Lecture on Liquidity and Short-term Return Reversals

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Outline

- Introduction
- Grossman and Miller (1988) theory of liquidity and short-term reversals & Brunnermeier & Pedersen (2009)
- Short-term reversals
- Liquidity premium

Liquidity and the Costs of Immediacy

Example2: Fire sales by mutual funds (Coval and Stafford, 2007)

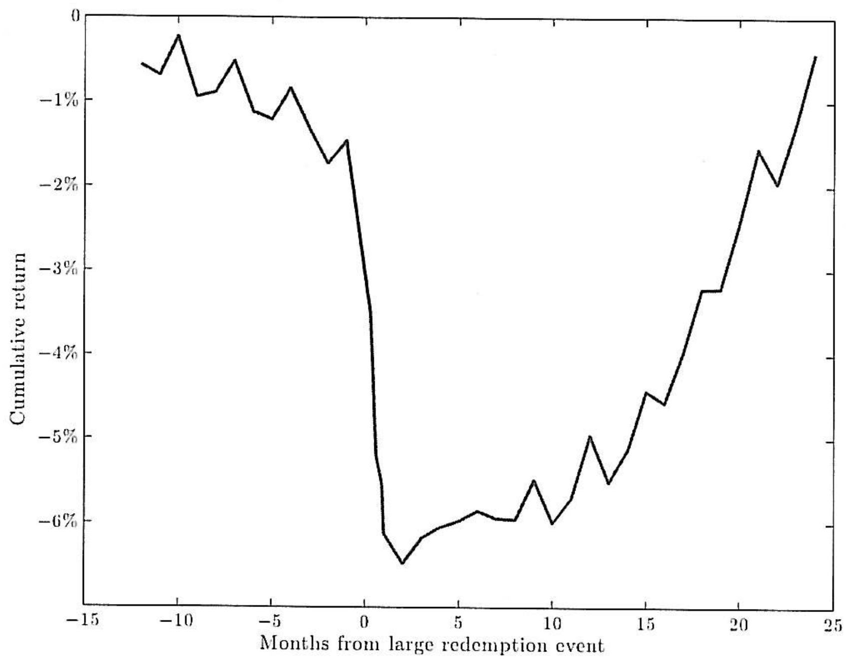

Figure 12. Average cumulative return of equities held by mutual funds experiencing large redemptions, counting months from the date of the large-redemption event. Mutual fund flow data from Thompson Financial were used by Edmans, Goldstein, and Jiang (2009) to calculate net outflows from each equity and each mutual fund. Total outflows across mutual funds, normalized by trading volume, determine "price pressure indices" for each equity, according to a specification stated by Edmans, Goldstein, and Jiang (2009). The cumulative returns plotted are those of equities in the top decile according to price pressure, as of the zero date. Source of cumulative return data: Edmans, Goldstein, and Jiang (2009).

Liquidity and the Costs of Immediacy

Index additions and deletions (Harris & Gurel, 1986)

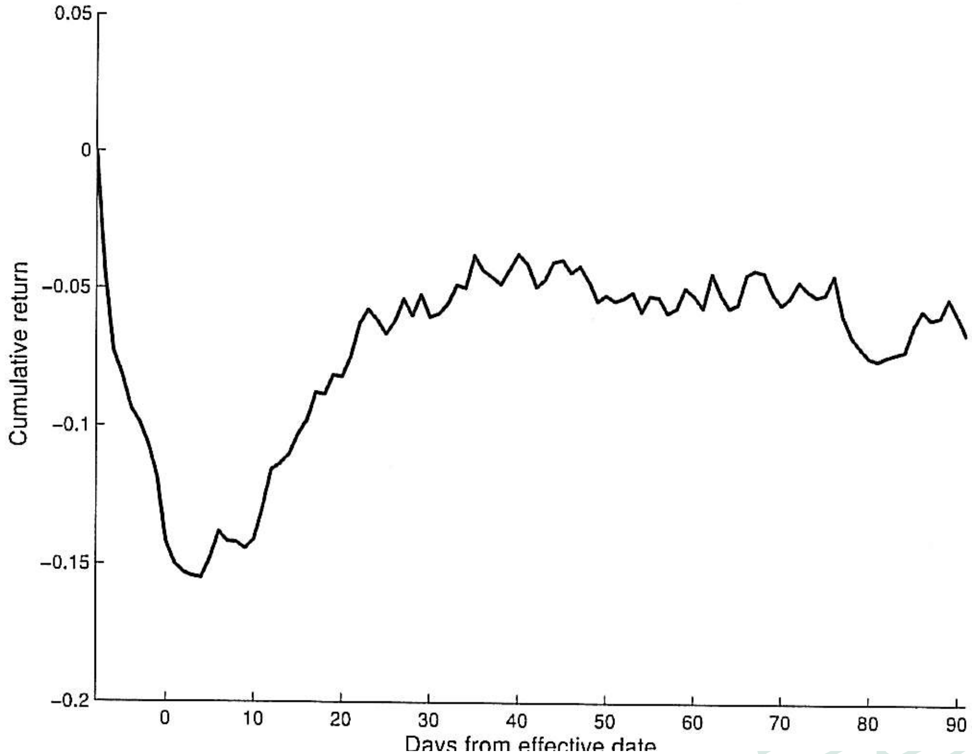

Figure 1. Average cumulative returns for deleted S&P 500 stocks, 1990-2001. The average number of days between the announcement and effective deletion dates is 7.56. The passage of time from announcement to deletion for each equity is re-scaled to 8 days before averaging the cumulative returns during this period across the equities. The original data provided by Jeremy Graveline were augmented by Haoxiang Zhu.

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What is going on ?

Grossman and Miller (1988, Journal of Finance) argue that in financial markets when sellers and buyers arrive to the market at different times, the market makers must carry risk temporarily to clear the market.

1. **If seller arrives first, he/she sells, market makers buy BUT ONLY AT A DISCOUNT TO THE FUNDAMENTAL PRICE.**

2. **When buyers later arrive, prices recover and market maker gets his compensation from carrying risk.**

3. **If buyer arrives first, then price rises temporarily above the fundamentals.**

Grossman, S., and M. Miller. "Liquidity and Market Structure." *Journal of Finance,* 43/3 (1988), 617-633.

Digression (a one period example to help understand the model)

How to find out optimal investment in stocks for investors with CARA utility. Here 2 period example. Invest at t = 1 and payoff realized at T=2.

Assumptions are made so that W_2 is normally distributed when evaluated at time 1

Investors maximize their utility (CARA utility function)

$$E_1 U = E_1 - e^{-aW_2} = E_1 - e^{-aW_1 - aX_1[P_2 - P_1]}$$

as $W_2 = W_1 + X_1 [P_2 - P_1]$

X_1 = amount invested in shares at time 1.

$a > 0$ *is the* coefficient of risk aversion

Digression (the one period example continued)

Now we use a mathematical result that holds for normally distributed variables (here first Z_2 then $a W_2$) to get

$$E_1 - e^{-Z_2} = -e^{-E_1 Z_2 + \frac{1}{2}\mathrm{var}(Z_2)}$$

$$E_1 - e^{-aW_2} = E_1 - e^{-a\left(E_1 W_2 - \frac{a}{2}\mathrm{var}\left[W_2\right]\right)} = E_1 - e^{-a\left(X_1\left(E_1 P_2 - P_1\right) - \frac{a}{2} X_1^2 \mathrm{var}\left[P_2\right]\right)}$$

Maximizing this means maximizing the term inside the brackets (take derivative, set to zero) implying optimal investment of

$$X_1^* = \frac{E_1 P_2 - P_1}{a \cdot \mathrm{var}\left[P_2\right]}$$

Grossman and Miller Model (read the article and the proofs of the results presented)

Grossman and Miller (1988, Journal of Finance):
Liquidity and Market Structure

Idea: Liquidity can be measured through price impact of trade. As someone sells, price temporarily declines (brokers job is to search for liquidity: call around to see if someone is willing to be a counterparty to trade).

Model:
- 3 periods
- All traders maximize expected utility

$$U = -e^{-aW_3}$$

Back to Grossman and Miller Model

Period 3 price P_3 is the fair value of the asset at time 3 (e.g. final dividend). No more uncertainty at time 3. Public information about P_3 arrives before trading at time 1 and 2 (a normally distributed shock to P_3). One customer arrives in period 1 who suddenly inherits a position i (liquidity need -i, i.e., inherited i in stock). Assume in period 2 another trader with opposing demand arrives and has liquidity need of $+i$. These assumptions guarantee that investors' wealth remains normally distributed at time 3 and analogous to our one period example it can be shown that

The customer at time 1 wants to buy (negative amount is selling):

$$x_1^c = \frac{E_1 \; P_3 - P_1}{a \cdot var_1[E_2 P_3]} - i$$

and the M market makers buy at time 1

$$x_1^m = \frac{E_1 P_3 - P_1}{a \cdot var_1[E_2 P_3]}$$

Model

Hence market clearing

$$M x_1^m + x_1^c = 0$$

or

$$\frac{E_1 P_3 - P_1}{a \cdot var_1[E_2 P_3]} = \frac{i}{M+1}$$

So that if i is positive (selling needs of customer) price declines below fair value as $P_1 < E_1 P_3$ (and vice versa if buying needs by the customer).

Factors that affect reversals: a (risk aversion), M (number of market makers), i = size of order imbalances, var(E_2P_3) = volatility of fair value

Model

Market makers make positive profits – this is reward for carrying excess risk for one period until the order imbalance is worked through the system (here until a customer with opposing need arrives).

Assume a cost for time = c for the market maker. Then in equilibrium number of market makers endogenous so that market maker profits equal their cost of being present. Liquid markets (or liquid securities) are such where the number of market makers is large. Either demand needs are frequent or the cost of being present in markets is small.

Impossibility of perfertly liquid markets!

More recent theoretical paper by Brunnermeier and Pedersen (RFS 2009) argue along the same lines, but stress the role of funding liquidity (market makers' ability to borrow)

"We provide a model that links an asset's market liquidity (i.e., the ease with which it is traded) and traders' funding liquidity (i.e., the ease with which they can obtain funding). Traders provide market liquidity, and their ability to do so depends on their availability of funding. Conversely, traders' funding, i.e., their capital and margin requirements, depends on the assets' market liquidity. We show that, under certain conditions, margins are destabilizing and market liquidity and funding liquidity are mutually reinforcing, leading to liquidity spirals. The model explains the empirically documented features that market liquidity (i) can suddenly dry up, (ii) has commonality across securities, (iii) is related to volatility, (iv) is subject to "flight to quality," and (v) co-moves with the market. The model provides new testable predictions, including that speculators' capital is a driver of market liquidity and risk premiums."

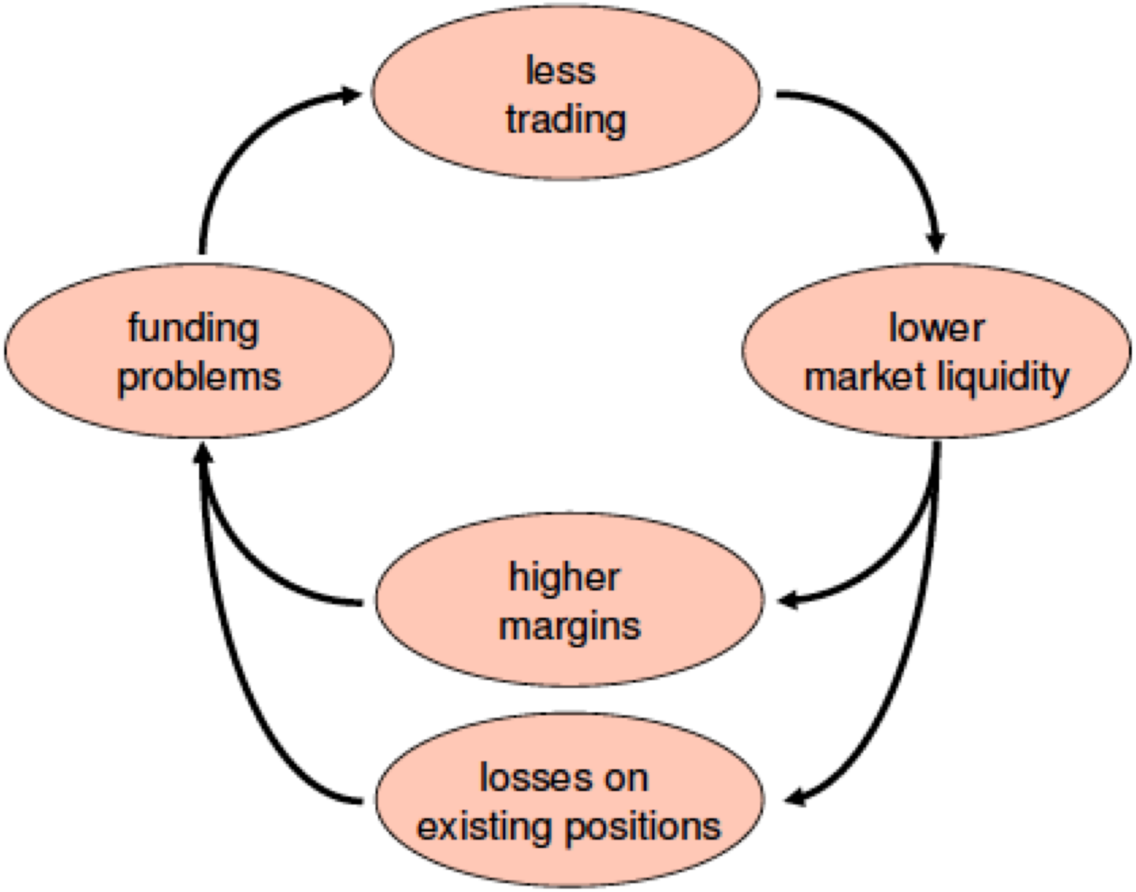

Figure 4: Liquidity Spirals

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Liquidity and Short-term reversals

There is also large evidence of more systematic cross-sectional short-term reversals:

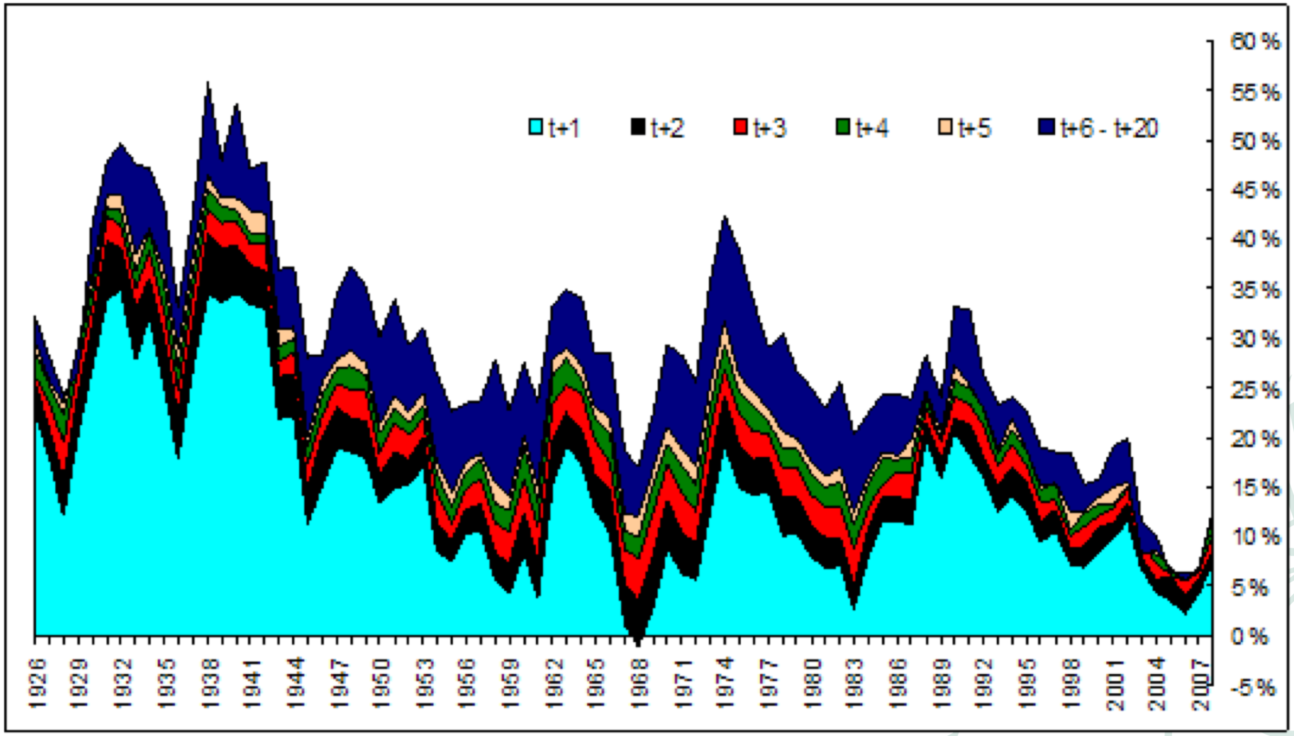
- Jegadeesh (1990)
- Lehmann (1990)
- Avramov, Chordia and Goyal (2006)

Several papers relate the mean reversion to illiquidity:

Grossman and Miller (1988), Jegadeesh and Titman (1993), Campbell, Grossman and Wang (1993), Chordia and Subrahmanyam (2004), Hendershott and Menkveld (2010).

There is significant cross-sectional variability and time variation in the amount of short-term return reversal.

Monthly Return Reversals at NYSE 1926-2008



On average 28% of daily returns revert within a month (24% within a week).

Temporary price movements associated with these return reversals have increased daily return volatility by 20%

Peaks often associated with recessions (when funding capital is scarce!)

Conclusions

- In the stock market the fact that investors arrive to the market in different times means that markets are necessarily somewhat illiquid. Any investor who wants to sell his stocks should expect that the execution price for his sell order is likely to be below the current market price

- Of course, some stocks are more liquid than others. In the illiquid stocks one should expect the decline in the price (from a sell order) and the return reversal to be larger.

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Do investors require a liquidity premium?

- In illiquid markets and in illiquid times, investors may be willing to give up some return in exchange for holding assets that can be sold easily.
- Evidence on this: Amihud (2002) develops a measure of illiquidity ”ILLIQ”
  - Defined by the average of stock specific absolute returns to volume ratios
    - High absolute returns with low volume are interpreted as a sign of illiquidity.
    - There is evidence that this measure of illiquidity is related to stocks expected returns in the cross-section
    - There is evidence that at an aggregate level, changes in average illiquidity affect stock indices. For instance, when illiquidity declines, stock prices rise.

Amihud, Y. “Illiquidity and Stock Returns: Cross-section and Time-series Effects.” *Journal of Financial Markets,* 5 (2002), 31-56.

Amihud ILLIQ measure

Amihud (2002)

Is liquidity priced?

A measure of liquidity for stock *i* in year y:

$$ILLIQ_{iy} = \frac{1}{D_{iy}} * \sum_{t=1}^{D_{iy}} \frac{|R_{iyd}|}{VOLD_{iyd}}$$

D = number of days
R_d = daily return
VOLD = dollar volume

CROSS-SECTIONAL RESULTS

To standardize we divide $ILLIQ_{iy}$ by its average across all stocks $AILLIQ_{iy}$ to get:

$$ILLIQMA_{iy} = ILLIQ_{iy}/AILLIQ_{y}.$$

Empirical results Table 2 in p. 41: Run a cross-sectional regression explaining stock returns with previous year´s ILLIQMA and controls:

- beta 1.183 (2.45)
- ILLIQMA 0.162 (6.55)
- R 100 (return for 100 days) 1.023 (3.83)
- R100YR (return for beginning of the year) 0.382 (2.98)

Hence liquidity seems to be very important in explaining cross sectional returns.

Amihud

AGGREGATE TIME-SERIES REGRESSION

Aggregate liquidity matters for aggregate returns. Define $AILLIQ_y^U$ as the unexpected change in liquidity in year y.

Test if

$$(R_M - R_f)_y = g_0 + g_1 \ln AILLIQ_{y-1} + g_2 \ln AILLIQ_y^U + \varepsilon_y$$

Coefficient for g_1 10.23 (2.68) and g_2 -23.56 (4.52) are significant and expected sign.

When testing the relationships for different size portfolios they find that the effect is highest for small stocks as one would expect.

Do investors require a liquidity premium?

- Pastor and Stambaugh (2002) and Sadka (2006) develop measures of illiquidity in the stock market.
- The Pastor and Stambaugh (2002) measure is based on time-variation in the degree of return reversal. They point out that to investors only the risks related to aggregate level of liquidity should matter.
  - Sort out stocks by their sensitivity to aggregate level liquidity risk.
  - A portfolio long in stocks that are sensitive to liquidity risk and short the stocks that are insensitive to liquidity risk earns abnormal returns up to 7.5% per annum.

Pastor, L., and R. Stambaugh. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy,* 111/3 (2003), 642-685.

The liquidity measure for stock i in month t is the ordinary least squares estimate of $\gamma_{i,t}$ in the regression

$$r^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,d,t} sign\left(r^e_{i,t,t}\right) \cdot v_{i,d,t} + \varepsilon_{i,d+1,t}$$

$r^e_{i,d+1,t}$ =excess return over CRSP value-weighted market index on day $d + 1$

$r_{i,d,t}$ = return on day d

$v_{i,d,t}$ = daily dollar volume for stock i on day d in month t.

Market wide monthly liquidity measure based on N stocks:

$$\hat{\gamma}_t = \frac{1}{N}\sum_{i=1}^{N} \hat{\gamma}_{i,t}$$

Scale $\hat{\gamma}_t = \frac{1}{N}\sum_{i=1}^{N}\hat{\gamma}_{i,t}$ by market volume m_t to obtain estimate of the total costs of immediacy.

Next, look at changes in scaled levels of liquidity:

$$\Delta\hat{\gamma}_t = \left(\frac{m_t}{m_1}\right)\frac{1}{N}\sum_{i=1}^{N}\left(\hat{\gamma}_{i,t} - \hat{\gamma}_{i,t-1}\right)$$

And to get an estimate of the unexpected changes in the costs of immediacy look at regression:

$$\Delta\hat{\gamma}_t = a + b\Delta\hat{\gamma}_{t-1} + c\left(\frac{m_{t-1}}{m_1}\right)\hat{\gamma}_{t-1} + u_t.$$

The innovations in liquidity (liquidity shocks) are then defined as:

$$L_t = \frac{1}{100} u_t .$$

Estimate liquidity betas:

$$r_{it} = \beta_i^0 + \beta_i^L L_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \varepsilon_{i,t} .$$

Sort stocks by their liquidity beta. Portfolio's that load up liquidity risk perform better.

	1	2	3	4	5	6	7	8	9	10	10–1
	A. January 1968–December 1999										
CAPM alpha	−2.06	−.36	.63	.49	.07	.49	1.42	1.36	−.02	2.60	4.66
	(−1.30)	(−.34)	(.76)	(.57)	(.10)	(.58)	(1.64)	(1.63)	(−.02)	(1.96)	(2.36)
Fama-French alpha	−.62	−.09	.46	.57	−.62	−.28	.90	.84	.03	3.53	4.15
	(−.42)	(−.08)	(.57)	(.68)	(−.86)	(−.35)	(1.06)	(1.00)	(.03)	(2.71)	(2.08)
Four-factor alpha	−1.20	−.04	.22	.34	−.29	−.25	1.05	.71	.29	3.67	4.87
	(−.79)	(−.04)	(.26)	(.40)	(−.40)	(−.31)	(1.20)	(.82)	(.29)	(2.74)	(2.38)
	B. January 1968–December 1983										
CAPM alpha	−1.10	1.04	.94	.35	−.28	.46	.09	.83	.33	2.51	3.62
	(−.46)	(.70)	(.79)	(.27)	(−.26)	(.34)	(.08)	(.72)	(.25)	(1.51)	(1.32)
Fama-French alpha	−1.24	2.32	1.66	1.53	−1.05	−.49	−.06	−.07	.17	1.61	2.85
	(−.53)	(1.56)	(1.41)	(1.21)	(−.98)	(−.38)	(−.05)	(−.06)	(.13)	(1.01)	(1.01)
Four-factor alpha	−3.74	1.50	.87	.86	−.20	.21	.59	−.18	.59	1.64	5.38
	(−1.58)	(.96)	(.71)	(.66)	(−.18)	(.16)	(.47)	(−.15)	(.43)	(.98)	(1.86)
	C. January 1984–December 1999										
CAPM alpha	−2.79	−1.63	.21	.40	.37	.23	3.12	1.70	−.11	2.70	5.49
	(−1.31)	(−1.04)	(.18)	(.36)	(.36)	(.23)	(2.51)	(1.40)	(−.08)	(1.28)	(1.90)
Fama-French alpha	.03	−2.04	−.60	−.33	−.40	−.55	2.21	1.50	−.11	4.41	4.38
	(.02)	(−1.29)	(−.53)	(−.30)	(−.40)	(−.59)	(1.83)	(1.22)	(−.07)	(2.20)	(1.54)
Four-factor alpha	.57	−1.50	−.50	−.28	−.39	−.87	2.06	1.35	.02	4.55	3.98
	(.30)	(−.94)	(−.44)	(−.25)	(−.38)	(−.93)	(1.68)	(1.08)	(.01)	(2.23)	(1.38)

NOTE.—See the note to table 7. The table reports the decile portfolios' postranking alphas, in percentage per year. The alphas are estimated as intercepts from the regressions of excess portfolio postranking returns on excess market returns (CAPM alpha), on the Fama-French factor returns (Fama-French alpha), and on the Fama-French and momentum factor returns (four-factor alphas). The *t*-statistics are in parentheses.

Much higher liquidity risk alpha spreads (up to 13%) are obtained when using rankings with predicted liquidity betas

Sadka documents that hedge funds that are exposed to liquidity risk earn superior returns

- Hedge funds' liquidity risk is measured by the covariance of the fund returns with unexpected changes in aggregate liquidity.

- The results show that funds that significantly load on liquidity risk subsequently outperform low-loading funds by about 6.5% annually, on average, over the period 1994-2009, while negative performance is observed during liquidity crises.

- Jylhä, Rinne and Suominen (2012) confirm that the average hedge fund is strongly exposed to liquidity risk (thus earning liquidity premium).

Sadka, R. (2010) Liquidity risk and the cross-section of hedge-fund returs, *Journal of Financial Economics* 98, 54-71.

OTHER RELATED RESEARCH: Acharya & Pedersen, JFE 2005

Asset pricing with liquidity risk

Abstract
This paper solves explicitly a simple equilibrium model with liquidity risk. In our liquidity adjusted capital asset pricing model, a security's required return depends on its expected liquidity as well as on the covariances of its own return and liquidity with the market return and liquidity.

In addition, a persistent negative shock to a security's liquidity results in low contemporaneous returns and high predicted future returns. The model provides a unified framework for understanding the various channels through which liquidity risk may affect asset prices. Our empirical results shed light on the total and relative economic significance of these channels and provide evidence of flight to liquidity.