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 \$2.4 trillion in 2014
  - Scores of academic papers studying hedge funds
- As of 2015Q2, the hedge fund industry has AUM of about \$2.5 trillion, small compared with mutual funds with around \$30 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 20/21 international equity indices, 31/42 corporate bond indices, 6/9 currencies
  - **Out-of-sample**: significantly beats the historical mean model for 18/21 international equity indices, 24/42 corporate bond indices, 4/9 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

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), Cao et al. (2013, wp)

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

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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

Autocorrelation as a measure of hedge fund illiquidity

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   - So *if* intentional smoothing occurs in reported returns, it is probably more prevalent when markets are less liquid

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   - So *if* intentional smoothing occurs in reported returns, it is probably more prevalent when markets are less liquid
3. Lo (2008) shows that average autocorrelations are higher in HF styles that are *ex ante* thought to be less liquid
   - Eg: Event driven and Emerging market funds vs. US Equity Hedge and Managed Futures funds

An index of hedge fund illiquidity

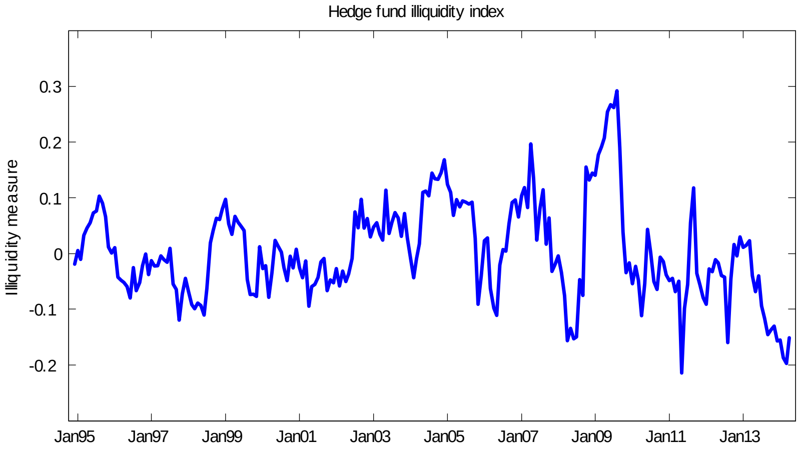
- We use a simple rolling-window estimate of average autocorrelation as our measure of HF illiquidity:

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

$$\textbf{Index} \quad \rho_t = \sum_{i=1}^{N_t}\omega_{i,t}\hat{\rho}_{i,t}$$

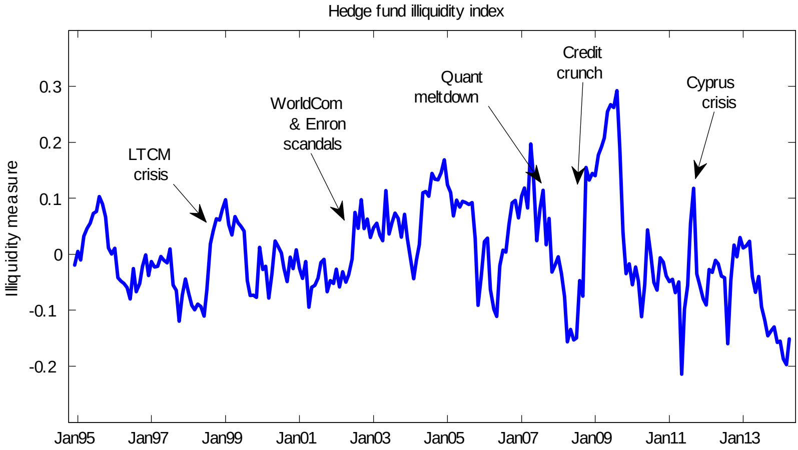
The hedge fund illiquidity index over time

Our measure of illliquidity exhibits substantial variation



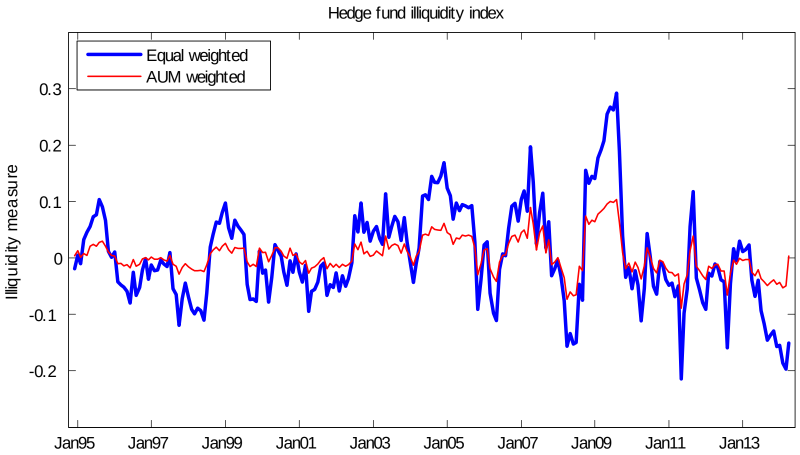
The hedge fund illiquidity index over time

High illiquidity during the great recession and hedge fund crisis periods



Equal-weighted vs AUM-weighted index

Similar dynamics, but lower level, for AUM-weighted index of illiquidity (corr=0.88)



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A first look at predictive power

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

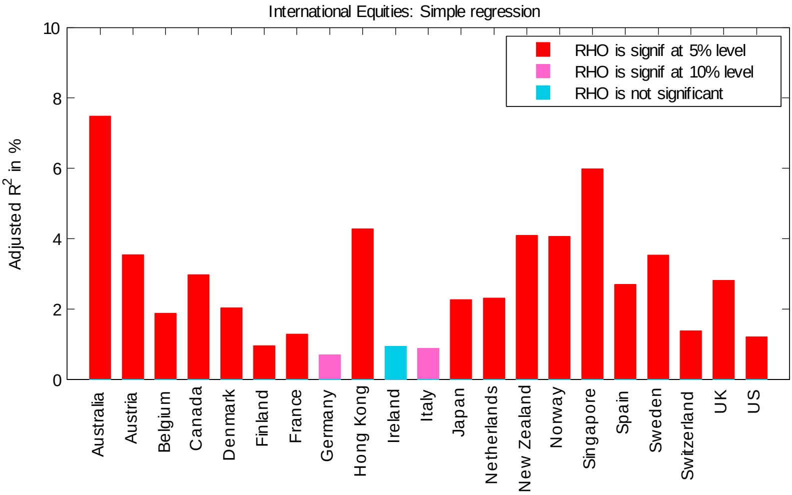
$$r_{i,t+1} = \alpha_i + \gamma_i \rho_t + \varepsilon_{i,t+1}$$

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)

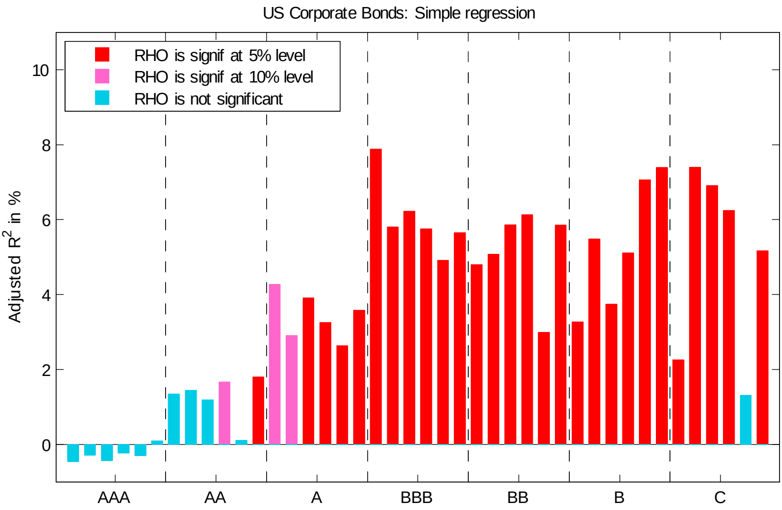
In-sample predictive power: International equities

Coeff on rho is significant for 20 of 21 markets (and positive for all 21)



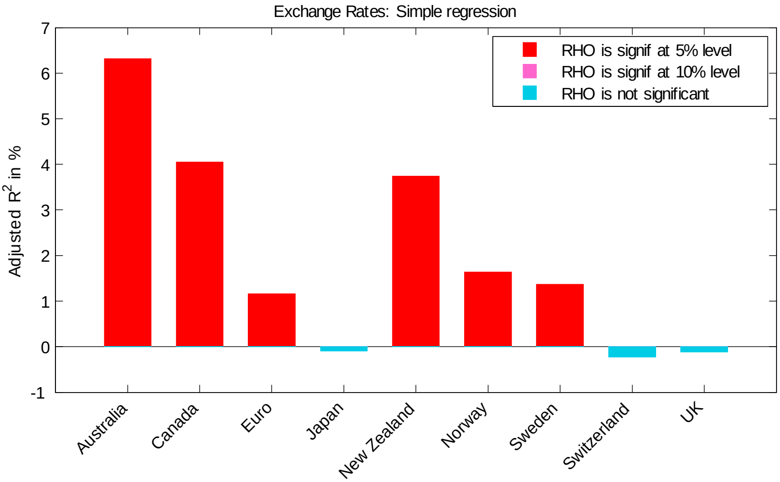
In-sample predictive power: US corporate bonds

Coeff on rho is significant for 31 of 42 indices (and positive for all 42)



In-sample predictive power: Currencies

Coeff on rho is significant for 6 of 9 currencies (and positive for all 9)



Including competitor predictor variables

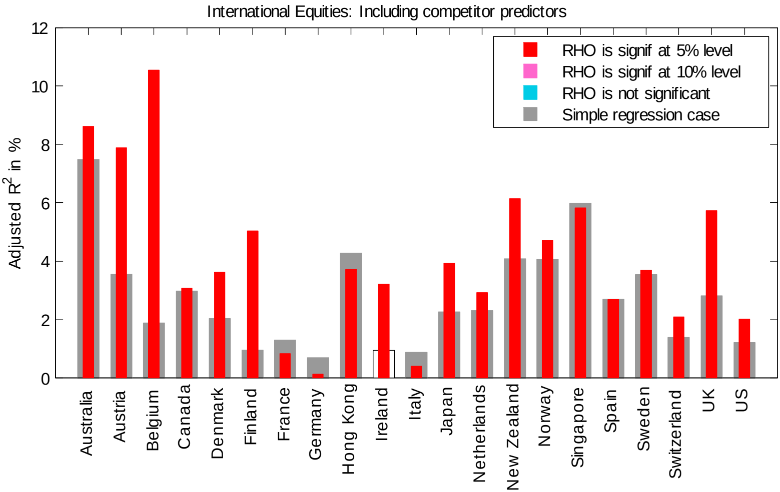
- Next, we include ρ together with **all** competitors in a **multiple regression:**

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

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

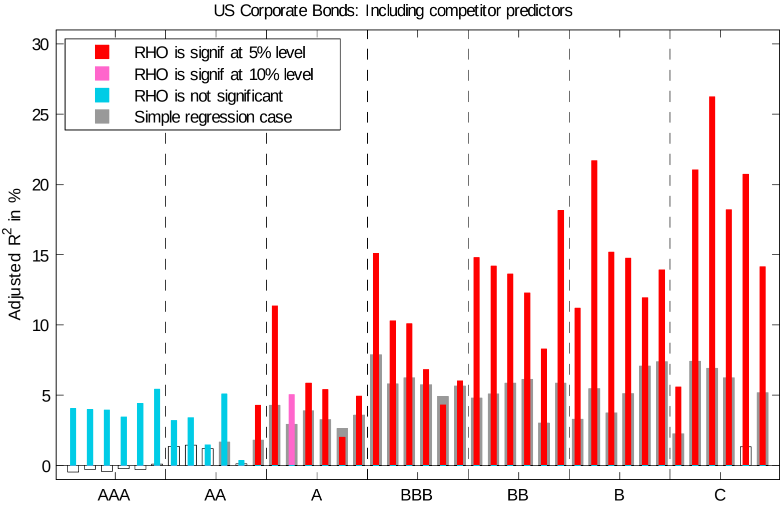
In-sample multiple predictors: International equities

Adjusted R2 generally increases, coefficient on rho more significant



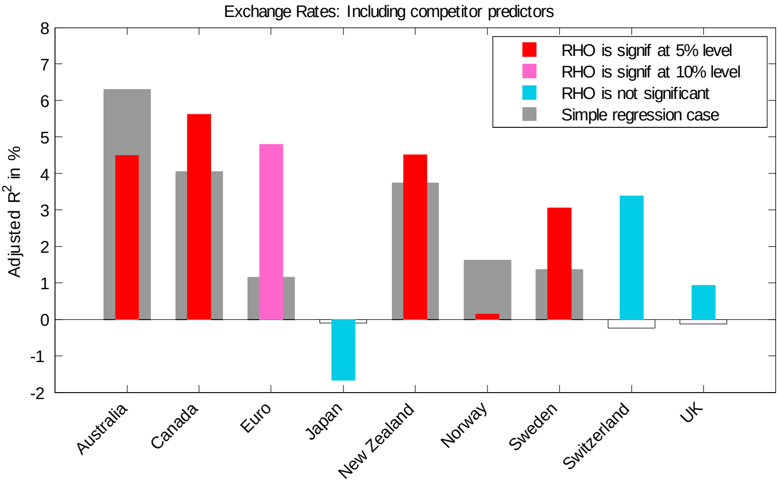
In-sample, multiple predictors: US corporate bonds

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



In-sample, multiple predictors: Currencies

Coefficient on rho remains significant for 6/9 currencies



Out-of-sample forecasting

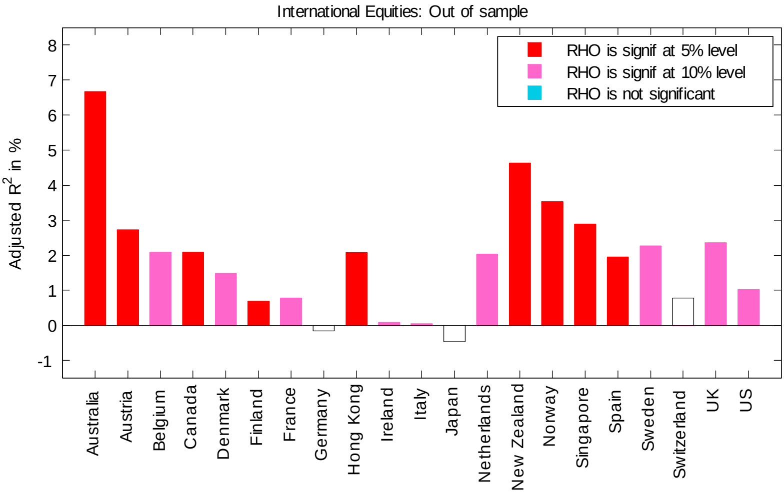
- We now consider the **out-of-sample** predictive power of our illiquidity index
- We use a rolling window of 60 months to estimate the model, and predict returns one month ahead
- Given the short sample, we only include predictor variables one at a time:

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

- 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).

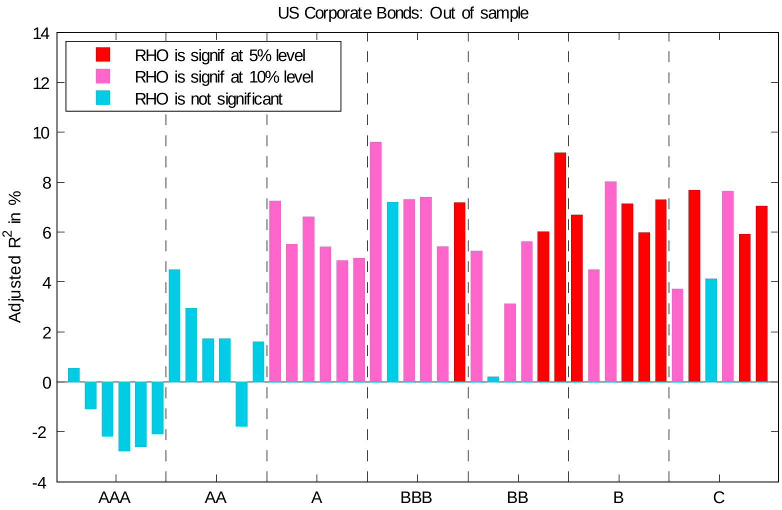
Out-of-sample forecasting: International equities

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



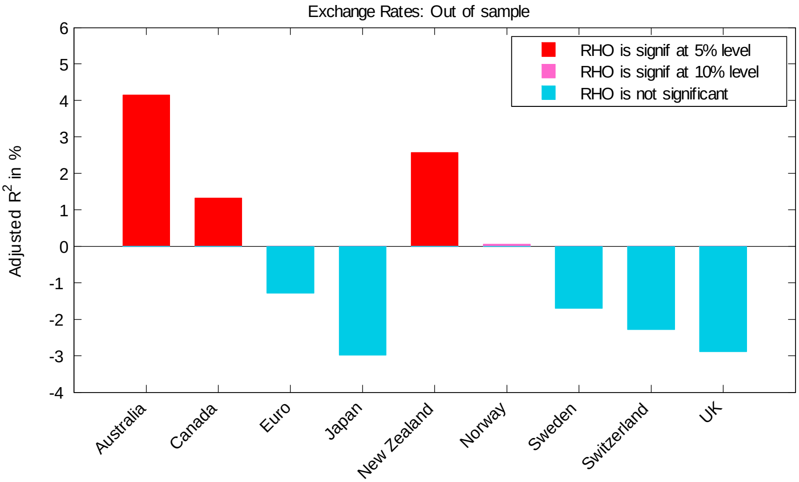
Out-of-sample forecasting: US corporate bonds

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



Out-of-sample forecasting: Currencies

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



Multi-step-ahead predictions

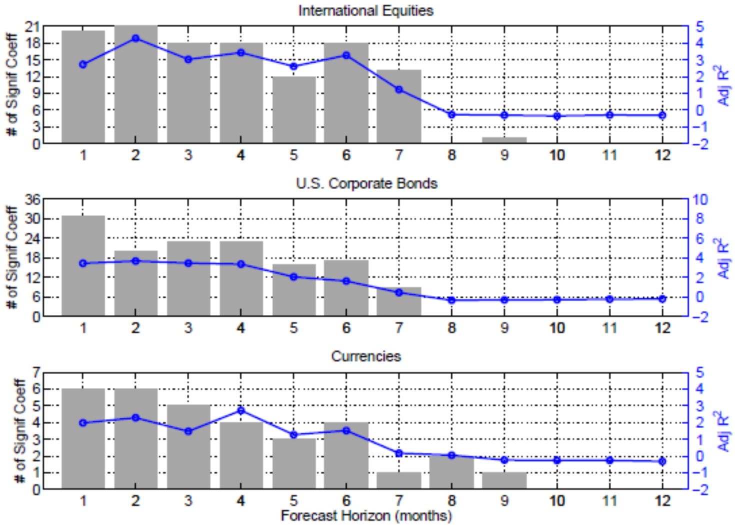
- Next we investigate the predictive power of our hedge fund illiquidity index **across forecast horizons** from 1 to 12 months
- We use a "**direct projection**" approach:

$$r_{i,t+h} = \alpha_{i,h} + \gamma_{i,h}\rho_t + \varepsilon_{i,t+h}$$

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

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

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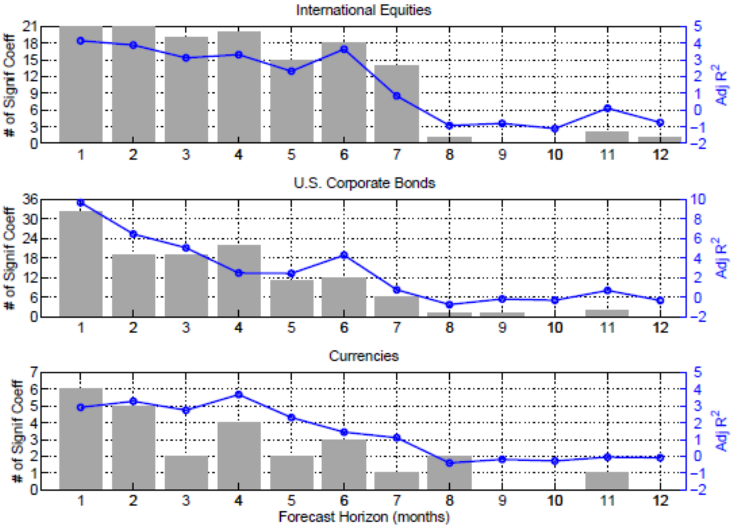

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Market makers and return reversal

- 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

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   - the noise trader must **sell** to an illiquid hedge fund for a **lower price** $\Rightarrow$ **larger reversal** following noise trader sales

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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**

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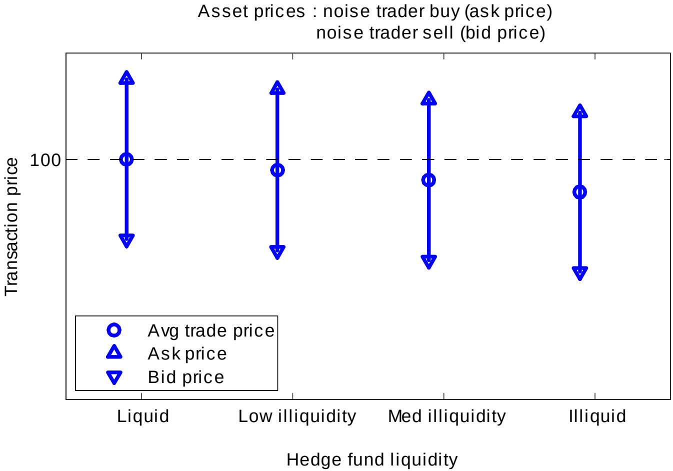
   $\Rightarrow$ larger return reversals when hedge fund liquidity is low
   $\Rightarrow$ **low hedge fund liquidity predicts high asset returns**
3. Both **effects are stronger** when the asset itself is **less liquid**

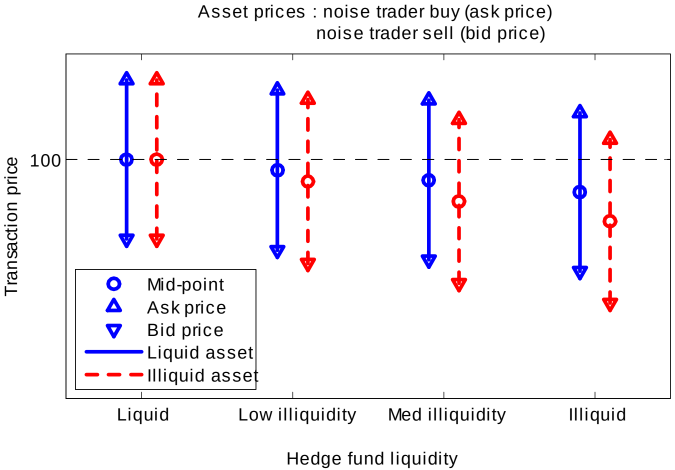
Buy and sell prices as a function of hedge fund liquidity

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	1.967**	0.977**	0.195*	0.309**	0.248	0.179
	(2.804)	(2.659)	(1.957)	(3.157)	(1.575)	(1.281)
$\rho_t I_{SmlCap}$	0.248**					
	(2.163)					
$\rho_t I_{LowTurn}$		0.227**				
		(2.148)				
$\rho_t I_{HiYield}$			0.577**			
			(2.470)			
$\rho_t I_{LongMat}$				0.199**		
				(2.722)		
$\rho_t I_{HiSpr}$					0.234**	
					(2.234)	
$\rho_t I_{HiInt}$						0.388**
						(3.314)

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 goes in the right direction, but is not significant

	Estimates and t-stats		
Variable	**Int'l equities**	**US corp bonds**	**Currencies**
γ^-	1.100**	0.287*	0.403**
	(2.903)	(1.798)	(2.588)
γ^+	0.531*	0.337**	0.126
	(1.645)	(3.327)	(0.883)
$\gamma^- - \gamma^+$	0.569	-0.050	0.277
	(1.143)	(-0.264)	(1.311)

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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**
6. Conduct a **"placebo" test** on extremely liquid assets to look for (lack of) predictability

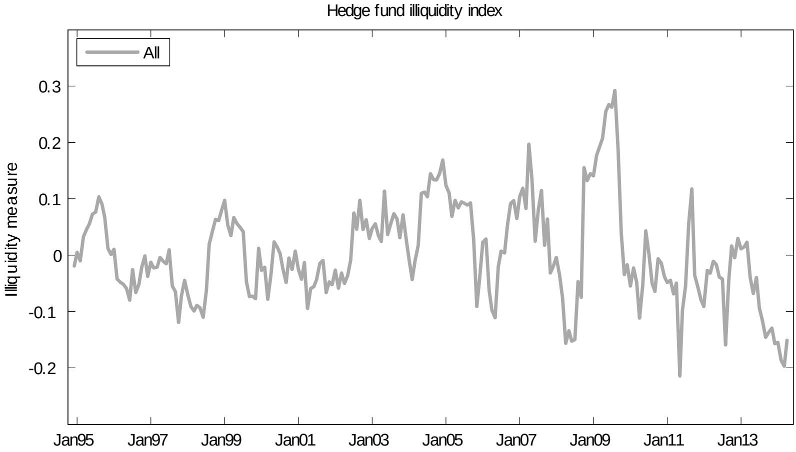
Conclusion

- 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: Additional slides

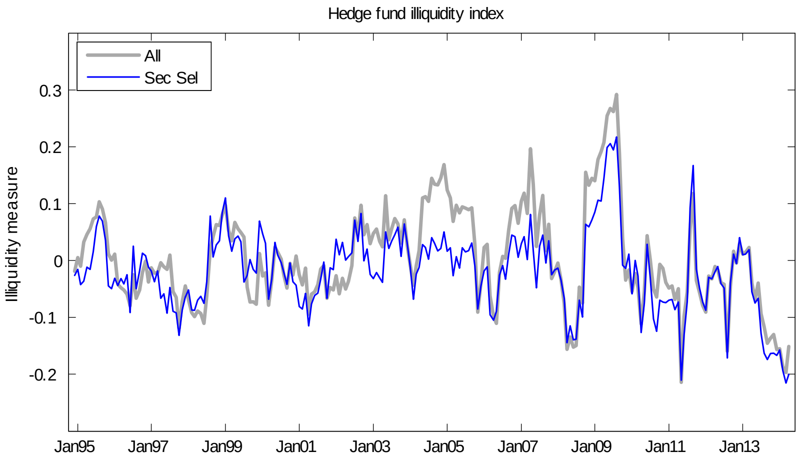
Illiquidity index by style: All funds

Our baseline index, using all funds



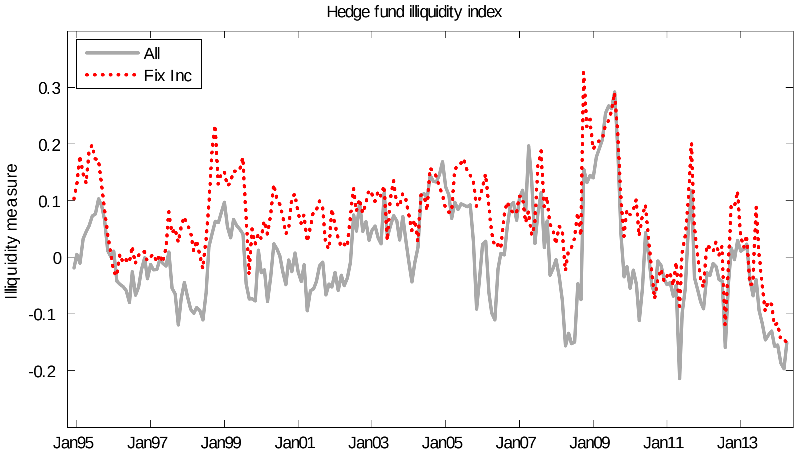
Illiquidity index by style: "Security Selection"

Index based on funds primarily in equity markets is very close to base case (corr=0.89)



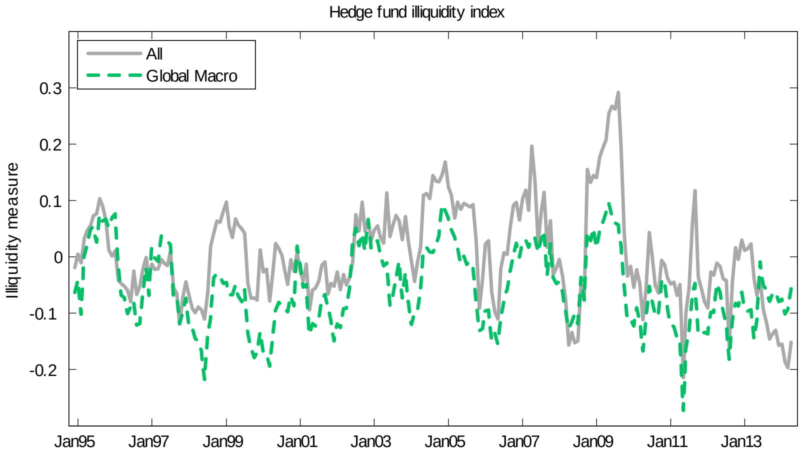
Illiquidity index by style: "Fixed Income"

Index based on fixed income funds differs somewhat from base case (corr=0.81)



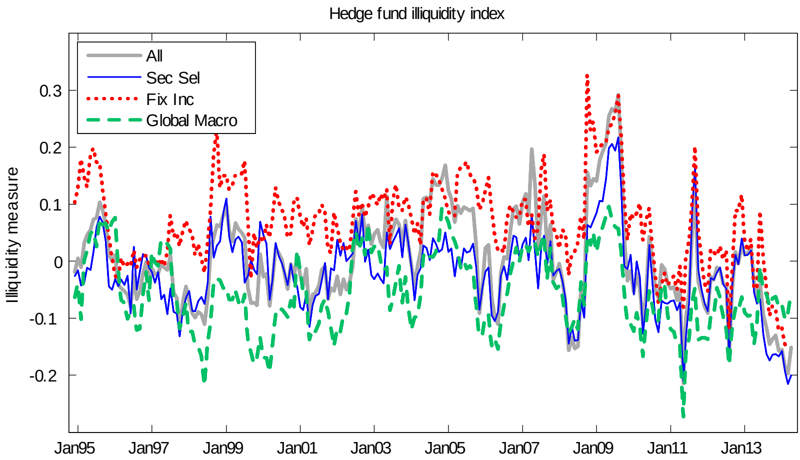
Illiquidity index by style: “Global Macro”

“Global macro” funds differ somewhat from base case, esp. in last recession (corr=0.76)



Illiquidity index by style: All funds

All indices clearly capture some of the same trends in illiquidity



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	$\bar{R}^2$	Pos/Neg	$\bar{R}^2$	Pos/Neg	$\bar{R}^2$	Pos/Neg
Base: AR(1)	4.131	21 / 0	9.661	32 / 0	3.088	6 / 0
MA(1)	4.336	21 / 0	9.345	31 / 0	2.881	5 / 0
AR(2)	2.170	13 / 0	8.223	31 / 0	1.755	1 / 0
MA(2)	2.673	18 / 0	5.671	32 / 0	1.858	1 / 0

Robustness check: Vary window length

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

Window length	Int'l equities $\overline{R}^2$	Int'l equities Pos/Neg	US corp bonds $\overline{R}^2$	US corp bonds Pos/Neg	Currencies $\overline{R}^2$	Currencies Pos/Neg
Base: 12 mths	4.131	21 / 0	9.661	32 / 0	3.088	6 / 0
9 months	1.941	7 / 0	9.444	33 / 0	1.733	1 / 0
18 months	2.694	15 / 0	8.462	28 / 0	2.295	3 / 0
24 months	1.718	6 / 0	7.946	29 / 0	1.802	2 / 0

Robustness check: Varying calculation of the index

Equal-weighting works better than value-weighting; trimming does not much affect results

	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: Untrim, EW	4.131	21 / 0	9.661	32 / 0	3.088	6 / 0
Untrimmed, VW	3.910	21 / 0	9.254	31 / 0	2.601	5 / 0
Trimmed, EW	3.992	21 / 0	9.670	31 / 0	2.810	5 / 0

Extension: Create illiquidity indices using style labels

Aggregating all funds seems to work better

Model	Int'l equities $\bar{R}^2$	Int'l equities Pos/Neg	US corp bonds $\bar{R}^2$	US corp bonds Pos/Neg	Currencies $\bar{R}^2$	Currencies Pos/Neg
Base: All funds	4.131	21 / 0	9.661	32 / 0	3.088	6 / 0
Direct. traders	3.523	19 / 0				
Sec. selection	3.586	17 / 0				
Fixed income			9.497	32 / 0		
Global macro					2.079	4 / 0

Additional control variables

- We next consider our baseline regression, including controls for some other possible explanations for our result:

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

  - 12-month average asset return
  - 12-month asset return autocorrelation
  - 12-month risk factor autocorrelation: Mkt, HML, SMB, MOM, PTFSBD, etc..
- We find that the coefficient on our hedge fund illiquidity index remains positive and significant
  - Rules out some other interpretations of our empirical finding

Additional control variables

Number of significant positive/negative coefficients on "rho"

		Int'l Equities	US Corp Bonds	Currencies
Base case (no controls)		20 / 0	31 / 0	6 / 0
Avg asset ret		20 / 0	34 / 0	6 / 0
Asset ret autocorrel		20 / 0	31 / 0	6 / 0
Risk factor autocorrel	Mkt	21 / 0	26 / 0	5 / 0
	HML	20 / 0	30 / 0	6 / 0
	SMB	20 / 0	31 / 0	6 / 0
	MOM	20 / 0	31 / 0	6 / 0
	PTFSBD	18 / 0	28 / 0	6 / 0
	PTFSCOM	21 / 0	27 / 0	4 / 0
	PTFSFX	19 / 0	27 / 0	6 / 0

A "placebo" test

- If our rationalization for the predictive ability of our hedge fund illiquidity index is correct, then this index should have poor power to predict returns on extremely liquid assets
- We consider using "rho" to predict excess returns on T-bills and 10-year bonds for ten countries
  - These are very liquid assets, and are unlikely to be affected by hedge fund liquidity levels

A "placebo" test

Our index is not significant for any country's T-bill or 10-year bond