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CAN WE MEASURE INFLATION EXPECTATIONS USING TWITTER?

by Cristina Angelico*, Juri Marcucci*, Marcello Miccoli* and Filippo Quarta‡

Abstract

Drawing on Italian tweets, we employ textual data and machine learning techniques to build new real-time measures of consumers' inflation expectations. First, we select some keywords to identify tweets related to prices and expectations thereof. Second, we build a set of daily measures of inflation expectations on the selected tweets, combining the Latent Dirichlet Allocation (LDA) with a dictionary-based approach, using manually labelled bi-grams and tri-grams. Finally, we show that Twitter-based indicators are highly correlated with both monthly survey-based and daily market-based inflation expectations. Our new indicators provide additional information beyond market-based expectations, professional forecasts, and realized inflation. Moreover, they anticipate consumers' expectations, proving to be a good real-time proxy. The results suggest that Twitter can be a new timely source for devising a method to elicit beliefs.

JEL Classification: E31, C53, C55, D84, E58.

Keywords: inflation expectations, Twitter data, text mining, big, data, survey-based measures, market-based measures, forecasting.

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Contents

1 Introduction [1]

Over the last years, Twitter has become one of the most famous social networking sites, with 200 million monthly active users worldwide and about 10 million active users in Italy in 2019.[2] The microblogging service is widely used - by both journalists and consumers - to quickly spread and get news in real-time and depicts a primary source of information for many users around the world. Moreover, discussions on this platform reflect trending topics across agents and reveal the collective opinions on several issues, such as politics, technology, economy, and so on. Hence it represents a unique opportunity for researchers interested in the study of consumers beliefs.

Given the consolidation of Twitter as a public forum for personal beliefs and experiences, in this study, we investigate whether tweets convey people's beliefs about short-term price dynamics and whether they can be used to elicit inflation expectations.

Inflation expectations are at the heart of any consumption and investment decision of households and firms in the economy. For this reason, inflation expectations dynamics is carefully studied by both academics and policymakers. Further, timely and accurate knowledge of inflation expectations is paramount for monetary policy since inflation expectations at longer horizons are a measure of the credibility of the central bank, while at shorter horizons they reflect a measure of the effectiveness of monetary policy.

There are two commonly used sources of inflation expectations: surveys and prices of financial assets linked to inflation. Both measures have relative advantages and drawbacks. Survey data reflect true expectations of a (small) selected sample of agents, such as professional forecasters, households or firms, but they are available only at a low frequency, usually monthly, or quarterly. Market-based measures instead, such as those derived from swap contracts linked to inflation or inflation-protected securities, are readily available at high-frequencies but are imperfect measures of consumers' inflation expectations. Indeed, they reflect investors' inflation expectations and time-varying

[1] We thank participants to the 2020 Banca d'Italia and Federal Reserve Board Joint Conference on "Nontraditional Data & Statistical Learning with Applications to Macroeconomics", the 2019 NBER Summer Institute on IT and Digitization, Fed Board Seminar series, 2018 (EC)2 Conference on "Big Data Econometrics with Applications", 2018 Bank of Korea Economic workshop on "Central Bank Macro Modeling and Forecasting", 2018 Bank of Italy workshop on "Harnessing Big Data and Machine Learning Technology for Central Banks" and Isaiah Hull, Filippo Natoli, Roberto Sabbatini, Alessandro Secchi and Paolo Sestito for their useful comments and suggestions. The views expressed herein are those of the authors and do not necessarily represent the views of the Bank of Italy or the Eurosystem. All remaining errors are our own. Authors' emails: C. Angelico (cristina.angelico@bancaditalia.it), J. Marcucci (juri.marcucci@bancaditalia.it), M. Miccoli (marcello.miccoli@bancaditalia.it), F. Quarta (filippo.quarta@bancaditalia.it).

[2] AGCOM (2020)

risk premia (Haubrich, Pennacchi and Ritchken (2012), Gurkaynak, Sack and Wright (2010)).

In this paper, we suggest Twitter as a source for eliciting consumers' inflation expectations that can be both timely (as in market-based expectations) and accurate (as in survey-based ones). The source is timely as Twitter messages are continuously updated; it is accurate since it provides information on the expected inflation rate of a large sample of consumers given its broad and diverse user base and it is not affected by the risk premia caveat. If successful, this approach may complement the existing inflation expectations data sources and provide daily indicators of consumers' beliefs. In this work, we thus address the following research questions: Do tweets say something about inflation expectations? Can we use tweets to get a daily proxy of inflation expectations? Would this proxy convey timely and correct information, additional to the existing sources of inflation expectations?

To address these questions, we first select some relevant keywords to identify the tweets related to goods' and services' prices (current and expected) in Italy, and build the initial dataset. We collect all tweets posted in the Italian language between 1 June 2013 and 31 December 2019 having in the text at least one of the selected keywords. We obtain a large number of tweets (11.1 million) related to inflation and expected price dynamics, but also about advertisements, e-commerce websites and sales. To reduce the noise and build a set of Twitter-based daily indicators, we adopt a three-step procedure. First, we filter out the noisy content and isolate valuable signals by implementing a topic analysis on the text of the messages using the Latent Dirichlet Allocation (LDA),[3] an unsupervised machine learning algorithm which statistically estimates topics (probabilistic collections of words) of a set of documents, enabling us to select tweets related to inflation developments. Second, on the filtered data, we apply a dictionary of manually labelled bi-grams and tri-grams to assign tweets to bins, each denoting expectations of increasing or decreasing inflation. Within each bin, we compute an index that considers the raw daily count of tweets. Finally, we aggregate the raw daily counts of tweets representing increasing or decreasing inflation expectations in *directional* indicators, that increase (decrease) with expectations of increasing (decreasing) inflation.

To validate the signals extracted from the Twitter messages, we investigate the extent to which they correlate with available sources of inflation expectations. As survey-based inflation expectations, we use the monthly survey on consumer and business confidence provided by the Italian national statistical institute, ISTAT. The survey asks respondents' qualitative expectations on price trends over the next 12 months. Besides, we

[3]Blei, Ng and Jordan (2003).

compare the Twitter-based indicators with the market-based inflation expectations to exploit the high frequency of the data (bearing in mind the mentioned caveat of time-varying risk premia). As market-based inflation expectations, we use swap contracts linked to Italian inflation with a one-year horizon. The analysis shows that the signal extracted from Twitter is significantly related to both survey-based and market-based expectations and is a consistent proxy of the dynamics of inflation expectations.

Finally, we analyze the extent to which the Twitter-based indicators can be used to predict survey-based inflation expectations and "artificially increase" their frequency. The Twitter-based indicators are significant for the in-sample and out-of-sample predictability of survey-based inflation expectations and convey additional information content beyond the existing data sources (i.e. survey- and market-based measures, realized inflation and predictions by professional forecasters).

Remarkably, Twitter-based indicators derived from a small sub-sample of users interested in economics or in news, in their self-published biographies, have similar predictive properties both in-sample and out-of-sample. Besides, to isolate the forward-looking component of the signal extracted from Twitter, we build a set of indicators obtained using future words (for example, "*long run*" or "*expect*") or verbs, which have similar but weaker properties due to lower volumes of tweets. These robustness checks confirm that our Twitter-based indicators capture the correct signal as they reflect beliefs of well-informed individuals as well as forward-looking expectations.

Our paper contributes to the literature in several aspects. Our main contribution is to propose a new source of data to elicit expectations that has some advantages compared to the standard ones. First, it involves a wide variety and a large number of individuals, relative to market-based data that reflect traders' opinions and survey measures that consider small samples of agents. Second, the high frequency of the data allows building daily indicators, whereas polls are available at the monthly or quarterly frequency. Lastly, this data source is not linked specifically to any country, so it can be used and replicated in several instances. These advantages make Twitter a possible powerful source from which to extract agents' expectations. In this respect, our contribution is also methodological, outlining how to extract meaningful numerical and directional indicators of inflation expectations from a written document.

Our work also contributes to the investigation of the usefulness of social media data in a new context. The increase in the use of social media has led social scientists to examine whether specific patterns in the stream of tweets might be able to predict real-world outcomes, such as asset returns or unemployment. The closest related works are Antenucci, Cafarella, Levenstein, Re and Shapiro (2014) and Mao, Counts and Bollen

(2015). The former uses Twitter data to create indexes of job loss, job search, and job posting: the work shows that the indexes track initial claims for unemployment insurance at medium and high frequency. The latter exploits the use of the term “bullish” and “bearish” in Twitter content to build up an investor sentiment index. The authors show that their index is positively correlated with other survey-based indexes of sentiment and is a predictor of shares’ price dynamics in some countries. Differently than these works, here we focus on expected inflation. Other papers have used social media data, not specifically Twitter data, to analyze asset returns (Chen, De, Hu and Hwang (2014)) and their volatility (Jiao, Veiga and Walther (2018)), or construct indexes of investors’ sentiment (Da, Engelberg and Gao (2015)).

Finally, our work is also a methodological contribution on how machine learning techniques of text analysis, together with a semantic approach, can be used to extract meaningful information on macroeconomic variables from noisy, textual and very large data. The LDA textual analysis has been recently used in the economics literature (see Hansen, McMahon and Prat (2018)); in this work, we combine LDA with a semantic approach to extract a directional signal of inflation expectations.

The rest of the paper is organised as follows. Section 2 describes the data and the keywords used to select the tweets. Section 3 reports the three-step procedure adopted to compute the Twitter-based indicators of inflation expectations. Section 4 compares these indexes with the survey- and market-based measures. Section 5 shows some robustness checks using sub-samples of users interested in economics or in the business news or based on future words and verbs. Section 6 shows the additional information content of the Twitter-based indicators in-sample, above and beyond the lagged survey- and market-based expectations, realized inflation and professionals’ forecasts. Section 7 shows the predictive superiority of Twitter-based indicators out-of-sample relative to the existing sources. Section 8 then concludes.

2 Twitter data and keywords to select tweets related to price dynamics

We use tweets from the social networking site Twitter. Tweets are short messages of at most 140 characters.[4] Once a sender (twitterer) writes a message and sends it out, the tweet reaches the users/people with whom the tweeterer is linked (followers), who can, in turn, forward the message to their followers (re-tweet). Tweets can also be searched

[4]Starting in November 2017, the platform allowed text messages of 280 characters in length.

within the search engine provided by the platform. Tweets are, therefore, publicly available on the social network platform. Tweets typically contain news, links, opinions, advertisements, or personal information that the twitterer wants to share with the public. The analysis of this significant amount of free texts characterized by informal language and possibly affected by misspelling, slang, and the so-called hashtags is challenging.

The main idea of our work is to extract from the tweets an aggregated signal that, being based on users' comments and their sharing of opinions about inflation, can be interpreted as an indicator of the dynamics of inflation expectations.

To build our database of tweets, we first identify which tweets are more likely to talk about inflation, prices, and price dynamics. For this purpose, we select several keywords in Italian related to prices, inflation, rents, bills, gasoline, and oil prices and extract all tweets mentioning at least one of them.

This dictionary of selected keywords in Italian [English] related to price(s) and price dynamics can be categorized as follows:

- *"prezzo" [price], "prezzi" [prices]*, and *"costo della vita" [cost of living]* capture tweets about prices in general, identifying messages that do not capture price dynamics if not further analyzed;[5]

- *"caro bollette" [expensive bills], "inflazione" [inflation], "caro" [expensive], "caro prezzi" [high prices], "caroprezzi" [high-prices], "benzina alle stelle" (high gas prices), "bolletta salata" [higher bill], "caro affitti" [higher rents], "caro benzina" [high gasoline price], "caro carburante" [high petrol prices]*, and *"caro gas" [high gas prices]* reflect instead some price dynamics in the tweets that contain them, showing expectations of increasing price(s);

- *"deflazione" [deflation], "disinflazione" [disinflation], "ribassi" [sales], "ribasso" [sale], "meno caro" [less expensive]*, and *"bollette più leggere" [less expensive bills]*[6] reveal tweets about decreasing prices.

Our initial dataset consists of 11.1 million tweets sent between 1 June 2013 and 31 December 2019, whose text contains one or more of the keywords on inflation/deflation listed above.[7] Our sample contains the full text of the tweet and the available metadata, which include, for instance, the public biography of the tweet sender, the number

[5] In a certain sense, one can consider tweets containing these set of keywords as neutral.

[6] Some of these words might seem unusual with respect to the English language, but they represent commonly used (collection of) words in the Italian language to express price dynamics.

[7] The tweets were collected using a private Application Programming Interface (API) from Twitter/GNIP called Historical Power Track.

of followers, etc.[8] While our baseline Twitter-based inflation expectations indicators are extracted only from the text of the tweet, as explained in the next section, the additional pieces of information given by the meta-data allow us to implement some refinements on the indicators by investigating the features of the user who writes them.

Note that we cannot exactly ascertain whether the selected tweets are a direct and straightforward revelation of inflation expectations, but we use keywords and combinations of words (n-grams) that can be part of either a tweet that explicitly communicates expected price dynamics or a tweet that reports or comments on some recently observed price dynamics. The latter reflect inflation perceptions rather than expectations, but still they are inputs to the expectations formation process. As in Bayesian learning, we consider that individuals form expectations on random variables, in this case, future inflation, by observing noisy signals. Given these signals, they update their distribution of future inflation outcomes. To exemplify our rationale, consider an individual with a prior distribution over annual inflation next year, π, which is normally distributed with mean $\bar{\pi}$ and variance $1/\tau$. She then observes on Twitter a noisy signal on π, $\hat{\pi}$, which is, conditional on π, normally and independently distributed with mean π and variance $1/\chi$. This tweet can say something about realized inflation (which, if the data generating process of inflation is autocorrelated, will also say something about future inflation) or about future inflation directly. It is important that she will use this signal to generate a posterior distribution on future inflation, thus updating her expectation. Assuming independence of signals, the posterior distribution of π will be normally distributed with mean $\bar{\pi}'(\hat{\pi}) = \frac{\tau}{\tau+\chi}\bar{\pi} + \frac{\chi}{\tau+\chi}\hat{\pi}$ and variance $1/\tau'$, where $\tau' = \tau + \chi$. This person might then also send a tweet with her mean expectation $\bar{\pi}'(\hat{\pi})$. With our data collection we observe either $\hat{\pi}$ or $\bar{\pi}'(\hat{\pi})$ (or both). If we observe the latter, we have a direct revelation of expectations. If we observe the former, $\hat{\pi}$, since it is an input in the expectation update process, it is still relevant for determining the expectation of inflation by the individuals observing it.

[8]Meta-data are information related to the sender and to the tweet itself. For example, it includes the biography of the sender if reported, the number of followers of the sender, if the tweet is a re-tweet from some other senders, how many times the tweet has been re-tweeted by other users and other characteristics.

3 Twitter-based inflation expectations

The tweets in our initial dataset, selected using the relevant keywords, are related to different themes. This is not surprising given the extent of the possible uses of the selected keywords in the Italian language. Indeed, our sample of tweets not only includes messages related to inflation developments (coming from personal experiences or news and official media outlets) or expectations thereof, but it also contains "noise", like advertisements, e-commerce tweets, or tweets that use the word inflation in a different context than price developments.

Table 1 provides a selection of tweets from our sample. The first three tweets refer to news about past inflation developments (real or perceived). The following three instead convey information about expected inflation developments (the Governing Council of the European Central Bank taking actions to avoid deflation; some users suggesting that maybe deflation is still possible). The seventh tweet instead refers to advertisements, while the last one shows the use of the word *"inflation"* with a different meaning from the economic one.

To reduce the noise and focus only on the tweets related to inflation developments, past or expected in the future, we adopt a three-step procedure. First, we filter out the noisy content and isolate valuable signals by implementing a topic analysis using Latent Dirichlet Allocation (LDA) as in Blei et al. (2003). Second, we implement a dictionary-based approach on the filtered data to build a set of indexes based on the raw daily count of tweets. To do this, we create a dictionary of bi-grams and tri-grams containing the words *"price(s)", "expensive", "inflation"* and *"deflation"* that are manually labeled depending on the fact that they are indicating increasing or decreasing inflation expectations. Finally, we aggregate these indexes in directional indicators: indicators that increase (decrease) with expectations of increasing (decreasing) inflation.

3.1 Step one: Topic analysis

To filter out the noise in our final dataset and isolate valuable signals, we implement a textual analysis on more than 11 million tweets, relying on the probabilistic topic analysis provided by the LDA. Here we provide a brief intuitive description of the LDA and how it is implemented.[9]

[9] For a more detailed description, we refer the reader to the Online Appendix. For a general introduction on probabilistic topic models, see Steyvers and Griffiths (2007).

Table 1: Selected tweets in the sample

	Italian	English
1.	#Eurozona: a marzo prosegue la deflazione con -0,1% di #inflazione annua #eurostat	#Eurozone: in March deflation continues with -0.1% YOY #inflation #eurostat
2.	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%
3.	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.
4.	Da domani sarà meno caro usare il cellulare in Europa. Ecco perchè	Starting tomorrow it will be less expensive to use the cellphone in Europe. This why
5.	RT SkyTG24: #Ultimora BCE, #Draghi: senza nostra azione saremmo in deflazione	RT SkyTG24: #breakingnews ECB, #Draghi: without our action we would be in deflation
6.	#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!
7.	Solo da Baby Glamour acquistando tre capi il meno caro è in regalo. Promozione fino al 10 Ottobre.	Only at Baby Glamour if you buy three items the least expensive is free. Promotional sales until October 10.
8.	Il più grande spettacolo dopo il #big-bang è l'inflazione cosmica	The greatest show after the #big-bang is cosmic inflation

The LDA is a way to reduce the dimensionality of large amounts of textual data and provide a "summary" description of what a document (a collection of words and their relative frequencies) is about. To do so, the LDA posits the way the document has been generated. It assumes that every document was generated by a document-specific mixture of topics and that each topic is defined by a distribution over words.[10] Both the mixture of topics and the distribution over words defining the topic are *hidden*. Thus the objective is to use the observed documents to infer, through Bayesian methods, the distribution over words which defines the topic, and the mixture of topics (relative importance of each topic) that describes a document. After fitting the LDA, one can assign a meaning to each topic by inspecting which words have the highest importance (i.e., the highest probability mass in the distribution),[11] and describe the content of each

[10]Note that the same word can appear in different topics, but with a different weight in each of them.

[11]In the words of Steyvers and Griffiths (2007): "Each topic is individually interpretable, providing a probability distribution over words that picks out a coherent cluster of correlated terms".

document by considering its most relevant topics (the highest weights in the mixture).

Several authors consider the shortness of tweets as a drawback for applying topic extraction algorithms like LDA. This aspect is managed by applying a tweet-pooling strategy based on users as suggested by Alvarez-Melis and Saveski (2016). Therefore a "document" is created by grouping the words of all the tweets written by the same author in the dataset. To uncover the hidden topics, we apply the LDA on this new corpus. We then select the topics related to inflation expectations and price dynamics (by inspecting the words with the highest probability mass) and use the LDA estimates to assign a probability to each tweet belonging to one of those topics. The tweets with the highest likelihood of being described by the topics related to inflation and deflation are the final outcome of the filtering procedure.

These are the necessary steps to implement the LDA, and the resulting estimated topics chosen to filter our textual data. The first processing stage is represented by a standard data preparation pipeline to transform the tweets into a suitable form for text mining. We adopt the following steps for each tweet:

- **cleaning**: we remove user mentions, URLs, punctuation, hashtag symbols, and other special characters;
- **splitting**: each tweet is converted in a bag-of-word representation;
- **rare words and stopword removal**: we use a filter based on the log-rank to remove the rarest words,[12] and afterward we also remove the Italian stopwords;
- **featurization**: at this point, each bag of words corresponding to a tweet is translated into a count vector of words.

After such data preparation pipeline, we obtain a cleaned dataset ready to implement the LDA.[13]

Like other dimension reduction techniques, in the estimation procedure, the LDA requires the ex-ante specification of the number of topics. In order to estimate automatically such a number, we adopted the log perplexity metric[14] and ran the LDA for

[12] We use a log-log plot of word frequencies vs. their rank, and we identify the log-rank at which the frequencies begin to drop sharply. In our case, the cut point in the log rank is about 3.76.

[13] We used the LDA implementation in Spark 2.1.1 with online optimizer - http://spark.apache.org/docs/2.1.1/ml-clustering.html#latent-dirichlet-allocation-lda.

[14] The log-perplexity ($\log(PP)$) is a metric to evaluate language models, which is linked to the evaluation of the likelihood. The log perplexity of a language model like the LDA on a held-out test set is equivalent to the inverse of the geometric mean per-word likelihood. In formula: $\log(PP(D_{test})) = -\frac{\sum_{d=1}^{M}\log(p(w_d))}{\sum_{d=1}^{M} N_d}$, where M is the number of documents in the test corpus D_{test}, w_d are the words in

topic numbers in the range $[20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75]$. We obtained the first minimum value for the log perplexity around 50 topics and, therefore we decided to use this value for the LDA (see Figure A.2 in the Appendix).

Table 2 shows three examples of the topics discovered by the LDA (out of 50). For each topic, we present the top 10 (i.e. with the highest likelihood) words in Italian, and in brackets the corresponding English translation. The first topic (Topic 13) refers to e-commerce for smart-phones, such as offers about Apple iPhone or Samsung Galaxy. The second one (Topic 19) is related to the context of interest and includes words like "*inflation*", "*wages*", "*deflation*", "*euro*", etc. The third topic (Topic 36) also refers to "*inflation*" and "*deflation*", but associated with "*oil*", "*stock exchange*", etc. Among all the 50 topics, only the two topics denominated Topic 19 and 36 in Table 2 appear to convey valuable signals for our purposes as they include words related to inflation and deflation and collect tweets that refer to these themes.[15] The remaining 48 topics are related to price(s) but in different contexts: for example in electronics, Amazon offers, tourism, sports, etc.[16] Hence in our analysis, we focus on these Topics 19 and 36 to filter out the set of tweets relevant for price dynamics, and disregard all the others.

Table 2: Examples of topics discovered by LDA

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*]

Notes: The table shows the ten words in Italian and in *[English]* with the highest likelihood in topics 13, 19 and 39 for the LDA with 50 topics.

document d, and N_d is the number of words in document d. Thus minimizing $\log(PP)$ is equivalent to maximize the test set probability of the language model and a lower perplexity is a sign of a better generalization performance (see Blei et al. (2003)).

[15] The two topics in Table 2 are the only ones containing the word "*inflation*" and/or "*deflation*" among the top 20 words in each topic.

[16] See the Appendix for further details on the 48 left-out topics.

Then, we assign a tweet to the topic with the highest likelihood and the tweets with the highest likelihood of being described by the selected topics related to inflation and deflation (Topic 19 and 36) are the final outcome of the filtering procedure.[17] This filtering step reduces the number of tweets to 1,534,743 that is the 14% of the initial data.

In the recent text mining literature, some authors questioned the stability of the topics discovered by the LDA across different executions of the algorithm.[18] Indeed, a strategy is needed to adequately take into account the possible variability of the results across different executions. To deal with this issue, we train three topic models, with three independent runs of the LDA procedure with 50 topics with no fixed seed for the random number generator. To confirm the robustness of the results across the three runs, we check how often the different LDA executions do agree in selecting a tweet. Overall for about 83% of the cases at least two LDA runs are in agreement to assign a tweet to the two topics of inflation/deflation. The remaining 17% has been sampled and after a careful inspection, we decided to keep it in our sample as it still contains some relevant content for the scope of our analysis.[19]

3.1.1 Which and whose tweets?

The topic analysis allows us to isolate valuable signals, filtering out many messages unrelated to inflation expectations, and primarily related to advertisements or e-commerce websites. Indeed, in the original data-set, around 4.6 million tweets are selected because they mention the word *"prezzo"/"prezzi" [price(s)]*, but only 406,430 survive to the second phase. The topic analysis allows us to filter out about the 92% of the tweets on "*price(s)*" from the original data-set which are mainly related to buying opportunities. This result sheds some light on the information content conveyed by the tweets mentioning "*price(s)*" that we can understand only exploiting text analysis techniques. The topic analysis is also useful to discern tweets that mention the words *"inflation"*, *"disinflation"*, even if in this case the discarded tweets are much less (only 9%), both in absolute and relative terms. Among these tweets in fact about 462,000 (out of almost 506,000) tweets survive to the topic analysis, suggesting that most of the tweets with

[17]To remove possible ambiguous cases, tweets in which the first two assignment probabilities (in descending order of magnitude) differ by less than 5% are discarded (this does not apply if the two topics in descending order are the topics on inflation/deflation, i.e. Topic 19 and 36 above).

[18]In fact, since topic extraction is based on a stochastic sampling procedure, two runs of the process might not give exactly the same results. See for example Belford, Namee and Greene (2017).

[19]Across the three LDA runs, we noticed negligible differences among the top 20 words in each topic in Table 2. For example, for Topic 19, only 4 words were not in common across the three runs, while for Topic 36, only 3 words were different; in addition, all these uncommon words have the lowest probabilities.

these keywords contain useful information about price dynamics.

The first step of the procedure leads to a final dataset of 1,534,743 tweets with 165,551 distinct users id.[20] The volume of tweets varies substantially over time, and we find considerable heterogeneity across keywords. For instance, tweets on inflation have a daily average of 131 and a maximum of 1,671, while those on deflation have a daily average of 67 and a maximum of 5,744 on August 29, 2014.[21] Further, the volume of tweets on price(s) is substantially larger, although the topic analysis filtered out many messages related to advertisements, and e-commerce. The tweets with the word "*price(s)*" are indeed on average around 170 per day, with a maximum of 1,089 and a standard deviation of 117.

It is of interest to understand who are the users whose tweets are selected with our filtering procedure. To do so, we can rely on the metadata, if the user has provided some description of her/his field(s) of interest or activity in the self-reported biography field. In Table 3 we present the thirty most common words adopted by the users in our sample who have filled in this field. Most users seem to be either involved in the news business or in politics/economics. It must be remarked that this is almost the full picture of twitterers because about 80% of the users in our sample have a non-empty value for their biography field.

According to AGCOM,[22] the number of active Twitter users in Italy goes from a minimum of 6.7 million in 2016 to 10.9 in 2019. Using Nielsen data, AGCOM analyzed the Twitter audience by target users in Italy, showing that with respect to the total Internet population for the category "Search, Portals, Communities", Twitter is characterized by a higher number of male employed users in the age group 33-54, with the highest number of graduates compared to the mean of other social networks.[23]

[20]Table C.1 in the Appendix shows additional descriptive statistics about the users and their behavior.

[21]On August 29, 2014 the year-on-year inflation rate was announced to be negative in Italy.

[22]AGCOM (2020). AGCOM is the Communication Authority for Italy. AGCOM regularly publishes information on the number of active users for the most visited websites, such as www.twitter.com.

[23]For more details on Twitter and other social network usages in Italy, see https://www.agcom.it/osservatorio-sulle-comunicazioni.

Table 3: 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
economia [economy/economics]	827	Italy	574
manager	817	online	573
ufficiale [official]	801	direttore [executive director]	570

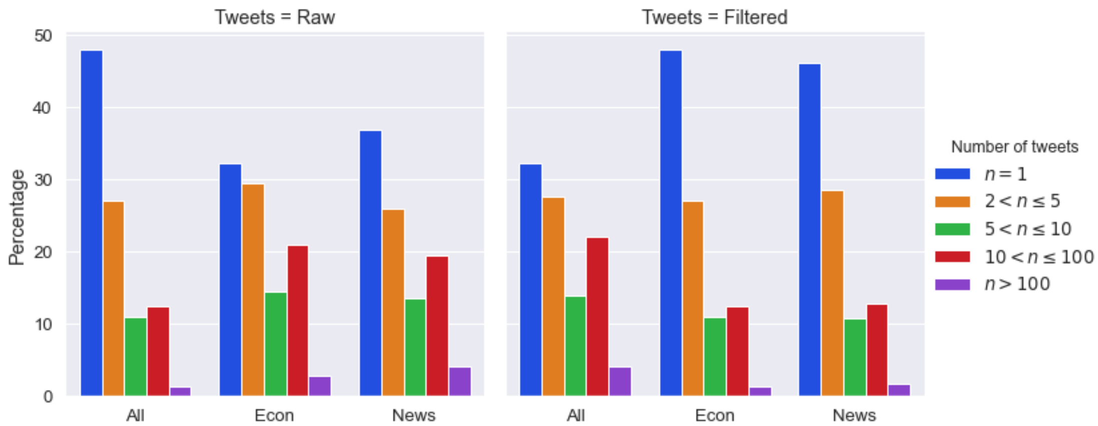
Note: Summary statistics on the the users' biographies of the filtered dataset. Sample: June 1, 2013 - December 31, 2019. The Table displays the most frequent words that appear in the users biography (excluding stop words).

Our sample starts from around 950,000 users for our full sample of tweets (that is, the tweets selected according to the keywords) and reduces to 165,551 once the tweets are filtered with the LDA. Figure 1 shows the distribution of the number of tweets written by the users in the full sample of tweets (left panel) and by those users in the sample of filtered tweets (right panel). Around 50% of the users in the full sample wrote just one tweet, around 25% wrote between 2 and 5 tweets, 10% wrote between 5 and 10 tweets, slightly more than one-tenth wrote between 10 and 100 tweets and around 1% wrote more than 100 tweets.[24] The sample of filtered tweets on the right panel of Figure 1 shows that the distribution of tweets becomes less skewed. In fact, for the filtered tweets, one third of the users wrote one tweet, one fourth between 2 and 5, one tenth between 5 and 10, one fourth between 10 and 100, and 5% more than 100 tweets. Therefore, the LDA filtering keeps users who tweet more often about price dynamics than in the full sample. Put differently, several users in the initial sample with very low activity are discarded, reflecting the contents of their tweets not really aligned to price dynamics. On the contrary, with respect to users interested in economics (Econ) or in news (News), the LDA filters tweets of users that are more active in the full sample. We interpret this

[24]Note that these are figures for the users that had tweets with the selected keywords, our full sample, not about overall activity of the users. However, even these partial figure are in line with Twitter usage in the USA, where around the 80% of tweets come from 10% of the users. See https://blog.hootsuite.com/twitter-statistics/

as the LDA discarding tweets not aligned with price dynamics content.

Figure 1: Distribution of tweeting activity by users and type of tweet



Notes: The figure shows the percentage of users in the sample of all tweets related to prices and inflation (left panel) and for the filtered tweets as selected by the LDA (right panel). Sample June 2013 - December 2019.

3.2 Step two: dictionary-based approach

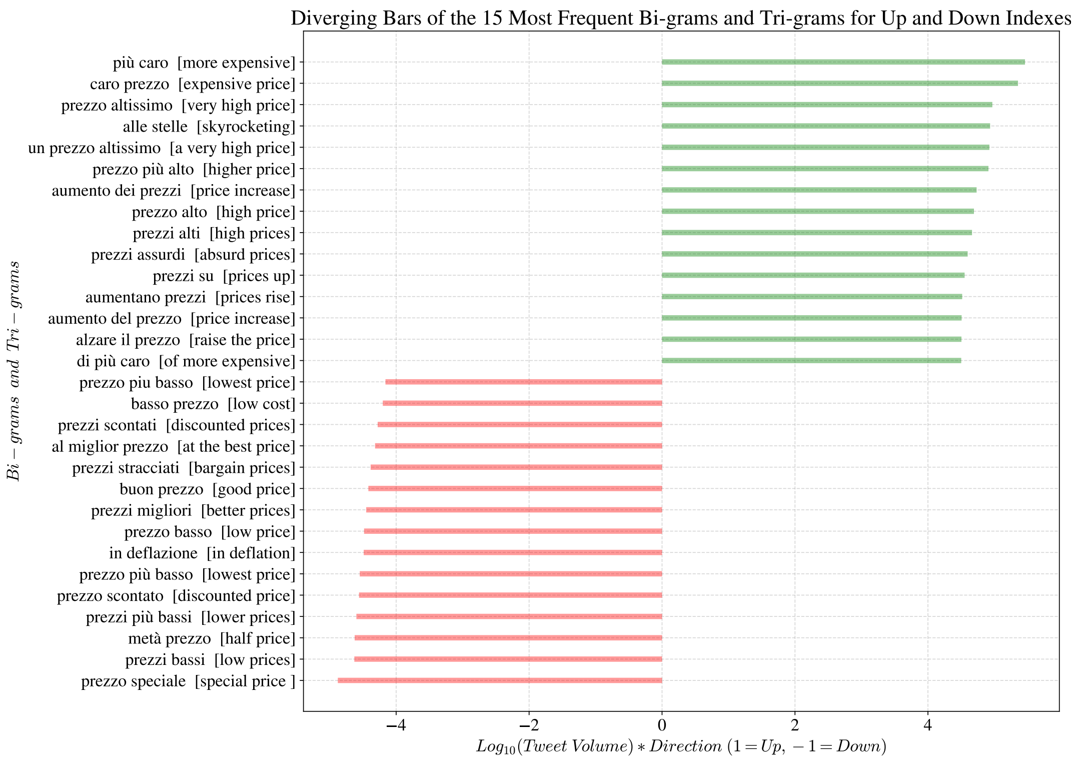
As a second step, we select the relevant tweets and aggregate them to get useful insights about economic agents' expectations.

To do that, we assume that the keywords' connotation reflects a message on the direction of the observed or expected price change. We thus implement a dictionary-based approach where we refine the rough initial dictionary used to select the tweets, creating a set of refined dictionaries made of manually labeled bi-grams and tri-grams.

In particular, we extract all the bi-grams and tri-grams containing the words *("price", "prices", "expensive", "inflation"*, and *"deflation"* and we manually label them as Up or Down, depending on all the authors' subjective interpretation of whether they indicate increasing or decreasing price dynamics, respectively. We create different dictionaries using 1) only bi-grams, 2) only tri-grams, or 3) both. In building our dictionaries, we use a different sets of bi-grams and/or tri-grams, depending on the average yearly volume of tweets containing them over the full sample. Thus, after sorting the n-grams in descending order with respect to the average yearly number of tweets containing them, we select A) the top 5%; B) the top 10%; C) a number of n-grams so that there are on average at least 100 tweets every year; and D) all the labeled bi-grams and/or tri-grams.

Figure 2 depicts the first 15 most frequent bi-grams and tri-grams for Up (green horizontal bars) and Down (red horizontal bars). On the horizontal axis, the log base 10 of the yearly average tweet volume between 2013 and 2019 is shown. The most common Up bi/tri-grams are *"più caro" [more expensive], "caro prezzo" [expensive price], or "un prezzo altissimo" [a very high price]* with an average yearly volume of tweets between 2013 and 2019 around 10,000. The most common Down bi/tri-grams are *"prezzo speciale" [special price], "prezzi bassi" [low prices], "metà prezzo" [half price], or "prezzi più bassi" [lower prices]* with an average yearly volume of tweets between 2013 and 2019 above 10,000. Further details and a complete list of the Up and Down bi- and tri-grams can be found in the Appendix.

Figure 2: First 15 most frequent labeled bi- and tri-grams to compute directional indexes



Notes: The figure shows the 15 most frequent bi- and tri-grams in Italian (English translation in squared brackets) manually labelled to compute Index Down (red) and Index Up (green) over the sample June 2013 - December 2019. On the x axis the log10 of the total volume of tweets containing that bi- or tri-grams is displayed (negative for Down and positive for Up).

We then build two Twitter-based indexes (Index Up and Index Down) by measuring the daily volume of tweets containing at least one of the bi-grams and/or tri-grams of our dictionary.[25] The rationale for focusing on pure raw tweets count is the intuitive notion that the more people talk about something, the larger is the probability that it reflects their opinion and that their view can influence other people's expectations. That is because the more people talk about a topic, the more attention they pay to it, and the stronger is the echo of the news that they provide. At the same time, the fact that they associate a possible direction of price variations in their message should influence (or reflect) expectations accordingly. For instance, the fact that agents talk about expensive bills should reflect expectations of higher inflation. On the other hand, people discussing declining oil prices should correspond to expectations of lower inflation.

In the rest of the paper, we present only the results for the dictionary obtained using both bi-grams and tri-grams in case C), i.e., for those labeled n-grams contained on average in at least 100 tweets each year. We call this our baseline case. Overall, results do not change that much by using a dictionary with only bi-grams or tri-grams with different thresholds. The Twitter-based indexes tend to be highly correlated with each other, and they present similar features to the ones presented here for the baseline.[26]

Figure 3 depicts how the Up and Down indexes, constructed using the baseline dictionary, vary over time. Both Index Up and Index Down appear to reflect news about current and future inflation. These indexes tend to spike after the Italian CPI flash estimate releases[27] by the Italian national statistical institute (ISTAT) or after ECB Governing Council press conferences or speeches by one of the ECB's Board members. For instance, Index Up peaked the day of President Mario Draghi's Marjolin Lecture on how central banks tackled the challenge of low inflation on February 4, 2016. Instead, the Inflation-Down index rose on August 29, 2014, when ISTAT announced the year-on-year (yoy) inflation rate to be negative at -0.1% for the first time since 1959. Hence, institutional announcements supposedly drive streams of tweets and discussions on inflation and price dynamics among journalists, economists, and consumers, and social networks may have an amplification effect on these announcements.

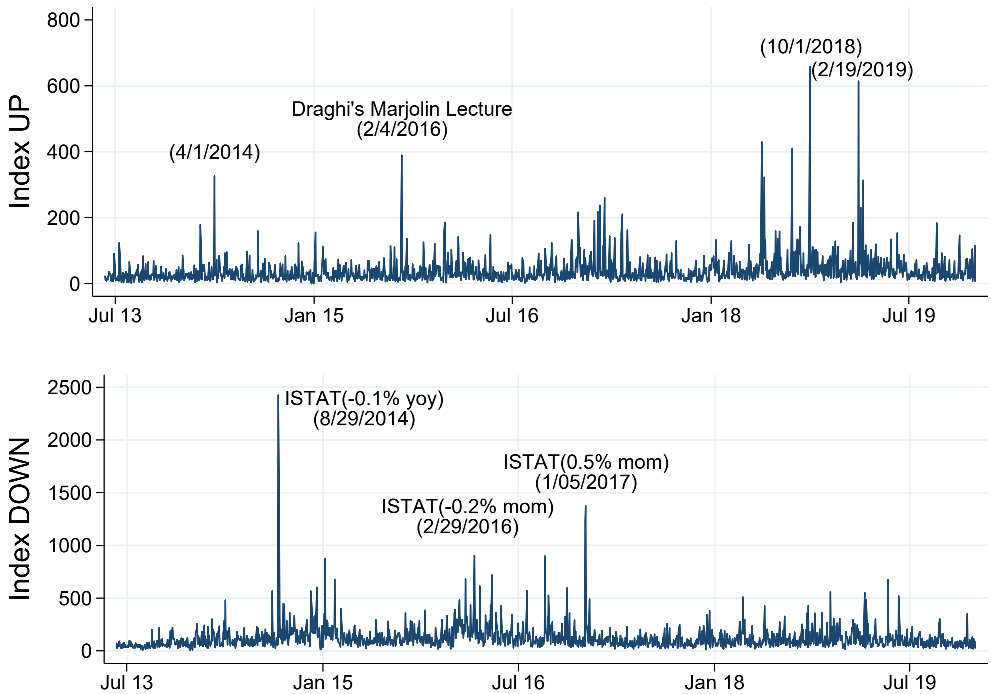
[25] If the same tweet mentions two or more bi-/tri-grams associated with a given index, the tweet is counted only once. For instance, if a tweet mentions both *"more expensive"* and *"a very high price"*, it is considered only once in the assessment of the index Inflation-Up. Similarly, for tweets with more Down bi- and tri-grams. On the other hand, if a tweet mentions an even number of positive and negative bi- and tri-grams, say, for example, both *"more expensive"* and *"lower prices"*, then it is labeled as a neutral tweet.

[26] Additional results with other dictionaries or thresholds are available from the authors upon request. In Appendix E results with an alternative method with respect to the use of bi-grams or tri-grims are presented. Please refer to the appendix for the description. Results are still robust to this alternative method of computing the dictionaries.

[27] Usually, the preliminary CPI releases are at the end of each month, but in some months (for instance, December), it can be postponed to the first business days of the following month.

Figure 3: Dictionary-based Inflation Indexes - Baseline

Dictionary with bi-grams and tri-grams



Notes: The figure depicts the two dictionary-based indexes Up and Down with some events when the volume of tweets is particularly high. The indexes are computed with the baseline dictionary of manually labelled bi-grams and tri-grams.

3.3 Step three: computation of aggregate directional indicators

We then combine the dictionary-based indexes showed in Figure 3 assuming that Index Up refers to expectations of higher inflation, and Index Down refers to expectations of lower inflation. There is no straightforward way to do this; hence, we propose here several indicators and check how each of these performs:

1. **Inflation Expectations Indicator #1**: We compute the difference between the two dictionary-based indexes that indicate increasing and decreasing inflation expectations, $\pi_0^e \equiv$(Index Up$-$Index Down). We then winsorize π_0^e, by cutting the extreme values, those greater than three standard deviations, and setting them to 100. Then we standardize the series dividing it by three times the standard

deviation. The resulting index are smoothed using a (backward-looking) moving average (MA) of 10, 30 and 60 days.

2. **Inflation Expectations Indicator #2**: We compute π_0^e as defined above and regress it on a set of dummies for the releases of the preliminary CPI in Italy and Germany, the ECB press conferences and the speeches by any member of the ECB Board and a single dummy for August 29, 2014, when the yoy Italian CPI inflation became negative for the first time after 1959. We take the residuals from such a regression, we standardize the residuals with respect to three times its standard deviation, and we winsorize the extreme values so that those values greater than three standard deviations were set to 100. The resulting index are smoothed using a (backward-looking) moving average (MA) of 10, 30 and 60 days.

3. **Inflation Expectations Indicator #3**: We apply an exponential smoothing on π_0^e, and we test three alternative values of the parameter α: 0.1, 0.3 and the optimal one which is chosen to minimise the in-sample sum-of-squared forecast errors (this is close to 0.1). The parameter controls how relevant are past observation, the lower the value of α the higher the weight on past values and the smoother the index.

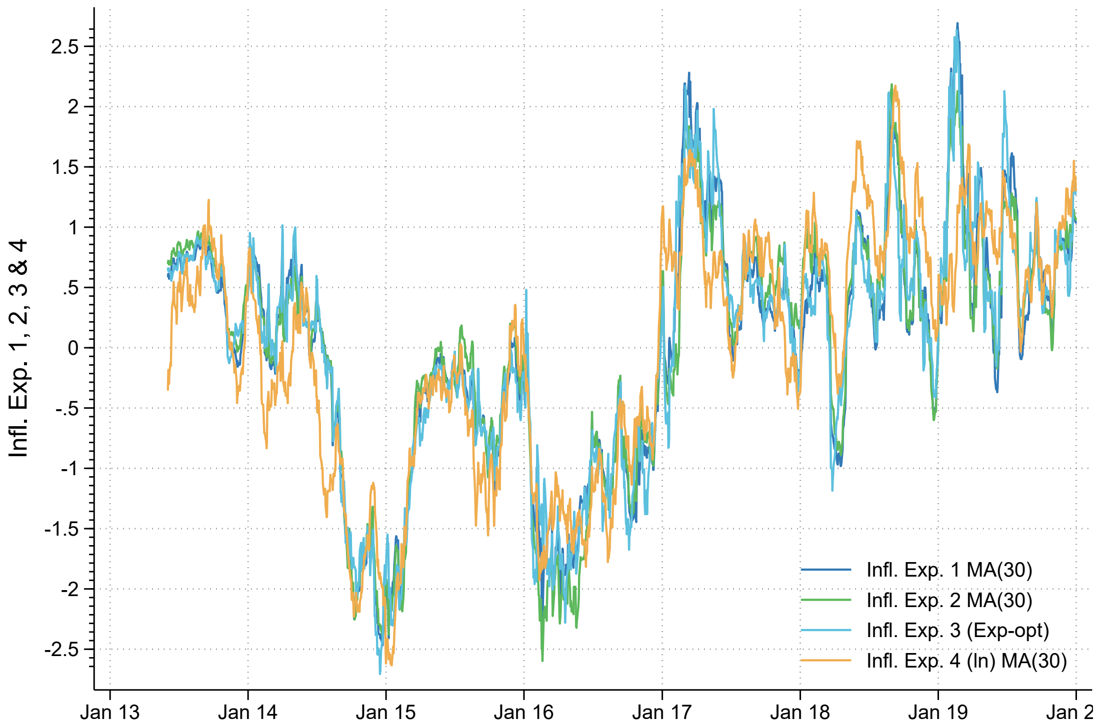
4. **Inflation Expectations Indicator #4**: We compute the following indicator: $\pi_{ln}^e \equiv (ln(\text{Index Up}+1) - ln(\text{Index Down}+1))$. The resulting indicator are smoothed using a (backward-looking) moving average (MA) of 10, 30 and 60 days.

Inflation Expectations Indicators #1, #2 and #3 are based on the difference between Index Up and Index Down indexes. This aggregation is necessary to generate a *directional* indicator, that is, one that points towards increasing or decreasing inflation expectations. Similarly to the rationale for using the raw count of tweets for creating the indexes, it reflects the intuitive idea that when there are more (less) tweets about expectations of higher inflation as there are about expectations of lower inflation, then the overall signal should be of increasing (decreasing) inflation expectations.[28] Indicator #1 purely reflects this aggregation and a standardization that removes extreme values. For Inflation Expectations Indicator #2 we also eliminated additional noise coming solely because our indexes tend to spike when news about inflation is released. Both Indicators #1 and #2 are then smoothed by taking a backward-looking moving average at several horizons. This smoothing wants to capture the idea that most likely it is not just the

[28] Indexes that reflect survey-based inflation expectations are also built in a similar fashion by national statistical institutes. They are presented in the following section.

single information received in a day that is important for inflation expectations, but also information obtained in the recent past. Indicator #3 explores this idea by computing an exponential smoothing on the absolute difference between Index Up and Index Down. In this case, all past values are taken into account in computing the value of the index (instead of just the last 10, 30 or 60 ones, as in the moving average computation), with the parameter α determining how fast memory fades away, or how more relevant is the new information with respect to the old one. Finally, with Indicator #4 we consider a different way to aggregate the information, which is by taking the natural log difference between Index Up and Index Down. Since we are taking the log, extreme values affect less the indicator, and we do not perform the standardization in this case. However, we do smooth the values by taking the backward-looking moving average at several horizons.

Figure 4: Twitter-based inflation expectations indicators - (Standardized values)



Notes: Data are at daily frequency, from June 1, 2013 through December 31, 2019. The Twitter-based inflation expectations indicators are computed using the baseline dictionary of bi- and tri-grams and are all standardized.

Figure 4 plots the four standardized Twitter-based inflation expectations indicators built using the baseline dictionary of bi- and tri-grams and considering the 30 days moving averages or optimal smoothing parameter in the case of the exponential smoothing index. The correlations among them are very high (around 0.9; it is slightly lower for shorter window's length used to compute the moving average), suggesting that the way aggregation is computed does not matter.

4 Twitter, survey and market-based inflation expectations measures

To ascertain whether the suggested Twitter-based inflation expectations indicators are capturing inflation expectations, we compare them with both survey-based and market-based measures. Survey-based ones are more accurate, but they are low-frequency (i.e., monthly). On the other hand, market-based inflation expectations are higher frequency since securities are traded continuously, but they might not truly represent expectations due to time-varying risk premia and liquidity characteristics of the contracts they are based upon. Our ideal analysis would be to compare the Twitter-based indicators with survey-based data only. Still, given the relatively short time sample and the monthly frequency of surveys, it is also instructive to compare our indicators with market-based indicators, exploiting their higher frequency.

4.1 Twitter expectations vs survey expectations

As survey-based inflation expectations, we use the monthly survey on consumer and business confidence provided by ISTAT. The survey is based on around 2,000 households with a stratified random sample and asks respondents' qualitative expectations on price trends over the next 12 months. The ISTAT's survey is run during the first 15 days of the reference month, and the results of the survey are published at the end of the same month.[29]

The questionnaire uses five alternative answers to elicit the respondent's expectations on price trends over the next 12 months by comparison with the past 12 months. Specifically respondents are asked: *"By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will..."*

- increase more rapidly (higher inflation);
- increase at the same rate (same inflation);

[29] Usually the monthly survey on consumer and business confidence is published at the end of the month to which it is referred. So, for example, the results of the October 2017 survey were published on ISTAT's website on October 26, 2017.

- increase at a slower rate (lower inflation);
- stay about the same (no inflation);
- fall (deflation);
- don't know.

A monthly survey-based measure of inflation expectations for the next 12 months is computed using the following formula:

$$E_t^{ISTAT}\pi_{t,t+12} = (\text{higher infl.} + \text{same infl.}/2 - \text{no infl.}/2 - \text{deflation}) \quad (1)$$

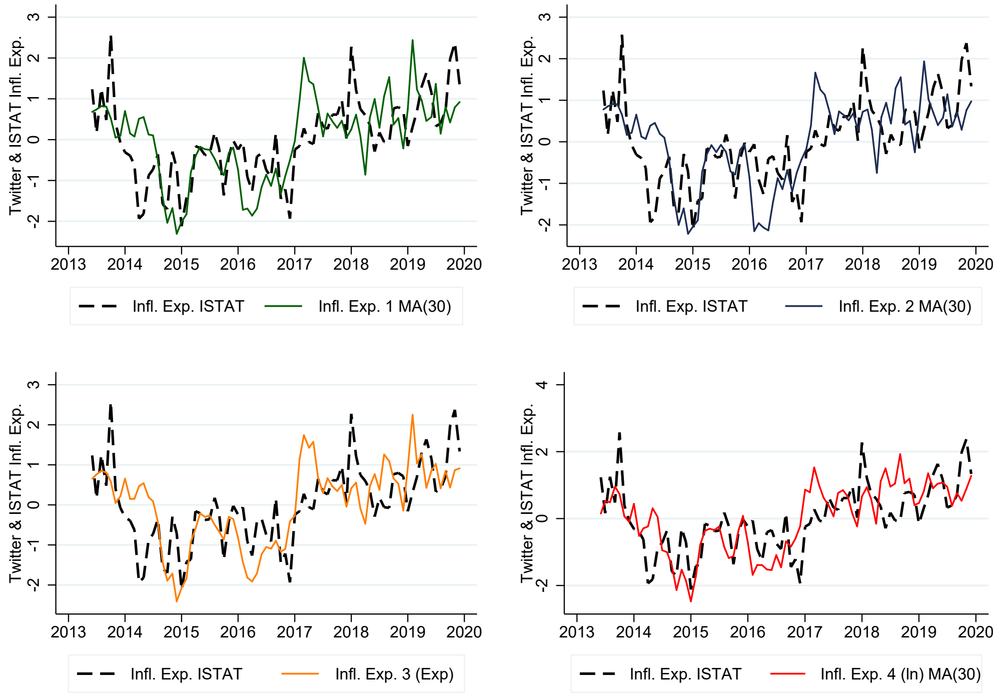
in which t is the month and '*infl.*' stands for inflation. Following the Eurostat/ISTAT approach, the index is computed by summing up the frequency rates of the respondents who said that in the next 12 months prices will increase *more rapidly* or *at the same rate* compared to the previous 12 months and subtracting the frequency rates of those who say that prices will stay *about the same* or *fall sharply*.[30]

Figure 5 depicts the time series plot of the Twitter-based inflation expectations indicators computed using the baseline dictionary of bi- and tri-grams and the survey-based measure of inflation expectations at the monthly frequency, computed as in equation (1) by ISTAT. Both indicators are standardized. Visually a strong correlation between these measures emerges.

Table 4 confirms these results. All our Twitter-based inflation expectations indicators are highly, significantly, and positively related to the survey-based expectations at the monthly frequency. Higher values of our indicators are associated with higher values of the survey-based inflation expectations. The proposed Twitter indicators explain between 23 to 43% of the variance of the survey-based inflation expectations. Indicator #4, based on the log difference, performs better in terms of variance explanation than all other indexes, suggesting that trimming data does not lead to more meaningful signals. The R^2 increases with the windows used to compute the backward-looking moving average, suggesting that the Twitter-based indicators are relatively more powerful for low-frequency movements in inflation expectations.

[30]Specifically, we use the seasonally adjusted series of this index provided by the Eurostat/ISTAT, and we adopt their approach in interpreting the alternative answers.

Figure 5: Twitter-based vs ISTAT Inflation Expectations - (Standardized values)



Note: Monthly data from June 2013 through December 2019. Daily indicators are collapsed at monthly frequency. Twitter-based inflation expectation indicators are computed using the baseline dictionary of bi- and tri-grams. All indicators are standardized.

There are instances in which our Twitter-based indicators seem to move in the opposite direction of the survey-based measures: for example, the period in the first half of 2014 in which survey-based measures fall and our Twitter-based indicators rise or remain stable, and the first half of 2017 when there is a surge in the Twitter-based indicators but only a regular increase in the survey-based measures. Analyzing the content of the tweets, we find that such strange behavior in these periods is due to a high volume of a few specific n-grams. For instance, looking at the first half of 2014, the path of the Twitter-based indicators is due to the high volumes of the tweets that mention *"più caro" [more expensive]* and *"più caro del" [more expensive than]* related to the news of a sale of the most expensive apartment in the world, an apartment located in One Hyde Park in London that was sold for 236$ million.[31] This example is a case of a false signal

[31] Figure D.2 in the Appendix shows how the one hundred most frequent Up and Down bi- and tri-grams contribute to the Twitter-based indicators in each month.

which was not filtered out by our procedure. Notwithstanding this and other few cases of false signals, the Twitter-based indicators are highly correlated with the survey-based measures.

It should be noted that both the Twitter-based indicators and the ISTAT surveys are qualitative; hence they don't provide information on the level of inflation expectations. Besides, the regression coefficients do not provide by themselves a gauge of the magnitude of the correlation. Table D.3 in the Appendix also reports the correlation magnitudes. The sample correlation goes from 0.48 to 0.66. As with the R^2, it increases with the length of the windows used to compute the average, and it is higher for Indicator #4. Overall, all proposed Twitter-based indicators provide a signal that is strongly correlated with survey-based inflation expectations, underscoring the usefulness of looking at tweets to elicit inflation expectations.[32]

Table 4: Univariate regressions, Twitter-based and ISTAT Inflation Expectations

	Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(10)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.189***	0.176***	0.219***	8.770***
	(0.038)	(0.030)	(0.042)	(1.360)
Cons.	-3.082**	-6.875***	-2.506*	3.941*
	(1.246)	(0.969)	(1.453)	(2.047)
N	79	79	79	79
R^2	0.233	0.254	0.273	0.35
	Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(30)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.228***	0.210***	0.249***	9.815***
	(0.042)	(0.028)	(0.042)	(1.343)
Cons.	-2.336	-6.908***	-1.934	5.239***
	(1.450)	(0.856)	(1.253)	(1.924)
N	79	79	79	79
R^2	0.287	0.316	0.315	0.4
	Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.274***	0.244***	0.185***	10.76***
	(0.036)	(0.038)	(0.039)	(1.335)
Cons.	-1.448	-6.935***	-3.164**	6.472***
	(1.410)	(0.852)	(1.265)	(1.898)
N	79	79	79	79
R^2	0.36	0.378	0.228	0.429

Note: The table displays results from estimating univariate regressions $E_t^{ISTAT}(\pi_{t,t+12}) = \alpha + \beta Infl.Exp_t + e_t$. The dependent variable is the ISTAT inflation expectations, while the independent variables are the Twitter inflation expectations indicators using the baseline dictionary of bi- and tri-grams. Data are at monthly frequency from June 2013 through December 2019. Daily indicators are collapsed at monthly frequency. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

[32] As a remark, performance of the indicator greatly benefits from the filtering process given by the LDA analysis. Correlations and R^2 of indicators computed without first filtering the data (step one of the procedure) are significantly lower.

4.2 Twitter expectations vs market expectations

To check the meaningfulness of the Twitter-based indicators, we also rely on the comparison with the market-based inflation expectations, because they are available at the daily frequency and convey updated information compared to survey-based measures. Further, they reveal the collective wisdom of many investors and, if the semi-strong form of the efficient market hypothesis holds, they convey all public information available at a particular point in time, including all survey forecasts.

Among market-based measures of inflation expectations, we focus on inflation swap contracts linked to the Italian inflation, due to these securities being relatively more liquid than inflation-linked Italian sovereigns. A swap is an agreement whereby one party pays to the other a variable amount, in this case, the realization of the inflation rate in Italy,[33] and the other pays a fixed amount, the swap rate, over the maturity of the contract. If investors are risk-neutral, these rates represent the expectation on average inflation over the maturity of the contract. Instead, with risk-averse investors there can be a wedge, the so-called inflation risk premium, between the swap rate and the expected average inflation rate.[34] Haubrich et al. (2012), Casiraghi and Miccoli (2019) indeed document the significant presence of time-varying risk premia in inflation swap rates, suggesting that these measures do not perfectly reflect inflation expectations.

We rely on swap contracts with a maturity of 1 year, consistently with the horizon of the survey based expectations measures. Figure 6 shows the time series plots of each Twitter-based inflation expectations index with the Italian inflation swap 1Y all standardized. All indexes are highly and significantly correlated with inflation swap rates, independently on how the Twitter-based indicators are computed or smoothed.[35]

Even when compared with the market-based inflation expectations, there are a few short time intervals in which our Twitter-based inflation expectations indicators do not co-move. For example, at the beginning of March 2017, there is a spike in any of the four Twitter-based indicators while the inflation swap stays constant. In this case, the increase in our indexes is due to a high volume of the n-grams *"inflazione sale" [inflation rises]* and *"rialzo dei prezzi" [rise in prices]*. These n-grams were due to a few newspaper articles commenting on the rise in February 2017 Italian inflation due to an increase in

[33] More precisely, the underlying of the contract is the yearly growth rate in the consumer price index ex-tobacco, which usually shows a negligible difference from the growth rate in the general consumer price index (CPI).

[34] The premium can be positive or negative, depending on whether the contract is a good or bad hedge for states of the world in which consumption is low.

[35] Figure D.1 in the Appendix depicts the same times series as Figure 6 but standardized to facilitate comparison across the indexes.

oil prices and food prices that were highly retweeted and commented during the first days of March.

Table 5 reports the estimates of a set of univariate regressions of the inflation swap rates on the Twitter-based indicators. The coefficients are all positive and significant, and the Twitter-based indicators explain from 19 to 54% of the variability in the inflation swap rates at 1 year horizon. This result suggests that the Twitter-based indicators track well the developments of inflation expectations also at the daily frequency, and not only at the aggregate monthly level. As with survey-based inflation expectations, the indicator computed on the log difference (Indicator #4) performs better, as do indicators based on larger windows for computing the average. Table D.4 in the Appendix also provides the correlation magnitudes. Values are in line with those ones found with survey-based expectations, ranging from 0.44 to 0.74.[36]

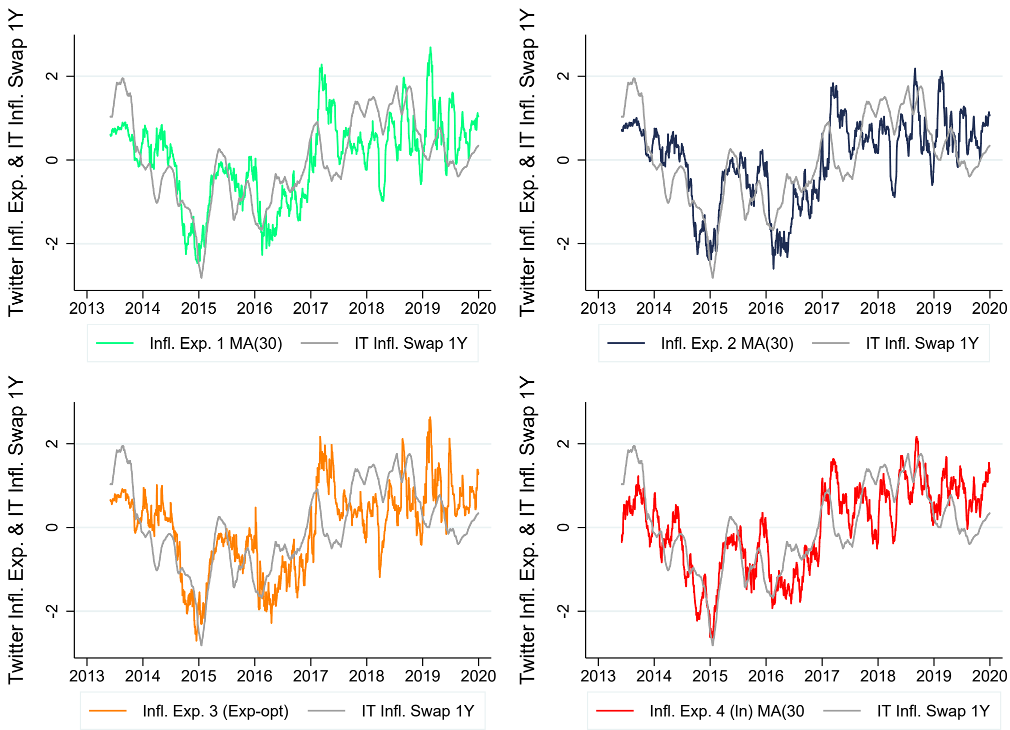
Table 5: Univariate regressions, Twitter-based and Market-based Inflation Expectations (Italian Inflation Swap 1Y)

	Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(10)
Infl. Swap 1Y	0.0139***	0.0138***	0.0185***	0.671***
	(0.002)	(0.002)	(0.003)	(0.075)
Cons.	1.016***	0.736***	1.103***	1.564***
	(0.069)	(0.048)	(0.080)	(0.101)
N	1717	1717	1717	1717
R^2	0.247	0.301	0.325	0.392
	Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(30)
Infl. Swap 1Y	0.0212***	0.0200***	0.0221***	0.935***
	(0.003)	(0.003)	(0.003)	(0.089)
Cons.	1.154***	0.729***	1.172***	1.886***
	(0.088)	(0.044)	(0.088)	(0.123)
N	1717	1717	1717	1717
R^2	0.373	0.431	0.379	0.541
	Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
Infl. Swap 1Y	0.0239***	0.0222***	0.0108***	0.985***
	(0.004)	(0.003)	(0.002)	(0.100)
Cons.	1.207***	0.728***	0.958***	1.954***
	(0.094)	(0.044)	(0.062)	(0.136)
N	1717	1717	1717	1717
R^2	0.393	0.45	0.192	0.517

Note: The table displays the results from estimating univariate regressions $(Infl.Swap1Y)_t = \alpha+\beta Infl.Exp_t+\varepsilon_t$. The dependent variable is the rate on the 1-year inflation swap contract linked to Italian inflation, while the independent variables are the Twitter-based inflation expectation indicators computed using the baseline dictionary of bi- and tri-grams. Data are at daily frequency, from June 1, 2013 through December 31, 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

[36] Once again the improvement associated to the LDA filter is not negligible as it increases the explained variability by up to 18%.

Figure 6: Twitter-based vs Market-based Inflation Expectations (Italian Inflation Swap 1Y) - (Standardized values)



Note: Daily data from June 1, 2013 through December 31, 2019. IT Infl. Swap 1Y is the rate on the 1-year inflation swap contract linked to the Italian inflation. The four Twitter-based inflation expectation indicators are computed using the baseline dictionary of bi- and tri-grams. All indicators are standardized.

5 Robustness

5.1 Subsample of users interested in economics or news

One key issue in analyzing social network data is to understand whether the information conveyed is actually able to shape expectations or is discarded by the receiver because for instance the source is not considered authoritative. With our data collection, we can also condition the selection of tweets to some characteristics that the users have published in their biographies on Twitter and focus on senders that could be considered authoritative on inflation by a general receiver.

First, we re-compute the Twitter-based indicators using only tweets from users interested in economics ("econ") in their self-published biographies.[37] These are all the users who mention in their biographies the words "*economista*" [*economist*], "*finanz*" [*finance*], "*economia*" [*economics/economy*]. There are overall 3,980 such users in our sample. Then we produce similar indicators considering only users who have "news" in their biographies; these are all the users who have the words "*giornal*" [*newspaper*], "*news/notizi*" [*news*], "*stampa*" [*press*], in their description, and there are in total 7,231 individual users with such characteristics.

The new series cover a smaller number of tweets but follow the same pattern of the Twitter-based indicators computed considering the entire pool of users (Figure 7). For instance, Index Down is on average equal to 14 when the index is computed on the Econ sub-sample, while it is 118 when computed on the full filtered data set.[38] Table 6 shows that the results of the estimates of the set of univariate regressions between the indicators computed on these sub-samples and the ISTAT inflation expectations index, for some selected indexes.[39] The coefficients are all positive and significant. The R^2 are slightly bigger compared to those of Table 4, suggesting that by further reducing the sample we are not missing useful information content, as we capture the tweets associated with a specific audience who is more knowledgeable about economics and inflation. We observe similar results when looking at the market-based measures (Table 7).[40]

The significance of the analysis goes in favour of the result that our Twitter-based indicators are actually capturing the correct signal on inflation expectations and are not strongly contaminated by noise. It seems that official announcements and professionals drive conversations on inflation on Twitter, and these may affect consumers conversations and expectations. This result is consistent with the empirical evidence that shows how professional forecasters expectations affect consumers' expectations in a rational inattention model (Carroll (2003)).

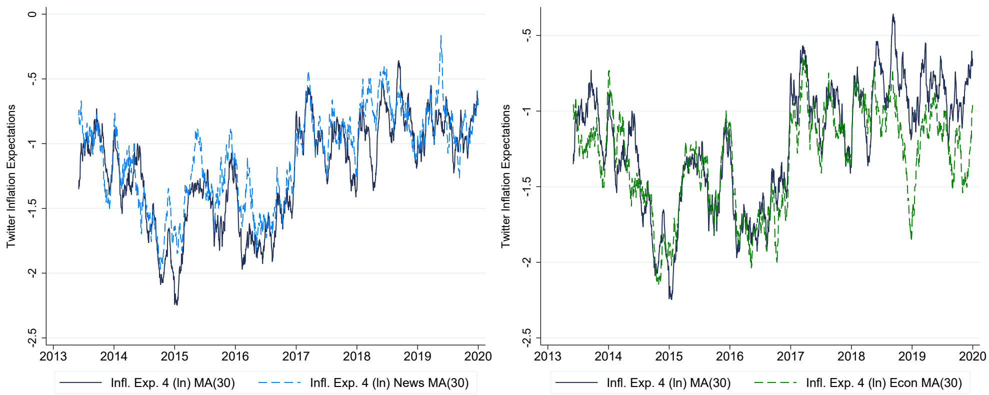
[37] We start form the filtered dataset and use this additional filter to select the tweets of interest.

[38] The Up index is 37 over the full set of tweets and 3 for the Econ subsample. The directional indexes for the News subsample have similar averages to the Econ one.

[39] The estimates for all the indexes are in Tables I.6 and I.7 in the Appendix.

[40] Tables I.2 and I.3 in the Appendix show that also correlations might be higher in value.

Figure 7: Twitter-based Inflation Expectations with News and Econ



Note: Data are at daily frequency, from June 1, 2013 through December 31, 2019. Twitter-based inflation expectations indicators are computed with baseline dictionary of bi- and tri-grams.

Table 6: Correlations between Twitter-based indicators for the News and Econ sub-samples and the ISTAT Inflation Expectations

		News		
	Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(30)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.0913***	0.261***	0.0948***	11.24***
	(0.011)	(0.056)	(0.012)	(1.489)
Cons.	-6.418***	-6.516***	-6.404***	5.753***
	(0.633)	(0.761)	(0.611)	(2.002)
N	79	79	79	79
R^2	0.405	0.431	0.417	0.417
		Econ		
	Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(30)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.0408***	0.236***	0.0438***	10.52***
	(0.004)	(0.041)	(0.005)	(1.427)
Cons.	-10.09***	-6.002***	-10.33***	7.242***
	(0.539)	(0.770)	(0.561)	(2.226)
N	79	79	79	79
R^2	0.383	0.384	0.408	0.303

Note: The table displays the results from the univariate regressions $E_t^{ISTAT}(\pi_{t,t+12}) = \alpha + \beta Infl.Exp_t + \varepsilon_t$. The dependent variable is the ISTAT inflation expectations, while the independent variables are the Twitter-based inflation expectation indicators computed on the sub-sample with "econ" and "news" in the users' bio and the baseline dictionary of bi- and tri-grams. Monthly observations from June 2013 through December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Correlations between Twitter-based indicators for the News and Econ sub-samples and the Italian Inflation Swap 1Y

	News			
	Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(30)
Infl. Swap 1Y	0.00722***	0.0241***	0.00741***	0.984***
	(0.001)	(0.003)	(0.001)	(0.111)
Cons.	0.772***	0.765***	0.773***	1.840***
	(0.048)	(0.040)	(0.047)	(0.132)
N	1717	1717	1717	1717
R^2	0.374	0.538	0.381	0.486
	Econ			
	Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(30)
Infl. Swap 1Y	0.00313***	0.0213***	0.00332***	0.963***
	(0.000)	(0.003)	(0.000)	(0.130)
Cons.	0.489***	0.811***	0.474***	2.025***
	(0.061)	(0.045)	(0.062)	(0.185)
N	1717	1717	1717	1717
R^2	0.334	0.462	0.345	0.393

Note: The table displays the results from univariate regressions $(ITInfl.Swap1Y)_t = \alpha + \beta Infl.Exp_t + \varepsilon_t$. The dependent variable is the rate on the 1-year inflation swap contract linked to Italian inflation, while the independent variables are the Twitter-based inflation expectation indicators computed on the sub-samples with "econ" and "news" in the bio and the baseline dictionary of bi- and tri-grams. Daily data from June 1, 2013 through December 31, 2020. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Tweets with future meaning

We are interested in measuring inflation expectations using Twitter, and expectations have an intrinsic prospective nature. Hence, to further corroborate our results, we identify the tweets talking about future price developments and with a future perspective and employ three alternative strategies. First, using the same bi-grams and/or tri-grams selected for the main indexes and commented in the previous sections, we build a dictionary which only contains future tenses.[41] As an alternative strategy, we also select those tweets containing one or more bi/tri-grams and a word with a future meaning (e.g. *"in the long run"*, *"forecast"*, *"predict"*, etc.) in the main text of the tweet. Then, to deal with the low volume of messages that contain either a future tense or a future word, we also collect the tweets that contain both. To build the directional indexes based on these three rules, we use the same strategy used before, using only bi-grams, only tri-

[41] To identify future verbs we select all the words ending with *"rò"*, *"rai"*, *"rà"*, *"remo"*, *"rete"*, and *"ranno"* which indicate all possible conjugations of future verbs in the Italian language. However, given the low volume of tweets selected with this feature, we consider all those tweets that contain our labelled bi/tri-grams and a future tense either within the bi/tri-grams or in other parts of the main text of the tweet.

grams or both, adopting different thresholds and using either the full sample of tweets or the sub-sample of tweets written by those users which according to their self-reported biography are either interested in economics (Econ) or in the news business (News).[42]

Figure B.1 in the Appendix depicts the top 15 most frequent Up bi- and tri-grams with future tense (green) and the 15 most frequent Down bi- and tri-grams with future tense (red). Notice that the bi- and tri-grams with future verbs are much less in volume than all the other bi- and tri-grams. In fact, positive tri-grams such as *"pagherà il prezzo" [she will pay the price] or "pagherà caro" [she will pay a lot]* are contained in around 1,000 (or 10^3) tweets per year. On the contrary, a negative bi-gram such as *"prezzi scenderanno" [prices will drop]* is contained in slightly more than 100 tweets per year.

Exploiting our dictionary combined with a) future verbs, b) future words, or c) both in the main text of the tweets we compute the directional indexes (Index Up and Down) and then the Twitter-based inflation expectations indicators. Since this procedure greatly reduces the volume of the tweets which are used to compute the indexes, the signal conveyed by the new indicators is slightly less strong than our baseline but anyway coherent with the dynamics of inflation expectations. The Twitter-based indicators computed using this dictionary are significantly correlated in-sample with survey-based measures, with correlations that vary between 0.26 and 0.48, whereas the correlations with the market-based measure are even higher (i.e., between 0.44 and 0.74). Furthermore the power of the signal conveyed by these indicators is evident when they are used to predict the survey-based inflation expectations out-of-sample, in particular for longer horizons.

6 Informativeness exercise

The analysis so far shows evidence to the conclusion that Twitter-based indicators can be taken as meaningful signals of inflation expectations. Now we investigate an additional question: does observing the Twitter-based indicators give an informative advantage on consumers expectations? That is, given that survey-based expectations are not frequently sampled, can we try to "fill-in" the gaps using the computed indexes? The rationale for doing such an exercise is the assumption that people form inflation expectations by observing signals coming from several sources including Twitter.

We focus on inflation expectations collected monthly by ISTAT, which we use in section 4.1. The responses to the survey are collected in the first half of the month

[42]For further details see the Appendix.

t, without specifying a single day. Therefore we assume that the information set of the individuals consists of signals received up to, and including, the 15th day of the month, from the news, the swap market and Twitter. Since we cannot observe all signals individuals receive, we assume that individuals use the signals conveyed by market-based inflation expectations, consensus forecasts, the CPI estimates and Twitter are sufficient statistics for the information set observed by individuals. To ascertain whether Twitter indicators anticipate inflation expectation we estimate the following regression model:

$$E_t^{ISTAT}\pi_{t,t+12} = \alpha + \rho\, E_{t-1}^{ISTAT}\pi_{t-1,t+11} + \beta\, IS_t^{1y} + \delta\, CF_{t-1}^{y+1} + \gamma\, Infl.exp._t + \eta\, CPI_{t-1} + \varepsilon_t \tag{2}$$

All the regressors are in the information set available when expectations are formed. $E_t^{ISTAT}\pi_{t,t+12}$ is the month t survey-based inflation expectations, and $E_{t-1}^{ISTAT}\pi_{t-1,t+11}$ the previous month value, IS_t^{1y} is the 1 year inflation swap rate and $Infl.exp._t$ is one of our Twitter-based indicators. For both IS_t^{1y} and $Infl.exp._t$ we use the value of the measure on the 15th day of the reference month t.[43] CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead, which accounts for the inflation expectations of a survey of professional forecasters.[44] CPI_{t-1} is the lagged value of the realized inflation which is included to account for possible effects of news on inflation on Twitter-based inflation expectations. By conditioning on the realized inflation in the previous month $t-1$ we test if our indexes have additional explanatory power beyond that explained by past inflation data. In Table 8, we report the results when we consider the *Infl. Exp. 4 (ln) MA(30)* as our Twitter-based indicator. In the first column, only the lagged term of the survey-based inflation expectations is used as a regressor, showing that expectations are significantly autocorrelated. In columns (2) - (4), we add the inflation swap rate, the average Consensus Forecast on the Italian inflation for one year ahead and the latest CPI estimates separately. With respect to the first column, the fit of the regression improves in all cases, leading to a higher value for the R^2. The regression with the inflation swap rates records the highest increase in the R^2. In column (5), we regress on the inflation swap rate, the average Consensus and the CPI, noticing that there are no gains in the adjusted R^2 relative to column (2). In column (6), the Twitter-based indicator is added separately. Now the R^2 increases even more than in the previous cases. These results tell us that the Twitter-based indicator

[43] Note that the Twitter index is computed using a backward looking moving average, hence it includes information available at least in the 10 days before the 15th. Using averages of first 15 days of the month for inflation swap rates does not alter the results.

[44] We have also considered the same regression when the Bloomberg Survey of Professional Forecasters median CPI is included. The results are equivalent to those reported here using Consensus Forecasts and they are not reported for brevity.

and the other regressors are relevant factors for predicting the evolution of survey-based inflation expectations, corroborating our view of expectations based on extracting signals from the economy.

Given that the dependent variable is not a numerical expectation of inflation, but only a qualitative measure, coefficients' magnitudes do not have a straightforward economic interpretation, however, they all have the correct sign and an increase in the Twitter-based indicator is associated with higher expected inflation.

When we add all the regressors in column (7), the R^2 is the highest, the coefficients have the correct positive sign except for the average Consensus, and the CPI; besides only the coefficient on the lagged survey-based expectations and on the Twitter-based indicators are significant. Overall, the R^2 improves with respect to columns (2)-(6) and the adjusted R^2 slightly decrease relative to column (6), showing that the Twitter index provides additional relevant information for predicting the survey-based inflation expectations even after controlling for the market-based expectations, the expectations of professional forecasters and the past level of CPI inflation.

Results are qualitatively similar if we use the Inflation Expectation Indicators #4 with different windows length for the moving average computation. All other indicators are significant when used alone in the above regression model, but in some cases their significance drops once all regresses are included (see Tables D.5, D.6, and D.7 in the Appendix), pointing to the conclusion that, of all the proposed indicators, only the one which does not rely on winsorizing nor trimming always provides additional orthogonal information relative to the other signals. Further, the Inflation Expectation Indicator #4 is the one with the highest explained variance and the highest correlation with both survey-based and market-based inflation expectations. This result sheds light on how to meaningfully extract a signal from tweets and suggests that days in which many tweets are exchanged seem to be important for inflation expectations so that any procedure that trims outliers will also discard relevant information.

Table 8: Informativeness exercise

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

Note: The dependent variable $E_t^{ISTAT}\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS_t^{1y} is the inflation swap rate at one year and *Infl. Exp. 4 (ln) MA(30)* is the Twitter-based inflation expectation indicator #4 in logs computed using the baseline dictionary of manually labeled bi-grams and tri-grams. CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Montly data from June 2013 through December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

Overall the exercise highlights that relevant information, not included in market-based or consensus expectations, is provided by Twitter and captured by our indicators. This result can still be coherent with the (semi-strong form of the) efficient market hypothesis, that is that prices incorporate all public information as soon as it becomes available, if we consider that inflation swap rates include time-varying risk premia. Therefore swap rates could include “extraneous” changes, that is, changes not driven by variations in inflation expectations, which allow our Twitter-based indicators to improve the predictability on survey-based inflation expectations. Another reason for the difference between our indicators and the market swap rate is that the information set of the marginal traders and that implied by our Twitter indicators might not be the same. Hence, prices do reflect the available information, but not at all times that implied by our Twitter indicators.

7 Predictive power out-of-sample

Finally, we check the predictive power of our Twitter-based indicators of inflation expectations and run a simple out-of-sample forecasting exercise. As in the in-sample informativeness exercise, the target variable to forecast is the monthly survey-based inflation expectation index produced by ISTAT. We use a recursive scheme with a window of 36 months, starting our forecasting exercise on May 2016 and adding an additional month to our in-sample until the end of our sample (December 2019). Our first in-sample consists of 36 monthly observations from June 2013 through May 2016. We use as a benchmark model an autoregressive model $AR(p)$ for the target variable $E_t^{ISTAT}\pi_{t,t+12}$, where at each forecast origin we choose the lag p according to the BIC criterion, starting from a maximum of 4 lags given the shortness of our sample (79 monthly observations).

Each competing model uses one of the 36 Twitter-based inflation expectation indicators we have discussed so far for each group, for a total of 1,104 models. In fact, we use all our four indicators, with three different moving averages (lag of 10, 30 or 60 days), also including different choices for the dictionary to compute the directional indexes and the indicators based on the subsample of users who, according to their biography, are either interested in economics (Econ) or in news (News). We augment the benchmark $AR(p)$ model with each one of our Twitter-based indicators. To be conservative, differently than in the previous exercise, we use end-of-month data for the Twitter-based indexes, so that each index enters the forecasting model with at least one lag.[45]

For each group of Twitter-based indicators,[46] we compare the outcome of the competing models that use the Twitter-based indicators with the benchmark, and two additional models. The first one augments the benchmark autoregressive model with the market-based inflation expectation at the end of month t, given by the inflation swap rate with one year maturity ($IS1Y_t$). The second one augments the benchmark with an inflation expectation indicators computed using two directional indexes (up and down indexes) obtained from Google Trends ($GTRD_t$) exploiting in the initial dictionary used to select the tweets.[47]

[45] If anything, this should lower the predictive power of our Twitter-based indexes, because, for example, to forecast our target variable in June 2016, we use information up to the end of May 2016.

[46] Each group of indicators differs for the dictionary used to compute the directional indexes. For example, the group we show in the paper adopts the baseline dictionary built with both bi-grams and tri-grams with threshold C), i.e. there must be on average at least 100 tweets every year between 2013 and 2019 that contain each labeled bi- or tri-gram.

[47] In particular, the index Up from Google Trends is computed using the monthly combined search volume index (SVI) for the keywords *"inflazione" [inflation], "benzina alle stelle" [skyrocketing gasoline prices], "caro carburante" [expensive gasoline prices], "caro benzina" [expensive gasoline], "caro prezzi" [high prices], and "caroprezzi' [high-prices].* The index Down from Google Trends is computed com-

Table 9 shows the forecasting results over the 36 Twitter-based indicators with the baseline dictionary of bi-grams and tri-grams. We forecast from 1 up to 6 months ahead. For the benchmark model $AR(p)$ the Root Mean Squared Error (RMSE) is reported. For all the other competing models that adopt one of the leading indicators in the first column, we report the ratio of the RMSE of that model with respect to the benchmark. A number above one means that the benchmark outperforms, while a number below one implies that the competing model in that row is better that the benchmark. We also run a Diebold-Mariano (1995) test of equal forecast accuracy, which shows that many Twitter-based indexes significantly outperform the benchmark across all the forecast horizons. Interestingly the market-based measure of inflation expectation hardly out-performs the benchmark and never significantly (RMSE ratio are very close to one). Also the Google-Trends-based inflation expectation index hardly outperforms the benchmark except for the longest horizons. Twitter-based indicators, instead, significantly out-perform the benchmark in many instances. For example, across all forecast horizons except for the fourth one, the indexes computed using the Econ or News sub-sets of tweets tend to be the best (RMSE ratios in boldface). Notwithstanding the small sample, we obtain very good results which show that our Twitter-based indicators have predictive power also out of sample.

To gauge the performance of competing models we can use the Cumulative Sum of Squared forecasting Errors Differences (CSSED) which is defined as

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

where $\hat{e}^2_{bm,\tau}$ are the squared forecast errors from the benchmark model in the out-of-sample, and $\hat{e}^2_{m,\tau}$ are the squared forecast errors from the competing model. A value of the CSSED below one at a certain point of the out-of-sample means that if we run the forecasting exercise by splitting the in-sample and the evaluation sample at that point, the benchmark model outperforms showing a lower RMSE than the competing model. On the contrary if the CSSED is above one, then the competing model outperforms the benchmark.

Figure 8 shows the CSSED for the forecast horizons from one-month ahead (top left) to six-months ahead (bottom right) when a 30-day backward-looking MA is used to

bining the following keywords: *"deflazione" [deflation], "disinflazione" [disinflation], " ribassi" [sales], "ribasso" [ribasso], "meno caro" [less expensive], "bollette più leggere" [less expensive bills].* The Google Trends index varies from 0 to 100, where 100 is maximum SVI in sample, computed using the number of Google searches that contain the chosen keywords with respect to all the searches.

Table 9: Out-of-sample exercise: forecasting the monthly survey-based inflation expectations by ISTAT using Twitter-based Inflation Expectations indicators with the baseline dictionary of bi- and tri-grams

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
$AR(p)-SS$ $(RMSE)$	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

Notes: The table present the RMSE for the benchmark $AR(p)$ model and the ratio of the RMSE of each model in the row with respect to the benchmark. A number below 1 means that the competing model outperforms the benchmark. Numbers in boldface represent the models with the lowest RMSE for each forecast horizon h (from 1 to 6 months ahead). Recursive scheme with first in-sample of 36 observations. ***, **, and * indicate significance at 1, 5, and 10% respectively of the Diebold-Mariano test of equal forecast accuracy.

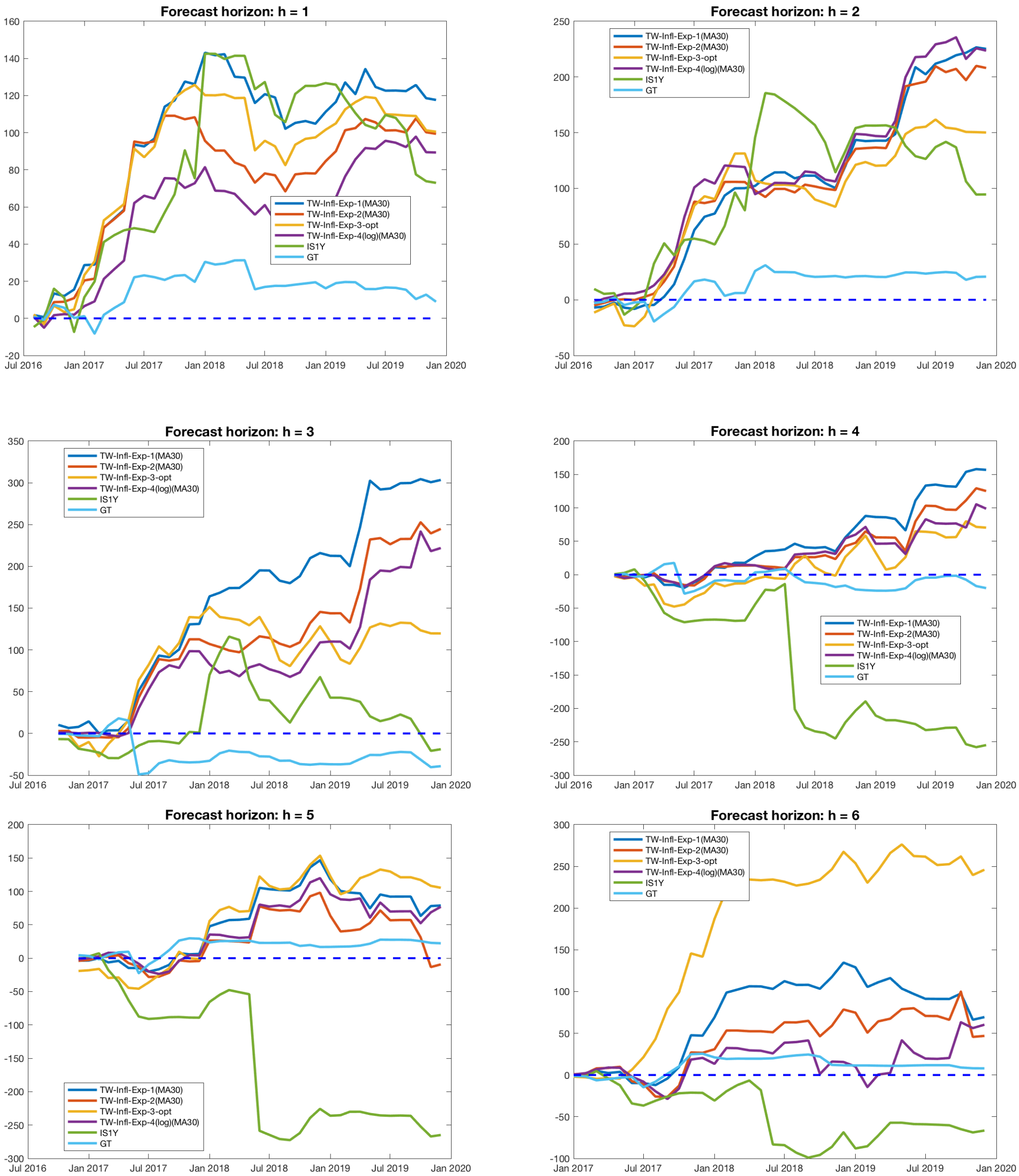
smooth the Twitter-based indicators.[48] The market-based index rarely helps in predicting the survey-based index out-of-sample; in fact the corresponding green line lies almost always below the others for the whole out-of-sample across all forecast horizons, except for a very short interval at two- and three-months horizons. The Google-Trends-based index is almost always the worst performing index except at 5-months ahead where it only beats $IS1Y_t$. All our Twitter-based indicators are outperforming the benchmark, especially at 1-month ahead which is the nowcasting exercise. At longer horizons, Twitter-based indicators tend to outperform with great gains at the end of the out-of-sample. The best indicator is the index #3 with exponential smoothing (the orange line).Furthermore, we obtain similar results both i) using different dictionaries to build the directional indexes, i.e. bi-grams and/or tri-grams with different thresholds for the yearly average volume of tweets; ii) using future verbs and future words combined with dictionaries of bi-grams and/or tri-grams; iii) using an AR(p) model augmented with the inflation swap index as benchmark.[49]

All these results corroborate our view that Twitter-based indicators of inflation expectations do convey meaningful information that can be used to more accurately forecast, or even fill-in, survey based inflation expectations.

[48] Figure I.4 and I.5 in the Appendix show the equivalent plot for the indicators based on the News and Econ sub-samples. Using these indicators, the predictive ability of our Twitter-based measures out-of-sample is even more evident.

[49] In case iii) the Google-Trends-based index is never significantly better than the benchmark and the Twitter-based indicators significantly outperform this more powerful benchmark, especially at longer horizons. These results are not reported here for the sake of brevity, but they are available from the authors upon request.

Figure 8: Out-of-sample comparison: Cumulative Sum of Squared Error Differences - Baseline case, with new baseline dictionary of Bi- and Tri-grams, MA(30) smoothing, recursive scheme with $R = 36$



Notes: $CSSED_{m,\tau} = \sum_{\tau=R}^{T}(\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau})$. CSSED is below one if the $AR(P)$ benchmark outperforms the competing model and above one if the competing model fairs better. Here we compare the four Twitter-based indexes with a backward-looking MA of 30 days with the market-based index $IS1Y$ and the Google-Trends-based inflation expectation index GT.

8 Concluding remarks

In this paper, we suggest a new way to measure consumers' inflation expectations using Big data techniques and Twitter feeds. As any Big data applications, the new measures are characterized by the fact that they are timely and they are not subject to a publication lag. We suggest different Twitter-based inflation expectations indicators built using a dictionary-based approach and Machine learning techniques. First, we select a set of keywords in Italian that are related to inflation and price dynamics. Next, we adopt a three-step procedure: (i) we filter out the noisy content by implementing a topic analysis using the Latent Dirichlet Allocation (LDA); (ii) we apply a dictionary-based approach to categorize signals of increasing (decreasing) inflation expectations, and (iii) we build directional Twitter-based inflation expectations indicators. Then to validate the signal extracted from tweets, we investigate the extent to which our proposed indicators correlate with available sources of inflation expectations (survey and market based). Comparing our Twitter-based measures with lower frequency survey-based measures of consumers' inflation expectations by ISTAT, we find that our new indicators are strongly correlated with them, but they have the advantage of being computed in almost real time. When comparing our Twitter-based measures of inflation expectations with the market-based ones available at the daily frequency, we find that our measures are also highly correlated with the Italian inflation swap rates. Overall, the analysis suggests that the Twitter-based indicators capture well the dynamics of consumers' inflation expectations and convey additional informative content in-sample with respect to existing sources such as lagged survey- and market-based measures, professional forecasts and realized inflation. Furthermore, out of sample our Twitter-based indicators significantly outperform models using market-based measures or those adopting Google-Trends-based measures. Finally, using a much smaller subsample of users interested in economics or in news we build Twitter-based indicators with similar good performances both in-sample and out-of-sample. When we build our indicators focusing on tweets relating to the future we find however a weaker signal due to lower volumes of messages but the out-of-sample results at longer horizons are still promising.

The analysis underscores the relevance and importance of information transmitted over social networks, also for policy purposes. This literature is quite new, and still plagued by some uncertainty, especially with respect to the extent to which information on social networks can be transformed into an efficient and understandable signal. More research on this topic, which needs cross-feed from computer scientists, statisticians and economists, is warranted.

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Appendices

Online Supplemental Material for

Can We Measure Inflation Expectations Using Twitter?

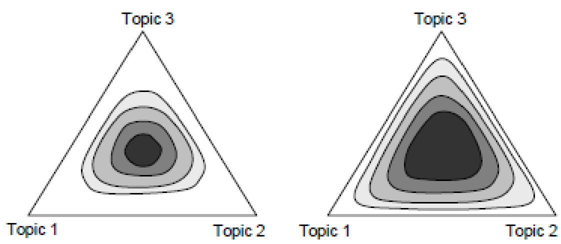
Cristina Angelico, Juri Marcucci, Marcello Miccoli, and Filippo Quarta

Appendix A A Note on Latent Dirichlet Allocation for topic analysis

In what follows we borrow from Steyvers and Griffiths (2007) to present more in detail how the LDA works. Probabilistic topic models, which counts the LDA among them, start from the same idea that a document is formed by a mixture of topics. Let $P(z|d)$ be the distribution over topic z in a given document d, and $P(w|z)$ be the probability distribution over words w given topic z. Probabilistic topic models assume that each word w_v in a document is generated first by extracting a topic from the topic distribution $P(z|d)$, and then by extracting a word from the topic-word distribution $P(w|z)$. Hence the distribution over words v that appear in a document d is given by $P(w_v|d) = \sum_{k=1}^{K} P(w_v|z = k)P(z = k|d)$, where $k = 1, \ldots, K$ are the topics, $v = 1, \ldots, V$ are the unique words in the documents, $d = 1, \ldots, D$ are the documents. The overall likelihood can thus be easily defined in term of the $P(w_v|d)$.

To simplify notation one can let $\phi^{(k)} \equiv P(w|z = k)$ to be the multinomial distribution over words for topic k, and $\theta^{(d)} \equiv P(z|d)$ to be the multinomial distribution over topics for document d. The objective is to estimate the objects ϕ and θ from the observed words in the documents. The LDA, with respect to other probabilistic topic models, assumes that the prior distributions for θ and ϕ are two symmetric Dirichlet distributions, with hyperparameters α and β respectively. The assumption of the Dirichlet distribution allows for smooth estimation procedures, given that estimates of the posterior in topic modelling are never exact, and so they need to be numerically approximated. The hyperparameters regulate how concentrated are observations in the K-1 dimensional simplex for topics (V-1 for words). For instance, consider Figure A.1 taken from Steyvers and Griffiths (2007). For higher values of the hyperparameter α the distribution over topics in a documents is assumed to be more concentrated, that is topics are more likely to be equally represented in a document. The opposite for lower values of α.

Figure A.1: Symmetric Dirichlet distribution



Symmetric Dirichlet distribution for three topics over a two dimensional simplex. Darker colors indicate higher probability. Left: $\alpha = 4$. Right: $\alpha = 2$. (taken from Steyvers and Griffiths (2007))

The inference problem in the LDA is thus how to estimate the distribution $\phi^{(k)}$ for every k and $\theta^{(d)}$ for every d, given the number of topics K and hyperparameters α, β.

In our analysis we use the LDA implementation available in the Apache Spark MLlib (vers. 2.1).[50] The posterior estimates are obtained through the online variational Bayes algorithm, which has been shown to be efficient with respect to large amounts of text data and as accurate as Markov Chain Monte Carlo sampling methods (Hoffman, Bach and Blei (2010)). The mixture model parameters learned from the set of documents are subsequently used for assigning a topic to each tweet. As for the value of hyperparameters, we used $\alpha = 1/K$, where $K = 50$ is the number of topics, and $\beta = 1/V$ where V is the number of unique words. These parameter values were the default value in the Apache Spark MLlib and represent diffuse priors. The low value of β generates very sparse distribution over words, so that topics have are characterized by limited relevant words.

To evaluate LDA models we use a metric called perplexity that indicates the highest likelihood in a held-out test set. Perplexity is monotonically decreasing in the likelihood of the test data. In particular we use the log-perplexity ($\log(PP)$) which is equivalent to the inverse of the geometric mean per-word likelihood, i.e.:

$$\log(PP(D_{test})) = -\frac{\sum_{d=1}^{M} \log(p(w_d))}{\sum_{d=1}^{M} N_d}, \tag{4}$$

where M is the number of documents in the test corpus D_{test}, w_d are the words in document d, and N_d is the number of words in document d. Thus minimizing $\log(PP)$ is equivalent to maximize the test set probability of the language model and a lower perplexity is a sign of a better generalization performance (see Blei et al. (2003)).

Figure A.2 depicts the log perplexity for the 3 runs of the LDA with a number of topics between 20 and 75. The minimum value for the log perplexity is around 50 and therefore we decided to use this value for the 3 runs of LDA.

Figures A.3 to A.5 depict the wordclouds for the 50 topics discovered by the three runs of the LDA. For each run and each topic the wordcloud shows the top 20 words that best characterize the topic, where the importance of each words is given by the probability of that word in the topic. The topics are numbered from 0 to 49. It is clear that except for topics 19 and 36 which contain the words "*inflation*" and "*deflation*", all topics are related to a particular sector or region. For example, commenting the topics of the first run of the LDA in Figure A.3, we can say the following:

1. The first topic (topic # 0) is a topic related to a particular set of promotions in the region Emilia Romagna.
2. The second topic is about Apple products (IPhone, IPad and MacBook) and the Amazon

[50] Apache Spark has been documented as successful for topic modeling of Big Data corpus (see "Topic Modeling and Visualization for Big Data in Social Sciences" - Sukhija et All - 2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress).

Kindle. The additional words *"limitato" [limited]* and *"prenotare" [reserve]* show that this topic contains also the tweets by the users who want to have the first Apple product once it is released.

3. The third topic is about fuel price(s) as indicated by the words *"diesel", "gasolio" [diesel fuel], "verde" [unleaded petrol], and "self" [self for self service].*

4. The fourth topic is about grocery product prices as indicated by the words "cibo" [food], "latte" [milk], "olio" [olive oil], etc.

5. The fifth topic is about salaries and wages ("salario", and "stipendio") with some political issues "sinistra" [left party].

6. The sixth topic is about e-commerce as indicated by "spedizione/spedizioni" [shipment(s)] and "consegna" [delivery].

7. The seventh topic talks about particular offers through company Groupalia, with "sconti" [sales], "ristoranti" [restaurants], "viaggi" [travels] usually offered through coupons.

8. The eighth topic is about social issues as indicated by the words "ricchi" [riches], "poveri" [poors], "futuro" [future], "lire" [lire, the Italian currency before the euro], "pubblicità" [advertising].

9. The ninth topic is difficult to characterize given that the main word is "prezzo" [price] with general words such as "amore" [love], "casa" [home], etc.

10. The tenth topic is about prices and cost of living in general as indicated by "stipendio" [salary], "biglietti" [tickets], "soldi" [money].

11. The eleventh topic is about "cinema" [cinema], reduced ("ridotto") prices on certain days of the week ("venerdí" [Friday], "sabato" [Saturday]).

12. The twelfth topic talks about prices with "video" [video], "autore" [author] and "pubblicato" [published].

13. The thirteenth topic deals with lodging prices with words such as "hotel", "stelle" [stars], "Venezia" [Venice], "notte" [night] or "ratechecker" which is an App to check the rates of hotels, and B&B's in the same neighborhood and to manage rooms in the online travel agencies.

14. The fourteenth topic is clearly dedicated to smartphones with words such as "smartphone", "galaxy", "huawei", "Samsung", "Xiaomi", "apple", "IPhone", "android", "caratteristiche" [features].

15. The fifteenth topic is about fashion with words such as "moda" [fashion], "listino" [price list], "scarpe" [shoes], "borse" [purses], "collezione" [collection], "cataloge" [catalogue], etc.

16. The sixteenth topic is clearly about prices of soccer players as the words “calcio” [soccer], “stipendi” [wages], in addition to the names of some major league soccer teams (‘Inter’, ‘Milan’, ‘Fiorentina’, ‘Juventus’, ‘Lazio’ or ‘Napoli’).

17. The seventeenth topic talks about wages in politics as the word “stipendio” [wage] shows, in addition to “parlamentari” [members of parliament] or “senatore“ [senator].

18. The eighteenth topic is similar to the sixteenth one where we talk about wages for soccer players. In fact, the words “giocatore” [player], “squadra” [team], “stipendio” [wage], “mln”, in addition to some names of major league teams such as “Inter”, “Juventus” or “Milan”.

19. The nineteenth topic is about “shopping”, “caro” [expensive], “compra” [she buys], and other words such are “rottamalatutela” which is a blog of notaries.

20. The twentieth topic deals with inflation, deflation, salaries, unemployment, ECB and it is one of the two topics we use to filter out the noise in the tweets.

21. The twenty-first topic is about e-commerce, with words such as Amazon, “offerte” [sales], “elettronica” [electronics], “kellieshop” an online fashion store.

22. The twenty-second topic talks about travelling with words such as “treni” [trains], “viaggio” [travel], “trenitalia” [the main Italian train operator], etc.

23. The twenty-third topic is about about “salario” [wage], “base” [base], “iva”, and some words in Spanish such as “holanda”, “espana” or “como”.[51]

24. The twenty-fourth topic is again about “stipendi” [salaries] of “politici” [politicians] and “parlamentari” [members of parliament].

25. The twenty-fifth topic is about “offerte” [sales] of “moto” [motorbikes].

26. The twenty-sixth topic is about “giardinaggio” [gardening], “guanti” [gloves]. It seems a topic related to sales of used cars or used tools for gardening.

27. The twenty-seventh topic is related to prices of “biglietti” [tickets] and “abbonamenti” [subscriptions] for soccer games.

28. The twenty-eighth topic is related to prices of women fashion with words such as “taglia” [size], “donna” [woman], “borsa” [purse], “pelle” [leather], etc.

29. The twenty-ninth topic is about low prices in electronics and web apps.

30. The thirtieth topic is about the labor market with words such as “sciopero” [strike], “salario” [salary], “scuola” [school], “diritti” [rights], “lavoro” [job], “contratto” [contract], and “sindacati” [unions].

[51] Probably the language filter did not manage to select the tweets in Italian and some of the tweets in our sample are in the Spanish language.

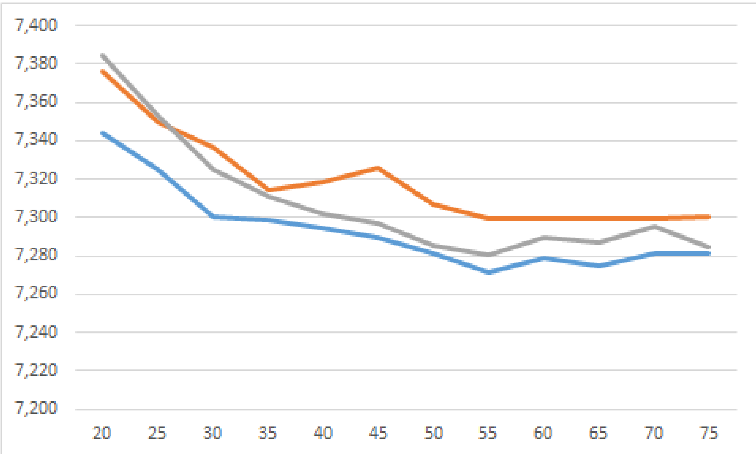
31. The thirty-first topic is related to Christmas-related sales, with words such as “offerta” [sale], “saldi” [sales], and “Natale” [Christmas].
32. The thirty-second topic is about the city of Rome (“roma”) with words like “tasse” [taxes], price, “confronta” [compare], “bar”, “falegnameria” [carpentry].
33. The thirty-third topic is more related to gasoline prices “benzina” [gasoline] and “tariffe” [tariffs].
34. The thirty-fourth topic is about a minimum (“minimo”) salary (“salario”) which is also guaranteed (“garantito”).
35. The thirty-fifth topic is again related to e-commerce with words such as “amazon”, “scarpe” [shoes], “ubs”, “edizione” [edition].
36. The thirty-sixth topic is again about e-commerce with “amazon”, “vino” [wine], “farmacia” [pharmacy].
37. The thirty-seventh topic is the second one that we have selected because it contains inflation or deflation, in addition to “petrolio” [oil], “istat”, “bce” [ECB], “economia” [economy].
38. The thirty-eighth topic is about special offers for the New Year’s Eve (“capodanno”) and July and August (respectively “luglio” and “agosto”), with words such as “hotel”, “volo” [flight], and “notti” [nights].
39. The thirty-ninth topic is related to special discounts for home (“casa”), books (“libri”) and shows (“spettacoli”).
40. The fortieth topic is about “itunes”, with special prices.
41. The forty-first topic is about “biglietti” (i.e. tickets) for “concerto” [concert] in famous cities of the Northern part of Italy (Milan, Prato, Bologna).
42. The forty-second topic is about “stipendio” [salary], “famiglia” (family) and similar arguments.
43. The forty-third topic talks about “stipendi” [salaries] for “dirigenti” [managers] or “dipendenti” [employees] in time of crisis (“crisi”).
44. The forty-fourth topic is again about “stipendio” (i.e. salary).
45. The forty-fifth topic deals with “parlamentari” [members of Parliament] and their ‘stipendi’ [salaries].
46. The forty-sixth topic is about sales of new cars (“auto”) with some brands such as Fiat, BMW, Honda, Volkswagen or Mercedes.
47. The forty-seventh topic is more about the real estate market with words such as “immobiliare’ [real estate], “vendita” [sale], “appartamento” [apartment] or “trilocale” [i.e. a three-room apartment].

48. The forty-eighth topic is about the cost of living, taxes ("tasse"), and wages and salaries ("stipendi" and "salari").

49. The forty-ninth topic is related to "informazioni" [information] on certain products.

50. The fiftieth topic is more about the populist parties and the salaries of members of parliament.

Figure A.2: Log perplexity for LDA by number of topics



Notes: The figure depicts the log perplexity for the three different LDA runs using a number of topics ranging from 20 to 75. The log perplexity is calculated on a hold-out sample of documents and it decreases up to around 50 topics.

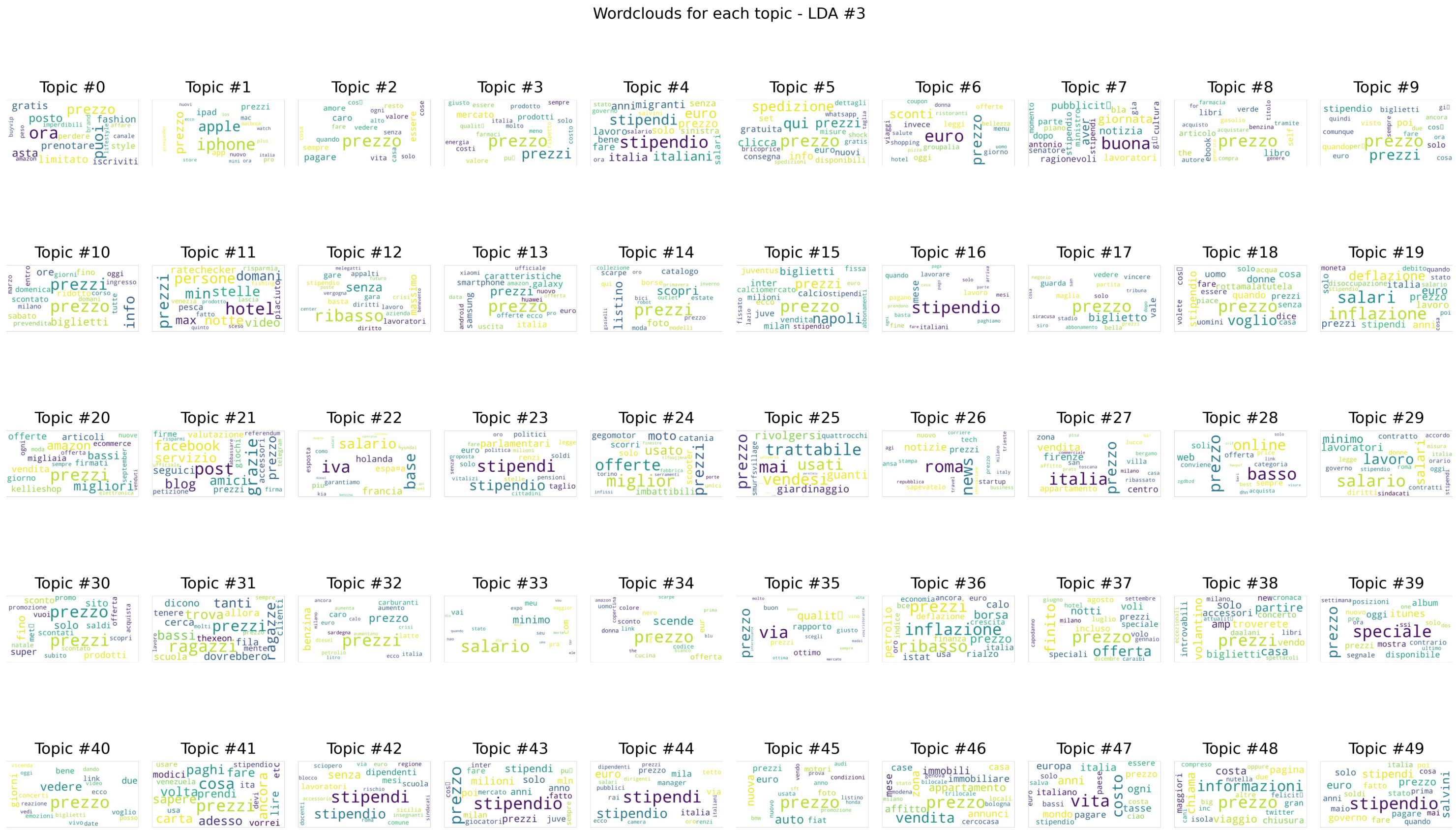
Figure A.3: Wordclouds of the top 20 words in the 50 topics of the first run

Notes: The figure depicts the wordcloud for each one of the 50 topics in the first LDA run. Only the top 20 words are represented and the word size depends on the probability of each word in the topic.

Figure A.4: Wordclouds of the top 20 words in the 50 topics of the second run

Notes: The figure depicts the wordcloud for each one of the 50 topics in the second LDA run. Only the top 20 words are represented and the word size depends on the probability of each word in the topic.

Figure A.5: Wordclouds of the top 20 words in the 50 topics of the third run



Notes: The figure depicts the wordcloud for each one of the 50 topics in the third LDA run. Only the top 20 words are represented and the word size depends on the probability of each word in the topic.

Appendix B A new dictionary of bi-grams and/or tri-grams for directional indexes

B.1 Steps to build the dictionary of bi-grams and tri-grams

In what follows we describe how we build a new dictionary of n-grams, and in particular of bi-grams and tri-grams, to compute our directional indexes in the second step described in Section 3. First we select all the bi-grams and tri-grams related to the tokens "*prezzo [price]*", "*prezzi [prices]*", "*caro/a/e/i [expensive]*", "*inflazione [inflation]*", and "*deflazione [deflation]*". Then we manually label them as indicating expectations of increasing, decreasing or stable prices (for example "*prices are rising*" or "*inflation is falling*").[52] To explore the robustness of this approach we have computed the directional indexes using different numbers of labelled n-grams.

We proceed as follows:

1. First we select all the 96,150 bi-grams and 48,734 tri-grams containing the words "*prezzo [price]*", "*prezzi [prices]*", "*caro/a/e/i [expensive]*", "*inflazione [inflation]*", and "*deflazione [deflation]*".
2. Then we manually label each bi-gram and tri-gram as indicating expectations of rising prices or inflation (Up), falling prices or inflation (Down) or stable prices (Neutral).
3. We therefore use this new dictionary to build our directional indexes (Index Up and Down), counting the volume of tweets that contained at least one of those bi-grams and/or tri-grams.
4. We build directional indexes using:
   a) only bi-grams;
   b) only the tri-grams;
   c) both the bi-grams and the tri-grams.
5. We also use a different number of bi-grams and tri-grams, depending on the average yearly volume of tweets containing them in the period 2013-2019. We consider the following four cases:

   In particular, first we sort all bi-grams and tri-grams according to the total number of tweets in which they are contained in the sample between June 1, 2013 and December 31, 2019. Then we select four thresholds to compute the directional indexes.

   A) The first threshold is given by the first 5% of the bi-grams (i.e. the first 4808 bi-grams sorted in descending order by total volume of tweets containing them between 2013 and 2019) and the tri-grams (i.e. the first 2,347), as shown in Case A of Table B.1.

[52] In the previous version of the paper we used a rough dictionary of terms that was the same as the one used to initially select the tweets. We would like to thank an anonymous referee for suggesting this improvement.

In this first case, to compute the directional indexes we use 67 bi-grams labelled as Up and 82 labelled as Down. When using tri-grams we use 102 labelled as Up and 114 labelled as Down.

B) In the second threshold we use only the labelled bi-grams and/or tri-grams for the first 10% of the bi-grams and tri-grams (i.e. the first 9,615 bi-grams and the first 4,874 tri-grams). To compute the directional indexes in this case we use 113 Up bi-grams and 106 Down bi-grams. We also use 167 Up tri-grams and 205 Down tri-grams.

C) We set the third threshold as the number of bi-grams and tri-grams such that the logarithm with base 10 of the yearly average volume of tweets between 2013 and 2019 was greater or equal to 2. We choose this value to have at least an average of 100 tweets each year containing the relevant n-grams. This leads us to label 10,691 bi-grams and 2,853 tri-grams. To compute the directional indexes we adopt 121 Up bi-grams and 111 Down ones, while the Up tri-grams were 112 and the Down ones 126.

D) In the fourth case, we use all the labelled bi-grams over the whole set of 96,150 bi-grams and 48,734 tri-grams. Thus to compute the directional indexes we use 515 Up bi-grams and 392 Down ones, while we adopt 495 Up tri-grams and 543 Down ones.

Figure 2 depicts the first 15 most frequent bi-grams and tri-grams both Up (green horizontal bars) and Down (red horizontal bars). On the horizontal axis the log base 10 of the yearly average tweet volume between 2013 and 2019 is depicted. As we can see the most common Up bi- and tri-grams are *"più caro'[more expensive], "caro prezzo'[expensive price], or "un prezzo altissimo'[a very high price]* with an average yearly volume of tweets between 2013 and 2019 around 10,000. The most common Down bi/tri-grams are *"prezzo speciale' [special price], "prezzi bassi' [low prices], "metà prezzo' [half price], or "prezzi più bassi' [lower prices]* with an average yearly volume of tweets between 2013 and 2019 above 10,000.

Tables B.2 and B.3 depict the first 200 Up tri-grams and Down tri-grams, respectively. Every tri-grams has in square brackets the translation in English and the count represents the total volume of tweets that contain that tri-gram between June 2013 and December 2019. Tables B.4 and B.5 show the first 200 Up bi-grams and Down bi-grams, respectively. We can see that bi-grams tend to be more frequent than tri-grams in tweets written in Italian.

Table 10 displays the number of bi- and tri-grams used to compute directional indexes with the different thresholds. Figure B.2 show the first 60 most frequent bi-grams both Up (green) and Down (red) with the corresponding average yearly volume. Figure B.3 depicts the first 60 most frequent tri-grams both Up (green) and Down (red) with the average yearly volume of tweets containing them.

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

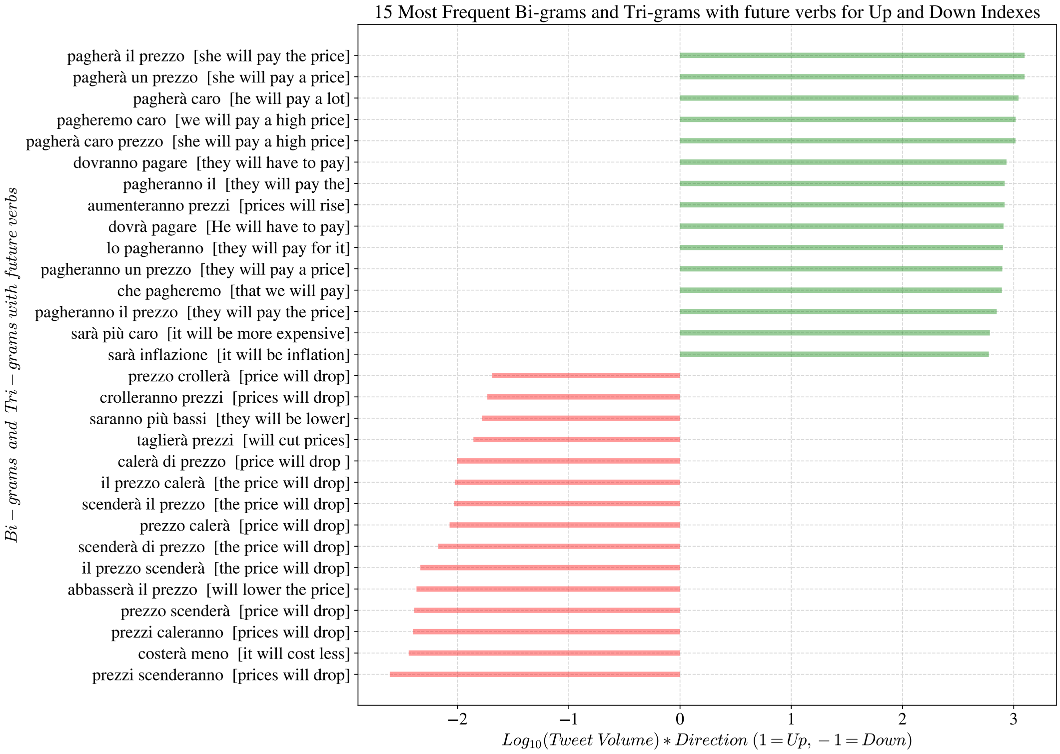
B.2 The dictionary with only future verbs

Since our aim is to measure inflation expectation, we also try to capture in our dictionaries those words expressing a future meaning as well as future tenses.

Therefore, we build a dictionary of bi/tri-grams only with future tenses. To identify future verbs we selected all the words ending with "*rò*", "*rai*", "*rà*", "*remo*", "*rete*", and "*ranno*" which indicate all possible conjugations of future verbs in the Italian language. We first build a dictionary from the labelled bi/tri-grams which contains future tenses, but given the low volume of tweets we enlarge our set to all those tweets that contain our labelled bi/tri-grams and a future tense within the bi/tri-grams and in other parts of the main text of the tweet. To build these dictionaries, we use exactly the same strategy used for all the bi/tri-grams, using only bi-grams, only tri-grams or both, adopting different thresholds and using the full sample of tweets or the sub-samples of tweets written by those users which according to their self-reported biography are either interested in economics (Econ) or in news (News).

Figure B.1 depicts the top 15 most frequent Up bi/tri-grams with future tense (green) and the 15 most frequent Down bi/tri-grams with future tense (red). It is clear that the bi/tri-grams with future tenses or contained in tweets where the author used a future tense are much less in volume than all the other bi/tri-grams. In fact, positive tri-grams such as *"pagherà il " [she will pay the price] or "pagherà caro" [he will pay a lot]* are contained in around 1,000 (or 10^3) tweets per year. On the contrary, a negative bi-gram such as *"prezzi scenderanno" [prices will drop]* is contained in slightly more than 100 tweets per year.

Figure B.1: First 15 most frequent bi- and tri-grams for Index Down and Up with future verbs



Notes: The figure shows the 15 most frequent bi- and tri-grams for Index Down (red) and Up (green) over the sample 2013-19.

B.3 The dictionary with only future words

To further capture future meaning in tweets' content, we build a dictionary of labelled bi/tri-grams contained in tweets where there were also other words with a future meaning, such as for example "*futuro [future]*", "*prospettiv* [perspective*]*", "*medio periodo [medium run]*", "*lungo periodo [long run]*", "*attend* [expect]*", "*preved* [forecast/predict]*", "*previs* [forecast/prediction]*", "*attes* [expectation*]*", and "*aspett* [expectation*/expect]*".

Even to build these dictionaries, we use the same strategy used for all the bi/tri-grams. We build Twitter-based inflation indexes using only bi-grams, only tri-grams or both, as well as adopting different thresholds or using either the full sample of tweets or the sub-sample of tweets written by those users which according to their self-reported biography are either interested in economics (Econ) or in the news business (News).

B.4 The dictionary with future words and future verbs combined

Given the low volume of tweets with labelled bi/tri-grams containing either a future word or a future tense, we also consider all those tweets containing either a future word or a future verb. Even in this case, we use the same strategy used for all the bi/tri-grams (i.e. we build indexes using only bi-grams, only tri-grams or both; we adopt different thresholds and we use the full sample of tweets or the sub-sample of tweets written by users interested in economics or in news.

B.5 The rough initial dictionary

Finally, assuming that the keywords' connotation reflects a message on the direction of the observed or expected price change, we considered also a coarse dictionary based on the keywords used to collect the and classified them as follows:

- Neutral: *("price","prices","cost of living")*
- Up: *("expensive bills", "inflation", "expensive", "high prices", "high-prices", "high gas prices", "high bill", "high rents", "high petrol", "gasoline prices", "high gas bills")*
- Down: *("deflation", "disinflation", "sales", "sale", "less expensive", "less expensive bills")*

The first set (Neutral) captures tweets about prices in general and it mainly identifies messages not related to the price dynamics. The second and the third one (Up and Down) intend to reflect expectations of increasing and decreasing inflation, respectively.

Table B.2: First 200 tri-grams for Index Up

N	tri-grams in Italian [in English]	count	N	tri-grams in Italian [in English]	count	N	tri-grams in Italian [in English]	count	N	tri-grams in Italian [in English]	count
1	un prezzo altissimo [a very high price]	16809	51	aspettative di inflazione [inflation expectations]	1333	101	molto pi caro [much more expensive]	672	151	pagherete caro prezzo [you will pay a high price]	436
2	prezzo pi alto [higher price]	16264	52	rialzo dei prezzi [price hike]	1287	102	prezzo cos elevato [so high price]	658	152	sono aumentati del [have increased by]	432
3	aumento dei prezzi [price increase]	10797	53	triplo del prezzo [triple the price]	1279	103	prezzo altissimo ma [very high price but]	643	153	aumentato prezzi di [increased prices of]	431
4	aumento del prezzo [price increase]	6425	54	raddoppio dei prezzi [doubling of prices]	1271	104	in aumento prezzi [rising prices]	643	154	prezzi sono saliti [prices have gone up]	430
5	alzare il prezzo [raise the price]	6385	55	il caro carburante [the expensive fuel]	1259	105	prezzo pi caro [more expensive price]	621	155	sempre pi alti [higher and higher]	429
6	di pi caro [of more expensive]	6336	56	prezzi sono alti [prices are high]	1259	106	sar pi caro [it will be more expensive]	611	156	si crea inflazione [inflation is created]	427
7	prezzo troppo alto [price too high]	6279	57	pagher il prezzo [she will pay the price]	1254	107	prezzi alti per [high prices for]	610	157	citt pi care [more expensive cities]	426
8	aumenta il prezzo [the price increases]	6248	58	pagher un prezzo [she will pay a price]	1253	108	hanno alzato prezzi [they raised prices]	610	158	aumenta di prezzo [it increases in price]	425
9	alza il prezzo [raise the price]	5597	59	aumenti dei prezzi [price increases]	1253	109	caro prezzo da [expensive price from]	610	159	inflazione in crescita [growing inflation]	419
10	prezzi pi alti [higher prices]	5498	60	alzano il prezzo [they raise the price]	1247	110	costano di pi [they cost more]	608	160	pagheremo il prezzo [we will pay the price]	418
11	prezzi alle stelle [skyrocketing prices]	5237	61	il prezzo aumenta [the price increases]	1173	111	aumento di prezzi [price increase]	606	161	alzer il prezzo [she will raise the price]	415
12	aumentare il prezzo [raise the price]	4747	62	inflazione alle stelle [skyrocketing inflation]	1126	112	aumentare prezzi di [raise prices of]	603	162	prezzo massimo di [maximum price of]	414
13	il pi caro [the most expensive]	4747	63	costa di pi [it costs more]	1113	113	per alzare prezzi [to raise prices]	595	163	un rialzo dei [a rise in the]	413
14	pi caro di [more expensive than]	4011	64	hanno aumentato prezzi [they raised prices]	1085	114	caro prezzo non [expensive price not]	585	164	ripresa dei prezzi [recovery in prices]	412
15	pagato caro prezzo [paid a high price]	3886	65	inflazione doppia cifra [double digit inflation]	1076	115	pagare di pi [pay more]	579	165	pagheremo un prezzo [we will pay a price]	408
16	un prezzo alto [a high price]	3828	66	pi caro in [more expensive in]	1070	116	aumenter il prezzo [the price will increase]	562	166	rialzo il prezzo [I raise the price]	405
17	inflazione due cifre [double digit inflation]	3804	67	aumentano prezzi del [prices rise by]	1046	117	un prezzo salato [a very expensive price]	560	167	un prezzo carissimo [a very expensive price]	405
18	pi caro del [more expensive than]	3667	68	lievitare il prezzo [rise the price]	1045	118	ad aumentare prezzi [to raise prices]	553	168	aumenta prezzi di [she increases prices by]	403
19	paga caro prezzo [she pays a high price]	3638	69	pagher caro prezzo [she will pay a high price]	1039	119	il caro bollette [expensive bills]	551	169	prezzo molto caro [very expensive price]	397
20	il prezzo alto [the high price]	3592	70	aumento dell inflazione [rising inflation]	1038	120	abbiamo pagato caro [we paid a very high price]	543	170	prezzi molto alti [very high prices]	392
21	raddoppia il prezzo [double the price]	3463	71	il prezzo aumentato [the price increased]	1031	121	paura dell inflazione [fear of inflation]	543	171	prezzo alto da [high price from/to]	392
22	pi caro della [more expensive than]	3443	72	prezzi in crescita [rising prices]	1003	122	aumentano prezzi dei [prices of rise]	530	172	prezzo in rialzo [rising price]	388
23	prezzi troppo alti [prices too high]	3389	73	un prezzo enorme [a huge price]	1000	123	pi costoso al [more expensive at]	526	173	prezzi piu alti [higher prices]	386
24	il caro benzina [the expensive petrol]	3345	74	po di inflazione [bit of inflation]	993	124	un alto prezzo [a high price]	521	174	prezzo molto elevato [very high price]	381
25	pi caro al [more expensive to]	3334	75	caro prezzo ma [expensive price but]	933	125	caro prezzo che [expensive price that]	506	175	ha alzato prezzi [she raised the prices]	380
26	pi caro che [more expensive than]	2751	76	il caro prezzo [the high price]	929	126	prezzi aumentati del [prices increased by]	503	176	caro prezzo in [expensive price in]	379
27	sale il prezzo [the price goes up]	2601	77	pi caro ma [more expensive but]	916	127	rialzo del prezzo [price hike]	494	177	ad alzare prezzi [to raise prices]	378
28	il prezzo sale [the price goes up]	2557	78	crescita dei prezzi [price growth]	898	128	inflazione in aumento [rising inflation]	490	178	prezzi non scendono [prices do not go down]	371
29	aumentato il prezzo [increased the price]	2489	79	il caro affitti [expensive rents]	865	129	pi caro non [more expensive not]	481	179	per prezzi alti [for high prices]	367
30	alzato il prezzo [raised the price]	2407	80	caro prezzo le [expensive price the]	860	130	prezzo piu alto [higher price]	480	180	alle stelle prezzi [skyrocketing prices]	367
31	prezzo molto alto [very high price]	2170	81	tutto pi caro [all more expensive]	818	131	prezzi sono raddoppiati [prezzi sono raddoppiati]	478	181	rincari dei prezzi [price increases]	366
32	alto il prezzo [high the price]	2126	82	prezzi sono aumentati [prices have gone up]	811	132	prezzo record per [record price for]	478	182	aumento il prezzo [I increase the price]	365
33	salire il prezzo [go up the price]	2079	83	prezzo alto per [high price for]	809	133	prezzi pi cari [more expensive prices]	475	183	aumento di stipendio [salary increase]	365
34	un caro prezzo [a high price]	2072	84	un prezzo elevato [a high price]	801	134	inflazione pi alta [higher inflation]	474	184	da pagare alto [payable high]	361
35	prezzo altissimo per [very high price for]	2060	85	impennata dei prezzi [soaring prices]	794	135	di alzare il [to raise the]	473	185	lotta all inflazione [fight against inflation]	359
36	prezzi in aumento [rising prices]	2018	86	pagheranno un prezzo [they will pay a price]	790	136	rincaro dei prezzi [rising prices]	471	186	aumentando il prezzo [increasing the price]	354
37	doppio del prezzo [double the price]	1968	87	aumenti di prezzo [price increases]	783	137	il prezzo salito [the price soared]	468	187	ne pagher il [she will pay for it]	351
38	sempre pi caro [more and more expensive]	1937	88	di aumentare prezzi [to raise prices]	772	138	prezzi aumentano se [prices rise if]	466	188	prezzi sono esagerati [prices are exaggerated]	343
39	pagare caro prezzo [pay a very high price]	1898	89	caff pi caro [more expensive coffee]	764	139	rilevazione dei prezzi [price reporting]	463	189	della benzina sale [of gasoline goes up]	343
40	alto da pagare [high to pay]	1898	90	il caro prezzi [the expensive prices]	738	140	sono alle stelle [they are skyrocketing]	462	190	corsa dei prezzi [rush of prices/rise of prices]	340
41	caro prezzo il [expensive price the]	1834	91	prezzi in salita [rising prices]	736	141	il prezzo elevato [the high price]	460	191	ancora pi caro [even more expensive]	336
42	acquisto pi caro [more expensive purchase]	1782	92	aumentano il prezzo [they increase the price]	728	142	caro prezzo un [expensive price a]	458	192	hanno raddoppiato prezzi [they doubled prices]	335
43	aumento di prezzo [price increase]	1713	93	aumenta il costo [it increases the cost]	725	143	alzare prezzi dei [raise prices of]	449	193	prezzi al rialzo [rising prices]	328
44	prezzi cos alti [such high prices]	1621	94	aumentano prezzi di [prices of rise]	707	144	ci sar inflazione [there will be inflation]	448	194	aumento dei salari [wages increase]	328
45	pi caro per [more expensive for]	1516	95	pagheranno il prezzo [they will pay the price]	704	145	prezzi sono altissimi [prices are very high]	443	195	del petrolio sale [of oil rises]	325
46	caro prezzo per [expensive price for]	1400	96	prezzo cos alto [price so high]	702	146	che pagheremo caro [that we will pay a lot]	443	196	caro prezzo gli [high price the]	323
47	prezzi in rialzo [rising prices]	1388	97	il prezzo altissimo [the very high price]	694	147	caro prezzo con [expensive price with]	443	197	del prezzo elevato [of the high price]	320
48	caro il prezzo [expensive price]	1375	98	pi caro se [more expensive if]	681	148	un prezzo maggiorato [a higher price]	442	198	caro prezzo di [high price of]	320
49	pagando caro prezzo [paying a high price]	1370	99	per aumentare prezzi [to raise prices]	681	149	il prezzo salato [the steep price]	437	199	il prezzo salir [the price will go up]	318
50	prezzo alle stelle [skyrocketing price]	1369	100	ha aumentato prezzi [he raised prices]	676	150	fa aumentare prezzi [it increases prices]	436	200	di alzare prezzi [to raise prices]	317

Note: The table depicts the first 200 tri-grams in Italian with the English translation in square brackets for directional index UP manually labelled. The tri-grams are sorted in descending order by the total volume of tweets containing them in the sample period (June 1, 2013-December 31, 2019).

Table B.3: First 200 tri-grams for Index Down

N	tri-grams	count	N	tri-grams	count	N	tri-grams	count	N	tri-grams	count
1	prezzi pi bassi [lower prices]	39627	51	in calo prezzi [falling prices]	1428	101	il prezzo ridotto [the reduced price]	629	151	diminuzione del prezzo [price drop]	454
2	prezzo pi basso [lowest price]	35247	52	prezzo ridotto per [reduced price for]	1403	102	riduce il prezzo [it reduces the price]	624	152	si chiama deflazione [it's called deflation]	449
3	al miglior prezzo [at the best price]	20757	53	prezzo troppo basso [price too low]	1379	103	met prezzo da [half price from]	624	153	basso prezzo del [low price of]	446
4	prezzo piu basso [lowest price]	14486	54	inflazione in calo [falling inflation]	1367	104	prezzo al ribasso [lower price]	622	154	cali di prezzo [price drops]	446
5	abbassare il prezzo [lower the price]	9372	55	con prezzi bassi [with low prices]	1338	105	diminuire il prezzo [decrease the price]	621	155	riduzione di prezzo [price reduction]	446
6	prezzo in offerta [price on offer]	9340	56	in piena deflazione [in full deflation]	1301	106	prezzo cos basso [so low price]	604	156	prezzi pi accessibili [more affordable prices]	444
7	la deflazione salariale [wage deflation]	8187	57	abbassare prezzi di [dropping prices by]	1279	107	dei prezzi bassi [of low prices]	601	157	diminuzione dei prezzi [drop in prices]	439
8	prezzi in calo [falling prices]	7086	58	riduzione dei prezzi [price reduction]	1250	108	alzando il prezzo [raising the price]	597	158	diminuisce il prezzo [the price decreases]	425
9	prezzi da saldo [sale prices]	6842	59	prezzi troppo bassi [prices too low]	1249	109	in deflazione da [in deflation from]	592	159	prezzi stracciati in [bargain prices in]	421
10	prezzo di saldo [bargain price/sale price]	6457	60	calo di prezzo [price drop]	1242	110	aumentare prezzi dei [raise prices of]	588	160	poco prezzo ma [little price but]	420
11	calo dei prezzi [price drop]	5622	61	ribasso dei prezzi [falling prices]	1222	111	un prezzo minore [a lower price]	584	161	in forte calo [falling sharply]	420
12	abbassa il prezzo [lower the price]	4667	62	scendere il prezzo [drop the price]	1220	112	prezzi sono bassi [prices are low]	581	162	pi bassi rispetto [lower than]	418
13	siamo in deflazione [we are in deflation]	4597	63	tenere bassa inflazione [keep inflation low]	1214	113	molto pi bassi [much lower]	580	163	con prezzi accessibili [with affordable prices]	414
14	crollo dei prezzi [collapse in prices]	3959	64	al minor prezzo [at the lowest price]	1209	114	prezzi bassi in [low prices in]	580	164	far abbassare prezzi [bring down prices]	412
15	crolla il prezzo [the price falls]	3930	65	prezzo scontato del [discounted price of]	1202	115	prezzi bassi la [low prices the]	578	165	prezzo minimo di [minimum price of]	396
16	crollo del prezzo [price drop]	3918	66	con lo sconto [with the discount]	1198	116	il prezzo crolla [the price falls]	578	166	calano prezzi delle [prices of drop]	395
17	prezzi di saldo [sale prices]	3898	67	ai minimi storici [at historic lows]	1154	117	basso prezzo per [low price for]	574	167	low cost per [low cost for]	395
18	met prezzo https [half price https]	3897	68	deflazione salariale la [wage deflation the]	1123	118	prezzo basso per [low price for]	559	168	prezzi da discount [discount prices]	393
19	prezzi piu bassi [lower prices]	3787	69	abbassamento dei prezzi [lower prices]	1039	119	ridotto il prezzo [reduced the price]	547	169	di bassa inflazione [of low inflation]	391
20	prezzi bassi https [low prices https]	3509	70	met prezzo con [half price with]	1032	120	prezzi stracciati ma [bargain prices but]	543	170	prezzi stracciati la [bargain prices]	385
21	prezzi bassi per [low prices for]	3464	71	un prezzo bassissimo [a very low price]	1031	121	ancora pi bassi [even lower]	540	171	prezzo in saldo [sale price]	384
22	taglio di prezzo [price cut]	3220	72	la bassa inflazione [low inflation]	1020	122	abbassi il prezzo [lower the price]	537	172	abbassamento del prezzo [lowering the price]	381
23	ridurre il prezzo [reduce the price]	3062	73	inflazione ai minimi [low inflation]	1002	123	taglio dei prezzi [price cut]	532	173	buon prezzo non [good price not]	377
24	cala il prezzo [the price drops]	2965	74	prezzi al ribasso [lower prices]	945	124	prezzi si abbassano [prices drop]	528	174	prezzi bassi con [low prices with]	374
25	met del prezzo [half the price]	2916	75	riduzione del prezzo [price reduction]	925	125	hanno abbassato prezzi [they lowered prices]	527	175	prezzo molto conveniente [very affordable price]	374
26	guerra dei prezzi [price war]	2910	76	un prezzo ridotto [a reduced price]	915	126	abbassano il prezzo [they lower the price]	524	176	dai prezzi bassi [with low prices]	369
27	sconto sul prezzo [discount on the price]	2871	77	prezzi pi convenienti [cheaper prices]	901	127	calo il prezzo [drop the price]	522	177	il basso prezzo [the low price]	367
28	di deflazione salariale [of wage deflation]	2762	78	caduta dei prezzi [falling prices]	899	128	piccoli prezzi https [small prices https]	513	178	cala di prezzo [drop in price]	367
29	un prezzo stracciato [a bargain price]	2735	79	di abbassare prezzi [to lower prices]	891	129	manodopera basso prezzo [low price labor]	511	179	prezzi da outlet [outlet prices]	365
30	si paga caro [you pay a lot]	2655	80	case in calo [falling house prices]	867	130	anni di deflazione [years of deflation]	510	180	ha abbassato prezzi [she has lowered prices]	363
31	met prezzo per [half price for]	2590	81	prezzi ridotti per [reduced prices for]	865	131	paghi la met [pay half]	508	181	euro di sconto [euro discount]	362
32	il meno caro [the least expensive]	2516	82	met prezzo il [half price the]	857	132	ribasso del prezzo [price drop]	508	182	meno caro di [less expensive than]	362
33	abbassate il prezzo [lower the price]	2452	83	per abbassare prezzi [to lower prices]	828	133	calare il prezzo [drop the price]	503	183	met prezzo non [half price not]	361
34	abbassare prezzi dei [lower prices of]	2401	84	scende di prezzo [it drops in price]	820	134	met prezzo in [half price in]	501	184	si sono abbassati [they have been lowered]	358
35	calo del prezzo [price drop]	2281	85	prezzi gi del [prices down by]	812	135	ancora pi basso [even lower]	499	185	contrazione dei prezzi [price contraction]	353
36	il prezzo scende [the price drops]	2257	86	in deflazione il [in deflation the]	805	136	euro la deflazione [euro deflation]	499	186	inflazione pi bassa [lower inflation]	352
37	della deflazione salariale [of wage deflation]	2186	87	gi il prezzo [down the price]	804	137	il prezzo speciale [the special price]	496	187	prezzo stracciato per [low price for]	351
38	prezzi scontati https [discounted prices https]	2107	88	prezzi cos bassi [such low prices]	790	138	caduta del prezzo [price drop]	493	188	con inflazione zero [with zero inflation]	349
39	un prezzo basso [a low price]	2021	89	sulla deflazione salariale [on wage deflation]	787	139	prezzi accessibili per [affordable prices for]	481	189	prezzi stracciati da [bargain prices from]	346
40	taglia il prezzo [cut the price]	2003	90	la deflazione che [deflation that]	764	140	deflazione salariale per [wage deflation for]	479	190	prezzo basso in [low price in]	342
41	un prezzo inferiore [a lower price]	1953	91	il prezzo cala [the price drops]	763	141	prezzi stracciati si [bargain prices]	478	191	prezzi in ribasso [falling prices]	339
42	prezzo di favore [preferential price]	1936	92	prezzo molto basso [very low price]	715	142	sempre pi gi [deeper and deeper]	478	192	scendere di prezzo [drop in price]	338
43	tutto met prezzo [all half price]	1925	93	crollare il prezzo [drop the price]	714	143	prezzi in caduta [falling prices]	476	193	prezzo ribassato per [lowered price for]	338
44	sono prezzi bassi [they are low prices]	1923	94	che costa poco [which costs little]	708	144	il pi basso [the lowest]	470	194	far scendere prezzi [bring prices down]	336
45	abbassato il prezzo [lowered the price]	1902	95	prezzi scontati su [discounted prices on]	694	145	prezzi bassi su [low prices on]	464	195	scendono prezzi delle [prices of drop]	331
46	ad abbassare prezzi [to lower prices]	1785	96	basso il prezzo [low the price]	689	146	prezzo stracciato con [bargain price with]	461	196	disoccupazione bassi salari [low wages unemployment]	327
47	prezzi stracciati per [bargain prices for]	1703	97	prezzo in calo [falling price]	655	147	prezzo si abbassa [price drops]	461	197	abbassare prezzi per [lower prices for]	318
48	scende il prezzo [the price drops]	1667	98	si abbassano prezzi [prices drop]	646	148	livello pi basso [lower level]	460	198	ribassato il prezzo [lowered the price]	316
49	il prezzo basso [the low price]	1655	99	prezzi molto bassi [very low prices]	639	149	un prezzo promozionale [a promotional price]	456	199	tagliare gli stipendi [cut wages]	315
50	prezzo pi conveniente [cheaper price]	1526	100	deflazione dei salari [wage deflation]	637	150	prezzi sono scesi [prices have come down]	455	200	prezzi scontati con [discounted prices of]	314

Note: The table depicts the first 200 tri-grams in Italian with the English translation in square brackets for directional index DOWN manually labelled. The tri-grams are sorted in descending order by the total volume of tweets containing them in the sample period (June 1, 2013-December 31, 2019).

Table B.4: First 200 bi-grams for Index Up

N	bi-grams	count	N	bi-grams	count	N	bi-grams	count	N	bi-grams	count
1	pi caro [more expensive]	57705	51	prezzo superiore [higher price]	1617	101	impennata dei [soaring of]	830	151	ne pagher [she will pay for it]	530
2	caro prezzo [expensive price]	45267	52	prezzi record [record prices]	1598	102	aumenteranno prezzi [prices will rise]	829	152	benzina aumenta [gasoline increases]	527
3	prezzo altissimo [very high price]	18598	53	caro prezzi [high prices]	1596	103	rialzo prezzi [price hike]	829	153	aspettative inflazione [inflation expectations]	526
4	alle stelle [skyrocketing]	17236	54	prezzo salato [very expensive price]	1592	104	prezzo raddoppiato [price doubled]	813	154	aumenta ancora [it still increases]	525
5	prezzo alto [high price]	9844	55	sale inflazione [inflation rises]	1583	105	dovr pagare [He will have to pay]	811	155	sempre caro [always expensive]	525
6	prezzi alti [high prices]	9209	56	prezzo assurdo [absurd price]	1570	106	prezzi spropositati [disproportionate prices]	807	156	forte inflazione [strong inflation]	522
7	prezzi assurdi [absurd prices]	7922	57	alzano prezzi [they raise prices]	1568	107	lo pagheranno [they will pay for it]	800	157	prezzi saliranno [prices will go up]	519
8	prezzi su [prices up]	7128	58	pi inflazione [more inflation]	1511	108	prezzi crescono [prices rise]	785	158	aumento inflazione [inflation increase]	518
9	aumentano prezzi [prices rise]	6550	59	prezzi stellari [sky-high prices]	1485	109	che pagheremo [that we will pay]	783	159	prezzo salatissimo [very high price]	518
10	in rialzo [on the rise]	6308	60	alzato prezzi [raised prices]	1478	110	sono aumentate [they have increased]	775	160	inflazione sar [inflation will be]	517
11	prezzi folli [crazy prices]	6032	61	prezzo aumenta [price increases]	1464	111	prezzo caro [expensive price]	773	161	pi costosi [more expensive]	515
12	caro benzina [high cost of gasoline]	6016	62	prezzo maggiore [higher price]	1452	112	prezzo doppio [double price]	772	162	aumentando prezzi [increasing prices]	509
13	aumentare prezzi [increase prices]	5459	63	aumento prezzo [price increase]	1447	113	crescita prezzi [price growth]	730	163	rincaro dei [rising prices]	507
14	pagato caro [paid a lot]	4329	64	pagando caro [paying a lot]	1436	114	iper inflazione [hyper inflation]	729	164	rischio inflazione [inflation risk]	505
15	aumenta prezzi [she increases prices]	4238	65	aumenta prezzo [increase price]	1426	115	prezzi stratosferici [stratospheric prices]	708	165	genera inflazione [it generates inflation]	500
16	aumento prezzi [price increase]	4151	66	salire prezzi [go up prices]	1407	116	bollette pi [bills more]	701	166	caro vita [high cost of living]	494
17	sono aumentati [they are increased]	4130	67	aumentati prezzi [raised prices]	1357	117	inflazione aumenta [inflation increases]	687	167	tornano crescere [they return to grow]	489
18	inflazione due [inflation two (digits)]	3937	68	troppo caro [too expensive]	1357	118	inflazione cresce [inflation grows]	686	168	perch costano [because they cost]	482
19	paga caro [she pays a lot]	3733	69	prezzi aumentati [prices increased]	1347	119	cresce inflazione [inflation is growing]	681	169	produce inflazione [it produces inflation]	473
20	prezzi gonfiati [inflated prices]	3591	70	alti prezzi [high prices]	1323	120	raddoppiare prezzi [double prices]	673	170	prezzo lievita [price rises]	473
21	prezzi altissimi [very high prices]	3575	71	prezzo aumentato [price increased]	1279	121	benzina sale [gasoline rises]	657	171	pagherete caro [you will pay a high price]	472
22	prezzi esorbitanti [exorbitant prices]	3407	72	molto caro [very expensive]	1262	122	rincari del [price increases of]	642	172	paga pi [pay more]	461
23	pi cara [more expensive]	3353	73	aumentare inflazione [increase inflation]	1210	123	costa molto [it is very expensive]	633	173	prezzo stellare [skyrocket price]	453
24	prezzo sale [price goes up]	3227	74	prezzi maggiorati [higher prices]	1200	124	prezzi triplicati [tripled prices]	632	174	crescere prezzi [grow prices]	448
25	alzare prezzi [raise prices]	3145	75	inflazione doppia [double inflation]	1171	125	non deflazione [not deflation]	630	175	rincari dei [price increases]	436
26	inflazione sale [inflation rises]	2966	76	inflazione galoppante [galloping inflation]	1168	126	combattere inflazione [fight inflation]	626	176	gonfiato prezzi [inflated prices]	436
27	inflazione su [inflation up]	2955	77	prezzo enorme [huge price]	1165	127	causa inflazione [it cuases inflation]	623	177	alzando prezzi [raising prices]	435
28	carissimo prezzo [very expensive price]	2921	78	alta inflazione [high inflation]	1154	128	creerebbe inflazione [it would create inflation]	614	178	prezzi volano [prices fly]	433
29	pi cari [more expensive]	2871	79	costano molto [they cost a lot]	1144	129	paghi caro [you pay a lot]	610	179	rincaro del [inflation of/increase the price of]	429
30	prezzi esagerati [exaggerated prices]	2840	80	inflazione ancora [inflation again]	1126	130	il rincaro [the increase]	609	180	aumentiamo prezzi [we raise prices]	405
31	alza prezzi [raise prices]	2625	81	prezzo gonfiato [inflated price]	1108	131	aumentare prezzo [increase price]	603	181	anche caro [also expensive]	404
32	prezzi aumentano [prices rise]	2562	82	pagher caro [he will pay a lot]	1105	132	sar inflazione [it will be inflation]	598	182	tutto caro [everything expensive]	402
33	aumentato prezzi [increased prices]	2439	83	prezzi raddoppiati [prices doubled]	1092	133	prezzo carissimo [very high price/very expensive price]	594	183	porta inflazione [it brings inflation]	395
34	prezzo esagerato [exxagerated price]	2377	84	inflazione crescita [inflation growth]	1079	134	troppo cara [too expensive]	592	184	inflazione risale [inflation goes back]	388
35	prezzi salgono [prices go up]	2359	85	prezzo eccessivo [excessive price]	1045	135	ripresa prezzi [recovery prices]	591	185	alzare inflazione [raise inflation]	387
36	lievitare prezzi [rise prices]	2301	86	pagheremo caro [we will pay a high price]	1042	136	pagheranno caro [they will pay a high price]	590	186	essere caro [being expensive]	385
37	pagano caro [they pay a lot]	2245	87	inflazione prezzi [price inflation]	1037	137	troppo cari [Too expensive]	586	187	rialzo inflazione [inflation rise]	383
38	caro bollette [expensive bills]	2153	88	volano prezzi [flying prices]	1020	138	in inflazione [in inflation]	569	188	prezzi esosi [expensive prices]	378
39	prezzo elevato [high price]	2096	89	paghiamo caro [we pay a lot]	1013	139	ripresa inflazione [recovery in inflation]	568	189	inflazione salita [rising inflation]	371
40	salgono prezzi [prices go up]	2092	90	aumenta inflazione [inflation increases]	1012	140	aumenter prezzi [she will increase prices]	566	190	arriva inflazione [inflation comes]	369
41	pagare caro [pay a high price]	2035	91	crescono prezzi [prices rise]	997	141	aumenti prezzi [increase prices]	562	191	gonfiare prezzi [inflate prices]	366
42	caro affitti [high rents]	2010	92	inflazione alta [high inflation]	964	142	inflazione salari [wage inflation]	560	192	prezzo salir [price will go up]	366
43	alto prezzo [high price]	1974	93	petrolio aumentato [increased oil]	926	143	petrolio sale [oil rises]	559	193	inflazione continua [inflation continues]	365
44	prezzi elevati [high prices]	1906	94	creare inflazione [create inflation]	897	144	inflazione attesa [expected inflation]	555	194	costa caro [it is expensive]	362
45	crescita inflazione [inflation growth]	1783	95	sono altissimi [they are very high]	871	145	prezzi aumenteranno [prices will rise]	550	195	un rincaro [an increase]	360
46	caro carburante [high cost of fuel]	1781	96	inflazione accelera [inflation accelerates]	863	146	prezzo salito [price soared]	547	196	sale prezzo [price goes up]	356
47	inflazione stabile [stable inflation]	1736	97	dovranno pagare [they will have to pay]	862	147	benzina costa [gasoline costs]	545	197	gonfiano prezzi [they inflate prices]	353
48	crea inflazione [it creates inflation]	1718	98	inflazione resta [inflation remains]	857	148	inflazione aumento [inflation rise]	545	198	costante aumento [constant increase]	344
49	costa troppo [it costs too much]	1709	99	raddoppiato prezzi [doubled prices]	845	149	costano troppo [they cost too much]	535	199	salari inflazione [inflation wages]	342
50	pi costoso [more expensive]	1654	100	pagheranno il [they will pay the]	830	150	quanto coster [how much will it cost]	532	200	prezzi lievitano [prices rise]	333

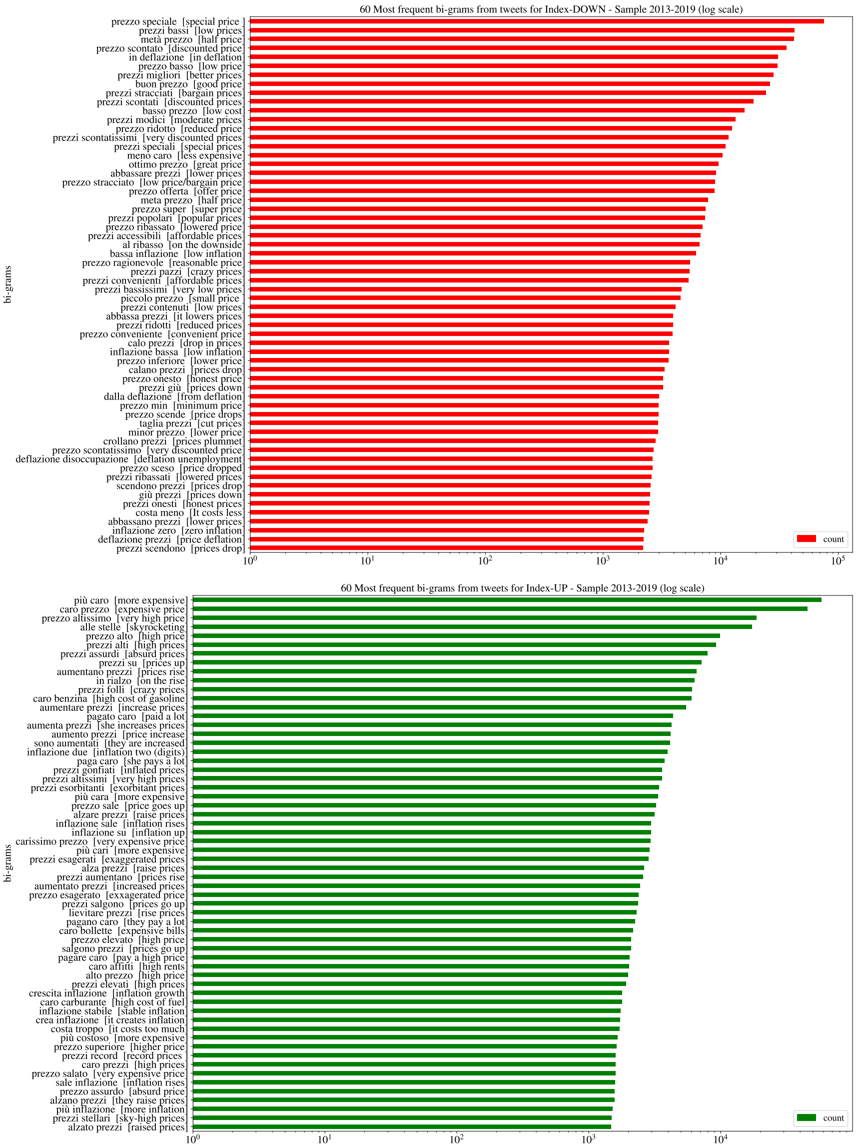
Note: The table depicts the first 200 bi-grams in Italian with the English translation in square brackets for directional index UP manually labelled. The bi-grams are sorted in descending order by the total volume of tweets containing them in the sample period (June 1, 2013-December 31, 2019).

Table B.5: First 200 bi-grams for Index Down

N	bi-grams	count	N	bi-grams	count	N	bi-grams	count	N	bi-grams	count
1	prezzo speciale [special price]	75385	51	prezzo sceso [price dropped]	2623	101	prezzi mini [mini prices]	588	151	prezzi tagliati [prices cut]	268
2	prezzi bassi [low prices]	42565	52	prezzi ribassati [lowered prices]	2587	102	fantastico prezzo [fantastic price]	586	152	tagliare prezzi [cut prices]	267
3	met prezzo [half price]	42049	53	scendono prezzi [prices drop]	2538	103	po caro [a bit expensive]	546	153	prezzi scesi [prices dropped]	260
4	prezzo scontato [discounted price]	36174	54	gi prezzi [prices down]	2503	104	pi economica [cheaper]	545	154	prezzi caleranno [prices will drop]	252
5	in deflazione [in deflation]	30743	55	prezzi onesti [honest prices]	2484	105	ribasso per [discount for]	539	155	frenano prezzi [prices hold back]	251
6	prezzo basso [low price]	30379	56	costa meno [It costs less]	2455	106	bassissimo prezzo [very low price]	538	156	prezzo abbassato [lowered price]	248
7	prezzi migliori [better prices]	28212	57	abbassano prezzi [lower prices]	2382	107	prezzo dimezzato [halved price]	534	157	prezzo scender [price will drop]	245
8	buon prezzo [good price]	26174	58	inflazione zero [zero inflation]	2237	108	petrolio basso [low oil]	517	158	massimo ribasso [maximum discount]	240
9	prezzi stracciati [bargain prices]	24189	59	deflazione prezzi [price deflation]	2213	109	riduce prezzi [it reduces prices]	487	159	meno costoso [less expensive]	231
10	prezzi scontati [discounted prices]	18966	60	prezzi scendono [prices drop]	2182	110	diminuiscono prezzi [prices drop]	485	160	prezzi diminuiscono [prices drop]	228
11	basso prezzo [low cost]	15871	61	prezzo bassissimo [very low price]	1908	111	abbassi prezzi [lower prices]	470	161	giu prezzi [down prices]	217
12	prezzi modici [moderate prices]	13387	62	in ribasso [down]	1876	112	ribasso prezzi [lower prices]	458	162	caduta prezzo [price drop]	211
13	prezzo ridotto [reduced price]	12531	63	bassi prezzi [low prices]	1871	113	chiama deflazione [call deflation]	458	163	scesi prezzi [dropped prices]	209
14	prezzi scontatissimi [very discounted prices]	11607	64	offerte amazon [amazon sales]	1828	114	abbassiamo prezzi [we lower prices]	448	164	ridurre prezzo [reduce price]	207
15	prezzi speciali [special prices]	10989	65	bassi salari [low wages]	1785	115	calare prezzi [price dropping]	435	165	inflazione riduce [inflation reduces]	206
16	meno caro [less expensive]	10333	66	prezzi minimi [minimum prices]	1774	116	deflazione salari [wage deflation]	434	166	prezzo diminuisce [price decreases]	199
17	ottimo prezzo [great price]	9542	67	inflazione scende [inflation drops]	1768	117	ed economico [and cheap]	429	167	prezzo calato [price dropped]	196
18	abbassare prezzi [lower prices]	9133	68	costa poco [it is cheap]	1627	118	meno prezzo [less price]	427	168	ribasso in [discount in]	196
19	prezzo stracciato [low price/bargain price]	8909	69	prezzi calano [prices drop]	1560	119	inflazione scesa [inflation dropped]	412	169	dimezzare prezzi [halve prices]	195
20	prezzo offerta [offer price]	8845	70	abbassato prezzi [lowered prices]	1504	120	abbatte prezzi [she lowers prices]	411	170	ridotto prezzi [reduced prices]	186
21	meta prezzo [half price]	7817	71	prezzi inferiori [lower prices]	1451	121	prezzi scenderanno [prices will drop]	407	171	cala prezzi [drop prices]	183
22	prezzo super [super price]	7428	72	petrolio scende [oil drops]	1394	122	crolla prezzo [price collapses]	405	172	dimezzati prezzi [halved prices]	180
23	prezzi popolari [popular prices]	7339	73	piena deflazione [full deflation]	1358	123	riduzione prezzi [price reduction]	390	173	calati prezzi [dropped prices]	174
24	prezzo ribassato [lowered price]	6973	74	non costa [it doesn't cost]	1346	124	ribasso prezzo [price drop]	382	174	ridurre inflazione [reduce inflation]	168
25	prezzi accessibili [affordable prices]	6706	75	taglia prezzo [cut price]	1264	125	prezzi minori [lower prices]	378	175	prezzo moderato [moderate price]	164
26	al ribasso [on the downside]	6625	76	costano meno [they cost less]	1229	126	inflazione gi [inflation down]	377	176	rallentamento inflazione [inflation slowdown]	162
27	bassa inflazione [low inflation]	6178	77	prezzo minore [lower price]	1210	127	sono abbassati [they are lowered]	372	177	inflazione moderata [moderate inflation]	161
28	prezzo ragionevole [reasonable price]	5472	78	pi economico [cheaper]	1150	128	meno cari [less expensive]	368	178	prezzo diminuito [price decreased]	156
29	prezzi pazzi [crazy prices]	5445	79	crollo prezzi [price collapse]	1048	129	met prezzo [half price]	365	179	prezzo scenda [price drop]	149
30	prezzi convenienti [affordable prices]	5324	80	scendere prezzi [drop prices]	1000	130	meno inflazione [less inflation]	354	180	inflazione bassissima [very low inflation]	146
31	prezzi bassissimi [very low prices]	4622	81	deflazione al [deflation at]	998	131	prezzo crollato [price plummeted]	353	181	ulteriori ribassi [further discounts]	144
32	piccolo prezzo [small price]	4553	82	il ribasso [the fall]	990	132	deflazione dal [deflation since]	348	182	inflazione bassi [low inflation]	142
33	prezzi contenuti [low prices]	4133	83	taglio prezzo [price cut]	975	133	prezzi stracciatissimi [rock bottom prices]	332	183	prezzi abbassati [lowered prices]	141
34	abbassa prezzi [it lowers prices]	3920	84	con offerta [with offer]	956	134	abbassare prezzo [lower price]	331	184	inflazione calata [inflation dropped]	139
35	prezzi ridotti [reduced prices]	3917	85	prezzi irrisori [ridiculous prices]	905	135	prezzi cinesi [Chinese prices]	328	185	frenare inflazione [curb inflation]	132
36	prezzo conveniente [convenient price]	3875	86	prezzo cala [price drops]	894	136	calano ancora [they are still falling]	324	186	ulteriore ribasso [further decline]	132
37	calo prezzi [drop in prices]	3636	87	nella deflazione [in deflation]	874	137	pagare meno [pay less]	324	187	inflazione scese [inflation went down]	129
38	inflazione bassa [low inflation]	3620	88	prezzi dimezzati [halved prices]	742	138	un ribasso [a fall]	320	188	tagliato prezzi [cut prices]	124
39	prezzo inferiore [lower price]	3589	89	petrolio cala [oil drops]	742	139	diminuire prezzi [decreasing prices]	313	189	prezzo caler [price will drop]	118
40	calano prezzi [prices drop]	3333	90	prezzo crolla [price collapses]	726	140	ribasso le [discount the]	312	190	minore inflazione [lower inflation]	117
41	prezzo onesto [honest price]	3228	91	salire inflazione [rise inflation]	717	141	ribassi dei [rebates of/discounts of]	312	191	troppa offerta [too much offer]	117
42	prezzi gi [prices down]	3225	92	ridurre prezzi [reduce prices]	695	142	sotto costo [under cost]	309	192	greggio scende [crude oil drops]	117
43	dalla deflazione [from deflation]	2988	93	crollo prezzo [price collapse]	674	143	prezzo gi [price down]	307	193	prezzo ribasso [discount price]	117
44	prezzo min [minimum price]	2971	94	prezzi crollano [prices plummet]	670	144	crolla inflazione [inflation collapses]	301	194	caro meno [expensive less]	113
45	prezzo scende [price drops]	2954	95	deflazione interna [internal deflation]	661	145	aumentate prezzi [raise prices]	286	195	gi inflazione [down inflation]	111
46	taglia prezzi [cut prices]	2938	96	prezzi fantastici [fantastic prices]	636	146	prezzi cari [expensive prices]	286	196	dimezzano prezzi [halve prices]	109
47	minor prezzo [lower price]	2920	97	inflazione cala [inflation drops]	615	147	caduta prezzi [falling prices]	284	197	ribassi su [fall on]	106
48	crollano prezzi [prices plummet]	2798	98	abbassando prezzi [lowering prices]	605	148	cala prezzo [price drops]	278	198	crollati prezzi [prices plummeted]	101
49	prezzo scontatissimo [very discounted price]	2697	99	calo inflazione [inflation drop]	599	149	coster meno [it will cost less]	275	199	flessione prezzi [falling prices]	99
50	deflazione disoccupazione [deflation unemployment]	2640	100	zero inflazione [zero inflation]	592	150	costano poco [They are cheap]	274	200	abbassare inflazione [lower inflation]	96

Note: The table depicts the first 200 bi-grams in Italian with the English translation in square brackets for directional index DOWN manually labelled. The bi-grams are sorted in descending order by the total volume of tweets containing them in the sample period (June 1, 2013-December 31, 2019).

Figure B.2: First 60 bi-grams for Index Down (red) and Up (green)



Notes: The top panel shows the 60 manually labelled most frequent bi-grams for Index Down (red), while the bottom panel depicts the 60 most frequent ones for Index Up (green), both over the sample 2013-19.

Figure B.3: First 60 tri-grams for Index Down (red) and Up (green)

Notes: The top panel shows the 60 manually labelled most frequent tri-grams for Index Down (red), while the bottom panel depicts the 60 most frequent ones for Index Up (green), both over the sample 2013-19.

Appendix C Who tweets about inflation and how often?

In this part of the Appendix we describe our sample of Twitter users who tweet in Italian about inflation and price dynamics.

Table C.1: Descriptive Statistics on Twitter Users

	Raw tweets				**Filtered Tweets**			
	Volume	%	Mean	Std. Dev.	Volume	%	Mean	Std. Dev.
All users								
Number of users with only 1 tweet	453,792	48.0	1	0	89,213	53.9	1	0
Number of users with 2 to 5 tweets	256,265	27.1	3	1	42,824	25.9	2.6	0.8
Number of users with 5 to 10 tweets	103,636	11.0	7	1	14,856	9.0	6.5	1.4
Number of users with 10 to 100 tweets	118,387	12.5	27	19	16,840	10.2	26.9	19.7
Number of user with more than 100 tweets	12,275	1.3	230	178	1,804	1.1	235.9	178.6
Total users	**944,512**	**100**	**8.2**	**34.3**	**165,551**	**100**	**7.1**	**32.0**
Econ users								
Number of users with only 1 tweet	2,328	32.3	1	0	1,463	36.8	1	0
Number of users with 2 to 5 tweets	1,993	27.7	3	1	1,035	26.0	2.68	0.788
Number of users with 5 to 10 tweets	1,002	13.9	7	1	542	13.6	6.59	1.4
Number of users with 10 to 100 tweets	1,585	22.0	30	21	771	19.4	29.89	20.73
Number of user with more than 100 tweets	293	4.1	278	233	169	4.2	267	230
Total Econ users	**7,204**	**100**	**20.0**	**72.5**	**3,980**	**100**	**19.1**	**71.8**
News users								
Number of users with only 1 tweet	7,239	32.3	1	0	3,343	46.2	1	0
Number of users with 2 to 5 tweets	6,574	29.4	3	1	2,058	28.5	3	1
Number of users with 5 to 10 tweets	3,235	14.4	7	1	777	10.7	7	1
Number of users with 10 to 100 tweets	4,686	20.9	28	20	925	12.8	28	20
Number of user with more than 100 tweets	654	2.9	254	205	128	1.8	253	179
Total News users	**22,394**	**100**	**15.4**	**56.0**	**7,231**	**100**	**9.9**	**41.9**

Note: The table presents some descriptive statistics on Twitter users in our sample of raw tweets and in the sample of filtered ones.

Appendix D Twitter-based inflation expectations with baseline dictionary - Summary statistics, additional tables and figures

Table D.1: Summary statistics of survey-based and market-based inflation expectations for Italy

Variable	Mean	Std. Dev.	Min.	Max	N
Infl. Perc. ISTAT	-3.16	9.73	-18.4	26.8	79
Infl. Exp. ISTAT	-6.66	5.96	-19.3	8.7	79
CPI	0.57	0.59	-0.6	1.9	79
Consensus Infl. Exp.	1.12	0.26	0.43	1.6	79
IT Infl. Swap 1Y	0.75	0.5	-0.76	1.8	1,717
IT Infl. Swap 1Y-1Y	0.77	0.35	-0.23	1.43	1,717
IT Infl. Swap 1Y-2Y	0.8	0.29	-0.06	1.35	1,717
IT Infl. Swap 5Y-5Y	1.59	0.25	0.93	2.23	1,717

Note: Summary statistics of the survey-based and market-based inflation expectations. Infl. Perc. ISTAT are the inflation perceptions while Infl. Exp. Istat are the inflation expectations from ISTAT survey. The table also reports the summary statistics for the Italian inflation swap with different maturities, the CPI and the average Consensus forecast for next year inflation. Daily sample from June 1, 2013 to December 31, 2019.

Table D.2: Summary statistics Twitter-based indicators with baseline dictionary

Variable	Mean	Std. Dev.	Min.	Max
Index Down	117.98	118.34	4.00	2425.00
Index Up	36.61	41.40	0.00	657.00
Infl. Exp. 1 MA(10)	-18.93	17.81	-76.42	41.98
Infl. Exp. 1 MA(30)	-18.98	14.41	-54.53	19.80
Infl. Exp. 1 MA(60)	-19.05	13.10	-50.39	7.89
Infl. Exp. 2 MA(10)	1.22	19.80	-65.46	68.20
Infl. Exp. 2 MA(30)	1.17	16.37	-41.34	36.92
Infl. Exp. 2 MA(60)	1.11	15.06	-36.07	26.00
Infl. Exp. 3 (Exp-0.1)	-18.96	15.40	-62.51	28.27
Infl. Exp. 3 (Exp-opt)	-18.99	13.90	-56.61	17.63
Infl. Exp. 3 (Exp-0.3)	-18.91	20.16	-81.83	63.54
Infl. Exp. 4 (ln) MA(10)	-1.21	0.47	-2.51	-0.01
Infl. Exp. 4 (ln) MA(30)	-1.21	0.39	-2.25	-0.36
Infl. Exp. 4 (ln) MA(60)	-1.22	0.36	-2.07	-0.59
Observations	1717			

Note: Summary statistics on the Twitter-based directional indexes, and the four Twitter-based indicators with the baseline dictionary of bi- and tri-grams and all the 3 MA smoothing windows. Daily sample from June 1, 2013 to December 31, 2019.

Table D.3: Correlations: Twitter-based inflation expectations indicators with baseline dictionary of bi- and tri-grams and ISTAT Inflation Expectations

Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp -opt)	Infl. Exp. 4 (ln) MA(10)
0.482***	0.504***	0.522***	0.591***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp -0.1)	Infl. Exp. 4 (ln) MA(30)
0.536***	0.562***	0.562***	0.633***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp -0.3)	Infl. Exp. 4 (ln) MA(60)
0.600***	0.615***	0.478***	0.655***

Note: Correlations between the Twitter-based inflation expectations indicators and ISTAT expectations. Directional indexes are computed using the baseline dictionary of bi- and tri-grams. Data are at the monthly frequency, from June 2013 through December 2019. Daily indicators are collapsed at monthly frequency. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D.4: Correlations: Twitter-based inflation expectations indicators with baseline dictionary and the Italian Inflation Swap 1Y

Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(10)
0.497***	0.548***	0.570***	0.626***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(30)
0.611***	0.657***	0.616***	0.736***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
0.627***	0.671***	0.438***	0.719***

Note: Correlations between the Twitter-based inflation expectations indicators and the Italian Infl. Swap 1Y. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation. Data are at daily frequency, from June 1, 2013 to December 31, 2019. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D.5: Informativeness exercise with all indexes with baseline dictionary, Consensus Forecast and CPI - MA(10)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$E_{t-1}^{ISTAT}\pi_{t-1,t+11}$'	0.673***	0.509***	0.560***	0.567***	0.511***	0.572***	0.503***	0.562***	0.502***	0.550***	0.499***	0.508***	0.487***
	(0.07)	(0.12)	(0.13)	(0.12)	(0.14)	(0.07)	(0.12)	(0.08)	(0.13)	(0.08)	(0.12)	(0.05)	(0.09)
IS_t^{1Y}		4.194***			4.048***		3.751***		3.743***		3.648**		2.560*
		(1.01)			(1.35)		(1.36)		(1.33)		(1.46)		(1.36)
CF_{t-1}^{y+1}			4.584**		-1.229		-1.307		-1.148		-1.308		-0.599
			(2.17)		(2.36)		(2.64)		(2.52)		(2.71)		(2.61)
CPI_{t-1}				2.279***	0.739		0.21		0.338		-0.0364		-0.364
				(0.86)	(0.69)		(0.88)		(0.97)		(0.92)		(0.94)
Infl. Exp. 1 MA(10)						0.0957***	0.043						
						(0.03)	(0.03)						
Infl. Exp. 2 MA(10)								0.0863***	0.0288				
								(0.03)	(0.03)				
Infl. Exp. 3 (Exp-opt)										0.114***	0.0605		
										(0.02)	(0.04)		
Infl. Exp. 4 (ln) MA(10)												5.297***	3.772**
												(0.91)	(1.70)
Cons.	-2.206***	-6.441***	-8.111**	-4.225**	-5.366	-1.063*	-3.983	-3.049***	-5.087	-0.853	-3.456	3.091***	0.0745
	(0.69)	(1.89)	(3.69)	(1.69)	(3.61)	(0.63)	(4.12)	(0.74)	(3.72)	(0.68)	(4.12)	(1.07)	(5.12)
N	78	78	78	78	78	78	78	78	78	78	78	78	78
R^2	0.451	0.544	0.478	0.491	0.547	0.501	0.553	0.5	0.55	0.511	0.556	0.554	0.571
$Adj.R^2$	0.444	0.532	0.464	0.478	0.522	0.488	0.522	0.487	0.519	0.498	0.525	0.542	0.541
$F-test$	101.2	86.97	143.2	147.7	56.66	102.1	58.69	70.31	55.25	109	61.31	114.8	64.52
$Prob > F$	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: Dependent variable: $E_t^{ISTAT}\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS_t^{1y} is the inflation swap rate at one year and *Infl. Exp. 1, 2 3 and 4* are the Twitter-based inflation expectation indexes with MA(10) with the baseline dictionary. CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Sample: June 2013, December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

Table D.6: Informativeness exercise with all indexes with baseline dictionary, Consensus Forecast and CPI - MA(30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$E^{ISTAT}_{t-1}\pi_{t-1,t+11}$'	0.673***	0.509***	0.560***	0.567***	0.511***	0.542***	0.497***	0.525***	0.491***	0.525***	0.489***	0.465***	0.461***
	(0.07)	(0.12)	(0.13)	(0.12)	(0.14)	(0.09)	(0.12)	(0.08)	(0.12)	(0.10)	(0.11)	(0.06)	(0.09)
IS^{1Y}_t		4.194***			4.048***		3.632**		3.445**		3.574**		2.248
		(1.01)			(1.35)		(1.53)		(1.60)		(1.52)		(1.75)
CF^{y+1}_{t-1}			4.584**		-1.229		-1.323		-1.04		-1.433		-0.464
			(2.17)		(2.36)		(2.71)		(2.86)		(2.84)		(2.89)
CPI_{t-1}				2.279***	0.739		-0.105		-0.123		-0.417		-0.775
				(0.86)	(0.69)		(0.94)		(0.87)		(1.01)		(1.02)
Infl. Exp. 1 MA(30)						0.119***	0.065						
						(0.03)	(0.04)						
Infl. Exp. 2 MA(30)								0.112***	0.0592				
								(0.02)	(0.04)				
Infl. Exp. 3 (Exp-opt)										0.133***	0.0885*		
										(0.04)	(0.05)		
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	-0.82	-3.319	-3.317***	-4.826	-0.665	-2.576	3.659***	1.638
	(0.69)	(1.89)	(3.69)	(1.69)	(3.61)	(0.69)	(4.00)	(0.85)	(3.57)	(0.74)	(4.18)	(1.00)	(4.56)
N	78	78	78	78	78	78	78	78	78	78	78	78	78
R^2	0.451	0.544	0.478	0.491	0.547	0.513	0.556	0.52	0.556	0.52	0.561	0.56	0.574
$Adj.R^2$	0.444	0.532	0.464	0.478	0.522	0.5	0.525	0.507	0.525	0.508	0.53	0.548	0.545
$F-test$	101.2	86.97	143.2	147.7	56.66	93.52	61.82	123.6	58.86	90.46	63.74	111.5	57.61
$Prob > F$	0	0	0	0	0	0	0	0	0	0	0	0	0

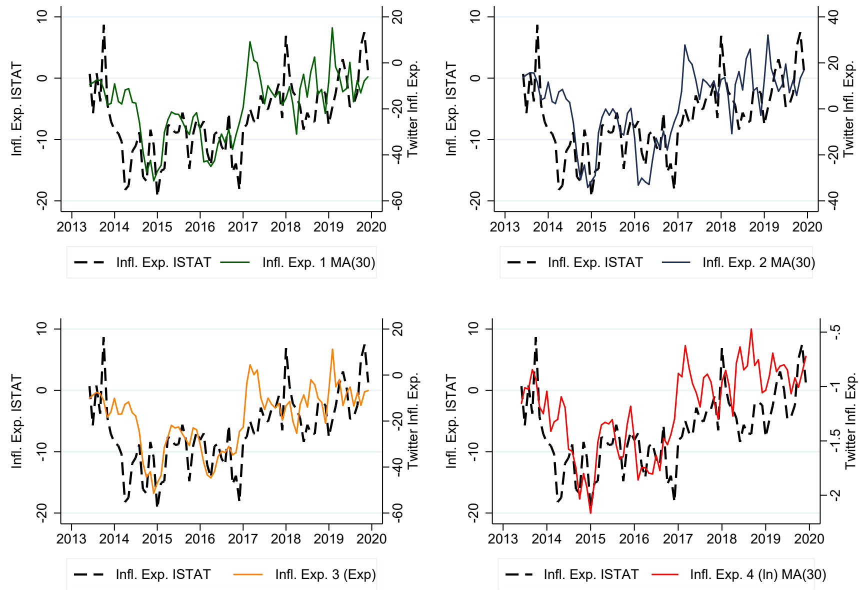
Note: Dependent variable: $E^{ISTAT}_t\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS^{1y}_t is the inflation swap rate at one year and *Infl. Exp. 1, 2 3 and 4* are the Twitter-based inflation expectation indexes with MA(30) with baseline dictionary. CF^{y+1}_{t-1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Sample: June 2013, December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

Table D.7: Informativeness exercise with all indexes with baseline dictionary, Consensus Forecast and CPI - MA(60)

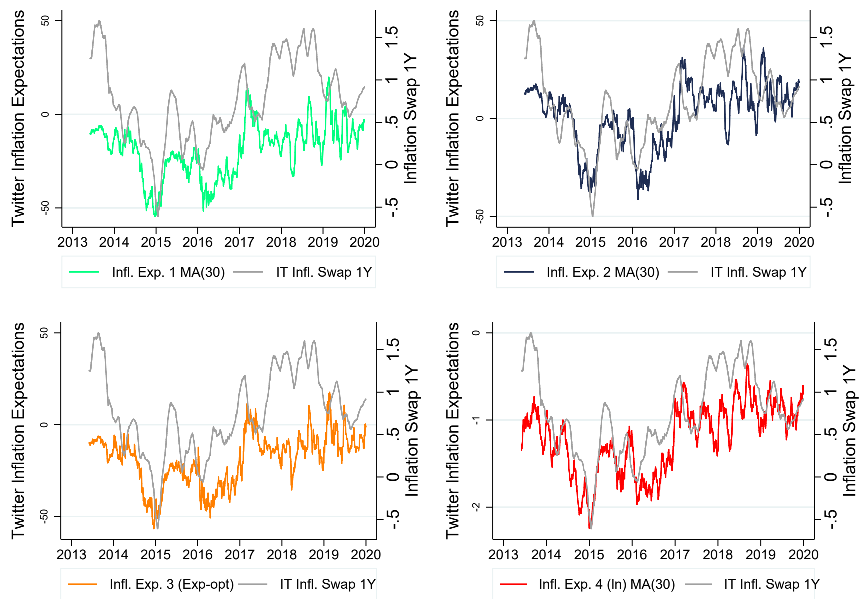
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$E_{t-1}^{ISTAT}\pi_{t-1,t+11}$	0.673***	0.509***	0.560***	0.567***	0.511***	0.493***	0.464***	0.479***	0.459***	0.574***	0.503***	0.418***	0.411***
	(0.07)	(0.12)	(0.13)	(0.12)	(0.14)	(0.11)	(0.10)	(0.10)	(0.13)	(0.07)	(0.12)	(0.08)	(0.08)
IS_t^{1Y}		4.194***			4.048***		3.645**		3.373**		3.777***		2.453
		(1.01)			(1.35)		(1.47)		(1.52)		(1.34)		(1.63)
CF_{t-1}^{y+1}			4.584**		-1.229		-1.742		-1.243		-1.28		-1.063
			(2.17)		(2.36)		(3.01)		(3.09)		(2.59)		(2.97)
CPI_{t-1}				2.279***	0.739		-1.049		-0.856		0.251		-1.676
				(0.86)	(0.69)		(1.31)		(1.44)		(0.91)		(1.38)
Infl. Exp. 1 MA(60)						0.150***	0.132*						
						(0.04)	(0.07)						
Infl. Exp. 2 MA(60)								0.135***	0.106				
								(0.02)	(0.07)				
Infl. Exp. 3 (Exp-opt)										0.0919***	0.0392		
										(0.03)	(0.03)		
Infl. Exp. 4 (ln) MA(60)												6.771***	7.159***
												(1.06)	(2.71)
Cons.	-2.206***	-6.441***	-8.111**	-4.225**	-5.366	-0.553	-1.264	-3.651***	-4.386	-1.122*	-4.132	4.318***	5.069
	(0.69)	(1.89)	(3.69)	(1.69)	(3.61)	(0.79)	(4.54)	(0.80)	(3.58)	(0.64)	(4.16)	(1.14)	(5.48)
N	78	78	78	78	78	78	78	78	78	78	78	78	78
R^2	0.451	0.544	0.478	0.491	0.547	0.528	0.571	0.53	0.566	0.499	0.552	0.559	0.584
$Adj.R^2$	0.444	0.532	0.464	0.478	0.522	0.516	0.541	0.518	0.535	0.485	0.521	0.547	0.555
$F-test$	101.2	86.97	143.2	147.7	56.66	79.01	61.92	77.58	36.28	93.23	56.76	85.32	46.81
$Prob > F$	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: Dependent variable: $E_t^{ISTAT}\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS_t^{1y} is the inflation swap rate at one year and *Infl. Exp. 1, 2 3 and 4* are the Twitter-based inflation expectation indexes with MA(60) with the baseline dictionary from Econ subsample. CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Sample: June 2013, December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

Figure D.1: Twitter-based Inflation Expectations vs survey-based and market-based measures



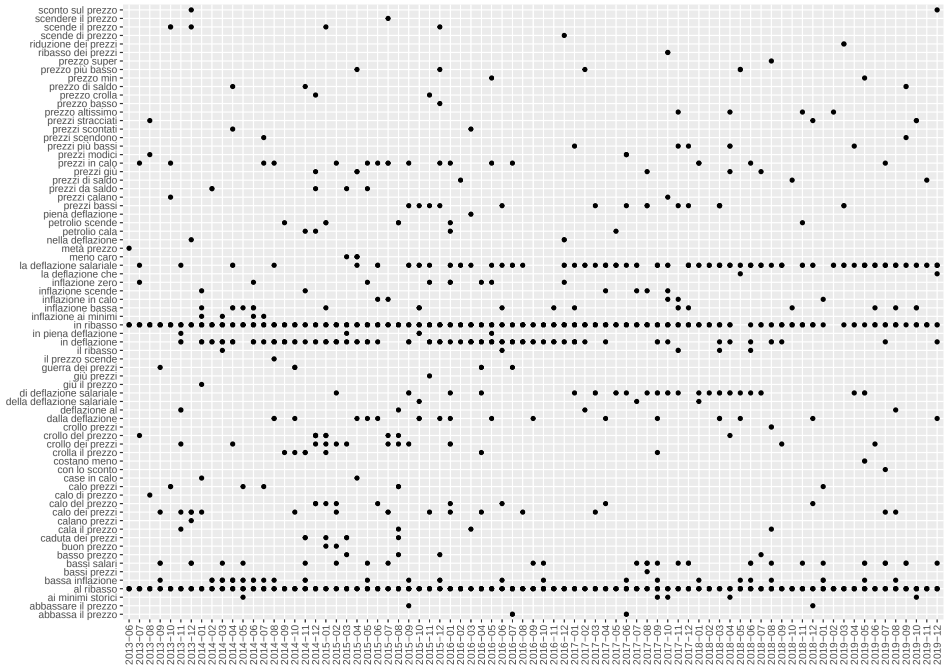
(a) Twitter-based vs ISTAT Inflation Expectations



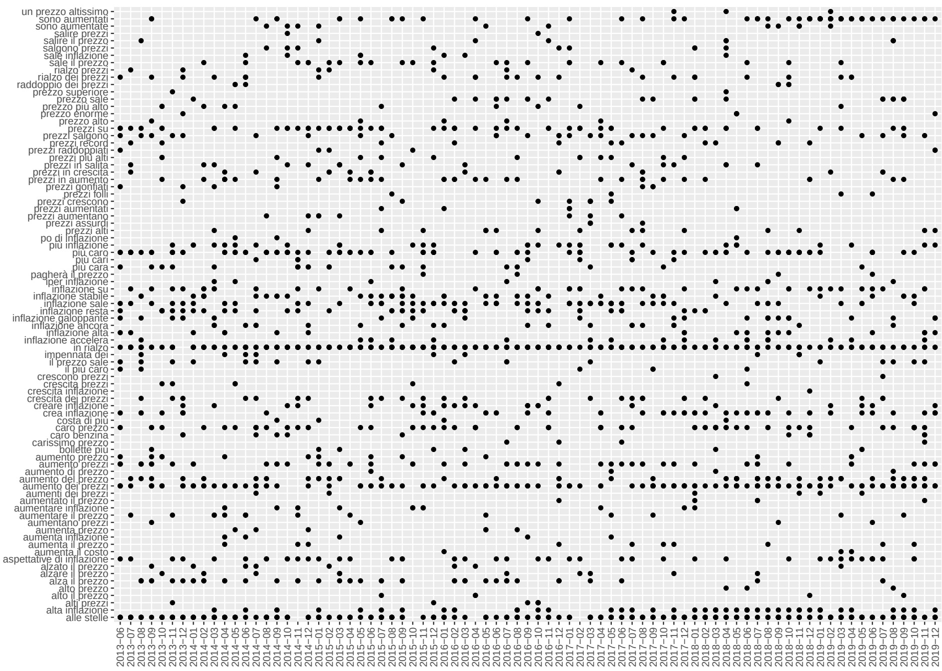
(b) Twitter-based Inflation Expectations vs the Italian Inflation Swap 1Y

Note: The top panel shows the monthly Twitter-based inflation expectation indicators from June 2013 through December 2019 vs the survey-based measures by ISTAT. Daily indicators are collapsed at the monthly frequency for clarity. Twitter-based inflation indexes are computed using the baseline dictionary. The bottom panel depicts the daily Twitter-based indexes vs the market-based measure. The sample is from June 1, 2013 through December 31, 2019. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation.

Figure D.2: Distribution over time of top 100 most frequent negative and positive bi/tri-grams



(a) Top 100 most frequent negative bi/tri-grams



(b) Top 100 most frequent positive bi/tri-grams

Notes: The top panel shows the top 100 most frequent negative bi/tri-grams and their distribution over the sample 2013-2019. The bottom panel depicts the distribution over time of the top 100 most frequent positive bi/tri-grams.

Appendix E Twitter-based inflation expectations with the rough initial dictionary

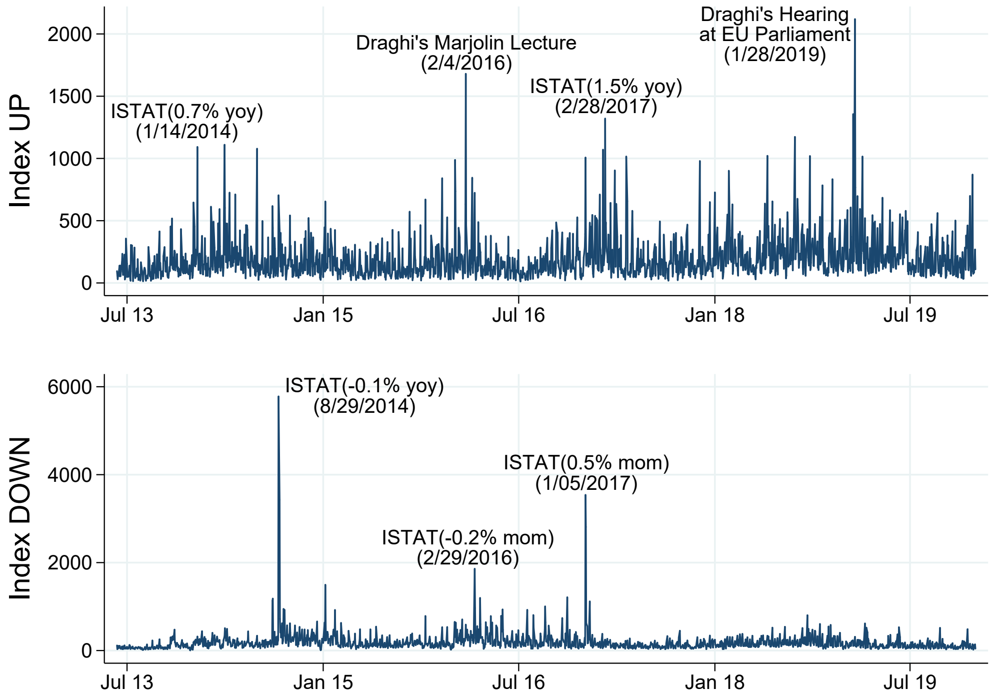
In this Appendix we present the results of an alternative method for computing the directional indexes - Step 2 of our procedure - which relies on the same coarse dictionary of words used to initially select the tweets (this method was used in a previous version of the paper).

In this alternative method, we build two indexes which measure the daily volume of tweets with at least one of the following selected words in Italian [English] related to incresing (Up) or decreasing (Down) price(s) and/or inflation:

- **Index Up**: *"caro bollette" [expensive bills], "inflazione" [inflation], "caro" [expensive], "caro prezzi" [high prices], "caroprezzi" [high-prices], "benzina alle stelle" (high gas prices), "bolletta salata" [higher bill], "caro affitti" [higher rents], "caro benzina" [high gasoline price], "caro carburante" [high petrol prices]*, and *"caro gas" [high gas prices]* reflect instead some price dynamics in the tweets that contain them, showing expectations of increasing price(s);
- **Index Down**: *"deflazione" [deflation], "disinflazione" [disinflation], "ribassi" [sales], "ribasso" [sale], "meno caro" [less expensive]*, and *"bollette più leggere" [less expensive bills]*[53] reveal tweets about decreasing prices.

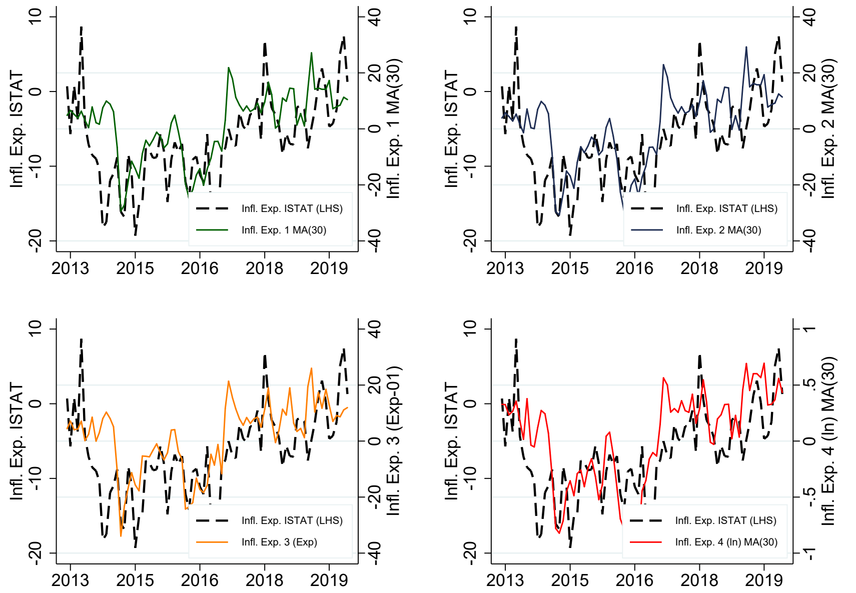
[53] Some of these words might seem unusual with respect to the English language, but they represent commonly used (collection of) words in the Italian language to express price dynamics.

Figure E.1: Dictionary-based Directional Indexes with the rough initial dictionary

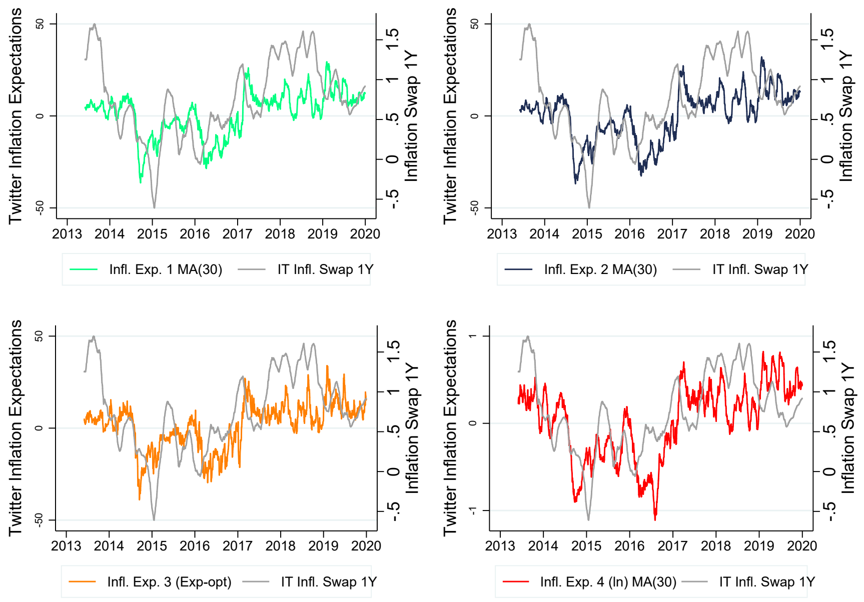


Notes: The figure depicts the two dictionary-based directional indexes Inflation-Up and Inflation-Down with some events when the volume of tweets is particularly high. The top panel shows the Index Up and the bottom one the Index Down when the directional indexes are computed with the initial coarse dictionary used to select the tweets.

Figure E.2: Twitter-based Inflation Expectations vs Survey- and Market measures (rough initial dictionary)



(a) Twitter-based vs ISTAT Inflation Expectations



(b) Twitter Inflation Expectations vs the Italian Inflation Swap 1Y

Note: The top panel shows the monthly Twitter-based inflation expectation indicators from June 2013 through December 2019 vs the survey-based measures by ISTAT. Daily indicators are collapsed at the monthly frequency for clarity. Twitter-based inflation indexes are computed using topics and the coarse initial dictionary of keywords used to select the tweets. The bottom panel depicts the daily Twitter-based indexes vs the market-based measure. The sample is from June 1, 2013 through December 31, 2019. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation.

Table E.1: Summary statistics Twitter-based indicators with the rough initial dictionary

Variable	Mean	Std. Dev.	Min.	Max
Index Down	180.57	239.83	5	5779
Index Up	186.2	171.29	12	2119
Infl. Exp. 1 MA(10)	1.49	14.27	-46.27	51.42
Infl. Exp. 1 MA(30)	1.43	12.16	-36.33	29.39
Infl. Exp. 1 MA(60)	1.37	11.17	-28.47	20.29
Infl. Exp. 2 MA(10)	0.37	15.85	-50.27	54.89
Infl. Exp. 2 MA(30)	0.29	13.59	-36.81	32.04
Infl. Exp. 2 MA(60)	0.21	12.55	-31.26	21.91
Infl. Exp. 3 (Exp-0.1)	1.46	12.76	-42.83	38.31
Infl. Exp. 3 (Exp-opt)	1.44	12.32	-38.9	33.95
Infl. Exp. 3 (Exp-0.3)	1.5	15.89	-63	65.75
Infl. Exp. 4 (ln) MA(10)	0.03	0.48	-1.44	1.4
Infl. Exp. 4 (ln) MA(30)	0.03	0.42	-1.11	0.82
Infl. Exp. 4 (ln) MA(60)	0.02	0.4	-0.89	0.72
Observations	1717			

Note: Summary statistics on the Twitter-based directional indexes, and the four Twitter-based indicators with the initial coarse dictionary and all the 3 MA smoothing windows. Daily sample from June 1, 2013 to December 31, 2019.

Table E.2: Correlations: Twitter-based inflation expectations indicators with the rough initial dictionary and ISTAT Inflation Expectations

Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp -opt)	Infl. Exp. 4 (ln) MA(10)
0.516***	0.525***	0.550***	0.590***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp -0.1)	Infl. Exp. 4 (ln) MA(30)
0.565***	0.570***	0.551***	0.623***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp -0.3)	Infl. Exp. 4 (ln) MA(60)
0.588***	0.593***	0.513***	0.643***

Note: Correlations between the Twitter-based inflation expectations indicators with the rough initial dictionary and ISTAT expectations. Directional indexes are computed using the coarse dictionary used to select the tweets. Data are at the monthly frequency, from June 2013 through December 2019. Daily indicators are collapsed at monthly frequency. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.3: Correlations: Twitter-based inflation expectations indicators with the rough initial dictionary and the Italian Inflation Swap 1Y

Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(10)
0.473***	0.474***	0.515***	0.506***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(30)
0.528***	0.526***	0.527***	0.558***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
0.539***	0.534***	0.428***	0.566***

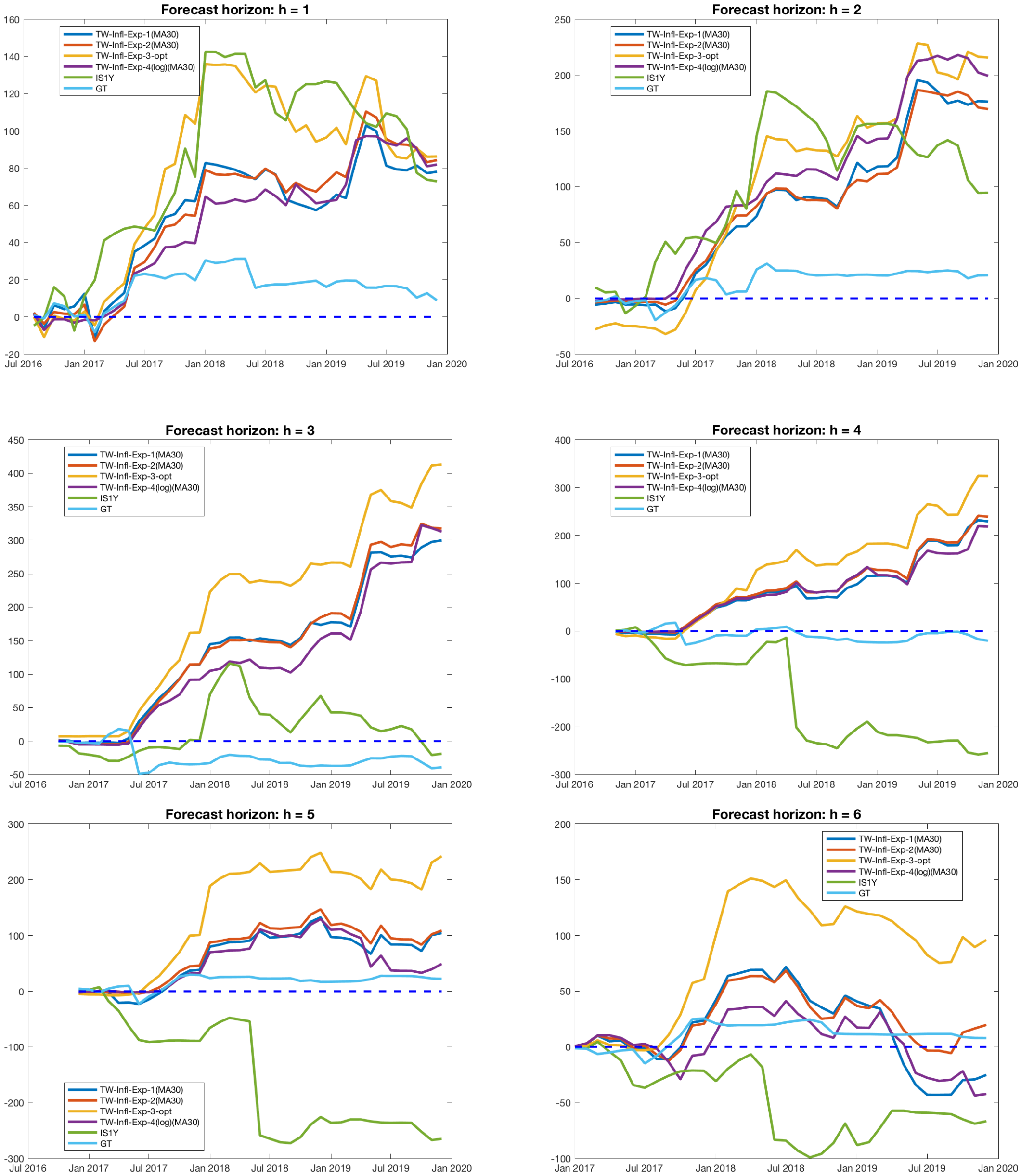
Note: Correlations between the Twitter-based inflation expectations indicators and the Italian Infl. Swap 1Y. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation. Data are at daily frequency, from June 1, 2013 to December 31, 2019. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.4: Informativeness exercise with all indexes with the rough initial dictionary, Consensus Forecast and CPI - MA(30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$E_{t-1}^{ISTAT}\pi_{t-1,t+11}$'	0.673***	0.509***	0.560***	0.567***	0.511***	0.517***	0.460***	0.513***	0.455***	0.520***	0.463***	0.472***	0.425***
	(0.07)	(0.12)	(0.13)	(0.12)	(0.14)	(0.09)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.07)	(0.09)
IS_t^{1Y}		4.194***			4.048***		3.850***		3.845**		3.833***		3.610**
		(1.01)			(1.35)		(1.45)		(1.46)		(1.43)		(1.56)
CF_{t-1}^{y+1}			4.584**		-1.229		-1.015		-0.914		-0.932		-0.573
			(2.17)		(2.36)		(2.88)		(2.89)		(2.84)		(3.04)
CPI_{t-1}				2.279***	0.739		-0.647		-0.668		-0.553		-0.959
				(0.86)	(0.69)		(1.11)		(1.11)		(1.16)		(1.08)
Infl. Exp. 1 MA(30)						0.147***	0.111**						
						(0.04)	(0.05)						
Infl. Exp. 2 MA(30)								0.132***	0.100**				
								(0.04)	(0.05)				
Infl. Exp. 3 (Exp-opt)										0.144***	0.103*		
										(0.05)	(0.05)		
Infl. Exp. 4 (ln) MA(30)												4.966***	4.096**
												(0.76)	(1.64)
Cons.	-2.206***	-6.441***	-8.111**	-4.225**	-5.366	-3.464***	-5.16	-3.322***	-5.164	-3.442***	-5.268	-3.681***	-5.481*
	(0.69)	(1.89)	(3.69)	(1.69)	(3.61)	(0.70)	(3.46)	(0.66)	(3.42)	(0.72)	(3.46)	(0.54)	(3.14)
N	78	78	78	78	78	78	78	78	78	78	78	78	78
R^2	0.451	0.544	0.478	0.491	0.547	0.514	0.567	0.515	0.567	0.511	0.564	0.533	0.578
$Adj.R^2$	0.444	0.532	0.464	0.478	0.522	0.501	0.537	0.502	0.537	0.498	0.533	0.52	0.549
$F-test$	101.2	86.97	143.2	147.7	56.66	85.04	62.13	86.67	60.69	78.17	67.47	102	69.77
$Prob > F$	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: Dependent variable: $E_t^{ISTAT}\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS_t^{1y} is the inflation swap rate at one year and *Infl. Exp. 1, 2 3 and 4* are the Twitter-based inflation expectation indexes with MA(30) with the coarse initial dictionary . CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Sample: June 2013, December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

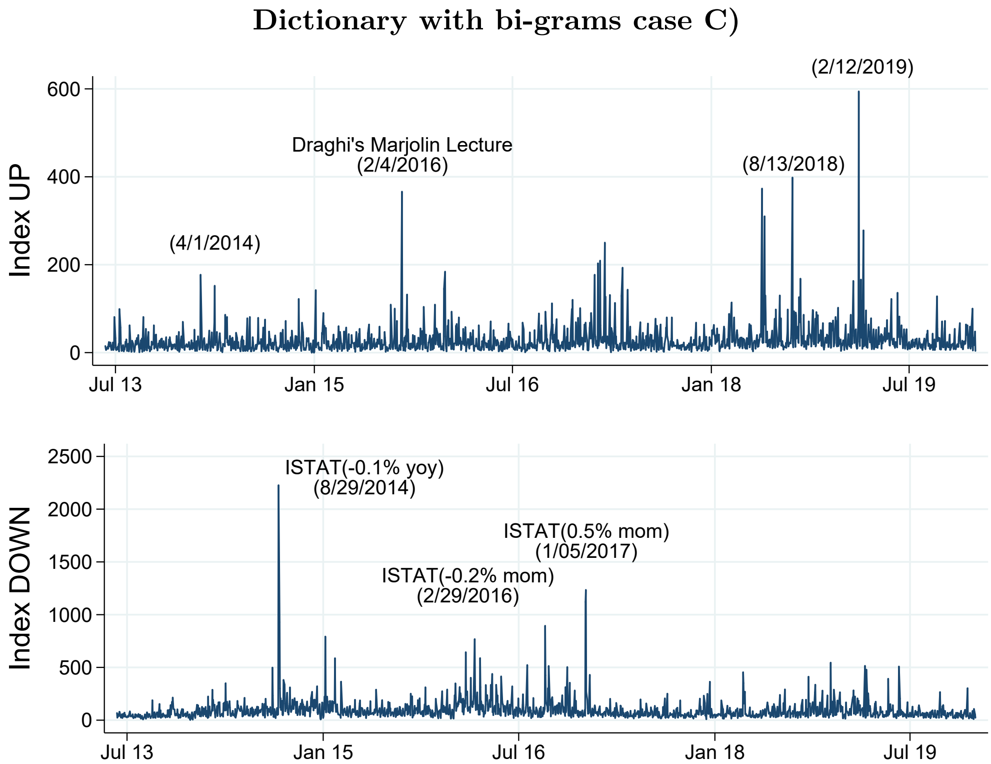
Figure E.3: Out-of-sample comparison: Cumulative Sum of Squared Error Differences - The rough initial dictionary, recursive scheme $R = 36$



Notes: $CSSED_{m,\tau} = \sum_{\tau=R}^{T}(\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau})$. CSSED is below one if the $AR(P)$ benchmark outperforms the competing model and above one if the competing model fairs better. Here we compare the four Twitter-based indexes with a backward-looking MA of 30 days with the market-based index $IS1Y$ and the Google-Trends-based inflation expectation index GT.

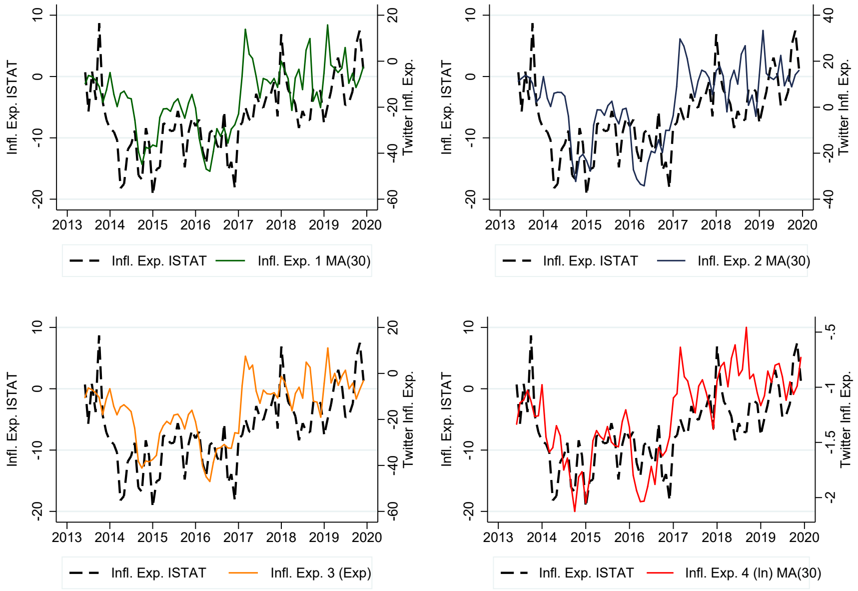
Appendix F Twitter-based inflation expectations with dictionary of only bi-grams

Figure F.1: Dictionary-based Directional Indexes with Bi-Grams

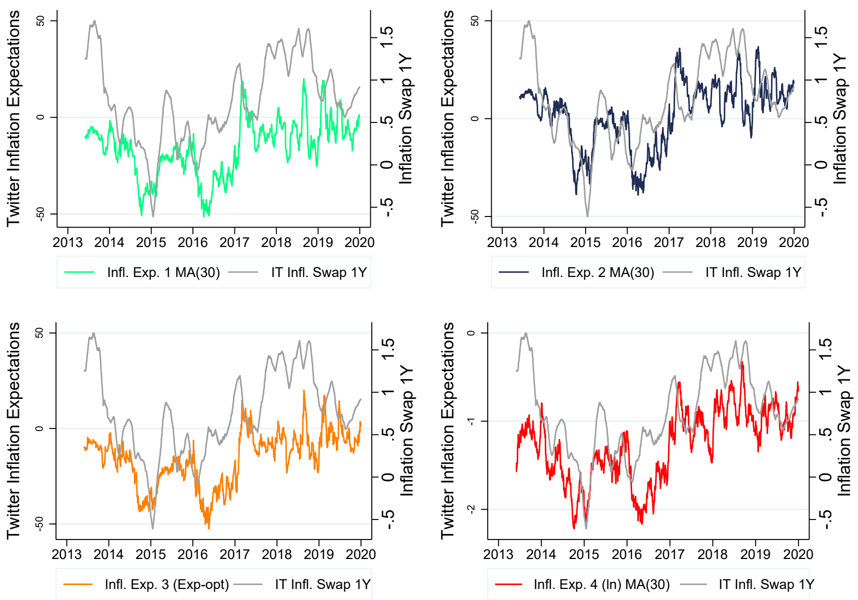


Notes: The figure depicts the two dictionary-based indexes Inflation-Up and Inflation-Down with some events when the volume of tweets is particularly high. The top panel shows the Index Up and the bottom one the Index Down when the directional indexes are computed with the dictionary of manually labelled bi-grams case C).

Figure F.2: Twitter-based Inflation Expectations with bi-grams vs Survey- and Market measures



(a) Twitter-based vs ISTAT Inflation Expectations



(b) Twitter Inflation Expectations vs the Italian Inflation Swap 1Y

Note: The top panel shows the monthly Twitter-based inflation expectation indicators from June 2013 through December 2019 vs the survey-based measures by ISTAT. Daily indicators are collapsed at the monthly frequency for clarity. Twitter-based inflation indexes are computed using topics and the dictionary of bi-grams case (C) to compute the directonal indexes. The bottom panel depicts the daily Twitter-based indexes vs the market-based measure. The sample is from June 1, 2013 through December 31, 2019. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation.

Table F.1: Summary statistics Twitter-based indicators with dictionary of only bi-grams

Variable	Mean	Std. Dev.	Min.	Max
Index Down	92.33	103.43	3.00	2226.00
Index Up	27.34	33.66	0.00	594.00
Infl. Exp. 1 MA(10)	-15.69	18.02	-64.11	60.00
Infl. Exp. 1 MA(30)	-15.77	14.47	-51.31	19.80
Infl. Exp. 1 MA(60)	-15.84	13.07	-50.39	10.44
Infl. Exp. 2 MA(10)	2.10	19.91	-56.71	68.65
Infl. Exp. 2 MA(30)	2.04	16.38	-39.00	36.71
Infl. Exp. 2 MA(60)	1.98	15.07	-37.60	29.61
Infl. Exp. 3 (Exp-0.1)	-15.73	15.52	-59.11	38.32
Infl. Exp. 3 (Exp-opt)	-15.78	13.75	-52.52	20.04
Infl. Exp. 3 (Exp-0.3)	-15.67	20.54	-81.66	73.44
Infl. Exp. 4 (ln) MA(10)	-1.27	0.48	-2.50	-0.04
Infl. Exp. 4 (ln) MA(30)	-1.27	0.40	-2.22	-0.33
Infl. Exp. 4 (ln) MA(60)	-1.28	0.37	-2.08	-0.65
Observations	1717			

Note: Summary statistics on the Twitter-based directional indexes, and the four Twitter-based indicators with dictionary of only bi-grams (case C) and all the 3 MA smoothing windows. Daily sample from June 1, 2013 to December 31, 2019.

Table F.2: Correlations: Twitter-based inflation expectations indicators with dictionary of bi-grams and ISTAT Inflation Expectations

Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp -opt)	Infl. Exp. 4 (ln) MA(10)
0.512***	0.522***	0.555***	0.637***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp -0.1)	Infl. Exp. 4 (ln) MA(30)
0.573***	0.578***	0.600***	0.656***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp -0.3)	Infl. Exp. 4 (ln) MA(60)
0.623***	0.611***	0.506***	0.653***

Note: Correlations between the Twitter-based inflation expectations indicators with dictionary of bi-grams and ISTAT expectations. Directional indexes are computed using the dictionary of bi-grams only case C. Data are at the monthly frequency, from June 2013 through December 2019. Daily indicators are collapsed at monthly frequency. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.3: Correlations: Twitter-based inflation expectations indicators with dictionary of bi-grams and the Italian Inflation Swap 1Y

Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(10)
0.461***	0.506***	0.528***	0.580***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(30)
0.562***	0.602***	0.577***	0.677***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
0.586***	0.617***	0.407***	0.661***

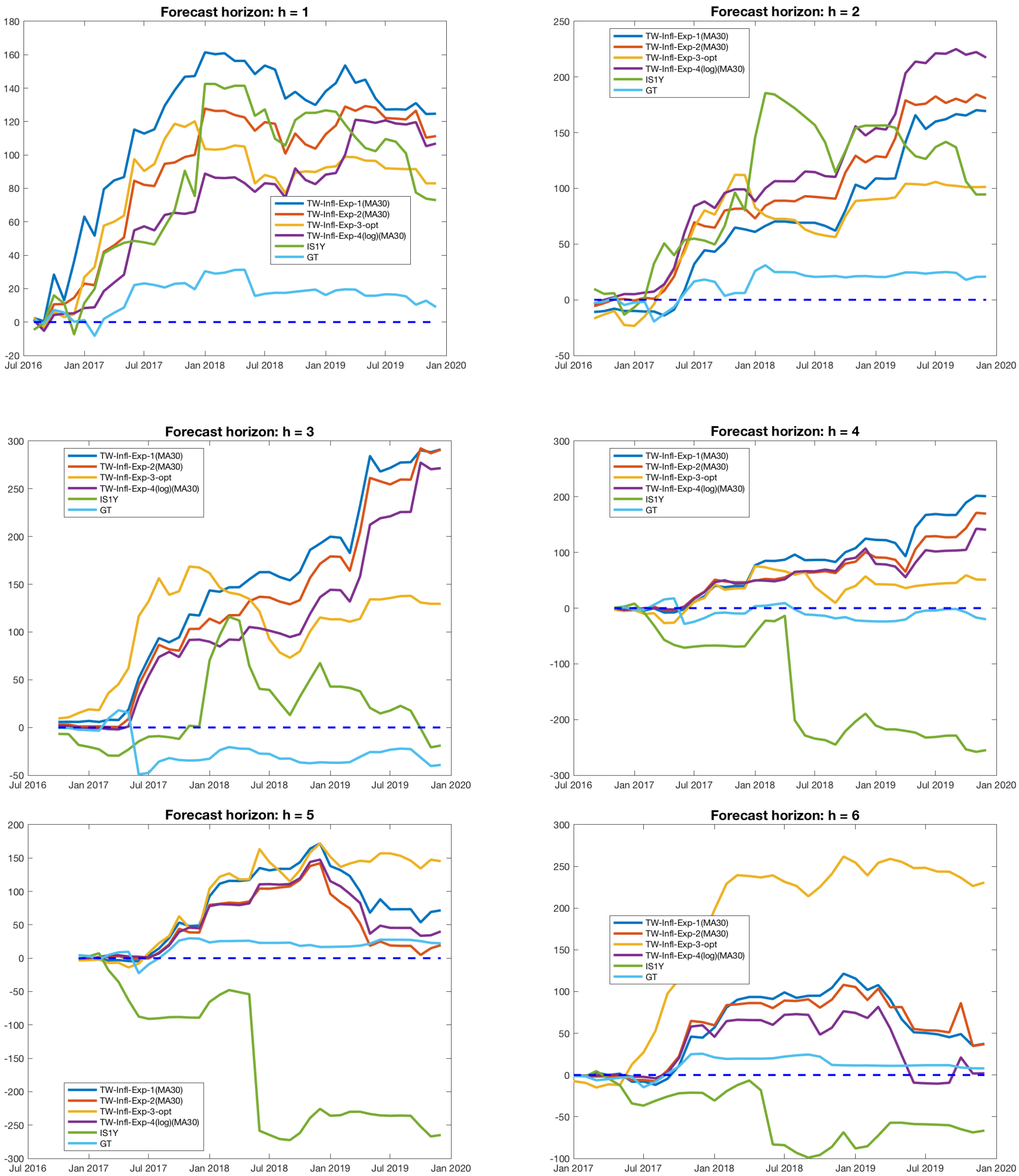
Note: Correlations between the Twitter-based inflation expectations indicators with dictionary of bi-grams and the Italian Infl. Swap 1Y. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation. Directional indexes are computed using the dictionary of bi-grams only case C. Data are at daily frequency, from June 1, 2013 to December 31, 2019. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.4: Informativeness exercise with all indexes with only bi-grams dictionary, Consensus Forecast and CPI - MA(30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$E_{t-1}^{ISTAT}\pi_{t-1,t+11}$'	0.673***	0.509***	0.560***	0.567***	0.511***	0.514***	0.464***	0.511***	0.468***	0.490***	0.447***	0.430***	0.407***
	(0.07)	(0.12)	(0.13)	(0.12)	(0.14)	(0.09)	(0.12)	(0.08)	(0.12)	(0.09)	(0.11)	(0.07)	(0.11)
IS_t^{1Y}		4.194***			4.048***		3.621***		3.448**		3.622***		2.32
		(1.01)			(1.35)		(1.34)		(1.51)		(1.35)		(1.52)
CF_{t-1}^{y+1}			4.584**		-1.229		-0.693		-0.541		-0.759		0.725
			(2.17)		(2.36)		(2.95)		(3.09)		(3.08)		(3.28)
CPI_{t-1}				2.279***	0.739		-0.733		-0.63		-1.076		-1.339
				(0.86)	(0.69)		(1.08)		(0.95)		(1.07)		(1.30)
Infl. Exp. 1 MA(30)						0.130***	0.0971**						
						(0.03)	(0.05)						
Infl. Exp. 2 MA(30)								0.116***	0.0806**				
								(0.02)	(0.04)				
Infl. Exp. 3 (Exp-opt)										0.147***	0.123***		
										(0.03)	(0.04)		
Infl. Exp. 4 (ln) MA(30)												6.214***	5.625***
												(1.23)	(2.10)
Cons.	-2.206***	-6.441***	-8.111**	-4.225**	-5.366	-1.214*	-3.582	-3.523***	-5.346	-1.113*	-3.016	4.045***	1.363
	(0.69)	(1.89)	(3.69)	(1.69)	(3.61)	(0.63)	(3.43)	(0.86)	(3.51)	(0.66)	(3.49)	(1.35)	(3.75)
N	78	78	78	78	78	78	78	78	78	78	78	78	78
R^2	0.451	0.544	0.478	0.491	0.547	0.522	0.567	0.524	0.564	0.528	0.572	0.564	0.585
$Adj.R^2$	0.444	0.532	0.464	0.478	0.522	0.509	0.537	0.511	0.533	0.515	0.542	0.552	0.556
$F-test$	101.2	86.97	143.2	147.7	56.66	87.76	38.22	77.82	66.12	74.52	49.27	82.71	73.17
$Prob > F$	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: Dependent variable: $E_t^{ISTAT}\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS_t^{1y} is the inflation swap rate at one year and *Infl. Exp. 1, 2 3 and 4* are the Twitter-based inflation expectation indexes with MA(30) with the dictionary of only Bi-grams (C). CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Sample: June 2013, December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

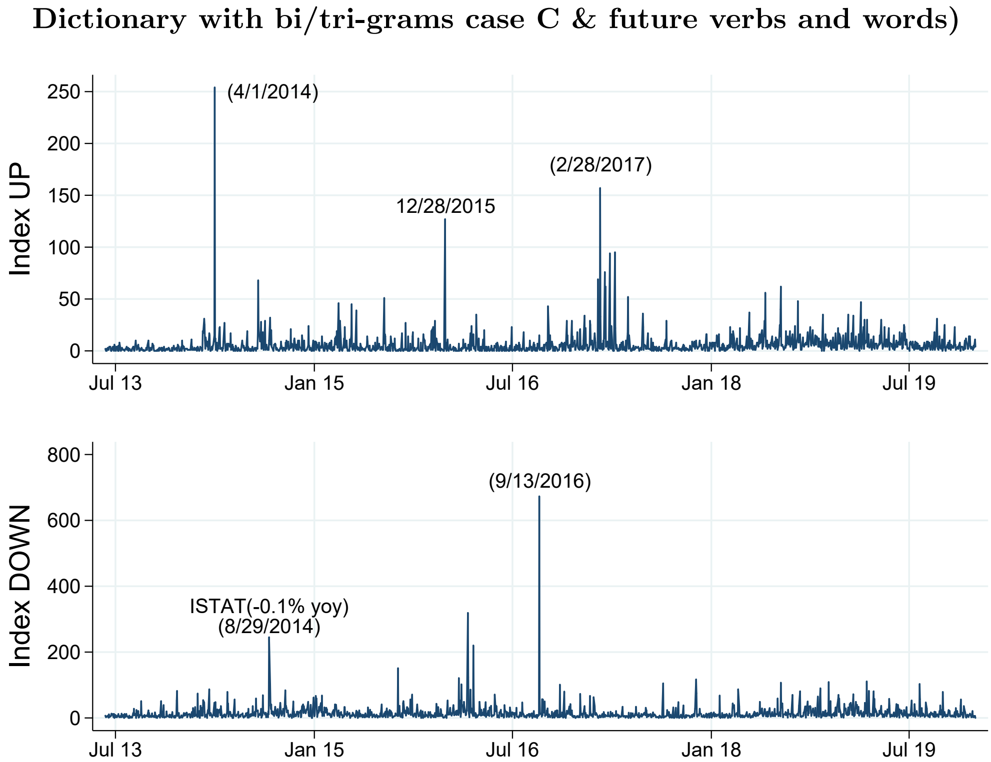
Figure F.3: Out-of-sample comparison: Cumulative Sum of Squared Error Differences - Dictionary with only bi-grams (case C), recursive scheme $R = 36$



Notes: $CSSED_{m,\tau} = \sum_{\tau=R}^{T}(\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau})$. CSSED is below one if the $AR(P)$ benchmark outperforms the competing model and above one if the competing model fairs better. Here we compare the four Twitter-based indexes with a backward-looking MA of 30 days with the market-based index $IS1Y$ and the Google-Trends-based inflation expectation index GT.

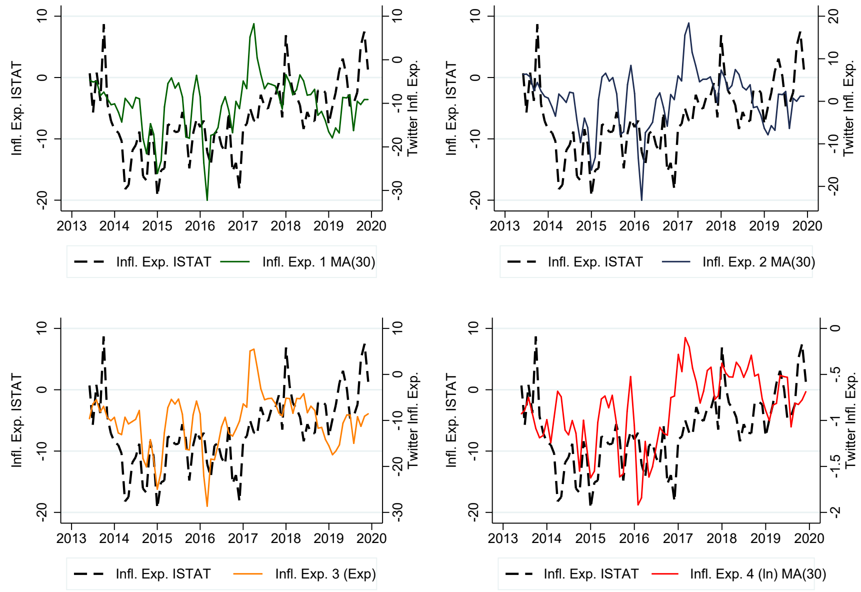
Appendix G Twitter-based inflation expectations with baseline dictionary combined with future verbs and future words

Figure G.1: Dictionary-based Directional Indexes with bi- and tri-grams and future verbs and words combined

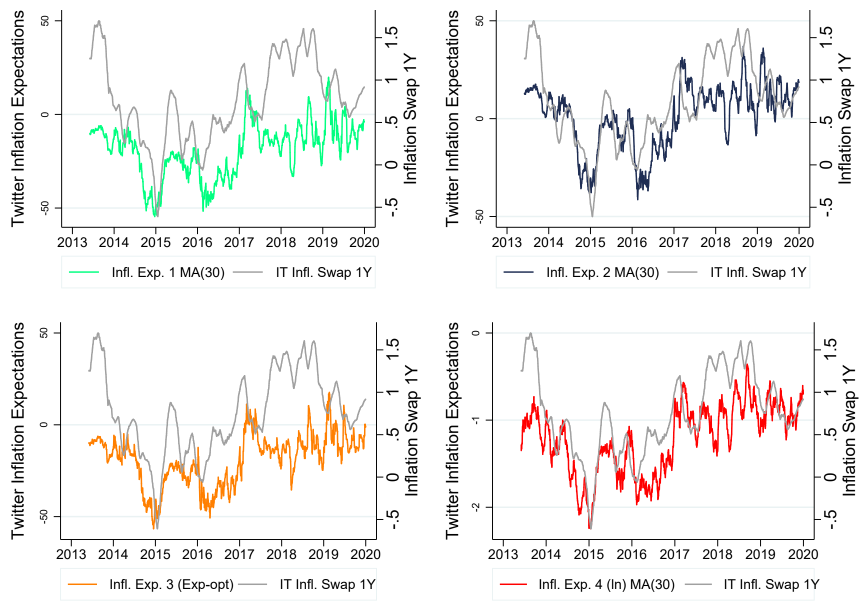


Notes: The figure depicts the two dictionary-based Index Up and Index Down with some events when the volume of tweets is particularly high. The top panel shows the Index Up and the bottom one the Index Down when the directional indexes are computed with the dictionary of manually labelled bi- and tri-grams case C) and future words and verbs in the tweet.

Figure G.2: Twitter-based Inflation Expectations with bi/tri-grams and future verbs and words vs Survey- and Market measures



(a) Twitter-based vs ISTAT Inflation Expectations



(b) Twitter Inflation Expectations vs the Italian Inflation Swap 1Y

Note: The top panel shows the monthly Twitter-based inflation expectation indicators from June 2013 through December 2019 vs the survey-based measures by ISTAT. Daily indicators are collapsed at the monthly frequency for clarity. Twitter-based inflation indexes are computed using the dictionary of bi/tri-grams as in case (C) with future verbs and words. The bottom panel depicts the daily Twitter-based indexes vs the market-based measure. The sample is from June 1, 2013 through December 31, 2019. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation.

Table G.1: Summary statistics Twitter-based indicators with dictionary of bi/tri-grams with future verbs and words

Variable	Mean	Std. Dev.	Min.	Max
Index Down	14.48	24.91	0.00	673.00
Index Up	5.71	11.05	0.00	254.00
Infl. Exp. 1 MA(10)	-10.23	9.12	-42.12	20.81
Infl. Exp. 1 MA(30)	-10.24	6.80	-39.04	13.50
Infl. Exp. 1 MA(60)	-10.20	5.74	-27.88	7.85
Infl. Exp. 2 MA(10)	0.57	9.33	-34.50	30.04
Infl. Exp. 2 MA(30)	0.57	7.01	-30.64	23.37
Infl. Exp. 2 MA(60)	0.61	5.94	-18.25	18.31
Infl. Exp. 3 (Exp-0.1)	-10.28	7.48	-41.14	16.71
Infl. Exp. 3 (Exp-opt)	-10.30	6.21	-34.16	9.49
Infl. Exp. 3 (Exp-0.3)	-10.25	10.95	-62.13	33.92
Infl. Exp. 4 (ln) MA(10)	-0.87	0.54	-2.60	0.80
Infl. Exp. 4 (ln) MA(30)	-0.87	0.41	-2.23	0.25
Infl. Exp. 4 (ln) MA(60)	-0.87	0.36	-1.83	-0.08
Observations	1717			

Note: Summary statistics on the Twitter-based directional indexes, and the four Twitter-based indicators with dictionary of bi/tri-grams (case C) with future verbs and words and all the 3 MA smoothing windows. Daily sample from June 1, 2013 to December 31, 2019.

Table G.2: Correlations: Twitter-based inflation expectations indicators with dictionary of bi-grams and tri-gras with future verbs and words and ISTAT Inflation Expectations

Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp -opt)	Infl. Exp. 4 (ln) MA(10)
0.278***	0.255***	0.334***	0.336***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp -0.1)	Infl. Exp. 4 (ln) MA(30)
0.381***	0.358***	0.376***	0.421***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp -0.3)	Infl. Exp. 4 (ln) MA(60)
0.395***	0.372***	0.263***	0.476***

Note: Correlations between the Twitter-based inflation expectations indicators with dictionary of bi/tri-grams and future words and verbs and ISTAT expectations. Directional indexes are computed using the dictionary of bi/tri-grams for case C. Data are at the monthly frequency, from June 2013 through December 2019. Daily indicators are collapsed at monthly frequency. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table G.3: Correlations: Twitter-based inflation expectations indicators with dictionary of bi-grams and tri-gras with future verbs and words and the Italian Inflation Swap 1Y

Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(10)
0.497***	0.548***	0.570***	0.626***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(30)
0.611***	0.657***	0.616***	0.736***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
0.627***	0.671***	0.438***	0.719***

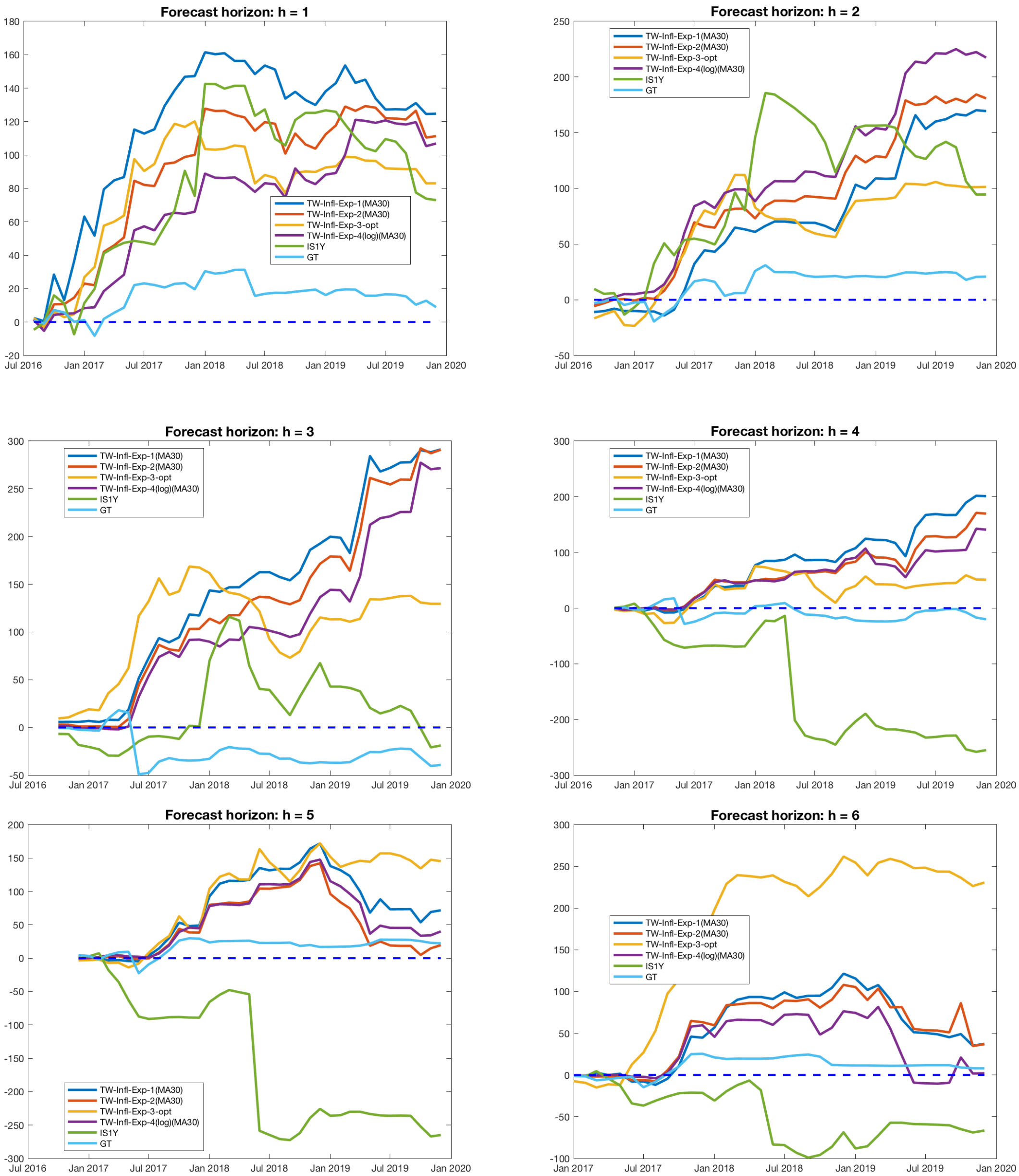
Note: Correlations between the Twitter-based inflation expectations indicators with dictionary of bi-grams and tri-grams with future verbs and words and the Italian Infl. Swap 1Y. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation. Data are at daily frequency, from June 1, 2013 to December 31, 2019. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table G.4: Informativeness exercise with all indexes with baseline dictionary and future verbs and words, Consensus Forecast and CPI - MA(30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$E_{t-1}^{ISTAT}\pi_{t-1,t+11}$'	0.673***	0.509***	0.560***	0.567***	0.511***	0.621***	0.511***	0.628***	0.513***	0.616***	0.508***	0.599***	0.508***
	(0.07)	(0.12)	(0.13)	(0.12)	(0.14)	(0.08)	(0.14)	(0.08)	(0.14)	(0.09)	(0.14)	(0.06)	(0.14)
IS_t^{1Y}		4.194***			4.048***		3.433**		3.515**		3.618***		3.375*
		(1.01)			(1.35)		(1.47)		(1.53)		(1.36)		(1.86)
CF_{t-1}^{y+1}			4.584**		-1.229		-0.297		-0.442		-0.513		0.0133
			(2.17)		(2.36)		(3.05)		(3.09)		(2.98)		(3.18)
CPI_{t-1}				2.279***	0.739		0.204		0.316		0.269		0.091
				(0.86)	(0.69)		(0.61)		(0.57)		(0.68)		(0.98)
Infl. Exp. 1 MA(30)						0.221***	0.108*						
						(0.07)	(0.06)						
Infl. Exp. 2 MA(30)								0.203***	0.0849				
								(0.07)	(0.07)				
Infl. Exp. 3 (Exp-opt)										0.224**	0.0923		
										(0.09)	(0.08)		
Infl. Exp. 4 (ln) MA(30)												3.828***	1.478
												(0.80)	(1.54)
Cons.	-2.206***	-6.441***	-8.111**	-4.225**	-5.366	-0.274	-4.527	-2.606***	-5.634	-0.273	-4.643	0.635	-4.615
	(0.69)	(1.89)	(3.69)	(1.69)	(3.61)	(0.72)	(3.32)	(0.95)	(3.78)	(0.75)	(3.28)	(0.79)	(3.64)
N	78	78	78	78	78	78	78	78	78	78	78	78	78
R^2	0.451	0.544	0.478	0.491	0.547	0.505	0.556	0.5	0.553	0.497	0.552	0.51	0.55
$Adj.R^2$	0.444	0.532	0.464	0.478	0.522	0.492	0.525	0.487	0.522	0.483	0.521	0.497	0.519
$F-test$	101.2	86.97	143.2	147.7	56.66	88.31	54.53	75.78	62.38	74.16	46.33	93.15	50.59
$Prob > F$	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: Dependent variable: $E_t^{ISTAT}\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS_t^{1y} is the inflation swap rate at one year and *Infl. Exp. 1, 2 3 and 4* are the Twitter-based inflation expectation indexes with MA(30) with the dictionary with Bi- and Tri-grams (C). CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Sample: June 2013, December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

Figure G.3: Out-of-sample comparison: Cumulative Sum of Squared Error Differences - Dictionary with bi/tri-grams as in case C) and future words and verbs, recursive scheme $R = 36$



Notes: $CSSED_{m,\tau} = \sum_{\tau=R}^{T}(\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau})$. CSSED is below one if the $AR(P)$ benchmark outperforms the competing model and above one if the competing model fairs better. Here we compare the four Twitter-based indexes with a backward-looking MA of 30 days with the market-based index $IS1Y$ and the Google-Trends-based inflation expectation index GT.

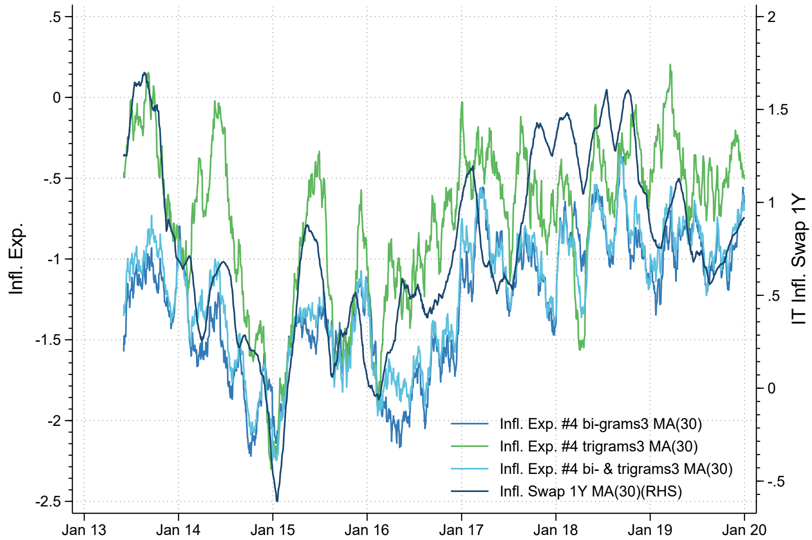
Appendix H Robustness across dictionaries

This section of the Appendix shows how the different dictionaries (made of only bi-grams, only tri-grams or bi- and tri-grams) affect the computation of the Twitter-based indexes of inflation expectations. It also shows how the different thresholds with respect to the yearly average number of tweets containing the bi- or tri-grams affect the final indexes.

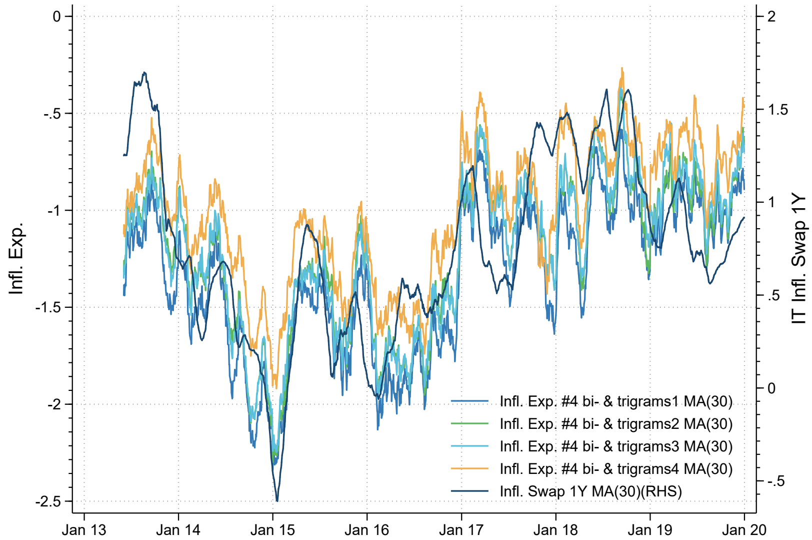
When we look at the behavior of the Twitter-based indicators across dictionaries we can see from the top panel of Figure H.1 the indexes computed with only bi-grams and bi- and tri-grams are highly correlated (0.96), while the correlation with the index computed with only tri-grams is lower (0.65). This can be seen in the large fluctuations of the green line related to tri-grams and it is due to the fact that the volume of tri-grams is much lower than that of bi-grams.

Looking at the behavior of the Twitter-based indexes with respect to the different thresholds to select the average yearly volume of tweets containing the n-grams (the bottom panel of Figure H.1), we can see that the different Twitter indexes are all highly correlated among them (between 0.97 and 0.99). Apparently, the signal that is captured by bi- and tri-grams is not affected by the threshold we select to build the dictionary. In fact, even choosing the top 5% and thus the most frequent n-grams is enough to capture the signal of the tweets on inflation and price dynamics.

Figure H.1: Twitter-based Inflation Expectations with different dictionaries of bi- and/or tri-grams vs Market-based measures



(a) Twitter-based Inflation Expectations vs Inflation Swap 1Y (across dictionaries)

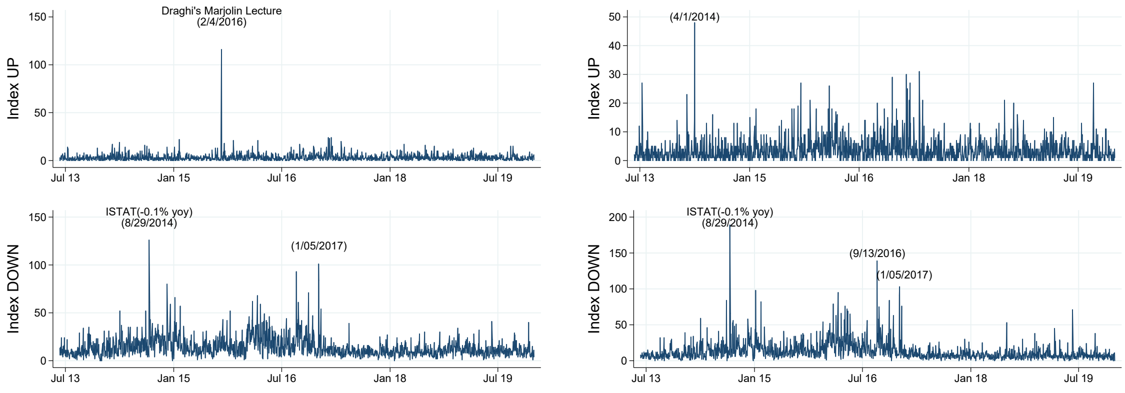


(b) Twitter-based Inflation Expectations vs Inflation Swap 1Y (across thresholds)

Note: The top panel shows the Twitter-based inflation expectation indicators from June 2013 through December 2019 vs the Inflation Swap 1Y. Twitter-based inflation indexes are computed across different dictionaries. The bottom panel depicts the daily Twitter-based indexes vs the market-based measure. Here the Twitter-based indexes are computed across thresholds. The sample is from June 1, 2013 through December 31, 2019. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation.

Appendix I Twitter-based inflation expectations with baseline dictionary from the Econ and News subsamples

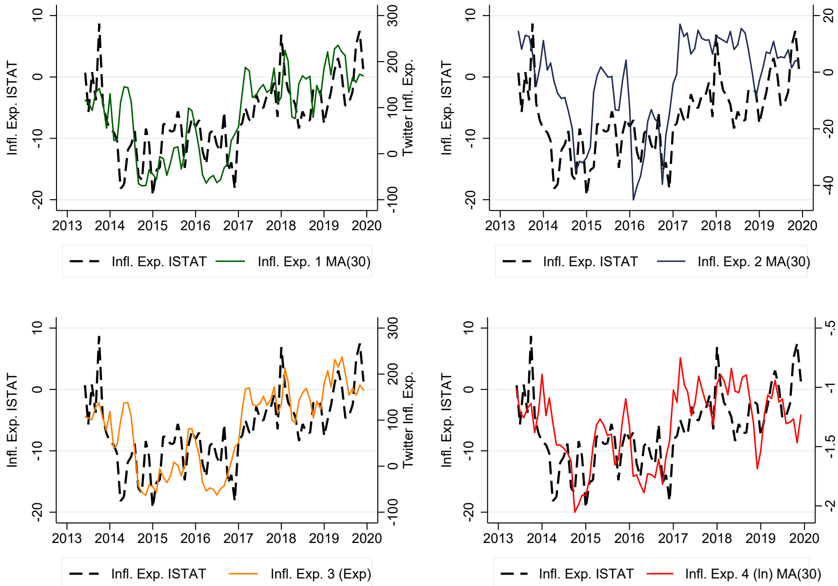
Figure I.1: Dictionary-based Directional Indexes with baseline dictionary from Econ and News subsamples



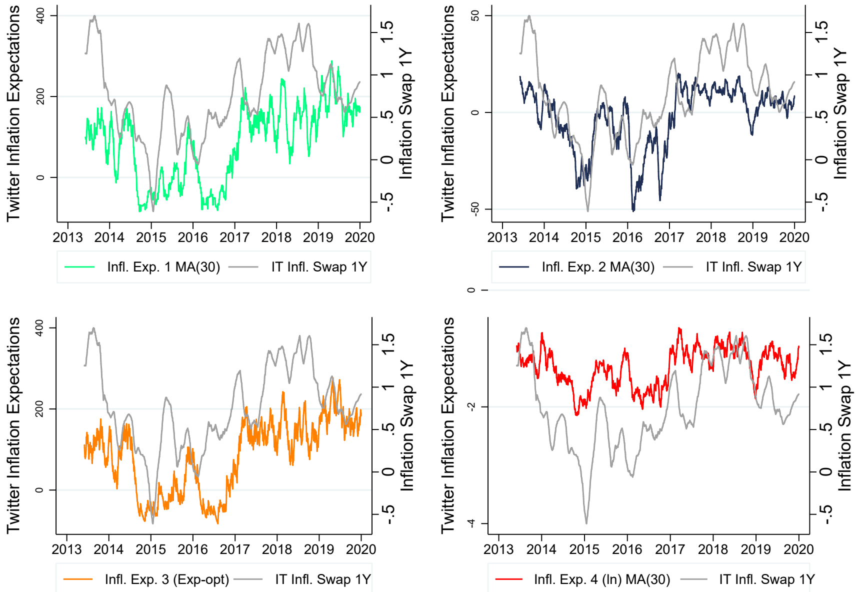
(a) **Baseline Dictionary from Econ subsample** (b) **Baseline Dictionary from News subsample**

Notes: The figure depicts the two dictionary-based indexes Index Up and Index Down with some events when the volume of tweets is particularly high. The left panel shows the Index Up and Down for the Econ subsample, while the right one the News subsample. Directional indexes are computed with the baseline dictionary of manually labelled bi- and tri-grams.

Figure I.2: Twitter-based Inflation Expectations with bi/tri-grams from Econ subsample vs Survey- and Market measures



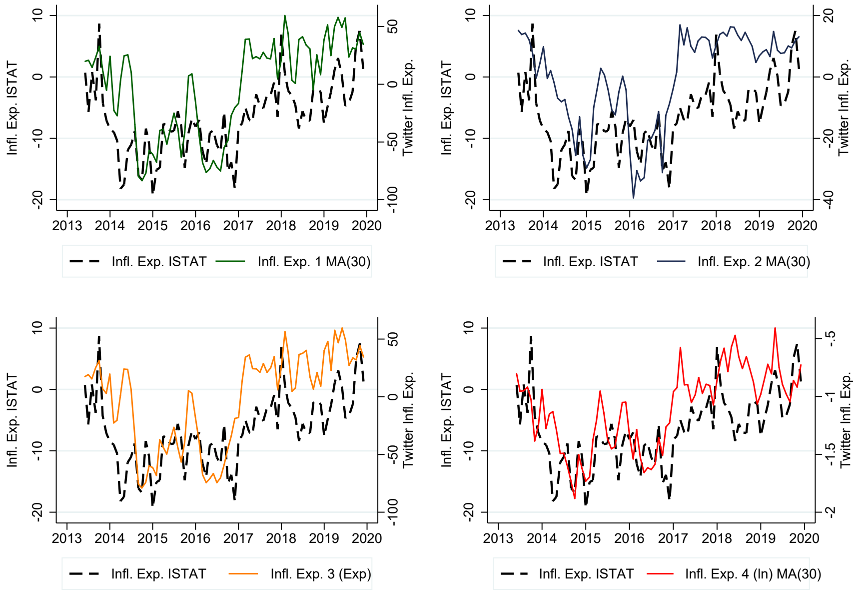
(a) Twitter-based vs ISTAT Inflation Expectations



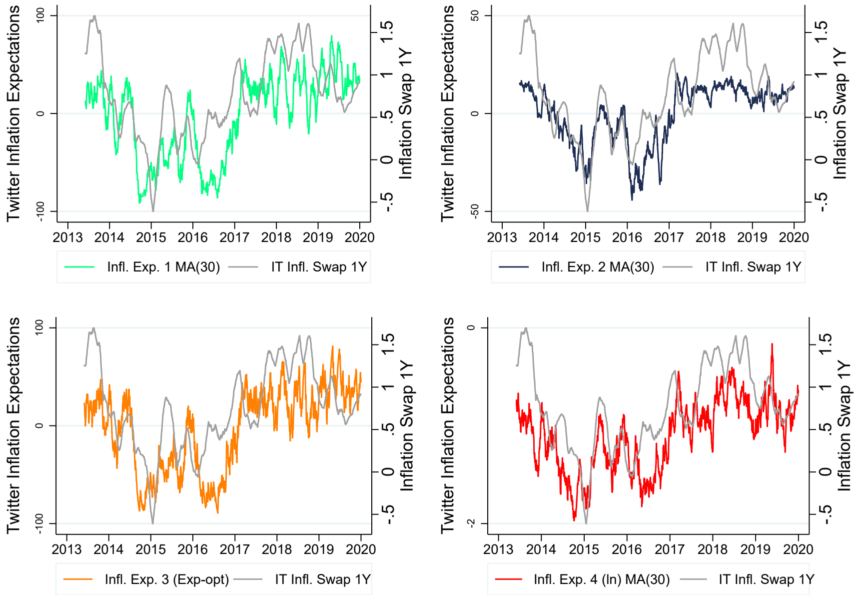
(b) Twitter Inflation Expectations vs the Italian Inflation Swap 1Y

Note: The top panel shows the monthly Twitter-based inflation expectation indicators from June 2013 through December 2019 vs the survey-based measures by ISTAT. Daily indicators are collapsed at the monthly frequency for clarity. Twitter-based inflation indexes are computed using the dictionary of bi/tri-grams as in case (C) from Econ subsample. The bottom panel depicts the daily Twitter-based indexes vs the market-based measure. The sample is from June 1, 2013 through December 31, 2019. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation.

Figure I.3: Twitter-based Inflation Expectations with bi/tri-grams from News subsample vs Survey- and Market measures



(a) Twitter-based vs ISTAT Inflation Expectations



(b) Twitter Inflation Expectations vs the Italian Inflation Swap 1Y

Note: The top panel shows the monthly Twitter-based inflation expectation indicators from June 2013 through December 2019 vs the survey-based measures by ISTAT. Daily indicators are collapsed at the monthly frequency for clarity. Twitter-based inflation indexes are computed using the dictionary of bi/tri-grams as in case (C) from News subsample. The bottom panel depicts the daily Twitter-based indexes vs the market-based measure. The sample is from June 1, 2013 through December 31, 2019. *IT Infl. Swap 1Y* is the rate on the 1-year inflation swap contract linked to the Italian inflation.

Table I.1: Summary statistics of Twitter-based indicators with baseline dictionary - Eco/News subsamples

Variable	Mean	Std. Dev.	Min	Max
Econ subsample				
Index Down	13.82	10.38	0.00	126.00
Index Up	3.23	4.19	0.00	116.00
Infl. Exp. 1 MA(10)	84.38	107.47	-101.82	328.43
Infl. Exp. 1 MA(30)	84.01	92.08	-84.03	287.94
Infl. Exp. 1 MA(60)	83.27	85.66	-79.77	255.29
Infl. Exp. 2 MA(10)	-2.81	18.41	-70.54	31.05
Infl. Exp. 2 MA(30)	-2.76	15.92	-51.12	20.13
Infl. Exp. 2 MA(60)	-2.64	14.99	-44.82	19.23
Infl. Exp. 3 (Exp-0.1)	84.17	96.52	-94.67	312.62
Infl. Exp. 3 (Exp-opt)	83.68	88.17	-82.73	276.65
Infl. Exp. 3 (Exp-0.3)	84.48	120.51	-103.15	328.36
Infl. Exp. 4 (ln) MA(10)	-1.32	0.41	-2.40	-0.05
Infl. Exp. 4 (ln) MA(30)	-1.32	0.32	-2.15	-0.65
Infl. Exp. 4 (ln) MA(60)	-1.32	0.30	-2.06	-0.83
News subsample				
Index Down	12.88	12.93	0.00	189.00
Index Up	3.58	4.00	0.00	48.00
Infl. Exp. 1 MA(10)	-2.52	48.76	-100.00	100.00
Infl. Exp. 1 MA(30)	-2.66	42.26	-91.28	79.36
Infl. Exp. 1 MA(60)	-2.91	39.42	-85.30	66.16
Infl. Exp. 2 MA(10)	-0.53	17.43	-64.33	28.48
Infl. Exp. 2 MA(30)	-0.53	15.20	-44.19	20.54
Infl. Exp. 2 MA(60)	-0.55	14.41	-36.56	18.27
Infl. Exp. 3 (Exp-0.1)	-2.59	44.10	-95.89	92.30
Infl. Exp. 3 (Exp-opt)	-2.69	41.56	-89.23	81.27
Infl. Exp. 3 (Exp-0.3)	-2.49	54.09	-99.99	99.97
Infl. Exp. 4 (ln) MA(10)	-1.10	0.45	-2.56	0.15
Infl. Exp. 4 (ln) MA(30)	-1.10	0.35	-1.97	-0.16
Infl. Exp. 4 (ln) MA(60)	-1.11	0.33	-1.80	-0.46
Observations	1717			

Note: Summary statistics on the filtered dataset with baseline dictionary (bi- and tri-grams) for Econ and News subsamples. Data are at daily frequency from June 1, 2013 to December 31, 2019.

Table I.2: Correlations: Twitter-based indicators from News/Econ subsamples and ISTAT Inflation Expectations

Econ			
Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(10)
0.584**	0.560**	0.610***	0.483***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(30)
0.619**	0.620***	0.639***	0.551***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
0.651**	0.654***	0.586**	0.564***
News			
Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(10)
0.602**	0.613**	0.627***	0.601***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(30)
0.636**	0.657***	0.646***	0.646***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
0.663**	0.673***	0.600**	0.658***

Note: Correlations between the Twitter inflation expectations indicators, computed on the sub-samples with Econ and News in the bio, and the ISTAT survey-based expectations. Data are at monthly frequency, from June 2013 through December 2019. Daily indicators are collapsed at the monthly frequency. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table I.3: Correlations: Twitter-based indicators from News/Econ subsamples and Italian Inflation Swap 1Y

Econ			
Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(10)
0.518***	0.606***	0.562***	0.507***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(30)
0.578***	0.679***	0.587***	0.627***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
0.576***	0.693***	0.0464***	0.666***
News			
Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(10)
0.553***	0.658***	0.597***	0.563***
Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(30)
0.612***	0.733***	0.617***	0.697***
Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
0.610***	0.724***	0.500***	0.722***

Note: Correlations between the Twitter inflation expectations indicators, computed on the sub-samples with Econ and News in the bio, and the Italian Inflation Swap 1Y. IT Infl. Swap 1Y is the rate on the 1-year inflation swap contract linked to Italian inflation. Data are at daily frequency, from June 1, 2013 through December 31, 2019. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table I.4: Informativeness exercise with all indexes with baseline dictionary from Econ subsample, Consensus Forecast and CPI - MA(30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$E_{t-1}^{ISTAT}\pi_{t-1,t+11}$'	0.673***	0.509***	0.560***	0.567***	0.511***	0.470***	0.433***	0.487***	0.468***	0.448***	0.415***	0.536***	0.495***
	(0.07)	(0.12)	(0.13)	(0.12)	(0.14)	(0.08)	(0.10)	(0.09)	(0.12)	(0.08)	(0.09)	(0.10)	(0.14)
IS_t^{1Y}		4.194***			4.048***		3.585**		2.717		3.575**		3.304*
		(1.01)			(1.35)		(1.54)		(1.74)		(1.53)		(1.73)
CF_{t-1}^{y+1}			4.584**		-1.229		-0.941		-0.599		-1.087		-1.109
			(2.17)		(2.36)		(2.64)		(3.23)		(2.65)		(2.90)
CPI_{t-1}				2.279***	0.739		-0.763		-0.461		-0.98		-0.0244
				(0.86)	(0.69)		(1.22)		(0.77)		(1.18)		(0.73)
Infl. Exp. 1 MA(30)						0.0226***	0.0176**						
						(0.00)	(0.01)						
Infl. Exp. 2 MA(30)								0.140***	0.102**				
								(0.03)	(0.04)				
Infl. Exp. 3 (Exp-opt)										0.0251***	0.0212**		
										(0.00)	(0.01)		
Infl. Exp. 4 (ln) MA(30)												5.821***	3.285**
												(1.53)	(1.56)
Cons.	-2.206***	-6.441***	-8.111**	-4.225**	-5.366	-5.468***	-6.480**	-3.039***	-4.374	-5.824***	-6.599**	4.591***	-0.256
	(0.69)	(1.89)	(3.69)	(1.69)	(3.61)	(0.72)	(2.99)	(0.85)	(3.75)	(0.73)	(2.92)	(1.73)	(3.58)
N	78	78	78	78	78	78	78	78	78	78	78	78	78
R^2	0.451	0.544	0.478	0.491	0.547	0.53	0.573	0.552	0.573	0.537	0.579	0.526	0.56
$Adj.R^2$	0.444	0.532	0.464	0.478	0.522	0.517	0.543	0.54	0.544	0.524	0.55	0.513	0.529
$F-test$	101.2	86.97	143.2	147.7	56.66	137.9	50.3	62.38	77.48	123.3	48.2	81.56	66.26
$Prob > F$	0	0	0	0	0	0	0	0	0	0	0	0	0

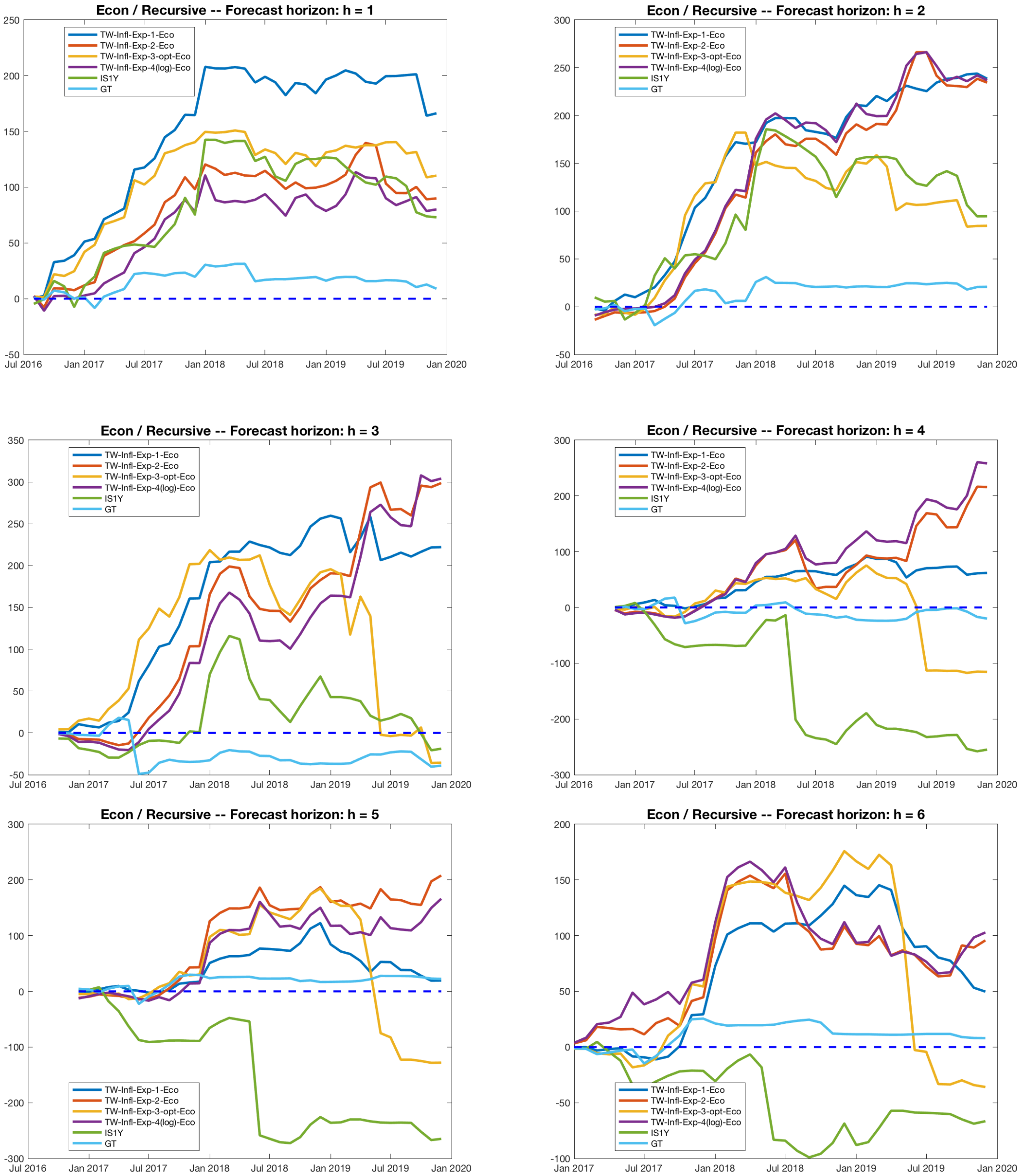
Note: Dependent variable: $E_t^{ISTAT}\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS_t^{1y} is the inflation swap rate at one year and *Infl. Exp. 1, 2 3 and 4* are the Twitter-based inflation expectation indexes with MA(30) with the baseline dictionary from Econ subsample. CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Sample: June 2013, December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

Table I.5: Informativeness exercise with all indexes with baseline dictionary from News subsample, Consensus Forecast and CPI - MA(30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$E_{t-1}^{ISTAT}\pi_{t-1,t+11}$'	0.673***	0.509***	0.560***	0.567***	0.511***	0.456***	0.429***	0.446***	0.437***	0.446***	0.421***	0.455***	0.443***
	(0.07)	(0.12)	(0.13)	(0.12)	(0.14)	(0.08)	(0.10)	(0.07)	(0.10)	(0.08)	(0.09)	(0.06)	(0.10)
IS_t^{1Y}		4.194***			4.048***		3.353**		2.261		3.306**		2.542
		(1.01)			(1.35)		(1.54)		(1.74)		(1.54)		(1.55)
CF_{t-1}^{y+1}			4.584**		-1.229		-0.848		0.105		-0.887		-0.148
			(2.17)		(2.36)		(2.84)		(3.10)		(2.86)		(2.60)
CPI_{t-1}				2.279***	0.739		-0.859		-0.925		-0.973		-0.39
				(0.86)	(0.69)		(1.14)		(1.00)		(1.13)		(1.05)
Infl. Exp. 1 MA(30)						0.0524***	0.0419**						
						(0.01)	(0.02)						
Infl. Exp. 2 MA(30)								0.158***	0.131**				
								(0.03)	(0.06)				
Infl. Exp. 3 (Exp-opt)										0.0553***	0.0460**		
										(0.01)	(0.02)		
Infl. Exp. 4 (ln) MA(30)												6.663***	4.664**
												(1.06)	(2.14)
Cons.	-2.206***	-6.441***	-8.111**	-4.225**	-5.366	-3.514***	-4.786	-3.618***	-4.976	-3.578***	-4.681	3.712***	-0.0958
	(0.69)	(1.89)	(3.69)	(1.69)	(3.61)	(0.56)	(3.18)	(0.80)	(3.48)	(0.55)	(3.16)	(1.20)	(4.50)
N	78	78	78	78	78	78	78	78	78	78	78	78	78
R^2	0.451	0.544	0.478	0.491	0.547	0.54	0.576	0.559	0.575	0.544	0.579	0.552	0.57
$Adj.R^2$	0.444	0.532	0.464	0.478	0.522	0.527	0.547	0.547	0.545	0.531	0.55	0.54	0.54
$F-test$	101.2	86.97	143.2	147.7	56.66	107.8	55.17	48.63	78.15	95.68	55.87	81.2	90.62
$Prob>F$	0	0	0	0	0	0	0	0	0	0	0	0	0

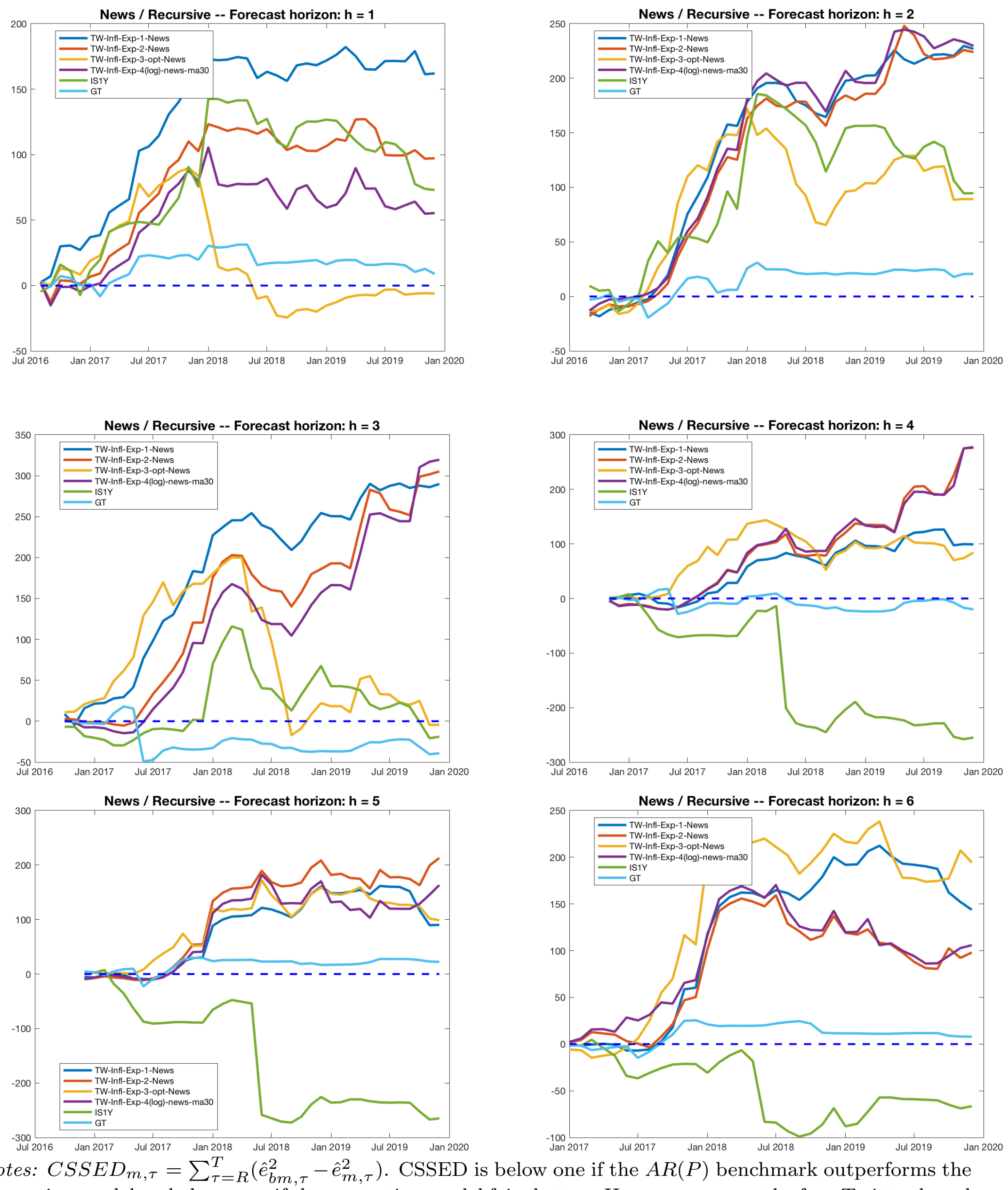
Note: Dependent variable: $E_t^{ISTAT}\pi_{t,t+12}$ is the survey-based inflation expectation measure (see text for details). IS_t^{1y} is the inflation swap rate at one year and *Infl. Exp. 1, 2 3 and 4* are the Twitter-based inflation expectation indexes with MA(30) with the baseline dictionary from News subsample. CF_{t-1}^{y+1} is the monthly average of Consensus Forecast on the Italian inflation for one year ahead. CPI_{t-1} is the lagged Italian CPI. Sample: June 2013, December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. Significance values based on small sample statistics. *** p<0.01, ** p<0.05, * p<0.1.

Figure I.4: Out-of-sample comparison: Cumulative Sum of Squared Error Differences - Baseline case, recursive scheme $R = 36$, Econ Bio



Notes: $CSSED_{m,\tau} = \sum_{\tau=R}^{T}(\hat{e}^2_{bm,\tau} - \hat{e}^2_{m,\tau})$. CSSED is below one if the $AR(P)$ benchmark outperforms the competing model and above one if the competing model fairs better. Here we compare the four Twitter-based indexes with a backward-looking MA of 30 days with the market-based index $IS1Y$ and the Google-Trends-based inflation expectation index GT.

Figure I.5: Out-of-sample comparison: Cumulative Sum of Squared Error Differences - Baseline case, recursive scheme $R = 36$, News Bio



Notes: $CSSED_{m,\tau} = \sum_{\tau=R}^{T}(\hat{e}_{bm,\tau}^2 - \hat{e}_{m,\tau}^2)$. CSSED is below one if the $AR(P)$ benchmark outperforms the competing model and above one if the competing model fairs better. Here we compare the four Twitter-based indexes with a backward-looking MA of 30 days with the market-based index $IS1Y$ and the Google-Trends-based inflation expectation index GT.

Table I.6: Correlations: Twitter and ISTAT Inflation Expectations (News in the bio)

	Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(10)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.0825***	0.237***	0.0893***	9.817***
	(0.011)	(0.036)	(0.012)	(1.336)
Cons.	-6.448***	-6.535***	-6.426***	4.173**
	(0.696)	(0.533)	(0.644)	(1.790)
N	79	79	79	79
R^2	0.362	0.376	0.393	0.361
	Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(30)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.0913***	0.261***	0.0948***	11.24***
	(0.011)	(0.056)	(0.012)	(1.489)
Cons.	-6.418***	-6.516***	-6.404***	5.753***
	(0.633)	(0.761)	(0.611)	(2.002)
N	79	79	79	79
R^2	0.405	0.431	0.417	0.417
	Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.100***	0.273***	0.0817***	11.99***
	(0.012)	(0.052)	(0.011)	(1.618)
Cons.	-6.368***	-6.515***	-6.447***	6.595***
	(0.604)	(0.750)	(0.702)	(2.092)
N	79	79	79	79
R^2	0.44	0.445	0.36	0.421

Note: Table displays results from estimating univariate regressions $E_t^{ISTAT}(\pi_{t,t+12}) = \alpha + \beta Infl.Exp_t + \varepsilon_t$. The dependent variable is the ISTAT inflation expectations, while the independent variables are the Twitter inflation expectations indicators computed on the sub-sample with news in the bio. Data are at monthly frequency from June 2013 through December 2019. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table I.7: Twitter and ISTAT Inflation Expectations (Econ in the bio)

	Infl. Exp. 1 MA(10)	Infl. Exp. 2 MA(10)	Infl. Exp. 3 (Exp-0.1)	Infl. Exp. 4 (ln) MA(10)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.0365***	0.209***	0.0398***	8.674***
	(0.004)	(0.041)	(0.004)	(1.729)
Cons.	-9.744***	-6.068***	-10.01***	4.808*
	(0.590)	(0.837)	(0.534)	(2.442)
N	79	79	79	79
R^2	0.341	0.314	0.372	0.233
	Infl. Exp. 1 MA(30)	Infl. Exp. 2 MA(30)	Infl. Exp. 3 (Exp-opt)	Infl. Exp. 4 (ln) MA(30)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.0408***	0.236***	0.0438***	10.52***
	(0.004)	(0.041)	(0.005)	(1.427)
Cons.	-10.09***	-6.002***	-10.33***	7.242***
	(0.539)	(0.770)	(0.561)	(2.226)
N	79	79	79	79
R^2	0.383	0.384	0.408	0.303
	Infl. Exp. 1 MA(60)	Infl. Exp. 2 MA(60)	Infl. Exp. 3 (Exp-0.3)	Infl. Exp. 4 (ln) MA(60)
$E_t^{ISTAT}(\pi_{t,t+12})$	0.0454***	0.261***	0.0365***	11.46***
	(0.005)	(0.040)	(0.004)	(1.429)
Cons.	-10.45***	-5.972***	-9.741***	8.451***
	(0.622)	(0.833)	(0.601)	(2.393)
N	79	79	79	79
R^2	0.424	0.428	0.343	0.318

Note: Table displays results from estimating univariate regressions $E_t^{ISTAT}(\pi_{t,t+12}) = \alpha + \beta Infl.Exp_t + \varepsilon_t$. The dependent variable is the ISTAT inflation expectations, while the independent variables are the Twitter inflation expectations indicators computed on the sub-sample with eco in the bio. Data are at the monthly frequency from June 2013 through December 2019. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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