much larger than hedge funds and mutual funds and could incur smaller transactions costs. We use fees, revenues, and age to control for these differences across portfolios that have nothing to do with the form of the contract.

It is reasonable to expect that hedge funds would produce a superior risk-return relation because hedge fund managers could invest in a wider variety of assets than mutual and institutional fund managers and because incentive schemes differ across industries. Ackermann, McEnally, and Ravenscraft (1999) find empirical evidence linking performance fees to improved hedge fund performance, but not to increased risk. We, therefore, control for the effect of fees on fund alphas in three ways. First, all returns are measured net of fees. Second, as an explanatory variable we include the fees of each fund. Finally, we include the revenue of the conglomerate from portfolio management.

Goetzmann, Ingersoll, and Ross (2003) find decreasing returns to scale among hedge funds that Berk and Green (2004) suggest is related to investor experience with managers. Empirically, Agarwal, Daniel, and Naik (2009) establish that management companies' age is negatively related to their performance. Therefore, age is an important control variable. We discuss the precise measurement of these variables in the next section.

3. Data collection and descriptive statistics

We identified 23 investment banks that managed all three portfolio types during 1990 – 2008. Our definition of an investment bank is that the organization had to engage in underwriting. All investment banks except Lehman Brothers and Nomura managed all three types simultaneously.[5] We matched the investment banks with investment organizations that reported returns, assets, and other data for all three types of portfolios over this period. The organization had to report data on all three portfolio types simultaneously for at least 12 months. This resulted in 48 investment organizations that we term conglomerates. Thus, our combined sample consists of 71 investment organizations (23 banks and 48 conglomerates) managing a total of 621 hedge funds, 2,679 institutional funds, and 2,865 mutual funds.[6]

3.1. Databases

The databases used in our sample are for hedge funds—Lipper TASS (Trading Advisor Selection System), Center for International Securities and Derivatives Markets (CISDM), Barclays Hedge Fund Data, Global Fund Analysis (for returns and fund descriptions), Mobius

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[5] Lehman stopped reporting on mutual funds in 1996 and started reporting hedge funds in 1997. Nomura stopped reporting mutual fund returns in 2001 and reported its first hedge fund in 2005. We treat Mercury asset management as an investment bank after its acquisition by Merrill Lynch in 1998.

[6] Sixty-three of the organizations had all three types of portfolios simultaneously for three or more years. Our sample size never consists of all these funds in any given year.

Hedge Fund Panel Data; mutual funds—Center for Research in Security Prices (CRSP) mutual fund database, Morningstar website (www.morningstar.com), Morningstar CDs of various months; and institutional funds—58 quarterly surveys from June 1993 to December 2007 from the Mobius Group, which reports returns and numerous other characteristics of institutional managers.[7] Until 2007, Mobius was one of the primary vendors of money management data that were used by most large pension fund sponsors and endowment funds to determine who would manage their money. We cross-check the returns of the lowest return decile of managers with another commercially available database (Informa PSN) and a private source of return data.[8] For 2008, we add data from Informa PSN, which acquired Mobius in 2006 and ended the product in 2007. We examine the returns and longevity of every money manager in these data who had full discretion over their accounts. To obtain addresses and legal company relations, we use Securities and Exchange Commission (SEC) Edgar Filings, Thompson Fund Database, websites of investment conglomerates, LexisNexis, Dow Jones, and general Internet searches.

All the databases include dead funds. However, the hedge fund databases drop funds from release to release. For CISDM we have annual releases for 2005, 2007, 2008 and 2009. For all funds in CISDM (not just those in our sample) CISDM dropped 1.23% of funds by 2009 from one of the previous releases that we have. For Lipper TASS, we have September 2005, February 2008, March 2009, and July 2009. Lipper TASS dropped 3.04% of its funds by July 2009 from one of the previous releases that we have. We hand-match the hedge fund data from all releases of both Lipper TASS and CISDM to get a complete hedge fund record for all 71 investment organizations. We have all releases of the institutional data from 1993 to 2008. We construct a

[7] Funds that were in Mobius Hedge Fund and also in either TASS or CISDM reported identical returns.

[8] Ten managers were in Mobius and hired by the Virginia Retirement System (VRS). We had access to the internal records of the VRS from 1993 to 1996. The data are identical to those in Mobius.

survivorship bias-free dataset of institutional returns. We use the 2009 CRSP survivorship bias-free mutual fund database (reporting returns through January 2009) for all our mutual fund data. For security issuance data we use Securities Data Company (SDC) and for lending data we use Dealscan.

3.2 Matching funds with investment organizations

No common identifiers appear across our databases. We hand-match the investment organizations across mutual fund and hedge fund databases by name. While the CISDM database has a family name identifier, the TASS database does not. Therefore, we extract the family name from the title of the hedge fund. For the funds that did not have the family name in the title, we use Barclays Hedge Fund Data, Global Fund Analysis database, LexisNexis, SEC filings, hedge fund web addresses, and general Internet queries.

We then check the address match between hedge funds and mutual funds. Several companies do not have a precise name match as their fund conglomerate mutual funds and hedge funds were offered by different subsidiaries. We require that the CRSP family names should be on record for at least two years with reported returns in one of those years. We then proceed with a mechanical match. Within the mechanical match, we use the first 12 letters from the CRSP family name to search the list of hedge fund names. We then match the investment organizations to institutional funds using our institutional fund database. The institutional database has a unique family name identifier and follows name changes for families. It also lists family legal addresses.

3.3 Fund-level filters and joining of assets classes

Next, we apply the following filters to the initial data set. We consider mutual and hedge funds that reported at least 12 monthly returns and institutional funds that reported at least eight quarterly returns. This eliminates 23 hedge funds, 220 institutional funds, and 77 mutual funds but no conglomerates from our sample. For institutional funds, we take funds that reported net assets at least once, eliminating a few newly created funds. For hedge funds, we eliminate funds that never reported asset values if other hedge funds in the same complex reported asset values. Mutual funds with no assets are excluded because they most often are an additional share class to a fund that already reports share class assets. We eliminate funds that did not report fees. We also do not include money market or municipal bond funds in our sample (CRSP codes MF, MG, MQ, MS, MT, and MY). These funds are mostly tax-exempt and passively managed, and we have no similar funds in the hedge fund or institutional fund sector. This eliminates 530 funds (about 1% of institutional portfolios are municipal portfolios and are excluded from further analysis).

We combine assets of mutual and hedge funds with multiple asset classes or return reports in multiple currencies. In combining the asset classes, we use the following rules. We keep the longest return series. If two return series were of similar length, we took class A or institutional shares to avoid the impact of a load return. If a particular asset class has assets that are significantly higher than all other return series, we keep the returns from the series with the highest assets. For mutual funds, we join regular and institutional share class assets. If an institutional fund is the only asset class available and a fund with a similar name is reported by the institutional database as a separate account, we exclude this fund from the sample. Conversely, if an institutional database reports an institutional mutual fund, we exclude it from the institutional sample. This way the mutual fund industry contains both retail and institutional accounts. Sometimes the institutional database offers both equally and asset weighted returns. We choose equally weighted returns when available. If two asset classes report time series of the same length, but just one has turnover indicated, we took the latter. We choose common over investor, and I over N asset classes. If a fund asset class with no load is offered we include it in the sample. Similarly, we prefer to keep US dollar denominated to other currency denominated hedge fund returns. If assets of multiple currency funds are equal across funds, we do not add the assets. We believe that in this case the total assets are already redundantly reported in all different share classes. We also prefer onshore to offshore funds. Again, we retain the longest return time series. We assume that the main difference between the onshore and offshore returns is the tax impact, which is not the subject of our study. We keep funds from three industries that report returns for at least a year.

3.4. Equity identifier

Next, we identify equity mutual, hedge, and institutional funds. For equity mutual funds we modify the selection method used in Cici, Gibson, and Moussawi (2010). We mark funds that have an equity position between 50% and 105% but belong to categories that are identified as equity.[9] For the funds that do not report equity position, we mark them as equity funds if they belong to the following equity classes with ICDI objective code in CRSP: aggressive growth (AG), growth and income (GI), global equity funds (GE), international equity funds (IE), long-term growth funds (LG), total return funds (TR), and sector funds (SF)[10]. Funds with missing entries are manually identified by examining the fund name. Among mutual funds, 1,093 are equity funds in our sample. We also exclude index funds from our sample as they represent a passive investment strategy. Because variables identifying index funds are available from 2003 only, we searched for "index" and "500" in names. In the institutional database, we define

[9] In identifying funds' equity percentage, or class membership, we take the last reported variable.

[10] Some sector funds include real estate funds.

international equity or domestic equity portfolios as equity. For hedge funds, we examine the styles reported in CISDM, Lipper TASS, or Mobius Hedge Fund Databases. If the styles suggest the use of equity, we define the fund as an equity fund. For example, CISDM equity funds have the following styles: sector, relative value multi-strategy, merger arbitrage, equity market neutral, and equity long or short. In Mobius the strategies are equity long or short, small or microcap, health care sector, and market-neutral equity. We eliminate the fund of fund class of hedge funds to avoid double counting. Over the entire database, 52.6% of funds are equity funds and 48% of hedge funds are equity funds, 66% of institutional funds are equity funds, and 52% of mutual funds are equity funds (see Tables 1 and 2 for the year-by-year statistics).

[Insert Tables 1 & 2 near here]

3.5. Dealing with biases in the data

Several studies have argued that hedge fund returns exhibit substantial serial correlation, in which the main source of the correlation is the presence of illiquid assets in a portfolio. Manager performance measurement could be biased if one does not account for serial correlation. Jagannathan, Malakhov, and Novikov (2010) show that the occurrence of positive alphas decreases in a sample after accounting for serial correlation. Lo (2002) shows that Sharpe ratios for auto correlated returns could also be biased upward. Several methods have been suggested for dealing with serial correlation. Getmansky, Lo, and Makarov (2004) use an MA(2) process to correct for the smoothing bias. Jagannathan, Malakhov, and Novikov (2010) suggests that serial correlation is especially severe for hedge funds in specific sectors. We follow Getmansky, Lo, and Makarov (2004) and unsmooth all hedge fund returns with an MA(2) process using the model

$$X_t^i = \theta_0^i \eta_t^i + \theta_1^i \eta_{t-1}^i + \theta_2^i \eta_{t-2}^i, \qquad (1)$$

where η_t^i is unsmoothed, or true return *i*, at time *t,* and $X_t^i = R_t^i - \mu_i$ is the demeaned return. We assume that $\eta_t^i \sim N(o, \sigma_i^2)$. Eq. (1) is a moving average process with lag 2. To identify this system, we impose the invariability constraint $\theta_0 + \theta_1 + \theta_2 = 1$. The economic meaning of this constraint is that the smoothing occurs over the most recent two periods.

If R_t^i follows an MA(2) process, we can estimate η_t^i from Eq. (1) using maximum likelihood estimation. Getmansky, Lo, and Makarov show that the concentrated likelihood function for Eq. (1) is

$$L_0(\theta) = \log[T^{-1} \sum_{t=1}^{T} (X_t - \hat{X}_t)^2 / r_{t-1}] + T^{-1} \sum_{t=1}^{T} \log r_{t-1}, \tag{2}$$

To ensure invariability, we divide the estimated MA factors by $1 + \theta_1 + \theta_2$. This follows from a well-known statistical property of the MA process, in which any noninvertible process can be transformed into an invertible process by adjusting the parameters and variance.

We estimate an MA(2) process for all fund returns (hedge fund, mutual fund, and institutional funds) that had at least 30 observations, unsmoothing those funds that exhibit at least a positive and significant first order autocorrelation. We find 180 out of 902 hedge funds yield significant positive θ_1 and 20 yield significant positive θ_1 and θ_2. We unsmooth returns for the 180 hedge funds by first unsmoothing the demeaned return and then adding back the mean. The average MA(2) parameters for the 180 hedge funds are as follows: θ_0 is 0.744, θ_1 is 0.246, and θ_2 is 0.01. Average σ_1 is 0.093 and σ_2 is 0.094. This means that just 74.4% of returns from a current month are directly reflected in the reported return for these 180 funds. All other hedge fund studies report a larger percentage of funds that need to be unsmoothed. Only a few mutual funds and institutional funds have significant MA(2) parameters and we chose not to unsmooth these funds following the practice in the mutual fund literature.

Bollen and Krepely-Pool (2009) find a significant discontinuity in the pooled distribution of reported hedge fund returns when the number of small gains far exceeds the number of small losses. They find that the discontinuity is present in live funds, defunct funds, and funds of all ages, suggesting that it is not caused by database biases. The discontinuity is absent in the three months culminating in an audit, funds that invest in liquid assets, and hedge fund risk factors. This suggests that it is generated by return manipulation rather than by the skill of managers to avoid losses or by nonlinearities in hedge fund asset returns. We check our hedge funds for this discontinuity and did not find any evidence of discontinuity.[11]

Our finding that fewer of our hedge funds have significant MA(2) coefficients and that the discontinuity bias is not in our sample suggests that financial conglomerates and investment banks have reporting standards that are stricter than nonconglomerates. It suggests that the well-documented reporting problems of hedge funds are mitigated when a large financial organization owns them. It clearly supports our research design of comparing only investment banks with other nonbank conglomerates.

3.6. Backfill bias

Funds frequently bring all their history with them when joining the sample and can choose how much and what, if any, history to bring. This could bias conclusions about a manager's superior performance in previous years. Ackerman, McEnally, and Ravenscraft (1999), Liang (2000), and Fung and Hsieh (2001) have found evidence of backfill bias. Several databases identify the date that funds enter the sample. In this case, the backfilled returns are

[11] We thank Veronika Krepely-Pool for examining our data for the discontinuity bias.

deleted from the sample. Jagannathan, Malakhov, and Novikov (2010) estimate the length of backfill bias in the HFR Database at between 12 months to 25 months. The difference in return between 12 months and 25 months of truncation is insignificant for our sample of hedge funds. Following Jagannathan, Malakhov, and Novikov (2010) we chose to truncate all hedge fund and institutional fund return series by 12 returns.[12]

3.7. Descriptive statistics

Table 1 shows the assets under management, the number of portfolios, and the size of the median portfolio, by year and by type of organizational form (industry). The financial conglomerates and investment banks clearly have very large assets under management. At their peak in 2007, they were managing almost \$8 trillion with \$5.9 trillion in equity portfolios. They are clearly the dominant force in mutual funds and institutional funds. In hedge funds, they do not manage nearly as much as nonconglomerates. The hedge fund industry had almost \$1 trillion under management in 2007, but conglomerates had only about 8% of the assets. The hedge fund industry has the reputation of being independent of large institutions, and these numbers support this reputation.

[Insert Table 1 near here]

[12] We tested for outliers in hedge fund returns by looking up returns that differ from the mean by more than 8 standard deviations. We found four suspects. For example, GAM Money Markets Fund (BP) reported a return of 904.48% on January 31, 1993 and the net asset value increased tenfold in that month, while GAM Money Markets Fund (DM) reported a return of -94.11 on December 31, 1996, its assets decreased tenfold in that month. The other two outliers were around negative 30% return and were related to the 1987 market crash. As a result, the identified occurrences were not marked as data errors.

Table 2 shows the same variables as Table 1 but for only equity portfolios. The same general conclusions are shown in this table. Hedge fund portfolios are a fraction of the institutional and mutual fund portfolios.

[Insert Table 2 near here]

Table 3, Panel A shows descriptive statistics of the Sharpe ratios for all 621 hedge funds, 2,679 institutional funds, and 2,865 mutual funds. The average Sharpe ratio over this sample depends on the contract form. Hedge funds and institutional funds have positive Sharpe ratios, and mutual funds have negative average Sharpe ratios. The hedge funds are the most volatile cross-sectionally while the mutual funds are the least volatile. Panel B shows the same statistics for the funds owned by investment banks. The statistics are very similar, with the means being slightly higher. These tables show the same results for hedge funds and mutual funds as Ackerman, McEnally, and Ravenscraft (1999), who conclude that hedge funds dominate mutual funds. We believe their data do not control for omitted variables and the possibility that Sharpe ratios can be manipulated by hedge funds.[13] Consequently, we follow the lead of recent researchers who have focused on alphas from return generating models.

[Insert Table 3 near here]

4. Methodology

There are two parts of the methodology. First, measuring the time-varying risk-adjusted return of portfolios consisting of many asset classes. Second, using control variables to measure the differences in alphas across investment bank or financial conglomerates, including

[13] See Goetzmann, Ingersoll, Spiegel, and Welch (2007). However, the findings that the Bollen and Krepely-Pool (2009) show suggest that the manipulation is less when funds are owned by large organizations.

differences in portfolio type. Section 4.1 discussed the details of our risk-adjustment and Section 4.2 describes the control variables.

4.1. Risk adjusted return

To compare the risk and return relation across industries, we use a multifactor model and check it for robustness. Following Fung and Hsieh (2001), we use seven factors: excess return on the value weighted market (R_m- R_f), size (SMB), value (HML), the Carhart (1997) momentum factor (PR1YR), Lehman High Yield Bond Index (MLHYB), Salomon World Government Bond Index (MLGG), and the Standard and Poor's Commodity Index (SPGSCI).[14] We estimate one, four, six, and seven-factor versions of the model. For portfolio *p*, the four models are as follows.

The one factor model is

$$R_{pt} – R_{ft} = \alpha_p + \beta_{p1}(R_{mt}-R_{ft}) + \varepsilon_{pt}. \tag{3}$$

The four factor model is

$$R_{pt} – R_{ft} = \alpha_p + \beta_{p1}(R_{mt}-R_{ft}) + \beta_{p2}SMB_t + \beta_{p3}HML_t + \beta_{p4}PR1YR_t + \varepsilon_{pt}. \tag{4}$$

The six factor model is

$$R_{pt} – R_{ft} = \alpha_p + \beta_{p1}(R_{mt}-R_{ft}) + \beta_{p2}SMB_t + \beta_{p3}HML_t + \beta_{p4}PR1YR_t + \beta_{p5}(MLHYB-R_{ft}) + \beta_{p6}(MLGG-R_{ft}) + \varepsilon_{pt}. \tag{5}$$

The seven factor model is

$$R_{pt} – R_{ft} = \alpha_p + \beta_{p1}(R_{mt}-R_{ft}) + \beta_{p2}SMB_t + \beta_{p3}HML_t + \beta_{p4}PR1YR_t + \beta_{p5}(MLHYB-R_{ft}) + \beta_{p6}(MLGG-R_{ft}) + \beta_{p7}(SPGSCI-R_{ft}) + \varepsilon_{pt}. \tag{6}$$

[14] The market factor is the CRSP value-weighted return on all NYSE, AMEX, and NASDAQ stocks. The risk free rate is the one-month Treasury bill rate from Ibbotson Associates. The SMB, HML, PR1YR are from Fama and French data library. The Lehman High Yield Index is proxied by "Merrill Lynch high yield bond C" index, and Salomon World Government Bond Index is proxied by "Merrill Lynch Global Governments" index, while commodity factor is proxied by SPGS Commodity Index.

To account for nonstationarity, we use a time-varying regression technique called flexible least squares regression (FLS) developed by Kalaba and Tesfatsion (1989, 1996) and Lutkepohl and Herwartz (1996) that avoids these problems. In the terminology of Lutkepohl and Herwartz (1996), we use the "standard form" of the model, which assumes that the regression coefficient vector, b_t, evolves continuously over time in the linear model $y_t = x_t'\beta_t + \varepsilon_t$, where x_t is the K × 1 vector of values of the independent variable at time t and ε_t is the error term with E[ε_t] = cov(ε_t, ε_{t-j}) = 0, and var(ε_t) = σ^2. There are two sources of error: measurement error is the (usual) difference between the dependent variable at time t, y_t, and its predicted value defined as

$$sse = \sum_{t=1}^{T}[y_t - x_t'\beta_t]^2 \tag{7}$$

Dynamic error is the sum of squared changes in the coefficient vector from time t to time $t + 1$.

$$ssd = \sum_{t=1}^{T}[\beta_{t+1} - \beta_t]'[\beta_{t+1} - \beta_t] \tag{8}$$

To estimate the model they minimize a weighted sum, $\gamma sse + (1 - \gamma)ssd$, where the user supplies the weight $\gamma \in (0, 1)$. Kalaba and Tesfatsion prove that the collection of all possible weighted sums attainable at time N, {sse, ssd |β, N}, is contained by a lower envelope that is bounded away from the origin. If time variation in betas exists, there is a combination of the two errors that will minimize the variation below the standard ordinary least squares solution. Nevertheless, Lutkepohl and Herwartz (1996) demonstrate that the model finds variation in betas when the true betas are constant because specifying the second error term forces periodicity on to constant betas. Thus, if there are no a priori reasons to believe that coefficients vary, the technique could reduce the explanatory power of a regression model. However, no shortage of studies shows that mutual fund betas and alphas are time-varying.[15] Lutkepohl and Herwartz (1996) demostrate that, if the betas are periodic, the second error term captures it well, even if the periodicity is combined with a discontinuous shift.

We weight the two sources of error unequally and set $\gamma = 0.95$. Our purpose is to estimate the time-varying regression coefficients over time in a manner that imposes the minimum variation attributed to time-varying styles and betas. Our assumption is that styles and betas change slowly over time.[16] For robustness, we reproduce all results with OLS.

Fig. 1 shows the time variation in flexible alphas over the 19 years in the sample. The alphas are averaged cross-sectionally for each industry and weighted by assets under management. For example, 178 hedge funds produced alphas in 2000. The flexible regression model produces an alpha monthly for each fund. We use the end of year assets under management for each fund to value weight the alphas for all 178 hedge funds in 2000. The graphs are constructed from these averages for hedge funds, mutual funds and institutional funds. The average hedge fund alpha is positive while the mutual fund and institutional fund averages are negative. All are significantly different from zero at the 5% level. Clearly the asset-weighted hedge fund alphas are much more volatile than the mutual fund and institutional fund alphas which have lower standard deviations. Before 1996, the hedge fund alphas are the highest. This corresponds to a period early in the sample when the hedge fund industry was rapidly expanding. After 1996, the hedge fund, mutual fund, and institutional fund alphas tend to move together.

[15] For example, see Ferson and Khang (2002) for one of many papers proposing a solution for time variation that involves asymptotic distributions. We have many portfolios with relatively short time series and could not use asymptotic techniques without a significant loss of observations in the cross-sectional results below.

[16] Flexible regression is not a random coefficient model. Kalaba and Tesfatsion (1989) argue that random coefficients are explicitly excluded from the development of the model. However, Lutkepohl (1993) shows that the solution algorithm could be interpreted as the coefficient values that maximize the conditional density $g(\beta_1,..\beta_T|y_1,\ldots,y_T)$ assuming that $g(\beta_1)$ is a constant.

Based on this graph, it seems that the hedge fund organizational form gives higher abnormal returns although the abnormal returns are more volatile. However, differences exist in the funds that are not captured by organizational form. Consequently, we use control variables to adjust the results.

[Insert Fig. 1 near here]

4.2. Measuring the effect of organizational form and ownership

To test the hypothesis that investment banks provide advantages to assets under management, we run cross-sectional regressions explaining cross-sectional differences in alpha. We use a dummy variable for investment bank. As a proxy for the differences in profit margins across portfolios, we use the dispersion of fees. As discussed in subsection 2.3, the empirical and theoretical literature predicts a positive coefficient on this dummy variable.

Control variables are selected to control for differences in the organizations that have nothing to do with being an investment bank but potentially allow an organization to generate higher risk adjusted returns. We think of these differences as differences in the ability to pay for information and in portfolio management skills. A conglomerate with many assets under management may be able to pay more for information (or skills) than a conglomerate with fewer assets under management. Similarly, a large fund could have an advantage over a small fund or a fund with more experience may have advantages over funds with less experience. The literature has found fees, assets under management, and age, both at the fund level and conglomerate level, as statistically significant factors in explaining performance. Our seven specific control variables are as follows.

1. Dummy variables for fund type: dHF denotes a hedge fund; dMF a mutual fund; and dIN an institutional fund. We also use a dummy variable if the fund is an equity fund.

2. Fee is computed as the fee per dollar of assets under management charged by the fund in year t. For institutional funds, fees are estimated from the fee schedule based on the median account size. For mutual funds, we use expense ratios or management fees if expense ratios are not available. For hedge funds, we use the management fee.
3. Ln(Revenue) is the natural log of MaxFee multiplied by assets under management for the fund. MaxFee is the same as the Fee for institutional and mutual funds, but for hedge funds we add any performance fees subject to approximated watermark adjustment.[17]
4. Ln(Age) is the natural log of the age of the fund.
5. Ln(Aum) is the natural log of assets under management for the fund
6. Ln(Aum Org) is the natural log of all assets under management by the conglomerate including all hedge fund, mutual fund, and institutional assets, for both passive and active funds.
7. Industry Concentration is number of portfolios by the fund-type (institutional, hedge funds, or mutual fund) divided by number of all portfolios under management in the firm.

5. Results

We present three sets of results. In section 5.1 we discuss the results of estimating the baseline model which does not measure conflicts of interests or information. In section 5.2 we discuss the impact of the conflict of interest and information variables. In section 5.3 we discuss the dollar costs of investment banking ownership.

[17] The mean (standard. deviation) of Fee is 0.94 (0.57), MaxFee is 1.13 (1.31). There is no material difference in the results using one or the other.

5.1 Baseline model

Table 4 shows the cross-sectional regression of alphas on dummy variables for industry, fund type, the control variables, and whether the fund is owned by an investment bank. The first line is the result of a pooled cross-sectional regression with all 53,304 fund-years in the regression. The robust standard errors are clustered by conglomerate. Coefficients in bold are significant with *p*-values of 5%; bold and italics indicate a *p*-value of 1%.

[Insert Table 4 about here]

The coefficient for the investment banking dummy variable is a statistically significant negative -0.0385, which means that being owned by an investment bank reduces the alpha of a fund by 3.85 basis points per month or about 46 basis points (0.0046) per year. This is in sharp contrast with the finance literature. Fig. 2 shows how the coefficient changes over time. The upper and lower lines are the 95% confidence intervals. Estimating the coefficient on an annual basis produces only three coefficients in which zero is not in the confidence bound (1990, 1991, and 1996) and 1993, 1994, and 2003 show positive insignificant coefficients.[18] But most are negative. Using this graph and the actual assets under active management by investment banks, we get a total economic loss of $127.978 billion or about $6.7 billion per year. Therefore, the benefits of investment bank asset management outweighed conflicts of interest only for five years of our 19-year sample. Investment bank asset management added value for only short periods. Consequently, our baseline investment banking hypothesis that being owned by an investment bank adds value to portfolios under management over being owned by a nonbank financial conglomerate does not appear to hold in general. We conclude that being owned by an investment bank statistically and economically reduces the return of a portfolio.

[18] The coefficient for the investment banking dummy variable in 1997 is negative and significant at 10%.

[Insert Fig. 2 about here]

Table 4 shows that, for the pooled data over 19 years, there is no advantage for any portfolio type. The apparent advantage for hedge funds in Fig. 2 disappears when control variables are added to the cross-sectional results. This confirms the Berk and Green hypothesis that the market is competitive enough to control agency costs among fund type. Consequently, we reject our two portfolio hypotheses: the management alignment hypothesis and the flexibility hypothesis. In other words, returns are not higher, the greater the alignment between management and clients or the fewer the restrictions placed on the manager.

The bottom three lines of Table 4 show the base results by confining the regression to one type of portfolio. The investment banking dummy variable is significant for only mutual funds, suggesting that these portfolios are the source of the economic rents. Moreover, the coefficient on the control variable Fee is significant only for mutual funds, suggesting that differences in fees explain how the investment banks extract money from the portfolios. Massa and Rehman (2008) find that mutual fund holdings of companies that receive loans from banks show a positive gross return. Table 4 shows that this return does not flow to investors in mutual funds.

It is instructive that the control variables are significant only for the hedge fund and mutual fund subsample. This suggests that the 71 conglomerates and banks are optimized for institutional clients. The differences of the control variables do not matter for institutional fund alphas. In fact, the equation has no explanatory power at all. In contrast, different control variables matter between hedge fund and mutual funds. Revenue, age, and assets under management, are statistically significant for hedge fund alphas. This suggests that information and risk control, which are size-related, are critical for hedge funds. In contrast, the fee variable and equity dummy variable is statistically significant for mutual funds, e.g., fees, possibly reflecting distribution expenses, are important for mutual fund alphas.

The baseline result in Table 4 is partially dependent on the measurement model for alphas. We estimate alphas alternatively using from one to seven factors and with both flexible regressions and OLS estimated both with all the available data for each portfolio and OLS applied to a rolling 36 month sample for each portfolio (assuming that at least 36 months are available). In results that are available upon request, the coefficient on investment banking depends on whether the estimation of alpha allows for time variation. The estimation method, however, does not matter. Regardless of whether we employ flexible least squares or rolling windows of 36 returns, we get similar results for a four- to seven-factor model with investment banking coefficients between -0.0317 (rolling windows with four factors) to -0.0496 (FLS with six factors).

5.2. Conflict of interest and information variables

Tables 4 and the robustness tests provide strong evidence that being owned by an investment bank is economically and statistically significant with the loss appearing to be borne primarily by mutual funds. We further examine two matters. First, the evidence so far shows the significance of a dummy variable representing investment bank ownership. Because intercepts are the residual claimant on problems with a regression equation, we could be capturing the effect of an omitted factor with the dummy variable that shifts only the intercept. The r-squared coefficients shown in Table 4 are statistically significant but quite low. Second, the tables do not show how the investment banks extract value from assets. As we discussed above, the finance literature provides some guidance. First, Bolton, Freixas, and Shapiro (2007) predict that conflicts of interest will be less for a multiproduct firm when profit margins on the product lines are equal. While we cannot accurately measure the profit margins on every product line for every firm, we can compute the cross-sectional dispersion of fees under the assumption that the costs are roughly the same across funds. This proxy variable allows us to compare investment banks with nonbank firms. Given the theoretical results, we expect this variable to have a negative sign. The greater the dispersion, the more scope for conflicts of interest.

Second, we have discussed the evidence that the loan and issuance activities of investment banks provide valuable information in managing mutual funds found in Ritter and Zhang (2007) and Massa and Rehman (2008). This suggests that variables measuring the lending and underwriting business of investment banks should reduce or eliminate the effect shown in Table 4. From the Dealscan database, we collect the dollar amount of the loans made in each year for each bank along with the number of loans the bank made and the number of lead loans the bank made. From the SDC database, we collect the issue fees, proceeds, market share and number of issues for new and seasoned equity, and bond issues in each year for each investment bank. The larger these variables, the larger the business activity of the investment bank and, presumably, the more information the bank has available for portfolio managers. This suggests a positive sign on these variables.

Table 5 shows the cross-sectional results, using robust standard errors clustered at the conglomerate level, from adding the cross-sectional fee dispersion and the percentage of lead loans variables to the base results of Table 4. Both variables are significant with the correct sign for investment banks. As predicted, the coefficient on the lead-loan variable is significant and positive, which is consistent with the empirical finance literature. As predicted by the Bolton, Freixas, and Shapiro theoretical model, the fee dispersion variable is significant only for investment banks in both the pooled sample and the subsamples by portfolio type. The incentives for conflicts of interest increase when the investment banking firm has different profit margins across its products. The investment banking dummy variable is now insignificant, indicating that the two variables suggested by the finance literature. Fee dispersion and lead loans entirely capture the negative effect of being owned by an investment bank. When the data are segmented by type, the investment bank dichotomous variable is never significant and fee dispersion of investment banks is significant for the institutional funds. This suggests that the pooled result is driven by the differences in fund type.

[Insert Table 5 about here]

If either of the variables is omitted, as in the first four rows of the table, the coefficient on the investment banking dummy variable is significant and negative. In these rows, when the data are split by portfolio type, the investment banking coefficient is significant only for the mutual fund subsample and only when fee dispersion is omitted. This confirms the finding of Table 4 and suggests that the fees on mutual funds offset the advantage for the clients of portfolios from the information gained by lending. When fee dispersion is included in the regression, the investment banking dummy variable is not significant, suggesting that the fee dispersion generating the conflict of interest occurs in the mutual fund portfolios, rather than in the institutional funds and hedge funds. However, the institutional subsample has a significant fee dispersion coefficient, which suggests that conflicts of interests play a role in the pricing of these portfolios. It is clear from this table that for this variable to fully capture differences in alpha, the full range of products needs to be included in the regression.

In contrast, Table 5 again shows that these organizations are optimized more for institutional clients than for clients in hedge funds and mutual funds because the control variables are not significant for the institutional fund subsample. In fact the only significant variables are fee dispersion and lead loan lending. Surprisingly the effect of any lead loan activity is negative. Only the investment banks use the information to help their portfolios. Evidently, the nonbanks subtract value from their portfolios to lead loan syndicates. Moreover, the nonbank lead loans primarily affect the institutional funds.

In unreported work available upon request, the underwriting variables of proceeds and fees from issuing debt and equity for each investment bank are insignificant, suggesting that the lending activities give investment banks an advantage in managing funds.[19] We also construct portfolios by averaging the fund alphas for a conglomerate or investment banks and by portfolio type. Our results are similar to Table 5 for the effect of investment banks.[20]

Table 6 shows the estimation of the equation of Table 5 with the investment banking variables year by year for the pooled results and the economic loss or benefit from being owned by an investment bank using the dummy variable, the conflict of interest variable (fee dispersion) and the information variable (percent lead loans). The pattern of the dummy variables and their magnitude are similar to Fig. 2, which shows the variation over time. The economic losses or benefits correspondingly vary over time. For five years in the sample, being owned by an investment bank is beneficial (1993, 1994, 2001, 2002 and 2003). For 14 years being owned by a bank is harmful. Ignoring present value, the total loss is $93.43 billion, which is about $4.9

[19]We use of number of lead loans versus the dollar amount of lead loans because the data limit our ability to observe the dollars invested in a loan by the conglomerate. We observe only the total loan size, in which a conglomerate is often one of many lenders. A conglomerate will likely have a policy in which it participates in a loan to *X* percent dollars [Ivashina and Scarfstein (2010) suggest on average *X* = 30% but that it is volatile]. We think the number of lead loans is a better proxy for investment banking involvement in loans than the dollar amount since the dollar amount can be distorted by a few large loans. The number or percentage number is always significant; the log of the dollar amount is not.

[20] However, the equally weighted average hedge fund outperforms the average institutional fund, which in turn outperforms the average mutual fund. This does not reject the Berk and Green (2004) hypothesis. They argue that assets will flow in response to better performing funds, and their theory is supported by the fact that equally weighted fund alphas show a difference while value weighted fund alphas do not.

billion per year. The information variable gives a smaller loss than calculated from Table 4, but we conclude that it is economically and statistically significant.[21]

[Insert Table 6 about here]

6. Conclusions

This study compares the investment performance of three types of delegated portfolios—mutual funds, hedge funds, and institutional funds— when they are owned by investment banks versus being owned by nonbank financial services groups (conglomerates). Our sample consists of all financial groups, both investment banks and nonbanks, which managed a mutual fund, hedge fund, and institutional fund at the same time for at least one year during 1990–2008. We have 23 investment banks and 48 noninvestment banks. We examine the impact of investment banks and investor contract form on the alphas of all portfolios that these financial groups operated during the time period. We compare investment banks only with other financial groups to control the effect of omitted variables. Comparing investment bank–operated portfolios with portfolios not in a financial group is likely to increase the effect of omitted variables. Comprehensive investment organizations centralize the cash flows from fees, allowing these organizations to centralize trading and information gathering, and to spread legal costs, monitoring costs, and the costs of client relations across portfolio type.

To examine the risk-return differences, we estimate alphas on unsmoothed returns using the moving average process developed by Getmansky, Lo, and Makarov (2004), accounting for differences in portfolio exposure to various risk factors by using a seven-factor model with time-

[21] Using both the levels of the variables and the slope dummy produces regressions in some years with very high condition indexes. The condition index for the pooled equation in the fourth row of Table 5 is 36.7, but using only 2003 data the condition index is 68.6 and remains above 40 in the years after. The condition index for the estimation of the economic loss in table 6 never is above 40. Furthermore, this equation gives us the lowest economic harm of being owned by an investment bank.

varying alphas. We test the hypothesis that investment banks produce different alphas relative to nonbank conglomerates by examining the cross-sectional regression of fund alphas on control variables and type of organization.

We find that the form of the contract offered to investors is not a statistically significant control variable. It appears that competition equalizes the impact of the three contract forms across time. We reject the hypotheses that some contracts better align incentives, that investment flexibility leads to better returns, and that those organizations with more money to spend on manager skill and information produce better returns. Our evidence is consistent with the Berk and Green (2004) hypothesis that investment organizations return a single competitive return to investors.

We find that the organizations are optimized for institutional funds and that control variables are critically important to examine hedge funds and mutual funds. We find that ownership matters. On average, investors experience a lower alpha by 46 basis points a year when a fund is operated by an investment bank versus being owned by a nonbank conglomerate, regardless of fund type. Consistent with the finance literature, the investment banks that participate more in lead loans add more value to their assets under management. Consistent with recent theory those with more disperse fees subtract more value. The effect of investment bank ownership is material amounting to at least a $4.9 billion loss per year over the 19-year sample, but the dollar loss is time-varying. In 1993–1994 and 2001–2003, the average investment banks added value to their funds. Investment banks subtract value during 1990–1992, 1995–2000, and 2004–2008. Finally, it appears that the mutual fund portfolios experience much of the economic loss.

Our study raises the question of why investment banks are able to extract economic rents this large over this many years. A partial answer to this question may be in the time variation of the rents. Perhaps five years of adding value conditioned investors enough to hold off the competition from nonbank conglomerates in the 14 years the investment banks subtracted value. The ability to do so suggests that bank competition in fund management is an important area for future research.

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Table 1
Assets for all portfolios

This table presents the asset time series for the funds managed by 23 investment banks and 48 conglomerates. Assets under active management at the end of the year are reported in millions of dollars. There are 621 unique hedge funds, 2,679 unique institutional funds, and 2,865 unique mutual funds.

	Hedge funds			Institutional funds			Mutual funds			
Year	n	Median	Total	n	Median	Total	n	Median	Total	Total
2008	240	105	63,375	1,368	745	4,298,597	1,630	206	1,395,156	5,757,128
2007	318	108	80,165	1,484	1,129	5,936,064	1,715	232	1,653,433	7,669,662
2006	316	83	66,223	1,607	986	5,686,343	1,790	204	1,436,643	7,189,209
2005	291	74	53,634	1,720	831	5,072,762	1,706	192	1,181,860	6,308,256
2004	278	65	45,310	1,781	708	4,472,861	1,661	172	977,769	5,495,941
2003	251	57	36,014	1,809	639	4,006,336	1,696	133	775,238	4,817,588
2002	219	54	30,197	1,795	521	3,365,344	1,730	115	759,703	4,155,243
2001	211	54	28,716	1,726	618	3,523,594	1,693	117	869,948	4,422,258
2000	178	51	26,680	1,600	603	3,173,526	1,623	112	993,443	4,193,648
1999	163	43	21,931	1,510	628	3,318,704	1,447	104	802,399	4,143,035
1998	148	43	20,294	1,436	576	3,049,936	1,233	86	666,012	3,736,242
1997	137	39	17,795	1,335	561	2,597,330	1,085	94	555,362	3,170,487
1996	124	34	12,533	1,227	533	2,130,769	941	82	425,958	2,569,260
1995	106	38	9,604	1,085	514	1,713,594	817	90	330,433	2,053,630
1994	83	42	8,947	956	453	1,300,139	739	86	280,847	1,589,933
1993	69	40	6,501	827	453	1,106,004	609	93	229,539	1,342,044
1992	57	31	4,371	562	333	624,466	499	87	173,939	802,777
1991	50	30	3,685	493	326	531,296	364	89	121,568	656,549
1990	46	31	3,477	415	296	407,649	305	95	100,122	511,247

Table 2

Assets for equity portfolios

This table presents the asset time series for the equity funds managed by 23 investment banks and 48 conglomerates. Assets under active management at the end of the year are reported in millions of dollars. There are 374 unique equity hedge funds, 1,840 unique equity institutional funds, and 2,248 unique mutual funds.

	Hedge funds			Institutional funds			Mutual funds			
Year	n	Median	Total	n	Median	Total	n	Median	Total	Total
2008	159	106	37,436	983	590	2,100,701	1,321	215	1,156,042	3,294,179
2007	204	111	45,029	1,065	894	3,748,033	1,384	264	1,405,083	5,198,146
2006	192	84	35,323	1,158	844	3,638,304	1,441	218	1,228,226	4,901,854
2005	180	72	28,555	1,210	699	3,145,100	1,369	197	995,131	4,168,787
2004	176	65	23,383	1,252	611	2,773,984	1,329	172	806,799	3,604,166
2003	172	54	20,910	1,276	517	2,482,777	1,365	128	622,981	3,126,669
2002	149	53	18,208	1,261	399	1,776,371	1,395	110	633,663	2,428,242
2001	129	59	17,279	1,201	509	1,980,567	1,373	119	756,811	2,754,657
2000	104	54	17,336	1,102	565	2,035,529	1,301	119	891,111	2,943,976
1999	89	54	12,845	1,032	614	2,145,132	1,139	107	697,737	2,855,714
1998	77	51	10,437	959	529	1,836,119	943	97	564,090	2,410,646
1997	76	44	9,115	873	550	1,570,765	828	101	470,577	2,050,458
1996	67	43	7,532	788	531	1,286,135	698	102	357,670	1,651,337
1995	61	43	5,617	683	496	983,315	602	104	272,041	1,260,974
1994	47	54	4,720	597	424	744,405	552	93	227,545	976,669
1993	41	54	3,792	520	401	637,140	463	100	181,805	822,736
1992	35	51	2,881	359	265	353,926	378	87	135,241	492,047
1991	31	51	2,606	310	259	296,188	277	94	96,166	394,960
1990	28	52	2,462	257	249	211,735	235	99	81,505	295,703

Table 3

Sharpe ratios of actively managed funds

These summary statistics are for the Sharpe ratios for all active funds in the investment bank and conglomerate sample (Panel A) and the investment banks (Panel B). We drop the first 12 return observations from hedge funds older than 24 months to control for backfill bias. We use mutual funds and institutional funds with at least 12 observations. Our institutional and mutual fund samples are free from backfill bias. We considered monthly returns from January 1990 to December 2008. The one month T-bill rate is from Ibbotson Associates. All returns are net of fees. The Sharpe ratio is calculated for each portfolio from the complete return series that are not backfilled.

	Hedge funds	Institutional funds	Mutual funds
Panel A: All investment banks and conglomerates 1990–2008			
n	621	2,679	2,865
Mean	0.076	0.101	-0.010
Median	0.074	0.097	0.019
Minimum	-1.000	-2.500	-1.800
Maximum	2.190	5.300	2.130
Standard Deviation.	0.300	0.245	0.189
Kurtosis	8.620	162.000	10.800
Skewness	1.590	7.550	-0.300
Panel B: Investment banks 1990–2008			
n	219	1,182	1,456
Mean	0.109	0.106	-0.010
Median	0.085	0.094	0.009
Minimum	-1.000	-0.720	-1.800
Maximum	2.190	5.240	2.130
Standard Deviation	0.359	0.258	0.201
Kurtosis	10.100	150.000	14.800
Skewness	2.020	8.340	-0.120

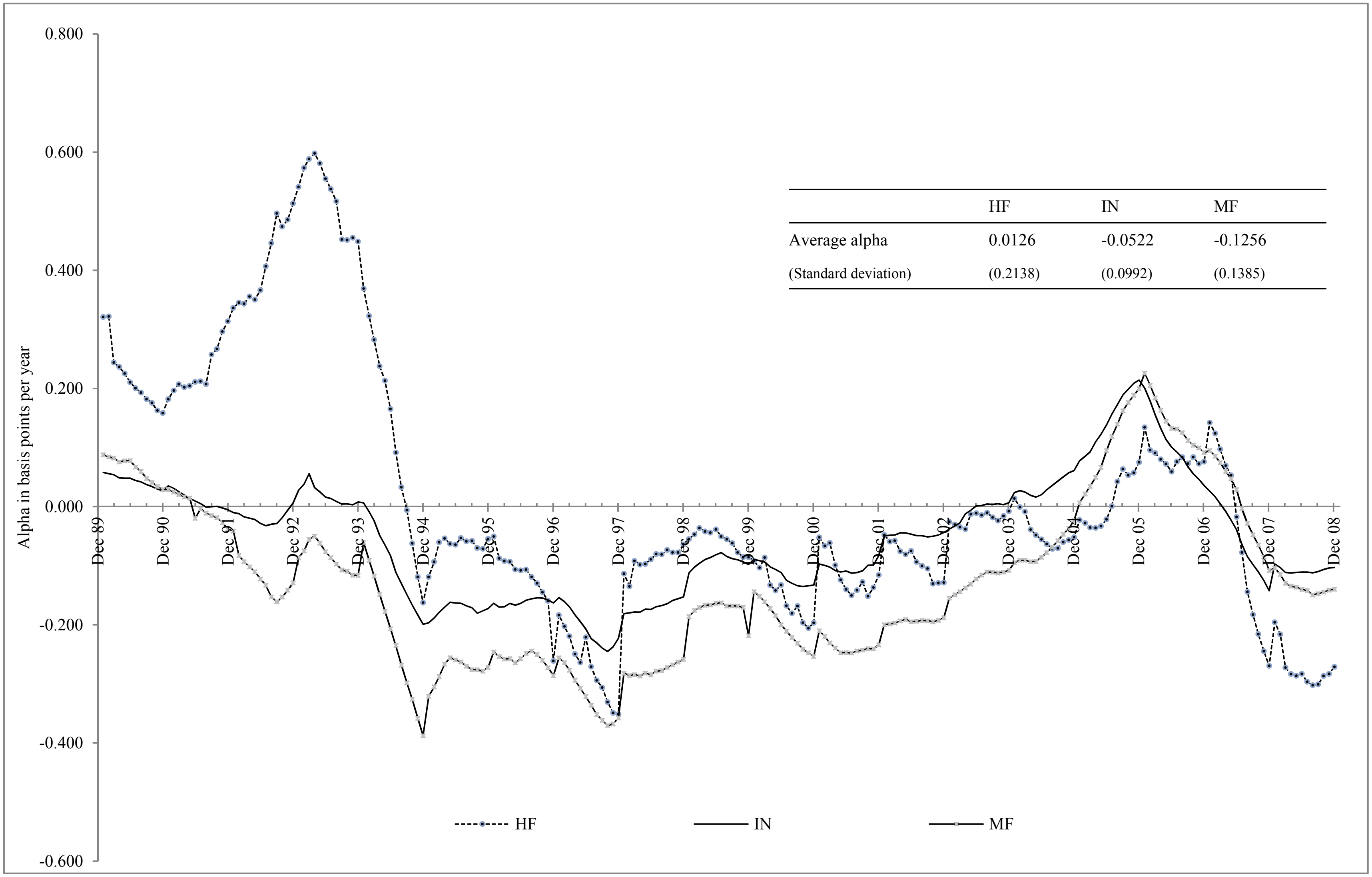

Fig. 1. Seven-factor flexible regression alphas over time.

This figure presents the value-weighted cross-sectional average alpha from a seven-factor time-varying flexible least squares model. End of year assets are used to weight the alpha in each month for each fund. The inset represents simple average and standard deviation from the resulting series. The statistic is calculated separately for hedge funds (HF), institutional funds (IN), and mutual funds (MF). The sample includes all active funds for all 23 investment banks and all 48 conglomerates.

Table 4

Baseline results

For each fund, we compute time-varying alphas with a seven-factor model estimated with a time-varying parameter model. For each fund we obtain an alpha for each month and average the alpha over the months in each year or part of year. We estimate this alpha for all funds owned by the conglomerate or investment bank excluding fund of funds, index funds, money market funds, and municipal bond funds. We regress the seven factor alphas on dummy variables for investment banks (Investment Bank), institutional funds (dIN), hedge funds (dHF), mutual funds (dMF), equity funds (dEquity), and continuous variables: fees charged (Fee), the natural log of fees times assets under management [Ln(Revenue)], the natural log of age of fund [Ln(Age)], the natural log of assets under management [Ln(Aum)], the natural log of assets under management for organization [Ln(Aum Org)], and the number of portfolios of the fund type (institutional, hedge fund, or mutual fund) divided by the number of portfolios of all funds under management by the firm (Industry Concentration). Regressions are estimated with the restriction: dIN+dHF+dMF=0. "*", "**", and "***" indicate the coefficient is significant at the 0.10, 0.05, and 0.01 level, respectively. Standard errors are clustered by investment bank or conglomerate and estimated with robust estimators. The rows labeled Hedge funds, Mutual funds, and Institutional funds restrict the sample to only those funds.

Sample	Investment Bank	dIN	dHF	dMF	dEquity	Fee	Ln(Revenue)	Ln(Age)	Ln(Aum)	Ln(Aum Org)	Industry Concentration	Constant	r^2	n
Pooled	-0.0385**	-0.0109	0.0403	-0.0294	-0.0424**	-0.1286***	0.0287**	0.0097	-0.0063	-0.0015	0.0027	0.0159	0.0156	51,304
Hedge funds	0.0076				-0.1634*	-0.0919	0.3655***	0.1135**	-0.2134***	-0.0097	-0.1332	0.1818	0.0363	3,285
Mutual funds	-0.0705***				-0.0529***	-0.1690***	0.0260	0.0026	0.0101	-0.0117	0.0245	0.1205	0.0316	23,283
Institutional funds	-0.0079				-0.0378	-0.0195	-0.0122	-0.0016	0.0029	0.0131	-0.0058	-0.1830	0.0022	24,736

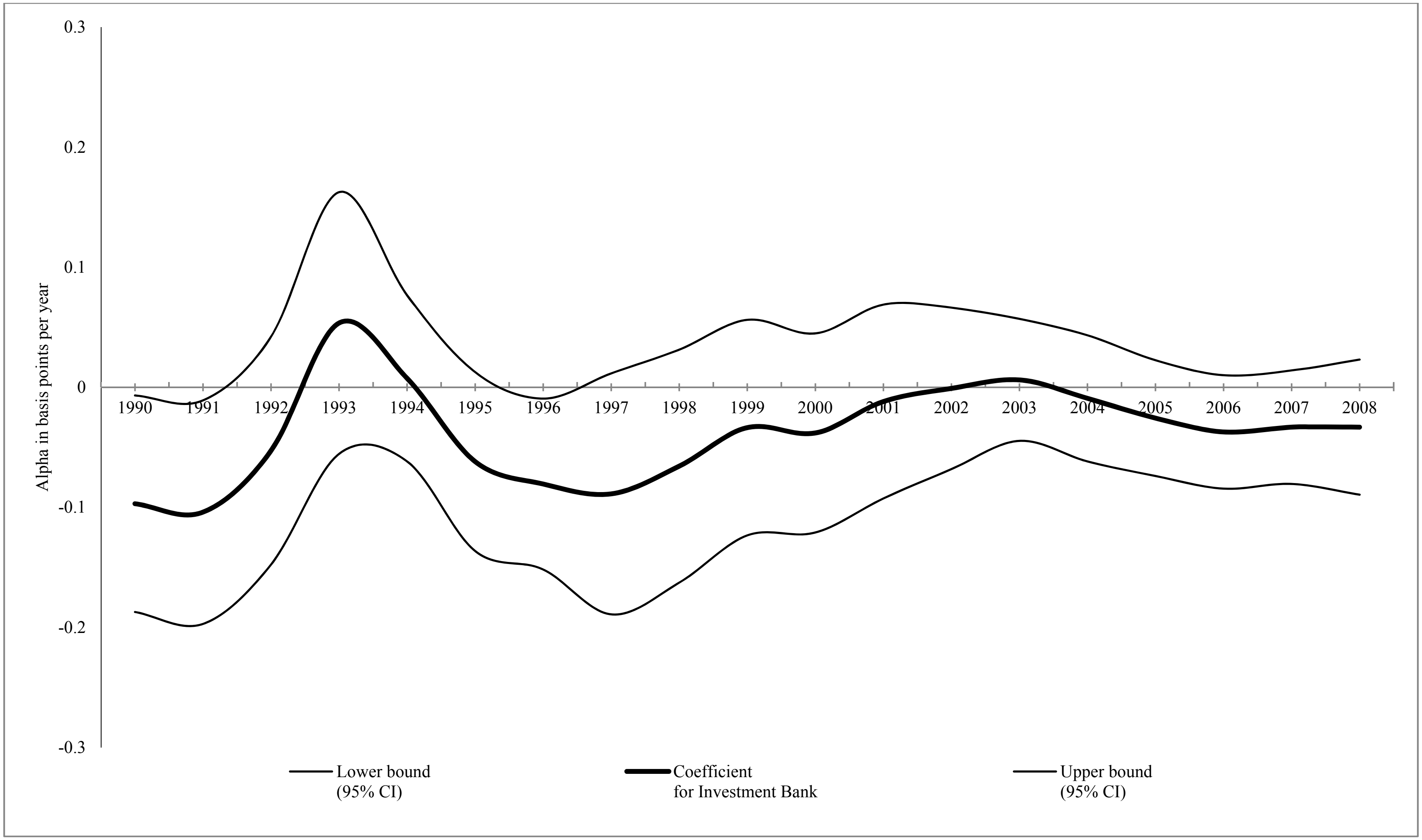

Fig. 2. Coefficient on investment banking dummy variable over time.

This figure presents the 95% confidence interval around the estimated investment banking coefficient (Investment Bank) from the base result regressions in Table 4 with the regressions run year by year. For each fund, we compute time-varying alphas with a seven-factor model estimated with a time-varying parameter model. For each fund, we obtain an alpha for each month and average the alpha over the months in each year or part of year. We estimate this alpha for all funds owned by the conglomerate or investment bank excluding fund of funds, index funds, money market funds, and municipal bond funds. We regress the seven-factor alphas on dummy variables for investment banks (Investment Bank), institutional funds (dIN), hedge funds (dHF), mutual funds (dMF), equity funds (dEquity), and continuous variables: fees charged (Fee), the natural log of fees times assets under management [Ln(Revenue)], the natural log of age of fund [Ln(Age)], the natural log of assets under management [Ln(Aum)], the natural log of assets under management for an organization [Ln(Aum Org)], and the number of portfolios of the fund type (institutional, hedge fund, or mutual fund) divided by the number of portfolios of all funds under management by the firm (Industry Concentration). Regressions are estimated with the restriction: dIN+dHF+dMF=0.

Table 5

Cross-sectional regression with conflicts of interest and information variables

For each fund, we compute time-varying alphas with a seven factor model estimated with a time-varying parameter model. For each fund, we obtain an alpha for each month and average the alphas over the months in each year. We estimate this alpha for all funds owned by the conglomerate or investment bank excluding fund of funds, index funds, money market funds, and municipal bond funds. We regress the seven-factor alphas on dummy variables for investment banks (Investment Bank), institutional funds (dIN), hedge funds (dHF), mutual funds (dMF), equity funds (dEquity), and continuous variables: fees charged (Fee), the natural log of fees times assets under management [Ln(Revenue)], the natural log of age of fund [Ln(Age)], the natural log of assets under management [Ln(Aum)], the natural log of assets under management for an organization [Ln(Aum Org)], the number of portfolios of the fund type (institutional, hedge fund, or mutual fund) divided by the number of portfolios of all funds under management by the firm (Industry Concentration), the cross-sectional dispersion of fees across all portfolios in a year for a firm (Fee Dispersion), and the percentage of number lead loans in a year that the organization originated (% Nr Lead Loans). Interaction variables are the investment banking dummy variable times the fee dispersion (Fee Dispersion * dIB) and the investment banking dummy variable times the percentage number of lead loans (% Nr Lead Loans * dIB). Regressions are estimated with the restriction: dIN+dHF+dMF=0. "*", "**", and "***" indicate the coefficient is significant at the 0.1, 0.05, and 0.01 level, respectively. Standard errors are clustered by investment bank or conglomerate and estimated with robust estimators. The rows labeled Hedge funds, Mutual funds and Institutional funds restrict the sample to only those funds.

Sample	Investment Bank	dIN	dHF	dMF	dEquity	Fee	Ln (Revenue)	Ln(Age)	Ln(Aum)	Ln(Aum Org)	Industry Concen-tration	Fee Dispersion	Fee Dispersion *dIB	% Nr Lead Loans	% Nr Lead Loans*dIB	Constant	r^2	n
Panel A																		
Pooled	-0.0977***	-0.0106	0.0428	-0.0322*	-0.0444**	-0.1263***	0.0281**	0.0082	-0.0057	-0.005	0.0097			-0.2709**	0.4673***	0.0642	0.018	51,304
Hedge funds	-0.0792				-0.1538	-0.1107	0.3738***	0.1266**	-0.2190***	-0.0076	-0.0376			0.3167	0.1809	0.1097	0.039	3,285
Mutual funds	-0.1494***				-0.0556***	-0.1664***	0.0286	0.0002	0.0093	-0.0172*	0.0213			-0.2513*	0.5164***	0.2	0.035	23,283
Institutional funds	-0.0538				-0.0387	-0.0191	-0.0156	-0.0035	0.0052	0.0116	0.0072			-0.3718***	0.5002***	-0.1606	0.006	24,736
Panel B																		
Pooled	0.0414	-0.0114	0.0416	-0.0303*	-0.0455**	-0.1294***	0.0289**	0.0096	-0.0064	-0.0068	0.0036	0.1190*	-0.2712**	-0.2553**	0.4467***	0.0239	0.019	51,281
Hedge funds	-0.0367				-0.1533	-0.107	0.3729***	0.1314**	-0.2193***	-0.0065	-0.0016	-0.043	-0.0856	0.318	0.1651	0.0941	0.04	3,283
Mutual funds	-0.1108				-0.0538***	-0.1737***	0.0269	0.0009	0.0099	-0.0167*	0.0102	0.1054	-0.0653	-0.2364	0.5000***	0.1473	0.036	23,272
Institutional funds	0.1252				-0.0417	-0.0247	-0.0117	-0.0028	0.0026	0.0078	-0.0417	0.102	-0.3821**	-0.3551***	0.4973***	-0.1346	0.007	24,726

Table 6

Economic loss from investment banking ownership of a delegated portfolio

This table reports the dollar loss based on year-by-year regressions. The economic loss is computed by taking the coefficients for the investment banking dummy variable (Investment Bank), the interaction of fee dispersion with investment banks dummy (Fee Dispersion * dIB), and the interaction of percent number of Lead Loans with the investment bank dummy variable (% Nr Lead Loans * dIB) all in year t, then using the value of that variable for each investment bank in year t to get the percentage harm. The dollar harm or benefit in year t is the percentage harm or benefit multiplied by the assets under management for each investment bank in year t. The entire equation is shown for completeness and is estimated in the following way: for each fund we compute time-varying alphas with a seven-factor model estimated with a time-varying parameter model. For each fund we obtain an alpha for each month and average the alphas over the months in each year. We estimate this alpha for all funds owned by the conglomerate or investment bank excluding fund of funds, index funds, money market funds, and municipal bond funds. We regress the seven factor alphas on dummy variables for investment banks (Investment Bank), institutional funds (dIN), hedge funds (dHF), mutual funds (dMF), equity funds (dEquity), and continuous variables: fees charged (Fee), the natural log of fees times assets under management [Ln(Revenue)], the natural log of age of fund [Ln(Age)], the natural log of assets under management [Ln(Aum)], the natural log of assets under management for an organization [Ln(Aum Org)] and the number of portfolios of the fund type (institutional, hedge fund or mutual fund) divided by the number of portfolios of all funds under management by the firm (Industry Concentration). We include two interaction variables- the investment banking dummy variable times fee dispersion (Fee Dispersion * dIB) and the investment banking dummy variable times the percentage number of lead loans (% Nr Lead Loans * dIB). Regressions are estimated with the restriction: dIN+dHF+dMF=0. Standard errors are clustered by investment bank or conglomerate and estimated with robust estimators. "*", "**", and"***" indicate the coefficient is significant at the 0.10, 0.05, and 0.01 level, respectively.

Year	Economic benefit or loss (dollars)	Investment Bank	Fee Dispersion *dIB	% Nr Lead Loans*dIB	dIN	dHF	dMF	dEquity	Fee	Ln(Revenue)	Ln(Age)	Ln(Aum)	Ln(Aum Org)	Industry Concentration	Constant	R^2	N
1990	--3,154	-0.1688**	0.1236	-0.0543	-0.0232	0.1024	-0.0793	0.0654	0.0009	0.2044	0.0369	-0.0274	-0.0349*	0.0110	0.1182	0.0252	759
1991	-4,032	-0.1080	0.1063	0.0770	-0.0643	0.1835*	-0.1192***	0.1324**	-0.0097	-0.0156	0.0320	-0.0217	-0.0236	0.0152	-0.0216	0.0324	904
1992	-3,128	-0.0896	0.1200	-0.1363	-0.0367	0.2083**	-0.1716***	0.2906***	-0.0188	0.1150	-0.0551	0.0087	0.0295	-0.0025	-0.3021	0.0807	1,118
1993	3,982	0.0032	-0.1051	0.0068	-0.0522	0.2164**	-0.1642***	0.5242***	0.0393	0.1018	-0.0353	0.0703***	0.0108	0.0042	-0.6047***	0.153	1,505
1994	1,571	-0.1035	-0.1154	0.3046**	-0.0055	0.0605	-0.0551	0.2495***	-0.1917***	0.1035	0.0499	0.1313***	-0.0398**	-0.0137	-0.3379	0.0870	1,778
1995	-4,409	-0.1674	-0.1521*	0.4866**	-0.0648	0.0625	0.0023	-0.0274	-0.2930***	0.0164	0.0490	0.0332	-0.0366**	-0.0284*	0.4438*	0.0510	2,008
1996	-11,613	-0.1662*	-0.0689	0.1431	-0.0144	0.0245	-0.0101	-0.0429	-0.2245***	0.1081	-0.0237	0.0307	0.0033	-0.0152	0.1096	0.0349	2,290
1997	-17,586	-0.2717*	-0.0503	0.0560	-0.0210	-0.0245	0.0455	-0.1262**	-0.4223***	0.3377	0.0687*	-0.0113	-0.0371*	-0.0303	0.6435***	0.0527	2,556
1998	-17,930	-0.1205	-0.0743	-0.1651	-0.0106	0.0449	-0.0342	-0.0839*	-0.2891***	0.1554	0.1250***	-0.1082***	-0.0669***	-0.0321*	1.1073***	0.0379	2,815
1999	-5,803	-0.0306	-0.0195	0.2142	-0.0474	0.1526*	-0.1052**	-0.0060	-0.1867***	-0.0596	0.0488	-0.1106***	-0.0132	-0.0318*	0.8942***	0.0336	3,118
2000	-4,827	-0.0706	0.0252	0.3470*	-0.0858**	0.2084***	-0.1226***	-0.1597***	-0.2269***	-0.0823	0.0537	-0.0368**	-0.0222	-0.0243	0.6717***	0.0531	3,400
2001	3,506	-0.0338	0.0423	0.1891	-0.0582	0.1209	-0.0627	-0.3205***	-0.1986***	-0.0552	0.0220	-0.0393	0.0047	-0.0092	0.4235*	0.0758	3,630
2002	6,366	0.0384	0.0444	0.2308**	-0.0140	0.0423	-0.0282	-0.3450***	-0.0920**	-0.2113*	0.0042	-0.0471***	0.0159	-0.0038	0.2937	0.0876	3,744
2003	2,877	0.1082	0.0283	0.0345	0.0095	-0.0094	-0.0002	-0.2466***	-0.0846***	-0.2348*	0.0379*	-0.0524***	-0.0033	0.0034	0.2763*	0.0624	3,756
2004	-1,805	0.0150	0.0385	0.1423**	0.0159	-0.0101	-0.0058	-0.1328***	-0.0679***	-0.1358	0.0380	-0.0600***	-0.0026	0.0105	0.1940	0.0288	3,720
2005	-7,439	-0.0111	0.0028	0.1394	0.1056***	-0.1421***	0.0365	0.0235	0.0157	-0.1165	0.0472**	-0.0656***	-0.0114	0.0064	0.2388*	0.0318	3,717
2006	-9,788	0.0728	0.0027	0.1268	0.0841***	-0.0909**	0.0068	0.1271***	0.0525**	-0.3274***	0.0183	-0.0040	0.0017	-0.0052	-0.0175	0.0312	3,713
2007	-9,833	0.0554	-0.1160	0.0647	0.0727***	-0.1069**	0.0342	0.0354	0.0191	-0.2499**	-0.0214	0.0649***	0.0229	-0.0201*	-0.2115	0.0389	3,515
2008	-10,386	0.0057	-0.1223	-0.0127	0.0657**	-0.1649***	0.0991***	-0.0887**	-0.0469	-0.0762	-0.0292	0.0761***	0.0307	-0.0148	-0.3649**	0.0434	3,235
Total	-93,430																
Per year	-4,917																