Three Essays on Corporate Governance and Institutional Investors

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ABSTRACT

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This dissertation analyzes the role of institutional investors in corporate governance. The first essay studies the effect of potential proxy contests on corporate policies. I find that when the likelihood of a proxy contest increases, companies exhibit increases in leverage, dividends, and CEO turnover. In addition, companies decrease R\&D, capital expenditures, stock repurchases, and executive compensation. Following these changes, there is an improvement in profitability. The second essay investigates the optimal contract with an informed money manager. Motivated by simple structure of portfolio managers' compensation and complex risk structure of returns, I show that it may be optimal for the principal to stay unaware about the true risk structure of returns. The third essay analyzes the biases related to self-reporting in the hedge funds databases by matching the quarterly equity holdings of a complete list of 13F-filing hedge fund companies to the union of five major commercial databases of self-reporting hedge funds between 1980 and 2008.

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DEDICATION

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The Disciplinary Effects of Proxy Contests[☆]

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Abstract

This paper studies the effect of potential proxy contests on corporate policies. I find that when the likelihood of a proxy contest increases, companies exhibit increases in leverage, dividends, and CEO turnover. In addition, companies decrease R&D, capital expenditures, stock repurchases, and executive compensation. Following these changes, there is an improvement in profitability. The evidence is provided using a hand-collected data set of proxy contests and an identification strategy which exploits exogenous changes in the legal environment, resulting from the 1992 proxy access reform and the second generation of state-level antitakeover laws in late 1980s. The study suggests that the existing proxy contest mechanism plays a disciplinary role despite the low frequency of materialized proxy contests.

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1. Introduction

The agency problem created by separation of ownership and control in public corporations is at the heart of the corporate governance literature, which studies mechanisms to discipline incumbents. One of those mechanisms is proxy contest. During a proxy contest shareholders vote to resolve a conflict between the firm's board of directors, referred to as 'incumbents', and a group of shareholders, referred to as 'dissidents'. The average number of proxy contests was 55 (80) per year during 1994-2008 (2006-2008) as compared to an average of 17 a year during 1979-1994 (see Figure 1 and Mulherin and Poulsen, 1998). In contrast, the frequency of hostile tender offers dropped sharply toward the end of 1980s. For example, the average number of hostile tender offers went from 60 per year in 1983-1987 to 5 per year in 2004-2008. Thus, the proxy contest has become the most common hostile mechanism to discipline an incumbent board and management.[1]

The consensus in the existing literature is that this mechanism is ineffective in disciplining an incumbent board and management because the frequency of materialized proxy contests is low (Bebchuk, 2007). Motivated by the existing evidence and the recent financial crisis, the SEC received authorization from the Dodd-Frank Act and adopted a significant proxy access reform in August 2010. This reform addresses concerns about the effectiveness of the proxy contest mechanism by facilitating the process of nominating directors by large long-term shareholders.

Should we conclude that the proxy contest mechanism is ineffective? The existing academic literature assumes that incumbents are passive and do not act until a potential contest materializes. There is an alternative view of the world – the theory of contestable markets – in which expectations of potential events affect corporate policies (Baumol et al., 1988). If expectations of potential

[1] A partial list of prominent proxy contest events includes Hewlett-Packard (2001), Yahoo (2007), Motorola (2007), Office Depot (2008), American Express (2007, 2009), Target (2009), and Barnes & Noble (2010). Dissident shareholders's proposals are usually related to election of directors, changes in company's bylaws, and M&A deals.

events affect corporate policies, two empirical implications are straightforward. First, since companies change corporate policies in anticipation of a proxy contest, fewer companies are targeted ex post. Therefore, the low frequency of materialized proxy contests does not imply that the proxy contest plays a weak disciplinary role. Second, since changes in the corporate policies are implemented before a proxy contest materializes, it is very hard to detect these changes in the post-targeted period.

To correctly assess the effect of a proxy contest, I examine whether companies change their financial policies in *anticipation* of the proxy contest. Using a manually collected data set of all proxy contests from 1994 to 2008, I show that when the likelihood of a proxy contest increases, companies increase leverage, dividends, and CEO turnover. In addition, companies decrease investment in research and development, capital expenditures, stock repurchases, and executive compensation. Following these changes, there is an improvement in profitability.

The estimation procedure I apply confronts three issues. First, the likelihood of a proxy contest is a latent variable and therefore has to be estimated. Second, the likelihood of a proxy contest can be endogenously determined, i.e., it can be correlated with an unobserved component of corporate policies. Finally, the effect of the likelihood of a proxy contest cannot be estimated using the regular two-stage method that accounts for endogeneity because the likelihood of a proxy contest is a latent variable.

The estimation procedure developed by Heckman (1978) and Amemiya (1978) addresses the first and third concerns. This procedure is applied as follows. First, I estimate a binary choice model (e.g., probit), where the dependent variable is a dummy variable that equals one when the company is targeted in the proxy contest. Next, using estimated coefficients, I construct a consistent estimator of the likelihood of a proxy contest. Finally, I assess the effect of the estimated likelihood of a proxy contest on the corporate policies. Importantly, the estimated likelihood of a proxy contest has to be constructed such that it includes at least one covariate that does not affect the corporate policies. That is, I have to impose an exclusion restriction, which resolves the endogeneity issue. I do this by using stock liquidity as a source of exogenous variation in the likelihood of a proxy contest.

Theory suggests that liquid stock markets are generally beneficial for corporate governance. Kyle and Vila (1991), Bolton and von Thadden (1998), and Maug (1998) show that greater liquidity trading facilitates monitoring by reducing free-riding. The general idea behind these papers is that liquid stock markets make it easier for investors to accumulate large stakes without substantially affecting the stock price. Kyle's (1985) lambda, the price impact measure, is the measure of liquidity that naturally corresponds to this theoretical insight. The microstructure literature suggests that the best empirical counterpart to Kyle's lambda is the Amihud (2002) measure of stock illiquidity.[2]

A valid excluded variable has to satisfy two criteria. First, it should significantly affect the likelihood of a proxy contest. Second, it should affect the outcome variable only through the likelihood of a proxy contest channel. I show that the Amihud measure of stock illiquidity is very likely to satisfy these criteria. First, the Amihud measure of stock illiquidity significantly affects the likelihood of a proxy contest. Second, using a placebo test I show that the Amihud measure of stock illiquidity is very likely to affect the outcome variable only through the likelihood of a proxy contest channel.

The placebo test exploits the following changes in the legal environment. The costs of hostile tender offers increased significantly after the widespread adoption of antitakeover defenses and the second generation of state-level antitakeover laws in late 1980s. In addition, the 1992 proxy reform reduced the costs of the proxy contest by relaxing constraints on communications among shareholders

[2]First, it is based on widely available data and can be calculated for a large number of stocks at a daily frequency. Second, Hasbrouck (2009) and Korajczyk and Sadka (2008) show that the Amihud measure is highly correlated with measures of liquidity that are based on intraday TAQ microstructure data. Recently, Goyenko et al. (2009) show that the Amihud measure does well measuring price impact. In section 5.3 I show that results are robust to using bid-ask spread as an alternative measure of stock liquidity.

of public corporations (Bradley, Brav, Goldstein, and Jiang, 2010). As a result, the frequency of proxy contests increased significantly after 1992. Thus, the threat of either a hostile tender offer or a proxy contest was relatively weak between the late 1980s and 1992. Therefore, I expect the effect of liquidity on the outcome variables to be weak in the placebo sample.

The results of the placebo test show that stock liquidity did not affect *any* of the outcome variables during the placebo period (1988-1992). Thus, it is unlikely that an omitted variable drives the correlation between stock liquidity and the outcome variables in the non-placebo sample. Therefore, the likelihood of a proxy contest is the major channel through which stock liquidity affects corporate policies.

The response to the threat of a proxy contest may be heterogeneous. Therefore, I conduct a cross-sectional variation test to further support the validity of the exclusion restriction. Specifically, I exploit heterogeneity in company's size and find that corporate policies in large companies are less sensitive to changes in stock liquidity. This evidence is consistent with the idea that it is hard to obtain control of a large company.

Having documented the effects of the likelihood of a proxy contest on the corporate polices, I show that companies experience positive and significant stock returns when a proxy contest materializes, without reversals in the long run. Hence shareholders of ex post targeted companies benefit from a proxy contest. In addition, I show that both materialized and potential proxy contests benefit shareholders by improving profitability.

I show that controlling for the likelihood of a proxy contest is crucial. Specifically, when companies are matched on the likelihood of a proxy contest (i.e., each targeted company is compared to a non-targeted company with similar likelihood of a proxy contest), significant improvements in the operating profitability of targeted companies are detected. In contrast, when companies are not matched on the likelihood of a proxy contest, I cannot detect significant improvements in the operating profitability of targeted companies.

This paper contributes to the corporate governance literature. It shows that companies experience monitoring pressure even when no event is observed. The rare proxy contests that actually occur are sufficient to create a threat, which provides companies with monitoring pressure. Importantly, this pressure causes significant changes in corporate policies. It suggests that the term "contestable corporate governance" might be the best description of modern hostile corporate governance. The evidence has important implications for the ongoing policy debate about proxy access. It suggests that the existing proxy access mechanism significantly affects corporate policies in all companies despite infrequent fights between incumbent and dissident shareholders in which dissidents obtain control.

The rest of the paper is organized as follows. Section 2 provides a description of the data, along with an overview of the institutional background of proxy contests. The ex post effect of the proxy contest on major corporate policies is analyzed in Section 3. The empirical methodology that affords identification of the ex ante effect of the proxy contest is developed in Section 4. Section 5 presents evidence on the ex ante effect of the proxy contest on major corporate policies, profitability, and shareholder wealth. Finally, Section 6 concludes.

2. Institutional Background and Sample Description

2.1. Institutional Background

In this section I summarize the procedure of the contested solicitation of votes that was relevant during the 1994-2008 sample period. Rule 14a-8 of the Securities Exchange Act of 1934 gives the shareholder who meets certain threshold requirements the right to require management to include his proposal in management's proxy materials.[3] Management, however, may exclude an eligible proposal from the proxy materials if the proposal relates to an election

[3]Rule 14a-8 is commonly referred to as the "shareholder proposal rule." It states that to be eligible to submit a proposal, a shareholder either must have continuously held at least $2,000 in market value or 1% of the company's securities for at least one year, or be a registered holder. In both circumstances, the shareholder must continue to hold those securities through the date of the annual meeting. In addition, the proposal itself must meet several requirements, including a five hundred word limit.

for membership on the company's board of directors or the proposal directly conflicts with one of the company's own proposals.[4]

If the proposal is excluded from the proxy materials, the dissident shareholder can initiate the proxy contest by soliciting the proxies using his own proxy materials. During the proxy contest, dissidents and incumbents forward proxy solicitation materials to shareholders, who sign and return the proxy form of their preferred group. The agents for each group accumulate votes via the returned proxies and cast these votes at the shareholders' meeting.[5]

2.2. Sample Description

In the incident of contested solicitation of votes, the following forms are submitted to the SEC through EDGAR: preliminary proxy statement in connection with contested solicitations (PREC14A) and definitive proxy statement in connection with contested solicitations (DEFC14A). I use submissions of these forms to identify the proxy contest events.[6]

The sample is constructed as follows. First, I identify 4,666 filings of either PREC14C or DEFC14A forms using an automatic searching script, which checks existence of either PREC14C or DEFC14A forms in EDGAR for each company in the Compustat universe. This method identifies *all* contested solicitations of votes in the universe of Compustat companies. Next, I check the sample of 4,666 filings *manually* and identify proxy contest events during 1994-2008. There are 5.9 filings of either PREC14C or DEFC14A forms during an average proxy contest. The final sample is the universe of all proxy contests during

[4]On August 25, 2010 the SEC adopted rules that allow shareholders access to a company's proxy materials to include their nominees to the corporate board of directors. These rules permit a shareholder to submit nominees for up to 25% of the company's board for inclusion in the company's proxy statement. The shareholder must hold 3% of the voting power at the company's annual meeting and have held such minimum amount continuously for at least three years. This reform, however, does not affect this study, which covers 1994-2008 sample period.

[5]Gantchev (2009) estimates the cost of an average proxy contest and reports that it is more than $5 million.

[6]Alexander, Chen, Seppi, and Spatt (2010) and Norli, Ostergaard, and Schindele (2010) use a similar approach to identify proxy contests.

1994-2008 and consists of 792 unique proxy contests.[7]

Figure 1 presents the time distribution of proxy contests and hostile tender offers. During the sample period, on average 55 unique proxy contests take place each year, which corresponds to 0.65% of the Compustat universe. The unconditional probability of the proxy contest increases from 0.2% in the early 1990s to 1.4% in 2007-2008. In contrast, the frequency of the hostile tender offers decreases to a very low level in recent years: 21 hostile tender offers take place during 2004-2008. The 1992 proxy reform is one potential explanation for both the increasing frequency of the proxy contest and the decreasing frequency of the hostile tender offers. This reform allowed independent shareholders to freely engage in communication without being monitored by the SEC.

I use two approaches to examine how the characteristics of companies targeted by proxy contests (hereafter "targets") compare to those of non-targeted companies. First, I compare the characteristics of targets with a set of size/book-to-market/industry/year matched firms (Table 2). Second, I use probit regressions to identify the partial effects of all covariates on the likelihood of a proxy contest (Table 3).

A typical proxy contest target is a medium-size mature company with a healthy cash flow. It is under-investing in new projects and suffering from low market valuation and poor stock performance, which dissidents usually use when they criticize the incumbent management. In addition, these targets are characterized by high institutional ownership, high stock liquidity, and weaker shareholder rights.[8]

The Amihud measure of stock illiquidity has the largest Average Partial

[7]This paper studies the proxy contest mechanism, which is a form of active "offensive" monitoring, during which activist shareholders take up sizable positions in companies in which they lacked a prior stake and agitate with sufficient vigor to end up involved in a proxy battle (see Armour and Cheffins, 2011). There are alternative channels for shareholder monitoring, including private negotiation (Carleton et al., 1998; Becht et al., 2009), and "Wall Street Walk" (Edmans, 2009; Admati and Pfleiderer, 2009; Edmans and Manso, 2010).

[8]Note that most of characteristics of targeted companies are consistent with predictions of Kahn and Winton (1998) and Gopalan (2005), who characterize companies that might experience a control challenge.

Effect (APE) on the likelihood of a proxy contest (Table 3). Particularly, a one standard deviation increase in stock liquidity leads to an increase of 0.44% in the likelihood of a proxy contest in the full sample. Since the unconditional likelihood of a proxy contest is 0.65% in the full sample, the APE effect of the stock liquidity is of high economic significance.

3. The Ex Post Effect of a Proxy Contest

In this section I present evidence on the ex post effects of the proxy contest. Since most of the existing literature uses pre-1992 proxy reform data, I study the ex post effect on corporate policies using a manually collected data set of all proxy contests during the 1994-2008 sample period.[9] The following equation estimates the ex post effects of the proxy contest on corporate policies:

$$y_{it} = X_{it}\alpha_1 + \beta_1 PostTarget_{it} + \eta_t + \eta_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is a outcome variable of interest, X_{it} is a vector of lagged covariates, $PostTarget_{it}$ is a dummy variable that equals to one if the company is targeted during years $(t-1, t-3)$, η_t are time fixed effects, and η_i are firm fixed effects. The coefficient β_1 measures the ex post effect of the proxy contest.[10]

Table 4 presents the results of the estimates in equation (1). The coefficients of the target dummy $PostTarget_{it}$ are insignificant in equations where the outcome variables are leverage, cash, repurchase ratio, R&D, CEO compensation, gross profit margin, return on assets, and cash flow. Dividend

[9] The effect of the proxy contest on stock returns has been widely studied (Dodd and Warner, 1983; DeAngelo and DeAngelo, 1989; Ikenberry and Lakonishok, 1993; Mulherin and Poulsen, 1998; Norli et al., 2010). Much less, however, is known about the effect of the proxy contest on the major corporate policies. Exceptions are DeAngelo and DeAngelo (1989), Mulherin and Poulsen (1998), and Bebchuk (2007), who study CEO turnover and show that targeted companies increase CEO turnover, and Ikenberry and Lakonishok (1993), who study dividend distributions and show that targeted companies decrease dividends. There is a paucity of literature about the effect of proxy contests on other corporate policies, such as leverage, repurchases, R&D expenditures, capital expenditures, and CEO compensation.

[10] Following Barber and Lyon (1996), I include the lagged left-hand side variable in the vector of controls to match on lagged performance. This procedure controls for potential mean reversion in the left-hand side variable.

payout ratio, capital expenditures, and CEO turnover are corporate policies that are affected significantly. The untabulated evidence suggests that these changes are driven by events in which dissident shareholders win the proxy contest.

The insignificance of most coefficients is not affected by considering the fight outcomes, splitting the $PostTarget$ dummy into three year dummies, and augmenting equation (1) with a dummy variable that equals one if the company is targeted during years $(t+1, t+3)$. When I further explore the augmented specification and test whether corporate policies change around the event year, I find that only dividend payout ratio, capital expenditures, and CEO turnover change significantly when companies are targeted. When the company is targeted, dividend payout ratio and capital expenditures decrease and CEO turnover increases.

Confirming evidence in the existing literature, I find that the ex post effect of the proxy contest mechanism on the targeted companies is indeed weak. Thus, the minor ex post effects of the proxy contest on corporate policies is not a sample-specific phenomenon of the pre-1992 proxy reform sample period. The empirical methodology that assesses the impact of the threat of a proxy contest is presented in the next section.

4. Empirical Methodology

4.1. Structural Model

In this section I outline the model I use to identify the ex ante effects of the proxy contest. The structural model, which is detailed in the Appendix, goes as follows:

$$y_{it} = X_{it}\alpha_{11} + \gamma_1 PC^*_{it} + \eta_t + \eta_i + u_{1it} \quad (2)$$

$$PC^*_{it} = X_{it}\alpha_{21} + Z_{it}\alpha_{22} + \zeta_t + u_{2it} \quad (3)$$

where y_{it} is an outcome variable of interest, PC^*_{it} is an unobserved latent-variable that captures the propensity of being the target of a proxy contest,

X_{it} is a vector of covariates that affect y_{it} and PC^*_{it}, Z_{it} is a vector of covariates that affect PC^*_{it} only, η_t and ζ_t are time fixed effects, and η_i are firm fixed effects. While PC^*_{it} is never observed, it determines the occurrence of the proxy contest:

$$PC_{it} = \begin{cases} 1, & PC^*_{it} > 0 \\ 0, & otherwise \end{cases} \tag{4}$$

where PC_{it} is a dummy variable that equals one if the company is targeted.

The main goal of this paper is to identify and estimate the structural coefficient γ_1. If the incumbent management anticipates the proxy contest and takes actions to change the company's policies in order to preempt the proxy contest, I expect $\gamma_1 \neq 0$. For example, consider dividend payout ratio. If incumbents increase dividend payout ratio when the threat of a proxy contest increases, I expect $\gamma_1 > 0$.

4.2. Reduced Form Model

The reduced form model can be written as:

$$y_{it} = X_{it}\pi_{11} + Z_{it}\pi_{12} + \eta_i + \eta_t + v_{1it} \tag{5}$$

$$PC^*_{it} = X_{it}\alpha_{21} + Z_{it}\alpha_{22} + \zeta_t + u_{2it} \tag{6}$$

where $\pi_{11} = \alpha_{11} + \alpha_{21}\gamma_1$, $\pi_{12} = \alpha_{22}\gamma_1$, and $v_{1it} = u_{1it} + \gamma_1 u_{2it}$.

4.3. Identification Strategy

To make a causal statement, the structural coefficient γ_1 in equation (2) has to be identified. Therefore, at least one exogenous variable needs to be excluded from the outcome equation (see Hausman, 1983). A valid excluded variable has to satisfy two criteria. First, it should significantly affect the likelihood of a proxy contest. Second, it should affect the outcome variable only through the likelihood of a proxy contest channel. I consider stock illiquidity as a candidate for the exclusion restriction.

Theory suggests that liquid stock markets are generally beneficial for corporate governance. Kyle and Vila (1991), Bolton and von Thadden

(1998), and Maug (1998) show that greater liquidity trading facilitates control challenges by reducing free-riding. The premise is that liquid stock markets make it easier for investors to accumulate large stakes without substantially affecting the stock price. Kyle's (1985) lambda, the price impact measure, is the measure of liquidity that naturally corresponds to this theoretical insight.

The best empirical counterpart to Kyle's lambda is the Amihud measure of stock illiquidity. First, it is based on widely available data and can be calculated for a large number of stocks at a daily frequency. Second, Hasbrouck (2009) and Korajczyk and Sadka (2008) show that the Amihud measure is highly correlated with two measures of liquidity, which are based on intraday TAQ microstructure data. Recently, Goyenko et al. (2009) show that the Amihud measure does well measuring price impact. Therefore, I consider the Amihud (2002) measure of stock illiquidity as a candidate for the exclusion restriction.[11]

The Amihud measure of stock illiquidity satisfies the first requirement. The full sample summary statistics and probit regressions, reported in Tables 2 and 3, suggest that targeted companies have significantly higher stock liquidity. Similar evidence is reported by Norli et al. (2010), who show that liquidity increases shareholders' incentive to monitor management. When I check for a potential weak effect of the Amihud measure of stock illiquidity on the likelihood of being a proxy contest target, I find no evident weakness of the excluded variable in the full sample (Stock and Yogo, 2002).[12]

Thus, the Amihud measure of stock illiquidity satisfies the first requirement because it significantly affects the likelihood of a proxy contest. Consistently with Kyle and Vila (1991), Bolton and von Thadden (1998), and Maug (1998), the effect of the stock liquidity on the likelihood of a proxy contest is positive (see Section 2.2). The final and the most challenging step is to check whether

[11] In section 5.3 I show that results are robust to using bid-ask spread as an alternative measure of stock liquidity.

[12] However, the effect is weak in the Executive Compensation sample probably because the variation in liquidity is low in the sample of large companies, which are covered by the executive compensation database. Therefore, the evidence in this sub-sample should be taken with a grain of salt.

this measure affects corporate policies only through the likelihood of a proxy contest channel.

I address this final concern by performing a placebo test, which exploits two changes in the legal environment. First, the cost of a hostile tender offer increases significantly after the widespread adoption of antitakeover defenses and the second generation of state-level antitakeover laws in late 1980s. Second, the 1992 proxy reform reduces the costs of communications among shareholders (Bradley et al., 2010, empirically demonstrate the effect of this reform on proxy contests by activist arbitrageurs). As a result, the frequency of proxy contests increases significantly. These two changes suggest that the threat of a control challenge is lower between late 1980s and 1992.

Table 5 reports the estimates of equation (5), which explore the reduced-form correlation of the instrument with the outcome variables in the 1994-2008 sample. The estimated coefficients of the Amihud measure of stock illiquidity are consistent with the hypothesis that liquidity is correlated with the outcome variables.

Next, I estimate the reduced form equation in the 1988-1992 sample.[13] If indeed the exclusion restriction is violated, we should observe significant correlation between stock liquidity and the outcome variables in the placebo sample. The violation of the exclusion restriction will be consistent with either a direct effect of liquidity on the outcome variables, as well as an omitted variable that affects stock liquidity and the outcome variables. In contrast, if the stock liquidity affects the outcome variables only through the likelihood of a proxy contest channel and there is no omitted variable that affects both stock liquidity and the outcome variables, there should be a weaker correlation between stock liquidity and the outcome variables in the placebo sample because the likelihood of a control challenge is weak.

Table 6 suggests that stock liquidity did not affect *any* of the six outcome

[13]The results are not affected if the placebo sample starts in 1989.

variables in the placebo sample.[14] Thus, it is unlikely that an omitted variable drives the correlation between the stock liquidity and the outcome variables. Moreover, it is unlikely that the stock liquidity directly effects the outcome variables. To address the possibility that relatively small sample size contributes to the absence of significance in the placebo sample, I report estimates in 1996-2000 and 2001-2005 sub-samples. The significance of the stock liquidity in these sub-samples rules out this concern.

To provide further support to the placebo test, I estimate the following regression in the 1988-2008 sample period:

$$y_{it} = X_{it}\pi_{11} + PRE1992 * X_{it}\pi_{12} + Z_{it}\pi_{13} + PRE1992 * Z_{it}\pi_{14} + \eta_i + \eta_t + v_{1it}, \quad (7)$$

where $PRE1992$ is a dummy variable that indicates the pre-1992 sample period. This specification tests whether the coefficient of the Amihud measure of stock illiquidity changed significantly around the 1992 proxy reform. The evidence in Table 7 is informative. First, it confirms that stock liquidity did not affect the outcome variables in the placebo sample: the hypothesis that $\pi_{13} + \pi_{14} = 0$ is not rejected. Second, the change in the effect of the Amihud measure of stock illiquidity on the outcome variables, π_{14}, is statistically significant for all outcome variables but dividend payout ratio. While the change in the effect of the Amihud measure of stock illiquidity on the dividend payout ratio is insignificant, the sign of the change corresponds to the evidence in Table 6.[15]

Finally, I explore heterogeneity in the response to the threat of a proxy contest and conduct the cross-sectional variation test. Large companies are expected to be less sensitive to the threat of a proxy contest because it is harder to obtain control in a large company. Therefore, I use heterogeneity in size (SALES) to conduct the cross-sectional variation test. The cross-sectional

[14] Since the Compustat Executive Compensation database is available only from 1992, it is impossible to perform the placebo test for the outcome variables from that database.

[15] The change in the effect of the Amihud measure of stock illiquidity on cash is insignificant in all specifications and is reported for completeness of the analysis.

variation test is performed by estimating the following reduced form equation:

$$y_{it} = X_{it}\pi_{11} + Z_{it}\pi_{13} + I_{top30^{th}pctl} * Z_{it}\pi_{14} + \eta_i + \eta_t + v_{1it}, \tag{8}$$

where $I_{top30^{th}pctl}$ is a dummy variable that equals one if the company belongs to the top 30^{th} percentile in terms of size (SALES).

The results are reported in Table 8. The evidence suggests that the hypothesis $\pi_{13}+\pi_{14} = 0$ is not rejected when the following corporate policies are concerned: leverage, R&D expenditures, capital expenditures, dividend payout ratio, repurchase ratio, CEO compensation, and CEO turnover. Thus, the corporate policies of large companies are not sensitive to the threat of a proxy contest.[16]

To summarize, both theory and empirical evidence suggest that the Amihud measure of stock illiquidity is not likely to violate the exclusion restriction.

4.4. Estimation Procedure

The structural form equation (2) cannot be estimated using the regular two-stage method because equation (3) is only partially observed. Therefore, I follow Heckman (1978) and Amemiya (1978) and apply the following estimation procedure.[17] First, I estimate the reduced form equation (6) using a binary choice model and obtain a consistent estimator $\widehat{PC^*_{it}}$ of PC^*_{it}. Second, I estimate the structural form equation (2) using $\widehat{PC^*_{it}}$ to obtain consistent estimators of

[16]There is an exception, however. The effect of stock liquidity on cash reserves is positive and significant when large companies are concerned. In general, there is no clear prediction regarding the effect of the threat of a control challenge on cash reserves. For example, firms with poor corporate governance can dissipate cash quickly (Dittmar and Mahrt-Smith, 2007; Harford et al., 2008; Bates et al., 2009). Alternatively, such companies can build larger cash reserves (Jensen, 1986).

[17]In Heckman's model a latent variable determines the occurrence of the discrete event and enters the equations as a right-hand-side variable. As an example, Heckman considers a model of the effect of antidiscrimination legislation on the status of African-Americans. He hypothesizes that the measured income in a state is affected not only by the presence of the antidiscrimination legislation for that state, but also by the population sentiment toward African-Americans in that state. Therefore, the objective is to study the effects of passage of the antidiscrimination legislation per se *after* allowing for the sentiment in favor of the antidiscrimination legislation.

structural parameters, α_1 and γ_1. Finally, I derive the asymptotic variance-covariance matrix of the structural parameters that corrects the standard errors for the generated regressor problem. In the Appendix I show that the unadjusted standard errors estimate is consistent under the null of $\gamma_1 = 0$.

5. Results

This section presents the main evidence. First, I show how the threat of a proxy contest affects several corporate policies. Then I examine the impact of the threat of a proxy contest on both the long-term profitability and the market value of targeted companies. Finally, I perform several robustness checks.

5.1. Corporate Policies

I analyze the effect of the threat of a proxy contest on the following corporate policies: the capital structure policy (leverage and cash reserves), the investment policy (R&D and capital expenditures), the payout policy (dividend payout and repurchase ratios), and the CEO compensation policy (CEO compensation and CEO turnover).

The results are reported in Tables 9 and 10, where each column corresponds to an outcome variable of interest. Table 9 reports the First Stage estimates (equation (3)), which are used to a construct consistent estimate of the likelihood of a proxy contest, $\widehat{PC^*}$. Table 10 reports the Second Stage estimates (equation (2)), where the dependent variable is an outcome variable of interest.

First, I consider the capital structure policy. The evidence in Table 10 suggests that when the likelihood of a proxy contest increases, companies increase leverage.[18] Following one standard deviation increase in the likelihood of a proxy contest, companies increase leverage by 2.4%.[19] While the changes

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[18] As a robustness check, I consider the gross book leverage and the market leverage. In both cases the results unchanged.

[19] The economic magnitude of the likelihood of a proxy contest is $\gamma_1 \sigma_{PC} / \overline{y_{it}}$, where γ_1 is estimated from equation (2), σ_{PC} is the standard deviation of the likelihood of a proxy contest, and $\overline{y_{it}}$ is the mean of the dependent variable. σ_{PC} is the standard deviation of estimated residuals ($\widehat{\varepsilon_{it}}$) in the following equation: $\widehat{PC^*} = \eta_t + \eta_i + \varepsilon_{it}$. That is, I rely only on the within firm variation in the likelihood of a proxy contest.

in leverage are significant, the current specification fails to detect significant changes in the cash reserves.

Similar effects of the threat of a control challenge on the capital structure are documented in literature that studies the implications of the second-generation antitakeover legislation (see Garvey and Hanka, 1999; Bertrand and Mullainathan, 2003). Moreover, it has been shown that leverage increases in the aftermath of entrenchment-reducing shocks to managerial security (see Berger et al., 1997; Safieddine and Titman, 1999). The documented evidence is also supported by the theoretical literature, which predicts a positive effect of the threat of a control challenge on leverage (see Grossman and Hart, 1982; Jensen, 1986; Harris and Raviv, 1988; Stulz, 1988, 1990; Hart and Moore, 1995; Zwiebel, 1996; Morellec, 2004).

As far as the investment policy is concerned, companies spend less on R&D and decrease capital expenditures when the likelihood of a proxy contest increases. Following one standard deviation increase in the likelihood of a proxy contest, companies decrease R&D expenditures by 4.4% and decrease the capital expenditures by 8.2%. Thus, the threat of a proxy contest is associated with a significantly lower level of investment.

These changes in the investment policy are consistent with evidence reported by Safieddine and Titman (1999) and Garvey and Hanka (1999), who document that when targets increase their leverage ratios to prevent the control challenge, they also reduce capital expenditures.[20] On the theoretical side, Jensen (1986) suggests that if the threat of a proxy contest alleviates the over-investment problem, it can reduce investments. Alternatively, Stein (1988) shows that the threat of a proxy contest can lead managers to sacrifice long-term interests in order to boost current profits.

The threat of a proxy contest significantly affects payout policy. Companies increase dividends and decrease repurchases when the likelihood of a proxy

[20]See also Becht et al. (2009), who show that activist shareholders often require more discipline in capital expenditures.

contest increases. Following one standard deviation increase in the likelihood of a proxy contest, companies increase dividend payout ratio by 2.8% and decrease repurchase ratio by 6%.

A survey by Allen and Michaely (2003) suggests that management can commit to pay out cash because of constant threat of some disciplinary action. For example, Zwiebel (1996) and Myers (2000) show that management has an incentive to pay dividends to prevent a control challenge. On the empirical side, Francis et al. (2011) show that dividend payout ratios and propensities fall when managers are insulated from control challenges. Moreover, the evidence is in line with the recent literature on shareholder activism, which suggests that activists often require companies to increase payouts to shareholders (see Brav et al., 2008; Klein and Zur, 2009; Becht et al., 2009).

Allen and Michaely (2003) provide a possible explanation for the opposite effect of the threat of a proxy contest on dividends and repurchases: the dividends can be a more effective mechanism than repurchases to impose discipline. Allen and Michaely suggest that the market strongly dislikes dividend reductions, and therefore management is reluctant to reduce dividends. Further empirical support to this conjecture is provided by Brav et al. (2005), who show that retail investors like dividends more than they like repurchases, and that there are fewer consequences to reducing repurchases.

Finally, I consider the CEO compensation policy. The evidence suggests that when the likelihood of a proxy contest increases, companies decrease CEO compensation and increase CEO turnover. Following one standard deviation increase in the likelihood of a proxy contest, companies decrease CEO compensation by more than 5.4% and increase CEO turnover by 4.1%.

The evidence finds support in the existing literature. First, the results are consistent with evidence provided by Borokhovich et al. (1997) and Bertrand and Mullainathan (1999), who explore changes in antitakeover legislation and show that CEOs of companies that face a lower threat of a control challenge are paid more than CEOs at similar firms that face a higher threat of a control challenge. Second, the recent shareholder activism literature documents similar changes in the CEO compensation policy (see Brav et al., 2008; Becht et al., 2009; Klein and Zur, 2009). Finally, the evidence is consistent with the idea that boards are more effective monitors when faced with the threat of a proxy contest. First, Core et al. (1999) show that CEOs earn lower compensation when governance structures are more effective. Second, Taylor (2010) implies that the threat of a proxy contest might reduce the perceived cost of the CEO turnover and lead to higher CEO turnover.

Taken together, the hypothesis that there is no ex ante effect of the proxy contest is rejected. The threat of a proxy contest is associated with significant changes in leverage, payout policy, investment policy, and CEO compensation. Thus, despite being a rare event, the proxy contest plays an active role in modern corporate governance and significantly affects major corporate policies.

5.2. Stock Returns and Operating Performance

The evidence in the previous section suggests that the proxy contest mechanism significantly affects major corporate policies. The fundamental question for the proxy contest mechanism is whether it creates value for shareholders. To address this question, I examine stock market returns and operating performance. I first analyze the effect of the proxy contest mechanism on targets and then study the effect of the threat of a proxy contest on non-targets.

I begin by examining the ex post effect of the proxy contest on targets. I use short-term announcement event-day returns to show how the market perceives the effect of the proxy contest on shareholders. Figure 2 plots the average buy-and-hold return, in excess of the buy-and-hold return on the value-weighed NYSE/AMEX/NASDAQ index from CRSP, from 20 days prior to the proxy contest announcement date to 20 days afterward. There is a run-up of about 4.2% between 10 days to 1 day prior to announcement. The announcement day and the following day see a jump of about 3%. After that the abnormal return keeps trending up to a total of 10.2% over 20 days.

Figure 2 also includes the average abnormal share turnover during the event window. I measure "normal" turnover over the (-100,-40) window preceding the proxy material filing dates. The spike in abnormal trading volume, defined as the percentage increase in the share turnover rate, occurs not only on the filing day and the following day but also during the 10-day period before the filing.[21] Finally, Figure 2 highlights the importance of stocks being liquid. The abnormal share turnover and the run-up of stock returns suggest that dissidents benefit from stock liquidity. Consistent with the theory, liquid stocks permit the accumulation of large stakes without substantially affecting the stock price and capitalization on governance-related activities.

One potential explanation for the high abnormal return is a temporary price impact caused by buying pressure. If the price impact is purely temporary and reflects a trading friction rather than information about prospective value changes, I should observe negative abnormal returns shortly after the event. In contrast with this scenario, Figure 2 shows no reversal after 20 days (when the abnormal turnover declines to close to zero). Moreover, the pattern persists if I extend the window for another 20 days. Finally, untabulated evidence from calendar-time portfolio regressions shows no evidence for possible mean reversion in prices.

While equity prices suggest that shareholders of targeted companies benefit from the proxy contest, I have not shown how the value is created. To provide the evidence, I consider the operating profitability, measured by return on assets (ROA).[22] Table 12 reports estimates of the following equation:

$$ROA_{it} = X_{it}\alpha_1 + \beta_1 \widehat{PC^*_{it}} + \sum_{\tau=k}^{3} \gamma_\tau D_{it+\tau} + \eta_t + \eta_i + \varepsilon_{it}, \tag{9}$$

Estimated coefficients of dummy variables from this equation, γ_τ, are plotted in Figure 3. The left plot presents the estimates from the unrestricted regression,

[21] The spike during the 10-day period before the filing is consistent with the fact that in some cases Schedule 13D is filed simultaneously with the proxy contest initiation. See Brav et al. (2008) for further details.

[22] Similar results are obtained when I use cash flow instead of ROA.

which allows controlling for $\widehat{PC^*}$. The right plot presents the estimates from the restricted regression, $\beta_1 = 0$, in which controlling for $\widehat{PC^*}$ is not allowed. The gray bars correspond to the specification in which $k = -3$ while the black bars correspond to the specification in which $k = 1$.

Consider first the left plot in Figure 3, which presents the estimates from the unrestricted regression and controls for the likelihood of a proxy contest. It shows that after companies are targeted, there is a significant improvement in operating profitability. This evidence is consistent with the positive abnormal announcement return documented above. It is important to highlight that the reverse causality critique does not work in this case. If dissident shareholders did not change companies but just identified those that are going to improve, they would save the enormous cost of a proxy contest by just buying stocks in these companies. Therefore, I conclude that the dissident shareholders indeed know how to improve both the valuation and the profitability of targeted companies.

The right plot in Figure 3 presents the estimates from the restricted regression, in which $\beta_1 = 0$, and therefore there is no controlling for the likelihood of a proxy contest. The sharp difference in the estimated coefficients in the post-targeted period highlights the importance of matching on the likelihood of a proxy contest. When two companies with a similar likelihood of a proxy contest are compared, the targeted company exhibits higher operating profitability than one that is not targeted.

Table 11 reports the results of regressions exploring the cross-sectional variation in market response to the proxy contest. The dependent variable is the abnormal return in the (-20,20) window around the proxy contest announcement. The negative coefficient of the Institutional Ownership Herfindahl Index (INSTHERFL) suggests that shareholders are more surprised when the proxy contest is announced in a company with more dispersed institutional ownership. A positive coefficient of the leverage suggests that potential expropriation of bondholders might be a source of shareholder gain.[23] A positive coefficient of

[23] Untabulated evidence supports this hypothesis and shows a significant deterioration in

cash reserves might also be explained by shareholders' belief that more value can be created in companies with high cash reserves, which possibly indicates an agency problem.

Consider the coefficient of the likelihood of a proxy contest, $\widehat{PC^*}$. The negative coefficient suggests that investors price the higher probability of a proxy contest. Importantly, the effect of the threat of a proxy contest on equity prices is positive: the more likely the proxy contest, the higher the value improvement priced.

An alternative story suggests that the effect of the threat of a proxy contest on equity prices is negative because the threat destroys value in targeted companies. To differentiate between these alternative explanations, I consider the effect of the threat of a proxy contest on the operating profitability of ex post targeted companies during the pre-targeting period. Table 13 presents estimates of the main structural equations, where the outcome variable is $\triangle ROA_{t+1}$. Column (2) reports results in the full sample, column (3) reports results in the sample of ex post non-targeted companies, column (4) reports results in the sample ex post targeted companies, and (5) reports results in the sample ex post targeted companies cover pre-targeting years only.

Estimates in Table 13 suggest that the threat of a proxy contest is not associated with a decline in the operating profitability of ex post targets. In contrast, the positive and significant coefficient of the threat of a proxy contest indicates that the profitability of the targeted companies actually improves when the threat of a proxy contest increases. Thus, the overall evidence is consistent with the positive effect of the threat of a proxy contest on both the profitability and valuation of ex post targets.[24]

Finally, I consider the effect of the threat of a proxy contest on the profitability of ex post non-targets. Similar to the positive effect on ex post

the credit-worthiness of the debt, which is measured by the Altman (1968) Z-score.

[24]To rule out a possibility that the improvement in the operating profitability is accompanied by an increase in riskiness, I considered changes in standard deviation of the operating profit. The unreported results suggest that there is no increase in the operating risk.

targets, the threat of a proxy contest benefits ex post non-targets. Therefore, the evidence suggests that the threat of a proxy contest is beneficial for profitability of both ex post targets and non-targets.[25]

To summarize, the proxy contest targets experience positive and significant stock returns when they are targeted. Importantly, there is no reversal in the long run. This implies that shareholders of targeted companies benefit from the proxy contest mechanism. Cross-sectional variation in returns suggests that ex post targeted companies that act in anticipation of the proxy contest create value for their shareholders. Similarly, the effect of the threat of a proxy contest on the profitability of ex post non-targets is positive.

5.3. Robustness

In this section I perform several robustness checks. First, I estimate the First Stage regression (3) in an out-of-sample manner. Particularly, for each year t I estimate the First Stage regression using a sample that ends in $t-1$ and then generate $\widehat{PC^*_{it}}$ for year t. Table 14 reports the results. All the results carry through in this specification except for the effect of the threat of a proxy contest on repurchase ratio, CEO turnover, and cash reserves. Particularly, the effect of the threat of a proxy contest on cash reserves becomes statistically significant and the effect of the threat of a proxy contest on the repurchase ratio and CEO turnover becomes statistically insignificant.

Second, I estimate the linear probability model in the First Stage regression to verify robustness to the First Stage specification. Table 15 reports the results. The evidence suggests that neither statistical significance nor the economic magnitude of the ex ante effect is affected. Thus, the estimation procedure is robust to the First Stage specification.

Third, I include firm fixed effects in the First Stage linear probability regression.[26] Table 16 reports the results. All the results carry through in

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[25] Fang et al. (2009) show that firms with liquid stocks have better performance as measured by the firm market-to-book ratio.

[26] I use the linear probability model with firm fixed effects because most nonlinear models,

this specification except for the effect of the threat of a proxy contest on the CEO turnover, which remains positive but statistically insignificant. Thus, the estimation procedure is robust to the inclusion of firm fixed effects in the First Stage specification. However, it comes at a cost: while the illiquidity is still statistically significant in the First Stage, t-statistics are lower. This is expected since firm fixed effects absorb part of illiquidity's explanatory power.

For space reasons, I will summarize without directly reporting other robustness tests I perform. First, I check whether the main conclusions change if I perform the analysis on differences instead of levels. Particularly, I estimate the following Second Stage regression:

$$\triangle y_{it} = \triangle X_{it}\alpha_1 + \beta_1 \triangle \widehat{PC^*_{it}} + \triangle \eta_t + \triangle \varepsilon_{it}, \tag{10}$$

where $\triangle$ is the first difference operator. The results are unaffected except for both the effect of the threat of a proxy contest on the repurchase ratio. The effect of the threat of a proxy contest on these outcome variables is insignificant in this specification. Second, I use regular shareholder proposals instead of the proxy contest events to show that the threat of a less hostile event has a weaker effect on corporate policies. The evidence confirms the intuition: there is no significant effect on leverage, dividend payout ratio, and R&D. Third, I check whether the main conclusions change if I control for the post shareholder proposal period. Particularly, I include in the set of control variables a dummy variable that equals to one if a regular shareholder proposal was submitted during years $(t-1, t-3)$. I find that controlling for the post shareholder proposal period does not affect the estimated coefficients of the ex ante effect either statistically or economically. Fourth, I verify whether the results are driven solely by targeted companies. Particularly, I exclude targeted companies from the Second Stage regressions. As a result, neither the statistical nor the economic significance of results is affected. Fifth, I study the potential

such as probit model, suffer from the incidental parameters problem.

inconsistency problem induced by the inclusion of a lagged dependent variable in the Second Stage (see Arellano and Bond, 1991).[27] Particularly, I exclude lagged performance from the First and the Second Stage regressions. The results are unaffected except for the effect of the threat of a proxy contest on leverage, which becomes statistically insignificant. However, when I apply the Arellano and Bond (1991) procedure, which uses lagged levels and the differences of the left-hand side variable as instruments, the coefficient of leverage is positive and significant. Sixth, I use the bid-ask-spread as an additional instrument and perform the overidentifying restrictions test. The results are unaffected except for the effect of the threat of a proxy contest on repurchases, which becomes statistically insignificant. The null hypothesis that both instruments are exogenous is not rejected at 5% significance level for all outcome variables except repurchases. Finally, I augment the set of control variables. The basic specification includes the following control variables: firm fixed effects and lagged level of the performance measure (RHS variable), log market value of equity, sales, book-to-market, and institutional ownership. The augmented specification includes all controls from the basic specification and lagged levels of repurchases, R&D, capital expenditures, ROA, cash flow, and GPM. I find that this has no significant effect on the results: the effect of the threat of a proxy contest on most corporate policies remains significant. The only exception is R&D, which is affected negatively but insignificantly by the threat of a proxy contest in this specification.

6. Conclusion

Motivated by the theory of contestable markets and using a manually collected data set of all proxy contests from 1994 to 2008, I show that the threat of a proxy contest impacts major corporate policies including capital

[27] In general, inclusion of lagged left-hand side variable in the set of control variables involves the following tradeoff: it addresses the mean reversion concern (Barber and Lyon, 1996) but generates inconsistency in the estimated coefficients. See discussion in Angrist and Krueger (1999), page 1295.

structure, investments, payout policy, and CEO compensation. Importantly, the effect of the threat of a proxy contest on the major corporate policies is causal. The identification strategy relies on the theoretical literature, which suggests that liquid stock markets are generally beneficial for corporate governance, and on empirical evidence, which supports the hypothesis that the Amihud (2002) measure of stock illiquidity affects corporate policies only through the threat of a proxy contest channel. The main empirical evidence that validates the identification strategy comes from a placebo test, which explores changes in the legal environment in the U.S.

I document that the proxy contest targets experience positive and significant stock returns when they are targeted, with no sign of reversal in the long run. This implies that shareholders of ex post targeted companies benefit from the proxy contest mechanism. Positive stock reaction to the proxy contest announcement is followed by significant improvements in the operating profitability of targeted companies. Importantly, significant improvements in the operating profitability of targeted companies are detected only when the likelihood of a proxy contest is controlled for.

This paper opens a new avenue for future research. What is the optimal frequency of control challenges? What is the most efficient way to create a credible threat and discipline boards of directors? Do outcomes of materialized proxy contests play any role in creating a credible threat? Answers to these and other related questions will improve our understanding of contestable corporate governance.

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Appendix A. The Structural Model Construction

Consider a mixed structure model:

$$y_{it} = X_{it}\alpha_{11} + \gamma_1 PC^*_{it} + \delta_1 PC_{it} + \eta_t + \eta_i + u_{1it} \quad \text{(A.1)}$$

$$PC^*_{it} = X_{it}\alpha_{21} + Z_{it}\alpha_{22} + \gamma_2 y_{it} + \delta_2 PC_{it} + \zeta_t + u_{2it} \quad \text{(A.2)}$$

where y_{it} is an outcome variable of interest, PC^*_{it} is a latent-variable that captures the propensity of being a proxy contest target, X_{it} is a vector of covariates that affect y_{it} and PC^*_{it}, η_t and ζ_t are time fixed effects, η_i are firm fixed effects, Z_{it} is a vector of covariates that affect PC^*_{it} only, and PC_{it} is a dummy variable that equals to one if the company is targeted:

$$PC_{it} = \begin{cases} 1, & PC^*_{it} > 0 \\ 0, & otherwise \end{cases} \quad \text{(A.3)}$$

The joint density of continuous random variables u_{1it} and u_{2it} is $g(u_{1it}, u_{2it})$, which is assumed to be a bivariate normal density.[28]

Consider a typical year, during which the proxy contest activity is observed. First, since the dissident shareholder who initiates the proxy contest during that year uses information available at the end of the previous year, I include lagged covariates in X_{it} and Z_{it} and impose $\gamma_2 = 0$. Second, since the ex post effect can be observed only *after* the company is targeted, I impose $\delta_1 = 0$. Note that X_{it} can include dummy variables that indicate post-targeting years. After imposing $\gamma_2 = 0$ and $\delta_1 = 0$, I obtain the following system of equations:

$$y_{it} = X_{it}\alpha_{11} + \gamma_1 PC^*_{it} + \eta_t + \eta_i + u_{1it} \quad \text{(A.4)}$$

$$PC^*_{it} = X_{it}\alpha_{21} + Z_{it}\alpha_{22} + \delta_2 PC_{it} + \zeta_t + u_{2it} \quad \text{(A.5)}$$

[28] Firm fixed effects are excluded from equation (A.2) because they introduce the incidental parameter problem in this specification. In Section 5.3 I report estimates of the linear probability with firm fixed effects and show that results are robust to their inclusion.

Models of this kind, in which the latent variables as well as their dichotomous observations occur in different structural equations, need some restrictions on the coefficients to be logically consistent. To achieve the logical consistency, the coefficient on the observed dichotomous variable in the reduced form of the latent variable equation has to be zero (see Maddala, 1983). Therefore, the necessary and sufficient condition for logical consistency is $\delta_2 = 0$. After imposing this restriction, the logically consistent structural model is:

$$y_{it} = X_{it}\alpha_{11} + \gamma_1 PC^*_{it} + \eta_t + \eta_i + u_{1it} \tag{A.6}$$

$$PC^*_{it} = X_{it}\alpha_{21} + Z_{it}\alpha_{22} + \zeta_t + u_{2it} \tag{A.7}$$

Dependence of PC^*_{it} and y_{it} on the shocks that take place during the calendar year t, i.e., $corr(u_{1it}, u_{2it}) \neq 0$, suggests estimating two structural equations as a system of equations. For instance, unexpected market fluctuations can prevent a dissident from initiating the proxy contest and simultaneously affect company's performance.

Appendix B. Asymptotic Properties of Estimated Coefficients

Consider a model:

$$\begin{aligned} y_{1it} &= \beta_1' x_{1it} + \gamma_1 y^*_{2it} + u_{1it} \\ y^*_{2it} &= \beta_{21}' x_{1it} + \beta_{22}' z_{it} + u_{2it} \end{aligned}$$

where:

$$d_t = \begin{cases} 1, & y^*_{2it} > 0 \\ 0, & otherwise \end{cases}$$

An econometrician observes y_{1it} and d_t but does not observe y^*_{2it}. Assume $\{x_{1it}, z_{it}\}$ are known constants and $\{u_{1it}, u_{2it}\}$ are bivariate variables with $corr(u_{1it}, u_{2it}) = \rho_{12}$, $corr(u_{1it}, u_{1is}) = \rho_1$, $corr(u_{2it}, u_{2is}) = \rho_2$, and $corr(u_{1it}, u_{2is}) = \rho_{12}^{ts}$, $t \neq s$. The structural model in the vector notation is:

$$
\begin{aligned}
Y_1 &= X_1\beta_1 + \gamma_1 Y_2^* + U_1 \\
Y_2^* &= X_1\beta_{21} + Z\beta_{22} + U_2 = X\beta_2 + U_2,
\end{aligned}
$$

where $X = [X_1 Z]$ and $\beta_2' = (\beta_{21}'\beta_{22}')$. Note that the second equation is both structural and reduced form equation. The reduced form of the first equation is:

$$
\begin{aligned}
Y_1 &= X_1\beta_1 + \gamma_1(X_1\beta_2 + Z\beta_{22} + U_2) + U_1 \\
&= X_1\pi_{11} + Z\pi_{12} + U_1 + \gamma_1 U = X\pi_1 + V_1,
\end{aligned}
$$

where $\pi_{11} = \beta_1 + \gamma_1\beta_2$, $\pi_{12} = \gamma_1\beta_{22}$, $\pi_1' = (\pi_{11}'\pi_{12}')$ and $V_1 = U_1 + \gamma_1 U_2$.

By inserting $Y_2^* = X\beta_2 + U_2$ into the structural form equation of Y_1 and using $V_1 = U_1 + \gamma_1 U_2$, I obtain:

$$
\begin{aligned}
Y_1 &= X_1\beta_1 + \gamma_1 X\beta_2 + V_1 \\
&= X_1\beta_1 + \gamma_1 X\widehat{\beta}_2 + V_1 - \gamma_1 X(\widehat{\beta}_2 - \beta_2) \\
&= X\widehat{H}\alpha_1 + W_1,
\end{aligned}
$$

where $W_1 \equiv V_1 - \gamma_1 X(\widehat{\beta}_2 - \beta_2)$, $\alpha' \equiv (\beta_1'\gamma_1)$, $J_1 X = X_1$, and $\widehat{H} \equiv (J_1, \widehat{\beta}_2)$. Heckman's (1978) estimator of α is defined as the least squares method applied to $Y_1 = X\widehat{H}\alpha_1 + W_1$:

$$
\begin{aligned}
\widehat{\alpha} &= (\widehat{H'}X'X\widehat{H})^{-1}\widehat{H'}X'Y_1 \\
&= \alpha_1 + (\widehat{H'}X'X\widehat{H})^{-1}\widehat{H'}X'(V_1 - \gamma_1 X(\widehat{\beta}_2 - \beta_2)) \\
&= \alpha_1 + (\widehat{H'}X'X\widehat{H})^{-1}\widehat{H'}X'W_1,
\end{aligned}
$$

Note that since $plim\widehat{\beta}_2 = \beta_2$ and $plim(X'V_1) = 0$, $plim\widehat{\alpha} = \alpha$. Thus, the estimator is consistent. The asymptotic variance-covariance matrix of $\widehat{\alpha}$ is [29]:

$$
\begin{aligned}
AVar(\widehat{\alpha}) &= AE\{(\widehat{\alpha}-\alpha)(\widehat{\alpha}-\alpha)'\} \\
&= (\widehat{H'}X'X\widehat{H})^{-1}\widehat{H'}AE(X'W_1W_1'X)\widehat{H}(\widehat{H'}X'X\widehat{H})^{-1}.
\end{aligned}
$$

Observe:

$$
\begin{aligned}
X'W_1W_1'X &= (X'V_1-\gamma_1X'X(\widehat{\beta}_2-\beta_2))(V_1'X-(\widehat{\beta}_2-\beta_2)'X'X\gamma_1) \\
&= X'V_1V_1'X+\gamma_1^2X'X(\widehat{\beta}_2-\beta_2)(\widehat{\beta}_2-\beta_2)'X'X \\
&\quad -2\gamma_1X'X(\widehat{\beta}_2-\beta_2)V_1'X,
\end{aligned}
$$

By taking the expectation, I obtain:

$$
\begin{aligned}
AE(X'W_1W_1'X) &= AE(X'V_1V_1'X)+\gamma_1^2X'XAVar(\widehat{\beta}_2)X'X \\
&\quad -2\gamma_1X'XAE\{(\widehat{\beta}_2-\beta_2)V_1'X\}.
\end{aligned}
$$

Observe that if $\gamma_1=0$, I am back to the unadjusted standard errors:

$$
\begin{aligned}
AE(X'W_1W_1'X) &= AE(X'V_1V_1'X)=AE(X'U_1U_1'X) \\
AVar(\widehat{\alpha}) &= (X_1'X_1)^{-1}AE(X_1'U_1U_1'X_1)(X_1'X_1)^{-1}.
\end{aligned}
$$

Thus, the following result follows.

Lemma *The unadjusted standard errors estimate is consistent under the null of* $\gamma_1=0$.

[29] $AVar(x)$ is the asymptotic variance-covariance matrix of r.v. x and $AE(x)$ denotes the asymptotic mean (or the mean of the limit distribution) of r.v. x.

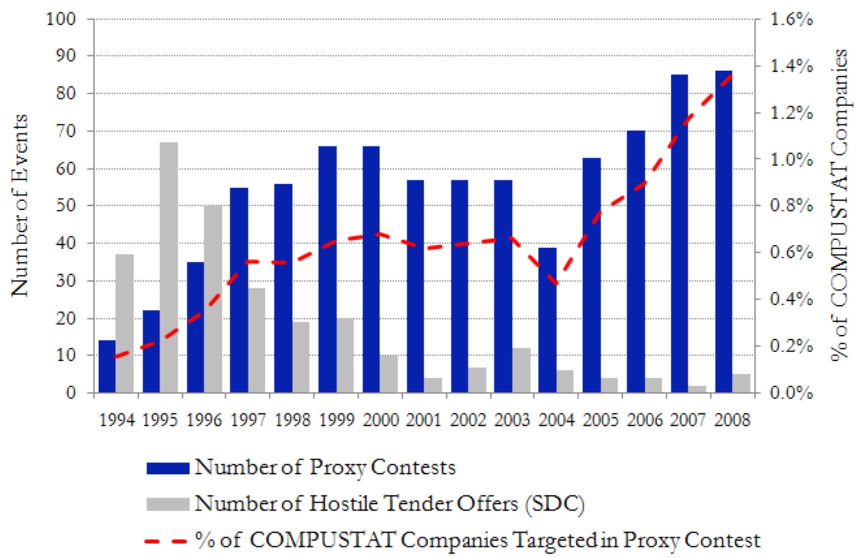


Figure 1: **Time Distribution of Proxy Contests.** The dark bars (left axis) plot the number of proxy contests initiated each year. The gray bars (left axis) plot the number of hostile tender offers initiated each year. The dashed line (right axis) plots the percentage of Compustat companies targeted in the proxy contest each year. The hostile tender offers data are from SDC database.

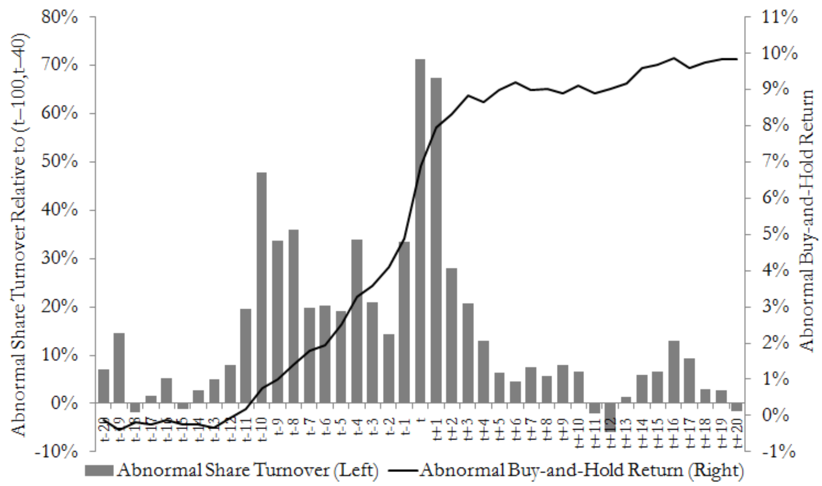
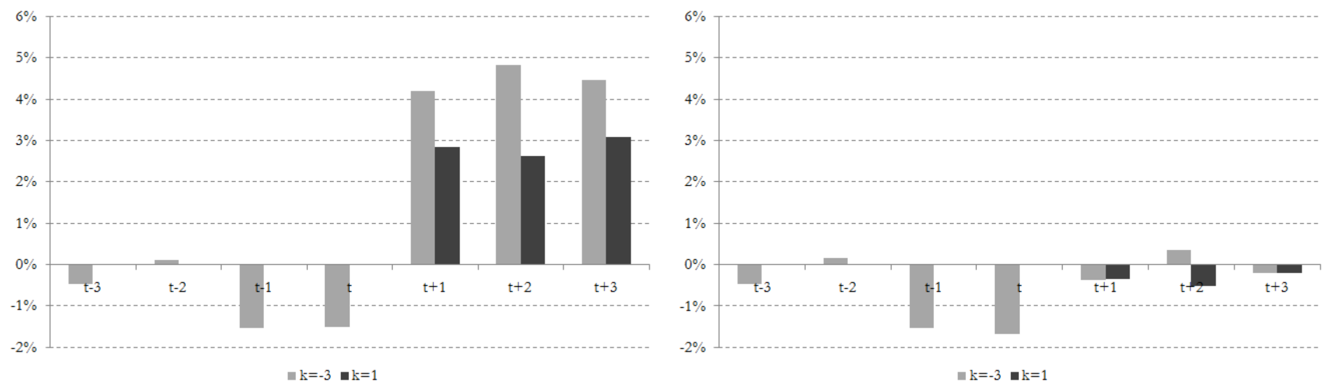


Figure 2: **Buy-and-Hold Abnormal Return around the Proxy Contest Announcement.** The solid line (right axis) plots the average buy-and-hold return around the proxy contest announcement, in excess of the buy-and-hold return of the value-weight market, from 20 days prior the announcement to 20 days afterwards. The bars (left axis) plot the increase (in percentage points) in the share trading turnover during the same time window compared to the average turnover rate during the preceding (-100, -40) event window.



(a) Matching on $\widehat{PC^*}$ is allowed.

(b) Matching on $\widehat{PC^*}$ is not allowed ($\beta_1 = 0$)

Figure 3: **Operating Profitability and Proxy Contest.** The gray (dark) bars plot the estimated coefficients γ_τ of the seven (three) dummy variables in equation (9): $ROA_{it} = X_{it}\alpha_1 + \beta_1\widehat{PC^*_{it}} + \sum_{\tau=k}^{3}\gamma_\tau D_{it+\tau} + \eta_t + \eta_i + \varepsilon_{it}$, where X_{it} is a vector of lagged covariates, $\widehat{PC^*_{it}}$ is the estimated likelihood of a proxy contest, $D_{it+\tau}$ is a dummy variable equals to one if the distance from the event year is τ years, η_t are year fixed effects, and η_i are firm fixed effects. The estimates of the regression are reported in Table 12. The left plot presents the estimates from the unrestricted regression while the right plot presents the estimates from the restricted regression, in which $\beta_1 = 0$. The plotted coefficients can be interpreted as changes in ROA relative to the regression-based matched level of ROA.

Table 1: **Variable Definitions.**

Variable	Definition
MV	Market capitalization in millions of dollars.
CRSP AGE	The number of years since first appearance on CRSP.
B2M	The ratio of the market value of equity to the book value of equity.
STOCK RETURN	The 12 months buy-and-hold return.
INST	The proportion of shares held by institutions.
AMIHUD	Amihud (2002) illiquidity measure, defined as the yearly average (using daily data) of $1000\sqrt{\frac{\lvert Return\rvert}{DollarTradingVolume}}$.
BID-ASK-SPREAD	The quoted percentage spread, defined as the yearly average (using daily data) of $(Ask - Bid)/(0.5Ask + 0.5Bid)$.
LEVERAGE	The net book leverage ratio defined as (book value of debt - cash)/(book value of debt + book value of equity).
CASH	The ratio of total cash and cash equivalents to total assets.
R&D	Research and development expense scaled by lagged total assets.
CAPEX	The capital expenditures less the sale of PP&E divided by mean total assets.
DIVIDENDS	Dividend payout ratio, defined as the ratio of total dividend payments to net income before extraordinary items.
REPURCHASE RATIO	The ratio of net repurchases (see footnote 7 in Skinner, 2008, for futher details) to income before extraordinary items.
GPM	Gross profit margin, defined as (1-COGS/Sales).
ROA	Return on assets, defined as earnings before interest, taxes, depreciation, and amortization divided by lagged total assets.
CF	Net cash flow (net income + depreciation and amortization) divided by lagged total assets.
CEOPAY	The total CEO contracted pay including options valued at granting ("TDC1" from Compustat Executive Compensation database), divided by sales.
NEW CEO	A dummy variable equals to one if the current CEO is assigned to the firm for the first year.
GINDEX	The Gompers et al. (2003) governance index.
SALES-TO-ASSET	The ratio of net sales to total assets.
HHISIC3	the Herfindahl index of net sales among all firms in the same SIC 3-digit code.

Table 2: **Summary Statistics of Proxy Contest Targets.** This table reports the summary statistics of proxy contest targets and comparisons with a set of matched companies. All variables are as defined in Table 1. The first three columns report the mean, median, and standard deviation of the target firms' characteristics in the year before they are targeted. Columns 4 and 5 report the estimates of the following matching regression: $y_{it} = \alpha_0 + \alpha_1 Target_{it} + \alpha_2 log(MV_{it}) + \alpha_3 B2M_{it} + \eta_t + \eta_{sic3} + \varepsilon_{it}$, where y_{it} is the relevant characteristic (i.e. leverage), $Target_{it}$ is a dummy variable equals to one if the company is targeted in a proxy contest during the year, $log(MV_{it})$ is the natural logarithm of the market capitalization, $B2M_{it}$ is the book-to-market ratio as defined in Table 1, η_{sic3} are industry dummies, and η_t are year dummies. When I describe target firms by size (MV), the $log(MV)$ variable is dropped from the matching regression and when I describe target firms by book-to-market (B2M), the $B2M$ variable is dropped from the matching regression. Column 4 reports the estimated coefficient α_1, which is the difference in level of the relevant characteristic between the targeted company and a regression-based matched company, and column 5 reports its t-statistic. t-statistics are calculated using heteroscedasticity robust standard errors. The regression covers all Compustat firm-year observations from 1994 to 2008 and includes both event and non-event observations. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	Summary Statistics			Matching Regression	
Firm Characteristic	Mean (1)	Median (2)	Std. Dev. (3)	coefficient (4)	t-stat (5)
MV ($, millions)	1,650	148	5,258	-487.1**	-2.30
CRSP AGE	17.69	13.00	15.47	4.0070***	6.62
B2M	0.8235	0.6278	0.7358	0.1161***	4.05
STOCK RETURN (annual)	0.0394	0.0777	0.5445	0.0077	0.34
INST	0.4158	0.3821	0.3430	0.0239**	2.25
AMIHUD	0.4575	0.2202	0.6228	-0.1516***	-6.94
BID-ASK-SPREAD (%)	2.4250	1.2860	3.2022	-0.3423***	-3.04
LEVERAGE	0.1734	0.1051	0.2053	0.0030	0.37
CASH	0.1722	0.0688	0.2233	0.0125	1.55
R&D	0.0335	0.0000	0.0841	-0.0108***	-3.31
CAPEX	0.0534	0.0402	0.1222	-0.0250***	-4.41
DIVIDENDS	0.1476	0.0000	0.2686	0.0061	0.56
REPURCHASE RATIO	0.2446	0.0000	0.7279	0.0690**	2.14
GPM	0.2460	0.3547	1.2184	0.0602	1.08
ROA	0.0489	0.0628	0.1577	0.0038	0.61
CF	0.0097	0.0270	0.1702	0.0036	0.49
CEOPAY	0.0052	0.0021	0.0122	-0.0005	-0.51
NEW CEO	0.2000	0.0000	0.3140	0.0989***	3.20
GINDEX	9.51	9.00	2.57	0.5440***	3.44

Table 3: **Probit Analysis of Proxy Contests.** This table reports estimates of the probit regression: $Pr(PC_{it} = 1) = \Phi(X_{it}\alpha_{21} + \zeta_t + \varepsilon_{it})$, where the dependent variable PC_{it} is a dummy variable equals to one if the company is targeted in a proxy contest during the year, Φ is the cumulative normal distribution, X_{it} is a vector of lagged covariates, and ζ_t are time fixed effects. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. All independent variables are as defined in Table 1. Since the variables from Compustat Executive Compensation database are only available for about one-third of firms on Compustat, the multivariate regressions with variables from the Compustat Executive Compensation database are reported separately. In each column, I report probit coefficients, average partial effects (APE), and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by industry (SIC3). APE corresponds to the change in the likelihood of a proxy contest due to a standard deviation change of a covariate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	Full Sample			ExecComp Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	coefficient	APE	t-stat	coefficient	APE	t-stat
MV	-0.0747***	-0.0028	-2.85	-0.0598	-0.0027	-1.55
CRSP AGE	0.0061***	0.0016	4.28	0.0042**	0.0013	2.08
BOOK-TO-MARKET	0.1545***	0.0016	3.63	0.0406	0.0005	0.44
STOCK RETURN	-0.1293***	-0.0015	-3.67	-0.2158**	-0.0031	-2.51
INST	0.2035**	0.0012	2.28	0.0697	0.0005	0.49
AMIHUD	-0.3009***	-0.0044	-4.23	-0.3230	-0.0059	-1.05
BID-ASK SPREAD	0.0123	0.0009	1.05	-0.0003	0.0000	-0.0
LEVERAGE	0.1977	0.0007	1.36	0.2628	0.0012	1.07
CASH	0.1436	0.0006	1.20	0.1559	0.0008	0.64
R&D	-0.1700	-0.0004	-0.74	-0.4676	-0.0014	-0.58
CAPEX	-0.1131	-0.0003	-0.78	0.1870	0.0007	0.70
DIVIDENDS	0.0293	0.0001	0.30	-0.1007	-0.0005	-0.55
REPURCHASE RATIO	0.0638**	0.0006	2.10	0.0713	0.0008	1.45
GPM	0.0400***	0.0012	3.72	0.1628	0.0059	0.88
ROA	-0.3701*	-0.0015	-1.76	-0.8141	-0.0040	-1.49
CF	0.3860*	0.0021	1.90	0.1290	0.0009	0.35
CEOPAY				-5.3437	-0.0014	-1.11
NEW CEO				-0.0373	-0.0002	-0.35
Constant	-2.1359***		-13.55	-1.8929***		-5.85
Observations	54,686			18,532		
Pseudo R^2	4.63%			4.48%		

Table 4: **The Ex Post Effect of the Proxy Contest.** This table reports estimates of equation (1): $y_{it} = X_{it}\alpha_1 + \beta_1 PostTarget_{it} + \eta_t + \eta_i + \varepsilon_{it}$, where y_{it} is a performance measure of interest, X_{it} is a vector of lagged covariates, $PostTarget_{it}$ is a dummy variable that equals to one if the company is targeted during years $(t-1, t-3)$, η_t are time fixed effects, and η_i are firm fixed effects. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. lag PERFORMANCE is the lagged level of y_{it}. All other variables are as defined in Table 1. In each column, I report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE	CASH	R&D	CAPEX	DIVIDENDS	REPURCHASE RATIO	CEOPAY	NEW CEO	GMP	ROA	CF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
POST TARGET	0.0001	0.0047	-0.0021	-0.0110**	-0.0176**	-0.0019	0.0002	0.0778**	-0.0539	-0.0025	0.0052
	[0.02]	[0.95]	[-0.78]	[-2.15]	[-2.07]	[-0.06]	[0.25]	[2.43]	[-1.12]	[-0.51]	[0.75]
lag PERFORMANCE	0.5396***	0.4272***	0.1532***	0.1301***	0.2026***	0.0307***	0.1238***	-0.1079***	0.3538***	0.4007***	0.1664***
	[68.61]	[58.08]	[13.75]	[14.03]	[22.09]	[3.71]	[5.04]	[-16.40]	[17.26]	[40.94]	[19.25]
lag log(MV)	0.0007	-0.0082***	-0.0107***	0.0137***	0.0105***	0.0454***	-0.0005***	0.0064	-0.0063	-0.0010	0.0147***
	[0.69]	[-8.29]	[-12.40]	[10.82]	[9.53]	[12.70]	[-2.58]	[1.34]	[-0.69]	[-0.77]	[6.54]
lag SALES	-0.0112***	0.0095***	0.0069***	0.0195***	-0.0049**	0.0152**	-0.0014***	-0.0071	0.0490***	0.0391***	0.0753***
	[-5.89]	[4.84]	[5.07]	[7.59]	[-2.35]	[2.41]	[-4.07]	[-0.74]	[3.89]	[15.19]	[16.96]
lag INST	-0.0003	-0.0007	-0.0125***	-0.0088**	-0.0196***	0.1030***	0.0001	-0.0268**	-0.0091	0.0042	0.0106**
	[-0.10]	[-0.25]	[-6.01]	[-2.25]	[-3.94]	[6.23]	[0.27]	[-1.96]	[-0.46]	[1.41]	[2.10]
lag B2M	0.0031*	-0.0073***	-0.0186***	-0.0289***	0.0012	0.0465***	-0.0015***	0.0614***	-0.0324***	-0.0156***	-0.0081**
	[1.86]	[-5.15]	[-16.71]	[-15.08]	[0.69]	[8.50]	[-5.70]	[5.81]	[-2.71]	[-9.13]	[-2.48]
Constant	0.0767***	0.1176***	0.1041***	-0.0339***	0.0514***	-0.1962***	0.0092***	0.0237	0.0984*	0.0143*	-0.1170***
	[11.97]	[18.97]	[21.53]	[-3.62]	[7.89]	[-9.48]	[4.89]	[0.51]	[1.84]	[1.86]	[-8.45]
Observations	76,710	76,704	76,225	57,699	76,464	76,646	21,864	22,446	75,693	76,080	75,303
R^2	28.60%	20.30%	6.50%	9.30%	5.20%	1.90%	3.40%	1.70%	13.50%	21.80%	8.20%

Table 5: **The Reduced Form Model.** This table reports estimates of equation (5): $y_{it} = X_{it}\pi_{11} + Z_{it}\pi_{12} + \eta_i + \eta_t + v_{1it}$, where y_{it} is a performance measure of interest, X_{it} is a vector of lagged covariates, Z_{it} is the Amihud (2002) measure of stock illiquidity, η_t are time fixed effects, and η_i are firm fixed effects. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. lag PERFORMANCE is the lagged level of the y_{it}. All other variables are as defined in Table 1. In each column, I report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE	CASH	R&D	CAPEX	DIVIDENDS	REPURCHASE RATIO	CEOPAY	NEW CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag AMIHUD	-0.0060***	-0.0009	0.0030***	0.0078***	-0.0032**	0.0200***	0.0042***	-0.0604*
	[-4.46]	[-0.68]	[3.18]	[4.60]	[-2.35]	[4.60]	[4.05]	[-1.94]
lag PERFORMANCE	0.5399***	0.4323***	0.1611***	0.1319***	0.2064***	0.0299***	0.1253***	-0.1076***
	[67.74]	[58.37]	[14.19]	[14.16]	[22.01]	[3.62]	[5.10]	[-16.24]
lag log(MV)	-0.0008	-0.0085***	-0.0101***	0.0160***	0.0099***	0.0524***	-0.0002	0.0017
	[-0.80]	[-8.12]	[-11.06]	[11.74]	[8.19]	[13.01]	[-1.00]	[0.31]
lag SALES	-0.0109***	0.0092***	0.0066***	0.0192***	-0.0052**	0.0155**	-0.0013***	-0.0070
	[-5.66]	[4.63]	[4.88]	[7.47]	[-2.41]	[2.43]	[-3.87]	[-0.71]
lag INST	-0.0001	-0.0007	-0.0121***	-0.0095**	-0.0208***	0.0989***	0.0003	-0.0318**
	[-0.03]	[-0.23]	[-5.87]	[-2.40]	[-4.10]	[5.86]	[0.71]	[-2.29]
lag B2M	0.0035**	-0.0075***	-0.0188***	-0.0293***	0.0015	0.0460***	-0.0015***	0.0617***
	[2.11]	[-5.33]	[-16.82]	[-15.19]	[0.88]	[8.33]	[-5.73]	[5.82]
Constant	0.0881***	0.1190***	0.0989***	-0.0496***	0.0580***	-0.2431***	0.0064***	0.0712
	[12.85]	[17.81]	[19.22]	[-5.03]	[7.91]	[-10.25]	[3.19]	[1.39]
Observations	75,795	75,789	75,315	57,662	75,550	75,731	21,827	22,400
R^2	28.50%	20.40%	6.80%	9.30%	5.30%	1.90%	3.60%	1.70%

Table 6: **Placebo Test.** This table reports estimated coefficient of the Amihud (2002) measure of stock illiquidity in equation (5): $y_{it} = X_{it}\pi_{11} + Z_{it}\pi_{12} + \eta_i + \eta_t + v_{1it}$, where y_{it} is a performance measure of interest, X_{it} is a vector of lagged covariates, Z_{it} is the Amihud measure of stock illiquidity, η_t are time fixed effects, and η_i are firm fixed effects. The equation is estimated in four samples, as defined at the top of each column. These regressions include both event and non-event observations. All variables are as defined in Table 1. Coefficients of the control variables (lag PERFORMANCE, lag log(MV), lag SALES, lag INST, lag B2M, and constant) are not reported for space reasons. I report estimated coefficient π_{12} and its t-statistic, calculated using heteroscedasticity robust standard errors and within correlation clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Sample Period	Effective Sample 1994-2008 (1)	1996-2000 (2)	2001-2005 (3)	Placebo Sample 1988-1992 (4)
CAPITAL STRUCTURE				
Leverage	-0.0060***	-0.0098***	-0.0042*	0.0018
	[-4.46]	[-3.58]	[-1.82]	[0.71]
Cash	-0.0009	0.0033	-0.0001	0.0029
	[-0.68]	[1.22]	[-0.05]	[1.44]
INVESTMENT POLICY				
R&D	0.0030***	0.0090*	0.0062**	0.0018
	[3.18]	[1.73]	[2.10]	[0.98]
CAPEX	0.0078***	0.0094**	0.0147***	0.0035
	[4.60]	[2.41]	[5.44]	[1.12]
PAYOUT POLICY				
Dividends	-0.0032**	-0.0038*	-0.0038*	-0.0013
	[-2.35]	[-1.90]	[-1.72]	[-0.47]
Repurchases	0.0200***	-0.0016	0.0224***	0.0077
	[4.60]	[-0.21]	[3.24]	[0.97]

Table 7: **Placebo Test: Pooled Regression.** This table reports estimates of equation (7): $y_{it} = X_{it}\pi_{11} + PRE1992 * X_{it}\pi_{12} + Z_{it}\pi_{13} + PRE1992 * Z_{it}\pi_{14} + \eta_i + \eta_t + v_{1it}$, where y_{it} is a performance measure of interest, X_{it} is a vector of lagged covariates, Z_{it} is the Amihud measure of stock illiquidity, $PRE1992$ is a dummy variable that indicates the pre-1992 sample period, η_t are time fixed effects, and η_i are firm fixed effects. The equation is estimated in the 1988-2008 sample period. These regressions include both event and non-event observations. All variables are as defined in Table 1. Coefficients of the control variables (lag PERFORMANCE, lag log(MV), lag SALES, lag INST, lag B2M, and constant) are not reported for space reasons. In each column, I report estimated coefficients π_{13} and π_{14} and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by firm. π_{13} is the effect of the illiquidity on the corporate policies in the full sample, π_{14} is the change in the effect of the illiquidity on the corporate policies in the pre-1992 sample relative to the full sample, and $\pi_{13} + \pi_{14}$ is the effect of the illiquidity on the corporate policies in the pre-1992 sample. The *F-test* tests the null of $\pi_{13} + \pi_{14} = 0$, i.e., no effect of the illiquidity on the outcome variables in the placebo sample. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE (1)	CASH (2)	R&D (3)	CAPEX (4)	DIVIDENDS (5)	REPURCHASE RATIO (6)
lag AMIHUD (π_{13})	-0.0040***	-0.0000	0.0013*	0.0057***	-0.0013	0.0221***
	[-3.37]	[-0.01]	[1.80]	[3.76]	[-1.05]	[6.25]
lag AMIHUD*PRE1992 (π_{14})	0.0045**	0.0012	-0.0021**	-0.0073***	0.0005	-0.0155***
	[2.47]	[0.75]	[-2.46]	[-3.38]	[0.22]	[-2.81]
F-test: $\pi_{13} + \pi_{14} = 0$						
Point estimate	0.0005	0.0012	-0.0008	-0.0016	-0.0005	0.0066
F-statistics	0.10	0.77	1.77	0.62	0.24	1.88
p-value	0.7510	0.3815	0.1835	0.4302	0.6234	0.1702

Table 8: **Cross-Sectional Variation Test.** This table reports estimates of equation (8): $y_{it} = X_{it}\pi_{11} + Z_{it}\pi_{13} + I_{top30^{th}pctl} * Z_{it}\pi_{14} + \eta_i + \eta_t + v_{1it}$, where y_{it} is a performance measure of interest, X_{it} is a vector of lagged covariates, Z_{it} is the Amihud (2002) measure of stock illiquidity, η_t are time fixed effects, and η_i are firm fixed effects. $I_{top30^{th}pctl}$ is a dummy variable equals to one if the company belongs to the top 30^{th} percentile in terms of size (SALES). These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. All other variables are as defined in Table 1. Coefficients of the control variables (lag PERFORMANCE, lag log(MV), lag SALES, lag INST, lag B2M, and constant) are not reported for space reasons. In each column, I report estimated coefficients π_{13} and π_{14} and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by firm. The *F-test* tests the null of $\pi_{13} + \pi_{14} = 0$. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE	CASH	R&D	CAPEX	DIVIDENDS	REPURCHASE RATIO	CEOPAY	NEW CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag AMIHUD (π_{13})	-0.0060***	-0.0008	0.0030***	0.0079***	-0.0031**	0.0202***	0.0051***	-0.0601*
	[-4.52]	[-0.61]	[3.21]	[4.62]	[-2.32]	[4.65]	[4.47]	[-1.87]
lag AMIHUD*$I_{top30^{th}pctl}$ (π_{14})	0.0146**	-0.0147***	-0.0047***	-0.0047	-0.0064	-0.0337*	-0.0071***	-0.0031
	[2.14]	[-3.78]	[-3.22]	[-0.55]	[-0.96]	[-1.87]	[-6.16]	[-0.07]
F-test: $\pi_{13} + \pi_{14} = 0$								
Point estimate	0.0086	-0.0155	-0.0017	0.0032	-0.0095	-0.0135	-0.0020	-0.0632
F-statistics	1.54	14.66	1.04	0.14	2.00	0.54	2.70	1.75
p-value	0.2154	0.0001	0.3071	0.7107	0.1572	0.4622	0.1007	0.1866

Table 9: **The Ex Ante Effect of the Proxy Contests - First Stage.** This table reports estimates of equation (3) using the probit model: $Pr(PC_{it} = 1) = \Phi(PC^*_{it}) = \Phi(X_{it}\alpha_{21} + Z_{it}\alpha_{22} + \zeta_t + u_{2it})$, where the dependent variable PC_{it} is a dummy variable equals to one if the company is targeted in a proxy contest during the year, Φ is the cumulative normal distribution, PC^*_{it} is an unobserved latent-variable that captures the propensity of being the target of a proxy contest, X_{it} is a vector of lagged covariates, Z_{it} is the Amihud (2002) measure of stock illiquidity, ζ_t are time fixed effects. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. lag PERFORMANCE is the lagged level of a PERFORMANCE MEASURE, reported at the top of each column. All other variables are as defined in Table 1. In each column, I report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by industry (SIC3). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE	CASH	R&D	CAPEX	DIVIDENDS	REPURCHASE RATIO	CEOPAY	NEW CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag PERFORMANCE	0.1440	-0.0399	-0.3949**	-0.1826	0.1526**	0.0871***	-7.5212	-0.0098
	[1.24]	[-0.38]	[-2.54]	[-1.25]	[2.13]	[3.18]	[-1.47]	[-0.10]
lag log(MV)	-0.0473**	-0.0468**	-0.0507***	-0.0515**	-0.0523***	-0.0477**	-0.0747**	-0.0580*
	[-2.45]	[-2.39]	[-2.63]	[-2.42]	[-2.60]	[-2.47]	[-2.29]	[-1.78]
lag SALES	-0.0131	-0.0147	-0.0207	-0.0156	-0.0085	-0.0129	-0.0920*	-0.0646
	[-0.52]	[-0.55]	[-0.81]	[-0.58]	[-0.34]	[-0.54]	[-1.88]	[-1.51]
lag INST	0.1523**	0.1571**	0.1548*	0.1922**	0.1742**	0.1498*	0.0331	0.0314
	[1.98]	[2.01]	[1.94]	[2.52]	[2.17]	[1.92]	[0.26]	[0.25]
lag B2M	0.2403***	0.2410***	0.2252***	0.2220***	0.2415***	0.2427***	0.1758**	0.2144***
	[7.54]	[7.06]	[6.93]	[6.03]	[7.48]	[7.50]	[2.14]	[2.73]
lag AMIHUD	-0.2319***	-0.2302***	-0.2357***	-0.2193***	-0.2324***	-0.2289***	-0.6272	-0.6483
	[-5.58]	[-5.34]	[-5.52]	[-5.08]	[-5.46]	[-5.58]	[-1.49]	[-1.54]
Constant	-2.1532***	-2.1313***	-2.0765***	-2.1058***	-2.1440***	-2.1612***	-1.5690***	-1.7515***
	[-17.26]	[-15.78]	[-16.60]	[-15.68]	[-17.16]	[-17.78]	[-5.37]	[-6.34]
Observations	75,802	75,799	75,424	57,992	75,701	75,778	23,287	23,724
Pseudo R^2	3.73%	3.69%	3.81%	3.42%	3.77%	3.86%	3.33%	3.24%

Table 10: **The Ex Ante Effect of the Proxy Contests - Second Stage.** This table reports estimates of equation (2): $y_{it} = X_{it}\alpha_{11} + \gamma_1 \widehat{PC^*_{it}} + \eta_t + \eta_i + u_{1it}$, where y_{it} is a performance measure of interest, $\widehat{PC^*_{it}}$ is the First Stage estimate of the likelihood of a proxy contest (see Table 9), X_{it} is a vector of lagged covariates, η_t are time fixed effects, and η_i are firm fixed effects. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. lag PERFORMANCE is the lagged level of y_{it}. All other variables are as defined in Table 1. In each column, I report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by firm. For $\widehat{PC^*_{it}}$ I also report the change in the outcome variable due to one standard deviation change of the likelihood of a proxy contest. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE	CASH	R&D	CAPEX	DIVIDENDS	REPURCHASE RATIO	CEOPAY	NEW CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{PC^*}$	0.0256***	-0.0010	-0.0173***	-0.0457***	0.0230***	-0.0554***	-0.0092***	0.1130**
	[4.42]	[-0.18]	[-4.60]	[-5.72]	[3.85]	[-2.73]	[-4.76]	[1.97]
	2.42%	0.08%	4.40%	8.15%	2.81%	6.07%	5.36%	4.09%
lag PERFORMANCE	0.5364***	0.4324***	0.1541***	0.1240***	0.2028***	0.0346***	0.0629**	-0.1065***
	[67.10]	[58.29]	[13.43]	[13.41]	[21.37]	[4.07]	[2.25]	[-16.07]
lag log(MV)	0.0004	-0.0082***	-0.0107***	0.0141***	0.0106***	0.0475***	-0.0008***	0.0078
	[0.44]	[-8.37]	[-12.26]	[11.06]	[9.44]	[12.86]	[-3.76]	[1.58]
lag SALES	-0.0106***	0.0091***	0.0062***	0.0184***	-0.0049**	0.0152**	-0.0021***	0.0004
	[-5.47]	[4.58]	[4.54]	[7.13]	[-2.27]	[2.38]	[-5.57]	[0.04]
lag INST	-0.0040	-0.0006	-0.0096***	-0.0010	-0.0246***	0.1079***	0.0007	-0.0354**
	[-1.30]	[-0.20]	[-4.49]	[-0.24]	[-4.83]	[6.43]	[1.43]	[-2.50]
lag B2M	-0.0021	-0.0073***	-0.0153***	-0.0200***	-0.0035	0.0591***	0.0000	0.0394**
	[-1.05]	[-3.93]	[-12.09]	[-8.38]	[-1.64]	[8.39]	[0.02]	[2.50]
Constant	0.1564***	0.1140***	0.0512***	-0.1489***	0.1237***	-0.3759***	-0.0089**	0.2723**
	[8.30]	[5.96]	[4.10]	[-6.79]	[6.07]	[-5.48]	[-2.17]	[2.08]
Observations	75,795	75,789	75,315	57,662	75,550	75,731	21,827	22,400
R^2	28.50%	20.40%	6.90%	9.40%	5.30%	1.90%	3.70%	1.70%

Table 11: **Abnormal Return and Firm Characteristics.** This table reports estimates of OLS regression in which the dependent variable is the abnormal return, in excess of the buy-and-hold return of the value-weight market, from days prior the proxy contest announcement to days afterward. $\widehat{PC^*}$ is the predicted likelihood of a proxy contest, calculated using estimates reported in Table 3. INSTHERFL is the Herfindahl index of the institutional ownership. MARKET BETA is the factor loading on the market access return. All other variables are as defined in Table 1. I report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

DEPENDENT VARIABLE:	ANNOUNCEMENT RETURN
$\widehat{PC^*}$	-0.0828**
	[-2.17]
INSTHERFL	-0.1727*
	[-1.95]
LEVERAGE	0.1918***
	[2.62]
CASH	0.0830*
	[1.66]
DIVIDENDS	0.0385
	[0.98]
REPURCHASE RATIO	-0.0134
	[-0.91]
R&D	0.0869
	[0.69]
CAPEX	-0.0352
	[-0.34]
MARKET BETA	-0.0231
	[-1.11]
log(MV)	0.0041
	[0.58]
B2M	0.0086
	[0.42]
CONSTANT	-0.1705*
	[-1.68]
Observations	313
R^2	6.80%

Table 12: **Ex Post Changes in Operating Profitability.** This table reports estimates of equation (9): $ROA_{it} = X_{it}\alpha_1 + \beta_1 \widehat{PC^*_{it}} + \sum_{\tau=k}^{3} \gamma_\tau D_{it+\tau} + \eta_t + \eta_i + \varepsilon_{it}$, where X_{it} is a vector of lagged covariates, $\widehat{PC^*_{it}}$ is the estimated likelihood of a proxy contest, $D_{it+\tau}$ is a dummy variable equals to one if the distance from the event year is τ years, η_t are year fixed effects, and η_i are firm fixed effects. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. $\widehat{PC^*}$ is the First Stage estimate of the likelihood of a proxy contest. All other variables are as defined in Table 1. The First Stage estimates and coefficients of the control variables (lag ROA, lag log(MV), lag SALES, lag INST, lag B2M, and constant) are not reported for space reasons. In columns (1) and (2) I report estimates from the unrestricted regression, while in columns (3) and (4) I report estimates from the restricted regression, in which $\beta_1 = 0$. In each column, I report estimated coefficients γ_τ and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	Unrestricted β_1		Restricted $\beta_1 = 0$	
	$k = 1$	$k = -3$	$k = 1$	$k = -3$
	(1)	(2)	(3)	(4)
D_{t-3}		-0.0048		-0.0047
		[-0.93]		[-0.93]
D_{t-2}		0.0011		0.0016
		[0.16]		[0.22]
D_{t-1}		-0.0154*		-0.0153*
		[-1.70]		[-1.68]
D_t		-0.0151		-0.0167*
		[-1.63]		[-1.80]
D_{t+1}	0.0284***	0.0420***	-0.0027	-0.0037
	[3.97]	[3.93]	[-0.49]	[-0.47]
D_{t+2}	0.0261***	0.0483***	-0.0050	0.0036
	[3.00]	[3.35]	[-0.63]	[0.27]
D_{t+3}	0.0309***	0.0445***	-0.0013	-0.0021
	[4.30]	[4.36]	[-0.24]	[-0.28]
$\widehat{PC^*}$	-0.0559***	-0.0686***		
	[-7.15]	[-6.51]		
Observations	54,504	32,066	54,540	32,088
R^2	21.70%	19.10%	21.50%	18.80%

Table 13: **Ex Ante Changes in Operating Profitability.** Column (1) reports estimates of the First Stage equation (3): $Pr(PC_{it}=1)=\Phi(PC^*_{it})=\Phi(X_{it}\alpha_{21}+Z_{it}\alpha_{22}+\zeta_t+u_{2it})$, where the dependent variable PC_{it} is a dummy variable equals to one if the company is targeted in a proxy contest during the year, Φ is the cumulative normal distribution, PC^*_{it} is an unobserved latent-variable that captures the propensity of being the target of a proxy contest, X_{it} is a vector of lagged covariates, Z_{it} is the Amihud (2002) measure of stock illiquidity, and ζ_t are time fixed effects. Columns (2)-(5) report estimates of the Second Stage equation (2): $\triangle ROA_{it+1}=X_{it}\alpha_{11}+\gamma_1\widehat{PC^*_{it}}+\eta_t+\eta_i+u_{1it}$, where $\triangle ROA_{it+1}=ROA_{it+1}-ROA_{it}$, X_{it} is a vector of lagged covariates, $\widehat{PC^*_{it}}$ is the First Stage estimate of the likelihood of a proxy contest, η_t are time fixed effects, and η_i are firm fixed effects. Column (2) reports results in the full sample, column (3) reports results in the sample of ex post non-targeted companies, column (4) reports results in the sample of ex post targeted companies, and (5) reports results in the sample of ex post targeted companies cover pre-targeting years only. All variables are as defined in Table 1. In each column, I report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered as specified in the table. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	First Stage	Second Stage			
		All Companies	Non-Targets	Targets	Future Targets
	(1)	(2)	(3)	(4)	(5)
$\widehat{PC^*}$		0.0336***	0.0317***	0.0675**	0.1219***
		[4.90]	[4.50]	[2.21]	[3.34]
lag PERFORMANCE	0.1065	-0.2548***	-0.2523***	-0.2941***	-0.3291***
	[1.27]	[-27.12]	[-25.89]	[-8.73]	[-13.60]
lag log(MV)	-0.0489**	-0.0050***	-0.0048***	-0.0074*	-0.0056
	[-2.49]	[-4.56]	[-4.21]	[-1.84]	[-1.14]
lag SALES	-0.0210	0.0009	0.0006	0.0062	0.0109
	[-0.78]	[0.38]	[0.25]	[0.74]	[1.09]
lag INST	0.1478*	-0.0005	-0.0002	-0.0019	-0.0121
	[1.87]	[-0.19]	[-0.08]	[-0.20]	[-0.69]
lag B2M	0.2415***	-0.0058***	-0.0053**	-0.0150**	-0.0228**
	[7.40]	[-2.91]	[-2.57]	[-2.03]	[-2.04]
lag AMIHUD	-0.2307***				
	[-5.55]				
Constant	-2.1205***	0.1069***	0.1008***	0.2677***	0.3516***
	[-16.50]	[5.72]	[5.23]	[2.82]	[3.61]
Observations	75,351	63,676	59,914	3,762	2,758
R^2	3.72%	7.20%	7.10%	9.40%	10.10%

Table 14: **Year-by-Year Estimation of the First Stage.** This table reports estimates of equation (2): $y_{it} = X_{it}\alpha_{11} + \gamma_1 \widehat{PC}^*_{it} + \eta_t + \eta_i + u_{1it}$, where y_{it} is a performance measure of interest, X_{it} is a vector of lagged covariates, η_t are time fixed effects, and η_i are firm fixed effects. $\widehat{PC}^*_{it}$ is the First Stage estimate of the likelihood of a proxy contest (see Table 9), estimated at the end of each year using information available at the end of that year. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. The First Stage estimates are not reported for space reasons. lag PERFORMANCE is the lagged level of the PERFORMANCE MEASURE. All other variables are as defined in Table 1. In each column, I report estimated coefficients and their t-statistics, calculated using heteroscedasticity robust standard errors and within correlation clustered by firm. For $\widehat{PC}^*$ I also report the change in the outcome variable due to one standard deviation change of the likelihood of a proxy contest. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE	CASH	R&D	CAPEX	DIVIDENDS	REPURCHASE RATIO	CEOPAY	NEW CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{PC}^*$	0.0465***	-0.0128**	-0.0195***	-0.0487***	0.0375***	-0.0423	-0.0039***	0.0138
	[8.36]	[-2.16]	[-3.48]	[-6.01]	[4.71]	[-1.53]	[-4.22]	[0.52]
	4.40%	0.99%	4.91%	8.70%	4.58%	4.64%	1.79%	0.50%
lag PERFORMANCE	0.5057***	0.4170***	0.1386***	0.1118***	0.1813***	0.0173*	0.0113	-0.1116***
	[55.07]	[50.48]	[10.49]	[11.61]	[17.57]	[1.93]	[0.32]	[-14.67]
lag log(MV)	-0.0008	-0.0087***	-0.0110***	0.0150***	0.0088***	0.0518***	-0.0004*	0.0050
	[-0.73]	[-8.02]	[-11.09]	[11.19]	[7.62]	[12.27]	[-1.68]	[0.94]
lag SALES	-0.0110***	0.0113***	0.0081***	0.0186***	-0.0063***	0.0225***	-0.0013***	-0.0129
	[-5.03]	[4.92]	[5.38]	[7.04]	[-2.76]	[3.04]	[-3.50]	[-1.19]
lag INST	-0.0012	0.0011	-0.0130***	-0.0070*	-0.0181***	0.1214***	0.0001	-0.0324**
	[-0.37]	[0.36]	[-5.70]	[-1.74]	[-3.39]	[6.56]	[0.22]	[-2.15]
lag B2M	-0.0075***	-0.0048**	-0.0151***	-0.0179***	-0.0071***	0.0632***	-0.0006*	0.0571***
	[-3.45]	[-2.41]	[-9.25]	[-7.30]	[-2.84]	[7.04]	[-1.82]	[4.26]
Constant	0.2198***	0.0991***	0.0557***	-0.1199***	0.1746***	-0.3365***	-0.0013	0.0833
	[12.10]	[5.29]	[3.27]	[-4.84]	[6.86]	[-3.73]	[-0.42]	[0.93]
Observations	64,418	64,412	64,093	53,189	64,194	64,360	18,960	19,470
R^2	26.40%	19.10%	6.70%	9.40%	4.40%	1.80%	4.40%	1.80%

Table 15: **Linear Probability Model in the First Stage.** Panel A reports estimates of the First Stage equation (3) using linear probability model: $Pr(PC_{it}=1) = X_{it}\alpha_{21} + Z_{it}\alpha_{22} + \zeta_t + u_{2it}$, where the dependent variable PC_{it} is a dummy variable equals to one if the company is targeted in a proxy contest during the year, X_{it} is a vector of lagged covariates, Z_{it} is the Amihud (2002) measure of stock illiquidity, and ζ_t are time fixed effects. Panel B reports estimates of the Second Stage equation (2): $y_{it} = X_{it}\alpha_{11} + \gamma_1 \widehat{PC^*_{it}} + \eta_t + \eta_i + u_{1it}$, where y_{it} is a performance measure of interest, $\widehat{PC^*_{it}}$ is the First Stage estimate of the likelihood of a proxy contest, X_{it} is a vector of lagged covariates, η_t are time fixed effects, and η_i are firm fixed effects. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. All variables are as defined in Table 1. The control variables (lag PERFORMANCE, lag log(MV), lag SALES, lag INST, lag B2M, and constant) are not reported for space reasons. In each column, I report estimated coefficients α_{22} and γ_1 and their t-statistics. In Panel A (Panel B) t-statistics are calculated using heteroscedasticity robust standard errors and within correlation clustered by SIC3 (firm). For $\widehat{PC^*}$ I also report the change in the outcome variable due to one standard deviation change of the likelihood of a proxy contest. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE	CASH	R&D	CAPEX	DIVIDENDS	REPURCHASE RATIO	CEOPAY	NEW CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: First Stage								
lag AMIHUD	-0.0028***	-0.0028***	-0.0028***	-0.0030***	-0.0028***	-0.0028***	-0.0099**	-0.0101**
	[-6.31]	[-5.97]	[-6.25]	[-5.77]	[-6.14]	[-6.28]	[-2.27]	[-2.38]
Observations	75,802	75,799	75,424	57,992	75,701	75,778	23,287	23,724
R^2	0.30%	0.30%	0.30%	0.30%	0.30%	0.30%	0.30%	0.30%
Panel B: Second Stage								
$\widehat{PC^*}$	1.9648***	-0.2148	-1.5518***	-3.3775***	2.1498***	-2.5949	-0.5622***	6.3171*
	[4.28]	[-0.45]	[-5.04]	[-5.89]	[4.34]	[-1.50]	[-4.90]	[1.83]
	2.52%	0.24%	5.44%	8.30%	3.57%	3.89%	4.54%	3.11%
Observations	75,795	75,789	75,315	57,662	75,550	75,731	21,827	22,400
R^2	28.50%	20.40%	6.90%	9.40%	5.30%	1.90%	3.70%	1.70%

Table 16: **Firm Fixed Effects in the First Stage.** Panel A reports estimates of the First Stage equation (3) using linear probability model: $Pr(PC_{it} = 1) = X_{it}\alpha_{21} + Z_{it}\alpha_{22} + \zeta_i + \zeta_t + u_{2it}$, where the dependent variable PC_{it} is a dummy variable equals to one if the company is targeted in a proxy contest during the year, X_{it} is a vector of lagged covariates, Z_{it} is the Amihud (2002) measure of stock illiquidity, ζ_i are firm fixed effects, and ζ_t are time fixed effects. Panel B reports estimates of the Second Stage equation (2): $y_{it} = X_{it}\alpha_{11} + \gamma_1 \widehat{PC^*_{it}} + \eta_t + \eta_i + u_{1it}$, where y_{it} is a performance measure of interest, $\widehat{PC^*_{it}}$ is the First Stage estimate of the likelihood of a proxy contest, X_{it} is a vector of lagged covariates, η_t are time fixed effects, and η_i are firm fixed effects. These regressions cover all Compustat firm-year observations from 1994 to 2008 and include both event and non-event observations. All variables are as defined in Table 1. The control variables (lag PERFORMANCE, lag log(MV), lag SALES, lag INST, lag B2M, and constant) are not reported for space reasons. In each column, I report estimated coefficients α_{22} and γ_1 and their t-statistics. In Panel A (Panel B) t-statistics are calculated using heteroscedasticity robust standard errors and within correlation clustered by SIC3 (firm). For $\widehat{PC^*}$ I also report the change in the outcome variable due to one standard deviation change of the likelihood of a proxy contest. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

PERFORMANCE MEASURE	LEVERAGE (1)	CASH (2)	R&D (3)	CAPEX (4)	DIVIDENDS (5)	REPURCHASE RATIO (6)	CEOPAY (7)	NEW CEO (8)
Panel A: First Stage								
lag AMIHUD	-0.0020***	-0.0019***	-0.0019***	-0.0027***	-0.0019***	-0.0019***	-0.0187***	-0.0189***
	[-3.00]	[-2.92]	[-2.88]	[-3.40]	[-2.86]	[-2.94]	[-2.68]	[-2.90]
Observations	75,802	75,799	75,424	57,992	75,701	75,778	23,287	23,724
R^2	0.30%	0.30%	0.30%	0.40%	0.40%	0.30%	0.50%	0.50%
Panel B: Second Stage								
$\widehat{PC^*}$	2.6407***	-0.3572	-1.6313***	-2.8048***	3.0683***	-7.2974***	-0.2638***	2.6879
	[4.31]	[-0.57]	[-3.73]	[-4.63]	[3.76]	[-3.12]	[-4.50]	[1.52]
	3.39%	0.40%	5.73%	6.89%	5.09%	10.93%	2.13%	1.32%
Observations	75,795	75,789	75,315	57,662	75,550	75,731	21,827	22,400
R^2	28.50%	20.40%	6.90%	9.40%	5.30%	1.90%	3.70%	1.70%

Optimal Contracts with Informed Money Manager[☆]

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Abstract

This article investigates the optimal contract with an informed money manager. Motivated by simple structure of portfolio managers' compensation and complex risk structure of returns, I show that it may be optimal for the principal to stay unaware about the true risk structure of returns. That is, the principal may choose to write an incomplete contract which ignores existence of some risk factors. Thus, the incompleteness of the contract raises endogenously. When the money manager can expend effort and discover new risk factors, the optimal risk sharing contract is characterized by the insufficient effort expenditure by the money manager in discovering new risk factors.

Keywords:

Delegated portfolio choice, incentive design, unawareness, moral hazard, incomplete contracts

JEL Classifications: D01, D86, D82, D83

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1. Introduction

Compensation of portfolio managers is an ongoing topic of debate among practitioners and regulators. A casual consideration of statistical models used by practitioners suggests that the risk structure of returns is complicated. For example, a typical product provided by an investment bank might consider hundreds of risk factors. If such a structure of portfolio returns is taken seriously, a classical contract theory suggests that a contract with portfolio managers should be very complicated: the compensation structure should depend on a verity of risk factors.

Professional portfolio managers, however, face relatively simple compensation contracts. For example, the "2-20" rule is independent (at least explicitly) of the number of risk factors used by the portfolio manager to generate returns. As a result, portfolio manager can affect his compensation fee by simply loading on risk factors. This discrepancy between theory, which predicts dependence of a contract on all risk factors, and actual contracts, which don't exhibit such a dependence, is at the center of this paper.

I show that optimal contracts with portfolio manager might exhibit an endogenous incompleteness. The principal might choose to ignore possible existence of a new risk factor when the benefit from discovering a new factor is lower than the cost of verifying existence of that factor. That is, there is a trade off between costs and benefits of being aware about the true risk structure of returns. It implies that when the risk structure of returns is complex in a sense that it is costly to know what the number of risk factors is, contracts with portfolio managers will exhibit simplicity.

I also show that under curtain assumptions the optimal risk sharing contract provides the portfolio manager with insufficient incentives to discover new risk factors. Since in this paper I consider linear contracts only, incentives to expend effort can be provide through either a fixed component of the fee or the share of portfolio returns that goes to the portfolio manager. I show that neither the fixed component nor the return component provides appropriate incentives.

The rest of the paper is organized as follows. In Section 2 I present the literature review. Section 3 presents the basic model in which the portfolio manager cannot change the number of risk factors in the economy. Implications of a secret risk factor which is available to the portfolio manager are discussed in Section 4. In Section 5 I present the main part of the paper, in which the portfolio manager can change the number of risk factors by costly effort expenditure. Justifiability of contracts is discussed in Section 6. Finally, Section 7 concludes.

2. Related Literature

This paper is related to the delegated portfolio management literature. This literature has studies the trade off between the optimal risk sharing and effort expenditure by an agent (e.g., Bhattacharya and Pfleiderer, 1985; Cohen and Starks, 1988; Stoughton, 1993; Heinkel and Stoughton, 1994; Li and Tiwari, 2009). The general conclusion is that deviations from the optimal risk-sharing arrangement are required to improve efficiency in effort expenditure.[1]

This paper also contributes to the literature on the foundations of contract incompleteness. The literature has proposed several reasons why contracting parties may not specify everything that is relevant for the interaction in the contract. Recent research has endogenized contractual incompleteness by limited cognition and strategic investment in cognition by the contracting parties (Bolton and Faure-Grimaun, 2010; Tirole, 2009). These papers take a less radical approach towards unawareness than Dekel et al. (1998), as they assume

[1] Bhattacharya and Pfleiderer (1985) show that deviations from the optimal risk-sharing arrangement are required to reduce revelation of information. Cohen and Starks (1988) derive conditions under which the manager exerts more effort but chooses a riskier portfolio than investors prefer. Starks (1987) shows that the "symmetric" contract, while not necessarily eliminating agency costs, dominates the "bonus" contract in aligning the manager's interests with those of the investor. Stoughton (1993) finds that the linear contract leads to a serious lack of effort expenditure by the manager and shows that this under-investment problem can be successfully overcome through the use of quadratic contracts. Heinkel and Stoughton (1994) show that ex post performance measurement is critical to future recontracting. Li and Tiwari (2009) show that the option-type incentive helps overcome the effort-under investment problem that undermines linear contracts and that with the appropriate choice of benchmark it is always optimal to include a bonus incentive fee in the contract.

that agents are aware of the fact that they may be unaware of some relevant elements of the contracting environment. In Gabaix and Laibson (2006) and Filiz-Ozbay (2009), contractual incompleteness arises because better informed agents shroud some contingencies or actions of the informed agents.

Recently, von Thadden and Zhao (2010) introduce the problem of unawareness into Principal-Agent theory and discusses optimal incentive contracts when the agent is unaware of her action space. Authors show under what conditions it is optimal for the principal to propose an incomplete contract (that keeps the agent unaware) or a complete contract. The key tradeoff is that of enlarging the agents choice set versus adding costly incentive constraints.[2] My paper shows that it may be optimal for the principal to write an incomplete contract, which ignores existence of a risk factors in the economy. Importantly, the incompleteness raises endogenously in this set up.

3. The Basic Model

Investment opportunity set consists of risky assets and a zero interest rate risk free asset. Return on any portfolio is $\widetilde{r} = B'f$, where $\{\widetilde{f}_i\}_{i=1}^N$ are returns on risk factors, $\{B_i\}_{i=1}^N$ are loadings on risk factors, and N is the number of risk factors. Risk factors are independent and normally distributed with mean μ_i and volatility σ_i. The portfolio choice problem is reduced to the choice of loadings on risk factors. This assumption implies that all portfolios that there is no idiosyncratic risk and all portfolios are efficient. Therefore, there is no role for benchmarking in providing incentives.[3]

There are two individuals in the economy: principal (capitalized letters) and portfolio manager (non-capitalized letters). Preferences are described by $U = E(\widetilde{R}) - K\sigma^2(\widetilde{R})$ and $u = E(\widetilde{r}) - k\sigma^2(\widetilde{r})$. There are three possible scenarios:

[2]For a theoretical interpretation of the unawareness see, for example, Heifetz et al. (2006), who introduce a generalized state-space model that allows for non-trivial unawareness among several individuals, and which satisfies strong properties of knowledge as well as all the desiderata on unawareness proposed in the literature.

[3]Effects of the benchmarking, however, have been analyzed (Roll, 1992; Admati and Pfleiderer, 1997; Ou-Yang, 2003; Basak et al., 2007).

(i) portfolio choice is made individually; (ii) individuals make portfolio choice together; and (iii) the Portfolio Manager is hired by the Principal to make the portfolio choice.[4]

When the principal makes the portfolio choice, the maximization problem is:

$$\max_B B\mu - \frac{1}{2}KB^2\sigma^2$$

The optimal loading on the risk factor is $B = \frac{\mu}{K\sigma^2}$ and the maximized expected utility is $U = \frac{\mu^2}{2K\sigma^2} \equiv \overline{U}$.[5] Similarly, portfolio manager's optimal loading on the risk factor is $b = \frac{\mu}{k\sigma^2}$ and the maximized utility is $u = \frac{\mu^2}{2k\sigma^2}$.

When two individuals share risk optimally, the maximization problem is:

$$\begin{aligned} &\max_{B_{RS},\alpha_{RS}} (1-\alpha_{RS}) B_{RS}\mu - \frac{1}{2}K(1-\alpha_{RS})^2 B_{RS}^2\sigma^2 \\ s.t. \quad : \quad & \alpha_{RS}B_{RS}\mu - \frac{1}{2}k\alpha_{RS}^2 B_{RS}^2\sigma^2 \geq \overline{u} = \frac{\mu^2}{2k\sigma^2} \end{aligned}$$

The optimal loading on the risk factor is $B_{RS} = \frac{\mu}{\frac{Kk}{K+k}\sigma^2}$. Portfolio manager gets share $\alpha_{RS} = \frac{K}{K+k}$ of the realized return. α_{RS} implies that when an individual becomes less risk averse, his share of the return increases. For example, if the principal is risk neutral ($K = 0$), his share of the portfolio return is 100%.

Note that the optimal risk sharing does not increase the aggregate risk taking in the economy. Since the individual loading on the risk factor of each individual is $b = \frac{\mu}{k\sigma^2}$ and $B = \frac{\mu}{K\sigma^2}$, the aggregating loading on the risk factor is $\frac{\mu}{k\sigma^2} + \frac{\mu}{K\sigma^2} = \frac{\mu}{\frac{Kk}{K+k}\sigma^2} = B_{RS}$. Moreover, since returns do not have an idiosyncratic component, individuals don't benefit from sharing the risk: the maximized expected utility of each individual is unchanged.

[4]While this paper abstracts from implications of limited liability, the impact of limited liability on agent's incentives has been investigated. Grinblatt and Titman (1989) show that if there is limited liability, the agent has an incentive to take on a riskier portfolio than otherwise. The solution they propose is that the loss (to the agent) of under-performance outweigh the gain from over-performance. Palomino and Prat (2003) consider the case in which the agent has limited liability and show that there exists an optimal contract which takes the form of a bonus contract.

[5]All proofs are in the Appendix.

When the portfolio choice is delegated to the portfolio manager, the linear contract between the principal and the portfolio manager is (α, T), where α is the fraction of the return paid to the portfolio manager and T is a fixed fee paid to the portfolio manager regardless of the realized portfolio return (Holmstrom and Milgrom, 1987). The expected utility of the portfolio manager is $u = \alpha E(\widetilde{R}) + T - \frac{1}{2}k\alpha^2 Var(\widetilde{R}) = \alpha b\mu + T - \frac{1}{2}k\alpha^2 b^2\sigma^2$.

Given the contract, the portfolio manager makes the portfolio choice by choosing b optimally. The FOC w.t. b yields $b = \frac{\mu}{\alpha k\sigma^2}$. Thus, the expected utility of the portfolio manager as function of the contract is $u = \frac{\mu^2}{2k\sigma^2} + T$. Please note that effective risk-aversion of the portfolio manager, αk, depends on his share of the portfolio return. Therefore, when $\alpha \to 0$ even very risk averse portfolio manager might invest as if he is almost risk neutral.

Next, I consider the First Best contract. Principal's maximization problem is:

$$\begin{aligned} &\max_{\alpha}\ (1-\alpha)E(\widetilde{r}) - T - \frac{1}{2}K(1-\alpha)^2\sigma^2(\widetilde{r}) \\ s.t.(IR):\quad &\alpha E(\widetilde{r}) + T - \frac{1}{2}k\alpha^2\sigma^2(\widetilde{r}) \geq \overline{u}_{RS} \end{aligned}$$

where the reservation utility of the portfolio manager equals to his expected utility when there is optimal risk sharing between two individuals, $\overline{u}_{RS}$. The optimal contract satisfies $\alpha_{FB} = \frac{K}{K+k}$ and $T = 0$. The maximized utility of the principal is $U = \frac{\mu^2}{2K\sigma^2}$. The utility of the portfolio manager is $u = \frac{\mu^2}{2k\sigma^2}$. Similarly, when two risk factors are available, the First Best contract satisfies $\alpha_{FB} = \frac{K}{K+k}$ and $T = 0$. The maximized utility of the principal is $U = \frac{\mu_1^2}{2K\sigma_1^2} + \frac{\mu_2^2}{2K\sigma_2^2}$. The utility of the portfolio manager is $u = \frac{\mu_1^2}{2k\sigma_1^2} + \frac{\mu_2^2}{2k\sigma_2^2}$.

Note that when the manager chooses portfolio composition only, the linear contract provides the manager with appropriate incentives. In general, principal has no incentive to co-invest or hire the portfolio manager. Therefore, individuals are indifferent between making the portfolio choice individually, co-investing (risk-sharing), or hiring someone to manage the portfolio. This is the starting point of this paper.

4. Secret Risk Factor

In this section I analyze the following case: the portfolio manager becomes aware of a new risk factor but the principal is unaware of it and therefore doesn't adjust the contract. The following proposition shows that the principal and the portfolio manager have no incentive to adjust the contract when the portfolio manager becomes aware of a new risk factor.

Proposition 1. *If the portfolio manager discovers a new risk factor, the loading on that factor is* $B_2 = \frac{\mu_2}{k\alpha_{FB}\sigma_2^2}$. *The maximized utility of the principal and the utility of the portfolio manager are not affected by the fact that the principal is not aware of the second risk factor.*

Proof. See Appendix. □

Next, I study a screening contract, which provides the portfolio manager with incentive to reveal his true type. I assume that there are two types of portfolio managers: the first type has access to one risk factor while the second type has access to two risk factors. The principal's problem in selecting the set of contracts is as follows:

$$
\begin{aligned}
\max_{\alpha_i, T_i} U \quad &= \quad \upsilon \left\{ [(1-\alpha_m)B_{m,1}\mu_1 - T_m] - \frac{1}{2}K(1-\alpha_m)^2 B_{m,1}^2 \sigma_1^2 \right\} \\
&\quad + (1-\upsilon)\{[(1-\alpha_M)(B_{M,1}\mu_1 + B_{M,2}\mu_2) - T_M] \\
&\quad - \frac{1}{2}K(1-\alpha_M)^2(B_{M,1}^2\sigma_1^2 + B_{M,2}^2\sigma_2^2)\}
\end{aligned}
$$

subject to:

$$
\begin{aligned}
(IR1): &\quad \alpha_m B_{m,1}\mu_1 + T_m - \frac{1}{2}k\alpha_m^2\left[B_{m,1}^2\sigma_1^2\right] \geqslant \overline{u}_{RS,1} \\
(IR2): &\quad \alpha_M(B_{M,1}\mu_1 + B_{M,2}\mu_2) + T_M - \frac{1}{2}k\alpha_M^2\left[B_{M,1}^2\sigma_1^2 + B_{M,2}^2\sigma_2^2\right] \geqslant \overline{u}_{RS,2} \\
(IC1): &\quad \max_{B_{m,1}} \alpha_m B_{m,1}\mu_1 + T_m - \frac{1}{2}k\alpha_m^2\left[B_{m,1}^2\sigma_1^2\right] \geqslant \\
&\quad \max_{\widehat{B}_{m,1}} \alpha_M \widehat{B}_{m,1}\mu_1 + T_M - \frac{1}{2}k\alpha_M^2\left[\widehat{B}_{m,1}^2\sigma_1^2\right] \\
(IC2): &\quad \max_{B_{M,1},B_{M,2}} \alpha_M(B_{M,1}\mu_1 + B_{M,2}\mu_2) + T_M - \frac{1}{2}k\alpha_M^2\left[B_{M,1}^2\sigma_1^2 + B_{M,2}^2\sigma_2^2\right] \geqslant \\
&\quad \max_{\widehat{B}_{M,1},\widehat{B}_{M,2}} \alpha_m(\widehat{B}_{M,1}\mu_1 + \widehat{B}_{M,2}\mu_2) + T_m - \frac{1}{2}k\alpha_m^2\left[\widehat{B}_{M,1}^2\sigma_1^2 + \widehat{B}_{M,2}^2\sigma_2^2\right],
\end{aligned}
$$

where υ is the probability of facing a portfolio manager who has access to one risk factor, (α_m, T_m) is contract for the portfolio manager who has access to one risk factor, and (α_M, T_M) is contract for the portfolio manager who has access to two risk factors.

Proposition 2. *The optimal linear contract archives the optimal outcome even when type of the portfolio manager is not verifiable. There is no benefit for the portfolio manager from hiding new risk factors. There is no benefit for the principal from being aware about the number of risk factors in the economy.*

Proof. See Appendix. □

Propositions 1 and 2 imply that the principal will stay unaware about the number of risk factors in the economy if being aware is costly. Therefore, a contract with portfolio managers will be endogenously incomplete in a sense that it will ignore existence of the second risk factor in the economy.

5. Discovering Risk Factors

In this section I introduce the possibility of discovering new risk factors by the portfolio manager. With probability p, which is common knowledge, there are two risk factors and with probability $(1-p)$ there is one risk factor. Suppose the portfolio manage can verify existence of the second risk factor if he expends effort C. If the portfolio manager doesn't expend the effort, he actually chooses $b_2 = 0$. The expected utility of the portfolio manager without expending the effort C under the optimal risk sharing contract is $u(c = 0) = \frac{\mu^2}{2k\sigma^2}$. The following lemma shows what is the private benefit of the portfolio manager from discovering a risk factor.

Lemma 3. *If there is no incentive to discover new risk factors is provided, the expected utility of the portfolio manager after expending the effort C is* $u(c = C) = -C + \frac{\mu_1^2}{2k\sigma_1^2} + p\frac{\mu_2^2}{2k\sigma_2^2}$.

Proof. See Appendix. □

Next, I show for what values of C the portfolio manager expends effort in discovering new risk factors. By comparing $u(c = C)$ and $u(c = 0)$, I obtain that when the principal is not aware of possible existence of new factors, the portfolio manager will expend effort if and only if $C \leq C^* \equiv p\frac{\mu_2^2}{2k\sigma_2^2}$. A portfolio manager is more likely to expend effort in discovering new risk factor if: (i) the private cost of effort expenditure (C) is low, (ii) the probability that there are two risk factors (p) is high, (iii) the portfolio manager is less risk averse (low k), and (iv) Sharpe ratio of a new factor ($\frac{\mu_2}{\sigma_2}$) is high.

The social benefit from discovering the new factor is $\frac{\mu_2^2}{2k\sigma_2^2} + \frac{\mu_2^2}{2K\sigma_2^2}$. Thus, socially optimal criteria for discovering new risk factors is $C \leq C^{**} \equiv p(\frac{\mu_2^2}{2k\sigma_2^2} + \frac{\mu_2^2}{2K\sigma_2^2}) = p(\frac{\mu_2^2}{2k\alpha_{RS}\sigma_2^2}) = \frac{1}{\alpha_{RS}}C^*$. Since $\frac{1}{\alpha_{RS}} > 1$, when $C \in (C^*, C^{**})$ the principal will find it optimal to look for the second factor but the portfolio manager will find it suboptimal. Therefore, without appropriate incentives the portfolio manager expends insufficient effort. Hereafter I assume $C < C^{**}$.

5.1. First Best Contract

In this section I assume that the portfolio manager's effort is verifiable and I derive an optimal linear contract with the portfolio manager who can discover new risk factors. I first analyze the case of $C \leqslant C^*$ and then the case of $C^* < C \leqslant C^{**}$.

Suppose $C \leqslant C^*$. I assume that if the portfolio manager rejects the proposed contract, he invests himself and discovers as many risk factors as optimal for himself. Thus, the reservation utility is: $\overline{u}_{PM} = \frac{\mu_1^2}{2k\sigma_1^2} - C + p\frac{\mu_2^2}{2k\sigma_2^2}$. Since $C \leqslant C^*$, the principal implements discovering the new risk factor in the contract. The maximization problem is:

$$\begin{aligned}
\max_{\alpha_M, T_M, \alpha_m, T_m} U \quad &= \quad p\left\{(1-\alpha_M)\left(\frac{\mu_1^2}{k\alpha_M\sigma_1^2} + \frac{\mu_2^2}{k\alpha_M\sigma_2^2}\right) - T_M \right.\\
&\quad \left. -\frac{1}{2}K(1-\alpha_M)^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2} + \frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right]\right\}\\
&\quad +(1-p)\left\{(1-\alpha_m)\frac{\mu_1^2}{k\alpha_m\sigma_1^2} - T_m - \frac{1}{2}K(1-\alpha_m)^2\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right\}\\
s.t.(IR) \quad &: \quad -C + \frac{\mu_1^2}{2k\sigma_1^2} + p\left\{\frac{\mu_2^2}{2k\sigma_2^2} + T_M\right\} + (1-p)T_m = \overline{u}_{PM}
\end{aligned}$$

Proposition 4. *The First Best contract satisfies:* $\alpha_M = \alpha_m = \frac{K}{K+k}$ *and* $T_M = Tm = 0$. *The maximized expected utility of the principal is* $U = \frac{\mu_1^2}{2K\sigma_1^2} + p\frac{\mu_2^2}{2K\sigma_2^2}$. *The utility of the portfolio manager is* $u = \frac{\mu_1^2}{2k\sigma_1^2} - C + p\frac{\mu_2^2}{2k\sigma_2^2}$.

Proof. See Appendix. □

The First Best contract suggests that when $C \leqslant C^*$, the principal "free rides" the portfolio manager. The principal's benefit is $p\frac{\mu_2^2}{2K\sigma_2^2}$.

Next, I consider the case when $C^* < C \leqslant C^{**}$. In this case the principal has to provide the portfolio manager with part of his own profits. I assume that if the portfolio manager rejects the proposed contract, he invests himself and discovers as many risk factors as optimal for himself. Thus, the reservation utility of the portfolio manager is: $\overline{u}_{PM} = \frac{\mu_1^2}{2k\sigma_1^2}$.

Proposition 5. *The First Best contract satisfies:* $\alpha_M = \alpha_m = \frac{K}{K+k}$, $T_M = \frac{1}{p}(-C + p\frac{\mu_2^2}{2k\sigma_2^2})$, *and* $T_m = 0$. *The maximized expected utility of the principal is* $U = \frac{\mu_1^2}{2K\sigma_1^2} + p\frac{\mu_2^2}{2K\sigma_2^2} + (-C + p\frac{\mu_2^2}{2k\sigma_2^2})$. *The expected utility of the portfolio manager is* $u = \frac{\mu_1^2}{2k\sigma_1^2}$.

Proof. See Appendix. □

The First Best contract suggests that when $C^* < C \leqslant C^{**}$, the principal pays to the portfolio manager for discovering new risk factors. This is zero-NPV project from portfolio manager's point of view. The maximized expected utility of the principal under the First Best is:

$$U = \begin{cases} \frac{\mu_1^2}{2K\sigma_1^2} + p\frac{\mu_2^2}{2K\sigma_2^2}, & \text{if } C \leqslant p\frac{\mu_2^2}{2k\sigma_2^2} \\ \frac{\mu_1^2}{2K\sigma_1^2} + p\frac{\mu_2^2}{2K\sigma_2^2} + (-C + p\frac{\mu_2^2}{2k\sigma_2^2}), & \text{if } p\frac{\mu_2^2}{2k\sigma_2^2} < C \leqslant p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2} \\ \frac{\mu_1^2}{2K\sigma_1^2}, & \text{if } C > p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2} \end{cases}$$

To summarize, there are three case. First, when $C \leqslant p\frac{\mu_2^2}{2k\sigma_2^2}$, it is profitable for the portfolio manager to expend effort even if only his private benefit is taken into account. Therefore, the principal doesn't compensate the portfolio manager for his disutility. Second, when $p\frac{\mu_2^2}{2k\sigma_2^2} < C \leqslant p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2}$, the principal compensate the portfolio manager for the effort expenditure. However, the portfolio manager is paid just enough to be indifferent between expending and not expending the effort. All the rent is going to the principal. Third, when $C > p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2}$, it is profitable for neither principal nor portfolio manager to discover new risk factor.

5.2. Second Best Contract

In this section I consider the optimal contract when portfolio manager's effort is not verifiable. The principal's problem is:

$$\begin{aligned} \max_{\alpha_M, T_M, \alpha_m, T_m} U \quad &= \quad p\left\{(1-\alpha_M)\left(\frac{\mu_1^2}{k\alpha_M\sigma_1^2} + \frac{\mu_2^2}{k\alpha_M\sigma_2^2}\right) - T_M \right. \\ &\quad \left. -\frac{1}{2}K(1-\alpha_M)^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2} + \frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right]\right\} \\ &\quad +(1-p)\left\{(1-\alpha_m)\frac{\mu_1^2}{k\alpha_m\sigma_1^2} - T_m - \frac{1}{2}K(1-\alpha_m)^2\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right\} \\ (IR) \quad &: \quad -C + \frac{\mu_1^2}{2k\sigma_1^2} + p\left\{\frac{\mu_2^2}{2k\sigma_2^2} + T_M\right\} + (1-p)T_m = \overline{u}_{PM} \end{aligned}$$

subject to two (IC) constraints that hold ex-ante (before expending effort):

$$(IC1): -C + \frac{\mu_1^2}{2k\sigma_1^2} + p\left\{\frac{\mu_2^2}{2k\sigma_2^2} + T_M\right\} + (1-p)T_m \geqslant T_m + \frac{\mu_1^2}{2k\sigma_1^2}$$

$$(IC2): -C + \frac{\mu_1^2}{2k\sigma_1^2} + p\left\{\frac{\mu_2^2}{2k\sigma_2^2} + T_M\right\} + (1-p)T_m \geqslant T_M + \frac{\mu_1^2}{2k\sigma_1^2}$$

and subject to two (IC) constraint that hold ex-post (after expending effort):

$$\begin{aligned} (IC3) \quad &: \quad T_m + \frac{\mu_1^2}{2k\sigma_1^2} \geqslant T_M + \frac{\mu_1^2}{2k\sigma_1^2} \\ (IC4) \quad &: \quad T_M + \frac{\mu_1^2}{2k\sigma_1^2} + \frac{\mu_2^2}{2k\sigma_2^2} \geqslant T_m + \frac{\mu_1^2}{2k\sigma_1^2} + \frac{\mu_2^2}{2k\sigma_2^2} \end{aligned}$$

Proposition 6. *The Second Best contract holds if and only if $C \leq C^*$. In this case the Second Best contract coincides with the First Best contract. If $C > C^*$, the principal **cannot** provide incentives to the portfolio manager to discover the risk factor.*

Proof. See Appendix. □

Please note that Proposition 6 implies that the optimal risk sharing contract is characterized by under-discovery of risk factors when a class of linear contracts is concerned (Stoughton, 1993; Admati and Pfleiderer, 1997). When $C^* < C \leq C^{**}$ the social loss from the non-verifiability of the number of risk factors is $-C + p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2} > 0$.

The intuition behind this result goes as follows. First, two ex-post (IC) constrains imply $T_m = T_M$. That is, a fixed component of the compensation should be independent of number of risk factors. Otherwise, the portfolio manager will find it beneficial to claim that he is of type that should receive higher T. Next, two ex-ante (IC) constraints imply that if $T_m = T_M$, the portfolio manager doesn't get any additional incentive to discover risk factors. That is, he takes into account only his private benefits and expends effort only if $C \leq C^*$.

If $p\frac{\mu_2^2}{2k\sigma_2^2} < C < p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2}$ and the cost of being aware (being able to impose the First Best contract) is higher than $-C + p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2}$, the principal will find it optimal to stay unaware of risk factor discovering. In this case the contract will be incomplete in a sense that it will ignore existence of the second risk factor in the economy. Importantly, this incompleteness raises endogenously.

The incompleteness of the contract can be measured by the probability that the outcome is socially sub-optimal and the magnitude of social loss. The first component depends on the distribution of C (given C^* and C^{**}, how likely it is that $C^* < C \leq C^{**}$?) and principal's risk aversion (K), which determines the magnitude of the "problematic" region $(C^*, C^{**}]$. Since C^{**} is decreasing in K, less risk averse principal will be more concerned about the unawareness. For a given $C \in (C^*, C^{**}]$, the social loss from the inability to verify the portfolio manager's effort is $-C + p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2}$.

6. Justifiability of Contracts

In the contest of unawareness a reasonable equilibrium concept should include the requirement that the Agent finds the contract justifiable, in the sense that the contract is optimal for the Principal (Agent) from the Agent's (Principal's) point of view (e.g., **?**). In this section I study the implication of this requirement for my analysis.

It is simple to see that the solution to the basic contracting problem in section 5.2 is justifiable in this sense. Both portfolio manager and principal understand that if the effort expenditure is unverifiable, it is optimal to have an incomplete contract when $C^* < C \leq C^{**}$ and the cost of being aware (being able to impose the First Best contract) is higher than $-C + p\frac{\mu_2^2}{2k\sigma_2^2} + p\frac{\mu_2^2}{2K\sigma_2^2}$. That is, the principal is unaware about the second risk factor and knows that it is optimal for him stay unaware.

7. Conclusion

This paper shows that optimal contracts with portfolio manager might exhibit an endogenous incompleteness. The principal might choose to ignore existence of some risk factors when the benefit from discovering these factors is lower than the cost of verifying existence of these factors. That is, there is a trade off between costs and benefits of being aware about the risk structure of returns. I also show that under curtain assumptions the optimal risk sharing contract provides the portfolio manager with insufficient incentives to discover new risk factors.

The findings imply that when the risk structure of returns is complex in a sense that it is costly to know what the number of risk factors is, contracts with portfolio managers might exhibit simplicity. Therefore, complex risk-structure of returns and simple compensation contracts can co-exist. Moreover, if the cost of discovering new risk factors increase, contracts will exhibit more simplicity.

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Appendix A. Proof of Results in Section 3

Proposition 7. *When the principal makes the investment decision, the optimal loading on the risk factor is* $B = \frac{\mu}{K\sigma^2}$*. The maximized expected utility of the principal is* $U = \frac{\mu^2}{2K\sigma^2} \equiv \overline{U}$*.*

Proof. The expected return and the variance of principal's portfolio are $E(\widetilde{R}) = B\mu$ and $\sigma^2(\widetilde{R}) = B^2\sigma^2$.[6] Principal's maximization problem is:

$$\max_{B} B\mu - \frac{1}{2}KB^2\sigma^2$$

The FOC w.t. B yields $B = \frac{\mu}{K\sigma^2}$. By substituting B the maximized expected utility of the principal is obtained. □

Proposition 8. *When two individuals share risk optimally, the loading on the risk factor is* $B_{RS} = \frac{\mu}{\frac{Kk}{K+k}\sigma^2}$*. The portfolio manager gets share* $\alpha_{RS} = \frac{K}{K+k}$ *of the realized return. The maximized expected utility of each individual is unchanged.*

Proof. The maximization problem is:

$$\begin{aligned} &\max_{B_{RS},\alpha_{RS}} (1-\alpha_{RS}) B_{RS}\mu - \frac{1}{2}K(1-\alpha_{RS})^2 B_{RS}^2\sigma^2 \\ s.t. \quad : \quad &\alpha_{RS}B_{RS}\mu - \frac{1}{2}k\alpha_{RS}^2 B_{RS}^2\sigma^2 \geq \overline{u} = \frac{\mu^2}{2k\sigma^2} \end{aligned}$$

The FOCs are:

$$\begin{aligned} \alpha_{RS}: &\quad 0 = -B_{RS}\mu + K(1-\alpha_{RS})B_{RS}^2\sigma^2 + \lambda\left(B_{RS}\mu - k\alpha_{RS}B_{RS}^2\sigma^2\right) \\ B_{RS}: &\quad 0 = (1-\alpha_{RS})\mu - K(1-\alpha_{RS})^2 B_{RS}\sigma^2 + \lambda\left(\alpha_{RS}\mu - k\alpha_{RS}^2 B_{RS}\sigma^2\right) \end{aligned}$$

where λ is the Lagrange multiplier. If $\lambda = 1$, $\alpha_{RS} = \frac{K}{K+k}$ and $B_{RS} = \frac{\mu}{\frac{Kk}{K+k}\sigma^2}$. By substituting α_{RS} and B_{RS} the expected utility of each individual is obtained:

[6] For simplicity, it is assumed that there is one risk factor only (N=1).

$U = \frac{\mu^2}{2K\sigma^2}$ and $u = \frac{\mu^2}{2k\sigma^2}$. □

Proposition 9. *When one risk factor is available, the First Best contract satisfies* $\alpha_{FB} = \frac{K}{K+k}$. *The maximized expected utility of the principal is* $U = \frac{\mu^2}{2K\sigma^2}$.

Proof. The maximization problem is:

$$\begin{aligned} & \max_{\alpha}(1-\alpha)E(\widetilde{r}) - T - \frac{1}{2}K(1-\alpha)^2\sigma^2(\widetilde{r}) \\ s.t.(IR) \quad : \quad & \alpha E(\widetilde{r}) + T - \frac{1}{2}k\alpha^2\sigma^2(\widetilde{r}) \geq \overline{u}_{RS} \end{aligned}$$

where the reservation utility of the portfolio manager is defined as u when there is optimal risk sharing between two individuals, $\overline{u}_{RS}$. Since (IR) constraint is binding, $T = \overline{u}_{RS} + \frac{1}{2}k\alpha^2\sigma^2(\widetilde{r}) - \alpha E(\widetilde{r})$ and principal's expected utility is:

$$\begin{aligned} U &= (1-\alpha)E(\widetilde{r}) + \alpha E(\widetilde{r}) - \frac{1}{2}\alpha^2 k\sigma^2(\widetilde{r}) - \overline{u}_{RS} - \frac{1}{2}(1-\alpha)^2 K\sigma^2(\widetilde{r}) \\ &= E(\widetilde{r}) - \frac{1}{2}\sigma^2(\widetilde{r})[\alpha^2 k + (1-\alpha)^2 K] - \overline{u}_{RS} \\ &= b\mu - \frac{1}{2}b^2\sigma^2[\alpha^2 k + (1-\alpha)^2 K] - \overline{u}_{RS} \end{aligned}$$

After substituting for $b = \frac{\mu}{\alpha k\sigma^2}$ we obtain:

$$\begin{aligned} U &= \frac{\mu^2}{k\alpha\sigma^2} - \frac{\mu^2}{2k^2\alpha^2\sigma^2}[\alpha^2 k + (1-\alpha)^2 K] - \overline{u}_{RS} \\ &= \frac{\mu^2}{k\alpha\sigma^2} - \frac{\mu^2}{2k\sigma^2} - \frac{\mu^2}{2k^2\sigma^2}K(\frac{1}{\alpha} - 1)^2 - \overline{u}_{RS} \\ &= \left(\frac{1}{\alpha} - \frac{1}{2}\left[1 + \frac{K}{k}(\frac{1}{\alpha} - 1)^2\right]\right)\frac{\mu^2}{k\sigma^2} - \overline{u}_{RS} \end{aligned}$$

The FOCs w.t. α yields:

$$0 = -\frac{\mu^2}{\alpha^2 k\sigma^2}\left[1 - \frac{K}{k}(\frac{1}{\alpha} - 1)\right]$$

If $\alpha > 0$, $\alpha_{FB} = \frac{K}{K+k}$. The optimal fixed component of the compensation is:

$$
\begin{aligned}
T_{FB} &= \frac{1}{2}\alpha_{FB}^2 k[\sigma^2(\widetilde{r})] + \overline{u}_{RS} - \alpha_{FB}E(\widetilde{r}) \\
&= \frac{1}{2}\alpha_{FB}^2 k \frac{\mu^2}{\alpha_{FB}^2 k^2 \sigma^2} + \frac{\mu^2}{2k\sigma^2} - \alpha_{FB}\frac{\mu^2}{k\alpha_{FB}\sigma^2} = 0
\end{aligned}
$$

Observe that $\frac{1}{\alpha} - \frac{1}{2}[1 + \frac{K}{k}(\frac{1}{\alpha} - 1)^2] = \frac{K+k}{K} - \frac{1}{2}\frac{K+k}{K} = \frac{1}{2\alpha_{FB}}$ and $\alpha_{FB}^2 + \frac{K}{k}(1-\alpha_{FB})^2 = \frac{K^2}{(K+k)^2} + \frac{Kk}{(K+k)^2} = \alpha_{FB}$. Therefore, the maximized expected utility of the principal is $U = \frac{\mu^2}{2k\alpha_{FB}\sigma^2} - \overline{u}_{RS} = \frac{\mu^2}{2K\sigma^2}$. $\square$

Appendix B. Proof of Proposition 1

Suppose that the portfolio manager has found an additional risk factor and knows that the principal is unaware of that factor. The correctly specified return on the portfolio is $\widetilde{r} = B_1\widetilde{f}_1 + B_2\widetilde{f}_2$, where $\widetilde{f}_2 \sim N(\mu_2, \sigma_2)$ and $cov(\widetilde{f}_1, \widetilde{f}_2) = 0$. The expected utility of the portfolio manager is $u = \alpha_{FB}(B_1\mu_1 + B_2\mu_2) + T_{FB} - \frac{1}{2}k\alpha_{FB}^2(B_1^2\sigma_1^2 + B_2^2\sigma_2^2)$. Substituting for $T_{FB} = 0$ and $B_1 = \frac{\mu_1}{k\alpha_{FB}\sigma_1^2}$ yields $u = \frac{\mu_1^2}{2k\sigma_1^2} + \alpha_{FB}B_2\mu_2 - \frac{1}{2}k\alpha_{FB}^2 B_2^2\sigma_2^2$. Since $\alpha_{FB} > 0$, the FOC w.t. B_2 yields $B_2 = \frac{\mu_2}{k\alpha_{FB}\sigma_2^2}$. The expected utility of the portfolio manager is $u = \frac{\mu_1^2}{2k\sigma_1^2} + \frac{\mu_2^2}{2k\sigma_2^2}$. Therefore, the expected utility of the portfolio manager is as one under the First Best contract with aware principal.

Appendix C. Proof of Proposition 2

The principal's problem in selecting the set of contracts is as follows:

$$
\begin{aligned}
\max_{\alpha_i, T_i} U &= \upsilon\left\{[(1-\alpha_m)B_{m,1}\mu_1 - T_m] - \frac{1}{2}K(1-\alpha_m)^2 B_{m,1}^2\sigma_1^2\right\} \\
&\quad + (1-\upsilon)\{[(1-\alpha_M)(B_{M,1}\mu_1 + B_{M,2}\mu_2) - T_M] \\
&\quad - \frac{1}{2}K(1-\alpha_M)^2(B_{M,1}^2\sigma_1^2 + B_{M,2}^2\sigma_2^2)\}
\end{aligned}
$$

subject to:

$$
\begin{aligned}
(IR1):&\quad \alpha_m B_{m,1}\mu_1 + T_m - \frac{1}{2}k\alpha_m^2\left[B_{m,1}^2\sigma_1^2\right] \geqslant \overline{u}_{RS,1} \\
(IR2):&\quad \alpha_M(B_{M,1}\mu_1 + B_{M,2}\mu_2) + T_M - \frac{1}{2}k\alpha_M^2\left[B_{M,1}^2\sigma_1^2 + B_{M,2}^2\sigma_2^2\right] \geqslant \overline{u}_{RS,2}
\end{aligned}
$$

$$\begin{aligned}(IC1): \quad & \max_{B_{m,1}} \alpha_m B_{m,1}\mu_1 + T_m - \frac{1}{2}k\alpha_m^2\left[B_{m,1}^2\sigma_1^2\right] \geqslant \\ & \max_{\widehat{B}_{m,1}} \alpha_M \widehat{B}_{m,1}\mu_1 + T_M - \frac{1}{2}k\alpha_M^2\left[\widehat{B}_{m,1}^2\sigma_1^2\right] \\ (IC2): \quad & \max_{B_{M,1},B_{M,2}} \alpha_M(B_{M,1}\mu_1 + B_{M,2}\mu_2) + T_M - \frac{1}{2}k\alpha_M^2\left[B_{M,1}^2\sigma_1^2 + B_{M,2}^2\sigma_2^2\right] \geqslant \\ & \max_{\widehat{B}_{M,1},\widehat{B}_{M,2}} \alpha_m(\widehat{B}_{M,1}\mu_1 + \widehat{B}_{M,2}\mu_2) + T_m - \frac{1}{2}k\alpha_m^2\left[\widehat{B}_{M,1}^2\sigma_1^2 + \widehat{B}_{M,2}^2\sigma_2^2\right]\end{aligned}$$

FOCs w.t. $B_{m,1}$, $\widehat{B}_{m,1}$, $B_{M,1}$, $B_{M,2}$, $\widehat{B}_{M,1}$, and $\widehat{B}_{M,2}$ yield: $B_{m,1} = \frac{\mu_1}{k\alpha_m\sigma_1^2}$, $\widehat{B}_{m,1} = \frac{\mu_1}{k\alpha_M\sigma_1^2}$, $B_{M,1} = \frac{\mu_1}{k\alpha_M\sigma_1^2}$, $B_{M,2} = \frac{\mu_2}{k\alpha_M\sigma_2^2}$, $\widehat{B}_{M,1} = \frac{\mu_1}{k\alpha_m\sigma_1^2}$, and $\widehat{B}_{M,2} = \frac{\mu_2}{k\alpha_M\sigma_2^2}$. Thus, the first (IC) constraint is:

$$\begin{aligned}\frac{\mu_1^2}{k\sigma_1^2} + T_m - \frac{1}{2}k\alpha_m^2\left[\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right] \quad &\geqslant \quad \frac{\mu_1^2}{k\sigma_1^2} + T_M - \frac{1}{2}k\alpha_M^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2}\right] \\ T_m \quad &\geqslant \quad T_M\end{aligned}$$

The second (IC) constraint is:

$$\begin{aligned}& \frac{\mu_1^2}{k\sigma_1^2} + \frac{\mu_2^2}{k\sigma_2^2} + T_M - \frac{1}{2}k\alpha_M^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2} + \frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right] \\ \geqslant \quad & \frac{\mu_1^2}{k\sigma_1^2} + \frac{\mu_2^2}{k\sigma_2^2} + T_m - \frac{1}{2}k\alpha_m^2\left[\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2} + \frac{\mu_2^2}{k^2\alpha_m^2\sigma_2^2}\right]\end{aligned}$$

$$T_M \geqslant T_m$$

From the inspection of two (IC) constraints it is clear that these constraints will be binding: $T_m = T_M$. Substituting the factor loadings into the maximization problem yields:

$$\begin{aligned}\max_{\alpha_i,T_i} U \quad &= \quad \upsilon\left\{(1-\alpha_m)\frac{\mu_1^2}{k\alpha_m\sigma_1^2} - T_m - \frac{1}{2}K(1-\alpha_m)^2\left[\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right]\right\} \\ &+ \quad (1-\upsilon)\left\{(1-\alpha_M)(\frac{\mu_1^2}{k\alpha_M\sigma_1^2} + \frac{\mu_2^2}{k\alpha_M\sigma_2^2}) - T_M\right. \\ &- \quad \left.\frac{1}{2}K(1-\alpha_M)^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2} + \frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right]\right\}\end{aligned}$$

subject to:

$$
\begin{aligned}
(IR1): &\quad \frac{\mu_1^2}{2k\sigma_1^2} + T_m \geqslant \overline{u}_{RS,1} = \frac{\mu_1^2}{2k\sigma_1^2} \\
(IR2): &\quad \frac{\mu_1^2}{2k\sigma_1^2} + \frac{\mu_2^2}{2k\sigma_2^2} + T_M \geqslant \overline{u}_{RS,2} = \frac{\mu_1^2}{2k\sigma_1^2} + \frac{\mu_2^2}{2k\sigma_2^2} \\
(IC): &\quad T_m = T_M
\end{aligned}
$$

(IC) implies that all (IR) constraints are binding and $T_m = T_M = 0$. The maximization problem is:

$$
\begin{aligned}
\max_{\alpha_i, T_i} U &= \upsilon \left\{ (1-\alpha_m) \frac{\mu_1^2}{k\alpha_m\sigma_1^2} - \frac{1}{2}K(1-\alpha_m)^2 \left[\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2} \right] \right\} \\
&\quad + (1-\upsilon) \left\{ (1-\alpha_M)\left(\frac{\mu_1^2}{k\alpha_M\sigma_1^2} + \frac{\mu_2^2}{k\alpha_M\sigma_2^2}\right) \right. \\
&\quad \left. - \frac{1}{2}K(1-\alpha_M)^2 \left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2} + \frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2} \right] \right\}
\end{aligned}
$$

If $\upsilon > 0$, the FOC w.t. α_m is:

$$
\begin{aligned}
0 &= \left(-\frac{1}{\alpha_m^2}\right)\frac{\mu_1^2}{k\sigma_1^2} - \frac{K}{k}\left(\frac{1}{\alpha_m} - 1\right)\left(-\frac{1}{\alpha_m^2}\right)\frac{\mu_1^2}{k\sigma_1^2} \\
0 &= \left(-\frac{1}{\alpha_m^2}\right)\frac{\mu_1^2}{k\sigma_1^2}\left[1 - \frac{K}{k}\left(\frac{1}{\alpha_m} - 1\right)\right] \\
\alpha_m &= \frac{K}{K+k}
\end{aligned}
$$

If $(1-\upsilon) > 0$, the FOC w.t. α_M is:

$$
\begin{aligned}
0 &= \left(-\frac{1}{\alpha_M^2}\right)\left(\frac{\mu_1^2}{k\sigma_1^2} + \frac{\mu_2^2}{k\sigma_2^2}\right) - \frac{K}{k}\left(\frac{1}{\alpha_M} - 1\right)\left(-\frac{1}{\alpha_M^2}\right)\left(\frac{\mu_1^2}{k\sigma_1^2} + \frac{\mu_2^2}{k\sigma_2^2}\right) \\
0 &= \left(-\frac{1}{\alpha_M^2}\right)\left(\frac{\mu_1^2}{k\sigma_1^2} + \frac{\mu_2^2}{k\sigma_2^2}\right)\left[1 - \frac{K}{k}\left(\frac{1}{\alpha_M} - 1\right)\right] \\
\alpha_M &= \frac{K}{K+k}
\end{aligned}
$$

Thus, the linear contract is still the optimal one.

Appendix D. Discovering Risk Factors

Lemma 10. *If there is no incentive to discover new risk factors is provided, the expected utility of the portfolio manager after expending the effort C is* $u(c = C) = -C + \frac{\mu_1^2}{2k\sigma_1^2} + p\frac{\mu_2^2}{2k\sigma_2^2}$.

Proof. The expected utility of the portfolio manager after expending the effort C is:

$$\begin{aligned}
u(c=C) &= -C + p\left\{\alpha_M E(\widetilde{r}) + T_M - \frac{1}{2}k^2\alpha_2^2\sigma^2(\widetilde{r}) \mid r = 2\right\} \\
&\quad +(1-p)\left\{\alpha_m E(\widetilde{r}) + T_m - \frac{1}{2}k\alpha_m^2\sigma^2(\widetilde{r}) \mid r = 1\right\} \\
&= -C + p\left\{\alpha_M(b_{M,1}\mu_1 + b_{M,2}\mu_2) + T_M - \frac{1}{2}k\alpha_M^2\left[b_{M,1}^2\sigma_1^2 + b_{M,2}^2\sigma_2^2\right]\right\} \\
&\quad +(1-p)\left\{\alpha_m b_{m,1}\mu_1 + T_m - \frac{1}{2}k\alpha_m^2\left[b_{m,1}^2\sigma_1^2\right]\right\}
\end{aligned}$$

FOCs are $b_{M,1} = \frac{\mu_1}{k\alpha_M\sigma_1^2}$, $b_{M,2} = \frac{\mu_2}{k\alpha_M\sigma_2^2}$, and $b_{m,1} = \frac{\mu_1}{k\alpha_m\sigma_1^2}$. After substituting the FOCs we obtain:

$$\begin{aligned}
u(c=C) &= -C + p\left\{\frac{\mu_1^2}{2k\sigma_1^2} + \frac{\mu_2^2}{2k\sigma_2^2} + T_M\right\} \\
&+ (1-p)\left\{\frac{\mu_1^2}{2k\sigma_1^2} + T_m\right\} \\
&= -C + \frac{\mu_1^2}{2k\sigma_1^2} + p\left\{\frac{\mu_2^2}{2k\sigma_2^2} + T_M\right\} + (1-p)T_m
\end{aligned}$$

When no incentives to discover new risk factors are provided, $\alpha_m = \alpha_M = \alpha_{RS}$ and $T_m = T_M = 0$. In this case: $u(c = C) = -C + \frac{\mu_1^2}{2k\sigma_1^2} + p\frac{\mu_2^2}{2k\sigma_2^2}$ □

Appendix E. Proof of Proposition 4

Since $C \leqslant C^*$, the principal implements discovering the new risk factor in the contract. The maximization problem is:

$$\begin{aligned}
\max_{\alpha_M, T_M, \alpha_m, T_m} U \quad &= \quad p\left\{(1-\alpha_M)(\frac{\mu_1^2}{k\alpha_M\sigma_1^2}+\frac{\mu_2^2}{k\alpha_M\sigma_2^2})-T_M\right.\\
&\quad \left.-\frac{1}{2}K(1-\alpha_M)^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2}+\frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right]\right\}\\
&\quad +(1-p)\left\{(1-\alpha_m)\frac{\mu_1^2}{k\alpha_m\sigma_1^2}-T_m-\frac{1}{2}K(1-\alpha_m)^2\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right\}\\
s.t.(IR) \quad &: \quad -C+\frac{\mu_1^2}{2k\sigma_1^2}+p\left\{\frac{\mu_2^2}{2k\sigma_2^2}+T_M\right\}+(1-p)T_m=\overline{u}_{PM}
\end{aligned}$$

or:

$$\begin{aligned}
\max_{\alpha_M, T_M, \alpha_m, T_m} U \quad &= \quad -\left[pT_M+(1-p)T_m\right]\\
&\quad +p\left\{\frac{\mu_1^2}{k\alpha_M\sigma_1^2}+\frac{\mu_2^2}{k\alpha_M\sigma_2^2}-(\frac{\mu_1^2}{k\sigma_1^2}+\frac{\mu_2^2}{k\sigma_2^2})\right.\\
&\quad \left.-\frac{1}{2}K(1-\alpha_M)^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2}+\frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right]\right\}\\
&\quad +(1-p)\left\{(1-\alpha_m)\frac{\mu_1^2}{k\alpha_m\sigma_1^2}-\frac{1}{2}K(1-\alpha_m)^2\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right\}\\
s.t.(IR) \quad &: \quad -C+\frac{\mu_1^2}{2k\sigma_1^2}+p\frac{\mu_2^2}{2k\sigma_2^2}-\overline{u}_{PM}=-\left[pT_M+(1-p)T_m\right]
\end{aligned}$$

Let's substitute the (IR) constraint:

$$\begin{aligned}
\max_{\alpha_M, \alpha_m} U \quad &= \quad -C+\frac{\mu_1^2}{2k\sigma_1^2}+p\frac{\mu_2^2}{2k\sigma_2^2}-\overline{u}_{PM}\\
&\quad +p\left\{\frac{\mu_1^2}{k\alpha_M\sigma_1^2}+\frac{\mu_2^2}{k\alpha_M\sigma_2^2}-(\frac{\mu_1^2}{k\sigma_1^2}+\frac{\mu_2^2}{k\sigma_2^2})\right.\\
&\quad \left.-\frac{1}{2}K(1-\alpha_M)^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2}+\frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right]\right\}\\
&\quad +(1-p)\left\{\frac{\mu_1^2}{k\alpha_m\sigma_1^2}-\frac{\mu_1^2}{k\sigma_1^2}-\frac{1}{2}K(1-\alpha_m)^2\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right\}
\end{aligned}$$

$$\begin{aligned}\max_{\alpha_M,\alpha_m} U &= -C-\overline{u}_{PM}+p\left\{(\frac{1}{\alpha_M}-\frac{1}{2}\left[1+\frac{K}{k}(\frac{1}{\alpha_M}-1)^2\right])(\frac{\mu_1^2}{k\sigma_1^2}+\frac{\mu_2^2}{k\sigma_2^2})\right\}\\ &\quad +(1-p)\left\{(\frac{1}{\alpha_m}-\frac{1}{2}\left[1+\frac{K}{k}(\frac{1}{\alpha_m}-1)^2\right])\frac{\mu_1^2}{k\sigma_1^2}\right\}\end{aligned}$$

FOCs yield $\alpha_m=\alpha_M=\alpha_{FB}=\frac{K}{K+k}$. The (IR) constraint implies:

$$pT_M+(1-p)T_m=-C+\frac{\mu_1^2}{2k\sigma_1^2}+p\frac{\mu_2^2}{2k\sigma_2^2}-\overline{u}_{RS}=0$$

Therefore, the principal sets $T_M=T_m=0$. The maximized expected utility of the principal is:

$$U=-C-\overline{u}_{PM}+\left(\frac{1}{\alpha_{FB}}-\frac{1}{2}\left[1+\frac{K}{k}(\frac{1}{\alpha_{FB}}-1)^2\right]\right)\left(\frac{\mu_1^2}{k\sigma_1^2}+p\frac{\mu_2^2}{k\sigma_2^2}\right)$$

Since $(\frac{1}{\alpha_{FB}}-\frac{1}{2}\left[1+\frac{K}{k}(\frac{1}{\alpha_{FB}}-1)^2\right])=\frac{1}{2\alpha_{FB}}$, the maximized expected utility is:

$$\begin{aligned}U &= -C-\overline{u}_{PM}+\frac{1}{2\alpha_{FB}}\left\{\frac{\mu_1^2}{k\sigma_1^2}+p\frac{\mu_2^2}{k\sigma_2^2}\right\}\\ &= -\frac{\mu_1^2}{2k\sigma_1^2}-p\frac{\mu_2^2}{2k\sigma_2^2}+\frac{1}{2\alpha_{FB}}\left\{\frac{\mu_1^2}{k\sigma_1^2}+p\frac{\mu_2^2}{k\sigma_2^2}\right\}\\ &= \frac{\mu_1^2}{2K\sigma_1^2}+p\frac{\mu_2^2}{2K\sigma_2^2}\end{aligned}$$

Appendix F. Proof of Proposition 5

Since $C\leqslant C^{**}$, the principal implements discovering of risk factors in the contract, the maximization problem is:

$$\begin{aligned}\max_{\alpha_M,T_M,\alpha_m,T_m} U &= p\left\{(1-\alpha_M)(\frac{\mu_1^2}{k\alpha_M\sigma_1^2}+\frac{\mu_2^2}{k\alpha_M\sigma_2^2})-T_M\right.\\ &\quad \left.-\frac{1}{2}K(1-\alpha_M)^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2}+\frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right]\right\}\\ &\quad +(1-p)\left\{(1-\alpha_m)\frac{\mu_1^2}{k\alpha_m\sigma_1^2}-T_m-\frac{1}{2}K(1-\alpha_m)^2\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right\}\\ s.t.(IR) &: -C+\frac{\mu_1^2}{2k\sigma_1^2}+p\left\{\frac{\mu_2^2}{2k\sigma_2^2}+T_M\right\}+(1-p)T_m=\overline{u}_{PM}=\frac{\mu_1^2}{2k\sigma_1^2}\end{aligned}$$

Following same steps as in the previous proposition we obtain the optimal incentive component of the contract $\alpha_m = \alpha_M = \frac{K}{K+k}$. The (IR) constraint implies:

$$\begin{aligned} pT_M + (1-p)T_m &= C - \frac{\mu_1^2}{2k\sigma_1^2} - p\frac{\mu_2^2}{2k\sigma_2^2} + \overline{u}_{RS} \\ pT_M + (1-p)T_m &= -(-C + p\frac{\mu_2^2}{2k\sigma_2^2}) > 0 \end{aligned}$$

Any combination of T_M and T_m that satisfies the (IR) constraint works. I choose, $T_m = 0$ and $T_M = -\frac{1}{p}(-C + p\frac{\mu_2^2}{2k\sigma_2^2}) > 0$. Since $\frac{1}{\alpha_{FB}} - \frac{1}{2}\left[1 + \frac{K}{k}(\frac{1}{\alpha_{FB}} - 1)^2\right] = \frac{1}{2\alpha_{FB}}$ and $(\frac{1}{\alpha_{FB}} - 1) - \frac{1}{2}\frac{K}{k}(\frac{1}{\alpha_{FB}} - 1)^2 = \frac{K}{k}$, the maximized expected utility of the principal is:

$$\begin{aligned} U &= -C + p\frac{\mu_2^2}{2k\sigma_2^2} + (\frac{1}{\alpha_{FB}} - 1)\frac{\mu_1^2}{k\sigma_1^2} - \frac{1}{2}K(\frac{1}{\alpha_{FB}} - 1)^2\frac{\mu_1^2}{k^2\sigma_1^2} \\ &\quad + p\left\{(\frac{1}{\alpha_{FB}} - 1)\frac{\mu_2^2}{k\sigma_2^2} - \frac{1}{2}K(\frac{1}{\alpha_{FB}} - 1)^2\frac{\mu_2^2}{k^2\sigma_2^2}\right\} \\ &= -C + \left[(\frac{1}{\alpha_{FB}} - 1) - \frac{1}{2}\frac{K}{k}(\frac{1}{\alpha_{FB}} - 1)^2\right]\frac{\mu_1^2}{k\sigma_1^2} + p\frac{\mu_2^2}{2\alpha_{FB}k\sigma_2^2} \\ &= -C + \frac{\mu_1^2}{K\sigma_1^2} + p\frac{\mu_2^2}{2\alpha_{FB}k\sigma_2^2} \\ &= -C + \frac{\mu_1^2}{K\sigma_1^2} + p\frac{1}{2}(\frac{1}{\alpha_{FB}} + 1 - 1)\frac{\mu_2^2}{k\sigma_2^2} \\ &= \frac{\mu_1^2}{K\sigma_1^2} + p\frac{\mu_2^2}{2K\sigma_2^2} + (-C + p\frac{\mu_2^2}{2k\sigma_2^2}) \end{aligned}$$

Appendix G. Proof of Proposition 6

(IC3) and (IC4) imply $T_m = T_M$. After simplifying (IC1) and (IC2) we obtain $C \leq C^* \equiv p\frac{\mu_2^2}{2k\sigma_2^2}$, which holds by the initial assumption. If $C \in (C^*, C^{**})$, (IC) constraints are violated. Therefore, the optimal linear contract cannot resolve the problem of the sub-optimal expenditure of effort by the portfolio manager. The principal's maximization problem is:

$$\begin{aligned}
\max_{\alpha_M, T_M, \alpha_m, T_m} U &= p\left\{(1-\alpha_M)(\frac{\mu_1^2}{k\alpha_M\sigma_1^2}+\frac{\mu_2^2}{k\alpha_M\sigma_2^2})-T_M\right.\\
&\left.-\frac{1}{2}K(1-\alpha_M)^2\left[\frac{\mu_1^2}{k^2\alpha_M^2\sigma_1^2}+\frac{\mu_2^2}{k^2\alpha_M^2\sigma_2^2}\right]\right\}\\
&+(1-p)\left\{(1-\alpha_1)(\frac{\mu_1^2}{k\alpha_m\sigma_1^2})-T_m\right.\\
&\left.-\frac{1}{2}K(1-\alpha_m)^2\left[\frac{\mu_1^2}{k^2\alpha_m^2\sigma_1^2}\right]\right\}
\end{aligned}$$

subject to:

$$\begin{aligned}
(IR) &: -C+\frac{\mu_1^2}{2k\sigma_1^2}+p\frac{\mu_2^2}{2k\sigma_2^2}+T_M=\overline{u}_{PM}\\
(IC3\,\&\,IC4) &: T_m=T_M\\
(IC1\,\&\,IC2) &: C\le C^*\equiv p\frac{\mu_2^2}{2k\sigma_2^2}
\end{aligned}$$

Some algebra yields:

$$\begin{aligned}
\max_{\alpha_M, T_M, \alpha_m, T_m} U &= -C-\overline{u}_{PM}\\
&+p\left\{\left[\frac{1}{\alpha_M}-\frac{1}{2}\frac{K}{k}(\frac{1}{\alpha_M}-1)^2\right](\frac{\mu_1^2}{k\sigma_1^2}+\frac{\mu_2^2}{k\sigma_2^2})\right\}\\
&+(1-p)\left\{\left[\frac{1}{\alpha_1}-\frac{1}{2}(1+\frac{K}{k}(\frac{1}{\alpha_1}-1)^2)\right]\frac{\mu_1^2}{k\sigma_1^2}+p\frac{\mu_2^2}{2k\sigma_2^2}\right\}
\end{aligned}$$

FOC w.t. α_m is:

$$0=(-\frac{1}{\alpha_m^2})\left[1-\frac{K}{k}(\frac{1}{\alpha_m}-1)\right]\frac{\mu_1^2}{k\sigma_1^2}$$

Therefore, $\alpha_m^{SB}=\alpha_m^{FB}=\frac{K}{K+k}=\alpha_{RS}$. FOC w.t. α_M yields $\alpha_M^{SB}=\alpha_M^{FB}=\frac{K}{K+k}=\alpha_{RS}$. Since $\alpha_M^{SB}=\alpha_m^{SB}$, (IC) constraint implies $T_m=T_M$. From (IR) constraint we obtain $T_M=T_m=\overline{u}_{PM}+C-\frac{\mu_1^2}{2k\sigma_1^2}-p\frac{\mu_2^2}{2k\sigma_2^2}=0$.

Inferring Reporting-Related Biases in Hedge Fund Databases from Hedge Fund Equity Holdings[1]

Vikas Agarwal[2] Vyacheslav Fos[3] Wei Jiang[4]

ABSTRACT

This paper formally analyzes the biases related to self-reporting in the hedge funds databases by matching the quarterly equity holdings of a complete list of 13F-filing hedge fund companies to the union of five major commercial databases of self-reporting hedge funds between 1980 and 2008. Conditional on self-reporting, we find significant evidence of a timing bias in both reporting initiation and termination (delisting): Funds initiate self-reporting after positive abnormal returns which do not persist into the reporting period; while termination of self-reporting is followed by both return deterioration and outflows from the funds. Unconditionally, the propensity to self-report is consistent with the trade-offs between the benefits (e.g., access to prospective investors) and costs (e.g., partial loss of trading secrecy and flexibility in selective marketing). Finally, self-reporting and non-reporting funds do not differ significantly in return performance, reflecting the offsetting factors motivating self-reporting.

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Hedge funds are pooled private investment vehicles. Unlike other financial institutions such as banks and mutual funds, they have largely escaped the regulations by raising capital via private placement (under the Securities Act of 1933) and from a limited number of "qualified investors," i.e., accredited institutions and high-net worth individuals (under the Investment Company Act of 1940). Due to their lightly regulated nature, hedge funds are not required to report information about their characteristics, strategies, and performance to any authority or database. As a result, hedge funds are among the least transparent major market participants though according to some estimates by Credit Suisse / Tremont, they managed 1.5 to 2.0 trillion dollars of assets and accounted for about one-third of the equity trading volume in the U.S. during 2007.

The importance of hedge funds has attracted a growing volume of research; and due to the lack of mandatory disclosure, the burgeoning research on hedge funds has mostly relied on commercial hedge fund databases to which hedge funds report voluntarily. Prior research has documented several biases in hedge fund databases including the survivorship bias, backfilling bias, and smoothing bias (e.g., Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000), Getmanksy, Lo, and Makarov (2004), and Bollen and Pool (2008)). However, the extant literature has not formally addressed the degree of self-reporting bias, arguably one of the most important biases in hedge fund databases. Self-reporting bias is a type of selection bias that results from hedge funds' choices to not report to any database, to initiate reporting at some time, or to discontinue reporting for various reasons, the common ones being liquidation and closed for new investment. Such a bias can potentially affect any study on the performance and risk characteristics of hedge funds but the magnitude or even the direction of the bias is yet unknown. Our paper fills this gap in the hedge fund literature by being the first to assess the extent of self-reporting bias in a comprehensive sample of hedge funds as well as to analyze the determinants of their self-reporting.

A hedge fund's choice to voluntarily report to a commercial database is likely to be non-random. Like all other economic activities, the reporting behavior of hedge funds should be determined by the cost-benefit trade-offs. On the benefit side, listing in a database enhances a fund's exposure to potential investors, which is likely to be more significant for small and medium sized fund companies that desire more publicity but lack the resources for aggressive direct marketing.[5] The main cost of reporting is a partial loss of secrecy and privacy that many hedge funds value.[6] Moreover, keeping the reporting status constitutes a commitment to revealing a fixed set of information at fixed time intervals, depriving a hedge fund of the flexibility in publicizing selective information (such as return performance of a particular period of time) that is most favorable to the fund. Finally, investors attracted to hedge funds through database subscription tend to be more "retail" and short-term. Hedge funds usually value institutional investors whose investing or divesting decisions are not sensitive to short-term performance. Hence, some hedge funds may not want to be exposed to the clientele that are typical of database subscribers.

Even after a fund decides to report to a commercial database, it exercises the discretion on the reporting initiation date and later may choose to exit from the database for both positive and negative reasons. On the positive side, if a hedge fund is closed to new investors due to its success and lack of scalable investment opportunities, then there would be no incentive to attract more capital. On the negative side, embarrassing losses or even the prospect of liquidation could be the reason for a hedge fund to stop reporting.

These scenarios related to the choice of reporting, as well as initiation and discontinuation of reporting indicate a potential selection bias among self-reporting databases. However, the magnitude, or even the direction of the bias, is hard to assess *a priori* (Fung and Hsieh (2000)). This paper is a first attempt at quantifying the degree of the self-reporting bias in the hedge funds databases by analyzing the quarterly equity holdings of a complete list of hedge fund companies that file the Form 13F to the Securities and Exchange Commission (SEC) between 1980 and 2008. Because of the mandatory nature

[5] In order to be exempt from the regulations of the 1934 Securities Exchange Act and the 1940 Investment Company Act (and their amendments), a hedge fund cannot advertise to the general public through mass media such as newspapers and TV channels. Moreover, the investors that the fund approaches directly must satisfy the requirement of "qualified investors". Therefore, reporting to a commercial database is often viewed as a cheap way to reach the target investor groups, where the database vendors bear the responsibility of ensuring that only qualified investors have access to their databases.

[6] Though self-reporting hedge funds in general do not reveal holdings information to hedge fund databases, the reported information, such as descriptions of style classification, asset allocation, monthly returns, and leverage/hedging ratios, is often revealing of the funds' investment strategies.

of the 13F filings,[7] this sample is largely free from the selection bias due to hedge funds' reporting incentives. Among all 13F-filing hedge fund companies, we determine their self-reporting status by matching them to the union of five major hedge fund databases – CISDM, HFR, Eureka, MSCI, and TASS. This represents the most comprehensive database of self-reporting hedge funds that has been used in the literature and hence minimizes the inaccuracy in the classification of funds' self-reporting status.

Upon classifying hedge funds' self-reporting status and imputing returns and other portfolio statistics from the quarter-end holdings of all hedge funds that file 13F forms, we conduct a two-step analysis. First, we analyze the return dynamics around the initial and last reporting dates and the impact of reporting on fund flows for the subsample of self-reporting funds. We then compare the performance and other characteristics of the self-reporting hedge funds to those of the non-reporting ones.

Conditional on self-reporting, we find significant evidence that performance deteriorates both after the initial reporting date and after the reporting termination date. The deterioration amounts to 73 and 24 basis points respectively, using monthly market-adjusted returns. These results indicate two forms of timing bias in returns reported to commercial databases. The first form of timing bias in reporting initiation suggests that hedge funds strategically initiate self-reporting after a run of superior performance; while the second form of timing bias indicates that reporting termination or "delisting" is usually a sign of deterioration. The latter is further supported by the fact that net flows to funds tend to decrease after reporting termination, even after controlling for performance. Good performance prior to initiation of reporting to some extent offsets the poor performance subsequent to termination of reporting, which biases the performance data accessible from the commercial databases toward average performance.

Unconditionally, we find that young and medium-sized fund companies that employ more diversified and higher-frequency trading strategies (using portfolio turnover rates as proxy) have a stronger incentive to self-report to databases, presumably to publicize their funds and attract potential investors. Given the characteristics of these funds, trading secrecy is less likely to be revealed through

[7] All institutions that have investment discretion over $100 million or more in Section 13(f) securities (mostly publicly traded equity; but also include convertible bonds, and some options) are required to disclose their quarter-end holdings in these securities.

voluntary disclosure because of their diversified nature and the high portfolio turnover rates, both of which reduce the costs of reporting. Interestingly, the difference in the return performance, though slightly in favor of the non-reporting funds, is small. Presumably the positive and negative reasons prompting reporting initiation and termination largely offset one another. This is good news for the large body of research on hedge fund performance because the self-reporting bias may not have a material impact when it comes to performance evaluation especially if researchers use a multitude of commercial databases to exhaustively cover the universe of self-reporting hedge funds.

The findings of our paper have implications for the growing research on hedge funds which examines their risk-return characteristics and persistence in their performance.[8] Our study contributes to the earlier work on hedge fund data biases by Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000, 2009), Liang (2000), Malkiel and Saha (2005), and Posthuma and Jelle van der Sluis (2003) among others. Researchers have made progress on addressing the self-reporting bias by using the data on funds of hedge funds (FOFs) (Fung and Hsieh, 2000; Aiken, Clifford, and Ellis, 2010) based on the premise that the returns and holdings of FOFs contain information of non-reporting hedge funds and of hedge funds that terminate reporting. These studies are limited to relative small samples of FOFs and rely on assumptions about randomness of the underlying funds that are selected by the FOFs.

Our approach avoids the limitations discussed above using a comprehensive sample of hedge funds that are mandatorily required to report their positions in 13F securities to the SEC. Needless to say, this approach has its own limitations as it relies on the quarter-end long-equity positions at the hedge fund company (rather than at the individual fund) level. As such, our estimates should be considered as self-reporting biases in the long-equity component of the portfolios of hedge fund companies. Given that the

[8] An incomplete list of studies examining hedge fund performance includes Amin and Kat (2003), Agarwal and Naik (2004), Agarwal, Bakshi, and Huij (2009), Agarwal, Daniel, and Naik (2010), Agarwal, Fung, Loon, and Naik (2010), Avramov, Kosowski, Naik, and Teo (2009), Bollen and Whaley (2009), Fung and Hsieh (1997, 2001, 2004), Fung, Hsieh, Naik, and Ramadorai (2008), Getmansky, Lo, and Makarov (2004), Hasanhodzic and Lo (2007), Mitchell and Pulvino (2001), Patton (2009) and those examining persistence in hedge fund performance include Kosowski, Naik, and Teo (2007), Boyson (2008), Jagannathan, Malakhov, and Novikov (2010). For a survey of the hedge fund literature, see Agarwal and Naik (2005).

potential limitations of the different approaches are unlikely to be correlated, findings from alternative approaches could be viewed as complementary in obtaining a more comprehensive picture of the self-reporting biases.

Our paper also determines the performance of funds both before they initiate reporting and after they cease reporting. Timing bias associated with delisting studied in this paper is related to the work by Hodder, Jackwerth, and Kolokolova (2008), who estimate the returns of hedge funds after their disappearance from the databases using data on FOFs that invest in a portfolio of hedge funds, assuming some independence between the component funds' self-reporting status and the FOFs' investment decision. One limitation of their approach is that they need to estimate the holdings of FOFs since this data is not commercially available. Moreover, the validity of their assumption is questionable if the FOFs are more likely to pull out the money from funds before or shortly after they disappear from the databases due to the funds' bad performance. Our approach, in contrast, avoids these limitations by exploiting the mandatory disclosure of equity holdings of hedge fund companies without any estimation of holdings.

In terms of using the hedge fund companies' 13F quarterly equity holdings, our paper is related to Griffin and Xu (2009) who use returns imputed from holdings of hedge funds to infer their overall performance. In addition to having a different sample (1,199 funds versus 306 funds in Griffin and Xu (2009)), the focus of our paper is also different as we relate the analysis of performance to the propensity and effects of voluntary reporting by hedge funds.

Our research contributes to the literature in several ways. It is the first study that uses a comprehensive sample of hedge funds to analyze the biases in hedge fund databases due to self-reporting, including the timing bias and the unconditional selection bias. Our results will offer important benchmarks and references for hedge fund researchers and investment managers who use such data sources. More generally, the study provides insights into the motivation and consequences of voluntary disclosure by hedge funds, and in the same spirit, by other financial institutions. Finally, it raises interesting questions about the role of hedge fund regulation if voluntary disclosures are deemed inadequate. This is particularly pertinent in view of the ongoing debate regarding the mandatory registration of hedge fund managers and more stringent disclosure rules.

The rest of the paper is organized as follows: Section I details data collection and classification, and provides an overview of the complete sample of 13F filing hedge fund companies. Section II develops hypotheses regarding the various types of data biases based on a discussion of the economics of self-reporting. Section III analyzes the change in performance of self-reporting funds before and after their initial and last reporting dates, as well as the effects of reporting initiation and termination on fund flows. Section IV compares the characteristics and return performance of self-reporting and non-reporting hedge fund companies. Finally, Section V concludes.

I. Data and Overview

A. Collection of Hedge Funds

The key inputs to our analyses are data from two sources. The first is the 13F quarter-end equity holdings data from the Thomson Reuters Ownership Data (formerly the CDA/Spectrum database), available through the Wharton Research Data Services (WRDS). The Form 13F filing, which discloses quarter-end holdings of an institution with a maximum of 45-day delay, is mandatory for all institutions that exercise investment discretion over $100 million of assets in equity and some other publicly traded securities.[9] The second source is a comprehensive self-reported hedge fund database created by the union of five major commercial hedge fund databases: CISDM, Eureka, HFR, MSCI, and TASS (henceforth, the "Union Hedge Fund Database" or simply the "Union Database"). Throughout the paper, we call a hedge fund company that appears in the first database a "13F-filing hedge fund company," and a hedge fund that appears in the second data source a "self-reporting hedge fund."

[9] More accurately, institutions are required to disclose all securities that appear on the official list of "Section 13(f) Securities," published by the SEC periodically. This list includes almost all publicly traded equity, some preferred stocks, bonds with convertible features, warrant, and publicly traded call and put options. The Thomson Reuters Ownership database contains only holdings of equity, and does not include other securities. See Aragon and Martin (2009) for an analysis of the original 13F filings for a random sample of 250 hedge fund companies.

It is worth noting that the level of reporting is often different between the two data sources. The 13F filings are usually aggregated at the institution level, comparable to the level of management companies or sponsors of hedge funds. The reporting unit in the self-reporting databases is usually at the fund level or at the level of pooled portfolio.[10] Hence, pairing a 13F filing institution to funds in the Union Hedge Fund Databases is often a one-to-multiple match (if a match exists). The matching between the two data sources is facilitated by the fact that the latter database reports the sponsors or management companies of individual funds in most cases.

The Thomson Reuters Ownership database consists of a list of 5,188 unique 13F-filing institutions for the 1980 -2008 period. We go through the list manually in order to identify whether each filing institution has major hedge fund management business. There is no official definition of a hedge fund. We adopt the generally accepted notion of hedge funds as pooled private investment vehicles that adopt performance-based compensation and that are operated outside of the securities regulation and registration requirements. As such, we classify a 13F-filing institution as a "hedge fund company" if it satisfies one of the following: (i) It matches the name of one or multiple funds from the Union Hedge Fund Database. (ii) It is listed by industry publications (Hedge Fund Group (HFG), Barron's, Alpha Magazine, and Institutional Investors) as one of the top hedge funds. (iii) The company's own website claims itself as a hedge fund management company or lists hedge fund management as a major line of business.[11] (iv) The company is featured by news articles in Factiva as a hedge fund manager/sponsor. (v) Some 13F filer names are those of individuals. In such cases we search the full individual names over the internet (mostly through the filer and co-filer identity information on various types of SEC filings) and classify the name as a hedge fund if the person is the founder, partner, chairman, or other leading personnel of a hedge fund company. Notable examples in this category include Carl Icahn (founder and

[10] A fund is usually defined at the level where participating clients combine their investment dollars and purchase/sell pooled portfolio units, rather than individual securities. The unit price is determined by dividing the market value of the pooled portfolio by the number of outstanding units.

[11] Even if a company's website does not formally mention hedge fund management as part of their business, we still classify the company as a hedge fund manager or sponsor if it manages investment vehicles whose descriptions fit our definition of hedge funds. We exclude private equity and venture capital businesses that also have performance-based compensation.

chairman of the hedge funds Icahn Capital, L.P. and Icahn Partners) and George Soros (founder and chairman of Soros Fund Management, a hedge fund management company).

Applying the above procedure yields 1,199 unique hedge fund companies among all 13F filing institutions. This number is low relative to the universe of hedge fund companies (our Union Database consists of 4,918 hedge fund companies). The difference is due to the minimum requirement of $100 million in equity positions for 13F-filing institutions, which rules out smaller hedge fund companies and most of the hedge fund companies which primarily invest in non-equities. Given that we use the long-equity holdings for our analysis, it is comforting to notice that the largest percentage of our sample funds belong to the "Equity" or "Equity Long/Short" category (38.4%). Other major categories include Event Driven (10.2%), Sectors (5.4%), and Multi-Strategy (5.7%), which are also likely to have substantial equity exposure.

Our sample is restricted to relatively "pure-play" hedge funds (such as Renaissance Technologies and Pershing Square, and investment companies where hedge funds represent their core business, such as D. E. Shaw and the Blackstone Group/Kailix Advisors), and do not include full-service banks whose investment arms engage in hedge funds business (such as Goldman Sachs Asset Management and UBS Dillon Read), nor do we include mutual fund management companies that enter the hedge fund business, a new phenomenon in recent years (Agarwal, Boyson, and Naik (2009), Cici, Gibson, and Moussawi (2010), and Nohel, Wang, and Zheng (2010)). The reason for the exclusion is that the equity holdings of these full-service institutions in their 13F filings may not be informative about the investments of their hedge funds. Our results are qualitatively similar if we include the institutions with major hedge fund business in the list of hedge funds, except their presence will skew the statistics related to portfolio size because they tend to be much larger than the other hedge funds on the list.

Due to our top-down approach, our list of 13F filing hedge funds companies is considerably longer than those used in prior literature. For example, Brunnermeier and Nagel (2004) analyze the role of hedge funds during the late 1990s technology bubble with a sample of 53 hedge fund companies, and Griffin and Xu (2009) examine the portfolio characteristics and performance of 306 hedge fund companies. In both papers, the authors use a one-sided match from published hedge fund lists to the 13F database for the purpose of their research and did not classify hedge funds that fail to make to a major published list or choose not to report to any database. Given that the focus of this paper is to analyze the selection bias, it is particularly important that we adopt the top-down approach to compile a complete list of 13F-filing hedge funds.

Equally important for our research is the composition of a comprehensive sample of self-reporting hedge funds given that a key variable of our analysis is the self-reporting status of a hedge fund. Most of the research in the area of hedge funds has been conducted using one or more of the self-reported databases. For example, Fung and Hsieh (1997) use monthly data from TASS Management and Paradigm LDC, Ackermann et al. (1999) use a combination of HFR and MAR databases, Liang (1999) uses HFR data and Liang (2000) compares the HFR and TASS databases for different biases in the data. More recently, Agarwal, Daniel, and Naik (2009) show that there is limited overlap among four commercial databases, and using one or two of them may result in exclusion of a large number of self-reporting hedge funds. We extend the approach of Agarwal, Daniel, and Naik (2009) by adding one more database (Eureka) to their list of four and use the union of five major databases to minimize the under-classification of the self-reporting status. Using multiple databases also enables us to resolve occasional discrepancies among different databases. Finally, critical importance of using multiple databases is emphasized by Fung and Hsieh (2009) who document that some funds, classified as defunct/graveyard funds by a database because they stopped reporting to this database, may be active and reporting to another database. We minimize such misclassification by using the superset of performance histories of a fund from the five databases.

The Union Hedge Fund Database contains a sample of 11,417 hedge funds, which includes 6,245 equity-oriented hedge funds, over our sample period.[12] Figure 1 plots a Venn diagram that shows the percentages of funds report to each database individually and to all possible combinations of multiple

[12] We take advantage of using multiple databases to fill the missing strategy information if the fund is covered by more than one database. However, despite this exercise, we still have strategy field missing for 483 out of the 11,417 funds in our sample and therefore we cannot determine if these funds are equity-oriented.

databases. One of the most striking observations from Figure 1 is that 71% of the funds are covered exclusively by only one database with CISDM and MSCI having the maximum (25.8%) and minimum (5.8%) fraction of unique funds.[13] This underscores the importance of using multiple databases in order to achieve a comprehensive coverage of the hedge fund universe.

[Insert Figure 1 here.]

B. Classification of the Self-Reporting Status of Hedge Funds

We next classify the self-reporting status of all the 1,199 hedge fund companies that file 13F by matching them to the Union Database. The classification entails two steps. In the first step, we match by name allowing minor variations. For example, "DKR Capital" from the 13F list is matched to "DKR Capital Inc." in the Union Database. The name-matching produces 645 self-reporting fund companies, or 53.8% of all 13F filing fund companies.

In the next step, we compute the correlation between returns imputed from the 13F quarterly holdings (henceforth, "13F portfolio returns") and returns reported in the Union Database (henceforth, "self-reported returns"). For the former, we compute the monthly returns of a fund company assuming it holds the most recently disclosed quarter-end holdings. For the latter, we compute the average monthly returns of all funds reported in the Union Database that belong to the same fund management company, weighted by their assets under management. 60 pairs (or 9.3% of the 645 self-reporting fund companies) turn out to have negative correlations[14], and for 219 pairs, the correlation is not defined due to lack of overlapping periods of data from both data sources. The self-reporting status of these funds is not convincingly established and therefore we exclude them from our main analysis (that is, they are

[13] A major determinant in the choice of databases to which funds report is the subscriber clientele of the databases (in terms of both characteristics and geography). Most of the funds choose not to report to multiple databases because of the additional cost due to the different requirement imposed by different data vendors on reporting funds, such as the types of data fields, availability of audited financial statements, etc.

[14] Griffin and Xu (2009) report the same percentage number in their sample as 8.5%. They discuss different reasons for correlation being less than one, including some funds within the 13F companies missing from commercial databases and short-term trading being not captured in the 13F database.

considered neither self-reporting nor non-reporting). As a result, we end up with 366 self-reporting funds and 554 non-reporting funds.

Figure 2 plots the distribution of all 13F-filings and the subset of self-reporting hedge fund companies over the years. Also plotted is the average portfolio size imputed from the 13F quarter-end holdings for both groups of fund companies, expressed in 2008 constant dollars using the Consumer Price Index (CPI) deflator. Figure 2 shows that both the number of 13F filing hedge fund companies and that of self-reporting fund companies have steadily increased over our sample period from 1980 to 2008, with a marked jump in the number of 13F filing hedge fund companies since 2001. Interestingly, the average portfolio size of self-reporting funds was higher than that of the non-reporting funds before 1988, but has been consistently lower than the latter since 1988.

Several forces underlie the changes in the relative size of the reporting and non-reporting funds. First, macro funds, which tend to be large in size, dominated the hedge fund industry prior to the 1990s. The trading strategies of these funds are hard to reverse engineer, implying lower costs of reporting to databases. In contrast, smaller long-equity short funds have become more popular since 1990s. These funds are more sensitive about trading secrecy and hence are less willing to report to databases. Second, there has been a structural change in the hedge fund investor profile in the 1990s. While high net-worth individuals were the predominant investors in the earlier period, institutional investors became the mainstay in the more recent time. This shift can potentially explain why large funds chose to report to commercial databases prior to 1988 to reach out to prospective retail investors but switched to alternative channels afterwards for marketing to institutional investors.

[Insert Figure 2 here.]

Once we identify the self-reporting status of hedge fund companies and the periods during which they report to the Union Database, our analyses almost exclusively rely on the information from 13F filings. As a result, the unit of observation is at the hedge fund management company level, which we will term interchangeably as “hedge funds” for the rest of the paper when there is no danger of confusion.

The main advantage of relying on the 13F data source is that there is little bias associated with selective reporting as long as they meet the minimum hurdle of assets under management ($100 million). Therefore, comparing the portfolio composition and return performance of self-reporting with non-reporting funds could offer an unbiased view of hedge fund performance and shed light on the selection bias introduced by self-reporting. Having said that, it is important to interpret and view our results in light of the limitations of the Thomson Reuters Ownership database. This database only captures the long-equity portfolios of hedge fund companies and masks intra-quarter trading. Hence, we cannot conclude on the reporting-related biases at the aggregate portfolio level or at the individual fund level, given the limitations of our data.

Our research methodology hinges on the proposition that long-equity positions are a substantive portion of the portfolios of equity-oriented hedge funds and that the returns imputed from quarter-end equity long positions are informative about the total returns of these hedge funds. This proposition is also the premise that underlies the earlier work by Brunnermeier and Nagel (2004) and Griffin and Xu (2009). We believe that this proposition is valid on average for several reasons.

First, among the self-reporting fund companies, we find that the average return correlation between their 13F holdings (equity-long positions only, and before fees) and their fund returns reported to hedge fund databases (aggregated at the fund company level and including returns from short positions and non-equity securities, and are net of fees) is 0.54; the median number is slightly higher at 0.57, and the inter-quartile range is 0.34 to 0.77.[15] The correlation is calculated using an average duration of data overlap of 12 years between a fund's appearance in the Union Database and that in the 13F database. Both numbers are comparable to the correlation of 0.55 (mean) and 0.64 (median) reported in Griffin and Xu's (2009) sample.

In addition, two pieces of evidence from hedge fund holdings data underscore the importance of long-equity positions for our sample funds. We obtain the first evidence from retrieving and evaluating

[15] A further investigation reveals that the ten hedge fund companies that exhibit the highest return correlations (ranging from 0.96 to 0.99) all have funds in equity-oriented strategies including long/short equity, equity hedge, event driven, and sector.

the call/put option positions disclosed in the original 13F filings[16] (rather than the data processed by Thomson Reuters). We find that 49% of the hedge fund companies in our sample never reported any option positions during our sample period. The average value of call (put) options as a percentage of the total portfolio for all sample funds is 4.1% (4.0%), indicating limited benefits of including these options for the purpose of our research. The second piece of evidence is provided by Ang, Gorovyy, and van Inwegen (2010). Using a proprietary dataset of funds of hedge funds, the authors report that hedge funds in the equity and event driven strategies (which constitute the great majority of our sample funds) mainly invest in equity and distressed corporate debt, and hence have relatively low leverage.

Second, the contribution of equity positions to the total returns of hedge funds is evident from the equity market betas of hedge funds. Using the monthly Credit Suisse/Tremont hedge fund indices from January 1993 to May 2009,[17] we find that the market beta of the index of all equity-oriented hedge funds is 0.48. Similarly, the average market beta from the four-factor model of the return index of all the self-reporting hedge funds in our sample is 0.40.

Finally, the constant resistance of hedge funds against ownership disclosure, including the 13F filings, implies that the equity positions are critically informative of their investment strategies. Philip Goldstein, an activist hedge fund manager at Bulldog Investors likens his stock holdings to “trade secrets” as much as the protected formula used to make Coke, and condemning the 13F rule for taking the fund’s “property without just compensation in violation of the Fifth Amendment to the Constitution.”[18] In the wake of the “quant meltdown” in August 2007, 13F filings that publicize equity positions of major quant hedge funds took much of the blame for inviting “copycats” into the increasingly correlated and crowded strategy space, which eventually contributed to the “death spiral” in the summer of 2007 when many funds employing similar strategies attempted to cut their risks simultaneously in response to their losses

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[16] Please note that generally only exchange-traded options are required to be disclosed in the Form 13F. Therefore the original 13F filings do not include all potential option positions of institutional investors.
[17] Available from: http://www.hedgeindex.com/hedgeindex/en/default.aspx?cy=USD.
[18] For a more detailed discussion, see Philip Goldstein’s interview in September 12, 2006 issue of *Business Week*: http://www.businessweek.com/print/investor/content/sep2006/pi20060913_356291.htm.

(Khandani and Lo (2007)). A recent paper by Agarwal, Jiang, Tang, and Yang (2010) presents large-sample evidence of strategic delays by hedge funds in their 13F disclosure.

C. Overview of Hedge Funds using Quarter-End Equity Holdings Data

Before we compare self-reporting hedge fund companies to non-reporting ones, we take advantage of the complete list of 13F filing hedge funds to report the summary statistics of their equity-portfolio characteristics and the return performance of their long-equity positions. Further, we compare their statistics with those of other categories of 13F-filing institutional investors. Such an analysis represents the most complete overview of the long-equity positions of hedge funds in the literature.

The other categories that we compare hedge funds to include: (1) banks and insurance companies (a combination of type 1 and type 2 institutions by the Thomson classification); (2) mutual fund management companies (type 3 institutions by the Thomson classification); (3) independent investment advisors (type 4 institutions by the Thomson classification, excluding hedge funds classified by us), and (4) others (the type 5 institutions by the Thomson classification, excluding hedge funds classified by us). The Thomson Reuters type code 5 since 1998 is known to be problematic in that the category could include many misclassified institutions that should be assigned with the other type codes (mostly, type code 4). Therefore, we reassign an institution which has type code 5 after 1998 to an earlier code if available and different from 5. The comparison is reported in Table I.

[Insert Table I here.]

Table I shows that hedge fund companies are much smaller in size compared to institutions of other categories where size is calculated as the total value of the quarter-end equity portfolio using reported shares and corresponding quarter-end stock prices reported in CRSP. In particular, the average size of a hedge fund company's long equity portfolio is 16.5% of that of a mutual fund management company; though the difference in the total assets under management is likely to be smaller because the former may have exposures while mutual funds are more or less constrained to hold long positions in publically traded securities.

Hedge funds also tend to be younger. Because age changes mechanically with the reporting year for the same institution in a panel data, we simply consider the inception year of a filing institution as a proxy for age. The inception year is left-censored at 1980 which is the earliest year that Thomson Reuters has data coverage. The median hedge fund company started 13F filing 19 years after the median bank/insurance company; and the same differences with mutual fund companies and investment advisors are 17 and 7 years, respectively. These differences are all statistically significant at the 1% level.

Three measures point uniformly to the more active nature of hedge funds in portfolio management. First, they are significantly (at the 1% level) less diversified than all other categories as measured by median portfolio Herfindahl index, and the biggest difference is with respect to the mutual funds (0.047 vs. 0.018). The same relation holds using the mean statistic except for the comparison with the "Other" category. Second, hedge funds' portfolio volatility is higher than all other categories using both mean (5.53%) and median (4.93%) standard deviation of monthly returns imputed from quarter-end holdings, and the differences are all significant at the 1% level.

Third, hedge funds' inter-quarter portfolio turnover rates, average (median) of 91.6% (81.5%) annually, is about twice as high as that of mutual funds, investment advisors, and other institutions, and more than three times that of bank and insurance companies, with all differences being significant at the 1% level. Here, the portfolio turnover rate is compounded from the inter-quarter turnover rates[19], calculated as the lesser of purchases and sales, divided by the average portfolio size of the last and the current quarter.[20] Purchases (sales) are calculated as the sum of the products of positive (negative) changes in the number of shares in the holdings from the previous quarter-end to the current quarter-end, and the average of the stocks prices at the two quarter-ends. The logic of using the *lesser* (rather than the average) of purchases and sales is to free the measure from the impact of net flows. The comparison between hedge

[19] It is possible that some hedge funds may be very high-frequency traders by actively trading within the quarter and therefore may not report any long equity positions at the end of a quarter. However, this will only result in our underestimating the actual portfolio turnover rates of such hedge funds.

[20] We follow the practice of Morningstar, the leading mutual fund research company, in defining portfolio turnover rates. It is worth pointing out that our turnover figures for mutual funds are lower than those reported in the Morningstar database because the 13F data does not account for intra-quarter trading, which may significantly contribute to the funds' turnover.

funds and mutual funds in terms of portfolio concentration and turnover rates is consistent with Griffin and Xu's (2009) findings using similar measures.

Does hedge funds' more active management bring about superior returns? The answer is not obvious from Table I. We compute monthly excess return for each institution as the difference between the imputed portfolio return and the CRSP value-weighted equity market return. For the former, we assume that in each month, the institution holds the portfolio disclosed at the most recent past quarter-end[21] and calculate the buy-and-hold return for the month. It turns out that all categories have average and median excess returns close to zero.[22] Moreover, hedge funds outperform all the other institutions on average, though only the differences between the average excess returns of hedge funds and those of investment advisors and other institutions are statistically significant. If we use median excess return as the metric, hedge funds outperform all other institutions significantly. When we use one-factor and four-factor alphas as the performance metric, hedge funds seem to underperform other institutions on average, with all pair-wise differences being significant except the difference in one-factor alphas of hedge funds and "Other" institutions.[23] However, the magnitude of the differences is small. The overall evidence suggests that hedge funds do not command superior returns from their long-equity positions on average.[24] We will analyze the performance within the hedge fund group in more detail in the following sections.

II. The Economics of Self-Reporting: Hypothesis Development

After characterizing the sample of all 13F filing hedge fund companies, the natural question to ask is when hedge funds choose to report to commercial hedge fund databases, or whether they ever choose to report at all. Answer to this question will shed light on the systematic differences, if any,

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[21] We code the monthly return as missing if the lag between the current month and the last quarter-end when the portfolio information is available exceeds six months.

[22] Given that institutions as a whole hold a majority stake in public equities (the percentage increased from 32% in the beginning to 66% to the end of our sample period), it is not surprising that on average they simply perform at par with the market.

[23] Since we examine the performance of long equity portfolios of institutions, we do not need to use multifactor models augmented by option factors as in Agarwal and Naik (2004) and Fung and Hsieh (2001, 2004).

[24] This does not rule out the possibility that hedge funds may be delivering superior performance on their non-equity component of the portfolios.

between hedge fund information (especially returns) accessible from the commercial databases and information that is hidden. Characterizing such differences is the key to understanding the selection bias in the databases, which has important implications for hedge fund research.

Like other economic activities, the reporting behavior of hedge funds is an outcome of cost-benefit trade-offs. The benefit that is most cited by hedge fund data vendors in marketing their services to hedge funds is that listing in a database enhances a fund's exposure to potential investors, including fund of funds, foundations, banks, endowments, pensions, consultants, and high net worth individuals. Such benefits are likely to be more significant for small- and medium-sized fund companies that desire more publicity but lack the resources for aggressive direct marketing.

The main cost of reporting is a partial loss of secrecy and privacy that some hedge funds value. The SEC's efforts to push for more disclosure by hedge fund companies have faced strong resistance,[25] indicating the industry's general reluctance for or even strong opposition to more transparency. Though self-reporting hedge funds in general do not reveal holdings information to hedge fund databases, the reported information, such as general descriptions of style classification, asset allocation, monthly returns, and leverage/hedging ratios, is often revealing of the funds' investment strategy. For example, proposed "hedge fund replication" strategies that promise to provide low-cost hedge fund exposure are mostly built on the self-reported information (Kat and Palaro (2006)). Moreover, keeping the reporting status constitutes a commitment to revealing a fixed set of information at fixed time intervals. Such a rigid schedule reduces a hedge fund company's flexibility in marketing, such as featuring a subset of information or a chosen period of return performance that is most favorable to the fund.

An additional cost is related to the clientele of database subscribers. Potential long-term investors targeted directly by hedge funds (mostly large institutions, fiduciaries, and some funds-of-funds) are different from those attracted to hedge funds through database subscription, which tend to be more "retail"

[25] Such resistance culminated in *Goldstein vs. Securities and Exchange Commission* (details in http://www.seclaw.com/docs/ref/GoldsteinSEC04-1434.pdf) where Phillip Goldstein, the manager of hedge fund Bulldog, challenged an SEC 2004 rule that required most hedge fund advisors to register with the SEC by early 2006. The decision of the Court, made in June 2006, was mostly in favor of Goldstein.

based and shorter-term, consisting disproportionately of small institutions and individuals. Stulz (2007) mentions that retail investors may require more "hand-holding" subsequent to poor performance. Mutual fund literature also provides some evidence on institutional money being more "sticky" than retail in that the former does not chase short-term performance as much as the latter (James and Karceski (2006), Chen, Goldstein, and Jiang (2009)). Hedge funds usually value long-term investors whose investing or divesting decisions are not sensitive to short-term performance. Hence, some hedge funds may not want to be exposed to the clientele that are typical of database subscribers.

While it is understandable that funds may not desire to appear in commercial databases during periods of poor performance because they do not wish to publicize the embarrassment, it is much less clear whether reporting funds are overall better or worse performers than non-reporting ones. On one hand, the extreme poor performers may be unlikely to appear in a database simply because they do not survive long enough to satisfy the requirement for track records by most data vendors. On the other hand, some successful hedge funds may prefer to voluntarily report as it serves as a strong signal for better transparency and institutional quality. At the same time, the very successful funds can also shun reporting given their low needs for enhanced visibility and possibly full capacity. In addition, Lhabitant (2006) offers one explanation to the general absence of the largest and most successful hedge funds in the commercial databases: these funds might be concerned that communicating performance to a data vendor may lead to inclusion in that data vendor's index, which automatically raises the performance of that index. As a result, these hedge funds' individual performance will appear less differentiated. If these arguments are valid, then both the periods of self-reporting and the sample of reporting funds will be biased toward average performance.

III. Biases Conditional on Self-Reporting: Reporting Initiation and Termination

We start with the first type of selection bias concerning the subsample of self-reporting funds: When do fund companies initiate reporting and when do they terminate? If funds tend to choose reporting initiation after a run of superior performance or to terminate reporting following subpar returns, examining the performance of funds while they appear in the database can contribute to a "timing bias." Until now, the extant literature has not been able to quantify these two forms of timing bias as the performance of funds "before birth" and "after death" (with respect to the databases) is not observable from the commercial databases. Since our return analysis is based on 13F filings, which are not constrained by funds' reporting status to the commercial databases, it allows us to shed light on these two biases, hitherto unexplored in the hedge fund literature.

A. First form of timing bias: Comparison of fund companies before and after the reporting initiation

The Union Hedge Fund Database provides information on the dates when the hedge funds enter the databases. If a fund company reports to multiple constituent sources in the Union Database, we use the earliest date. Among all 13F-filing hedge fund companies, 103 out of the 366 self-reporting funds afford the before-after analysis if we require a minimum of 12 months of return information around the initial reporting date and the existence of such information on both sides of the date. For 77 funds, there is accurate information on the initial reporting dates provided by one commercial database. For rest of the funds, such exact information is not available and all we can observe is the first date of the performance data recorded in the database. Following the practice of the literature (e.g., Ackermann, McEnally, and Ravenscraft (1999)), for such funds we add 24 months to the first performance dates to form the approximate first reporting dates, effectively assuming a typical practice of 24 months' back-filling by reporting funds. This assumption could be problematic as Fung and Hsieh (2009) document periods longer than 24 months between the inception and first reporting dates. Hence, for robustness, we conduct our analyses using both the entire sample and the subsample with accurate information on initial reporting date. We focus more on the latter results for our discussion that follows. Please note that since we already account for the backfilling bias in our analysis, first form of the timing bias examined here is distinct from the backfilling bias.

For each fund whose reporting date falls within the 1980-2008 period, we compare the return measures (imputed from the 13F holdings) during the 24-month period before reporting to the Union

Database and the 24-month period thereafter (or as many months as possible subject to a minimum of 12 months in total on both sides of the reporting initiation month). Results are reported in Table II.

[Insert Table II here.]

Panel A of Table II shows that performance is overall worse after initial reporting compared to the period before, though the difference is not statistically significant. The difference in the average raw monthly return is 52 basis points, or 6 percent on an annualized basis.

Importantly, when we use the subsample of funds for which we have accurate initial reporting dates, we observe from Panel B of Table II that the performance after initial reporting is significantly lower than that before reporting. The average raw returns and measures of risk-adjusted performance (excess returns, CAPM alpha, and four-factor alpha) are lower by 90, 73, 58, and 24 basis points per month respectively, and all except four-factor alpha differences being statistically significant at the 1% level in addition to being economically meaningful. We obtain similar results using the median performance with the corresponding figures being 49, 32, 33, and 19 basis points per month respectively. Finally, a difference-in-difference approach, which computes the difference around the initial reporting date between raw returns of reporting and non-reporting hedge funds also indicate significant deterioration using both the median and mean values.

The results in Panel B are much more significant and coherent, compared to the full-sample results in Panel A, albeit with a smaller sample, indicating that accurate reporting dates are essential to identify the selection bias around reporting initiation for the sample of self-reporting funds, providing support to the arguments in Fung and Hsieh (2009).

The interpretation of this difference is further facilitated by Figure 3. Panels A and B plot the time series of the monthly raw returns and excess returns averaged across the 77 hedge funds (with accurate initial self-reporting dates) from 24 months before the reporting month, to 24 months afterwards. The two dotted horizontal lines marked the time-series averages of the two sub-periods. The figure indicates that funds choose to initiate self-reporting after a run of superior performance, but such performance does not persist in that it mean-reverts to levels at par with the market after reporting initiation.

[Insert Figure 3 here.]

The subsequent normal performance after a run of superior one supports the hypothesis of strategic timing in initiating self-reporting by hedge funds, if they decide to report at some time. Given the customary back-filling practice (that is, hedge funds usually send retrospective return data to commercial databases), our analysis shows that the early periods of reported returns contain an upward bias for inferring the reported funds' normal performance. Hence, the trimming of early-period returns in return analysis as adopted by the literature is justified. However, the different results between Panels A and B of Table II also points to the limitation of the simple 24-month trimming practice as it does not seem to identify the true initial reporting dates, and hence does not completely clear the first type of timing bias in reporting initiation.

B. Hazard Analysis for reporting initiation

To relate the timing bias to other time-varying fund characteristics in addition to return performance, we present the hazard analysis of reporting initiation for the subsample of fund companies with accurate initial reporting date information. In the language of hazard analysis, in our case, the "failure" event is the hedge fund's first appearance in the hedge fund Union Database. Thus, the hazard rate $h(t)$ is the hedge fund's probability of reporting initiation in a given period t, conditional on the fact that it did not initiate reporting in any of the previous periods. We start with a time-varying sample of non-reporting funds. Once a hedge fund has initiated reporting, it exits the sample because the spell has "failed". We estimate our instantaneous hazard model with respect to a set of time-varying explanatory variables (X), such as fund characteristics. That is, the values of these variables are tracked dynamically since the fund's first appearance in the Thomson Reuters database until its first reporting date to the Union Hedge Fund Database (observations of completed spells) or to the end of our sample period (observations of censored spells).

We adopt the semi-parametric Cox proportional hazard model (Cox (1972)) which estimates the relation between the instantaneous hazard rates and the covariates by maximizing a partial-likelihood function. In this model, the hazard rate is assumed to be:

$$h(t) = h(0)e^{X_t{}'\beta} \tag{1}$$

where t is the number of periods since the fund company's first appearance in the Thomson Reuters database. In this setting, a positive coefficient β_k indicates that an increase in the covariate X_k is associated with an increase in the instantaneous probability of hedge funds' initiating reporting to a database during period t. We conduct the analysis at the quarterly frequency and results are reported in Table III. Following the norm adopted in hazard analyses and to facilitate interpretation, Table III reports the hazard ratio (also called "exponentiated coefficient") associated with each covariate rather than the raw coefficients β_k where the ratio is defined as: $h(t \mid X_k^{'} = X_k + 1, X_{-k}) / h(t \mid X_k) = e^{\beta_k}$. A hazard ratio that is greater (smaller) than unit indicates a positive (negative) contribution of the covariate to the instantaneous probability of reporting initiation. The z-statistics in the table testifies the significance of raw coefficient (β_k) being different from zero, or of the hazard ratio (e^{β_k}) being different from unit.

[Insert Table III here]

According to Table III, hedge funds after better performing periods have higher probability of reporting initiation during the current period: hazard ratios associated with performance (lagged) are significantly higher than one. This result supports evidence in Figure 3: hedge fund's performance tends to be abnormally high before reporting initiation. When risk-adjusted measures of performance are considered (columns (2)-(4) in Table III) and market returns are controlled for, the evidence suggests that hedge funds have higher probability of reporting initiation after a period of good market performance. This result is consistent with the ease in marketing funds when overall market performs well. The coefficient of the market return is insignificant when performance is measured by raw returns because the latter already contains information about market returns.

Table III highlights additional elements in hedge funds' strategic timing in reporting initiation. First, when the proxy for the aggregate flow to hedge fund industry is high, hedge funds have significantly lower probability of reporting initiation. Here we approximate the aggregate flow by the total increase in the equity portfolio value of all 13F-filing hedge funds, netting out the increase due to stock price appreciation. This evidence suggests that a boom in the hedge fund industry provides enough capital to many funds, leading to their lowered needs to enhance exposure to potential investors by reporting initiation.

Second, hedge funds are less likely to initiate reporting during periods of higher portfolio return volatility. Prior literature shows that flows to hedge funds and mutual funds are dampened by return volatility conditional on performance (Ding, Getmansky, Liang, and Wermers (2009), Huang, Wei, and Yan (2007)), indicating that investors tend to discount fund returns when the volatility is also high. Moreover, the Sharpe Ratio is a common performance measure adopted by commercial databases, and this metric is unfavorable to funds with volatile returns. As a result, funds are reluctant to publicize themselves to commercial databases when their returns are volatile.

Finally, hedge funds have higher probability of reporting initiation in their youth stage if they decide to report: the hazard ratios associated with fund age are significantly lower than one. This result is expected as young funds are the most likely to benefit from reporting initiation. The impact of the portfolio concentration (as measured by the average portfolio Herfindahl index) on the reporting initiation is negative and significant at the 10% level. Thus, hedge funds operating more concentrated portfolios are less likely to initiate reporting. This is consistent with the costs of revealing trading secrecy when funds report to databases, an issue that we will discuss in more detail in Section IV.

C. Second form of timing bias: Comparison of fund companies before and after reporting termination

There are 187 funds in our sample that terminated reporting to the Union Database at some point during the 1980-2007 period. For these funds, we are able to analyze the determinants of reporting termination using the same method as we used in Table II for reporting initiation. Moreover, for these funds we have more information about their termination decision due to their reporting status when the decision is made. Results are reported in Table IV.

[Insert Table IV here.]

We observe that the performance after termination of reporting is significantly lower than that before termination. This is not surprising given that most funds exit from commercial databases when their performance starts deteriorating (Ackermann, McEnally, and Ravenscraft (1999), Liang (2000), and Fung and Hsieh (2000, 2002) among others). What is interesting and unique about our analysis here is that we are able to determine the performance of funds after they disappear from the commercial databases. Our analysis is thus analogous to computing the delisting returns for stocks in Shumway (1997) and Shumway and Warther (1999), hence this second form of the timing bias is analogous to a "delisting bias."

Table IV shows that the average monthly raw returns and the three measures of risk-adjusted performance: excess returns, CAPM alpha, and four-factor alpha, are lower by 1.9%, 0.3%, 0.1%, and 0.2% on a monthly basis after the termination of reporting (the first two being significant at the 1% and 5% levels).[26] We obtain similar results for median performance differences with the corresponding figures being 1.5%, 0.2%, 0.03%, and 0.2% per month, with the first and last differences being significant at the 1% level. A graphical illustration of the performance around the reporting termination date is provided in Panels C and D of Figure 3. The message is also similar to what is conveyed by the table.

About 64% of the funds (119 funds) that terminate reporting in our sample provide reasons for termination to the commercial databases. In 112 out of the 119 cases, the given reasons indicate distress (such as liquidation, fund being dormant or data vendor being unable to contact the fund). Other given reasons could be positive (such as being closed to new investors) or unclear (such as being merged to another fund) but such cases are rare. When we focus on the subsamples partitioned by stated reasons, we

[26] The magnitude of excess returns is qualitatively similar to but compares favorably with Hodder, Jackwerth, and Kolokolova's (2008) finding that the average delisted hedge fund held by a sample of fund of hedge funds had a monthly return of -1.86% immediately after it is delisted.

do not find significant differences across the subsamples in the changes in performance after reporting termination, mostly due to the much reduced sample sizes.

In summary, exiting from commercial databases by the reporting funds is overall a sign of deterioration. Interestingly, negative market returns also contribute to higher incidences of report termination—manifested by the higher before-after return gap in raw returns than benchmark-adjusted returns as shown in Table IV. These findings about hedge fund reporting termination are consistent with the patterns associated with stock delisting but with a much milder magnitude, reflecting the fact that fundamental failure is a less dominant reason for hedge fund report termination than for stock delisting. Finally, the combination of good performance prior to reporting initiation (results in the previous section) and poor performance following reporting termination act as offsetting forces that bias the performance tracked by the commercial database toward average.

D. Effects of Self-Reporting on Hedge Fund Flows

D1. Reporting initiation

We discussed in Section II and hypothesize that a primary benefit of reporting to hedge fund databases is enhancing a hedge fund company's exposure to potential clients. If such a motive is justified, then a hedge fund should experience, on average, an increase in flows after the initiation of reporting compared to the counterfactual of not reporting. For all funds that initiate reporting during our sample period, we can isolate the quarterly observations from four quarters before the initial reporting date to four quarters afterwards. We then conduct the following regression at the fund (indexed by *i*)-quarter (indexed by *t*) level:

$$Flow_{i,t} = \sum_{j=-4}^{4} \lambda_j D_{t-j} + \beta Performance_{t-3:t} + \gamma Control_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

In (2), $Flow_{i,t}$ is calculated as $(Size_{i,t} - Ret_{i,t} * Size_{i,t-1}) / Size_{i,t-1}$, all using disclosed holdings in Form 13F. It measures the change in the value of a fund's equity portfolio due to changes in investment by the funds' investors (and not due to the changes in the stock prices), and is a proxy for the net fund flows. The all-sample average (median) percentage flow to hedge funds companies is 3.6% (1.4%). D_{t-j} are the dummy variables for four quarters before and after the initial reporting date. $Performance_{t\text{-}3:t}$ is the monthly average of the performance measure during the past four quarters that end in the current quarter, and $Control_{i,t\text{-}1}$ are lagged control variables including portfolio size (in log), fund age (numbers of quarters since first appearance on Thomson Reuters, in log), portfolio turnover rates, and portfolio volatility. Based on the lessons learnt from Table II (discussed in Section III.A), we focus on the subsample of funds with accurate initial reporting dates only. Results are reported in Panel A of Table V.

[Insert Table V here.]

The three columns in Table V Panel A estimate equation (2) using three benchmark-adjusted return performance measures: return in excess of the market, CAPM one-factor alpha, and four-factor alpha. The coefficients on *Performance* tell us that flows are highly responsive (significant at the 1% level) to risk-adjusted returns, regardless of whether we use a simple market benchmark (return in excess of the market) or alphas from one-factor or four-factor models. Our findings are economically significant too. For example, for a one percentage point increase in monthly return in excess of the market (or 12 percentage points during the four quarters when performance is measured), net flows to a fund increase by 2.5% of the total portfolio value (see column 1 of Table V Panel A). This flow pattern is similar to what the literature has documented for mutual funds (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)).

Table V shows a small increase in flows during quarters *t+1* and *t+2* using four-factor alphas, where *t* is the initial reporting quarter. However, this increase is transient and does not persist into future quarters, possibly due to a deterioration in performance after reporting initiation, as we show earlier in our paper. When we test for changes in flows over the full window through a formal F-test: $\sum_{j=0}^{4}\lambda_j - \sum_{j=-4}^{-1}\lambda_j = 0$, we are unable to reject the null of equality. Therefore, reporting to databases does not lead to higher flows over a longer window comparing flows during the year following initiation to those during the year preceding reporting initiation.

It is worth pointing out that we do not observe the counterfactuals—flows that would prevail had the reporting funds chosen not to initiate reporting. It is possible that funds anticipating loss of flows from existing sources would choose to report to databases, and such a decision process biases down the estimate for the incremental flows from exposure through the databases.

D2. Reporting Termination

Lastly, we repeat the analysis used in regression (2) on reporting termination. Results reported in Panel B of Table V show that funds encounter significantly lower net flows (or more outflows) after reporting termination. An F-test of $\sum_{j=0}^{4}\lambda_j - \sum_{j=-4}^{-1}\lambda_j = 0$ is strongly rejected (at the 1% level) in favor of a negative change in net flows across all regression specifications. More specifically, the cumulative net outflows during the quarter of reporting termination and four quarters afterwards amount to 29-34 percent of the lagged portfolio size. This evidence adds further support to a negative delisting bias, i.e., delisting from hedge fund databases is in general a sign of deterioration.

IV. The Unconditional Self-Reporting Bias: Comparing Self-Reporting and Non-Reporting Hedge Funds

As a next step, we move up from the subsample of self-reporting funds to the full sample and ask the question "who report." Our answer relies on the comparison of the pooled sample of 13F-filing hedge fund companies that never appear in the Union Database (there are 554 such non-reporting companies) and those that appear in the database for some time during our sample period (there are 366 such self-reporting companies). To reduce noise, we do not include the 279 fund companies whose reporting status cannot be accurately verified.

A. Comparison of fund characteristics

Table VI reports the comparison of fund companies and portfolio characteristics: portfolio size, portfolio concentration, returns volatility, portfolio turnover rate, and fund company inception year.

[Insert Table VI here.]

In Panel A, we compare the characteristics of never-reporting funds with those of ever-reporting ones using information from all time periods as available on the Thomson Reuters. Panel A of Table VI reveals several patterns regarding the all-time characteristics of self-reporting funds. First, the portfolio size of self-reporting hedge funds are more or less comparable to the non-reporting ones, though the latter has much higher standard deviation. The self-reporting funds are slightly smaller by the mean statistic but somewhat larger by median comparison, indicating that the largest fund companies are under-represented in the set of self-reporting funds. This finding is intuitive as the larger funds are more likely to be the successful ones that are possibly facing decreasing returns to scale and capacity constraints. Such funds may have weaker incentives to report to commercial databases for attracting more capital.

Second, the self-reporting hedge funds have lower portfolio concentration than that of the non-reporting funds as measured by the average portfolio Herfindahl index (average of 0.08 versus 0.11, significant at 1% level). The average monthly return volatilities of the two categories are almost identical, but the self-reporting funds have considerably higher portfolio annualized turnover rates (106%) than that of the non-reporting funds (79%) and the difference is significant at the 1% level. Again these findings conform to the economics of reporting as less concentrated (or more diversified) and higher turnover funds need to worry less about their trading strategies being revealed through self-reporting. Finally, the average inception year (defined as a fund company's first appearance in the Thomson Reuters database) is very similar for both groups, though the median self-reporting fund is two years younger than its non-reporting counterpart.

Table VI Panel A further compares the loadings on common risk factors for self-reporting and non-reporting funds. Interestingly, the equity positions of self-reporting funds have significantly higher exposure to the size (SMB) and book-to-market (HML) factors where the differences in both mean and median are significant at the 1% level. The difference in the loadings on the market factor follows the same pattern using the median statistic only, and the difference in the loadings on the momentum factor is not significant. To the extent that exposure to common risk factors hardly constitutes trading secrecy, these results support the hypothesis that fund with less conventional trading strategies (i.e., lower factor loadings) are more reluctant to reveal their information to databases.

The two pooled samples compared in Panel A of Table VI are not necessarily directly comparable in that self-reporting and non-reporting fund companies may exist in the Thomson database for different periods and different lengths of time. To refine the comparison, we make the following adjustments: For each self-reporting fund, we crop out the period for which it appears in the Thomson Reuters Ownership database (which may contain periods before, during, and after its reporting to the Union Database). We then find non-reporting fund companies that have 13F data over the same period (or with the maximum overlap). If there are ties in matches, we choose the one that is closest in portfolio size as the self-reporting fund to be the "matching fund." Panel B of Table VI reports the results from such refined comparison.

The comparisons between the two groups regarding the differences in mean and median of turnover rates in Panel B are qualitatively similar to those shown in Panel A, but the magnitudes of the differences are strengthened. Moreover, the differences in the median portfolio concentration are now positive and significant. The portfolio sizes of the paired funds are almost identical, only due to the matching algorithm that is based on this variable. Finally, the matching non-reporting funds are now much older, which is again an artifact of the algorithm which favors matching funds with longer periods of 13F filings.

Please note that the pair-wise comparison analyses reported in Table VI and the hazard analysis (reported in Table III) do not necessarily yield coefficients of the same sign or of similar significance levels. While the former relates the fund characteristics (averaged over the time series) to their propensity to ever report, the latter focuses on how the time-variation in fund characteristics prompt report initiation at certain point of time. For example, the hazard analysis indicates that funds are less likely to initiate reporting during the period of volatile returns; but reporting funds as a whole do not have less return volatility as compared to non-reporting funds.

B. Comparison of return performance

We next move on to return performance comparison, which underlies the important consequences of the self-reporting-related biases in commercial databases. Such results are reported in Table VII, where Panels A and B adopt the same classification schemes as in the Panels A and B of Table VI.

[Insert Table VII here.]

We observe from Panel A (which uses all-time information as available on Thomson Reuters) that average (median) raw returns of self-reporting funds are significantly higher, at the 1% (5%) level, than those of the non-reporting funds. However, both the magnitude and significance of the differences drop precipitously when the returns are adjusted by the market benchmark (i.e., return in excess of the market), or by the CAPM one-factor or using the four factors (market, size, book-to-market, and momentum) first used in Carhart (1997).

The return differences between the mean and median return measures over the matched time period, reported in Table VII Panel B, indicate that self-reporting funds underperform non-reporting funds by 2-8 basis points monthly using the various performance measures, but none of the differences are statistically significant. Interestingly, the differences by percentile values indicate that for lower percentiles (e.g., the 5th percentile), self-reporting funds perform significantly worse (at the 5% and 10% levels) using two of the three benchmark-adjusted return measures, while the pattern does not hold at percentiles above median. Combined evidence indicates that a small fraction of reporting funds has poor performance and may be struggling; while the most successful ones are no more prone to self-reporting.

The only conflicting difference between the results from Panel A and those from Panel B is the relative ranking of raw performance between the two groups of funds: it is significantly positive in favor of the self-reporting funds in the former while negative (but short of significance) in the latter. But such an inconsistency is not observed using any of the benchmark-adjusted returns. Taken together, these figures indicate timing of hedge fund reporting based on the market condition: hedge funds that were active during years when the overall market performed well were more likely to report to hedge fund databases. This evidence of timing based on market information complements the analysis in Section III regarding timing on individual fund performance.

The overall evidence is consistent with the hypothesis that young and medium-sized fund companies have a stronger incentive to report to databases to publicize their funds and attract potential investors. Moreover, self-reporting funds are more diversified, employ higher-frequency trading strategies (using portfolio Herfindahl index and turnover rates as proxies), and have higher loadings on common factors—presumably trading secrecy is less likely to be revealed through voluntary disclosure or is less important when portfolio involves more stocks, evolves more quickly, and have more exposure to common risk factors. This pattern echoes Agarwal, Jiang, Tang, and Yang's (2010) finding that hedge funds adopting less conventional investment strategies are more likely to resort to confidential 13F filing in order to delay revealing their quarter-end positions. In both cases, funds who value privacy more are more likely to refrain from voluntary disclosures or to seek exemptions from mandatory ones.

Finally, the difference in the return performance, though slightly in favor of the non-reporting funds, is small.[27] This is good news for the existing and ongoing studies on hedge fund performance because the self-reporting bias may not have a material impact when it comes to performance evaluation. In Section II, we hypothesize that the sample of self-reporting funds might be over-represented by funds with average performance. Therefore the selection bias due to self-reporting could be offset by the absence of both the most and least successful funds. Fung and Hsieh (2000) conjectured, with the support of some anecdotal evidence, that the selection bias due to self-reporting is limited because on the one hand "only funds with good performance want to be included in a database," while on the other hand "managers with superior performance did not necessarily participate in vendors' databases." Our results are supportive of their conjecture.

[27] This result is consistent with Brav, Jiang, Partnoy, and Thomas (2008) who find that hedge funds reporting to two commercial databases perform worse than the non-reporting ones among the sample of activist hedge funds, but the difference is not statistically significant. Their performance measure is different in that they use the abnormal returns of the companies targeted by the activist funds during the event window.

V. Conclusion

This paper presents a comprehensive study that formally analyzes the self-reporting-related biases in hedge fund databases. We show that a union of commercial databases largely eliminates the unconditional bias in performance due to offsetting effects motivating self-reporting. This is good news for the expanding volume of research based on commercial hedge fund databases. Yet our analyses also demonstrate the desirability of merging multiple databases, the systematic differences in the characteristics between reporting and non-reporting funds, as well as significant forms of timing bias corresponding to the deterioration in performance after both reporting initiation and termination (or delisting) among the subsample of reporting funds. These findings can be important in certain contexts. For example, timing bias related to reporting initiation has implications for examining the performance of emerging funds and managers (Aggarwal and Jorion (2010)).

Relatedly, our analyses indicate non-trivial impacts of market-wide returns on fund reporting initiation/termination and fund flows in that both variables are more sensitive to raw returns than to risk-adjusted returns. Such evidence suggests that hedge funds investors chase absolute as well as excess returns, even though market-wide conditions cannot be attributed to skills of fund managers. As a result, hedge funds time their reporting or termination of reporting in response to their own performance as well as to the market-wide conditions.

Taken together, our research provides important references and benchmarks for hedge fund researchers and investment managers who use commercial databases and publicly available information on portfolio holdings of institutions. Our findings shed light on the motivation and consequences of voluntary disclosure by hedge funds. Finally, by comparing databases from mandatory and voluntary sources, our research also contributes to the ongoing debate regarding more stringent disclosure rules for hedge funds.

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Figure 1
Venn Diagram of the Union Hedge Fund Database

The Union Hedge Fund Database contains a sample of 11,417 hedge funds by merging the following databases: CISDM, Eureka, HFR, MSCI, and TASS. This figure shows the percentage of funds covered by each database individually and by all possible combinations of multiple databases.

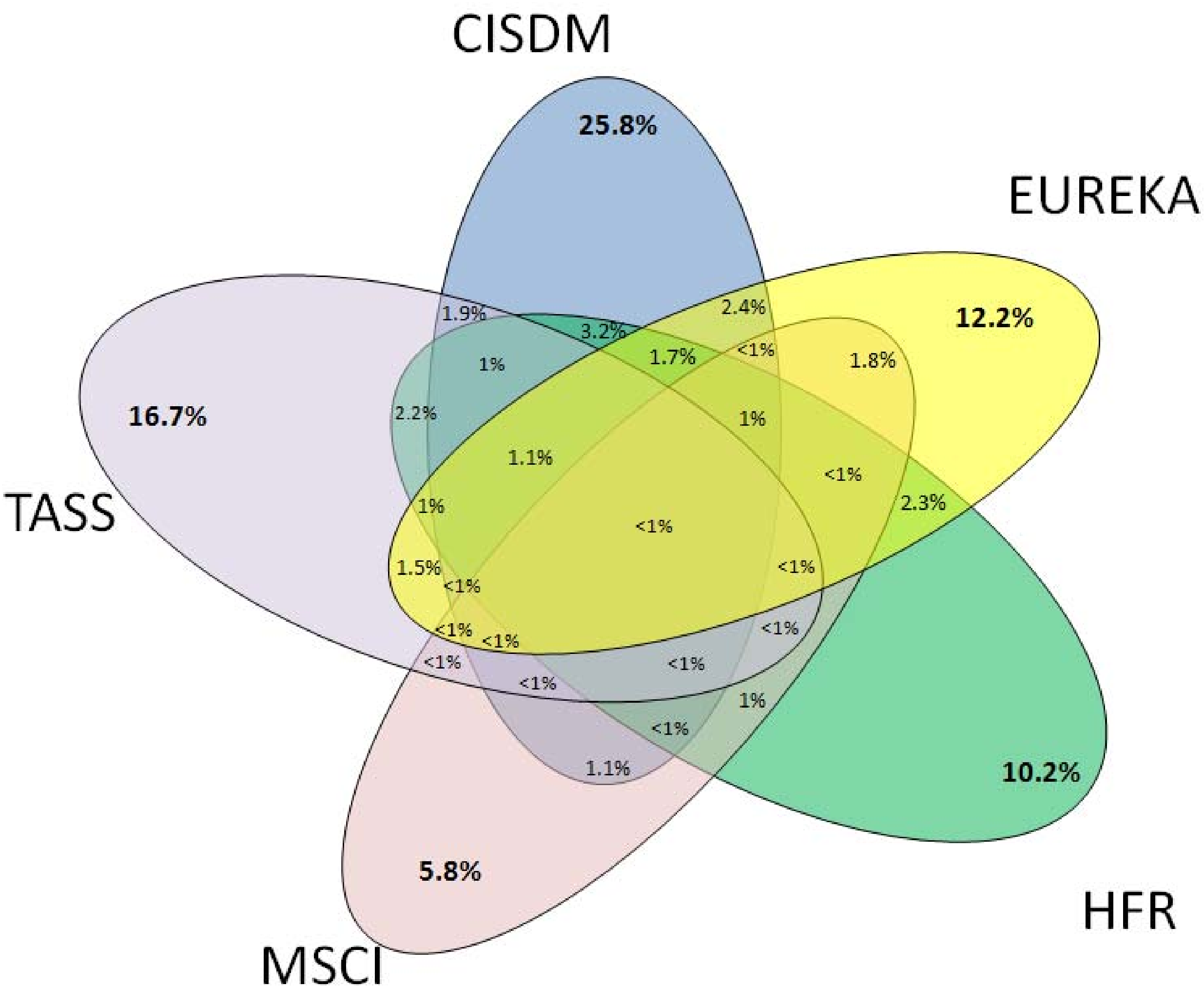


Figure 2
Number of Hedge Funds and Average Portfolio Size

The two solid lines (scale to the left axis) plot the number of 13F-filing hedge funds and the number of self-reporting hedge funds over the period 1980-2008. The two dashed lines (scale to the right axis) plot the average equity portfolio size of self-reporting hedge funds and non-reporting ones. The portfolio size is calculated using the quarter-end holdings disclosed in 13F filings, and is expressed in 2008 constant dollars using the CPI deflator.

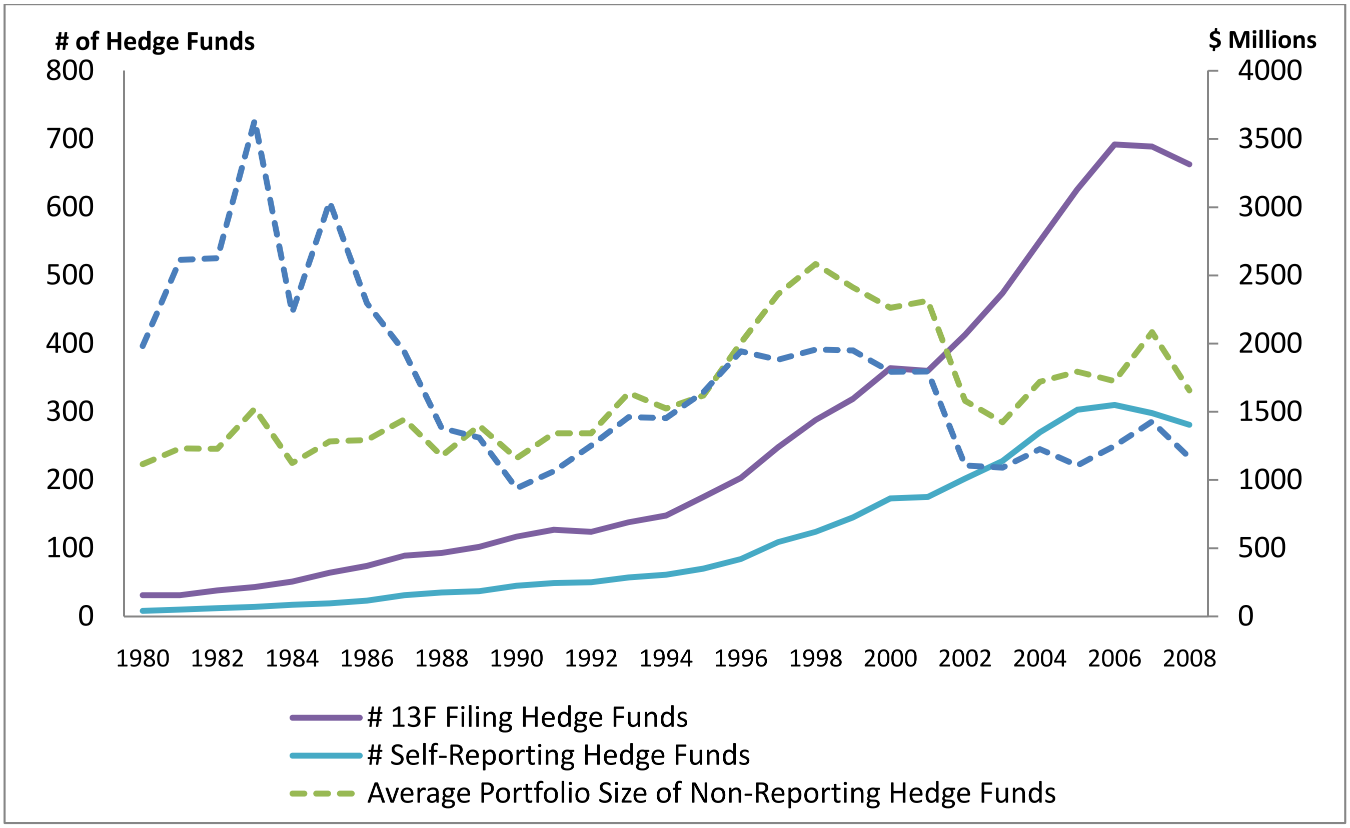
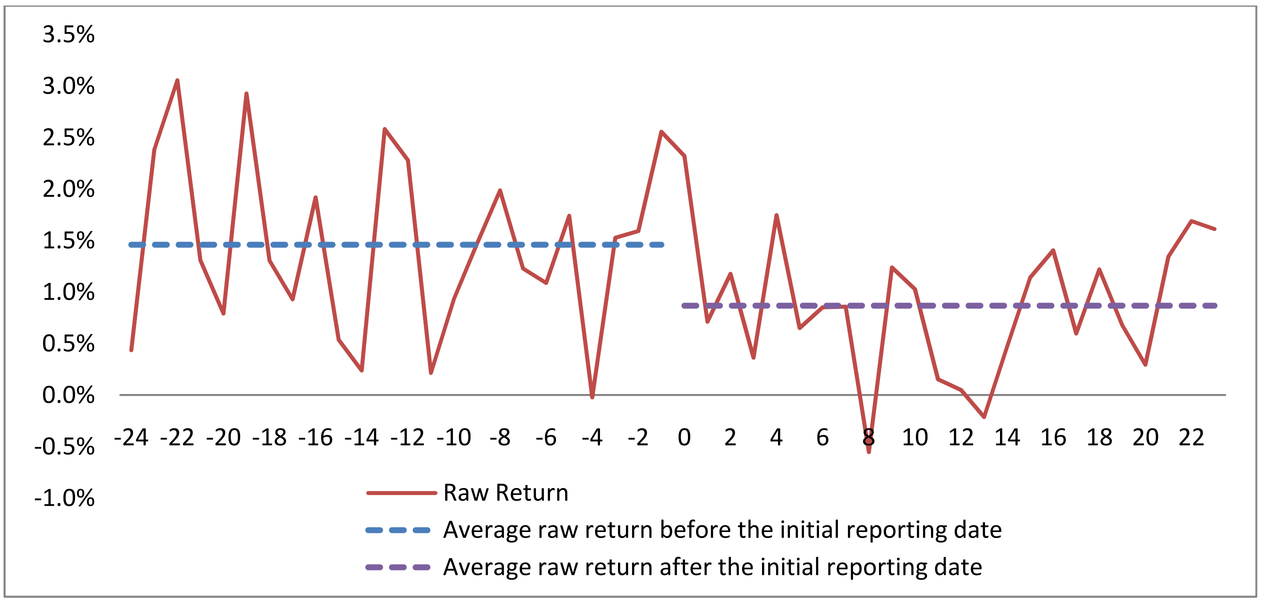


Figure 3

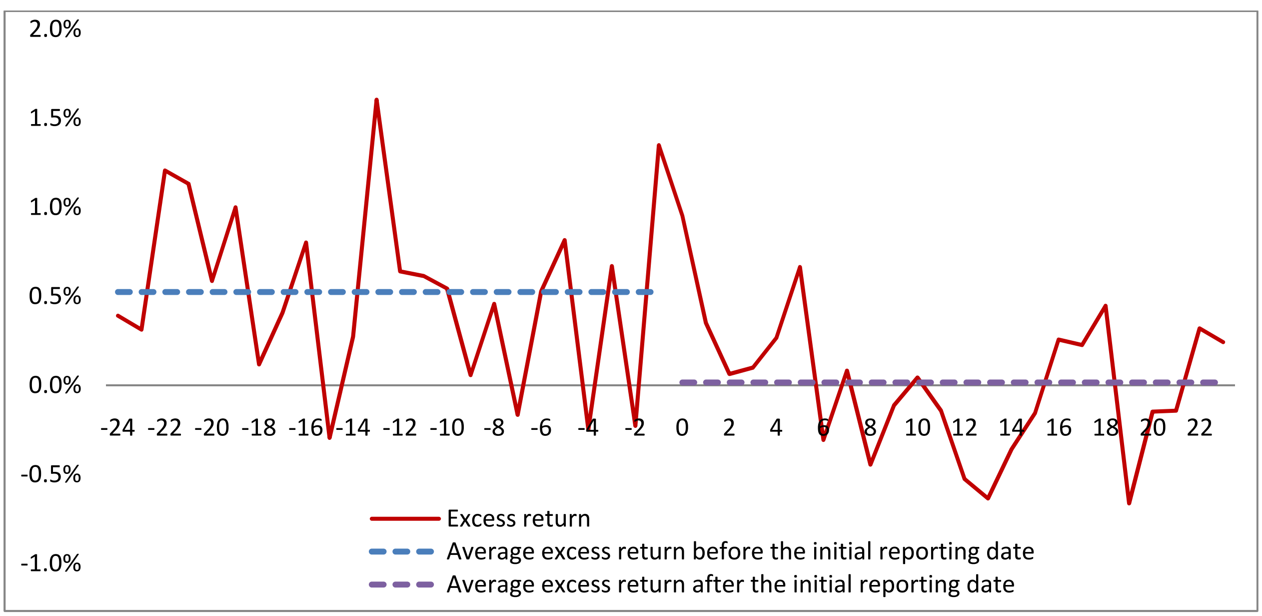
Return Performance around the Initial Reporting Date and the Reporting Termination Date

Panel A shows the time series of monthly raw return for the self-reporting hedge funds from 24 months before the initial reporting date to 24 months afterwards. The imputed portfolio return is constructed by calculating the buy-and-hold return for the month using the most recent past disclosed quarter-end holdings. Panel B shows the time series of monthly excess return for the self-reporting hedge funds from 24 months before the initial reporting date to 24 months afterwards. The excess return is the difference between the imputed portfolio return and the CRSP value-weighted equity market return. Panel C repeats the analyses in Panel A for the reporting termination date. Panel D repeats the analyses in Panel B for the reporting termination date.

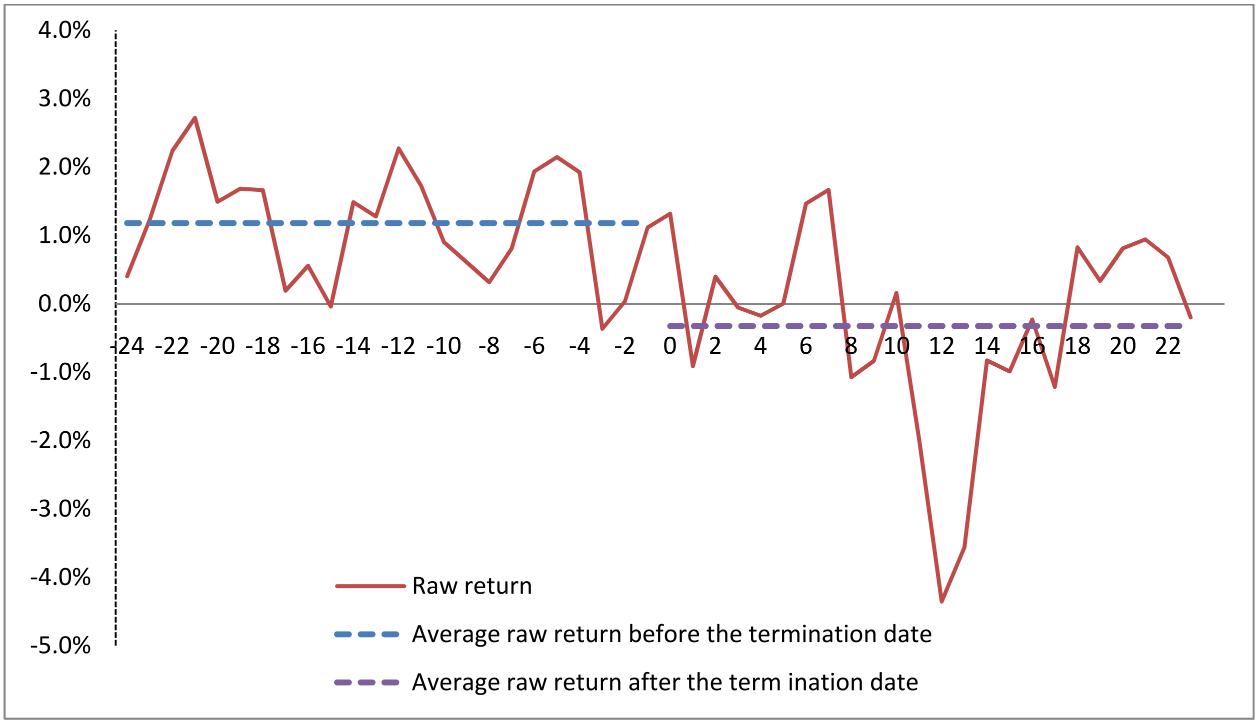
Panel A: Raw Returns around the Initial Reporting Date



Panel B: Excess Returns around the Initial Reporting Date



Panel C: Raw Returns around the Reporting Termination Date



Panel D: Excess Returns around the Reporting Termination Date

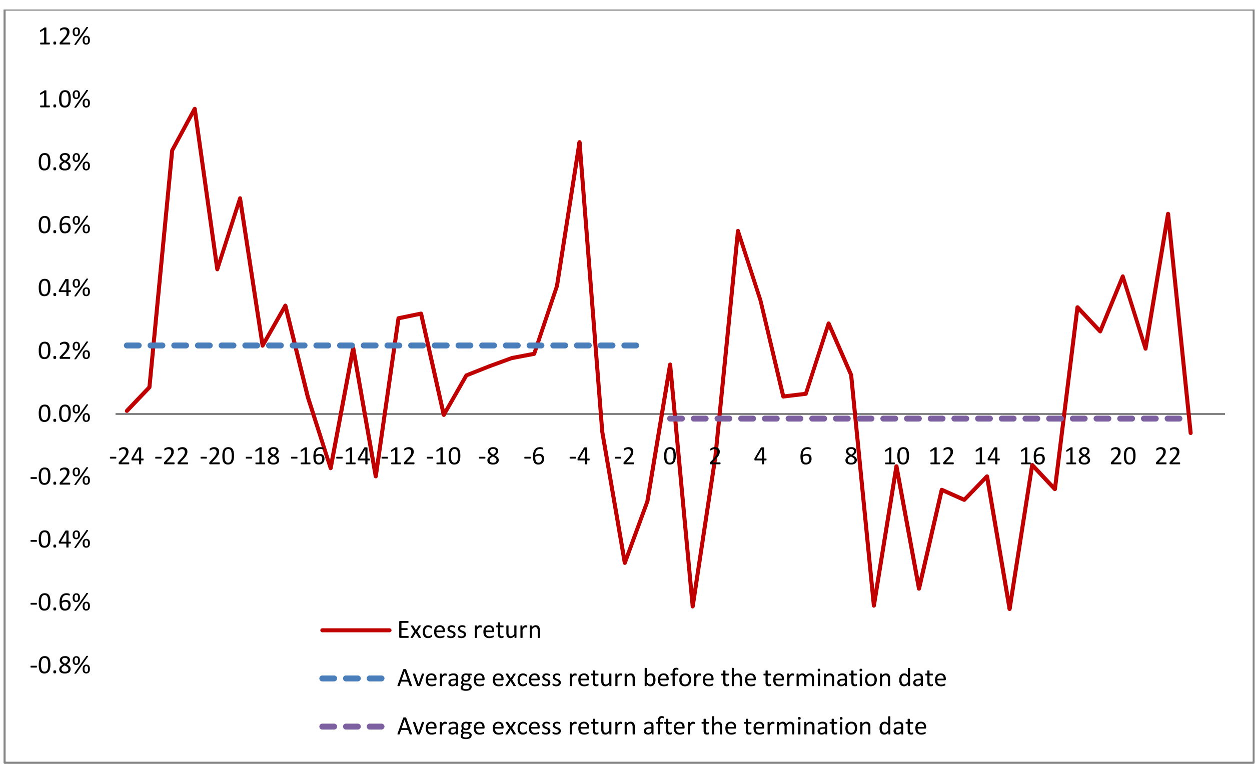


Table 1

Comparison of Hedge Funds with Other Categories of 13F-Filling Institutional Investors

The "Hedge fund" category is manually classified (see section I.A.). The "Bank/insurance" category is a combination of type 1 and type 2 institutions by the classification of Thomson Reuters Ownership Database for 13F filings. The "Mutual fund" category consists of type 3 institutions by Thomson Reuters. The "Investment advisor" category consists of type 4 institutions by Thomson Reuters. The "Other" category includes type 5 institutions by Thomson Reuters (with corrections for coding after 1998). All non-hedge-fund categories exclude classified hedge funds. The portfolio size is calculated as the total value of quarter-end equity portfolio using reported shares and corresponding quarter-end stock prices reported in CRSP. The *Portfolio Herfindahl index* is the Herfindahl index of the disclosed quarter-end equity holdings. The *Monthly return volatility* is the volatility of the imputed portfolio return. The imputed portfolio return is same as defined in Figure 3. The *Annualized portfolio turnover rate* is compounded from the quarterly turnover rates, calculated as the lesser of purchases and sales, divided by the average portfolio size of the last and the current quarter. The *Inception year* is the year of the institution's first appearance in Thomson Reuter (censored at 1980). The *Return in excess of the market* is the same as defined in Figure 3. *One-Factor Alpha* and *Four-Factor Alpha* are the intercepts from CAPM one-factor and Carhart (1997) four-factor models using all available data. *Market Factor*, *SMB Factor*, *HML Factor*, and *Momentum Factor* are estimated factor loadings from Carhart (1997) four-factor model. The t-statistics correspond to the difference between the "Hedge fund" category and other categories. The sample period is 1980-2008. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

	(1) Hedge fund	(2) Bank/insurance	(3) Mutual fund	(4) Investment advisor	(5) Other
<u>Portfolio size ($, million)</u>					
Mean	1041	2609***	6305***	1809***	2431***
t-statistic of the difference	–	−6.58	−5.38	−5.37	−6.76
Median	368	600***	1036***	371	304***
t-statistic of the difference	–	−5.71	−3.71	−0.13	2.97
<u>Portfolio Herfindahl index</u>					
Mean	0.0953	0.0664***	0.0549***	0.0693***	0.1059*
t−statistic of the difference	–	5.23	3.48	4.70	−1.84
Median	0.0465	0.0285***	0.0175***	0.0277***	0.0341***
t-statistic of the difference	–	9.51	14.19	10.77	6.72
<u>Monthly return volatility</u>					
Mean	0.0553	0.0420***	0.0499***	0.0535*	0.0533*
t-statistic of the difference	–	14.28	3.23	1.94	1.96
Median	0.0493	0.0406***	0.0448***	0.0466***	0.0453***
t-statistic of the difference	–	10.02	4.35	2.99	4.02
<u>Annualized portfolio turnover rate</u>					
Mean	0.9162	0.2683***	0.4901***	0.5217***	0.6026***
t-statistic of the difference	–	29.72	13.42	18.40	13.23
Median	0.8149	0.2313***	0.4258***	0.3948***	0.4044***
t-statistic of the difference	–	27.02	11.30	20.19	16.55

	(1) Hedge fund	(2) Bank/insurance	(3) Mutual fund	(4) Investment advisor	(5) Other
Inception year					
Mean	1999	1986***	1987***	1994***	2000**
t-statistic of the difference	–	36.56	25.04	14.07	−2.20
Median	2002	1983***	1985***	1995***	2003*
t-statistic of the difference	–	25.98	23.25	16.65	−1.69
Return in excess of the market					
Mean	0.0008	0.0005	0.0007	0.0000**	0.0001*
t-statistic of the difference	–	0.83	0.04	2.26	1.85
Median	0.0011	0.0007***	0.0007**	0.0008**	0.0008*
t-statistic of the difference	–	2.73	2.17	2.39	1.78
One-Factor Alpha					
Mean	−0.0006	0.0002*	0.0016***	0.0006**	−0.0003
t-statistic of the difference	–	−1.66	−3.44	−2.49	−0.62
Median	−0.0002	0.0002	0.0002	0.0001	−0.0002
t-statistic of the difference		−1.42	−1.18	−0.96	0.10
Four-Factor Alpha					
Mean	−0.0020	0.0008***	−0.0003**	−0.0003***	0.0003***
t-statistic of the difference	–	−6.49	−2.27	−3.87	−5.17
Median	−0.0011	0.0004***	−0.0003**	−0.0002***	0.0000***
t-statistic of the difference	–	−6.01	−2.36	−3.60	−4.40
Market Factor					
Mean	1.0917	0.9573***	1.0439***	1.0418***	1.0398***
t-statistic of the difference	–	10.59	2.71	3.96	4.03
Median	1.0553	0.9628***	1.0309**	1.0209***	1.0014***
t-statistic of the difference	–	10.72	2.16	3.90	5.74
SMB Factor					
Mean	0.3344	−0.0780***	0.1600***	0.1448***	0.1267***
t-statistic of the difference	–	22.60	5.43	10.28	11.82
Median	0.2861	−0.1038***	0.0724***	0.0560***	0.0278***
t-statistic of the difference	–	19.18	7.95	11.06	13.14
HML Factor					
Mean	0.0781	−0.0356***	−0.0953***	−0.0477***	0.0344*
t-statistic of the difference	–	5.42	4.12	6.18	1.88
Median	0.0706	−0.0311***	−0.0599***	−0.0275***	0.0251***
t-statistic of the difference	–	7.18	4.29	7.71	2.98
Momentum Factor					
Mean	−0.0126	−0.0156	−0.0044	−0.0048	−0.0087
t-statistic of the difference	–	0.26	−0.40	−0.64	−0.29
Median	−0.0047	−0.0147	0.0050	−0.0084	−0.0121
t-statistic of the difference	–	1.52	−0.93	0.68	1.16

	(1) Hedge fund	(2) Bank/insurance	(3) Mutual fund	(4) Investment advisor	(5) Other
Number of institutions	1199	804	204	2007	1801

Table 2

Comparison of Return Performance before and after the Initial Reporting Date

This table compares the return measures (defined as in Table 1) for fund companies during the 24-month period before the initial reporting date, and during the 24-month period afterwards. The pooled 48-month period is used to estimate the beta loadings for the one-factor alpha and four-factor alpha. The one-factor alpha and four-factor alpha are coded as missing if there are fewer than 12 observations during the estimation window. The *Difference-in-Difference* is the difference around the initial reporting date between raw returns of reporting and non-reporting hedge funds. Panel A includes the full sample of self-reporting fund companies where the initial reporting dates for some companies are imputed from the first performance dates. Panel B uses only the subsample where such information is accurately recorded. The t-statistics for the differences between the two samples are reported below difference estimates in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

Panel A: Full Sample

	(1) Raw return	(2) Return in excess of the market	(3) One-factor alpha	(4) Four-factor alpha	(5) Difference-in-Difference
Before initial reporting					
5th Percentile	−0.0346	−0.0331	−0.0237	−0.0228	−0.0282
25th Percentile	−0.0013	−0.0041	−0.0038	−0.0043	−0.0063
Median	0.0129	0.0009	0.0018	0.0010	−0.0010
75th Percentile	0.0211	0.0079	0.0073	0.0060	0.0044
95th Percentile	0.0448	0.0290	0.0254	0.0199	0.0275
Mean	0.0115	0.0036	0.0035	0.0021	0.0010
Std. Dev.	0.0299	0.0253	0.0224	0.0175	0.0236
# funds	103	103	102	102	103
After initial reporting					
5th Percentile	−0.0286	−0.0184	−0.0134	−0.0135	−0.0183
25th Percentile	0.0015	−0.0039	−0.0032	−0.0041	−0.0065
Median	0.0084	0.0016	0.0013	0.0005	0.0001
75th Percentile	0.0174	0.0083	0.0072	0.0055	0.0054
95th Percentile	0.0291	0.0173	0.0164	0.0129	0.0170
Mean	0.0063	0.0012	0.0014	0.0003	−0.0010
Std. Dev.	0.0170	0.0118	0.0093	0.0091	0.0114
# funds	103	103	102	102	103

	(1) Raw return	(2) Return in excess of the market	(3) One-factor alpha	(4) Four-factor alpha	(5) Difference-in-Difference
Differences (t-statistics)					
5th Percentile	0.0061	0.0147	0.0103	0.0093	0.0099
	[0.76]	[0.74]	[0.96]	[0.86]	[0.71]
25th Percentile	0.0028	0.0003	0.0007	0.0002	−0.0002
	[0.18]	[0.10]	[0.26]	[−0.06]	[−0.08]
Median	−0.0046	0.0007	−0.0005	−0.0006	0.0010
	[−1.46]	[0.71]	[−0.54]	[−0.37]	[0.57]
75th Percentile	−0.0037*	0.0004	−0.0002	−0.0005	0.0010
	[−1.82]	[0.09]	[−0.27]	[−0.01]	[0.20]
95th Percentile	−0.0157	−0.0118	−0.0090	−0.0070	−0.0105
	[−1.18]	[−0.91]	[−0.85]	[−0.91]	[−1.02]
Mean	−0.0052	−0.0024	−0.0021	−0.0018	−0.0021
	[−1.52]	[−0.88]	[−0.86]	[−0.90]	[−0.80]

Panel B: Subsample of Fund Companies with Accurate Initial Reporting Date Information

	(1) Raw return	(2) Return in excess of the market	(3) One-factor alpha	(4) Four-factor alpha	(5) Difference-in-Difference
Before initial reporting					
5th Percentile	−0.0147	−0.0094	−0.0116	−0.0099	−0.0116
25th Percentile	0.0075	−0.0006	−0.0013	−0.0030	−0.0040
Median	0.0161	0.0033	0.0018	0.0011	0.0012
75th Percentile	0.0238	0.0094	0.0077	0.0048	0.0057
95th Percentile	0.0454	0.0394	0.0255	0.0136	0.0317
Mean	0.0160	0.0059	0.0034	0.0007	0.0024
Std. Dev.	0.0176	0.0141	0.0114	0.0089	0.0118
# funds	77	77	76	76	76
After initial reporting					
5th Percentile	−0.0333	−0.0226	−0.0236	−0.0159	−0.0257
25th Percentile	0.0029	−0.0041	−0.0053	−0.0046	−0.0062
Median	0.0112	0.0001	−0.0014	−0.0008	−0.0014
75th Percentile	0.0174	0.0056	0.0047	0.0035	0.0036
95th Percentile	0.0271	0.0147	0.0119	0.0102	0.0106
Mean	0.0070	−0.0014	−0.0024	−0.0017	−0.0033
Std. Dev.	0.0185	0.0132	0.0135	0.0119	0.0130
# funds	76	76	76	76	76
Differences (t-statistics)					
5th Percentile	−0.0186	−0.0133	−0.0120	−0.0060	−0.0141
	[−1.31]	[−1.21]	[−1.06]	[−0.35]	[−1.27]
25th Percentile	−0.0046	−0.0035**	−0.0040**	−0.0016	−0.0022
	[−1.02]	[−2.36]	[−2.55]	[−1.21]	[−1.20]
Median	−0.0049***	−0.0032**	−0.0033**	−0.0019	−0.0026*
	[−2.88]	[−2.36]	[−2.51]	[−1.33]	[−1.97]
75th Percentile	−0.0064***	−0.0039	−0.0030	−0.0013	−0.0021
	[−3.34]	[−1.56]	[−1.27]	[−1.19]	[−1.36]
95th Percentile	−0.0184*	−0.0248**	−0.0135*	−0.0034	−0.0211**
	[−1.99]	[−2.51]	[−1.74]	[−0.74]	[−2.04]
Mean	−0.0090***	−0.0073***	−0.0058***	−0.0024	−0.0057***
	[−3.09]	[−3.32]	[−2.85]	[−1.42]	[−2.82]

Table 3
Hazard Analysis of the Reporting Initiation

This table presents the hazard analysis of reporting initiation for the subsample of fund companies with accurate initial reporting date information using the Cox proportional hazard model. *Performance*, *Flow*, *Aggregate Flow to Hedge Fund Industry*, and *Market Return* are calculated over [−1, 0] quarters relative to the quarter of reporting initiation. *Portfolio size* (in log), *Turnover*, and *Return volatility* are as defined in Table 1. *Manager age* (in log) is the number of years since the fund company's first appearance in Thomson Reuters. Flow is defined as the change in total portfolio value during the current quarter net of the asset value appreciation/depreciation due to returns, scaled by the portfolio value at the end of the previous quarter. Reported coefficients are hazard ratios which are greater (smaller) than unit when the original coefficients are positive (negative). The z-statistics are calculated using the original coefficients (not hazard ratios) and are reported below coefficient estimates in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

	(1)	(3)	(5)	(7)
Performance Measure	Raw Return	Return in excess of the market	One-factor alpha	Four-factor alpha
Performance	228.13***	190.80***	83.09***	40.60**
	[2.90]	[2.76]	[3.12]	[2.01]
Aggregate Flow to Hedge Fund Industry	0.2509***	0.2517***	0.2619***	0.2659***
	[−4.84]	[−4.85]	[−4.67]	[−4.68]
Portfolio volatility (%)	0.8245***	0.8242***	0.8287***	0.8342***
	[−6.05]	[−6.05]	[−5.89]	[−5.70]
Manager age (log)	0.9243***	0.9238***	0.9236***	0.9216***
	[−3.17]	[−3.19]	[−3.19]	[−3.28]
Portfolio Herfindahl Index	0.1280*	0.1307*	0.1200*	0.1331*
	[−1.74]	[−1.73]	[−1.83]	[−1.78]
Portfolio size (log)	1.0000	1.0000	1.0000	1.0000
	[0.62]	[0.63]	[0.72]	[0.66]
Turnover	0.6650	0.6623	0.6723	0.6975
	[−1.17]	[−1.18]	[−1.14]	[−1.05]
Flow	0.8962	0.8959	0.9183	0.9230
	[−1.14]	[−1.13]	[−0.93]	[−0.90]
Market Return	2.16	475.4**	257.0**	233.0**
	[0.27]	[2.52]	[2.25]	[2.26]
Observations	23618	23618	23618	23619

Table 4

Comparison of Return Performance before and after Reporting Termination

This table presents the same analyses as in Table 2 except replacing the event with reporting termination. The t-statistics are reported below coefficient estimates in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

	(1) Raw return	(2) Return in excess of the market	(3) One-factor alpha	(4) Four-factor alpha	(5) Diff-in-Diff
Before reporting termination					
5th Percentile	-0.0148	-0.0143	-0.0148	-0.0115	-0.0163
25th Percentile	0.0081	-0.0009	-0.0027	-0.0024	-0.0033
Median	0.0133	0.0032	0.0016	0.0019	0.0004
75th Percentile	0.0183	0.0078	0.0069	0.0058	0.0051
95th Percentile	0.0289	0.0178	0.0173	0.0152	0.0132
Mean	0.0117	0.0027	0.0017	0.0015	0.0000
Std. Dev.	0.0132	0.0102	0.0102	0.0092	0.0095
# funds	182	182	182	182	182
After reporting termination					
5th Percentile	-0.0567	-0.0294	-0.0224	-0.0191	-0.0264
25th Percentile	-0.0270	-0.0047	-0.0040	-0.0033	-0.0036
Median	-0.0020	0.0015	0.0013	0.0002	0.0006
75th Percentile	0.0122	0.0060	0.0065	0.0046	0.0061
95th Percentile	0.0302	0.0183	0.0178	0.0148	0.0215
Mean	-0.0070	0.0000	0.0006	0.0000	0.0003
Std. Dev.	0.0263	0.0148	0.0139	0.0120	0.0142
# funds	182	182	182	182	182
Differences (t-statistics)					
5th Percentile	-0.0419	-0.0151	-0.0076	-0.0076	-0.0101
	-3.84	-1.64	-1.01	-1.24	-1.33
25th Percentile	-0.0351	-0.0038	-0.0013	-0.0009	-0.0003
	-11.32	-3.11	-1.30	-0.64	-0.39
Median	-0.0153	-0.0018	-0.0003	-0.0017	0.0003
	-4.64	-1.73	-0.78	-2.57	0.26
75th Percentile	-0.0061	-0.0018	-0.0004	-0.0012	0.0010
	-3.59	-1.69	-0.38	-0.94	0.97
95th Percentile	0.0013	0.0005	0.0005	-0.0003	0.0082
	0.20	0.49	0.44	0.08	1.62
Mean	-0.0188	-0.0027	-0.0011	-0.0015	0.0003
	-8.61	-2.02	-0.86	-1.31	0.24

Table 5
Flow to Fund Companies before and after the Initial Reporting Date

This table reports the results of multivariate regressions that examine the flow to fund companies before and after the initial reporting date. The dependent variable is the net percentage flow to a fund company in a given quarter, where the flow is defined as the change in total portfolio value during the current quarter net of the asset value appreciation/depreciation due to returns, scaled by the portfolio value at the end of the previous quarter. Panel A reports the estimates of equation (1) for the subsample of fund companies with accurate initial reporting date information using three benchmark-adjusted *Performance* measures: return in excess of the market, CAPM one-factor alpha, and Carhart (1997) four-factor alpha. *Q+j*, where *j=-4,…, 4,* is the dummy variable for *j* quarters relative to the quarter of initial reporting. *Portfolio size* (in log), *Turnover*, and *Return volatility* are as defined in Table 1. *Manager age* (in log) is the number of years since the fund company's first appearance in Thomson Reuters. All covariates lag the dependent variable by one quarter. The F-test reported at the bottom of the table test the null hypothesis that sum of coefficients on Q to Q+4 and the sum of coefficients of Q-4 to Q-1 are equal. The F-test reported at the bottom of the table tests the null hypothesis that sum of coefficients on Q to Q+4 and the sum of coefficients of Q-4 to Q-1 are equal. Panel B presents the same analyses as in Panel A for the full sample except examining the flows to fund companies before and after reporting termination. The t-statistics are reported below coefficient estimates in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

Panel A: Effects of Reporting Initiation on Flows

	(1)	(2)	(3)
Performance Measure	Return in excess of the market	One-factor alpha	Four-factor alpha
Q-4	0.0854	0.0960	0.1062
	[1.20]	[1.34]	[1.43]
Q-3	−0.0083	0.0033	−0.0526*
	[−0.17]	[0.07]	[−1.71]
Q-2	0.0650	0.0733	0.0209
	[1.16]	[1.29]	[0.48]
Q-1	0.0280	0.0345	0.0363
	[0.51]	[0.63]	[0.61]
Q	0.0387	0.0470	0.0273
	[0.97]	[1.17]	[0.69]
Q+1	0.1282	0.1345	0.1798**
	[1.56]	[1.64]	[2.08]
Q+2	0.0601	0.0683	0.0760*
	[1.40]	[1.60]	[1.75]
Q+3	−0.0034	0.0026	0.0047
	[−0.06]	[0.04]	[0.08]
Q+4	0.0504	0.0515	0.0522
	[0.65]	[0.66]	[0.67]
Performance	2.4853***	0.8716***	0.8689***
	[16.32]	[7.79]	[6.34]

	(1)	(2)	(3)
Performance Measure	Return in excess of the market	One-factor alpha	Four-factor alpha
Portfolio size	−0.0281***	−0.0273***	−0.0256***
	[−31.00]	[−30.10]	[−27.94]
Manager age	−0.0077***	−0.0082***	−0.0029
	[−4.69]	[−4.99]	[−1.59]
Turnover	0.0098***	0.0114***	0.0119***
	[3.10]	[3.64]	[3.63]
Portfolio volatility	0.3101***	0.2984***	0.3904***
	[5.23]	[5.03]	[6.27]
Non-Reporting Funds Dummy	−0.0042	−0.0026	−0.0018
	[−0.56]	[−0.34]	[−0.23]
Constant	0.2647***	0.2613***	0.2322***
	[25.61]	[25.21]	[21.94]
N	141090	141089	131544
R-squared	0.016	0.014	0.012
F-test			
Point estimate	0.1002	0.1000	0.1435
F-statistics	1.04	1.04	1.85
p-value	0.3074	0.3075	0.17

Panel B: Effects of Reporting Termination on Flows

	(1)	(2)	(3)
Performance measure	Return in excess of the market	One-factor alpha	Four-factor alpha
Q-4	−0.0106	−0.0063	−0.0354
	[−0.30]	[−0.18]	[−1.20]
Q-3	0.0136	0.0163	0.0268
	[0.34]	[0.41]	[0.65]
Q-2	−0.0079	−0.0055	−0.0236
	[−0.34]	[−0.23]	[−1.07]
Q-1	0.0475	0.0526	0.0520
	[1.05]	[1.16]	[1.17]
Q	−0.0568	−0.0584	−0.0654*
	[−1.52]	[−1.57]	[−1.73]
Q+1	−0.0418	−0.0427	−0.0354
	[−1.00]	[−1.02]	[−0.84]
Q+2	−0.0508	−0.0522	−0.0470
	[−1.41]	[−1.44]	[−1.29]
Q+3	−0.0272	−0.0286	−0.0256
	[−0.69]	[−0.73]	[−0.65]
Q+4	−0.1030***	−0.1050***	−0.1003***
	[−2.78]	[−2.82]	[−2.71]
Performance	2.9684***	1.4168***	1.4327***
	[5.66]	[3.60]	[2.89]
Portfolio size	−0.0602***	−0.0587***	−0.0567***
	[−9.30]	[−9.13]	[−8.84]
Manager age	−0.0160*	−0.0188**	−0.0114
	[−1.80]	[−2.11]	[−1.20]
Annualized portfolio turnover rate	0.0026	0.0031	0.0036
	[0.24]	[0.28]	[0.32]
Portfolio volatility	−0.0131	−0.0453	0.0454
	[−0.05]	[−0.19]	[0.18]
Constant	0.5052***	0.5092***	0.4770***
	[11.45]	[11.59]	[10.68]
N	6301	6301	5934
R-Squared	0.048	0.045	0.041

	(1)	(2)	(3)
Performance measure	Return in excess of the market	One-factor alpha	Four-factor alpha
F-test			
Point estimate	−0.3222	−0.3440	−0.2935
F-statistics	8.48	9.56	7.03
p-value	0.0036	0.002	0.008

Table 6
Comparison of Self-Reporting and Non-Reporting Fund Companies

Panel A shows the characteristics of the self-reporting and the non-reporting fund companies. The sample of self-reporting fund companies includes all 13F-filing hedge fund companies that report to the Union Hedge Fund Database (as defined in Figure 1) for some period of time. The sample of non-reporting fund companies includes all 13F-filing hedge fund companies that never report to the Union Hedge Fund Database. The Portfolio *size*, the *Portfolio Herfindahl index*, the *Monthly return volatility*, the *Annualized portfolio turnover rate*, the *Inception year*, and the factor loadings are the same as defined in Table 1. The t-statistics correspond to the difference between the self-reporting fund companies and the non-reporting fund companies. The sample period is 1980-2008. Panel B repeats the analyses in Panel A except using a sample of non-reporting fund companies that is matched with the sample of reporting fund companies through the following procedure: For each self-reporting fund, we crop out the period for which it appears in the Thomson Reuters 13F database. We then find non-reporting fund companies that have 13F data over the same period (or with the maximum overlap). If there are ties in matches, we choose the one that is closest in portfolio size as the self-reporting fund to be the "matching fund." Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

Panel A: Comparison of Fund Characteristics

	(1) Self-reporting fund companies	(2) Non-reporting fund companies	(3) Difference	(4) t-statistics of the difference
Portfolio size ($, million)				
Mean	927	1029	−102	−0.76
Median	415	341	74**	2.12
Std. Dev.	1517	2394	−877**	−2.34
Portfolio Herfindahl index				
Mean	0.0798	0.1056	−0.0258***	−3.24
Median	0.0458	0.0480	−0.0022	−0.50
Std. Dev.	0.0922	0.1547	−0.0625***	−4.27
Monthly return volatility				
Mean	0.0557	0.0556	0.0002	0.11
Median	0.0509	0.0474	0.0036**	2.40
Std. Dev.	0.0213	0.0295	−0.0081***	−3.25
Annualized portfolio turnover rate				
Mean	1.0562	0.7937	0.2626***	7.19
Median	0.9909	0.6243	0.3666***	5.72
Std. Dev.	0.5526	0.5946	−0.0420**	−2.03
Inception year				
Mean	1998.7	1999.0	−0.3	−0.60
Median	2000	2002	−2.0**	−2.48
Std. Dev.	6.6	7.8	−1.2***	−3.08
Market Factor				
Mean	1.0940	1.0900	0.0040	0.18
Median	1.0787	1.0373	0.0414***	2.69
Std. Dev.	0.2652	0.3624	−0.0973***	−3.34

	(1) Self-reporting fund companies	(2) Non-reporting fund companies	(3) Difference	(4) t-statistics of the difference
SMB Factor				
Mean	0.3863	0.2980	0.0883**	2.56
Median	0.3416	0.2383	0.1033***	3.63
Std. Dev.	0.3912	0.5335	−0.1423***	−3.95
HML Factor				
Mean	0.1284	0.0428	0.0855***	2.60
Median	0.1140	0.0407	0.0733***	3.05
Std. Dev.	0.4333	0.5821	−0.1489***	−3.81
Momentum Factor				
Mean	−0.0083	−0.0156	0.0074	0.34
Median	−0.0019	−0.0059	0.0039	0.30
Std. Dev.	0.2740	0.3366	−0.0626*	−1.94
Number of institutions				
	366	554	–	–

Panel B: Comparison of Fund Characteristics – Matched Sample

	(1) Self-reporting fund companies	(2) Non-reporting "matching fund companies	(3) Difference	(4) t-statistics of the difference
Portfolio Size				
Mean	927	846	81	0.84
Median	415	394	21	0.49
Std. Dev.	1517	1133	384**	2.09
Portfolio Herfindahl Index				
Mean	0.0798	0.0709	0.0089	1.41
Median	0.0458	0.0377	0.0082***	2.88
Std. Dev.	0.0922	0.0926	−0.0004	−0.02
Volatility				
Mean	0.0557	0.0550	0.0007	0.43
Median	0.0509	0.0479	0.0030	1.58
Std. Dev.	0.0213	0.0214	0.0000	−0.02
Annualized portfolio turnover rate				
Mean	1.0562	0.6484	0.4079***	11.59
Median	0.9909	0.4389	0.5521***	9.77
Std. Dev.	0.5526	0.5002	0.0524**	2.09
Inception year				
Mean	1998.7	1993.5	5.2***	9.91
Median	2000	1995	5.0***	4.78
Std. Dev.	6.6	7.3	−0.7**	−2.16
Market Factor				
Mean	1.0940	1.0674	0.0267	1.48
Median	1.0787	1.0330	0.0457***	3.12
Std. Dev.	0.2652	0.2250	0.0402	1.54
SMB Factor				
Mean	0.3863	0.2949	0.0913***	3.27
Median	0.3416	0.2153	0.1263***	4.46
Std. Dev.	0.3912	0.3875	0.0037	0.13
HML Factor				
Mean	0.1284	−0.0221	0.1504***	4.65
Median	0.1140	0.0113	0.1028***	3.72
Std. Dev.	0.4333	0.3926	0.0406	1.42
Momentum Factor				
Mean	−0.0083	−0.0085	0.0003	0.02
Median	−0.0019	−0.0109	0.0089	0.71
Std. Dev.	0.2740	0.1796	0.0944***	3.95
Number of institutions				
	366	366	–	–

Table 7
Comparison of Self-Reporting and Non-Reporting Matching Fund Companies

Panel A shows the performance measures of the self-reporting fund companies and the non-reporting fund companies. All return performance measures are calculated at the monthly frequency assuming the companies hold their most recently disclosed quarter-end holdings. *Raw return* is the portfolio returns without adjustment. *Excess return* is the portfolio return in excess of the CRSP value-weighted return. *One-Factor Alpha* and *Four-Factor Alpha* are the intercepts from CAPM one-factor and Carhart (1997) four-factor models using all available data. Panel B repeats the analyses in Panel A except using a sample of non-reporting fund companies that is matched with the sample of reporting fund companies through the procedure described in Table 6. The t-statistics for the differences are reported. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

Panel A: Comparison of Return Performance

	(1) Raw return	(2) Return in excess of the market	(3) One-Factor Alpha	(4) Four-Factor Alpha
Self-reporting fund companies				
5th Percentile	−0.0178	−0.0139	−0.0096	−0.0105
25th Percentile	−0.0019	−0.0011	−0.0010	−0.0021
Median	0.0047	0.0017	0.0016	0.0009
75th Percentile	0.0095	0.0048	0.0047	0.0038
95th Percentile	0.0164	0.0108	0.0117	0.0086
Mean	0.0025	0.0009	0.0014	0.0005
Std. Dev.	0.0112	0.0082	0.0067	0.0059
# funds	366	366	355	355
Non-reporting fund companies				
5th Percentile	−0.0322	−0.0183	−0.0137	−0.0109
25th Percentile	−0.0073	−0.0025	−0.0018	−0.0021
Median	0.0028	0.0011	0.0009	0.0006
75th Percentile	0.0095	0.0041	0.0039	0.0032
95th Percentile	0.0185	0.0120	0.0124	0.0105
Mean	−0.0006	0.0000	0.0005	0.0003
Std. Dev.	0.0178	0.0107	0.0083	0.0081
# funds	554	554	512	512

	(1) Raw return	(2) Return in excess of the market	(3) One-Factor Alpha	(4) Four-Factor Alpha
Differences (t-statistics)				
5th Percentile	0.0144***	0.0043	0.0041	0.0004
	[3.05]	[1.19]	[1.53]	[0.18]
25th Percentile	0.0054***	0.0015**	0.0008	0.0000
	[4.37]	[2.09]	[1.28]	[−0.03]
Median	0.0019**	0.0007**	0.0007	0.0003
	[2.09]	[2.04]	[1.75] *	[1.20]
75th Percentile	0.0001	0.0007	0.0007	0.0006
	[0.11]	[1.19]	[1.41]	[1.31]
95th Percentile	−0.0021	−0.0011	−0.0007	−0.0018
	[−0.74]	[−0.58]	[−0.42]	[−1.23]
Mean	0.0031***	0.0009	0.0009*	0.0003
	[3.21]	[1.44]	[1.85]	[0.54]

Panel B: Comparison of Return Performance – Matched Sample

	(1) Raw return	(2) Return in excess of the market	(3) One-factor alpha	(4) Four-factor alpha
Self-reporting fund companies				
5th Percentile	−0.0181	−0.0146	−0.0113	−0.0105
25th Percentile	−0.0020	−0.0009	−0.0007	−0.0020
Median	0.0047	0.0018	0.0017	0.0010
75th Percentile	0.0095	0.0048	0.0047	0.0039
95th Percentile	0.0156	0.0108	0.0113	0.0092
Mean	0.0024	0.0009	0.0015	0.0005
Std. Dev.	0.0113	0.0082	0.0067	0.0059
# funds	366	366	355	355
Non-reporting fund companies				
5th Percentile	−0.0134	−0.0091	−0.0088	−0.0069
25th Percentile	−0.0025	−0.0013	−0.0009	−0.0012
Median	0.0045	0.0013	0.0014	0.0008
75th Percentile	0.0091	0.0040	0.0048	0.0032
95th Percentile	0.0174	0.0118	0.0119	0.0098
Mean	0.0032	0.0013	0.0017	0.0011
Std. Dev.	0.0096	0.0065	0.0061	0.0051
# funds	366	366	357	357
Differences (t-statistics)				
5th Percentile	−0.0047*	−0.0055*	−0.0025	−0.0036**
	[−1.66]	[−1.81]	[−1.11]	[−2.21]
25th Percentile	0.0004	0.0004	0.0002	−0.0008**
	[0.40]	[0.68]	[0.35]	[−2.34]
Median	0.0002	0.0005	0.0003	0.0002
	[0.24]	[1.05]	[0.65]	[0.54]
75th Percentile	0.0005	0.0008	−0.0001	0.0007
	[0.66]	[1.38]	[−0.24]	[1.20]
95th Percentile	−0.0018	−0.0009	−0.0007	−0.0006
	[−1.28]	[−0.64]	[−0.46]	[−0.40]
Mean	−0.0008	−0.0004	−0.0002	−0.0005
	[−1.06]	[−0.79]	[−0.37]	[−1.32]