Google it!

Forecasting the US unemployment rate with a Google job search index

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Outline

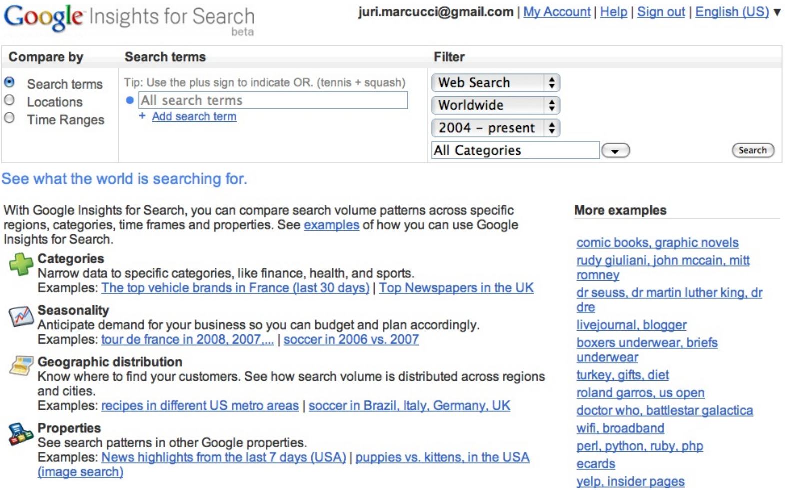
- Introduction and Motivations
- Data and Leading indicators for the US unemployment rate
  - Initial jobless claims (traditional!)
  - Google job web search index (New!)
- Forecasting models
- Out-of-sample evaluation
  - Tests Equal forecast accuracy and forecast encompassing
  - Reality Check test for superior predictive ability
- Some Robustness
  - Results from aggregation of States' forecasts
  - Comparison with Survey of Professional Forecasters
- Discussion and Conclusion

Introduction

- Having *reliable* and *updated* unemployment forecasts has become increasingly important, in particular during economic downturns
- The literature on US unemployment forecasting has primarily dealt either with simple **linear** models or with **non-linear** models
  - For example Montgomery, Zarnowitz, Tsay and Tiao (JASA, 1998), Proietti (CSDA, 2003) or Rothman (RESTAT, 1998)
- These linear models have been augmented with some **leading indicators**: in particular the Initial jobless Claim (IC) seem to be the best indicator for the US unemployment, so far...

Motivation

Google 'job' web search weekly index from **Google Insights**



Our Contribution

- In this paper we suggest an ***alternative leading indicator*** to forecast the US unemployment rate
  ⇒ a **Google** job web search index
- To the best of our knowledge, this indicator has only been used by:
  - Askitas & Zimmermann (2009) to forecast German unemployment
  - D'Amuri (2009) to forecast Italian unemployment
  - Suhoy (2009) to forecast unemployment in Israel
  - Choi and Varian (2009) to predict the US initial claims
- Running an extensive out-of-sample forecasting *horse-race*, we compare the predictive power of linear forecasting models using the Google Index (GI) with those using the Initial Claims or combinations of both.
- Our interest is on *short-term forecasting*, i.e. in forecasting the US monthly unemployment rate from 1- to 3-months ahead

Our results

- Our results show that the **Google index really helps** in predicting the monthly US unemployment rate, even after controlling for the effects of data-snooping.
  - Linear models with GI ***outperform*** all the other models using IC as a leading indicator, both in terms of **equal forecast accuracy** and **superior predictive ability**
- Moreover, linear *models augmented with the GI* ***outperform*** also at the **state level** (to predict the unemployment rate in each state) and in comparison to the *Survey of Professional Forecasters*.
- Our preferred models with *GI* also ***outperform*** standard *non-linear* models

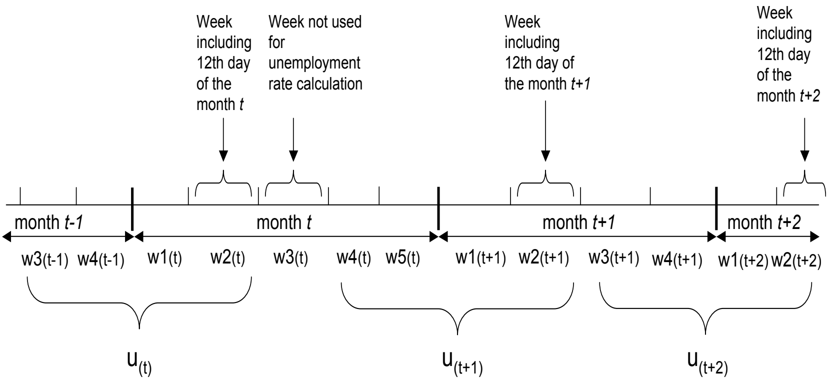
Data

1) Unemployment rate (US and state level)

- Monthly unemployment rate (u_t) seasonally adjusted from BLS
  - Current Unemployment Statistics (national level)
    - Sample: **1948.1-2009.6** (738 obs.)
  - Local Area Unemployment Statistics (state level)
    - Sample: **1976.1-2009.6** (402 obs.)
- u_t for month t refers to:
  - people who **don't have a job**, but are **available for work**, in the week including the 12^{th} of month t...
  - ...and who **have looked for a job** in the previous 4 weeks (*reference week* included)

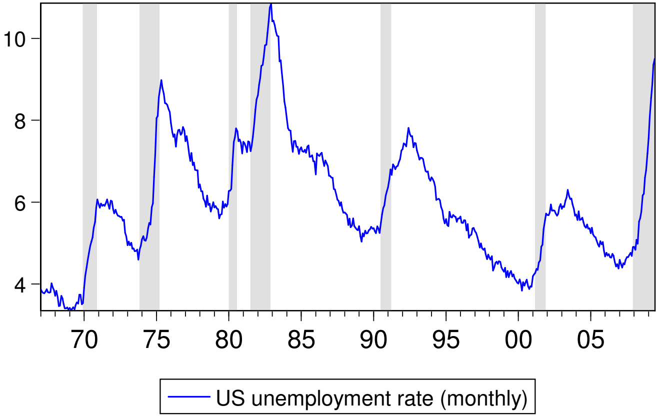
Data (Cont.)

1) Unemployment rate: Exact timing of US monthly unemployment rate



Data (Cont.)

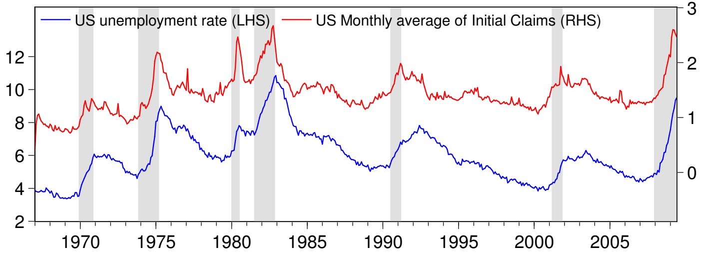
1) Unemployment rate (US) - Sample: 1967.1-2009.6 (NBER recessions - shaded areas)



Data (Cont.)

2) Initial Jobless Claims (US and state level)

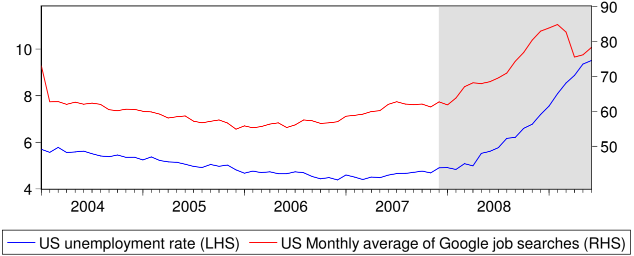
- Weekly **Initial Jobless Claims** (IC) seasonally adjusted from the US Department of Labor
  $\Rightarrow$ well-known Leading Indicator (Montgomery et al., 1998)
  - National level
    - Sample: **1967.1-2009.6** (510 obs.)
  - State level (SA w/ Tramo-Seats)
    - Sample: **1987.1-2009.6** (271 obs.)



Data (Cont.)

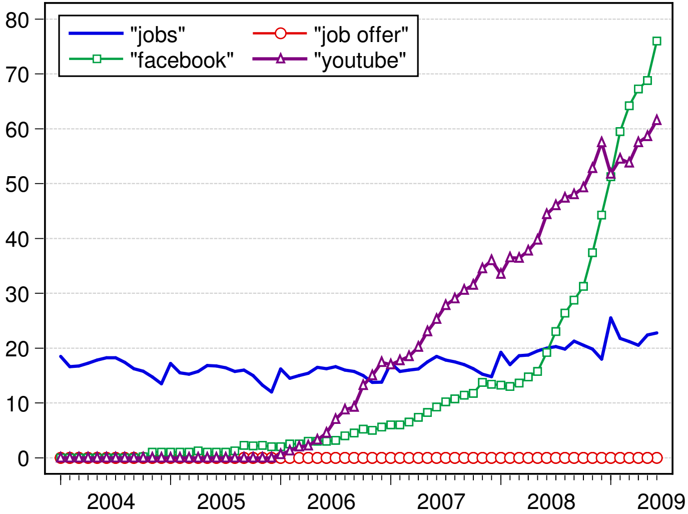
3) Google 'job' web search index from Google Insights (US and state level)

- **Weekly Google Index** (GI) seasonally adjusted from Google Insights (available almost in real time)
  ⇒ suggested Leading Indicator
  (Incidence of "*jobs*" queries on total web queries in relevant week)
  - National level
    - Sample: **2004.1-2009.6** (66 obs.)
  - State level
    - Sample: **2004.1-2009.6** (66 obs.)



Data (Cont.)

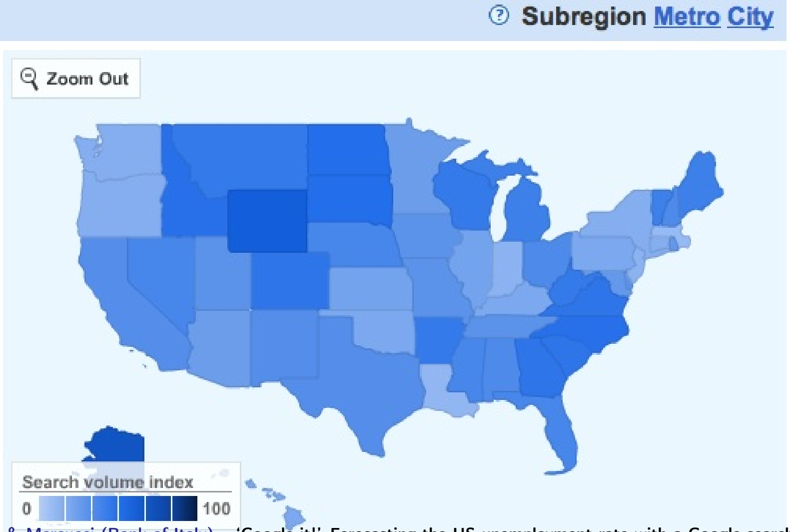
3) Incidence of keyword "jobs" vs other popular keywords



Data (Cont.)

3) Google 'job' web search index from Google Insights

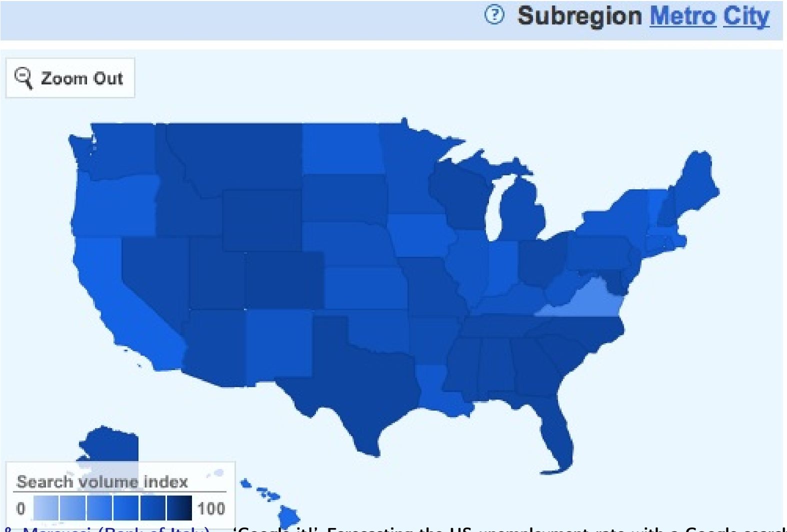
Pre-crisis period: Jan.-Apr. 2007



Data (Cont.)

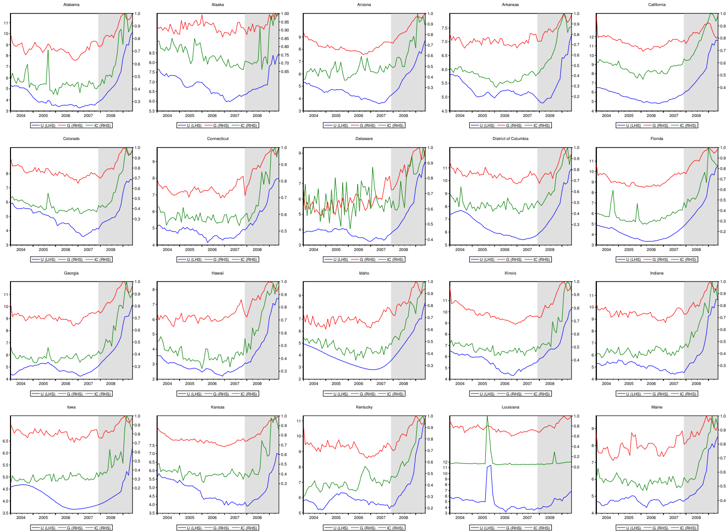
3) Google 'job' web search index from Google Insights

During the crisis: Jan.-Apr. 2009



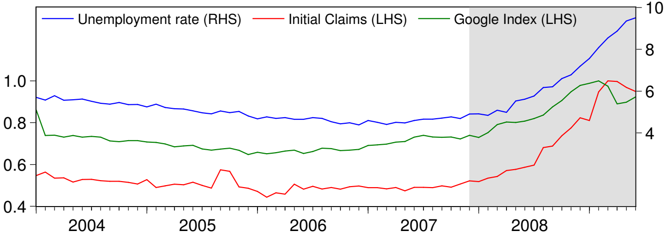
Data (Cont.)

3) Google 'job' web search index and Initial Claims (state level) [from Alabama to Maine]



Data (Cont.)

Unemployment rate (US), Initial Claims and Google index - Sample: 2004.1-2009.6



Data (Cont.)

Correlations. Sample: 2004.1-2009.6

	u_t	$d(u_t)$	$\log(u_t)$	u_t^{logit}	u_t^{LHP}	u_t^{LLD}		u_t	$d(u_t)$	$\log(u_t)$	u_t^{logit}	u_t^{LHP}	u_t^{LLD}
u_t	1												
$u_t - u_{t-1}$	0.667	1											
$\log(u_t)$	0.994	0.674	1										
u_t^{logit}	0.995	0.674	1.000	1									
u_t^{LHP}	0.940	0.542	0.953	0.953	1								
u_t^{LLD}	0.992	0.662	0.999	0.999	0.962	1							
IC_t	0.962	0.711	0.951	0.952	0.844	0.942	G_t	0.851	0.745	0.866	0.865	0.706	0.854
IC_{t-1}	0.973	0.673	0.956	0.957	0.864	0.949	G_{t-1}	0.885	0.734	0.897	0.896	0.752	0.886
IC_{t-2}	0.973	0.632	0.951	0.953	0.873	0.946	G_{t-2}	0.919	0.743	0.927	0.927	0.812	0.920
$IC_{W1,t}$	0.962	0.700	0.948	0.949	0.842	0.940	$G_{W1,t}$	0.852	0.735	0.861	0.861	0.709	0.850
$IC_{W1,t-1}$	0.970	0.664	0.951	0.953	0.859	0.945	$G_{W1,t-1}$	0.873	0.677	0.880	0.880	0.743	0.871
$IC_{W1,t-2}$	0.964	0.604	0.941	0.943	0.860	0.936	$G_{W1,t-2}$	0.900	0.707	0.904	0.904	0.785	0.896
$IC_{W2,t}$	0.954	0.699	0.941	0.942	0.832	0.933	$G_{W2,t}$	0.842	0.709	0.848	0.848	0.708	0.837
$IC_{W2,t-1}$	0.963	0.681	0.947	0.948	0.854	0.940	$G_{W2,t-1}$	0.881	0.717	0.879	0.879	0.756	0.870
$IC_{W2,t-2}$	0.960	0.596	0.938	0.940	0.856	0.932	$G_{W2,t-2}$	0.904	0.654	0.896	0.897	0.789	0.889
$IC_{W3,t}$	0.950	0.706	0.939	0.940	0.842	0.931	$G_{W3,t}$	0.819	0.718	0.838	0.837	0.696	0.828
$IC_{W3,t-1}$	0.957	0.640	0.940	0.942	0.858	0.934	$G_{W3,t-1}$	0.854	0.707	0.869	0.868	0.744	0.861
$IC_{W3,t-2}$	0.955	0.632	0.933	0.935	0.866	0.929	$G_{W3,t-2}$	0.898	0.710	0.904	0.904	0.799	0.897
$IC_{W4,t}$	0.949	0.713	0.940	0.941	0.831	0.932	$G_{W4,t}$	0.809	0.722	0.824	0.823	0.649	0.810
$IC_{W4,t-1}$	0.962	0.679	0.947	0.948	0.852	0.940	$G_{W4,t-1}$	0.843	0.733	0.854	0.854	0.694	0.842
$IC_{W4,t-2}$	0.968	0.665	0.949	0.951	0.870	0.944	$G_{W4,t-2}$	0.885	0.730	0.889	0.889	0.745	0.878

Data (Cont.)

ADF-GLS Unit Root tests by Elliott et al. (1996). Short and Full Sample

Sample: 1967:1-2009:6			Sample: 2004:1-2009:6		
Variable	Test	Test stat.	Variable	Test	
u_t	$DF-GLS^{\mu}$	-1.054	u_t	$DF-GLS^{\mu}$	-2.881***
	$DF-GLS^{\tau}$	-2.282		$DF-GLS^{\tau}$	-2.902*
$\log(u_t)$	$DF-GLS^{\mu}$	-0.901	$\log(u_t)$	$DF-GLS^{\mu}$	-2.792***
	$DF-GLS^{\tau}$	-2.190		$DF-GLS^{\tau}$	-2.797
u_t^{logit}	$DF-GLS^{\mu}$	-0.912	u_t^{logit}	$DF-GLS^{\mu}$	-2.801***
	$DF-GLS^{\tau}$	-2.203		$DF-GLS^{\tau}$	-2.804
u_t^{HPlog}	$DF-GLS^{\mu}$	-3.752***	u_t^{HPlog}	$DF-GLS^{\mu}$	-2.659***
	$DF-GLS^{\tau}$	-4.414***		$DF-GLS^{\tau}$	-2.523
u_t^{LLD}	$DF-GLS^{\mu}$	-1.344	u_t^{LLD}	$DF-GLS^{\mu}$	-2.823***
	$DF-GLS^{\tau}$	-2.190		$DF-GLS^{\tau}$	-2.797

The setup of the forecasting horse-race

- **Timing:** $T = R + P$ observations.
  - In the '**full-sample**' (**1967.1-2009.6**) we have $T = 510$
  - In the '**short-sample**' (**2004.1-2009.6**) we have $T = 66$
- The first R are used to estimate the models (**in-sample**) while the last P are used for **out-of-sample** evaluation.
- Want to predict u_t (or transformations) using linear ARMA models w/ and w/o exogenous leading indicators x_t:
  - $x_t = \{IC_t, ..., IC_{t-k}\}$
  - $x_t = \{IC_{wj,t}, ..., IC_{wj,t-k}\}, j = 1, \ldots, 4, k = 1, 2$
  - $x_t = \{G_t, ..., G_{t-k}\}$
  - $x_t = \{G_{wj,t}, ..., G_{wj,t-k}\}, j = 1, \ldots, 4, k = 1, 2$
  - combinations IC and G

The setup of the forecasting horse-race (Cont.)

Forecasting Models: $\phi(L)y_t = \mu + x_t'\beta + \theta(L)\varepsilon_t$

	Full Sample: 1967.1-2007.2								Short Sample: 2004.1-2007.2							
	AR(1)	#	AR(2)	#	ARMA(1,1)	#	ARMA(2,2)	#	AR(1)	#	AR(2)	#	ARMA(1,1)	#	ARMA(2,2)	#
w/o LI																
	u_{t-1}	1	u_{t-k}	1	$u_{t-1}, \varepsilon_{t-1}$	1	$u_{t-k}, \varepsilon_{t-k}$	1	u_{t-1}	1	u_{t-k}	1	$u_{t-1}, \varepsilon_{t-1}$	1	$u_{t-k}, \varepsilon_{t-k}$	1
w/ LI x_t																
(t)																
IC	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1
IC_{wj}	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4
G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
G_{wj}	-		-		-		-		✓	4	✓	4	✓	4	✓	4
IC, G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
IC_{wj}, G_{wj}	-		-		-		-		✓	5	✓	5	✓	5	✓	5
$(t-1)$																
IC	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1
IC_{wj}	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4
G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
G_{wj}	-		-		-		-		✓	4	✓	4	✓	4	✓	4
IC, G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
IC_{wj}, G_{wj}	-		-		-		-		✓	5	✓	5	✓	5	✓	5
$(t-2)$																
IC	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1
IC_{wj}	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4
G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
G_{wj}	-		-		-		-		✓	4	✓	4	✓	4	✓	4
IC, G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
IC_{wj}, G_{wj}	-		-		-		-		✓	5	✓	5	✓	5	✓	5

$j = 1, \ldots, 4; k = 1, 2$ - w/ or w/o SAR/SMA

The setup of the forecasting horse-race (Cont.)

- Forecasting scheme: we use a **rolling** scheme.
  - 'Short-sample': $T = 66$ with $R = 38$ and $P = 28$.
    - In-sample: 2004.1-2007.2, 2004.2-2007.3, etc.
  - 'Full-sample': $T = 510$ with $R = 482$ and $P = 28$.
    - In-sample: 1967.1-2007.2, 1967.2-2007.3, etc.
- We use **only** the information available **at month** t when we make the prediction.
  - Thus at t we need to forecast future values of our exogenous LI's
  - To predict them, we use different auxiliary ARMA-like models (we present results only for the $AR(1)$ case).

Out-of-sample Results

- For u_t and $u_t - u_{t-1}$ (and all the other transformations) the **best models** out of sample in terms of the lowest MSE are **those including GI** as the leading indicator
- The **best 15 models** at all forecast horizons (1- to 3-months-ahead) **always include GI** as the exogenous variable
- However, the best 3, 5 and 11 models at respectively 1-, 2- and 3-months ahead include **GI *only*** as the LI
- We test for
    - **Equal Forecast Accuracy** (EFA) using the Diebold & Mariano (1995) test
    - **Forecast Encompassing** (FE) using the Harvey, Leybourne & Newbold (1998) (HLN) test

Out-of-sample Results (Cont.)

- DM test and HLN test almost always reject the null at 10% at 1-month horizon and mostly reject at 2-month horizon.
- This means that our best model with GI outperforms all those models that use the *longest* available time series of u_t and IC, even though our best model is estimated over a rolling sample of 38 obs.
- Our best models with GI outperforms also those models not using GI over the short sample.

Out-of-sample Results (Cont.)

Best Forecasting Models: 1-month ahead

	1-step ahead				
n.	**Model**	**MSE**	**Rank**	**DM**	**HLN**
Panel A1: Best models					
261	$ARX(1) - G_t$	0.0166	1	-	-
398	$ARMAX(1,1) - G_t - SA$	0.0167	2	0.060	2.145**
327	$ARX(2) - G_t$	0.0172	3	0.448	1.063
491	$ARMAX(2,2) - IC_{t-1} - G_{t-1}$	0.0177	4	0.328	1.912*
305	$ARX(1) - G_{t-2}$	0.0179	5	0.616	1.289
464	$ARMAX(2,2) - G_t - SA$	0.0179	6	0.312	1.370
371	$ARX(2) - G_{t-2}$	0.0181	7	0.614	1.642
283	$ARX(1) - G_{t-1}$	0.0182	8	1.516	1.701*
463	$ARMAX(2,2) - G_{w4,t} - SA$	0.0184	9	0.442	2.116**
277	$ARX(1) - IC_t - G_t - SA$	0.0186	10	0.852	1.326
271	$ARX(1) - IC_t - G_t$	0.0186	11	0.709	1.605
266	$ARX(1) - G_t - SA$	0.0188	12	0.998	1.122
337	$ARX(2) - IC_t - G_t$	0.0191	13	0.799	1.875*
343	$ARX(2) - IC_t - G_t - SA$	0.0192	14	0.870	1.550
270	$ARX(1) - IC_{w4,t} - G_{w4,t}$	0.0192	15	0.778	1.807*
Panel B1: Best models without Google					
122	$ARMAX(2,2) - IC_{w4,t-2}$	0.0234	73	2.491**	3.074***
133	$ARMA(1,1)$	0.0301	197	2.152**	2.485**
Panel C1: Non-linear models					
521	$SETAR(2)$	0.0332	258	2.434**	2.925***
522	$LSTAR(2)$	0.0368	362	2.497**	3.015***
523	$AAR(2)$	0.0342	276	2.337**	2.903***

Out-of-sample Results (Cont.)

Best Forecasting Models: 2-month ahead

		2-step ahead			
n.	**Model**	**MSE**	**Rank**	**DM**	**HLN**
Panel A2: Best models					
261	$ARX(1) - G_t$	0.0157	1	-	-
464	$ARMAX(2,2) - G_t - SA$	0.0163	2	0.136	1.291
398	$ARMAX(1,1) - G_t - SA$	0.0166	3	0.177	1.219
327	$ARX(2) - G_t$	0.0172	4	0.633	0.864
266	$ARX(1) - G_t - SA$	0.0175	5	0.700	0.869
277	$ARX(1) - IC_t - G_t - SA$	0.0186	6	0.952	1.142
332	$ARX(2) - G_t - SA$	0.0194	7	0.955	1.192
343	$ARX(2) - IC_t - G_t - SA$	0.0206	8	1.150	1.285
283	$ARX(1) - G_{t-1}$	0.0208	9	1.514	1.543
420	$ARMAX(1,1) - G_{t-1} - SA$	0.0217	10	0.981	1.373
288	$ARX(1) - G_{t-1} - SA$	0.0220	11	1.402	1.551
305	$ARX(1) - G_{t-2}$	0.0220	12	1.551	1.718*
349	$ARX(2) - G_{t-1}$	0.0222	13	1.915*	2.024**
293	$ARX(1) - IC_{t-1} - G_{t-1}$	0.0233	14	1.989**	1.994**
299	$ARX(1) - IC_{t-1} - G_{t-1} - SA$	0.0234	15	1.392	1.468
Panel B2: Best models without Google					
122	$ARMAX(2,2) - IC_{w4,t-2}$	0.0514	180	1.814*	1.618
234	$ARMAX(2,2) - IC_{w3,t} - SA$	0.0565	191	1.389	1.131
Panel C2: Non-linear models					
521	$SETAR(2)$	0.0388	97	1.053	1.720*
522	$LSTAR(2)$	0.0447	140	1.190	1.779*
523	$AAR(2)$	0.0436	134	1.183	1.721*

Out-of-sample Results (Cont.)

Best Forecasting Models: 3-month ahead

3-step ahead					
n.	**Model**	**MSE**	**Rank**	**DM**	**HLN**
Panel A3: Best models					
398	$ARMAX(1,1)-G_t-SA$	0.0350	1	-	-
327	$ARX(2)-G_t$	0.0372	2	0.230	0.793
332	$ARX(2)-G_t-SA$	0.0379	3	0.244	0.671
261	$ARX(1)-G_t$	0.0382	4	0.308	0.852
464	$ARMAX(2,2)-G_t-SA$	0.0382	5	0.295	0.579
266	$ARX(1)-G_t-SA$	0.0383	6	0.299	0.777
349	$ARX(2)-G_{t-1}$	0.0488	7	1.164	1.300
354	$ARX(2)-G_{t-1}-SA$	0.0495	8	1.115	1.440
393	$ARMAX(1,1)-G_t$	0.0508	9	0.722	1.060
288	$ARX(1)-G_{t-1}-SA$	0.0510	10	1.142	1.501
283	$ARX(1)-G_{t-1}$	0.0513	11	1.217	1.383
343	$ARX(2)-IC_t-G_t-SA$	0.0528	12	0.659	0.811
277	$ARX(1)-IC_t-G_t-SA$	0.0531	13	0.681	0.852
365	$ARX(2)-IC_{t-1}-G_{t-1}-SA$	0.0548	14	1.275	1.658*
265	$ARX(1)-G_{w4,t}-SA$	0.0555	15	0.938	1.219
Panel B3: Best models without Google					
122	$ARMAX(2,2)-IC_{w4,t-2}$	0.1406	191	1.309	1.249
215	$ARMAX(1,1)-IC_{w4,t-1}-SA$	0.1294	173	1.748*	1.752*
Panel C3: Non-linear models					
521	$SETAR(2)$	0.0589	24	0.758	1.447
522	$LSTAR(2)$	0.0620	30	0.790	1.411
523	$AAR(2)$	0.0652	35	0.814	1.389

Out-of-sample Results (Cont.)

Some Forecasting Models in the **Full sample** (models from # 1 to #128)

		MSE						DM			HLN		
	Model	1-Step	Rank	2-Step	Rank	3-Step	Rank	1-St	2-St	3-St	1-St	2-St	3-St
1	$AR(1)$	0.0564	500	0.1842	513	0.4270	507	3.328***	2.108**	1.819*	3.629***	1.961**	1.582
2	$AR(1)-SA$	0.0577	501	0.1894	514	0.4391	510	3.310***	2.119**	1.824*	3.570***	1.973**	1.582
3	$AR(2)$	0.0388	397	0.1063	446	0.2826	451	2.993***	1.959*	1.737*	3.426***	1.871*	1.534
4	$AR(2)-SA$	0.0395	414	0.1094	453	0.2905	458	3.044***	1.998**	1.755*	3.423***	1.902*	1.544
5	$ARMA(1,1)$	0.0354	304	0.0834	318	0.2048	312	2.530**	1.800*	1.625	3.054***	1.765*	1.470
6	$ARMA(1,1)-SA$	0.0357	323	0.0954	398	0.2339	394	2.577***	1.985**	1.783*	3.096***	1.907*	1.550
7	$ARMA(2,2)$	0.0314	225	0.0718	244	0.1833	250	2.314**	1.684*	1.583	2.911***	1.689*	1.431
8	$ARMA(2,2)-SA$	0.0324	248	0.0886	362	0.2172	359	2.564**	1.852*	1.760*	3.095***	1.868*	1.548
9	$ARX(1)-IC_{w1,t}$	0.0458	464	0.1365	481	0.3286	472	2.895***	2.072**	1.869*	3.232***	1.942*	1.639
10	$ARX(1)-IC_{w2,t}$	0.0454	458	0.1357	480	0.3256	470	2.913***	2.040**	1.868*	3.248***	1.922*	1.634
11	$ARX(1)-IC_{w3,t}$	0.0452	454	0.1303	475	0.3145	466	2.933***	2.174**	1.957*	3.307***	2.044**	1.716*
12	$ARX(1)-IC_{w4,t}$	0.0418	434	0.1170	469	0.2843	453	2.805***	2.202**	1.999**	3.251***	2.079**	1.756*
13	$ARX(1)-IC_{t}$	0.0439	442	0.1263	474	0.3044	463	2.857***	2.110**	1.926*	3.233***	1.988**	1.689*
14	$ARX(1)-IC_{w1,t}-SA$	0.0470	469	0.1418	486	0.3423	477	2.961***	2.094**	1.882*	3.238***	1.957*	1.646*
15	$ARX(1)-IC_{w2,t}-SA$	0.0465	467	0.1407	485	0.3387	475	2.971***	2.063**	1.881*	3.251***	1.937*	1.642
16	$ARX(1)-IC_{w3,t}-SA$	0.0462	465	0.1348	479	0.3261	471	2.979***	2.183**	1.961**	3.301***	2.046**	1.715*
17	$ARX(1)-IC_{w4,t}-SA$	0.0424	437	0.1204	472	0.2937	460	2.836***	2.207**	2.002**	3.235***	2.076**	1.755*
18	$ARX(1)-IC_{t}-SA$	0.0448	452	0.1307	476	0.3160	467	2.902***	2.118**	1.929*	3.226***	1.992**	1.689*
19	$ARX(1)-IC_{w1,t-1}$	0.0487	478	0.1493	494	0.3568	485	3.038***	2.087**	1.847*	3.352***	1.948*	1.617
20	$ARX(1)-IC_{w2,t-1}$	0.0481	474	0.1471	493	0.3510	482	3.037***	2.067**	1.850*	3.354***	1.938*	1.618
21	$ARX(1)-IC_{w3,t-1}$	0.0484	476	0.1456	491	0.3476	481	3.066***	2.152**	1.899*	3.404***	2.012**	1.660*
22	$ARX(1)-IC_{w4,t-1}$	0.0453	456	0.1328	477	0.3193	468	2.971***	2.171**	1.934*	3.355***	2.033**	1.691*
23	$ARX(1)-IC_{t-1}$	0.0474	472	0.1422	488	0.3397	476	3.019***	2.113**	1.882*	3.356***	1.978**	1.647*
24	$ARX(1)-IC_{w1,t-1}-SA$	0.0504	489	0.1565	502	0.3740	493	3.111***	2.118**	1.861*	3.361***	1.971**	1.623
25	$ARX(1)-IC_{w2,t-1}-SA$	0.0498	483	0.1543	499	0.3683	491	3.112***	2.100**	1.867*	3.364***	1.962**	1.626
26	$ARX(1)-IC_{w3,t-1}-SA$	0.0501	486	0.1529	498	0.3649	490	3.131***	2.171**	1.905*	3.404***	2.025**	1.659*
27	$ARX(1)-IC_{w4,t-1}-SA$	0.0469	468	0.1398	484	0.3364	474	3.044***	2.186**	1.937*	3.353***	2.042**	1.688*
28	$ARX(1)-IC_{t-1}-SA$	0.0491	480	0.1494	495	0.3571	486	3.091***	2.136**	1.890*	3.361***	1.995**	1.648*
29	$ARX(1)-IC_{w1,t-2}$	0.0462	466	0.1559	501	0.3768	498	2.653***	1.954*	1.757*	2.889***	1.840*	1.554
30	$ARX(1)-IC_{w2,t-2}$	0.0446	448	0.1511	496	0.3648	489	2.671***	1.875*	1.770*	2.902***	1.783*	1.554
31	$ARX(1)-IC_{w3,t-2}$	0.0501	487	0.1517	497	0.3622	488	3.123***	2.094**	1.867*	3.439***	1.983**	1.631
32	$ARX(1)-IC_{w4,t-2}$	0.0446	449	0.1376	482	0.3342	473	3.066***	2.159**	1.917*	3.543***	2.038**	1.667*

Out-of-sample Results (Cont.)

Some Forecasting Models in the **Short sample** w/o GI (models from # 129 to #256)

Table 16 – continued

	Model	MSE 1-Step	Rank	MSE 2-Step	Rank	MSE 3-Step	Rank	DM 1-St	DM 2-St	DM 3-St	HLN 1-St	HLN 2-St	HLN 3-St
150	$ARX(1)-IC_{w4,t-1}$	0.0319	233	0.0707	237	0.1816	243	2.192**	1.940*	1.793*	3.121***	1.819*	1.797*
151	$ARX(1)-IC_{t-1}$	0.0346	281	0.0787	282	0.2019	301	2.416**	1.703*	1.236	2.980***	1.442	1.134
152	$ARX(1)-IC_{w1,t-1}-SA$	0.0375	373	0.0869	348	0.2032	305	2.301**	1.396	0.938	2.515**	1.147	0.865
153	$ARX(1)-IC_{w2,t-1}-SA$	0.0362	345	0.0938	393	0.2183	363	2.442**	1.667*	1.279	2.973***	1.442	1.209
154	$ARX(1)-IC_{w3,t-1}-SA$	0.0384	388	0.0856	336	0.2280	381	2.414**	2.038**	1.633	3.154***	2.047**	1.616
155	$ARX(1)-IC_{w4,t-1}-SA$	0.0329	253	0.0746	267	0.1880	266	2.285**	1.936*	1.828*	3.242***	1.823*	1.835*
156	$ARX(1)-IC_{t-1}-SA$	0.0357	315	0.0823	308	0.2078	327	2.462**	1.733*	1.278	3.015***	1.482	1.174
157	$ARX(1)-IC_{w1,t-2}$	0.0396	416	0.1047	438	0.2435	406	2.308**	1.539	1.105	2.691***	1.303	1.019
158	$ARX(1)-IC_{w2,t-2}$	0.0383	385	0.1048	440	0.2499	414	2.495**	1.746*	1.292	2.981***	1.549	1.230
159	$ARX(1)-IC_{w3,t-2}$	0.0387	394	0.0882	358	0.2297	386	2.415**	1.772*	1.366	2.991***	1.627	1.280
160	$ARX(1)-IC_{w4,t-2}$	0.0350	293	0.0720	245	0.1870	261	2.265**	1.795*	1.484	2.744***	1.517	1.378
161	$ARX(1)-IC_{t-2}$	0.0366	357	0.0865	345	0.2180	362	2.350**	1.638	1.204	2.700***	1.394	1.092
162	$ARX(1)-IC_{w1,t-2}-SA$	0.0409	427	0.1093	452	0.2500	415	2.310**	1.540	1.128	2.665***	1.313	1.040
163	$ARX(1)-IC_{w2,t-2}-SA$	0.0390	399	0.1119	462	0.2653	434	2.437**	1.760*	1.344	2.951***	1.605	1.278
164	$ARX(1)-IC_{w3,t-2}-SA$	0.0398	420	0.0930	387	0.2357	397	2.521**	1.757*	1.390	2.974***	1.604	1.303
165	$ARX(1)-IC_{w4,t-2}-SA$	0.0361	340	0.0752	274	0.1915	276	2.347**	1.791*	1.523	2.804***	1.519	1.417
166	$ARX(1)-IC_{t-2}-SA$	0.0379	379	0.0933	391	0.2300	387	2.427**	1.656*	1.261	2.749***	1.432	1.145
167	$ARX(2)-IC_{w1,t}$	0.0383	384	0.0895	369	0.2131	350	2.620***	1.607	1.154	3.060***	1.339	1.084
168	$ARX(2)-IC_{w2,t}$	0.0357	321	0.0872	353	0.2042	309	2.845***	1.753*	1.417	3.503***	1.487	1.385
169	$ARX(2)-IC_{w3,t}$	0.0365	355	0.0743	263	0.2102	338	2.292**	1.887*	1.433	2.837***	1.792*	1.387
170	$ARX(2)-IC_{w4,t}$	0.0319	232	0.0679	225	0.1780	234	2.208**	1.913*	1.748*	3.055***	1.746*	1.752*
171	$ARX(2)-IC_{t}$	0.0358	327	0.0796	286	0.2012	297	2.667***	1.707*	1.248	3.123***	1.413	1.145
172	$ARX(2)-IC_{w1,t}-SA$	0.0394	408	0.0911	381	0.2178	361	2.641***	1.709*	1.211	3.083***	1.428	1.137
173	$ARX(2)-IC_{w2,t}-SA$	0.0406	425	0.0998	422	0.2122	346	3.365***	1.614	1.458	2.994***	1.316	1.427
174	$ARX(2)-IC_{w3,t}-SA$	0.0396	415	0.0835	319	0.2173	360	2.683***	1.916*	1.468	3.220***	1.707*	1.432
175	$ARX(2)-IC_{w4,t}-SA$	0.0353	302	0.0767	277	0.1798	239	2.790***	1.874*	1.737*	3.066***	1.541	1.733*
176	$ARX(2)-IC_{t}-SA$	0.0395	411	0.0890	367	0.2027	303	3.178***	1.575	1.217	2.928***	1.261	1.117
177	$ARX(2)-IC_{w1,t-1}$	0.0357	318	0.0833	315	0.2029	304	2.226**	1.441	0.931	2.543**	1.183	0.861
178	$ARX(2)-IC_{w2,t-1}$	0.0358	326	0.0897	373	0.2116	345	2.504**	1.698*	1.244	3.097***	1.450	1.180
179	$ARX(2)-IC_{w3,t-1}$	0.0356	314	0.0739	261	0.2095	333	2.203**	1.944*	1.552	2.891***	1.939*	1.543
180	$ARX(2)-IC_{w4,t-1}$	0.0323	243	0.0678	224	0.1773	231	2.197**	1.902*	1.752*	3.066***	1.771*	1.750*
181	$ARX(2)-IC_{t-1}$	0.0353	300	0.0785	280	0.2023	302	2.483**	1.741*	1.245	3.079***	1.472	1.145
182	$ARX(2)-IC_{w1,t-1}-SA$	0.0363	349	0.0809	298	0.2008	294	2.152**	1.572	0.949	2.485**	1.288	0.875
183	$ARX(2)-IC_{w2,t-1}-SA$	0.0360	333	0.0900	374	0.2168	357	2.333**	1.780*	1.293	2.931***	1.567	1.227
184	$ARX(2)-IC_{w3,t-1}-SA$	0.0363	346	0.0728	255	0.2096	334	2.255**	1.935*	1.589	2.807***	2.022**	1.576
185	$ARX(2)-IC_{w4,t-1}-SA$	0.0339	270	0.0721	249	0.1830	249	2.392**	1.933*	1.808*	3.292***	1.801*	1.809*

Out-of-sample test of Superior Predictive Ability

White's (2000) Reality Check (RC) test

- The RC is a test for **superior unconditional predictive ability** that also accounts for the ***dependence*** among forecasting models (*data-snooping*).
- The **null** hypothesis is that ***all the competing models are no better than the benchmark*** model, i.e. $H_0 : \max_{1 \leq k \leq L} E(f_k) \leq 0$, where $f_k = e_{0,t}^2 - e_{k,t}^2$
- The ***alternative*** is that H_0 is false, that is, ***there exists a best model which is superior to the benchmark***.
- White's (2000) RC test statistic for H_0 is formed as $\bar{V} = \max_{1 \leq k \leq L} \sqrt{P} \bar{f}_k$, where $\bar{f}_k = P^{-1/2} \sum_{t=R+1}^{T} \hat{f}_{k,t}$
- Using the stationary bootstrap of Politis and Romano (1994), the empirical distribution of $\bar{V}^* = \max_{1 \leq k \leq L} \sqrt{P}(\bar{f}_k^* - \bar{f}_k)$ is used to compute the RC p-value

Out-of-sample test of Superior Predictive Ability (Cont.)

Reality Check p-values (in **bold** p-values$\geq$**5%** $\Rightarrow$ fail to reject H_0)

	B=2000	B=5000		B=2000	B=5000
	u_t			u_t^{LLD}	
1-step	Benchmark=403		1-step	Benchmark=327	
q=0.50	**0.073**	**0.070**	q=0.50	**0.076**	**0.076**
q=0.10	**0.053**	**0.057**	q=0.10	**0.053**	**0.060**
2-step	Benchmark=332		2-step	Benchmark=327	
q=0.50	0.037	0.039	q=0.50	0.043	0.040
q=0.10	**0.053**	**0.052**	q=0.10	**0.061**	**0.057**
3-step	Benchmark=332		3-step	Benchmark=266	
q=0.50	0.037	0.045	q=0.50	0.029	0.025
q=0.10	0.046	**0.052**	q=0.10	**0.050**	**0.052**
	$\log(u_t)$			$u_t - u_{t-1}$	
1-step	Benchmark=327		1-step	Benchmark=261	
q=0.50	**0.099**	**0.100**	q=0.50	**0.107**	**0.098**
q=0.10	**0.050**	0.045	q=0.10	**0.055**	**0.057**
2-step	Benchmark=327		2-step	Benchmark=261	
q=0.50	**0.080**	**0.080**	q=0.50	**0.098**	**0.097**
q=0.10	**0.058**	**0.058**	q=0.10	**0.053**	0.045
3-step	Benchmark=266		3-step	Benchmark=398	
q=0.50	**0.114**	**0.114**	q=0.50	**0.073**	**0.073**
q=0.10	**0.058**	**0.066**	q=0.10	0.048	0.048
	u_t^{logit}			u_t^{HPlog}	
1-step	Benchmark=327		1-step	Benchmark=327	
q=0.50	**0.083**	**0.083**	q=0.50	**0.073**	**0.083**
q=0.10	**0.073**	**0.068**	q=0.10	**0.057**	**0.060**
2-step	Benchmark=327		2-step	Benchmark=327	
q=0.50	0.027	0.033	q=0.50	**0.065**	**0.062**
q=0.10	**0.054**	**0.056**	q=0.10	**0.057**	**0.057**
3-step	Benchmark=266		3-step	Benchmark=266	
q=0.50	0.028	0.027	q=0.50	0.041	0.038
q=0.10	**0.052**	**0.054**	q=0.10	**0.061**	**0.052**

Further robustness checks out-of-sample

- Also **recursive** scheme with similar results (unreported).
- Different **auxiliary** models to predict the LI's: $AR(2)$, $ARMA(1,1)$, $ARMA(2,2)$ with similar (unreported) results.
- Comparison of our best models (overall and without Google indicator) with the **Survey of Professional Forecasters** for the quarterly unemployment rate
- **State-level** forecasts with different aggregation schemes
- Some **non-linear models** typically adopted in the literature
- We also ran the horse-race for different **transformation** of u_t typically used in the literature, such as
    - $\log(u_t)$
    - $u_t^{LLD} = \log(u_t) - \hat{\alpha} - \hat{\beta}t$
    - $u_t^{logit} = \log[u_t/(1 - u_t)]$
    - $u_t^{HPlog} = \log(u_t) - [\log(u_t)]^{HP}$.

A further out-of-sample check: comparison with the SPF

Sample: 2007:Q1-2009:Q2

- We also compared our forecasting models with the Survey of Professional Forecasters (SPF) (mean, median and best)
- At the 'middle' of $Q(J)$ (around Feb, May, Aug and Nov 15) SPF issues forecasts for $Q(J+1)$ to $Q(J+5)$ (true deadline for forecasters is around 10th of same month)
- We compare SPF^{best}, SPF^{median} and SPF^{mean} with 3 different forecasts of quarterly US unemployment from the following models (for u_t)
  - Best model overall, i.e. model with Google (# 403)
  - Best model overall without Google, i.e. model with Initial Claims (# 128)
  - Best model in the short sample without Google (# 205)

A further check: comparison with the SPF (Cont.)

Sample: 2007:Q1-2009:Q2

- For each model we compute 3 sets of quarterly forecasts
  1. At the end of $Q(J)$, e.g. 2007.3: forecast 1-month ahead
  $$\hat{u}_{t+1|t} \Rightarrow \mathbf{x}^{\mathbf{1st-month}}$$
  is our forecast for $Q(J+1)$ (conservative)
  2. At the end of $Q(J)$, e.g. 2007.3: forecast 2-month ahead
  $$\hat{u}_{t+2|t} \Rightarrow \mathbf{x}^{\mathbf{2nd-month}}$$
  is our forecast for $Q(J+1)$ (conservative)
  3. Around the 10^{th} of the second month of $Q(J)$, e.g. 2007.5: forecast 1- and 2-month ahead
  $$[u_t + \hat{u}_{t+1|t} + \hat{u}_{t+2|t}]/3 \Rightarrow \mathbf{x}^{\mathbf{Comb}}$$
  is our forecast for $Q(J+1)$ (less conservative and similar timing to SPF)

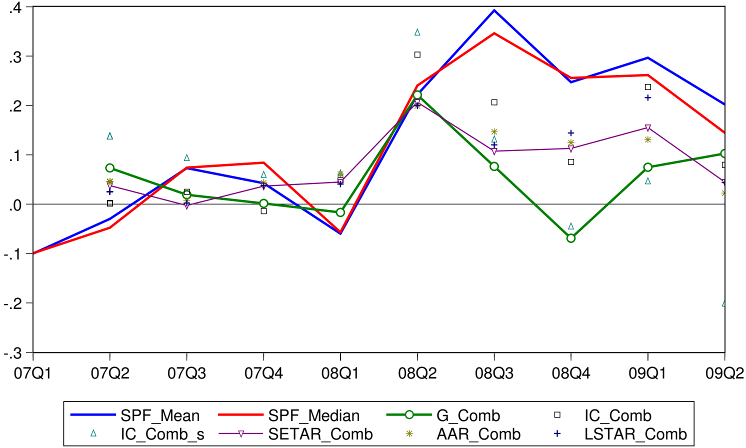
A further check: comparison with the SPF (Cont.)

Sample: 2007:Q1-2009:Q2. Benchmark: G^{Comb}

	MSE	Rank	DM	HLN
SPF^{best}	1.373	21	1.911*	2.177**
SPF^{mean}	0.415	11	1.545	2.784***
SPF^{med}	0.360	7	1.317	2.892***
$G^{1st-month}$	0.530	15	-1.522	2.401**
$G^{2nd-month}$	0.419	12	1.724*	1.925*
G^{Comb}	**0.082**	1	-	-
$IC^{1st-month}$	0.893	17	-0.337	2.621***
$IC^{2nd-month}$	0.361	8	-0.919	1.457
IC^{Comb}	0.208	5	-2.012**	-1.875*
$IC_s^{1st-month}$	0.612	16	0.048	2.386**
$IC_s^{2nd-month}$	0.413	10	1.810*	1.759*
IC_s^{Comb}	0.218	6	1.306	1.239
$SETAR^{1st-month}$	1.123	19	2.881***	2.596***
$SETAR^{2nd-month}$	0.373	9	1.098	2.902***
$SETAR^{Comb}$	*0.098*	2	-1.401	2.587***
$LSTAR^{1st-month}$	1.228	20	2.558**	2.407**
$LSTAR^{2nd-month}$	0.433	14	1.550	2.723***
$LSTAR^{Comb}$	0.127	4	-1.265	2.315**
$AAR^{1st-month}$	1.060	18	2.630***	2.418**
$AAR^{2nd-month}$	0.432	13	1.768*	2.900***
AAR^{Comb}	0.102	3	-1.37	2.662***

A further check: comparison with the SPF (Cont.)

Forecast errors ($\hat{e}_{k,t+\tau} = u_{t+\tau} - \hat{u}_{k,t+\tau|t}$) of 'best' models - Sample: 2007:Q1-2009:Q2



A further check: aggregation of State-level forecasts

- For each 51 states (including District of Columbia) we ran the same horse-race with the same 520 forecasting models.
- For $u_t - u_{t-1}$ the percentage of best models for each state using the Google indicator as a LI ranges between 75% and 84% for 1-, 2- and 3-month-ahead forecasts.
- For u_t such percentage ranges between 69 and 82%.
- We test whether the **aggregation** of the 51 best state models could improve the forecasting performance over the federal benchmark. We use the following weights:
  - equal weight
  - % or share of labor force w.r.t. US total
  - % of labor force $\times$ share of internet use among labor force
  - % of labor force $\times$ share of internet use among active
  - % of labor force $\times$ share of internet use among unemployed
  - % of unemployed w.r.t. US total $\times$ share of internet use among unemployed

A further check: aggregation of State-level forecasts (Cont.)

	1-Step					2-Step					3-Step				
Variable: $d(u_t)$	MSE	Rk1	Rk2	DM	HLN	MSE	Rk1	Rk2	DM	HLN	MSE	Rk1	Rk2	DM	HLN
Model															
best	0.0166	1	1	-	-	0.0157	1	1	-	-	0.0350	1	4	-	-
simple avg	0.2845	7	525	5.30^a	4.92^a	0.3391	7	524	2.77^a	2.31^b	0.3966	7	510	1.99^b	2.31^b
labor force (LF)	0.0292	2	181	-0.13	2.68^a	0.0310	2	48	-0.30	1.31	0.0411	2	7	-1.17	1.31
IU all × LF	0.0299	5	196	-0.06	2.75^a	0.0314	3	51	-0.28	1.32	0.0413	3	8	-1.16	1.32
IU active × LF	0.0296	3	190	-0.09	2.69^a	0.0318	4	56	-0.26	1.30	0.0423	4	9	-1.14	1.30
IU UN × LF	0.0298	4	194	-0.07	2.71^a	0.0322	5	57	-0.25	1.31	0.0425	5	10	-1.13	1.31
IU UN × UN	0.0917	6	519	2.33^b	3.33^a	0.0690	6	239	0.65	1.66^c	0.0618	6	32	-0.53	1.66^c
Variable: u_t	MSE	Rk1	Rk2	DM	HLN	MSE	Rk1	Rk2	DM	HLN	MSE	Rk1	Rk2	DM	HLN
Model															
best	0.0167	1	1	-	-	0.0169	1	7	-	-	0.0482	6	15	-	-
simple avg	0.3000	7	526	5.29^a	4.70^a	0.3700	7	522	2.48^b	2.15^b	0.4560	7	514	1.83^c	1.73^c
labor force (LF)	0.0280	2	120	0.24	2.95^a	0.0293	2	29	-1.23	0.37	0.0459	3	3	-1.06	0.54
IU all × LF	0.0283	3	131	0.26	2.98^a	0.0294	3	30	-1.24	0.36	0.0454	2	2	-1.07	0.54
IU active × LF	0.0286	4	137	0.29	2.94^a	0.0303	5	33	-1.21	0.38	0.0474	5	5	-1.04	0.55
IU UN × LF	0.0287	5	140	0.30	2.96^a	0.0302	4	32	-1.21	0.38	0.0469	4	4	-1.05	0.56
IU UN × UN	0.0709	6	513	2.06^b	3.31^a	0.0519	6	152	-0.65	1.41	0.0373	1	1	-1.16	0.70

^{a}, ^{b}, and ^{c} significant at 1, 5 & 10%

A further check: forecasts from some non-linear models

- We use the following non-linear models
- A SETAR(2)

$$\begin{aligned} u_t = {} & [\phi_{01} + \phi_{11} u_{t-1} + \phi_{21} u_{t-2}]\, I(u_{t-1} \leq c) \\ & + [\phi_{02} + \phi_{12} u_{t-1} + \phi_{22} u_{t-2}]\, I(u_{t-1} > c) + \varepsilon_t \end{aligned} \tag{1}$$

- An LSTAR(2)

$$\begin{aligned} u_t = {} & [\phi_{01} + \phi_{11} u_{t-1} + \phi_{21} u_{t-2}]\, [1 - G(\gamma, c, u_{t-1})] \\ & + [\phi_{02} + \phi_{12} u_{t-1} + \phi_{22} u_{t-2}]\, G(\gamma, c, u_{t-1}) + \varepsilon_t \end{aligned} \tag{2}$$

- and an AAR(2)

$$u_t = \mu + \sum_{i=1}^{m} s_i(u_{t-(i-1)d}) + \varepsilon_t \tag{3}$$

Conclusion and discussion

- In this paper we have suggested **a new leading indicator** based on **Google job web search index** (GI) to forecast the monthly US unemployment rate
- We have tested the predictive power of different models using the Google index running an out-of-sample horse-race for 1- to 3-month-ahead forecasts
- Our results show that simple time series models augmented with GI **outperform** similar models using IC even when estimated over *longer* samples

Conclusion and discussion (Cont.)

- We assess the out-of-sample predictive ability of our best model (with GI) using DM and HLN test of EFA and FE, finding that **our best model is more accurate**
- We also assess the **superior predictive ability** of our best models with the Reality Check, thus controlling for *data-snooping* biases.
- Our results are robust to **different transformations** of u_t, to **state-level** data and aggregation, and our models also **outperform the SPF**
- Some **caveats** remain: we have a *very short* sample but our results seem very *promising*.