Lecture 9

liquidity risk premia

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Two thoughts

- Today's lecture
- Homework 1 will be returned
  - I am writing a script to send a member of your group the written up assignment automatically
- Homework 3

Today's lecture is based on the idea of imperfect markets

- When we talk about risk, we assume the market reacts to the macroeconomy
  - There are no "frictions" … in other words, the market simply processes information and people trade.
  - There are transaction costs, but the market never shuts down or varies over time in how difficult it is to trade
  - It does not matter who your other participants are

- The premise of what we're doing today is to argue markets are imperfect
  - You will have difficulty trading
  - It does matter who other participants are

Liquidity risk and intermediation

- Traditional asset pricing, we basically ignore liquidity
  - Liquidity means transaction costs

- In this lecture, we consider the importance of "changes" in liquidity

- There is no strict definition in that many measures capture it. Market liquidity is the price and depth at which transactions can be traded …
  - Quickly
  - without moving the price dramatically
  - anonymously

- When liquidity dries up, we observe large changes in risk premia
  - Traders who need to sell, when they sell, may push prices very dramatically
  - It may be difficult to finance a position

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- Time allowing, we also will hear about intermediary asset pricing

Liquidity is first order

- Liquidity is defined as either
  - Market liquidity
  - Funding liquidity

- Market liquidity is the ability to sell positions or buy positions quickly

- Funding liquidity is the ability to get funding to finance a position
  - Long/short positions, for example, require margin
  - Derivatives require funding
  - When funding is difficult to obtain, this distorts asset prices in tradeable ways

What is *market* liquidity

- market liquidity is the ability to get in and out of a position quickly, without incurring large transaction costs

- problem: spreads may be very thin, but large volumes might be difficult to obtain
  - I need market depth

- problem: the order book may be very thick, but the spread is 50 basis points
  - I need smaller spreads

- problem: I am the only trader who trades this time of day. Thus, all other traders when seeing my order will move the price!
  - I need anonymity

Who provides liquidity?

- what does it mean to provide liquidity?
  - If an investor wants to buy, you sell
  - If an investor wants to sell, you buy

- Whether or not you are officially a market-maker, this is called “market-making”

- Problem for the market maker:
  - Does not want to hold to much inventory (price risk)
  - Does not want to trade with smart traders (information risk)
  - These two concepts are a powerful framework for understanding why liquidity impacts short-term price movements. For more, please read the O’Hara (1987), a book on market microstructure

A few of many liquidity metrics

- Spread – the cost from the midpoint * 2
  - For example, if you have a share of Microsoft worth \$94, and you sell at \$93, the spread is \$1*2=\$2
  - Intuition: the cost of selling one share.
  - Higher spreads are bad for liquidity

- Turnover – how much is traded as a percentage of shares outstanding
  - For example, if 10 million shares are traded and there are 100 million shares tradeable, the turnover is .1 or 10%

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- Turnover – how much is traded as a percentage of shares outstanding
  - For example, if 10 million shares are traded and there are 100 million shares tradeable, the turnover is .1 or 10%
  - How much is traded – gives you a sense of if its possible to sell a large volume at a point in time
  - High turnover is *good for liquidity*

A few of many liquidity metrics

- Amihud illiquidity –
  - $\frac{|return|}{(prc*volume)} = \frac{absolutereturn}{dollarvolume}$
  - Intuition: how much does dollar volume move a stock return?
  - Lower Amihud => better for liquidity

reversal could proxy for liquidity provision

- intuition: suppose you see someone continuing to sell
  - you’re not sure why this person wants to get rid of the stock, but this person wants to get rid of it
  - It could be that there is information
  - It could be that this person just has a liquidity need

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- Rational: lower the price such that the seller will still sell, but you will profit

- Next day, when the selling stops, the price will recover

reversal


New Zealand Dollar/U.S. Dollar, D
O0.68733 H0.69002 L0.68246 C0.68551
78.60%(0.73916)
2018 Open
61.80%(0.70502)
50.00%(0.69307)
38.20%(0.67612)
50.00%(0.66969)
61.80%(0.66326)
LDC
0.74370
0.74000
0.73000
0.72000
0.70935
0.70577
0.70000
0.69000
0.68551
0.68510
0.67537
0.66992
0.66000
0.65000
0.64552
75.0000
50.0000
25.0000
01 Jan '18
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
2019
Feb

Three liquidity risks – Acharya and Pedersen (2004)

- Generally, return increases when a stock's liquidity moves when the market illiquidity moves

- Second, a security's *return* moves with market liquidity, then
  - "this covariance affects required returns negatively because investors are willing to accept a lower return on an asset with a high return in times of market illiquidity. "

- Third, a security's *liquidity* may move with market liquidity
  - "an investor is willing to accept a discounted return on stocks with low illiquidity costs in states of poor market return"

the literature on liquidity risk

- there are two ways liquidity risk is investable
  - Levels : do stocks that are illiquid earn a higher return?
  - Changes : do “shocks” or unexpected changes to liquidity measures predict future stock returns?

- Levels: more illiquid stocks should earn…

- Changes:
  - Comovement with aggregate liquidity should…
  - Changes to individual stock liquidity should …

the literature on liquidity risk

- there are two ways liquidity risk is investable
  - Levels : do stocks that are illiquid earn a higher return?
  - Changes : do “shocks” or unexpected changes to liquidity measures predict future stock returns?

- Levels: more illiquid stocks should earn… higher expected return

- Changes:
  - Comovement with aggregate liquidity should… mean a stock is risky because it covaries with times when the market may change a lot
  - Increases to individual stock liquidity should … lower expected stock returns

Amihud (2002) liquidity premium

- This paper documents that returns are increasing when stocks are more exposed to "aggregate illiquidity"
  - They are after a risk-factor interpretation

- Said differently, one could just do the following: sort on Amihud illiquidity

Amihud (2002) liquidity premium

- This paper documents that returns are increasing when stocks are more exposed to "aggregate illiquidity"
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- Said differently, one could just do the following: sort on Amihud illiquidity

- Signal:
  - Every month, calculate Amihud illiquidity
  - Filter out stocks below $100 million USD, less than $1 prc per share
  - Create decile breakpoints
  - Hold the stock next month, voila

Decile-sorts on Amihud illiquidity

Q1 Amihud	Short
Q2 Amihud	
Q3 Amihud	
Q4 Amihud	
Q5 Amihud	
Q6 Amihud	
Q7 Amihud	
Q8 Amihud	
Q9 Amihud	
Q10 Amihud	Long

Amihud (2002)

Monthly cross-sectional regerssions

at the extreme 1% upper and lower tails of the respective distribu

Variable	All months	Excl. January	1964–1980
Constant	−0.364	−0.235	−0.904
	(0.76)	(0.50)	(1.39)
BETA	1.183	0.816	1.450
	(2.45)	(1.75)	(1.83)
ILLIQMA	0.162	0.126	0.216
	(6.55)	(5.30)	(4.87)
R100	1.023	1.514	0.974
	(3.83)	(6.17)	(2.47)
R100YR	0.382	0.475	0.485
	(2.98)	(3.70)	(2.55)
Ln *SIZE*			
SDRET			
DIVYLD			

[a] *t*-statistics in parentheses.

The declining illiquidity premium

- Markets are becoming more liquid over time

- Could be due to different regulatory reforms have made markets more liquid
  - Decimalization
  - Implementation of the national best bid and offer

- Another possibility is the rise of electronic trading - more participants, who are all becoming smarter

- Question: is the liquidity premium diminishing?

The declining illiquidity premium

Figure 1-A — NYSE

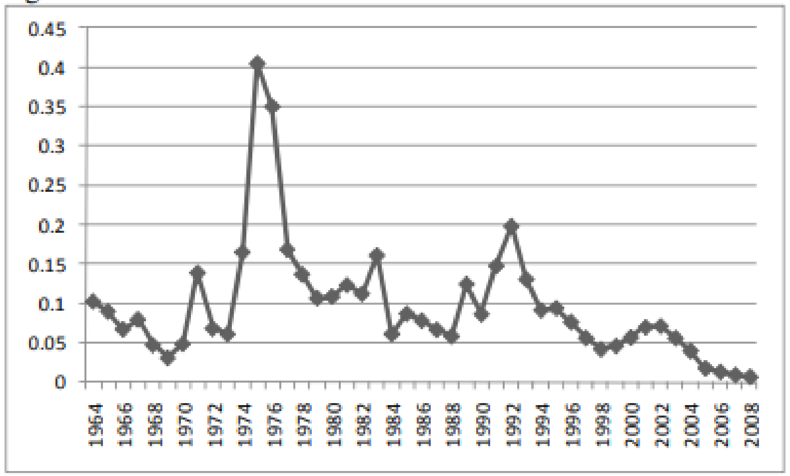


Figure 1-B —AMEX

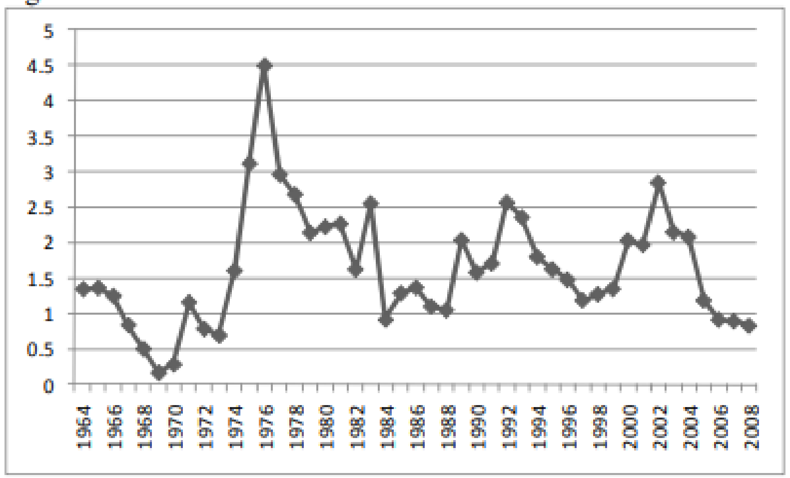
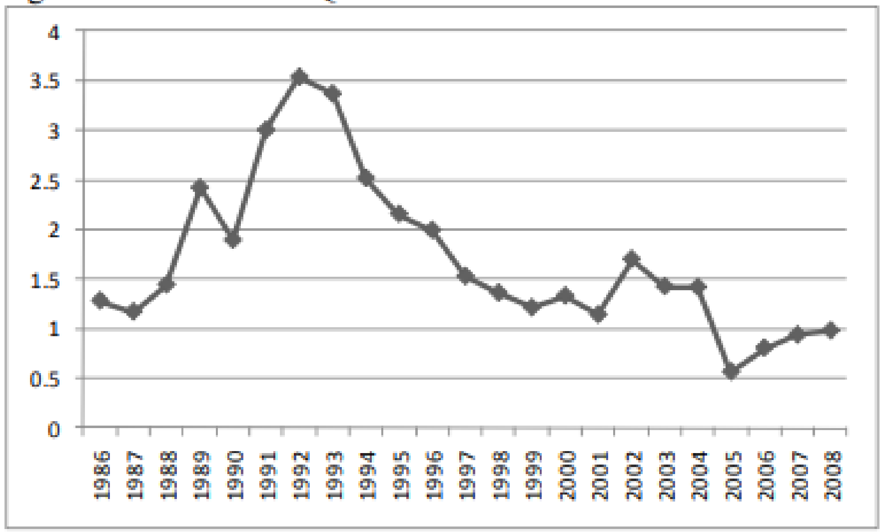


Figure 1-C — NASDAQ



The declining illiquidity premium

Figure 3: Alphas of Long-Short Liquidity Portfolios Based on Amihud's Measure

Figure 3-A — NYSE

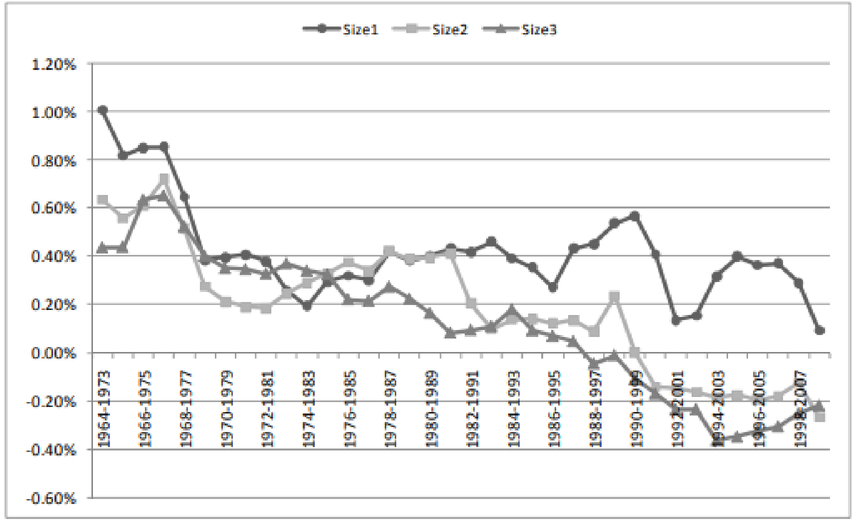
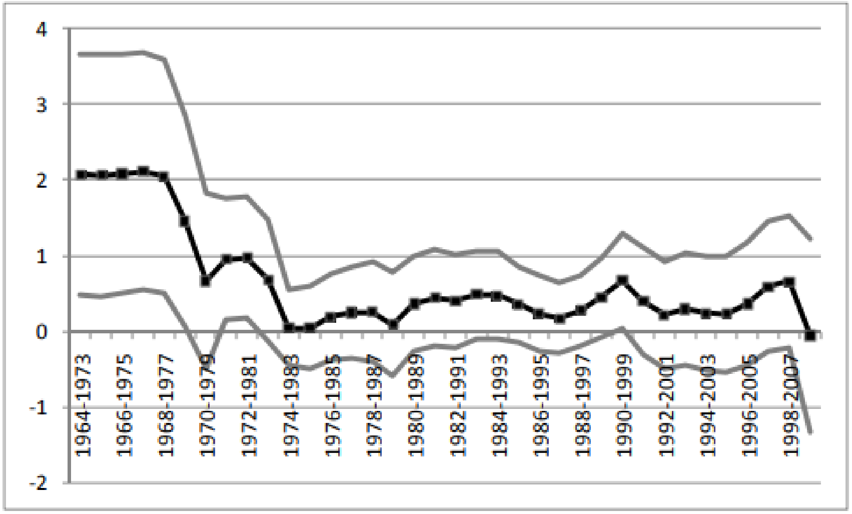


Figure 2: Average Illiquidity Cross-Sectional Regression Coefficients

Figure 2-A — NYSE



Liquidity shocks and stock market reactions – Bali, Peng, Shen and Tang (2013)

- they find: increases to liquidity predict higher future returns
- Odd logic: increases to liquidity should make a stock less risky, shouldn’t it?
- Shouldn’t this result in lower future returns?
- Argument : liquidity shocks are difficult to interpret, and investors are under-reacting

Liquidity shocks and stock market reactions – Bali, Peng, Shen and Tang (2013)

Create a simple signal, what is the change in the last month's liquidity relative to its 12 month average?

$$\Delta liquidity = LiquidityMeasure_{i,t} - AVGLiquidityMeasure_{i,[t-1,t-12]}$$

They emphasize the Amihud liquidity measure, but find similar results with turnover

$1.017^{12} - 1$ = 15% annualized *alpha*

	LIQU			
	Equal-weighted		Value-weighted	
Decile	Avg. RET	Alpha	Avg. RET	Alpha
1 (Low)	0.51	−0.75	0.43	−0.73
	(1.84)	(−8.75)	(1.68)	(−7.45)
10 (High)	1.69	0.48	1.60	0.45
	(6.02)	(6.88)	(6.01)	(6.01)
High–Low	1.18	1.23	1.17	1.17
	(10.18)	(10.13)	(8.01)	(7.64)

We will see a cool cumulative return graph soon

Let’s replicate this strategy

- it is currently being commercialized. Very valuable strategy!

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The ExtractAlpha Tactical Model 1 (TM1) is a quantitative stock selection model designed to capture the technical dynamics of single US equities over one to ten trading day horizons. TM1 is a *tactical* factor, in that it can assist a longer-horizon investor in timing their entry or exit points, or be used in combination with existing systematic or qualitative strategies with similar holding periods.

TM1 expands upon simple reversal factors in several key ways, by identifying stocks which are likely to trend or reverse and by incorporating liquidity and seasonality effects.

In historical simulations, high-scoring stocks according to TM1 outperform low-scoring stocks by 59% per annum with a market-neutral Sharpe ratio of 4.4 before transaction costs, versus 25% and a Sharpe of 1.1 for a basic reversal factor with comparable turnover. Unlike many quantitative stock selection factors, TM1 exhibits comparable returns for large-cap stocks and small-cap stocks, and it is particularly effective in volatile regimes.

ruleset

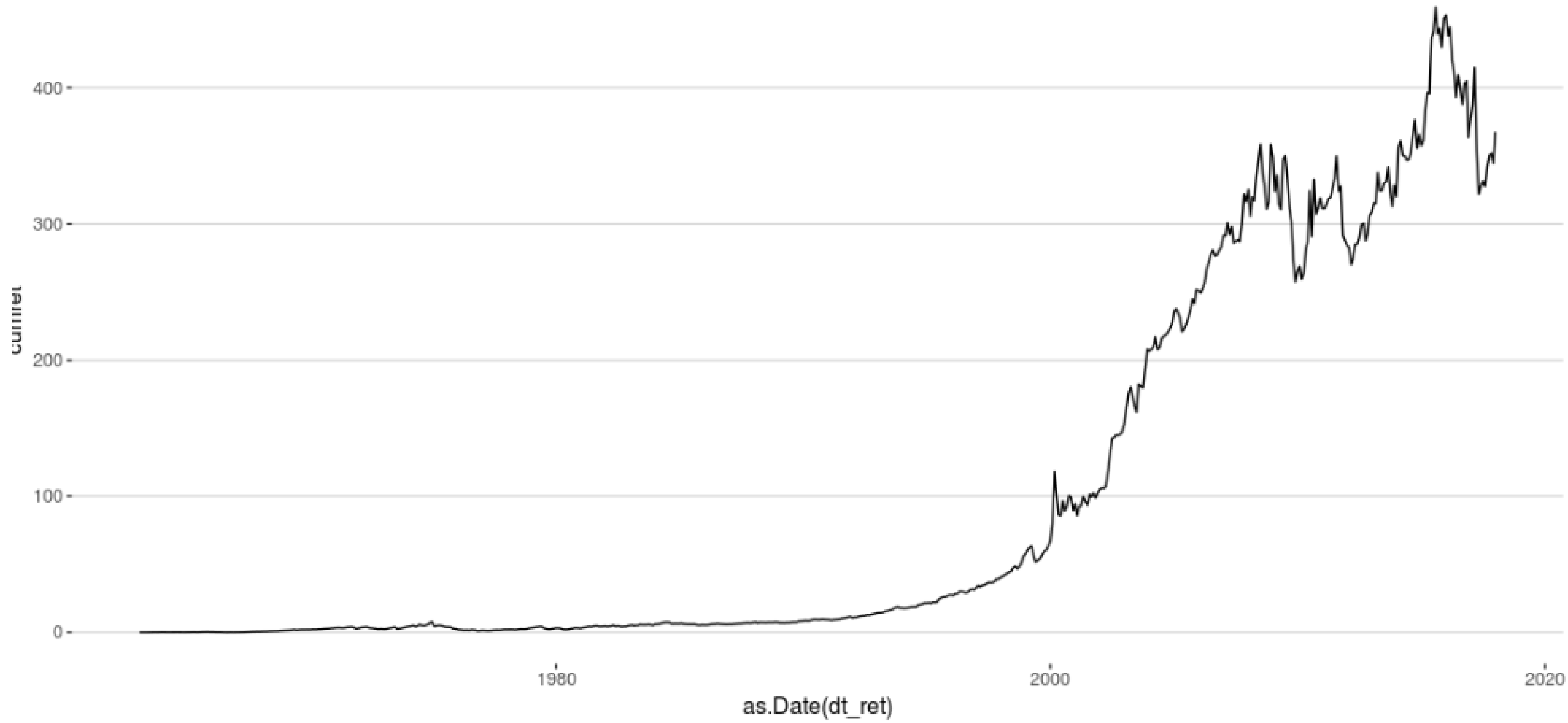
Our sample includes all common stocks traded on the NYSE, AMEX, and NASDAQ exchanges, covering the period from July 1963 through December 2010. We eliminate stocks with price per share less than $5 or more than $1,000. The daily and monthly return and volume data are from CRSP. We adjust stock returns for delisting in order to avoid survivorship bias (Shumway 1997).[5] Accounting variables are obtained from the Merged CRSP/Computstat database. Analysts' earnings forecasts come from the I/B/E/S dataset and cover the period from 1983 to 2010. Spreads are calculated using Trade and Quotes (TAQ) data for the period of 1993–2010. The institutional ownership data are from Thompson 13F filings for the period of 1980–2010.

Their rule set in Engrish

- $5 per share or $1000
  - Shares that are $1000 are difficult to trade, and may be outliers in liquidity
- Try to use liquidity data calculated from intraday data, where possible

- Let’s try to replicate… without the complications

Replication time



Other papers on liquidity risk

- Stambaugh (2004) - comovement with aggregate market liquidity is priced.
  - This is somewhat complicated to replicate

- Fund returns can be explained by their exposure to liquidity risk
  - Dong, Feng and Sadka (2018) – mutual fund performance increase in liquidity risk exposure
  - Sadka (2010) – liquidity risk explains the cross-section of h edge fund returns

Funding liquidity

- Funding liquidity is necessary for many types of financial risk-taking
  - Holding margin to use leverage
  - Margin held against a derivative security
  - A maturity mismatch with your liabilities
- Moreover, not every investor can or wants to take leverage
  - Some mutual funds are not allowed to
  - The sophistication required to take leverage is not available to every retail investor
  - We will see this has asset pricing implications.
    - **If you've ever heard of risk parity, this is it.**
  - Who lends you money? Your broker may not want to give you this money
- There are times when it becomes difficult to finance these positions, because funding runs out

Example - liabilities

- “illiquid but not insolvent”

- Suppose you have a 20 million dollar portfolio
  - The assets are difficult to sell, for example a corporate loan
  - Suppose the asset starts paying $1.3 million coupons every year for the next 20 years

- But this year
  - You all of a sudden need 2 million dollars
  - You are short $600,000

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- It is in principle possible to borrow that money from somewhere?

Example - liabilities

- It is in principle possible to borrow that money from somewhere?
  - The overnight market if you are a bank
  - Money market funds if you are any other type of entity
- During the financial crisis, many of these short-term markets disappeared
  - GE for example had difficulty rolling its commercial paper
    - Some economists thought this was the “end of the world”

Margin example …

- Let's take a cross-listed stock. Ignore transaction costs
  - Suppose I told you that it cost $45.01 in one market
  - And it cost $45.03 in another market
  - Their prices will converge after a month

- If I don't have transaction costs, I can pocket 2 cents on the same asset. This is obviously an arbitrage, correct?
  - Correct!

- But it's unattractive….
  - .02 / 45.03 = .00044
  - Annualized, 50 basis points

- What if I could borrow 100x?
  - Now it becomes 4.4%. Not bad.

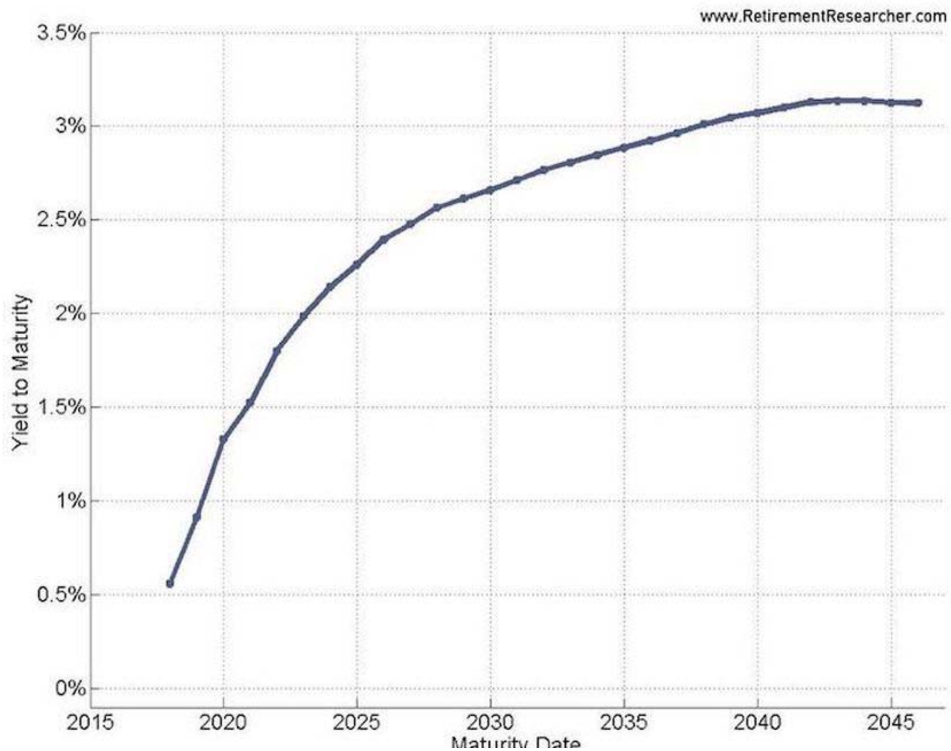
Measures of funding liquidity

- The idea:
  - If we can measure funding liquidity, we can explain why some strategies do and don’t work
  - If we can measure or even predict funding liquidity, we can forecast when certain strategies that take advantage of these market imperfections may work even better

- Here are three measures of funding liquidity
  - The TED spread
  - “Noise”
  - The health of financial intermediaries

Noise – Hu Pan and Wang (2013)

- The idea:
  - Generally, there are certain arbitrage relationships
  - One arbitrage relationship is the term structure of zero coupon bond yields



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- Bond curve can become erratic once in awhile
  - When there is a lot of error based on current market prices relative to model-implied bond yields, it is attractive to buy
  - "Arbitrage" the model. It is a common strategy

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- But this arbitrage strategy is only exciting with leverage

N

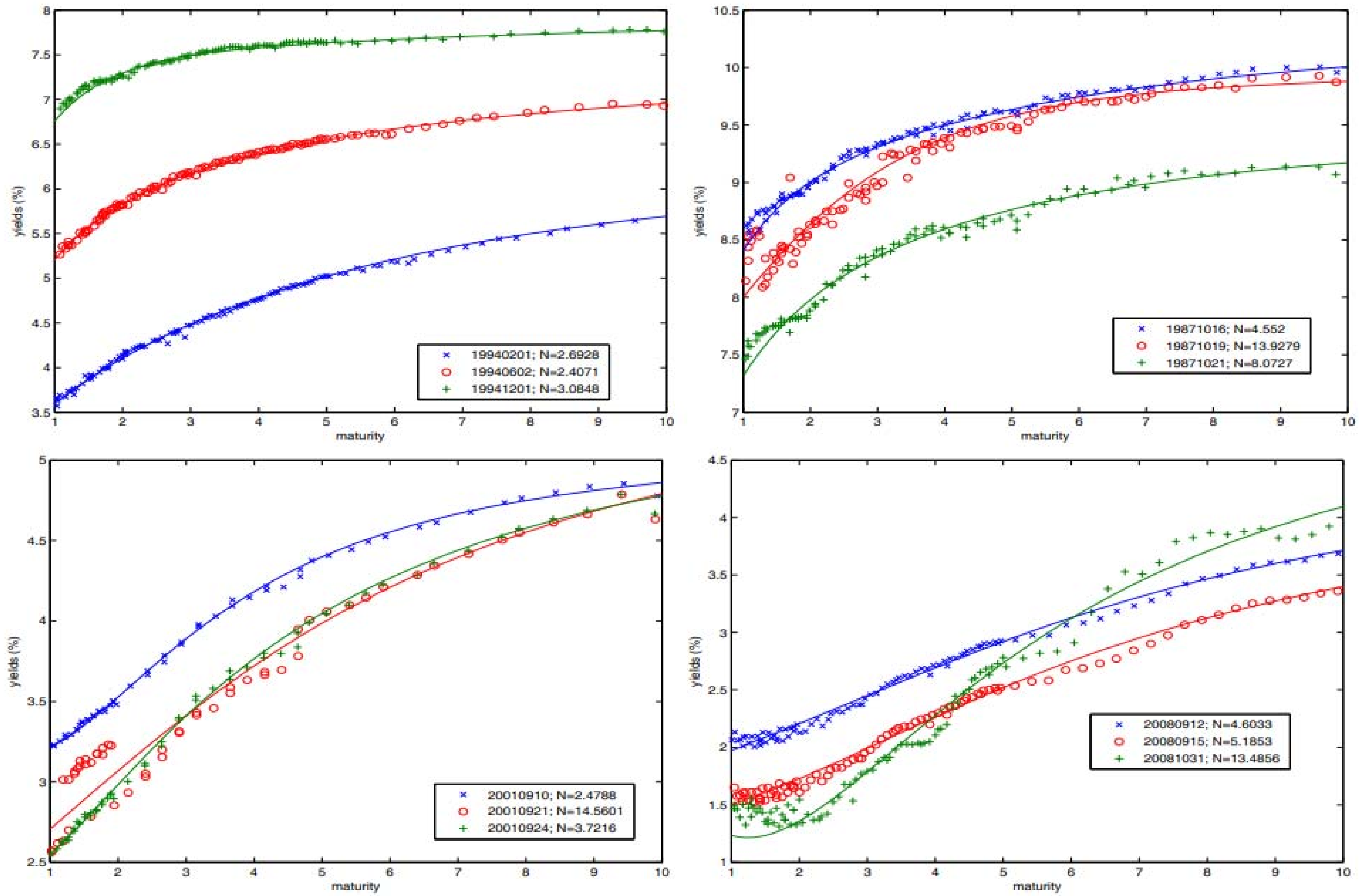

Figure 1: Examples of par-coupon yield curves and the market-observed bond yields, marked by "x", "o", or "+". The top left panel plots three random days in 1994. The other three panels focus on the days surrounding three events: the 1987 stock market crash, the September 11, 2001 terrorist attack, and the Lehman default in September 2008. Marked in the legends are the date of observation and the level of the noise measure for that day.

Noise – Hu Pan and Wang (2013)

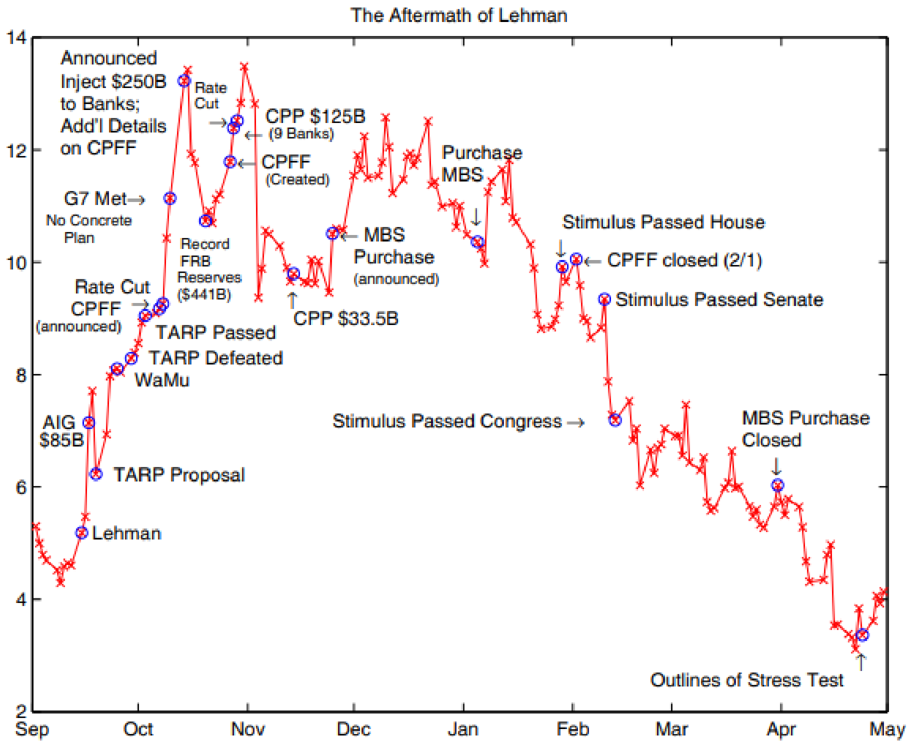

Figure 3: Daily time-series of the noise measure in late 2008 and early 2009. TARP: Troubled Asset Relief Program; CPP: Capital Purchase Program; CPFF: Commercial Paper Funding Facility; and the MBS Program is Fed's $1.25 trillion program to purchase agency mortgage-backed securities.

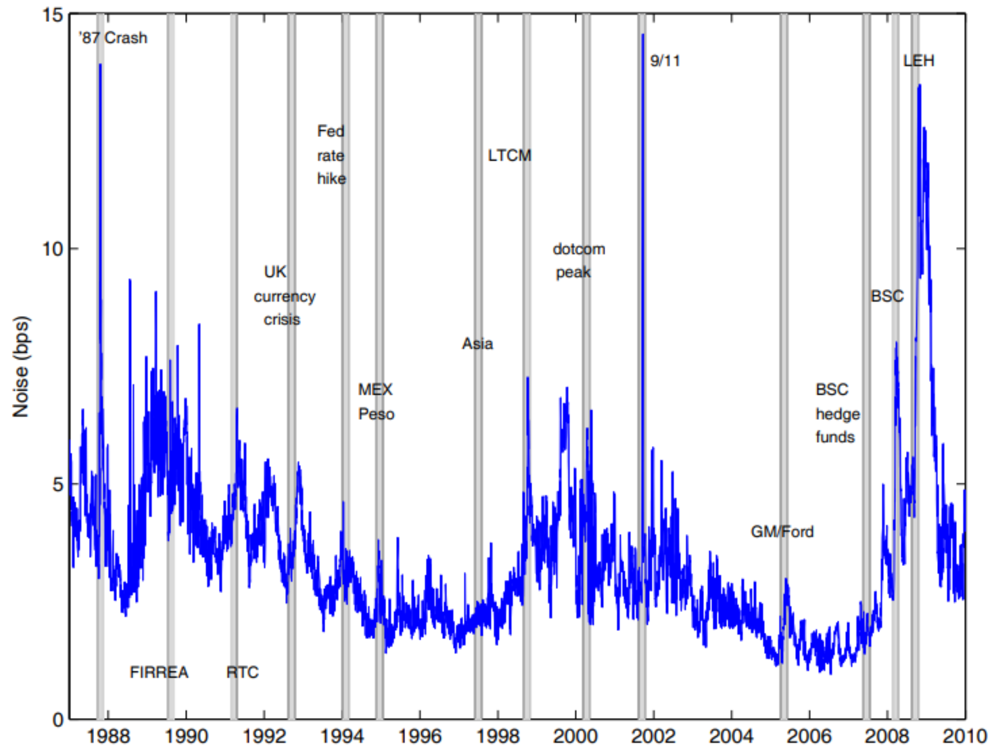

Figure 2: Daily time-series of the noise measure (in basis points).

Noise – Hu Pan and Wang (2013)

- In order to better identify this impact, **we need to consider returns that are potentially sensitive to the market-wide liquidity shocks.** For this purpose, we employ two sets of returns for our tests. The first set consists of returns on hedge funds, whose trading activities cover a broad spectrum of asset classes and whose capital adequacy is a good representation of the amount of arbitrage capital available in the market. The second set of returns are those from currency carry trades, which are also known to be connected with the overall arbitrage capital in the market. We conduct separate empirical tests on these two sets returns.

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Table 8: **Liquidity Premiums from Currency Carry Returns**

Panel A: Returns and Beta's

Rank	exret (%)	β^N	β^M	Adj-R2 (%)
1	-0.20	0.27	-0.01	1.5
	[-1.50]	[1.91]	[-0.18]	
2	-0.06	0.07	0.04	0.9
	[-0.51]	[0.44]	[1.06]	
3	0.16	0.17	0.06	2.1
	[1.25]	[1.06]	[1.32]	
4	0.31	-0.07	0.07	2.5
	[2.33]	[-0.36]	[1.31]	
5	0.34	-0.04	0.12	6.0
	[2.41]	[-0.25]	[2.64]	
6	0.81	-0.43	0.14	8.3
	[4.47]	[-1.83]	[2.15]	

Panel B: Estimated Risk Premiums

	constant	Noise	Market	month
estimate	4×10^{-6}	-0.82	2.93	276
t-stat	[0.003]	[-2.54]	[2.29]	

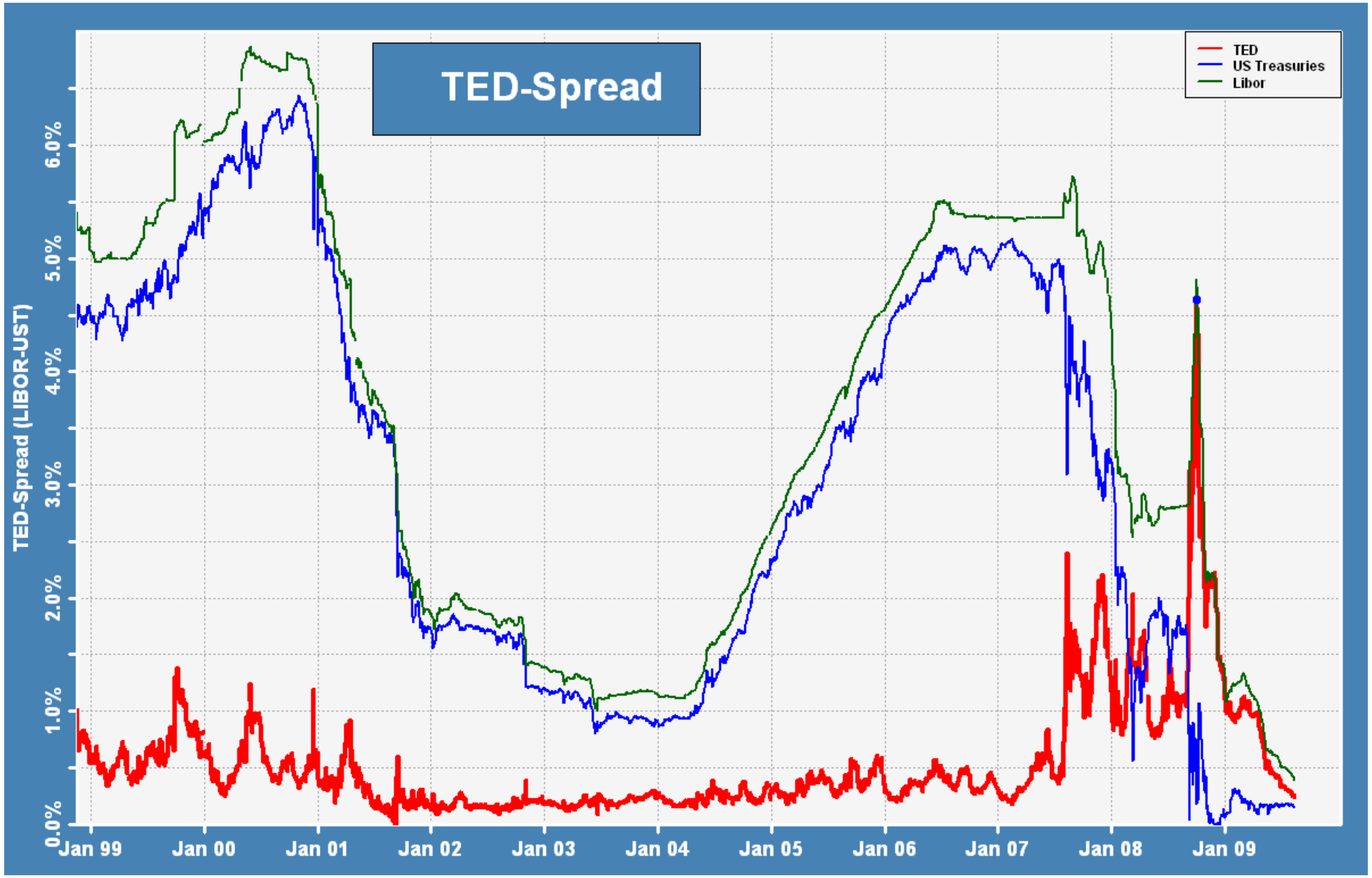
Portfolios are formed by sorting currencies by their forward discount. Currencies in portfolio 1 have the smallest forward discount and the lowest interest rate and are often used as the funding currency in a carry trade, while currencies in portfolio 6 are often used as the asset currency. Returns are monthly in excess of the riskfree rate.

TED spread

- the TED spread is the difference between three-month Treasury Bill and three-month LIBOR in US dollars

- In other words, the interest rate on short-term US debt vs interest rate on interbank loans
  - How much more expensive is it for banks to borrow than the US government (presumably safer).
  - If banks cannot borrow, then banks will find it difficult to take leverage at the 3-month mark.
  - The 3-month mark is safe, so this has implications for other maturities.
  - Moreover, other financial participants will find it difficult to take leverage.

TED spread



TED-Spread
TED
US Treasuries
Libor
TED-Spread (LIBOR-UST)
0.0%
1.0%
2.0%
3.0%
4.0%
5.0%
6.0%
Jan 99
Jan 00
Jan 01
Jan 02
Jan 03
Jan 04
Jan 05
Jan 06
Jan 07
Jan 08
Jan 09

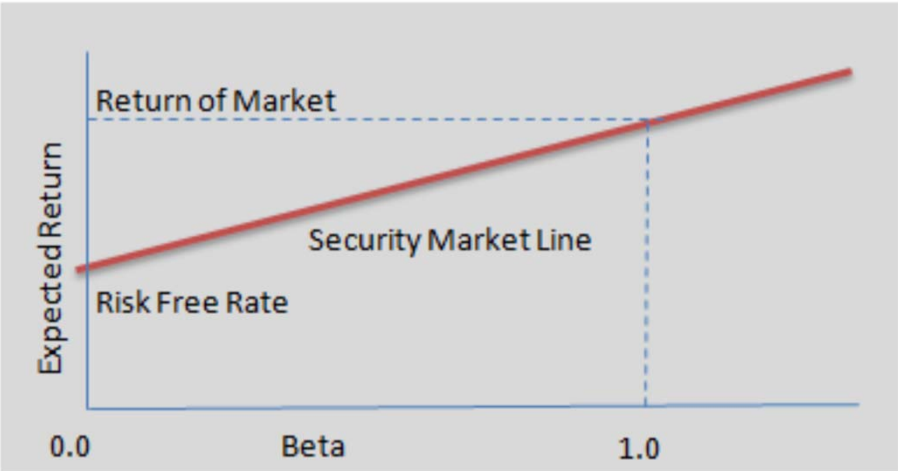
Replicate betting against beta

- First thing to do is see the security market line is flat
- Second thing to do is to exploit the flatness of the risk-return relation
  - Short the high-beta stocks
  - Long the low-beta stocks
- Question: isn't this going to produce negative returns?
  - Answer… not with *leverage*
  - This is why funding liquidity can be important – this strategy loads on funding liquidity risk

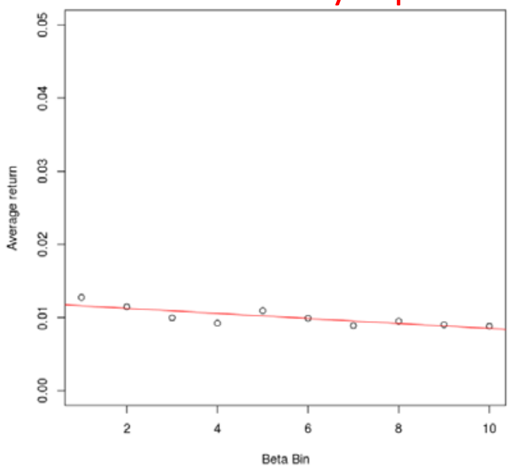
Failure of CAPM + low volatility anomaly

- The classical CAPM model suggests that exposure to the market is non-diversifiable

- If this is true, then following the intuition of the CAPM, we should expect the left graph while in reality we observe the right:



My replication



Replicating the failure of the CAPM

- First we have to calculate betas
  - I have provided this table
  - Challenge to yourself:
    - Calculate rolling 200 day betas using your choice of model
    - Do it under 1 day on your laptop

- Then, every month, we sort stocks into beta portfolios
  - Deciles, say, of trailing 200 day market betas

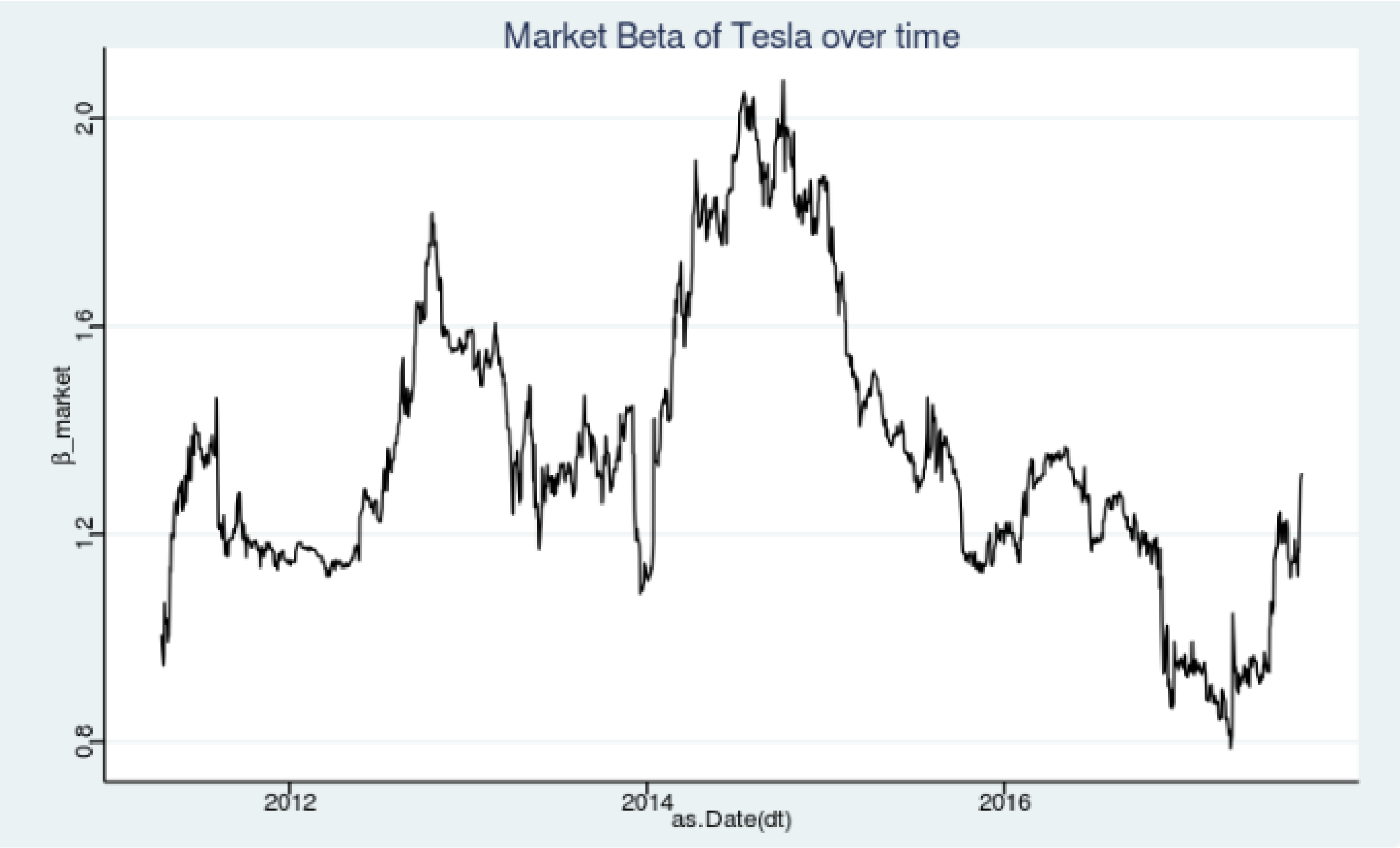
- Then, we need to create average portfolios that have
  - Next month's return
  - This month's average beta

Time-varying β

- Betas vary over time frequently, either because of changing risk exposure or original mis-estimation

- For fundamental reasons betas could change
  - Firm could change capital structure – more debt, the use of derivatives
  - Firm change line of business

Time-varying β - example



If you calculated TESLA market betas every 200 days, its covariance loads differently over time

Skip (calculating TESLA beta , rolling)

```
> a2[,beta:=NA %>% as.numeric]
>   for(i in 200:nrow(a2)){
+     res=coef(lm(data=a2[seq(i-199,i),],ret ~ mkt_rf))['mkt_rf']
+     a2[i,beta:=res,]
+   }
>   print(a2[195:205,])
            dt permno          ret  mkt_rf     SMB     HML     RMW     CMA RF      beta
 1: 2011-04-06  93436 -0.007865205  0.0021 -0.0016  0.0060 -0.0013  0.0021  0        NA
 2: 2011-04-07  93436  0.028312571 -0.0020 -0.0022 -0.0016  0.0021 -0.0013  0        NA
 3: 2011-04-08  93436 -0.027533039 -0.0047 -0.0053 -0.0027  0.0004 -0.0022  0        NA
 4: 2011-04-11  93436 -0.046055090 -0.0039 -0.0063 -0.0011  0.0043 -0.0023  0        NA
 5: 2011-04-12  93436 -0.024535054 -0.0084 -0.0066  0.0003  0.0053 -0.0019  0        NA
 6: 2011-04-13  93436  0.011359055  0.0011  0.0009 -0.0068 -0.0007 -0.0014  0 1.0055032
 7: 2011-04-14  93436  0.008423549  0.0000  0.0034 -0.0035 -0.0008 -0.0018  0 1.0097403
 8: 2011-04-15  93436  0.017502010  0.0044  0.0053 -0.0006 -0.0003  0.0029  0 0.9885986
 9: 2011-04-18  93436 -0.021501143 -0.0115 -0.0041 -0.0034  0.0030 -0.0030  0 0.9516044
10: 2011-04-19  93436  0.005193734  0.0050 -0.0035 -0.0016  0.0003  0.0024  0 0.9695709
11: 2011-04-20  93436  0.023449928  0.0145  0.0051 -0.0061 -0.0035  0.0009  0 1.0703754
```

Rolling window – what is β_t^s

K can be whatever you want greater than 1 so you minimize look-ahead bias. Although, in some cases we want that look-ahead bias

Some conventions about calculating beta

- Here are some conventions
  - Apply beta at day *t* from at least t-m where m>0 (calculate betas using some lagged data)
  - 200 day lookback

- Typically, people use multiple factors as there may be many different risks

- Rolling window calculations are used, but computationally expensive
  - I have seen this as a quant trading coding exercise even for PhD students at top trading shops

Skip :Calculating betas faster is a real industry problem

- Here's how many betas we have to calculate through August 2017 / how long 100000 betas takes
  - 74415116 betas.
  - 100,000 took 226 seconds (plus data reading time)… $74 * 10^6 betas * \frac{226seconds}{100000betas}\frac{hour}{3600\ seconds} = 46.45\ hours$

```
> benchmark<-aqfast('select  permno,date as dt,ret from crsp.dsf where ret
 is not null limit 1000000')

> a=merge(benchmark,aqfast('select * from ff.five_factor'),by='dt')
> a2=copy(a)
>   a2[,beta:=NA %>% as.numeric]
>   # this makes no sense, but just for sake of argument
>   system.time(
+     for(i in 200:100000){
+       res=coef(lm(data=a2[seq(i-199,i),],ret ~ mkt_rf))['mkt_rf']
+       a2[i,beta:=res,]
+     })
user  system elapsed
223.916   2.068 225.961
```

- A few key performance tricks:
  - Matrix calculations are a direct operation that CPUs know how to do faster than functions
  - Parallelization
  - Memory pre-allocation
  - We can talk if you are interested

Here are some massive tables

```
list.files('/yuge/googledrive_aak87/class_quant_trading/feather/',pattern='loading',recursive=TRUE)

x=read_feather('returns_loading_five_factor_10000_19999')
nrow(x) %>% print
head(x)
```

11176221 rows

beta_intercept	beta_mktrf	beta_smb	beta_hml	beta_RMW	beta_CMA	resid	fitted	dt	ret	permno
-0.0000796780	0.9651139	0.1501777	0.2104834	-0.03011707	-0.3003221	-0.009730259	-0.001844025	2017-02-02	-0.0115542831	16000
-0.0000286888	0.9651034	0.1477933	0.2239936	-0.04484487	-0.3158610	0.003272020	0.009232354	2017-02-03	0.0125243738	16000
-0.0001548739	0.9881644	0.1412385	0.2515788	0.03964684	-0.2894427	0.003471588	-0.003491588	2017-02-06	0.0000000000	16000
-0.0002200505	0.9834298	0.1456682	0.2621779	0.02344938	-0.2959028	-0.011052140	-0.001337314	2017-02-07	-0.0123694539	16000
-0.0002833562	0.9817562	0.1580099	0.2683998	0.02696261	-0.2933876	-0.003252264	-0.001081646	2017-02-08	-0.0043139099	16000
-0.0003027158	0.9792260	0.1588816	0.2770819	0.04886253	-0.2823528	-0.008417519	0.007698665	2017-02-09	-0.0006988546	16000

Skip: Augmented beta models

- I honestly forget the cite, but here's something you may want to consider

- In a lot of countries or asset classes, there are a lot of "zero return days". For example, bonds often times there is no trade.
  - Very common in power
  - In bond trading
  - In options trading

- Not just zero return, but also zero turnover

- The net effect is that beta models (particularly at the shorter frequencies) have unbelievably difficult to believe factor loadings, or may, depending on the context

Skip: Augmented beta models

$$r_t^s - r_F$$
$$= \beta_1\left(r_t^{mkt} - r_f\right) + \beta_2\left(r_{t-1}^{mkt} - r_f\right) + \beta_3\left(r_{t-3}^{mkt} - r_f\right) + \epsilon_t^s$$

Using this strategy, you can account for lags and deficits in price synchronities

Skip : what % of days are zero turnover

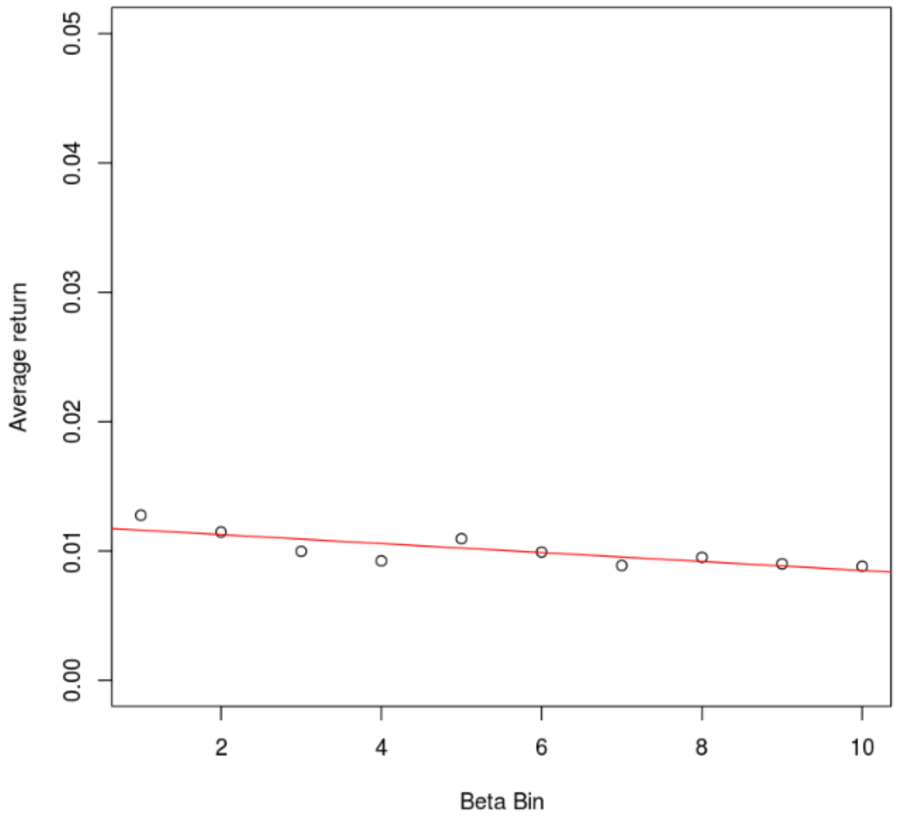
```
stocks=aqfast('select permno from crsp.dsenames where shrcd in (10,11)')$permno %>% unlist %>% unique
keep=data.table()
for(year in c(1960,1970,1980,1990,2000,2010)){
    print(paste(year,Sys.time()))
    aqfast('select ret,vol,date,permno from crsp.dsf
        where year(date) = %s' %>% sprintf(year)) -> x
    x=x[permno %in% stocks,]
    gc()

    keep=rbind(keep,x[,list(year=year,'%zero ret days'=mean(round(ret,10)==0,na.rm=TRUE),
           '%zero volume days'=mean(round(vol,10)==0,na.rm=TRUE)
           ),])

    # for garbage collection
    rm(x) ;gc()
}
```

year	%zero ret days	%zero volume days
1960	0.17293577	0.060050226
1970	0.18932342	0.054888038
1980	0.38739372	0.047000591
1990	0.38894260	0.191723830
2000	0.13466482	0.057600673
2010	0.03557359	0.007830803

Replicating the failure of the CAPM



Possible explanations

- It is a failure – "we should Bet Against Beta"
  - The security market line is too flat because of good reasons
  - We can exploit these reasons if we can leverage

- Conditional CAPM
  - On most days, macroeconomic events do not move the market
  - Therefore, covariance with the market is meaningless
  - But, betas on important episodes are important

A precursor to CAPM betas

- Savor and Wilson (2014) document a huge macroeconomic announcement effect

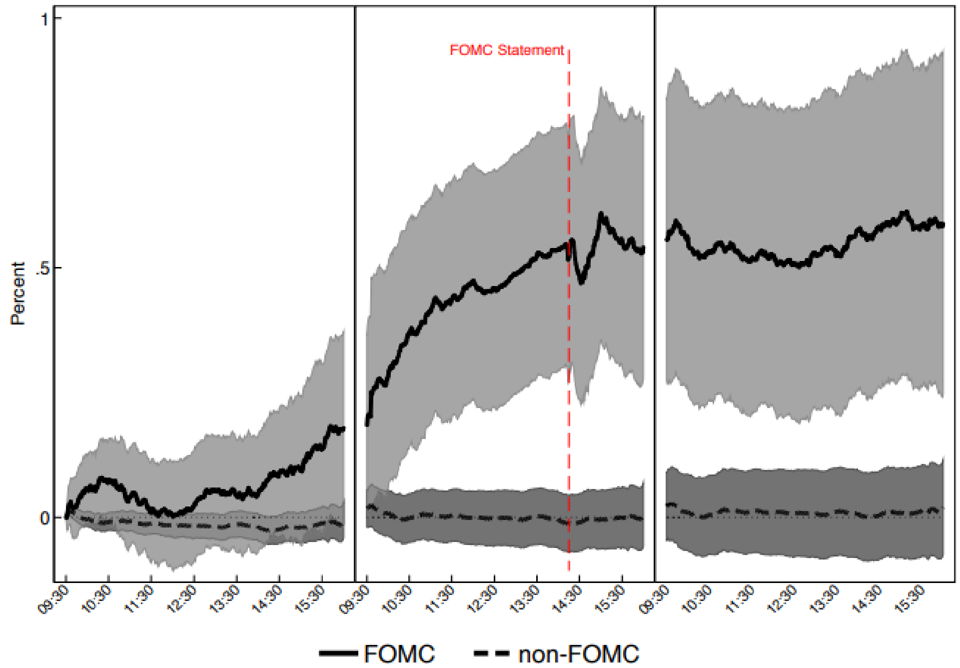
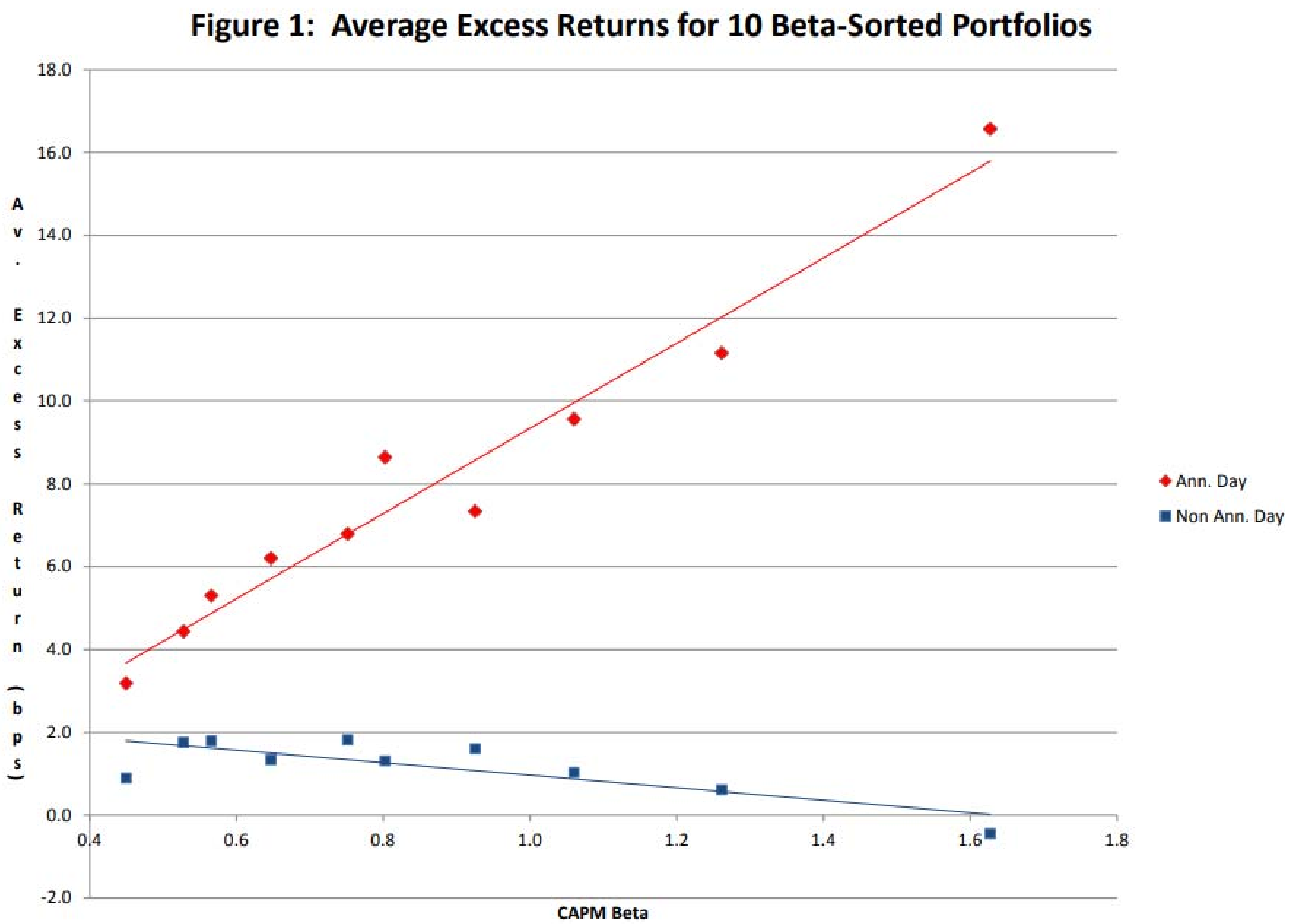


Figure 1. Cumulative Returns on the S&P500 index. This chart shows the average cumulative minutely return on the S&P500 index on three day windows. The solid black line is the average cumulative return on the SPX from 9:30 a.m. EST on days prior to scheduled FOMC announcements to 4:00 p.m. EST on days after scheduled FOMC announcements. The dashed

These decisions impact the market. Savor and Wilson JFE (2015)

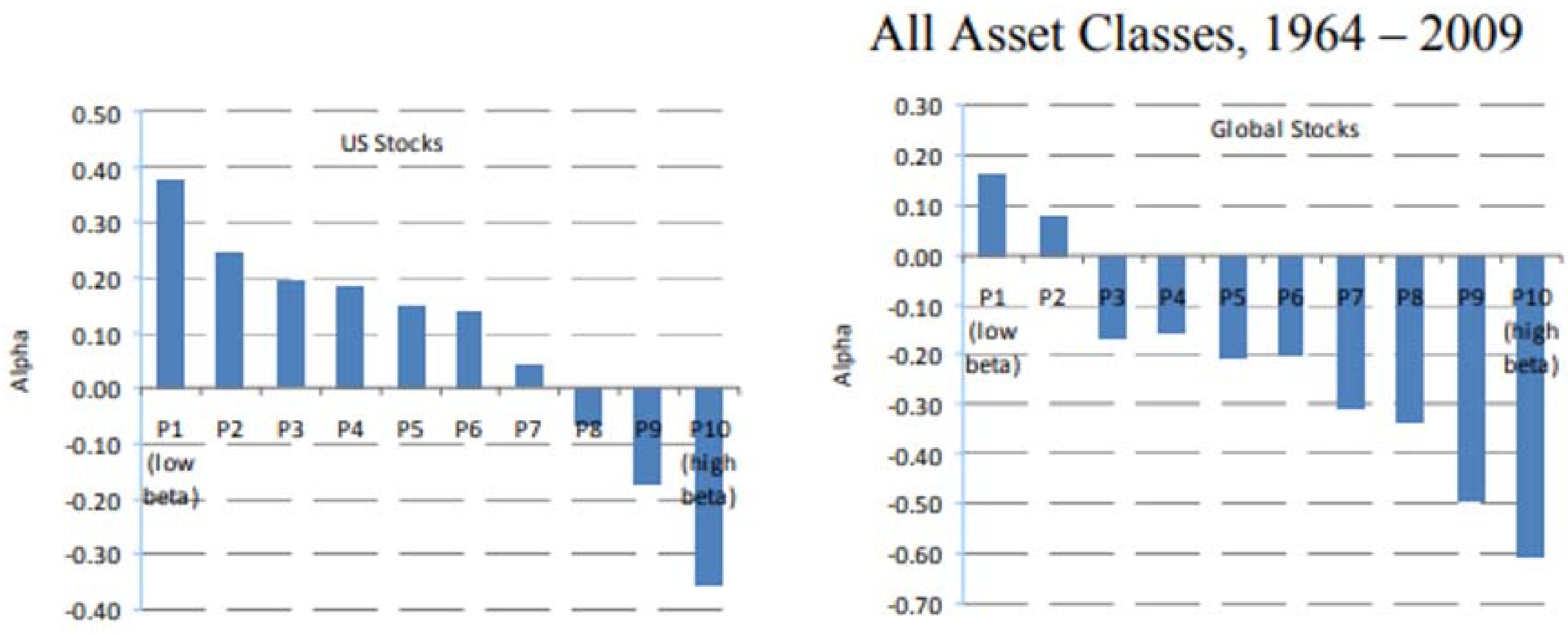


Betting Against Beta

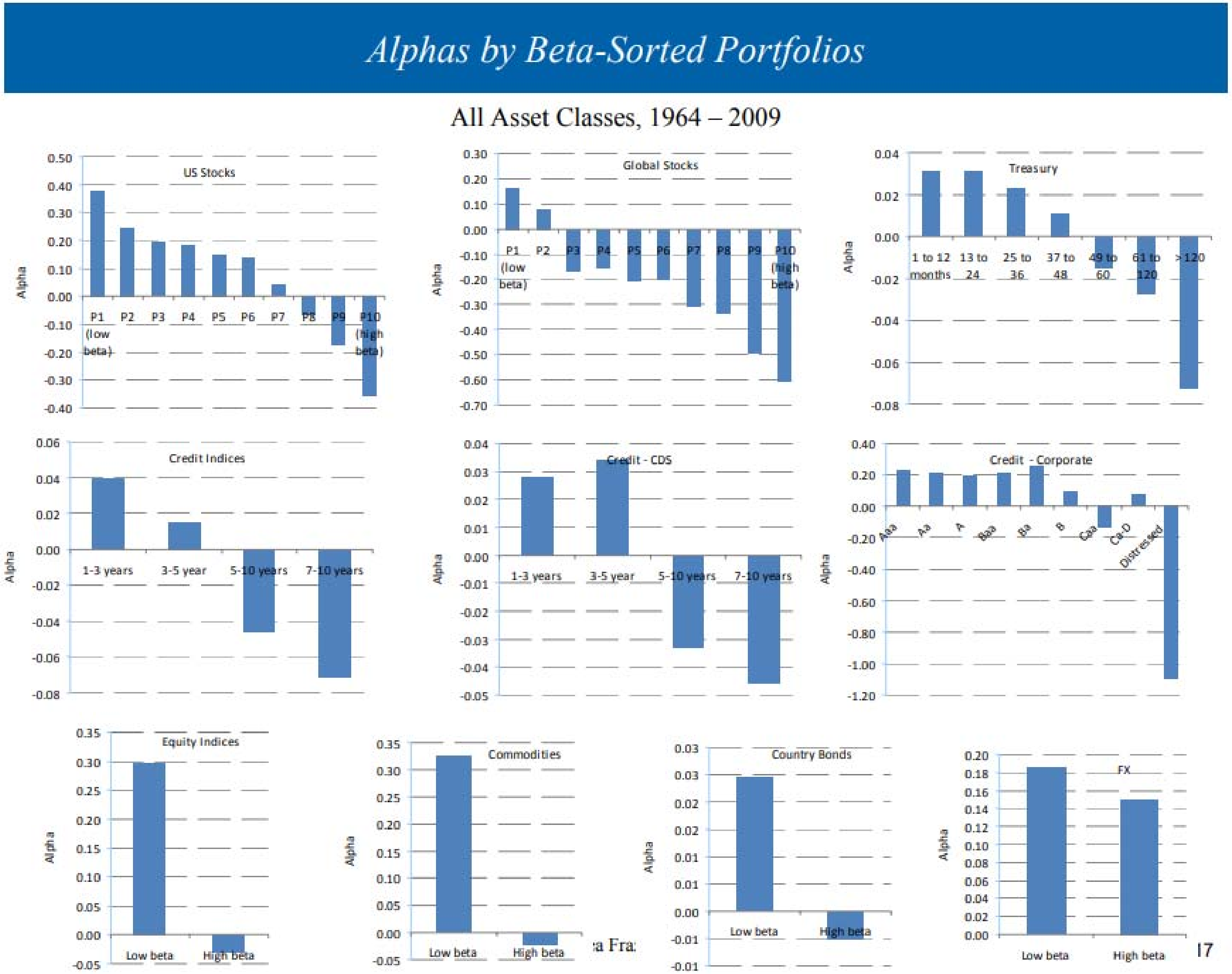
- This paper is **hot**

- Intuition underlies the risk parity argument that Sharpe ratios are underpriced because investors are not sophisticated enough

Across asset classes



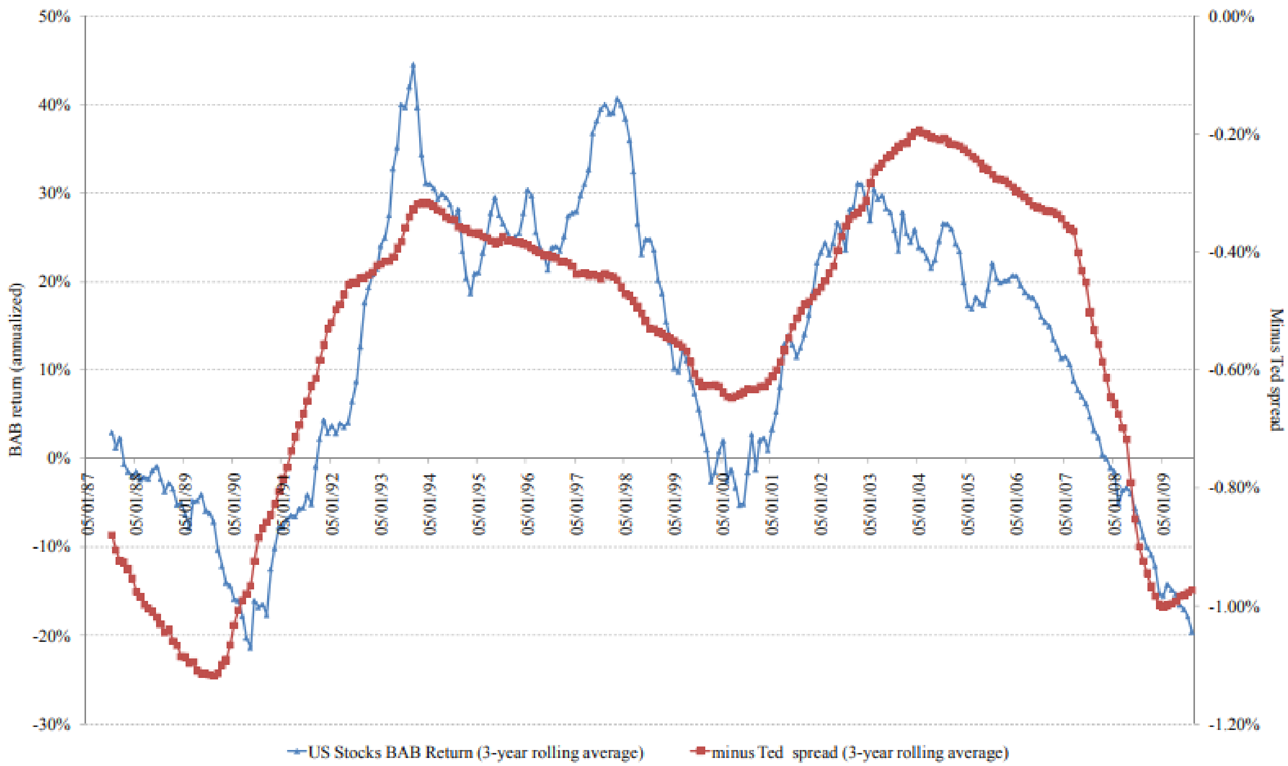
Across asset classes



Margin constraints might explain BAB

US equity BAB and TED Spread

This figures shows annualized 3-year return of the US stocks BAB factor (left scale) and 3-year (negative) average rolling TED spread (right scale) . BAB is a portfolio short (de-levered) high beta stocks and long (levered) low beta stocks



Here's their ruleset

TLDR

Estimating Ex-ante Betas

We estimate pre-ranking betas from rolling regressions of excess returns on market excess returns. Whenever possible, we use daily data rather than monthly as the accuracy of covariance estimation improves with the sample frequency (Merton (1980)).[12] Our estimated beta for security i is given by

$$\hat{\beta}_i^{ts} = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m} \qquad (14)$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the stock and the market and $\hat{\rho}$ is their correlation. We estimate volatilities and correlations separately for two reasons.

Here's their ruleset

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where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the stock and the market and $\hat{\rho}$ is their correlation. We estimate volatilities and correlations separately for two reasons. First, we use a 1-year rolling standard deviation for volatilities and a 5-year horizon for the correlation to account for the fact that that correlations appear to move more slowly than volatilities.[13] Second, we use 1-day log returns to estimate volatilities and overlapping 3-day log returns, $r_{i,t}^{3d} = \sum_{k=0}^{2} \ln(1+r_{t+k}^{i})$, for correlation to control for non-synchronous trading (which obviously only affects correlations). We require at least 6 months (120 trading days) of non-missing data to estimate volatilities and at least 3 years (750 trading days) of non-missing return data for correlations. If we only have access to monthly data, we use rolling 1 and 5-year windows and require at least 12 and 36 observations.

Finally, to reduce the influence of outliers, we follow Vasicek (1973) and Elton, Gruber, Brown, and Goetzmann (2003) and shrink the time-series estimate of beta (β_i^{TS}) toward the cross-sectional mean (β^{XS}):

$$\hat{\beta}_i = w_i \hat{\beta}_i^{TS} + (1-w_i)\hat{\beta}^{XS} \qquad (15)$$

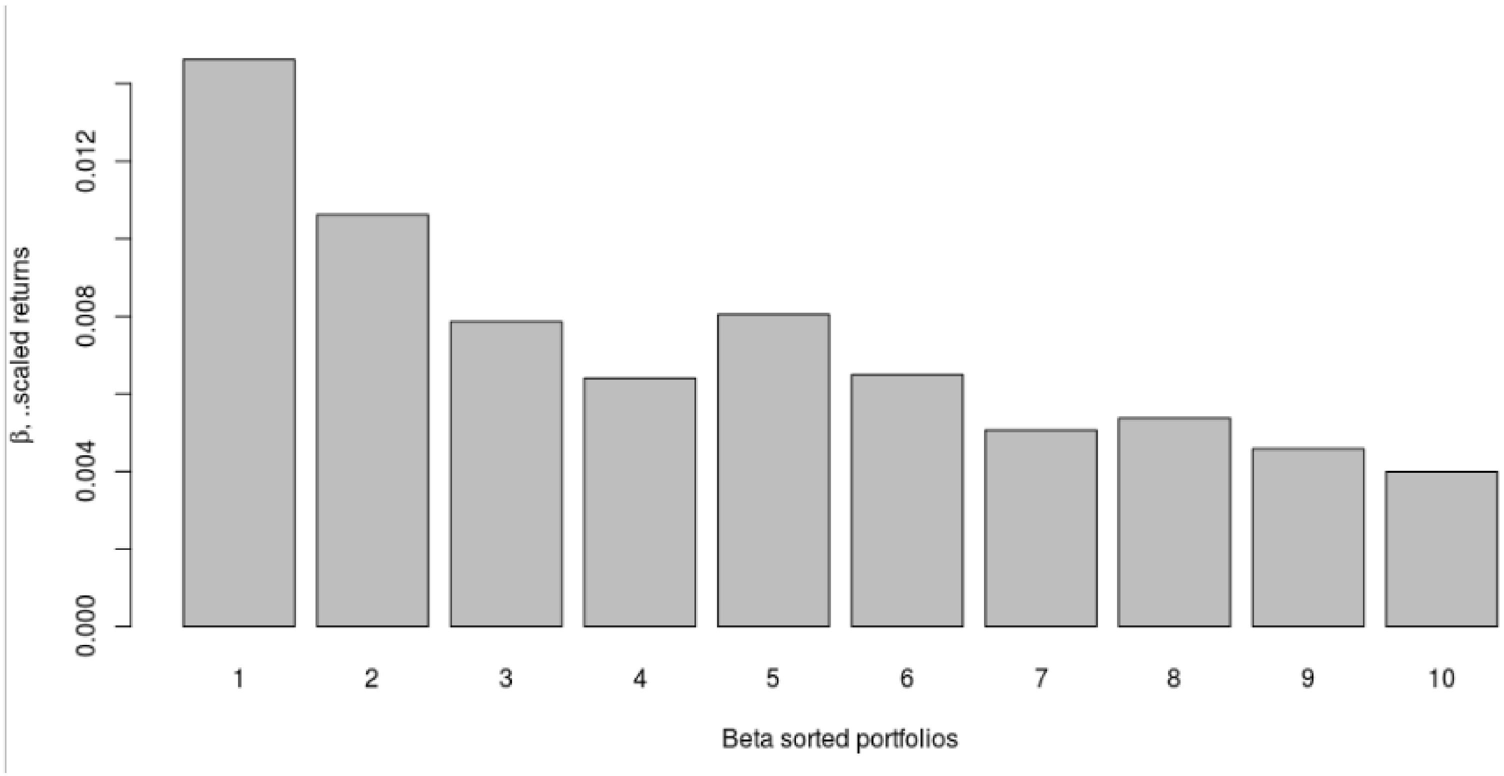
TLDR

Then, they compress the betas

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}\left(r_{t+1}^L - r^f\right) - \frac{1}{\beta_t^H}\left(r_{t+1}^H - r^f\right) \qquad (17)$$

Translating their ruleset into words

Quick dirty replication - 80 basis point spread



Why does beta arbitrage work?

- One explanation: leverage aversion
- In order to replicate strategy, must leverage
- Leverage is avoided for many reasons
  - It requires sophistication – constant maintenance of account, knowledge of a Sharpe ratio
  - There are leverage and short-sale restrictions for many entities, for example mutual funds
  - Leverage is risky: it may disappear when you most want it

Funding liquidity + intermediary asset pricing

- a new branch of economics – and potentially soon quant trading – will be based on trading risk premia during the time financial intermediaries are facing financial difficulty

- the basic idea:
  - When financial firms are weaker, they take less risk
  - When they take less risk, risk premia are larger

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- Open question: what intermediary?

Etula, Muir and Adrian (2014) Financial Intermediaries and the Cross-Section of Asset Returns

- Plot the average returns versus the covariance between returns in the past and intermediary wealth factor

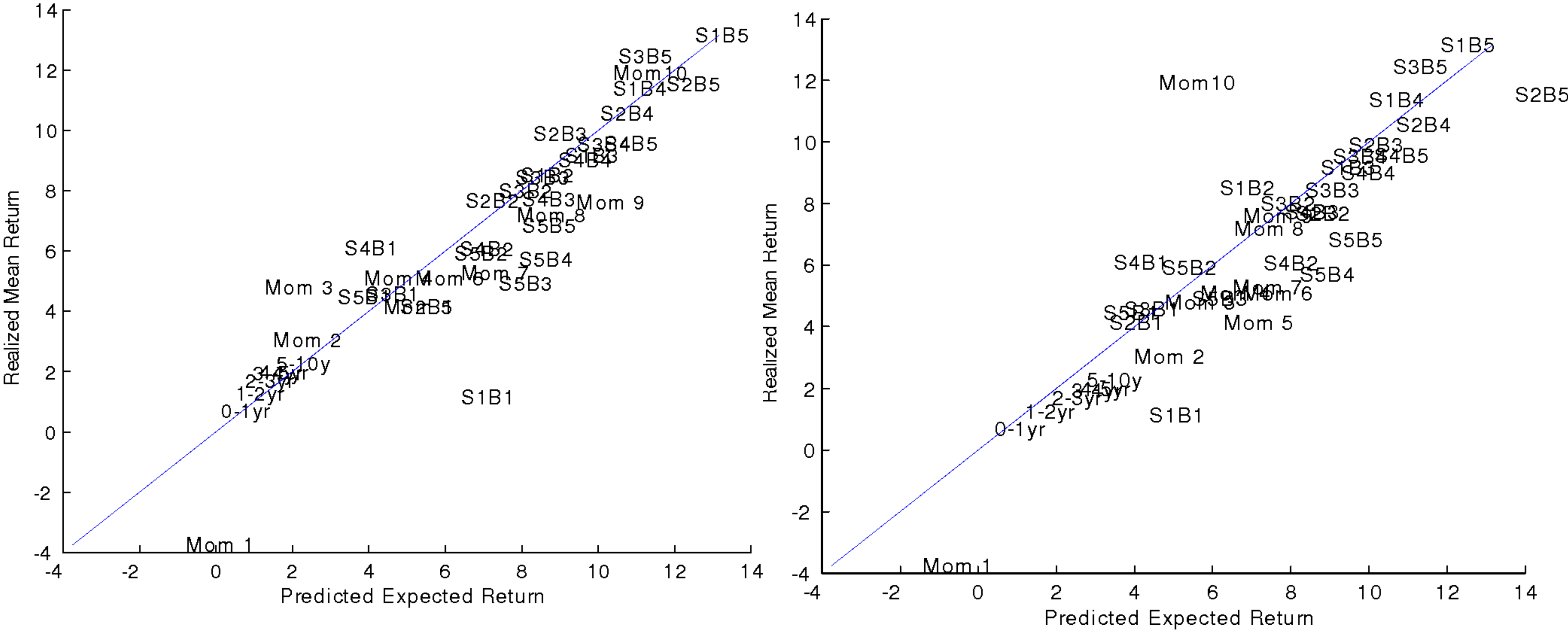
$$r - r_f = \alpha + \beta x_t \ + \epsilon$$

What is the intermediary wealth factor?

$$Leverage_t^{BD} = \frac{Total\ Financial\ Assets_t^{BD}}{Total\ Financial\ Assets_t^{BD} - Total\ Liabilities_t^{BD}}. \qquad (4)$$

In their world, the correct intermediary is a "broker dealer"

Etula, Muir and Adrian (2014) Financial Intermediaries and the Cross-Section of Asset Returns



He et al ("intermediary asset pricing, evidence from many asset classes"

Primary Dealer	Start Date	End Date	Primary Dealer	Start Date	End Date
ABN Amro	9/29/1998	9/15/2006	HSBC	5/9/1994	Current
Aubrey Lanston	5/19/1960	4/17/2000	Hutton	11/2/1977	12/31/1987
BA Securities	4/18/1994	9/30/1997	Irving	5/19/1960	7/31/1989
Banc One	4/1/1999	8/1/2004	Jefferies	6/18/2009	Current
Bank of America	5/17/1999	11/1/2010	JP Morgan	5/19/1960	Current
Bank of America	11/17/1971	4/15/1994	Kidder Peabody	2/7/1979	12/30/1994
Bank of Nova Scotia	10/4/2011	Current	Kleinwort Benson	2/13/1980	12/27/1989
Bankers Trust	5/19/1960	10/22/1997	Lehman	11/25/1976	9/22/2008
Barclays	4/1/1998	Current	Lehman	2/22/1973	1/29/1974
Barclays De Zoete Wedd	12/7/1989	6/30/1996	LF Rothschild	12/11/1986	1/17/1989
Bartow Leeds	5/19/1960	6/14/1962	Lloyds	12/22/1987	4/28/1989
Bear Stearns	6/10/1981	10/1/2008	Malon Andrus	5/19/1960	11/24/1965
Becker	11/17/1971	9/10/1984	Manufac. Hanover	8/31/1983	12/31/1991
Blyth	4/16/1962	1/14/1970	Merrill Lynch	5/19/1960	2/11/2009
Blyth Eastman Dillon	12/5/1974	12/31/1979	Merrill Lynch	11/1/2010	Current
BMO	10/4/2011	Current	MF Global	2/2/2011	10/31/2011
BMO Nesbitt	2/15/2000	3/31/2002	Midland-Montagu	8/13/1975	7/26/1990
BNP Paribas	9/15/2000	Current	Mizuho	4/1/2002	Current
BNY	8/1/1989	8/9/1990	Morgan Stanley	2/1/1978	Current
Brophy, Gestal, Knight	5/8/1987	6/19/1988	NationsBanc	7/6/1993	5/16/1999
BT Alex Brown	10/23/1997	6/4/1999	Nesbitt Burns	6/1/1995	2/14/2000
BZW	7/1/1996	3/31/1998	Nikko	12/22/1987	1/3/1999
Cantor Fitzgerald	8/1/2006	Current	Nomura	12/11/1986	11/30/2007
Carroll McEntee	9/29/1976	5/6/1994	Nomura	7/27/2009	Current
CF Childs	5/19/1960	6/29/1965	Northern Trust	8/8/1973	5/29/1986
Chase	7/15/1970	4/30/2001	Nuveen	11/18/1971	8/27/1980
Chemical	5/19/1960	3/31/1996	NY Hanseatic	2/8/1984	7/26/1984
CIBC	3/27/1996	2/8/2007	Paine Webber	11/25/1976	12/4/2000
Citigroup	6/15/1961	Current	Paine Webber	6/22/1972	6/27/1973
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Financial intermediation

- Key state variable in this paper is the **intermediary capital ratio**.
- Aggregate value of market equity divided by aggregate market equity plus aggregate book debt of primary dealers active in quarter t:

$$x_t = \frac{\sum_i \text{Market Equity}_{i,t}}{\sum_i \left(\text{Market Equity}_{i,t} + \text{Book Debt}_{i,t}\right)}$$

- Fit AR(1) model to x_t to get innovations:

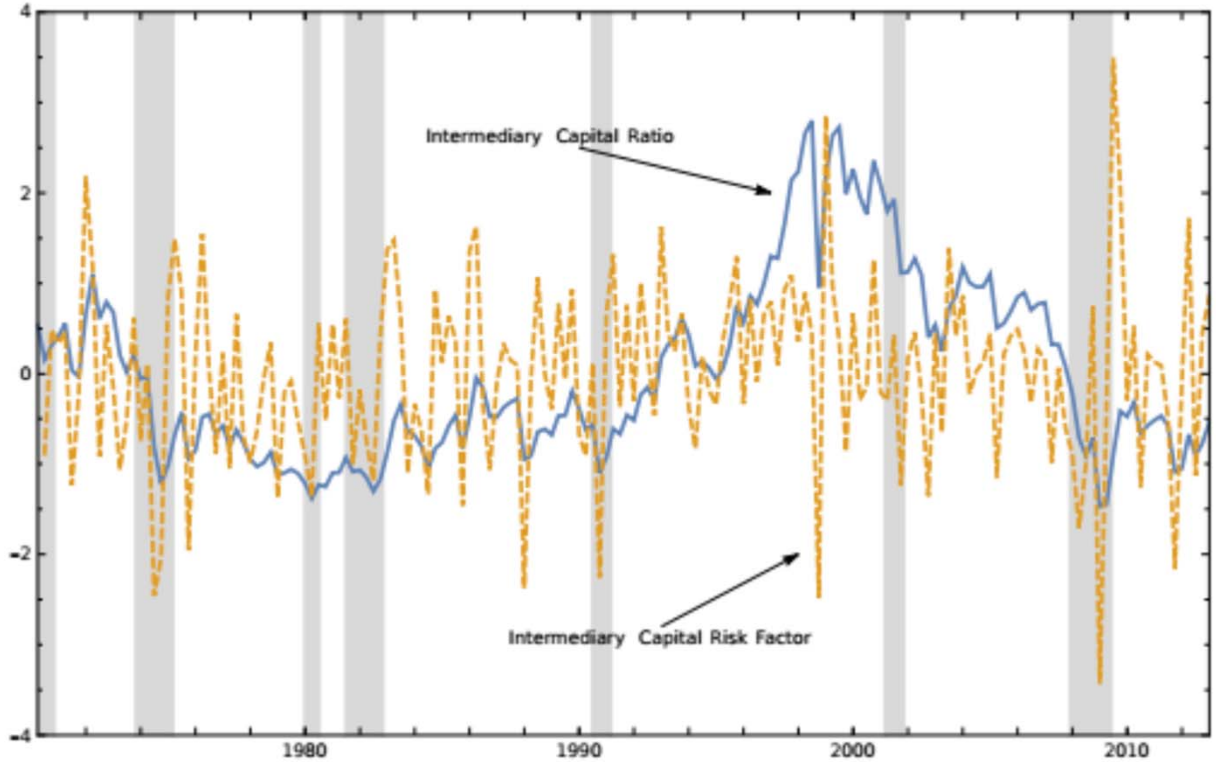
$$x_{t+1} = \rho_0 + \rho x_t + \epsilon_{t+1}$$

- Convert to growth rate:

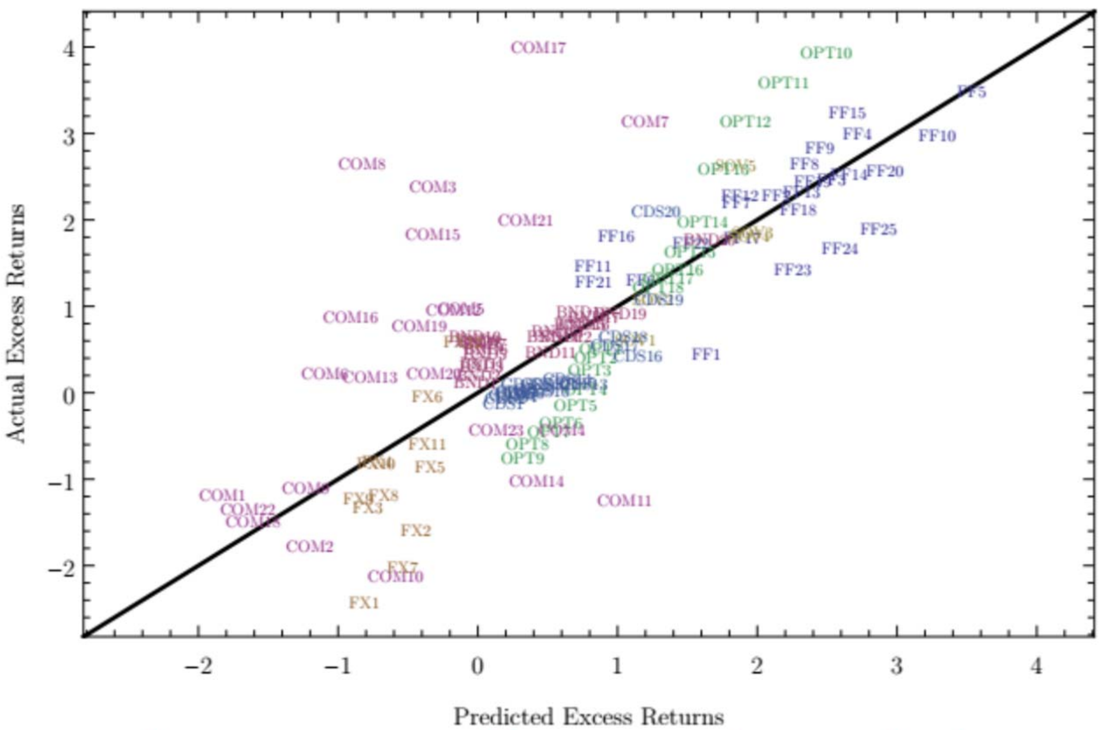
$$x_t^{\Delta} = \frac{\epsilon_t}{x_{t-1}}$$

- This is the risk factor used in the cross-sectional tests.

Financial intermediation



Covariance with intermediation factor explains stock returns



- Plot the average returns versus the covariance between returns in the past and intermediary wealth factor

$$r - r_f = \alpha + \beta x_t^{\Delta} + \epsilon$$