Juri Marcucci

DG Economics and Statistics, Research (Bank of Italy)

(*Disclaimer*: The views expressed are those of the authors and do not involve the responsibility of the Bank of Italy, the IMF board or its staff.)

Using Twitter for Macroeconomic Indicators
Can we measure inflation expectations?

Invited Lecture at the Big Data and Machine Learning in Finance
Online Conference
Politecnico di Milano – Milan, June 10^{th}–11^{th}, 2021

Outline

Motivation

Data from Twitter

Twitter-based Directional Indexes (3 steps)

Comparison with Survey- and Market-based Measures

Robustness

In-sample Informativeness and Predictability out-of-sample

Conclusion

Outline

Motivation

Data from Twitter

Twitter-based Directional Indexes (3 steps)

Comparison with Survey- and Market-based Measures

Robustness

In-sample Informativeness and Predictability out-of-sample

Conclusion

General Motivation: Big data and Machine Learning for Macroeconomics

- **New strand of literature** on using **Big data**, **Non-traditional data**, **machine learning**, **text analysis**, to get real-time measures/forecast of macro variables
- The Covid-19 crisis and the "**Great Lockdown**" have emphasized the role of **high-frequency (HF)** data for nowcasting/forecasting macro variables.
- Weekly, daily or even hourly data have been used to gauge the real-time impact of the Lockdown (**news, mobility, electricity consumption, credit/debit cards, online prices, social media, etc...**)
- This data is i) HF, ii) with global coverage, iii) without local bias, iv) highly granular, and sometimes v) completely free

Today, I am going to present the following working paper:

- **Can We Use Twitter To Measure Inflation Expectations?** by Cristina Angelico, Juri Marcucci, Marcello Miccoli, and Filippo Quarta, Bank of Italy Working Paper n. 1318.

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

- 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?

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

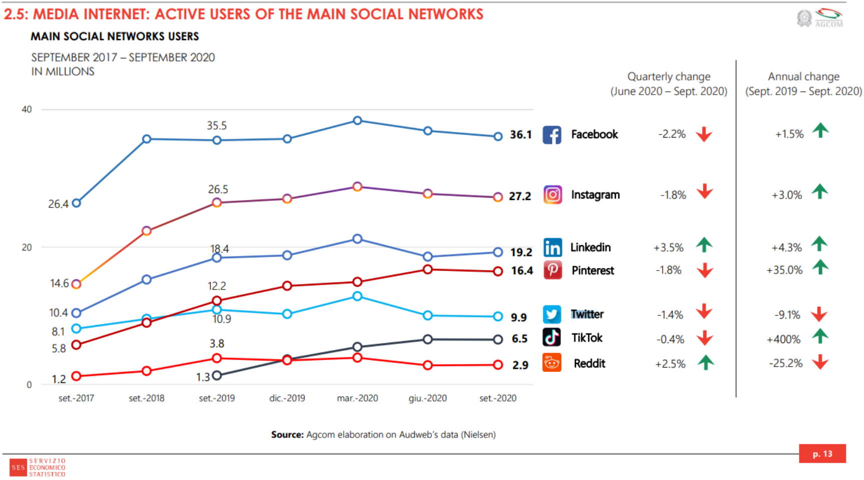
- Dictionary of bi/tri-grams
- Directional indexes
- (Index UP - Index DOWN)

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

Outline

- Motivation
- **Data from Twitter**
- Twitter-based Directional Indexes (3 steps)
- Comparison with Survey- and Market-based Measures
- Robustness
- In-sample Informativeness and Predictability out-of-sample
- Conclusion

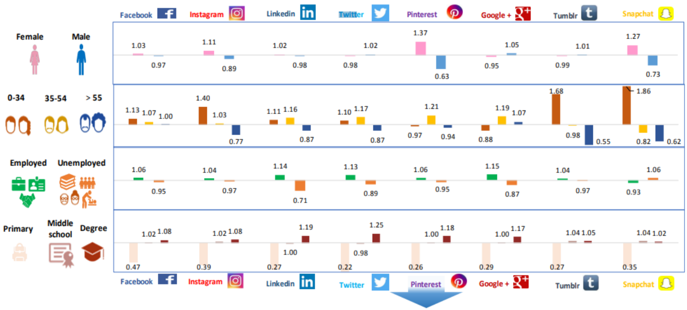
Why Twitter? – Social Network Users In Italy



Why Twitter? – Social Network Users In Italy

2.5 Media: Internet Social network audience by target users

Main news program affinity index – December 2017



Composition Index

The Composition Index measures the concentration of a particular target group of consumers on a given website or ad network, compared to the concentration of that target in the total Internet population for the category "Search, Portals, Communities".

In case this figure is higher than 1, it means that the programme/medium is well targeted for our Target Audience. The higher this index the better the targeting is.

Fonte: Agcom elaboration on Audiweb's (Nielsen) data

- **Gender:** Pinterest and Snapchat, among the category «Search portals and communities», are those characterized by a wider female audience
- **Age:** Instagram, Tumblr and Snapchat, are the social media platforms most preferred by young people (age 0-34)
- **Occupational status:** Google+, Linkedin and Twitter are the most preferred social media by employed people
- **Educational status:** Twitter and Linkedin have a wider audience of graduates compared to the mean

AUTORITÁ PER LE GARANZIE NELLE COMUNICAZIONI AGCOM

18

Servizio Economico Statistico

Data from Twitter

Data

- **11.1 millions tweets** in Italian
- **1 June 2013 – 31 December 2019**
- About **944,000** individual users
- Full text and the meta-data (i.e. users' bio, ReTweets, # of followers, geo-localization, etc.)
- Tweets contain one or more of the keywords on inflation/deflation (rough initial dictionary)
- Private API, Historical Power Track (HPT)

Intuition

- Tweets reflect info on current or future prices
- They can be inputs to the expectations formation process

Keywords (EN/ IT) of our **"rough" initial Dictionary**

(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*

NB: **N**: Neutral; **U**: Up; **D**: Down

Example of selected tweets (Different Themes)

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 these **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**

- **Different themes**: #1 & #2 are on news about past inflation; #3 & #4 are on expected inflation development; #5 is on advertisements; #6 is on a concept unrelated to economics

Example of selected tweets (Noise due to advertisements)

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 these **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~~)

Motivation

Data from Twitter

Twitter-based Directional Indexes (3 steps)

Comparison with Survey- and Market-based Measures

Robustness

In-sample Informativeness and Predictability out-of-sample

Conclusion

Building Twitter-based Inflation Expectation Indexes

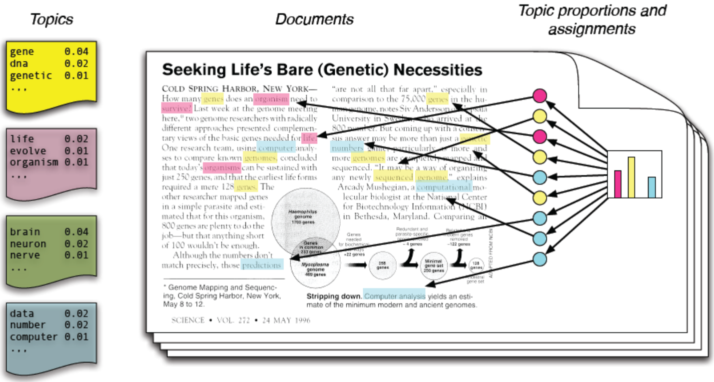
To select tweets related to price dynamics we adopt a
Three-step procedure

1. Topic analysis - Latent Dirichlet Allocation (LDA)
   - Exploit the full text of tweets
   - Isolate valuable signals and filter out noise
2. Dictionary-based approach
   - Exploit the semantic of manually labeled bi-grams and tri-grams to categorize tweets
   - Build a set of raw indexes: daily counts of tweets (the more you talk about it, the more expectations change)
3. Directional indexes
   - Final indexes increase in value when inflation expectations increase (same logic of survey-based)

- Text cleaning
  - Removal of Stopwords
  - Removal of punctuation
  - log-rank to eliminate the rarest words (Zipf-s law)
- **User-pooling**
  - To get a set of documents given the shortness of tweets (only 140 characters, 280 after November 2017) as in Alvarez-Melis and Saveski (2016)
- Rough text
  - news, links, opinions, advertisements, informal language, misspelling, slang, ...

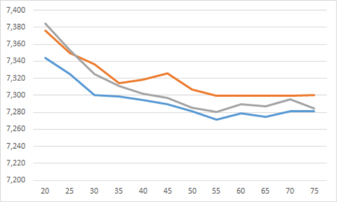
Latent Dirichlet Allocation (LDA)

- Probabilistic generative model (*unsupervised*)
- Documents are random mixtures over latent topics
- Each topic is described by a distribution over words



Latent Dirichlet Allocation (LDA)

- $\mathbf{K} = \mathbf{50}$ topics
- Minimizing Log-perplexity with $\mathbf{K} = [20, 25, 30, 35, 40, 45, \mathbf{50}, 55, 60, 65, 70, 75]$
- 3 independent LDA runs to check stability of topics (stochastic sampling procedure)



LDA runs	Number of tweets	%	Cumulative %
3	1,064,734	69.4	69.4
2	209,074	13.6	83.0
1	260,935	17.0	100.0
Total	1.534.743	100	

Topic #1

Topic #2

Topic #6

Topic #37

Topic #19

Topic #36

- # 1: Apple products; # 2: gasoline/diesel prices; # 6: coupons for restaurants/hotels; #37: hotels and air fares for vacations (New Year’s Eve, Summer); $\Rightarrow$ Should we consider them?
- Maybe no or maybe yes...
- #19 inflation, deflation and prices; #36: inflation, deflation, price dynamics
- **#19 & #36 for sure!**

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*]

- Two topics (#19 & #36) convey valuable signals on on price developments: (*'inflazion/deflazion' [inflat/deflat]*)
- Assigns to every tweet a probability distribution over the topics
- Each tweet is assigned to the topic with the highest likelihood
- Final data set: **1,534,743 tweets** (about 14%), **165,551 users**.
- Discarded tweets: 92% on *'price(s)'* and only 9% on *'inflation/deflation'* due to advertisements/e-commerce.

LDA-1	Prob.	LDA-2	Prob.	LDA-3	Prob.	English
debito	0,005	debito	0,005	debito	0,005	debt
deflazione	0,014	**deflazione**	0,014	**deflazione**	0,013	**deflation**
disoccupazione	0,005	disoccupazione	0,005	disoccupazione	0,005	unemployment
euro	0,010	euro	0,010	euro	0,009	euro
inflazione	0,024	**inflazione**	0,024	**inflazione**	0,023	**inflation**
italia	0,006	italia	0,007	italia	0,006	italy
lavoro	0,006	lavoro	0,006	lavoro	0,006	job
moneta	0,005	moneta	0,005	moneta	0,005	money
prezzi	0,008	prezzi	0,008	prezzi	0,007	prices
prezzo	0,009	prezzo	0,009	prezzo	0,008	price
quando	0,004	quando	0,004	quando	0,004	when
salari	0,024	salari	0,024	salari	0,022	salaries
salario	0,004	salario	0,004	salario	0,004	salary
solo	0,005	solo	0,005	solo	0,005	only
stipendi	0,006	stipendi	0,006	stipendi	0,006	wages
stato	0,004	stato	0,004	stato	0,005	state
				stipendio	0,004	wage
		poi				after
germania	0,003	germania	0,004			germany
salariale	0,004	salariale	0,004			related to wage

Italian Original	English translation	LDA1		LDA2		LDA3		Sel.
		1^{st}	2^{nd}	1^{st}	2^{nd}	1^{st}	2^{nd}	
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%	**36**	8	**36**	2	**36**	2	Y
Il bf 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 these **high prices** are becoming unbearable.	32	41	10	43	9	32	N
RT SkyTG24: #Ultimora BCE, #Draghi: senza nostra azione saremmo in **deflazione**	RT SkyTG24: #breakingnews BCE, #Draghi: without our action we would be in **deflation**	**36**	42	**36**	**19**	**36**	12	Y
#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!	**19**	48	**19**	48	**19**	48	Y
~~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.~~	30	10	30	10	30	10	N
Il più grande spettacolo dopo il #big-bang è l'**inflazione** cosmica	The greatest show after the #big-bang is cosmic **inflation**	8	**36**	10	**36**	17	**36**	N

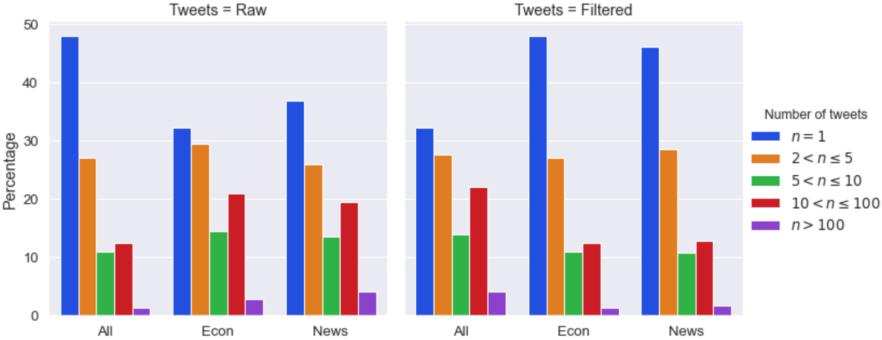
Who is tweeting about inflation/deflation/price dynamics?

The most frequent words in users' biography

Word [Translation]	Count	Word [Translation]	Count
giornalista [journalist]	2,265	media	800
mondo [world]	1,761	presidente [president]	771
politica [politics/policy]	1,390	marketing	756
appassionato [enthusiast]	1,220	libero [free (as in freedom)]	743
lavoro [work/job]	1,119	politica [politics/policy]	717
italia [italy]	1,051	musica [music]	681
tempo [time]	1,028	business	672
social	988	consulente [consultant]	668
notizie [news]	929	nazionale [national]	665
studente [student]	909	comunicazione [communication]	619
amante [lover]	872	account	605
italian [italian]	847	opinioni [opinions]	592
manager	817	online	573
ufficiale [official]	801	direttore [executive director]	570

Note: Summary statistics on the the users' biographies of the filtered dataset. Sample: June 1, 2013 - December 31, 2019.

Who is tweeting about inflation/deflation/price dynamics?



- ▷ Raw: 11.1 millions tweets ⇒ Filtered: 1.534 millions tweets
- ▷ From 950k users to 166k users

Step Two: Dictionary-based approach

How can we aggregate tweets to get insights on agents’ beliefs?

- The **more people talk about a subject**, the more likely the message will influence their perceptions and behavior
- Problem: if tweets talk about ‘**prices**’ $\Rightarrow$ do they mean **increasing** or **decreasing** prices?
- And what about ‘*inflation*’?
- **Keywords reflect a message on the direction of price changes** $\Rightarrow$ aggregate tweets with similar direction
- Indexes computed as **daily raw counts** of tweets
  - **Index Up:**
  - **Index Down:**
- **(Up)** and **(Down)** indexes peak at relevant events: e.g. releases by Istat (NSO) or speeches by CBs

Step Two: Dictionary-based approach

- We refine our rough initial dictionary creating a **set of refined dictionaries** using **manually labelled bi-grams and tri-grams**.
- We start from all bi-grams and tri-grams containing the words/tokens:
    - *“price”[“prezzo”]*
    - *“prices”[“prezzi”]*
    - *“inflation”[“inflazione”]*
    - *“deflation”[“deflazione”]* and
    - *“expensive”[“caro/a/e/i”]*
- **91,650 bi-grams** and **48,734 tri-grams manually labelled** using all authors’ subjective interpretation

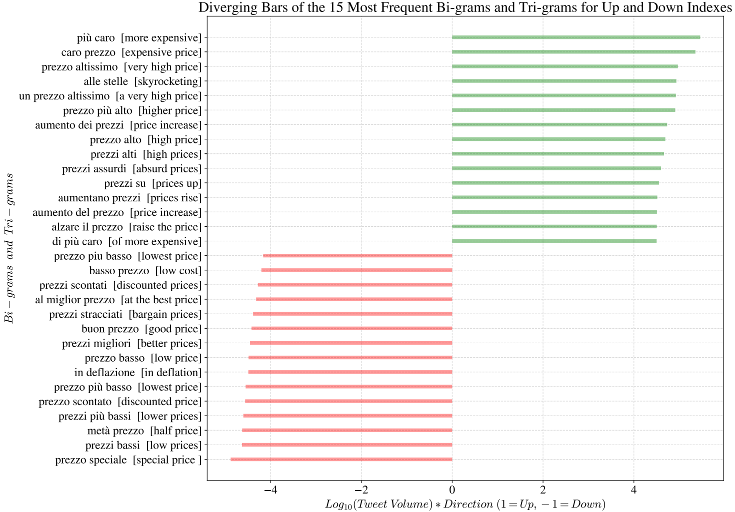
- **Different dictionaries**: depending on the n-gram
  1) Only bi-grams
  2) Only tri-grams
  3) **Both bi-grams and tri-grams**
- or depending on the yearly average volume of tweets containing them over the full sample
  A) Top 5%
  B) Top 10%
  C) A number s.t. on average there are **at least 100 tweets every year** containing them
  D) All
- Our **baseline case** is **C) + 3)**
- We also tried the rough initial dictionary

Step Two: Dictionary-based approach - Bi-grams and Tri-grams

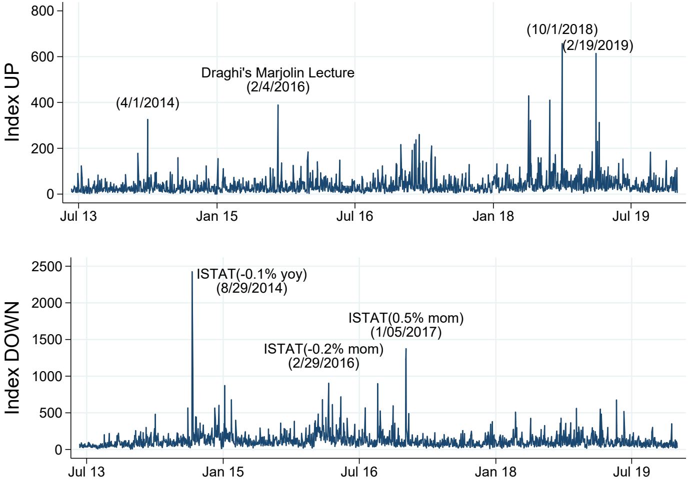
Number of bi- and tri-grams used to compute directional indexes

	Number of bi-grams to label	*Number of bi-grams labeled as Up*	*Number of bi-grams labeled as Down*
Case A (first 5%)	4808	67	82
Case B (first 10%)	9615	113	106
Case C (at least 100 tweets/year)	10691	121	111
Case D (all n-grams, n=(1,2))	96150	515	392
	Number of tri-grams to label	*Number of tri-grams labeled as Up*	*Number of tri-grams labeled as Down*
Case A (first 5%)	2347	102	114
Case B (first 10%)	4874	167	205
Case C (at least 100 tweets/year)	2853	112	126
Case D (all n-grams, n=(1,2))	48734	495	543
	Number of bi-grams and tri-grams labeled as UP	*Number of bi-grams and tri-grams labeled as Down*	
Case A (first 5%)	169	196	
Case B (first 10%)	280	311	
Case C (at least 100 tweets/year)	233	237	
Case D (all n-grams, n=(1,2))	1010	935	

Step Two: Dictionary-based approach - The 15 Most Frequent Bi/Tri-grams



Step Two: Dictionary-based approach - Up and Down indexes



Step Three: Directional indexes

$\boxed{\pi_0^e \textbf{ = Index Up - Index Down}}$

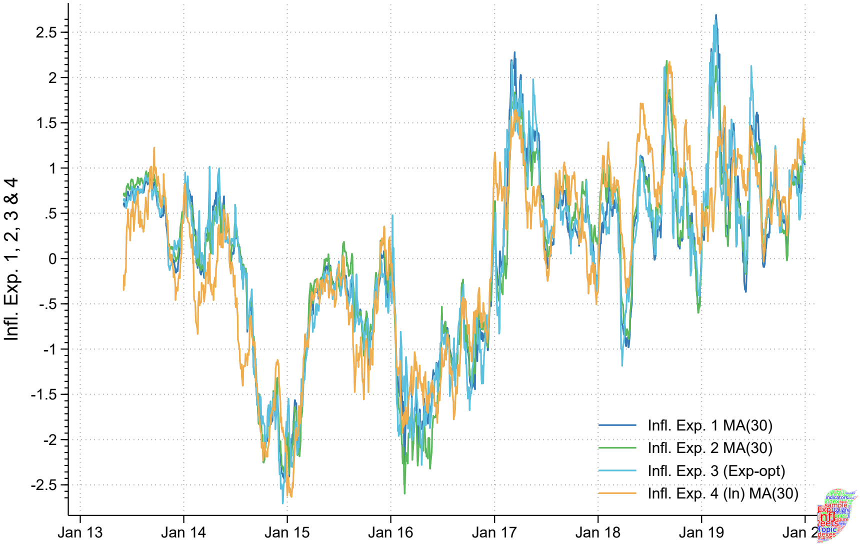
- Infl. Exp. #1: standardization, winsorizing, backward-looking MA 10, 30, 60 days
- Infl. Exp. #2: filtering on **event dummies**, standardization, winsorizing, backward-looking MA 10, 30, 60 days
- Infl. Exp. #3: exponential smoothing (optimal, 0.1, 0.3)

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

- 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 (standardized)



Outline

Motivation

Data from Twitter

Twitter-based Directional Indexes (3 steps)

Comparison with Survey- and Market-based Measures

Robustness

In-sample Informativeness and Predictability out-of-sample

Conclusion

Comparison with survey-based and market-based measures

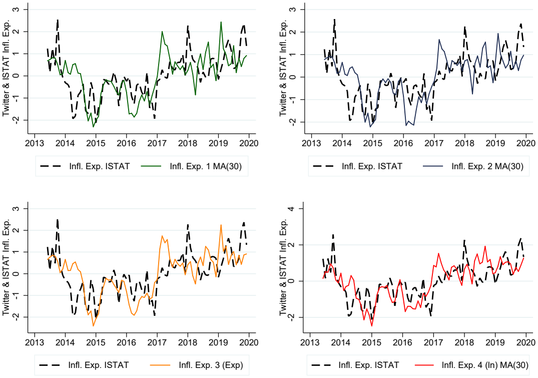
- Twitter-based indexes are compared with **survey-based measures** on expected price trends over the next 12 motnhs
- They are also compared with **market-based measures**, i.e. daily rates of swap contracts linked to the Italian inflation over the next 12 months
- We find that all indexes **strongly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

Survey-based inflation expectations by Istat (Italian NSO)

- **Monthly survey** by Istat on consumer and business confidence: 2,000 households with stratified random sample
- Ask **qualitative expectations on price trends** in the **next 12 months**
- Run on **first 15 days of month** t and realesed at the *end of the month*
- *“By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will...”*
  1. increase more rapidly (**higher inflation**)
  2. increase at the same rate (**same inflation**)
  3. increase at a slower rate (lower inflation)
  4. stay about the same (**no inflation**)
  5. fall (**deflation**)
  6. don’t know

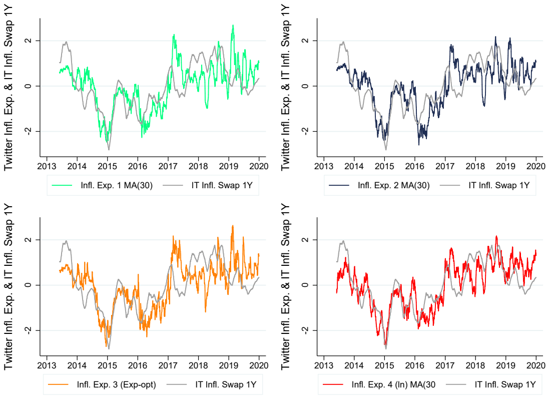
$$\boxed{E_t^{ISTAT}\pi_{t,t+12} = (\textbf{higher infl.} + \textbf{same infl.}/2 - \textbf{no infl.}/2 - \textbf{deflation})}$$

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



	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



	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

Outline

Motivation

Data from Twitter

Twitter-based Directional Indexes (3 steps)

Comparison with Survey- and Market-based Measures

Robustness

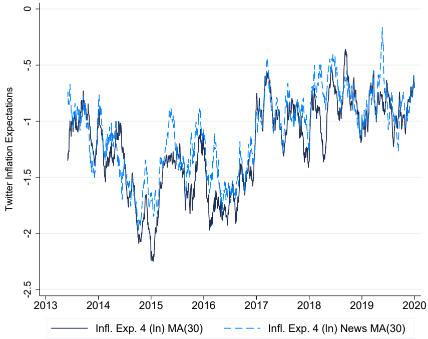
In-sample Informativeness and Predictability out-of-sample

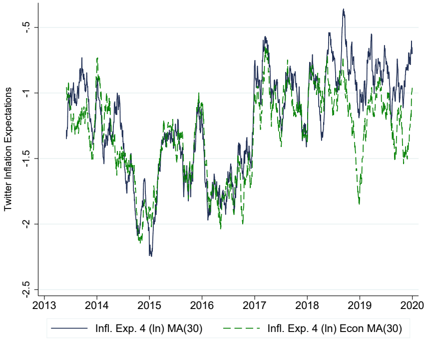
Conclusion

Robustness: Econ and News in users' bio

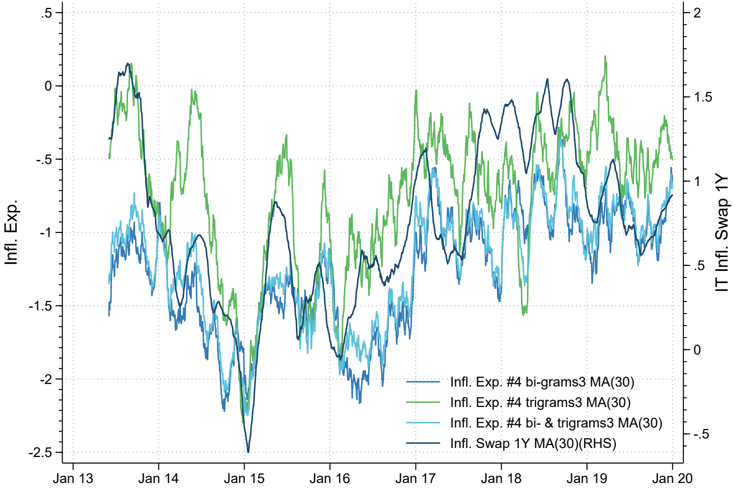
- We focus on **authoritative users** that can shape expectations.
- We focus only on the tweets by users whose bio includes '**Econ**' or '**News**'
- **Econ:** *economista* [*economist*], *finanz* [*finance*], *economia* [*economics*] (about 3,088 users in our sample)
- **News:** *giornal* [*newspaper*], *news* [*news*], *stampa* [*press*] (about 5,305)
- Professionals drive conversations and may affect consumers' expectations
- 80% of users fill their bio

Figure: Twitter Inflation Expectations with News and Econ

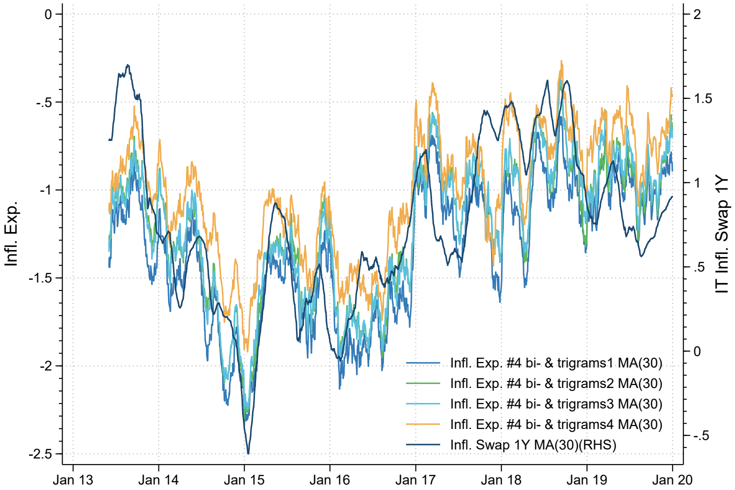




Robustness across Dictionaries: bi-grams, tri-grams or both vs IS1Y



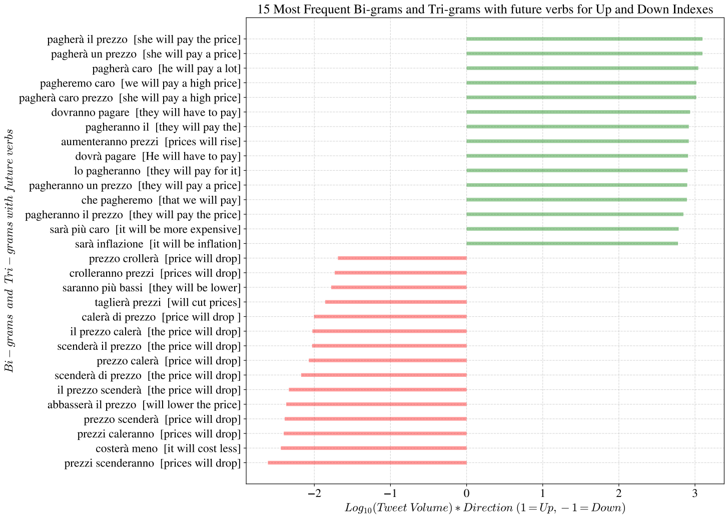
Robustness across Dictionaries: tri-grams across different thresholds



Robustness: Dictionary with only Future Verbs

- We further refine our **set of refined dictionaries** using **future verbs and/or future words** in each tweet.
- We build a dictionary of all bi-grams and tri-grams containing **only future tenses** with all words ending in all possible conjugations of future verbs in Italian (same strategy as baseline):
  - *-“rò”*
  - *-“rai”*
  - *-“rà”*
  - *-“remo”*
  - *-“ranno”*
  - *-“rete”*
- Problem $\Rightarrow$ low volume of tweets
- Dictionary with labelled bi- and tri-grams and a future tense either within the bi/tri-gram or in other parts of each tweet

Robustness: Dictionary with only Future Verbs - The 15 Most Frequent Bi/Tri-grams



- We also build dictionaries of all bi-grams and tri-grams containing **only words with future meaning** in Italian (same strategy as baseline):
  - *"future"["futuro"]*
  - *"perspective*"["prospettiv*"]*
  - *"medium run"["medio termine"]*
  - *"long run"["lungo periodo"]*
  - *"expect"["attend*"]*
  - *"forecast/predict"["preved*"]*
  - *"forecast/prediction"["previs*"]*
  - *"expectation*"["attes*"]*
  - *"expectation*/expect"["aspett*"]*
- Better properties
- We also build a **combined dictionary of future verbs and words with future meaning**

Outline

Motivation

Data from Twitter

Twitter-based Directional Indexes (3 steps)

Comparison with Survey- and Market-based Measures

Robustness

In-sample Informativeness and Predictability out-of-sample

Conclusion

Do we gain an informative advantage on consumers expectations?

$$\boxed{\begin{aligned} E_t^{ISTAT}\pi_{t,t+12} = \alpha + \rho\, E_{t-1}^{ISTAT}\pi_{t-1,t+11} + \beta\, IS_t^{1y} + \gamma\, CF_{t-1}^{y+1} \\ + \delta\, Infl.exp._t + \eta\, CPI_{t-1} + \varepsilon_t \end{aligned}}$$

- Let $I_t = \{E_{t-1}^{ISTAT}\pi_{t-1,t+11}, IS_t^{1y}, Infl.exp._t, CF_{t-1}^{y+1}, CPI_{t-1}\}$

1. $E_{t-1}^{ISTAT}\pi_{t-1,t+11} \Rightarrow$ lagged survey-based inflation expectations
2. $IS_t^{1y} \Rightarrow$ IT inflation swap rate 1 year, 15th day of month t
3. $Infl.exp._t \Rightarrow$ Twitter-based indicator, 15th day of month t
4. $CF_{t-1}^{y+1} \Rightarrow$ Consensus forecast at $y+1$
5. $CPI_{t-1} \Rightarrow$ lagged realized CPI inflation

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

- 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 for estimation (**in-sample**), while last P are used for **out-of-sample** evaluation.
- Benchmark model: AR(p) on $E_t^{ISTAT}\pi_{t,t+12}$ (lag p chosen according to BIC)
- $4(ind.) \times 3(MA) \times 3(All/Econ/News) = 36$ Competing models for a total of 1,104 possible models
- Predict from 1 up to 6 months ahead
- Predict $E_t^{ISTAT}\pi_{t,t+12}$ using linear AR models w/ and w/o exogenous leading indicators x_t (BIC selection IS):
    - $x_t = \{TW_{1,t}, ..., TW_{36,t-k}\}, k = 1, \ldots, 4\}$
    - $x_t = \{G_t, ..., G_{t-k}\}$ - Google Trends (rough dict.)
    - $x_t = \{IS1Y_t, ..., IS1Y_{t-k}\}$

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***	**0.86 *****	0.88 ***	0.88 ***
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***	**0.84 *****	**0.84 *****	0.89 *	0.95	0.93 *
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	**0.89 *****	0.88 ***	0.87 ***	0.95 ***	0.96 **	0.92 **
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***	**0.82 *****
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***	**0.86 *****	0.84 ***
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

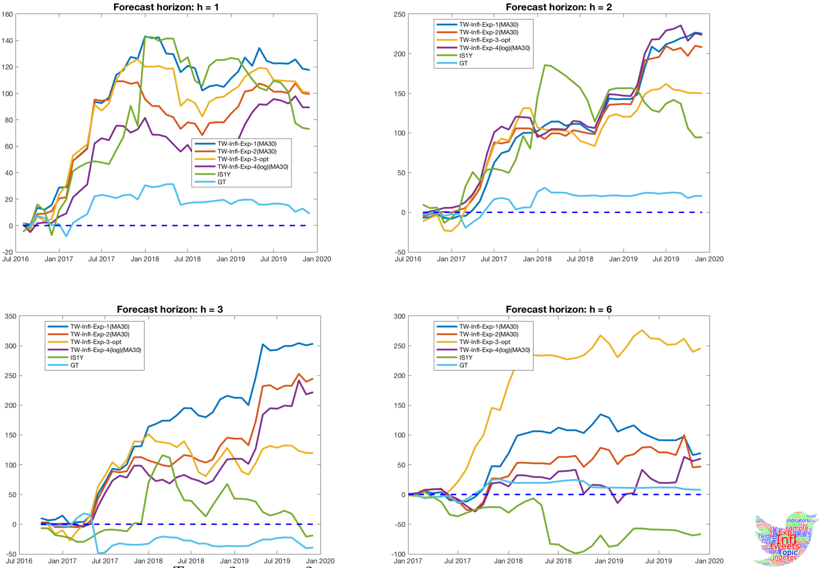
Cumulative Sum of Squared (Forecast) Error Differences (CSSED)

- 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

Outline

Motivation

Data from Twitter

Twitter-based Directional Indexes (3 steps)

Comparison with Survey- and Market-based Measures

Robustness

In-sample Informativeness and Predictability out-of-sample

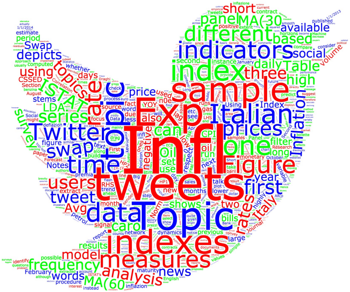
Conclusion

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**



- 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 very much!

Thank you!

juri.marcucci@bancaditalia.it

`https://sites.google.com/site/jurimarcucci/`