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# Can We Measure Inflation Expectations Using Twitter?

BoI-FRB Conference on Nontraditional Data & Statistical Learning with Applications to Macroeconomics
Rome (Italy) – November 11-12, 2020

# Motivation

Inflation Expectations play a **crucial role** in macroeconomic:

- Key to understand consumption and investment choices
- Informative on the effectiveness of a central bank's actions

Available sources of expectations:

- **Survey-based**: "**true**" expectations, but **low frequency**
- **Market-based**: **high frequency**, but **risk and liquidity premia**

Social media:

- Are widely used to spread news
- Reflect trending topics and collective opinions

**Can we use social media to elicit inflation expectations?**

# This work

- Uses Twitter to capture consumers' inflation expectations
- We **select tweets** related to inflation
- Filter **meaningful signals** from the data
- Build a set of **daily proxies** of inflation expectations
- Examine the **information content** vs existing sources
- Examine their **predictive power** vs existing sources

# Main findings

- We **find** that our **Twitter-based Indicators** convey **meaningful high frequency signals** on inflation expectations.
  1. Our **Twitter-based Inflation Expectation indexes are significantly correlated** with both **survey-based and market-based** measures
  2. Our **Twitter-based indexes** are also **informative**, i.e. they convey additional **predictive power** both in-sample and out-of-sample
  3. Our results are similar when we concentrate on a **subset of Twitter users** who are interested in economics (Econ) or work in the press (News)
- The suggested procedure is **easily applicable to different countries and languages**

# Contributions

- **Use Twitter to elicit inflation expectations** $\Rightarrow$ **new source**
  - Nice features: 1) Wide variety and **large volume of users**; 2) **high frequency**; and 3) available in **several countries**
- Analyze the **usefulness of social media** in a new context
  - Current literature focus on political elections, firms' revenues, marketing, and asset returns
- Combine **machine learning** and **semantic approach**
  - Extract meaningful information from noisy and very large textual data

# The paper in one chart

- 11.1 million tweets in Italian
- Jun 1 2013 - Dec 31 2019
- 944,512 users

**Data (Twitter)**
Relevant keywords

**Three STEPS:**
1. LDA
2. Dictionary-based
3. Directional indexes

- Text mining pipeline
- Machine Learning
- Signal vs noise
- Daily frequency

- Dictionary of bi/tri-grams
- Directional indexes
- (Index UP - Index DOWN)

**We find:**
a) Significant correlation with survey- & market-based expectations
b) Informative-ness
c) Predictive power

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

(EN / IT)

**(N)** *price(s), cost of living*

- *prezzo, prezzi, costo della vita*

**(U)** *expensive bills, inflation, expensive, high prices, high-prices, high gas prices, higher bill, higher rents, high gasoline price, high oil prices, high gas bills*

- *caro bollette, inflazione, caro, caro prezzi, caroprezzi, benzina alle stelle, bolletta salata, caro affitti, caro benzina, caro carburante, caro gas*

**(D)** *deflation, disinflation, sale(s), less expensive, less expensive bills*

- *deflazione, disinflazione, ribassi, ribasso, meno caro, bollette più leggere*

# Example of selected tweets

| Italian original | English translation |
|---|---|
| RT istat_it: Secondo la stima preliminare, a marzo 2015 la #deflazione è stabile a -0,1% | RT istat_it: According to the flash estimate, in March 2015 #deflation is stable at -0.1% |
| Il prezzo del mio abbonamento sale del 10% ogni anno, ovviamente a qualcuno il caro prezzi inizia a pesare | The price of my subscription increases by 10% every year. Obviously this high prices are becoming unbearable. |
| RT SkyTG24: #Ultimora BCE, #Draghi: senza nostra azione saremmo in deflazione | RT SkyTG24: #breakingnews BCE, #Draghi: without our action we would be in deflation |
| #Draghi: ”Abbiamo salvato l’Europa dalla deflazione” Non dire gatto se non ce l’hai nel sacco! | #Draghi: “We saved Europe from deflation”. Do not count your chickens before they are hatched! |
| Solo da Baby Glamour acquistando tre capi il meno caro è in regalo. Promozione fino al 10 Ottobre. | Only at Baby Glamour when you buy three items the least expensive is free. Promotional sales until October 10. |
| Il più grande spettacolo dopo il #big-bang è l’inflazione cosmica | The greatest show after the #big-bang is cosmic inflation |

- A large number of tweets related to different themes
- The sample contains ”noise” (i.e. advertisements)

# Example of selected tweets

| Italian original | English translation |
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| RT istat_it: Secondo la stima preliminare, a marzo 2015 la #deflazione è stabile a -0,1% | RT istat_it: According to the flash estimate, in March 2015 #deflation is stable at -0.1% |
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| RT SkyTG24: #Ultimora BCE, #Draghi: senza nostra azione saremmo in deflazione | RT SkyTG24: #breakingnews BCE, #Draghi: without our action we would be in deflation |
| #Draghi: ”Abbiamo salvato l’Europa dalla deflazione” Non dire gatto se non ce l’hai nel sacco! | #Draghi: “We saved Europe from deflation”. Do not count your chickens before they are hatched! |
| ~~Solo da Baby Glamour acquistando tre capi il meno caro è in regalo. Promozione fino al 10 Ottobre.~~ | ~~Only at Baby Glamour when you buy three items the least expensive is free. Promotional sales until October 10.~~ |
| Il più grande spettacolo dopo il #big-bang è l’inflazione cosmica | The greatest show after the #big-bang is cosmic inflation |

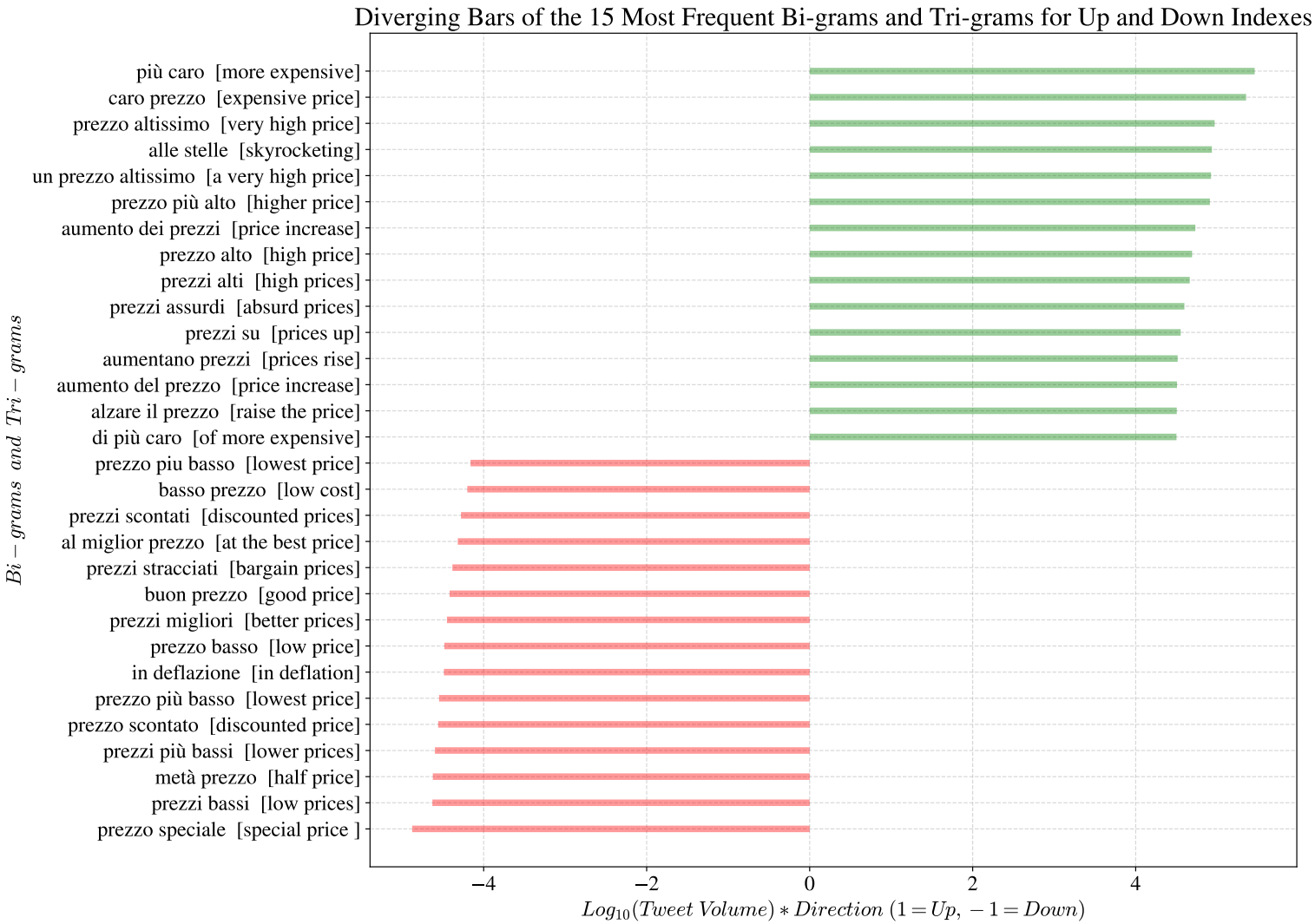
- A large number of tweets related to different themes
- The sample contains ”noise” (i.e. advertisements)

# Topics discovered by LDA: Examples

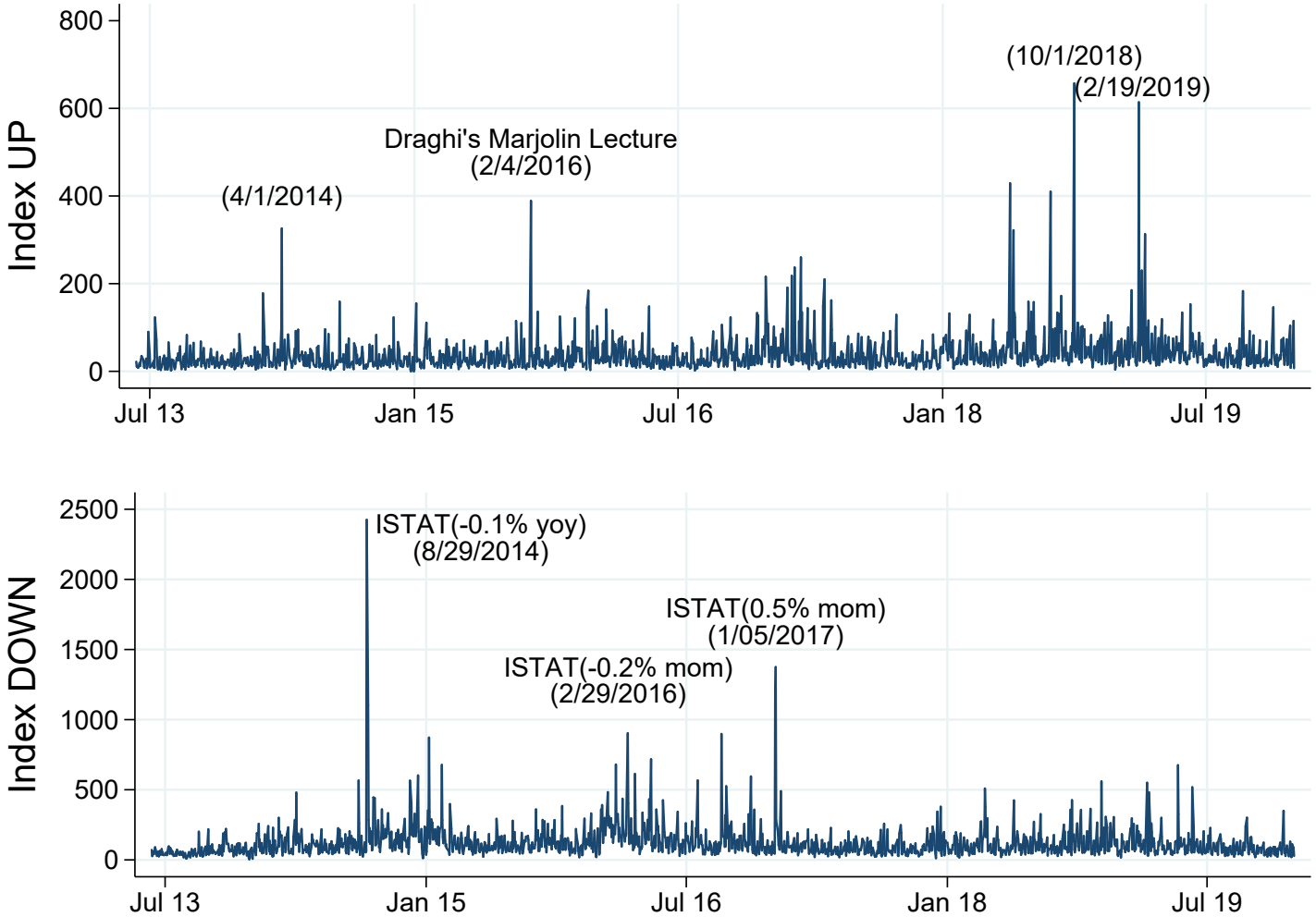
| Topic 13 | | Topxic 19 | | Topic 36 | |
|---|---|---|---|---|---|
| **Italian** | **[English]** | **Italian** | **[English]** | **Italian** | **[English]** |
| prezzo | [*price*] | inflazione | [*inflation*] | prezzi | [*prices*] |
| prezzi | [*prices*] | salari | [*wages*] | ribasso | [*sale*] |
| iphone | [*iphone*] | deflazione | [*deflation*] | inflazione | [*inflation*] |
| samsung | [*samsung*] | euro | [*euro*] | prezzo | [*price*] |
| caratteristiche | [*features*] | prezzo | [*price*] | petrolio | [*oil*] |
| galaxy | [*galaxy*] | prezzi | [*prices*] | borsa | [*stock exchange*] |
| smartphone | [*smartphone*] | anni | [*years*] | calo | [*drop*] |
| uscita | [*launch*] | italia | [*italy*] | istat | [*istat*] |
| apple | [*apple*] | lavoro | [*job*] | italia | [*italy*] |
| ecco | [*here it is*] | stipendi | [*wages*] | rialzo | [*rise*] |

- LDA: $\Rightarrow$ 50 topics (min perplexity)
- Assigns to every tweet a probability distribution over the topics
- Each tweet is assigned to the topic with the highest likelihood

# Step Two: Dictionary-based approach




# Step Two: Dictionary-based approach




$\pi_0^e$ **= Index Up - Index Down**

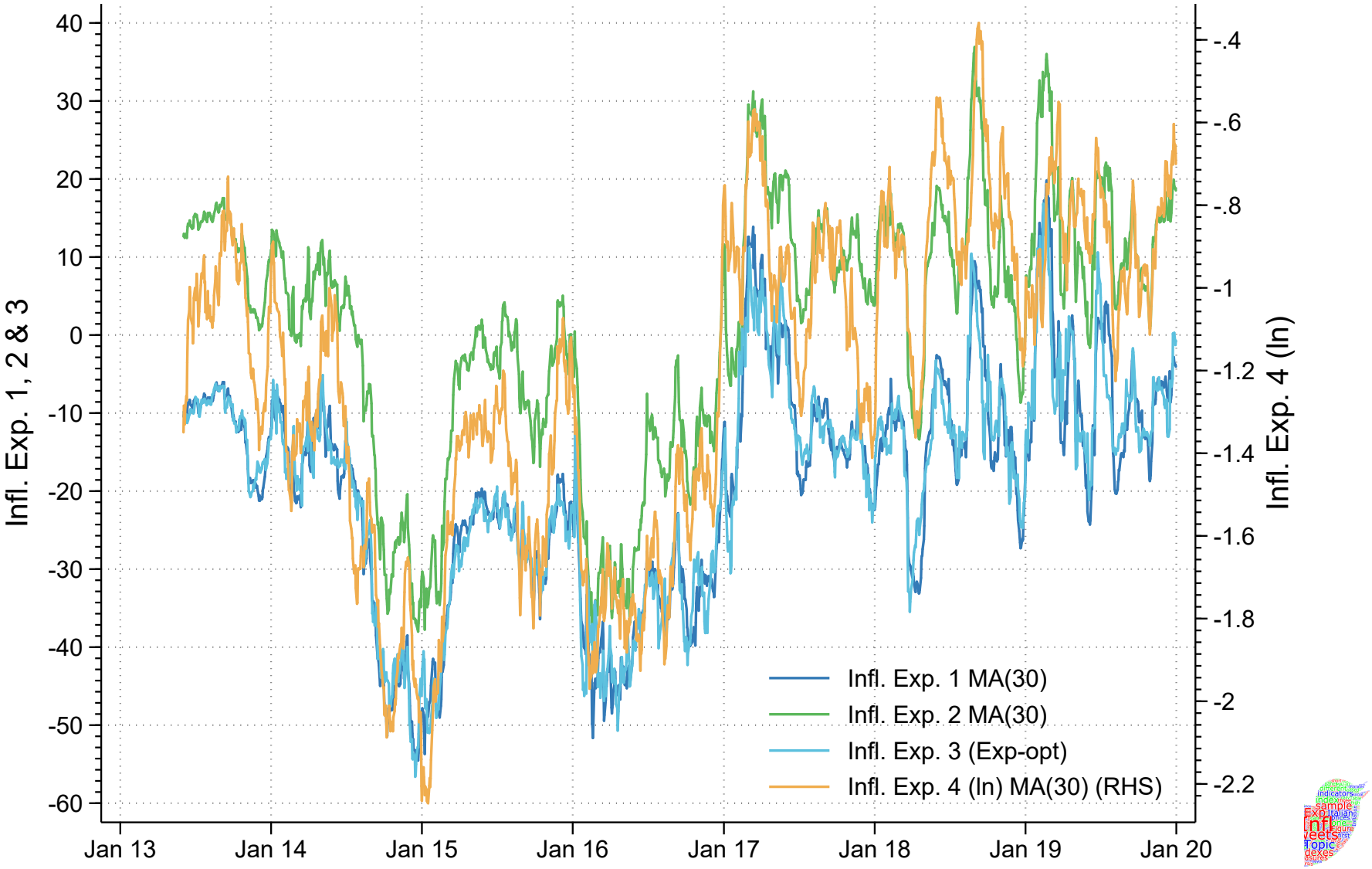
- Infl. Exp. #1: standardization, winsorizing, backward-looking MA 10, 30, 60 days
- Infl. Exp. #2: filtering on event dummies, standardization, winsorizing, backward-looking MA 10, 30, 60 days
- Infl. Exp. #3: exponential smoothing (optimal, 0.1, 0.3)

$\pi_{ln}^e$ **=(**$ln$**(Index Up+1)-**$ln$**(Index Down+1))**

- Infl. Exp. #4: backward looking MA 10, 30, 60 days


$\Rightarrow$ Same logic as in the survey-based measure by Istat!

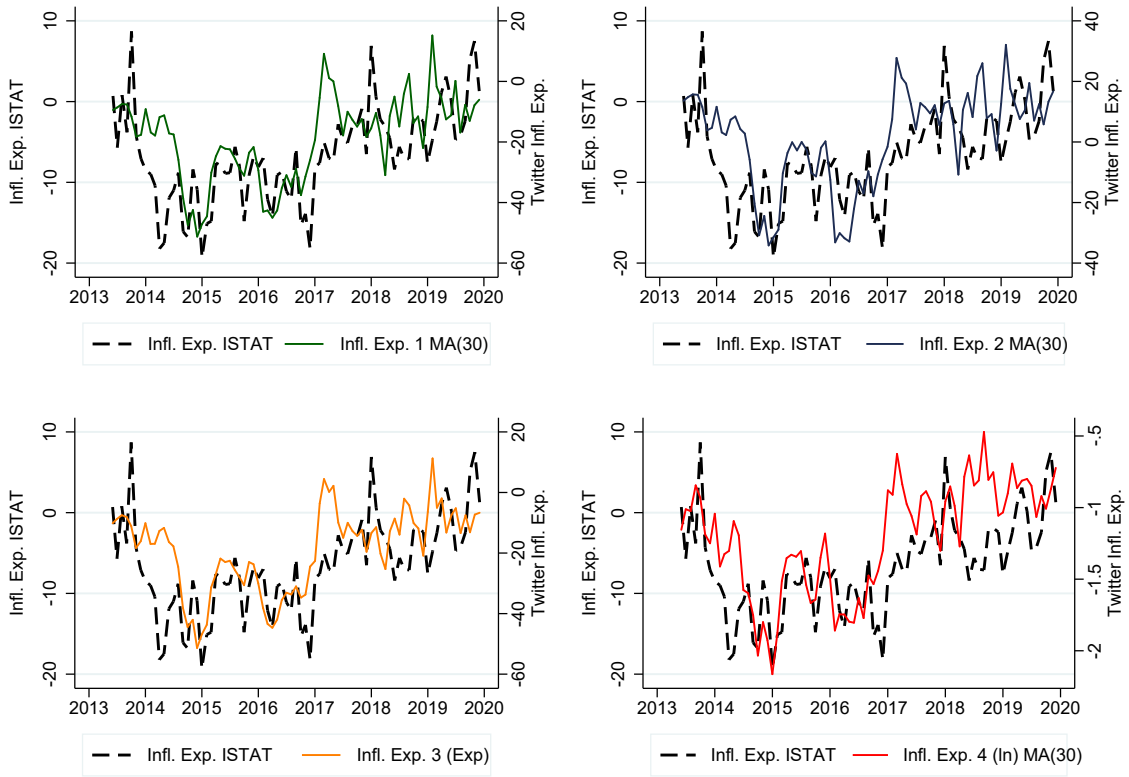
# Twitter-based indexes of inflation expectations for Italy



# Comparison with survey-based and market-based measures

- Twitter-based indexes are compared with **survey-based measures** on expected price trends over the next 12 motnhs
- They are also compared with **market-based measures**, i.e. daily rates of swap contracts linked to the Italian inflation over the next 12 months
- We find that all indexes **strongly co-move** with both traditional measures of inflation expectations

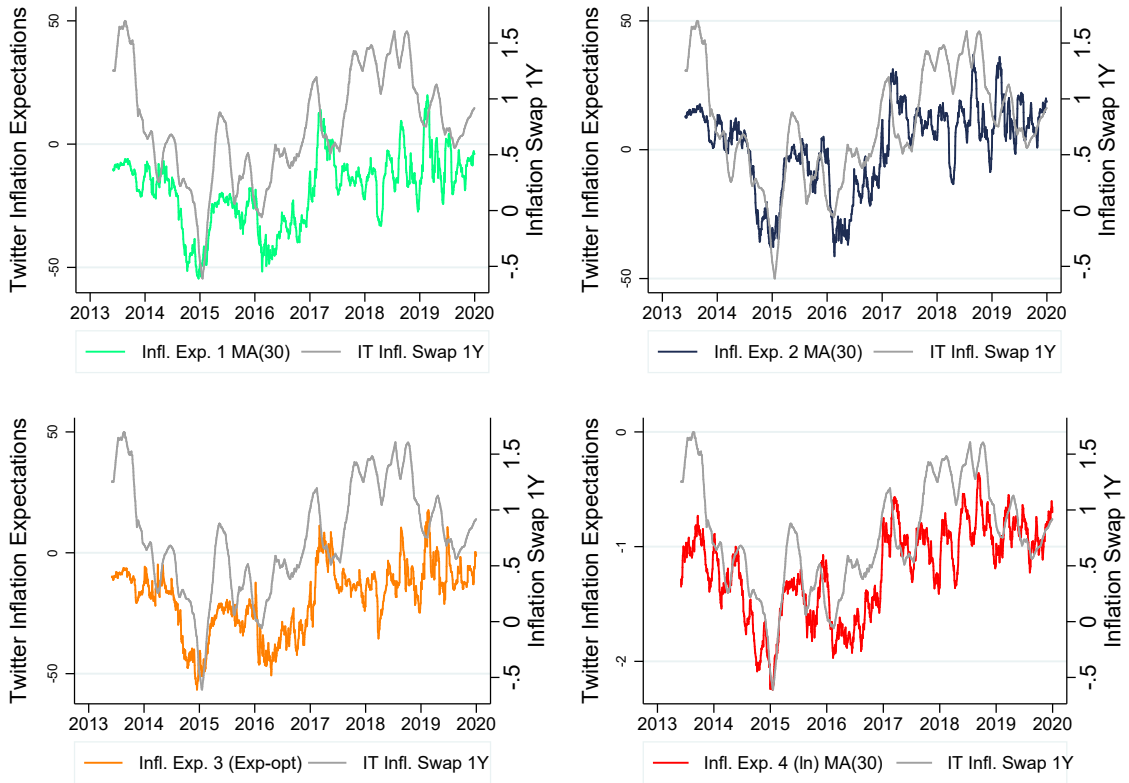
# Twitter-based vs survey-based inflation expectations (ISTAT)




| | Infl. Exp. 1 | Infl. Exp. 2 | Infl. Exp. 3 (exp-o) | Infl. Exp. 4 (ln) |
|---|---|---|---|---|
| $E_t^{ISTAT}(\pi_{t,t+12})$ | 0.228*** | 0.210*** | 0.249*** | 9.815*** |
| $R^2$ | 0.287 | 0.316 | 0.315 | 0.400 |
| N | 79 | 79 | 79 | 79 |

Significance values: *** p<0.01, ** p<0.05, * p<0.1

# Twitter-based vs market-based inflation expectations (IT 1Y Infl Swap)




| | Infl. Exp. 1 | Infl. Exp. 2 | Infl. Exp. 3 (exp-o) | Infl. Exp. 4 (ln) |
|---|---|---|---|---|
| Infl. Swap 1Y | 0.0212*** | 0.0200*** | 0.0221*** | 0.935*** |
| $R^2$ | 0.373 | 0.431 | 0.379 | 0.541 |
| N | 1,717 | 1,717 | 1,717 | 1,717 |

Significance values: *** p<0.01, ** p<0.05, * p<0.1

# Do we gain an informative advantage on consumers expectations?

| Dependent Variable | $E_t^{ISTAT}\pi_{t,t+12}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $E_{t-1}^{ISTAT}\pi_{t-1,t+11}$' | 0.673*** | 0.509*** | 0.560*** | 0.567*** | 0.511*** | 0.465*** | 0.461*** |
| | (0.07) | (0.12) | (0.13) | (0.12) | (0.14) | (0.06) | (0.09) |
| $IS_t^{1Y}$ | | 4.194*** | | | 4.048*** | | 2.248 |
| | | (1.01) | | | (1.35) | | (1.75) |
| $CF_{t-1}^{y+1}$ | | | 4.584** | | -1.229 | | -0.464 |
| | | | (2.17) | | (2.36) | | (2.89) |
| $CPI_{t-1}$ | | | | 2.279*** | 0.739 | | -0.775 |
| | | | | (0.86) | (0.69) | | (1.02) |
| Infl. Exp. 4 (ln) MA(30) | | | | | | 5.992*** | 4.935** |
| | | | | | | (0.91) | (1.97) |
| Cons. | -2.206*** | -6.441*** | -8.111** | -4.225** | -5.366 | 3.659*** | 1.638 |
| | (0.69) | (1.89) | (3.69) | (1.69) | (3.61) | (1.00) | (4.56) |
| N | 78 | 78 | 78 | 78 | 78 | 78 | 78 |
| $R^2$ | 0.451 | 0.544 | 0.478 | 0.491 | 0.547 | 0.560 | 0.574 |
| $Adj.R^2$ | 0.444 | 0.532 | 0.464 | 0.478 | 0.522 | 0.548 | 0.545 |
| $F-test$ | 101.2 | 87.0 | 143.2 | 147.7 | 56.7 | 111.5 | 57.6 |
| $Prob > F$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

- $E_t^{ISTAT}\pi_{t,t+12}$: survey
- $Infl.exp._t$: Twitter-based index
- $IS_t^{1y}$: infl. swap rate
- $CF_{t-1}^{y+1}$: consensus forecast
- $CPI_{t-1}$: price index

- Twitter-based indexes provides **additional informative power** to existing sources

# Predictive Content of Twitter-Based Indicators

- Simple forecasting exercise to see if our Twitter-based indexes can **predict out-of-sample** the monthly survey-based measures by Istat
- **Timing:** $T = R + P$ observations & Recursive scheme
- $R$ obs. used to estimate the models (**in-sample**), while the last $P$ are used for **out-of-sample** evaluation.
- Benchmark model is AR(p) on $E_t^{ISTAT}\pi_{t,t+12}$ (lag p chosen according to BIC criterion)
- Competing models add our Twitter indicators
- Predict from 1 up to 6 months ahead

# Predictive Content of Twitter-Based Indicators

| | $h=1$ | $h=2$ | $h=3$ | $h=4$ | $h=5$ | $h=6$ |
|---|---|---|---|---|---|---|
| $AR(p) - SS$ *(RMSE)* | 4.386 | 5.286 | 5.925 | 6.144 | 6.443 | 6.734 |
| $IS1Y_t$ | 1.033 | 1.013 | 0.962 | 0.999 | 1.010 | 1.001 |
| $GTRD_t$ | 0.996 | 0.998 | 1.000 | 1.008 | 0.984* | 0.989 |
| Infl. Exp. 1 MA(10) | 0.952 | 0.917*** | 0.906*** | 0.956** | 0.963** | 0.948** |
| Infl. Exp. 2 MA(10) | 0.934* | 0.905*** | 0.861*** | 0.916** | 0.917*** | 0.935*** |
| Infl. Exp. 3 (Exp-0.1) | 0.971 | 0.921 | 0.865*** | **0.868**** | 0.885*** | 0.885*** |
| Infl. Exp. 4 (ln) MA(10) | 0.960 | 0.905*** | 0.883*** | 0.944** | 0.984 | 0.997 |
| Infl. Exp. 1 MA(30) | 0.940 | 0.904*** | 0.873*** | 0.949** | 0.979* | 0.969* |
| Infl. Exp. 2 MA(30) | 0.935* | 0.881*** | 0.872*** | 0.951* | 0.979* | 0.988 |
| Infl. Exp. 3 (Exp-opt) | 0.937 | 0.902*** | 0.866*** | 0.941** | 0.942** | 0.872*** |
| Infl. Exp. 4 (ln) MA(30) | 0.928** | 0.885*** | 0.886*** | 0.967 | 0.977* | 0.990 |
| Infl. Exp. 1 MA(60) | 0.930** | 0.880*** | 0.886*** | 0.958** | 0.978** | 0.991 |
| Infl. Exp. 2 MA(60) | 0.924** | 0.869*** | 0.897*** | 0.960 | 0.979 | 0.999 |
| Infl. Exp. 3 (Exp-0.3) | 0.949 | 0.898*** | 0.883*** | 0.937** | 0.909*** | 0.903*** |
| Infl. Exp. 4 (ln) MA(60) | 0.928** | 0.895*** | 0.936** | 0.985 | 1.012 | 0.986 |
| Infl. Exp. 1 MA(10) Econ | 0.924** | 0.896*** | 0.910*** | 0.976 | 1.011 | 0.995 |
| Infl. Exp. 2 MA(10) Econ | 0.958 | 0.926*** | 0.885*** | 0.949** | 0.983 | 0.998 |
| Infl. Exp. 3 (Exp-0.1) Econ | 0.964 | 0.917*** | 0.882*** | 0.908** | 0.933* | 0.922** |
| Infl. Exp. 4 (ln) MA(10) Econ | 0.925** | 0.880*** | 0.862*** | 0.905** | 0.900*** | 0.935** |
| Infl. Exp. 1 MA(30) Econ | 0.890** | 0.894*** | 0.904*** | 0.981 | 0.990 | 0.969 |
| Infl. Exp. 2 MA(30) Econ | 0.911** | 0.859*** | 0.850*** | 0.893** | 0.926* | 0.954 |
| Infl. Exp. 3 (Exp-opt) Econ | 0.943 | 0.966 | 0.938 | 1.001 | 0.996 | 0.965 |
| Infl. Exp. 4 (ln) MA(30) Econ | 0.910*** | 0.854*** | 0.856*** | 0.888** | 0.930* | 0.950 |
| Infl. Exp. 1 MA(60) Econ | 0.929* | 0.902*** | 0.935*** | 0.989 | 0.989 | 0.978 |
| Infl. Exp. 2 MA(60) Econ | 0.893*** | **0.842**** | **0.842**** | 0.895* | 0.954 | 0.939* |
| Infl. Exp. 3 (Exp-0.3) Econ | 0.974 | 0.953 | 0.963 | 1.000 | 0.983 | 0.969 |
| Infl. Exp. 4 (ln) MA(60) Econ | 0.891*** | 0.851*** | 0.846*** | 0.940 | 0.966 | 0.955 |
| Infl. Exp. 1 MA(10) News | 0.951 | 0.958 | 0.946** | 0.984 | 0.991 | 1.000 |
| Infl. Exp. 2 MA(10) News | 0.930* | 0.892*** | 0.862*** | 0.912** | 0.902*** | 0.925*** |
| Infl. Exp. 3 (Exp-0.1) News | 0.963 | 0.964 | 0.956 | 0.979 | 0.981 | 1.013 |
| Infl. Exp. 4 (ln) MA(10) News | 0.930** | 0.892*** | 0.863*** | 0.910** | 0.915*** | 0.935*** |
| Infl. Exp. 1 MA(30) News | **0.890**** | 0.887*** | 0.877*** | 0.957*** | 0.962** | 0.927** |
| Infl. Exp. 2 MA(30) News | 0.919*** | 0.872*** | 0.853*** | 0.902** | 0.920*** | 0.946*** |
| Infl. Exp. 3 (Exp-opt) News | 0.963 | 0.970 | 0.897** | 0.909*** | 0.882*** | **0.829**** |
| Infl. Exp. 4 (ln) MA(30) News | 0.923*** | 0.865*** | 0.860*** | 0.901** | 0.938** | 0.958** |
| Infl. Exp. 1 MA(60) News | 0.922** | 0.880*** | 0.894*** | 0.961** | 0.956** | 0.941** |
| Infl. Exp. 2 MA(60) News | 0.909*** | 0.858*** | 0.848*** | 0.901** | 0.937** | 0.950*** |
| Infl. Exp. 3 (Exp-0.3) News | 0.961 | 0.925* | 0.878** | 0.898*** | **0.865**** | 0.841*** |
| Infl. Exp. 4 (ln) MA(60) News | 0.898*** | 0.857*** | 0.854*** | 0.961 | 0.968 | 0.962 |

- Ratio of RMSE w.r.t. $AR(p)$ benchmark. *, **, *** indicate 10%, 5% and 1% significance of Diebold-Mariano test of EPA.
- Recursive scheme, $T = 79$, $R_1 = 36$, $P_1 = 43$. First in-sample: Jun. 2013–May. 2016. First out-of-sample: Jun. 2016-Dec. 2019

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

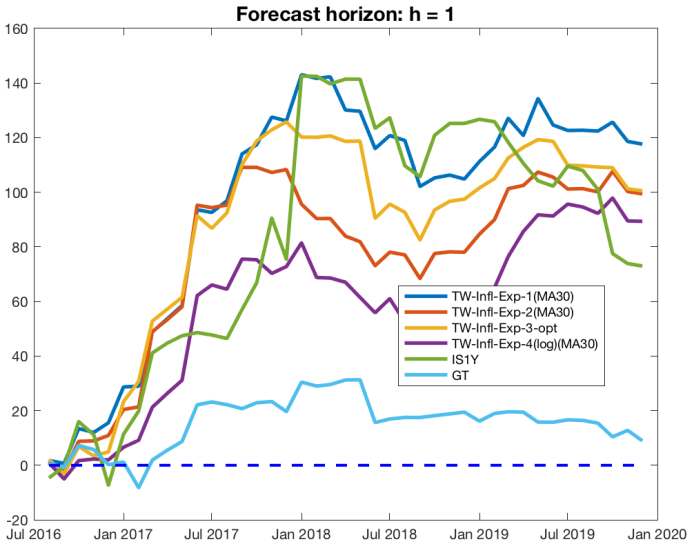
- We also used CSSED to compare models throughout the out-of-sample
-

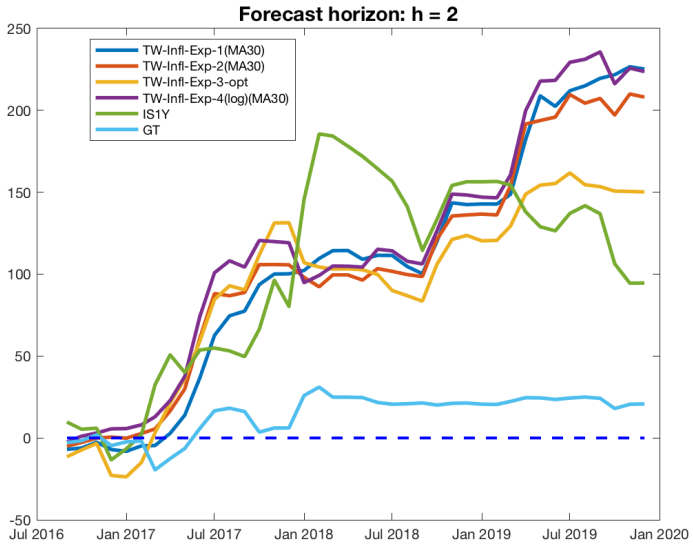
$$\boxed{CSSED_{m,\tau} = \sum_{\tau=R}^{T} (\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau})} \tag{1}$$

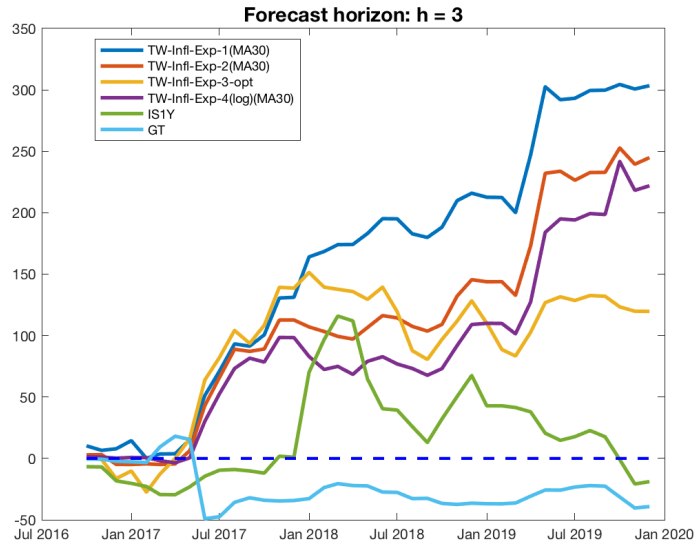
$$\hat{e}_{k,\tau} = y_\tau - \hat{y}_{k,\tau|t} \tag{2}$$

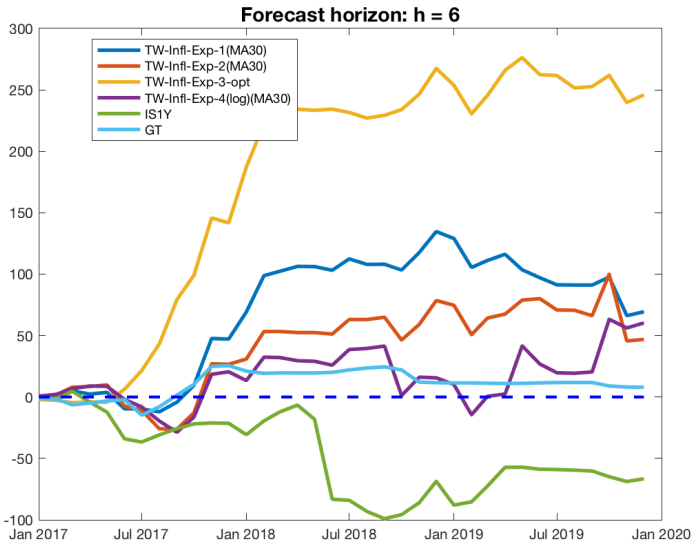
- What happens if the benchmark model ($bm$) outperforms the competing model ($m$)?
- $\hat{e}^2_{bm,\tau} < \hat{e}^2_{m,\tau} \quad \Rightarrow \quad CSSED_{m,\tau} < 0$
- And if the competing model $m$ beats the benchmark $bm$?
- $\hat{e}^2_{bm,\tau} > \hat{e}^2_{m,\tau} \quad \Rightarrow \quad CSSED_{m,\tau}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

# Cumulative Sum of Squared (Forecast) Error Differences (CSSED) - MA(30)



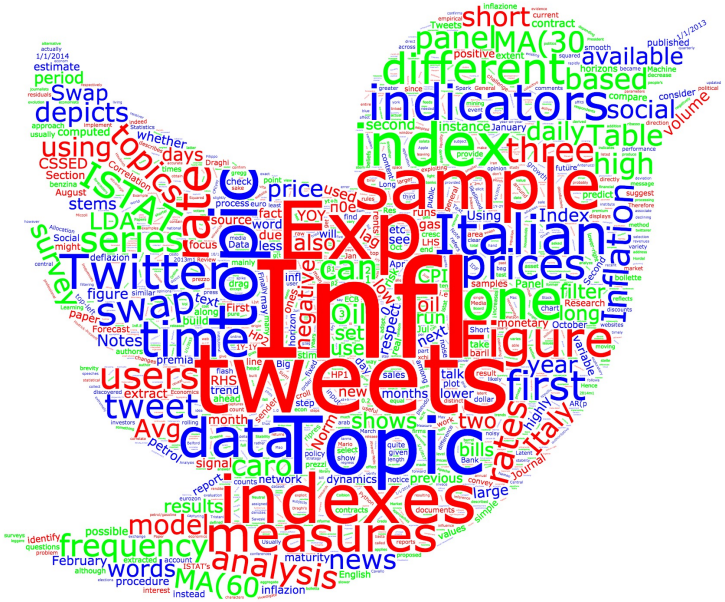




- $CSSED_{m,\tau} = \sum_{\tau=R}^{T}(\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau})$ 'best' competing model w.r.t. the $AR(P)$ benchmark

# The paper in one wordcloud: Conclusions




- Novel way to elicit inflation expectations
- Twitter-based indexes convey meaningful and high-frequency signals on inflation expectations
- Procedure easily applicable to different countries

# Thank you!

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