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Hedge Funds: Pricing Controls and the Smoothing of Self-reported Returns

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We investigate the extent to which hedge fund managers smooth self-reported returns. In contrast to prior research on the "anomalous" properties of hedge fund returns, we observe the mechanisms used to price the fund's investment positions and report the fund's performance to investors, thereby allowing us to differentiate between asset illiquidity and misreporting-based explanations. We find that funds using less verifiable pricing sources and funds that provide managers with greater discretion in pricing investment positions are more likely to have returns consistent with intentional smoothing. Traditional controls, however, such as removing the manager from the setting and reporting of the fund's net asset value and the use of reputable auditors and administrators, are not associated with lower levels of smoothing. With respect to asset illiquidity versus misreporting, investment style and portfolio characteristics explain 14.0–24.3% of the variation in our smoothing measures, and pricing controls explain an additional 4.1–8.8%, suggesting that asset illiquidity is the major factor driving the anomalous properties of self-reported hedge fund returns. (*JEL* G12, G23, M41, M42)

Several studies find substantial positive serial correlation in the self-reported monthly returns of hedge funds. Getmansky, Lo, and Makarov (2004; hereafter GLM) attribute this "anomalous" serial correlation either to funds holding illiquid assets in their portfolios or to the intentional smoothing of reported

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performance by hedge fund managers. Several recent studies further examine the statistical properties of hedge fund returns to determine the extent of intentional smoothing and misreporting (e.g., Bollen and Pool 2008, 2009; Agarwal, Daniel, and Naik 2009). These studies confirm the anomalous properties of hedge fund returns across the various investment styles, but they observe neither the characteristics of the funds' portfolios nor the discretion that managers possess in the performance reporting process. Hence, the extent to which these anomalous properties are driven by intentional misreporting as opposed to illiquid assets remains an open empirical question.

This question is of economic importance because intentional smoothing can reduce the observed volatility of returns, thereby distorting commonly used risk-adjusted performance measures such as Sharpe ratios and market betas. Fung et al. (2008) find that risk-adjusted performance is a major determinant of hedge fund capital flows. Therefore, fund managers have incentives to increase their funds' observed risk-adjusted performance because they receive a percentage of assets under management (GLM). In addition, actions that delay the reporting of poor performance can decrease the likelihood that investors will immediately withdraw capital, thereby allowing a manager to continue collecting fees and to possibly benefit from future positive shocks to performance. Moreover, intentional smoothing can lead to wealth transfers among entering and exiting investors in the same way that stale prices can lead to wealth transfers among mutual fund investors (Boudoukh et al. 2002).

We investigate the association between hedge funds' pricing controls and the statistical properties of their self-reported returns. We define pricing controls as the mechanisms used to value, verify, and report the level and change in a fund's asset values. Some examples are the use of external parties to value individual investment positions, the use of external service providers to aggregate the values of individual investment positions to form the fund's official net asset value (NAV), and the use of reputable auditors. We posit that returns of hedge funds with more stringent controls over pricing, asset valuations, and reporting are less likely to have statistical properties that are consistent with manipulation after controlling for other fund characteristics such as investment style and portfolio characteristics.

To observe pricing controls and portfolio characteristics, we use a database of hedge fund due diligence reports prepared by the Hedge Fund Due Diligence Group at Analytical Research (HedgeFundDueDiligence.com). These reports provide an extensive array of detail regarding fund characteristics, pricing controls, reporting mechanisms, asset valuation mechanisms, and asset liquidity. We match these due diligence reports with the returns that the sample funds reported to the three largest commercial databases of hedge fund returns. Using these self-reported returns, we estimate three measures of smoothing and find that all three vary systematically with the discretion that fund managers possess in setting and reporting performance. In other words, some of the smoothness in reported returns can be explained by cross-sectional variation in the pricing controls that constrain the managers' discretion in pricing investment positions.

We find that the returns are smoother for funds that provide managers with greater discretion in sourcing the prices used to value the fund's investment positions. For the various sources, we find the lowest level of serial correlation in the returns of funds that source prices primarily from exchange quotes, while we find the highest levels of smoothing in the returns of funds that use either dealer quotes or prices determined by the manager.

We next examine the extent to which who prices the positions is associated with our smoothing measures. We find that returns are smoother for funds in which the manager prices investment positions with no external oversight. The economic magnitude of who prices on smoothed performance is, however, smaller than that of the pricing sources. Nevertheless, the smoothness of reported returns increases in the discretion that the manager possesses in reporting performance.

Finally, more reputable auditors and administrators are not associated with lower levels of smoothing. This finding is not surprising in the hedge fund setting given that the primary responsibility of the auditor is to evaluate the fund's annual financial statement as opposed to evaluating the fund's monthly performance reports. We also do not find lower levels of smoothing in the returns of funds in which the manager is not involved in setting and reporting the fund's official NAV to investors. Overall, the reputation of those who calculate and review the fund's financial statements and NAV plays a relatively smaller role in the reduction of misreporting in monthly returns than do the sources of prices and who prices the fund's investment positions.

With respect to the economic magnitude of intentional smoothing, we find that investment style and portfolio characteristics explain 14.0–24.3% of the variation in our three smoothing measures. Pricing controls explain an additional 4.1–8.8%, suggesting that asset illiquidity is the major factor driving the anomalous properties of self-reported hedge fund returns. Our findings are robust to varying the estimation periods and to examining the effects of pricing controls within investment styles and other portfolio characteristics. We further corroborate our results by examining the distributions of self-reported monthly returns and find, consistent with intentional manipulation, that funds with either dealer-sourced or manager-provided prices are more likely to report slightly positive than slightly negative returns.

This study extends prior research on hedge fund return smoothing by examining whether the association between pricing controls and reported returns is consistent with intentional manipulation. Furthermore, our data allow us to distinguish between asset illiquidity-based and misreporting-based explanations for the anomalous properties in reported hedge fund returns. Consequently, we can directly investigate how managerial discretion in pricing controls affects the properties of hedge fund returns.

Our estimates can assist investors or researchers who use self-reported hedge fund returns to evaluate hedge fund investment opportunities and/or hedge funds as an asset class. Moreover, recent research documents an illiquidity premium in hedge fund returns (e.g., Aragon 2007; Khandani and Lo 2009). These studies use the same smoothing measures to estimate the illiquidity of assets held in hedge fund portfolios. We provide insight into the extent that such an illiquidity premium is associated with the actual illiquidity of the fund's underlying assets as opposed to misreporting by hedge fund managers. Finally, by examining the extent of intentional smoothing, we inform the current debate about proposed changes in hedge fund regulation.

Furthermore, several features make hedge funds a powerful setting to investigate the effect of managerial valuation discretion on reported performance. First, prior research on the effectiveness of pricing controls is limited primarily to publicly traded firms, for which most pricing controls are mandated by regulation and generally accepted accounting principles. In contrast, hedge funds exercise substantial discretion in the use and choice of explicit pricing controls and reporting mechanisms. Second, the managerial incentives to manipulate asset valuations and reported performance are far clearer in investment vehicles than in operating firms (Chandar and Bricker 2002). For example, all hedge fund managers have an incentive to undertake smoothing. In contrast, it is not clear whether all managers of operating firms have incentives to smooth (for a discussion, see Dechow, Ge, and Schrand 2010). We also contribute to the current debate on “mark to market” accounting by demonstrating how pricing controls affect the valuation of investment positions and by highlighting the practical consequences of allowing managers to obtain valuations from apparently objective sources, such as dealer quotes (Laux and Leuz 2009).

1. Sample and Empirical Measures

1.1 Sample

We use several commercial data sources to investigate hedge fund pricing controls and reported returns. We start with a database of 427 due diligence reports prepared by HedgeFundDueDiligence.com over the period 2003–2007. Investors commissioned these reports to assist them in evaluating whether to invest in the funds. HedgeFundDueDiligence.com specializes exclusively in hedge fund due diligence and obtains the information contained in these reports from several sources, including on-site visits and interviews with key staff, discussions with service providers, review of offering memorandums, examinations of public filings and registrations, verifications of key staff backgrounds, and auditor and accounting reviews. Consequently, the HedgeFundDueDiligence.com database overcomes potential concerns related to the fact that commercial databases are based on self-reported fund and manager characteristics. The reports provide an extensive array of detail regarding fund and manager characteristics, portfolio characteristics, pricing controls, and contract terms.

Next, we merge these funds with monthly returns reported on at least one of the three major commercial databases: Lipper-TASS, Hedge Fund Research, and the Center for International Securities and Derivatives Markets (CISDM). Lipper-TASS is commonly used for empirical investigations of hedge fund returns (for a detailed description, see Lo 2008). Hedge Fund Research and CISDM are also used in academic research but to a lesser extent (for discussion of the Hedge Fund Research and CISDM databases and their overlaps in fund coverage with Lipper-TASS, see Agarwal, Daniel, and Naik 2009). When funds report to multiple databases, we obtain returns first from the Lipper-TASS database, then Hedge Fund Research, and finally CISDM. After we require at least 12 months of returns and convergence of the smoothing measures, our sample consists of 260 funds.[1] The distribution of fund returns by commercial database is as follows: Lipper-TASS, 158 funds; Hedge Fund Research, 72 funds; and CISDM, 30 funds.[2] The returns cover the period starting in July 1990 and ending in January 2009, with the mean fund having 66 months of self-reported returns.[3]

1.2 Pricing Controls

We define pricing controls as mechanisms used to value, verify, and disclose the level and change in a fund's investment positions and official NAV. We classify pricing controls into four categories: (i) the sources of prices used to value the fund's investment positions; (ii) who prices the individual investment positions; (iii) who calculates and reports the portfolio's NAV to investors; and (iv) the reputation of the service providers who prepare and review the valuations and financial statements provided to fund investors. Practitioner surveys show that no one method has emerged as a dominant methodology for any asset class and that there is substantial heterogeneity in the pricing of similar assets across various hedge funds (Deloitte Research 2007, p. 16; Managed Funds Association 2009).

We posit that more extensive pricing controls decrease bias and increase the precision of asset valuations and returns reported to hedge fund investors. The use of external parties and objective sources to value investment positions and the use of independent and reputable service providers to report and verify NAV provide the most objective measurements of fund performance, thereby reducing the likelihood of manipulation. Therefore, hedge funds with these

1 The smoothing measures do not converge for ten funds that have at least 12 months of returns.

2 To investigate the robustness of our findings to our sample requirement of at least 12 months of returns, we repeat the analysis for the 259 funds with at least 18 months of returns and for the 256 funds with at least 24 months of returns. The results using these alternative sample criteria are quantitatively similar, suggesting that our findings are not driven by the sample criteria.

3 Prior research finds that there is backfill bias in Lipper-TASS returns from prior to 1996 (Aggarwal and Jorion 2010; Aragon 2007). We rerun the analysis dropping returns prior to 1996, and the results are quantitatively and qualitatively similar to those reported in the tables.

Table 1
Descriptive Statistics

Panel A:

Variable (%)	Overall %
Source of Prices:	
Manager Provided	15.8
Model Based	11.2
Dealer Quotes	36.2
OTC Quotes	4.6
Exchange Quotes	32.2
Who Prices Positions:	
Manager Only	19.6
Collaborative	11.5
Administrator Only	59.6
Dual/Triple Entity	9.3
Other:	
NAV Manager	16.2
Auditor Not Ranked	22.7
Administrator Not Ranked	67.7

Panel B:

Variable (%)	Overall %
Investment Style:	
Convertible Arbitrage	5.0
Emerging Markets	5.0
Equity Market Neutral	3.1
Event Driven	14.6
Fixed Income Arbitrage	5.8
Global Macro	9.6
Long/ Short Equity	28.8
Multi-Strategy	12.7
Fund of Funds	10.8
Miscellaneous	4.6
Portfolio Characteristics:	
1000+ Positions	2.7
200–999 Positions	5.0
100–199 Positions	13.1
40–99 Positions	37.7
1–39 Positions	41.5
Years	34.6
Quarters	34.6
Months	13.5
Weeks	7.7
Days	9.6
Fund Offshore	83.1

This table presents summary statistics of the investment style, portfolio characteristics, and pricing control measures for the 260 hedge funds in our sample. *Manager Provided*, *Model Based*, *Dealer Quotes*, *OTC Quotes*, and *Exchange Quotes* are indicator variables representing the primary source of prices used to value the fund's investment positions. *Manager Only* is an indicator variable for whether the manager prices investment positions with no outside oversight. *Collaborative* is an indicator variable for whether the manager and an outside administrator collaborate on the pricing of positions. *Administrator Only* is an indicator variable for whether only an outside administrator prices the positions. *Dual/Triple Entity* is an indicator variable for whether the fund uses at least one internal service and one external service to price the portfolio. *NAV Manager* is an indicator variable for whether the manager is involved in reporting the net asset value to the fund's investors. *Auditor Not Ranked* and *Administrator Not Ranked* are indicator variables for whether the fund's auditor and administrator are not included in *Institutional Investor*'s annual lists of top hedge fund service providers. Appendix A describes the investment style variables. *1000+ Positions*, *200–999 Positions*, *100–199 Positions*, *40–99 Positions*, and *1–39 Positions* are indicator variables for the average number of positions held in the fund's portfolio. *Years*, *Quarters*, *Months*, *Weeks*, and *Days* are indicator variables for the average holding period of a position. *Fund Offshore* is an indicator variable for whether the fund is domiciled offshore.

more stringent pricing controls are less likely to have returns consistent with manipulation; that is, they have lower levels of serial correlation and smoothing in their self-reported returns.

Table 1, Panel A, reports the descriptive statistics for the least objective pricing controls implemented by our sample funds.[4] Hedge funds obtain periodic

[4] We use the least objective source to best capture the discretion that fund managers have when obtaining asset values. Rather than using an indicator variable for whether the manager has discretion in pricing, we allow the smoothing measures to vary across the various pricing controls in order to evaluate the effectiveness of the various pricing controls. In additional analyses, we use every pricing source used by the fund. Our results are robust to this alternative specification.

valuations of their investment positions from several sources. We find that exchange quotes are used by 31% of the funds (*Exchange Quotes*), while over-the-counter (OTC) quotes are the least objective source used by 5% of the funds (*OTC Quotes*). Exchange-based valuations are based on market prices, such as the last trade or a function of the most recent bid and ask. OTC quotes are determined from actual trades or quotes from participants in OTC markets. These prices are often obtained from published quotes by Bloomberg, Markit, or similar media.

While exchange and market-based quotes are generally considered less biased and more objective, the use of market-based sources for thinly traded and hard-to-value assets can result in unreliable estimates (Deloitte Research 2007, p. 15). For example, in less liquid or thinly traded markets, the practitioner literature documents how investment managers can manipulate reported performance through the strategic buying and selling of assets around periods of valuation (Spurgin 2001; Weisman 2002).

Rather than use market or published quotes, 36% of the funds in our sample determine asset values using quotes solicited directly from broker/dealers (*Dealer Quotes*). Although dealers represent an external source of prices, the use of dealers can allow managers to "dealer-shop," i.e., approach various dealers for quotes and employ the quote that is most consistent with the fund manager's objectives or request and receive a desired quote from the fund's dealer (Scholtes and Tett 2007).

We find that 11% of our sample hedge funds determine valuations by using financial models, whereby investment position values are generated as a function of predetermined inputs, such as changes in observable market, state, or firm indicators (*Model Based*). Finally, 16% of our hedge funds value their investment assets using internally generated prices (*Manager Provided*), whereby fund managers themselves determine the value of investment positions (President's Working Group 2008, p. 47). Manager-based internally generated prices allow managers to exercise professional judgment to incorporate all available information into the asset valuation. This approach, however, provides managers with greater opportunities to manipulate asset values.

Hedge funds also possess discretion with respect to who obtains the values for the funds' investments. The simplest approach is for the fund manager to obtain the prices for each investment position. This approach, however, also provides managers with the greatest discretion to smooth returns (Alternative Investment Management Association 2004, p. 7; Deloitte Research 2007, p. 16). In our sample, 20% of the funds obtain prices internally with no external oversight (*Manager Only*). The remaining hedge funds employ external services to value or verify their investment positions. We find that 12% of funds use collaborative pricing (*Collaborative*), whereby an external pricing service collaborates with the fund manager to determine the value of the fund's investment positions. Moreover, we find that 60% exclusively use external services to price the portfolio (*Administrator Only*). Under this approach, an external party, such as an administrator, determines the price of each invested asset based on the source of prices contracted on in the private placement memorandums (PPMs). Finally, we observe that 9% of funds employ at least one internal source and one external service to price investment positions (*Dual/Triple Entity*). When an external party is involved in this pricing process, it typically verifies the positions in the portfolio with the fund's prime broker.

Although the practitioner literature strongly advocates against allowing fund managers to perform final valuations or to communicate their valuations to an administrator (Lhabitant 2008, p. 100), some authors suggest that for assets with no simple or accepted valuation approach, external pricing services often accept the valuation provided by the fund manager, thereby limiting the benefit of external service providers that value individual investment positions (for a discussion, see McVea 2008).

The entity that sets and reports the fund's official NAV to investors can differ from the entity that prices the individual investment positions. Pricing is done on a position-by-position basis, while NAV is determined by aggregating the prices of the individual investment positions. While pricing takes place on a regular and frequent basis, NAV is typically estimated and reported to investors monthly. The most objective approach is to remove the manager from determining and reporting the fund's official NAV (President's Working Group 2008). Nevertheless, some funds allow the manager to calculate and report NAV alone, while other funds opt for a collaborative approach with a third party, usually an administrator. With respect to our sample, we find that the majority of funds (84%) have no manager involvement in the determination and reporting of NAV.

The final category of pricing controls consists of the quality and reputation of the fund's service providers, specifically its auditor and administrator. Similar to engagements with publicly traded firms, auditors undertake annual audits of hedge funds to ensure that the financial information provided to investors complies with the relevant accounting standards. The role of fund administrators varies substantially across engagements, but they typically provide back-office support, such as performing day-to-day administrative operations and accounting and valuation services and serving as the interface with investors (Securities and Exchange Commission 2003, p. 56). Therefore, hedge fund third-party service providers with valuable reputations have incentives to reduce financial misstatements and returns manipulation.

However, the ability of service providers, such as administrators and auditors, to prevent or detect opportunistic smoothing in monthly returns is likely to be limited by the scope and focus of their duties. For example, although many auditors review the consistency of how funds value investment positions, they do not review the validity of valuations (Lhabitant 2008, p. 105). When auditors do review how funds value their assets, the sampling tests are less comprehensive than the standards for registered investment companies (Securities and Exchange Commission 2003, p. 66). Furthermore, the audit engagement typically focuses on the accuracy of financial year-end valuations, rather than on the month-to-month valuations (Bollen and Pool 2009). Moreover, external administrators may defer to managers with respect to valuations.

To represent the quality and reputation of the service providers employed by our funds, we use annual hedge fund industry-specific rankings of audit firms and administrators. We obtain these rankings from the Alpha Survey of *Institutional Investor*, which is based on voting by industry participants. We use industry-specific rankings because hedge fund auditing could require specialized skills that differ from those required to audit publicly traded firms. All funds in the sample are audited, but there is heterogeneity in auditor quality and reputation. We find that 77% of our funds employ ranked auditors, while 32% of our funds employ ranked administrators.

1.3 Investment Style and Portfolio Characteristics

Asset illiquidity varies with investment style. For example, funds that invest in convertible arbitrage typically hold less liquid assets than funds that follow an equity-based long/short strategy. Therefore, we create indicator variables for the major hedge fund investment styles to control for the mean illiquidity of each style. Because style designations vary across the three commercial databases, we create a series of combined classifications based on ten investment styles, namely: *Convertible Arbitrage, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income, Macro, Long/Short Equity, Multi-Strategy, Fund of Funds, and Miscellaneous.*[5] Appendix A reconciles our classifications with those of the commercial databases.[6] Investment style on its own may not sufficiently control for a fund's liquidity. We therefore hand-collected two additional sets of measures from the due diligence reports. The first set consists of indicator variables that capture the typical holding period of an investment position (*Year, Month, Quarter, Week, and Day*). The second set consists of indicator variables that capture the typical number of the fund's investment positions (*1000+ Positions, 200–999 Positions, 100–199 Positions, 40–99 Positions, 1–39 Positions*). HedgeFundDueDiligence.com evaluated each fund's portfolio to determine the typical holding period and the typical number of positions. These measures provide additional controls for the underlying liquidity of the fund's portfolio. For example, funds that hold small numbers of positions presumably hold less liquid assets than funds that hold thousands of positions.

Table 1, Panel B, provides descriptive detail on the funds' investment styles and portfolio characteristics. With respect to investment style, the most

[5] Although the classifications *Equity Market Neutral* and *Long/Short Equity* appear similar, the TASS and CISDM databases classify them separately.

[6] Several of the funds classified by CISDM as Multi-Strategy also report returns to Lipper-TASS and Hedge Fund Research. For those funds, Lipper-TASS and Hedge Fund Research consistently classify these funds as Fund of Funds. We therefore include the CISDM Multi-Strategy style in our *Fund of Funds* classification.

prevalent type in our sample is *Long/Short Equity* (29%). The remaining styles range from *Equity Market Neutral* (3%) to *Event Driven* (15%). Compared with the sample of hedge funds used by GLM, our distribution of investment styles is similar except that it is more weighted toward Long/Short Equity (18% in their sample).

We find substantial variation in the number of investment positions typically held in the funds' portfolios, with 42% holding fewer than 40 positions, and 3% holding 1,000 or more positions. We also find variation in our sample funds' typical holding periods for the investments, with 10% of the funds holding investment positions for only days, and 35% holding their investment positions for more than a year.

1.4 Pricing Controls Classified by Style and Portfolio Characteristics

Table 2 reports the pricing controls tabulated by the funds' investment styles and portfolio characteristics. We observe substantial variation in pricing controls across funds with similar investment styles and portfolio characteristics. These differences are consistent with practitioner surveys and prior research that finds wide variation in the pricing controls used by hedge funds even within similar investment characteristics (Deloitte Research 2007; McVea 2008). Nevertheless, pricing controls vary with investment style and portfolio characteristics. For example, 92% of the *Convertible Arbitrage* funds in our sample obtain prices primarily from dealers, while 88% of *Equity Market Neutral* funds use exchange-based prices. Therefore, we control for investment style and portfolio characteristics in our multivariate tests. Moreover, in robustness tests, we partition the sample on portfolio characteristics. The extent to which pricing controls are predetermined by a fund's characteristics will reduce the likelihood of observing significant differences in the smoothing measures attributable to pricing controls.

1.5 Smoothing Measures

In this subsection, we discuss the three measures used to investigate smoothing of returns. In general, hedge fund returns exhibit greater serial correlation than do returns on other investment securities and portfolios (for a discussion, see Lo 2008). GLM investigate several potential reasons for the high serial correlations and conclude that the two most likely reasons are asset illiquidity and managerial manipulation. Therefore, our first smoothing measure is the monthly serial correlation in reported returns $\hat{\rho}_1$ (*Serial Correlation*).

To investigate the potential sources of serial correlation in reported returns, GLM assume that hedge funds do not report true economic returns. Instead, funds report a monthly observed return R_t^O that is a weighted average of the funds' true economic returns R_t over the most recent $k+1$ months:

$$R_t^O = \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k} \quad (1)$$

$$1 = \theta_0 + \theta_1 + \cdots + \theta_k. \tag{2}$$

This process is consistent with managers estimating holding period returns on illiquid assets and/or manipulating reported returns. Under this process, serial

Table 2
Pricing Controls Conditional on Investment Style and Portfolio Characteristics

Panel A: Source of Prices

Variable (%)	Manager	Model	Dealer	OTC	Exchange
Investment Style:					
Convertible Arbitrage	0	7.7	92.3	0	0
Emerging Markets	15.4	38.5	46.2	0	0
Equity Market Neutral	0	0	0	12.5	87.5
Event Driven	26.3	7.9	57.9	0	7.9
Fixed Income Arbitrage	0	33.3	60	6.7	0
Global Macro	0	0	32.0	28.0	40.0
Long/Short Equity	1.3	9.3	16.0	4.0	69.3
Multi-Strategy	12.1	15.2	60.0	0	12.1
Fund of Funds	78.6	0	10.7	0	10.7
Miscellaneous	16.7	25.0	16.7	0	41.7
Portfolio Characteristics:					
1000+ Positions	42.9	14.3	0	0	42.9
200–999 Positions	15.4	23.1	30.8	7.7	23.1
100–199 Positions	2.9	8.8	41.1	2.9	44.1
40–99 Positions	11.2	10.2	42.9	3.1	32.7
1–39 Positions	22.2	11.1	31.5	6.5	28.7
Years	30.0	15.6	35.6	1.1	17.8
Quarters	7.8	8.9	38.9	5.6	38.9
Months	5.7	11.4	34.3	11.4	37.1
Weeks	5.0	5.0	45.0	5.0	40.0
Days	16.0	8.0	24.0	4.0	48.0
Fund Offshore	13.9	10.6	39.8	5.1	30.6

Panel B: Who Prices Positions

Variable (%)	Manager	Collaborative	Administrator	Dual /Triple
Investment Style:				
Convertible Arbitrage	23.1	7.7	69.2	0
Emerging Markets	38.5	7.7	53.8	0
Equity Market Neutral	12.5	0	87.5	0
Event Driven	21.1	31.6	28.9	18.4
Fixed Income Arbitrage	40.0	13.3	33.3	13.3
Global Macro	8.0	4.0	68.0	20.0
Long/Short Equity	9.3	8.0	76.0	6.7
Multi-Strategy	24.2	12.1	54.5	9.1
Fund of Funds	21.4	0	75.0	3.6
Miscellaneous	41.7	25.0	25.0	8.3
Portfolio Characteristics:				
1000+ Positions	14.3	28.6	57.1	0
200–999 Positions	30.8	7.7	53.8	7.7
100–199 Positions	8.8	8.8	67.6	14.7
40–99 Positions	19.4	10.2	64.3	6.1
1–39 Positions	22.2	13.0	53.7	11.1
Years	20.0	8.9	63.3	7.8
Quarters	17.8	11.1	62.2	8.9
Months	28.6	17.1	48.6	5.7
Weeks	15.0	5.0	60.0	20.0
Days	16.0	20.0	52.0	12.0
Fund Offshore	14.8	12.5	62.5	10.2

(*continued*)

Table 2
Continued

Panel C: *NAV No Manager, Auditor Ranked, and Administrator Ranked*

Variable (%)	*NAV Manager*	*Auditor Not Ranked*	*Administrator Not Ranked*
Investment Style:			
Convertible Arbitrage	23.1	23.1	76.9
Emerging Markets	7.7	7.7	69.2
Equity Market Neutral	12.5	25.0	62.5
Event Driven	23.7	21.1	65.8
Fixed Income Arbitrage	33.3	20.0	86.7
Global Macro	4.0	20.0	64.0
Long/Short Equity	8.3	18.7	56.0
Multi-Strategy	21.2	30.3	78.8
Fund of Funds	17.9	25.0	75.0
Miscellaneous	25.0	50.0	75.0
Portfolio Characteristics:			
1000+ Positions	14.3	14.3	42.9
200–999 Positions	30.8	30.8	76.9
100–199 Positions	5.9	17.6	61.8
40–99 Positions	21.4	19.4	66.3
1–39 Positions	13.0	26.9	71.3
Years	18.9	27.8	67.8
Quarters	10.0	18.9	71.1
Months	25.7	14.3	74.3
Weeks	15.0	20.0	40.0
Days	16.0	32.0	68.0
Fund Offshore	9.3	17.6	63.0

This table presents distributions of the pricing controls measures conditional on investment styles and portfolio characteristics. Panel A presents the conditional distributions of pricing sources. Panel B presents the conditional distributions of who prices the investment positions. Panel C presents the conditional distributions of *NAV Manager*, *Auditor Not Ranked*, and *Administrator Not Ranked*. Variable definitions are provided in the notes to Table 1.

correlation in observed returns depends on the values of θ_k:

$$Corr(R_t^O, R_{t-m}^O) = \frac{Cov(R_t^O, R_{t-m}^O)}{Var(R_t^O)} = \frac{\sum_{j=0}^{k-m} \theta_j \theta_{j+m}}{\sum_{j=0}^{k} \theta^2} \quad if\ 0 \le m \le k. \quad (3)$$

The process does not affect expected returns. It does, however, lead to observed volatilities that are lower than actual volatilities and observed Sharpe ratios that are greater than actual Sharpe ratios:[7]

$$Var(R) = (\theta_0^2 + \theta_1^2 + \cdots + \theta_k^2)\sigma^2 <= \sigma^2 \quad (4)$$

$$SR^O \equiv \frac{1}{\sqrt{\theta_0^2 + \theta_1^2 + \cdots + \theta_k^2}} \frac{E[R_t]}{\sqrt{Var(R_t)}} >= \frac{E[R_t]}{\sqrt{Var(R_t)}} \equiv SR. \quad (5)$$

[7] Spurgin (2001) and Weisman 2002 describe hedge fund trading strategies that smooth returns with the express purpose of decreasing a fund's observed volatility and increasing its Sharpe ratio. Such strategies may affect both expected returns and volatility.

Therefore, managers who follow such a smoothing process can improve their funds' observed risk-adjusted performance, which has been shown by Fung et al. (2008) to be a major determinant of capital flows. This process is, however, also consistent with the pricing of illiquid assets (Fisher et al. 2003; Kadlec and Patterson 1999). For example, nonsynchronous trading of assets can introduce serial correlation into returns (Dimson 1979; Scholes and Williams 1977). Moreover, GLM find that serial correlation in hedge fund reported monthly returns varies by the liquidity of the fund's investment style.

To estimate the coefficients of the smoothing process, we follow GLM by using maximum likelihood to estimate a moving average model with two lags. Specifically, GLM define the demeaned return process as

$$X_t = R_t^O - \mu. \tag{6}$$

They then assume that actual monthly performance innovations are normally distributed, leading to the following properties:

$$X_t = \theta_0 \eta_t + \theta_1 \eta_{t-1} + \theta_2 \eta_{t-2} \tag{7}$$

$$1 = \theta_0 + \theta_1 + \theta_2 \tag{8}$$

$$\eta_k \sim Nor(0, \sigma_\eta^2). \tag{9}$$

We then transform the estimated coefficients by dividing each $\hat{\theta}_i$ by $1+\hat{\theta}_1+\hat{\theta}_2$ to normalize them. Our second empirical smoothing measure is the first coefficient $\hat{\theta}_0$ (*Theta Coefficient*) from the above estimation. The economic interpretation of this coefficient is the percentage of the month's actual performance innovation that is included in the month's reported return.

As a summary statistic for the smoothing process, GLM suggest using a Herfindahl index to measure the concentration of the θ_k weights:

$$\xi = \sum_{j=0}^{k} \theta_j^2. \tag{10}$$

We use $\hat{\xi}$ estimated with two lags as our third empirical measure of smoothing and refer to it further as the *Smoothing Index*. Lower values of ξ represent greater smoothing.

In the empirical analysis, we use the two measures from GLM in addition to the *Serial Correlation* measure, as they potentially provide greater power in detecting smoothing because they take into account more than one lag. Furthermore, the *Theta Coefficient* provides a simple economic interpretation: the percentage of the month's actual performance innovation that is included in the month's reported return. And, the *Smoothing Index* provides a summary

Table 3
Summary Statistics of Smoothing Measures

Panel A: Summary Statistics

Variable	Mean	SD	Q1	Median	Q3	N
Serial Correlation ($\hat{\rho}_1$)	0.247	0.196	0.111	0.223	0.402	260
Theta Coefficient ($\hat{\theta}_0$)	0.767	0.194	0.623	0.739	0.881	260
Smoothing Index ($\hat{\xi}$)	0.694	0.301	0.475	0.595	0.808	260
Months	79.996	36.868	56.000	72.000	97.500	260

Panel B: Pearson Correlations

	$\hat{\rho}_1$	$\hat{\theta}_0$	$\hat{\xi}$
Serial Correlation ($\hat{\rho}_1$)	1.000	−0.838	−0.757
Theta Coefficient ($\hat{\theta}_0$)		1.000	0.960
Smoothing Index ($\hat{\xi}$)			1.000

This table presents summary statistics of the three smoothing measures used in the empirical analyses. The first measure is the monthly first-order serial correlation ($\hat{\rho}_1$) of reported returns, which we estimate over the entire history of returns available on either the Lipper-TASS, Hedge Fund Research, or CISDM database. To estimate the other two measures, we follow GLM and assume that actual monthly performance innovations are independently and normally distributed but are smoothed using a moving average model with two lags (MA(2)):

$$X_t = \theta_0 \eta_t + \theta_1 \eta_{t-1} + \theta_2 \eta_{t-2}$$
$$1 = \theta_0 + \theta_1 + \theta_2$$
$$\eta_k \sim Nor(0, \sigma_\eta^2).$$

We estimate the MA(2) coefficients using maximum likelihood and then transform the estimated coefficients by dividing each $\hat{\theta}_i$ by $1+\hat{\theta}_1+\hat{\theta}_2$ to normalize them. Our second smoothing measure is the first coefficient $\hat{\theta}_0$ from the above estimation. $\hat{\theta}_0$ represents the percentage of the month's actual performance innovation that is included in the reported return. Our third measure is the Herfindahl index measure of the concentration of the θ_k weights:

$$\xi = \sum_{j=0}^{2} \theta_j^2.$$

Lower values of ξ represent greater smoothing. We winsorize all three measures to the 1st and 99th percentiles. Panel A presents summary statistics for the three smoothing measures, and Panel B presents their Pearson correlations.

measure that takes into account smoothing over the current and two lagged months.

Table 3 presents summary statistics for the three smoothing measures applied to our sample's fund returns. We winsorize all three measures to the 0.5 and 99.5 percentiles to remove the effects of outliers. The mean serial correlation for our sample funds is 0.250, and its standard deviation is 0.300.[8] For comparison, the serial correlation in monthly returns for the S&P 500

[8] Brown et al. (2010) use the same database to examine the determinants of due diligence. They report an average autocorrelation coefficient of 0.15 for returns, while for our sample it is 0.247. There are, however, two differences between our sample and their sample. First, if they were unable to merge a fund in the due diligence database with the commercial databases, they use the returns provided in the due diligence report. In contrast, we use only the returns obtained from the commercial databases to focus on the same data used in prior academic research on the anomalous properties of hedge fund returns. Second, because they focus on the determinants of due diligence, they use only returns reported prior to the due diligence report. In contrast, we use all available returns, reported both before and after the due diligence report, to both maximize the precision of and minimize the small sample bias in our fund-level autocorrelation estimates. For comparison, our sample average autocorrelation of returns reported prior to the due diligence report is 0.175, which is similar in magnitude to their estimate.

Index over the same period is –0.005.[9] The mean *Theta Coefficient* for the funds in the sample is 0.767, implying that, on average, approximately three-quarters of each month's observed return represents an innovation to fund performance. The mean *Smoothing Index* is 0.694, and the standard deviation of this measure is 0.301.

Panel B presents the Pearson correlations among the three measures. Although there are differences in the number of months used in the estimation of the three measures, all three are highly correlated. For example, the correlation between the *Serial Correlation* and *Theta Coefficient* is −0.838, and the correlation between the *Theta Coefficient* and *Smoothing Index* is 0.960. In the empirical analyses, we use all three measures because of differences in interpretation and in the number of months' returns that the measures take into account.

2. Empirical Tests

Consistent with prior research on hedge funds, to identify the effect of pricing controls, we assume that the fund's investment style is constant over the period for which we have self-reported returns. This assumption is reasonable given that fund managers typically start a new fund rather than change the investment style of an existing fund (for a discussion, see Agarwal, Daniel, and Naik 2009). With respect to pricing controls, we assume that they are constant over the sample period because they are typically defined in the fund's PPM and consequently require investor approval to change (Ackermann, McEnally, and Ravenscraft 1999; Cassar and Gerakos 2010).

2.1 Univariate Findings

Table 4 compares the means of the smoothing measures across the various pricing controls. Starting with the source of prices, we find that sources that involve greater managerial discretion have smoother returns than those with less discretion. For example, the returns of funds in which the manager sets prices have a mean *Serial Correlation* of 0.326, while the returns of funds in

9 A potential explanation for serial correlation in hedge fund returns is that funds pursue momentum strategies. To investigate this possibility, we estimated the monthly serial correlation in the momentum factors over the period starting January 1978 and ending September 2008. The monthly serial correlation of the momentum factor over this period is –0.017 and is not significantly different from zero. We obtain the momentum factor from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Another potential source of positive serial correlation is that funds pursue trading strategies that short liquid securities, such as writing out of the money put options. To investigate this potential source, we implemented a trading strategy similar to the "Capital Decimation Partners" strategy described by Lo (2002, 2008). Specifically, the strategy consists of writing put options on the S&P 500 Index that are three or fewer months until expiration and are approximately 7% out of the money. To implement the strategy, we obtained the S&P 500 Index put option data from Option Metrics and ran the strategy from January 1996 through June 2008, which roughly corresponds to our sample period. We find the serial correlation of this strategy to be negative (–0.12) and not significantly different from zero at conventional levels ($p = 0.13$). Nevertheless, this strategy generates negative returns approximately half as often as the S&P 500, which is presumably higher than the goal of such strategies. Therefore, we cannot conclusively rule out the possibility that liquidity bets based on writing index put options drive the positive serial correlation over our sample period.

Table 4
Univariate Tests of Pricing Controls and Smoothing Measures

	Mean		
Variable	$\hat{\rho}_1$	$\hat{\theta}_0$	$\hat{\xi}$
Source of Prices			
Manager Provided	0.326	0.682	0.569
Model Based	0.268	0.747	0.661
Dealer Quotes	0.311	0.706	0.613
OTC Quotes	0.174[a,c]	0.876[a,b,c]	0.846[a,b,c]
Exchange Quotes	0.139[a,b,c]	0.867[a,b,c]	0.836[a,b,c]
Who Prices			
Manager Only	0.278	0.732	0.632
Collaborative	0.294	0.738	0.655
Administrator Only	0.234	0.772	0.702
Dual/Triple Entity	0.204	0.843[d,e]	0.825[d,e]
NAV			
Manager Involved	0.270	0.758	0.680
Manager Not Involved	0.242	0.769	0.697
Auditor			
Not Ranked	0.221	0.773	0.712
Ranked	0.254	0.765	0.689
Administrator			
Not Ranked	0.251	0.763	0.691
Ranked	0.237	0.775	0.701

This table presents means for the three smoothing measures classified by the pricing controls. Differences between means are tested using two-sided *t*-tests. Variable definitions for the pricing controls are provided in Table 1. Variable definitions for the smoothing measures are provided in Table 3.
[a] Significantly different from *Manager Provided* at the .05 level, two-sided test.
[b] Significantly different from *Model Based* at the .05 level, two-sided test.
[c] Significantly different from *Dealer Quotes* at the .05 level, two-sided test.
[d] Significantly different from *Manager Only* at the .05 level, two-sided test.
[e] Significantly different from *Collaborative* at the .05 level, two-sided test.

which prices are exchange based have a mean *Serial Correlation* of 0.139. The means for these two pricing sources are significantly different at the 0.01 level for all three of our smoothing measures. Furthermore, we observe for all three smoothing measures the same ordering in smoothing magnitudes, from most to least: *Manager Provided, Dealer Quotes, Model Based, OTC Quotes, and Exchange Quotes*. The higher levels of smoothing for *Manager Provided* and *Dealer Quotes* are consistent with managers using discretion when personally pricing assets and with managers "dealer-shopping" quotes to smooth reported performance.

When we tabulate the smoothing measures by who prices the fund's investment positions, we find a similar pattern. Pricing controls that provide managers with greater discretion are associated with smoother returns than those that allow managers less discretion or involve greater external oversight. For example, funds in which the manager prices investment positions with no external oversight have a mean *Smoothing Index* (*Theta Coefficient*) of 0.632 (0.732), while the mean *Smoothing Index* (*Theta Coefficient*) for funds that use *Dual/Triple Entity* pricing is 0.825 (0.843). The means for these two alternative pricing controls for all three smoothing measures are significantly different at the 0.05 level.

Finally, we compare the means of the smoothing measures conditional on whether the fund uses a reputable auditor or administrator and whether the manager is involved in setting and reporting the fund's NAV to investors. Means across these traditional internal controls are not significantly different at the 0.10 level.

2.2 Multivariate Findings

Table 5 presents benchmark ordinary least squares regressions modeling our three smoothing measures: *Serial Correlation, Theta Coefficient,* and *Smoothing Index*.[10] These regressions include control variables that proxy for investment style and portfolio characteristics, both of which can be associated with both the choice of pricing controls and the statistical properties of reported returns. We therefore include indicator variables for the investment styles and indicator variables for the typical number of investment positions, and the typical investment durations. We also include an indicator variable of whether the fund is located offshore, because Cumming and Dai (2010) find differences in return characteristics based on this status.

The coefficients on our investment style measures for the *Theta Coefficient* and *Smoothing Index* are similar to those presented by GLM. Consistent with their results, we find negative and significant coefficients on the following investment styles: *Convertible Arbitrage, Emerging Markets, Event Driven,* and *Fund of Funds*. The negative and significant coefficients on *Convertible Arbitrage, Emerging Markets,* and *Event Driven* are consistent with the illiquid securities that underlie these investment strategies. The negative and significant coefficients on *Fund of Funds* are consistent with funds of hedge funds investing in individual hedge funds that hold illiquid securities.[11] Furthermore, the overall explanatory power of our models is consistent with previous empirical evidence (GLM; Lo 2008). For example, our models without pricing controls explain 24.3% of the variation in *Serial Correlation*, 14.6% of the variation in the *Smoothing Index*, and 18.1% of the variation in *Theta Coefficient*.

Table 6, Panels A, B, and C, present regressions modeling our three smoothing measures as a function of the fund's pricing controls. In the presented models, we exclude the pricing control that we posit provides the least discretion for fund managers to manipulate reported performance. Therefore, the coefficient

[10] We estimate the smoothing measures separately from the cross-sectional regressions. An alternative approach would be to estimate them jointly using the generalized method of moments (GMM). Note, however, that the median number of months used to estimate fund-level serial correlation is 72, implying a standard error of 0.014 (Brockwell and Davis 1991), which is smaller than nearly all of the standard errors of the coefficients presented in the first column of Table 5. Given the magnitude of the standard errors, the benefit of using GMM to estimate both the smoothing measure and the cross-sectional regressions is marginal.

[11] Our results are robust to the removal of *Fund of Funds* from the analysis.

Table 5
Benchmark Specification

Dependent Variable	$\hat{\rho}_1$	$\hat{\theta}_0$	$\hat{\xi}$
Convertible Arbitrage	0.288**	−0.280**	−0.398**
	(0.074)	(0.077)	(0.121)
Emerging Markets	0.134	−0.188*	−0.328**
	(0.072)	(0.074)	(0.118)
Equity Market Neutral	−0.030	−0.003	−0.048
	(0.089)	(0.092)	(0.146)
Event Driven	0.166**	−0.198**	−0.292**
	(0.060)	(0.061)	(0.097)
Fixed Income Arbitrage	0.124	−0.175*	−0.302**
	(0.070)	(0.072)	(0.114)
Global Macro	−0.049	−0.027	−0.052
	(0.065)	(0.067)	(0.106)
Long/ Short Equity	−0.002	−0.088	−0.174
	(0.057)	(0.059)	(0.094)
Multi-Strategy	0.172**	−0.210**	−0.302**
	(0.062)	(0.064)	(0.101)
Fund of Funds	0.128	−0.169**	−0.255*
	(0.077)	(0.064)	(0.101)
1000+ Positions	−0.018	−0.007	−0.060
	(0.077)	(0.080)	(0.126)
200–999 Positions	−0.014	−0.020	−0.050
	(0.058)	(0.060)	(0.094)
100–199 Positions	0.029	−0.030	−0.049
	(0.038)	(0.039)	(0.061)
40–99 Positions	0.007	0.004	0.004
	(0.027)	(0.028)	(0.044)
Years	0.004	−0.016	−0.034
	(0.045)	(0.047)	(0.074)
Quarters	0.019	−0.031	−0.044
	(0.044)	(0.045)	(0.072)
Month	0.003	0.033	0.046
	(0.051)	(0.052)	(0.083)
Weeks	−0.004	−0.033	−0.045
	(0.056)	(0.058)	(0.092)
Fund Offshore	0.022	−0.016	−0.014
	(0.031)	(0.032)	(0.050)
Intercept	0.133	0.933**	0.958**
	(0.071)	(0.073)	(0.116)
R^2	0.243	0.177	0.140
Adj. R^2	0.186	0.116	0.076
p-Value	0.000	0.000	0.004
Number of funds	260	260	260

This table presents ordinary least squares regressions that use the smoothing measures as the dependent variable but exclude the pricing controls. The omitted categories are *Miscellaneous*, *1–39 Positions*, and *Days*. Standard errors are reported in parentheses. Variable definitions for the smoothing measures are provided in Table 3.
**, * Significantly different from zero at the .01 and .05 levels, two-sided test.

on each pricing control represents additional smoothing relative to the most stringent pricing control. The rightmost columns present the full model, which includes all of the control variables and pricing controls. We report the series of models to demonstrate how the inclusion/exclusion of the various pricing controls influences the explanatory power of the overall model and that of the control variables. We discuss our findings from Panels A, B, and C jointly below by each of the pricing controls investigated.

Table 6
Multivariate Tests of Pricing Controls and Smoothing Measures

Panel A: Serial Correlation

	Dependent Variable: $\hat{\rho}_1$					
	(1)	(2)	(3)	(4)	(5)	(6)
Source of Prices						
Manager Provided	0.142**					0.141**
	(0.046)					(0.049)
Model Based	0.076					0.082
	(0.044)					(0.046)
Dealer Quotes	0.086*					0.081*
	(0.035)					(0.037)
OTC Quotes	0.071					0.073
	(0.058)					(0.059)
Who Prices						
Manager Only		0.054				0.036
		(0.047)				(0.051)
Collaborative		0.062				0.028
		(0.050)				(0.052)
Administrator Only		0.039				0.031
		(0.041)				(0.041)
NAV Manager			0.002			−0.004
			(0.034)			(0.043)
Auditor Not Ranked				−0.032		−0.036
				(0.028)		(0.029)
Administrator Not Ranked					−0.012	−0.011
					(0.025)	(0.025)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.277	0.249	0.243	0.247	0.244	0.284
Adj. R^2	0.210	0.182	0.183	0.187	0.184	0.198
p-Value	0.000	0.000	0.000	0.000	0.000	0.000
ΔR^2 from pricing controls	0.034	0.006	0.000	0.004	0.001	0.041
p-Value ΔR^2	0.029	0.609	0.944	0.256	0.648	0.208
Number of funds	260	260	260	260	260	260

Panel B: Theta Coefficient

	Dependent Variable: $\hat{\theta}_0$					
	(1)	(2)	(3)	(4)	(5)	(6)
Source of Prices						
Manager Provided	−0.202**					−0.195**
	(0.047)					(0.049)
Model Based	−0.106*					−0.110*
	(0.044)					(0.046)
Dealer Quotes	−0.126**					−0.125**
	(0.035)					(0.037)
OTC Quotes	−0.024					−0.031
	(0.059)					(0.059)
Who Prices						
Manager Only		−0.115*				−0.087
		(0.048)				(0.051)
Collaborative		−0.101				−0.042
		(0.051)				(0.052)
Administrator Only		−0.083*				−0.068
		(0.042)				(0.042)
NAV Manager			0.0002			0.020
			(0.036)			(0.043)
Auditor Not Ranked				0.001		0.004
				(0.029)		(0.029)

(*continued*)

Table 6
Continued

Panel B: Theta Coefficient

	Dependent Variable: $\hat{\theta}_0$					
	(1)	(2)	(3)	(4)	(5)	(6)
Administrator Not Ranked					−0.0004	0.003
					(0.026)	(0.026)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.246	0.198	0.177	0.177	0.177	0.258
Adj. R^2	0.176	0.128	0.112	0.112	0.112	0.169
p-Value	0.000	0.000	0.000	0.000	0.000	0.000
ΔR^2 from pricing controls	0.069	0.021	0.000	0.000	0.000	0.081
p-Value ΔR^2	0.000	0.609	0.996	0.982	0.987	0.007
Number of funds	260	260	260	260	260	260

Panel C: Smoothing Index

	Dependent Variable: $\hat{\xi}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Source of Prices						
Manager Provided	−0.323**					−0.307**
	(0.075)					(0.078)
Model	−0.163*					−0.165*
	(0.070)					(0.073)
Dealer Quotes	−0.202**					−0.196**
	(0.056)					(0.059)
OTC Quotes	−0.050					−0.059
	(0.093)					(0.094)
Who Prices						
Manager Only		−0.198**				−0.161*
		(0.076)				(0.081)
Collaborative		−0.165*				−0.074
		(0.081)				(0.083)
Administrator Only		−0.131*				−0.105
		(0.066)				(0.066)
NAV Manager			−0.002			0.043
			(0.056)			(0.068)
Auditor Not Ranked				0.009		0.015
				(0.046)		(0.046)
Administrator Not Ranked					0.003	0.009
					(0.042)	(0.041)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.213	0.165	0.140	0.140	0.140	0.228
Adj. R^2	0.140	0.092	0.072	0.072	0.072	0.135
p-Value	0.000	0.002	0.007	0.007	0.007	0.000
ΔR^2 from pricing controls	0.073	0.025	0.000	0.000	0.000	0.088
p-Value ΔR^2	0.000	0.069	0.965	0.839	0.937	0.005
Number of funds	260	260	260	260	260	260

Regressions are estimated using ordinary least squares and include the control variables used in Table 5. Standard errors are reported in parentheses. The omitted pricing control categories are *Exchange Quotes* and *Dual/Triple Entity*. Panel A presents results for the *Serial Correlation*. Panel B presents results for the *Theta Coefficient*. Panel C presents results for the *Smoothing Index*.
**, * Significantly different from zero at the .01 and .05 levels, two-sided test.

Examining the full model for Panel A, we find that the source of prices is significantly associated with *Serial Correlation*, with the returns of funds using manager-based sources having serial correlations on average 0.142 higher than the returns of funds that use exchange-based sources. We observe similar findings for our *Theta Coefficient* and *Smoothing Index*—manager-based sources exhibiting significantly greater manipulation in reported returns compared with exchange-based sources at the 0.01 level. Furthermore, the manager-based coefficient of –0.323 for the *Theta Coefficient* implies that Sharpe ratios for funds that use manager-based prices are upwardly biased by approximately 22% (Lo 2008, p. 70). Consistent with exchange-based sources being the most objective or stringent pricing source, the returns of funds that use model, dealer, and OTC sources all have higher levels of smoothing than the returns of funds that use exchange-based sources.

For all three measures, we observe that returns of funds that use manager-based sources have the highest level of smoothing, followed by funds that used dealer-sourced prices. For example, from the *Theta Coefficient* results presented in Panel B, the mean monthly self-reported return of a fund using manager-based sources represents 20% less of the month's actual performance innovation than the mean self-reported return of a fund that uses exchange-based sources, 13% less than a fund that uses dealer sources, and 11% less than model-based sources. For all three measures, the ordering of smoothing from most to least is manager, dealer, model, OTC, and exchange. These findings are consistent with fund managers using discretion to smooth their funds' reported performance. Furthermore, the multivariate and univariate results are consistent with managers dealer-shopping quotes to smooth reported performance. In general, the results for *Theta Coefficient* and *Smoothing Index* are stronger with respect to statistical significance, which is consistent with these measures having greater power to detect manipulation because they take into account multiple lags.

We next examine who prices the fund's investment positions and find evidence consistent with greater discretion resulting in smoother returns. The highest level of smoothing is for funds in which the manager prices investment positions with no external oversight. The economic magnitude of who sets the prices is, however, smaller than that for the pricing sources, with only *Theta Coefficient* and *Smoothing Index* being significantly different between funds in which the manager sets prices with no external oversight and funds that use *Dual/Triple Entity* pricing. Nevertheless, the results across the three smoothing measures are consistent with observed smoothing increasing monotonically in the manager's involvement in the pricing of investment positions.

Consistent with the univariate evidence, we do not find lower levels of smoothing in the returns of funds that use more reputable service providers and that exclude the manager from setting and reporting NAV. These findings suggest that (i) the managerial involvement in the reporting of NAV to the fund investors; and (ii) the relative reputation of those who calculate and review the reported fund investments and performance play a smaller role in the reduction of hedge fund smoothing than pricing controls related to the source and who prices the fund's individual investments. Our results with respect to auditors, administrators, and NAV do not, however, preclude the possibility that these controls affect other outcomes, such as the quality of the fund's annual financial statements or the likelihood of fraud.

Examining the relative contribution of our various pricing controls to the additional explanatory power gained suggests that the source of prices is the most influential in explaining cross-sectional variation in the smoothness of self-reported hedge fund returns. With respect to asset illiquidity versus misreporting, including all of the pricing controls increases the overall explanatory power of the models by 4.1% (*Serial Correlation*), 8.1% (*Theta Coefficient*), and 7.3% (*Smoothing Index*), with the increases for *Theta Coefficient* and *Smoothing Index* significant at the 0.10 level.[12] With respect to the types of pricing controls, the source of prices provides the largest increases in explanatory power, which are significant at the 0.05 level for all three smoothing measures. Nevertheless, the investment style and portfolio characteristics explain between 14% and 24% of the variation in the smoothing measures, while pricing controls explain at most only an additional 9%, suggesting that asset illiquidity is the major factor that drives the anomalous properties of self-reported hedge fund returns.

2.3 Within Typical Holding Period and Typical Number of Positions

To control for liquidity, the results presented in Tables 5 and 6 include indicator variables for the typical holding period and the typical number of positions. An alternative approach is to examine the associations among the pricing controls and smoothing measures within each typical holding period and within each typical number of positions. An advantage of this approach is that it can better hold the liquidity of the fund's portfolio constant.

We therefore partition the funds into three cells of similar size based on the typical holding period of an investment position (Year, $n = 90$; Quarter, $n = 90$; and Month/Week/Day, $n = 80$) and then examine the means of the smoothing measures within each cell. Table 7 presents the results from these tests. Consistent with results presented in Table 6, the returns of funds that price positions using *Manager Provided* and *Dealer Quotes* exhibit significantly higher levels of smoothing than the returns of funds that use *Exchange Quotes*. Moreover, for the Quarter and Month/Week/Day cells, *Model Based* returns are significantly smoother than Exchange Quotes, and in several of the specifications the returns of funds that use *OTC Quotes* exhibit lower levels of smoothing than the returns of funds that use *Manager Provided*, *Model Based*, and *Dealer Quotes*.

With respect to the typical number of positions, we again classify funds into three cells (100+ Positions, $n = 54$; 40–99 Positions, $n = 98$; and 1–39

[12] Note that the R^2 for *Serial Correlation*, *Smoothing Index*, and *Theta Coefficient* with only the pricing controls are 17.3%, 15.2%, and 16.9%. Therefore, the inclusion of the control variables increases the overall explanatory power of the models by 11.1%, 7.5%, and 8.5%.

Table 7
Within Typical Holding Period

Variable	Mean $\hat{\rho}_1$	$\hat{\theta}_0$	$\hat{\xi}$
Panel A: Year			
Source of Prices			
Manager Provided	0.327	0.707	0.604
Model Based	0.239	0.784	0.731
Dealer Quotes	0.286	0.714	0.625
OTC Quotes	0.180	0.895	0.841
Exchange Quotes	0.134[a,c]	0.867[a,c]	0.819[a,c]
Number of funds	90	90	90
Panel B: Quarter			
Source of Prices			
Manager Provided	0.285	0.609	0.501
Model Based	0.288	0.712	0.599
Dealer Quotes	0.373	0.675	0.567
OTC Quotes	0.173[c]	0.812[a]	0.740
Exchange Quotes	0.140[a,b,c]	0.855[a,b,c]	0.819[a,b,c]
Number of funds	90	90	90
Panel C: Month/Week/Day			
Source of Prices			
Manager Provided	0.364	0.658	0.504
Model Based	0.303	0.716	0.594
Dealer Quotes	0.259	0.739	0.659
OTC Quotes	0.174	0.926[a,b,c]	0.936[a,b,c]
Exchange Quotes	0.141[a,b,c]	0.880[a,b,c]	0.863[a,b,c]
Number of funds	80	80	80

This table examines the associations among the pricing controls and the smoothing measures within the typical holding period of an investment position. Within each typical holding period, means are presented for each pricing source.
[a]Significantly different from *Manager Provided* at the .05 level, two-sided test.
[b]Significantly different from *Model Based* at the .05 level, two-sided test.
[c]Significantly different from *Dealer Quotes* at the .05 level, two-sided test.

Positions, $n = 108$). Consistent with results presented in Tables 6 and 7, the means for *Manager Provided* and *Dealer Quotes* are significantly different than those for Exchange Quotes for each of the three smoothing measures. Moreover, for the 1–39 Positions and 100+ Positions cells, the returns of funds that price positions using *Model Based* sources exhibit significantly smoother returns than those that use *Exchange Quotes*. Further, in several of the specifications, the returns of funds that use *OTC Quotes* exhibit lower levels of smoothing than funds that use *Manager Provided*, *Model Based*, and *Dealer Quotes*.

In unreported tests, we cross-classify funds by duration and positions, thereby creating nine cells. Within each cell, we examine the association between the smoothing measures and the measures of who prices and the source of prices. In all nine cells, the returns of funds that price their positions using *Manager Provided* and *Dealer Quotes* sources have higher levels of smoothing than funds that use *Exchange Quotes*.

Table 8
Within Typical Number of Positions

Variable	Mean $\hat{\rho}_1$	$\hat{\theta}_0$	$\hat{\xi}$
Panel A: 1–39 Positions			
Source of Prices			
Manager Provided	0.284	0.690	0.580
Model Based	0.296	0.744	0.660
Dealer Quotes	0.318	0.698	0.606
OTC Quotes	0.175	0.921[a,b,c]	0.922[a,b,c]
Exchange Quotes	0.119[a,b,c]	0.902[a,b,c]	0.907[a,b,c]
Number of funds	108	108	108
Panel B: 40–99 Positions			
Source of Prices			
Manager Provided	0.387	0.683	0.589
Model Based	0.210[a]	0.812	0.759
Dealer Quotes	0.289	0.740	0.654
OTC Quotes	0.179	0.701	0.554
Exchange Quotes	0.144[a,c]	0.849[a,c]	0.802[a,c]
Number of funds	98	98	98
Panel C: 100+ Positions			
Source of Prices			
Manager Provided	0.383	0.647	0.493
Model Based	0.302	0.661	0.524
Dealer Quotes	0.350	0.643	0.532
OTC Quotes	0.165	0.979[a,b,c]	1.018[a,b,c]
Exchange Quotes	0.163[a,b,c]	0.844[a,b,c]	0.785[a,b,c]
Number of funds	54	54	54

This table examines the associations among the pricing controls and the smoothing measures within the typical number of positions. Within each typical number of positions, means are presented for each pricing source.
[a]Significantly different from *Manager Provided* at the .05 level, two-sided test.
[b]Significantly different from *Model Based* at the .05 level, two-sided test.
[c]Significantly different from *Dealer Quotes* at the .05 level, two-sided test.

2.4 Time to Liquidate Portfolio

To further control for portfolio liquidity, we hand-collected from the due diligence reports the managers' estimates of the days required to liquidate their portfolios. This estimate provides an additional control for the underlying liquidity of the portfolio. The disadvantage of this measure is that it reported for only 218 of the sample funds. For these estimates, if a manager provided a range, we use the midpoint.

Table 9, Panel A, presents the descriptive statistics of the estimated days to liquidate. The mean number of days is 48, and the median is 7. To address the skewness of this variable, in subsequent tests we use the natural logarithm of the estimated days to liquidate (*Ln*(*Days to Liquidate*)). Panel B presents the correlations between the natural logarithm of the estimated days to liquidate and the smoothing measures. Consistent with the measure capturing liquidity, its correlation with the smoothing measures are 0.241 with the *Serial Correlation*, –0.295 with the *Theta Coefficient*, and –0.298 with the *Smoothing Index*.

Panel C of Table 9 presents ordinary least squares regressions that examine the association among the smoothing measures and the pricing sources,

Table 9
Time to Liquidate Portfolio

Panel A: Descriptive Statistics

Variable	Mean	SD	Q1	Median	Q3	N
Days to Liquidate	48.00	117.16	2.00	7.00	30.42	218

Panel B: Correlations with Smoothing Measures

Variable	$\hat{\rho}_1$	$\hat{\theta}_0$	$\hat{\xi}$
Ln (Days to Liquidate)	0.241	−0.295	−0.298

Panel C: Multivariate Tests

	Dependent Variable		
	$\hat{\rho}_1$	$\hat{\theta}_0$	$\hat{\xi}$
Ln(Days to Liquidate)	0.005	−0.018*	−0.037*
	(0.008)	(0.009)	0.014
Source of Prices			
Manager Provided	0.129*	−0.180**	−0.291**
	(0.055)	(0.056)	0.090
Model Based	0.058	−0.054	−0.086
	(0.049)	(0.051)	0.081
Dealer Quotes	0.107**	−0.128**	−0.199**
	(0.038)	(0.038)	0.081
OTC Quotes	0.039	0.005	0.001
	(0.064)	(0.065)	0.104
Controls included	Yes	Yes	Yes
R^2	0.325	0.297	0.265
Adj. R^2	0.245	0.214	0.177
p-Value	0.000	0.000	0.000
Number of funds	218	218	218

This table examines the manager's estimate of the number of days required to liquidate the fund's portfolio. Panel A presents descriptive statistics of the estimated number of days required to liquidate the portfolio. Panel B presents the Pearson correlations of the natural logarithm of the estimated number of days and the smoothing measures. Panel C presents multivariate tests of the associations between the pricing controls and the smoothing measures controlling for the manager's estimate of the number of days required to liquidate the fund's portfolio. Regressions are estimated using ordinary least squares and include the control variables used in Table 5. Standard errors are reported in parentheses. The omitted pricing control category is *Exchange Quotes*.
**, * Significantly different from zero at the .01 and .05 levels, two-sided test.

including the estimated days to liquidate as an additional control for liquidity. The coefficient for the natural logarithm of the estimated days to liquidate is in the predicted direction for all three smoothing measures and significantly different from zero at the 0.05 level for the *Theta Coefficient* and the *Smoothing Index*. Furthermore, the coefficients on *Manager Provided* and *Dealer Quotes* are significantly different from zero in the predicted directions, implying that funds that price their positions using prices provided by either the manager or a dealer have smoother reported returns.

3. Robustness Tests

3.1 Manager Skill

A hedge fund investment is effectively a bet on the fund manager's proprietary investment strategies and/or investing skill (Edwards and Caglayan 2001;

Table 10
Manager Skill and Pricing Controls

Variable	Mean $\hat{\alpha}$
Source of Prices	
Manager Provided	0.00545
Model Based	0.01288[a,b]
Dealer Quotes	0.00882[a,b]
OTC Quotes	0.00561[b]
Exchange Quotes	0.00833[a,b]
Who Prices	
Manager Only	0.00916
Collaborative	0.01210[c]
Administrator Only	0.00756[d]
Dual/Triple Entity	0.00809[d]

This table presents mean alphas tabulated by the funds' pricing controls. The alphas were estimated over the life of the fund using Fung and Hsieh's eight-factor model (the returns of S&P 500, the small capitalization minus large capitalization factor, the bond trend following factor, the currency trend following factor, the commodity trend following factor, the stock index trend following factor, the bond market factor, and the credit spread factor).
[a]Significantly different from *Manager Provided* at the .05 level, two-sided test.
[b]Significantly different from *Model Based* at the .05 level, two-sided test.
[c]Significantly different from *Manager Only* at the .05 level, two-sided test.
[d]Significantly different from *Collaborative* at the .05 level, two-sided test.
[e]Significantly different from *Administrator Only* at the .05 level, two-sided test.

Lo 2008). If a fund manager has greater investment ability, both the manager and the investors are likely to have incentives to mask the fund's investment strategy to other investors. One method to reduce the likelihood of outsiders being able to ascertain the fund's investment strategy from reported returns is to allow better managers to smooth returns. But managers choose whether to self-report returns to commercial databases, and higher-ability managers may therefore not report. Nevertheless, in this section we examine whether the pricing controls are associated with manager skill.

To investigate this issue, we first estimate a measure of fund manager skill, namely the alphas estimated over the life of the fund. To calculate fund-level alphas, we regress each fund's monthly returns on Fung and Hsieh's (2001) eight hedge fund risk factors (the returns of S&P 500, the small capitalization minus large capitalization factor, the bond trend following factor, the currency trend following factor, the commodity trend following factor, the stock index trend following factor, the bond market factor, and the credit spread factor).[13] The intercept from each fund-level regression represents the fund's alpha.

Table 10 tabulates the means for sample funds' alphas by the various pricing controls. We observe no obvious association between discretion in reporting, as represented by weaker pricing controls. For example, the mean alpha for

[13] We obtained the factors from David Hsieh's website: http://faculty.fuqua.duke.edu/∼dah7/HFData.htm.

funds in which the manager provides prices is significantly lower than that for funds that use exchange-based prices. And, the alphas for funds in which the manager prices investment positions with no external oversight are not significantly different from the alphas for funds that use *Dual/Triple Entity* pricing. Furthermore, we find similar results when we control for the funds' investment styles and portfolio characteristics. These analyses suggest that manager skill is not a correlated omitted variable.

3.2 Regulatory Jurisdiction

Cumming and Dai (2010) find that variation in hedge fund regulation is associated with the probability that reported returns are marginally positive, as opposed to zero or negative. They argue that greater regulatory oversight provides additional value-added governance, eliminates lower-quality funds, and enables engagement in surveillance. Rather than use an indirect measure of hedge fund manager reporting discretion based on jurisdiction, we directly observe the pricing controls employed by funds and find variation in pricing mechanisms conditional on the funds' domiciles. For example, Cassar and Gerakos (2010) report variation in several internal control choices, including pricing controls, both across and within the fund domiciles in our sample. Nevertheless, we examine the robustness of our findings by including the fund domicile variables in the reported analyses with indicator variables for each country with ten or more funds. Our results are not altered in terms of both magnitude and statistical significance of our main coefficient estimates by the inclusion of country dummies.

3.3 Before and After Due Diligence

We assume that the relation between pricing controls and the smoothing measures is constant over the reporting history of the fund. To investigate this assumption, in unreported tests we repeat the analyses presented in Table 4 using smoothing measures estimated from returns reported before and after the due diligence reports. One issue arises from examining only returns that were reported either before or after the due diligence report—the sample size drops to 161 funds before the due diligence report and to 222 funds after.[14] The results are qualitatively similar to those presented in Table 6 except for the following point. For returns reported before the due diligence report, we find no differences between the smoothing measures estimated before due diligence for who prices the investment positions. An explanation for this result is the smaller sample size and potential differences between established funds and newly established funds that would not be included in the tests based on returns reported prior to the due diligence report.

[14] The before and after sample sizes are not equivalent because we require a minimum of 12 months of returns, and some funds initiated or terminated reporting to the commercial databases within 12 months before or after the due diligence report was completed.

3.4 Alternative Measure of Pricing Sources

In the presented analyses, we employ the least objective pricing source used by the fund to value its investment positions. We use the least objective source to capture the discretion that fund managers have when obtaining asset values. But many hedge funds use multiple sources to obtain prices (Deloitte Research 2007, p. 15; Hedge Fund Working Group 2007, p. 18; President's Working Group 2008, p. 46). We therefore repeat the analyses using every pricing source that the fund employs. We find that the results obtained using this alternative measure are similar to those presented and are consequently not reported.

3.5 Biases in Serial Correlation Estimates

Previous research shows that observed estimates of serial correlation can be systematically biased as a function of the length of the time series observed (Kendall 1954) and the underlying variance (Davis and Peles 1992). To account for these biases, we reestimate the Table 6 regressions with the ratio of one over the number of monthly returns used to estimate the smoothing measures and the variance of the fund's returns as additional control variables. The coefficient on the ratio of one over the number of months is negative for the autocorrelation measure. It is not, however, statistically significant. This insignificance is not surprising given that the mean sample length of returns is 80 months and the standard deviation is 37 months. The coefficient on variance is not significantly different from zero. Furthermore, the pricing control results are unaffected by the inclusion of either of these additional control variables.

3.6 Contract Parameters

Cassar and Gerakos (2010) find that several fund characteristics are associated with the choice of pricing controls and that pricing controls correlate with fee structure. We do not include these contract parameters and characteristics in our main analysis because they are potentially endogenous to pricing controls. Nevertheless, to investigate whether fees and fund characteristics explain the observed correlations in our analysis, we examine the robustness of our results to the inclusion of the following variables: fund age at the time of due diligence; fund size at the time of due diligence; the percentage of the fund's assets under management that the manager receives annually for managing the fund; the percentage of positive profits that the manager receives annually as compensation; whether the fund has an investor lockup; whether the fund has a redemption gate; and whether the fund uses leverage. To summarize this analysis, except for fund age in the *Serial Correlation* specification, not one of these variables is significantly associated with our smoothing measures, and their inclusion does not affect the reported results.

3.7 Event Driven Style

In contrast to the other investment styles, *Event Driven* includes several subcategories that can differ in their underlying liquidity. For example, merger arbitrage can involve more liquid securities than distressed strategies. We therefore pulled the style subcategories from the commercial databases and classified the *Event Driven* funds into three non–mutually exclusive style subcategories: Special Situations, Distressed, and Arbitrage. Funds that do not fit at least one of these three style subcategories were classified as Other Event. We then reran all of our analyses using this finer classification of *Event Driven*, and the results are the same in terms of signs and statistical significance as those reported in the tables.

3.8 The Working Effect

Working (1960) shows that using the average of observed prices over an interval for an end-of-period valuation can induce positive serial correlation. Therefore, a potential explanation for the positive serial correlations is that some managers who hold illiquid assets legitimately believe that an average of the prices over the past interval is an accurate and unbiased estimate of value. Nevertheless, in our setting, several factors appear to mitigate the impact of such an effect on our empirical results. First, the more illiquid the asset, the less likely it is that the manager has access to a frequently reported series of volatile prices to average over. Working (1960) demonstrates that the positive correlation induced by averaging decreases as the number of prices in an interval decreases. Second, we find a similar association between manager-based prices and manipulation when we examine the return imbalance around zero, which is probably not driven by the Working effect. Third, the associations between dealer-based pricing and smoothing are not likely to be driven by such averaging.

3.9 Biased Self-attribution

Prior research finds that the actions of investors and managers may exhibit overconfidence and biased self-attribution (Doukas and Petmezas 2007; Gervais and Odean 2001). With respect to our setting, fund managers can on average believe that they possess superior ability in acquiring assets at prices below their “true” values. To the extent that these beliefs manifest themselves in valuations, they would result primarily in newly acquired investments exhibiting an increase in reported asset values and, potentially, a decrease in reported values once the assets are sold. These effects imply that any such biases would induce negative serial correlation into monthly returns. In contrast, for our sample, we find higher serial correlations in the returns of funds with greater manager discretion, which are also the funds for which valuations are most likely influenced by such biases.

4. Distribution Tests

In this section, we examine whether the likelihood of reporting a small positive versus a small negative return varies with the source of prices. This approach allows us to further validate our identification of the effect of pricing controls on reported returns because the liquidity of the fund's investment is not likely to affect the likelihood of small positive versus small negative returns.

Bollen and Pool (2009) find a significant discontinuity around zero in the pooled distribution of monthly hedge fund returns, with the number of small gains far exceeding the number of small negative returns.[15] Further, they observe that there is no discontinuity in the three months culminating in an audit and that the presence of the discontinuity varies by some fund investment styles. They posit that some managers distort returns and that this distortion is more likely when managers have greater discretion due to the liquidity of their invested assets and when managers are not closely monitored.

Figure 1 presents histograms of reported returns for the full sample and for each pricing source. To determine bin size and statistical significance, we follow Bollen and Pool (2009) and set bin width using Silverman's (1986) heuristic:

$$1.364\alpha \min(\sigma, Q/1.340)N^{-\frac{1}{5}}, \tag{11}$$

in which σ is the sample's standard deviation, Q is its interquartile range, and N is the sample size. We assume a normal distribution and therefore set α equal to 0.776. With respect to statistical significance, we fit a Gaussian kernel and then compare the predicted versus actual number of observations in each bin. We determine significance using the Demoivre–Laplace theorem, which states that the number of observations in each bin is asymptotically normal. Consistent with Bollen and Pool (2009), Panel A shows that when we pool the returns of all funds in our sample, small positive returns are more likely than predicted and that small negative returns are less likely than predicted, with both effects statistically significant at the 5% level.

When we classify funds by the source of prices, we find results similar to those presented in Table 6. Panels D and F show that for *Dealer Quotes* and *Manager Provided*, small positive returns are more likely than predicted and small negative returns are less likely than predicted, with all effects statistically significant at the 1% level except for small positive returns for *Manager Provided*, which is significant at the 10% level. In contrast, Panels B, C, and E show that for *Exchange Quotes*, *OTC Quotes*, and *Model Based*, small positive returns are statistically more likely than predicted at the 5% level, while small negative returns are not statistically different than predicted at the 10% level. In unreported tests, we classify funds by the typical number of positions

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[15] Burgstahler and Dichev (1997) document a similar discontinuity around zero in corporate earnings.

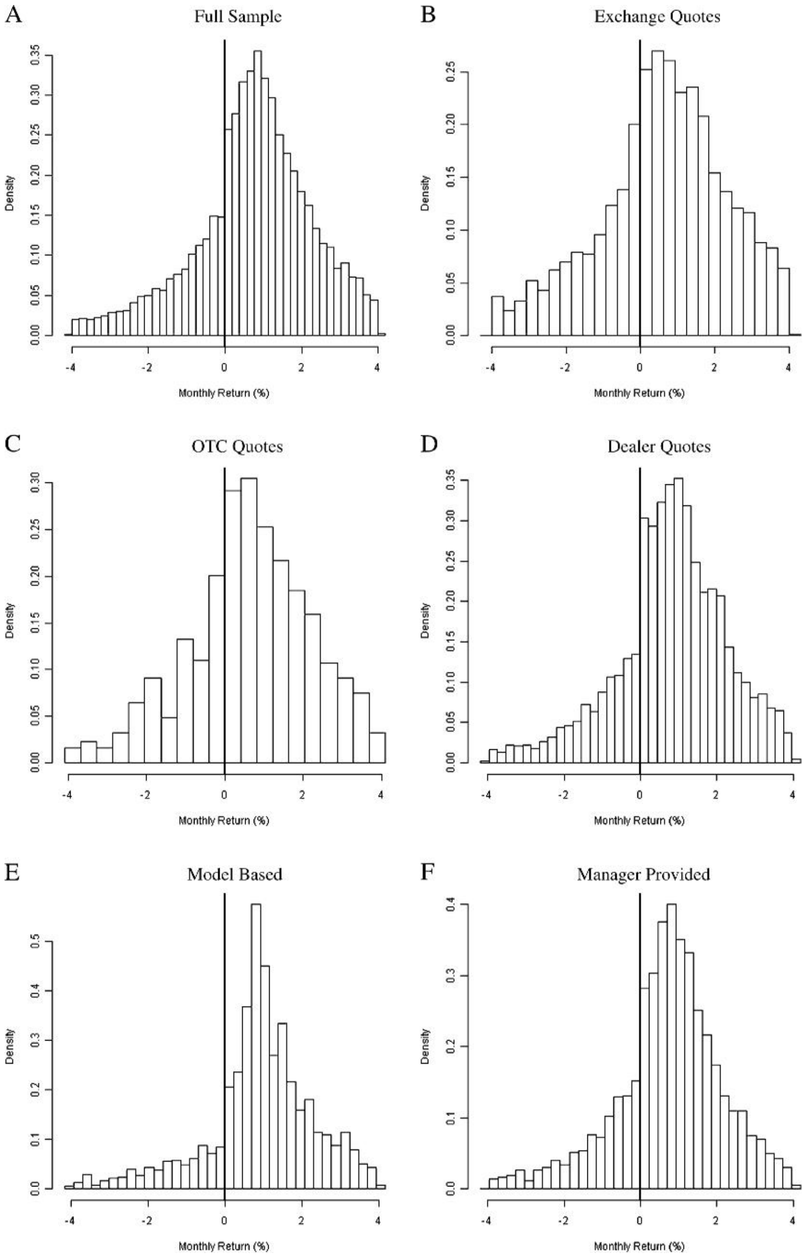

Figure 1

This figure presents histograms of the monthly returns for the full sample (Panel A) and for each source of prices (Panels B, C, D, E, and F). Bin width is determined by using Silverman's (1986) heuristic:

$$1.364\alpha \min(\sigma, Q/1.340)N^{-\frac{1}{5}},$$

in which σ is the sample's standard deviation, Q is its interquartile range, and N is the sample size.

and the typical holding period of an investment position. For these histograms, the magnitude of the jump at zero is similar for all positions and all holding periods, suggesting that asset illiquidity does not drive the discontinuities at zero.

To further investigate the association between pricing controls and the return imbalance, we next examine whether the discontinuity varies by pricing controls at the fund level. We use Bollen and Pool's (2009) fund-specific measure of discontinuity, *Kink*, which is the proportion of positive monthly returns less than 50 basis points minus the proportion of negative returns greater than –50 basis points. Table 11, Panel A, presents descriptive statistics for this measure. As expected, the mean and median of *Kink* are positive (0.062 and 0.051). Furthermore, *Kink* is positively and significantly correlated with *Serial Correlation* (0.129, $p = 0.04$) and negatively but not significantly correlated with *Theta Coefficient* and *Smoothing Index* (–0.099, $p = 0.11$; –0.098, $p = 0.11$).

Comparing the mean *Kink* across the source of prices (Table 11, Panel B), we again find that pricing sources involving greater managerial discretion have returns more consistent with manipulation. For example, the mean *Kink* is 0.083 for funds in which the manager provides prices, while the mean *Kink* for funds in which prices are exchange based is 0.038. Furthermore, funds that use dealer quotes have a mean *Kink* of 0.078. We do not find univariate differences in *Kink* across who prices, whether the manager is involved in reporting NAV, whether the auditor is ranked, and whether the administrator is ranked.

Panel C of Table 11 presents regressions in which *Kink* is the dependent variable. Consistent with the univariate evidence, we find that funds with manager-based prices have a significantly greater discontinuity around zero than funds that use exchange-based sources. Furthermore, the ordering of the coefficients by magnitude is the same as for the smoothing measures: *Manager Provided*, *Dealer Quotes*, *Model Based*, and *OTC Quotes*. Consistent with the univariate tests, the coefficients on the remaining pricing controls are not significantly different from zero.

Overall, the greater return imbalance for funds that use manager-provided and dealer quotes for pricing sources is consistent with the evidence from the smoothing measures, suggesting that managers use discretion to manipulate reported hedge fund performance.

5. Conclusion

We investigate the extent that hedge fund managers smooth self-reported returns. In contrast to prior research on the anomalous properties of hedge fund returns, we observe the mechanisms used to price the fund's investment positions and report the fund's performance to investors, thereby allowing us

Table 11
Return Imbalance Around Zero

Panel A: Descriptive Statistics

Variable	Mean	SD	Q1	Median	Q3	N
Kink	0.062	0.082	0.005	0.051	0.108	260

Panel B: Univariate Tests

Variable	*Kink*
Source of Prices	
Manager Provided	0.083
Model Based	0.053
Dealer Quotes	0.078
OTC Quotes	0.053
Exchange Quotes	0.038[a,b]
Who Prices	
Manager Only	0.071
Collaborative	0.057
Administrator Only	0.058
Dual/Triple Entity	0.075
NAV	
Manager Involved	0.056
Manager Not Involved	0.063
Auditor	
Not Ranked	0.063
Ranked	0.057
Administrator	
Not Ranked	0.062
Ranked	0.061

Panel C: Multivariate Tests

	Dependent Variable: *Kink*					
	(1)	(2)	(3)	(4)	(5)	(6)
Source of Prices						
Manager Provided	0.037					0.045*
	(0.021)					(0.022)
Model Based	0.006					0.011
	(0.020)					(0.021)
Dealer Quotes	0.029					0.033
	(0.016)					(0.017)
OTC Quotes	−0.006					−0.010
	(0.027)					(0.027)
Who Prices						
Manager Only		−0.007				−0.006
		(0.021)				(0.023)
Collaborative		−0.014				−0.028
		(0.023)				(0.024)
Administrator Only		−0.006				−0.015
		(0.019)				(0.019)
NAV Manager			0.015			0.021
			(0.016)			(0.020)
Auditor Not Ranked				0.011		0.009
				(0.013)		(0.013)
Administrator Not Ranked					0.009	0.009
					(0.012)	(0.012)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.120	0.101	0.103	0.102	0.102	0.135
Adj. R^2	0.039	0.022	0.032	0.031	0.031	0.030

(*continued*)

Table 11
Continued

Panel C: Multivariate Tests

	Dependent Variable: *Kink*					
	(1)	(2)	(3)	(4)	(5)	(6)
p-Value	0.084	0.195	0.105	0.109	0.113	0.160
ΔR^2 from pricing controls	0.021	0.002	0.004	0.003	0.003	0.037
p-Value ΔR^2	0.234	0.942	0.328	0.373	0.437	0.487
Number of funds	260	260	260	260	260	260

This table presents tests of whether the return imbalance around zero varies with the fund's pricing controls. To measure the imbalance between small positive and small negative returns, we use Bollen and Pool's (2009) fund-specific measure of discontinuity, *Kink*, which is the proportion of positive monthly returns less than 50 basis points minus the proportion of negative returns greater than –50 basis points. Panel A presents descriptive statistics for *Kink*. Panel B compares the mean levels of *Kink* by pricing control. Panel C presents multivariate tests of whether *Kink* varies by the fund's pricing controls. The control variables used in the multivariate tests are the same as those used in Tables 5 and 6. Standard errors are reported in parentheses. The omitted pricing control categories are *Exchange Quotes* and *Dual/Triple Entity*.

[a]Significantly different from *Manager Provided* at the .01 level, two-sided test.

[b]Significantly different from *Dealer Quotes* at the .01 level, two-sided test.

**, * Significantly different from zero at the .01 and .05 levels, two-sided test.

to differentiate between asset illiquidity and misreporting-based explanations. We find that funds using less verifiable pricing sources and funds that provide managers with greater discretion in pricing investment positions are more likely to have returns that are consistent with intentional smoothing. Traditional controls, however, such as removing the manager from setting and reporting the fund's net asset value and the use of reputable auditors and administrators, are not associated with lower levels of smoothing. With respect to asset illiquidity versus misreporting, investment style and portfolio characteristics explain 14.0–24.3% of the variation in our smoothing measures and pricing controls explain an additional 4.1–8.8%, suggesting that asset illiquidity is the major factor driving the anomalous properties of self-reported hedge fund returns.

This study extends both the hedge fund and financial reporting literatures. We extend the hedge fund literature by estimating the magnitudes of intentional smoothing. These estimates have important implications for investors or researchers who use reported hedge fund returns to evaluate hedge fund investment opportunities and/or hedge funds as an asset class. The study also extends the financial reporting literature by demonstrating how pricing controls affect the "marking to market" of investment positions. Managerial discretion in marking-to-market investment positions is a controversial subject given the issues associated with the recent credit crisis and the implementation of Financial Accounting Standard 157. Our evidence demonstrates the effectiveness of various pricing controls in constraining managerial manipulation of mark-to-market accounting.

Appendix A

Style Classification

Style	Vendor Style	Vendor
Convertible Arbitrage	Convertible Arbitrage	CISDM
	Convertible Arbitrage	TASS
Emerging Markets	Emerging Markets	CISDM
	Emerging Markets	TASS
Equity Market Neutral	Equity Market Neutral	CISDM
	Market Neutral	CISDM
	Equity Market Neutral	TASS
Event Driven	Event Driven Multi-Strategy	CISDM
	Capital Structure Arbitrage	CISDM
	Merger Arbitrage	CISDM
	Option Arbitrage	CISDM
	Event Driven	HFR
	Event Driven	TASS
Fixed Income Arbitrage	Fixed Income	CISDM
	Fixed Income—MBS	CISDM
	Fixed Income Arbitrage	CISDM
	Fixed Income Arbitrage	TASS
Global Macro	Global Macro	CISDM
	Macro	HFR
	Global Macro	TASS
Long/Short Equity	Equity Long/Short	CISDM
	Equity Hedge	HFR
	Long/Short Equity Hedge	TASS
Multi-Strategy	Relative Value Multi-Strategy	CISDM
	Relative Value	HFR
	Multi-Strategy	TASS
Fund of Funds	Multi-Strategy	CISDM
	Fund of Funds	HFR
	Fund of Funds	TASS
Miscellaneous	Dedicated Short Bias	TASS
	Commodity Pool Operator	CISDM
	Managed Futures	TASS
	Equity Long Only	CISDM
	Regulation D	CISDM
	Sector	CISDM
	Single Strategy	CISDM
	Systematic	CISDM

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