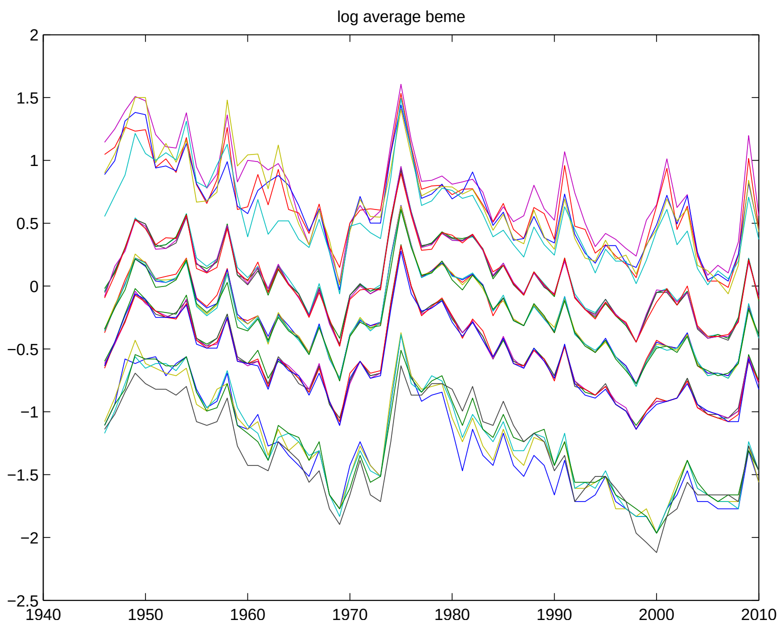
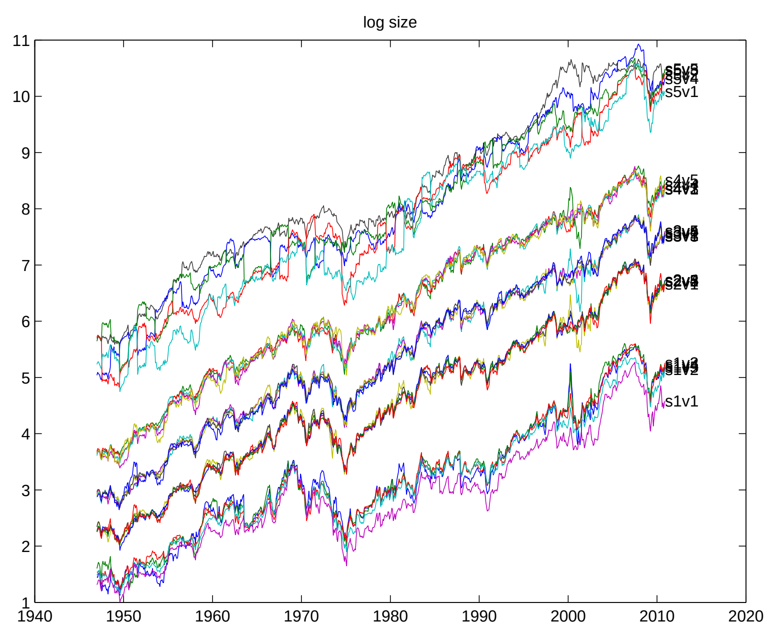
Problem Set 7 answers

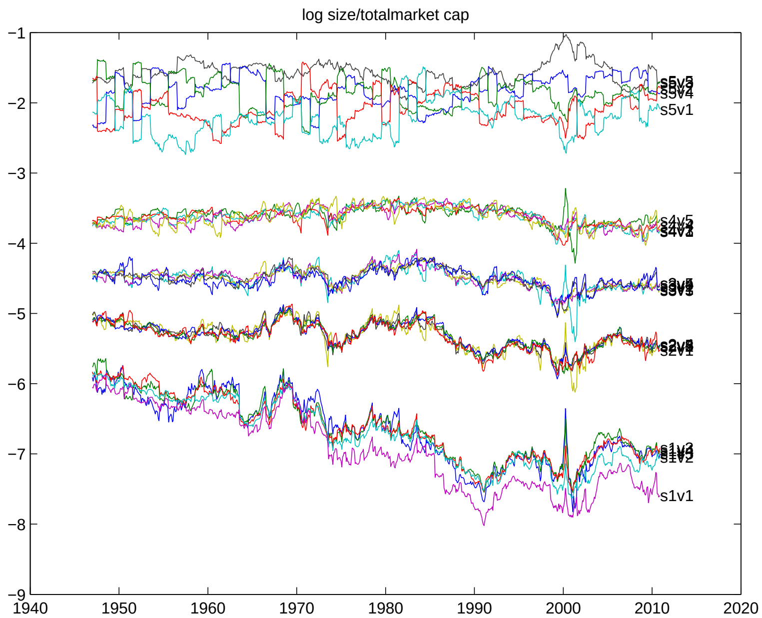
1. My bar plot of average returns is below, along with the fitted values.

a) here are my plots over time.



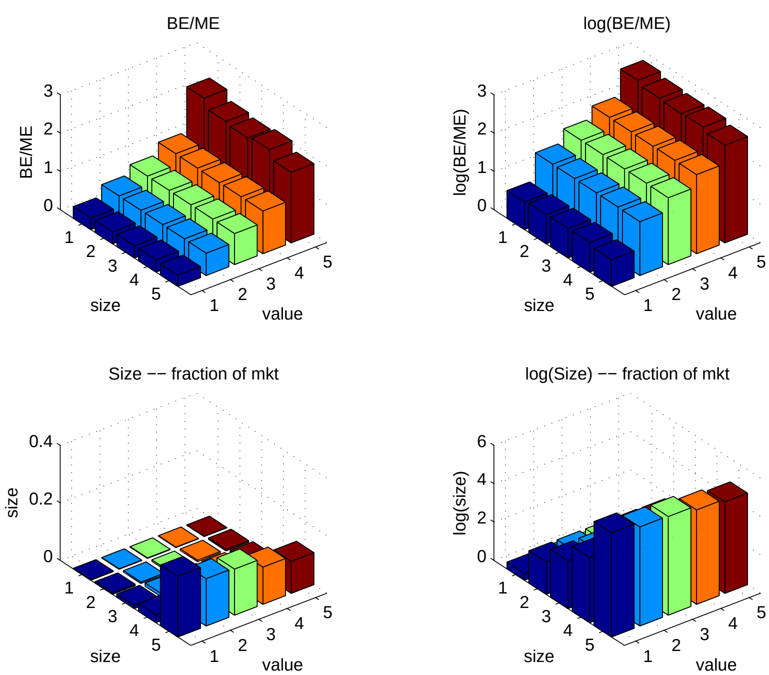


You can see the trend in log size. We can't use that as a stable relationship across time, and its time average in a pure cross sectional regression doesn't mean that much either. Here's my plot of $\log(me_i/\sum_i me_i)$



There is a bit of a trend that small stocks have gotten smaller, but I'm content to leave this one as with beme for now. Regressions that forecast returns over time with portfolio dummies will still be very affected by these trends, and will mostly capture any slow decline in returns of the s1 portfolio relative to the others. But maybe that's there. The jumps in the large/cap sizes across value categories when the latter are reformed seem to be real, but need more investigation.

b)



Here is my plot of average size and BEME. A not so unsubtle hint to take logs, as Fama and French did, so you have right hand variables that are linear across portfolios just as the left hand variable (expected returns) seems to be.

Alas, this plot shows that the variation in beme across size portfolios and the variation in size across beme portfolios is nearly nothing. That means average size and beme are pretty much a linear function of portfolio number. Later, we'll need a cross effect, which more variation across the buckets might have avoided.

c)

Here are my cross sectional regressions and two sets of plots. The "a" are errors, average returns minus the fitted values, the same as the "errors" in the first plot.

We see in the first plot of $E(R^e)$ the standard picture of a strong value effect, and a modest size effect, together with a bit of negative size effect in the growth stocks.

Top right, and second row. Fitting that with size and book to market separately gives a strong value effect but a small and statistically insignificant size effect.

A cross term is a natural idea. I added that in the third row, and you see it's very significant, and leads to a good deal smaller a's. In the bottom left graph you see that allows for the negative size effect in growth and the positive effect in value. The last graph of errors shows we're still missing the small growth premium and a little bit of the size effect in the blue portfolios.

The second plot gives a sense of the improved performance with a cross term. You see the better performance in the left (growth) and right (value) portfolios across size by letting them have different size coefficients. I included error bars in this plot, which give you a sense that we might be pushing too hard here!

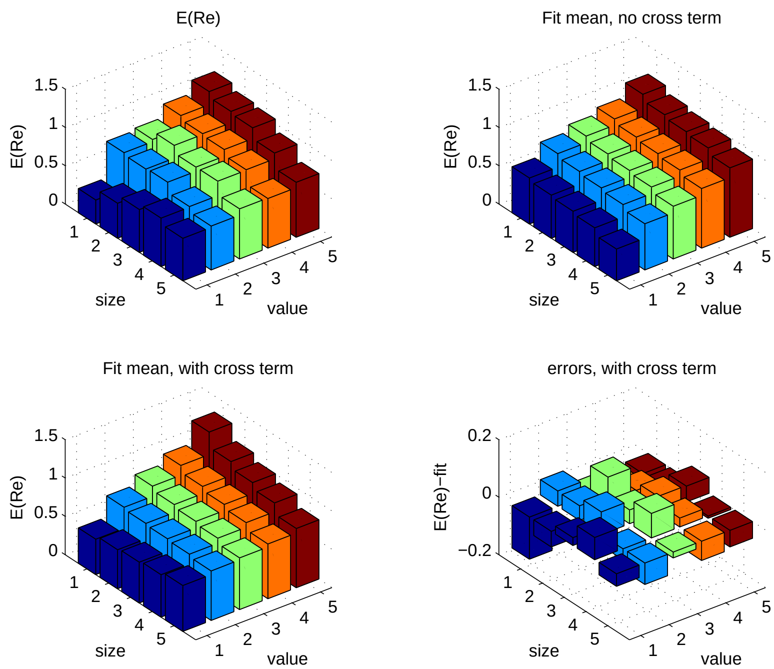
The extra rows of regressions include my efforts to explore the specification. Row 4 checks the standard errors by using fama macbeth. Row 5 tries $E(\log(beme)\times\log(size))$ rather than $E(\log(beme))\times E(\log(size))$. You can see it makes no difference.

Rows 6 -8 explore dropping the linear terms with the cross term. You can see in 7 that size and the cross term are almost exactly as good as all three terms. That seems a useful simplification.

```
Data sample
    194701      201012

             const     beme     size   bm x s   rmse_a      |a|

1.      b    0.845    0.259                      0.112    0.094
        t    4.857    4.088

2.      b    0.687    0.253   -0.035             0.096    0.073
        t    4.121    3.868   -1.124

3.      b    0.592   -0.039   -0.056   -0.065    0.066    0.056
        t    3.454   -0.410   -1.817   -4.193

by FMB with same right hand variable at each date
4.      b    0.592   -0.039   -0.056   -0.065    0.066    0.056
        t    3.454   -0.410   -1.817   -4.193
```

cross variables not means

		const	beme	size	bm x s	rmse_a	|a|
5.	b	0.587	-0.041	-0.057	-0.065	0.066	0.056
	t	3.426	-0.439	-1.861	-4.213		
6.	b	0.843	0.114		-0.033	0.105	0.090
	t	4.813	1.009		-1.316		
7.	b	0.605		-0.053	-0.057	0.067	0.056
	t	3.702		-1.771	-4.428		
8.	b	0.836			-0.054	0.109	0.091
	t	4.855			-4.036		



The bottom graph here includes one-standard error bars for mean returns, suggesting that I may be looking too hard for a specification. It's not obvious that the small growth anomaly is that significant. Of course, that's really a question of differences of returns not levels of returns. The right hand panel actually shows two ways of doing it, solid and triangles. They are almost exactly the same. This shows that dropping the bm factor in the presence of the cross-term is pretty good.

2. The first step is

$$\begin{aligned} E(R^{ei}|C) &= a + b' \left[E(\ln bm_i) \quad E(\ln me_i) \right] \\ b_i &= c_b + d_b' \left[E(\ln bm_i) \quad E(\ln me_i) \right] \\ h_i &= h_b + h_b' \left[E(\ln bm_i) \quad E(\ln me_i) \right] \\ s_i &= c_s + d_s' \left[E(\ln bm_i) \quad E(\ln me_i) \right] \end{aligned}$$

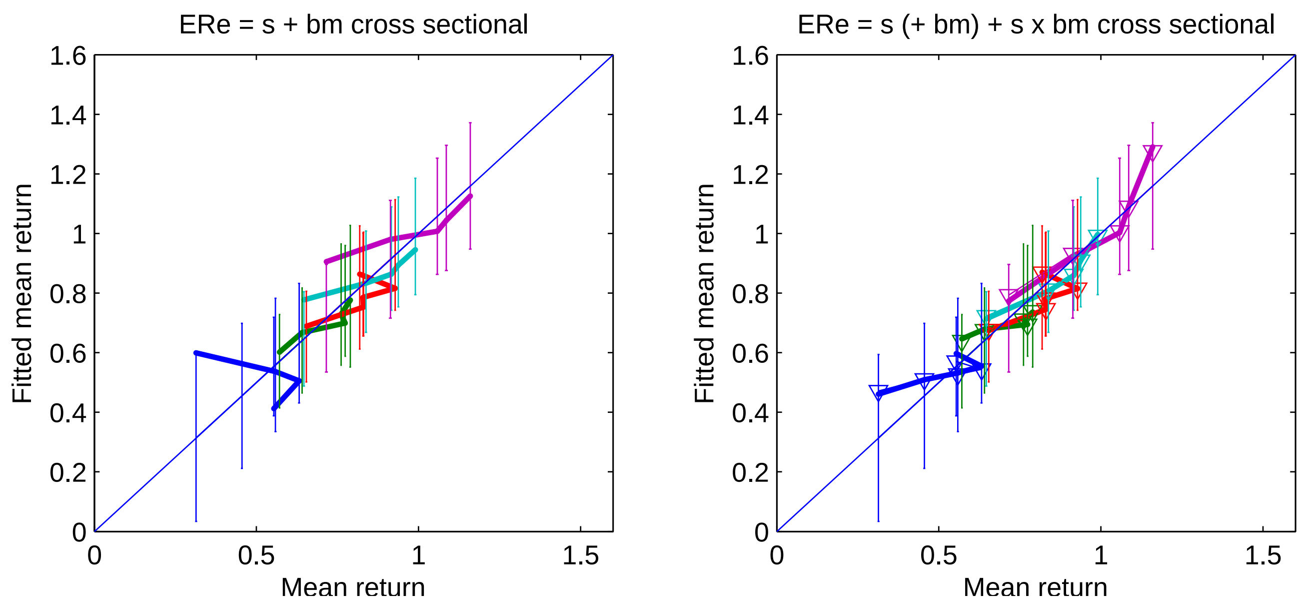


Figure 1:

First, run the standard 25 time series regressions to get a_i, b_i, h_i, s_i, then run cross sectional regressions to characterize how the betas line up with those characteristics. We're fitting unconstrained *betas* as we fit unconstrained *means* before.

As you see below, we get a clear picture – b is a constant 1.026 plus very small size and bm slopes. h has a strong bm slope and s has a strong size slope. Note size has a wider dispersion, so coefficients will be smaller. We're fitting with the characteristic value, not with the portfolio number.

Next, a reminder, the cross sectional regression of mean returns on size and bm, with the strong bm slope and smaller size slope.

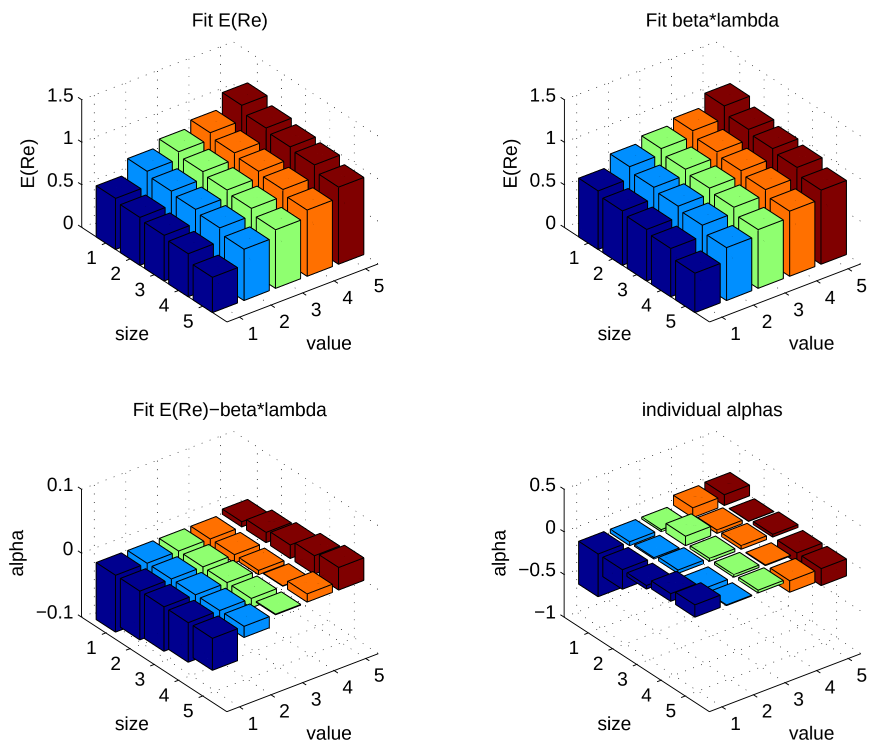
Now, how well do the beta rows, weighted by factor risk premia, line up with the Er row? Pretty darn well, I'd say! the b*l row is nearly the same as the Er row. This is the sense in which FFs' model does nicely.

The difference between the cross sectional Er coefficients and the cross sectional beta coefficients is the implied $\alpha(C)$ function. Note it is the same here as the fitted regression of alphas on characteristics. So this is the model's failure. These loadings are not zero, and add up to a small growth puzzle. But they are an order of magnitude smaller than the loadings of expected returns or betas, which is what we argued looking at FF's table.

```
 betas
using size and beme
              const     beme     size   bm x s
cross sectional regression of betas on characteristics
        a     0.026    0.049    0.008
        b     1.026   -0.014    0.004
        h     0.490    0.600    0.009
        s    -0.807   -0.104   -0.296
cross sectional regression of means on characteristics
       Er     0.687    0.253   -0.035
```

```
sum of betas weighted by factor risk premia
      b*l    0.661    0.204   -0.043
 Er-  b*l    0.026    0.049    0.008
        a    0.026    0.049    0.008
```

Here is a picture



You can see the pattern of betas is very similar to the pattern of mean returns. Watch the vertical scale! The alphas are all less than 10 bp! The individual alphas are much larger, with the small growth alpha the usual - 50bp. That's because the fit $E(R^e)$ didn't match the individual mean return of this portfolio. This technique *cannot* pick up an idiosyncratic failure like the small growth portfolio, unless your mean return model is sufficiently flexible to pick that up.

Are the alphas jointly zero? Is the expected return function statistically different from the covariance function? There's lots to do here!

Variations

I tried it using both size, beme and the cross term. You see the same patterns in the betas. However, the b*l does not show the same pattern as ER. I think these right hand variables are too correlated, so the individual coefficients are poorly measured.

```
using size beme and cross term
             const     beme     size   bm x s
cross sectional regression of betas on characteristics
```

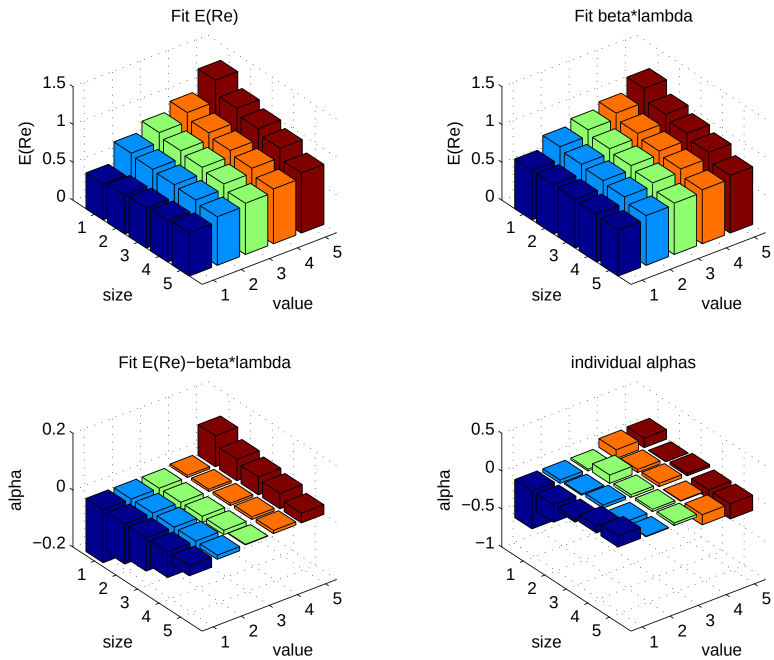
```
       a   -0.117   -0.388   -0.022   -0.097
       b    1.057    0.081    0.010    0.021
       h    0.545    0.766    0.020    0.037
       s   -0.755    0.053   -0.285    0.035
cross sectional regression of means on characteristics
      Er    0.592   -0.039   -0.056   -0.065
sum of betas weighted by factor risk premia
     b*l    0.709    0.350   -0.033    0.032
 Er- b*l   -0.117   -0.388   -0.022   -0.097
       a   -0.117   -0.388   -0.022   -0.097
```

Here are the results using my "preferred specification" with log size and the cross term. Once again, b is just a constant. h loads on the bm*size and negatively on size, to give a bm loading, and s loads on size. The Er looks very much like the B*l, with a slight difference in the $bm \times size$ loading which is where we'll see alphas. The alpha loadings are much smaller than the Er and beta loadings, again showing the sense in which the model "works."

```
using size and cross term
             const     beme     size   bm x s
cross sectional regression of betas on characteristics
       a    0.013              0.003   -0.021
       b    1.030              0.005    0.005
       h    0.288             -0.029   -0.112
       s   -0.773             -0.288    0.025
cross sectional regression of means on characteristics
      Er    0.605             -0.053   -0.057
sum of betas weighted by factor risk premia
     B*l    0.591             -0.056   -0.036
  Er-B*l    0.013              0.003   -0.021
       a    0.013              0.003   -0.021
```

Here is a plot, using the last specification. Fit E(Re) is the fitted value from the characteristic regression. Fit beta*lambda gives the fitted values of the betas, added up so the units of the results are average returns. The model "works" to the extent that the top two graphs are the same. The bottom left gives the difference, the characteristic function fitted alpha. As you can see, *there wasn't quite as much "cross term" in the betas as there was in the expected returns, so the alpha function loads on the cross term.* The individual alphas reflect some of this pattern. (Note change in scale). But the huge small growth anomaly is something the "smooth function of characteristics" prior won't allow.

This plot like all the others should really be a function of characteristics, not of portfolio number. Alas, I'm not good enough with matlab graphics to do those 3d plots, and fortunately these portfolio numbers seem pretty linear in characteristics.



3.

FORECASTS -- using BM only

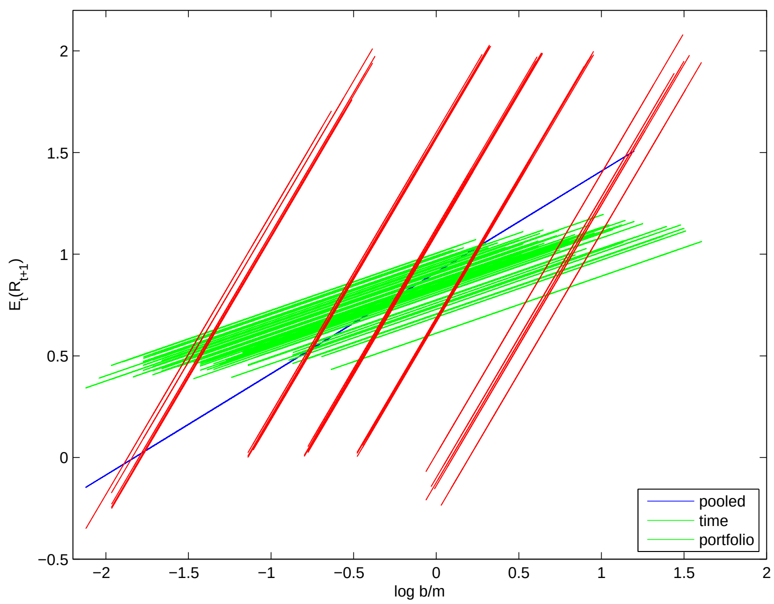
	const	beme	size	bm x s	R2
cross-sec	0.845	0.259			
pooled forecast estimates					
coeffs	0.911	0.498			0.437
t	5.162	4.180			0.437
time dummies					
coeffs	0.775	0.281			0.112
t	4.397	4.515			0.112
portfolio dummies					
coeffs	0.775	1.382			0.716
t	4.416	2.722			0.716
check -- individual portfolios (means portfolio dummy)					
avg coeff	1.107	1.400			0.749
avg t	3.304	2.276			

The pooled regression gives a coefficient twice the cross section! Why? The time dummy regression is almost the same as the cross section, but the portfolio dummies regression is much higher.

Message *variation in one portfolio's bm over time is a much stronger signal about expected returns than is variation in bm across portfolios.*

One strong reason for this is industry effects. Book value means different things in different industries. Others have found that the value effect is much stronger within industries than across industries.

As a way to see this visually here is plot of bm vs. expected returns across the three ways of doing it (portfolio should be red in the legend)



FORECASTS -- using BM and SIZE

	const	beme	size	bm x s	R2
cross-sec	0.687	0.253	-0.035		
pooled forecast estimates					
coeffs	0.731	0.495	-0.040		0.452
t	4.040	4.116	-1.232		0.452
time dummies					
coeffs	0.775	0.275	-0.037		0.124
t	4.397	4.284	-1.176		0.124
portfolio dummies					
coeffs	0.775	1.582	-0.849		0.878
t	4.423	3.138	-2.169		0.878
check -- individual portfolios					
avg coeff	-6.124	1.808	-1.533		1.059
avg t	-0.939	2.662	-1.231		

What happens with beme and size? Again, time dummies give almost the same answer as the pure cross section, but portfolio dummies are much stronger.

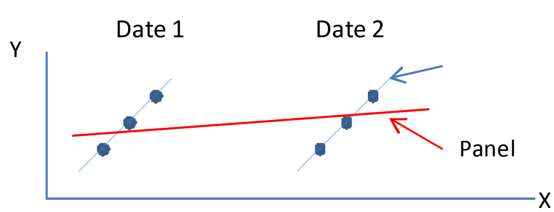
FORECASTS -- using size, BMxsize

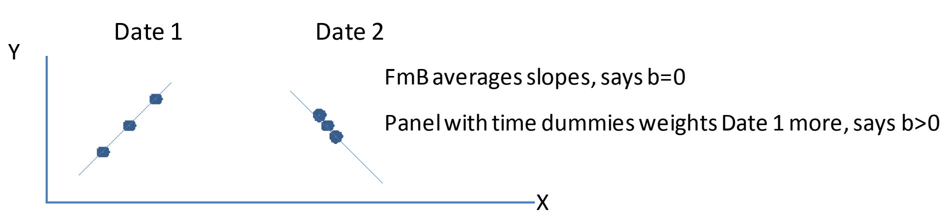
	const	beme	size	bm x s	R2
cross-sec	0.605		-0.053	-0.057	
pooled forecast estimates					
coeffs	0.558		-0.077	-0.105	0.468

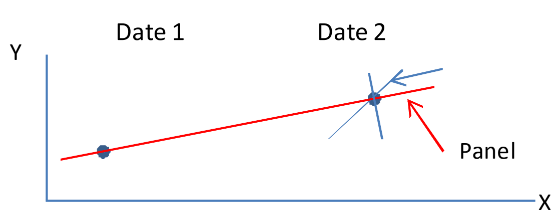
```
       t      3.289              3.289   -2.497   -4.340
       t      0.468 time dummies
  coeffs      0.775             -0.058   -0.062    0.149
       t      4.397              4.397   -1.956   -4.955
       t      0.149 portfolio dummies
  coeffs      0.775             -1.102   -0.340    0.889
       t      4.424              4.424   -2.688   -3.241
       t      0.889 check -- individual portfolios
 avg coeff   -6.753             -1.698   -0.440    1.049
 avg t       -1.042             -1.322   -2.638
pooled forecast estimates
 lambda      0.623                                0.186   -0.064   -0.069    0.169    0.138
pooled forecast estimates
 lambda      0.623                                0.186   -0.064   -0.069    0.169    0.138
```

What happened with my favorite specification? More of the same

Note: FmB regression with a constant each period uses only cross sectional information, and it's not exactly the same thing as a pooled regression with time dummies. Consider the following two examples. In the top, FmB has an intercept each date, so only uses cross sectional information. You might think that FmB is the same as a panel with time dummies, but that's not quite right either. The second example illustrates. FmB does an unweighted average of slopes. Panel regression with time dummies will of course pay more attention to dates with a bigger spread of x data. The final example hammers home the point. Suppose there were no beta (X) spread on any day, but x and y were associated over time. FmB of course could not measure the slope. (Of course you couldn't put in a full set of time dummies either.)







The lesson of all this is *understanding the source of variation in panel data regressions with dummies, fixed effects, and controls is really hard!*

Readings questions

Dissecting anomalies

1. New anomaly variables might just be proxying for value. For example, high B/M companies should have low investment (Q theory) so if investment forecasts returns, that fact might just be a proxy for the value effect. In Table II, do Fama and French control for this somehow?

   A: they are "characteristic-adjusted", explained 1658 below II. sorts. This means, find the portfolio of 25 size/book/market whose size and B/M are closest, and subtract off that return. The text says that true size and book/market alphas gives similar results, though since there are some big alphas (small/growth) separating average returns and betas in the 25, I'm not alltogether convinced. OTOH, FF argue that individual-stock hml, smb betas are measured badly and wander over time. Thus, they say, the characteristic is a better measure of beta than beta itself. Anyway, read the table as FF's ideas about alphas *after* controlling for size and b/m.

2. Why are the t- statistics for the High-Low portfolio so much better than for the individual portfolios? Is this cheating?

   A: We're really not that interested in whether portfolio excess returns are different from zero. We want to know if they're different *from each other*. If all averages were equal to each other but different from zero, it wouldn't be that interesting. Each portfolio could be within a standard error of zero, but if the long-short portfolio is significant, you have a trading strategy/anomaly.

3. Which anomalies produce strong average returns for all three size groups? What numbers in Table 2 document your answer?

   A: read 1662 pp3. Issues, accruals, and momentum. Look at the High-Low number. Look for consistency across 4 size groupings, and consistency across VW and EW results.

4. Which anomaly gives the highest Sharpe ratio in Table 2?

   A: $t = E(R)/\left(\sigma(R)/\sqrt{T}\right); E(R)/\sigma(R) = t/\sqrt{T}$. To annualize $E(R)/\sigma(R)_{annual} = \sqrt{12} \times t/\sqrt{T} = t/\sqrt{T_{years}}$, $\sqrt{T_{years}} = \sqrt{42.5} = 6.52$. Thus, a $t = 3.26$ translates to the market Sharpe ratio 0.5, and a t=6.52 translates to a Sharpe ratio of 1. Hedge funds think they can find Sharpes of 2 or more – good luck. Most of the ts are between 3 and 5, especially if you only look at big firms.

5. The Profitability sort seems not to work in Table 2. (Point to numbers). How did people think it was there? (Hint: 1663 pp2)

   A: 1663 pp2 *With controls for cap and B/M.* There is a profitability effect on its own, but size and B/M pick it up. This is a good instance of the point of the paper – what works *in the presence of the others*, what has *marginal* power, what is the *multiple* regression forecast of returns, not each variable at a time.

6. On p. 1163, FF ask "Which anomalies are present in all size groups and produce returns that vary systematically from the low to the high ends of the sorts?" and they note that stock issues do not satisfy that criterion. Why is this important? How does Table III illuminate the issue?

   A: Graph in class. The 1/5 of extreme values of any distribution is way spread out. Thus if expected returns are linear in issues, we expect to see that the middle quantile portfolios have less variation. Thus, I think it's a lot less important than they do. On the other hand, they make a good point that information in the extremes is dominated by small, high volatility companies. It's an indication that the behavior is driven by microcaps or outliers.

7. p. 1667. "The novel evidence is that the market cap (MC) result draws much of its power from microcaps." What numbers are behind this conclusion?

   A: This is the disappearance of the size coefficient in the other groups in the top left part of Table 4. Note size is also much weaker post 1979 – when the effect was published and small stock funds started. (not in this paper)

8. What is a "good" pattern of results in Table 4? Which variables have it, and which do not?

   A: We're looking for a large coefficient and t stat, and we want the coefficient to be consistent in the size groupings. Issues, momentum, and positive accruals do.

9. Asset growth and profitability have nice big t stats in the top rows of Table 4. Yet FF dump on them Why?

   A: look at the size groupings – it only works for tiny stocks.

10. P. 1675, FF say "the evidence from the sorts and the regressions is consistent with the standard valuation equation that says that controlling for B/M, higher expected net cash flows (earnings minus investment, per dollar of book value) imply higher expected stock returns." Isn't this the fallacy that "profitable companies have higher stock returns" , or "confusing good companies with good stocks"?

    A: Note the crucial "holding B/M fixed." Holding price fixed, anything that forecasts cashflows must also forecast returns. Go back to our linearized present value formula,

    $$p_t - d_t = E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} - E_t \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}$$

    The fallacy is that high Δd_{t+j} means nothing about r, because it just means high $p - d$. But *holding p-d constant* high Δd must also come with high r. In that sense, the cashflow variables can be thought of as "cleaning up" B/M for the fact that B/M forecasts both cashflows and returns. *There are lots of cleanup variables in the cross section.*

11. Do these new average returns correspond to new dimensions of common movement across stocks, as B/M and size corresponded to B/M and size factors? (Warning, this is a bit of a trick question)

    A: This paper does not go on to do the next obvious question: do we now have 5 or 6 factors? Do we need a "new issues factor?" *Low-hanging fruit: ok, we know there are new dimensions of ER not captured by size, b/m and momentum. Do these correspond to known $cov(R, f)$ or do we need a new-issues HML factor etc.? Are we going to have new factors for every anomaly?*

12. What is the highest Sharpe ratio you can get from combining all these anomalies and exploiting them as much as possible? (Also a trick question)

    A: Again, we don't know without knowing a) are there new common factors b) how correlated are the new common factors. Low hanging fruit!

Value and Momentum Everywhere

1. For stocks, value is price/book. But there's no "book" for commodities. How to Asness et al measure "value" for commodities, currencies, and bonds?

   A: See the bottom of p. 10. Lagged 5 year returns for commodities. The strong association between reversal and value in FF Multifactor anomalies makes sense of this idea. Currencies are also a 5 year return minus interest differential. An alternative might have been PPP. Bonds are the real yield.

2. Is the alpha in Table 1 with respect to the CAPM or the FF 3 factor model?

   A: MSCI world index

3. What is the RW factor in Table 1?

   A: p. 11. It's like a "factor," meaning the weights are not just zero-one, but are proportional to a characteristic. However, the characteristic is the rank not the numerical value of the characteristic. This is very interesting – it's a way of chopping off the tails, which FF worry a lot about. Maybe functions of rank rather than functions of the numerical value of the characteristic makes sense!

4. Asness et al link the poor performance of momentum in Japan to the strong performance of value. How?

   A: That's the whole point. The two are negatively correlated. So there is one puzzle, a strong realization of the "long value, short momentum" factor in Japan.

5. How does the "combo" portfolio do so much better than value and momentum alone? After all, the mean return of a portfolio is the average of the mean returns of its constituents.

   A: But the variance is not. Value and momentum are negatively correlated, the whole point

6. p. 15 says "The last row of Panel A of Table 1 shows the power of combinbing value and momentum portfolios everywhere" and is proud of the larger Sharpe ratios. Are these Sharpe ratios indeed larger than what you'd expect if the individual strategies were uncorrelated?

   A. No. If the 4 strategies were uncorrelated we'd expect a doubling of the Sharpe ratio. In fact, it's much less than that. The real point of the table is that Sharpe ratios *do not* rise as much as you'd expect, so that the *rows are strongly positively correlated.*

7. What's the point of Figure 1?

   A. This is the loading on the first principal component of return, long value and short momentum.

8. Does the single "long value short momentum" factor explain average returns?

   A. It's a natural question. The words on the bottom pf p. 20 says no, we need separate (possibly orthogonalized) factors, but I'm having trouble tracking those words back to table numbers.

Lamont and Thaler

1. How are there two ways to buy Palm stock at different prices? What are the two prices?

   A:

   (a) p. 230. March 2, 2000 3com did an equity carve-out – 5% of palm sold in IPO, 3Com keeps 95%. 3Com shareholders to receive the rest of Palm in 6 months
   (b) Day before: 3Com = \$104.13. Day after: Palm at \$95.06, meaning 3Com should be at least \$145. Instead 3Com falls to \$81.81, for a -\$63 Stub!
   (c) This mispricing was widely noted yet persisted for months.

2. Do L&T claim to have found an exploitable arbitrage opportunity?

   A: p. 231, middle Short costs explain why arbitrage didn't eliminate the mispricing.

3. If there is no way to make money, how can they say markets are inefficient?

   A: Remember "inefficiency" = "prices don't reveal information" NOT "you can make money". The puzzle is *why are prices wrong in the first place*?

4. Is a short Palm / long 3Com position riskfree at a monthly horizon?

   A: No. It can go against you in the short run, becoming even more "overpriced." See p. 246, there is a substantial standard deviation of return. Table 4 CAPM. Yes, alpha.

   Note: A 10 year bond is riskfree at 10 year horizon, but has lots of risk at a monthly horizon. Every price drop means expected return rises. It's a mistake to evaluate bond risk at monthly horizon! Spread trades are the same – when they lose money they are better deals. (If you can hold them to maturity!) The risks are being closed out, or if you have a horizon shorter than the end point.

   (a) 245. CAPM evaluation Though it may be risk free in the end, there is substantial risk over 1 month, etc. horizon. The spread can get worse before it gets better (and does).
   (b) Still, though the arbitrage is not pure, the huge difference in price for (Palm) and (Palm + 3com) is weird. The big question: can small limits to arbitrage add up to huge difference in price? A: seems like yes, at least here.

5. How is "real world" shorting different from our frictionless textbook? What are the extra costs and risks?

   A: p.248 ff description of shorting process and my notes; p. 256 ff problems in shorting

   (a) Must borrow shares, typically from institutional investors.
   (b) Must post collateral – no "short x, buy y, no money out of pocket" This is why long-short funds need your money!
   (c) Interest rate rebate may be negative – you pay for the priviledge of borrowing–or there may be none to borrow at any price.
   (d) Then p. 256, bottom, lender has the right to call the loan at any time, forcing you to sell at a loss; you may have to post more collateral if the price rises, and rebate may increase.

       256ff:
   (e) Cost of finding a lender – Lending just after IPO is frowned on – supply of lendable shares is low. .
   (f) May need to post more collateral if Palm goes up
   (g) Palm lender might recall the loan, forced to close out the position
   (h) Cost of shorting may be high, and may increase at any time (daily loans)
   (i) *You cannot use short proceeds to buy stock – long/short is not a zero investment strategy in the real world. Hedge funds need investors to provide the collateral for a long-short trade.*

6. Why do they say a short constraint lead to overpricing? Would it ever make sense to buy a stock that you *know* is overpriced, and there is no chance that the price will rise further (no "greater fool")?

   A 249. The Miller theory that only optimists express their views. It's not so easy though – why don't optimists know this, and become less optimistic? It's a little better than morons, but static.

   A: p.249. It may be rational to buy an overpriced stock, if you can earn money from lending it out equal to its expected price decline. Still this does not answer why price is high in the first place. Someone has to buy overpriced shares! 250 "someone has to own the shares...not all owners can lend their shares."

7. Was there a lot of shorting in the "overpriced" subsidiaries? Was there more or less than in the parents? Did the sub shorting increase or decrease over time?

   A: Short facts

(a) Table 5 *huge* amount of shorting is in fact going on. The trouble is, there are not many shares outstanding.

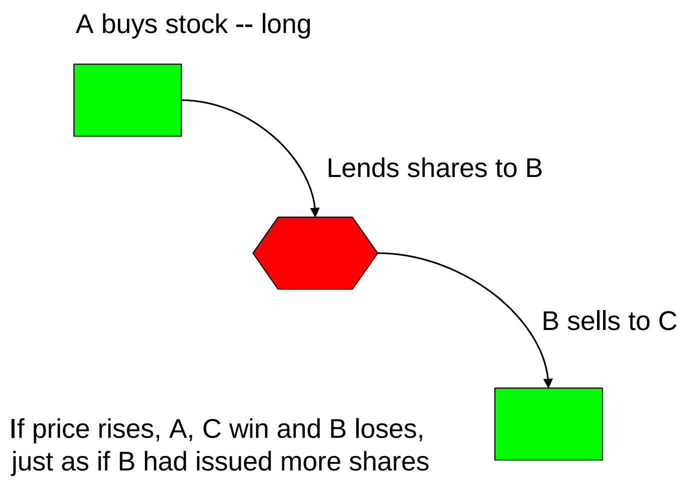
(b) It builds up over time. (compare 1st, second month).

(c) Who in the heck are the 2.6% *short 3Com???*

8. What do you learn from Fig. 5, 6?

A: Sort of seems like a "demand for shares" is at work - more shorting creates more supply, price discrepancy goes away. Note "demand for shares" should not exist in a frictionless market.

(a) 252. How shorting generates extra "supply of shares." (This is just like the way that banks "create money" from reserves.) This is how we get more than 100% shorted.



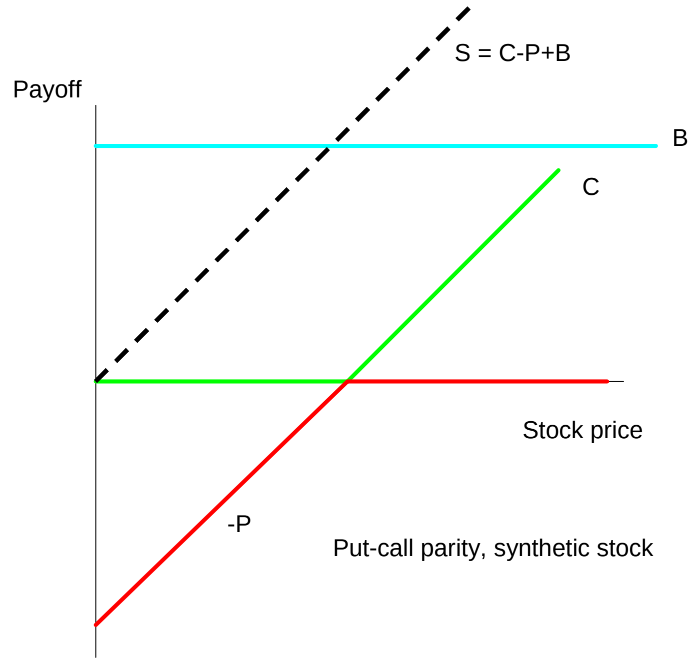
(b) Fig 5,6: As shorts rise, "supply of shares" increases, price declines!252 "One might interpret this pattern as roughly tracing out the demand curve for the overpriced subsidiary. As the supply of shares grows via short sales, ... the price falls.."

9. If we can't short, let's buy November (data of spinoff) puts, or create a synthetic short position in options markets. Will this work and if not why not?

A: Option market.

(a) If you can't short the stock, short calls/buy puts!

(b) Put call parity, "synthetic stock" reminder.



(c) Table 6 256: synthetic short at \$39.12 is much less than actual stock price at \$55.12. So much for arbitrageur shorting in the options market!

(d) Call price is less than put price!

(e) But why don't people who want to buy palm buy synthetic palm at \$39.12 rather than the real thing at \$55.12? Like buying 3Com instead, that's the puzzle! (Like "buy the cheaper generic" – a bit we can excuse but this much?) (note though: writing puts is hard) 257.

(f) Table 6. Nov at the money puts are more expensive than at the money calls! Reflects a lot of put demand, but can't write more puts and hedge the position, because you can't short stock.

(g) 260, middle: Back to the central point: *why is anyone buying Palm*? You can buy 3Com cheaper, you can buy synthetic palm cheaper.

10. How do turnover and institutional ownership of Palm compare to that of 3Com? What conclusions do L&T draw from these facts?

    A: Table 8., conclusions p. 262 Huge palm turnover, 37.8% per day much less for 3Com. (Smaller denominator though; *dollar* volume is not so different)

    JC: So nobody is in fact being a Moron and holding Palm for 6 months rather than buying 3com. And why do woefully uninformed morons change their minds so quickly? They admit, (261) on the "greater fool" theory. They see the slight differences in institutional ownership as indication of "morons."

11. p. 261 Is Palm more or less liquid than 3Com?

    A: This is an important and subtle point. Palm turns over more, but has higher bid/ask spreads. Let's not mix supply and demand! High turnover can come from a very low cost to trading with the usual demand for trading, or high turnover can come from a huge demand for trading despite high cost. I see the latter in Palm – it's trading a lot *despite illiquidity* not *because of liquidity.* Also high bid/ask spreads indicate a lot of asymmetric information – another indication of lots of "information trading"

12. What happened to 3Com price during this episode? What conclusions to L&T draw?

    A: 264, Table 9 263. Amazing fact that parents *decline* as sub explodes, even though they hold 95% of sub stock! This is a real challenge for frictionless pricing! They just say "mystifying" (p. 264) – it's central in my explanation!

Cochrane stocks as money questions and answers

1. According to Cochrane, how are money and bonds like 3Com/Palm ?

   A:

   (a) p. 4 Both are claims to $1 in 6 months/both are claims to Palm in 6 months, one is "overpriced"

2. How does the monetary/convenience yield view say overpricing is associated with

   (a) Turnover
   (b) Supply
   (c) Short sales constraints
   (d) "Specialness" of the security (Palm, money); presence of substitutes

   A: Mispricing comes with

   (a) Higher turnover of money. Nobody is in fact a moron. You hold money for at most a few weeks. And more mispricing = higher interest rates = more turnover. When interest rates are high, you take out less, go to the bank more often.
   (b) Restricted supply of money. When the Fed supplies less, interest rates go up, and like part a.
   (c) Binding short sales constraints. You can't print money. Banks can't expand checking accounts without reserves.
   (d) Money is special. It is required for transactions. If credit cards, foreign currency, other substitutes arise, mispricing is lower for a given money supply.

3. Is turnover associated with "overpricing" for 3Com/Palm?

   A: p. 5 (ms) Turnover is *huge.* See L&T, or Figure 2. 19% per day of Palm in first 20 days post ipo. 38% average *daily* turnover in all their cases (T8). 4.5% 3Com; 2% is typical. (Much of this reflects tiny denominator – small "float"). Figure 4: Volume is higher when price is higher. Figure 2. Notice the huge drop when 3com issues the remaining shares. There seems to be a demand for *dollar* not *proportional* volume. When there are only a few shares outstanding, that is a much larger *turnover.*

4. How much does a typical Palm investor lose by holding Palm, not 3Com? Is this "a lot" or "not much"?

   A: p. 6 At 1-5 day horizon, even this huge price error is only 0.2% loss per day. This is not "moronic" to a day trader. It's less than bid/ask spread; much less than typical weekly variation (Fig 3). p. 6: "Overpricing" means 2/10 percent per day drag; this is tiny compared to 7% σ of daily returns or 1% typical round-trip cost. *A day trader really doesn't care about even the huge Palm/3Com price difference.* As you really don't care about lost interest from $40 in wallet. Figure 3: .2-1% loss is trivial in the one - five day return distribution. (This is admittedly the "greater fool" theory – why do people want to trade so much? I don't know!)

5. What's the point of Figure 5?

   A: 8, Fig. 5 As massive shorting of small number of available shares increases supply, price goes down. Just like banks meeting money supply by creating checking accounts. This is the same as L&T's figure, with a different interpretation.

6. Wait, monetary theory says you are willing to put up with low returns on money because there is no substitute. If you want to bet on Palm, why not buy 3Com or use options instead? (Point to evidence here in Table 1, Figure 7.)

   A p. 10. Poor substitutes. (Crucial). *If you want to day trade you must hold Palm shares.* This is vital for a money-like explanation. If you can day-trade in 3com or the options market, there is nothing special about Palm shares. We need a special demand for *Palm* shares, not even these closest of substitutes.

   (a) Palm and 3com do move together – Figure 1.
   (b) But surprisingly little at the hourly, 1, 5 day horizon. (This is especially surprising since the entire value of 3com is Palm).
   (c) Evidence: Table 1, a) $R^2$of only $0.5 - 0.6$. b) $\sigma(\varepsilon)$ is the tracking error of buying 3com to bet on palm; it is half or more of the standard deviation of Palm. 11, bottom "At short horizons, Palm prices and 3Com prices are delinked."
   (d) Figure 7. Intraday evidence. Buying 3com is a *really* bad way of betting on Palm.

7. To Cochrane, the fact that 3Com *fell* is explained. How? What do Lamont and Thaler say about it?

   A: p. 13 Why did 3com fall? All the day-trade action betting on the future of Palm moves over to Palm stock. L&T are silent. ("mystifying")

8. What evidence does Cochrane give that this "money" story might apply more broadly?

   (a) The bubble was very concentrated, Figure 8; p. 17. Why should irrational enthusiasm apply only to a narrow category of stocks?
   (b) Volume was high where price was high, Figure 9,10. Fig 8, 9,10 *are the stars in the volume/price correlation.*
   (c) The same thing happened in 1929, Figure 11, for the market as a whole!
   (d) Price and volume are associated across stocks. Table 3
   (e) Ofek, Richardson: Bubble burst more generally as lockups expired, share supply increased.
   (f) Theory comparison p. 22: Only money accounts for everything, in particular the association of price with turnover.

9. Cochrane admits a big hole in the money comparison. What is it?

   A: why is there so much information trading in the first place?

Brandt and Kavajecz questions

1. Why might price and signed volume be correlated, beyond the simple "price pressure" "downward sloping demand" "theory?"

   (a) Macro announcement; prices change, no immediate volume. Volume follows as people rebalance.

(b) "Price discovery." People with ideas trade, markets move. (p. 2624.)

(c) "Price impact" downward sloping demand in any given market – "selling pressure".

(d) "Trend followers." Price changes, then afterward we see a lot of volume. (Like a, but 'piling on' rather than 'rebalancing')

(e) "Inventory"

2. How do B&K measure "orderflow?" You see a trade; how do you know if it's a "buy" or a "sell?" ("The market went up on a wave of buying" is a classic *fallacy* – for every buy, someone sold!)

   p. 2672 pp2, 2628 pp2, the data do include "who initiated."

3. Table IV: Central table. ***What does the number -0.72 in the top left corner of table IV mean? (This is a question about units – if x moves by what, what happens to y)

   A: see 2635, bottom. The units seem to be basis points of yield on orderflow relative to standard deviation. Thus, a one standard deviation move in 0-6 months orderflow means -0.72 bp movement in yield. He says this is a lot (?)

4. (Overall, how much of the unexpected daily change in yields is accounted for (notice I'm not saying "caused by"!) orderflow?)

   A: R^2 values around 0.15 in Table IV

5. There is a pattern in the coefficients of Table IV – which orderflows are most important for explaining each kind of yield change?

   A: 2637, top. It's own orderflow, and also the 2-5 year flow. Brandt interprets this as a "bell-weather" effect of the 5 year bond.

6. Is the orderflow effect stronger or weaker on days with big macro announcements? Why do we care?

   A: Weaker, see "all days adj R2" and discussion 2637. On macro announcement you get big price changes with no trading. This means price discovery, not rebalancing.

7. How well would you do forecasting yield changes with one "order flow in all maturities" variable, rather than separate order flows?

   A: Last column; TIV 2636. Almost as well. The bond-specific order flows don't really matter all that much.

8. What is the "inventory premium" view of the correlation between orders and price changes?

   A: p. 2640. For traders to stick around and absorb (say) big sales, the big sales must depress price a bit, so that the traders make a bit of money.

9. (The most important question) Overall, what three pieces of evidence lead Brandt to a "price discovery" view of the impact of order flow on prices, rather than the simpler view that "selling pressure does reduce prices after all" or there is an "inventory premium". (Hint: Tables IV VI and VII matter here as well as Brandt's discussion.)

   A: 2640-2641.

   (a) The fact that *other* bond's order flow (2-5) so significantly affects *this* bond's price in Table IV.

   (b) The fact that numbers in T IV are larger for liquid on the run rather than illiquid off the run. Inventory premiums should be higher in illiquid markets.

   (c) More strongly in VI, off the run bond yields respond to *on* the run order flow.

(d) VII no response to one-day lagged – no "recovery" following a "depressed" price (as Carhart found for the bounce back after mutual fund last minute sales.) i.e. The fact that orderflow imbalances are associated with *permanent* rather than temoporary price changes.

10. Note