Appendices

Online Supplemental Material for

The power of text-based indicators in forecasting Italian economic activity

Valentina Aprigliano,[*] **Simone Emiliozzi,**[*] **Gabriele Guaitoli,**[**]

Andrea Luciani,[*] **Juri Marcucci,**[*] **and Libero Monteforte**[*,†]

[*] *Bank of Italy,* [**] *University of Warwick,* [†] *UPB*

December 2021

Contents

A Additional Material (Not for publication)

In this Appendix we provide further details on the textual data we use in our empirical exercise. We also outline further details on the empirical results not reported in the main paper.

A.1 Data and Methodology

We extract the textual data from Dow Jones Factiva Analytics (previously called Dow Jones Factiva Data, News and Analytics or Factiva DNA), taking all available articles in Italian containing economic or financial keywords, published in the paper and online edition from 1 January 1995 in four newspapers: i) *Il Sole 24 Ore*; ii) *Il Corriere della Sera*; iii) *La Repubblica*; and iv) *La Stampa*. The exact query is as follows:[1]

> ((*economi** OR *finanza* OR *finanziar** OR *finanze* OR *moneta* OR *monetari** OR ``*banca centrale*'' OR *BCE* OR *bankit** OR ``*banca d'italia*'' OR NS=(e12 OR ecat or mcat or ccat) or *prezzo* OR *prezzi* OR ``*costo della vita*'' OR *inflaz** OR ``*caro bollette*'' OR ``*caro prezzi*'' OR *caroprezzi* OR ``*benzina alle stelle*'' OR ``*bolletta salata*'' OR ``*caro affitti*'' OR ``*caro benzina*'' OR ``*caro carburante*'' OR ``*caro gas*'' OR *deflaz** OR *disinflaz** OR *ribass** OR ``*meno caro*'' OR ``*bollette più leggere*'' OR *salar** OR *stipend**) NOT (ns=gspo OR ns=gent OR ns=gwere)) AND (rst=cordes OR rst=coronl OR rst=stma OR rst=stampon OR rst=sole OR rst=soleo OR rst=larep OR rst=reponl) AND (la=It) and date from 01/01/1995

This query[2] collects all articles in Italian containing words related to economics or

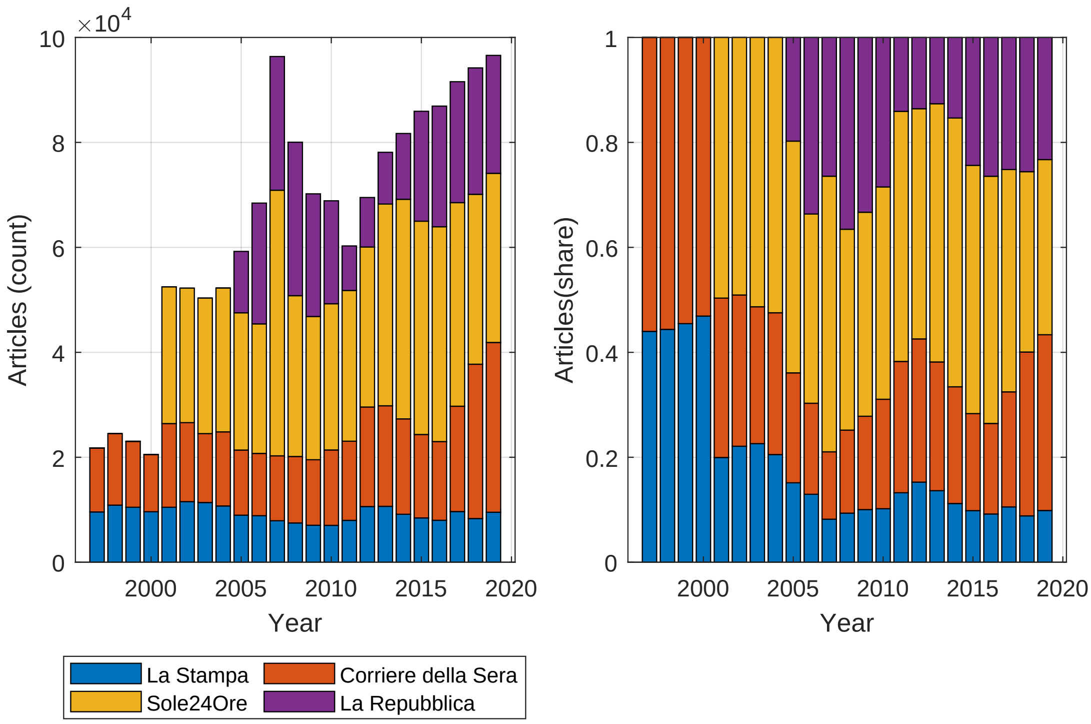
[1]With respect to Baker et al. (2016) we add to the (P)olicy keywords the word "*bankitalia*" which is often used for "Banca d'Italia" by journalists.

[2]The query looks for articles containing the words related to the follwoing stems: 'econom' (*economi**), 'financ' (*finanz**), 'monet/money' (*moneta/monetari**), 'central bank' (*banca centrale*), 'Bank of Italy' (*banca d'italia/bankit**). The query also collects articles related to 'price(s)' (*prezzo/prezzi*), 'cost of living' (*costo della vita*), 'inflation' (*inflaz**), 'high bills' (*caro bollette*), 'high prices' (*caro prezzi/caroprezzi*), 'high gasoline/petrol/gas prices (*caro benzina/caro carburante/caro gas*), 'deflation' (*deflaz**), 'disinflation' (*disinflaz**), 'sales' (*ribass**), 'less expensive' (*meno caro*), 'less expensive bills' (*bollette più leggere*). It also collects articles related to 'wage(s)' (*salar*/stipend**).

finance. We also include all articles of major economic news subjects (indicated with *ns*), such as 'Economic news' (*ecat*), 'financial market news' (*mcat*), 'corporate and industrial news' (*ccat*), 'monetary policy' (*e12*). To further account for the Italian journalistic jargon, we include a few inflation-related n-grams typical of the way journalists refer to inflation events, or inflation figures (i.e. "*caro prezzi*", which means "*high prices*"). We also include words related to wages ("*salar**" or "*stipend**"). We exclude all articles, which are not related to economics or finance, such as those in the Factiva news subjects "sport" (`ns=gspo`), "entertainment" (`ns=gent`) or "weather" (`ns=gwere`).

Figure A.1 shows in the left panel the number of articles by year and source; the right panel displays the share of articles by year and source.

Figure A.1: Counts and shares of articles by year and newspaper



Note: the left panel shows the number of articles by newspaper and by year, while the right panel displays the yearly share of articles by newspaper. The figures are computed on the articles retained after the data-cleaning procedure explained in sub-section 2.2 of the paper.

A.1.1 Dictionary

Table A.1 displays a snapshot of our dictionary. The first panel presents the polarity terms; we provide the English translation of the corresponding Italian n-gram for clarity. The polarity is always either -1 or 1, with a negative value indicating a negative sentiment weight.

Valence shifters are presented in a similar fashion. Recall that the role of these shifters is multiplicative, so a shifter with value -1 will flip the polarity of close words. A shifter with value 0.5 halves the polarity of the closest term; instead, a value of 2 will double it. In the original dataset, we also include an additional column coded following the instructions of Sentometric for the additional inclusion of adversative terms. For example, consider how a word such as “but”, which does not negate the meaning of the preceding phrase, but gives it a different light, depending on the meaning of the following expression.

Table A.1: Dictionary sample

DICTIONARY		
Term (Italian)	**Term (Translation)**	**Polarity**
turbolenza	turbolences	-1
tendono la mano	lend an helping hand	1
tasso di disoccupazione	unemployment rate	-1
tapering	tapering	-1
stimoli alla crescita	growth stimulus	1
spread tra btp e bund	BTP-Bund rates spread	-1
sotto stress	under stress	-1
sotto controllo	under control	1
situazione rosea	comfortable situation	1
sfiducia	lack of confidence	-1
rallentamento economico	economic slowdown	-1
prospettive positive	positive outlooks	1
mancanza di fondi	lack of funds	-1
il PIL calato	GDP has fallen	-1

VALENCE SHIFTERS		
Term (Italian)	**Term (Translation)**	**Shift Value**
una contrazione della	reduction of	-1
riduzione del	reduction of	-1
rallentamento del	slowdown of	-1
negativa	negative	-1
frenata del	pulled the break	-1
al di sotto delle aspettative	below expectations	-1
improbabile	unlikely	0.5
debole	weak/low	0.5
poco	little	0.5
un rialzo	increase	2
oltre le aspettative	above expectations	2
rilevante	relevant	2

Note: the first column reports the words as they appear, before stemming and processing, in our dictionary. The second column provides the correspondent English translation. Notice that, as we use only articles about economics and finance, one needs to interpret their meaning as when used in an economic context. The last column shows the polarity (for dictionary terms) and the multiplier value (for valence shifters).

A.1.2 Cleaning algorithm applied to articles and dictionary

Both the text of newspaper articles and the dictionary undergo the following cleaning procedure:

1. Remove all stopwords;
2. Remove all extra white spaces;
3. Remove all numbers, and text particles (such as apostrophes) that are not a strict alphabetic character or end-of-sentence punctuation;
4. Remove all accented letters;
5. Impose a white space before and after punctuation, to separate words at the end of a sentence from the punctuation terminating it;
6. Remove again all extra white spaces generated during the cleaning procedure.

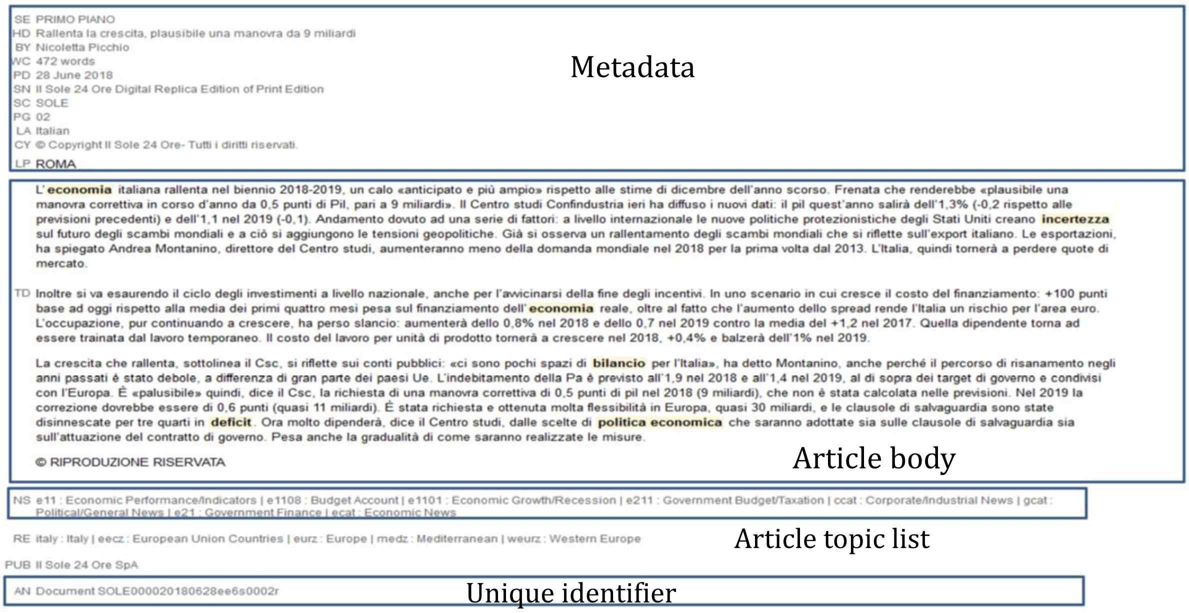
In order to make the text of the articles ready for sentiment computation, we need to account for the fact that our dictionary includes n-grams both among polarity terms and valence shifters. Before stemming, we modify the text as follows. We loop over each n-gram in the dictionary in descending alphabetical order, and substitute in the corpus of each article any occurrence with that n-gram, removing the white spaces between the words. In this way, each n-gram will be read, both in the dictionary and in the corpus, as a "unique" word, compatibly with *Sentometrics*' algorithm requirements. We follow these steps first for polarity terms and then for valence shifters. Finally, we stem both the corpus of newspaper articles and the dictionary using the same rules.

A.1.3 Additional information on data structure

In Figure A.2 we present the structure of an article as downloaded from Factiva Analytics. In our database, each section and each metadata entry is a separate column of a data frame.

The unique identifier of each article in Factiva differs for the online and the paper version of a given newspaper, allowing us to disentangle the two if needed. Topics and sectors are assigned through a proprietary algorithm of Factiva, based on a mix of unsupervised and supervised methods.

Figure A.2: Article information in Factiva dataset



SE PRIMO PIANO
HD Rallenta la crescita, plausibile una manovra da 9 miliardi
BY Nicoletta Picchio
WC 472 words
PD 28 June 2018
SN Il Sole 24 Ore Digital Replica Edition of Print Edition
SC SOLE
PG 02
LA Italian
CY © Copyright Il Sole 24 Ore- Tutti i diritti riservati.
LP ROMA

L'**economia** italiana rallenta nel biennio 2018-2019, un calo «anticipato e più ampio» rispetto alle stime di dicembre dell'anno scorso. Frenata che renderebbe «plausibile una manovra correttiva in corso d'anno da 0,5 punti di Pil, pari a 9 miliardi». Il Centro studi Confindustria ieri ha diffuso i nuovi dati: il pil quest'anno salirà dell'1,3% (-0,2 rispetto alle previsioni precedenti) e dell'1,1 nel 2019 (-0,1). Andamento dovuto ad una serie di fattori: a livello internazionale le nuove politiche protezionistiche degli Stati Uniti creano **incertezza** sul futuro degli scambi mondiali e a ciò si aggiungono le tensioni geopolitiche. Già si osserva un rallentamento degli scambi mondiali che si riflette sull'export italiano. Le esportazioni, ha spiegato Andrea Montanino, direttore del Centro studi, aumenteranno meno della domanda mondiale nel 2018 per la prima volta dal 2013. L'Italia, quindi tornerà a perdere quote di mercato.

TD Inoltre si va esaurendo il ciclo degli investimenti a livello nazionale, anche per l'avvicinarsi della fine degli incentivi. In uno scenario in cui cresce il costo del finanziamento: +100 punti base ad oggi rispetto alla media dei primi quattro mesi pesa sul finanziamento dell'**economia** reale, oltre al fatto che l'aumento dello spread rende l'Italia un rischio per l'area euro. L'occupazione, pur continuando a crescere, ha perso slancio: aumenterà dello 0,8% nel 2018 e dello 0,7 nel 2019 contro la media del +1,2 nel 2017. Quella dipendente torna ad essere trainata dal lavoro temporaneo. Il costo del lavoro per unità di prodotto tornerà a crescere nel 2018, +0,4% e balzerà dell'1% nel 2019.

La crescita che rallenta, sottolinea il Csc, si riflette sui conti pubblici: «ci sono pochi spazi di **bilancio** per l'Italia», ha detto Montanino, anche perché il percorso di risanamento negli anni passati è stato debole, a differenza di gran parte dei paesi Ue. L'indebitamento della Pa è previsto all'1,9 nel 2018 e all'1,4 nel 2019, al di sopra dei target di governo e condivisi con l'Europa. È «palusibile» quindi, dice il Csc, la richiesta di una manovra correttiva di 0,5 punti di pil nel 2018 (9 miliardi), che non è stata calcolata nelle previsioni. Nel 2019 la correzione dovrebbe essere di 0,6 punti (quasi 11 miliardi). È stata richiesta e ottenuta molta flessibilità in Europa, quasi 30 miliardi, e le clausole di salvaguardia sono state disinnescate per tre quarti in **deficit**. Ora molto dipenderà, dice il Centro studi, dalle scelte di **politica economica** che saranno adottate sia sulle clausole di salvaguardia sia sull'attuazione del contratto di governo. Pesa anche la gradualità di come saranno realizzate le misure.

© RIPRODUZIONE RISERVATA

NS e11 : Economic Performance/Indicators | e1108 : Budget Account | e1101 : Economic Growth/Recession | e211 : Government Budget/Taxation | ccat : Corporate/Industrial News | gcat : Political/General News | e21 : Government Finance | ecat : Economic News

RE italy : Italy | eecz : European Union Countries | eurz : Europe | medz : Mediterranean | weurz : Western Europe

PUB Il Sole 24 Ore SpA

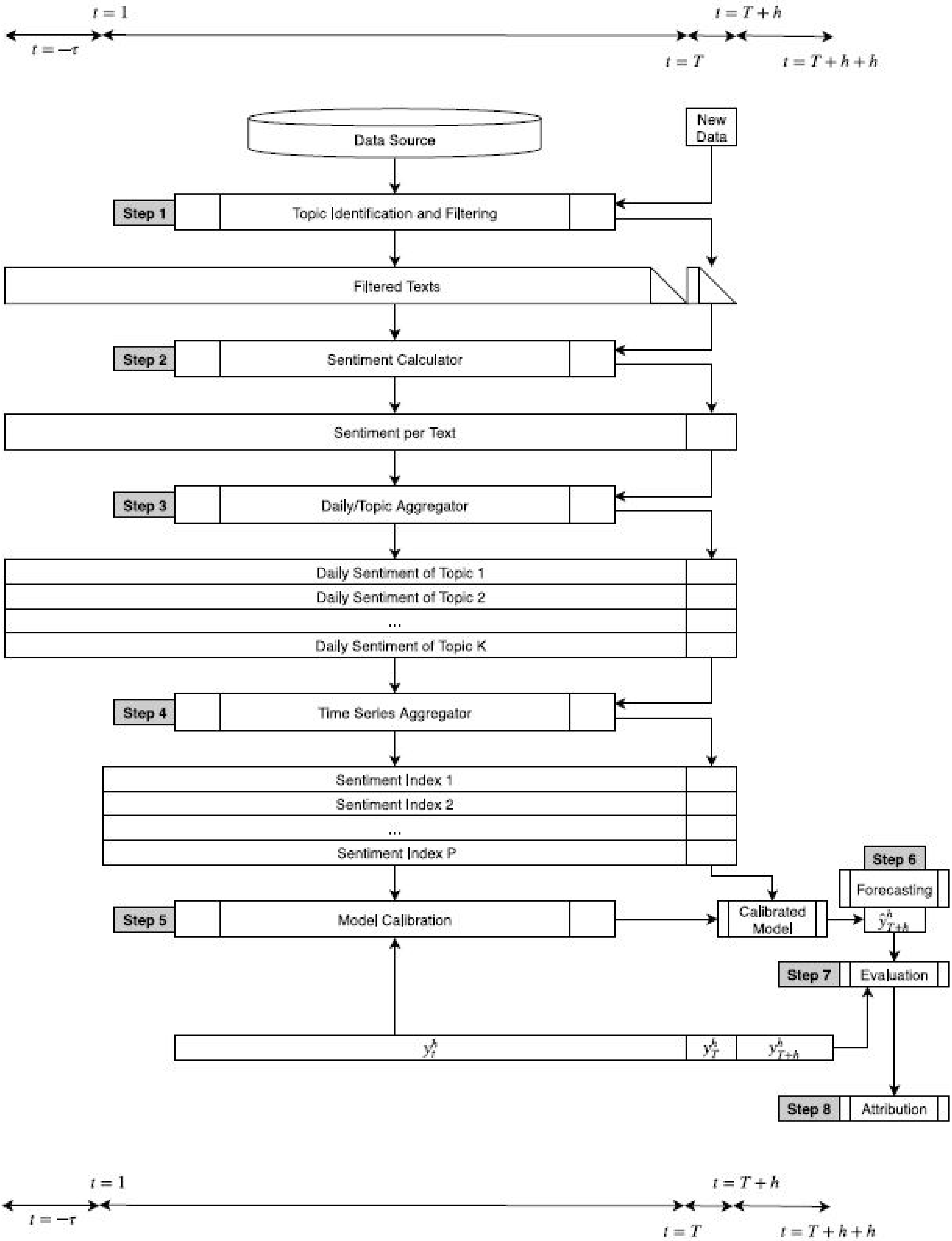
AN Document SOLE000020180628ee6s0002r

Note: Factiva articles come with metadata which include the title, the body, the list of topics that are assigned via the Factiva's proprietary classification algorithm to each article, and the unique identifier.

A.1.4 Sentometrics for TESI calculation

For the construction of our overall and topical/sectoral sentiment indicators (TESI), we use the R package *sentometrics* put forward by Ardia et al. (2021). This package implements an intuitive framework to efficiently compute sentiment scores from numerous articles, and aggregate those scores into multiple time series, to be used to predict other target variables. We refer to their paper and the R package vignette for all the details in the implementation of their algorithm. Below, we report an image taken from Ardia et al. (2021) that summarizes the package workflow.

Figure A.3: Pipeline to calculate sentiment in *Sentometrics*



Source: taken from Ardia et al. (2021)

A.2 Additional results on TESI

A.2.1 Topical and sectoral sentiment indices

Table A.2 describes the 16 topics and 21 sectors for which we compute our TESI and TEPU indicators. The first column shows the aggregate topics composed by Factiva Analytics' medatada (i.e. news subject) listed in detail below. The second column lists the detailed sectoral breakdowns that we aggregate for our two empirical applications.

Table A.2: Sentiment by Topic and Sector

N.	Sentiment by Topic	N.	Sentiment by Sector
1)	Economic Condition	1)	Automation
2)	Finance	2)	Agriculture - Mining*
3)	Domestic Policy	3)	Manufacturing*
4)	Foreign Policy	4)	Services*
5)	Government	5)	Agriculture
6)	Institutions	6)	Automotive
7)	Labor	7)	Basic Materials & Resources
8)	Fraud	8)	Business Consumer Services
9)	Migration	9)	Consumer Goods
10)	Monetary Policy	10)	Energy
11)	Natural Disasters	11)	Financial Services
12)	Prices	12)	Healthcare & Life Sciences
13)	Private Sector	13)	Industrial Goods
14)	Terrorism	14)	Leisure, Arts & Hospitality
15)	Pandemic	15)	Media & Entertainment
16)	Automation	16)	Real Estate & Construction*
		17)	Retail & Wholesale
		18)	Technology
		19)	Telecommunication Services
		20)	Transportation Logistics
		21)	Utilities

Note: Topical and Sectoral categories for which we generate TESI and TEPU indicators. Starred sectors * are aggregation produced starting from Factiva's articles sectoral tags. Non-starred sectors are original Factiva's sectoral tags.

Here we provide further details on how the topics in the first column of Table A.2 are constructed using Factiva Analytics' metadata, such as the news subjects and other fields:

1. **Economic Conditions**: Economic News, Sales Figures, Small/Medium Businesses, Corporate/Industry Imports, Risk News, Output/Production, Transport, Corporate/Industry Exports, Domestic/Foreign Markets, Consumer Affairs, Real Estate/Property, Non-Government Contracts/Orders, Existing Products/Services, Mortgage Planning/Trends, Real Estate Markets, Small Business Lending, Divestments, Usage/Consumption Statistics, IMF, European Commission, Services Sector Figures,

Buying/Selling a Home, Commerce Department, OECD, Purchasing Managers Index, Economic Zones, Foreign Direct Investment, Balance of Payments/Current Account, Cars, Home Improvements, Consumer Spending/Budgeting, Economic Zones

2. **Finance**: Commodity/Financial Market News, Euro Zone/Currency, Routine Market/Financial News, Personal Finance, Stock Listings, Earnings Surprises, Insider Stock Sales/Purchases, Profit Warnings, Stock Trading Disruptions, Fixed Income Investing, Retirement Planning, Personal Investments in Stocks, High-yield Corporate Bonds, Personal Investments in Bonds, Warrants, Family Finance, Financial Advisors, Foreign Exchange, Personal Investments in Government Debt, Mortgage Planning/Trends, Leveraged Loans, Management Buyouts, Private Equity/Venture Funding
3. **Domestic Policy**: Domestic Politics, Regional Politics, Upper House, Surveys/Polls, Lower House, National/Presidential Elections Political Appointments/Terminations
4. **Foreign policy**: Politics/International Relations, International Pol-Econ Organizations, International Relations, Global/World Issues, Globalization, The Group of Seven, World Trade Organization, EU Parliament, World Bank, Federal Reserve Survey Data, Council of the European Union
5. **Government**: Government Bodies, Earnings Projections, Government Finance, Government Debt/Bond Markets, National Government Debt/Bond Markets, Treasury Department, Corporate Taxation, Welfare/Social Services, Government Aid/Grants, Government Contracts/Orders, Interior Department, Defense Contracts
6. **Institutions**: Regulation/Government Policy, Marketing, Corporate Crime/Legal Action, National/Public Security, Legislative Branch, Financial Crime, Anti-Competition Issues, Education, Elections, Social Issues, Independent Advisory Bodies, Military Action, Judicial Branch, Facility Openings, Civil Unrest, Armed Forces, Deregulation, Law Enforcement, Settlements/Out-of-Court Agreements, Investment Ideas/Investor Education, Recipes, Class Action Lawsuits, Foreclosures, State Security Measures/Policies, War Crimes, Weapons Programs, Gross Misconduct/Malpractice, Network Neutrality, e-government, Movement Disorders
7. **Labor**: Labor/Personnel, General Labor Issues, Lay-offs/Redundancies, Employment/Unemployment Figures, Recruitment, Executive Pay, Labor Disputes, Workers Pay, Employment Cost/Productivity Figures, Employee Training/Development, Outsourcing, Business-to-Employee (B2E), Labor Department, Jobless Claims
8. **Fraud**: Crime/Legal Action, Fraud, Corruption, Money Laundering, Burglary/Theft, Criminal Enterprises, Securities Fraud, Robbery, Regulatory Breach, Cybercrime/Hacking, Tax Fraud, Identity Theft, Assault, Counterfeit/Forgery, Trafficking/Smuggling, Privacy Issues/Information Security, Drug Trafficking/Dealing, Welfare/Benefit Fraud, Data Security Breaches, Bribery, Check Fraud, Ponzi/Pyramid Scheme, Malware
9. **Migration**: Human Migration, Illegal Immigration
10. **Monetary** policy: Monetary Policy, Fund Markets, European Central Bank, Money Supply Figures
11. **Natural disasters**: Disasters/Accidents, Natural Environment, Natural Disasters/Catastrophes, Accidents/Man-made Disasters, Geological Disasters, Floods/Tidal Waves, Building Fires / Explosions / Collapses, Wildfires, Storms, Fire/Rescue Services, Nuclear Accidents
12. **Prices**: Pricing, Inflation Figures/Price Indices, Energy Markets, Crude Oil Markets, Metals Markets, Precious Metals Markets, Gold Markets, Non-ferrous Metals Markets, Aluminum Markets, Crude Oil/Natural Gas Product Markets, Motor Fuel Markets, Natural Gas Markets, Steel Markets, OPEC, Copper Markets, Housing Prices, Producer/Wholesale Price Index, Soft Commodity Markets, Consumer Price Index, Energy Department, Iron Ore Markets, Coal Markets, Coffee Markets, Corn Markets, Electricity Markets, Emission Markets, Platinum/Palladium Markets, Silver Markets
13. **Private sector**: Corporate/Industrial News, Executive Branch, Budget Figures, Corporate Bankruptcy Figures, Corporate Digests, Interviews with Corporate Executives, Asset Allocation

14. **Terrorism**: Terrorism
15. **Pandemic**: Infectious Diseases, H1N1 Flu/Influenza, Outbreaks/Epidemics, SARS/MERS Viruses, Vector-borne/Zoonotic Diseases, Respiratory Tract Diseases
16. **Automation**: Automation, Robotics

The sectors are generated from Factiva's taggings in the following way. Except for "Agriculture and mining" (n. 2 in Table A.2), "Services" (n. 4), "Manufacturing" (n. 3), and "Real Estate and Construction" (n. 16), each sector is built by matching one-to-one Factiva's tagging to the similarly named sector. Instead, the remaining sectors are constructed by aggregating multiple Factiva sectorial tags as follows:

1. **Agriculture and mining**: Agriculture, Basic Materials/Resources
2. **Manufacturing**: Automotive, Energy, Industrial Goods, Consumer Goods
3. **Services**: Business/Consumer Services, Financial Services, Healthcare/Life Sciences, Leisure/Arts/Hospitality, Media/Entertainment, Real Estate, Architectural Design Services, Retail/Wholesale, Technology, Telecommunication Services, Transportation/Logistics, Utilities
4. **Real Estate and Construction**: Construction, Building Materials/Products

Properties of Topical and Sectoral TESI. Since the same newspaper article can simultaneously contain information related to multiple topics and sectors, it can enter the computation of several topical/sectoral sentiment indices.[3] Table A.3 reports the counts of articles used in the computation of the overall Sentiment indicator since January 2001, as well as for selected topics and sectors, which are included in our main BMA estimation. Moreover, we report the average daily and monthly counts of articles, as well as similar statistics for the number of articles that *actively* contribute to the sentiment indicators, having non-zero sentiment values.

Correlation between TESI and topics. Figure A.4a displays the contemporaneous correlation between the overal TESI and the 15 TESI indicators by topic. The first row of

[3] Suppose that a given article is composed of only two topics and that it is talking with a positive tone about monetary policy and with a negative one about labor market conditions in Italy. Suppose further that its overall score is positive. The article will be classified as positive in both topics. However, comparing the topical index with the overall sentiment TESI, it is still possible to see if the press is speaking about a given topic with a relatively better (or worse) tone, giving rise to interesting comparisons.

Table A.3: Articles count, per TESI topic

	All	Labor	Manufacturing	Services	Retail
Total	1,418,497	147,003	176,763	417,701	43,260
Per day (mean)	201.3	20.9	25.1	59.3	6.1
Per month (mean)	6,114.2	633.6	761.9	1,800.4	186.5
Non-zero Sentiment	1,339,884	143,447	166,230	391,812	40,639
Per day (non-zero)	190.2	20.4	23.6	55.6	5.8
Per month (non-zero)	5,775.4	618.3	716.5	1,688.8	175.2

Note: the table reports the summary statistics for overall TESI, as well as for selected topics and sectors (Labor, Manufacturing, etc.), for the period between 01/01/2001 and 20/04/2020. The number of days in the sample is calculated as the distance between the first and the last available observation, plus one. Months are calculated in a similar fashion.

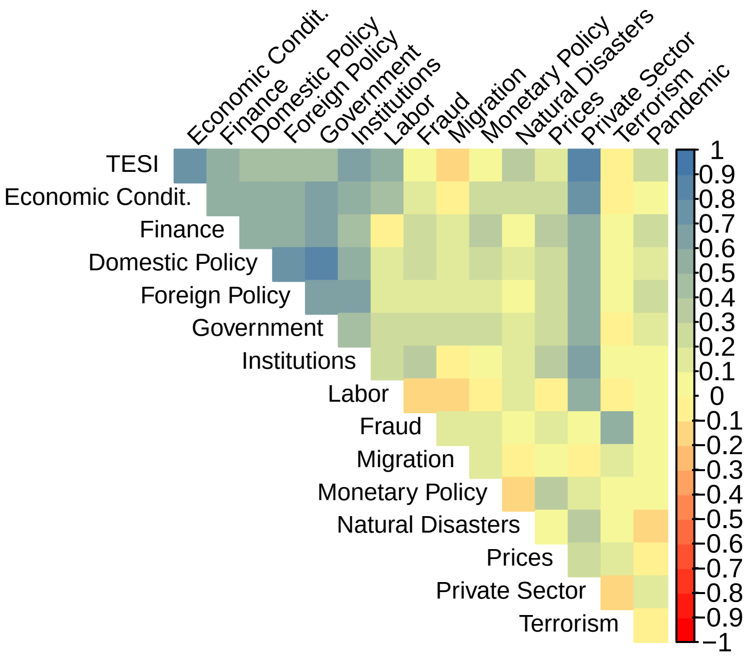
the graph shows a high correlation between TESI and those sentiment indicators related to economic conditions and to the private sector; those related to finance, government and monetary policy display a lower degree of association. Figure A.4b shows the contemporaneous correlations between the overall TESI and the 21 TESI indicators by sectors. The former strongly correlates with the indicators calculated for services, manufacturing, wholesale & retail, business consumer services and real estate & construction, which are the most important sectors in the National Accounts.

A.2.2 Discussion of individual topic sentiment series

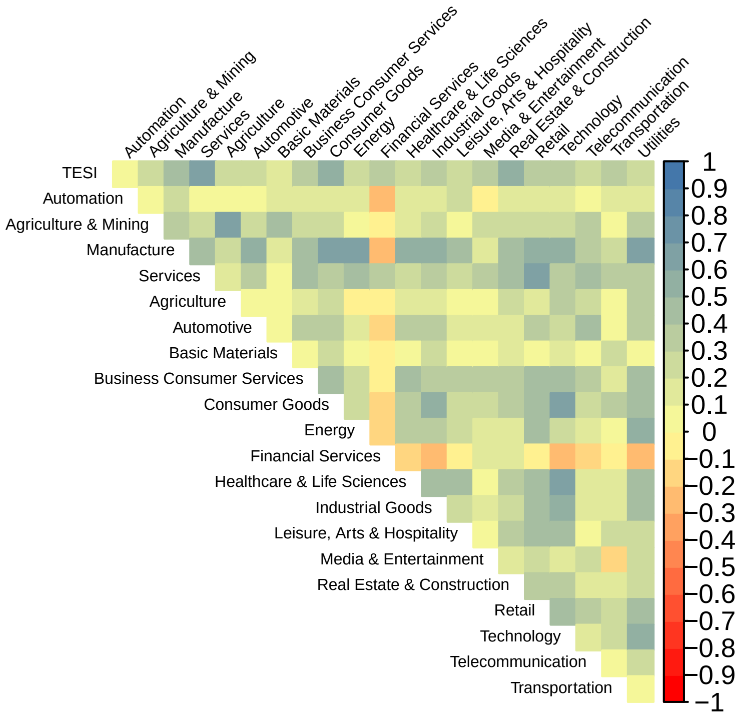
Figure A.5 displays three of the most important sentiment indicators out of the 15 computed by topic: 1) government/fiscal policy; 2) monetary policy and 3) labor market.

The Sentiment about the topic "government/fiscal policy" (Figure A.5a) is calculated building on Factiva sub-categories about government finance, budget and taxation, public debt, sales and income taxes, and many others. It is highly correlated with TESI (0.7) and its dynamics matches up well with key events of the Italian politics and fiscal policy. It tends to decrease sharply before national elections and to rebound thereafter (es. in 2001, 2006 and 2013). It reaches historical low levels during the Sovereign Debt Crisis in 2011, with the fall of Berlusconi's Government in November 2011, during harsh political and public debates about Budget Laws (i.e. September 2002; July 2004 when Siniscalco

Figure A.4: Correlation between TESI and a) the 15 TESI indices by topics; b) the 21 TESI indices by sectors. Series are aggregated at the monthly frequency



(a) Correlation between TESI and the 15 topic-specific indices; monthly frequency.



(b) Correlation between TESI and the sectoral indices; monthly frequency.

took over Tremonti as the Italian Minister of economy and finance) and finally during the last Government crisis in August 2019.

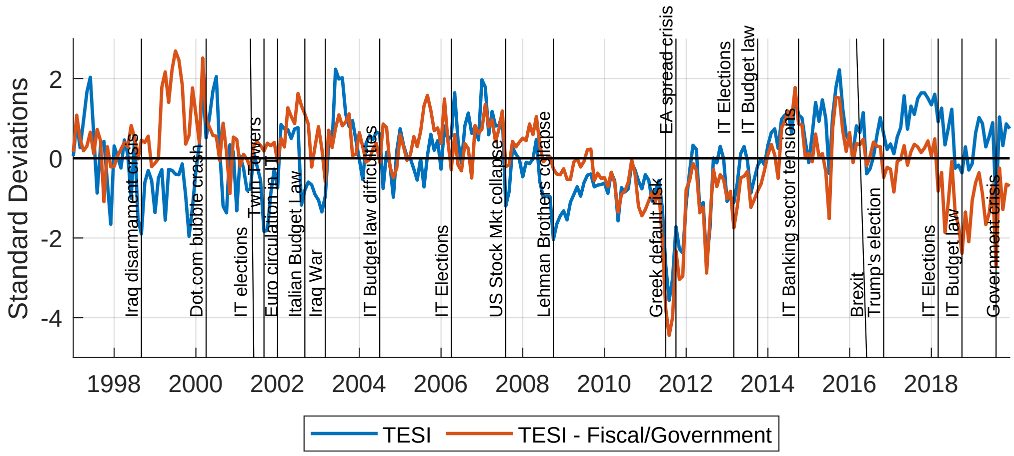
Figure A.5b displays the sentiment about monetary policy conditions and it is calculated aggregating categories such as ECB, Central Bank interventions, interest rates, and money supply among others. This index peaks with the introduction of the euro in January 1999, and with the change of the ECB monetary policy strategy in March 2003. It reaches minimal values during the episode of the stock market crash in August 2007, the Lehman collapse in September 2008, the Sovereign Debt Crisis, and with the announced reductions of the Asset Purchase Programme. In addition, this index sharply increases after important monetary policy interventions by the ECB, such as the fixed rate full allotment tender procedure introduced in October 2008, the launch of the Security Market Programme in May 2010, the Very Longer Term Refinancing Operations (VLTRO) in December 2011, Draghi's "Whatever it takes" in July 2012, the launch of Outright Market Transactions (OMT) in September 2012, the launch of Targeted Longer-Term Refinancing Operations (TLTRO) in 2014, the start of the Asset Purchase Programme announced in January 2015 and its restart in September 2019 (Hartmann and Smets, 2018; Neri and Siviero, 2019).

Finally Figure A.5c shows the sentiment index for Labor Market conditions, computed using articles tagged in categories such as: employment/unemployment, general labor issues, lay-offs/redundancies, job search. The index increases in months where important labor market reforms were passed in Italy, such as the Treu reform in June 1997, the Biagi's law in September 2003, the Fornero reform in June 2012, the first tranche of the Jobs Act in December 2014, its second tranche in June 2015, and the Dignity decree in July 2018.

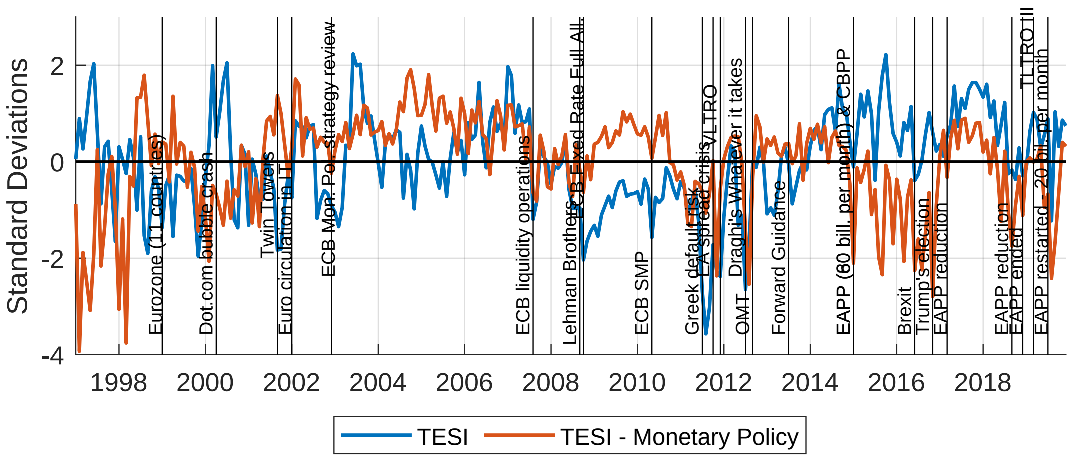
Some of the TESI indicators by sector used in the empirical applications in section 5 are displayed in Figure A.6.[4]

[4] All the sentiment indicators not reported in the paper are available from the authors upon request.

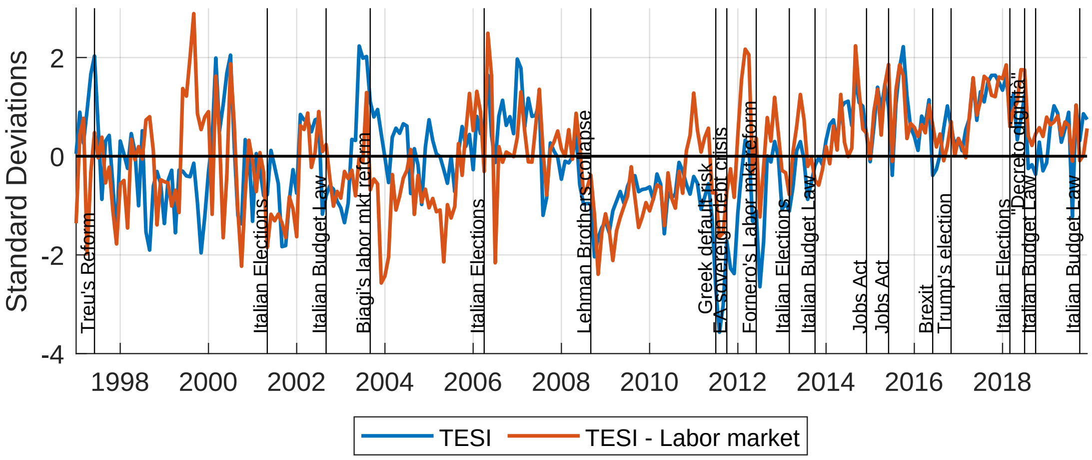
Figure A.5: Sentiment (TESI) for three major macro topics



(a) TESI on Government macro-topic



(b) TESI on Monetary Policy macro-topic

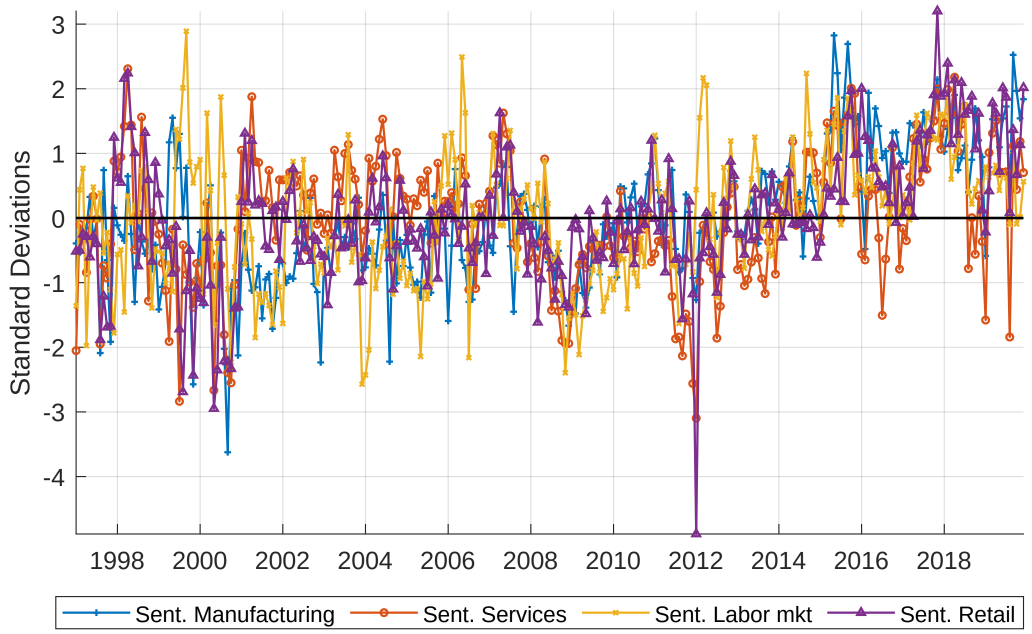


(c) TESI on Labor markets macro-topic

A.2.3 Validation with non-economic dictionary

To provide insights into the value added by our economic dictionary tailored for forecasting, we compare our TESI with a "placebo" sentiment measure (a generic sentiment)

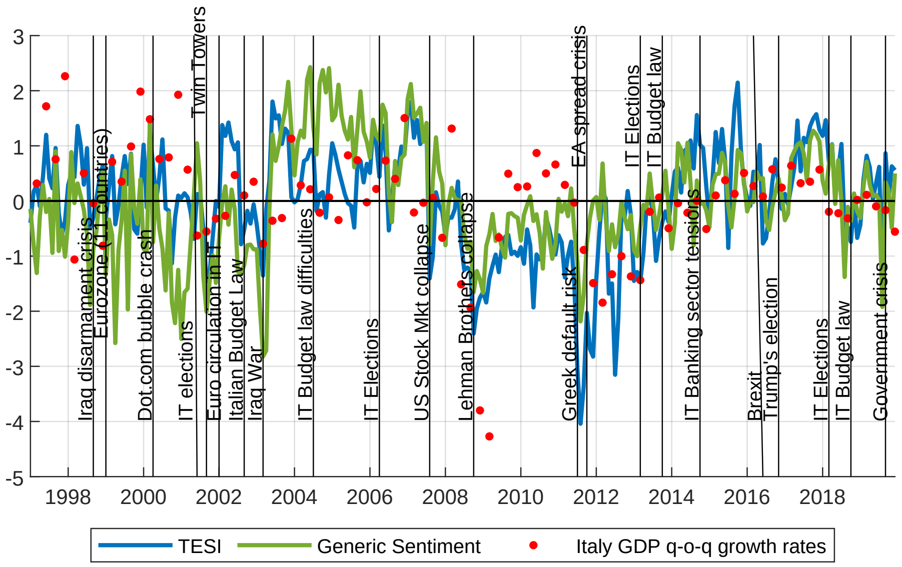
Figure A.6: Sentiment indicators (TESI) by sector



Note: the series are standardized to have zero mean and unit variance.

obtained using both the generic polarity dictionary developed by Maks et al. (2014) and our valence shifters, to mantain comparability. Our economics sentiment seems to outperform the placebo during the first part of the sample, as our TESI tracks GDP growth much better than the placebo. Instead, the two series have more similar behaviors in the latter part of the sample. Moreover, our TESI is sharper at capturing negative economic events, such as the 2007 financial crisis and the sovereign debt crisis, while being less reactive to non-economic political events.

Figure A.7: Italian GDP (QOQ growth rates), TESI, and a generic sentiment alternative.



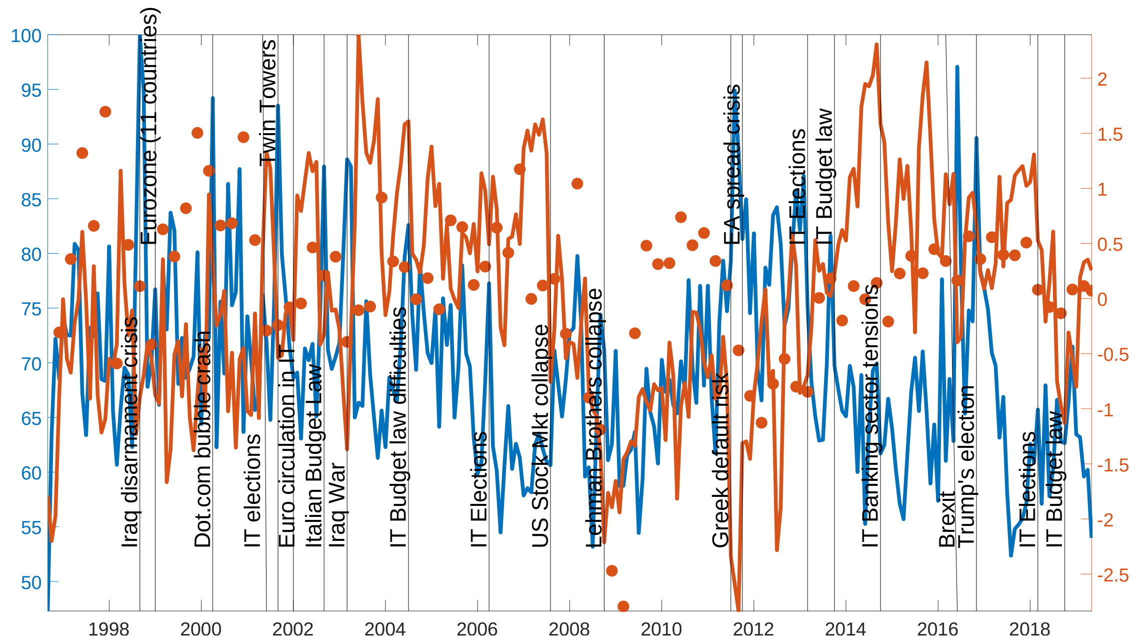
Note: the TESI and the Generic Sentiment are calculated using daily articles in *real time*, while GDP growth rates are calculated using the vintage published by Istat in January 2020. All series are standardized to have zero mean and unit variance. The two sentiment series are both derived using the same valence shifters, while employing different polarity terms. Vertical bars represent important events for the Italian economy.

A.3 Additional results on TEPU

A.3.1 Properties of TEPU

Figure A.8 plots TEPU and TESI together with GDP growth rates. In most periods, a negative correlation between uncertainty and sentiment is evident. This is a well consolidated result in the literature using firms' survey data to assess business cycle conditions (Bachmann et al., 2013). Indeed, we find that this pattern holds also for our TESI and TEPU measures derived from newspaper articles, with a correlation around -0.4.

Figure A.8: TESI and TEPU for Italy - overall indices



A.3.2 TEPU by Topics and Sectors

Figures A.9a and A.9b show the time series of TEPU indicators by topics and sectors, together with a dating of important events for the Italian economy. Depending on their nature, key events generate strong movements in specific TEPU indicators. Table A.4 reports the number of articles used in the computation of the overall, manufacturing and services TEPU indices, which are included in our two empirical applications, starting from January 2001.

Table A.4: Articles count, per TEPU topic

	All	Manufacturing	Services
Total	$106,375$	$9,835$	$25,313$
Per day (mean)	15.1	1.4	3.6
Per month (mean)	458.5	42.4	109.1

Note: the table reports the summary statistics for the overall TEPU, as well as that one of selected sectors, for the period between 01/01/2001 and 20/04/2020. The number of days in the sample is calculated as the distance between the first and the last available observation plus one. Months are calculated in a similar fashion.

TEPU by topic is meant to capture the uncertainty in different sides of the economy such as monetary or fiscal policy, or labor markets: from Figure A.9a it is clear that these topics seem to explain a lot of variation in the TEPU indices. TEPU indices by sector are useful in detecting which sectors are mainly contributing to the business cycle uncertainty in a certain period. Figure A.10a shows the contemporaneous correlation between the overall TEPU index and its 15 components. The correlation patterns are similar to those previously described in section A.2.2 for TESI: the highest correlation is reached by the topics on the top left part of the figure. Figure A.10b displays the contemporaneous correlation between the overall TEPU index and the TEPU by economic sector. Results are similar to those described in section A.2.2: the correlation is higher for indices calculated on articles about services, manufacturing and retail sales.

Figure A.11 depicts the three main macro topic TEPU indicators out of the 15 computed: 1) TEPU about government/fiscal policy; 2) TEPU about monetary policy, and 3) TEPU about labor markets.

Figure A.11a displays our TEPU index on government and fiscal policy. In the first part of the sample, the main peaks are around the Iraq's disarmament crisis towards the end of 1998, the *Dot-com* bubble in April 2000, Bush's election in November 2000. Afterwards, it moderately increases in periods when controversial Budget Laws had to pass the Parliament scrutiny and during national elections. In the second part of the sample, high uncertainty episodes are the Sovereign Debt crisis, the Brexit referendum, Trump's election, the fall of Renzi's government in December 2016 after the failed Constitutional Law referendum, and the Government crisis in August 2019. TEPU index reaches its minimum when Italy adopted the euro at the beginning of 1999.

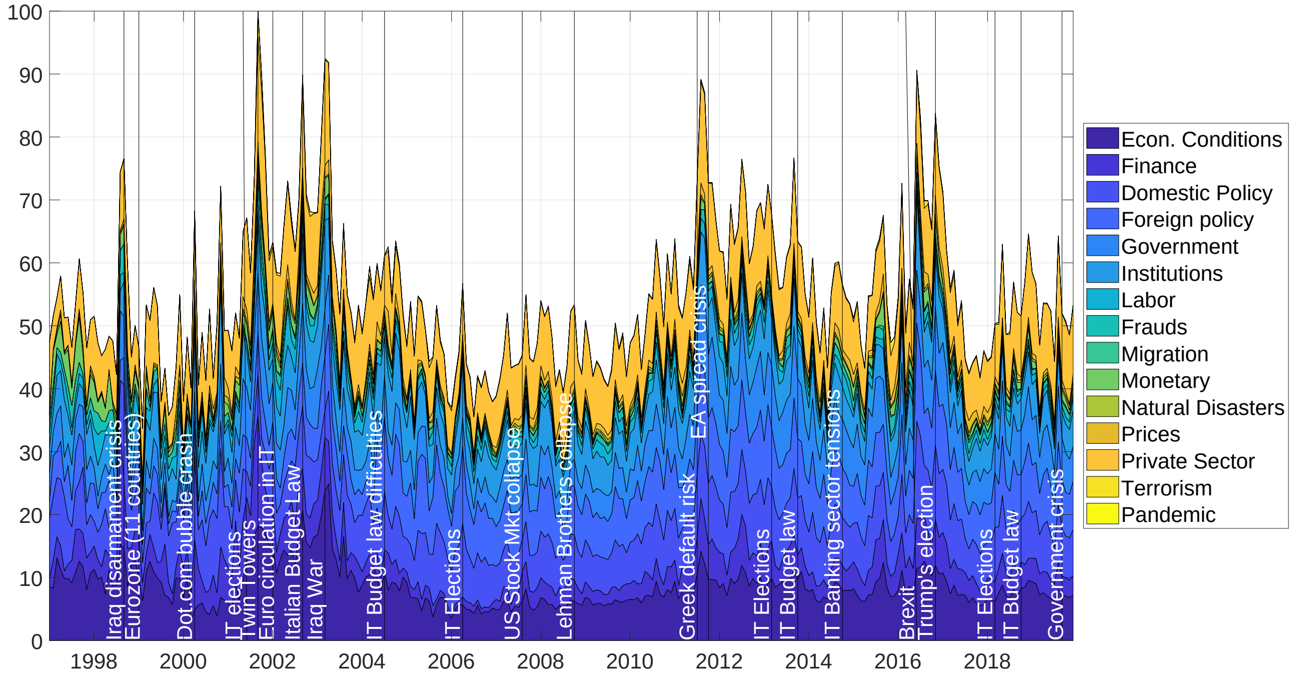
Figure A.11b shows TEPU stemming from monetary policy articles (Husted et al., 2019). Uncertainty regarding monetary measures was low when the euro was adopted. After that moment it stayed on low levels until the Great Financial Crisis (GFC), when ECB started to adopt several unconventional measures such as the Fixed Rate Full Allotment Procedure after the Lehman collapse in October 2008 (Hartmann and Smets, 2018). The monetary policy TEPU decreases after the approval of important measures taken by the ECB, such as the institution of the Security Market Programme in May 2010; the launch of the VLTROs in December 2011; the OMTs in September 2012; the announcement of the Expanded Asset Purchase Programme in January 2015, and the its restart after the announcement of APP purchases announced by the ECB Governing Council in June 2019. On the contrary, the index jumps up after the announcement of the reduction of the APP Programme in July 2017.

Finally, Figure A.11c shows TEPU for news concerning the labor market. The index increases after the approval of important reforms for Italy such as the Treu's labor market reform in June 1997, or the Biagi's reform in September 2003.

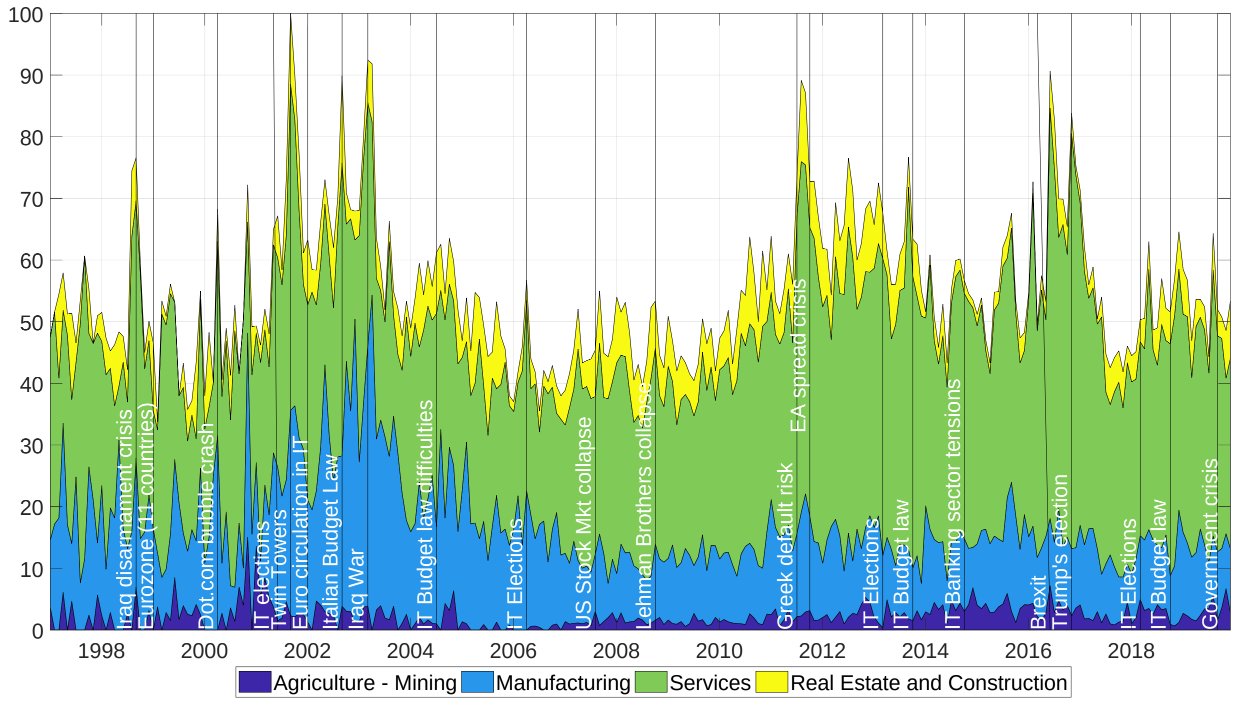
TEPU indicators by sector are displayed in Figure A.12.[5]

[5]The TEPU indices not reported in the paper are available from the authors upon request.

Figure A.9: TEPU by topic and by sector for Italy (monthly shares of articles)

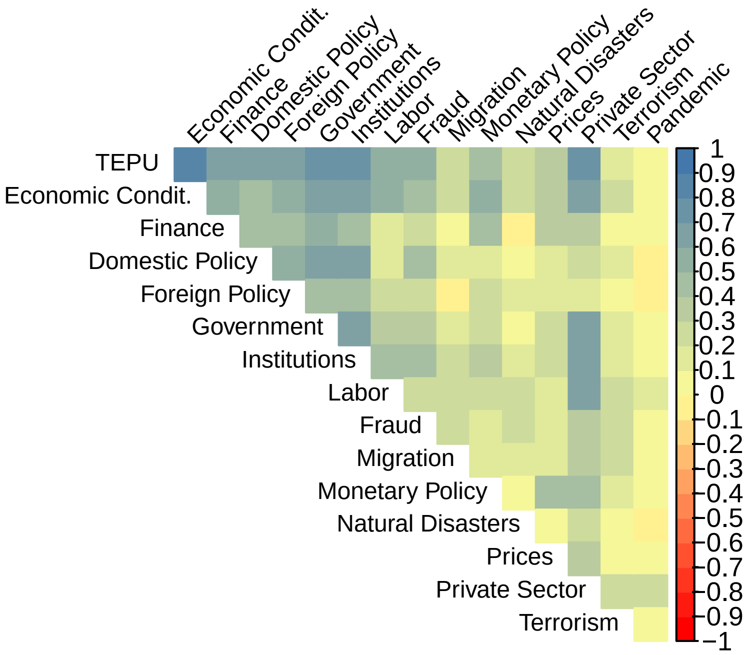


(a) TEPU by topic

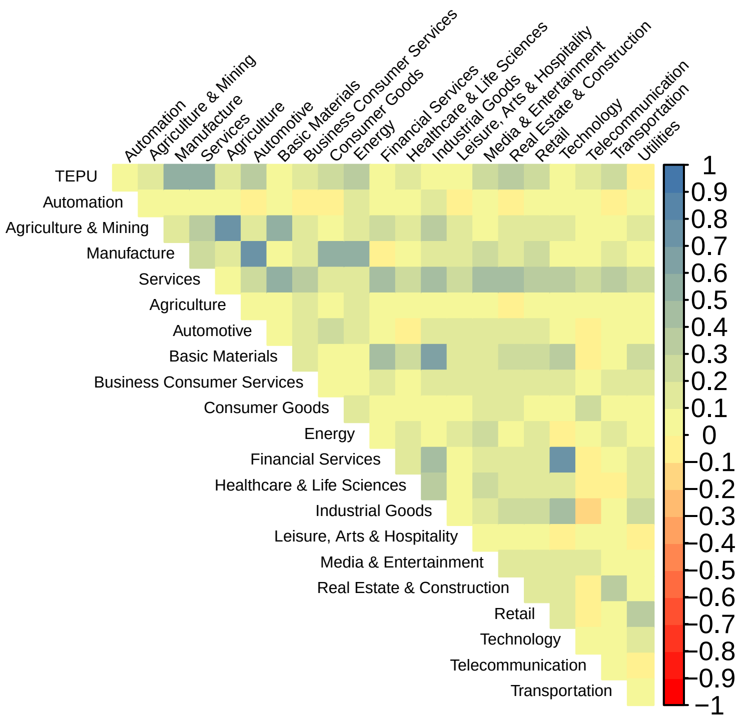


(b) TEPU by sector

Figure A.10: Correlation between TEPU indices for Italy

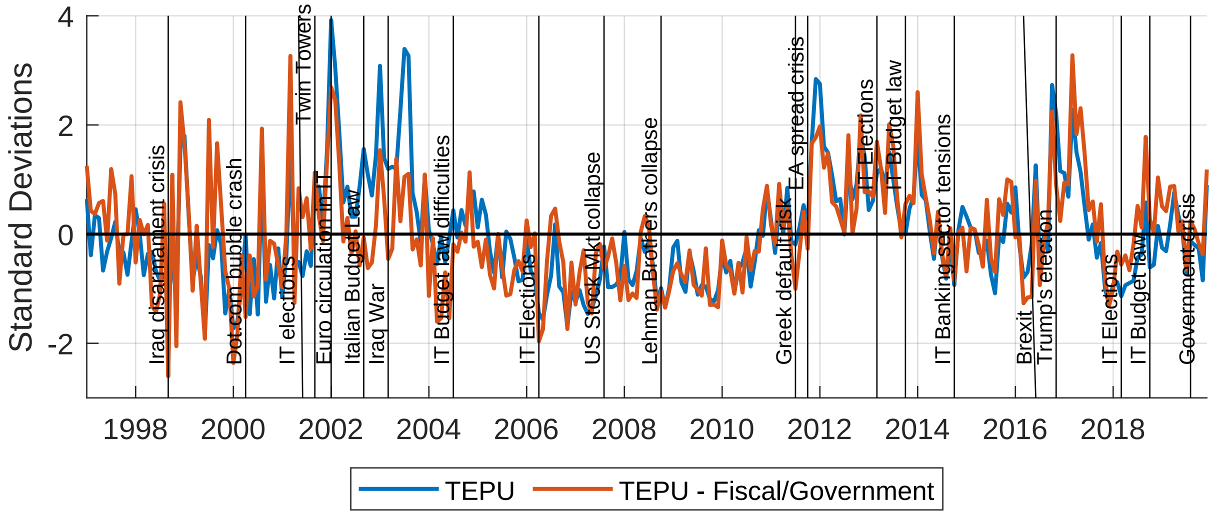


(a) Correlation between TEPU (overall) and TEPU calculated by topic

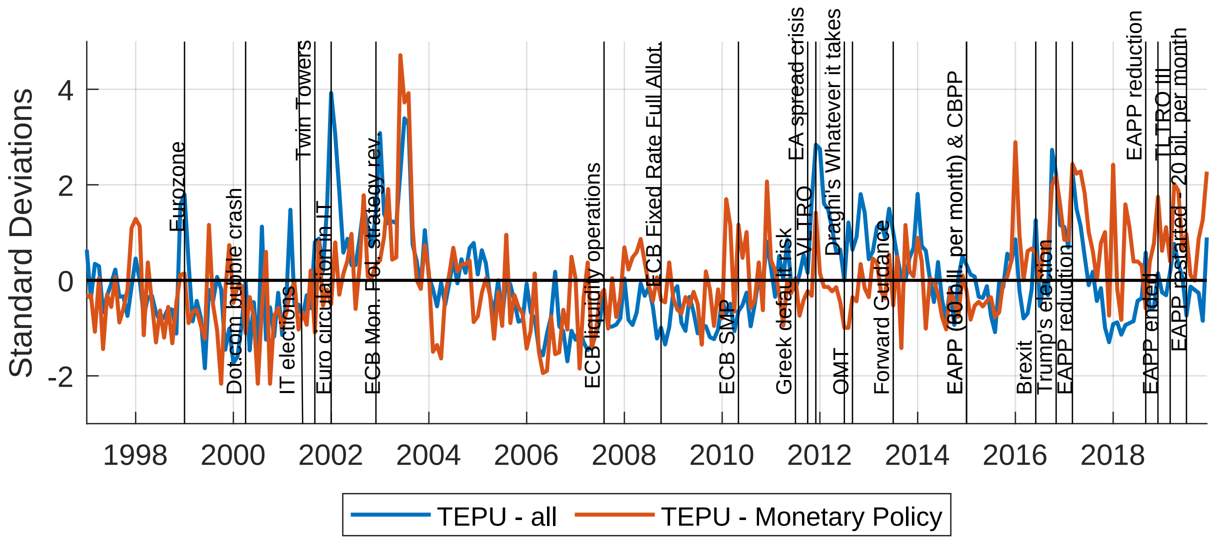


(b) Correlation between TEPU (overall) and TEPU calculated by sector

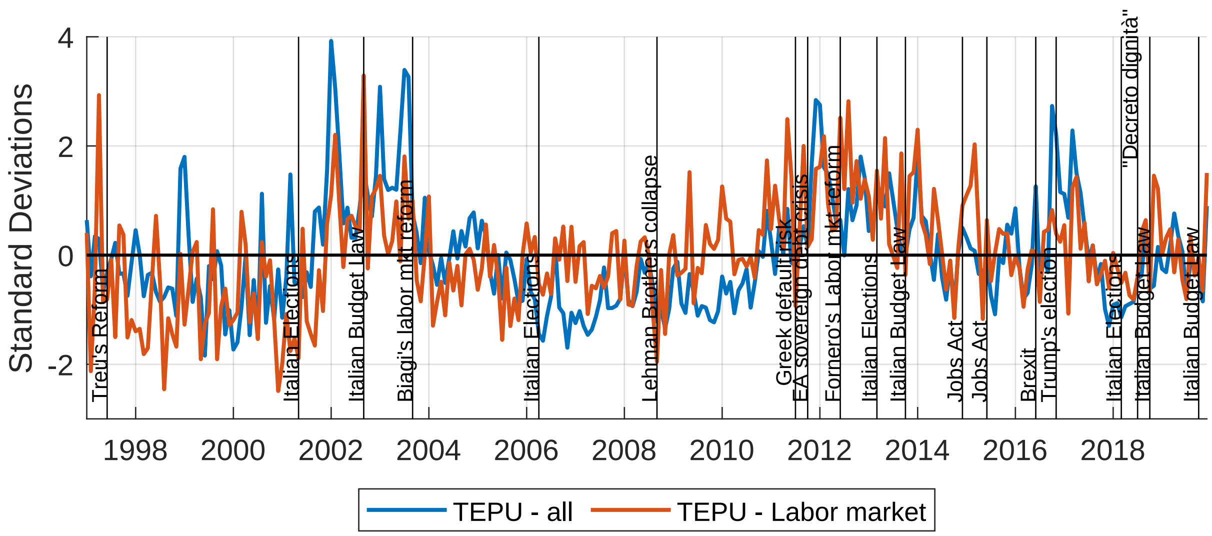
Figure A.11: TEPU indices for three major macro topics: 1) Government; 2) Monetary Policy ; 3) Labor Markets



(a) TEPU on Fiscal/Government topic compared with the overall TEPU index

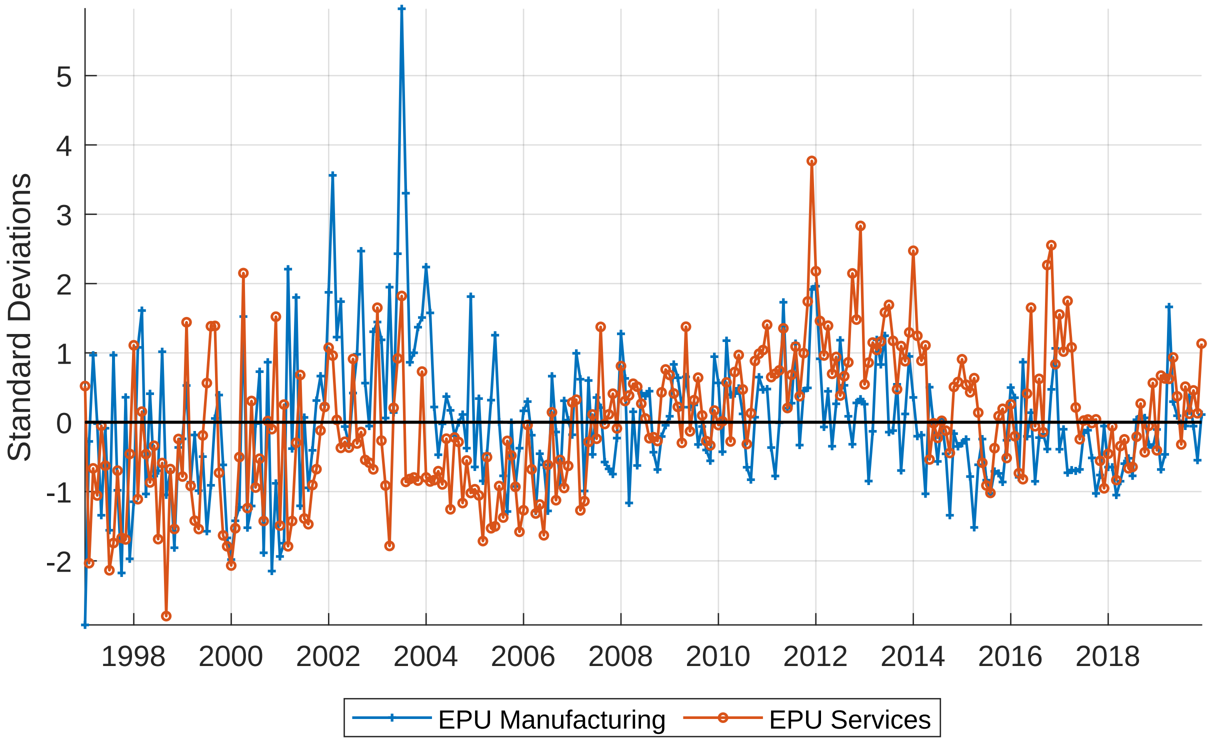


(b) TEPU on Monetary Policy compared with the overall TEPU index



(c) TEPU on Labor markets topic compared with the overall TEPU index

Figure A.12: TEPU indices by sector



Note: the series are standardized to have zero mean and unit variance.

A.4 Heterogeneity by newspaper

A.4.1 TESI

Newspapers may differ by political slant, main focus (generalist/economic), geographical interest (national/local) and style. The editorial staff can be differently biased towards the government in power, as documented in a number of contributions such as Groseclose and Milyo (2005) and Gentzkow and Shapiro (2010); Gentzkow et al. (2019). Moreover, the newspapers considered in our sample have a different topical or geographical specialization, suggesting the possibility of composition effects. In order to investigate the impact of this heterogeneity (by source) on our indices, we compute the sentiment indicators by newspaper. Figure A.13a diplays the four TESI indces for *Il Corriere della Sera*, *La Repubblica*, *Il Sole 24 Ore*, and *La Stampa*.[6] The degree of commonality between the series is strong: all important events and economic trends show up in all the four newspapers, with some differences arising in some sub-periods.

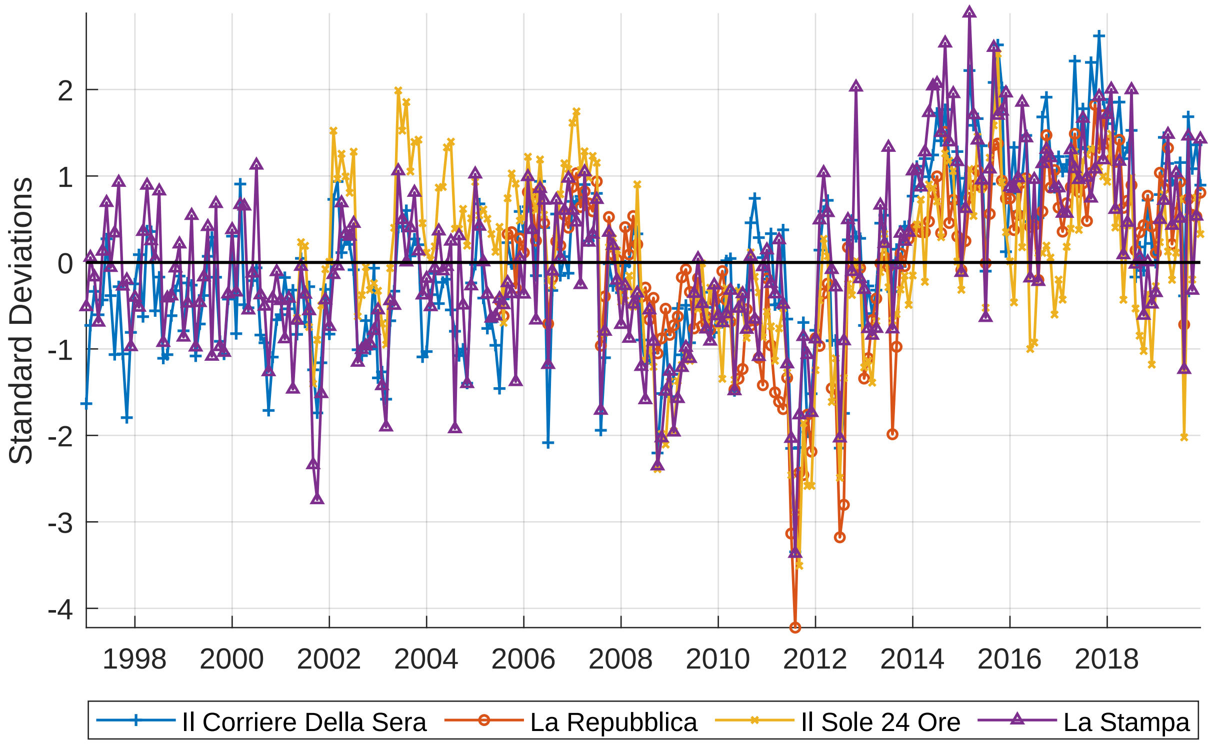
The sentiment heterogeneity across Italian newspapers mainly shows up in the first and second moments of the newspaper-specific TESI series: the different tone and heterogeneous views about the economy drive the differences on the means and variances of the time series.

A.4.2 TEPU

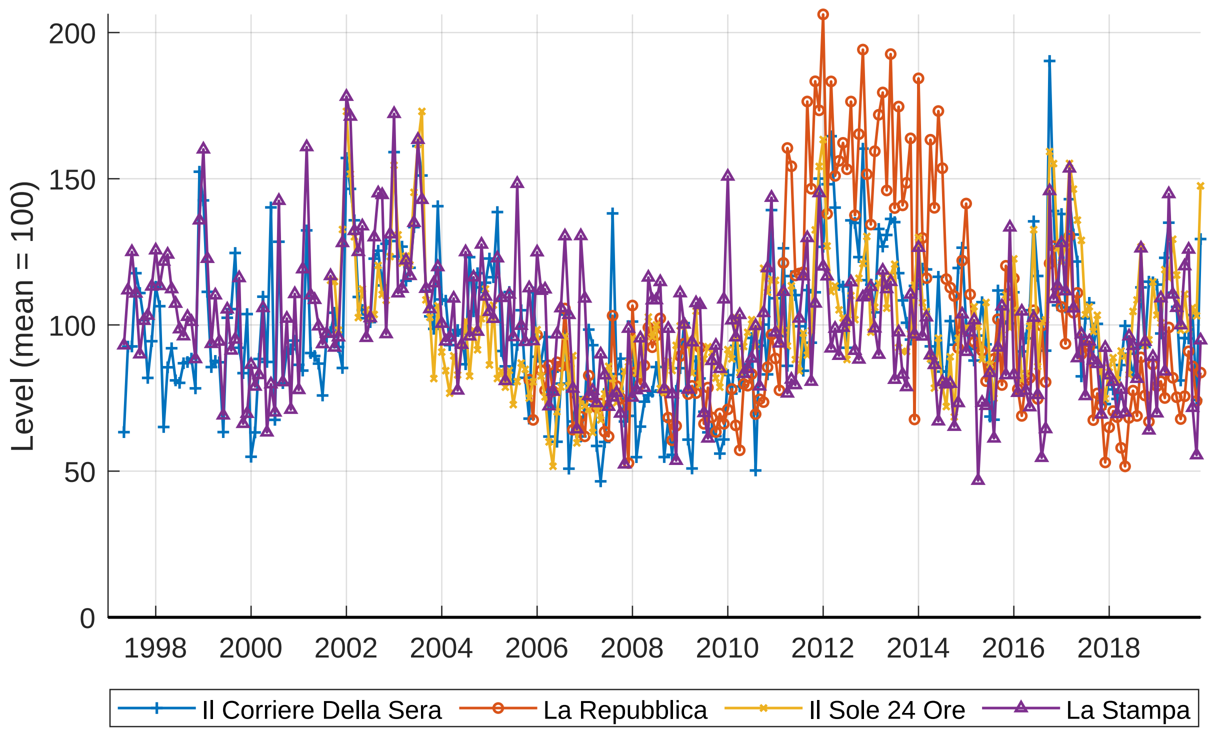
As for TESI, we discuss the heterogeneity of the four newspapers with respect to the policy uncertainty indicator. The degree of commonality across the newspaper-specific TEPU series is very high in our sample, except for the period 2012-2014, when *La Repubblica* shows a much higher TEPU than all other newspapers. As there are temporary deviations in TEPU series across journals, our choice of using more than one newspaper has the advantage of smoothing these noisy fluctuations, achieving a more robust and stable signal.

[6] The series are normalized to have zero mean unit variance on the sample.

Figure A.13: Heterogeneity across source, TESI and TEPU



(a) Newspaper-specific TESI



(b) Newspaper-specific TEPU

Note: the TEPU series are normlized to have mean 100 between January 1997 and December 2010.

A.5 Empirical Applications

A.5.1 Bayesian Model Averaging - Coefficients

In order to disentangle the contribution of TESI and TEPU in the BMA forecasting application, we check the estimated coefficients through time, as shown in Figures from A.14 to A.17.

For GDP projections, the text-based indices' coefficients display the expected sign and are often larger than those attached to other popular indicators. TESI for manufacturing outperforms Istat's confidence indices for manufacturing and consumers, and it is a strong competitor for the industrial production index. Instead PMIs coefficients are shrunk towards zero, and take a negative and counter-intuitive sign almost throughout the whole sample. As expected TEPU gives a negative contribution, with a sizeable parameter especially during the most turbulent period. Investors' expected earnings (TEPU's most direct and effective competitor) displays significant close-to-zero coefficients that become counter-intuitively positive after 2015.

In the Services Value Added model (VAS), the coefficients associated to the Istat confidence indices display a better pattern than that one of TESI, while PMI-services performs poorly. TEPU is, again, more weighted than investors' expected earnings. For the Gross Fixed Investments (GFI), which is a very volatile component of the GDP, TESI has a higher parameter during the most critical periods; the investors' expected earnings index has a negative and sizable coefficient up to 2015, when its contribution starts to fade, while TEPU plays an important role during the whole sample. Finally in the Household Consumption equation, the labor-market TESI has a significant and positive contribution throughout the sample; TEPU enters in the forecasting models on average with a significant and negative coefficient during the Sovereign Debt Crisis in 2011. In this period, important short-term forecasting variables, such as new cars registrations, and Istat consumers' confidence glaringly loose their informative power.

Figure A.14: Coefficients and confidence bands (25th-75th percentile) for the GDP model

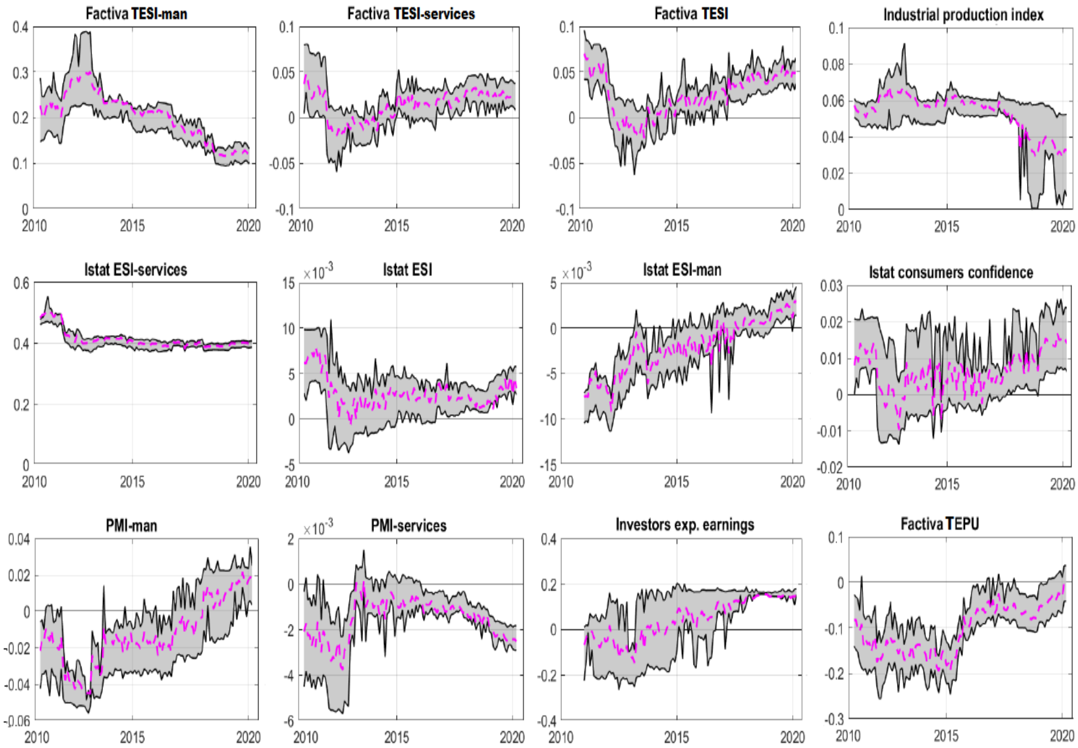


Figure A.15: Coefficients and confidence bands (25th-75th percentile) for the VAS model

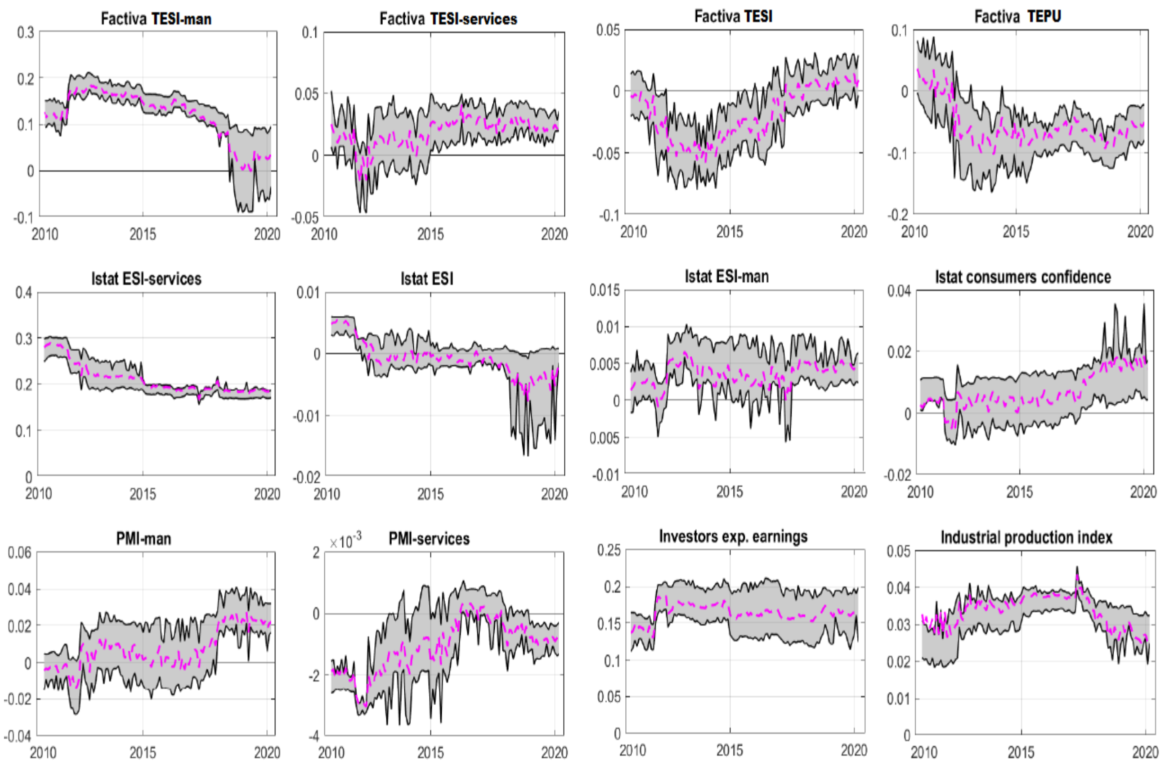


Figure A.16: Coefficients and confidence bands (25th-75th percentile) for the GFI model

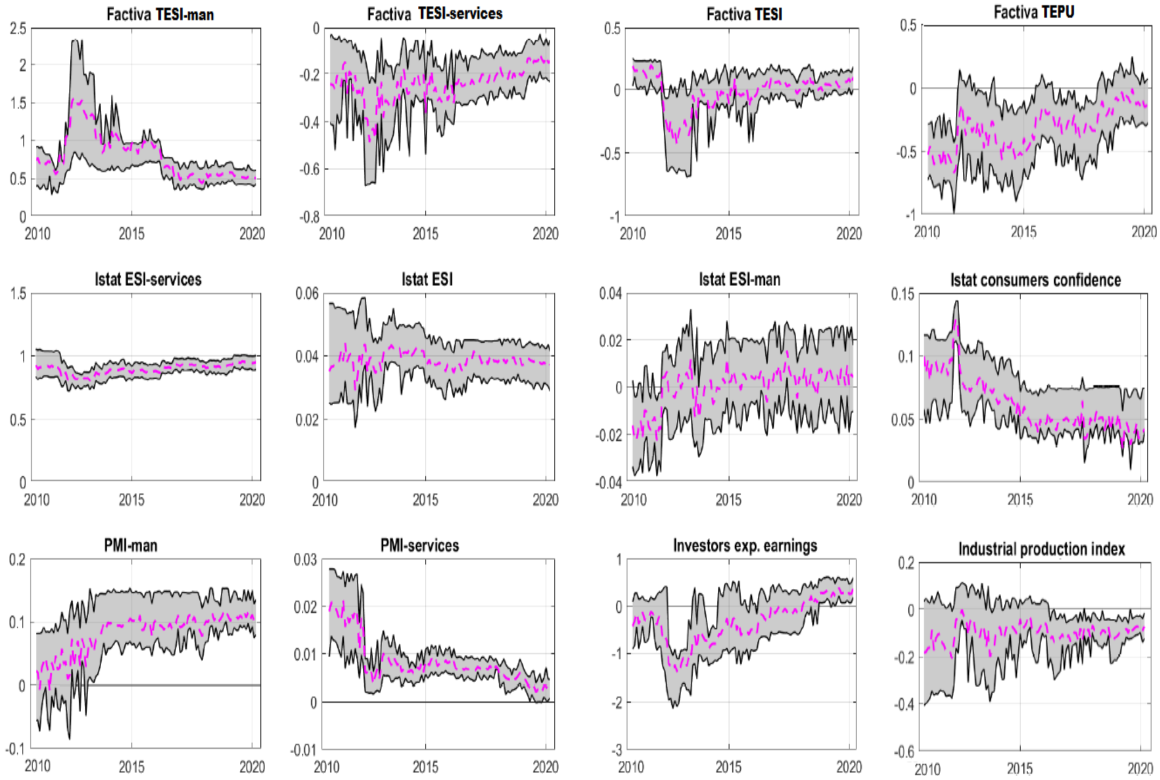
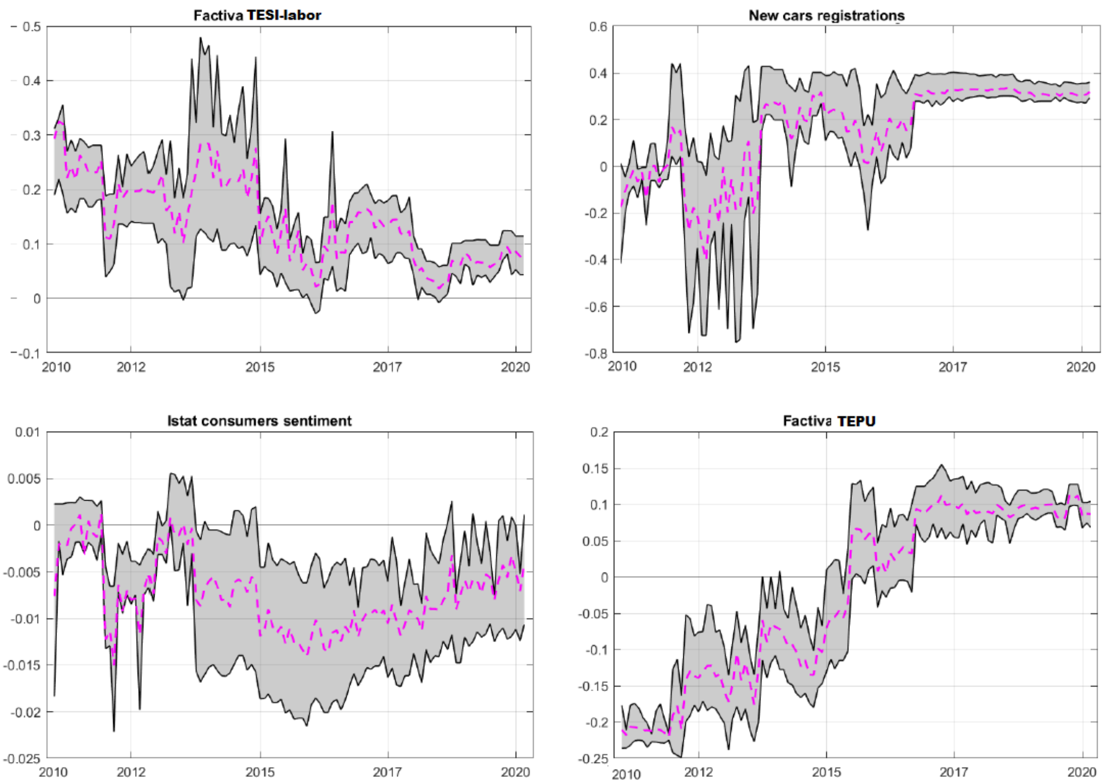


Figure A.17: Coefficients and confidence bands (25th-75th percentile) for the HHC model



A.5.2 Bayesian Model Averaging - Robustness to alternative features of the dictionary

One contribution of our paper is the new dictionary in Italian, with two distinctive aspects compared to a traditional bag-of-words approach: i) n-grams, and ii) valence shifters. We show the impact on the forecasting performance of these two additional features of our dictionary, by constructing three alternative TESI series: i) TESI with *no valence-shifter*;ii) TESI with *no n-grams* ; iii) TESI with *uni-grams only*, where the influence of both valence-shifters and n-grams is shut down. Figure A.18 shows the benchmark TESI used in the main text, along with the three alternative series. The four series display a high degree of correlation, although there appear to be some relevant deviations during important events.

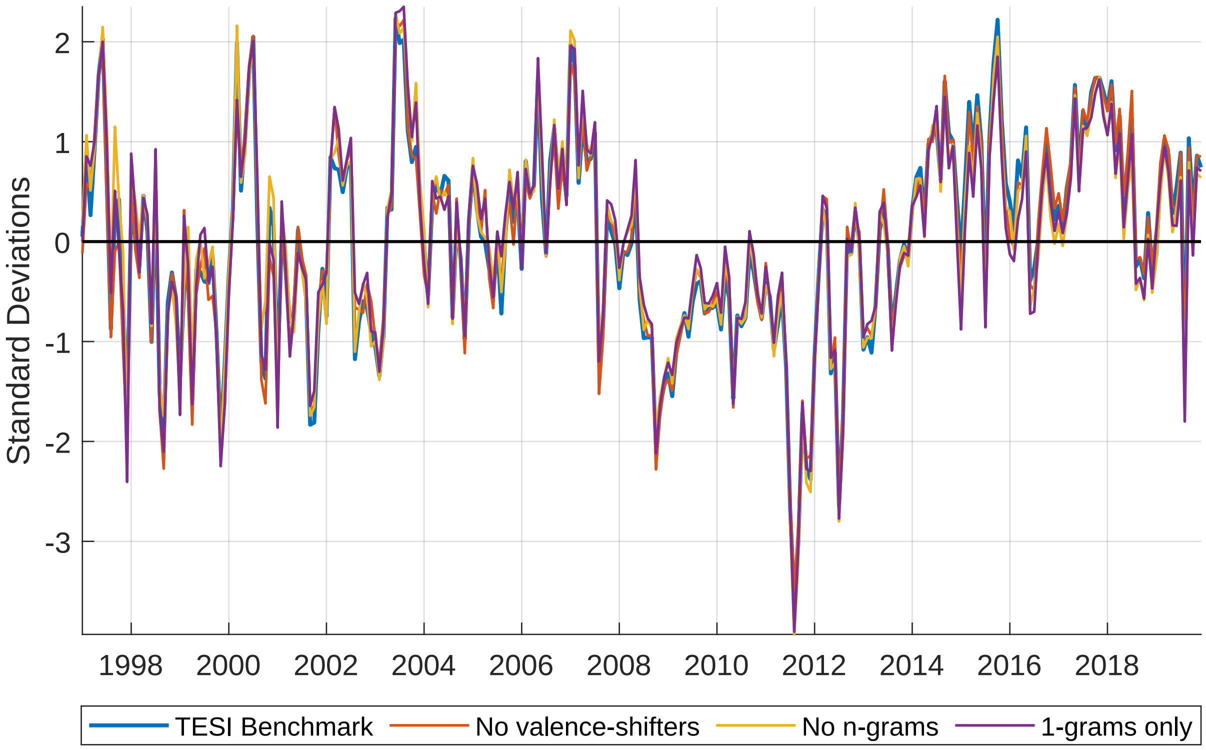
In order to assess the impact of including n-grams and valence shifters on the forecasting ability of our text-based indices, we perform a sensitivity analysis with the BMA model comparing each of this three alternative dictionary configurations, with the benchmark results described in Section 5.1. For each alternative specification, we replace all the TESI series (both the overall one, and the sector/topic-specific ones) with those derived with alternative features.

Tables A.5 and Tables A.6 report the outcome of a set of pair-wise tests of equal predictive ability (relative RMSFE and average log-score) for BMA models that include the text-based indexes and a baseline BMA with only traditional macroeconomic variables (e.g. PMIs or industrial production). The test are performed for all the target variables of the National Accounts (GDP, VAS, GFI, and HHC).

In terms of the point-forecast performance, there are no significant accuracy improvements in including text-based indices, echoing the results presented in the main text. The relative RMSFE are close to one, and their differences are not statistically significant using a Diebold-Mariano test on the full sample or in each sub-sample.

In contrast, using the benchmark TESI series (featuring n-grams, and valence-shifters), the accuracy of density forecasts outperforms the alternatives, for most targets, forecast horizons, and samples.

Figure A.18: Sentiment by dictionary features



Note: the benchmark TESI, described in Section 3, is compared with three alternatives with different features of the dictionary: i) TESI with *No valence-shifters*; ii) TESI with *no n-grams* ; iii) TESI with *uni-grams only*.

Table A.5: Relative RMSFE for nowcasts (n) and 1-step-ahead forecasts (f)

	2011.1 - 2014.12		**2015.1 - 2019.12**		**Whole Sample**	
	n	f	n	f	n	f
GDP						
Benchmark	0.93	0.91	1.17	1.16	1.00	1.00
No valence-shifters	0.96	0.96	1.12	1.11	1.00	1.00
No n-grams	0.97	0.96	1.12	1.11	1.00	1.00
1-grams only	0.96	0.96	1.12	1.09	1.00	1.00
VAS						
Benchmark	0.97	1.21	1.08	1.08	1.00	1.00
No valence-shifters	0.98	1.00	1.07	1.06	1.00	1.00
No n-grams	0.97	1.00	1.07	1.05	1.00	1.00
1-grams only	0.97	0.99	1.08	1.05	1.00	1.00
GFI						
Benchmark	1.03	0.94	1.13	1.08	1.03	1.00
No valence-shifters	0.99	0.96	1.12	1.07	1.01	1.00
No n-grams	1.00	0.95	1.09	1.07	1.01	1.00
1-grams only	0.99	0.94	1.12	1.07	1.01	0.99
HHC						
Benchmark	0.83	0.79	1.46	1.29	0.99	1.00
No valence-shifters	0.93	0.95	1.19	1.14	0.99	1.01
No n-grams	0.94	0.98	1.17	1.10	0.99	1.01
1-grams only	0.93	0.97	1.19	1.12	0.99	1.01

Note: the relative RMSFE is the ratio between the RMSFE of the BMA with text-based indices (TB-model) and a baseline BMA, which excludes them. Using a Diebold-Mariano test, we do not find statistically significant improvements in predictive accuracy in the nowcasts or the 1-step-ahead forecasts for the samples and macroeconomic variables considered. The *Benchmark* row displays results presented in section 5.1 of the main text for comparison. Smaller values of the *Benchmark* model with respect to alternative specifications indicate that the *benchmark dictionary*, with both valence-shifters and n-grams, performs better than the alternative ones.

Table A.6: Weighted Likelihood Ratio Test for nowcasts (n) and 1-step-ahead forecasts (f)

	2011.1 - 2014.12		**2015.1 - 2019.12**		**Whole sample**	
	n	f	n	f	n	f
GDP						
Benchmark	**9.1*****	**8.6*****	-15.6***	-22.4***	**6.1*****	**6.6*****
No valence-shifters	**7.7*****	**8.7*****	-25.0***	-21.7***	**2.7*****	**7.4*****
No n-grams	**6.2*****	**8.3*****	-28.4***	-20.7***	-0.1	**4.9*****
1-grams only	**5.3*****	**8.2*****	-23.5***	-21.7***	0.8	**7.9*****
VAS						
Benchmark	**5.3*****	**6.6*****	-7.1***	-10.3***	**3.7*****	**6.4*****
No valence-shifters	**2.5*****	**1.7****	-9.0***	-14.3***	1.4*	1.3*
No n-grams	**4.5*****	**3.4*****	-8.8***	-9.2***	**4.1*****	**4.2*****
1-grams only	**4.4*****	**3.1*****	-8.9***	-13.1***	**4.0*****	**3.4*****
GFI						
Benchmark	**3.6*****	**23.7*****	**6.9*****	**10.5*****	**4.6*****	**24.5*****
No valence-shifters	**4.7*****	**25.7*****	-4.5***	-4.2***	1.5*	**16.1*****
No n-grams	**7.5*****	**21.2*****	-2.3***	-3.4***	**5.6*****	**16.6*****
1-grams only	**2.9*****	**24.8** ***	-5.7***	-4.6***	-1.0	**17.7*****
HHC						
Benchmark	**14.6*****	**12.2*****	-9.4***	-11.8***	**11.4*****	**11.8*****
No valence-shifters	**12.5*****	**12.1*****	-5.4***	-6.5***	**9.1*****	**11.4*****
No n-grams	**10.5*****	**8.5*****	-1.9**	0.6	**8.7*****	**8.4*****
1-grams only	**11.3*****	**10.5*****	-6.5***	-6.0***	**8.7*****	**10.1*****

Note: positive values of the Weighted Likelihood Ratio Test (in boldface) imply that the BMA with textual data (TB-model) has a greater density forecast accuracy than the BMA without them. The *Benchmark* row reports results presented in section 5.1 of the main text for comparison. Greater values of the *Benchmark* model with respect to alternative specifications indicate that the *benchmark dictionary*, with both valence-shifters and n-grams, performs better than the alternative ones. Significance at the 1%, 5%, and 10% levels is indicated with ***,**,*, respectively.

A.5.3 Bayesian Model Averaging - Robustness with respect to the original EPU by BBD2016

In this section, we assess the impact of TEPU in the forecasting application, by replacing it with the original EPU from Baker et al. (2016) (BBD2016). To make a fair comparison, we leave all the TESI indices in the dataset (see Table 3).As the BBD2016 EPU is not available by sector, we exclude from the Benchmark all TEPU variables (baseline, manufacturing, services) and replace them with the original EPU series.
For more information on how TEPU and the original BBD2016 EPU differ, see Section 4 in the main text.

Overall, we find that TEPU and BBD2016 EPU perform quite similarly with respect to point forecast gains. TEPU performs better in the first half of the sample, while EPU in the second half. No statistically significant difference emerges in terms of overall performance. However, Table A.8 shows that the set of TEPU indices reduce the density forecasts uncertainty, especially for the GDP and the VAS.

Table A.7: Relative RMSFE for nowcasts (n) and 1-step-ahead forecasts (f)

	2011.1 - 2014.12		**2015.1 - 2019.12**		**Whole sample**	
	n	f	n	f	n	f
GDP						
Benchmark	0.93	0.91	1.17	1.16	1.00	1.00
EPU BBD2016	0.96	0.96	1.07	1.06	1.00	1.00
VAS						
Benchmark	0.97	1.21	1.08	1.08	1.00	1.00
EPU BBD2016	0.98	0.99	1.08	1.05	1.02	1.01
GFI						
Benchmark	1.03	0.94	1.13	1.08	1.03	1.00
EPU BBD2016	1.04	0.92	1.12	1.08	1.02	0.99
HHC						
Benchmark	0.83	0.79	1.46	1.29	0.99	1.00
EPU BBD2016	0.83	0.79	1.29	1.17	0.98	0.99

Note: the relative RMSFE is the ratio between the RMSFE of the BMA with text-based indices (TB-model) and a baseline BMA without them. Using a Diebold-Mariano test, we do not find statistically significant improvements in predictive accuracy in the nowcasts and the 1-step-ahead forecasts for the samples and macroeconomic variables considered. The *Benchmark* row reports results presented in section 5.1 of the main text for comparison. Smaller values of the *Benchmark* model with respect to alternative specifications indicate that the *Benchmark* TEPU indices perform better than the EPU proposed by BBD2016 when included in a BMA model with TESI.

Table A.8: Weighted Likelihood Ratio Test for nowcasts (n) and 1-step-ahead forecasts (f)

	2011.1 - 2014.12		**2015.1 - 2019.12**		**Whole sample**	
	n	f	n	f	n	f
GDP						
Benchmark	**9.1*****	**8.6*****	-15.6***	-22.4***	**6.1*****	**6.6*****
EPU BBD2016	**6.6*****	**8.1*****	-29.9***	-24.9***	1.8**	**4.1*****
VAS						
Benchmark	**5.3*****	**6.6*****	-7.1***	-10.3***	**3.7*****	**6.4*****
EPU BBD2016	**2.8*****	**4.6*****	-8.0***	-12.2***	-2.0**	**1.9****
GFI						
Benchmark	**3.6*****	**23.7*****	**6.9*****	**10.5*****	**4.6*****	**24.5*****
EPU BBD2016	**5.6*****	**30.5*****	-2.8***	**3.8*****	**5.5*****	**23.0*****
HHC						
Benchmark	**14.6*****	**12.2*****	-9.4***	-11.8***	**11.4*****	**11.8*****
EPU BBD2016	**14.8*****	**12.2*****	-5.1***	-2.4***	**12.6*****	**12.7*****

Note: positive values of the Weighted Likelihood Ratio Test (in boldface) imply that the BMA with textual data (TB-model) has a greater density forecast accuracy than the BMA without them. The *Benchmark* row reports the results presented in section 5.1 of the main text for comparison. Greater values of the *Benchmark* model with respect to alternative specifications indicate that the Benchmark TEPU performs better than the BBD2016 when included in a BMA model with TESI. Significance at the 1%, 5%, and 10% levels is indicated with ***,**,*, respectively.

A.5.4 Bayesian Model Averaging - robustness to weighting for newspaper circulation

In this section, we perform a robustness exercise by building a TESI index where the newspaper's contribution to the overall measure is given by its average daily circulation in the month (as opposed to the number of articles, as in the Benchmark).[7]

Figure A.19 shows how the circulation-weighted TESI is similar to the benchmark described in section 3. This result is due to the fact that individual newspaper sentiment series display a strong common component. In fact, the largest deviation can be observed in the 2015-2016 period, where *Il Sole 24 Ore* (which publishes almost half of the available economic articles, but has lower circulation than *La Repubblica* and *Il Corriere della Sera*, thus entering less frequently in the circulation-weighted TESI).

Then, we compare how the benchmark and the circulation-weighted TESI perform in the forecasting application with the BMA model. The two series have a similar point-forecast performance, but the circulation-weighted TESI performs much worse in terms of density forecasts. The likelihood ratio tests show that the circulation-weighted TESI has a statistically significant loss in performance with respect to the model without text-based indices when forecasting and nowcasting GDP and VAS. While it has gains over the No-Factiva benchmark for GFI and HHC, the circulation-weighted TESI always performs worse than the standard one in all remaining exercises.

Further, for truly real-time applications, it should be considered that newspaper circulation data are not available at the daily frequency, but only monthly and with a delay.

[7] We download the circulation data from Accertamenti Diffusione Stampa https://www.adsnotizie.it/index.asp. The data are available until 2003, for the preceding years we use the 2003 data.

Figure A.19: Benchmark TESI and Circulation-Weighted TESI

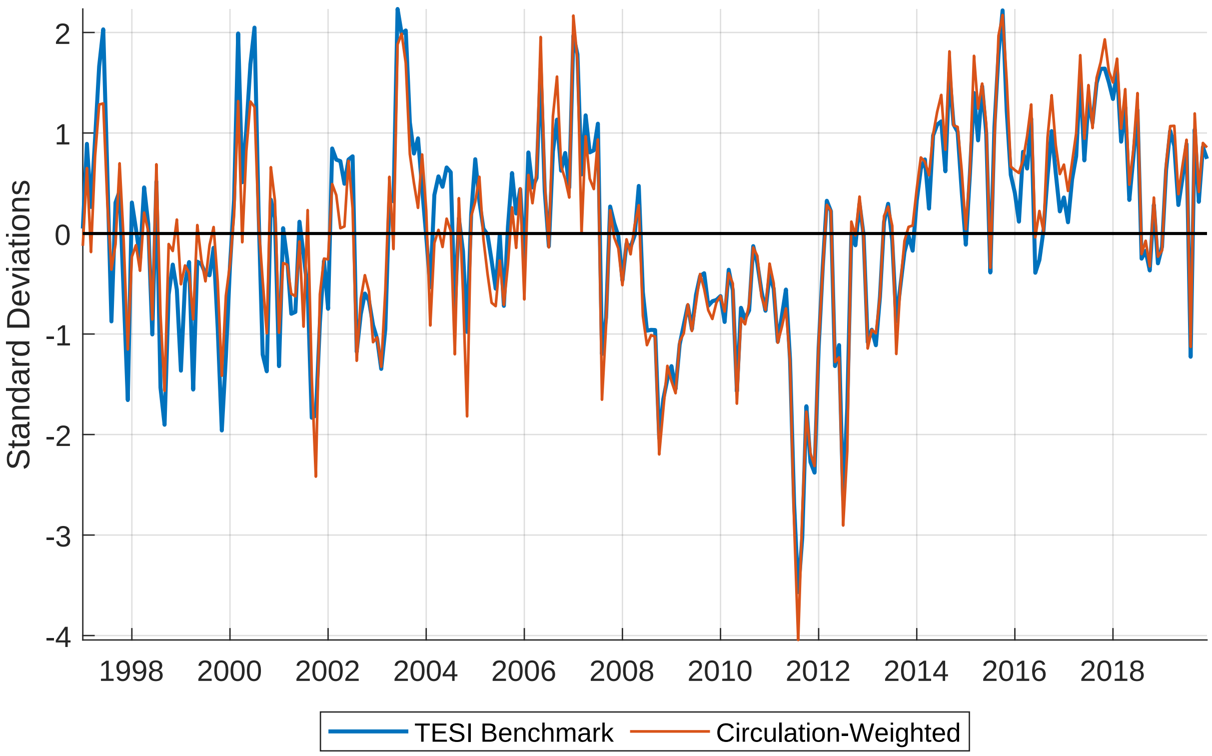


Table A.9: Relative RMSFE for nowcasts (n) and 1-step-ahead forecasts (f)

	2011.1 - 2014.12		**2015.1 - 2019.12**		**Whole sample**	
	n	f	n	f	n	f
GDP						
Benchmark	0.93	0.91	1.17	1.16	1.00	1.00
Newspaper circulation TESI	0.98	0.99	1.09	1.08	1.00	1.00
VAS						
Benchmark	0.97	1.21	1.08	1.08	1.00	1.00
Newspaper circulation TESI	1.01	1.01	1.05	1.04	1.00	1.00
GFI						
Benchmark	1.03	0.94	1.13	1.08	1.03	1.00
Newspaper circulation TESI	0.99	0.97	1.08	1.05	1.01	1.00
HHC						
Benchmark	0.83	0.79	1.46	1.29	0.99	1.00
Newspaper circulation TESI	0.95	0.99	1.13	1.12	0.99	1.02

Note: the relative RMSFE is the ratio between the RMSFE of the BMA with text-based indices (TB-model) and a baseline BMA without them. Using a Diebold-Mariano test, we do not find statistically significant improvements in predictive accuracy in the nowcasts and the 1-step-ahead forecasts for the samples and macroeconomic variables considered. The *Benchmark* row reports results presented in section 5.1 of the main text for comparison. Smaller values of the *Benchmark* model with respect to alternative specifications indicate that the unweighted TESI indices presented in section 3 perform better than the circulation-weighted TESI.

Table A.10: Weighted Likelihood Ratio Test for nowcasts (n) and 1-step-ahead forecasts (f)

	2011.1 - 2014.12		**2015.1 - 2019.12**		**Whole Sample**	
	n	f	n	f	n	f
GDP						
Benchmark	**9.1*****	**8.6*****	-15.6***	-22.4***	**6.1*****	**6.6*****
Newspaper circulation TESI	-2.0**	-1.0	-17.4***	-13.2***	-5.8***	-2.8***
VAS						
Benchmark	**5.3*****	**6.6*****	-7.1***	-10.3***	**3.7*****	**6.4*****
Newspaper circulation TESI	0.1	-1.8**	-9.9***	-8.1***	-4.1***	-6.4***
GFI						
Benchmark	**3.6*****	**23.7*****	**6.9*****	**10.5*****	**4.6*****	**24.5*****
Newspaper circulation TESI	-5.2***	**15.7*****	1.0	-2.6***	-7.7***	**13.5*****
HHC						
Benchmark	**14.6*****	**12.2*****	-9.4***	-11.8***	**11.4*****	**11.8*****
Newspaper circulation TESI	**12.5*****	**9.1*****	1.6*	1.4*	**9.2*****	**7.8*****

Note: positive values of the Weighted Likelihood Ratio Test (bold) imply that the BMA with textual data (TB-model) has a greater density forecast accuracy than the BMA without them. The *Benchmark* row reports results presented in section 5.1 of the main text for comparison. Greater values of the *Benchmark* model with respect to alternative specifications indicate that the unweighted TESI indices in section 3 perform better than the circulation-weighted TESI. Significance at the 1%, 5%, and 10% levels is indicated with ***,**,*, respectively.

References

Ardia, David, Keven Bluteau, Samuel Borms, and Kris Boudt, "The R package sentometrics to compute, aggregate and predict with textual sentiment," *Journal of Statistical Software*, 2021, *99* (2), 1–40. A.1.4, A.3

Bachmann, Rüdiger, Steffen Elstner, and Eric R. Sims, "Uncertainty and economic activity: Evidence from business survey data," *American Economic Journal: Macroeconomics*, 2013, *5* (2), 217–49. A.3.1

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, "Measuring economic policy uncertainty," *The Quarterly Journal of Economics*, 2016, *131* (4), 1593–1636. 1, A.5.3

Gentzkow, Matthew and Jesse M. Shapiro, "What drives media slant? Evidence from US daily newspapers," *Econometrica*, 2010, *78* (1), 35–71. A.4.1

_ , _ , and Matt Taddy, "Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech," *Econometrica*, 2019, *87* (4), 1307–1340. A.4.1

Groseclose, Tim and Jeffrey Milyo, "A measure of media bias," *The Quarterly Journal of Economics*, 2005, *120* (4), 1191–1237. A.4.1

Hartmann, Philipp and Frank Smets, "The first 20 years of the European Central Bank: Monetary policy," in "Brookings Papers on Economic Activity Conference Draft, Fall" 2018. A.2.2, A.3.2

Husted, Lucas, John Rogers, and Bo Sun, "Monetary policy uncertainty," *Journal of Monetary Economics*, 2019. A.3.2

Maks, Isa, Ruben Izquierdo, Francesca Frontini, Rodrigo Agerri, Piek Vossen, and Andoni Azpeitia, "Generating Polarity Lexicons with WordNet propagation in 5 languages," in "Proceedings of the Ninth International Conference on Language

Resources and Evaluation (LREC'14)" European Language Resources Association (ELRA) Reykjavik, Iceland May 2014, pp. 1155–1161. A.2.3

Neri, Stefano and Stefano Siviero, "The non-standard monetary policy measures of the ECB: motivations, effectiveness and risks," *Bank of Italy Occasional Paper*, 2019, (486). A.2.2