Forecasting with Many Predictors
Examples in Finance and Macroeconomics

Bryan Kelly

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Frontier “big data” work is happening in other fields
- Stats/machine learning/data mining/computer science
- The great advantage of economics is its ability to understand mechanisms and equilibria that statistical correlations represent
- This is a huge opportunity for economists
Examples from My Work

1. Improved understanding of the “Equity Risk Premium”
   ▶ Relying on prices of many assets
2. Detecting systemic risk in the financial system
   ▶ Relying on many (weak) distress signals
3. Text data from financial print media, patents
Market Expectations in the Cross Section of Present Values

Bryan Kelly and Seth Pruitt

Journal of Finance, 2013
Some Background: Understanding the Equity Risk Premium
Background on Expected Market Returns

- Equity risk premium is the expected return of equity index in excess of risk free rate

\[ E[r_{t+1}] - r_f \]

- Equivalently, it determines rate used to discount equity

\[ P = E \left[ \frac{D}{r - g} \right] \]

- For a long time (until 30 years ago) we thought of this as constant
- This has changed. Theory and data suggest returns move in subtly predictable ways

\[ E_t[r_{t+1}] - r_{f,t} \]
Why do Expected Returns Vary?

- Why are EMH disciples ok with this?
- Need not be a violation of efficient markets....
- Theory: Investors require compensation for assets that are “risky”
- High compensation (lots of discounting) for assets that do poorly in “bad times” (think catastrophe insurance or short OTM puts on S&P 500)
- Conversely, willing to pay a premium for assets that do well in bad times. “Flight to quality” (think Treasuries, or long OTM puts on S&P 500)
Why do Expected Returns Vary?

- When risks changes, required compensation changes
- High risk $\rightarrow$ lots of discounting $\rightarrow$ high expected returns
- Implication: If risk is predictable, expected returns move in predictable way!
- Is this a free lunch?
- No. You can market time when ER is high, but must take on extra risk to capture that return

Implication: Expectations reflect required compensation given what we know today. In other words, $E_t[r_{t+1}]$ is a function of the risks that we perceive at time $t$
Who Benefits from Return Predictability?

- Is it all about risk compensation?
- Investor heterogeneity matters. If you’re less risk averse than the typical investor, you can indeed profit from predictability in returns.

- What about “mispricing”?
- Expected returns can come from “beta” (risk compensation) or “alpha” (being smarter than the next guy).
- Research suggests lots of correlated errors by investors.
- These may also be predictable.
Where Are We?

- Expected returns likely to move in predictable ways
- Some investors may be able to profit from it
- Measurement is the crux
Measurement and Pitfalls

- **History**
  - Returns of the future will look like returns of the past
  - Pitfall: Economies evolve
- **Data mining**
  - Pitfall: Out-of-sample? Can we trust data-mined forecasts?
- **Theory**
  - Pitfall: Over-simplification?
- **Leading indicators**
  - Theory + history
  - “Guided” data mining
The Leading Example of a Leading Indicator

- Predicting market returns with market valuation ratios
- Ratios include $B/M$, $P/D$, $P/E$, ...
- Motivated by theory
  - Value investing rationale
  - Gordon Growth Model: $P = E \left[ \frac{D}{r-g} \right]$
- In all cases, can manipulate into the general form

$$\text{val ratio}_t = \text{expected future returns} + \text{expected future cash flow growth}$$

- Gordon model example:

$$\log D/P_t \approx E_t[r_{t+1}] - E_t[g_{t+1}]$$

- Turns out to encompass many economic theories for $r$ and $g$.
- $B/M$, $P/D$, $P/E$ ... all capture the same information
How Good Are Aggregate Valuation Ratios?

Figure 1. Dividend yield and following 7-year return. The dividend yield is multiplied by four. Both series use the CRSP value-weighted market index.

Source: Cochrane (2011)
How Good Are Aggregate Valuation Ratios?

- Use $B/M$ for value-weight US market portfolio 1927-2010...
- ...to forecast that portfolios return 1 month, 12 months ahead

<table>
<thead>
<tr>
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<th>$b$</th>
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<tr>
<td>1 Month</td>
<td>0.02</td>
<td>3.4</td>
<td>0.7%</td>
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<tr>
<td>1 Year</td>
<td>0.20</td>
<td>3.1</td>
<td>9.2%</td>
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- A $1\sigma$ increase in $B/M$ forecasts...
  - ... 0.5% higher return next month
  - ... 5.5% higher return next year
  - ... 0.7% monthly $R^2$ increases Sharpe ratio 20-30%
- Predictive power grows with horizon: $R^2$ of 40% at 5 years
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- Predictive power grows with horizon: $R^2$ of 40% at 5 years
- Reality check: This is in-sample
How to Test Out-of-Sample: Recursive Procedure

Let the data be arranged as:

\[
\begin{pmatrix}
 r_2 & \cdots & r_{t-1} & r_t & r_{t+1} & r_{t+2} & \cdots & r_T \\
 v_1 & \cdots & v_{t-2} & v_{t-1} & v_t & v_{t+1} & \cdots & v_{T-1}
\end{pmatrix}
\]

For each \( t \):

1. Split sample into estimation period and test period
2. Run forecasting regression in estimation period to get predictive coefficient
3. Fix this coefficient, and evaluate how this rule would have worked during test period (summarized as an OOS \( R^2 \))
Out-of-Sample $R^2$ (%) by Sample Split, Monthly Returns
Out-of-Sample $R^2$ (%) by Sample Split, Annual Returns
The Summary Academic View (circa 2010)

- Cochrane (2011 *JF*)
  “The central fact: *High prices, relative to dividends, have reliably preceded many years of poor returns. Low prices have preceded high returns.*”

- Goyal and Welch (2008 *RFS*)
  “...by and large, these [forecasting variables] have predicted poorly both in-sample and out-of-sample for 30 years now; these models seem unstable, as diagnosed by their out-of-sample predictions and other statistics; and these models would not have helped an investor with access only to available information to profitably time the market”

- Where is the tension? Methodology, interpretation, hypotheses
Why the Difference in Conclusions?

- One important reason: In-sample vs. out-of-sample tests
  - Testing for existence – do not run out-of-sample tests
  - Formulating a trading strategy with real capital at stake – run (lots) out-of-sample tests
- A truly robust phenomenon would show up both IS and OOS if there’s enough data
  - Otherwise, the IS test tends to be more powerful
- Macro/finance = scarce data (one time series) / can’t run experiments
- This is why Cochrane relies on IS tests, but why a practitioner would question reliability
Which Predictor Variables?

- Valuation ratios
  - B/M, P/D, P/E, CAY, I/K
  - These do not link to business cycle directly, but *mechanically* link with time variation in risk premium

- Credit
  - E.g. term spread (10yr-3mo), default spread (BAA-AAA), T-bill

- Other
  - Net issues, dividend payout, tail risk

- Notable non-results
  - Volatility, “real”/business cycle variables, sentiment measures

- For *all* of these, IS vs. OOS tension remains
Overview: The Idea in Kelly and Pruitt (2013)

- Present value relation: prices, discount rates and future cash flows
  \[ \text{val ratio}_t = \text{expected future returns} + \text{expected future cash flow growth} \]

- Aggregate \( PD, BM \) among most informative predictors
  - Forecasts 10% in-sample annual return variation (1% of div growth)
  - Nothing out-of-sample

- Drastic understatement of price and cash flow predictability

- Key: *Use the cross section of value ratios*, but mind parsimony
Overview: Our Approach

- Cross section of asset-specific valuation ratios is latent factor model, relate factors to aggregate expected returns and cash flows

  Example: \( v_{i,t} = a_i - b_{i,\mu} \mu_t + b_{i,g} g_t + e_{i,t} \)

- Intuition: Same state variables driving aggregate expectations also govern dynamics of entire panel of asset-specific valuation ratios

- Partial Least Squares: Easily-implemented OLS-based approach to estimating latent factor that is optimal for forecasting

- Parsimony: Univariate predictor
We predict...
  ▶ ... aggregate US market returns (1 month and 1 year)
  ▶ ... aggregate US cash flow growth (1 year)
  ▶ ... characteristic-sorted US portfolio returns (1 month and 1 year)
  ▶ ... world index returns (ex-US)

We form our predictions by applying PLS to the cross section of...
  ▶ ... portfolio-level book-to-market ratios
  ▶ ... stock-level book-to-market ratios
  ▶ ... stock-level moving average price ratios
  ▶ ... country-level book-to-market ratios
Overview: Results

Annual forecasts from 25/100 portfolio BM ratios
- 10% of out-of-sample variation in market returns (25% for div growth)
- Similar for returns on characteristic-sorted portfolios

Monthly forecasts from 25/100 portfolio BM ratios
- 1% out-of-sample for market returns, characteristic-sorted portfolio returns

Monthly forecasts from individual stock price ratios
- 2% out-of-sample for market returns

Monthly forecasts from country-level BM ratios
- 2% out-of-sample for world index (ex-U.S.) returns

Conclusion
- Market returns much more predictable (hence expectations more volatile and less autocorrelated) than shown previously. Contrast with stable and persistent conditional expectations implied by standard models
The Forecasting Problem

Use cross section information...

\[ v_{i,t} = \phi_{i,0} + \phi_i F_t + \epsilon_{i,t} \]

...to forecast...

\[ r_{m,t+1} = \mu_t + \eta^r_{t+1} \]
\[ \Delta cf_{m,t+1} = g_t + \eta^c_{t+1} \]

→ How to estimate predictive factors \( F_t \)?
How Our Approach Works: The Intuition

- We have many predictors, $v_i, \ i = 1, \ldots, N$
- Run a separate predictive regression for each predictor
  \[ R_{t+1} = a + b_i v_{i,t} + e_{t+1} \]
- $b_i$ summarizes predictive strength of $v_i$
- Form a “super” predictor that is a weighted average of all the predictors
- Weights are given by $b_i$ (impose weights sum to one)
- Can show that this approach has excellent statistical properties
- Key property is parsimony. Parsimony $\equiv$ robustness
Cross Section 1: Value Ratios of Fama-French Portfolios

- From French’s website: 6/25/100 Fama-French size and book-to-market portfolios
- Monthly portfolio-level BE/ME

**Implementation**

- Annual forecasts use overlapping monthly regressions, corrected SE’s
- In-sample (small sample overfit bias)
  - Use full sample to estimate model
- Recursive out-of-sample forecasts (bias-free)
  - Use data through time $t$ to estimate model parameters, then use $t$-data and $t$-estimated parameters to forecast $t + 1$
## Return Predictions

### In-Sample and Out-of-Sample $R^2$ (%), 1930-2009

<table>
<thead>
<tr>
<th>Portfolio Size</th>
<th>One Year Forecasts</th>
<th>One Month Forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$ (%)</td>
<td>$p$ (KP/CM)</td>
</tr>
<tr>
<td>6 Portfolios</td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-Sample</td>
<td>3.84</td>
<td>0.126</td>
</tr>
<tr>
<td>Out-of-Sample</td>
<td>5.85</td>
<td>$&lt; 0.050$</td>
</tr>
<tr>
<td>25 Portfolios</td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-Sample</td>
<td>25.04</td>
<td>$&lt; 0.001$</td>
</tr>
<tr>
<td>Out-of-Sample</td>
<td>9.79</td>
<td>$&lt; 0.010$</td>
</tr>
<tr>
<td>100 Portfolios</td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-Sample</td>
<td>32.87</td>
<td>$&lt; 0.001$</td>
</tr>
<tr>
<td>Out-of-Sample</td>
<td>9.88</td>
<td>$&lt; 0.010$</td>
</tr>
</tbody>
</table>
## Return Predictions

### Comparison with Other Predictors

<table>
<thead>
<tr>
<th>100 Pts</th>
<th>Panel A: One Year Forecasts</th>
<th>Panel B: One Month Forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>In-Sample</td>
<td>Out-of-Sample</td>
</tr>
<tr>
<td></td>
<td>$R^2$ (%) p (Hodrick) p (NW)</td>
<td>$R^2$ (%) p (CM)</td>
</tr>
<tr>
<td>32.87</td>
<td>&lt; 0.001 &lt; 0.001</td>
<td>9.88 &lt; 0.010</td>
</tr>
<tr>
<td>dfy</td>
<td>0.31 0.674 0.664</td>
<td>-0.13 -</td>
</tr>
<tr>
<td>infl</td>
<td>0.00 0.853 0.747</td>
<td>-0.31 -</td>
</tr>
<tr>
<td>svar</td>
<td>0.00 0.995 0.650</td>
<td>-0.13 -</td>
</tr>
<tr>
<td>csp</td>
<td>0.36 0.401 0.492</td>
<td>1.29 &lt; 0.050</td>
</tr>
<tr>
<td>de</td>
<td>0.80 0.527 0.525</td>
<td>-5.59 -</td>
</tr>
<tr>
<td>lty</td>
<td>0.79 0.351 0.279</td>
<td>-0.73 -</td>
</tr>
<tr>
<td>tms</td>
<td>1.10 0.195 0.151</td>
<td>0.41 &lt; 0.100</td>
</tr>
<tr>
<td>tbl</td>
<td>0.16 0.680 0.661</td>
<td>-3.74 -</td>
</tr>
<tr>
<td>dfr</td>
<td>0.00 0.553 0.614</td>
<td>-0.27 -</td>
</tr>
<tr>
<td>pd</td>
<td>3.57 0.090 0.062</td>
<td>-3.08 -</td>
</tr>
<tr>
<td>dy</td>
<td>3.84 0.080 0.047</td>
<td>-6.31 -</td>
</tr>
<tr>
<td>ltr</td>
<td>0.89 0.002 &lt; 0.001</td>
<td>0.89 &lt; 0.050</td>
</tr>
<tr>
<td>ep</td>
<td>8.04 &lt; 0.001 &lt; 0.001</td>
<td>1.35 &lt; 0.010</td>
</tr>
<tr>
<td>bm</td>
<td>9.99 0.002 &lt; 0.001</td>
<td>-18.67 -</td>
</tr>
<tr>
<td>ntis</td>
<td>8.19 0.081 0.071</td>
<td>-56.44 -</td>
</tr>
<tr>
<td>cay</td>
<td>14.93 0.004 &lt; 0.001</td>
<td>2.48 &lt; 0.010</td>
</tr>
<tr>
<td>pc1</td>
<td>1.96 0.182 0.115</td>
<td>-2.19 -</td>
</tr>
<tr>
<td>pc2</td>
<td>0.08 0.811 0.790</td>
<td>-0.32 -</td>
</tr>
<tr>
<td>pc3</td>
<td>0.02 0.960 0.882</td>
<td>-0.55 -</td>
</tr>
</tbody>
</table>
Closer Look at Out-of-Sample Results

Out-of-Sample $R^2$ by Sample Split Date, One Year Returns

Graph showing the out-of-sample $R^2$ for 25 Fama-French portfolio BMs over different sample period dates from 12/1955 to 12/1995.
## Forecasting Annual Returns on Characteristic Portfolios

Out-of-Sample Predictive $R^2$ (%) Using 100 Size/BM Portfolios

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>One Year</th>
<th>One Month</th>
<th>Portfolio</th>
<th>One Year</th>
<th>One Month</th>
</tr>
</thead>
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<tr>
<td><strong>Panel A: Value Portfolios</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Growth</td>
<td>9.08 ***</td>
<td>0.10 *</td>
<td>1 Small</td>
<td>-17.66</td>
<td>-5.76</td>
</tr>
<tr>
<td>2</td>
<td>12.11 ***</td>
<td>0.36 **</td>
<td>2</td>
<td>-0.62</td>
<td>-1.75</td>
</tr>
<tr>
<td>3</td>
<td>6.80 ***</td>
<td>-0.86</td>
<td>3</td>
<td>5.96 ***</td>
<td>-0.67</td>
</tr>
<tr>
<td>4</td>
<td>3.93 ***</td>
<td>-1.92</td>
<td>4</td>
<td>6.95 ***</td>
<td>0.20 **</td>
</tr>
<tr>
<td>5 Value</td>
<td>4.56 ***</td>
<td>-1.98</td>
<td>5 Big</td>
<td>11.94 ***</td>
<td>0.16 *</td>
</tr>
<tr>
<td><strong>Panel B: Size Portfolios</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Past Losers</td>
<td>0.16</td>
<td>-0.96</td>
<td>Cons. Non-Dur.</td>
<td>17.07 ***</td>
<td>1.35 ***</td>
</tr>
<tr>
<td>2</td>
<td>2.25 ***</td>
<td>-2.04</td>
<td>Cons. Dur.</td>
<td>2.31 **</td>
<td>-2.64</td>
</tr>
<tr>
<td>3</td>
<td>11.39 ***</td>
<td>-0.22</td>
<td>Manufacturing</td>
<td>7.46 ***</td>
<td>-1.12</td>
</tr>
<tr>
<td>4</td>
<td>9.28 ***</td>
<td>-1.26</td>
<td>Energy</td>
<td>0.68 **</td>
<td>-0.34</td>
</tr>
<tr>
<td>5</td>
<td>7.50 ***</td>
<td>-0.95</td>
<td>Technology</td>
<td>2.42 *</td>
<td>-0.32</td>
</tr>
<tr>
<td>6</td>
<td>12.21 ***</td>
<td>0.13 **</td>
<td>Telecom</td>
<td>9.31 ***</td>
<td>0.61 **</td>
</tr>
<tr>
<td>7</td>
<td>14.56 ***</td>
<td>0.03 *</td>
<td>Retail</td>
<td>11.11 ***</td>
<td>0.15</td>
</tr>
<tr>
<td>8</td>
<td>9.81 ***</td>
<td>0.11 **</td>
<td>Healthcare</td>
<td>6.56 ***</td>
<td>-0.05</td>
</tr>
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<td>9</td>
<td>15.22 ***</td>
<td>1.17 ***</td>
<td>Unilities</td>
<td>2.76 ***</td>
<td>-1.18</td>
</tr>
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<td>10 Past Winners</td>
<td>4.40 **</td>
<td>-0.32</td>
<td>Other</td>
<td>8.59 ***</td>
<td>-0.74</td>
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Encompassing test statistic: * if $p < 0.10$, ** if $p < 0.05$ and *** if $p < 0.01$
Cross Section 2: Value Ratios of Individual Stocks

- Stock-level $BM$ (Fama-French 1992)
- Stock-level “price-to-MA” ratio (Miller-Scholes 1982, Fama-French 1988)

$$PMA = \frac{P_t}{\frac{1}{36} \sum_{k=1}^{36} P_{t-k}}$$
Closer Look at Out-of-Sample Results

Out-of-Sample $R^2$ by Sample Split Date, One Month Returns
Forecasting World (ex-US) Monthly Return
21 Country-Level Portfolio Book-to-Market Ratios (Fama-French)

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

Out-of-Sample $R^2$ (%)
Conclusion

- Intuition: Same factors driving aggregate $B/M$ drive entire panel of individual stock-level $B/M$s

- It is difficult (and hence non-standard) to use all of this info for forecasting

- We solve this problem by proposing a simple way of reducing many predictors to a single “super” predictor

- Previous literature drastically understates predictability of price movements
Systemic Risk and the Macroeconomy: An Empirical Evaluation


Stefano Giglio, Bryan Kelly, and Seth Pruitt
Introduction

- Many systemic risk measures proposed in aftermath of 2007 financial crisis

- Individual measures explored separately, little/no empirical analysis as a group

- Preliminary step: provide a basic quantitative description of existing SR measures
  - Construct 17 previously proposed measures of systemic risk in the US and 10 measures for the UK and EU
    - Extend series as far as possible, at least past 1990s (contrast with last decade)

- Each measure shown to work to capture some particular aspects of financial distress

- Not a clear picture of which aspects of systemic risk they are capturing or what is the criterion to judge them
Introduction

Three fundamental questions about systemic risk

- **Definition** - What is SR?
- **Measurement** - How do we measure and detect SR?
- **Welfare** - How does SR affect us?

We start from Welfare to evaluate Measurement, and aim to provide stylized facts that say something about Definition.
Three Main Objectives

1. Propose a criterion for evaluating SR measures
   
   ▶ To be relevant for \textit{policy}, interested in SR to the extent that it has consequences for economic welfare
   
   ▶ Can we detect ways that SR affects the \textit{real economy}?
   
   ▶ Quantify this by looking at \textit{conditional quantiles} of real activity variables and their relation with SR measures
Three Main Objectives

- We apply the criterion and evaluate how many proposed measures of SR actually associate with greater risk for the real economy
  - Only a few SR measures are associated with higher risks to the real economy

- Perhaps each measure contains *some* information that is useful to capture SR
  - Do not always move together
  - May capture different aspects of distress in financial markets
Three Main Objectives

2. **Propose dimension reduction techniques** to detect relationship between the real economy and SR measures jointly
   - Suppose a latent SR factor drives the SR measures and the quantiles of future real macro variables
   - We propose two dimension reduction estimators to estimate this factor; prove they are asymptotically unbiased
   - Empirical finding: **Information gain from aggregation** $\rightarrow$ SR measures as group informative about macro variables
Three Main Objectives

3. **Produce stylized facts** on the relation between SR and the macroeconomy
   - We can study which measures work and which don’t work, by our metric
   - These stylized facts can aid future work to dig deeper into the underlying mechanisms
Summary: Systemic Risk and the Real Economy

- Results reach **positive** conclusion regarding the empirical systemic risk literature.

- Increases in SR index associated with a large widening in the left tail of economic activity.

- One s.d. increase in SR shifts the 20th percentile of the IP growth distribution down by more than 50%, from around -1.4% per quarter unconditionally, to -2.2%.

- During crises 20th percentile drops below -3% per quarter, twice as large as in normal times.

- SR index also predicts reactions of policymakers: the 20th percentile of changes in the federal funds rate drops by 60%, from -50bps to -80bps.
Landscape of Systemic Risk Measures
Which Measures?

1. Aggregated versions of institution-specific measures: CoVar, $\Delta$CoVar, MES, SES, MES-BE.


3. Liquidity and credit: AIM, TED Spread, Default spread, Term spread

4. Instability and volatility: Volatility, Turbulence, Book Leverage, Market Leverage, Size Concentration

- We do not cover direct linkages and CDS-based measures

- We construct measures for the US, plus UK and Euro Area (France, Germany, Italy, Spain)
Summary of Comovement Among Measures

- All spiked during financial crisis, not surprising given *a posteriori* origins.

- Correlations among measures are low on average $\sim 0.2$.
  - Some measures lead others (CoVaR, credit spreads, volatility), some only “coincident” indicators.

- In long sample, many reached similar levels as in recent crisis.
  Interpretations include
  - Measures are simply noisy.
  - Sometimes capture stress in financial system that does not result in economic crises either because either policy response diffused instability or system stabilized itself.
Macroeconomic Criterion and Accompanying Tests
Motivation

- Financial distress impacts real outcomes through capital / credit / liquidity contraction


- Emphasis on **non-linearity**. Distribution of **real outcomes** changes when degree of SR changes. Particularly interested in effects at low quantiles of real outcomes

- “... what measurements will be the most fruitful to support our understanding of linkages between financial markets and the macroeconomy is an open issue.” Hansen (2012)
A Criterion for Evaluating Measures

- SR indicator should demonstrably associated with future macroeconomic outcomes
  - Important from regulatory point of view
  - Summarizes vast amount of economic activity and decision-making

- This criterion addresses the field’s need of an empirical description of link between proposed financial markets and the real economy
Operationalizing Criterion: Quantile Regression

- Operationalize: Quantile regression test for the SR measure’s ability to predict distribution of future macro shocks
  - OLS models the *conditional mean* relationship between $X$ and $y$
  - QR models the *conditional quantile* relationship between $X$ and $y$

- Main advantages
  - Reduced-form implementation of theoretical SR/macro association (e.g. He and Krishnamurthy)
  - Broader view of the conditional distribution of $y$ given $X$
  - Can flexibly evaluate the relationship at different parts of $y$’s distribution
    - e.g. lower tail, central tendency, upper tail
Quantile Regression in Thirty Seconds

\[ Q_\tau(y_{t+1} | I) = \alpha(\tau) + \beta(\tau)'x_t \]

- Varying \( \tau' \) leads to different \( \alpha(\tau') \), \( \beta(\tau') \) in general
  - Different \( x, y \) relationships at different parts of \( y \)'s distribution

- The quantile loss function estimates \( \alpha, \beta \) and evaluates the forecasts
  - in OLS: mean-squared-error estimates parameters and evaluates the forecasts
Loss Functions

\[ \text{Errors: } y - (\alpha + \beta x) \]

Loss Functions Graph:
- Least Squares Regr
- Median Regr
- 20th Pctile Regr
Example of No Quantile Relation: Absorption Ratio
Example of Strong Quantile Relation: Turbulence
Dependent Variable: Macroeconomic Shocks

Macroeconomic target $y_t$ is a shock derived from:

- **Industrial Production**

- **CFNAI, or CFNAI subcomponent**
  - Aggregate index (Total)
  - Production and Income (PI)
  - Employment, Unemployment and Hours (EUH)
  - Personal Consumption and Housing (PH)
  - Sales, Orders and Inventory (SOI)

- $y_t$ is a one quarter-ahead “shock,” or innovation to $AR(p)$


Robust: Recursive; AIC; ARX(p)
Benchmark Quantile Forecast Analysis

\[ Q_\tau(y_{t+1}|x_t) = \alpha + \beta x_t \]

- Benchmark results use 20\(^{th}\) percentile (\(\tau = 0.2\))
  - A more stringent F-test
- Report the QR “\(R^2\)”

\[
R^2 = 1 - \frac{\text{Mean Quantile Loss Using Predictors}}{\text{Mean Quantile Loss Using Unconditional Quantile}}
\]
Out-of-Sample 20\textsuperscript{th} Percentile IP Shock Forecasts

<table>
<thead>
<tr>
<th>Out-of-Sample start</th>
<th>US</th>
<th>UK</th>
<th>EU</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1950</td>
<td>1970</td>
<td>1985</td>
</tr>
<tr>
<td>Absorption</td>
<td>$-2.80$</td>
<td>$-4.38$</td>
<td>$-3.96$</td>
</tr>
<tr>
<td>AIM</td>
<td>$2.99^*$</td>
<td>$4.01^*$</td>
<td>$4.07^*$</td>
</tr>
<tr>
<td>CoVaR</td>
<td>$1.71$</td>
<td>$2.11$</td>
<td>$1.85$</td>
</tr>
<tr>
<td>$\Delta$CoVaR</td>
<td>$-0.45$</td>
<td>$-0.86$</td>
<td>$-0.97$</td>
</tr>
<tr>
<td>MES</td>
<td>$-0.10$</td>
<td>$0.21$</td>
<td>$0.97$</td>
</tr>
<tr>
<td>MES-BE</td>
<td>$-1.24$</td>
<td>$-0.78$</td>
<td>$-6.70$</td>
</tr>
<tr>
<td>Book Lvg.</td>
<td>$-$</td>
<td>$-$</td>
<td>$3.87^{***}$</td>
</tr>
<tr>
<td>DCI</td>
<td>$-1.61$</td>
<td>$-1.75$</td>
<td>$-2.92$</td>
</tr>
<tr>
<td>Def. Spr.</td>
<td>$-0.29$</td>
<td>$0.69$</td>
<td>$8.60^{***}$</td>
</tr>
<tr>
<td>$\Delta$Absorption</td>
<td>$-0.83$</td>
<td>$-0.10$</td>
<td>$-0.27$</td>
</tr>
<tr>
<td>Intl. Spillover</td>
<td>$-$</td>
<td>$0.34$</td>
<td>$1.41$</td>
</tr>
<tr>
<td>Size Conc.</td>
<td>$-2.48$</td>
<td>$-7.37$</td>
<td>$-3.59$</td>
</tr>
<tr>
<td>Mkt. Lvg.</td>
<td>$-$</td>
<td>$-$</td>
<td>$12.70^{***}$</td>
</tr>
<tr>
<td>Volatility</td>
<td>$3.27^{**}$</td>
<td>$6.19^{**}$</td>
<td>$8.03^*$</td>
</tr>
<tr>
<td>TED Spr.</td>
<td>$-$</td>
<td>$-$</td>
<td>$10.18^{***}$</td>
</tr>
<tr>
<td>Term Spr.</td>
<td>$0.32$</td>
<td>$2.13$</td>
<td>$1.14$</td>
</tr>
<tr>
<td>Turbulence</td>
<td>$3.50^{***}$</td>
<td>$6.93^{***}$</td>
<td>$12.78^{***}$</td>
</tr>
</tbody>
</table>
Out-of-Sample 20\textsuperscript{th} Percentile CFNAI Shock Forecasts

<table>
<thead>
<tr>
<th>Measure</th>
<th>Total</th>
<th>PH</th>
<th>PI</th>
<th>SOI</th>
<th>EUH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absorption</td>
<td>-4.58</td>
<td>-1.85</td>
<td>-2.66</td>
<td>-3.11</td>
<td>-3.00</td>
</tr>
<tr>
<td>AIM</td>
<td>-3.42</td>
<td>-2.60</td>
<td>-2.69</td>
<td>-3.44</td>
<td>-1.67</td>
</tr>
<tr>
<td>CoVaR</td>
<td>-1.82</td>
<td>-2.98</td>
<td>-2.83</td>
<td>-3.27</td>
<td>-0.94</td>
</tr>
<tr>
<td>ΔCoVaR</td>
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<td>-4.11</td>
<td>-4.49</td>
<td>-4.31</td>
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<tr>
<td>MES</td>
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<td>-3.09</td>
</tr>
<tr>
<td>MES-BE</td>
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<td>-0.60</td>
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<td>-2.50</td>
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<tr>
<td>Book Lvg.</td>
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<td>1.36</td>
<td>-0.47</td>
<td>1.19</td>
</tr>
<tr>
<td>DCI</td>
<td>-2.14</td>
<td>-0.67</td>
<td>-2.28</td>
<td>-3.50</td>
<td>-2.42</td>
</tr>
<tr>
<td>Def. Spr.</td>
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<td>-3.88</td>
<td>-0.84</td>
<td>-3.15</td>
<td>-3.19</td>
</tr>
<tr>
<td>ΔAbsorption</td>
<td>-0.37</td>
<td>-1.92</td>
<td>1.16</td>
<td>-0.53</td>
<td>0.59</td>
</tr>
<tr>
<td>Intl. Spillover</td>
<td>-2.52</td>
<td>-3.62</td>
<td>-0.94</td>
<td>-1.78</td>
<td>-2.38</td>
</tr>
<tr>
<td>Size Conc.</td>
<td>-1.84</td>
<td>-1.66</td>
<td>-0.60</td>
<td>-2.77</td>
<td>-0.17</td>
</tr>
<tr>
<td>Mkt. Lvg.</td>
<td>4.26*</td>
<td>-0.78</td>
<td>4.14*</td>
<td>5.70**</td>
<td>4.14*</td>
</tr>
<tr>
<td>Volatility</td>
<td>1.65</td>
<td>-0.07</td>
<td>1.00</td>
<td>2.97</td>
<td>2.14</td>
</tr>
<tr>
<td>Term Spr.</td>
<td>3.03</td>
<td>0.64</td>
<td>3.32</td>
<td>2.64</td>
<td>2.36</td>
</tr>
<tr>
<td>Turbulence</td>
<td>7.37**</td>
<td>4.82**</td>
<td>7.97***</td>
<td>8.40***</td>
<td>4.46*</td>
</tr>
</tbody>
</table>
Results for Individual Measures

- Individual predictors: Mixed, somewhat weak out-of-sample performance
  - Notable exception: Financial volatility variables, leverage

- Can we fruitfully put them together?
Dimension Reduction Techniques
Quantile Regression with Many Predictors

- How do we forecast quantiles when number of predictor variables is large?

- Multiple QR works poorly due to standard “many-predictor” issues

- Two new methodologies:
  - Principal Component Quantile Regression
  - Partial Quantile Regression: Analogue of PLS for quantiles
Quantiles of $y_{t+1}$, conditional on $t$ info, as a linear in unobservable factor $f_t$,

$$Q_\tau(y_{t+1}|I_t) \equiv Q_\tau(y_{t+1}|f_t) = \alpha f_t$$

Assume large set of observable predictors $x_t$ that are linear in $f_t$, as well as other factors $g_t$

$$x_t = \phi f_t + \Psi g_t + \varepsilon_t$$
Principal Component Quantile Regression (PCQR)

\[ Q_\tau(y_{t+1}|I_t) \equiv Q_\tau(y_{t+1}|f_t) = \alpha f_t \]

\[ x_t = \phi f_t + \Psi g_t + \varepsilon_t \]

Stage 1: Use PCA to extract common factors among \( x_t \), denoted
\[ \hat{F}_t = (\hat{f}_t, \hat{g}_t) \]

Stage 2: Use \( \hat{F}_t \) to forecast \( Q_\tau(y_{t+1}|I_t) \)

- Construct systemic risk index that assigns more weight to \( x_{it} \)'s that better capture the comovement among \( x_t \)
Partial Quantile Regression (PQR)

\[ Q_{\tau}(y_{t+1}|I_t) = Q_{\tau}(y_{t+1}|f_t) = \alpha f_t \]

\[ x_t = \phi f_t + \Psi g_t + \varepsilon_t \]

Stage 1: Estimate \( Q_{\tau}(y_{t+1}|x_t) = \alpha_i + \beta_i x_{it} \) for each \( i \)

Stage 2: Construct \( \hat{f}_t \) as weighted average of \( x_{it} \)'s in which \( \hat{\beta}_i \)'s are weights

Stage 3: Use \( \hat{f}_t \) to forecast \( Q_{\tau}(y_{t+1}|I_t) \)

- Construct \( f_t \) by assigning more weight to \( x_{it} \)'s with strongest predictive content for \( Q_{\tau}(y_{t+1}|\cdot) \)
Comparison of PCQR and PQR

\[ Q_{\tau}(y_{t+1}|I_t) \equiv Q_{\tau}(y_{t+1}|f_t) = \alpha f_t \]

\[ x_t = \phi f_t + \Psi g_t + \varepsilon_t \]

- PCQR optimal when you’re confident you can extract all factors via PCA
  - This is case when forecast-relevant factors are dominant source of variation in \( x_{it} \)’s

- PQR works generally, including cases in which PCA may extract \( g_t \) and miss \( f_t \)
Econometrics

- PCQR: asymptotically unbiased as $N, T \to \infty$, assuming all factors extracted in first stage

- PQR: asymptotically unbiased as $N, T \to \infty$, assuming a bit more structure on problem

Contribution: A methodology for constructing systemic risk indices that are asymptotically unbiased in large SR panels

Real test is how they work in finite samples
  - Simulation evidence supports the asymptotics
  - Empirically successful, as we now see ...
## Out-of-Sample 20\textsuperscript{th} Percentile Shock Forecasts

### Industrial Production

<table>
<thead>
<tr>
<th>Out-of-Sample start</th>
<th>US</th>
<th>UK</th>
<th>EU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple QR</td>
<td>−23.66</td>
<td>−18.52</td>
<td>15.21\textsuperscript{***}</td>
</tr>
<tr>
<td>PCQR1</td>
<td>0.68</td>
<td>0.13</td>
<td>1.61</td>
</tr>
<tr>
<td>PCQR2</td>
<td>6.47\textsuperscript{***}</td>
<td>10.52\textsuperscript{***}</td>
<td>16.67\textsuperscript{***}</td>
</tr>
<tr>
<td>PQR</td>
<td>6.58\textsuperscript{***}</td>
<td>10.82\textsuperscript{***}</td>
<td>12.39\textsuperscript{***}</td>
</tr>
</tbody>
</table>

### CFNAI

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>PH</th>
<th>PI</th>
<th>SOI</th>
<th>EUH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple QR</td>
<td>−36.74</td>
<td>−47.07</td>
<td>−52.06</td>
<td>−20.00</td>
<td>−54.18</td>
</tr>
<tr>
<td>PCQR1</td>
<td>−1.07</td>
<td>−0.73</td>
<td>−1.96</td>
<td>−2.06</td>
<td>−0.24</td>
</tr>
<tr>
<td>PCQR2</td>
<td>0.89</td>
<td>−2.44</td>
<td>0.20</td>
<td>−0.65</td>
<td>0.28</td>
</tr>
<tr>
<td>PQR</td>
<td>7.09\textsuperscript{**}</td>
<td>2.16</td>
<td>5.36\textsuperscript{*}</td>
<td>9.72\textsuperscript{***}</td>
<td>2.15</td>
</tr>
</tbody>
</table>
What do we learn from these results?

- There is a SR factor strongly related to future downside macroeconomic risk
  - One s.d. increase in SR shifts the 20th percentile of the IP growth distribution down by more than 50%, from around -1.4% per quarter unconditionally, to -2.2%
  - During crises 20th percentile drops below -3% per quarter, twice as large as in normal times

- Financial-sector volatility may be most “fruitful” for understanding the linkages between financial markets and the macroeconomy

- Next: What can we say about the nature of SR?
Downside Macroeconomic Risk

- So far we have shown the ability of SR measures to predict the lower tail of the distribution of future macroeconomic outcomes.
- What happens if we look at medians?
## Downside Macroeconomic Risk

### Median Coefficient vs. 20\textsuperscript{th} Percentile Coefficient: \( t \) Tests

<table>
<thead>
<tr>
<th></th>
<th>Median</th>
<th>20\textsuperscript{th} Pctl.</th>
<th>Difference</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absorption</td>
<td>−0.0021</td>
<td>−0.0010</td>
<td>0.0012</td>
<td>1.88</td>
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<tr>
<td>AIM</td>
<td>0.0003</td>
<td>−0.0072</td>
<td>−0.0075</td>
<td>−11.84</td>
</tr>
<tr>
<td>CoVaR</td>
<td>−0.0030</td>
<td>−0.0048</td>
<td>−0.0019</td>
<td>−2.89</td>
</tr>
<tr>
<td>ΔCoVaR</td>
<td>−0.0024</td>
<td>−0.0031</td>
<td>−0.0007</td>
<td>−1.02</td>
</tr>
<tr>
<td>MES</td>
<td>−0.0024</td>
<td>−0.0040</td>
<td>−0.0016</td>
<td>−2.54</td>
</tr>
<tr>
<td>Book Lvg.</td>
<td>−0.0014</td>
<td>−0.0023</td>
<td>−0.0009</td>
<td>−1.36</td>
</tr>
<tr>
<td>DCI</td>
<td>0.0001</td>
<td>−0.0014</td>
<td>−0.0016</td>
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<tr>
<td>Def. Spr.</td>
<td>−0.0036</td>
<td>−0.0033</td>
<td>0.0003</td>
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<td>ΔAbsorption</td>
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<td>−0.0023</td>
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</tr>
<tr>
<td>Intl. Spillover</td>
<td>0.0000</td>
<td>−0.0019</td>
<td>−0.0019</td>
<td>−2.87</td>
</tr>
<tr>
<td>Mkt. Lvg.</td>
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<td>−2.13</td>
</tr>
<tr>
<td>TED Spr.</td>
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<td>−0.0057</td>
<td>−0.0031</td>
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</tr>
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<tr>
<td>Turbulence</td>
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<td>−0.0060</td>
<td>−0.0020</td>
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</tr>
<tr>
<td>PQR</td>
<td>−0.0037</td>
<td>−0.0052</td>
<td>−0.0015</td>
<td>−2.32</td>
</tr>
</tbody>
</table>
Downside Macroeconomic Risk

- All of these measures, *including* volatility, are much more successful for the **lower tail** of macro outcomes

- Financial market distress creates or makes the economy susceptible to **downside macroeconomic risk**
Conclusion

- Propose macro/welfare relevance criterion for evaluating systemic risk measures
  - Only a few provide this information

- Propose (factor estimation) approach to aggregating systemic risk measures and overcoming measurement difficulties faced by individual measures
  - Systemic risk factor strongly related to future macroeconomic outcomes

- Stylized facts can guide model-building
  1. Systemic risk is strongly related to downside macro risk
  2. Policy responds to SR but has limited effectiveness
  3. Financial firms’ equity volatility is most informative for future macro outcomes
Work in Progress: Analyzing Text of Financial Print Media and Patents
New technologies make available vast quantities of digital text

Records ever increasing share of human interaction, communication, culture

For social scientists, information encoded in text is rich complement to more structured data traditionally used in research
Text as Data: Examples in Literature

- Finance: Text from financial news used predict asset price movements
- Macro: News text used to forecast variation in inflation and unemployment, estimate the effects of policy uncertainty
- Industrial organization and marketing: text from ads and product reviews used to study consumer decision making
- Political economy: Text from congressional speeches used to study political agendas and debate
Regressing on to Text Data

- **What is text data?**

- **Answer:** Panel of counts, $x_{i,t}$, by word $i$ and by document $t$

- **Example:** FOMC mtg. minutes (using www.writewords.org.uk/word_count.asp)

<table>
<thead>
<tr>
<th>Document</th>
<th>Word list</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>committee</td>
<td>communications</td>
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<td>Dec 18, 2013 meeting</td>
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<tr>
<td>Jan 28, 2014 meeting</td>
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<td>121</td>
</tr>
</tbody>
</table>

- In this paper, a “document” is comprised of all abstracts of WSJ articles (p.1) in a calendar month

- Hundreds of thousands of time series
Regressing on to Text Data

- **Goal:** Time series regression of $TARGET$ onto $X$

$$\overbrace{TARGET}^{T \times 1} = w_0 + \underbrace{X}_{T \times N} \cdot \underbrace{W}_{N \times 1} + e$$

- Infeasible with OLS, feasible with penalized LS or related approach

$$\min_{w_0, W} \sum_t g(\overbrace{TARGET_t}^{T \times 1} - w_0 - W'x_t) + c\|W\|^q$$

- Typically use very large penalties so that a very small fraction of words have meaningful loadings $w_i$

- Economic content comes from studying $w_i$ estimates
Text as Data: Summary

- Very brief sense of opportunity that (big) text data represents for researchers
- Text regression is tip of the iceberg – rapidly growing methodologies
- Survey for JEL in progress: “Text as Data” by Gentzkow, Kelly, Taddy
Closing

- A summary of 1-2 of my research agendas that focus on high dimensional data
- I also work on
  - Banks bailouts and role of intermediaries in asset markets
  - Tail risk, volatility, and correlation models (financial econometrics)
  - Production networks
  - Role of information asymmetry in asset markets
- Always looking for ambitious RA’s
- Happy to answer questions