The Impact of Hedge Funds on Asset Markets

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26 June 2013

Motivation

- Regulators, policymakers, and academics have been concerned about the hedge fund industry for some time now.
  - Avalanche of new regulations, worries about systemic risk.
- The hedge fund industry has AUM of only about U.S.$ 1.5 trillion
  - But substantial leverage, high trading volume in underlying asset markets.
  - Act as "arbitrageurs," make returns by providing liquidity in asset markets.
- **Yet, compelling evidence for hedge fund's impact on markets is scarce.**

Our paper

- Measure the ability of hedge funds to provide liquidity to asset markets.
  - Create aggregate measure of hedge fund portfolio illiquidity.
- Show that this measure has predictive power for returns across three of the major global asset classes.
- Data spans 72 portfolios of international equities, US corporate bonds, and currencies, and the predictive power is remarkably consistent across all three asset classes.
- We build an equilibrium model of hedge funds who are concerned about redemptions, and provide liquidity to noise traders.
  - Test and verify empirical implications of the equilibrium model.

Our main findings

- Our hedge fund illiquidity index predicts returns on US corporate bonds, currencies, and international equities.
- In-sample, our measure is significant for:
  - **31 out of 42** US corporate bond portfolios
  - **6 out of 9** currencies
  - **21 out of 21** international equities portfolios
- Out-of-sample, our predictor beats the historical mean return model, and a range of competitors for:
  - **35 out of 42** US corporate bond portfolios
  - **4 out of 9** currencies
  - **18 out of 21** international equities portfolios

Related literature

- Hedge funds are significantly exposed to systematic risk, proxied by return indexes of equities, bonds, and options.
  - Agarwal and Naik (2004, RFS), Fung and Hsieh (1997, 2001, 2004), Jagannathan et al. (2010, JF), Bollen and Whaley (2009, JF), Mamaysky, Spiegel and Zhang (2007, RFS), Patton and Ramadorai (2012, JF).
- Exposure to illiquidity risk is an important feature of hedge funds:
  - Getmansky, Lo, and Makarov (2004, JFE), Aragon (2007, JFE), Sadka (2009, JFE)
- Hedge funds' impact on asset markets:
  - Reduce idiosyncratic risk: Kang, Kondor, and Sadka (2012, JFQA); Help in the security price formation process: Cao, Chen, Goetzmann, and Liang (2012)

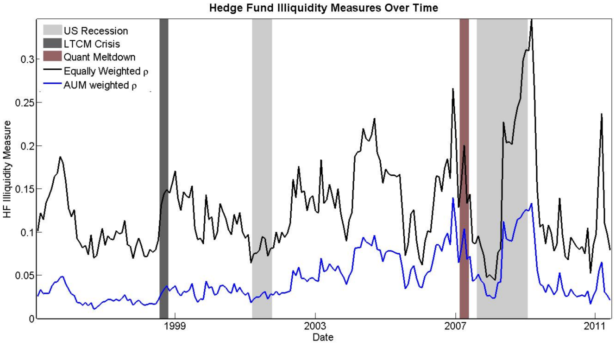
Outline of the talk

- **Creating an index of aggregate hedge fund illiquidity, and testing its predictive power in-sample**
- Out-of-sample predictive performance of the hedge fund illiquidity index
- Equilibrium model and model implications
- Empirically test model predictions
- Robustness checks
- Conclusion

Estimation of our hedge fund illiquidity index

- Getmansky, Lo, and Makarov (2004, JFE) and Lo (2007) propose using autocorrelation in hedge fund returns as a proxy for the illiquidity of their holdings.
- We use a panel with $30,000$ hedge funds and monthly return data from January 1994 to December 2011.
- We estimate an illiquidity measure ρ for each month t:
  1. Estimate the autocorrelation of individual hedge fund returns over a 12 month window.
  2. Impose a lower bound of zero.
  3. Average estimates across all hedge funds.
- High ρ implies hedge fund portfolio is illiquid.

The hedge fund illiquidity index over time



High illiquidity during the great recession and hedge fund crisis periods.

A first look at the predictive power

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

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

  where i denotes assets, and t denotes months.

- For US corporate bonds and international equities, $r_{i,t+1}$ is the log excess return.

- For currencies, $r_{i,t+1}$ is the log difference in spot rates.

- We use the following data sources:
  - **US corporate bonds:** Total return indices from Bank of America/Merrill Lynch (1M 1997 to 12M 2011)
  - **Currencies:** Spot rates from Bloomberg against USD (1M 1995 to 12M 2011)
  - **International equities:** Country returns from Ken French's website (1M 1995 to 12M 2011)

In-sample predictive power

US corporate bonds

Estimates of the model $r_{i,t+1} = \alpha_i + \gamma_i \rho_t + \epsilon_{i,t+1}$

Rating/Mat. (# Port.)	$\overline{R}^2$ **(**$\gamma > 0$**/**$\gamma < 0$**)**
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 All (42)	**4.498 (31/0)**

ρ is significant for 17 out of 18 high yield portfolios.

In-sample predictive power

Currencies

Currencies	$\overline{R}^2$**/**γ **sig./**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)**

ρ is significant for 6 out of 9 currencies.

In-sample predictive power

International equities

Country	$\overline{R}^2/\gamma$ sig./γ sign	Country	$\overline{R}^2/\gamma$ sig./γ sign
Australia	8.220** (+)	Japan	2.745** (+)
Austria	3.954** (+)	NL	3.255** (+)
Belgium	2.608** (+)	NZ	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** (+)
HK	4.638** (+)	UK	4.025** (+)
Ireland	2.741** (+)	US	1.583** (+)
Italy	1.632** (+)		
Across 21 Countries		**3.422 (21/0)**	

ρ is significant for all 21 markets.

In-sample multiple predictors

- Next, including ρ together with competitors in a multiple predictor in-sample regression.
- In-sample estimation of

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

  for each asset i.
- As competitors we use:
  - **US corporate bonds:**
    Lagged Returns, Pastor-Stambaugh Traded Liq. Factor, VIX Innovations, and VWM Excess Returns on the S&P 500 (Bongaerts, de Jong, and Driessen, 2012)
  - **Currencies:**
    Inflation Differential and Interest Rate Differential (Meese and Rogoff, 1983)
  - **International Equities:**
    Dividend Yield, Lagged Returns, and VIX Innovations (Goyal and Welch, 2008)

In-sample multiple predictor results

US corporate bonds

Estimates of the model $r_{i,t+1} = \alpha_i + \gamma_i \rho_t + \beta_i Competitors_t + epsilon_{i,t+1}$

Rating/Mat. (# Port.)	$\overline{R}^2$ **($\gamma > 0$/$\gamma < 0$)**
Inv Grade (24)	6.594 (14/0)
High Yield (18)	19.647 (18/0)
1-3Y (7)	11.873 (5/0)
3-5Y (7)	14.003 (5/0)
5-7Y (7)	14.021 (5/0)
7-10Y (7)	11.784 (6/0)
10-15Y (7)	10.002 (5/0)
15+Y (7)	11.446 (6/0)
Across All (42)	**12.460 (32/0)**

Including the competitors **enhances** the performance of ρ.

In-sample multiple predictor results

Currencies

Currencies	$\overline{R}^2$/γ **sig.**/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)**

ρ is significant for 5 out of 9 currencies.

In-sample multiple predictor results

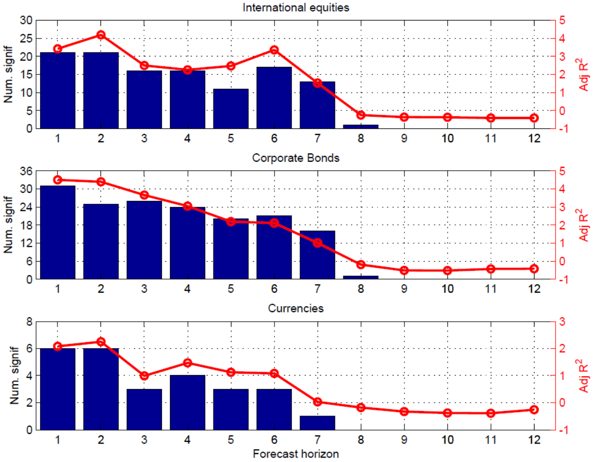
International equities

Country	$\overline{R}^2/\gamma$ sig./γ sign	Country	$\overline{R}^2/\gamma$ sig./γ sign
Australia	10.746** (+)	Japan	5.881** (+)
Austria	12.239** (+)	NL	8.828** (+)
Belgium	12.617** (+)	NZL	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)**	

ρ remains significant for all 21 markets.

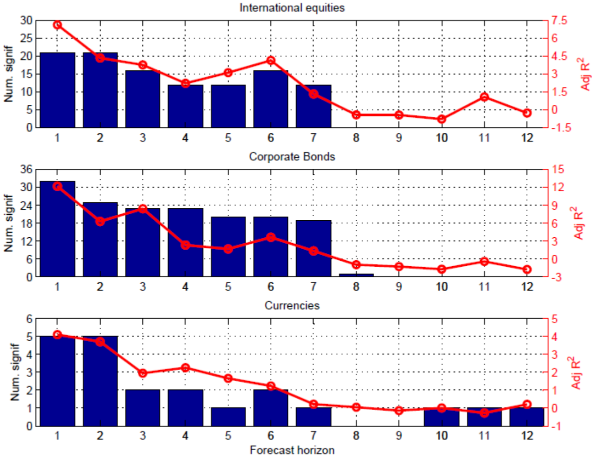
How long does predictability last?

For the single predictor regression:



How long does predictability last?

For the multiple predictor regression:



Outline of the presentation

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Out-of-sample forecasting procedure

- We run an OOS exercise for every asset individually.
- The only predictor in the model is ρ:

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

- The parameters are estimated with a rolling 5 year window.
- We assess the forecasting performance of ρ against the historical mean return model.

Out-of-sample forecasting

US corporate bonds

Rolling OOS estimation of $r_{i,t+1} = \alpha_i + \gamma_i \rho_t + \epsilon_{i,t+1}$

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

Rejection of historical mean return model for 28 portfolios (8 with competitor VWM Excess Return).

Out-of-sample forecasting

Currencies

Currency	**OOS R^2/Reject Hist. Avg.**
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)**

Rejection of historical mean return model for 3 currencies
(3 with competitor inflation differential).

Out-of-sample forecasting

International equities

Country	OOS R^2/ Reject Hist. Avg.	Country	OOS R^2/ Reject Hist. Avg.
Australia	9.039**	Japan	-0.887*
Austria	4.366**	NL	3.679*
Belgium	3.260**	NZL	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
HK	3.328**	UK	4.653**
Ireland	2.739*	US	1.657*
Italy	2.311**		
Across 21 Country		**3.219 (20)**	

Reject. of hist. mean ret. model for 15 assets
(4 with competitors VIX and lagged returns).

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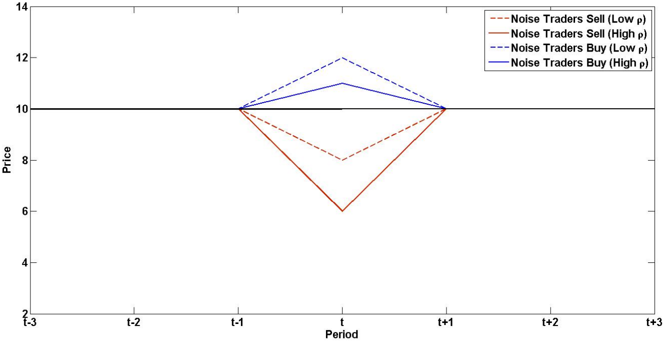
Market makers and return reversal

- We incorporate liquidity constraints into the limits to arbitrage framework of Gromb and Vayanos (2010).
- The hedge fund in the model acts as a market maker for a risky asset and absorbs buying and selling pressure from noise traders.
- The hedge fund faces the threat of investors withdrawing funds, and thus needs to hold enough liquid assets.
- The hedge fund's portfolio can vary in terms of illiquidity.

Hedge fund portfolio illiquidity and return reversal (1/2)

- In the model, the risky asset for which the hedge fund acts as a market maker is assumed to be less liquid than cash.
- Hence, a hedge fund with an illiquid portfolio is reluctant to buy the risky asset and eager to sell it.
- Compared to a liquid hedge fund, an illiquid hedge fund:
  1. Buys for a **lower** price when noise traders sell
     $\Longrightarrow$ **greater return reversal**
  2. Sells for a **lower** price when noise traders buy
     $\Longrightarrow$ **smaller return reversal**
- The model implies that high ρ predicts high returns.

Hedge fund portfolio illiquidity and return reversal (2/2)



Lower equilibrium price when hedge fund portfolios are illiquid (ρ is high).

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Testing the implications of our model

- We follow Pastor and Stambaugh (2003, JPE) and assume that a positive (negative) return in period t is an indicator that noise traders buy (sell).
- We estimate the following regression as a panel with fixed effects:

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

  for each asset class i.
- We expect an **amplified** return reversal when ρ is high and $r_{i,t} < 0$, γ^- is **positive**.
- We expect a **mitigated** return reversal when ρ is high and $r_{i,t} > 0$, γ^+ is **positive**.

Empirical data confirms the implication of our model

Fixed effects panel estimation of

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

	Coefficient Estimates and T-Stats		
Variable	**US Corp. Bonds**	**Currencies**	**Int. Equities**
Lagged Returns	0.415*	0.074	0.842
	(1.923)	(0.407)	(1.572)
$\rho_t \times I_{r_{i,t}<0}$	0.450*	0.764**	1.857**
	(1.918)	(2.720)	(2.809)
$\rho_t \times I_{r_{i,t}>0}$	0.542**	0.237	0.793*
	(3.844)	(1.154)	(1.846)
Adj R2 (%)	**6.174**	**2.649**	**5.687**

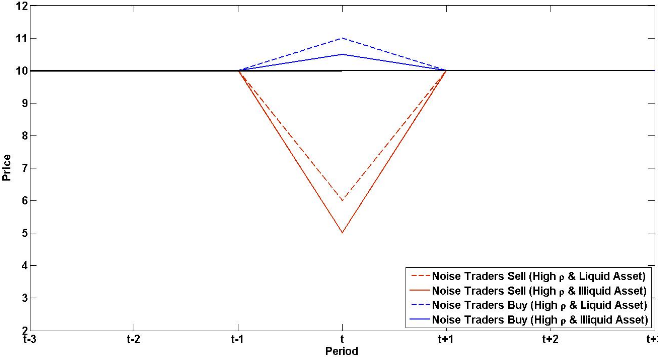
More pronounced effect for illiquid assets (1/2)

- We saw that a hedge fund with an illiquid portfolio demands a lower price when buying from and selling to noise traders.
- The model shows that the illiquidity of the risky asset for which the hedge fund acts as a market maker amplifies this.
  $\Longrightarrow \rho$ **should have a more pronounced effect for illiquid than liquid assets.**
- To test this, we estimate a fixed effects model for each asset class:

$$r_{i,t+1} = \alpha_i + \beta Competitors_t + \gamma \rho_t \times I_{Illiq.,i} + \epsilon_{i,t+1}$$

- $I_{Illiq.,i}$ is equal to 1 and (0 otherwise) for asset for a more illiquid subgroup:
  - High yield bonds and bonds with a maturity greater than 5Y
  - AUD,CAD,CHF,NOK,NZD, and SEK
  - Markets with lower capitalization (market cap below 500bn USD)

More pronounced effect for illiquid assets (2/2)



Lower equilibrium price for illiquid assets.

Better performance for illiquid assets

Fixed effects panel estimation of

$$r_{i,t+1} = \alpha_i + \beta Competitors_t + \gamma \rho_t + \phi \rho_t \times I_{Illiq.,i} + \epsilon_{i,t+1}$$

Variables	**Estimates and T-Stats**			
	US Corp. Bonds		**Currenc.**	**Int. Eq.**
ρ	0.229*	0.375**	0.093	1.019**
	(1.955)	(3.137)	(0.627)	(2.783)
$\rho \times I_{High\ Yield}$	0.666**			
	(2.626)			
$\rho \times I_{Maturity>5Y}$		0.197**		
		(2.713)		
$\rho \times I_{Small\ Market\ Curr.}$			0.345**	
			(2.646)	
$\rho \times I_{Small\ Market\ Int.Eq.}$				0.446**
				(3.554)
Adj R2 (in %)	**10.335**	**9.090**	**3.953**	**6.499**

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AUM weighted and investment styles

In-sample estimates of

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

	US Corp. Bonds 42 Assets	**Currencies 9 Assets**	**Int. Equities 21 Assets**
All Funds ρ	$\overline{R}^2$ **($\gamma > 0/ < 0$)**		
Base Case (Eq. W.)	12.186 (32/0)	4.110 (5/0)	7.133 (21/0)
AUM Weighted	10.123 (17/0)	4.003 (4/0)	5.577 (17/0)

Style Specific ρ	$\overline{R}^2$ **($\gamma > 0/ < 0$)**		
Fixed Income	12.280 (34/0)		
Global Macro		3.196 (2/0)	
Directional Traders			6.401 (21/0)
Security Selection			6.420 (21/0)

The performance of style specific ρ's is robust.

Varying window length and autocorrelation

In-sample estimates of

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

Estimation of ρ	**US Corp. Bonds 42 Assets**	**Currencies 9 Assets**	**Int. Equities 21 Assets**
Window Length	$\overline{R}^2$ **($\gamma > 0 / < 0$)**		
Base Case (12M)	12.186 (32/0)	4.110 (5/0)	7.133 (21/0)
9M	12.494 (33/0)	3.202 (1/0)	4.686 (12/0)
18M	10.921 (28/0)	3.606 (2/0)	5.276 (14/0)
24M	10.597 (32/0)	3.212 (0/0)	4.281 (8/0)
Autocorr. 12M	$\overline{R}^2$ **($\gamma > 0 / < 0$)**		
MA1 Coeff. Trim.	12.418 (30/0)	4.714 (5/0)	7.922 (21/0)

ρ is robust to varying window lengths and different autocorrelation measures.

Hedge fund flows as a competitor

In-sample estimates of

$$r_{i,t+1} = \alpha_i + \gamma_i \rho_t + \epsilon_{i,t+1}$$
vs.
$$r_{i,t+1} = \alpha_i + \gamma_i Flows_t + \epsilon_{i,t+1}$$

	US Corp. Bonds 42 Assets	**Currencies 9 Assets**	**Int. Equities 21 Assets**
ρ / Flows	$\overline{R}^2$ **($\gamma > 0$/< 0)**		
Base Case ρ	4.498 (31/0)	2.083 (6/0)	3.422 (21/0)
9M	0.355 (0/4)	-0.329 (0/0)	-0.255 (0/0)
18M	0.318 (0/2)	-0.379 (0/0)	-0.145 (0/0)

Hedge fund flows are a very poor measure of hedge fund illiquidity.

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Conclusion

- Our hedge fund illiquidity measure ρ is a highly significant predictor in-sample and OOS for US corporate bonds, currencies, and international equities.
- The empirical results are consistent with model implications.
- Results are robust when using a variety of different estimation methods for ρ.