The Impact of Hedge Funds on Asset Markets*

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Abstract

While there has been enormous interest in hedge funds from academics, prospective and current investors, and policymakers, rigorous empirical evidence of their impact on asset markets has been difficult to find. We construct a simple measure of the aggregate illiquidity of hedge fund portfolios, and show that it has strong in- and out-of-sample forecasting power for 72 portfolios of international equities, corporate bonds, and currencies over the 1994 to 2011 period. The forecasting ability of hedge fund illiquidity for asset returns is in most cases greater than, and provides independent information relative to, well-known predictive variables for each of these asset classes. We construct a simple equilibrium model to rationalize our findings, and empirically verify auxiliary predictions of the model.

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1. Introduction

Hedge funds have sparked enormous interest from a number of different constituencies. Wealthy individual investors and pools of institutional capital are interested in them as a potential source of high returns with the promise of low risk. Academics have been deeply interested in whether these high returns are persistent and whether there are important risk exposures underlying these returns, in addition to studying hedge fund fees, capital accumulation, and disclosure policies. Regulators and policymakers have been wary about the industry ever since the Long-Term Capital Management episode in 1998 nearly sparked a financial crisis episode. The periodic collapses of major hedge funds such as Amaranth and Madoff have perpetuated these concerns, because of the perception that such collapses could impact the underlying asset markets in which these funds are invested. These concerns are understandable: While the global hedge fund industry has only around U.S.$ 1.5 trillion of assets under management (AUM), hedge funds' substantial leverage and the high levels of trading volume that they generate in underlying asset markets means that their impact may well be disproportionately large.

Despite this high level of interest and concern, there has been a paucity of compelling empirical evidence that connects the activity of hedge funds to returns in underlying asset markets. Our paper attempts to fill this gap, by providing evidence that hedge funds have an important, measurable, impact on expected returns. We do so by constructing a simple measure of their aggregate ability to provide liquidity to asset markets, and show that this measure has strong predictive power for a wide range of assets spanning three broad categories, namely, international equities, corporate bonds, and currencies.

Hedge funds are often characterized as "arbitrageurs" in financial markets. Canonically, this term refers to the generation of a riskless return by the simultaneous trade of under- and over-valued securities. However the term is often abused when applied to hedge funds, and generally describes the exploitation of profitable, albeit risky investment opportunities, with an emphasis on managing risk to the greatest possible extent. One particularly important source of such investment opportunities for hedge funds has been the provision of liquidity to asset markets (see, for example, Aragon (2007), Sadka (2011), and Jylha, Rinne, and Suominen (2013) among others). As a result of exploiting these opportunities, hedge funds are exposed to illiquidity risk, and impose investment restrictions on their outside investors to safeguard against the withdrawal of hedge fund capital over short horizons when illiquidity-driven price pressure is likely most acute. The extent of their exposure can be measured: Getmansky, Lo, and Makarov (2004) cleverly identify that hedge funds holding the most illiquid investments are likely to exhibit persistent returns, and propose that the extent of illiquidity for any given fund at a point in time can be ascertained by the autocorrelation of its returns.

We take this insight as the starting point for our analysis. We measure the extent of return autocorrelation for each fund in our comprehensive universe of roughly 30,000 hedge funds, in each month over the period from 1994 to 2011. We then aggregate this measure by simply averaging the fund-specific first-order autocorrelation estimates each month. We find that the resulting measure of the aggregate illiquidity of hedge funds, which we dub "ρ," has strong and consistent predictive power for 72 portfolios of assets spanning three major asset classes. In-sample, our measure is significant for 21 out of 21 international equity indexes, 31 out of 42 US corporate bond portfolios spanning the ratings and maturity spectrum, and 6 out of 9 developed-world currencies that we consider. This is strong, and broad, support for the importance of our new measure.

This predictive power of ρ is not just in-sample; we also find evidence that the measure has appreciable out-of-sample forecasting power. Out-of-sample, our predictor beats the historical mean return model, and a range of competitors for 20 out of 21 international equities portfolios, 28 out of 42 US corporate bond portfolios, and 3 out of 9 currencies. In both in-sample and out-of-sample predictive regressions, our proposed measure generally outperforms, and always contributes incremental explanatory power relative to, a range of competitor variables which are known from the relevant asset class-specific literatures to be useful forecasters of asset returns.

To rationalize our findings, we build a simple equilibrium model, which incorporates liquidity constraints into the limits to arbitrage framework of Gromb and Vayanos (2010). In our model, the hedge fund begins with an endowment of illiquid assets and cash, and makes returns by providing liquidity to absorb buying and selling pressure from noise traders. The hedge fund thus acts as a quasi-market-maker for the risky asset. However, the liquidity provision capacity of the hedge fund is limited by the threat of its outside investors withdrawing their funds, which forces it to hold a sufficient quantity of cash to satisfy these redemptions, meaning that an illiquid hedge fund is (relatively) reluctant to purchase the risky asset, and (relatively) eager to sell it. We evaluate the comparative statics in the model as we vary the starting endowment of illiquid assets held by the hedge fund, and find that this impacts expected returns – the higher the measure of illiquidity of the hedge fund's portfolio, the higher are expected asset returns.

The model yields additional predictions about both the time-series and the cross-sectional relationship between hedge fund illiquidity and the expected impacts on asset markets, which we verify in empirical tests. For example, the model predicts, in line with intuition, that the higher the starting level of illiquidity of the underlying assets, the greater the impact on the asset of hedge fund illiquidity, and thus the greater the level of return predictability from ρ. Consistent with this prediction, we find the highest levels of predictability in relatively small equity markets, high-yield corporate bonds, and high interest rate currencies.

The literature on hedge funds is fast-growing – many authors, such as Agarwal and Naik (2004), Fung and Hsieh (1997, 2001, 2004), Bollen and Whaley (2009), Mamaysky, Spiegel, and Zhang (2007), and Patton and Ramadorai (2012) have documented that hedge funds are significantly exposed to systematic risk, proxied by indexes of equity, bond, and options returns. Rigorous empirical evidence on the reverse direction, namely the impact of hedge funds on asset markets, has been less well-documented. Kang, Kondor, and Sadka (2012) provide evidence suggesting that hedge funds affect idiosyncratic risk in equity markets, and Cao, Chen, Liang, and Lo (2012) suggest that hedge funds help in the security price formation process, pushing equity returns to be more in line with the efficient frontier. Our paper provides wide-ranging evidence about hedge funds' impact on a variety of asset markets using a relatively simply constructed variable, which we view as a useful contribution to this emerging literature.

Our paper also adds to the literature on the impacts of liquidity and liquidity risk on asset markets by contributing an important new variable, aggregate hedge fund illiquidity. We view our newly introduced variable as a complement to a number of asset-class-specific liquidity measures (see for example, Acharya and Pedersen (2005), Pastor and Stambaugh (2003), Khandani and Lo (2011), and Bongaerts, de Jong, and Driessen (2012)) that have been utilized extensively in the literature.

The remainder of the paper is organized as follows. Section 2 describes the construction of our hedge fund illiquidity index as well as the asset return data employed in our study. Section 3 presents the in-sample and out-of-sample forecasting results using the illiquidity index. Section 4 presents our model, and empirically tests additional model predictions. Section 5 considers the robustness of our results to a number of different variations, and the final section concludes.

2. Data description

2.1. Asset return data

Our empirical analysis covers three major asset classes: international equities, corporate bonds, and currencies. Within each asset class, we study a broad range of individual assets. As our hedge fund data is only available monthly, and our total time series length is under 20 years, we focus on monthly asset return predictability rather than higher- or lower-frequency returns. For each of the asset classes, we compare the predictive performance of our hedge fund illiquidity measure with that of a range of benchmarks from the extant literature. We describe this set of "competing" predictor variables utilized for each asset class below.

We employ 21 national international equity index returns in our analysis, namely, Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, UK, and US. We source our data on returns from Kenneth French's website. We compute log excess returns on each of these indices over the sample period 1995 to 2011. As "competitor" predictor variables, we employ the dividend yield for each equity index from Kenneth French's website, as well as innovations in the VIX index, computed using an AR(2) model.[1]

Our dataset on U.S. corporate bonds comprises 42 indices from Bank of America–Merrill Lynch, of which 24 are investment-grade portfolios and 18 are high-yield portfolios, with maturities ranging from one year to over fifteen years. Our corporate bond data begin in 1997 and ends in 2011. Following Bongaerts, de Jong, and Driessen (2012) we compare the return prediction performance of our hedge fund illiquidity measure with that of the Pastor-Stambaugh liquidity factor acquired from CRSP, innovations to the VIX estimated as described above, and market-capitalization weighted excess returns on the S&P 500 index, also from CRSP.

Our data on currencies comprises nine currency rates against the US dollar, namely Australian Dollar, Canadian Dollar, Euro, Japanese Yen, New Zealand Dollar, Norwegian Krone, Swedish Krona, Swiss Franc, and British Pound. The data are sourced from Bloomberg and cover the period 1995 to 2011 (we use the Deutsche Mark prior to the introduction of the Euro). Our monthly log currency returns are measured as US dollar per unit of foreign currency.[2] Given the findings of Meese and Rogoff (1983), we expect that these returns will be extremely difficult to predict. The competitor variables for predicting currency returns include the inflation differential from the OECD database and the one month Libor interest rate differential from Bloomberg.

Summary statistics for all three asset classes can be found in Table 1. Given the large number of individual bond return series (42 in total), when reporting summary statistics we group them into "Investment Grade" and "High Yield" bonds, as well as separating them by maturity.

[Insert Table 1 here]

[1] Goyal and Welch (2008) consider a wider array of predictor variables than those here, however our focus on international equity returns, rather than just U.S. returns, means that the number of available competitors is restricted by data limitations.

[2] We also considered excess currency returns (over the interest rate differential), and found that the results were very similar.

2.2. An index of hedge fund illiquidity

To compute our hedge fund illiquidity index, we employ monthly hedge fund returns over the period from January 1994 to December 2011, consolidated from data in the TASS, HFR, CISDM, Morningstar, and BarclayHedge databases. These data represent the most comprehensive set of hedge fund data available from public sources, and comprise a total of 29,496 individual hedge funds, including all births and deaths of funds over the period. (Details of the process followed to consolidate these data can be found in Patton, Ramadorai, and Streatfield (2013).) Reported returns are net of management and incentive fees.

Getmansky, Lo, and Makarov (2004) and Lo (2007) propose using autocorrelation in a hedge fund's returns as a proxy for the illiquidity of its asset holdings. Their rationale is that hedge fund managers mark their portfolios to market at the end of each month, and may be forced to use models to estimate portfolio values owing to the illiquidity of the assets in the portfolio. One such simple model is linear extrapolation of returns in the portfolio, which would lead to reported hedge returns exhibiting positive autocorrelation. Another factor generating spurious positive autocorrelation is holding both liquid and illiquid assets in a portfolio, generating non-synchroneity of returns (see, for example, Scholes and Williams (1977) and Dimson (1979)). Thus autocorrelation in hedge fund returns provides a (noisy) measure of the degree of illiquidity of the hedge fund's holdings – higher levels of autocorrelation are associated with higher levels of illiquidity.

Getmansky, Lo, and Makarov (2004) also consider the case that hedge fund managers engage in "performance smoothing," whereby reported returns are a smoothed version of the true returns (see Bollen and Pool (2008, 2009) and Agarwal, Daniel, and Naik (2011) for related work). Intentional "smoothing" leads to the same features as the smoothing that arises from "marking to model": reported returns have positive autocorrelation even when the underlying true returns do not. If some managers engage in smoothing regardless of market conditions, then this will work against us finding a significant result: the relationship between hedge fund portfolio illiquidity and asset returns will be muddied by individual fund illiquidity estimates that are unrelated to true illiquidity. If, however, these managers engage in "opportunistic smoothing", i.e., they make choices when "marking to model" that smooth their returns in a favorable way, then the degree of intentional smoothing will be correlated with underlying asset liquidity, which will maintain the direction of the relationship between hedge fund illiquidity and asset returns.

Our aggregate measure of hedge fund portfolio illiquidity (which we denote by ρ_t in month t) is computed using the following simple procedure. First, we compute the first-order autocorrelation of each hedge fund's returns using a rolling 12-month window. Having computed these return autocorrelations for all individual funds for which we have the prior 12 months of returns available in each month, we impose a lower bound of zero on any autocorrelation estimate which is estimated to be negative.[3] We then simply average these autocorrelations across all funds for each month in our sample t, yielding ρ_t. In our main analysis we use an equal-weighted average of these individual illiquidity estimates, and in our robustness checks we show that using an AUM-weighted measure leads to similar results.

Given the 12-month "burn-in" period for estimating rolling autocorrelations, our time series of the hedge fund illiquidity measure begins in December 1994 and ends in December 2011. Figure 1 plots the AUM weighted and the equally weighted hedge fund illiquidity measures over time, and shows that hedge fund illiquidity spikes during the LTCM crisis of 1998 and the "Quant meltdown" of August 2007 (see Khandani and Lo (2011)), as well as during the Great Recession. However, the recession following the NASDAQ crash at the turn of the millennium did not appear to affect the measure greatly. It is also evident from the plot that the equal-weighted illiquidity measure has far greater volatility than the value-weighted measure, which suggests that larger funds manage their liquidity more effectively. This may not be surprising given that funding liquidity pressure imposed by prime-brokerage relationships and capital inflows to funds may be less of an issue for larger, better-established hedge funds.

[Insert Figure 1 here]

Summary statistics for the measure are reported in Table 2. The funds in the combined database come from a broad range of vendor-classified strategies, which we consolidate into nine main strategy groups: Security Selection, Macro, Relative Value, Directional Traders, Funds-of-Funds, Multi-Process, Emerging Markets, Fixed Income, and Managed Futures (see Patton, Ramadorai, and Streatfield (2013) for detailed mappings between self-reported classifications and these broad categories).

The table reports summary statistics for hedge fund illiquidity indices computed for each individual style, followed by those computed across all funds, regardless of style. The table reveals cross-sectional variation in illiquidity that is consistent with intuition. For example, the Fixed Income style has a high mean level of illiquidity, while the Managed Futures funds are the least illiquid. In our analysis, we focus on the illiquidity index based on all funds, rather than that derived from a specific style. This is partly motivated by a desire for simplicity, and

[3] We impose the filter simply because the interpretation of positive autocorrelation estimates is conceptually far easier. In our robustness checks, we don't impose this filter, and find that our results actually strengthen. Estimation error can drive positive autocorrelation estimates below zero when the true values are above zero.

partly by a desire for robustness to potential style drift and misclassification arising from the static and self-reported style classifications in our hedge fund databases. The supplemental appendix contains an analysis of how these features can lead to an index based on all funds can deliver better results than one which relies upon noisy style classifications. In Section 5, we show results obtained when employing illiquidity indices based on hedge funds in styles that are, in theory, more closely related to a given asset class, and find that they are similar.

[Insert Table 2 here]

3. Empirical results on asset returns and hedge fund illiquidity

We now present our main analysis of the predictive power of the hedge fund illiquidity measures for future asset returns. We study this relationship using a variety of simple models. Our first set of results are based on full-sample estimation of the relationship, and we conclude with an out-of-sample forecasting analysis.

3.1. Does hedge fund illiquidity predict asset returns?

Our first analysis of the relationship between hedge fund illiquidity and asset returns is based on a simple predictive regression, in which we use the hedge fund illiquidity measure described above, denoted ρ_t, to predict one-month-ahead returns $r_{i,t+1}$ on asset i. (Newey-West (1987) standard errors are employed in all time-series regressions):

$$r_{i,t+1} = \alpha_i + \gamma_i \rho_t + \epsilon_{i,t+1}. \quad (3.1)$$

For comparison, we also estimate the same univariate model using various competitor variables, suggested by the asset-class-specific literatures, in place of ρ_t. We also include hedge fund flows as a competitor, as they affect the liquidity of a hedge fund's portfolio, and Jylha et al. (2013) find that increases in hedge fund flows reduce the amount of short-term return reversal and volatility in the U.S. equity market. Moreover, our model (below) discusses the different roles of flows and the starting endowment of a fund's illiquid assets, making flows a natural competitor for ρ. We compute these flows fund-by-fund using the standard approach (see, for example, Fung, Hsieh, Naik, and Ramadorai (2008)), winsorize them at the 1% and 99% percentile points, and AUM-weight them to construct an aggregate flow index.

The results of estimating this model on the international equity index returns are presented in Panel A of Table 3. This panel shows that the coefficient on our hedge fund illiquidity index is positive and significant at the 5% level for all 21 countries, generating an adjusted R^2 of between 1.3% (Finland) and 8.2% (Australia), with an average of 3.4%. Of the three competing predictor variables, the innovations to the VIX index are the next most important, with 8 out of 21 index returns having a coefficient on VIX that is significant at the 5% level, and another 3 significant at the 10% level. The average R^2 from models using the VIX is 2.7%. Models based on the dividend yield, lagged returns, and hedge fund flows perform relatively poorly – this last suggests that the total endowment of hedge fund illiquid assets, and not just the per-period capital flows, are what matter for identifying the predictive relationship.

Next, we estimate a multivariate regression model where we include all of the "competitor" predictor variables together with the hedge fund illiquidity measure in the same in-sample predictive regression:

$$r_{i,t+1} = \alpha_i + \beta_i X_t + \gamma_i \rho_t + \epsilon_{i,t+1}, \tag{3.2}$$

where X_t is a vector that contains all of the competitor variables. The last two columns of Panel A present the results from this model with and without the hedge fund illiquidity index included, to reveal the additional explanatory power of including our measure of hedge fund illiquidity. We see that the average adjusted R^2 jumps from 3.2% to 7.1% with the inclusion of our measure. Furthermore, our measure remains positive and significant at the 5% level for all 21 country indices even after the inclusion of the competitor variables. This provides strong support that there is substantial incremental predictive power in hedge fund illiquidity for international equity returns.

[Insert Table 3 here]

The next panel of the table conducts the same in-sample predictive analysis using returns data on U.S. corporate bonds. Given the large number of individual bonds (42) in our sample, we report just summaries of those results, aggregating first by ratings class (investment grade or high yield) and then by maturity.[4] The results are presented in the second panel of Table 3. For investment grade bonds, the hedge fund illiquidity index is the most successful single predictor across the set of five predictor variables, generating an average adjusted R^2 of 3.1%, and having a significant coefficient for 14 out of the 24 individual bonds. The next most successful is the simple lagged return on corporate bonds, which generates an R^2 of 1.8% and is significant for 12 out of 24 bonds. For high yield bonds many of the individual variables are significant: our hedge fund illiquidity index has the second-highest R^2 (6.4%, compared with 8.0% from lagged returns) and the second-highest number of significant coefficients (17 out of 18, compared with 18 for the lagged value-weighted equity return).

[4] Results for the individual bonds can be found in the online appendix.

Turning to the results from the multiple regression model, we see that the hedge fund illiquidity index adds substantial predictive power beyond the four competitor variables: the adjusted R^2 rises from 4.3% to 6.6% for investment grade bonds, and from 14.6% to 19.6% for high yield bonds. The number of bonds with significant coefficients on the hedge fund illiquidity index is 14 (out of 24) for investment grade bonds and 18 out of 18 for high yield bonds. Thus the hedge fund illiquidity index is a significant predictor of corporate bond returns, and appears particularly useful for high yield bonds.

The lower part of Panel B of Table 3 presents results across bond maturity. We find that the results are robust across both the short and long ends of the yield curve, with a slight increase in predictive ability as measured by R^2 for the longest maturity instruments. We explore the cross-sectional variation in predictive ability along both the maturity and the ratings dimensions further as part of our empirical tests of the predictions of the equilibrium model presented in the next section.

Panel C of Table 3 presents the results of in-sample regressions for currency returns. As is well known (see, for example Meese and Rogoff (1983) and a large literature thereafter), currencies are generally very hard to predict, and this is confirmed by our analysis. However, our hedge fund illiquidity index performs well: in univariate regressions it generates an average adjusted R^2 of 2.1% (slightly lower than that for the inflation differential, with 2.9%), and is statistically significant for six out of the nine currencies under consideration. In the multiple regression results we see that the R^2 increases from 3.1% to 4.1% with the inclusion of the hedge fund illiquidity index, and the variable is significant for five out of the nine currencies. Thus even for the notoriously challenging task of predicting currency returns, our hedge fund illiquidity index adds value.

Figure 2 shows the length of time over which the hedge fund illiquidity index retains predictive ability for future equity, bond, and currency returns. The top panel of the figure shows the results for the single-variable predictive regressions, and the bottom panel for the multiple-variable predictive regressions. The line in each figure shows the average adjusted R^2, while the bars show the number of assets for which the hedge fund illiquidity index is statistically significant. Along the horizontal axis, we vary the forecast horizon: $h = 1$ corresponds to our baseline regression where we forecast returns using the one-month lagged illiquidity index, and $h = 6$ corresponds to forecasting returns using six-month lagged hedge fund illiquidity. The figure shows that the forecasting power of the hedge fund illiquidity index is quite long-lasting: the forecasting performance for all three asset classes only deteriorates significantly at the 7 to

8 month horizons.[5] Given our motivation for considering this variable, namely, the illiquidity of hedge fund portfolios as a signal of their ability to provide liquidity to markets, this long-lasting forecasting power is not particularly surprising – it could easily take up to six months for an illiquid hedge fund to unwind its portfolio and return to the role of liquidity provision to asset markets. We motivate this insight more rigorously in our discussion of our model in Section 4.

[Insert Figure 2 here]

3.2. The out-of-sample predictive power of hedge fund illiquidity

The above analyses used the full sample of data to estimate the relationship between hedge fund illiquidity and asset returns. In this section we consider the out-of-sample (OOS) performance of models based on hedge fund illiquidity, as well as competitor predictor variables. Out-of-sample evaluation is increasingly an important metric for predictive models of asset returns, on account of its greater relevance for real-world investors (see for example, Goyal and Welch (2008), and Campbell and Thompson (2008) for analyses of the predictive ability of various models for the equity premium). In this sub-section, we take the perspective of a real-world investor engaging in forecasting the set of asset returns introduced earlier, using our index of hedge fund illiquidity.

Given the well-known difficulty of out-of-sample asset return prediction, we focus on simple single-variable predictive models, as in equation (3.1). We estimate the parameters of the models using a rolling window of 60 months of data, so our in-sample period is January 1995 to December 1999, and our out-of-sample period is January 2000 to December 2011. We report the OOS R^2 from each of the models, and we extend the Clark and West (2006) test to enable formal comparison of the above model with a model that only includes a constant. (The original Clark-West test requires the smaller model to contain no parameters at all, whereas for asset returns it is more reasonable to take as a benchmark a model with just a constant term.) The details of this simple extension are presented in the Appendix, and a small simulation study in the supplemental appendix that verifies its finite sample performance.

Panel A of Table 4 presents the OOS results for predicting international equity index returns. Forecasts based on our hedge fund illiquidity index generate an average OOS R^2 of 3.2%, ranging from -0.9% for Japan to 9.0% for Australia. In only a single case (Japan) is the OOS R^2 negative,

[5] We note here that the hedge fund illiquidity index is persistent, with first-order autocorrelation of 0.84, and a 95% confidence interval of [0.72,0.96]. However, an augmented Dickey-Fuller test for a unit root very strongly rejects the null in favor of stationarity, and the point estimate suggests that the persistence should not cause us any real problems with inference in forecasting. Thus this persistence in predictive power is not attributable to excessive persistence in our illiquidity index.

and for 20 out of the 21 countries the (extension of the) Clark-West test rejects the constant model in favor of a model based on the hedge fund illiquidity index.[6] In contrast, the OOS forecasts based on the three competing variables (dividend yield, lagged returns and shocks to the VIX index) generate negative average OOS R^2, and are significant for a maximum of four countries in the sample. These results thus provide support for the result obtained in our full-sample analysis that hedge fund illiquidity is useful for predicting international equity index returns.

In Panel B of Table 4 we find similarly good results for U.S. corporate bonds. The average OOS R^2 from forecasts based on our hedge fund illiquidity index is 4.4%, and is positive for all ratings and maturity subsets of these bonds. Further, we formally reject the constant model in favor of our model for 28 out of the 42 bonds. The forecasts based on the competing variables (lagged returns, shocks to the VIX index, and the lagged market return) perform much worse: all three generate negative average R^2. The forecasts based on the lagged market return perform the best of these three variables, with an average OOS R^2 of -2.8%, and significantly beating the benchmark constant model for 17 out of 42 bonds. For the lagged market return, the only subset of bonds for which the average OOS R^2 is positive is the high yield group, and even there the performance of this predictor variable is inferior to that obtained when using our index of hedge fund illiquidity.

Panel C of Table 4 presents results for OOS currency return prediction. As might be expected given the well-documented difficulty of predicting currency returns, the OOS R^2 is lower for this asset class, and indeed for all four variables we find a negative average OOS R^2, with the highest (-0.03%) coming from our hedge fund illiquidity index. For three of these currencies we are able to reject the constant model in favor of a model based on the hedge fund illiquidity index: Australia, Canada and New Zealand; the forecasts for Norway have a positive OOS R^2, but we do not reject the null. It is noteworthy that these are all relatively high interest-rate commodity currencies – which are generally associated with the long side of the frequently studied carry trade (see Burnside, Eichenbaum and Rebelo (2011) for an overview of the carry trade literature). This finding is explored further when we test our model predictions below. Finally, when we compare the performance of the illiquidity index to forecasts of currency returns based on competing variables, the primary significant result is the usefulness of the inflation differential for predicting the euro return: this forecast generated an OOS R^2 of 4.8%

[6] Note that a higher OOS R^2 does not necessarily translate to greater significance in the Clark-West test. For example, the forecasts based on the hedge fund liquidity index have an R^2 of 3.7% for the Netherlands, but do not reject the null that the constant model is best, while for Italy the R^2 is 2.3% and we do reject the null in favor of the larger model.

and is significantly better than the constant model. The interest rate differential rejects the constant model for New Zealand and Sweden. The lagged returns fail to generate a positive R^2 or reject the constant model for all currencies.

[Insert Table 4 here]

It is worth noting here that our out-of-sample period, 2000 to 2011, spans the financial crisis and the "great recession." Unfortunately, hedge fund data only became available in the early to mid 1990s, and so we are unable to conduct formal analysis of the impact of recessions on the predictive relationships we document here. To gain some insight into the impact, we constructed a time series of the cumulative sum of squared errors of the historical mean return model and the predictive regression, similar to that used in Goyal and Welch (2008). For all three asset classes we find that our hedge fund illiquidity index performs particularly well during the financial crisis. We view this as consistent with our explanation for the source of the predictive power: during this period, capital constraints on hedge fund portfolios ("funding liquidity" a la Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2008)) were likely most binding, translating into constraints on hedge funds' liquidity provision to asset markets.

The next section presents a simple model which provides a more rigorous foundation for this and our other results, and generates additional empirical predictions which we subsequently test.

4. A model of hedge fund illiquidity and asset return determination

Our model is based on the limits of arbitrage framework laid out in Gromb and Vayanos (2010). In our simple model, there is one risky asset, which is traded by a risk-averse hedge fund and by noise traders. The hedge fund effectively acts as the market maker for the risky asset, which is subject to demand shocks originated by the noise traders.

4.1. The timeline of the model

The model contains three periods, with a timeline as follows. In period 0, the hedge fund in our model inherits an illiquid endowment θ, which we assume it cannot sell, and a cash endowment C_0. For simplicity, the return on both the illiquid endowment and the cash endowment are set to zero. In period 1, the hedge fund determines its demand for the risky asset as a function of price. The net demand of the noise traders is then realized and trading occurs, which determines the equilibrium price and quantity traded for the risky asset. In period 2 the dividend on the risky asset is realized and paid.

In the next section we describe the hedge fund's optimization problem, and then we find an expression for the equilibrium price and quantity of risky asset traded.

4.2. The hedge fund's objective function

The objective function of the hedge fund is assumed to take a simple quadratic form, and the fund is subject to one additional, important constraint. In our model, the hedge fund is concerned about the illiquidity of its portfolio, because it potentially faces outflows from its investors. As a result, it requires a sufficient quantity of liquid assets in each period to pay out investors who withdraw their funds.

We model the illiquidity constraint in a straightforward fashion. The hedge fund has an expectation of the maximum level of fund outflows in a given time period, denoted $\Phi_{\max}$, which we assume to be increasing in both C_0 and θ. (Below we specialize to the case that it is proportional to $C_0 + \theta$.) We model a convex "shortfall penalty" if the fund does not hold sufficient liquid assets to cover $\Phi_{\max}$ once it trades in the risky asset. Letting x_1 denote the demand of the hedge fund for the risky asset, and p_1 the equilbrium price of the risky asset in period 1, the convex shortfall penalty is given by:

$$\begin{array}{ccc} 0 & if & \Phi_{\max} < C_1 \\ \frac{1}{2}(\Phi_{\max} - C_1)^2 & if & \Phi_{\max} \geq C_1 \end{array} \tag{4.1}$$

where $C_1 = C_0 - x_1 p_1$ is the new level of liquid assets that the fund holds after its purchases or sales of the risky asset.

The fund's objective function can therefore be written as:

$$Q(x_1) = x_1(E[d_2] - p_1) - \frac{\alpha}{2} x_1^2 \sigma^2 - \lambda \frac{1}{2} (\Phi_{\max} - C_0 + x_1 p_1)^2 \mathbf{1}\{\Phi_{\max} \geq C_0 - x_1 p_1\} \tag{4.2}$$

Here, d_2 is the dividend, which has variance σ^2, α is the risk aversion of the fund, and λ is the weight on the illiquidity constraint in the fund's objective function.

The first order condition of the hedge fund's maximization problem is:

$$(E[d_2] - p_1) - \alpha x_1 \sigma^2 - \lambda(\Phi_{\max} - C_1) p_1 \mathbf{1}\{\Phi_{\max} \geq C_0 - x_1 p_1\} = 0, \tag{4.3}$$

This results in the period 1 demand function:

$$x_1 = \frac{(E[d_2] - p_1) - \lambda(\Phi_{\max} - C_0) p_1 \mathbf{1}\{\Phi_{\max} \geq C_0 - x_1 p_1\}}{\alpha\sigma^2 + \lambda p_1^2 \mathbf{1}\{\Phi_{\max} \geq C_0 - x_1 p_1\}}. \tag{4.4}$$

The demand function reveals that the lower the value of C_0, and the higher the illiquid endowment θ (which raises $\Phi_{\max}$) the lower is the quantity of the risky asset x_1 which the hedge fund will hold. This yields an important prediction: an illiquid hedge fund is more willing to sell the risky asset than to buy it. This feature of the model, which we explain more fully below, is what underpins the model's explanation for the predictive power of our hedge fund illiquidity index for asset returns.

4.3. Market clearing and the equilibrium price

The demand of the noise traders u_1 is an exogenous shock, and determines the price that the hedge fund demands to absorb this shock in equilibrium. To compute the equilibrium price we need to clear markets. As in Gromb and Vayanos (2010), we interpret the demand shock u_1 as net aggregate demand, which implies that the risky asset is in zero net supply. The market clearing condition therefore takes the form:

$$\frac{(E[d_2]-p_1)-\lambda(\Phi_{\max}-C_0)p_1\mathbf{1}\left\{\Phi_{\max}\geq C_0-x_1p_1\right\}}{\alpha\sigma^2+\lambda p_1^2\mathbf{1}\left\{\Phi_{\max}\geq C_0-x_1p_1\right\}}+u_1=0. \tag{4.5}$$

For the case where $\Phi_{\max} > C_0 - x_1p_1$, solving for p_1 results in the following equilibrium price:[7]

$$p_1=\frac{(1+\lambda(\Phi_{\max}-C_0))-\sqrt{(1+\lambda(\Phi_{\max}-C_0))^2-4(\lambda u_1)(E[d_2]+\alpha\sigma^2u_1)}}{2\lambda u_1}. \tag{4.6}$$

4.4. Model-implied hedge fund illiquidity and asset returns

We measure the model-implied illiquidity level of the hedge fund's portfolio at time 1 as the ratio of the value of its holdings of illiquid assets to the value of its total assets under management:

$$\rho_1^{\text{model}}=\frac{\theta+x_1p_1}{(\theta+x_1p_1)+(C_0-x_1p_1)}. \tag{4.7}$$

Hence the lower C_0 relative to θ, the greater the illiquidity of the hedge fund's portfolio. The implicit assumption here is that the illiquid endowment and the risky asset contribute equally to illiquidity. (This can of course be relaxed, and we look at comparative statics along this dimension when testing model-implied predictions.)

We next specify parameters and simulate the model to better understand its predictions. For this analysis, we set $\Phi_{\max} = \phi_{\max}(\theta + C_0)$. For example, when $\phi_{\max} = 0.5$, the hedge fund

[7] The quadratic equation for the equilibrium price has a second root. However, we ignore the second root, as the implied equilibrium price is not sensible regardless of the parameter values. When the hedge fund buys, the price is negative and generally smaller than -100. When the hedge fund sells, the price is positive and generally greater than 100.

expects that in the worst case scenario its investors will withdraw 50% of the AUM in the next period. Panel A of Table 5 shows the specific parameter values that we use. The two sources of uncertainty in our model, d_2 and u_1, are drawn from normal distributions with means $\mathrm{E}[d_2] = 1$ and $\mathrm{E}[u_1] = 0$, and variances $\sigma_d^2 = 0.01$ and $\sigma_u^2 = 0.5$ respectively. λ, the weight on the shortfall penalty in the hedge fund's objective function, is set to 0.01, α, the risk-aversion of the hedge fund to 3, and θ, the starting endowment of the illiquid asset to 10.

[Insert Table 5 here]

Panel B of Table 5 looks at comparative statics as we vary C_0, which determines the level of illiquidity of the fund. In this exercise, values for d_2 and u_1 are drawn from their distributions whose parameters are given in Panel A, while the value of C_0 is varied across different simulations. We simulate the two period model 10,000 times for each value of C_0 and compute the average expected return, ρ_1^{model}, and the "price discounts" relative to expected fundamental value $\mathrm{E}[d_2] = 1$ at which noise traders buy from and sell to the hedge fund in each case.[8]

The top row in this panel simply sets the liquidity constraint on the fund to zero, i.e., $\lambda = 0$, as a benchmark, so the values of C_0 and $\phi_{\max}$ are not relevant. The expected return is computed as the average realization of $\frac{1}{p_1}$. The noise traders buy from the hedge fund at a price slightly above expected fundamental value, and sell to the hedge fund at a slightly lower price than expected fundamental value as compensation for the hedge fund's market-making services.

As we move down the rows of Panel B of the table, we impose the liquidity constraint, and vary the level of starting cash C_0, resulting in a cash-to-liquid assets ratio of 50%, 40%, and 30% respectively for each of the bottom three rows. $\Phi_{\max} = \phi_{\max}(\theta + C_0)$ varies as we vary the level of cash, but always maintains the maximum 50% of AUM withdrawal expectation. The ρ_1^{model} values that these correspond to are shown in the next column, and we can see that a decrease in C_0 leads to a higher average ρ_1^{model}, as well as in the next column, to a higher average expected return. This expected return is higher than the return in the benchmark case, which reflects the extra compensation needed to convince the illiquid hedge fund to purchase more of the risky asset, as well as the price discount offered by the hedge fund to the noise traders when they purchase the risky asset. While the illiquid hedge fund is willing to sell the risky asset for a lower price in the face of a positive noise trader demand shock, in order to increase the liquidity of its portfolio and avoid hitting the shortfall penalty, the fund is reluctant to buy the risky asset, and requires more compensation to do so. Relative to expected fundamental value, the price

[8] In all of the 10,000 simulations, the shortfall penalty is positive.

discount to the noise traders is substantial given our parameter values – reaching roughly 3% when the hedge fund discounts the price to sell to noise traders, and roughly −3.75% when the hedge fund demands compensation in order to accept more of the risky asset into its portfolio, when $C_0 = 3$.

Finally, we again simulate the model 10,000 times, with C_0 drawn from a normal distribution with a mean of 4 and a standard deviation of 0.5, and d_2 and u_1 drawn as described above. We then take the 10,000 observations of ρ_1^{model} derived from each one of these simulations and the realized returns in the second period r_2, derived from these simulations, and regress:

$$r_2^{\text{realized}} = \beta_0 + \beta_1 \rho_1^{\text{model}} + \epsilon_2. \tag{4.8}$$

The model-implied β_0 and β_1 are reported in the first column of Panel C of Table 5. We also separately estimate β_0 and β_1 conditional on the sign of realized u_1, corresponding to realizations in which noise traders buy and noise traders sell. This reveals that the coefficient γ is positive regardless of the sign of the shock, which is consistent with the intuition of the model, and a feature that we confirm in our auxiliary empirical tests below.

Figure 3 A provides a graphical representation of the model predictions – the figure shows the comparative static of the price path compared across levels of illiquidity ρ_1^{model} of the hedge fund. Compared to a liquid hedge fund, an illiquid hedge fund buys for a *lower* price when noise traders sell, which implies a *greater* return reversal. It also sells for a *lower* price when noise traders buy the risky asset, implying a *smaller* return reversal. When these predictions are taken together, the model implies that high ρ_1^{model} predicts high returns. Figure 3 B shows what would happen if there is exogenous variation in the illiquidity of the underlying asset for reasons unrelated to our model. As might be expected, for a more illiquid asset, there would be an amplification of the effects seen in our model. The next subsection tests some of the additional predictions implied by our model.

[Insert Figure 3 here]

4.5. Empirical predictions of the model

This section presents tests of predictions from the model described above, using “real world” data. Above, we showed that regardless of the sign of the noise trader shock, the model predicts that the coefficient on ρ will be positive. To test this, we use an approach from Pastor and Stambaugh (2003), who identify positive and negative noise trader demand shocks using the sign of the lagged return. We thus estimate a specification which includes the lagged return, as well as a dummy for the sign of the lagged return that we interact with our hedge fund illiquidity index:

$$r_{i,t+1} = \alpha_i + \beta r_{i,t} + \gamma^{\text{NoiseSell}} \rho_t I_{\{r_{i,t}<0\}} + \gamma^{\text{NoiseBuy}} \rho I_{\{r_{i,t}>0\}} + \epsilon_{i,t+1}. \tag{4.9}$$

The prediction of our theoretical model is that both $\gamma^{\text{NoiseSell}}$ and γ^{NoiseBuy} will be positive. When estimating the above specification, to increase the precision of the parameter estimates, we estimate it as a panel, grouping all assets i within each of the three broad asset classes. We allow for an asset-specific fixed effect in estimation, and we impose that the slope coefficients are the same across all assets within each class. In all panel regressions, standard errors are adjusted for contemporaneous correlation using a delete-cross-section jackknife method (see Shao and Wu (1989) and Shao (1989) for examples of the implementation of the jackknife estimator).

Equation (4.9) nests our specification from Section 3.1, as when $\gamma^{\text{NoiseSell}} = \gamma^{\text{NoiseBuy}}$ the indicator variable effectively drops out. We consider the full model, and also restricted versions where we include just one or the other of the interaction terms, and Table 6 presents the results from this model for the three asset classes. In all three asset classes, corresponding to the three panels in the table, we see that the coefficients $\gamma^{\text{NoiseSell}}$ and γ^{NoiseBuy} are estimated to be positive, and statistically significant (with the one exception of currencies, for which γ^{NoiseBuy} is positive, but not statistically significant.

[Insert Table 6 here]

A second prediction from the model is that more illiquid assets will have higher predictability. To test this prediction, for each asset class we run another fixed-effect panel regression, in which we include ρ, ρ interacted with a dummy which captures assets with greater illiquidity, and the set of all "competitor" predictor variables X for the asset returns in a given class. As before, the model is estimated for each asset class. The specification is:

$$r_{i,t+1} = \alpha_i + \gamma \rho_t + \gamma^{\text{Illiq.}} \rho_t I_i + \beta X_t + \epsilon_{i,t+1}, \tag{4.10}$$

The liquidity dummy I_i takes the value one if portfolio i is more illiquid, and we set this equal to one for high yield corporate bonds, longer maturity (over 5 years) corporate bonds, international equity markets with average market capitalization lower than the median, and currencies with Libor interest rates higher than the median.[9] We expect the coefficient of the illiquidity dummy

[9]We expect that these popular long carry trade currencies will be the first to be avoided in the event of a "flight to liquidity" or to a "safe haven" resulting in their liquidity being lower. See, for example, Campbell, *et al.* (2010).

to be significant and positive, and Table 7 shows that this is indeed the case, consistently for all asset classes.

[Insert Table 7 here]

Overall, the simple model presented in this section helps explain our main predictive results in Section 3, and generates additional testable predictions that are confirmed in our data.

5. Robustness checks

This section presents a variety of robustness checks of our main analyses. The top row of Table 8 (labelled "Base case") corresponds to the bottom-right elements of Panels A, B and C of Table 3. The figures reported are the average adjusted R^2 from the mutiple predictor regression, and the number of coefficients (across the individual assets in a given asset class) that are significantly positive and significantly negative.

[Insert Table 8 here]

First, we consider varying the length of the window over which we compute return autocorrelations, which form the basis of our hedge fund illiquidity index. Our baseline analysis uses 12 months, and this table considers the use of 9 months, 18 months and 24 months. The trade-off here is estimation error (longer windows have less estimation error) against timeliness (shorter windows are less "stale"). For international equities and currencies we see that a 12-month window strikes the optimum balance between these competing goals, outperforming the other choices, particularly the shorter, 9-month, window. The results for corporate bonds, on the other hand, are reasonably insensitive to the choice of window length.

We next consider alternative models for obtaining an estimate of the degree of autocorrelation in hedge fund returns. Our baseline model uses simple first-order autocorrelation, which can be interpreted as the autoregressive parameter in an AR(1) model. We consider variations based on an AR(2), an MA(1) and an MA(2), all estimated using a rolling 12-month window. For the second-order models there are two parameters that capture autocorrelation, and to summarize these into a single number we use the R^2 from the model. For the MA(1) model we simply use the estimated MA parameter. Table 8 shows that the second-order models tend to do worse than the first-order models, likely due to the increased estimation error from the additional parameter. The MA(1) model actually performs slightly better than our baseline AR(1) model, though the gains are small.

Third, we consider using hedge fund illiquidity indices based only on funds that are in style categories that are "close" to the asset class under consideration.[10] For international equities we consider two hedge fund styles, "Directional Traders" and "Security Selection." For corporate bonds the natural style to consider is "Fixed Income," and for currencies we use "Global Macro." For international equities we find that the two style-specific illiquidity indices generate the same number of significant coefficients, but slightly lower average R^2. For corporate bonds the Fixed Income hedge fund illiquidity index generates slightly stronger results than that based on all funds, while for currencies the Global Macro index performs slightly worse. In the supplemental appendix we present a theoretical analysis of the choice between asset-specific indices and a broader "all" index, highlighting the trade-offs between averaging across more funds and gaining robustness to style-misclassification, against greater precision of the illiquidity information.

Finally, we consider two further variations of our index. The first is based on estimated autocorrelations that are "untrimmed," in contrast to our baseline analysis which imposes that the autocorrelations are weakly positive. The second uses AUM weighting rather than equal weighting to construct the index. We see that the index based on untrimmed autocorrelation performs approximately as well as our baseline index, and in fact, slightly better for international equities and currencies. Constructing the index using AUM weights slightly worsens performance relative to the baseline case, consistent with Figure 1, which showed that the AUM-weighted index had smaller fluctuations than the equal-weighted index. As noted above, this is not too surprising, as larger funds may be less senstive to funding liquidity pressures imposed by prime-brokerage relationships and capital inflows.

6. Conclusion

Detecting evidence of hedge funds' impact on asset markets is an important endeavour given their size, leverage, and significant role in the provision of liquidity. We create a simple measure of aggregate hedge fund illiquidity by averaging fund-specific return autocorrelations across a large universe of hedge funds. We find that the resulting measure is a highly significant and robust predictor of returns, both in-sample and out-of-sample, for international equity indexes, US corporate bonds, and currencies.

We build a simple model of liquidity provision by hedge funds who are endowed with illiquid asset holdings, and face a shortfall penalty for not holding sufficient cash to cover the threat of withdrawals by their outside investors. The model is able to explain our main empirical

[10] Details on the mapping from individual fund styles, as reported to a given hedge fund database, to the ten style categories that we consider in this paper, are provided in Patton, Ramadorai, and Streatfield (2013).

findings, and yields additional testable implications which are supported in the data.

We view these results as a useful addition to the literatures on hedge funds and the effects of asset-market liquidity on returns. In future work, we hope to explore the implications of this and other measures of the impact of hedge funds on asset markets to explain a broader range of asset market outcomes.

Appendix: An extension of Clark and West (2006)

Clark and West (2006) consider the problem of testing equal predictive accuracy of a linear regression and a model with no parameters. In this appendix we propose a simple generalization that allows the "smaller" model to include a constant. Denote the two forecasts as:

$$\begin{aligned} \hat{Y}^{(1)}_{t+1|t} &= \hat{\gamma}_t \\ \hat{Y}^{(2)}_{t+1|t} &= X'_{t+1}\hat{\beta}_t \end{aligned} \tag{A.1}$$

The second forecast is based on a set of predictor variables X_{t+1}, which includes a constant, and so nests the smaller model. Both forecasts are based on parameters estimated using a rolling window of data (and so they are not constant through the sample) of fixed length R. The sample period runs from $t = 1, 2, ..., R, R+1, ..., R+P+1 \equiv T$. The mean squared prediction errors (MSPEs) over the out of sample period ($t = R+1, ..., R+P$) are:

$$\begin{aligned} \hat{\sigma}^2_1 &= \frac{1}{P}\sum_{t=R+1}^{R+P} (y_{t+1} - \hat{\gamma}_t)^2 \\ \hat{\sigma}^2_2 &= \frac{1}{P}\sum_{t=R+1}^{R+P} \left(y_{t+1} - X'_{t+1}\hat{\beta}_t\right)^2 \end{aligned} \tag{A.2}$$

The null and alternative hypotheses are

$$H_0 : \sigma^2_1 = \sigma^2_2 \quad \text{vs.} \quad H_1 : \sigma^2_1 > \sigma^2_2 \tag{A.3}$$

That is, the small and large models are equally good under the null, while under the alternative the small model is worse than the large model. Note that under the null, where the smaller model is correct, we have

$$y_{t+1} = \gamma^* + \varepsilon_{t+1}, \;\; E_t\left[\varepsilon_{t+1}\right] = 0 \tag{A.4}$$

The difference in the MSPEs of these two forecasts is:

$$\begin{aligned} \hat{\sigma}^2_1 - \hat{\sigma}^2_2 &= \frac{1}{P}\sum_{t=R+1}^{R+P} \left\{(y_{t+1} - \hat{\gamma}_t)^2 - \left(y_{t+1} - X'_{t+1}\hat{\beta}_t\right)^2\right\} \\ &= \frac{1}{P}\sum_{t=R+1}^{R+P} \hat{\gamma}^2_t - 2\frac{1}{P}\sum_{t=R+1}^{R+P} y_{t+1}\hat{\gamma}_t - \frac{1}{P}\sum_{t=R+1}^{R+P}\left(X'_{t+1}\hat{\beta}_t\right)^2 + 2\frac{1}{P}\sum_{t=R+1}^{R+P} y_{t+1}X'_{t+1}\hat{\beta}_t \end{aligned} \tag{A.5}$$

and so

$$\hat{\sigma}_1^2 - \hat{\sigma}_2^2 \xrightarrow{p} E\left[\hat{\gamma}_t^2\right] - E\left[\left(X_{t+1}'\hat{\beta}_t\right)^2\right] - 2\gamma^* E\left[\left(\hat{\gamma}_t - X_{t+1}'\hat{\beta}_t\right)\right] \text{ under } H_0 \text{ as } P \to \infty \quad \text{(A.6)}$$

using the fact that $E\left[\varepsilon_{t+1}X_{t+1}'\hat{\beta}_t\right] = E\left[\varepsilon_{t+1}\hat{\gamma}_t\right] = 0$.

When $\hat{\gamma}_t = 0\ \forall t$ and $\gamma^* = 0$ we are in the Clark-West framework, and they note that:

$$\hat{\sigma}_1^2 - \hat{\sigma}_2^2 \xrightarrow{p} -E\left[\left(X_{t+1}'\hat{\beta}_t\right)^2\right] \text{ under } H_0 \text{ as } P \to \infty \quad \text{(A.7)}$$

That is, when the smaller model is correct, the difference in MSPEs will be centered on a *negative value*, even though the two models are both correct (the larger model nests the smaller model, so it is also correct). The makes the test conservative (since we use a standard Normal as the asymptotic distribution of the test statistic, which is centered on zero) and so it will be hard to reject in favor of the larger model when it is correct. Clark and West suggest adjusting $\hat{\sigma}_2^2$ so that the difference between the MSPEs is centered on zero under the null:

$$\hat{\sigma}_{2,adj}^2 = \hat{\sigma}_2^2 - \frac{1}{P}\sum_{t=R+1}^{R+P}\left(X_{t+1}'\hat{\beta}_t\right)^2 \quad \text{(A.8)}$$

They show that this provides better properties under the null and under the alternative.

We extend this adjustment to allow the smaller model to include a constant. Intuitively, allowing for a constant adds a small amount of variability to Forecast 1, making the extra penalty faced by Forecast 2 slightly lower in relative terms. It also introduces some cross-product terms that need to be handled. Let us define an adjusted difference in MSPEs to correct for these terms:

$$\begin{aligned}\hat{\Delta}_{adj} &= \hat{\sigma}_1^2 - \hat{\sigma}_2^2 - \frac{1}{P}\sum_{t=R+1}^{R+P}\hat{\gamma}_t^2 + \frac{1}{P}\sum_{t=R+1}^{R+P}\left(X_{t+1}'\hat{\beta}_t\right)^2 \\ &\quad + 2\hat{\gamma}^*\frac{1}{P}\sum_{t=R+1}^{R+P}\left(\hat{\gamma}_t - X_{t+1}'\hat{\beta}_t\right),\end{aligned} \quad \text{(A.9)}$$

where

$$\hat{\gamma}^* = \frac{1}{P}\sum_{t=R+1}^{R+P} y_{t+1}. \quad \text{(A.10)}$$

Next we need to get a limiting distribution for $\hat{\Delta}_{adj}$. In the Clark-West case $\hat{\Delta}_{adj}$ is just a linear combination of sample averages, and so this can be obtained by defining an "adjusted difference in per-period loss variable" ($\hat{f}_{t+1}$ in their equation 3.3), and conducting a t-test that

that variable is zero mean. In our case, the cross-product term introduces a *product* of sample averages, and so we cannot use that approach. Instead, we use the delta method to get the limiting distribution of our test statistic. Let

$$\underset{(6\times 1)}{\mathbf{g}_t} = \left[(y_{t+1}-\hat{\gamma}_t)^2, -\left(y_{t+1}-X'_{t+1}\hat{\beta}_t\right)^2, -\hat{\gamma}_t^2, \left(X'_{t+1}\hat{\beta}_t\right)^2, 2\left(\hat{\gamma}_t - X'_{t+1}\hat{\beta}_t\right), y_{t+1}\right]' \quad \text{(A.11)}$$

Under standard regularity conditions we obtain:

$$\sqrt{P}\left(\bar{\mathbf{g}}_P - \bar{\mathbf{g}}_0\right) \xrightarrow{d} N\left(0, V_g\right) \text{ as } P \to \infty \quad \text{(A.12)}$$

As in Clark and West (2006), the asymptotic covariance matrix, V_g, should be estimated using a HAC estimator (e.g., Newey-West). Our test statistic is a nonlinear function of $\bar{\mathbf{g}}_P$

$$\hat{\Delta}_{adj} = f\left(\bar{\mathbf{g}}_P\right) = \bar{g}_1 + \bar{g}_2 + \bar{g}_3 + \bar{g}_4 + \bar{g}_5\bar{g}_6 \quad \text{(A.13)}$$

and so by the delta method we obtain:

$$\begin{aligned} \sqrt{P}\left(f\left(\bar{\mathbf{g}}_P\right) - f\left(\mathbf{g}_0\right)\right) &= \sqrt{P}\left(\hat{\Delta}_{adj} - \Delta_0\right) \xrightarrow{d} N\left(0, \nabla_g f\left(\bar{\mathbf{g}}_P\right) V_g \nabla_g f\left(\bar{\mathbf{g}}_P\right)'\right) \quad \text{(A.14)} \\ \text{where } \nabla_g f\left(\bar{\mathbf{g}}_P\right) &= \partial f\left(\bar{\mathbf{g}}_P\right) / \partial \mathbf{g}' = \left[1, 1, 1, 1, \bar{g}_6, \bar{g}_5\right] \end{aligned}$$

We can use this to obtain a Clark-West style test for the larger model versus a model just including a constant. Specifically, we compute the test statistic $\sqrt{P}\hat{\Delta}_{adj}/\sqrt{\partial f\left(\bar{\mathbf{g}}_P\right)\hat{V}_g \partial f\left(\bar{\mathbf{g}}_P\right)'}$ and compare it to the right-tail critical values of the $N(0,1)$ distribution (1.28, 1.65, 2.33) to get a test at the 10%, 5% or 1% level.

The supplemental appendix presents a small simulation study verifying that this test has satisfactory finite-sample properties, and confirming that it also leads to power gains relative to the unadjusted test.

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Table 1: Summary Statistics of Asset Returns

Reported are the average, the standard deviation, the mean, the maximum, and the minimum, for monthly log excess returns in % of international equities and US corporate bonds. For currencies, the statistics are based on monthly returns with USD as the base currency. For international equities and currencies, the time series starts in January 1995 and ends in December 2011. For US corporate bonds, the time series starts in January 1997 and ends in December 2011.

Panel A: International Equities				
	Average	**Std Dev**	**Max**	**Min**
Australia	0.625	6.403	15.989	-32.581
Austria	0.339	7.058	17.756	-42.588
Belgium	0.356	6.020	15.331	-36.274
Canada	0.721	6.178	19.901	-31.179
Denmark	0.587	5.950	16.635	-28.925
Finland	0.575	9.239	26.508	-34.564
France	0.392	6.211	13.916	-24.795
Germany	0.316	6.679	19.782	-26.658
Hong Kong	0.401	7.560	27.622	-34.038
Ireland	0.325	6.356	16.202	-26.787
Italy	0.195	7.091	18.914	-27.153
Japan	-0.282	5.462	15.200	-14.452
Netherlands	0.365	6.551	15.452	-34.552
New Zealand	0.186	6.390	14.453	-21.282
Norway	0.592	7.891	17.681	-36.923
Singapore	0.209	7.792	25.642	-33.974
Spain	0.519	6.661	18.231	-26.032
Sweden	0.680	7.686	22.440	-32.318
Switzerland	0.495	5.044	12.130	-16.435
UK	0.379	4.766	13.208	-22.279
US	0.448	4.622	10.356	-18.347
Panel B: US Corporate Bonds				
Rating				
Inv Grade (24 Portfolios)	0.346	1.703	15.146	-16.070
High Yield (18 Portfolios)	0.375	3.811	31.302	-36.268
Maturity				
1-3Y (7 Portfolios)	0.325	1.827	31.302	-22.596
3-5Y (7 Portfolios)	0.325	1.931	14.882	-24.184
5-7Y (7 Portfolios)	0.344	2.280	20.874	-25.359
7-10Y (7 Portfolios)	0.279	2.774	17.899	-30.674
10-15Y (7 Portfolios)	0.347	3.230	23.176	-36.268
15+Y (7 Portfolios)	0.532	3.596	24.717	-28.694
Panel C: Currencies				
Monthly Log Returns from Jan 1995 to Dec 2011				
Australia	0.135	3.653	9.899	-17.108
Canada	0.155	2.455	8.936	-13.009
Euro	0.019	3.017	9.609	-10.196
Japan	0.127	3.259	16.273	-9.698
New Zealand	0.096	3.640	12.507	-13.931
Norway	0.061	3.201	7.785	-13.739
Sweden	0.037	3.318	9.127	-11.621
Switzerland	0.163	3.244	12.368	-11.945
UK	-0.003	2.441	9.044	-10.215

Table 2: Summary Statistics of Hedge Fund Illiquidity Measure

For the illiquidity measure of each investment style, we report the average, the standard deviation, and the correlation with the All hedge fund illiquidity measure. The hedge fund illiquidity measure for a specific hedge fund in month t is the autocorrelation of the hedge fund's monthly returns estimated over the last 12 months. The hedge fund illiquidity measure shown in the table is an equally or AUM weighted average across all the hedge funds of a particular investment style. Negative autocorrelations are not included in the average.

	Equally Weighted			AUM Weighted		
Styles	**Average**	**Std Dev**	**Corr. with All**	**Average**	**Std Dev**	**Corr. with All**
CTA	0.085	0.035	0.720	0.022	0.013	0.591
Directional Traders	0.115	0.054	0.857	0.029	0.028	0.865
Emerging Markets	0.136	0.070	0.791	0.044	0.028	0.688
Fixed Income	0.174	0.051	0.788	0.055	0.025	0.750
Funds of Funds	0.153	0.088	0.958	0.061	0.053	0.972
Global Macro	0.093	0.034	0.777	0.028	0.018	0.817
Multi-Strategy	0.146	0.055	0.905	0.060	0.031	0.920
Relative Value	0.103	0.039	0.657	0.026	0.033	0.648
Security Selection	0.111	0.037	0.876	0.046	0.018	0.797
All	**0.126**	**0.053**	**1.000**	**0.046**	**0.027**	**1.000**

Tabel 3: In-Sample Predictive Performance

For international equities and currencies, reported are the signs of the predictors (in the case of multiple predictors, it stands for the sign of the hedge fund illiquidity measure), the adjusted R^2 of the in-sample predictive regression in %, and the significance of the hedge fund illiquidity measure (* for 10% and ** for 5%). The last row shows the average adjusted R^2, the total number of series for which the coefficient of the predictor is significant (at the 10% level) and positive, and the total number of series for which the coefficient of the predictor is significant and negative (in the case of multiple predictors, only the coefficients of the hedge fund liquidity measure are considered). For US corporate bonds, the number of portfolios for which the hedge fund illiquidity measure is significant at the 10% level are reported, and the adjusted R^2 is averaged across all portfolios. For all three asset classes, the AUM weighted flows are not included in the multiple predictor regression. For international equities and currencies, the time series starts in January 1995 and ends in December 2011. For US corporate bonds, the time series starts in January 1997 and ends in December 2011. Newey-West standard errors are used.

Panel A: International Equities							
	Single Predictor					**Multiple Predictors**	
Country	**Hedge Fund Illiq. Measure**	**Dividend Yield**	**Lagged Returns**	**VIX AR(2) Shocks**	**Hedge Fund Flows**	**Competitors Excl. HF Illiq. Measure**	**Competitors Incl. HF Illiq. Measure**
Australia	(+) 8.220**	(+) 2.302	(+) 0.642	(-) 1.289	(+) -0.437	3.158	(+) 10.746**
Austria	(+) 3.954**	(-) -0.469	(+) 5.932*	(-) 8.126**	(+) 0.429	8.252	(+) 12.239**
Belgium	(+) 2.608**	(-) -0.113	(+) 7.404**	(-) 7.597*	(+) -0.001	10.228	(+) 12.617**
Canada	(+) 3.057**	(+) -0.250	(+) 1.437	(-) 4.875*	(-) -0.484	4.058	(+) 7.526**
Denmark	(+) 2.920**	(+) 2.982**	(+) 1.142	(-) 6.277**	(+) 0.019	7.945	(+) 11.129**
Finland	(+) 1.327**	(+) 0.007	(+) 3.342**	(-) -0.482	(-) -0.487	3.600	(+) 4.414**
France	(+) 2.148**	(-) -0.298	(+) 0.778	(-) 2.175*	(+) -0.176	1.508	(+) 3.947**
Germany	(+) 1.611**	(-) -0.433	(+) -0.119	(-) 1.679*	(+) -0.001	1.078	(+) 2.990**
Hong Kong	(+) 4.638**	(+) -0.223	(+) 0.825	(-) 0.941	(-) -0.072	0.467	(+) 4.806**
Ireland	(+) 2.741**	(+) -0.331	(+) 4.893*	(-) 3.032*	(+) -0.269	4.280	(+) 6.583**
Italy	(+) 1.632**	(-) -0.015	(+) -0.238	(-) 1.967*	(+) -0.232	1.789	(+) 3.897**
Japan	(+) 2.745**	(+) -0.414	(+) 2.673**	(-) 3.082**	(-) -0.374	3.483	(+) 5.881**
Netherlands	(+) 3.255**	(+) -0.480	(+) 1.716	(-) 5.669**	(+) -0.450	4.876	(+) 8.828**
New Zealand	(+) 4.722**	(+) -0.449	(-) -0.461	(-) 4.000**	(+) -0.497	5.158	(+) 11.606**
Norway	(+) 4.509**	(-) -0.152	(+) 1.199	(-) 4.419**	(+) -0.407	4.044	(+) 9.142**
Singapore	(+) 6.560**	(+) -0.494	(+) 1.009	(-) 1.595	(-) -0.418	0.832	(+) 7.960**
Spain	(+) 3.836**	(-) -0.497	(+) 0.793	(-) 1.343*	(+) -0.492	0.463	(+) 4.443**
Sweden	(+) 4.022**	(-) -0.404	(+) 1.306	(-) 1.393	(-) -0.305	1.144	(+) 5.270**
Switzerland	(+) 1.739**	(+) -0.190	(+) 1.537*	(-) 4.250**	(+) -0.105	3.381	(+) 5.217**
UK	(+) 4.025**	(+) 1.528*	(+) 3.489*	(-) 3.978**	(+) -0.458	5.167	(+) 8.396**
US	(+) 1.583**	(+) 0.866*	(+) 0.607	(-) 0.892	(+) -0.128	1.077	(+) 2.148**
Across 21 Countries	**3.422 (21/0)**	**0.118 (3/0)**	**1.900 (7/0)**	**3.243 (0/15)**	**-0.255 (0/0)**	**3.618**	**7.133 (21/0)**

Panel B: US Corporate Bonds

	Single Predictor						Multiple Predictors	
Rating / Maturity (# of Portfolios)	**Hedge Fund Illiq. Measure**	**Lagged Returns**	**Pastor-Stambaugh Traded Liq. Factor**	**VIX AR(2) Shocks**	**VWM Excess Return**	**Hedge Fund Flows**	**Competitors Excl. HF Illiq. Measure**	**Competitors Incl. HF Illiq. Measure**
Inv Grade (24)	3.099 (14/0)	1.816 (12/0)	0.893 (0/8)	1.028 (6/1)	1.352 (0/8)	0.256 (0/1)	4.276	6.591 (14/0)
High Yield (18)	6.364 (17/0)	8.023 (14/0)	-0.013 (0/0)	9.741 (0/17)	7.268 (18/0)	0.487 (0/3)	14.596	19.646 (18/0)
1-3Y (7)	3.886 (5/0)	4.205 (5/0)	0.241 (0/0)	4.281 (1/4)	2.666 (3/1)	1.140 (0/2)	8.786	11.862 (5/0)
3-5Y (7)	4.995 (5/0)	6.446 (6/0)	0.294 (0/1)	5.715 (1/3)	4.893 (3/1)	0.298 (0/0)	10.302	14.002 (5/0)
5-7Y (7)	4.865 (5/0)	5.658 (5/0)	0.167 (0/1)	6.171 (1/3)	4.925 (3/1)	0.048 (0/0)	10.380	14.021 (5/0)
7-10Y (7)	4.911 (6/0)	3.978 (5/0)	0.709 (0/2)	4.168 (1/2)	3.750 (3/2)	0.206 (0/1)	8.137	11.785 (6/0)
10-15Y (7)	3.244 (4/0)	3.554 (3/0)	0.177 (0/0)	4.140 (1/3)	3.647 (3/2)	0.326 (0/1)	7.205	10.001 (5/0)
15+Y (7)	5.088 (6/0)	3.017 (2/0)	0.144 (0/4)	4.097 (1/3)	3.444 (3/1)	0.111 (0/0)	7.381	11.445 (6/0)
Across All (42)	**4.498 (31/0)**	**4.476 (26/0)**	**0.505 (0/8)**	**4.762 (6/18)**	**3.887 (18/8)**	**0.355 (0/4)**	**8.698**	**12.186 (32/0)**

Panel C: Currencies

	Single Predictor				Multiple Predictors	
Currencies	**Hedge Fund Illiq. Measure**	**Inflation Differential**	**Interest Rate Differential**	**Hedge Fund Flows**	**Competitors Excl. HF Illiq. Measure**	**Competitors Incl. HF Illiq. Measure**
Australia	(+) 5.885**	(+) 3.316**	(+) -0.412	(-) -0.362	2.923	(+) 7.187**
Canada	(+) 4.111**	(+) 3.681**	(-) -0.489	(-) -0.330	3.362	(+) 5.230**
Euro	(+) 1.406**	(+) 6.148**	(+) 0.303	(+) -0.434	5.711	(+) 5.529
Japan	(+) -0.367	(+) -0.119	(+) 1.448**	(-) -0.062	1.126	(-) 0.633
New Zealand	(+) 4.565**	(+) 4.872**	(-) 0.065	(+) -0.414	5.473	(+) 7.086**
Norway	(+) 1.883**	(+) 0.065	(+) -0.023	(+) -0.344	-0.166	(+) 1.449**
Sweden	(+) 1.468**	(+) 3.832**	(+) -0.233	(+) -0.398	4.047	(+) 4.698*
Switzerland	(+) -0.207	(+) 4.188**	(+) 2.093**	(+) -0.473	5.047	(-) 4.713
UK	(+) -0.001	(+) 0.132	(-) 0.964	(+) -0.142	0.676	(+) 0.465
Across 9 Currencies	**2.083 (6/0)**	**2.902 (6/0)**	**0.413 (2/0)**	**-0.329 (0/0)**	**3.133**	**4.110 (5/0)**

Table 4: Out-of-Sample Forecast Performance

Reported are the results of rolling 5 year OOS forecasts with single predictor regressions. The dependent variable is the mothly log excess return for international equities and US corporate bonds and the monthly log return for currencies. For international equities and currencies, we report the OOS R^2 and whether we can reject the historical average model based on an extension of the Clark-West test-statistic, which is denoted by * for 10% significance and ** for 5% significance. For US corporate bonds, the number of portfolios for which we can reject the historical average model at the 10% level is in parentheses. The last row in every panel shows the average OOS R^2 and the total number of portfolios for which the historical average model is rejected. For international equities and currencies, the time series starts in January 1995 and ends in December 2011. The time series for US corporate bonds starts in January 1997 and ends in December 2011.

Panel A: International Equities				
Country	**Hedge Fund Illiq. Measure**	**Dividend Yield**	**Lagged Returns**	**VIX AR(2) Shocks**
Australia	9.039**	-3.051	-1.423	-7.714
Austria	4.366**	-0.986*	1.006	-1.871*
Belgium	3.260**	-2.540	5.024*	-1.187*
Canada	2.711**	-4.085	-3.368	-2.121
Denmark	2.680**	0.064	0.240	-3.062*
Finland	1.815**	-4.952	1.623**	-3.190
France	2.296**	-8.358	-1.619	-4.776
Germany	0.720*	-17.077*	-2.637	-3.694
Hong Kong	3.328**	-5.041	-1.155	-8.238
Ireland	2.739*	-10.150	7.579*	0.027
Italy	2.311**	-3.413	-1.336	-3.742
Japan	-0.887*	-2.384	0.533*	-0.360**
Netherlands	3.679*	-8.505	-2.661	-5.643
New Zealand	5.764**	-46.369	-2.256	-0.818
Norway	4.836**	-4.737	-2.499	-1.102
Singapore	3.973**	-7.015	-2.210	-7.410
Spain	4.569**	-4.332	-2.177	-5.448
Sweden	3.119**	-11.399	-0.857	-7.212
Switzerland	0.963	-4.609	0.200	-0.155
UK	4.653**	-6.286	1.520	-2.912
US	1.657*	-1.283	-1.300	-5.120
Across 21 Countries	**3.219 (20)**	**-7.453 (2)**	**-0.370 (4)**	**-3.596 (4)**

Panel B: US Corporate Bonds

Rating/Maturity	**Hedge Fund Illiq. Measure**	**Lagged Returns**	**VIX AR(2) Shocks**	**VWM Ex. Return**
Inv Grade (24 Portfolios)	3.300 (11)	-7.016 (0)	-8.238 (2)	-7.392 (0)
High Yield (18 Portfolios)	5.835 (17)	-4.076 (10)	0.236 (3)	3.259 (17)
1-3Y (7 Portfolios)	4.343 (5)	-17.113 (1)	-3.332 (1)	-3.591 (2)
3-5Y (7 Portfolios)	5.053 (4)	-2.460 (3)	-3.417 (1)	-1.658 (3)
5-7Y (7 Portfolios)	4.664 (5)	-3.829 (1)	-5.024 (2)	-2.417 (3)
7-10Y (7 Portfolios)	4.594 (5)	-5.427 (1)	-7.021 (0)	-3.671 (3)
10-15Y (7 Portfolios)	3.059 (4)	-0.438 (1)	-5.100 (0)	-2.803 (3)
15+Y (7 Portfolios)	4.604 (5)	-5.268 (3)	-3.743 (1)	-2.824 (3)
Across 42 Portfolios	**4.386 (28)**	**-5.756 (10)**	**-4.606 (5)**	**-2.827 (17)**

Panel C: Currencies

Currency	**Hedge Fund Illiq. Measure**	**Inflation Diff.**	**Interest Rate Diff.**	**Lagged Returns**
Australia	4.098**	-0.342	-0.631	-2.847
Canada	1.372**	0.744*	0.875	-2.364
Euro	-0.405	4.786**	-1.682	-2.663
Japan	-4.229	-2.231	-6.230	-4.658
New Zealand	3.545**	1.143*	1.770*	-1.910
Norway	0.790	-2.565	-1.268	-4.893
Sweden	-1.365	1.012	1.067**	-3.304
Switzerland	-2.186	-0.109*	-2.174	-2.316
UK	-1.895	-2.905	0.196	-1.250
Across 9 Currencies	**-0.030 (3)**	**-0.052 (4)**	**-0.897 (2)**	**-2.912 (0)**

Table 5: Model Simulation

Panel A reports the parameter values used for the model simulations in Panel B and C. Panel B reports the statistics for model simulations based on fixed values of C_0. For each value of C_0, the model is simulated $10,000$ times. The parameters d_2 and u_1 are drawn randomly from normal distributions with mean 1 and 0 (variance 0.01 and 0.5), respectively, for each of the $10,000$ simulations. The ρ, returns, and prices, are averaged across the $10,000$ simulations. Panel C reports the estimates of α and γ for the predictive regression $r_{t+1} = \alpha + \gamma\rho_t + \epsilon_{t+1}$ estimated with $10,000$ data points of simulated data from our model. The parameters d_2, u_1, and C_0 are drawn randomly for each of the $10,000$ simulations. The parameters d_2 and u_1 are drawn from the same distributions as in Panel B. C_0 is drawn from a normal distribution with mean of 4 and variance of 0.50.

Panel A: Parameter Values for Model

$E[d_2]$	σ_d^2	λ	α	θ	ϕ_{max}	$E[u_1]$	σ_u^2
1	0.01	0.01	3	10	0.5	0	0.5

Panel B: Model Simulation for Fixed C_0

No Liquidity Constraint

C_0	C_0/θ	$\phi_{max}(\theta + C_0)$	ρ^{model}	**Expected Return**	**Noise Traders Buy Price**	**Noise Traders Sell Price**
NA	NA	NA	NA	0.005%	1.012	0.988

With Liquidity Constraint

					Price Discount	
C_0	C_0/θ	$\phi_{max}(\theta + C_0)$	ρ^{model}	**Expected Return**	**NT Buy**	**NT Sell**
5.0	0.5	7.5	0.666	2.517%	2.075%	-2.834%
4.0	0.4	7.0	0.714	3.017%	2.569%	-3.239%
3.0	0.3	6.5	0.768	3.517%	2.964%	-3.745%

Panel C: Predictive Regression on Simulated Data

	Estimates		
	All Observations	**Noise Traders Buy**	**Noise Traders Sell**
β_0	-0.241	-0.157	-0.199
β_1	15.400	5.539	6.930

Table 6: Panel Estimation Conditioning on Sign of Lagged Return

Reported are the results of a fixed effects panel estimation with jackknife standard errors clustered by time. The dependent variables are monthly log excess returns or monthly log returns in the case of currencies. The independent variables are lagged by one month and divided by their respective standard deviations, such that the parameter estimates are comparable. For international equities and currencies, the time series start in January 1995 and end in December 2011. The time series for US corporate bond starts in January 1997 and end in December 2011. Estimates significant at the 10% level are denoted by *, and estimates significant at the 5% level are denoted by **.

Panel A: International Equities	(1)	(2)	(3)
Lagged Returns	0.912*	0.844	0.842
	(1.718)	(1.598)	(1.572)
HF Illiq. Measure*Negative Lag Ret. Dummy	1.857**		1.857**
	(2.818)		(2.809)
HF Illiq. Measure*Positive Lag Ret. Dummy		0.793*	0.793*
		(1.846)	(1.846)
Adj R2 (%)	**4.852**	**2.714**	**5.687**
Panel B: US Corporate Bonds			
Lagged Returns	0.495**	0.406*	0.415*
	(2.411)	(1.888)	(1.923)
HF Illiq. Measure*Negative Lag Ret. Dummy	0.454*		0.450*
	(1.954)		(1.918)
HF Illiq. Measure*Positive Lag Ret. Dummy		0.544**	0.542**
		(3.849)	(3.844)
Adj R2 (%)	**3.879**	**5.282**	**6.174**
Panel C: Currencies			
Lagged Returns	0.095	0.064	0.074
	(0.526)	(0.362)	(0.407)
HF Illiq. Measure*Negative Lag Ret. Dummy	0.765**		0.764**
	(2.724)		(2.720)
HF Illiq. Measure*Positive Lag Ret. Dummy		0.239	0.237
		(1.160)	(1.154)
Adj R2 (%)	**2.376**	**0.348**	**2.649**

Table 7: Panel Estimation with Illiquidity Dummy Variables

Reported are the coefficient estimates and t-stats, which are computed with jackknife standard errors clustered by time, of a fixed effects panel estimation. The dependent variables are monthly log excess returns. The independent variables are lagged by one month and divided by their respective standard deviations. For international equities, the illiquidity dummy is equal to one for all the countries with a market cap below the median market cap of the 21 countries over the sample period. For US corporate bonds, the High Yield Dummy is equal to 1, when the portfolio is rated as high yield. The Maturity >5Y Dummy is equal to 1, when the portfolio contains corporate bonds with a maturity greater than 5 years. For currencies, the illiquidity dummy is equal to one for all the currencies with an average 1M Libor rate over the sample period above the median across the 9 currencies. For currencies and international equities, the time series starts in January 1995 and ends in December 2011. The time series for corporate bonds starts in January 1997. Estimates significant at the 10% level are denoted by *, and estimates significant at the 5% level are denoted by **.

Panel A: International Equities	
VIX AR(2)	-1.046*
	(-1.669)
Dividend Yield	-0.034
	(-0.126)
Lagged Returns	0.057
	(0.150)
HF Illiquidity Measure	1.166**
	(3.066)
HF Illiquidity Measure*(Illiquidity Dummy)	0.272**
	(2.128)
Adj R2 (in %)	**6.433**

Panel B: US Corporate Bonds	(1)	(2)
Pastor Stambaugh Traded Liq. Factor	-0.282**	-0.282**
	(-2.044)	(-2.042)
VWM Excess Return	-0.144	-0.144
	(-0.569)	(-0.569)
VIX AR(2) Shocks	-0.549	-0.549
	(-1.553)	(-1.551)
Lagged Returns	0.341**	0.338**
	(2.158)	(2.110)
Hedge Fund Illiquidity Measure	0.229*	
	(1.955)	
Hedge Fund Illiquidity Measure*(High Yield Dummy)	0.666**	
	(2.626)	
Hedge Fund Illiquidity Measure		0.375**
		(3.137)
Hedge Fund Illiquidity Measure*(Maturity >5Y Dummy)		0.197**
		(2.713)
Adj R2 (in %)	**10.335**	**9.090**

Panel C: Currencies	
Inflation Differential	0.437**
	(3.228)
Interest Rate Differential	0.031
	(0.187)
Hedge Fund Illiquidity Measure	0.206
	(1.134)
Hedge Fund Illiquidity Measure*(High Int. Rate Dummy)	0.264**
	(2.463)
Adj R2 (in %)	**3.860**

Table 8: Robustness Checks

This table presents robustness checks of our main results, and the first row of this table corresponds to the bottom-right elements of Panels A, B and C of Table 3. We present the average adjusted R^2 of multiple predictor regressions across all assets within an asset class, the number of assets for which the coefficient of the hedge fund illiquidity measure is significant (at the 10% level) and positive and significant and negative. All predictors are lagged by one month. The dependent variables are the mothly log excess return for US corporate bonds and international equities, and the monthly log return for currencies. The time series for US corporate bonds starts in January 1997 and ends in December 2011. For currencies and international equities, the time series starts in January 1995 and ends in December M2011. The time series for all hedge fund illiquidity measures start before January 1995, except *AR(1) 18M*, which starts in June 1995, and *AR(1) 24M*, which starts in December 1995. The style specific hedge fund illiquidity factors are computed with Fixed Income funds for US corporate bonds, Global Macro funds for currencies, and Directional Traders and Security Selection funds for international equities.

	Int. Equities	**US Corp. Bonds**	**Currencies**
Base Case	7.133 (21/0)	12.186 (32/0)	4.110 (5/0)
Varying Window Length			
9 Months	4.686 (12/0)	12.494 (33/0)	3.202 (1/0)
18 Months	5.276 (14/0)	10.921 (28/0)	3.606 (2/0)
24M Months	4.281 (8/0)	10.597 (32/0)	3.212 (0/0)
Varying Autocorr. Measures			
AR(2)	4.842 (17/0)	10.729 (32/0)	3.194 (1/0)
MA(1)	7.922 (21/0)	12.418 (30/0)	4.714 (5/0)
MA(2)	5.501 (20/0)	10.966 (31/0)	3.335 (1/0)
Different Styles			
Directional Traders	6.401 (21/0)		
Security Selection	6.420 (21/0)		
Fixed Income		12.280 (34/0)	
Global Macro			3.196 (2/0)
Other Variations			
AUM Weighted	5.577 (17/0)	10.123 (17/0)	4.033 (4/0)
Untrimmed	7.647 (21/0)	12.036 (32/0)	4.513 (5/0)

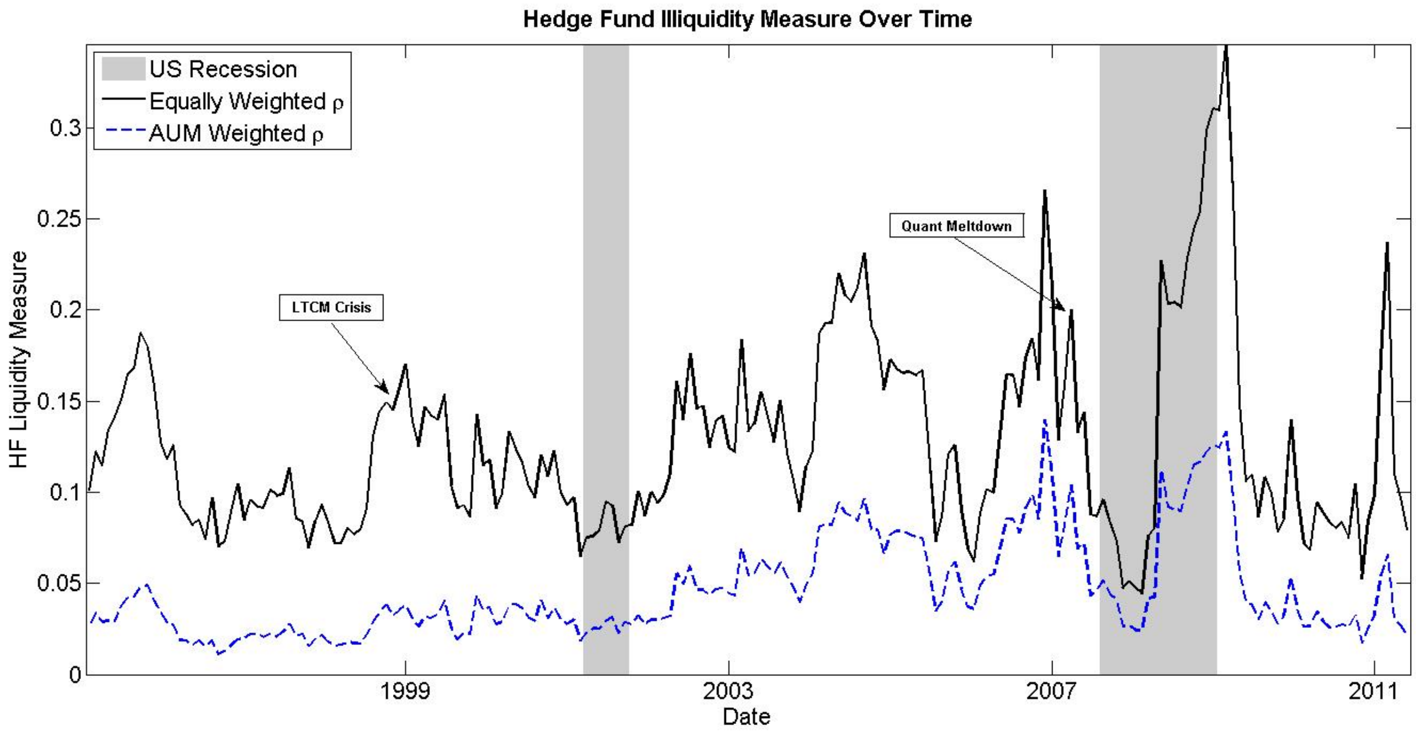

Figure 1: This figure shows the AUM weighted and the equally weighted hedge fund illiquidity measure from December 1994 to December 2011.

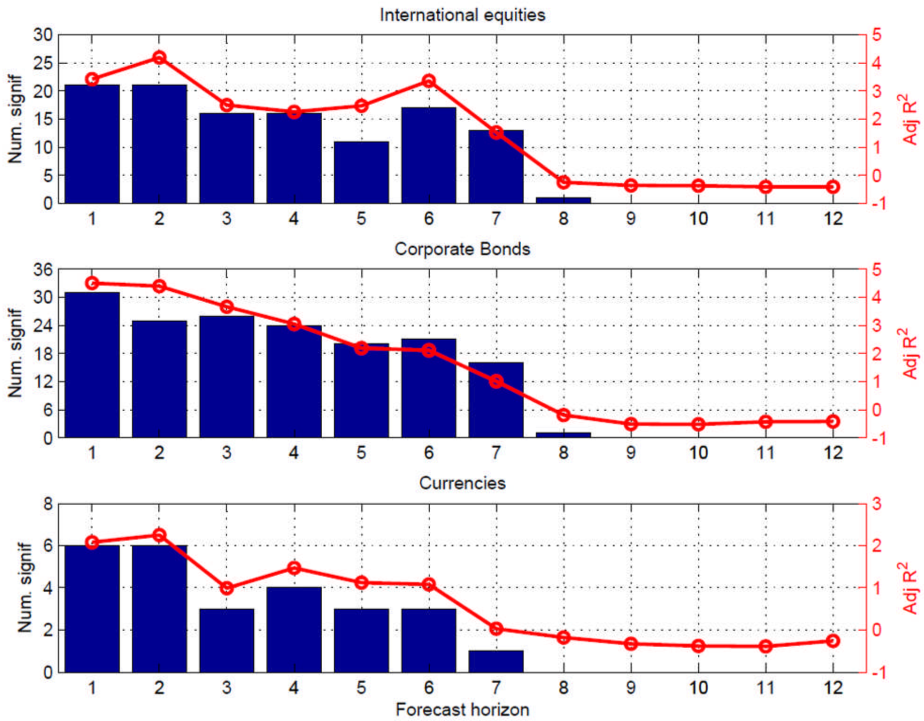

Figure 2 A: This figure shows the average adjusted R^2 and number of significant coefficients of the hedge fund illiquidity measure for different forecast horizons (in months). The results are for single predictor in-sample regressions, i.e. the only predictor is the hedge fund illiquidity measure.

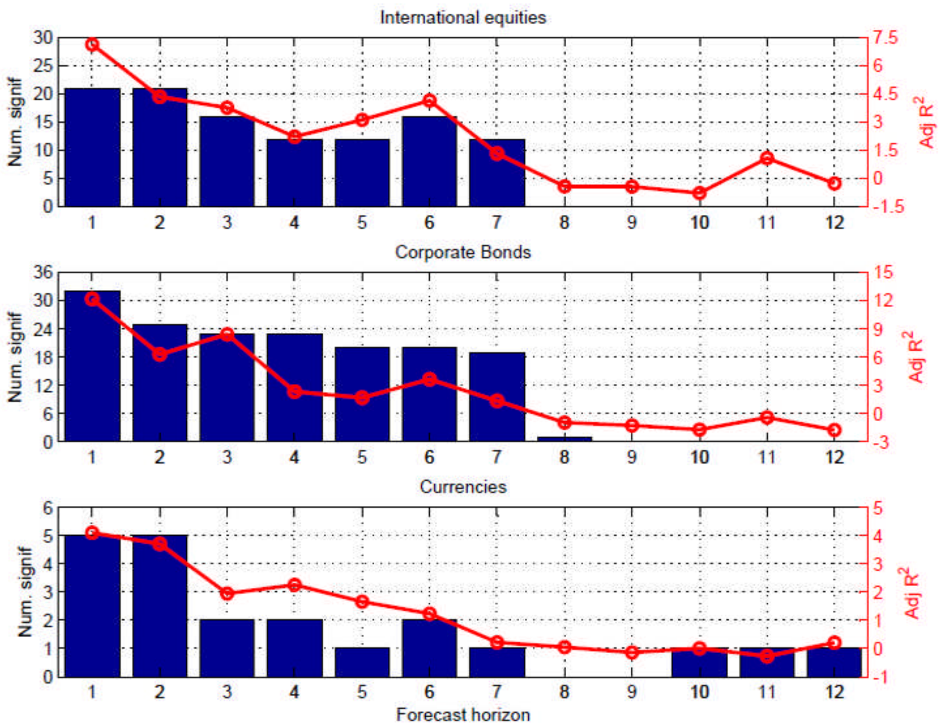

Figure 2 B: This figure shows the average adjusted R^2 and number of significant coefficients of the hedge fund illiquidity measure for different forecast horizons (in months). The results are for multiple predictor in-sample regressions, i.e. the hedge fund illiquidity measure is included together with competitor variables.

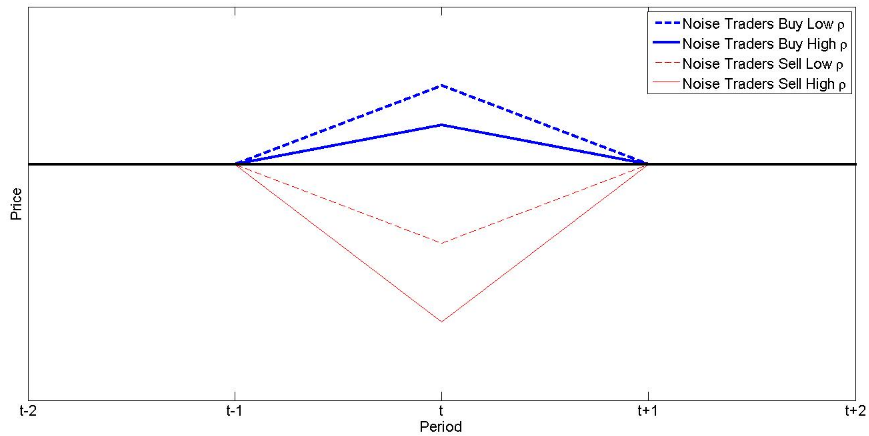

Figure 3 A: The return reversal for low and high ρ is shown. The values in this figure are not directly related to our model or the empirical analysis.

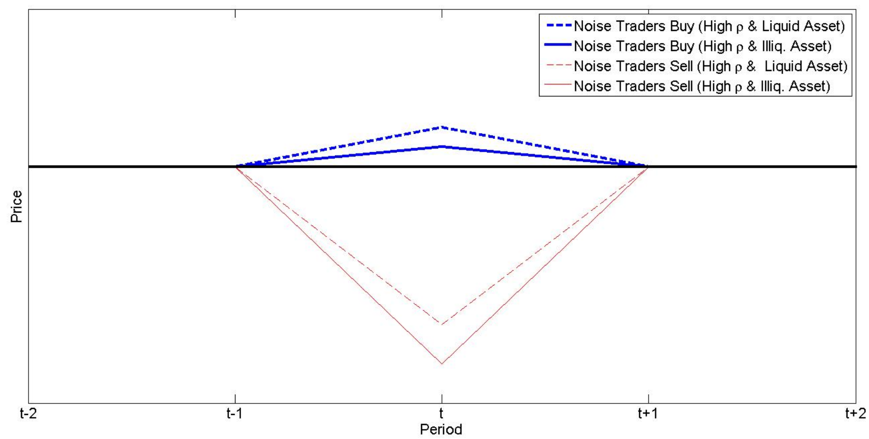

Figure 3 B: The return reversal for a liquid and an illiquid asset is shown. ρ is assumed to be high in both cases. The values in this figure are not directly related to our model or the empirical analysis.