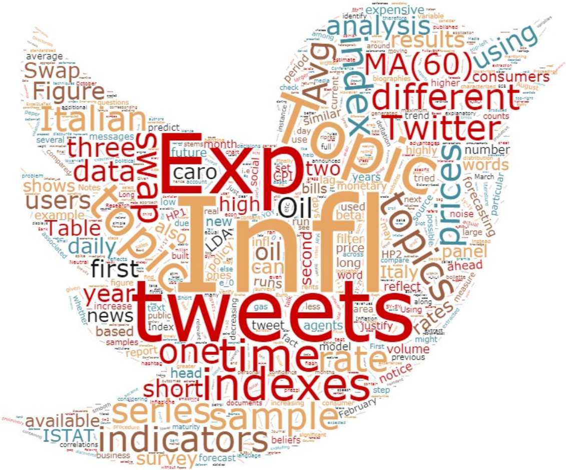
Cristina Angelico, Juri Marcucci, Marcello Miccoli, and Filippo Quarta
DG Economics and Statistics, Research & DG for Information Technology
Bank of Italy

Can We Measure Inflation Expectations Using Twitter?

Harnessing Big Data & Machine Learning Technologies for Central Banks

Rome, March 26, 2018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Motivation

Inflation Expectations are **fundamental** for Central Banks

- Determine real interest rates - consumption and savings choices
- Provide input on need to intervene and effectiveness of central bank actions

Available sources of expectations:

- **Survey-based**: **“true” expectations**, but **low frequency**
- **Market-based**: **high frequency**, but variable and uncertain **risk premia**

- A data source that combines “true” expectations with high frequency sampling would be important for policy makers

Can social media be used to elicit inflation expectations?

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Can social media be used to elicit inflation expectations?

- Social media allow a large number of users to both receive and send information (perception/expectations)
- Scanning social media messages can thus be informative to broadly capture people views.

This work:

- Propose a way to **filter social media messages (Twitter) on price expectations**
- Combine information in **meaningful indexes of inflation expectations**
- Examine how **they behave with respect to existing sources of expectations**

Motivation (Cont.)

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Results & Contributions

Preliminary Results

- Indexes extracted from tweets counts give a **meaningful signal on inflation expectations**
  - Significant correlations with other sources of expectations

Contribution

- Explore **Twitter** as a **new source of data** to elicit expectations.
  - Wide variety and large volume of users
  - High frequency
- Analyze the **usefulness of social media** data in a **new context**
  - Current literature uses Twitter to predict political elections, firms' revenues, marketing, and asset returns
- Evaluation of different **signal extraction techniques**

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Roadmap – The paper in one slide

1. **Data**
   - Twitter data and Keywords
2. **Twitter-based Inflation expectation indexes**
   - “Dictionary rules” (keywords)
   - “Topic analysis”
3. **Preliminary Results**
   - Correlations
     - Suvey-based measures (ISTAT)
     - Market-based measures (inflation swap rate)
   - Forecasting
4. **Conclusion and next steps**

Data selection: Which tweets talk about inflation? – Relevant Keywords

Selection of tweets with following (italian) **keywords**:

- *prezzo, prezzi, 'costo della vita'*
  - *price + prices + "cost of living"*
- *'caro bollette', inflazione, caro, 'caro prezzi', caroprezzi, 'benzina alle stelle', 'bolletta salata', 'caro affitti', 'caro benzina', 'caro carburante', 'caro gas'*
  - *"expensive bills" + inflation + expensive + "high prices" + "high-prices" + "high gas prices" + "higher bill" + "higher rents" + "high petrol/gasoline price" + "high petrol/gasoline prices" + "high gas bills"*
- *deflazione, disinflazione, ribassi, ribasso, 'meno caro', 'bollette più leggere'*
  - *deflation + disinflation + sales + sale + "less expensive" + "less expensive bills"*

Data selection: Which tweets talk about inflation? – Samples

- Two samples depending on Twitter private API:
  - **Long sample**: **January 2013 – October 2016**
    - API: Full Search Archive (FSA).
    - Just **counts**
  - **Short sample**: **April 2015 – May 2016**
    - API: Historical Power Track (HPT).
    - **Full text and metadata** (e.g. users' biography, geo-localization, etc.). About **1.5 ml tweets** for 278,584 individual users

Example of selected tweets

(a) #Eurozona: a marzo prosegue la deflazione con -0,1% di #inflazione annua #eurostat

(b) RT istat_it: Secondo la stima preliminare, a marzo 2015 la #deflazione é stabile a -0,1%

(c) RT SkyTG24: #Ultimora BCE, #Draghi: senza nostra azione saremmo in deflazione

(d) Draghi: ”Abbiamo salvato l’Europa dalla deflazione” Non dire gatto se non ce l’hai nel sacco!

(e) Il timido aumento di maggio dell’inflazione é poca cosa. Adesso chi grida alla ripresa?

(f) Il prezzo del mio abbonamento sale del 10% ogni anno, ovviamente a qualcuno il caro prezzi inizia a pesare

(g) Da domani sará meno caro usare il cellulare in Europa. Ecco perché

(h) Solo da Baby Glamour acquistando tre capi il meno caro é in regalo. Promozione fino al 10 Ottobre.

(i) Il piú grande spettacolo dopo il #big-bang é l’inflazione cosmica

Translation:

(a) #Eurozone: in March #deflation continues with -0.1% YOY #Eurostat

(b) RT istat_it: According to the flash estimate, in March 2015 #deflation is stable at -0.1%

(c) RT SkyTG24: #breakingnews BCE, #Draghi: without our action we would be in deflation

(d) #Draghi: “We saved Europe from deflation”. Do not count your chickens before they are hatched!

(e) The increase of inflation in May is abysmal. Now who’s saying that economic recovery is ongoing?

(f) The price of my subscription increases by 10% every year. Obviously this high prices are becoming unbearable.

(g) Starting tomorrow it will be less expensive to use the cellphone in Europe.

(h) Only at Baby Glamour if your buy three items the least expensive is free. Promotional sales until October 10.

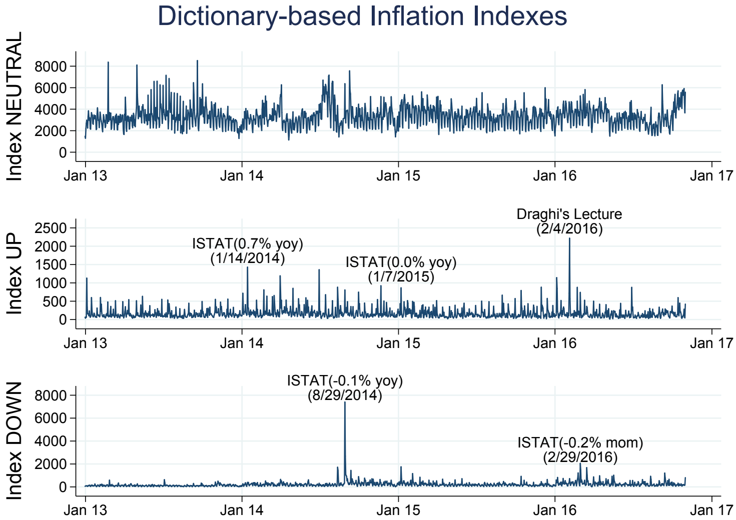
(i) The greatest show after the #big-bang is the cosmic inflation

Inflation indexes - Dictionary-based approach

- Problem: if tweets talk about '*prices*' $\Rightarrow$ increasing or decreasing prices? And what about '*inflation*'?

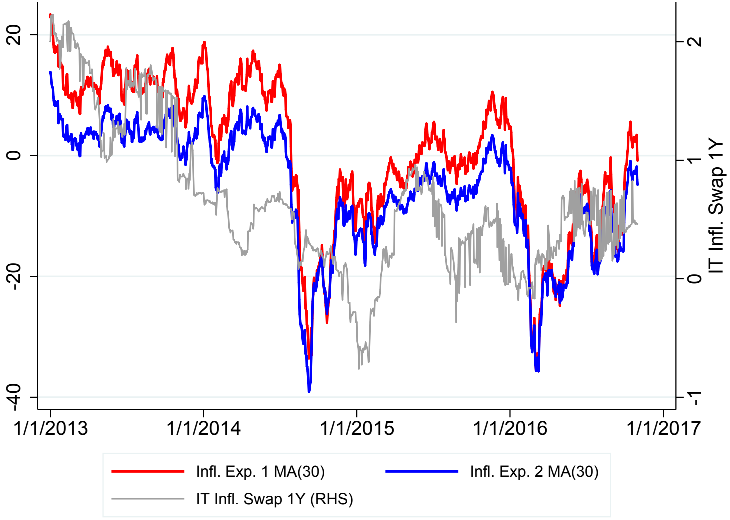
- Dictionary-based approach: **keywords' connotation reflects the message**
  - **Inflation_Neutral**: (*price + prices + "cost of living"*)
  - **Inflation_Up**: (*"expensive bills" + inflation + expensive + "high prices" + "high-prices" + "high gas prices" + "higher bill" + "higher rents" + "high petrol/gasoline price" + "high petrol/gasoline prices" + "high gas bills"*)
  - **Inflation_Down**: (*deflation + disinflation + sales + sale + "less expensive" + "less expensive bills"*)

- Index computed as **daily raw count of tweets**


Dictionary-based Inflation Indexes
Index NEUTRAL
8000
6000
4000
2000
0
Jan 13
Jan 14
Jan 15
Jan 16
Jan 17
Index UP
2500
2000
1500
1000
500
0
ISTAT(0.7% yoy)
(1/14/2014)
ISTAT(0.0% yoy)
(1/7/2015)
Draghi's Lecture
(2/4/2016)
Index DOWN
ISTAT(-0.1% yoy)
(8/29/2014)
ISTAT(-0.2% mom)
(2/29/2016)

- **Inflation_Neutral** index has relevant noise (e.g. advertisement, e-commerce, etc...): Discarded for now
- **Inflation_Up** and **Inflation_Down** cleaner and more meaningful signal
- Using both we define:
  Inflation_Exp = Inflation_Up - Inflation_Down
  - **Inflation Expectations #1**: Filtering on event dummies, standardization, winsorizing
  - **Inflation Expectations #2**: only standardization, winsorizing

Inflation Expectations (IE) indexes and Inflation swaps at 1Y for Italy



Indexes in the short sample: Topic analysis

- In the short sample **exploit the full text** of tweets to filter out noise (ads, e-commerce ...)
- **Let the text speak!** Topics extraction through **Latent Dirichlet Allocation (LDA)**
  - Intuitively, the methods identifies some topics from text
  - Each topic defined by a collection of word
- From identified topics we **selected those more related to price evolution**
- Index computed as **daily raw counts of tweets belonging to selected topic**

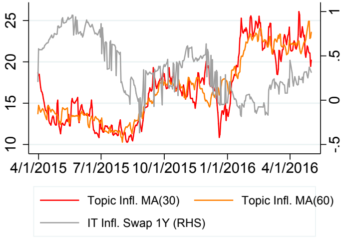
Selection of Topics

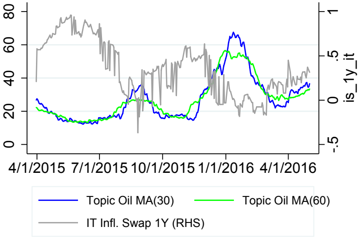
Smartphone e-commerce		Energy and Fuel		Inflation/Deflation/Growth	
Italian	**[English]**	**Italian**	**[English]**	**Italian**	**[English]**
Iphon		Petrol	[oil]	inflazion	[inflat]
apple		croll	[collaps]	deflazion	[deflat]
uscit	[exit]	dollar		cresc	[growth]
galaxy		baril	[barrel]	istat	
samsung		russ	[Russ]	drag	[Draghi]
offert	[discount]	elettr		stim	[estim]
caratterist	[featur]	gregg	[crud]	ripres	[recover]
tecnic	[technic]	york		conferm	[confirm]
compres	[incl]	iran		gzag	
test		arab		eurozon	

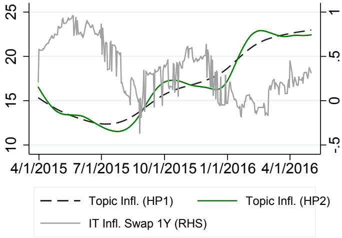
Selection of Topics

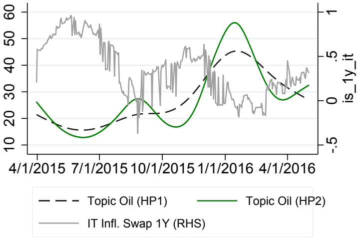
Smartphone e-commerce		Energy and Fuel		Inflation/Deflation/Growth	
Italian	**[English]**	**Italian**	**[English]**	**Italian**	**[English]**
Iphon		Petrol	[oil]	inflazion	[inflat]
apple		croll	[collaps]	deflazion	[deflat]
uscit	[exit]	dollar		cresc	[growth]
galaxy		baril	[barrel]	istat	
samsung		russ	[Russ]	drag	[Draghi]
offert	[discount]	elettr		stim	[estim]
caratterist	[featur]	gregg	[crud]	ripres	[recover]
tecnic	[technic]	york		conferm	[confirm]
compres	[incl]	iran		gzag	
test		arab		eurozon	

Short sample: Topics on inflation and oil and market-based measures









Dictionary- vs. Topics-based indexes

- **Topics-based** seemingly **less noisy** than dictionary-based
- But **not directional**

Twitter-based indexes vs market-based (survey-based) inflation expectations

- Twitter-based indexes give a **signal consistent with available inflation expectations**?
- **Compare Twitter signals with:**
- **Survey-based**: consumers’ inflation expectations over next 12m(ISTAT)
  - Caveat (monthly frequency)
- **Market-based**: inflation swap rates on IT inflation
  - Daily, but caveat of risk premia
- Significant correlations. Negative for topics-based indicators

Correlations with survey-based measures of IE - Dictionary based (Long sample)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
(a) IE 1 MA(10)	1						
(b) IE 1 MA(30)	0.864***	1					
(c) IE 1 MA(60)	0.740***	0.953***	1				
(d) IE 2 MA(10)	0.979***	0.823***	0.701***	1			
(e) IE 2 MA(30)	0.892***	0.993***	0.934***	0.871***	1		
(f) IE 2 MA(60)	0.766***	0.961***	0.995***	0.740***	0.951***	1	
(g) IE Consumers (ISTAT)	**0.500****	**0.612*****	**0.647*****	**0.461***	**0.601*****	**0.643*****	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Correlations with survey-based measures of IE - Topics-based (Short sample)

		(b)	(c)	(d)	(e)	(f)	(g)	(l)
(b)	Topic Infl. Avg. MA(10)	1						
(c)	Topic Infl. Avg. MA(30)	0.794***	1					
(d)	Topic Infl. Avg. MA(60)	0.645***	0.862***	1				
(e)	Topic Oil Avg. MA(10)	0.14	0.228	0.442	1			
(f)	Topic Oil Avg. MA(30)	0.277	0.312	0.507	0.968***	1		
(g)	Topic Oil Avg. MA(60)	0.264	0.327	0.578***	0.936***	0.962***	1	
(l)	IE Consumers (ISTAT)	-0.378	**-0.539*** **	**-0.686*** **	0.169	0.15	0.064	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Correlations with market-based measures of IE - Dictionary-based (long sample)

	IT Infl. Swap 1Y	IT Infl. Swap 1Y-1Y	IT Infl. Swap 1Y-2Y
Infl. Exp. 1 MA(10)	0.531***	0.419***	0.261***
Infl. Exp. 1 MA(30)	0.611***	0.456***	0.278***
Infl. Exp. 1 MA(60)	0.645***	0.458***	0.285***
Infl. Exp. 2 MA(10)	0.517***	0.412***	0.257***
Infl. Exp. 2 MA(30)	0.599***	0.451***	0.271***
Infl. Exp. 2 MA(60)	0.637***	0.459***	0.278***
IT Infl. Swap 1Y	1	0.687***	0.487***
IT Infl. Swap 1Y-1Y		1	0.464***
IT Infl. Swap 1Y-2Y			1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Correlations with market-based measures of IE - Topics-based (short sample)

	IT Infl. Swap 1Y	IT Infl. Swap 1Y-1Y	IT Infl. Swap 1Y-2Y
Topic Infl. Avg. MA(10)	-0.373***	-0.303***	-0.399***
Topic Infl. Avg. MA(30)	-0.501***	-0.459***	-0.606***
Topic Infl. Avg. MA(60)	-0.567***	-0.434***	-0.662***
Topic Oil Avg. MA(10)	-0.625***	-0.201***	-0.319***
Topic Oil Avg. MA(30)	-0.681***	-0.184***	-0.375***
Topic Oil Avg. MA(60)	-0.721***	-0.174***	-0.432***
IT Infl. Swap 1Y	1	0.130***	0.614***
IT Infl. Swap 1Y-1Y		1	0.417***
IT Infl. Swap 1Y-2Y			1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Summing up

- Dictionary-based Twitter indexes give a **meaningful signal**
  - co-move significantly with available data on inflation expectation
- Topics-based Twitter indexes **negatively correlated with expectations**
  - Index **does not take into account direction of expectations**
  - Short sample (April 2015 - May 2016): very low or negative realized inflation
- **Twitter-indexes** signals if **inflation expectations are increasing or decreasing**, but **no info on level**

- Can Twitter indexes predict the evolution of market-based inflation swap rates?
- Rolling scheme. We use direct forecasts
  - Benchmark model: $AR(p)$ with p selected by BIC in-sample

$$y_{t+h}^{h} = \beta_0 + \beta_1(L)y_t + \eta_{t+h}, \qquad t = 1, 2, \ldots, T \qquad (1)$$

  - Competing models: $AR - X(p)$ model w x_t with lags p and q selected by BIC ($p_{max} = q_{max} = 4$)

$$y_{t+h}^{h} = \beta_0 + \beta_1(L)y_t + \beta_2(L)x_t + \varepsilon_{t+h}, \qquad t = 1, 2, \ldots, T \quad (2)$$

- Results for the long sample (Jan 2013 - Oct 2016)
  Timing: $T = R + P$ obs. $T = 1001$, $R = 250$, $P = 751$
- R observations used to estimate the models (in-sample), last P for out-of-sample evaluation.

Forecasting Exercise Results –Inflation Swap 1Y-1Y

x_t	1	2	3	4	5	6	10	12	15	20	25	30
$AR(p)$	0.150	0.153	0.158	0.163	0.170	0.173	0.190	0.197	0.203	0.213	0.219	0.223
$IE_{neutral,t}$	1.004†	1.003	1.003	1.005†	1.010	1.007	0.997	0.987	0.978	0.977	0.971	0.988
$IE_{up,t}$	1.002	1.004†††	1.002	1.004†	1.004	1.002	0.999	1.000	1.002	1.008	0.994	0.998
$IE_{down,t}$	1.003	1.013	1.010	1.008	1.009	1.008	1.011	1.014	1.014	1.003	1.004	1.009
$IE_{up-down,t}$	1.005††	1.003	1.004	1.008	1.003	1.007	1.006	1.004	1.003	1.000	1.002†	1.001
$IE_{1,ma10,t}$	1.002	1.000	1.005	1.004	1.002	1.000	0.998	0.999	1.000	0.998	0.995	0.996
$IE_{1,ma30,t}$	1.002	1.001	1.006	1.005	1.004	1.003	1.006	1.006	1.005	1.015	1.017	1.012
$IE_{2,ma10,t}$	1.002	1.001	1.007	1.004	1.003	1.001	0.999	1.000	1.000	0.998	0.996	0.996
$IE_{2,hp,t}$	1.001	1.001	1.001	0.998	0.995	0.992	0.986	0.979	0.969	0.960	0.955	0.967
$IE_{2,ma30,t}$	1.001	1.000	1.005	1.004	1.003	1.002	1.005	1.006	1.005	1.015	1.017	1.011

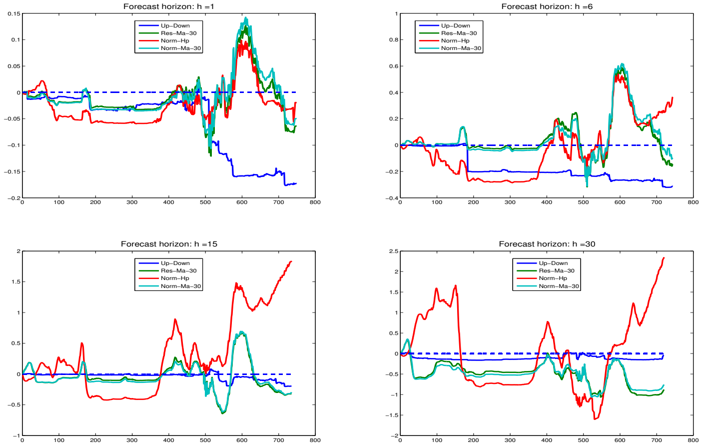
- For benchmark $AR(p)$: RMSFE
- For all other models: ratio of RMSFE of row model to RMSFE of benchmark
- *, **, ***, DM test significant at 10, 5, and 1%, respectively
- †, ††, † † †, DM test significant at 10, 5, and 1%, respectively but benchmark outperforms
- Forecast horizons: from 1 to 6 days, 10, 12, 15, 20, 25 and 30 days ahead.

Cumulative Sum of Squared (Forecast) Error Differences (CSSED)

- $$\boxed{CSSED_{m,\tau} = \sum_{\tau=R}^{T} (\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau})} \tag{3}$$

$$\hat{e}_{k,\tau} = u_\tau - \hat{u}_{k,\tau|t} \tag{4}$$

- What happens if the benchmark model (bm) outperforms the competing model (m)?
- $\hat{e}^2_{bm,\tau} < \hat{e}^2_{m,\tau} \quad \Rightarrow \quad CSSED_{m,\tau} < 0$
- And if the competing model m beats the benchmark bm?
- $\hat{e}^2_{bm,\tau} > \hat{e}^2_{m,\tau} \quad \Rightarrow \quad CSSED_{m,\tau} > 0$


Forecast horizon: h =1
Forecast horizon: h =6
Forecast horizon: h =15
Forecast horizon: h =30
Up–Down
Res–Ma–30
Norm–Hp
Norm–Ma–30

Work in progress...

- **Tweets generate meaningful signals on inflation expectations: high frequency and large users base**
- Daily Twitter-based indexes of inflation expectations are highly and significantly correlated with both daily market-based and monthly survey-based inflation expectations
- Indexes can say whether expectations are for higher or lower inflation, but cannot shed light on level

Next steps:

- Validation with a longer time series
- New ways of extracting/cleaning signal?