I. Summary

II. Comments

- G7 countries, 1980-2010
- Two variables of interest:
  - GDPG ≡ GDP growth
  - FS ≡ equity returns for important financial firms, relative to the market returns
- Aims:

  (1)construct conditional densities for GDPG and FS, and tell us how the lower tails shift over time

  (2)tell us how GDP and FS respond to certain “structural” shocks

(1)how the lower tails shift over time

Condition each of the two densities (i.e., density of GDPG and of FS) on:

(a)factors constructed from wide cross section of macro data

- ultimately use factors to construct time series of shocks

(b)own lags (i.e., GDPG(t-1) in GDPG equation, FS(t-1) in FS equation

Compare the weight in the left tail at a given date to the typical weight ("reduced form stress tests": Figure 3)

(2)how GDPG and FS respond to certain shocks

Apply Choleski decomposition to factors, then:

•Look at signs of response of certain macro variables to decide how to label the shocks (aggregate demand, aggregate supply, bank credit demand, bank credit supply)

•answer: seems that agg D + bank credit D are the right labels

•Compare responses in 1993-2007 vs. 1980-2007 to see how absolute value of response has changed ("structural stress tests"). Answer:

(a)For US, less resilience in a later sample: size of response has increased

(b)For other countries: more resilience

II. Comments

- Nice paper!

- On an important topic, and technically well done, interesting results

  - We would like to have advance warning of increase in tail risk

  - Use of quantiles (and factors) is nice way to incorporate multivariate information in density estimation

  - Allows flexible shape to density, for example skewness

- Increase in tail risk can come about because
    - whole distribution shifts down (to the left)–“mean shift”
    - increased spread of distribution–“variance shift”
- Typical linear models for GDPG or FS
    - certainly capture mean shift for GDPG, but absence of substantial GARCH-type effects implies that variance shifts–perhaps modeled via Hamilton regime changes–are hard to detect
    - certainly capture variance shift for FS, but noisiness of FS implies that mean shift is hard to detect

- This paper’s technique of estimating a conditional density potentially captures both types of shift, and does so in a flexible way

- This paper’s technique of estimating a conditional density potentially captures both types of shift, and does so in a flexible way

- My job as discussant is to focus on what I think might be done better, or explained better

- I first discuss the application to FS, then to GDPG

    - Not much connection in the paper between GDPG and FS; might want to split the paper in two

- I will direct all my comments on the results for the U.S.

- Virtually everything I say will be on (1)conditional densities and shifts of lower tails; I will have little to say on (2)responses to certain “structural shocks”

FS:

•My reading of prior literature on equity returns

- •mean: expected equity returns are hard to model

- •variance: low dimensional parametric models capture the major elements of the dynamics of stock return volatility.

Expand on each of these:

•Mean: It is unclear that this paper's approach–which leaves the expected return unconstrained–leads to densities with reliable implied means (implied expected returns). In the simple linear world, unconstrained equity predictions often are negative (e.g., Campbell and Thompson (2008)).

- Variance:
  - There is some evidence that variance shifts are plausibly captured by this paper; in particular, the lower panel of Figure 1 suggests that the estimates reflect the stylized fact that conditional volatility tends to go up in a recession.
  - Certain statistical tests fail to find fault with the estimated densities.
  - But in a horse race of macro factors vs: GARCH type models, with the goal being to accurately calibrate the size of the tail of the density of FS in future periods, which would win out?
  - Use of macro factors of course allows economic interpretation; the present approach would be more appealing if it were used to tell us about specific episodes.

- In sum: For FS, the authors need to make a better case for their approach.   Previous literature suggests to me that well established techniques may well do as well or better.

GDPG:

- The paper makes a strong case for its approach to estimation of tail risk.
    - There is also analysis of impulse responses, labeled "structural stress tests." I don't think the paper makes as good a case for its identification scheme or the interpretation it supplies.
- My reading of prior literature
    - Conditional means for basic macro variables are well modeled via factor models.
    - Well established models (such as regime switching) are awkward and not all that useful in forecasting (as noted above)

- The econometric technique (factors + quantiles) is a nice way to
    - incorporate multivariate information in density estimation
    - allow skewed distributions
- I make a few specific remarks, then a general comment.

•Certain statistical tests fail to find fault with the estimated densities.

•As a specific example, we see (Figure 3) an increase in weight in the tails in one quarter ahead densities in 2008:Q1 and 2008:Q3.

•What is the economic underpinning of this result: please trace the link from macro variables to factors to densities.

•It would be interesting to see the tail risk in 2008:Q3 and 2008:Q4

•I would like to see a multiquarter ahead density–say one or two years ahead, based in perhaps 2007:Q4: was there any hint of the disaster to come?

•More generally, if this paper's technique is applied on a sample that by good fortune has few big shocks, I would think the density and tail risk will prove unreliable ex-post, if asked to calibrate tail risk for a sample that ex-post has very big shocks.

- •For example, Chung et al. (2010) and Tamboletti (2010) construct confidence intervals, base quarter 2007:Q4, for multistep forecasts of the output gap or GDP growth, for certain structural and nonstructural models. The actual outcomes are
  - •amazing (well below 95% intervals) if Great Moderation samples are used
  - •surprising (barely within or barely outside 95% intervals) if Great Moderation regression parameters and pre-Great Moderation variances are used

•A practical roadblock to using this or any other technique is of course finding a sample that is representative of outcomes that might occur in the future.

In sum: on an important topic, and technically well done, interesting results.

I’m looking forward to future developments in this research.