The Impact of Hedge Funds on Asset Markets

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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
Hedge funds are significantly exposed to systematic risks, proxied by return indexes of equities, bonds, and options.


- Exposure to illiquidity risk is an important feature of hedge funds


Some work on hedge funds affecting asset markets

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
Outline

- Introduction

- **Data description and illiquidity index construction**

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- Robustness checks

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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
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. Expected returns are always smoother than realized returns.
- Intentional "performance smoothing" is easier to do when marking to model ("opportunistic smoothing").
- So if intentional smoothing occurs in reported returns, it is probably more prevalent when markets are less liquid.
- 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.
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

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

Individual fund $i$ \[ \hat{\rho}_{i,t} = \frac{\sum_{j=0}^{W-1} (r_{i,t-j} - \bar{r}_t,t) (r_{i,t-j-1} - \bar{r}_t,t)}{\sum_{j=0}^{W-1} (r_{i,t-j} - \bar{r}_t,t)^2} \]

Index \[ \rho_t = \sum_{i=1}^{N_t} \omega_{i,t} \hat{\rho}_{i,t} \]
The hedge fund illiquidity index over time

Our measure of illiquidity exhibits substantial variation
The hedge fund illiquidity index over time

High illiquidity during the great recession and hedge fund crisis periods

Hedge fund illiquidity index

- LTGM crisis
- WorldCom & Enron scandals
- Quant meltdown
- Credit crunch
- Cyprus crisis

Jan95 Jan97 Jan99 Jan01 Jan03 Jan05 Jan07 Jan09 Jan11 Jan13

Illiquidity measure
Equal-weighted vs AUM-weighted index

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

US Corporate Bonds: Simple regression

Adjusted $R^2$ in %

- **RHO is signif at 5% level**
- **RHO is signif at 10% level**
- **RHO is not significant**
In-sample predictive power: Currencies

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

Exchange Rates: Simple regression

Adjusted $R^2$ in %

Australia: RHO is significant at 5% level
Canada: RHO is significant at 5% level
Euro: RHO is not significant
Japan: RHO is significant at 10% level
New Zealand: RHO is significant at 10% level
Norway: RHO is not significant
Sweden: RHO is not significant
Switzerland: RHO is not significant
UK: RHO is not significant

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Next, we include $\rho$ together with all competitors in a **multiple regression**:

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

**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

US Corporate Bonds: Including competitor predictors

- RHO is significant at 5% level
- RHO is significant at 10% level
- RHO is not significant
- Simple regression case

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In-sample, multiple predictors: Currencies

Coefficient on rho remains significant for 6/9 currencies

Exchange Rates: Including competitor predictors

Australia | Canada | Euro | Japan | New Zealand | Norway | Sweden | Switzerland | UK

- RHO is significant at 5% level
- RHO is significant at 10% level
- RHO is not significant
- Simple regression case

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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:

\[
\begin{align*}
    r_{i,t+1} &= \alpha_i + \gamma_i \rho_t + \varepsilon_{i,t+1} \\
    r_{i,t+1} &= \alpha_i + \beta_{ij} Competitor_{j,t} + \varepsilon_{i,j,t+1}
\end{align*}
\]

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)

International Equities: Out of sample

Adjusted $R^2$ in %

- Australia
- Austria
- Belgium
- Canada
- Denmark
- Finland
- France
- Germany
- Hong Kong
- Ireland
- Italy
- Japan
- Netherlands
- New Zealand
- Norway
- Singapore
- Spain
- Sweden
- Switzerland
- UK
- US

RHO is significant at 5% level
RHO is significant at 10% level
RHO is not significant
Out-of-sample forecasting: US corporate bonds

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

US Corporate Bonds: Out of sample

- RHO is significant at 5% level
- RHO is significant at 10% level
- RHO is not significant
Out-of-sample forecasting: Currencies
Significantly beat historical mean for 3/9 indices (inflation diff gets 4/9 at 10% level, worse R2)

Exchange Rates: Out of sample

<table>
<thead>
<tr>
<th>Country</th>
<th>Adjusted R² in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>4.2</td>
</tr>
<tr>
<td>Canada</td>
<td>0.8</td>
</tr>
<tr>
<td>Euro</td>
<td>-0.2</td>
</tr>
<tr>
<td>Japan</td>
<td>-1.5</td>
</tr>
<tr>
<td>New Zealand</td>
<td>-3.1</td>
</tr>
<tr>
<td>Norway</td>
<td>-3.6</td>
</tr>
<tr>
<td>Sweden</td>
<td>-2.0</td>
</tr>
<tr>
<td>Switzerland</td>
<td>-3.8</td>
</tr>
<tr>
<td>UK</td>
<td>-3.3</td>
</tr>
</tbody>
</table>

- **RHO is significant at 5% level**
- **RHO is significant at 10% level**
- **RHO is not significant**

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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:

\[
   r_{i,t+h} = \alpha_{i,h} + \gamma_{i,h} \rho_t + \epsilon_{i,t+h}
\]

\[
   r_{i,t+h} = \alpha_{i,h} + \gamma_{i,h} \rho_t + \beta_{i,h} Competitors_{i,t} + \epsilon_{i,t+1}
\]
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

Predictability is strongest at $h=1$, but remains strong even out to 6 months
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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).
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 (smaller reversal following noise trader purchases). The noise trader must sell to an illiquid hedge fund for a lower price (larger reversal following noise trader sales).

2. Average transaction prices are lower when hedge fund liquidity is low, leading to larger return reversals when hedge fund liquidity is low. Low hedge fund liquidity predicts high asset returns.

3. Both effects are stronger when the asset itself is less liquid.
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,

   - **Lower transaction prices** when hedge fund liquidity is low
   - **Larger return reversals** when hedge fund liquidity is low
   - **Low hedge fund liquidity predicts high asset returns**

Both effects are stronger when the asset itself is less 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**
     - ⇒ *smaller reversal* following noise trader purchases
   - the noise trader must *sell* to an illiquid hedge fund for a **lower price**
     - ⇒ *larger reversal* following noise trader sales
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   ⇒ larger return reversals when hedge fund liquidity is low
   ⇒ **low hedge fund liquidity predicts high asset returns**
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   ⇒ larger return reversals when hedge fund liquidity is low
   ⇒ **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

Asset prices: noise trader buy (ask price)
noise trader sell (bid price)

Hedge fund liquidity

Transaction price

Avg trade price
Ask price
Bid price

Liquid  Low illiquidity  Med illiquidity  Illiquid
Buy and sell prices, when asset is liquid and illiquid

Effect is even more pronounced when risky asset is more illiquid

Asset prices: noise trader buy (ask price)
noise trader sell (bid price)

Transaction price

Mid-point
Ask price
Bid price
Liquid asset
Illiquid asset

Hedge fund liquidity

Liquid
Low illiquidity
Med illiquidity
Illiquid

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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:

\[ r_{i,t+1} = \alpha_i + \beta \text{Competitors}_{i,t} + \gamma \rho_t + \phi \rho_t \times I_{\text{Iliq},i} + \varepsilon_{i,t+1} \]

- \( I_{\text{Iliq},i} \) 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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Int’l Equities</th>
<th>US corp bonds</th>
<th>Currencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_t$</td>
<td>1.967**</td>
<td>0.195*</td>
<td>0.248</td>
</tr>
<tr>
<td></td>
<td>(2.804)</td>
<td>(1.957)</td>
<td>(1.575)</td>
</tr>
<tr>
<td>$\rho_t</td>
<td>SmlCap$</td>
<td>0.977**</td>
<td>0.309**</td>
</tr>
<tr>
<td></td>
<td>(2.659)</td>
<td>(3.157)</td>
<td>(1.281)</td>
</tr>
<tr>
<td>$\rho_t</td>
<td>LowTurn$</td>
<td>0.248**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.163)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho_t</td>
<td>HiYield$</td>
<td>0.227**</td>
<td>0.577**</td>
</tr>
<tr>
<td></td>
<td>(2.148)</td>
<td>(2.470)</td>
<td></td>
</tr>
<tr>
<td>$\rho_t</td>
<td>LongMat$</td>
<td></td>
<td>0.199**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.722)</td>
<td></td>
</tr>
<tr>
<td>$\rho_t</td>
<td>HiSpr$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(2.234)</td>
</tr>
<tr>
<td>$\rho_t</td>
<td>Hilnt$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3.314)</td>
</tr>
</tbody>
</table>
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:

\[ r_{i,t+1} = \alpha_i + \beta_{\text{Competitors}}_{i,t} + \gamma^- \rho_t \times I_{r_{i,t}<0} + \gamma^+ \rho_t \times I_{r_{i,t}>0} + \varepsilon_{i,t+1} \]

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Int’l equities</th>
<th>US corp bonds</th>
<th>Currencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma^{-}$</td>
<td>1.100**</td>
<td>0.287*</td>
<td>0.403**</td>
</tr>
<tr>
<td></td>
<td>(2.903)</td>
<td>(1.798)</td>
<td>(2.588)</td>
</tr>
<tr>
<td>$\gamma^{+}$</td>
<td>0.531*</td>
<td>0.337**</td>
<td>0.126</td>
</tr>
<tr>
<td></td>
<td>(1.645)</td>
<td>(3.327)</td>
<td>(0.883)</td>
</tr>
<tr>
<td>$\gamma^{-} - \gamma^{+}$</td>
<td>0.569</td>
<td>-0.050</td>
<td>0.277</td>
</tr>
<tr>
<td></td>
<td>(1.143)</td>
<td>(-0.264)</td>
<td>(1.311)</td>
</tr>
</tbody>
</table>
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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
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
Illiquidity index by style: All funds

Our baseline index, using all funds

Hedge fund illiquidity index

Illiquidity measure

Jan95 Jan97 Jan99 Jan01 Jan03 Jan05 Jan07 Jan09 Jan11 Jan13

All

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

<table>
<thead>
<tr>
<th>Model</th>
<th>Int’l equities $\overline{R}^2$</th>
<th>Pos/Neg</th>
<th>US corp bonds $\overline{R}^2$</th>
<th>Pos/Neg</th>
<th>Currencies $\overline{R}^2$</th>
<th>Pos/Neg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base: AR(1)</td>
<td>4.131</td>
<td>21 / 0</td>
<td>9.661</td>
<td>32 / 0</td>
<td>3.088</td>
<td>6 / 0</td>
</tr>
<tr>
<td>MA(1)</td>
<td>4.336</td>
<td>21 / 0</td>
<td>9.345</td>
<td>31 / 0</td>
<td>2.881</td>
<td>5 / 0</td>
</tr>
<tr>
<td>AR(2)</td>
<td>2.170</td>
<td>13 / 0</td>
<td>8.223</td>
<td>31 / 0</td>
<td>1.755</td>
<td>1 / 0</td>
</tr>
<tr>
<td>MA(2)</td>
<td>2.673</td>
<td>18 / 0</td>
<td>5.671</td>
<td>32 / 0</td>
<td>1.858</td>
<td>1 / 0</td>
</tr>
</tbody>
</table>
Robustness check: Vary window length

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

<table>
<thead>
<tr>
<th>Window length</th>
<th>Int’l equities</th>
<th>US corp bonds</th>
<th>Currencies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \bar{R}^2 )</td>
<td>Pos/Neg</td>
<td>( \bar{R}^2 )</td>
</tr>
<tr>
<td>Base: 12 mths</td>
<td>4.131</td>
<td>21 / 0</td>
<td>9.661</td>
</tr>
<tr>
<td>9 months</td>
<td>1.941</td>
<td>7 / 0</td>
<td>9.444</td>
</tr>
<tr>
<td>18 months</td>
<td>2.694</td>
<td>15 / 0</td>
<td>8.462</td>
</tr>
<tr>
<td>24 months</td>
<td>1.718</td>
<td>6 / 0</td>
<td>7.946</td>
</tr>
</tbody>
</table>

Patton (NYU / Duke)
Robustness check: Varying calculation of the index

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

<table>
<thead>
<tr>
<th>Calc method</th>
<th>Int’l equities</th>
<th>US corp bonds</th>
<th>Currencies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>Pos/Neg</td>
<td>$R^2$</td>
</tr>
<tr>
<td>Base: Untrim, EW</td>
<td>4.131</td>
<td>21 / 0</td>
<td>9.661</td>
</tr>
<tr>
<td>Untrimmed, VW</td>
<td>3.910</td>
<td>21 / 0</td>
<td>9.254</td>
</tr>
<tr>
<td>Trimmed, EW</td>
<td>3.992</td>
<td>21 / 0</td>
<td>9.670</td>
</tr>
</tbody>
</table>
Extension: Create illiquidity indices using style labels

Aggregating all funds seems to work better

<table>
<thead>
<tr>
<th>Model</th>
<th>Int’l equities $R^2$</th>
<th>Pos/Neg</th>
<th>US corp bonds $R^2$</th>
<th>Pos/Neg</th>
<th>Currencies $R^2$</th>
<th>Pos/Neg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base: All funds</td>
<td>4.131</td>
<td>21 / 0</td>
<td>9.661</td>
<td>32 / 0</td>
<td>3.088</td>
<td>6 / 0</td>
</tr>
<tr>
<td>Direct. traders</td>
<td>3.523</td>
<td>19 / 0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sec. selection</td>
<td>3.586</td>
<td>17 / 0</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed income</td>
<td></td>
<td>9.497</td>
<td>32 / 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global macro</td>
<td></td>
<td></td>
<td>2.079</td>
<td>4 / 0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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, PTF, SBD, 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”

<table>
<thead>
<tr>
<th></th>
<th>Int’l Equities</th>
<th>US Corp Bonds</th>
<th>Currencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case (no controls)</td>
<td>20 / 0</td>
<td>31 / 0</td>
<td>6 / 0</td>
</tr>
<tr>
<td>Avg asset ret</td>
<td>20 / 0</td>
<td>34 / 0</td>
<td>6 / 0</td>
</tr>
<tr>
<td>Asset ret autocorrel</td>
<td>20 / 0</td>
<td>31 / 0</td>
<td>6 / 0</td>
</tr>
<tr>
<td>Risk factor</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mkt</td>
<td>21 / 0</td>
<td>26 / 0</td>
<td>5 / 0</td>
</tr>
<tr>
<td>HML</td>
<td>20 / 0</td>
<td>30 / 0</td>
<td>6 / 0</td>
</tr>
<tr>
<td>SMB</td>
<td>20 / 0</td>
<td>31 / 0</td>
<td>6 / 0</td>
</tr>
<tr>
<td>MOM</td>
<td>20 / 0</td>
<td>31 / 0</td>
<td>6 / 0</td>
</tr>
<tr>
<td>PTFSBD</td>
<td>18 / 0</td>
<td>28 / 0</td>
<td>6 / 0</td>
</tr>
<tr>
<td>PTFSCOM</td>
<td>21 / 0</td>
<td>27 / 0</td>
<td>4 / 0</td>
</tr>
<tr>
<td>PTFSEX</td>
<td>19 / 0</td>
<td>27 / 0</td>
<td>6 / 0</td>
</tr>
</tbody>
</table>
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

International T-bills and 10-year bonds

- RHO is significant at 5% level
- RHO is significant at 10% level
- RHO is not significant (T-bill)
- RHO is not significant (Bond)

Adjusted $R^2$ in %

Australia, Canada, Denmark, Germany, Japan, Norway, Sweden, Switzerland, UK, US