The Impact of Hedge Funds on Asset Markets

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Motivation

- Regulators, investors, and academics are deeply interested in hedge funds
  - The financial stability panel established under Dodd-Frank introduced new disclosure regulations in 2012 ("Form PF")
  - Assets under management has grown from $50 billion in 1990 to $500 billion in 2000, and to $2 trillion in 2013
  - Scores of academic papers studying hedge funds
- As of 2013Q3, the hedge fund industry has AUM of about $2 trillion, small compared with mutual funds with around $28 trillion
  - But hedge funds employ substantial leverage and have high trading volume
  - Impact of hedge fund activity may be greater than its AUM suggests

★ Yet evidence of hedge funds' impact on markets is relatively scarce

What we do in this paper

- We create a simple index of the ability of hedge funds to provide liquidity to asset markets
    - Liquidity provision is thought to be a source of profitability for hedge funds
    - Our index is an aggregate measure of the illiquidity of hedge funds' holdings
- We study the predictive power of our measure of hedge fund illiquidity across 72 assets in three different asset classes
    - Indices of international equities, US corporate bonds and currencies
- We present a simple theoretical model of hedge funds' willingness to provide liquidity
    - The model provides additional predictions on where our new illiquidity measure should be particularly useful

Main findings of the paper

- We find that our simple index of hedge fund illiquidity is a powerful predictor of asset returns
  - **In sample**: significant for 21/21 international equity indices, 31/42 corporate bond indices, 6/9 currencies
  - **Out-of-sample**: significantly beats the historical mean model for 20/21 international equity indices, 28/42 corporate bond indices, 3/9 currencies
  - Both in and out of sample, our index is as good or better than best alternative predictor for each asset class
- Our simple **theoretical model** of hedge funds willingness to provide liquidity explains our main results, and generates two further predictions
  - Predictive power should be (and is) greater for less liquid assets
  - Predictive power should (and is) greater following negative asset returns

Outline

- Introduction
- **Data description and illiquidity index construction**
- Predictive performance, with and without competitor variables
    - In sample
    - Out of sample
- A simple model of hedge fund liquidity provision
    - Empirical tests of predictions of the model
- Robustness checks
- Conclusion

Data description

- **Hedge fund data:** we merge five databases to construct a universe of around 30,000 hedge funds
  - HFR, TASS, CISDM, Morningstar, BarclayHedge
  - Sample period is January 1994 – December 2011, 216 months of data
- **International equities:** 21 country equity indices, from K. French's web site
- **US corporate bonds:** 42 indices, from Bank of America-Merrill Lynch
  - 24 investment grade, 18 high yield
  - Six different maturity buckets: 1-3, 3-5, 5-7, 7-10, 10-15, 15+ years
- **Currencies:** 9 exchange rates, all against the USD, from Bloomberg
  - We use the DM/USD rate in place of the Euro/USD pre-1999

An index of hedge fund illiquidity

- Getmansky, et al. (2004, JFE) and Lo (2008) propose using **autocorrelation in hedge fund returns** as a proxy for the illiquidity of their holdings
  - "Marking to model" leads to greater autocorrelation
  - Intentional "performance smoothing" is easier to do when marking to model ("opportunistic smoothing")
  - Lo (2008) shows that average autocorrelations are higher in HF styles that are *ex ante* thought to be less liquid

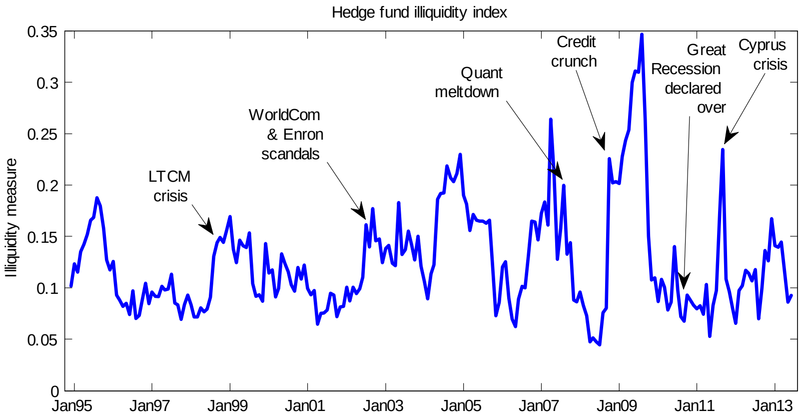
- We use a simple rolling-window estimate of average autocorrelation as our measure of HF illiquidity:

$$\textbf{Individual fund } i \quad \hat{\rho}_{i,t} = \frac{\sum_{j=0}^{W-1}\left(r_{i,t-j}-\bar{r}_{i,t}\right)\left(r_{i,t-j-1}-\bar{r}_{i,t}\right)}{\sum_{j=0}^{W-1}\left(r_{i,t-j}-\bar{r}_{i,t}\right)^2}$$

$$\textbf{Index} \quad \rho_t = \sum_{i=1}^{N}\omega_{i,t}\max\left\{\hat{\rho}_{i,t},0\right\}$$

The hedge fund illiquidity index over time

High illiquidity during the great recession and hedge fund crisis periods



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A first look at predictive power

- We estimate a single variable predictive regression in-sample:

$$r_{i,t+1} = \alpha_i + \gamma_i \rho_t + \varepsilon_{i,t+1}$$

  where i denotes assets, and t denotes months

  - For equities and corporate bonds, $r_{i,t+1}$ is the log excess return
  - For currencies, $r_{i,t+1}$ is the log difference in spot rates (Results are very similar when using excess currency returns, i.e., including the interest rate differential)

In-sample predictive power: International equities

Coeff on rho is positive and significant at the 5% level for all 21 markets

Country	$\overline{R}^2$	/ γ signif	/ γ sign	Country	$\overline{R}^2$	/ γ signif	/ γ sign
Australia	8.220	**	$+$	Japan	2.745	**	$+$
Austria	3.954	**	$+$	Netherlands	3.255	**	$+$
Belgium	2.608	**	$+$	New Zealand	4.722	**	$+$
Canada	3.057	**	$+$	Norway	4.509	**	$+$
Denmark	2.920	**	$+$	Singapore	6.560	**	$+$
Finland	1.327	**	$+$	Spain	3.836	**	$+$
France	2.148	**	$+$	Sweden	4.022	**	$+$
Germany	1.611	**	$+$	Switzerland	1.739	**	$+$
Hong Kong	4.638	**	$+$	UK	4.025	**	$+$
Ireland	2.741	**	$+$	US	1.583	**	$+$
Italy	1.632	**	$+$				
Across 21 countries					**3.422 (21/0)**		

In-sample predictive power: US corporate bonds

Coeff on rho is positive for all 42 bond indices, and significant for 31 indices

		Coeff is signif and	
Rating/Mat. (# Port.)	$\overline{R}^2$	**Positive**	**Negative**
Inv Grade (24)	3.099	14	0
High Yield (18)	6.364	17	0
1-3Y (7)	3.886	5	0
3-5Y (7)	4.995	5	0
5-7Y (7)	4.865	5	0
7-10Y (7)	4.911	6	0
10-15Y (7)	3.244	4	0
15+Y (7)	5.088	6	0
Across 42 indices	**4.498**	31	0

In-sample predictive power: Currencies

Coeff on rho is positive for all 9 currencies, and significant for 6 currencies

Currencies	$\overline{R}^2$ /	γ **signif** /	γ **sign**
Australia	5.885	**	+
Canada	4.111	**	+
Euro	1.406	**	+
Japan	-0.367		+
New Zealand	4.565	**	+
Norway	1.883	**	+
Sweden	1.468	**	+
Switzerland	-0.207		+
UK	-0.001		+
Across 9 currencies	**2.083 (6/0)**		

Competitor predictor variables

- Next, consider competitor variables for forecasting asset returns:

$$r_{i,t+1} = \alpha_i + \beta_{ij} Competitor_{j,t} + \varepsilon_{i,j,t+1}$$

- **International Equities:** Lagged returns, dividend yield, VIX Innovations (Goyal and Welch, 2008 RFS)
- **US corporate bonds:** Lagged returns, Pastor-Stambaugh traded liquidity factor, VIX Innovations, and VWM excess returns on the S&P 500 (Bongaerts, de Jong, and Driessen, 2012, wp)
- **Currencies:** Inflation differential and interest rate differential (Meese and Rogoff, 1983, AER)

★ Below I present the results for the **best** competitor variable for each asset class; results for all competitors are in the paper.

In-sample predictive power: Int'l equities with VIX shocks

Adj R2 is slightly lower, and coeff is significant for 15/21 markets, compared with 21/21

Country	$\overline{R}^2$	/ β **signif**	/ β **sign**	**Country**	$\overline{R}^2$	/ β **signif**	/ β **sign**
Australia	1.289		-	Japan	3.082	**	-
Austria	8.126	**	-	Netherlands	5.669	**	-
Belgium	7.597	*	-	New Zealand	4.000	**	-
Canada	4.875	*	-	Norway	4.419	**	-
Denmark	6.277	**	-	Singapore	1.595		-
Finland	-0.482		-	Spain	1.343	*	-
France	2.175	*	-	Sweden	1.393		-
Germany	1.679	*	-	Switzerland	4.250	**	-
Hong Kong	0.941		-	UK	3.978	**	-
Ireland	3.032	*	-	US	0.892		-
Italy	1.967	*	-				
Across 21 countries					**3.243 (0/15)**		

In-sample predictive power: US corp bonds with lag rets

Adj R2 is similar; coeff is significant for 26/42 indices, compared with 31/42 for our index

Rating/Mat. (# Port.)	$\overline{R}^2$	**Coeff is signif and**	
		Positive	**Negative**
Inv Grade (24)	1.816	12	0
High Yield (18)	8.023	14	0
1-3Y (7)	4.205	5	0
3-5Y (7)	6.446	6	0
5-7Y (7)	5.658	5	0
7-10Y (7)	3.978	5	0
10-15Y (7)	3.554	3	0
15+Y (7)	3.017	2	0
Across 42 indices	**4.476**	26	0

In-sample predictive power: Currencies with inflation diff

Adj R2 is slightly higher; coeff is significant for 6/9 currencies, same as for our index

Currencies	$\overline{R}^2$	/ β signif	/ β sign
Australia	3.316	**	$+$
Canada	3.681	**	$+$
Euro	6.148	**	$+$
Japan	-0.119		$+$
New Zealand	4.872	**	$+$
Norway	0.065		$+$
Sweden	3.832	**	$+$
Switzerland	4.188	**	$+$
UK	0.132		$+$
Across 9 currencies	**2.902 (6/0)**		

Including competitor predictor variables

- Next, we include ρ together with **all** competitors in a **multiple regression:**

$$r_{i,t+1} = \alpha_i + \gamma_i \rho_t + \beta_i Competitors_{i,t} + \varepsilon_{i,t+1}$$

- Competitors are the same as before:
- **International Equities:** Lagged returns, dividend yield, VIX Innovations (Goyal and Welch, 2008 RFS)
- **US corporate bonds:** Lagged returns, Pastor-Stambaugh traded liquidity factor, VIX Innovations, and VWM excess returns on the S&P 500 (Bongaerts, de Jong, and Driessen, 2012, wp)
- **Currencies:** Inflation differential and interest rate differential (Meese and Rogoff, 1983, AER)

In-sample multiple predictors: International equities

Adjusted R2 increases, but coefficient on rho remains as significant as before

Country	$\overline{R}^2$	/ γ signif	/ γ sign	Country	$\overline{R}^2$	/ γ signif	/ γ sign
Australia	10.746	**	+	Japan	5.881	**	+
Austria	12.239	**	+	Netherlands	8.828	**	+
Belgium	12.617	**	+	New Zealand	11.606	**	+
Canada	7.526	**	+	Norway	9.142	**	+
Denmark	11.129	**	+	Singapore	7.960	**	+
Finland	4.414	**	+	Spain	4.443	**	+
France	3.947	**	+	Sweden	5.270	**	+
Germany	2.990	**	+	Switzerland	5.217	**	+
Hong Kong	4.806	**	+	UK	8.396	**	+
Ireland	6.583	**	+	US	2.148	**	+
Italy	3.897	**	+				
Across 21 countries					**7.133 (21/0)**		

In-sample, multiple predictors: US corporate bonds

Adjusted R2 increases, but coefficient on rho remains as significant as before

Rating/Mat. (# Port.)	$\overline{R}^2$	Coeff is signif and Positive	Coeff is signif and Negative
Inv Grade (24)	8.110	14	0
High Yield (18)	25.491	17	0
1-3Y (7)	15.431	5	0
3-5Y (7)	18.368	5	0
5-7Y (7)	18.373	5	0
7-10Y (7)	15.229	6	0
10-15Y (7)	12.466	4	0
15+Y (7)	13.493	6	0
Across 42 indices	**15.560**	31	0

In-sample, multiple predictors: Currencies

Coefficient on rho is significant for 5/9 rather than 6/9 currencies; two sign changes

Currencies	$\overline{R}^2$	/ γ **signif**	/ γ **sign**
Australia	7.187	**	+
Canada	5.230	**	+
Euro	5.529		+
Japan	0.633		-
New Zealand	7.086	**	+
Norway	1.449	**	+
Sweden	4.698	*	+
Switzerland	4.713		-
UK	0.465		+
Across 9 currencies	**4.110 (5/0)**		

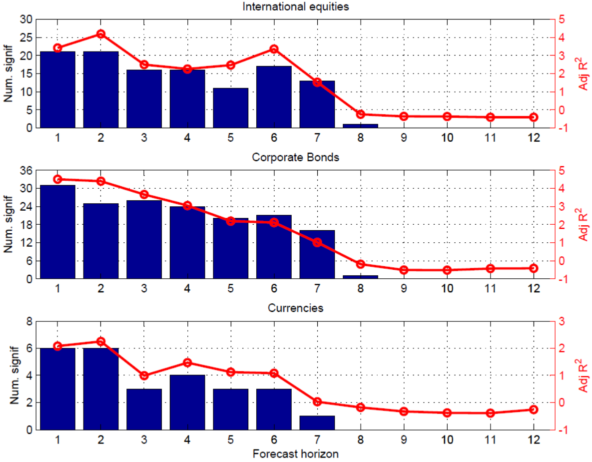
Multi-step-ahead predictions

- Next we investigate the predictive power of our hedge fund illiquidity index **across forecast horizons** from 1 to 12 months
- We use a "**direct projection**" approach:

$$
\begin{aligned}
r_{i,t+h} &= \alpha_{i,h} + \gamma_{i,h}\rho_t + \varepsilon_{i,t+h} \\
r_{i,t+h} &= \alpha_{i,h} + \gamma_{i,h}\rho_t + \beta_{i,h} Competitors_{i,t} + \varepsilon_{i,t+1}
\end{aligned}
$$

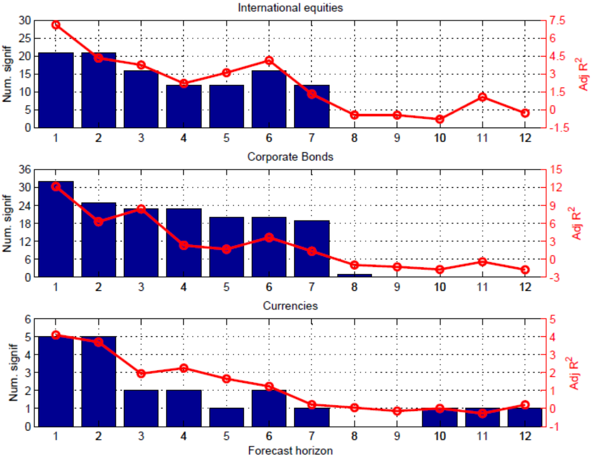
How long does predictability last? Just illiquidity index

Predictability is strongest at h=1, but remains strong even out to 6 months



How long does predictability last? All predictor variables

Predictability is strongest at h=1, but remains strong even out to 6 months



Out-of-sample forecasting

- We now consider the **out-of-sample** predictive power of our illiquidity index
- We use a rolling window of 60 months to estimate the model, and predict returns one month ahead
- Given the short sample, we only include predictor variables one at a time:

$$
\begin{aligned}
r_{i,t+1} &= \alpha_i + \gamma_i \rho_t + \varepsilon_{i,t+1} \\
r_{i,t+1} &= \alpha_i + \beta_{ij} Competitor_{j,t} + \varepsilon_{i,j,t+1}
\end{aligned}
$$

- We compare the OOS forecasts with those from a **historical mean** return model
- The significance of the difference between the two forecasts is assessed using an **extension of the Clark and West test** (2006, JoE), see appendix

Out-of-sample forecasting: International equities

Significantly beat historical mean for 20/21 countries (just 4/21 for VIX shocks)

Country	R^2_{OOS}	/ signif	Country	R^2_{OOS}	/ signif
Australia	9.039	**	Japan	-0.887	*
Austria	4.366	**	Netherlands	3.679	*
Belgium	3.260	**	New Zealand	5.764	**
Canada	2.711	**	Norway	4.836	**
Denmark	2.680	**	Singapore	3.973	**
Finland	1.815	**	Spain	4.569	**
France	2.296	**	Sweden	3.119	**
Germany	0.720	*	Switzerland	0.963	
Hong Kong	3.328	**	UK	4.653	**
Ireland	2.739	*	US	1.657	*
Italy	2.311	**			
All 21 countries				**3.219 (20)**	

Out-of-sample forecasting: US corporate bonds

Significantly beat historical mean for 28/42 indices (17/42 for mkt rets)

Rating/Mat. (# Port.)	**R^2_{OOS}**	**Signif**
Inv Grade (24)	3.300	11
High Yield (18)	5.835	17
1-3Y (7)	4.343	5
3-5Y (7)	5.053	4
5-7Y (7)	4.664	5
7-10Y (7)	4.594	5
10-15Y (7)	3.059	4
15+Y (7)	4.604	5
Across 42 indices	4.386	28

Out-of-sample forecasting: Currencies

Significantly beat historical mean for 3/9 indices (inflation diff gets 4/9 at 10% level, worse R2)

Currencies	**R^2_{OOS} / signif**	
Australia	4.098	**
Canada	1.372	**
Euro	-0.405	
Japan	-4.229	
New Zealand	3.545	**
Norway	0.790	
Sweden	-1.365	
Switzerland	-2.186	
UK	-1.895	
Across 9 currencies	**-0.030 (3)**	

Summary of results so far

- Our simple index of hedge fund illiquidity:

1. Is better (int'l equities and corporate bonds) or as good (currencies) than the best alternative predictor, in-sample
2. Remains just as significant when all main competitor variables are included in a predictive regression
3. Has predictive power as far out as 6 months, though strongest at 1-2 months
4. Is as good or better better than the best alternative predictor for each of the three asset classes, out-of-sample

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Market makers and return reversal

- We incorporate liquidity constraints into the **limits to arbitrage** framework of Gromb and Vayanos (2010)
- The hedge fund effectively acts as a **market maker** for a risky asset, which is subject to demand shocks from noise traders
- The hedge fund faces the threat of investors withdrawing funds, and needs to hold sufficient liquid assets to **cover potential outflows**
- The hedge fund's initial portfolio can vary in terms of **illiquidity,** represented by its relative weights in the risky asset (illiquid) and cash (liquid)

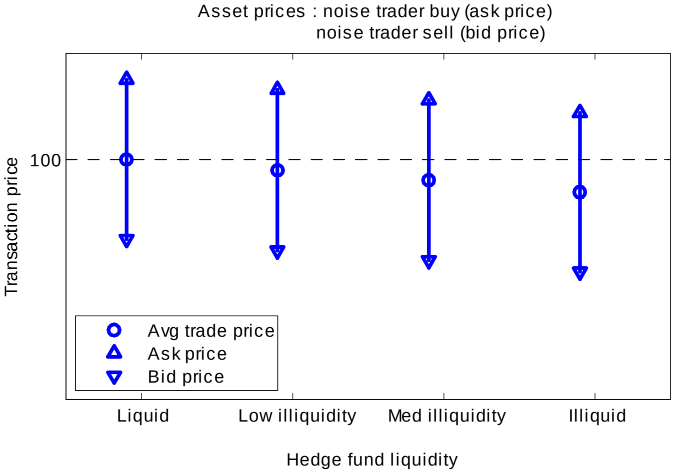
Hedge fund portfolio illiquidity and return reversal

- A hedge fund with an illiquid portfolio is **reluctant to buy** the risky asset and **eager to sell** it. This has three implications:

1. **Sign asymmetry**: Compared with a liquid hedge fund,
   - the noise trader can **buy** from an illiquid hedge fund for a **lower price** $\Rightarrow$ **smaller reversal** following noise trader purchases
   - the noise trader must **sell** to an illiquid hedge fund for a **lower price** $\Rightarrow$ **larger reversal** following noise trader sales
2. Average transaction prices are lower when hedge fund liquidity is low
   $\Rightarrow$ larger return reversals when hedge fund liquidity is low
   $\Rightarrow$ **low hedge fund liquidity predicts high asset returns**
3. Both **effects are stronger** when the asset itself is **less liquid**

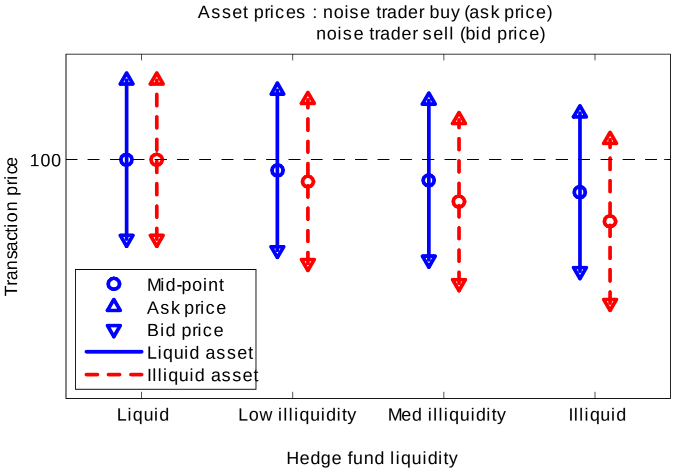
Buy and sell prices as a function of hedge fund liquidity

Return reversals more greater when hedge fund is illiquid



Buy and sell prices, when asset is liquid and illiquid

Effect is even more pronounced when risky asset is more illiquid



Three empirical predictions from the model

1. High hedge fund illiquidity predicts higher asset returns
   - This was strongly supported in our earlier empirical analysis
2. Predictive power of illiquidity measure is greater for less liquid assets
   - Will test this below
3. Asset return reversals are amplified (dampened) when current returns are negative (positive)
   - Will test this below
   - This uses the assumption that negative (positive) returns are an indicator that noise traders sold (bought), as in Pastor and Stambaugh (2003, JPE)

Is predictive power greater for less liquid assets?

- To test whether the predictive power of our illiquidity measure is more pronounced for illiquid assets, we estimate a fixed effect panel model for each asset class:

$$r_{i,t+1} = \alpha_i + \beta Competitors_{i,t} + \gamma \rho_t + \phi \rho_t \times I_{Illiq,i} + \varepsilon_{i,t+1}$$

  - $I_{Illiq,i}$ is a dummy variable for assets belonging to a less liquid subgroup
  - Using panel estimation improves the power to detect this effect

- We identify "less liquid" assets as follows:
  - **International equities**: market capitalization is below the median; turnover is below median
  - **Corporate bonds**: bond is high yield; bond has a maturity greater than 5 years (Bao, Pan and Wang, 2011, JF)
  - **Currencies**: spread is above median; 1-month interest rate is above the median (Campbell et al., 2010, JF)

Predictive power is greater for illiquid assets

All models also include a fixed effect and all competitor variables

	Estimates and t-stats					
Variable	**Int'l Equities**		**US corp bonds**		**Currencies**	
ρ_t	1.166** (3.066)	1.179** (2.900)	0.229* (1.955)	0.375** (3.137)	0.203 (1.255)	0.206 (1.134)
$\rho_t I_{SmlCap}$	0.272** (2.128)					
$\rho_t I_{LowTurn}$		0.248** (2.161)				
$\rho_t I_{HiYield}$			0.666** (2.626)			
$\rho_t I_{LongMat}$				0.197** (2.713)		
$\rho_t I_{HiSpr}$					0.269** (2.229)	
$\rho_t I_{HiInt}$						0.264** (2.463)

Predictive power and the sign of the current return

- To test whether the predictive power of our illiquidity measure is different following noise trader buys vs. sells, we again estimate a fixed effect panel model for each asset class:

$$r_{i,t+1} = \alpha_i + \beta Competitors_{i,t} + \gamma^- \rho_t \times I_{r_{i,t}<0} + \gamma^+ \rho_t \times I_{r_{i,t}>0} + \varepsilon_{i,t+1}$$

- Our model predicts that there will be return reversals for both buys and sells from noise traders (proxied by $I_{r_{i,t}>0}$ and $I_{r_{i,t}<0}$)
  - So we expect $\gamma^+ > 0$ and $\gamma^- > 0$
- The model further predicts that the reversal will be stronger following a noise trader sell
  - So we expect $\gamma^- > \gamma^+ > 0$
  - In the absence of any asymmetry on sells/buys, we expect $\gamma^- = \gamma^+$

Predictive power somewhat stronger following neg returns

Asymmetry is significant at 10% level for two out of three asset classes

	Estimates and t-stats		
Variable	**Int'l equities**	**US corp bonds**	**Currencies**
γ^-	2.029**	0.630**	0.640**
	(2.949)	(2.018)	(2.200)
γ^+	0.870*	0.456**	0.117
	(2.005)	(3.576)	(0.569)
$\gamma^- - \gamma^+$	1.159*	0.174	0.523*
	(1.425)	(0.516)	(1.470)

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Extensions and robustness checks

- We consider a variety of checks of the robustness of our results

1. Use **hedge fund style information** when computing the index
2. Include a **measure of factor illiquidity** to see if that is driving our results
3. Vary the **measure of autocorrelation**: AR(1), AR(2), MA(1), MA(2)
4. Vary the **window** used to compute autocorrelations: 9, 12, 18, 24 months
5. Alter how we compute the aggregate index: **trimmed**/**untrimmed**, **EW/VW**

- **Summary**: Results are broadly robust to all of the above; see appendix

Conclusion

- We present a simple index of time-varying illiquidity of hedge funds' holdings
- We show that this index has substantial predictive power for across 72 assets in three different asset classes
  - It is as good or better than the best individual alternative predictor variables
  - It remains significant when all other predictor variables are also included
  - Is significantly better, out-of-sample, than a historical mean forecast for most individual assets
- We present a simple theoretical model of hedge funds' willingness to provide liquidity
  - The model provides additional testable predictions, which are (mostly) borne out in the data

Appendix

Related literature: Hedge funds $\leftrightarrows$ Asset Markets

- Hedge funds are significantly **exposed to systematic risks**, proxied by return indexes of equities, bonds, and options
  - Agarwal and Naik (2004, RFS), Fung and Hsieh (1997, 2001, 2004), Mamaysky, Spiegel and Zhang (2007, RFS), Bollen and Whaley (2009, JF), Patton (2009, RFS), Jagannathan et al. (2010, JF), Patton and Ramadorai (2012, JF), Buraschi, Kosowski, and Trojani (2013, RFS)
- Exposure to **illiquidity risk** is an important feature of hedge funds
  - Getmansky, Lo, and Makarov (2004, JFE), Aragon (2007, JFE), Sadka (2009, JFE), Cassar and Gerakos (2011, RFS)

★ Some work on **hedge funds affecting asset markets**
  - Jylhä and Suominen (2011, JFE), Aragon and Strahan (2012, JFE), Kang, Kondor, and Sadka (2012, JFQA), Ben-David, Franzoni, Landier, and Moussawi (2012, JF)

The Clark-West test

- Clark and West (2006, JoE) consider the comparison of a linear predictive model with a benchmark model that contains **no variables**
  - i.e., the benchmark model is based on the target variable being a **martingale difference sequence**
- They note that under the null that the smaller model is correct, the larger model (which nests the smaller model, and so is *also* correct) will perform worse in finite samples due to **increased estimation error**.
- Clark and West propose a simple **adjustment** to the MSFE of the larger model to correct for this
  - The adjustment subtracts off an estimate of the impact of estimation error from the larger model's MSFE
- This adjustment yields a test of equal predictive accuracy that is **less conservative** and has **higher power**

Extending the Clark-West test

- In our study the smaller model is a **constant**, not a model with no params:

$$\hat{Y}^{(1)}_{t+1|t} = \hat{\gamma}_t \qquad \text{vs.} \qquad \hat{Y}^{(2)}_{t+1|t} = X_t'\hat{\beta}_t$$

- Thus both "models" have some estimation error, though the larger model continues to have more, as in the original Clark-West framework
- A term based on the **cross-product** of estimation errors arises in this case
  - This term complicates the adjustment slightly; details are in the paper
- We show how to implement this extended Clark-West test, and the appendix contains a small simulation study showing that the extension has the same benefits in the original Clark-West paper
  1. The test is **less conservative** under the null
  2. The test is **more powerful** under the alternative

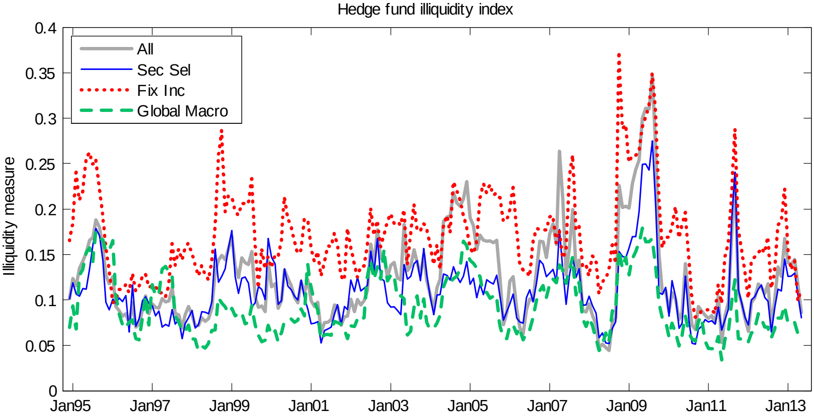
Extensions and robustness checks

- We consider a variety of checks of the robustness of our results

1. Use **hedge fund style information** when computing the index
2. Include a **measure of factor illiquidity** to see if that is driving our results
3. Vary the **measure of autocorrelation**: AR(1), AR(2), MA(1), MA(2)
4. Vary the **window** used to compute autocorrelations: 9, 12, 18, 24 months
5. Alter how we compute the aggregate index: **trimmed**/**untrimmed**, **EW/VW**

Illiquidity index by style: All funds

All indices clearly capture some of the same trends in illiquidity



Extension: Create illiquidity indices using style labels

Aggregating all funds seems to work better, except for corporate bonds

	Int'l equities		US corp bonds		Currencies	
Model	$\overline{R}^2$	Pos/Neg	$\overline{R}^2$	Pos/Neg	$\overline{R}^2$	Pos/Neg
Base: All funds	7.133	21 / 0	12.186	32 / 0	4.110	5 / 0
Direct. traders	6.401	21 / 0				
Sec. selection	6.420	21 / 0				
Fixed income			12.280	34 / 0		
Global macro					3.196	2 / 0

Robustness check: Vary model for autocorrelation

AR(1) and MA(1) do about equally well; AR(2) and MA(2) slightly worse

	Int'l equities		**US corp bonds**		**Currencies**	
Model	$\overline{R}^2$	Pos/Neg	$\overline{R}^2$	Pos/Neg	$\overline{R}^2$	Pos/Neg
Base: AR(1)	7.133	21 / 0	12.186	32 / 0	4.110	5 / 0
MA(1)	7.922	21 / 0	12.418	30 / 0	4.714	5 / 0
AR(2)	4.842	17 / 0	10.729	32 / 0	3.194	1 / 0
MA(2)	5.501	20 / 0	10.966	31 / 0	3.335	1 / 0

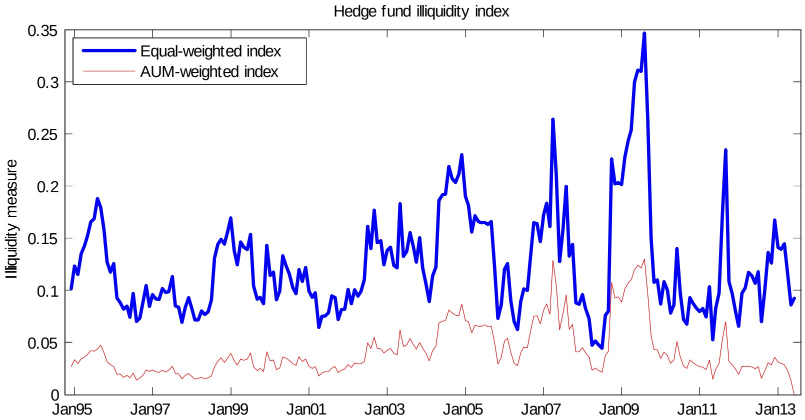
Robustness check: Vary window length

Results for bonds are robust to window length; equities and currencies best for 12 months

Window	**Int'l equities**		**US corp bonds**		**Currencies**	
length	$\overline{R}^2$	Pos/Neg	$\overline{R}^2$	Pos/Neg	$\overline{R}^2$	Pos/Neg
Base: 12 mths	7.133	21 / 0	12.186	32 / 0	4.110	5 / 0
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
24 months	4.281	8 / 0	10.597	32 / 0	3.212	0 / 0

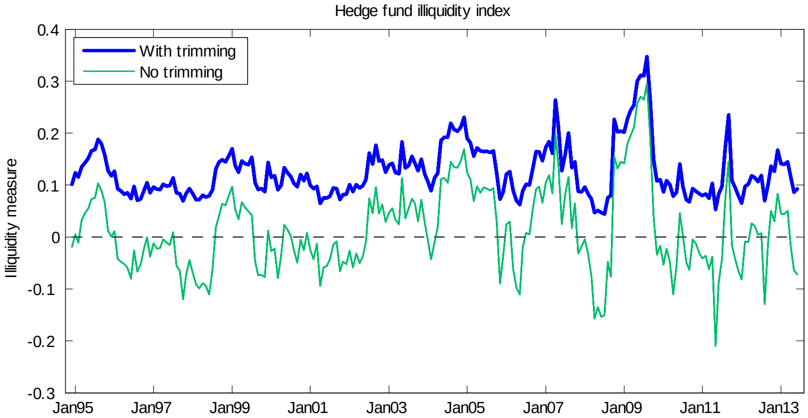
Robustness check: Equal weight vs AUM weight

Similar dynamics, but lower level, for AUM-weighted index of illiquidity (corr=0.90)



Robustness check: Trimming vs No trimming

Similar dynamics for index of illiquidity with no trimming (corr=0.97)



Robustness check: Varying calculation of the index

Trimming does not really affect results; equal-weighting works better than value-weighting

	Int'l equities		US corp bonds		Currencies	
Calc method	$\overline{R}^2$	Pos/Neg	$\overline{R}^2$	Pos/Neg	$\overline{R}^2$	Pos/Neg
Base: Trim, EW	7.133	21 / 0	12.186	32 / 0	4.110	5 / 0
Untrimmed, EW	7.647	21 / 0	12.036	32 / 0	4.513	5 / 0
Untrimmed, VW	8.329	21 / 0	11.886	32 / 0	4.499	5 / 0
Trimmed, VW	5.577	17 / 0	10.123	17 / 0	4.033	4 / 0

Including autocorrelation of risk factors as competitors

Coefficients on our illiquidity index are almost all unaffected by including these variables

	Coeff signif positive / negative		
	Int'l equities	**US corp bonds**	**Currencies**
Base: no extra variable	*21 / 0*	*31 / 0*	*6 / 0*
HML US	21 / 0	30 / 0	6 / 0
Mkt-RF US	21 / 0	31 / 0	3 / 0
Momentum US	21 / 0	30 / 0	6 / 0
SMB US	21 / 0	31 / 0	6 / 0
HML Global	21 / 0	31 / 0	6 / 0
Mkt-RF Global	21 / 0	33 / 0	6 / 0
SMB Global	21 / 0	31 / 0	6 / 0
WML Global	21 / 0	31 / 0	6 / 0
PTFSBD	21 / 0	28 / 0	6 / 0
PTFSFX	21 / 0	29 / 0	6 / 0
PTFSCOM	21 / 0	31 / 0	3 / 0