Illiquidity Premia in Asset Returns: An Empirical Analysis of Hedge Funds, Mutual Funds, and U.S. Equity Portfolios*

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This Revision: June 24, 2009

Abstract

We establish a link between illiquidity and positive autocorrelation in asset returns among a sample of hedge funds, mutual funds, and various equity portfolios. For hedge funds, this link can be confirmed by comparing the return autocorrelations of funds with shorter vs. longer redemption-notice periods. We also document significant positive return-autocorrelation in portfolios of securities that are generally considered less liquid, e.g., small-cap stocks, corporate bonds, mortgage-backed securities, and emerging-market investments. Using a sample of 2,927 hedge funds, 15,654 mutual funds, and 100 size- and book-to-market-sorted portfolios of U.S. common stocks, we construct autocorrelation-sorted long/short portfolios and conclude that illiquidity premia are generally positive and significant, ranging from 2.74% to 9.91% per year among the various hedge funds and fixed-income mutual funds. We do not find evidence for this premium among equity and asset-allocation mutual funds, or among the 100 U.S. equity portfolios. The time variation in our aggregated illiquidity premium shows that while 1998 was a difficult year for most funds with large illiquidity exposure, the following four years yielded significantly higher illiquidity premia that led to greater competition in credit markets, contributing to much lower illiquidity premia in the years leading up to the Financial Crisis of 2007–2008.

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1 Introduction

One of the most important characteristics of a financial asset is the ease with which it can be traded, i.e., its liquidity. Although fundamental to the very meaning of an "asset", liquidity is remarkably difficult to define, and even more challenging to measure. At the most intuitive level, a liquid asset is one that can be: (1) traded quickly; (2) traded in large quantities; and (3) traded with little impact on the prevailing price. While appealing from a practitioner's perspective, these qualitative traits do not easily lend themselves to quantitative analysis, hence it is not a simple task to use these traits to identify illiquidity risk or to estimate an illiquidity premium from asset-return data.[1] However, the need for an easily computed liquidity measure has never been more urgent as investors, portfolio managers, and regulators struggle to address the cascade of repercussions from the so-called "toxic assets" at the center of the Financial Crisis of 2007–2008.

One commonly cited measure of liquidity is the magnitude of the bid/offer spread, measured as a percentage of the average of bid and offer prices (see, for example, Amihud and Mendelson, 1986). However, this measure can only be applied to those securities for which we observe regular bids and offers, i.e., those that trade on organized exchanges and with designated marketmakers. Since these are, by construction, among the most liquid securities of all, to limit our attention to this narrow class seems counter to our primary objective of developing a broadly applicable measure of illiquidity risk.

Another possible liquidity measure is trading volume—either dollar volume or percentage turnover (see, for example, Brennan, Chordia and Subrahmanyam, 1998, and Lo and Wang, 2000). While this measure can be applied more broadly in principle than the percentage bid/offer spread, it is impractical because volume data is rarely available and virtually impossible to hand-collect for hedge-fund investments and other private partnerships.

However, in their studies of hedge-fund returns, Lo (2001) and Getmansky, Lo, and Makarov (2004) observe that illiquid hedge funds such as private-equity and emerging-market debt funds typically have large positive return autocorrelation, while more liquid hedge funds

[1] A short digression on terminology may be appropriate here. While much of the literature on liquidity refers to a "liquidity premium", we prefer to use the term "illiquidity premium" because, in the same way that risk (not safety) requires a premium, illiquidity is the undesirable characteristic that, *ceteris paribus*, requires additional compensation for investors to willingly hold a security with such a characteristic.

such as equity market-neutral and managed futures funds have statistically insignificant return autocorrelations. Accordingly, they argue that autocorrelation can serve as a proxy for liquidity. Their logic is disarmingly simple: in a frictionless market, any predictability in asset returns can be immediately exploited, eliminating such predictability as Samuelson (1965) first observed in his paper "Proof That Properly Anticipated Prices Fluctuate Randomly".

Of course, the more formal general-equilibrium extensions by LeRoy (1973) and Lucas (1978) that account for time-varying expected returns due to risk aversion and other factors imply only that marginal-utility-weighted prices are martingales. But over sufficiently short holding periods, expected returns should not vary much, hence the martingale hypothesis should be a reasonable approximation for prices, implying serially uncorrelated returns. Therefore, if returns exhibit statistically significant autocorrelation, either the market for that security is grossly inefficient, or some market friction is preventing arbitrageurs from exploiting such predictability. Lo (2001) and Getmansky, Lo, and Makarov (2004) argue that this friction is generally an indication of some form of illiquidity.

In this paper, we test their argument explicitly by analyzing the relation between liquidity and autocorrelation among a broad sample of hedge funds, mutual funds, and portfolios of U.S. stocks. We begin by confirming that autocorrelation is indeed a proxy for illiquidity by showing that a hedge fund's redemption-notice period—a direct and measurable form of illiquidity specified through contractual terms—is positively related to its return autocorrelation. In particular, using over 2,900 hedge funds in the Lipper/TASS Database from 1986 to 2006, a cross-sectional regression of individual funds' redemption-notice periods against return autocorrelation yields a positive slope coefficient with a t-statistic of 14.8.

Having established the fact that liquidity can indeed be captured by return autocorrelation, we then turn to the task of estimating the risk premium associated with illiquidity by applying the standard asset-pricing approach of computing expected-return spreads between the extreme quintile portfolios of assets sorted according to their autocorrelations. Among hedge funds, this spread—which can be viewed as an illiquidity premium—is 3.96% on an annualized basis. Within hedge-fund categories, those that are known to involve illiquid assets, e.g., Convertible Arbitrage and Fixed Income Arbitrage, exhibited the largest illiquidity premia (9.91% and 7.08%, respectively), but even the Managed Futures category—usually considered among the most liquid of hedge funds—exhibited an illiquidity premium of about

4.91%, suggesting significant variability in liquidity among such funds.

For our sample of mutual funds and U.S. equity portfolios—by construction, highly liquid investment vehicles—the only group that exhibit any statistically significant illiquidity premia are the fixed-income mutual funds, for which the spread is 2.74%.

Finally, we analyze the time-series evolution of these illiquidity premia over the period from 1998 to 2006, and show that while 1998 was a difficult year for funds with significant illiquidity exposure, the four years subsequent to 1998 were filled with great returns for these funds. However, we argue that from 2002 to 2006, increased competition and higher levels of leverage eventually reduced the illiquidity premium to near zero.

In Section 2, we provide a brief review of the literature, and in Section 3 we summarize the data used throughout our study. Section 4 contains the cross-sectional regression analysis of hedge-fund redemption periods and return autocorrelation. In Section 5, we report the results of our expected-return spreads for autocorrelation-sorted portfolios, and in Section 5.5, we investigate the time-series properties of the illiquidity premia since 1998. We conclude in Section 6.

2 Literature Review

At the most basic level, the notion of liquidity is related to the ease of trading a security. While the standard frictionless asset-pricing models cannot address this issue directly, a number of extensions of the neoclassical framework have been proposed to account for trading activity. For example, the seller of a hard-to-trade asset may incur an inventory cost that arises because a buyer may not be present at the time a seller needs to cash out, and the seller may be forced to enter into a transaction with a designated marketmaker. The marketmaker will charge the seller a fee by giving the seller an amount less than the fair price of the security to take on the risk of holding that security until a buyer is found. The connection between marketmaking activity and transaction costs has been considered in many studies including Grossman and Miller (1988), Amihud and Mendelson (1986, 1988), and Biais (1993). Search friction, associated with trading assets that lack a centralized market, is another approach to incorporating illiquidity into asset-pricing models. Duffie, Garleanu and Pedersen (2005, 2007) model such search and bargaining features and derive their impact on asset prices.

Private information has been proposed as another source of illiquidity risk in asset-pricing models. In any transaction, designated marketmakers—who are required to trade with *all* counterparties—are disadvantaged when trading against more informed agents and will therefore increase their bid-offer spreads to protect against such adverse selection. Naturally this effect is most pronounced among securities that trade less frequently, and, therefore, have a slower information discovery process. This view of transaction costs has been developed in Glosten and Milgrom (1985), Easley and O'Hara (1987), and Easley, Hvidkjaer, and O'Hara (2002), among others. Amihud, Mendelson, and Pedersen (2005) provide a comprehensive review of this literature.

More generally, the literature on the impact of illiquidity on asset prices seems to divide into two distinct perspectives. One perspective is to view liquidity as just another deterministic characteristic of a security such as a transaction cost, and because economic agents' preferences are based on an asset's net return, net of transaction costs, assets with higher costs must offer a higher gross expected return, ceteris paribus. This is the approach taken by Amihud and Mendelson (1986), Eleswarapu and Reinganum (1993), Eleswarapu (1997), and Aragon (2004).

Alternatively, liquidity can be viewed as a systematic risk factor. From this perspective, a deterministic transaction cost is not sufficient to capture liquidity risk. As argued by Chacko (2005), if trading costs exist but are not time-varying, the buyer or seller of a security can incorporate these costs into his decision-making process, and such costs should have no first-order effects on asset prices in equilibrium. Along this line of reasoning, theoretical models such as Vayanos (1998) and Vayanos and Vila (1999) have shown that illiquidity-related costs can only be a second-order determinant of asset prices since bid-offer spreads are so small relative to typical equilibrium risk premia. Alternatively, some models predict that illiquidity should not matter in equilibrium because agents would simply reduce the impact of such costs by adjusting their portfolios less frequently. But, as noted in Hasbrouck (2005), the extent to which agents actually do this is unclear, since observed levels of trading volume are much higher than those predicted by standard equilibrium asset-pricing models.

But if trading costs are time-varying and unknown in advance, then their impact on equilibrium asset-prices can be more substantial because of the additional risks they impose on investors if such risks were not diversifiable or readily insurable. Pastor and Stambaugh

(2003) and Acharya and Pedersen (2005) have examined the systematic nature of illiquidity risk.

But as Hasbrouck (2005) observes, these two perspectives are not mutually exclusive. Cross-sectional and deterministic variation in liquidity can be priced as a simple characteristic, while stochastic and systematic variation over time may give rise to a risk factor. But while these two perspectives may both apply, they have very different empirical implications. In estimating a security's liquidity at a point in time, if such costs are assumed to be relatively stable and non-stochastic, then a reasonable approach is to compute its average trading cost relative to a simple benchmark over the recent past. However, under the risk-factor perspective, a much longer time series is needed, long enough to be able to estimate its stochastic properties with a reasonable degree of precision.

These two distinct perspectives, and the challenges they pose for empirical work, may explain why there has been relatively little consensus on how to measure illiquidity risk. One manifestation of these challenges is the irony that the literature most directly focused on measuring liquidity—the market microstructure literature—relies almost exclusively on transactions data from standardized exchange-traded equity securities, among the most liquid assets in the world. While transactions costs still matter even in these highly competitive markets, their stochastic properties may have little bearing on the illiquidity risk premia that characterize the broader universe of investment opportunities available to investors.

A major advantage of our study—and the main reason we are able to detect larger and more dynamic illiquidity premia—is that we make use of hedge-fund returns. It is well known that certain types of hedge funds invest in illiquid assets and generate a significant portion of their returns from providing liquidity to the market, i.e., from bearing illiquidity risk. Therefore, hedge-fund returns should be an ideal place to search for illiquidity premia. Lo (2001, 2002) and Getmansky, Lo, and Makarov (2004) were among the first to document the fact that the monthly returns of many hedge funds are highly serially correlated, with autocorrelations as high as 60% in some cases—and that such persistence is due to the presence of illiquid assets in which the hedge funds invested.

Their argument is based on Samuelson's (1965) observation that forward-looking asset prices—formed rationally and using all publicly available information—should approximate a random walk with respect to that information.[2] If not, then it should be possible to construct a trading strategy that exploits deviations from the random walk. Apart from issues such as risk aversion and time-varying expected returns—which should not be as relevant at shorter time scales such as with monthly returns—hedge funds should exhibit the most random returns of all, given their broad and unrestricted investment mandates, their incentives for producing positive returns, and the competitiveness of the industry. Yet Lo (2001, 2002) and Getmansky, Lo, and Makarov (2004) document much larger deviations from the random walk for certain hedge funds than for the returns of typical individual U.S. equities. They conclude that the only reason such predictability persists in hedge-fund returns is that it *cannot* be exploited in the same way that such predictability can be exploited in publicly traded securities.[3] And the most likely reason why such predictability cannot be exploited is that some of the underlying securities cannot easily be traded to take advantage of the persistence in monthly returns, i.e., they are too illiquid to be traded the same way that exchange-listed securities are traded.[4]

Illiquidity in hedge-fund returns has several other potentially important implications. For example, Asness, Krail and Liew (2001) show that hedge funds tend to have significant exposure to lagged market returns, and argue this is due to difficulties in properly marking-to-market the values of their portfolios. But such difficulties arise only if those assets do not trade frequently, i.e. if the assets are illiquid. In a more recent study by Agarwal, Daniel,

[2]More precisely, prices should follow martingales with respect to the particular filtration that characterizes the information structure of the economy.

[3]For example, if the monthly returns of stock XYZ exhibited significant positive autocorrelation, then an investor could follow a simple trading rule in which he buys XYZ when XYZ's return this month is positive, sells XYZ when XYZ's return this month is negative, and holds the position until next month. Such a strategy would yield a positive expected return due to the predictability in monthly returns, and if enough securities exhibited such autocorrelation, a very profitable portfolio trading strategy can be constructed, eventually eliminating much of the predictability in returns. See Lehmann (1990), Lo and MacKinlay (1990a), and Khandani and Lo (2007, 2008) for further discussion of such strategies and their implications for the random walk.

[4]Getmansky, Lo, and Makarov (2004) consider several other possible explanations such as time-varying expected returns, time-varying leverage, and incentive fees and high-water marks, and conclude that these other sources cannot account for the empirical levels of autocorrelation observed in the historical data. However, they do acknowledge that another possibility that cannot easily be ruled out is "return smoothing", the deliberate (and fraudulent) manipulation of monthly portfolio net asset values (NAVs) to reduce the volatility of monthly returns, which improves the hedge fund's reported Sharpe ratio. Of course, as Getmansky, Lo, and Makarov (2004) observe, the only types of assets for which a hedge-fund manager has sufficient discretion and latitude to manipulate NAVs to any appreciable extent are illiquid assets, so this interpretation is still consistent with the argument that return autocorrelation in hedge-fund returns is a sign of illiquidity.

and Naik (2007), the authors argue that hedge-fund managers have an incentive and the ability to inflate their returns in December by either under-reporting in an earlier month or borrowing from next January's returns. This reflects a great level of flexibility on the manager's part in "marking" the value of their holdings.

These two studies are closely related to the "nonsynchronous trading" phenomenon in the market microstructure literature, in which return-autocorrelation is spuriously induced by using stale prices to compute returns (see, for example, Campbell, Lo, and MacKinlay 1997, Chapter 3). In contrast to the studies by Lo and MacKinlay (1990b) and Kadlec and Patterson (1999), which conclude that it is difficult to generate return autocorrelations in weekly U.S. equity portfolios much greater than 10% to 15% through nonsynchronous trading effects alone, Getmansky, Lo, and Makarov (2004) argue that in the context of hedge funds, a significantly higher levels of autocorrelation can be explained by the interactions of illiquidity and performance smoothing, of which nonsynchronous trading is a special case. To see why, note that the empirical analysis in the nonsynchronous-trading literature is devoted exclusively to exchange-traded equity returns, while hedge funds often include hard to price over-the-counter products in their portfolios, hence the corresponding conclusions for equity returns may not be relevant in this context.

Of course, the challenges of marking hard-to-value assets to market, and the consequences for computing risk-adjusted performance are not unique to hedge funds, and can be even more severe for private equity and venture capital investments. Gompers and Lerner (1997) argue that inaccurate marking-to-market of private equity investments can result in significant under-estimation of their exposures to standard risk factors like the aggregate stock market, leading to an over-estimate of their risk-adjusted returns if the risk factors carry positive risk premia. This is also related to the well-documented impact of stale prices on the computation of daily NAVs of certain open-end mutual funds, as documented by Bhargava, Bose, and Dubofsky (1998), Chalmers, Edelen, and Kadlec (2001), Goetzmann, Ivkovic, and Rouwenhorst (2001), Boudoukh et al. (2002), Greene and Hodges (2002), and Zitzewitz (2003), among others. In these studies, spurious return-autocorrelations—driven by badly marked mutual fund NAVs—imply significant wealth transfers from buy-and-hold shareholders to opportunistic investors who decide to buy or sell positions in these funds based on forecasted future returns.

3 The Data

To investigate illiquidity across as broad a spectrum of assets as possible, we use three types of return data in our analysis—hedge funds, mutual funds, and U.S. equity portfolios—which we describe in Sections 3.1–3.3, respectively. To construct risk-adjusted returns, we also make use of several broad-based market indexes which are described in Section 3.4.

3.1 Hedge Funds

The hedge-fund data we use is obtained from the Lipper/TASS Database, which contains historical returns as well as the legal structure, investment style, management fee type, contact information, fund flows, and self-reported sources of risk exposures of several thousand individual hedge funds. The database is divided into two parts: "Live" and "Graveyard" funds. Hedge funds are included in the Live database if they are considered active as of the date of the snapshot. Once a hedge fund decides not to report its performance, liquidates, closes to new investment, restructures, or merges with other hedge funds, the fund is transferred into the Graveyard database. A hedge fund can only be listed in the Graveyard database after having been listed in the Live database. Since the Lipper/TASS database fully represents returns and asset information for live and dead funds, the effects of "survivorship bias" are minimized. However, the Graveyard database became active only in 1994, so funds that were dropped from the Live database prior to 1994 are not included in the Graveyard database, creating the possibility of a certain degree of survivorship bias.[5]

However, the database is subject to "backfill bias", which is created when a newly admitted fund's prior return history is included in the database. Since funds do not need to meet any specific requirements to be included in the Lipper/TASS database, funds are more likely to become part of the database after having achieved an attractive return history. Given the voluntary nature of reporting, another potential issue is the "self-selection bias" arising from the fact that funds with very good or very bad performance may decide to stop reporting their returns. Agarwal and Naik (2005) provide a more comprehensive review of

[5]For studies attempting to quantify the degree and impact of survivorship bias, see Brown, Goetzmann, Ibbotson, and Ross (1992), Schneeweis and Spurgin (1996), Fung and Hsieh (1997b, 2000), Hendricks, Patel, and Zeckhauser (1997), Brown, Goetzmann, and Ibbotson (1999), Carpenter and Lynch (1999), Horst, Nijman, and Verbeek (2001), Baquero, Horst, and Verbeek (2002), and Carhart et al. (2002).

other hedge-fund data sources and their corresponding biases.

We obtained our snapshot of the Lipper/TASS data in January 2008. However, because funds sometimes report their returns with a delay of several months, we use data only up to December 2006 in our study.[6] As of January 2008, this database contained 8,729 funds, with each fund assigned to one of 11 investment-style categories listed in Appendix A, based on the fund's self-reported description of its activities. We have limited our study to funds with at least 5 years of monthly return history in our sample period from January 1986 to December 2006. Funds that report returns at frequencies other than monthly, e.g., quarterly, have also been excluded from the study. These filters yield 2,927 funds that comprise the sample used in our study. Table 1 gives a breakdown of the funds used in this study, and Table 2 reports some summary statistics for our sample.

3.2 Mutual Funds

Our sample of mutual funds is obtained from the University of Chicago's Center for Research in Security Prices Survivor-Bias-Free U.S. Mutual Fund Database, based on a February 2008 download. This data set also suffers from some biases as noted in the accompanying documentation provided by CRSP. For example, there is an obvious selection bias that favors the historical data of the best past-performing private funds that become public. See the CRSP documentation for further discussion of this and other biases.

As with our hedge-fund sample, we include only those mutual funds with at least 5 years of monthly returns during our sample period from January 1986 to December 2006. Funds with missing months were excluded from the study. For purposes of comparison with our sample of hedge funds, we have assigned "Live" and "Graveyard" classifications to mutual funds in our sample based on their reporting history—a mutual fund is counted as Live if it reported returns in December 2006, and is considered a Graveyard fund otherwise. We use the "Main Category" field to classify funds into one of the following categories: Asset Allocation, Convertible, Equity, Fixed Income, and Money Market. We discard all Money

[6]This may bias our sample to slightly overestimate Graveyard funds, and underestimate Live funds as of December 2006, since Lipper/TASS categorizes funds based on the information available until January 2008. This effect is not as relevant in our analysis because we do not perform separate analyses based on the Live/Graveyard classification. We break out Live and Graveyard funds in Table 1 only to provide a better sense for the diversity in our sample.

Panel A: Hedge Funds

Category	Live	Graveyard	Combined
Convertible Arbitrage	57	44	101
Dedicated Short Bias	12	13	25
Emerging Markets	102	80	182
Equity Market Neutral	106	47	153
Event Driven	157	97	254
Fixed Income Arbitrage	69	39	108
Fund of Funds	437	194	631
Global Macro	56	70	126
Long/Short Equity Hedge	562	344	906
Managed Futures	135	173	308
Multi-Strategy	110	23	133
	To be Used in the Study		2,927

Panel B: Mutual Funds

Category	Live	Graveyard	Combined	Failed the Unit Root Test
Asset Allocation	981	152	1,133	1
Convertible	59	15	74	0
Equity	6,580	1,046	7,626	88
Fixed Income	3,578	510	4,088	53
Info. N/A	10	3,068	3,078	395
Money Market	1,335	225	1,560	1,460
Unclear (Multiple Categories)	50	0	50	0
	To be Used in the Study		17,609 -1,560-395 = 15,654	

Table 1: Breakdown for the composition of hedge-fund and mutual-fund data used in this study. Funds with less than 5 years of monthly returns over the January 1986 to December 2006 sample period are excluded. Hedge funds are categorized as either "Live" or "Graveyard" by Lipper/TASS. For purposes of comparison, we categorize mutual funds as "Live" if they reported returns in December 2006, and as "Graveyard" otherwise. We exclude mutual funds in the "Money Market" category, as well as funds for which we do not have category information and which failed the unit-root test outlined in the Appendix.

Market funds since such funds exhibit very little variation in illiquidity exposure (at least until the Financial Crisis of 2007–2008), and have very different return properties than those of typical mutual funds. In particular, such low-risk vehicles exhibit very little return variation over time, and are highly liquid by construction.

Because the "Main Category" field has only been available since July 2003, about 20% (3,078) of the funds that meet our minimum return-history requirement do not have any category information. These funds are included in any analysis that does not require category information, with the following exception. As noted above, we exclude all Money Market funds from our sample. Some of the funds that lack category information are in fact Money Market funds. To identify such funds, we apply a standard unit-root test and exclude any funds for which we fail to reject the null hypothesis of a unit root at the 5% level of significance (see Appendix A.2 for the details of the unit-root test used). 395 funds are excluded due to this filter.

Because we use historical end-of-year category information, there are 50 funds that have had multiple classifications over our sample period. These funds are included in any analysis that does not require category information, but are omitted from any analysis in which fund category is relevant.

These filters leave a total of 15,654 mutual funds in our sample. Table 1 contains a breakdown of these funds by category and status, and Table 2 provides basic summary statistics for these funds.

Category	Count	Mean (%)		SD (%)		Skewness		Kurtosis		Sharpe Ratio		ρ_1 (%)		Q-Stat (3 Lags) p-Value (%)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Hedge Fund Categories															
Convertible Arbitrage	101	0.82	0.40	1.93	1.52	-0.27	1.55	7.63	11.77	0.77	1.37	38	17	5	13
Dedicated Short Bias	25	0.21	0.47	5.91	3.34	0.30	0.39	5.28	2.60	0.09	0.16	9	12	37	26
Emerging Markets	182	1.33	1.12	6.63	4.10	-0.33	1.50	9.17	7.89	0.27	0.24	17	11	24	27
Equity Market Neutral	153	0.72	0.39	2.16	1.48	0.34	0.93	5.57	3.99	0.46	0.33	11	20	27	29
Event Driven	254	0.98	0.61	2.45	2.57	-0.20	1.34	7.93	9.20	0.54	0.29	23	15	15	23
Fixed Income Arbitrage	108	0.75	0.53	2.13	1.66	-1.32	2.91	17.22	23.58	0.57	0.45	19	20	26	32
Fund of Funds	631	0.70	0.36	2.25	1.68	-0.13	1.27	7.27	7.36	0.43	0.25	19	15	23	28
Global Macro	126	0.86	0.94	4.70	2.90	0.38	0.97	6.16	3.83	0.23	0.17	8	14	35	28
Long/Short Equity Hedge	906	1.18	0.64	4.75	2.79	0.39	1.14	6.72	5.72	0.30	0.17	13	14	30	29
Managed Futures	308	0.91	0.72	6.05	3.85	0.31	0.81	5.41	3.91	0.18	0.13	0	12	40	30
Multi-Strategy	133	0.95	0.54	3.04	2.78	-0.05	1.97	9.97	13.19	0.48	0.35	18	17	19	25
Mutual Fund Categories															
Asset Allocation	1,133	0.52	0.24	2.63	0.79	-0.50	0.39	4.13	1.84	0.22	0.10	5	7	65	24
Convertible	74	0.72	0.20	3.24	0.81	-0.35	0.48	5.41	2.20	0.23	0.08	10	6	48	28
Equity	7,626	0.73	0.49	5.34	1.91	-0.35	0.52	4.34	3.23	0.15	0.10	8	8	55	28
Fixed Income	4,088	0.44	0.13	1.25	0.62	-0.49	0.60	4.94	4.90	0.41	0.20	8	11	26	22
Info. N/A	3,078	0.53	0.39	2.92	2.64	-0.38	0.92	5.08	7.13	0.75	1.22	21	30	37	32
Money Market	1,560	0.28	0.50	0.41	6.59	-0.01	0.81	2.76	7.45	1.84	0.39	94	10	0	6
Unclear (Multiple Categories)	50	0.56	0.28	3.31	1.87	-0.39	0.60	4.00	1.34	0.41	0.64	11	11	62	29

Table 2: Summary statistics for all hedge funds and mutual funds with at least 5 years of monthly returns during the January 1986 to December 2006 sample period. Results are given for different categories of hedge funds and mutual funds. All entries are based on monthly returns and not annualized. The last column contains the p-value of the Ljung-Box Q-statistic using the first 3 return autocorrelations.

3.3 U.S. Equity Portfolios

Our sample of U.S. equity portfolios consists of the now-standard 100 size- and book-to-market-sorted portfolios constructed at the end of each June by double-sorting portfolios into market-capitalization and book-to-market deciles.[7] We use value-weighted-portfolio returns in our analysis. The historical data for these portfolios is available for a much longer period but we confine our attention to the January 1986 to December 2006 period to facilitate comparisons across all three of our datasets. Out of the 100 portfolios, 3 portfolios had missing data due to the absence of securities in the relevant intersection of size and BE/ME decile;[8] we include these portfolios in our analysis when they do have data for the relevant time periods.

Table 3 contains summary statistics of the monthly returns of these portfolios, and to conserve space, we aggregate the data in two ways, either by size or book-to-market deciles. When sorted by size, the relation between autocorrelation and liquidity becomes apparent given the fact that smaller-capitalization stocks are generally considered less liquid and harder to trade.[9]

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[7]This data was obtained from Kenneth French's web site:

`http : //mba.tuck.dartmouth.edu/pages/faculty/ken.french/`

According to the description supplied with the data, the size decile breakpoints for year t are the NYSE market-cap deciles at the end of June. The book-to-market value at the end of June in year t is defined as the book equity for the last fiscal year-end in year $t-1$ divided by the market value of equity for December of year $t-1$, and the book-to-market decile breakpoints also correspond to those of the NYSE book-to-market deciles. The portfolios for July of year t to June of year $t+1$ include all NYSE, AMEX, and NASDAQ stocks for which we have market equity data for December of year $t-1$ and June of year t, and positive book-equity for year $t-1$. Firms with negative book-equity are not included in any portfolio. Please see French's documentation for further details.

[8] In particular, size-decile-6/book-to-market-decile-10 and size-decile-10/book-to-market-decile-8 did not contain any observations for the period from July 2000 to June 2001, and size-decile-10/book-to-market-decile-10 did not contain any observations from July 1999 to June 2000 and again from February 2001 to June 2001.

[9]See, for example, Mech (1993) and Lewellen (2002).

Decile	Mean (%)			SD (%)			Skewness			Kurtosis			Sharpe Ratio			ρ_1 (%)			Q-Stat (3 Lags) p-Value (%)		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
S1	0.15	1.24	1.65	5.04	6.41	8.81	-0.83	-0.12	1.04	6.05	8.38	15.54	0.02	0.21	0.31	13	23	33	0	0	3
S2	0.19	1.22	1.80	5.21	6.56	9.02	-1.20	-0.34	0.66	5.48	7.73	11.92	0.02	0.20	0.31	7	15	26	0	3	10
S3	0.56	1.24	1.60	4.76	6.04	8.48	-1.24	-0.82	-0.05	5.11	6.67	8.60	0.07	0.22	0.30	3	14	23	0	5	27
S4	0.69	1.15	1.54	4.96	6.00	8.34	-1.33	-0.78	-0.11	4.79	6.74	8.67	0.08	0.20	0.29	6	11	21	0	9	30
S5	0.75	1.22	1.43	4.93	5.85	7.98	-1.12	-0.78	-0.07	4.07	6.78	8.48	0.09	0.22	0.29	0	10	16	3	15	32
S6*	0.74	1.20	1.84	4.63	5.47	7.86	-0.93	-0.67	-0.27	4.62	6.07	6.93	0.09	0.22	0.30	4	9	13	0	29	86
S7	1.05	1.27	1.44	4.54	5.36	7.10	-1.14	-0.69	0.33	4.40	7.01	9.00	0.18	0.24	0.30	-2	6	14	3	36	97
S8	1.02	1.22	1.48	4.45	5.44	7.57	-0.92	-0.58	-0.02	3.90	5.81	8.52	0.15	0.23	0.30	-4	4	12	3	45	89
S9	1.05	1.21	1.50	4.18	5.05	6.24	-1.08	-0.58	-0.32	3.76	5.18	6.72	0.20	0.24	0.30	-6	3	10	14	52	95
S10*	0.58	1.06	1.25	4.59	5.30	6.97	-0.92	-0.39	0.43	4.21	5.68	10.16	0.11	0.20	0.26	-5	0	4	8	66	97
BE/ME1	0.15	0.77	1.26	5.02	7.64	9.02	-0.37	-0.09	0.42	4.07	5.50	7.85	0.02	0.11	0.21	1	8	23	0	32	92
BE/ME2	0.60	1.03	1.22	4.79	6.33	8.18	-0.93	-0.37	0.53	4.61	6.15	8.25	0.07	0.17	0.24	0	8	20	0	16	79
BE/ME3	0.81	1.12	1.33	4.98	5.99	7.71	-0.95	-0.54	0.28	5.23	6.95	8.52	0.13	0.19	0.26	-1	9	21	0	16	73
BE/ME4	1.03	1.22	1.50	4.87	5.70	7.43	-1.24	-0.64	0.66	4.97	7.43	11.92	0.19	0.22	0.26	-3	8	23	0	21	97
BE/ME5	1.04	1.22	1.37	4.59	5.19	5.78	-1.19	-0.87	-0.31	5.59	6.90	9.00	0.20	0.24	0.27	1	11	20	0	9	33
BE/ME6	1.05	1.28	1.60	4.49	5.15	6.24	-1.22	-0.60	1.04	5.00	7.35	15.54	0.21	0.25	0.30	-2	9	20	0	28	95
BE/ME7	1.07	1.36	1.80	4.76	5.08	5.74	-1.33	-0.77	-0.39	4.21	6.60	9.18	0.22	0.27	0.31	-5	10	24	0	37	89
BE/ME8*	0.58	1.28	1.55	4.18	4.92	5.81	-1.05	-0.65	-0.27	3.90	6.09	8.72	0.11	0.26	0.31	-6	10	25	0	32	97
BE/ME9	1.13	1.35	1.65	4.59	5.32	6.97	-1.20	-0.66	0.43	4.55	7.25	10.16	0.16	0.26	0.31	2	11	27	0	31	78
BE/ME10*	0.99	1.38	1.84	5.50	6.17	6.89	-0.95	-0.54	0.08	3.76	5.83	7.29	0.14	0.22	0.30	-4	15	33	0	29	86

Table 3: Summary statistics for the raw monthly returns of 100 size- and book-to-market-sorted decile portfolios from January 1998 to December 2006, aggregated by size or book-to-market decile, for value-weighted returns. Some deciles have missing data for certain months, and are marked with asterisks (see footnote 8 for details).

3.4 Risk Factors

To control for common factors other than illiquidity in our sample of asset returns, we propose using various subsets of the following 9 risk factors:[10]

1. Fama-French U.S. Market Index
2. Lehman U.S. Aggregate Government Bond Index[11]
3. Lehman Universal High-Yield Corporate Index
4. Goldman Sachs Commodities Index
5. Traded-Weighted U.S. Dollar Index
6. Fama-French High-Minus-Low (HML) Book-to-Market Index
7. Fama-French Small-Minus-Big (SMB) Capitalization Index
8. Fama-French Momentum Index
9. First-difference of the VIX Volatility Index

The first 5 factors capture broad sources of common risk due to equities, fixed-income, credit, commodities, and currency markets. The next 3 factors have been studied extensively in the recent asset-pricing literature, and the last factor measures exposure to aggregate volatility shifts, which is particularly relevant for certain types of hedge funds.[12]

Table 4 contains summary statistics for these 9 factors over the sample period from January 1986 to December 2006. It is worth noting that the only two factors with statistically significant autocorrelation are the Lehman Universal High-Yield Corporate Index and the CBOE Volatility factor. The former index exhibits significant positive autocorrelation, which, we argue below, is a sign of illiquidity. This is consistent with the fact that such

[10] For a discussion of common factors in hedge-fund returns, see Fung and Hsieh (1997a, 2001), Agarwal and Naik (2004), Capocci and Hübner (2004), and Hasanhodzic and Lo (2007). For common factors in mutual-fund returns, see Sharpe (1992). The Fama-French U.S. Market, SMB, HML, and Momentum factors are obtained from the Wharton Research Data Services (WRDS). The Goldman Sachs Commodities Index and the Trade Weighted U.S. Dollar Index are obtained from the Global Financial Database. The total return of the Lehman U.S. Aggregate Government Bond and Universal High-Yield Corporate Indexes are obtained from Datastream. We use the monthly total returns for the U.S. Market, Lehman U.S. Government Bond, Lehman High-Yield, and the Goldman Sachs Commodities Index to capture the effects of any dividend and/or coupon payments on the time series of returns.

[11] Following the acquisition of Lehman Brothers by Barclays Bank in 2008, all Lehman indexes have now been rebranded "Barclays" indexes.

[12] For example, funds using options-based strategies will have exposure to this volatility factor. Because this factor has much higher volatility than the others, we rescale it to have the same monthly volatility as the U.S. Stock Market factor. This has no effect on the factor's explanatory power, but merely affects the interpretation of its factor loading.

an index likely suffers from non-trading and mark-to-market issues since it is the tracking index for high-yield corporate bonds, which generally trade less frequently. The volatility factor exhibits negative autocorrelation, not a sign of illiquidity, but rather a well-known implication of the volatilities of financial asset returns, which tend to be highly persistent GARCH processes, implying negatively autocorrelated first-differences.

Name	Mean (%)	SD (%)	Skewness	Kurtosis	Rho1 (%)	Rho2 (%)	Rho3 (%)	Q-Stat (3 Lags) p-Value (%)
Fama-French US Market Index	1.03	4.38	-1.03	6.42	3.92	-5.40	-4.11	67.70
Lehman US Aggregate Government Bond Index	0.73	1.63	0.06	3.67	11.77	-9.42	-1.13	9.30
Lehman US Universal High-Yield Corporate	1.24	3.67	0.38	11.05	37.50	6.27	-2.53	0.00
Goldman Sachs Commodities Index	0.90	5.42	0.34	4.14	9.11	-10.78	2.57	11.80
Trade Weighted USD Index	-0.12	2.54	0.34	3.46	7.91	0.61	-1.42	67.00
Change in the CBOE Volatility Index	-2.58	451.25	2.78	26.82	-17.32	-7.71	-13.17	0.37
Rescaled CBOE Volatility Index*	-0.03	4.38	2.78	26.82	-17.32	-7.71	-13.17	0.37
Fama-French Small-Minus-Big Index	0.06	3.50	0.83	10.98	-3.40	2.67	-13.42	16.95
Fama-French High-Minus-Low Index	0.38	3.18	0.09	6.04	9.40	5.72	8.74	17.51
Fama-French Momentum Index	0.78	4.44	-0.68	9.25	-3.70	-6.22	4.72	59.42

Table 4: Summary statistics for risk factors used to account for common sources of variation among the monthly returns of hedge funds, mutual funds, and portfolios of U.S. equities, from January 1986 to December 2006 . All statistics are based on monthly returns and are not annualized. The "Rescaled CBOE Volatility Index" has been rescaled to have the same volatility as the U.S. Stock Market factor over the entire sample period.

Correlation (%)	MARKT	LH_GO	LH_HY	GSCI	USD	VIX_S	SMB	HML	UMD
MARKT	100.00	7.07	51.71	-3.26	8.45	-61.75	20.07	-48.86	-8.26
LH_GO		100.00	23.16	-1.73	-20.98	14.72	-19.04	6.66	13.89
LH_HY			100.00	-12.10	9.60	-32.99	26.04	-13.21	-18.62
GSCI				100.00	-11.55	-0.21	8.08	3.41	11.24
USD					100.00	-11.68	6.11	4.07	-7.28
VIX_S						100.00	-21.75	24.42	10.01
SMB							100.00	-43.59	12.30
HML								100.00	-8.68
UMD									100.00

Table 5: Correlation matrix of the monthly returns of 9 risk factors, from January 1986 to December 2006. MARKT: U.S. Stock Market; LH_GO: Lehman U.S. Aggregate Government Bond Index; LH_HY: Lehman U.S. Universal High-Yield Corporate Index; GSCI: Goldman Sachs Commodities Index; USD: Trade Weighted U.S. Dollar Index; VIX_S: Rescaled CBOE Volatility Index; SMB: Small-Minus-Big Index; HML: High-Minus-Low Index; UMD: Momentum Index.

Finally, for purposes of illustrating the relation between illiquidity and return autocorrelation in commonly cited equity, fixed-income, and emerging-market indexes, we use the monthly total returns of several popular indexes for these asset classes listed in Table 6, over the sample period from January 1986 to December 2006 whenever possible.[13]

Name	Mean (%)	SD (%)	Skewness	Kurtosis	Rho1 (%)	Rho2 (%)	Rho3 (%)	Q-Stat (3 Lags) p-Value (%)
S&P 500 Large Cap Index	1.05	4.33	-0.83	5.96	-1.25	-3.78	-0.97	93.75
S&P 400 Mid Cap Index	1.27	4.79	-0.86	6.21	6.43	-8.54	-9.09	17.01
S&P 600 Small Cap Index	1.01	5.27	-1.19	7.62	11.30	-3.84	-13.71	3.97
Wilshire 5000 Index	1.03	4.37	-1.03	6.55	3.64	-5.01	-3.82	72.71
Wilshire 750 Large Cap Index	1.03	4.42	-0.84	5.72	0.49	-5.12	-1.35	86.91
Wilshire 1750 Small Cap Index	1.09	5.41	-1.06	6.84	13.28	-6.17	-11.98	3.30
					0.00	0.00	0.00	
S&P/IFC Emerging Markets Composite Global Index	0.96	6.43	-0.57	4.70	17.45	8.99	-4.20	1.72
S&P/IFC Emerging Markets Investable Composite Index	1.07	6.47	-0.57	4.73	13.86	6.04	-2.80	15.91
US Gov - 5 Year Index	0.57	1.37	-0.08	3.00	14.42	-6.63	1.34	8.38
US Gov - 10 Year Index	0.68	2.19	-0.02	3.43	9.30	-11.14	0.25	10.37
US Gov - 30 Year Index	0.84	3.34	0.14	3.94	6.91	-11.37	3.20	11.55
US AAA Corp. Bond Index	0.77	1.51	-0.09	4.27	15.47	-6.57	-2.12	4.61
Merrill Lynch Mortgages Index	0.68	1.07	-0.16	4.07	15.09	-11.71	-2.16	3.79

Table 6: Summary statistics for the monthly returns of various equity, fixed-income, and emerging market indexes, from January 1986 to December 2006 (except for the Wilshire 1750 Small Cap, Merrill Lynch Mortgages, and the S&P/IFC Emerging Markets Investable Composite Indexes; see footnote 13). All values are based on monthly total returns and are not annualized.

4 Autocorrelation and Illiquidity

Following Lo (2001) and Getmansky, Lo, and Makarov (2004), we propose using return autocorrelation as a measure of an asset's degree of illiquidity. To gauge the universality of this proposed measure of illiquidity, Table 6 shows the characteristics of the monthly returns for several representative equity and fixed-income factors, including the p-values of the Ljung-Box Q-statistic that measures the joint significance of the first three sample autocorrelation coefficients.[14] The null hypothesis of no autocorrelation cannot be rejected for the indexes that include the largest and most liquid sets of assets, such the S&P 500 and the Wilshire 750 Large Cap indexes. But the story is quite different for the smaller stocks

[13]These data were obtained from the Global Financial Database. The Wilshire 1750 Small Cap Index is available until March 2006, the Merrill Lynch Mortgages Index is available until February 2004, and the S&P/IFC Emerging Markets Investable Composite Index starts in January 1989.

[14]Box and Pierce (1970) proposed the following statistic for test the significance of the first k auto correlation values

$$Q_m = T \sum_{k=1}^{m} \rho^2(k) \cdot$$

Under the null hypothesis of no auto correlation, this statistic is asymptotically distributed as χ^2_m. Ljung and Box (1978) proposed the following finite-sample correction which provides a better fit to the χ^2_m for smaller samples sizes:

$$Q_m = T(T+2) \sum_{k=1}^{m} \frac{\rho^2(k)}{T-k} \; .$$

in the same market, i.e., the S&P 600 Small Cap or the Wilshire 1750 Small Cap indexes, for which the null of no autocorrelation can be rejected at the 5% significance level.

To highlight the differences in predictability between tradable and non-tradable assets, we compute the same statistics for two emerging-markets indexes. The first index, the S&P/IFC Emerging Markets Composite Index, is simply a "tracking" index while the second, the S&P/IFC Emerging Markets Investable Composite, is an "investable" index that is presumably more easily tradable by construction. Observe that the null hypothesis can be easily rejected for the "tracking" index while the null cannot be rejected in the case of the "investable" index. This difference is consistent with Samuelson's (1965) argument that "properly anticipated prices fluctuate randomly". Because the investable index is more easily tradable, any significant autocorrelation in its returns can be more easily exploited than in case of the non-investable index. In short, tradability is directly related to the degree to which future price movements can be "properly anticipated".

We find a similar pattern among fixed-income indexes—for the most liquid U.S. government bond funds, the Q-statistics cannot reject the null hypothesis of white noise, but they do reject the null hypothesis for indexes tracking corporate bonds and mortgage-backed securities, which are considerably more illiquid.

These results motivate the more formal empirical analysis of Sections 4.1–4.2, in which we show more directly that return autocorrelation is, indeed, a measure of illiquidity among a broad set of financial assets.

4.1 Redemption-Notice and Lock-Up Periods

To demonstrate that return autocorrelation captures illiquidity, we begin by focusing on hedge funds, for which we have auxiliary measures of illiquidity such as redemption-notice and lock-up periods. The former is the amount of notice that hedge-fund investors must provide to a fund manager before being able to withdraw an investment from the fund, which can vary from one day to several months. The latter is the amount of time for which a hedge-fund investor agrees to leave an investment in a fund, typically one year. Liang (1999) has advocated the use of "lock-up periods" as a measure of the liquidity of hedge funds, and Aragon (2004) uses both the lock-up and redemption-notice periods as control variables to account for different liquidity characteristics of hedge funds.

To develop some intuition for the variability of these measures in our sample of funds, we report in Table 7 some summary statistics for both variables across the different categories of hedge funds in our sample.[15] Each part of this table is sorted by the relevant measure in descending order. Categories known to involve strategies with illiquid securities such as Event Driven and Convertible Arbitrage appear near the top of the rankings of both measures, while categories that involve more liquid exchange-traded securities such as Managed Futures and Global Macro are at the bottom. Also, note that a substantial percentage of funds in each category have no lock-ups at all, hence the redemption-notice period is the primary liquidity constraint imposed on hedge-fund investors.

Panel A: Redemption Notice Period

Category	Count	Average Redemption Notice Period (Days)	Redemption Distribution (Days)		
			< 10	10-30	> 30
Event Driven	254	50	10%	33%	57%
Fund of Funds	631	40	16%	26%	58%
Convertible Arbitrage	101	37	15%	47%	39%
Fixed Income Arbitrage	108	34	29%	33%	38%
Multi-Strategy	133	34	20%	44%	35%
Equity Market Neutral	153	32	16%	50%	33%
Long/Short Equity Hedge	906	31	15%	59%	26%
Emerging Markets	182	27	32%	43%	24%
Dedicated Short Bias	25	25	28%	60%	12%
Global Macro	126	20	33%	55%	13%
Managed Futures	308	8	62%	34%	4%

Panel B: Lockup Period

Category	Count	Average Lockup Period in Months	Lockup Distribution		
			None	Up to 1 Year	More
Event Driven	254	5.4	60%	35%	6%
Long/Short Equity Hedge	906	4.4	65%	32%	3%
Convertible Arbitrage	101	3.1	74%	25%	1%
Multi-Strategy	133	2.8	74%	25%	2%
Equity Market Neutral	153	2.5	78%	20%	1%
Emerging Markets	182	2.1	84%	13%	3%
Fixed Income Arbitrage	108	1.9	82%	17%	1%
Dedicated Short Bias	25	1.9	80%	20%	0%
Fund of Funds	631	1.9	86%	12%	1%
Global Macro	126	1.0	93%	6%	1%
Managed Futures	308	0.5	96%	4%	0%

Table 7: Summary statistics for redemption-notice and lock-up periods among Lipper/TASS hedge funds from January 1996 to December 2006, sorted by the average values of each of the two measures by category. See Appendix A for the definitions of these categories.

To quantify the degree of association between return autocorrelation and redemption-notice periods, we estimate a simple cross-sectional regression of one measure on the other.

[15]See Section 3.1 for the empirical properties of our sample of hedge funds, and Appendix A.1 for the definitions of the various hedge fund categories.

Table 8 contains the estimates for the cross-sectional regression:

$$\text{Redemption}_i \;\; = \;\; \alpha \; + \; \lambda\rho_{1,i} \; + \; \epsilon_i \tag{1}$$

for all hedge funds in our data set, as well as by category. These results show strong positive relations between redemption-notice periods and return autocorrelations for the entire sample of hedge funds and for almost all categories. For the entire sample of hedge funds, the estimated slope coefficient of 42.1 implies that for every 10 percentage points of a hedge fund's return autocorrelation, the expected redemption-notice period is higher by $42.1 \times 0.10 = 4.2$ days. This illiquidity/autocorrelation relation is even stronger for multi-strategy funds, where the cross-sectional regression has an R^2 of 11.5% and a 10-percentage-point increase in autocorrelation adds 5.5 days to the expected redemption-notice period.

Category	Count	Alpha	T-stat	RSQ (%)
All	2927	25.8(40.6)	42.1(14.8)	7.0
Convertible Arbitrage	101	26.0(4.64)	28.5(2.14)	4.4
Dedicated Short Bias	25	21.9(4.42)	35.7(1.11)	5.2
Emerging Markets	182	21.6(6.18)	31.8(1.88)	1.9
Equity Market Neutral	153	27.9(12.9)	37.0(3.97)	9.5
Event Driven	254	42.7(11.4)	31.6(2.31)	2.1
Fixed Income Arbitrage	108	27.6(7.25)	34.1(2.51)	5.6
Fund of Funds	631	32.9(18.5)	39.7(5.38)	4.4
Global Macro	126	19.4(10.4)	12.4(1.03)	0.9
Long/Short Equity Hedge	906	31.7(34.7)	-3.7(-0.7)	0.1
Managed Futures	308	8.22(10.6)	16.6(2.53)	2.1
Multi-Strategy	133	24.1(7.21)	55.4(4.11)	11.5

Table 8: Estimates of the cross-sectional regression $\text{Redemption}_i = \alpha + \lambda\rho_{1,i} + \epsilon_i$ for all hedge funds in our sample as well for each of the 11 categories, using data from January 1986 to December 2006. Redemption-notice periods are measured in days, and t-statistics are reported in parenthesis.

In fact, the only hedge-fund category for which the λ coefficient is negative is Long/Short Equity Hedge, but given the liquidity of such strategies, it is not surprising that the λ coefficient is small in magnitude and statistically insignificant, and the regression's explanatory power is virtually zero ($R^2 = 0.1\%$).

These results provide more direct confirmation that return autocorrelation is indeed a useful proxy for illiquidity.

4.2 A Comparison of Hedge Funds and Mutual Funds

Having established a direct empirical link between illiquidity and return autocorrelation in Section 4.1, we now apply this measure to mutual funds, for which measures such as redemption-notice periods are not relevant. Figure 1 shows the histogram of estimated first-order autocorrelations for all the mutual funds in our sample (see Section 3.2), and also include the corresponding histogram for our sample of hedge funds for comparison. Figure 1 shows that hedge-fund returns tend to have higher autocorrelation than mutual funds, with the exception of a group of mutual funds that seem to have autocorrelation values near 1. This anomalous group consists of money market mutual funds that have near-unit roots in the time series of their returns due to their short-term interest-rate exposures, hence their unusually high autocorrelation coefficients. For funds with such non-stationary returns, autocorrelation is not well-defined and is therefore not a relevant measure of illiquidity. For this reason, we test for unit roots in our dataset and exclude those funds for which the null hypothesis of a unit root cannot be rejected (see Appendix A.2 for further details).

When funds with unit roots are excluded, Figure 1 shows that mutual funds are considerably more liquid than hedge funds as measured by their autocorrelations. In particular, Table 2 shows that the average p-values of the Q-statistics of the first three autocorrelations range from 65% (Asset Allocation) to 26% (Fixed Income) for mutual funds, but range from 40% (Managed Futures) to 5% (Convertible Arbitrage) for hedge funds. These extremes conform well to common intuition regarding liquidity—among mutual funds, asset-allocation funds are among the most liquid and fixed-income among the most illiquid, and among hedge funds, managed futures are considered among the most liquid while convertible arbitrage funds are much less liquid (see Table A.1 of Appendix A.2 for the results of formal statistical significance tests).

5 Estimating Illiquidity Premia

Having established a significant relationship between return autocorrelation and illiquidity in Section 4, we now exploit this relationship to estimate the illiquidity premia in asset returns. In Section 5.1 we describe our methodology, and in Sections 5.2 and 5.3, we apply this methodology to raw and risk-adjusted mutual-fund and hedge-fund returns, respectively.

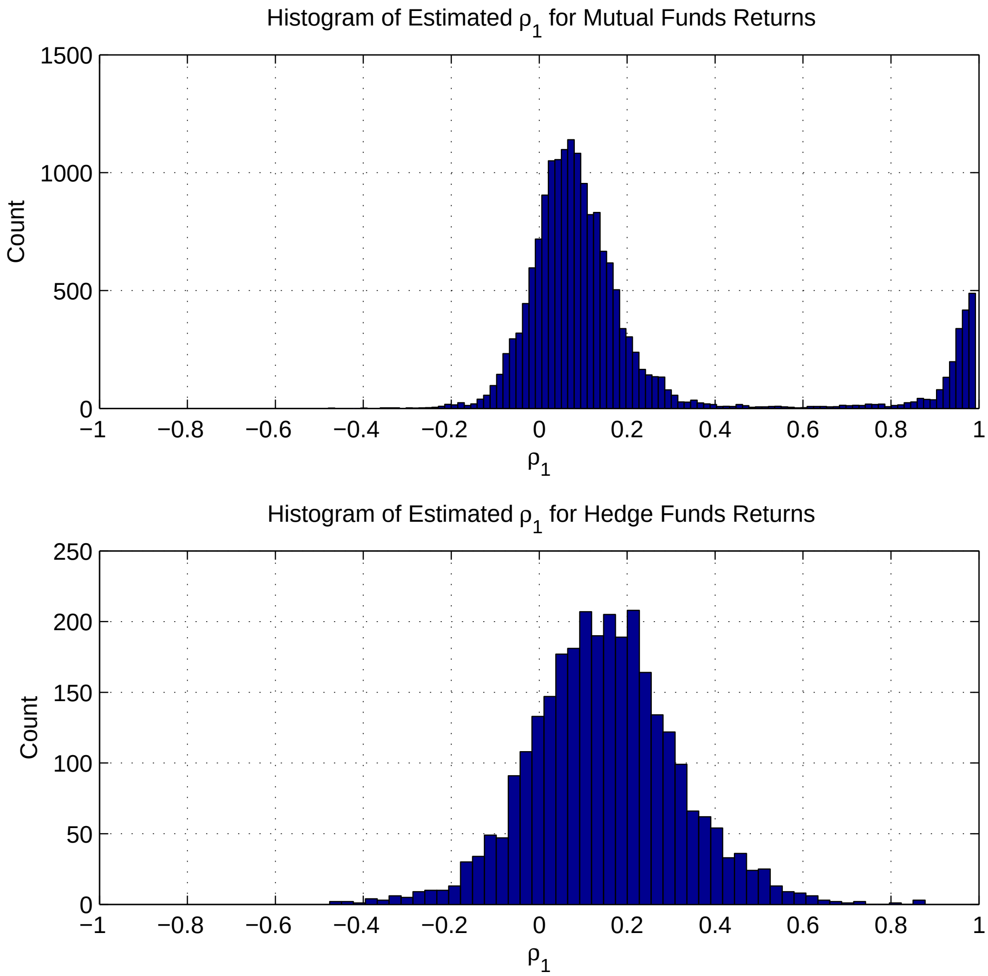

Figure 1: Histogram of first-order autocorrelation coefficients of mutual funds and hedge funds, based on raw returns from January 1986 to December 2006. Note that some mutual funds have unusually high autocorrelation due to near-unit roots in their returns.

To see how illiquidity might be related to specific investment styles, in Section 5.4 we estimate the illiquidity premia associated with each of the 11 hedge-fund categories in the Lipper/TASS database.

5.1 Methodology

Our approach for estimating the illiquidity premia of a collection of assets begins by ranking them by their estimated autocorrelation coefficients on a rolling basis over past 5-year periods, and creating 5 quintile portfolios based on these rankings in January of each year. The first such ranking is constructed for January 1991 since our sample period begins January 1986 and the first 5-year subperiod is available as of January 1991. We then calculate the equal-weighted raw or risk-adjusted returns of these quintile portfolios, based on risk adjustments that will be explained shortly, for each month of the subsequent year. The time series of these 5 portfolio returns—which we will refer to as the *liquidity portfolios*—will serve as the input to much of our analysis. To get a more direct measure of the impact of liquidity, we also compute the time series of the return differences between the least- and most-liquid portfolios, i.e., the return differences of the highest and lowest serial-correlation quintile portfolios. We shall refer to this portfolio as the *liquidity spread portfolio* in the discussion that follows.

Of course, the return differences of serial-correlation-sorted portfolios may also be due to differences in non-liquidity-based risk factors, and we attempt to control for such factors in two ways:

1. **Time-Series Regression**. Estimate the following regression for each of the 5 quintile portfolios from January 1991 to December 2006, and take the estimated alphas as the risk-adjusted measure of the portfolios' expected returns:

$$R_{p,t} \;=\; \alpha_p \;+\; \sum_{k=1}^{K} \beta_{p,k} \Lambda_{k,t} \;+\; \epsilon_{p,t} \quad , \quad p = 1, \ldots, 5 \tag{2}$$

   where $\{\Lambda_{k,t}\}$ is a collection of K risk factors. Repeat the same analysis for the returns of the liquidity spread portfolio.

2. **Rolling Residuals**. Using betas estimated from a rolling 5-calendar-year window for

each fund i and the realized factors $\{\Lambda_{k,t}\}$ in each month t, compute the fitted value of the regression for fund i in month t and subtract it from the total monthly return to yield the risk-adjusted return for that fund:[16]

$$\tilde{R}_{i,t} \equiv R_{i,t} - \sum_{k=1}^{K} \hat{\beta}_{i,k,t^*} \Lambda_{k,t} \tag{3}$$

where $\hat{\beta}_{i,k,t^*}$ is obtained from the time series regression (2) applied to fund i's returns over the 5-calendar-year window ending in the most recent December prior to month t. Then, average these risk-adjusted returns within each quintile portfolio p to construct the risk-adjusted quintile portfolio return $\tilde{R}_{p,t}$:

$$\tilde{R}_{p,t} = \frac{1}{m} \sum_{i=1}^{m} \tilde{R}_{i,t} \ . \tag{4}$$

where m is the number of funds or securities in quintile p, $p = 1, \ldots, 5$.

The first approach is the most natural way to address the most immediate question regarding the link between risk-adjusted returns and liquidity, but it suffers from two shortcomings. First, by conducting a single time-series regression over the entire sample, we implicitly assume that the factor loadings are constant through time. Such an assumption is often used in studies of equity portfolios, but may be less reasonable for hedge funds that exhibit more dynamic investment strategies. Second, obtaining an estimate of risk-adjusted expected returns for the entire sample period does not allow us to gauge the time variation in illiquidity premia, which we suspect is substantial. The second approach is designed to deal with these two shortcomings.

The time-series average of the residuals from the second approach yields a measure similar to the alpha calculated from the first approach, but the monthly realizations of the residuals provide additional information about the evolution of illiquidity premia over time, and we focus on this issue in Section 5.5.[17]

[16]Note that in (3) we adopt the assumption that the alpha from the first regression is zero, and use only the estimated slope terms to calculate the residual returns.

[17]Of course, the residuals from (2) can also be used as measure of liquidity premium for each month, but the second approach is preferable for this purpose as it uses two non-overlapping time periods for the estimation of betas and the subsequent residual calculation, respectively.

To check the robustness of our analysis to the risk-adjustment process, we use the following four sets of factors in each of the two approaches described above:

1. **Market Only**: The U.S. Stock Market index only;
2. **4-Factor Set**: The U.S. Stock Market index plus size (SMB), value (HML), and momentum;
3. **Broad Factor Set**: All 9 factors listed in Table 4;
4. **Lagged Market**: Current and first lagged return of the U.S. Stock Market index.

Our proposal to use both current and lagged returns of the stock market in the "Lagged Market" factor set is motivated by Scholes and Williams (1977), who first argued that the "total" beta of a portfolio is best measured by the sum of both current and lagged market exposures, particularly in the presence of stale prices. Asness, Krail and Liew (2001) demonstrate that many hedge funds have significant exposure to lagged market returns, and Getmansky, Lo, and Makarov (2004) show that a lagged market beta can proxy for more general forms of illiquidity. While this lagged coefficient may be sufficient for capturing illiquidity exposures in portfolios of U.S. equities, it may not adequately capture the illiquidity of certain hedge funds with little equity exposure, e.g., fixed-income or convertible arbitrage strategies (see Table 9).

Before turning to our main analysis, we provide some summary statistics in Table 9 for the exposures of various assets to the risk factors in the Broad Factor Set. These risk factors explain a larger proportion of the time-series variation in the returns of mutual funds and portfolios of stocks than the returns of hedge funds. For example, the median R^2 values for mutual funds are all above 80%, whereas for all but one category of hedge funds (Dedicated Short Bias), the median R^2 values are below 51%. As expected, by far the most dominant risk factor among equity mutual funds and stock portfolios is the MARKT factor, while the Lehman U.S. Aggregate Government Bond Index is the most important factor among fixed-income mutual funds. Due to the more complex and dynamic nature of the investment strategies employed by hedge funds, their risk exposures are not as clear as those of mutual funds, except for the large negative exposure to the market factor among Dedicated Short Biased funds.

Because some of the risk factors are also serially correlated,[18] we must consider the potential relation between the autocorrelation of asset returns and their beta exposures to various factors. This can be accomplished by treating the estimated betas and autocorrelations for each fund in each of the 5-calendar-year estimation windows as an observation of a pair of random variables $(\rho_i,\ \beta_{i,k})$. All such observations are then pooled together and the cross-sectional correlation is calculated and reported in Table 10. Note that funds with higher autocorrelation also tend to have higher exposure to the Lehman U.S. Universal High-Yield Corporate Index (shown under column LH_HY) in Table 10, and to size (shown under column SMB in Table 10).

Also, the momentum factor seems like a logical candidate to "explain" positively autocorrelated returns. However, Table 10 shows that this is not the case, hence any premium arising from our analysis is apparently distinct from the well-known momentum premium.

[18]For example, Table 4 shows that the Lehman U.S. Universal High-Yield Corporate Index has a first-order autocorrelation of 37.5%.

Asset	Count	Alpha (bps)			MARKT x 100			LH_GO x 100			LH_HY x 100			GSCI x 100		
		Med	25%	75%	Med	25%	75%	Med	25%	75%	Med	25%	75%	Med	25%	75%
Hedge Funds																
All	11,666	**43.9**	7.3	82.7	**21.2**	3.0	52.8	**4.6**	-16.5	27.8	**4.4**	-7.5	17.6	**2.0**	-1.1	6.6
Convertible Arbitrage	408	**64.7**	36.8	92.2	**-0.8**	-8.0	6.5	**-2.4**	-16.9	7.7	**13.0**	6.1	24.5	**0.6**	-0.6	2.6
Dedicated Short Bias	119	**61.2**	33.8	122.3	**-108.7**	-140.5	-50.3	**4.7**	-13.0	30.3	**-1.2**	-10.6	10.0	**0.6**	-4.5	6.1
Emerging Markets	749	**51.1**	-38.3	111.4	**62.2**	23.9	101.8	**-15.0**	-119.8	24.6	**21.4**	4.4	50.7	**3.4**	-1.2	12.3
Long/Short Equity	3,409	**50.8**	8.4	95.3	**51.7**	24.1	81.4	**3.6**	-20.0	25.1	**0.1**	-11.8	14.9	**2.3**	-2.1	7.7
Equity Market Neutral	445	**45.5**	20.9	88.4	**2.7**	-2.9	16.3	**3.9**	-7.8	16.9	**0.1**	-5.2	7.7	**0.7**	-1.6	3.2
Event Driven	1,138	**63.0**	36.6	88.2	**10.3**	2.1	25.9	**-6.2**	-21.7	6.5	**14.5**	2.8	29.8	**0.7**	-1.7	3.4
Fixed Income Arbitrage	379	**54.3**	24.9	82.9	**0.8**	-4.1	6.9	**4.8**	-11.7	22.3	**5.3**	-1.4	16.9	**0.5**	-1.0	2.8
Fund of Funds	2,514	**29.6**	7.2	56.0	**20.3**	7.9	37.6	**4.8**	-10.6	19.3	**5.8**	-0.7	12.4	**2.4**	0.5	5.2
Global Macro	467	**42.5**	-9.8	87.8	**11.3**	-3.7	45.7	**20.5**	-3.3	55.5	**3.4**	-13.2	20.9	**0.9**	-3.5	6.9
Managed Futures	1,469	**19.4**	-25.2	75.6	**6.6**	-13.0	27.4	**61.6**	8.0	114.7	**-13.4**	-34.9	8.0	**6.4**	-2.8	16.5
Multi-Strategy	569	**50.4**	15.1	81.5	**15.7**	2.1	47.9	**0.4**	-14.2	15.3	**4.9**	-3.1	16.0	**1.6**	-0.5	4.4
Mutual Funds																
All	85,845	**-4.4**	-19.3	10.6	**65.9**	2.9	99.2	**14.1**	-7.3	55.1	**2.8**	-3.0	9.7	**0.0**	-1.4	2.5
Asset Allocation	6,172	**-5.6**	-16.9	5.0	**59.9**	49.3	68.3	**21.5**	10.7	31.2	**1.6**	-2.1	6.7	**0.3**	-0.8	1.8
Equity	40,038	**-6.1**	-28.9	15.6	**99.1**	87.0	112.8	**-4.3**	-19.7	8.6	**-1.8**	-9.3	7.3	**1.6**	-1.6	5.8
Fixed Income	30,121	**-2.8**	-12.5	8.1	**1.6**	-0.7	4.7	**61.5**	43.8	73.0	**5.2**	2.2	11.6	**-0.6**	-1.4	0.2
Convertible	562	**0.8**	-13.5	18.1	**63.2**	54.1	72.2	**-0.2**	-14.2	11.0	**14.8**	7.4	22.0	**2.5**	0.3	4.7
Stock Portfolios	1,681	**4.3**	-22.6	31.6	**103.9**	89.9	118.1	**-0.8**	-18.7	18.4	**-2.6**	-15.1	9.3	**-0.5**	-5.6	4.5

Asset	USD x 100			VIX_S x 100			SMB x 100			HML x 100			UMD x 100			R^2 (%)		
	Med	25%	75%	Med	25%	75%	Med	25%	75%	Med	25%	75%	Med	25%	75%	Med	25%	75%
Hedge Funds																		
All	**4.4**	-7.4	19.2	**5.3**	-3.5	16.9	**10.0**	1.3	23.5	**6.5**	-3.1	20.0	**2.7**	-2.7	11.2	**42.0**	27.4	58.6
Convertible Arbitrage	**2.5**	-5.7	12.6	**0.5**	-4.4	5.7	**4.2**	1.1	10.1	**0.8**	-3.3	5.1	**-0.8**	-2.9	1.8	**32.8**	21.5	42.5
Dedicated Short Bias	**-4.1**	-15.0	7.0	**-1.6**	-21.2	6.9	**-17.7**	-57.8	-5.7	**18.4**	1.9	42.5	**-6.3**	-15.7	8.0	**73.5**	66.0	80.4
Emerging Markets	**15.1**	-4.7	48.6	**2.4**	-14.4	20.0	**16.7**	4.7	32.5	**15.7**	2.3	36.7	**4.7**	-4.7	15.8	**43.3**	30.4	55.6
Long/Short Equity	**5.6**	-9.1	22.0	**8.8**	-4.6	23.9	**21.3**	7.1	41.6	**9.5**	-10.1	30.5	**3.6**	-5.7	15.8	**51.3**	36.0	67.3
Equity Market Neutral	**1.1**	-9.4	8.8	**0.3**	-4.6	7.1	**1.2**	-4.8	9.8	**0.8**	-5.8	11.5	**1.9**	-2.3	8.4	**27.0**	19.9	39.1
Event Driven	**3.6**	-3.6	11.3	**1.4**	-4.7	7.6	**7.7**	2.8	16.1	**8.3**	2.8	16.5	**0.9**	-1.9	4.1	**42.7**	29.8	56.1
Fixed Income Arbitrage	**2.4**	-1.9	8.3	**1.7**	-2.9	8.3	**1.1**	-1.8	4.6	**1.9**	-2.0	9.1	**0.4**	-1.6	3.1	**26.3**	18.2	39.4
Fund of Funds	**6.2**	-2.9	18.7	**6.8**	1.1	14.5	**9.4**	3.6	17.3	**6.2**	0.6	14.1	**5.3**	0.6	11.1	**48.5**	34.1	63.5
Global Macro	**3.9**	-18.5	28.1	**3.5**	-8.2	16.9	**7.7**	-2.0	21.0	**10.2**	-5.6	24.4	**3.2**	-3.8	13.2	**30.1**	20.0	45.9
Managed Futures	**-1.4**	-28.2	26.2	**9.1**	-6.0	25.1	**4.1**	-15.4	18.6	**4.3**	-16.1	19.7	**1.7**	-7.7	16.6	**26.9**	19.3	36.6
Multi-Strategy	**3.8**	-7.4	13.0	**5.8**	-2.2	16.9	**8.1**	2.0	18.7	**4.5**	-1.6	13.6	**2.3**	-1.2	6.9	**41.2**	25.3	57.0
Mutual Funds																		
All	**-0.7**	-5.6	2.8	**0.4**	-3.3	4.4	**1.5**	-2.4	14.0	**4.2**	-1.5	15.9	**0.3**	-3.1	3.9	**87.0**	72.8	93.2
Asset Allocation	**-1.4**	-5.4	2.5	**0.6**	-2.3	4.0	**-1.1**	-6.3	4.4	**6.5**	0.9	15.0	**-0.8**	-4.3	2.3	**93.8**	88.9	96.6
Equity	**-0.9**	-13.4	8.1	**1.9**	-4.3	10.6	**10.8**	-6.2	37.9	**10.3**	-13.2	35.5	**0.9**	-6.4	10.9	**89.3**	81.1	93.7
Fixed Income	**-0.4**	-2.1	1.2	**-0.2**	-2.8	1.9	**0.6**	-1.2	2.5	**3.0**	0.1	6.3	**0.3**	-1.1	1.3	**80.0**	68.3	90.4
Convertible	**-1.6**	-7.5	2.8	**6.2**	2.6	10.8	**18.6**	14.7	26.2	**2.9**	-5.1	14.4	**4.9**	-1.6	12.8	**87.4**	83.1	91.0
Stock Portfolios	**1.9**	-8.6	12.5	**0.1**	-8.5	7.9	**58.7**	19.4	93.1	**35.7**	1.2	66.1	**-5.0**	-13.1	4.1	**84.0**	77.6	88.3

Table 9: Summary of the estimated exposures to 9 risk factors based on all 5-calendar-year estimation windows from 1986 to 2006. For each factor, the median (boldface) and the 25th and 75th percentiles are reported. Also included are the same statistics for the regression intercept, α, and R^2. The alphas are multiplied by 10,000, i.e., measured in units of basis points, and the factors exposures are multiplied by 100 for expositional convenience. The number of observations for each fund type is reported. MARKT: U.S. Stock Market; LH_GO: Lehman U.S. Aggregate Government Bond Index; LH_HY: Lehman U.S. Universal High-Yield Corporate Index; GSCI: Goldman Sachs Commodities Index; USD: Trade Weighted U.S. Dollar Index; VIX_S: Rescaled CBOE Volatility Index; SMB: Small-Minus-Big Index; HML: High-Minus-Low Index; UMD: Momentum Index.

	Count	MARKT	LH_GO	LH_HY	GSCI	USD	VIX_S	SMB	HML	UMD
Panel A: Hedge Funds										
All	11,666	-3	-17	12	-3	3	3	8	4	-7
Convertible Arbitrage	408	-32	-2	-4	-20	-27	-14	-12	5	1
Dedicated Short Bias	119	15	-6	5	22	-6	-2	-7	-17	9
Emerging Markets	749	-1	-14	1	-6	8	6	13	8	-3
Long/Short Equity	3,409	-5	-10	4	-2	10	9	8	2	-6
Equity Market Neutral	445	4	7	-3	-7	0	-6	5	8	-12
Event Driven	1,138	-6	-18	14	5	6	14	6	10	2
Fixed Income Arbitrage	379	-15	-15	-3	-11	-7	-12	8	0	4
Fund of Funds	2,514	8	-20	15	4	5	12	15	5	-3
Global Macro	467	-2	-9	-4	6	-9	-5	-2	14	0
Managed Futures	1,469	-3	10	-5	7	-18	13	7	-8	-9
Multi-Strategy	569	-14	-31	15	1	6	13	4	9	-4
Panel B: Mutual Funds										
All	85,845	-5	-9	10	-1	0	15	17	0	-2
Asset Allocation	6,172	-1	-13	13	-5	-3	12	30	15	-5
Equity	40,038	8	-12	2	-2	1	23	32	5	-1
Fixed Income	30,121	-2	-28	21	3	-7	16	-11	-21	-3
Convertible	562	-41	13	17	-18	-19	-11	3	26	-39
Panel C: U.S. Stock Portfolios	1,681	-17	-2	10	-12	5	5	53	3	-5

Table 10: Cross-sectional correlations between estimated autocorrelations, $\hat{\rho}_i$, and factor exposures, $\hat{\beta}_{i,k}$. These values are calculated based on the estimates for autocorrelation and factor exposure values over all 5-calendar-year estimation windows between 1986 and 2006 for each specified subgroup of assets. MARKT: U.S. Stock Market; LH_GO: Lehman U.S. Aggregate Government Bond Index; LH_HY: Lehman U.S. Universal High-Yield Corporate Index; GSCI: Goldman Sachs Commodities Index; USD: Trade Weighted U.S. Dollar Index; VIX_S: Rescaled CBOE Volatility Index; SMB: Small-Minus-Big Index; HML: High-Minus-Low Index; UMD: Momentum Index.

5.2 Illiquidity Premia in Raw Returns

Table 11 gives a summary of the average returns for the 5 liquidity portfolios as well as the liquidity spread portfolio based on raw returns, i.e., returns unadjusted for risk exposures, from 1986 to 2006.[19] These results are limited by certain data availability issues. For example, our mutual-fund sample contains only 74 Convertible mutual funds, hence we do not report the results for this subgroup in Table 11 since, in most years, each of the 5 liquidity portfolios would have contained too few funds to eliminate the noise and yield statistically reliable numbers. This limitation is even more severe among hedge funds (see, for example, Table 1), hence we have combined all hedge funds into three sub-groups based on a priori knowledge regarding the liquidity of the instruments used in their investment strategies and the length of their redemption notice period as reported in Table 7. These three sub-groups are: (1) the "Most Illiquid" subset, containing Convertible Arbitrage, Fixed Income Arbitrage, and Event Driven categories; (2) the "Most Liquid" subset, containing Managed Futures, Dedicated Short Bias, and Global Macro categories; and (3) the remaining 5 categories, which we refer to as the "Medium Liquidity" subset.[20]

The results shown in Table 11 provide some initial evidence that there is a link between expected returns and autocorrelation, even before adjusting for other sources of risk. For example, the average return is almost monotonically increasing in portfolio liquidity when all hedge funds are used in constructing the portfolios (see the first row in Table 11). Also, the difference between the highest and lowest portfolios, i.e., the liquidity spread, is also positive, although not statistically significant. A surprising observation is that the subset of hedge funds that contains the most liquid set of strategies shows the largest value for the liquidity spread, 4.24%, versus only 1.69% among the illiquid subset of funds. We will see later that this holds even after adjusting for various risk exposures, suggesting substantial variation in liquidity within this category.

In contrast, for the entire sample of mutual funds, there is no evidence for a link between autocorrelation and expected returns (see row 5 of Table 11). However, the link is much

[19]These averages, and the average liquidity spread, are annualized arithmetically, i.e., by multiplying the monthly values by 12.

[20]Note that we include the Fund of Funds category in this group even though they have a slightly longer redemption-notice period compared to Convertible Arbitrage and Fixed Income Arbitrage, since we believe that the longer period is partially due to the delegated nature of fund management in these funds.

clearer among the Fixed Income mutual funds and, to some extent, among the Equity mutual funds, while there is no relation among Asset Allocation Funds. This should be expected as Asset Allocation funds typically implement their investment views through highly liquid index futures and forward contracts. In fact, as seen in Table A.1 in Appendix A.2, the null hypothesis of zero autocorrelation can only be rejected for 0.4% of Asset Allocation mutual funds while the same metric is 5.5% and 15.2% for Equity and Fixed Income funds, respectively.

Finally, Table 11 points to a potential link between expected returns and autocorrelation even among the 100 stock portfolios used in this study. Given the strong link between autocorrelation and size reported in Table 3, one may suspect that the effect captured here is the well-known size effect. We will see in Section 5.3 that controlling for size (using the SMB factor) does not fully eliminate this effect.

Funds Used	Average Return (% Annualized)						Count
	Low	2	3	4	High	Difference	
All Hedge Funds	7.73 (4.17)	9.60 (5.02)	10.43 (4.50)	11.77 (6.00)	11.28 (6.25)	3.54 (1.70)	192
Illiquid Hedge Funds	9.09 (5.64)	11.20 (7.71)	10.95 (7.42)	11.70 (7.63)	10.78 (8.63)	1.69 (1.47)	192
Medium Liq. Hedge Funds	11.12 (5.99)	11.80 (5.40)	13.51 (5.56)	11.91 (4.77)	11.97 (5.35)	0.86 (0.49)	192
Liquid Hedge Funds	3.31 (1.20)	6.75 (2.49)	7.72 (2.47)	6.92 (2.46)	7.55 (2.70)	4.24 (1.48)	192
All Mutual Funds	9.22 (3.84)	9.44 (3.89)	8.65 (4.48)	8.02 (4.39)	8.95 (4.94)	-0.27 (-0.12)	192
Asset Allocation Mutual Funds	8.87 (4.73)	9.27 (4.54)	8.90 (4.40)	8.67 (4.25)	8.73 (5.08)	-0.14 (-0.15)	192
Equity Mutual Funds	11.48 (3.68)	11.58 (3.45)	11.69 (3.39)	12.15 (3.31)	13.28 (3.53)	1.80 (0.96)	192
Fixed Income Mutual Funds	5.70 (5.77)	5.88 (5.74)	5.94 (6.06)	6.12 (6.33)	7.40 (7.61)	1.70 (2.56)	192
Stocks (100 Value Weighted)	15.18 (4.36)	14.91 (4.04)	15.58 (3.90)	16.97 (4.05)	18.88 (3.91)	3.70 (1.25)	192

Table 11: Average returns of autocorrelation-sorted portfolios for mutual funds, hedge funds, and U.S. equity portfolios. Assets in the specified subset are grouped into 5 portfolios based on the first-order autocorrelation coefficients of returns estimated over the prior 5 years. The equal-weighted average return for each of the 5 quintiles is calculated for each month in the following year. This procedure is repeated from 1991 to 2006, yielding a total of 192 data points between January 1991 to December 2006. Reported t-statistics are based on Newey-West estimators using 3 lags. The "Difference" column reports the average of the difference in returns of the high- minus low-autocorrelation quintiles. The 3 subsets of hedge funds are defined as: "Illiquid Hedge Funds" = {Convertible Arbitrage, Fixed Income Arbitrage, Event Driven}, "Liquid Hedge Funds" = {Managed Futures, Global Macro, Dedicated Short Bias}. The remaining 5 categories are placed in the "Medium Liquidity Hedge Funds" group. Stock portfolios are the standard 100 two-way sorted portfolio based on market capitalization and book-equity/market-equity.

5.3 Illiquidity Premia in Risk-Adjusted Returns

Tables 12 and 13 report the average annualized returns of the liquidity portfolios based on the two risk adjustments and four sets of risk factors described in Section 5.1. We have also repeated the relevant row from Table 11 (labeled “raw”) to facilitate the comparison of these risk-adjusted-return results with those using raw returns. The results from the two approaches for risk adjustment are qualitatively similar to those with raw returns. The average annualized risk-adjusted return for the liquidity spread portfolios, i.e. the difference between the least and most liquid set of funds, reported in the column “Difference”, is almost always positive and very often statistically different from zero. It seems that our risk adjustments have been successful is reducing the volatility of the portfolio returns, hence the estimated spreads are more precise and more often statistically significant than for raw returns.

Based on the data presented in Panel A of Tables 12 and 13, the illiquidity premium is even visible among all funds after risk adjustment. But, as expected, the premium is more pronounced among hedge funds since they contain the most significant and exotic forms of illiquidity. The liquidity spread for hedge funds, estimated using the first method of risk adjustment with the Broad Factor Set is 3.96% per year. With the same Broad Factor Set, the second risk-adjustment method produces a premium of 4.85%. The estimated premium among the most illiquid hedge funds is 3.90% and 3.87% based on the first and second risk-adjustment methods, respectively, in both cases using the Broad Factor Set. Similar to the pattern in Table 11 for raw returns, the liquidity spread seems to be larger among the most liquid hedge funds. For example, Table 12 produces a risk-adjusted liquidity spread of 4.95% for this subset of funds based on the Broad Factor Set, while Table 13 shows that the second risk-adjustment method produces even a larger spread of 7.42%. Note that in all these cases, the results produced by the Lagged Market model is very similar to those produced by the other risk models, suggesting that including a lagged U.S. stock market factor does not adequately capture illiquidity as measured by autocorrelation.

Among the mutual funds categories, the Asset Allocation mutual funds do not exhibit any statistically significant liquidity spreads (see rows 6 through 10 in Panel C of Tables 12 and 13). However, the Fixed Income funds do show positive liquidity spreads which are, in all but one case, statistically significant (see rows 16 through 20 in Panel C of Tables 12 and 13). For example, the liquidity spread based on the Broad Factor Set using the first risk-adjustment method is 2.74% while the second method produces a slightly smaller but still statistically significant spread of 1.11%. The results among the Equity mutual funds (rows 11 through 15 in Panel C of Tables 12 and 13) are not as clear. For example, the first risk-adjustment method produces illiquidity premia that are not distinguishable from zero for this subset of funds, while the second method produces a premium that come close to the critical level in only one case (see row 14 in Panel C of Table 13). Contrary to the case of hedge funds, the Lagged Market Model seems to capture most of the illiquidity premium among equity mutual funds. This is not surprising since the lagged exposure to the market factor is no doubt due to the illiquidity of the underlying equities. Hedge funds, on the other hand, have considerably more heterogeneous sources of illiquidity, hence controlling for a lagged U.S. equity factor does not change the results in a any significant way as seen in Tables 12 and 13.

The results from the 100 stock portfolios shown in Panel D of these two tables are also mixed. For all but the second risk-adjustment method and the Lagged Market model, the estimated liquidity spreads are positive, but not statistically significant in most cases. Controlling for the size (SMB) factor seems to reduce the magnitude of this premium—for example, from 4.37% to 2.14% in Table 13—it does not seem to make it economically irrelevant. In fact, after controlling for size, the estimates seem to be more accurate as seen by the larger t-statistics (compare rows 2 vs. 3 in Panel D in Tables 12 and 13). Lagged exposure to the U.S. Stock Market Factor seems to capture most of the illiquidity premium among this group of assets.

5.4 Illiquidity Premia Among Hedge-Fund Categories

In this section, we apply the same analysis of Section 5.3 to each of the 11 hedge-fund categories in the Lipper/TASS database, and the results are summarized in Table 14. Given the wide array of strategies used by hedge funds and, in particular, the nonlinearities and volatility exposures of some of those strategies, it would be reasonable to expect that risk adjustments based on the Broad Factor Set would produce the most accurate set of results. Therefore, we only report the risk-adjusted results using the Broad Factor Set to conserve space. Due to data availability issues discussed in Section 5.2, for certain categories we can only construct liquidity portfolios for the more recent part of the sample period. For this reason, we report the number of monthly observations available for each category in Table 14.

Table 14 shows that the most illiquid categories of funds—in particular Convertible Arbitrage and Fixed Income Arbitrage funds—exhibit large and, in most cases, statistically significant illiquidity premia. In fact, these results suggest that the high illiquidity premium in the "Most Liquid" category of hedge funds found in Table 12 and 13 (recall that this subset includes Global Macro, Dedicated Short Bias, and Managed Futures) is primarily driven by the large premium among Managed Futures funds.

One surprising result in Table 14 is the negative illiquidity premium among Global Macro hedge funds. Although the premium is only statistically significant in Panel A, the result does seem to be robust as it is negative in all three cases. This also seems to be robust to different sets of factors used for risk adjustment; for example, using the second method with the U.S. Stock Market index as the only risk factor produces a premium of -6.5%, while using the 4-Factor Set produces a premium of -8.2% (note that these results are not reported in Table 14).

Table 14 also reports the results for the average of the 11 individual time-series, one for each of the 11 categories. This result is labeled as "All (Category Neutral)" since it includes all available hedge fund returns, and the liquidity spread is estimated as 3.93%, which is in line with earlier estimates. The reason for the qualifier "Category Neutral" is the fact that, by construction, the autocorrelation quintiles are not biased toward any one category of funds, in contrast to Tables 12 and 13 where the highest-autocorrelation

Funds Used	Factor Set	Alpha (Annualized in %) Low	2	3	4	High	Difference	Count
Panel A: All Funds								
All	Raw	9.18 (4.06)	9.42 (4.18)	8.94 (4.64)	8.33 (4.65)	9.25 (5.66)	0.07 (0.03)	192
All	Market Only	1.61 (1.61)	1.63 (1.87)	2.69 (3.17)	3.61 (3.08)	5.47 (5.02)	3.86 (2.20)	192
All	4-Factor Set	1.00 (0.95)	0.60 (0.71)	0.89 (1.26)	1.42 (1.16)	3.15 (2.81)	2.15 (1.13)	192
All	Broad Factor Set	-0.75 (-0.84)	-0.90 (-1.22)	-0.75 (-1.06)	-0.70 (-0.68)	0.94 (1.04)	1.69 (1.04)	192
All	Lagged Market	1.45 (1.42)	1.55 (1.69)	2.64 (2.83)	3.44 (2.73)	5.07 (4.62)	3.62 (2.08)	192
Panel B: Hedge Funds								
All Hedge Funds	Raw	7.73 (4.17)	9.60 (5.02)	10.43 (4.50)	11.77 (6.00)	11.28 (6.25)	3.54 (1.70)	192
All Hedge Funds	Market Only	4.93 (2.71)	7.00 (4.28)	7.03 (3.76)	7.59 (5.44)	7.82 (4.69)	2.89 (1.20)	192
All Hedge Funds	4-Factor Set	3.30 (1.91)	5.45 (3.04)	5.25 (2.64)	5.24 (4.13)	6.04 (3.66)	2.74 (1.16)	192
All Hedge Funds	Broad Factor Set	0.99 (0.64)	2.95 (1.78)	3.05 (1.76)	3.42 (3.03)	4.95 (3.86)	3.96 (2.30)	192
All Hedge Funds	Lagged Market	5.52 (3.00)	6.70 (4.04)	6.88 (3.59)	6.78 (4.46)	6.61 (3.54)	1.09 (0.43)	192
Illiquid Hedge Funds	Raw	9.09 (5.64)	11.20 (7.71)	10.95 (7.42)	11.70 (7.63)	10.78 (8.63)	1.69 (1.47)	192
Illiquid Hedge Funds	Market Only	6.39 (4.80)	9.07 (7.52)	8.67 (6.16)	9.82 (6.94)	9.66 (7.66)	3.27 (3.24)	192
Illiquid Hedge Funds	4-Factor Set	5.44 (3.61)	7.52 (7.15)	7.36 (5.48)	8.83 (5.90)	8.62 (7.43)	3.18 (3.08)	192
Illiquid Hedge Funds	Broad Factor Set	3.75 (3.17)	6.29 (5.38)	6.99 (6.06)	7.81 (6.24)	7.65 (7.12)	3.90 (4.10)	192
Illiquid Hedge Funds	Lagged Market	5.55 (3.81)	8.00 (6.93)	7.66 (5.39)	8.43 (5.65)	8.59 (6.69)	3.04 (2.87)	192
Medium Liq. Hedge Funds	Raw	11.12 (5.99)	11.80 (5.40)	13.51 (5.56)	11.91 (4.77)	11.97 (5.35)	0.86 (0.49)	192
Medium Liq. Hedge Funds	Market Only	6.22 (5.10)	6.97 (4.54)	7.78 (4.74)	6.23 (3.44)	7.56 (3.77)	1.34 (0.66)	192
Medium Liq. Hedge Funds	4-Factor Set	5.08 (4.64)	5.72 (3.78)	5.40 (3.74)	3.56 (2.18)	5.44 (2.85)	0.37 (0.17)	192
Medium Liq. Hedge Funds	Broad Factor Set	2.95 (2.61)	4.68 (3.07)	3.30 (2.45)	2.19 (1.68)	4.29 (2.88)	1.34 (0.78)	192
Medium Liq. Hedge Funds	Lagged Market	6.31 (5.33)	6.31 (4.13)	6.93 (4.04)	5.09 (2.59)	6.31 (2.86)	0.00 (0.00)	192
Liquid Hedge Funds	Raw	3.31 (1.20)	6.75 (2.49)	7.72 (2.47)	6.92 (2.46)	7.55 (2.70)	4.24 (1.48)	192
Liquid Hedge Funds	Market Only	2.61 (0.88)	6.75 (2.39)	9.72 (2.96)	8.02 (2.91)	7.76 (3.00)	5.15 (2.03)	192
Liquid Hedge Funds	4-Factor Set	-0.58 (-0.19)	3.28 (1.09)	7.96 (2.29)	5.46 (1.82)	5.67 (2.06)	6.26 (2.30)	192
Liquid Hedge Funds	Broad Factor Set	-3.43 (-1.25)	-0.87 (-0.32)	2.44 (0.85)	1.11 (0.43)	1.52 (0.56)	4.95 (1.88)	192
Liquid Hedge Funds	Lagged Market	3.85 (1.29)	8.16 (2.72)	10.67 (3.19)	8.49 (3.07)	8.90 (3.29)	5.05 (1.98)	192

Table 12a: Average returns of risk-adjusted liquidity portfolios, adjusted according to a time-series regression using the entire historical sample. Assets in the specified subset are grouped into 5 portfolios based on autocorrelations estimated over the preceding 5 years. Equal-weighted average returns for each of the 5 groups are calculated for each month in the following year. The resulting 192 such monthly returns (January 1991 to December 2006) are used to estimate the regression $R_{p,t} = \alpha_p + \sum \beta_{p,k}\Lambda_{k,t} + \epsilon_{p,t}$, from which α_p is used to measure risk-adjusted return. The four sets of factors used to estimate the α_p's are: "Market Only", which contains the concurrent return of the aggregate U.S. stock market; the "Four-Factor Set", which contains the return for the aggregate U.S. stocks market plus size, value, and momentum factors; the "Broad Factor Set", which contains 9 risk factors (the Fama-French U.S. Market Index, the Lehman U.S. Aggregate Government Bond Index, the Lehman Universal High-Yield Corporate Index, the Goldman Sachs Commodities Index, the traded-weighted U.S. Dollar Index, the Fama-French High-Minus-Low (HML) Book-to-Market Index, the Fama-French Small-Minus-Big (SMB) Capitalization Index, the Fama-French Momentum Index, and the first-difference of the VIX Volatility Index); and "Lagged Market", which contains the concurrent and lagged return of the aggregate U.S. stock market.

Funds Used	Factor Set	Alpha (Annualized in %) Low	2	3	4	High	Difference	Count
Panel C: Mutual Funds								
All Mutual Funds	Raw	9.22 (3.84)	9.44 (3.89)	8.65 (4.48)	8.02 (4.39)	8.95 (4.94)	-0.27 (-0.12)	192
All Mutual Funds	Market Only	1.17 (1.17)	1.00 (0.94)	2.29 (2.70)	3.30 (2.60)	4.89 (3.73)	3.71 (1.82)	192
All Mutual Funds	4-Factor Set	0.63 (0.58)	0.13 (0.12)	0.63 (0.87)	1.16 (0.84)	2.46 (1.68)	1.84 (0.79)	192
All Mutual Funds	Broad Factor Set	-1.05 (-1.12)	-1.03 (-1.13)	-1.09 (-1.57)	-1.00 (-0.90)	0.25 (0.22)	1.30 (0.68)	192
All Mutual Funds	Lagged Market	0.93 (0.90)	0.90 (0.81)	2.29 (2.47)	3.20 (2.35)	4.57 (3.39)	3.64 (1.75)	192
Asset Allocation Mut. Funds	Raw	8.87 (4.73)	9.27 (4.54)	8.90 (4.40)	8.67 (4.25)	8.73 (5.08)	-0.14 (-0.15)	192
Asset Allocation Mut. Funds	Market Only	2.34 (3.52)	2.12 (3.76)	1.89 (2.89)	1.54 (2.11)	3.46 (3.49)	1.12 (1.17)	192
Asset Allocation Mut. Funds	4-Factor Set	1.50 (2.20)	1.12 (2.51)	0.75 (1.50)	0.09 (0.19)	1.55 (2.39)	0.05 (0.07)	192
Asset Allocation Mut. Funds	Broad Factor Set	-0.37 (-0.92)	-0.65 (-2.40)	-0.73 (-2.17)	-1.38 (-3.27)	-0.46 (-0.76)	-0.09 (-0.13)	192
Asset Allocation Mut. Funds	Lagged Market	2.45 (3.85)	2.18 (3.79)	1.95 (2.93)	1.62 (2.04)	3.26 (3.01)	0.81 (0.81)	192
Equity Mutual Funds	Raw	11.48 (3.68)	11.58 (3.45)	11.69 (3.39)	12.15 (3.31)	13.28 (3.53)	1.80 (0.96)	192
Equity Mutual Funds	Market Only	0.67 (0.85)	-0.08 (-0.10)	-0.36 (-0.44)	-0.31 (-0.28)	1.26 (0.72)	0.60 (0.33)	192
Equity Mutual Funds	4-Factor Set	-0.92 (-1.26)	-1.19 (-1.42)	-1.39 (-1.89)	-1.37 (-1.61)	-1.39 (-1.47)	-0.47 (-0.41)	192
Equity Mutual Funds	Broad Factor Set	-0.58 (-0.77)	-0.60 (-0.69)	-0.87 (-1.16)	-0.60 (-0.70)	-1.20 (-1.28)	-0.62 (-0.52)	192
Equity Mutual Funds	Lagged Market	0.37 (0.45)	-0.28 (-0.30)	-0.56 (-0.61)	-0.58 (-0.50)	0.51 (0.29)	0.14 (0.08)	192
Fixed Income Mutual Funds	Raw	5.70 (5.77)	5.88 (5.74)	5.94 (6.06)	6.12 (6.33)	7.40 (7.61)	1.70 (2.56)	192
Fixed Income Mutual Funds	Market Only	4.89 (4.59)	5.45 (4.94)	5.45 (5.29)	5.68 (5.58)	6.89 (7.16)	2.00 (2.89)	192
Fixed Income Mutual Funds	4-Factor Set	3.69 (2.94)	3.96 (3.12)	3.94 (3.47)	4.24 (3.82)	5.65 (5.45)	1.96 (2.66)	192
Fixed Income Mutual Funds	Broad Factor Set	-1.12 (-1.74)	-0.86 (-1.44)	-0.64 (-1.31)	-0.35 (-0.95)	1.62 (3.35)	2.74 (3.56)	192
Fixed Income Mutual Funds	Lagged Market	4.92 (4.49)	5.55 (4.81)	5.52 (5.14)	5.83 (5.54)	6.80 (6.96)	1.87 (2.98)	192
Panel D: Stocks								
Stocks (100 Value Weighted)	Raw	15.18 (4.36)	14.91 (4.04)	15.58 (3.90)	16.97 (4.05)	18.88 (3.91)	3.70 (1.25)	192
Stocks (100 Value Weighted)	Market Only	3.84 (1.77)	3.39 (1.48)	2.71 (1.34)	4.66 (1.75)	6.88 (1.99)	3.04 (1.00)	192
Stocks (100 Value Weighted)	4-Factor Set	0.08 (0.09)	-1.39 (-1.19)	-0.64 (-0.63)	-0.48 (-0.47)	2.19 (2.13)	2.10 (1.55)	192
Stocks (100 Value Weighted)	Broad Factor Set	0.94 (0.91)	-0.33 (-0.29)	-0.66 (-0.65)	-0.17 (-0.16)	1.69 (1.79)	0.75 (0.54)	192
Stocks (100 Value Weighted)	Lagged Market	2.89 (1.19)	2.42 (0.98)	1.78 (0.80)	3.15 (1.12)	3.72 (1.12)	0.83 (0.29)	192

Table 12b: (Continued).

Funds Used	Factor Set	Average Return (% Annualized) Low	2	3	4	High	Difference	Count
Panel A: All Funds								
All	Raw	9.18 (4.06)	9.42 (4.18)	8.94 (4.64)	8.33 (4.65)	9.25 (5.66)	0.07 (0.03)	192
All	Market Model	1.69 (2.47)	1.43 (2.13)	1.70 (2.55)	2.31 (3.24)	4.73 (6.11)	3.04 (3.71)	192
All	4-Factor Set	0.56 (0.84)	0.85 (1.40)	0.97 (1.58)	1.40 (2.02)	2.95 (4.91)	2.39 (3.26)	192
All	Broad Factor Set	-0.52 (-1.09)	-0.26 (-0.51)	-0.12 (-0.25)	0.08 (0.21)	2.00 (4.33)	2.52 (4.62)	192
All	Lagged Market	2.08 (3.09)	1.37 (1.92)	1.39 (1.88)	1.80 (2.37)	3.69 (4.67)	1.61 (1.89)	192
Panel B: Hedge Funds								
All Hedge Funds	Raw	7.73 (4.17)	9.60 (5.02)	10.43 (4.50)	11.77 (6.00)	11.28 (6.25)	3.54 (1.70)	192
All Hedge Funds	Market Model	4.71 (2.82)	7.92 (4.39)	8.09 (3.88)	8.38 (5.36)	7.64 (5.53)	2.93 (1.51)	192
All Hedge Funds	4-Factor Set	3.56 (2.13)	6.01 (3.51)	6.60 (3.26)	6.34 (4.79)	5.21 (4.51)	1.64 (0.94)	192
All Hedge Funds	Broad Factor Set	1.19 (0.64)	4.38 (2.32)	5.41 (2.46)	5.71 (3.85)	6.04 (5.46)	4.85 (2.67)	192
All Hedge Funds	Lagged Market	5.52 (3.37)	8.71 (4.40)	7.92 (3.96)	7.76 (4.81)	5.93 (4.43)	0.41 (0.23)	192
Illiquid Hedge Funds	Raw	9.09 (5.64)	11.20 (7.71)	10.95 (7.42)	11.70 (7.63)	10.78 (8.63)	1.69 (1.47)	192
Illiquid Hedge Funds	Market Model	4.67 (3.97)	7.34 (6.09)	9.31 (7.16)	8.33 (5.94)	8.90 (8.08)	4.23 (4.14)	192
Illiquid Hedge Funds	4-Factor Set	2.66 (2.11)	5.44 (4.14)	5.73 (4.16)	4.94 (2.69)	5.59 (4.76)	2.93 (2.40)	192
Illiquid Hedge Funds	Broad Factor Set	2.58 (2.07)	7.27 (6.17)	7.39 (5.41)	5.27 (3.10)	6.45 (5.72)	3.87 (2.73)	192
Illiquid Hedge Funds	Lagged Market	4.26 (3.67)	5.81 (4.77)	7.86 (6.01)	6.50 (4.67)	7.22 (7.06)	2.97 (2.88)	192
Medium Liq. Hedge Funds	Raw	11.12 (5.99)	11.80 (5.40)	13.51 (5.56)	11.91 (4.77)	11.97 (5.35)	0.86 (0.49)	192
Medium Liq. Hedge Funds	Market Model	7.11 (6.05)	8.02 (5.28)	8.58 (5.21)	6.42 (3.46)	7.42 (4.43)	0.31 (0.18)	192
Medium Liq. Hedge Funds	4-Factor Set	5.21 (4.27)	5.89 (4.55)	6.30 (4.63)	4.58 (2.95)	5.71 (4.24)	0.50 (0.32)	192
Medium Liq. Hedge Funds	Broad Factor Set	3.04 (2.55)	4.79 (3.11)	5.98 (4.54)	3.28 (1.50)	6.62 (5.04)	3.58 (2.26)	192
Medium Liq. Hedge Funds	Lagged Market	7.04 (6.12)	7.37 (4.81)	7.66 (4.57)	4.87 (2.60)	5.43 (3.33)	-1.61 (-0.96)	192
Liquid Hedge Funds	Raw	3.31 (1.20)	6.75 (2.49)	7.72 (2.47)	6.92 (2.46)	7.55 (2.70)	4.24 (1.48)	192
Liquid Hedge Funds	Market Model	0.84 (0.29)	8.13 (2.79)	7.79 (2.44)	9.25 (3.15)	8.42 (2.91)	7.58 (2.59)	192
Liquid Hedge Funds	4-Factor Set	-1.18 (-0.41)	7.35 (2.58)	6.33 (2.00)	9.37 (3.06)	6.74 (2.29)	7.92 (2.70)	192
Liquid Hedge Funds	Broad Factor Set	-3.44 (-1.23)	3.42 (1.13)	2.20 (0.62)	4.42 (1.45)	3.98 (1.31)	7.42 (2.62)	192
Liquid Hedge Funds	Lagged Market	2.60 (0.92)	9.70 (3.26)	9.50 (2.98)	10.79 (3.48)	9.76 (3.21)	7.17 (2.28)	192

Table 13a: Average returns of risk-adjusted liquidity portfolios, adjusted according to a rolling-window method. Assets in the specified subset are grouped into 5 portfolios based on autocorrelations estimated over the preceding 5 years. The risk adjustment is performed by subtracting the sum of the product of a pre-specified set of factor realizations and their estimated loadings or $\hat{\beta}$'s, where the $\hat{\beta}$ values are estimated with the preceding 5 calendar years of data. The equal-weighted average of the residual returns of funds within each of the 5 quintiles is then averaged each month to yield the quintile portfolio's risk-adjusted return for that month. Finally, the average of these risk-adjusted portfolio returns is computed across the 192 months between January 1991 to December 2006. Reported t-stats are based on the Newey-West estimator with 3 lags. The four sets of factors used to estimate the β_{i,k,t^*}'s are: "Market Only", which contains the concurrent return of the aggregate U.S. stock market; the "Four-Factor Set", which contains the return for the aggregate U.S. stocks market plus size, value, and momentum factors; the "Broad Factor Set", which contains 9 risk factors (the Fama-French U.S. Market Index, the Lehman U.S. Aggregate Government Bond Index, the Lehman Universal High-Yield Corporate Index, the Goldman Sachs Commodities Index, the traded-weighted U.S. Dollar Index, the Fama-French High-Minus-Low (HML) Book-to-Market Index, the Fama-French Small-Minus-Big (SMB) Capitalization Index, the Fama-French Momentum Index, and the first-difference of the VIX Volatility Index); and "Lagged Market", which contains the concurrent and lagged return of the aggregate U.S. stock market.

Funds Used	Factor Set	Average Return (% Annualized) Low	2	3	4	High	Difference	Count
Panel C: Mutual Funds								
All Mutual Funds	Raw	9.22 (3.84)	9.44 (3.89)	8.65 (4.48)	8.02 (4.39)	8.95 (4.94)	-0.27 (-0.12)	192
All Mutual Funds	Market Model	1.37 (2.01)	0.82 (1.16)	1.09 (1.63)	1.77 (2.48)	4.01 (5.12)	2.64 (2.99)	192
All Mutual Funds	4-Factor Set	0.30 (0.47)	0.38 (0.63)	0.42 (0.65)	0.94 (1.30)	2.34 (3.72)	2.04 (2.47)	192
All Mutual Funds	Broad Factor Set	-0.68 (-1.43)	-0.71 (-1.39)	-0.59 (-1.21)	-0.38 (-0.96)	1.00 (2.56)	1.67 (3.15)	192
All Mutual Funds	Lagged Market	1.68 (2.49)	0.74 (0.97)	0.82 (1.09)	1.32 (1.75)	3.04 (3.86)	1.35 (1.48)	192
Asset Allocation Mutual Funds	Raw	8.87 (4.73)	9.27 (4.54)	8.90 (4.40)	8.67 (4.25)	8.73 (5.08)	-0.14 (-0.15)	192
Asset Allocation Mutual Funds	Market Model	1.67 (2.91)	1.35 (2.41)	1.23 (1.88)	1.21 (1.73)	2.61 (2.95)	0.94 (1.45)	192
Asset Allocation Mutual Funds	4-Factor Set	1.07 (2.03)	0.86 (1.84)	0.58 (1.17)	0.38 (0.62)	1.20 (1.78)	0.14 (0.29)	192
Asset Allocation Mutual Funds	Broad Factor Set	-0.55 (-1.53)	-0.54 (-1.65)	-0.62 (-1.79)	-0.93 (-1.86)	-0.24 (-0.49)	0.30 (0.68)	192
Asset Allocation Mutual Funds	Lagged Market	2.24 (3.93)	1.46 (2.57)	1.29 (1.94)	0.94 (1.32)	1.78 (1.91)	-0.47 (-0.66)	192
Equity Mutual Funds	Raw	11.48 (3.68)	11.58 (3.45)	11.69 (3.39)	12.15 (3.31)	13.28 (3.53)	1.80 (0.96)	192
Equity Mutual Funds	Market Model	0.17 (0.23)	-0.08 (-0.11)	-0.28 (-0.37)	-0.13 (-0.13)	1.40 (0.83)	1.24 (0.68)	192
Equity Mutual Funds	4-Factor Set	-1.20 (-1.51)	-0.89 (-1.30)	-0.74 (-1.07)	-0.68 (-0.92)	0.12 (0.13)	1.32 (1.15)	192
Equity Mutual Funds	Broad Factor Set	-1.15 (-1.71)	-0.47 (-0.65)	-0.31 (-0.45)	-0.18 (-0.24)	0.88 (0.91)	2.04 (1.98)	192
Equity Mutual Funds	Lagged Market	0.71 (0.94)	-0.00 (-0.00)	-0.61 (-0.82)	-1.13 (-1.04)	-0.76 (-0.43)	-1.47 (-0.75)	192
Fixed Income Mutual Funds	Raw	5.70 (5.77)	5.88 (5.74)	5.94 (6.06)	6.12 (6.33)	7.40 (7.61)	1.70 (2.56)	192
Fixed Income Mutual Funds	Market Model	4.05 (3.87)	4.04 (3.74)	4.05 (4.03)	4.40 (4.58)	5.49 (6.24)	1.45 (2.25)	192
Fixed Income Mutual Funds	4-Factor Set	3.04 (2.81)	3.14 (2.86)	3.24 (3.22)	3.72 (3.84)	4.58 (5.37)	1.55 (2.48)	192
Fixed Income Mutual Funds	Broad Factor Set	0.12 (0.24)	0.16 (0.32)	0.09 (0.24)	0.24 (1.06)	1.23 (4.08)	1.11 (2.05)	192
Fixed Income Mutual Funds	Lagged Market	4.18 (3.92)	4.20 (3.83)	4.28 (4.08)	4.47 (4.49)	4.73 (5.09)	0.55 (0.87)	192
Panel D: Stocks								
Stocks (100 Value Weighted)	Raw	15.18 (4.36)	14.91 (4.04)	15.58 (3.90)	16.97 (4.05)	18.88 (3.91)	3.70 (1.25)	192
Stocks (100 Value Weighted)	Market Model	2.64 (1.47)	2.19 (1.16)	2.29 (1.18)	3.87 (1.64)	7.02 (2.19)	4.37 (1.48)	192
Stocks (100 Value Weighted)	4-Factor Set	-0.36 (-0.36)	-0.96 (-0.97)	-1.02 (-1.02)	0.06 (0.05)	1.78 (1.98)	2.14 (1.94)	192
Stocks (100 Value Weighted)	Broad Factor Set	-0.40 (-0.37)	-0.68 (-0.69)	-0.63 (-0.63)	0.08 (0.07)	2.00 (2.08)	2.41 (2.09)	192
Stocks (100 Value Weighted)	Lagged Market	2.90 (1.64)	1.31 (0.68)	0.32 (0.16)	0.77 (0.31)	1.89 (0.57)	-1.01 (-0.34)	192

Table 13b: (Continued).

quintile is biased toward the more illiquid funds such as Convertible Arbitrage and the lowest-autocorrelation quintile is biased toward the more liquid funds such as Managed Futures and Global Macro. In fact, each quintile in the "All (Category Neutral)" row contains approximately the same number of funds, and the same distribution across the 11 categories of hedge funds. One potentially important benefit of this construction is the fact that missing risk factors unrelated to illiquidity for a particular hedge-fund category are less likely to confound the liquidity spread estimate because the missing factor will affect all autocorrelation quintiles in approximately the same way (due to the assumption that the missing factor is not related to illiquidity). This characteristic suggests that an illiquidity premium of 3.93% may be the most robust estimate for the hedge-fund industry as a whole.

5.5 Dynamics of Illiquidity Premia: 1998–2006

Given the liquidity shocks that have affected traditional and alternative investments over the past decade, a natural application of our autocorrelation-based illiquidity premium is to see whether its time variation during that period reflects such shocks. We focus on the

Panel A: Raw Returns

Funds Used	Mean (% Annualized) Lowest	2	3	4	Highest	Difference	Count
Convertible Arbitrage	7.34 (1.57)	10.80 (4.49)	10.49 (4.63)	6.01 (2.65)	9.81 (7.12)	2.47 (0.56)	144
Dedicated Short Bias	-3.00 (-0.44)	-8.04 (-1.08)	-4.97 (-0.51)	1.68 (0.25)	4.38 (0.90)	7.37 (1.22)	120
Emerging Markets	8.46 (1.47)	13.15 (1.91)	13.75 (2.13)	16.39 (2.64)	10.47 (1.72)	2.01 (0.65)	144
Long/Short Equity	14.14 (5.75)	14.69 (5.23)	13.43 (4.51)	14.82 (5.18)	15.46 (5.78)	1.32 (0.75)	192
Equity Market Neutral	9.48 (5.39)	-2.06 (-0.83)	6.99 (3.82)	8.59 (4.08)	8.10 (4.45)	-1.38 (-0.67)	120
Event Driven	11.28 (6.73)	12.14 (8.03)	12.64 (7.11)	11.77 (7.47)	11.77 (8.33)	0.49 (0.45)	192
Fixed Income Arbitrage	-0.81 (-0.41)	8.55 (4.24)	5.19 (2.56)	6.23 (3.51)	3.95 (1.17)	4.76 (1.30)	131
Fund of Funds	7.53 (3.91)	8.84 (5.05)	9.96 (4.92)	10.22 (4.12)	9.87 (5.64)	2.34 (1.02)	192
Global Macro	10.74 (3.57)	9.54 (2.39)	6.79 (1.71)	13.22 (2.91)	3.48 (1.32)	-7.26 (-2.11)	180
Managed Futures	3.63 (1.23)	6.08 (2.00)	8.50 (2.72)	6.94 (2.01)	7.53 (2.38)	3.91 (1.51)	192
Multi-Strategy	11.42 (3.00)	9.80 (1.99)	15.59 (3.31)	11.82 (4.03)	6.93 (1.85)	-4.49 (-0.82)	108
All (Category Neutral)	7.93 (5.62)	9.18 (6.02)	9.72 (6.15)	10.74 (6.15)	9.52 (6.67)	1.59 (1.30)	192

Table 14a: Average returns of raw (Panel A) and risk-adjusted (Panels B and C) liquidity portfolios for each of 11 Lipper/TASS hedge-fund categories, risk adjusted using two methods, and using the following 9 risk factors: the Fama-French U.S. Market Index, the Lehman U.S. Aggregate Government Bond Index, the Lehman Universal High-Yield Corporate Index, the Goldman Sachs Commodities Index, the traded-weighted U.S. Dollar Index, the Fama-French High-Minus-Low (HML) Book-to-Market Index, the Fama-French Small-Minus-Big (SMB) Capitalization Index, the Fama-French Momentum Index, and the first-difference of the VIX Volatility Index. Assets in the specified subset are grouped into 5 portfolios based on autocorrelations estimated over the preceding 5 years, and quintile returns are computed as equal-weighted averages of monthly returns of funds in the autocorrelation quintile. The first risk-adjustment method (Panel B) involves regressing the entire time series of quintile returns on all factors and taking the estimated intercept term as the risk-adjusted return. The second risk-adjustment method (Panel C) is performed by subtracting the sum of the product of a pre-specified set of factor realizations and their estimated loadings or β's, where the β values are estimated with the preceding 5 calendar years of data. The equal-weighted average of the residuals of funds in each of the 5 autocorrelation-quintiles is computed each month to yield the quintile portfolio's risk-adjusted return for that month. Finally, the average of these risk-adjusted portfolio returns is computed across all months from January 1991 to December 2006 for which we have at least 5 funds (the minimum number needed to construct 5 autocorrelation-ranked portfolios) in the given category. Reported t-stats are based on the Newey-West estimator with 3 lags. The "All (Category Neutral)" is the equal-weighted average of the above 11 time-series. It is "Category Neutral" in the sense that each of the 5 quintile portfolios involved in calculating the time series used in creating the values reported in this table contains the same number of funds from each category.

Panel B: Alpha After Adjusting for Broad Factor Set

Funds Used			Alpha (Annualized in %)				Count
	Low	2	3	4	High	Difference	
Convertible Arbitrage	-0.23 (-0.07)	6.45 (2.89)	6.91 (4.19)	4.53 (2.24)	9.69 (6.70)	9.91 (2.98)	144
Dedicated Short Bias	2.92 (0.49)	2.36 (0.52)	1.46 (0.17)	12.24 (3.33)	7.49 (2.47)	4.57 (0.62)	120
Emerging Markets	-0.09 (-0.02)	-2.05 (-0.44)	0.54 (0.11)	2.29 (0.48)	-1.08 (-0.25)	-0.99 (-0.28)	144
Long/Short Equity	6.74 (5.15)	3.33 (2.73)	2.62 (1.64)	4.03 (2.33)	4.19 (3.76)	-2.55 (-1.82)	192
Equity Market Neutral	9.42 (5.25)	-3.59 (-1.55)	2.29 (1.22)	5.79 (3.03)	5.10 (3.14)	-4.32 (-2.05)	120
Event Driven	5.76 (4.21)	6.81 (5.28)	7.99 (6.54)	7.15 (4.90)	7.61 (7.01)	1.86 (1.90)	192
Fixed Income Arbitrage	-2.51 (-1.73)	3.01 (1.38)	3.87 (1.69)	2.23 (0.99)	4.57 (1.44)	7.08 (2.08)	131
Fund of Funds	0.28 (0.13)	2.39 (1.41)	3.01 (1.70)	3.92 (2.16)	3.73 (2.97)	3.45 (1.36)	192
Global Macro	4.43 (1.58)	3.46 (0.86)	-3.21 (-0.77)	5.07 (1.04)	-1.30 (-0.47)	-5.73 (-1.51)	180
Managed Futures	-3.90 (-1.23)	-1.24 (-0.43)	2.66 (0.82)	-1.56 (-0.51)	1.00 (0.29)	4.91 (1.73)	192
Multi-Strategy	3.43 (1.34)	5.96 (1.20)	9.77 (2.73)	7.73 (4.70)	3.64 (1.02)	0.21 (0.05)	108
All (Category Neutral)	2.30 (2.16)	2.99 (2.37)	3.34 (2.34)	4.44 (2.82)	3.92 (3.38)	1.62 (1.39)	192

Panel C: Residual After Adjusting for Broad Factor Set

Funds Used			Average Return (% Annualized)				Count
	Low	2	3	4	High	Difference	
Convertible Arbitrage	-1.93 (-0.52)	5.57 (3.11)	5.83 (2.95)	3.88 (2.03)	8.06 (5.51)	9.99 (2.72)	144
Dedicated Short Bias	5.49 (1.17)	4.18 (0.85)	3.37 (0.57)	5.53 (0.84)	8.63 (2.84)	3.15 (0.71)	120
Emerging Markets	1.43 (0.33)	6.23 (1.18)	11.90 (2.14)	12.01 (2.24)	8.03 (1.38)	6.59 (1.66)	144
Long/Short Equity	4.49 (3.70)	5.73 (4.40)	4.24 (3.12)	2.35 (1.16)	7.95 (5.42)	3.45 (2.11)	192
Equity Market Neutral	8.13 (4.95)	-4.86 (-1.64)	4.86 (1.90)	8.32 (3.13)	8.39 (3.34)	0.26 (0.10)	120
Event Driven	4.68 (3.41)	7.75 (5.85)	5.45 (3.18)	6.98 (5.23)	5.99 (4.02)	1.31 (1.03)	192
Fixed Income Arbitrage	-2.58 (-1.06)	2.00 (0.90)	5.59 (2.70)	3.33 (1.75)	4.08 (1.26)	6.66 (1.60)	131
Fund of Funds	1.51 (0.66)	4.03 (2.12)	3.26 (1.85)	3.79 (1.34)	5.26 (4.37)	3.75 (1.68)	192
Global Macro	5.90 (1.92)	6.71 (1.75)	-0.47 (-0.12)	3.65 (0.74)	-0.39 (-0.15)	-6.28 (-1.70)	180
Managed Futures	-2.94 (-0.95)	0.37 (0.10)	4.32 (1.26)	2.82 (0.73)	4.59 (1.40)	7.53 (2.78)	192
Multi-Strategy	1.85 (0.46)	1.40 (0.34)	7.83 (1.63)	9.20 (4.72)	7.39 (3.02)	5.54 (1.24)	108
All (Category Neutral)	2.03 (1.41)	4.26 (2.75)	4.36 (2.92)	4.53 (2.34)	5.96 (4.82)	3.93 (3.23)	192

Table 14b: (Continued).

evolution of the illiquidity premium from 1998 to 2006 since 1998 is the first year for which all 11 hedge fund categories have at least 5 funds with the minimum of 5 years of history, i.e., this is the first year for which we can construct 5 autocorrelation-ranked portfolios for each of the 11 categories of hedge funds. However, even this truncated sample holds great interest because it begins shortly before the fall of Long-Term Capital Management in August 1998, and ends with several years of great stability, low volatility, and significant increases in risk-taking during the 2004–2006 period.

We begin by creating an overall measure of the illiquidity premium by taking the equal-weighted average of the 11 liquidity spreads corresponding to each of the 11 Lipper/TASS hedge fund categories. This corresponds to the time series of returns used in computing the row labeled "All (Category Neutral)" in Table 14. Figure 2 shows the cumulative sum of this measure between January 1998 and December 2006. This figure shows that the first year of the sample period—particularly the second half of 1998—was a challenging one for funds holding illiquid assets. However, in the following four years, funds holding these assets performed quite well. In fact, by the end of 2002, the cumulative return of the illiquidity spread portfolio reached 30% (using arithmetic cumulation). The last four years of the sample show a substantial drop in this premium.

Figure 3 shows the cumulative return of the liquidity spread portfolio for each of the 11 categories.[21] As reported in Table 14, Global Macro funds seem to have a negative liquidity spread while categories such as Fixed Income and Convertible Arbitrage experienced two of the highest cumulative returns during this period. Without exception, the slopes for all 11 time series in Figure 3 declined towards zero in the second half of the sample, providing strong evidence that the pattern observed in the average of the series (Figure 2) is not driven by a small subset of them.

Overall, the behavior of the aggregate illiquidity premium is remarkably consistent with the common wisdom of the evolution of liquidity in the hedge fund industry from 1998 to 2006. We would expect funds holding the most illiquid assets to be hit hard during the second half of 1998 as credit spreads widened dramatically and volatility increased due to the LTCM crisis. This global flight to quality and heightened volatility likely forced a number

[21] Note the data reported in this figure is based on the return since January 1998, while the results in Table 14 use all available data for each category, which goes back farther than 1998 in most cases.

of fund managers out of the market, resulting in a higher illiquidity premium in the year following 1998. However, the tremendous growth in assets under management in the hedge-fund industry in the years after LTCM, coupled with the secular decline in volatility across most major asset classes which allowed greater leverage to be deployed, would have increased the demand for these illiquid assets. This, in turn, would have increased the liquidity of such illiquid assets, thereby reducing their required rate of return over the latter part of our sample period.

This explanation for the time variation in the estimated illiquidity premium from 1998 to 2006 is also consistent with the patterns documented by Chan et al. (2006, 2007), Khandani and Lo (2007, 2008), and Lo (2008) during this period, which showed temporary disruption in the hedge-fund industry immediately after LTCM's demise, but then a broad and rapid recovery, followed by a period of nearly uninterrupted growth from 2000 to 2006.

Of course, these inferences are based on estimated autocorrelation coefficients that are subject to the usual sampling variation of any statistical estimator. Nevertheless, even a simple split-sample test of stability suggests that illiquidity risk premia are not constant over time, or over varying market conditions. For example, basic economic intuition would suggest that illiquidity risk premia were considerably higher after the global flight-to-safety in August 1998 than before, and credit spreads before and after LTCM's demise are consistent with this intuition. Such dynamics underscore the importance of incorporating measures of illiquidity risk into the portfolio construction process as in Lo, Petrov, and Wierzbicki (2003), and motivates the need for overlay strategies such as the "beta-blockers" of Healy and Lo (2009) to hedge liquidity constraints.

6 Conclusions

In this paper, we provide empirical evidence that adds further support to the use of autocorrelation as a measure of illiquidity in hedge funds, mutual funds, and U.S. equity portfolios. While other measures of illiquidity exist, e.g., percentage bid/offer spreads, trading volume, etc., autocorrelation is the only measure that applies to both publicly traded and private securities, and requires only returns to compute.

Using the standard asset-pricing approach of constructing autocorrelation-sorted port-

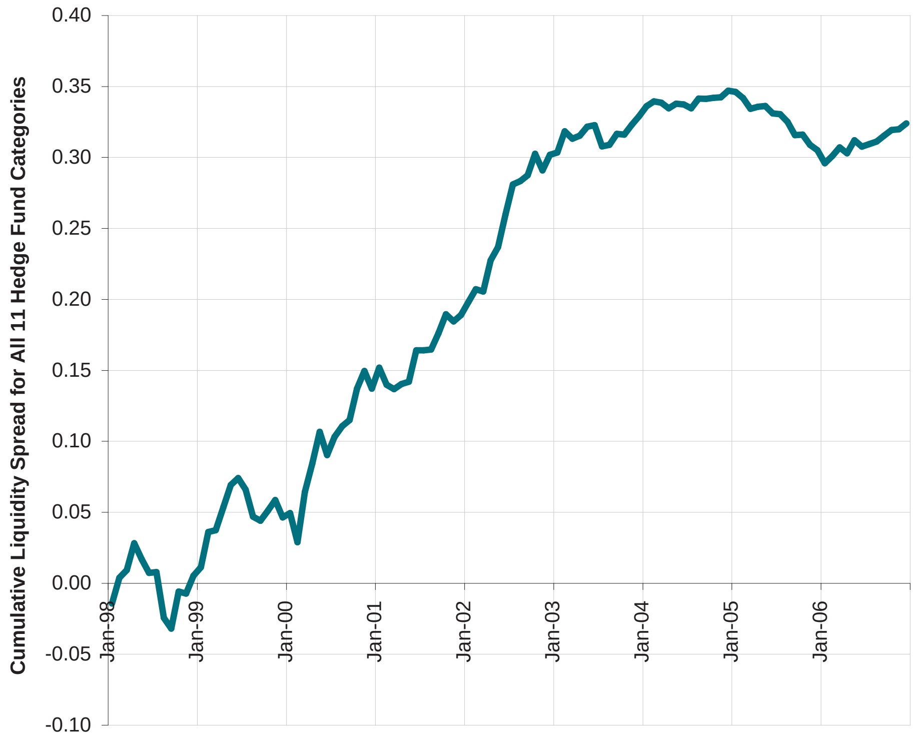

Figure 2: Cumulative monthly returns of the "Category-Neutral Liquidity Spread Portfolio" from January 1998 to December 2006, which is the cumulative return of the equal-weighted average of the 11 "liquidity spread" portfolios. Each liquidity spread portfolio is the difference between the equal-weighed average residual return for all funds in the high-autocorrelation minus the low-autocorrelation quintile, where the portfolios are constructed based on autocorrelations computed over the prior 5-year period, and the residuals are computed relative to the "Broad Factors Set" of 9 risk factors (the Fama-French U.S. Market Index, the Lehman U.S. Aggregate Government Bond Index, the Lehman Universal High-Yield Corporate Index, the Goldman Sachs Commodities Index, the traded-weighted U.S. Dollar Index, the Fama-French High-Minus-Low (HML) Book-to-Market Index, the Fama-French Small-Minus-Big (SMB) Capitalization Index, the Fama-French Momentum Index, and the first-difference of the VIX Volatility Index), and estimated using the prior 5 calendar years of monthly returns.

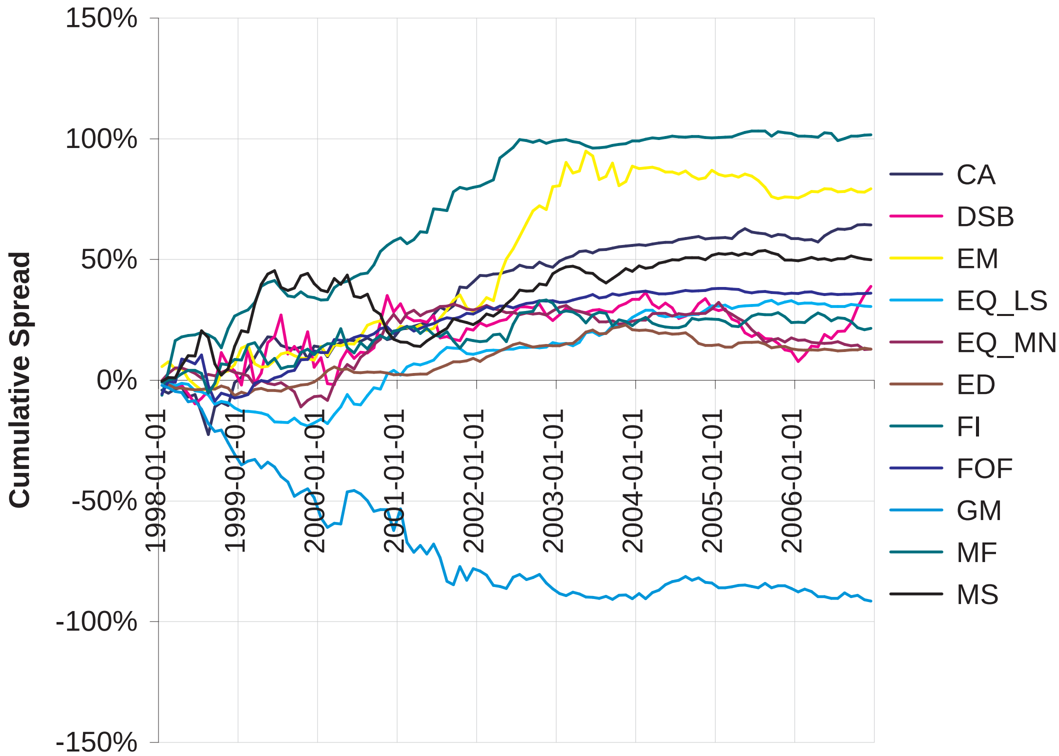

Figure 3: Cumulative monthly returns of the "liquidity spread" portfolios for 11 categories of hedge funds based on monthly returns from January 1998 to December 2006. Each liquidity spread portfolio is the difference between the equal-weighed average residual return for all funds in the high-autocorrelation minus the low-autocorrelation quintile, where the portfolios are constructed based on autocorrelations computed over the prior 5-year period, and the residuals are computed relative to the "Broad Factors Set" of 9 risk factors (the Fama-French U.S. Market Index, the Lehman U.S. Aggregate Government Bond Index, the Lehman Universal High-Yield Corporate Index, the Goldman Sachs Commodities Index, the traded-weighted U.S. Dollar Index, the Fama-French High-Minus-Low (HML) Book-to-Market Index, the Fama-French Small-Minus-Big (SMB) Capitalization Index, the Fama-French Momentum Index, and the first-difference of the VIX Volatility Index), and estimated using the prior 5 calendar years of monthly returns. The hedge-fund categories are defined as: Convertible Arbitrage (CA), Dedicated Short Bias (DSB), Emerging Markets (EM), Long/Short Equity (EQ_LS), Equity Market Neutral (EQ_MN), Event Driven (ED), Fixed Income Arbitrage (FI), Fund of Funds (FOF), Global Macro (GM), Managed Futures (MF), and Multi-Strategy (MS).

folios, we are able to measure the illiquidity risk premia for all three types of investment vehicles, and for the 11 hedge-fund investment categories. While even raw returns point to a link between autocorrelation and expected returns, the link becomes even stronger after returns are adjusted for various common risk factors. The estimated liquidity spread among hedge funds in our sample is 3.96% per year, and the comparable estimate among Fixed Income mutual funds is 2.74%. We did not find much evidence for an illiquidity premium among Equity and Asset Allocation mutual funds, or the 100 portfolios of U.S. common stocks.

Among hedge-fund categories known to involve illiquid assets, e.g., Convertible Arbitrage and Fixed Income Arbitrage, the estimated illiquidity premia are substantial—9.91% and 7.08%, respectively—but even Managed Futures, a category not usually associated with illiquid assets, exhibited an illiquidity premium of 4.91%. Global Macro funds exhibited a statistically insignificant but negative illiquidity premium in our sample.

Our autocorrelation-based illiquidity premia also suggest that the price of illiquidity risk varies over time, presumably as a function of market conditions. Based on the time variation in the estimated aggregate illiquidity premium from 1998 to 2006, we can empirically measure the challenges to illiquid hedge funds in 1998, their sharp reversal to profitability in the following four years, and the increasing competition and leverage that characterized the last few years of our sample.

Together, these empirical results suggest that autocorrelation is a useful measure for gauging illiquidity exposure in a broad spectrum of asset returns. Given the central role that liquidity has played in virtually every major financial crisis, any quantitative measure of illiquidity risk should be a welcome addition to the toolkit of investors, portfolio managers, and regulators.

A Appendix

Appendix A.1 contains the definitions of the Lipper/TASS hedge fund categories, obtained directly from the Lipper/TASS documentation, and Appendix A.2 develops some formal statistical tools for analyzing autocorrelation under IID and unit-root assumptions.

A.1 Lipper/TASS Primary Category Definitions

The following is a list of hedge-fund categories in the Lipper/TASS Database:[22]

1. **Convertible Arbitrage**. This strategy is identified by investment in the convertible securities of a company. A typical investment is to be long the convertible bond and short the common stock of the same company. Positions are designed to generate profits from the fixed-income security as well as the short sale of stock, while protecting principal from market moves.

2. **Dedicated Short Bias**. This strategy is to maintain net short as opposed to pure short exposure. Short biased managers take short positions in mostly equities and derivatives. The short bias of a managers portfolio must be constantly greater than zero to be classified in this category.

3. **Emerging Markets**. This strategy involves equity or fixed-income investing in emerging markets around the world. Because many emerging markets do not allow short selling, nor offer viable futures or other derivative products with which to hedge, emerging market investing often employs a long-only strategy.

4. **Equity Market Neutral**. This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a country. Market neutral portfolios are designed to be either beta or currency neutral, or both. Well designed portfolios typically control for industry, sector, market capitalization, and other exposures. Leverage is often applied to enhance returns.

5. **Event Driven**. This strategy is defined as "special situations" investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy or reorganization. There are three popular sub-categories in event driven strategies: risk arbitrage, distressed securities, and multi-strategy.

    (a) **Risk Arbitrage**. Specialists invest simultaneously in long and short positions in both companies involved in a merger or acquisition. Risk arbitrageurs are typically long the stock of the company being acquired and short the stock of the acquiring company. The principal risk is deal risk, should the deal fail to close.

[22] See `http://www.hedgeworld.com/education/index.cgi?page=hedge_fund_styles`.

(b) **Distressed**. Hedge fund managers invest in the debt, equity or trade claims of companies in financial distress and general bankruptcy. The securities of companies in need of legal action or restructuring to revive financial stability typically trade at substantial discounts to par value and thereby attract investments when managers perceive a turn-around will materialize. Managers may also take arbitrage positions within a company's capital structure, typically by purchasing a senior debt tier and short selling common stock, in the hopes of realizing returns from shifts in the spread between the two tiers.

(c) **Multi-Strategy**. This subset refers to hedge funds that draw upon multiple themes, including risk arbitrage, distressed securities, and occasionally others such as investments in micro and small capitalization public companies that are raising money in private capital markets. Hedge fund managers often shift assets between strategies in response to market opportunities.

6. **Fixed Income Arbitrage**. The fixed-income arbitrageur aims to profit from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, the United States and non-U.S. government bond arbitrage, forward yield curve arbitrage, and mortgage-backed securities arbitrage. The mortgage-backed market is primarily U.S.-based, over-the-counter and particularly complex.

7. **Global Macro**. Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and or events. The portfolios of these hedge funds can include stocks, bonds, currencies, and commodities in the form of cash or derivatives instruments. Most hedge funds invest globally in both developed and emerging markets.

8. **Long/Short Equity**. This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional, such as long/short U.S. or European equity, or sector specific, such as long and short technology or health-care stocks. Long/Short Equity hedge funds tend to build and hold portfolios that are substantially more concentrated than those of traditional stock hedge funds.

9. **Managed Futures**. This strategy invests in listed financial and commodity futures markets and currency markets around the world. The managers are usually referred to as Commodity Trading Advisors, or CTAs. Trading disciplines are generally systematic or discretionary. Systematic traders tend to use price and market specific

information (often technical) to make trading decisions, while discretionary managers use a judgmental approach.

10. **Multi-Strategy**. Multi-Strategy hedge funds are characterized by their ability to dynamically allocate capital among strategies falling within several traditional hedge fund disciplines. The use of many strategies, and the ability to reallocate capital between strategies in response to market opportunities, means that such hedge funds are not easily assigned to any traditional category. The Multi-Strategy category also includes hedge funds employing unique strategies that do not fall under any of the other descriptions.

11. **Fund of Funds**. A 'Multi Manager' fund will employ the services of two or more trading advisors or hedge funds who will be allocated cash by the trading manager to trade on behalf of the fund.

A.2 Statistical Inference for Autocorrelation Coefficients

In this section, we develop the formal sampling theory for the estimator of the first-order autocorrelation of returns and apply this sampling theory to our datasets. Let R_t denote a date-t asset return and asume that we have T time-series observations of this series. The first-order autocorrelation coefficient is estimated by the following expression:

$$\hat{\rho}_1 = \frac{(T-1)^{-1}\sum_{t=1}^{T-1} R_t R_{t+1} - \left[(T-1)^{-1}\sum_{t=1}^{T-1} R_t\right]\left[(T-1)^{-1}\sum_{t=2}^{T} R_t\right]}{(T-1)^{-1}\sum_{t=1}^{T-1} R_t^2 - \left[(T-1)^{-1}\sum_{t=1}^{T-1} R_t\right]^2} \,. \tag{A.1}$$

We consider the sampling distribution of $\hat{\rho}_1$ under two different null hypotheses.

Case 1: Constant Mean and Uncorrelated Returns

Consider the case where the data is generated by the following data generating process (DGP):

$$H_0: \qquad R_t \;=\; \mu \;+\; \epsilon_t \tag{A.2}$$

where μ is the expected return and ϵ_t is the unpredictable part of the return, so we have $\mathrm{E}[\epsilon_t|\mathcal{H}_t] = 0$, where $\mathcal{H}_t \equiv \sigma(\epsilon_1, \cdots, \epsilon_t)$ is the set of all available information at time t.[23] This null hypothesis corresponds to the weakest form of the random walk hypothesis, the uncorrelated increments version (see, for example, Campbell, Lo, and MacKinlay, 1997, Chapter

[23]More formally, $\sigma(\epsilon_1, \cdots, \epsilon_t)$ is the σ-algebra generated by $\{\epsilon_1, \cdots, \epsilon_t\}$.

2). Under this hypothesis, the first-order autocorrelation has the following asymptotic distribution:

Proposition 1 *Under the null hypothesis of (A.2) where ϵ_t is a martingale difference sequence adopted to the filtration $\mathcal{H}_t \equiv \sigma(\epsilon_1, \cdots, \epsilon_t)$ and under some additional technical regularity conditions (see Hansen, 1982), the first-order autocorrelation coefficient has the following asymptotic distribution:*

$$\sqrt{T}\hat{\rho} \quad \overset{a}{\sim} \quad \mathcal{N}(0, \theta^2) \quad , \quad \theta^2 \quad \equiv \quad \frac{\lim_{T\to\infty} E[T^{-1}\sum(R_t - \mu)^2(R_{t-1} - \mu)^2]}{[\lim_{T\to\infty} E[T^{-1}(R_t - \mu)^2]]^2} \ . \tag{A.3}$$

Furthermore, the following is a consistent estimator of θ^2:

$$\hat{\theta}^2 \quad \equiv \quad \frac{T^{-1}\sum(R_t - \hat{\mu})^2(R_{t-1} - \hat{\mu})^2}{[T^{-1}\sum(R_t - \hat{\mu})^2]^2} \quad , \quad \hat{\mu} \quad \equiv \quad T^{-1}\sum_{t=1}^{T} R_t \ . \tag{A.4}$$

Proof: This proposition can be proved using the Generalized Method of Moments (GMM) by setting up the usual moment conditions for the autocorrelation coefficient, from which the asymptotic distribution of the standard GMM estimator follows directly from Hansen (1982). ∎

Case 2: Unit-Root Process

Consider the null hypothesis in which the DGP is given by:

$$H_0 : \qquad R_t \;=\; \mu_t \,+\, \epsilon_t \quad , \quad \mu_t \;=\; \mu_{t-1} \,+\, \nu_t \tag{A.5}$$

where both ϵ_t and ν_t are martingale difference sequences adapted to the filtration $\sigma(\nu_1, \cdots, \nu_t, \epsilon_1, \cdots, \epsilon_t)$. Under this null hypothesis, it is assumed that:

$$\begin{aligned} \mathrm{E}[\epsilon_t|\mathcal{H}_{t-1}] &= 0 \\ \mathrm{E}[\nu_t|\mathcal{H}_{t-1}] &= 0 \\ \mathrm{E}[\nu_t\epsilon_t|\mathcal{H}_{t-1}] &= 0 \ . \end{aligned}$$

Our assumptions imply that shocks to expected returns and the unexpected part of the return are unforecastable, and that these shocks are concurrently uncorrelated. These assumptions are quite general and include many forms of leptokurtosis such as the AutoRegressive Conditional Heteroskedasticity (ARCH) model and many of its generalizations. It can be shown that the limiting distribution for the sample autocorrelation in this case is given by the following proposition:

Proposition 2 *Under the null hypothesis that the data is generated by the process given in (A.5) where both ϵ_t and ν_t are martingale difference sequence adapted to the filtration $\sigma(\nu_1, \cdots, \nu_t, \epsilon_1, \cdots, \epsilon_t)$, and under some additional technical requirements, we have the following limiting distribution for the sample autocorrelation as T increases without bound:*

$$T(\hat{\rho} - 1) \ \Rightarrow \ \frac{\frac{1}{2}(W(1)^2 - 1) - W(1)\int_0^1 W(u)du - \frac{\sigma_\epsilon^2}{\sigma_\nu^2}}{\int_0^1 W(u)^2 du - (\int_0^1 W(u)du)^2} \tag{A.6}$$

where $W(u)$ is a standard Brownian motion over interval $[0,1]$ and '$\Rightarrow$' denotes weak convergence (see Billingsley, 1968).

Proof: The proof is similar to the derivation of the standard Dicky-Fuller test statistic based on the Functional Central Limit Theory, hence we omit it to conserve space. Interested readers should consult Phillips (1987) for further details. ∎

Note that the limiting distribution (A.6) is identical to the standard test statistic for a unit root except for the impact of ϵ_t—the final expression depends on the ratio $\sigma_\epsilon/\sigma_\nu$. Any consistent estimator of this ratio can be used to conduct asymptotic inferences. In our empirical application, we use the estimator outlined in the following corollary:

Corollary 1 *Under the null hypothesis (A.5), the following holds:*

$$\frac{-Corr(\Delta R_t, \Delta R_{t-1})}{2Corr(\Delta R_t, \Delta R_{t-1}) + 1} \ \stackrel{p}{\to} \ \frac{\sigma_\epsilon^2}{\sigma_\nu^2}$$

where $\Delta R_t \equiv R_t - R_{t-1}$ and '$\stackrel{p}{\to}$' denotes convergence in probability.

Proof: This result follows immediately from (A.5). ∎

Empirical Results

Tables A.1 and A.2 summarize the results of autocorrelation tests applied to our sample of data. As seen in Table A.1, the estimated first-order autocorrelation coefficients are statistically significant among a large fraction of certain categories of hedge funds, e.g., 79% of all Convertible Arbitrage funds, and 52% of Event Driven funds. However, only 4% of Managed Futures and 8% of Dedicated Short Biased hedge funds have statistically significant first-order autocorrelations. This does not imply that ranking funds in these two categories by their autocorrelations is without merit. As seen in Table 2, funds in these two categories have two of the highest levels of volatility among hedge fund categories, hence the statistical insignificance of their autocorrelations may be more of a symptom of the noisiness of their returns rather than a lack of differences in illiquidity among funds in these categories.

Among mutual funds, Asset Allocation funds have the lowest level of autocorrelation and the estimates are significant among less than 1% of these funds. This is in contrast to Fixed

Income mutual funds, for which the null hypothesis can be rejected in 15% of these funds. Moreover, note that Money Market funds show a very high level of autocorrelation, and the null hypothesis can be rejected for over 99% of these funds. As we argued in Section 4.2, these funds contain a unit-root in their expected returns due to the fact that they are mostly driven by short-term interest rates.

Note that the purpose of the unit-root test is to determine whether or not to include mutual funds with no category information. These are typically older funds, since the category information we use is only available after July 2003. However, the ratio of $\frac{\sigma_\epsilon^2}{\sigma_\nu^2}$ is undefined under the null of $\rho_1 = 0$, and our unit-root test is invalid for such funds. Therefore, we will only ignore mutual funds with no category information for which the null hypothesis of $\rho_1 = 0$ is rejected but the null of a unit root is not rejected. There are 1,460 such funds that we drop from our sample. Table A.2 shows the result of the unit-root tests based on Proposition 2 and Corollary 1.

Fund Type	Category	Count	Average Rho_1 (%)	Average p-Value (%)	Null of Rho_1=0 Rejected Using 5% Test		
					Total (%)	And Positive Rho_1 (%)	And Negative Rho_1 (%)
Hedge Fund	Convertible Arbitrage	101	38.31	5.68	79.21	79.21	0.00
Hedge Fund	Dedicated Short Bias	25	9.25	40.83	8.00	8.00	0.00
Hedge Fund	Emerging Markets	182	17.38	24.13	36.26	36.26	0.00
Hedge Fund	Equity Market Neutral	153	11.42	33.54	28.76	24.18	4.58
Hedge Fund	Event Driven	254	22.75	16.08	52.36	51.57	0.79
Hedge Fund	Fixed Income Arbitrage	108	19.15	26.52	25.93	25.00	0.93
Hedge Fund	Fund of Funds	631	18.86	21.14	42.00	41.52	0.48
Hedge Fund	Global Macro	126	7.68	41.30	8.73	7.94	0.79
Hedge Fund	Long/Short Equity Hedge	906	12.63	34.97	16.11	15.45	0.66
Hedge Fund	Managed Futures	308	0.43	51.17	3.57	2.60	0.97
Hedge Fund	Multi-Strategy	133	17.85	20.94	42.11	41.35	0.75
Mutual Fund	Asset Allocation	1,133	5.31	58.91	0.35	0.35	0.00
Mutual Fund	Convertible	74	9.99	36.51	6.76	6.76	0.00
Mutual Fund	Equity	7,626	7.66	48.26	5.49	5.46	0.04
Mutual Fund	Fixed Income	4,088	8.17	40.98	15.22	15.22	0.00
Mutual Fund	Info. N/A	3,078	21.07	35.27	26.77	26.61	0.16
Mutual Fund	Money Market	1,560	94.18	0.31	99.42	99.42	0.00
Mutual Fund	Unclear (Multiple Categories)	50	10.83	44.38	12.00	12.00	0.00

Table A.1: Statistical significance of first-order autocorrelation coefficients of monthly returns of hedge funds and mutual funds from January 1996 to December 2006.

Fund Type	Category	Count	Average Rho_1 (%)	Null of Rho_1=0 Rejected Using 5% Test: Total (%)	Null of Rho_1=0 Rejected Using 5% Test: And Null of Unit Root Not Rejected Using 5% Test (%)
Mutual Fund	Asset Allocation	1,133	5.31	0.35	0.09
Mutual Fund	Convertible	74	9.99	6.76	0.00
Mutual Fund	Equity	7,626	7.66	5.49	1.15
Mutual Fund	Fixed Income	4,088	8.17	15.22	1.30
Mutual Fund	Info. N/A	3,078	21.07	26.77	12.83
Mutual Fund	Money Market	1,560	94.18	99.42	93.59
Mutual Fund	Unclear (Multiple Categories)	50	10.83	12.00	0.00

Table A.2: Unit-root tests for mutual funds in various categories using monthly returns from January 1996 to December 2006. Among funds with no category information (the row labeled "Info. N/A"), funds for which the unit-root null hypothesis cannot be rejected and the null hypothesis of $\rho_1 = 0$ can be rejected are dropped from our sample. We also drop all funds with a declared category of "Money Market".

References

Acharya, V. and L. Pedersen, 2005, “Asset Pricing with Liquidity Risk”, *Journal of Financial Economics* 77, 375–410.

Agarwal, V., Daniel, N. D., and N. Naik, 2007, “Why Is Santa So Kind To Hedge Funds? The December Return Puzzle!”, Working Paper.

Agarwal, V. and N. Naik, 2004, “Risks and Portfolio Decisions Involving Hedge Funds”, *Review of Financial Studies* 17, 63–98.

Agarwal, V. and N. Naik, 2005, “Hedge Funds”, *Foundations and Trends in Finance* 1, 103–169.

Amihud, Y., 2002, “Illiquidity and Stock Returns Cross-Section and Time-Series Effects”, *Journal of Financial Markets* 5, 31–56.

Amihud, Y. and H. Mendelson, 1986, “Asset Pricing and the Bid-Ask Spread.” *Journal of Financial Economics* 17, 223–249.

Amihud, Y. and H. Mendelson, 1988, “Liquidity and Asset Prices: Financial Management Implications”, *Financial Management* Spring, 1–15.

Amihud, Y., Mendelson, H., and L. Pedersen, 2005, “Liquidity and Asset Prices”, *Foundations and Trends in Finance* 1, 269–364.

Aragon, G., 2004, “Share Restrictions And Asset Pricing: Evidence From The Hedge Fund Industry”, *Journal of Financial Economics* 83, 33–58.

Asness, C., Krail, R., and J. Liew, 2001, “Do Hedge Funds Hedge?”, *Journal of Portfolio Management* 28, 6–19.

Baquero, G., Horst, J., and M. Verbeek, 2002, “Survival, Look-Ahead Bias and the Performance of Hedge Funds”, Unpublished working paper, Erasmus University, Rotterdam, Netherlands.

Bhargava, R., Bose, A., and D. Dubofsky, 1998, “Exploiting International Stock Market Correlations with Open-End International Mutual Funds”, *Journal of Business, Finance, and Accounting* 25, 765–773.

Biais, B., 1993, ”Price Formation and Equilibrium Liquidity in Fragmented and Centralized Markets”, *Journal of Finance* 48, 157–185.

Billingsley, P., 1968, *Convergence of Probability Measures.* New York: John Wiley and Sons.

Boudoukh, J., Richardson, M., Subrahmanyam, M., and R. Whitelaw, 2002, “Stale Prices and Strategies for Trading Mutual Funds”, *Financial Analysts Journal* 58, 53–71.

Box, G. and D. Pierce, 1970, "Distribution of the Autocorrelations in Autoregressive Moving Average Time Series Models", *Journal of American Statistical Association* 65, 1509–1526.

Brennan, M., Chordia, T. and A. Subrahmanyam, 1998, "Alternative Factor Specifications, Security Characteristics, and the Cross Section of Expected Stock Returns", *Journal of Financial Economics* 49, 345–373.

Brown, S., Goetzmann, W., and R. Ibbotson, 1999, "Offshore Hedge Funds: Survival and Performance 1989–1995", *Journal of Business* 72, 91–118.

Brown, S., Goetzmann, W., Ibbotson, R., and S. Ross, 1992, "Survivorship Bias In Performance Studies", *Review of Financial Studies* 5, 553–580.

Campbell, J., 2002, "Asset Pricing at the Millennium", *Journal of Finance* 55, 1515–1567.

Campbell, J., Lo, A., and MacKinlay, C., 1997, "The Econometrics of Financial Markets". Princeton University Press, Princeton, NJ.

Capocci, D. and G. Hübner, 2004, "Analysis of Hedge Fund Performance", *Journal of Empirical Finance* 11, 55–89.

Carhart, M., 1997, "On Persistence in Mutual Fund Performance", *Journal of Finance* 52, 57–82.

Carhart, M., Carpenter, J., Lynch, A., and D. Musto, 2002. "Mutual Fund Survivorship", *Review of Financial Studies* 15, 1439–1463.

Carpenter, J. and A. Lynch, 1999, "Survivorship Bias And Attrition Effects in Measures of Performance Persistence", *Journal of Financial Economics* 54, 337–374.

Chacko, G., 2005, "Liquidity Risk in the Corporate Bond Markets", Working Paper, SSRN (`http://ssrn.com/abstract=687619`).

Chalmers, J., Edelen, R., and G. Kadlec, 2001, "On the Perils of Security Pricing by Financial Intermediaries: The Wildcard Option in Transacting Mutual-Fund Shares", *Journal of Finance* 56, 2209–2236.

Chan, N., Getmansky, M., Haas, S., and A. Lo, 2006, "Do Hedge Funds Increase Systemic Risk?", *Federal Reserve Bank of Atlanta Economic Review* Q4, 49–80.

Chan, N., Getmansky, M., Haas, S., and A. Lo, 2007, "Systemic Risk and Hedge Funds", in M. Carey and R. Stulz, eds., *The Risks of Financial Institutions and the Financial Sector*, 2007. Chicago, IL: University of Chicago Press.

Duffie, D., Garleanu, N., and L. Pedersen, 2005, "Over-the-Counter Markets", *Econometrica* 73, 1815–1847.

Duffie, D., Garleanu, N., and L. Pedersen, 2007, "Valuation in Over-the-Counter Markets", *Review of Financial Studies* 20, 1865–1900.

Easley, D., Hvidkjaer, S., and M. O'Hara, 2002, "Is Information Risk a Determinant of Asset Returns", *Journal of Finance* 57, 2185–2222.

Easley, D. and M. O'Hara, 1987, "Price, Trade Size, and Information in Securities Markets", *Journal of Financial Economics* 19, 69–90.

Eleswarapu, V., 1997, "Cost of Transacting and Expected Returns in the Nasdaq Market", *Journal of Finance* 52, 2113–2127.

Eleswarapu, V. and M. Reinganum, 1993, "The Seasonal Behavior of Liquidity Premium in Asset Pricing", *Journal of Financial Economics* 34, 373–386.

Fung, W. and D. Hsieh, 1997a, "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds", *Review of Financial Studies* 10, 275–302.

Fung, W. and D. Hsieh, 1997b, "Investment Style and Survivorship Bias in the Returns of CTAs: The Information Content of Track Records", *Journal of Portfolio Management* 24, 30–41.

Fung, W. and D. Hsieh, 2000, "Performance Characteristics of Hedge Funds and Commodity Funds: Natural Versus Spurious Biases", *Journal of Financial and Quantitative Analysis* 35, 291–307.

Fung, W. and D. Hsieh, 2001, "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers", *Review of Financial Studies* 14, 313–341.

Getmansky, M., Lo, A., and I. Makarov, 2004, "An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns", *Journal of Financial Economics* 74, 529–609.

Glosten, L. and P. Milgrom, 1985, "Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders", *Journal of Financial Economics* 14, 71–100.

Goetzmann, W., Ingersoll, J., Spiegel, M., and I. Welch, 2007, "Portfolio Performance Manipulation and Manipulation-Proof Performance Measures", *Review of Financial Studies* 20, 1503–1546.

Goetzmann, W., Ivkovic, Z., and G. Rouwenhorst, 2001, "Day Trading International Mutual Funds: Evidence and Policy Solutions", *Journal of Financial and Quantitative Analysis* 36, 287–309.

Gompers, P. and J. Lerner, 1997, "Risk and Reward in Private Equity Investments: The Challenge of Performance Assessment", *Journal of Private Equity* Winter, 5–12.

Greene, J. and C. Hodges, 2002, "The Dilution Impact of Daily Fund Flows on Open-End Mutual Funds", *Journal of Financial Economics* 65, 131–158.

Grossman, S. and M. Miller, 1988, "Liquidity and Market Structure", *Journal of Finance* 43, 617–633.

Hansen, L., 1982, "Large Sample Properties of Generalized Method of Moments Estimators", *Econometrica* 50, 1029–1054.

Hasanhodzic, J. and A. Lo, 2007, "Can Hedge-Fund Returns Be Replicated?: The Linear Case", *Journal of Investment Management* 5, 5–45.

Hasbrouck, J., 2005, "Trading Costs and Returns for U.S. Equities: The Evidence from Daily Data", Working Paper, SSRN (`http://ssrn.com/abstract=388360`).

Healy, A. and A. Lo, 2009, "Jumping the Gates: Using Beta-Overlay Strategies to Hedge Liquidity Constraints", to appear in *Journal of Investment Management*.

Hendricks, D., Patel, J., and R. Zeckhauser, 1997. "The J-Shape of Performance Persistence Given Survivorship Bias", *Review of Economics and Statistics* 79, 161–170.

Horst, J., Nijman, T., and M. Verbeek, 2001. "Eliminating Look-Ahead Bias in Evaluating Persistence in Mutual Fund Performance", *Journal of Empirical Finance* 8, 345–373.

Kadlec, G. and D. Patterson, 1999, "A Transactions Data Analysis of Non Synchronous Trading", *Review of Financial Studies* 12, 609–630.

Khandani, A. and A. Lo, 2007, "What Happened to the Quants in August 2007?", *Journal of Investment Management* 5, 5–54.

Khandani, A. and A. Lo, 2008, "What Happened to the Quants in August 2007?: Evidence from Factors and Transactions Data", Working Paper, SSRN (`http://ssrn.com/abstract=1288988`).

Lehmann, B., 1990, "Fads, Martingales, and Market Efficiency", *Quarterly Journal of Economics* 105, 1–28.

LeRoy, S., 1973, "Risk Aversion and the Martingale Property of Stock Returns", *International Economic Review* 14, 436–446.

Lewellen, J., 2002, "Momentum and Autocorrelation in Stock Returns", *Review of Financial Studies* 15, 533–563.

Liang, B., 1999, "On the Performance of Hedge Funds", *Financial Analysts Journal* 55, 72–85.

Ljung, G. and G. Box, 1978, "On a Measure of a Lack of Fit in Time Series Models", *Biometrika* 65, 297–303.

Lo, A., 2001, "Risk Management For Hedge Funds: Introduction and Overview", *Financial Analysts Journal* 57, 16–33.

Lo, A., 2002, "The Statistics of Sharpe Ratios", *Financial Analysts Journal* 58, 36–50.

Lo, A., 2008, *Hedge Funds: An Analytic Perspective.* Princeton, NJ: Princeton University Press.

Lo, A. and C. MacKinlay, 1988, "Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test", *Review of Financial Studies* 1, 41–66.

Lo, A. and C. MacKinlay, 1990a, "When Are Contrarian Profits Due To Stock Market Overreaction?", *Review of Financial Studies* 3, 175–205.

Lo, A. and C. MacKinlay, 1990b, "An Econometric Analysis of Nonsynchronous Trading", *Journal of Econometrics* 45, 181–212.

Lo, A., Petrov, C. and M. Wierzbicki, 2003, "It's 11pm—Do You Know Where Your Liquidity Is? The Mean-Variance-Liquidity Frontier", *Journal of Investment Management* 1, 55–93.

Lo, A. and J. Wang, 2000, "Trading Volume: Definitions, Data Analysis, and Implications of Portfolio Theory", *Review of Financial Studies* 13, 257–300.

Lucas, R., 1978, "Asset Prices in an Exchange Economy", *Econometrica* 46, 1429–1446.

Mech, T., 1993, "Portfolio Return Autocorrelation", *Journal of Financial Economics* 34, 307–344.

Pastor, L. and R. Stambaugh, 2003, "Liquidity Risk and Expected Stock Returns", *Journal of Political Economy* 111, 642–685.

Phillips, P., 1987, "Time Series Regression with a Unit Root", *Econometrica* 55, 277–301.

Samuelson, P., 1965, "Proof that Properly Anticipated Prices Fluctuate Randomly", *Industrial Management Review* 6, 41–49.

Sharpe, W., 1992, "Asset Allocation: Management Style and Performance Measurement", *Journal of Portfolio Management* 18, 7–19.

Schneeweis, T. and R. Spurgin, 1996, "Survivor Bias in Commodity Trading Advisor Performance", *Journal of Futures Markets* 16, 757–772.

Schneeweis, T. and R. Spurgin, 1998, "Multi-Factor Analysis of Hedge Fund, Managed Futures, and Mutual Fund Return and Risk Characteristics", *Journal of Alternative Investments* 1, 1–24.

Scholes, M. and J. Williams, 1977, "Estimating Betas From Nonsynchronous Data", *Journal of Financial Economics* 5, 309–327.

Vayanos, D., 1998, "Transaction Costs and Asset Prices: A Dynamic Equilibrium Model", *Review of Financial Studies* 11, 1–58.

Vayanos, D. and J. Vila, 1999, "Equilibrium Interest Rates and Liquidity Premium with Transaction Costs", *Economic Theory* 13, 509–539.

Zitzewitz, E., 2003, "Who Cares About Shareholders? Arbitrage-Proofing Mutual Funds", *Journal of Law, Economics, and Organization* 19, 245–280.