

Text as Data[†]

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An ever-increasing share of human interaction, communication, and culture is recorded as digital text. We provide an introduction to the use of text as an input to economic research. We discuss the features that make text different from other forms of data, offer a practical overview of relevant statistical methods, and survey a variety of applications. (JEL C38, C55, L82, Z13)

1. Introduction

New technologies have made available vast quantities of digital text, recording an ever-increasing share of human interaction, communication, and culture. For social scientists, the information encoded in text is a rich complement to the more structured kinds of data traditionally used in research, and recent years have seen an explosion of empirical economics research using text as data.

To take just a few examples: In finance, text from financial news, social media, and company filings is used to predict asset price movements and study the causal impact of new information. In macroeconomics, text is used to forecast variation in inflation and unemployment, and estimate the effects of policy uncertainty. In media economics, text from news and social media is used to study the drivers and effects of political slant. In industrial organization and marketing, text

from advertisements and product reviews is used to study the drivers of consumer decision making. In political economy, text from politicians' speeches is used to study the dynamics of political agendas and debate.

The most important way that text differs from the kinds of data often used in economics is that text is inherently high dimensional. Suppose that we have a sample of documents, each of which is w words long, and suppose that each word is drawn from a vocabulary of p possible words. Then the unique representation of these documents has dimension p^w . A sample of thirty-word Twitter messages that use only the one thousand most common words in the English language, for example, has roughly as many dimensions as there are atoms in the universe.

A consequence is that the statistical methods used to analyze text are closely related to those used to analyze high-dimensional data in other domains, such as machine learning and computational biology. Some methods, such as lasso and other penalized regressions, are applied to text more or less exactly as they are in other settings. Other methods, such as topic models and multinomial inverse regression, are close cousins of more general

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methods adapted to the specific structure of text data.

In all of the cases we consider, the analysis can be summarized in three steps:

1. Represent raw text \mathcal{D} as a numerical array \mathbf{C} ;
2. Map \mathbf{C} to predicted values $\hat{\mathbf{V}}$ of unknown outcomes \mathbf{V} ; and
3. Use $\hat{\mathbf{V}}$ in subsequent descriptive or causal analysis.

In the first step, the researcher must impose some preliminary restrictions to reduce the dimensionality of the data to a manageable level. Even the most cutting-edge high-dimensional techniques can make nothing of 1,000³⁰-dimensional raw Twitter data. In almost all the cases we discuss, the elements of \mathbf{C} are counts of *tokens*: words, phrases, or other predefined features of text. This step may involve filtering out very common or uncommon words; dropping numbers, punctuation, or proper names; and restricting attention to a set of features such as words or phrases that are likely to be especially diagnostic. The mapping from raw text to \mathbf{C} leverages prior information about the structure of language to reduce the dimensionality of the data prior to any statistical analysis.

The second step is where high-dimensional statistical methods are applied. In a classic example, the data is the text of emails, and the unknown variable of interest \mathbf{V} is an indicator for whether the email is spam. The prediction $\hat{\mathbf{V}}$ determines whether or not to send the email to a spam filter. Another classic task is sentiment prediction (e.g., Pang, Lee, and Vaithyanathan 2002), where the unknown variable \mathbf{V} is the true sentiment of a message (say positive or negative), and the prediction $\hat{\mathbf{V}}$ might be used to identify positive reviews or comments about a product. A

third task is predicting the incidence of local flu outbreaks from Google searches, where the outcome \mathbf{V} is the true incidence of flu.

In these examples, and in the vast majority of settings where text analysis has been applied, the ultimate goal is prediction rather than causal inference. The interpretation of the mapping from \mathbf{V} to $\hat{\mathbf{V}}$ is not usually an object of interest. Why certain words appear more often in spam, or why certain searches are correlated with flu is not important so long as they generate highly accurate predictions. For example, Scott and Varian (2014, 2015) use data from Google searches to produce high-frequency estimates of macroeconomic variables such as unemployment claims, retail sales, and consumer sentiment that are otherwise available only at lower frequencies from survey data. Groseclose and Milyo (2005) compare the text of news outlets to speeches of congresspeople in order to estimate the outlets' political slant. A large literature in finance following Antweiler and Frank (2004) and Tetlock (2007) uses text from the internet or the news to predict stock prices.

In many social science studies, however, the goal is to go further and, in the third step, use text to infer causal relationships or the parameters of structural economic models. Stephens-Davidowitz (2014) uses Google search data to estimate local areas' racial animus, then studies the causal effect of racial animus on votes for Barack Obama in the 2008 election. Gentzkow and Shapiro (2010) use congressional and news text to estimate each news outlet's political slant, then study the supply and demand forces that determine slant in equilibrium. Engelberg and Parsons (2011) measure local news coverage of earnings announcements, then use the relationship between coverage and trading by local investors to separate the causal effect of news from other sources of correlation between news and stock prices.

In this paper, we provide an overview of methods for analyzing text and a survey of current applications in economics and related social sciences. The methods discussion is forward looking, providing an overview of methods that are currently applied in economics as well as those that we expect to have high value in the future. Our discussion of applications is selective and necessarily omits many worthy papers. We highlight examples that illustrate particular methods and use text data to make important substantive contributions even if they do not apply methods close to the frontier.

A number of other excellent surveys have been written in related areas. See Evans and Aceves (2016) and Grimmer and Stewart (2013) for related surveys focused on text analysis in sociology and political science, respectively. For methodological surveys, Bishop (2006), Hastie, Tibshirani, and Friedman (2009), and Murphy (2012) cover contemporary statistics and machine learning in general while Jurafsky and Martin (2009) overview methods from computational linguistics and natural language processing. The Spring 2014 issue of the *Journal of Economic Perspectives* contains a symposium on “big data,” which surveys broader applications of high-dimensional statistical methods to economics.

In section 2 we discuss representing text data as a manageable (though still high-dimensional) numerical array \mathbf{C} ; in section 3 we discuss methods from data mining and machine learning for predicting \mathbf{V} from \mathbf{C} . Section 4 then provides a selective survey of text analysis applications in social science, and section 5 concludes.

2. Representing Text as Data

When humans read text, they do not see a vector of dummy variables, nor a sequence of unrelated tokens. They interpret words in light of other words, and extract meaning

from the text as a whole. It might seem obvious that any attempt to distill text into meaningful data must similarly take account of complex grammatical structures and rich interactions among words.

The field of computational linguistics has made tremendous progress in this kind of interpretation. Most of us have mobile phones that are capable of complex speech recognition. Algorithms exist to efficiently parse grammatical structure, disambiguate different senses of words, distinguish key points from secondary asides, and so on.

Yet virtually all analysis of text in the social sciences, like much of the text analysis in machine learning more generally, ignores the lion’s share of this complexity. Raw text consists of an ordered sequence of language elements: words, punctuation, and white space. To reduce this to a simpler representation suitable for statistical analysis, we typically make three kinds of simplifications: dividing the text into individual documents i , reducing the number of language elements we consider, and limiting the extent to which we encode dependence among elements within documents. The result is a mapping from raw text \mathcal{D} to a numerical array \mathbf{C} . A row \mathbf{c}_i of \mathbf{C} is a numerical vector with each element indicating the presence or count of a particular language token in document i .

2.1 What Is a Document?

The first step in constructing \mathbf{C} is to divide raw text \mathcal{D} into individual documents $\{\mathcal{D}_i\}$. In many applications, this is governed by the level at which the attributes of interest \mathbf{V} are defined. For spam detection, the outcome of interest is defined at the level of individual emails, so we want to divide text that way too. If \mathbf{V} is daily stock price movements that we wish to predict from the prior day’s news text, it might make sense to divide the news text by day as well.

In other cases, the natural way to define a document is not so clear. If we wish to

predict legislators' partisanship from their floor speeches (Gentzkow, Shapiro, and Taddy 2016), we could aggregate speech so a document is a speaker-day, a speaker-year, or all speech by a given speaker during the time she is in Congress. When we use methods that treat documents as independent (which is true most of the time), finer partitions will typically ease computation at the cost of limiting the dependence we are able to capture. Theoretical guidance for the right level of aggregation is often limited, so this is an important dimension along which to check the sensitivity of results.

2.2 Feature Selection

To reduce the number of features to something manageable, a common first step is to strip out elements of the raw text other than words. This might include punctuation, numbers, HTML tags, proper names, and so on.

It is also common to remove a subset of words that are either very common or very rare. Very common words, often called "stop words," include articles ("the," "a"), conjunctions ("and," "or"), forms of the verb "to be," and so on. These words are important to the grammatical structure of sentences, but they typically convey relatively little meaning on their own. The frequency of "the" is probably not very diagnostic of whether an email is spam, for example. Common practice is to exclude stop words based on a predefined list.¹ Very rare words do convey meaning, but their added computational cost in expanding the set of features that must be considered often exceeds their diagnostic value. A common approach is to exclude all words

that occur fewer than k times for some arbitrary small integer k .

An approach that excludes both common and rare words and has proved very useful in practice is filtering by "term frequency-inverse document frequency" (tf-idf). For a word or other feature j in document i , term frequency (tf_{ij}) is the count c_{ij} of occurrences of j in i . Inverse document frequency (idf_j) is the log of one over the share of documents containing j : $\log(n/d_j)$ where $d_j = \sum_i \mathbf{1}_{[c_{ij}>0]}$ and n is the total number of documents. The object of interest tf-idf is the product $tf_{ij} \times idf_j$. Very rare words will have low tf-idf scores because tf_{ij} will be low. Very common words that appear in most or all documents will have low tf-idf scores because idf_j will be low. (Note that this improves on simply excluding words that occur frequently because it will keep words that occur frequently in some documents but do not appear in others; these often provide useful information.) A common practice is to keep only the words within each document i with tf-idf scores above some rank or cutoff.

A final step that is commonly used to reduce the feature space is *stemming*: replacing words with their root such that, e.g., "economic," "economics," "economically" are all replaced by the stem "economic." The Porter stemmer (Porter 1980) is a standard stemming tool for English language text.

All of these cleaning steps reduce the number of unique language elements we must consider and thus the dimensionality of the data. This can provide a massive computational benefit, and it is also often key to getting more interpretable model fits (e.g., in topic modeling). However, each of these steps requires careful decisions about the elements likely to carry meaning in a particular application.² One researcher's

¹There is no single stop word list that has become a standard. How aggressive one wants to be in filtering stop words depends on the application. The web page <http://www.ranks.nl/stopwords> shows several common stop word lists, including the one built into the database software SQL and the list claimed to have been used in early versions of Google search. (Modern Google search does not appear to filter any stop words.)

²Denny and Spirling (2018) discuss the sensitivity of unsupervised text analysis methods such as topic modeling to preprocessing steps.

stop words are another's subject of interest. Dropping numerals from political text means missing references to "the first 100 days" or "September 11." In online communication, even punctuation can no longer be stripped without potentially significant information loss :-).

2.3 *n*-grams

Producing a tractable representation also requires that we limit dependence among language elements. A fairly mild step in this direction, for example, might be to parse documents into distinct sentences and encode features of these sentences while ignoring the order in which they occur. The most common methodologies go much further.

The simplest and most common way to represent a document is called *bag-of-words*. The order of words is ignored altogether, and \mathbf{c}_i is a vector whose length is equal to the number of words in the vocabulary and whose elements c_{ij} are the number of times word j occurs in document i . Suppose that the text of document i is

Good night, good night!
Parting is such sweet sorrow.

After stemming, removing stop words, and removing punctuation, we might be left with "good night good night part sweet sorrow." The bag-of-words representation would then have $c_{ij} = 2$ for $j \in \{\text{good}, \text{night}\}$, $c_{ij} = 1$ for $j \in \{\text{part}, \text{sweet}, \text{sorrow}\}$, and $c_{ij} = 0$ for all other words in the vocabulary.

This scheme can be extended to encode a limited amount of dependence by counting unique phrases rather than unique words. A phrase of length n is referred to as an n -gram. For example, in our snippet above, the count of 2-grams (or "bigrams") would have $c_{ij} = 2$ for $j = \text{good.night}$, $c_{ij} = 1$ for j including *night.good*, *night.part*, *part.sweet*, and *sweet.sorrow*, and $c_{ij} = 0$ for all other possible 2-grams. The bag-of-words

representation then corresponds to counts of 1-grams.

Counting n -grams of order $n > 1$ yields data that describe a limited amount of the dependence between words. Specifically, the n -gram counts are sufficient for estimation of an n -order homogeneous Markov model across words (i.e., the model that arises if we assume that word choice is only dependent upon the previous n words). This can lead to richer modeling. In analysis of partisan speech, for example, single words are often insufficient to capture the patterns of interest: "death tax" and "tax break" are phrases with strong partisan overtones that are not evident if we look at the single words "death," "tax," and "break" (see, e.g., Gentzkow and Shapiro 2010).

Unfortunately, the dimension of \mathbf{c}_i increases exponentially quickly with the order n of the phrases tracked. The majority of text analyses consider n -grams up to two or three at most, and the ubiquity of these simple representations (in both machine learning and social science) reflects a belief that the return to richer n -gram modeling is usually small relative to the cost. Best practice in many cases is to begin analysis by focusing on single words. Given the accuracy obtained with words alone, one can then evaluate if it is worth the extra time to move on to 2-grams or 3-grams.

2.4 Richer Representations

While rarely used in the social science literature to date, there is a vast array of methods from computational linguistics that capture richer features of text and may have high return in certain applications. One basic step beyond the simple n -gram counting above is to use sentence syntax to inform the text tokens used to summarize a document. For example, Goldberg and Orwant (2013) describe syntactic n -grams where words are grouped together whenever their meaning depends upon each

other, according to a model of language syntax.

An alternative approach is to move beyond treating documents as counts of language tokens, and to instead consider the *ordered* sequence of transitions between words. In this case, one would typically break the document into sentences, and treat each as a separate unit for analysis. A single sentence of length s (i.e., containing s words) is then represented as a binary $p \times s$ matrix \mathbf{S} , where the nonzero elements of \mathbf{S} indicate occurrence of the row-word in the column-position within the sentence, and p is the length of the vocabulary. Such representations lead to a massive increase in the dimensions of the data to be modeled, and analysis of this data tends to proceed through *word embedding*: the mapping of words to a location in \mathbb{R}^K for some $K \ll p$, such that the sentences are then sequences of points in this K dimensional space. This is discussed in detail in section 3.3.

2.5 Other Practical Considerations

It is worth mentioning two details that can cause practical social science applications of these methods to diverge a bit from the ideal case considered in the statistics literature. First, researchers sometimes receive data in a pre-aggregated form. In the analysis of Google searches, for example, one might observe the number of searches containing each possible keyword on each day, but not the raw text of the individual searches. This means documents must be similarly aggregated (to days, rather than individual searches), and it also means that the natural representation where c_{ij} is the number of occurrences of word j on day i is not available. This is probably not a significant limitation, as the missing information (how many times per search a word occurs conditional on occurring at least once) is unlikely to be essential, but it is useful to note when mapping practice to theory.

A more serious issue is that researchers sometimes do not have direct access to the raw text and must access it through some interface such as a search engine. For example, Gentzkow and Shapiro (2010) count the number of newspaper articles containing partisan phrases by entering the phrases into a search interface (e.g., for the database ProQuest) and counting the number of matches they return. Baker, Bloom, and Davis (2016) perform similar searches to count the number of articles mentioning terms related to policy uncertainty. Saiz and Simonsohn (2013) count the number of web pages measuring combinations of city names and terms related to corruption by entering queries in a search engine. Even if one can automate the searches in these cases, it is usually not feasible to produce counts for very large feature sets (e.g., every two-word phrase in the English language), and so the initial feature selection step must be relatively aggressive. Relatedly, interacting through a search interface means that there is no simple way to retrieve objects like the set of all words occurring at least twenty times in the corpus of documents, or the inputs to computing tf-idf.

3. Statistical Methods

This section considers methods for mapping the document-token matrix \mathbf{C} to predictions $\hat{\mathbf{V}}$ of an attribute \mathbf{V} . In some cases, the observed data is partitioned into submatrices $\mathbf{C}^{\text{train}}$ and \mathbf{C}^{test} , where the matrix $\mathbf{C}^{\text{train}}$ collects rows for which we have observations $\mathbf{V}^{\text{train}}$ of \mathbf{V} and the matrix \mathbf{C}^{test} collects rows for which \mathbf{V} is unobserved. The dimension of $\mathbf{C}^{\text{train}}$ is $n^{\text{train}} \times p$, and the dimension of $\mathbf{V}^{\text{train}}$ is $n^{\text{train}} \times k$, where k is the number of attributes we wish to predict.

Attributes in \mathbf{V} can include observable quantities such as the frequency of flu cases, the positive or negative rating of movie reviews, or the unemployment rate, about

which the documents are informative. There can also be latent attributes of interest, such as the topics being discussed in a congressional debate or in news articles.

Methods to connect counts \mathbf{c}_i to attributes \mathbf{v}_i can be roughly divided into four categories. The first, which we will call *dictionary-based* methods, do not involve statistical inference at all: they simply specify $\hat{\mathbf{v}}_i = f(\mathbf{c}_i)$ for some known function $f(\cdot)$. This is by far the most common method in the social science literature using text to date. In some cases, researchers define $f(\cdot)$ based on a prespecified dictionary of terms capturing particular categories of text. In Tetlock (2007), for example, \mathbf{c}_i is a bag-of-words representation and the outcome of interest \mathbf{v}_i is the latent “sentiment” of *Wall Street Journal* columns, defined along a number of dimensions such as “positive,” “optimistic,” and so on. The author defines the function $f(\cdot)$ using a dictionary called the General Inquirer, which provides lists of words associated with each of these sentiment categories.³ The elements of $f(\mathbf{c}_i)$ are defined to be the sum of the counts of words in each category. (As we discuss below, the main analysis then focuses on the first principal component of the resulting counts.) In Baker, Bloom, and Davis (2016), \mathbf{c}_i is the count of articles in a given newspaper-month containing a set of prespecified terms such as “policy,” “uncertainty,” and “Federal Reserve,” and the outcome of interest \mathbf{v}_i is the degree of “policy uncertainty” in the economy. The authors define $f(\cdot)$ to be the raw count of the prespecified terms divided by the total number of articles in the newspaper-month, averaged across newspapers. We do not provide additional discussion of dictionary-based methods in this section, but we return to them in section 3.5 and in our discussion of applications in section 4.

The second and third groups of methods are distinguished by whether they begin from a model of $p(\mathbf{v}_i|\mathbf{c}_i)$ or a model of $p(\mathbf{c}_i|\mathbf{v}_i)$. In the former case, which we will call *text regression* methods, we directly estimate the conditional outcome distribution, usually via the conditional expectation $E[\mathbf{v}_i|\mathbf{c}_i]$ of attributes \mathbf{v}_i . This is intuitive: if we want to predict \mathbf{v}_i from \mathbf{c}_i , we would naturally regress the observed values of the former (\mathbf{V}^{train}) on the corresponding values of the latter (\mathbf{C}^{train}). Any generic regression technique can be applied, depending upon the nature of \mathbf{v}_i . However, the high dimensionality of \mathbf{c}_i , where p is often as large as or larger than n^{train} , requires use of regression techniques appropriate for such a setting, such as penalized linear or logistic regression.

In the latter case, we begin from a *generative model* of $p(\mathbf{c}_i|\mathbf{v}_i)$. To see why this is intuitive, note that in many cases the underlying causal relationship runs from outcomes to language rather than the other way around. For example, Google searches about the flu do not cause flu cases to occur; rather, people with the flu are more likely to produce such searches. Congresspeople’s ideology is not determined by their use of partisan language; rather, people who are more conservative or liberal to begin with are more likely to use such language. From an economic point of view, the correct “structural” model of language in these cases maps from \mathbf{v}_i to \mathbf{c}_i , and as in other cases familiar to economists, modeling the underlying causal relationships can provide powerful guidance to inference and make the estimated model more interpretable.

Generative models can be further divided by whether the attributes are observed or latent. In the first case of *unsupervised* methods, we do not observe the true value of \mathbf{v}_i for any documents. The function relating \mathbf{c}_i and \mathbf{v}_i is unknown, but we are willing to impose sufficient structure on it to allow us to infer \mathbf{v}_i from \mathbf{c}_i . This class includes methods

³<http://www.wjh.harvard.edu/~inquirer/>.

such as topic modeling and its variants (e.g., latent Dirichlet allocation, or LDA). In the second case of *supervised* methods, we observe training data \mathbf{V}^{train} and we can fit our model, say $f_{\theta}(\mathbf{c}_i; \mathbf{v}_i)$ for a vector of parameters θ , to this training set. The fitted model \hat{f}_θ can then be *inverted* to predict \mathbf{v}_i for documents in the test set and can also be used to interpret the structural relationship between attributes and text. Finally, in some cases, \mathbf{v}_i includes both observed and latent attributes for a *semi-supervised* analysis.

Lastly, we discuss *word embeddings*, which provide a richer representation of the underlying text than the token counts that underlie other methods. They have seen limited application in economics to date, but their dramatic successes in deep learning and other machine learning domains suggest they are likely to have high value in the future.

We close in section 3.5 with some broad recommendations for practitioners.

3.1 Text Regression

Predicting an attribute \mathbf{v}_i from counts \mathbf{c}_i is a regression problem like any other, except that the high dimensionality of \mathbf{c}_i makes ordinary least squares (OLS) and other standard techniques infeasible. The methods in this section are mainly applications of standard high-dimensional regression methods to text.

3.1.1 Penalized Linear Models

The most popular strategy for very high-dimensional regression in contemporary statistics and machine learning is the estimation of *penalized* linear models, particularly with L_1 penalization. We recommend this strategy for most text regression applications: linear models are intuitive and interpretable; fast, high-quality software is available for big sparse input matrices like our \mathbf{C} . For simple text-regression tasks with input dimension on the same order as the sample size, penalized linear models

typically perform close to the frontier in terms of out-of-sample prediction.

Linear models in the sense we mean here are those in which \mathbf{v}_i depends on \mathbf{c}_i only through a linear index $\eta_i = \alpha + \mathbf{x}_i' \beta$, where \mathbf{x}_i is a known transformation of \mathbf{c}_i . In many cases, we simply have $E[\mathbf{v}_i | \mathbf{x}_i] = \eta_i$. It is also possible that $E[\mathbf{v}_i | \mathbf{x}_i] = f(\eta_i)$ for some known link function $f(\cdot)$, as in the case of logistic regression.

Common transformations are the identity $\mathbf{x}_i = \mathbf{c}_i$, normalization by document length $\mathbf{x}_i = \mathbf{c}_i/m_i$ with $m_i = \sum_j c_{ij}$, or the positive indicator $x_{ij} = \mathbf{1}_{[c_{ij} > 0]}$. The best choice is application specific, and may be driven by interpretability; does one wish to interpret β_j as the added effect of an extra count for token j (if so, use $x_{ij} = c_{ij}$) or as the effect of the presence of token j (if so, use $x_{ij} = \mathbf{1}_{[c_{ij} > 0]}$)? The identity is a reasonable default in many settings.

Write $l(\alpha, \beta)$ for an unregularized objective proportional to the negative log likelihood, $-\log p(\mathbf{v}_i | \mathbf{x}_i)$. For example, in Gaussian (linear) regression, $l(\alpha, \beta) = \sum_i (\mathbf{v}_i - \eta_i)^2$ and in binomial (logistic) regression, $l(\alpha, \beta) = -\sum_i [\eta_i \mathbf{v}_i - \log(1 + e^{\eta_i})]$ for $\mathbf{v}_i \in \{0, 1\}$. A penalized estimator is then the solution to

$$(1) \quad \min \left\{ l(\alpha, \beta) + n\lambda \sum_{j=1}^p \kappa_j(|\beta_j|) \right\},$$

where $\lambda > 0$ controls overall penalty magnitude and $\kappa_j(\cdot)$ are increasing “cost” functions that penalize deviations of the β_j from zero.

A few common cost functions are shown in figure 1. Those that have a non-differentiable spike at zero (lasso, elastic net, and log) lead to sparse estimators, with some coefficients set to exactly zero. The curvature of the penalty away from zero dictates the weight of shrinkage imposed on the nonzero coefficients: L_2 costs increase with coefficient size; lasso’s L_1 penalty has zero curvature and imposes constant shrinkage, and as curvature

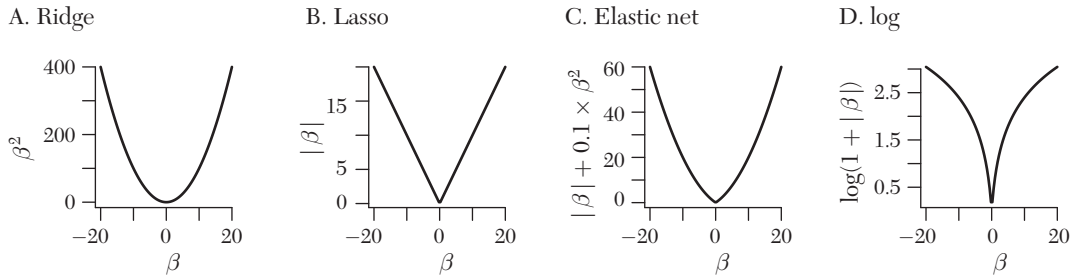


Figure 1

Note: From left to right, L_2 costs (ridge, Hoerl and Kennard 1970), L_1 (lasso, Tibshirani 1996), the “elastic net” mixture of L_1 and L_2 (Zou and Hastie 2005), and the log penalty (Candès, Wakin, and Boyd 2008).

goes toward $-\infty$ one approaches the L_0 penalty of subset selection. The lasso’s L_1 penalty (Tibshirani 1996) is extremely popular: it yields sparse solutions with a number of desirable properties (e.g., Bickel, Ritov, and Tsybakov 2009; Wainwright 2009; Belloni, Chernozhukov, and Hansen 2013; Bühlmann and van de Geer 2011), and the number of nonzero estimated coefficients is an unbiased estimator of the regression degrees of freedom (which is useful in model selection; see Zou, Hastie, and Tibshirani 2007).⁴

Focusing on L_1 regularization, rewrite the penalized linear model objective as

$$(2) \quad \min \left\{ l(\alpha, \beta) + n\lambda \sum_{j=1}^p \omega_j |\beta_j| \right\}.$$

A common strategy sets ω_j so that the penalty cost for each coefficient is scaled by the

sample standard deviation of that covariate. In text analysis, where each covariate corresponds to some transformation of a specific text token, this type of weighting is referred to as “rare feature up-weighting” (e.g., Manning, Raghavan, and Schütze 2008) and is generally thought of as good practice: rare words are often most useful in differentiating between documents.⁵

Large λ leads to simple model estimates in the sense that most coefficients will be set at or close to zero, while as $\lambda \rightarrow 0$ we approach maximum likelihood estimation (MLE). Since there is no way to define an optimal λ a priori, standard practice is to compute estimates for a large set of possible λ and then use some criterion to select the one that yields the best fit.

Several criteria are available to choose an optimal λ . One common approach is to leave out part of the training sample in estimation and then choose the λ that yields the best out-of-sample fit according to some criterion such as mean squared error. Rather than work with a single leave-out sample, researchers most often use K -fold cross-validation (CV).

⁴Penalties with a bias that diminishes with coefficient size—such as the log penalty in figure 1 (Candès, Wakin, and Boyd 2008), the smoothly clipped absolute deviation (SCAD) of Fan and Li (2001), or the adaptive lasso of Zou (2006)—have been promoted in the statistics literature as improving upon the lasso by providing consistent variable selection and estimation in a wider range of settings. These diminishing-bias penalties lead to increased computation costs (due to a non-convex loss), but there exist efficient approximation algorithms (see, e.g., Fan, Xue, and Zou 2014; Taddy 2017b).

⁵This is the same principle that motivates “inverse-document frequency” weighting schemes, such as tf-idf.

This splits the sample into K disjoint subsets, and then fits the full regularization path K times excluding each subset in turn. This yields K realizations of the mean squared error or other out-of-sample fit measure for each value of λ . Common rules are to select the value of λ that minimizes the average error across these realizations, or (more conservatively) to choose the largest λ with mean error no more than one standard error away from the minimum.

Analytic alternatives to cross-validation are Akaike's information criterion (AIC; Akaike 1973) and the Bayesian information criterion (BIC) of Schwarz (1978). In particular, Flynn, Hurvich, and Simonoff (2013) describe a bias-corrected AIC objective for high-dimensional problems that they call AICc. It is motivated as an approximate likelihood maximization subject to a degrees of freedom (df_λ) adjustment: $AICc(\lambda) = 2l(\alpha_\lambda, \beta_\lambda) + 2df_\lambda \frac{n}{n - df_\lambda - 1}$. Similarly, the BIC objective is $BIC(\lambda) = l(\alpha_\lambda, \beta_\lambda) + df_\lambda \log n$, and is motivated as an approximation to the Bayesian posterior marginal likelihood in Kass and Wasserman (1995). AICc and BIC selection choose λ to minimize their respective objectives. The BIC tends to choose simpler models than cross-validation or AICc. Zou, Hastie, and Tibshirani (2007) recommend BIC for lasso penalty selection whenever variable selection, rather than predictive performance, is the primary goal.

3.1.2 Dimension Reduction

Another common solution for taming high dimensional prediction problems is to form a small number of linear combinations of predictors and to use these derived indices as variables in an otherwise standard predictive regression. Two classic dimension reduction techniques are *principal components regression* (PCR) and *partial least squares* (PLS).

Penalized linear models use shrinkage and variable selection to manage high dimensionality by forcing the coefficients on most regressors to be close to (or, for lasso, exactly) zero. This can produce suboptimal forecasts when predictors are highly correlated. A transparent illustration of this problem would be a case in which all of the predictors are equal to the forecast target plus an i.i.d. noise term. In this situation, choosing a subset of predictors via lasso penalty is inferior to taking a simple average of the predictors and using this as the sole predictor in a univariate regression. This predictor averaging, as opposed to predictor selection, is the essence of dimension reduction.

PCR consists of a two-step procedure. In the first step, principal components analysis (PCA) combines regressors into a small set of K linear combinations that best preserve the covariance structure among the predictors. This amounts to solving the problem

$$(3) \quad \min_{\Gamma, B} \text{trace}[(C - \Gamma B')(C - \Gamma B')'],$$

subject to

$$\text{rank}(\Gamma) = \text{rank}(B) = K.$$

The count matrix \mathbf{C} consists of n rows (one for each document) and p columns (one for each term). PCA seeks a low-rank representation $\Gamma B'$ that best approximates the text data \mathbf{C} . This formulation has the character of a factor model. The $n \times K$ matrix Γ captures the prevalence of K common components, or "factors," in each document. The $p \times K$ matrix B describes the strength of association between each word and the factors. As we will see, this reduced-rank decomposition bears a close resemblance to other text analytic methods such as topic modeling and word embeddings.

In the second step, the K components are used in standard predictive regression. As an

example, Foster, Liberman, and Stine (2013) use PCR to build a hedonic real estate pricing model that takes textual content of property listings as an input.⁶ With text data, where the number of features tend to vastly exceed the observation count, regularized versions of PCA such as predictor thresholding (e.g., Bai and Ng 2008) and sparse PCA (Zou, Hastie, and Tibshirani 2006) help exclude the least informative features to improve predictive content of the dimension-reduced text.

A drawback of PCR is that it fails to incorporate the ultimate statistical objective—forecasting a particular set of attributes—in the dimensionality reduction step. PCA condenses text data into indices based on the covariation *among* the predictors. This happens prior to the forecasting step and without consideration of how predictors associate with the forecast target.

In contrast, PLS performs dimension reduction by directly exploiting covariation of predictors with the forecast target.⁷ Suppose we are interested in forecasting a scalar attribute v_i . PLS regression proceeds as follows. For each element j of the feature vector \mathbf{c}_i , estimate the univariate covariance between v_i on c_{ij} . This covariance, denoted φ_j , reflects the attribute's "partial" sensitivity to each feature j . Next, form a single predictor by averaging all attributes into a single aggregate predictor $\hat{v}_i = \sum_j \varphi_j c_{ij} / \sum_j \varphi_j$. This forecast places the highest weight on the strongest univariate predictors, and the least weight on the weakest. In this way, PLS performs its dimension reduction with the ultimate forecasting objective in mind. The description of \hat{v}_i reflects the $K = 1$ case, i.e., when text

is condensed into a single predictive index. To use additional predictive indices, both v_i on c_{ij} are orthogonalized with respect to \hat{v}_i , the above procedure is repeated on the orthogonalized data set, and the resulting forecast is added to the original \hat{v}_i . This is iterated until the desired number of PLS components K is reached. Like PCR, PLS components describe the prevalence of K common factors in each document. And also like PCR, PLS can be implemented with a variety of regularization schemes to aid its performance in the ultra-high-dimensional world of text. Section 4 discusses applications using PLS in text regression.

PCR and PLS share a number of common properties. In both cases, K is a user-controlled parameter which, in many social science applications, is selected *ex ante* by the researcher. But, like any hyperparameter, K can be tuned via cross-validation. And neither method is scale invariant—the forecasting model is sensitive to the distribution of predictor variances. It is therefore common to variance-standardize features before applying PCR or PLS.

3.1.3 Nonlinear Text Regression

Penalized linear models are the most widely applied text regression tools due to their simplicity, and because they may be viewed as a first-order approximation to potentially nonlinear and complex data generating processes (DGPs). In cases where a linear specification is too restrictive, there are several other machine learning tools that are well suited to represent nonlinear associations between text \mathbf{c}_i and outcome attributes \mathbf{v}_i . Here we briefly describe four such nonlinear regression methods—generalized linear models, support vector machines, regression trees, and deep learning—and provide references for readers interested in thorough treatments of each.

GLMs and SVMs.—One way to capture nonlinear associations between \mathbf{c}_i and \mathbf{v}_i is

⁶See Stock and Watson (2002a, b) for development of the PCR estimator and an application to macroeconomic forecasting with a large set of numerical predictors.

⁷See Kelly and Pruitt (2013, 2015) for the asymptotic theory of PLS regression and its application to forecasting risk premia in financial markets.

with a generalized linear model (GLM). These expand the linear model to include nonlinear functions of \mathbf{c}_i such as polynomials or interactions, while otherwise treating the problem with the penalized linear regression methods discussed above.

A related method used in the social science literature is the support vector machine, or SVM (Vapnik 1995). This is used for text classification problems (when \mathbf{V} is categorical), the prototypical example being email spam filtering. A detailed discussion of SVMs is beyond the scope of this review, but from a high level, the SVM finds hyperplanes in a basis expansion of \mathbf{C} that partition the observations into sets with equal response (i.e., so that \mathbf{v}_i are all equal in each region).⁸

GLMs and SVMs both face the limitation that, without a priori assumptions for which basis transformations and interactions to include, they may overfit and require extensive tuning (Hastie, Tibshirani, and Friedman 2009; Murphy 2012). For example, multi-way interactions increase the parameterization combinatorially and can quickly overwhelm the penalization routine, and their performance suffers in the presence of many spurious “noise” inputs (Hastie, Tibshirani, and Friedman 2009).⁹

Regression Trees.—Regression trees have become a popular nonlinear approach for incorporating multi-way predictor interactions into regression and classification

problems. The logic of trees differs markedly from traditional regressions. A tree “grows” by sequentially sorting data observations into bins based on values of the predictor variables. This partitions the data set into rectangular regions, and forms predictions as the average value of the outcome variable within each partition (Breiman et al. 1984). This structure is an effective way to accommodate rich interactions and nonlinear dependencies.

Two extensions of the simple regression tree have been highly successful thanks to clever regularization approaches that minimize the need for tuning and avoid overfitting. Random forests (Breiman 2001) average predictions from many trees that have been randomly perturbed in a bootstrap step. Boosted trees (e.g., Friedman 2002) recursively combine predictions from many oversimplified trees.¹⁰

The benefits of regression trees—nonlinearity and high-order interactions—are sometimes lessened in the presence of high-dimensional inputs. While we would generally recommend tree models, and especially random forests, they are often not worth the effort for simple text regression. Often times, a more beneficial use of trees is in a final prediction step after some dimension reduction derived from the generative models in section 3.2.

Deep Learning.—There is a host of other machine learning techniques that have been applied to text regression. The most common techniques not mentioned thus far are neural networks, which typically allow the inputs to act on the response through one

⁸Hastie, Tibshirani, and Friedman (2009, chapter 12) and Murphy (2012, chapter 14) provide detailed overviews of GLMs and SVMs. Joachims (1998) and Tong and Koller (2001) (among others) study text applications of SVMs.

⁹Another drawback of SVMs is that they cannot be easily connected to the estimation of a probabilistic model and the resulting fitted model can sometimes be difficult to interpret. Polson and Scott (2011) provide a pseudo-likelihood interpretation for a variant of the SVM objective. Our own experience has led us to lean away from SVMs for text analysis in favor of more easily interpretable models. Murphy (2012, chapter 14.6) attributes the popularity of SVMs in some application areas to an ignorance of alternatives.

¹⁰Hastie, Tibshirani, and Friedman (2009) provide an overview of these methods. In addition, see Wager, Hastie, and Efron (2014) and Wager and Athey (2018) for results on confidence intervals for random forests, and see Taddy et al. (2015) and Taddy et al. (2016) for an interpretation of random forests as a Bayesian posterior over potentially optimal trees.

or more layers of interacting nonlinear basis functions (e.g., see Bishop 1995). A main attraction of neural networks is their status as *universal approximators*, a theoretical result describing their ability to mimic general, smooth nonlinear associations.

In high-dimensional and very noisy settings, such as in text analysis, classical neural nets tend to suffer from the same issues referenced above: they often overfit and are difficult to tune. However, the recently popular “deep” versions of neural networks (with many layers, and fewer nodes per layer) incorporate a number of innovations that allow them to work better, faster, and with little tuning, even in difficult text analysis problems. Such deep neural nets (DNNs) are now the state-of-the-art solution for many machine learning tasks (LeCun, Bengio, and Hinton 2015).¹¹ DNNs are now employed in many complex natural language processing tasks, such as translation (Sutskever, Vinyals, and Le 2014; Wu et al. 2016) and syntactic parsing (Chen and Manning 2014), as well as in exercises of relevance to social scientists—for example, Iyyer et al. (2014) infer political ideology from text using a DNN. They are frequently used in conjunction with richer text representations such as word embeddings, described more below.

3.1.4 Bayesian Regression Methods

The penalized methods above can all be interpreted as posterior maximization under some prior. For example, ridge regression maximizes the posterior under independent Gaussian priors on each coefficient, while Park and Casella (2008) and Hans (2009) give Bayesian interpretations to the lasso. See also the horseshoe of Carvalho, Polson, and Scott (2010) and the double Pareto of Armagan,

Dunson, and Lee (2013) for Bayesian analogues of diminishing bias penalties like the log penalty on the right of figure 1.

For those looking to do a full Bayesian analysis for high-dimensional (e.g., text) regression, an especially appealing model is the spike-and-slab introduced in George and McCulloch (1993). This models the distribution over regression coefficients as a mixture between two densities centered at zero—one with very small variance (the spike) and another with large variance (the slab). This model allows one to compute posterior variable inclusion probabilities as, for each coefficient, the posterior probability that it came from the slab and not the spike component. Due to a need to integrate over the posterior distribution, e.g., via Markov chain Monte Carlo (MCMC), inference for spike-and-slab models is much more computationally intensive than fitting the penalized regressions of section 3.1.1. However, Yang, Wainwright, and Jordan (2016) argue that spike-and-slab estimates based on short MCMC samples can be useful in application, while Scott and Varian (2014) have engineered efficient implementations of the spike-and-slab model for big data applications. These procedures give a full accounting of parameter uncertainty, which we miss in a quick penalized regression.

3.2 Generative Language Models

Text regression treats the token counts as generic high-dimensional input variables, without any attempt to model structure that is specific to language data. In many settings it is useful to instead propose a generative model for the text tokens to learn about how the attributes influence word choice and account for various dependencies among words and among attributes. In this approach, the words in a document are viewed as the realization of a generative process defined through a probability model for $p(\mathbf{c}_i | \mathbf{v}_i)$.

¹¹ Goodfellow, Bengio, and Courville (2016) provide a thorough textbook overview of these “deep learning” technologies, while Goldberg (2016) is an excellent primer on their use in natural language processing.

3.2.1 Unsupervised Generative Models

In the unsupervised setting, we have no direct observations of the true attributes \mathbf{v}_i . Our inference about these attributes must therefore depend entirely on strong assumptions that we are willing to impose on the structure of the model $p(\mathbf{c}_i|\mathbf{v}_i)$. Examples in the broader literature include cases where the \mathbf{v}_i are latent factors, clusters, or categories. In text analysis, the leading application has been the case in which the \mathbf{v}_i are topics.

A typical generative model implies that each observation \mathbf{c}_i is a conditionally independent draw from the vocabulary of possible tokens according to some document-specific token probability vector, say $\mathbf{q}_i = [q_{i1} \cdots q_{ip}]'$. Conditioning on document length, $m_i = \sum_j c_{ij}$, this implies a *multinomial* distribution for the counts

$$(4) \quad \mathbf{c}_i \sim \text{MN}(\mathbf{q}_i, m_i).$$

This multinomial model underlies the vast majority of contemporary generative models for text.

Under the basic model in (4), the function $\mathbf{q}_i = q(\mathbf{v}_i)$ links attributes to the distribution of text counts. A leading example of this link function is the *topic model* specification of Blei, Ng, and Jordan (2003),¹² where

$$(5) \quad \mathbf{q}_i = v_{i1} \boldsymbol{\theta}_1 + v_{i2} \boldsymbol{\theta}_2 + \cdots + v_{ik} \boldsymbol{\theta}_k \\ = \boldsymbol{\Theta} \mathbf{v}_i.$$

¹²Standard least-squares factor models have long been employed in “latent semantic analysis” (LSA; Deerwester et al. 1990), which applies PCA (i.e., singular value decompositions) to token count transformations such as $\mathbf{x}_i = \mathbf{c}_i/m_i$ or $x_{ij} = c_{ij} \log(d_j)$ where $d_j = \sum_i \mathbf{1}_{[c_{ij}>0]}$. Topic modeling and its precursor, probabilistic LSA, are generally seen as improving on such approaches by replacing arbitrary transformations with a plausible generative model.

Many readers will recognize the model in (5) as a *factor model* for the vector of normalized counts for each token in document i , \mathbf{c}_i/m_i . Indeed, a topic model is simply a factor model for multinomial data. Each *topic* is a probability vector over possible tokens, denoted $\boldsymbol{\theta}_l$, $l = 1, \dots, k$ (where $\theta_{lj} \geq 0$ and $\sum_{j=1}^p \theta_{lj} = 1$). A topic can be thought of as a cluster of tokens that tend to appear in documents. The latent attribute vector \mathbf{v}_i is referred to as the set of *topic weights* (formally, a distribution over topics, $v_{il} \geq 0$ and $\sum_{l=1}^k v_{il} = 1$). Note that \mathbf{v}_i describes the proportion of language in document i devoted to the l th topic. We can allow each document to have a mix of topics, or we can require that one $v_{il} = 1$ while the rest are zero, so that each document has a single topic.¹³

Since its introduction into text analysis, topic modeling has become hugely popular.¹⁴ (See Blei 2012 for a high-level overview.) The model has been especially useful in political science (e.g., Grimmer 2010), where researchers have been successful in attaching political issues and beliefs to the estimated latent topics.

Since the \mathbf{v}_i are of course latent, estimation for topic models tends to make use of some alternating inference for $\mathbf{V}|\boldsymbol{\Theta}$ and $\boldsymbol{\Theta}|\mathbf{V}$. One possibility is to employ a version of the expectation-maximization (EM) algorithm to either maximize the likelihood implied by

¹³Topic modeling is alternatively labeled as “latent Dirichlet allocation,” (LDA) which refers to the Bayesian model in Blei, Ng, and Jordan (2003) that treats each \mathbf{v}_i and $\boldsymbol{\theta}_l$ as generated from a Dirichlet-distributed prior. Another specification that is popular in political science (e.g., Quinn et al. 2010) keeps $\boldsymbol{\theta}_l$ as Dirichlet-distributed but requires each document to have a single topic. This may be most appropriate for short documents, such as press releases or single speeches.

¹⁴The same model was independently introduced in genetics by Pritchard, Stephens, and Donnelly (2000) for factorizing gene expression as a function of latent populations; it has been similarly successful in that field. Latent Dirichlet allocation is also an extension of a related mixture modeling approach in the latent semantic analysis of Hofmann (1999).

(4) and (5) or, after incorporating the usual Dirichlet priors on \mathbf{v}_i and $\boldsymbol{\theta}_i$, to maximize the posterior; this is the approach taken in Taddy (2012; see this paper also for a review of topic estimation techniques). Alternatively, one can target the full posterior distribution $p(\boldsymbol{\Theta}, \mathbf{V} | \mathbf{c}_i)$. Estimation, say for $\boldsymbol{\Theta}$, then proceeds by maximization of the estimated *marginal* posterior, say $p(\boldsymbol{\Theta} | \mathbf{c}_i)$.

Due to the size of the data sets and dimension of the models, posterior approximation for topic models usually uses some form of variational inference (Wainwright and Jordan 2008) that fits a tractable parametric family to be as close as possible (e.g., in Kullback–Leibler divergence) from the true posterior. This variational approach was used in the original Blei, Ng, and Jordan (2003) paper and in many applications since. Hoffman et al. (2013) present a *stochastic variational inference* algorithm that takes advantage of techniques for optimization on massive data; this algorithm is used in many contemporary topic modeling applications. Another approach, which is more computationally intensive but can yield more accurate posterior approximations, is the MCMC algorithm of Griffiths and Steyvers (2004). Alternatively, for quick estimation without uncertainty quantification, the posterior maximization algorithm of Taddy (2012) is a good option.

The choice of k , the number of topics, is often fairly arbitrary. Data-driven choices do exist: Taddy (2012) describes a model selection process for k that is based upon Bayes factors, Airolidi et al. (2010) provide a cross-validation (CV) scheme, while Teh et al. (2006) use Bayesian nonparametric techniques that view k as an unknown model parameter. In practice, however, it is very common to simply start with a number of topics on the order of ten, and then adjust the number of topics in whatever direction seems to improve interpretability. Whether this ad hoc procedure is problematic depends

on the application. As we discuss below, in many applications of topic models to date, the goal is to provide an intuitive description of text, rather than inference on some underlying “true” parameters; in these cases, the ad hoc selection of the number of topics may be reasonable.

The basic topic model has been generalized and extended in variety of ways. A prominent example is the dynamic topic model of Blei and Lafferty (2006), which considers documents that are indexed by date (e.g., publication date for academic articles) and allows the topics, say $\boldsymbol{\Theta}_t$, to evolve smoothly in time. Another example is the supervised topic model of Blei and McAuliffe (2007), which combines the standard topic model with an extra equation relating the weights \mathbf{v}_i to some additional attribute y_i in $p(y_i | \mathbf{v}_i)$. This pushes the latent topics to be relevant to y_i as well as the text \mathbf{c}_i . In these and many other extensions, the modifications are designed to incorporate available document metadata (in these examples, time and y_i respectively).

3.2.2 Supervised Generative Models

In supervised models, the attributes \mathbf{v}_i are observed in a training set and thus may be directly harnessed to inform the model of text generation. Perhaps the most common supervised generative model is the so-called naive Bayes classifier (e.g., Murphy 2012), which treats counts for each token as independent with class-dependent means. For example, the observed attribute might be author identity for each document in the corpus with the model specifying different mean token counts for each author.

In naive Bayes, \mathbf{v}_i is a univariate categorical variable and the token count distribution is factorized as $p(\mathbf{c}_i | \mathbf{v}_i) = \prod_j p_j(c_{ij} | \mathbf{v}_i)$, thus “naively” specifying conditional independence between tokens j . This rules out the possibility that by choosing to say one token (say, “hello”) we reduce the probability

that we say some other token (say, “hi”). The parameters of each independent token distribution are estimated, yielding \hat{p}_j for $j = 1, \dots, p$. The model can then be inverted for prediction, with classification probabilities for the possible class labels obtained via Bayes’s rule as

$$(6) \quad p(\mathbf{V}|\mathbf{c}_i) = \frac{p(\mathbf{c}_i|\mathbf{V})\pi_v}{\sum_a p(\mathbf{c}_i|a)\pi_a} \\ = \frac{\prod_j p_j(c_{ij}|\mathbf{V})\pi_v}{\sum_a \prod_j p_j(c_{ij}|a)\pi_a},$$

where π_a is the prior probability on class a (usually just one over the number of possible classes). In text analysis, Poisson naive Bayes procedures, with $p(c_{ij}|\mathbf{V}) = \text{Pois}(c_{ij}; \theta_{vj})$ where $E[c_{ij}|\mathbf{V}] = \theta_{vj}$, have been used as far back as Mosteller and Wallace (1963). Some recent social science applications use binomial naive Bayes, which sets $p(c_{ij}|\mathbf{V}) = \text{Bin}(c_{ij}; \theta_{vj})$ where $E[c_{ij}/m_i|\mathbf{V}] = \theta_{vj}$. The Poisson model has some statistical justification in the analysis of text counts (Taddy 2015a), but the binomial specification seems to be more common in off-the-shelf software.

A more realistic sampling model for text token counts is the multinomial model of (4). This introduces limited dependence between token counts, encoding the fact that using one token for a given utterance must slightly lower the expected count for all other tokens. Combining such a sampling scheme with generalized linear models, Taddy (2013b) advocates the use of multinomial logistic regression to connect text counts with observable attributes. The generative model specifies probabilities in the multinomial distribution of (4) as

$$(7) \quad q_{ij} = \frac{e^{\eta_{ij}}}{\sum_{h=1}^p e^{\eta_{ih}}}, \quad \eta_{ij} = \alpha_j + \mathbf{v}_i' \boldsymbol{\varphi}_j.$$

Taddy (2013a,b) applies these models in the setting of univariate or low-dimensional

\mathbf{v}_i , focusing on their use for prediction of future document attributes through an inversion strategy discussed below. More recently, Taddy (2015a) provides a distributed-computing strategy that allows the model implied by (7) to be fit (using penalized deviance methods as detailed in section 3.1.1) for high-dimensional \mathbf{v}_i on massive corpora. This facilitates language models containing a large number of sources of heterogeneity (even document-specific random effects), thus allowing social scientists to apply familiar regression analysis tools in their text analyses.

Application of the logistic regression text models implied by (7) often requires an *inversion* step for inference about attributes conditional on text—that is, to map from $p(\mathbf{c}_i|\mathbf{v}_i)$ to $p(\mathbf{v}_i|\mathbf{c}_i)$. The simple Bayes’s rule technique of (6) is difficult to apply beyond a single categorical attribute. Instead, Taddy (2013b) uses the inverse regression ideas of Cook (2007) in deriving *sufficient projections* from the fitted models. Say $\Phi = [\boldsymbol{\varphi}_1 \cdots \boldsymbol{\varphi}_p]$ is the matrix of regression coefficients from (7) across all tokens j ; then the token count projection $\Phi \mathbf{c}_i$ is a sufficient statistic for \mathbf{v}_i in the sense that

$$(8) \quad \mathbf{v}_i \perp\!\!\!\perp \mathbf{c}_i | \Phi \mathbf{c}_i,$$

i.e., the attributes are independent of the text counts conditional upon the projection. Thus, the fitted logistic regression model yields a map from high-dimensional text to the presumably lower dimensional attributes of interest, and this map can be used instead of the full text counts for future inference tasks. For example, to predict variable \mathbf{v}_i you can fit the low dimensional OLS regression of \mathbf{v}_i on $\Phi \mathbf{c}_i$. Use of projections built in this way is referred to as multinomial inverse regression (MNIR). This idea can also be applied to only a subset of the variables in \mathbf{v}_i , yielding projections that are sufficient for the text content relevant to those variables

after conditioning on the other attributes in \mathbf{v}_i . Taddy (2015a) details use of such sufficient projections in a variety of applications, including attribute prediction, treatment effect estimation, and document indexing.

New techniques are arising that combine MNIR techniques with the latent structure of topic models. For example, Rabinovich and Blei (2014) directly combine the logistic regression in (7) with the topic model of (5) in a mixture specification. Alternatively, the structural topic model of Roberts et al. (2013) allows both topic content (θ_i) and topic prevalence (latent \mathbf{v}_i) to depend on observable document attributes. Such semi-supervised techniques seem promising for their combination of the strong text-attribute connection of MNIR with topic modeling's ability to account for latent clustering and dependency within documents.

3.3 Word Embeddings

Throughout this article, documents have been represented through token count vectors, \mathbf{c}_i . This is a crude language summarization. It abstracts from any notion of similarity between words (such as *run*, *runner*, *jogger*) or syntactical richness. One of the frontiers of textual analysis is in developing new representations of text data that more faithfully capture its meaning.

Instead of identifying words only as an index for location in a long vocabulary list, imagine representing words as points in a large vector space, with similar words colocated, and an internally consistent arithmetic on the space for relating words to one another. For example, suppose our vocabulary consists of six words: $\{\textit{king}, \textit{queen}, \textit{prince}, \textit{man}, \textit{woman}, \textit{child}\}$. The vector space representation of this vocabulary based on similarity of their meaning might look something like the figure 2 panel A.¹⁵

In the vector space, words are relationally oriented and we can begin to draw meaning from term positions, something that is not possible in simple bag-of-words approaches. For example, in the right figure, we can see that by subtracting the vector *man* from the vector *king*, and then adding to this *woman*, we arrive spatially close to *queen*. Likewise, the combination *king* – *man* + *child* lies in close proximity to the vector *prince*.

Such *word embeddings*, also known as distributed language representations, amount to a preprocessing of the text data to replace word identities—encoded as binary indicators in a vocabulary-length vector—with an embedding (location) of each vocabulary word in \mathbb{R}^K , where K is the dimension of the latent representation space. The dimensions of the vector space correspond to various aspects of meaning that give words their content. Continuing from the simplified example vocabulary, the latent (and, in reality, unlabeled) dimensions and associated word embeddings might look like:

Dimension	<i>king</i>	<i>queen</i>	<i>prince</i>	<i>man</i>	<i>woman</i>	<i>child</i>
Royalty	0.99	0.99	0.95	0.01	0.02	0.01
Masculinity	0.94	0.06	0.02	0.99	0.02	0.49
Age	0.73	0.81	0.15	0.61	0.68	0.09
...						

This type of text representation has long been applied in natural language processing (Rumelhart, Hinton, and Williams 1986; Morin and Bengio 2005). The embeddings must be estimated and are chosen to optimize, perhaps approximately, an objective function defined on the original text (such as a likelihood for word occurrences). They form the basis for many deep learning applications involving textual data (see, e.g., Chen and Manning 2014; Goldberg 2016). They are also valuable in their own right for mapping from language to a vector space where we can compute distances

¹⁵This example is motivated by <https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/>.

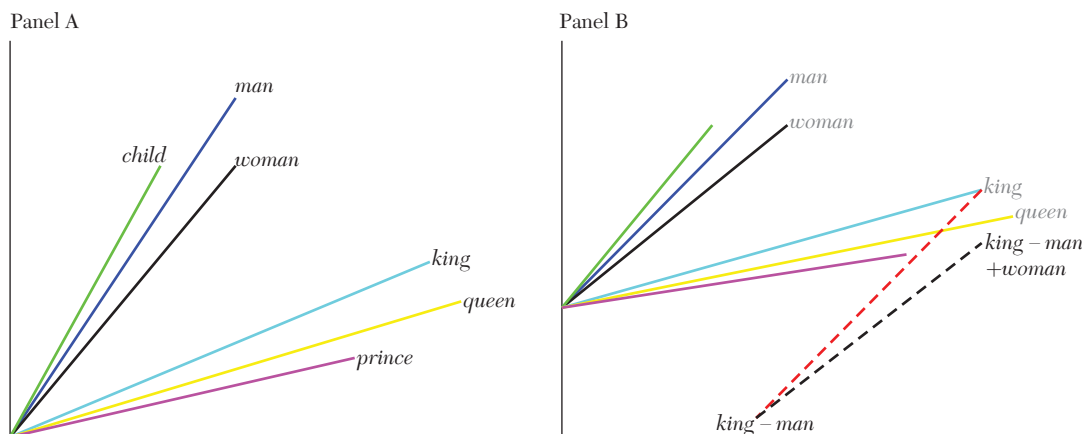


Figure 2. A Graphical Example of Word Embeddings

and angles between words for fundamental tasks such as classification, and have begun to be adopted by social scientists as a useful summary representation of text data.

Some popular embedding techniques are Word2Vec (Mikolov et al. 2013) and Global Vector for Word Representation (GloVe, Pennington, Socher, and Manning 2014). The key preliminary step in these methods is to settle on a notion of *co-occurrence* among terms. For example, consider a $p \times p$ matrix denoted *CoOccur*, whose (i, j) entry counts the number of times in your corpus that the terms i and j appear within, say, b words of each other. This is known as the *skip-gram* definition of co-occurrences.

To embed *CoOccur* in a K -dimensional vector space, where K is much smaller than p (say a few hundred), we solve the same type of problem that PCA used to summarize the word count matrix in equation (3). In particular, we can find rank- K matrices Γ and B that best approximate co-occurrences among terms:

$$\text{CoOccur} \approx \Gamma B'.$$

The j th rows of Γ and B (denoted γ_j and β_j) give a K -dimensional embedding of the j th word, so co-occurrences of terms i and j are approximated as $\gamma_i \beta_j'$. This geometric representation of the text has an intuitive interpretation. The inner product of terms' embeddings, which measures the closeness of the pair in the K -dimensional vector space, describes how likely the pair is to co-occur.

Researchers are beginning to connect these vector-space language models with the sorts of document attributes that are of interest in social science. For example, Le and Mikolov (2014) estimate latent document scores in a vector space, while Taddy (2015b) develops an inversion rule for document classification based upon Word2Vec. In one especially compelling application, Bolukbasi et al. (2016) estimate the direction of *gender* in an embedding space by averaging the angles between female and male descriptors. They then show that stereotypically male and female jobs, for example, live at the corresponding ends of the implied gender vector. This information is used to derive an algorithm for removing these gender biases, so as to provide a more "fair" set of inputs

for machine learning tasks. Approaches like this, which use embeddings as the basis for mathematical analyses of text, can play a role in the next generation of text-as-data applications in social science.

3.4 Uncertainty Quantification

The machine learning literature on text analysis is focused on point estimation and predictive performance. Social scientists often seek to interpret parameters or functions of the fitted models, and hence desire strategies for quantifying the statistical uncertainty around these targets – that is, for statistical inference.

Many machine learning methods for text analysis are based upon a Bayesian modeling approach, where uncertainty quantification is often available as part of the estimation process. In MCMC sampling, as in the Bayesian regression of Scott and Varian (2014) or the topic modeling of Griffiths and Steyvers (2004), the software returns samples from the posterior and thus inference is immediately available. For estimators relying on variational inference—i.e., fitting a tractable distribution as closely as possible to the true posterior—one can simulate from the approximate distribution to conduct inference.¹⁶

Frequentist uncertainty quantification is often favored by social scientists, but analytic sampling distributions are unavailable for most of the methods discussed here. Some results exist for the lasso in stylized settings (especially Knight and Fu 2000), but these assume low-dimensional asymptotic scenarios that may be unrealistic for text analysis.

More promising are computation algorithms that approximate the sampling distribution, the most common being the familiar *non-parametric bootstrap* (Efron 1979). This repeatedly draws samples with replacement of the same size as the original data set and reestimates parameters of interest on the bootstrapped samples, with the resulting set of estimated parameters approximating the sampling distribution.¹⁷

Unfortunately, the nonparametric bootstrap fails for many of the algorithms used on text. For example, it is known to fail for methods that involve non-differentiable loss functions (e.g., the lasso), and with-replacement resampling produces overfit in the bootstrap samples (repeated observations make prediction seem easier than it actually is). Hence, for many applications, it is better to look to methods more suitable for high-dimensional estimation algorithms. The two primary candidates are the parametric bootstrap and subsampling.

The *parametric bootstrap* generates new unrepeatable observations for each bootstrap sample given an estimated generative model (or other assumed form for the data generating process).¹⁸ In doing so, it avoids pathologies of the nonparametric bootstrap that arise from using the empirical sample distribution. The cost is that the parametric bootstrap is, of course, parametric: It makes strong assumptions about the underlying generative model, and one must bear in mind that the resulting inference is conditional upon these assumptions.¹⁹

¹⁷See, e.g., Horowitz (2003) for an overview.

¹⁸See Efron (2012) for an overview that also makes interesting connections to Bayesian inference.

¹⁹For example, in a linear regression model, the parametric bootstrap requires simulating errors from an assumed, say Gaussian, distribution. One must make assumptions on the exact form of this distribution, including whether the errors are homoskedastic or not. This contrasts with our usual approaches to standard errors for linear regression that are robust to assumptions on the functional form of the errors.

¹⁶Due to its popularity in the deep learning community, variational inference is a common feature in newer machine learning frameworks; see, for example, Edward (Tran et al. 2016, 2017) for a python library that builds variational inference on top of the TensorFlow platform. Edward and similar tools can be used to implement topic models and the other kinds of text models that we discussed above.

An alternative method, *subsampling*, provides a nonparametric approach to inference that remains robust to estimation features such as non-differentiable losses and model selection. The book by Politis, Romano, and Wolf (1999) gives a comprehensive overview. In subsampling, the data are partitioned into subsamples without replacement (the number of subsamples being a function of the total sample size) and the target parameters are reestimated separately on each subsample. The advantage of subsampling is that, because each subsample is a draw from the true DGP, it works for a wide variety of estimation algorithms. However, since each subsample is smaller than the sample of interest, one needs to know the estimator's rate of convergence in order to translate between the uncertainty in the subsamples and in the full sample.²⁰

Finally, one may consider *sample splitting* with methods that involve a model selection step (i.e., those setting some parameter values to zero, such as lasso). Model selection is performed on one "selection" sample, then the standard inference is performed on the second "estimation" sample conditional upon the selected model.²¹ Econometricians have successfully used this approach to obtain accurate inference for machine learning procedures. For example, Chernozhukov et al. (2018) use it in the context of treatment effect estimation via lasso, and Athey and Imbens (2016) use sample splitting for

inference about heterogeneous treatment effects in the context of a *causal tree* model.

3.5 Some Practical Advice

The methods above will be compared and contrasted in our subsequent discussion of applications. In broad terms, however, we can make some rough recommendations for practitioners.

3.5.1 Choosing the Best Approach for a Specific Application

Dictionary-based methods heavily weight prior information about the function mapping features \mathbf{c}_i to outcomes \mathbf{v}_i . They are therefore most appropriate in cases where such prior information is strong and reliable, and where information in the data is correspondingly weak. An obvious example is a case where the outcomes \mathbf{v}_i are not observed for any i , so there is no training data available to fit a supervised model, and where the mapping of interest does not match the factor structure of unsupervised methods such as topic models. In the setting of Baker, Bloom, and Davis (2016), for example, there is no ground truth data on the actual level of policy uncertainty reflected in particular articles, and fitting a topic model would be unlikely to endogenously pick out policy uncertainty as a topic. A second example is where some training data do exist, but it is sufficiently small or noisy that the researcher believes a prior-driven specification of $f(\cdot)$ is likely to be more reliable.

Text regression is generally a good choice for predicting a single attribute, especially when one has a large amount of labeled training data available. As described in Ng and Jordan (2001) and Taddy (2013c), supervised generative techniques such as naive Bayes and MNIR can improve prediction when p is large relative to n ; however, these gains diminish with the sample size due to the asymptotic efficiency of many text regression techniques. In text regression, we have

²⁰For many applications, doing this translation under the assumption of a standard \sqrt{n} learning rate is a reasonable choice. For example, Knight and Fu (2000) show conditions under which the \sqrt{n} rate holds for the lasso. However, in many text-as-data applications the dimension of the data (the size of the vocabulary) will be large and growing with the number of observations. In such settings \sqrt{n} learning may be optimistic, and more sophisticated methods may need to be used to infer the learning rate (see, e.g., Politis, Romano, and Wolf 1999).

²¹For example, when using lasso, one might apply OLS in the second stage using only the covariates selected by lasso in the first stage.

found that it is usually unwise to attempt to learn flexible functional forms unless n is much larger than p . When this is not the case, we generally recommend linear regression methods. Given the availability of fast and robust tools (gamlr and glmnet in R, and scikit-learn in Python), and the typically high dimensionality of text data, many prediction tasks in social science with text inputs can be efficiently addressed via penalized linear regression.

When there are multiple attributes of interest, and one wishes to resolve or control for interdependencies between these attributes and their effects on language, then one will need to work with a generative model for text. Multinomial logistic regression and its extensions can be applied to such situations, particularly via distributed multinomial regression. Alternatively, for corpora of many unlabeled documents (or when the labels do not tell the whole story that one wishes to investigate), topic modeling is the obvious approach. Word embeddings are also becoming an option for such questions. In the spirit of contemporary machine learning, it is also perfectly fine to combine techniques. For example, a common setting will have a large corpora of labeled documents as well as a smaller set of documents about which some metadata exist. One approach is to fit a topic model on the larger corpora, and to then use these topics *as well as* the token counts for supervised text regression on the smaller labeled corpora.

3.5.2 Model Validation and Interpretation

Ex ante criteria for selecting an empirical approach are suggestive at best. In practice, it is also crucial to validate the performance of the estimation approach ex post. Real research often involves an iterative tuning process with repeated rounds of estimation, validation, and adjustment.

When the goal is prediction, the primary tool for validation is checking out-of-sample

predictive performance on data held out from the main estimation sample. In section 3.1.1, we discussed the technique of cross-validation (CV) for penalty selection, a leading example. More generally, whenever one works with complex and high-dimensional data, it is good practice to reserve a test set of data to use in estimation of the true average prediction error. Looping across multiple test sets, as in CV, is a common way of reducing the variance of these error estimates. (See Efron 2004 for a classic overview.)

In many social science applications, the goal is to go beyond prediction and use the values $\hat{\mathbf{V}}$ in some subsequent descriptive or causal analysis. In these cases, it is important to also validate the accuracy with which the fitted model is capturing the economic or descriptive quantity of interest.

One approach that is often effective is *manual audits*: cross-checking some subset of the fitted values against the coding a human would produce by hand. An informal version of this is for a researcher to simply inspect a subset of documents alongside the fitted $\hat{\mathbf{V}}$ and evaluate whether the estimates align with the concept of interest. A formal version would involve having one or more people manually classify each document in a subset and evaluating quantitatively the consistency between the human and machine codings. The subsample of documents does not need to be large in order for this exercise to be valuable—often as few as twenty or thirty documents is enough to provide a sense of whether the model is performing as desired.

This kind of auditing is especially important for dictionary methods. Validity hinges on the assumption that a particular function of text features—counts of positive or negative words, an indicator for the presence of certain keywords, etc.—will be a valid predictor of the true latent variable \mathbf{V} . In a setting where we have sufficient prior information to justify this assumption, we

typically also have enough prior information to evaluate whether the resulting classification looks accurate. An excellent example of this is Baker, Bloom, and Davis (2016), who perform a careful manual audit to validate their dictionary-based method for identifying articles that discuss policy uncertainty.

Audits are also valuable in studies using other methods. In Gentzkow and Shapiro (2010), for example, the authors perform an audit of news articles that their fitted model classifies as having a right-leaning or left-leaning slant. They do not compare this against hand coding directly, but rather count the number of times the key phrases that are weighted by the model are used straightforwardly in news text, as opposed to occurring in quotation marks or in other types of articles such as letters to the editor.

A second approach to validating a fitted model is inspecting the estimated coefficients or other parameters of the model directly. In the context of text regression methods, however, this needs to be approached with caution. While there is a substantial literature on statistical properties of estimated parameters in penalized regression models (see Bühlmann and van de Geer 2011 and Hastie, Tibshirani, and Wainwright 2015), the reality is that these coefficients are typically only interpretable in cases where the true model is extremely sparse, so that the model is likely to have selected the correct set of variables with high probability. Otherwise, multicollinearity means the set of variables selected can be highly unstable.

These difficulties notwithstanding, inspecting the most important coefficients to see if they make intuitive sense can still be useful as a validation and sanity check. Note that “most important” can be defined in a number of ways; one can rank estimated coefficients by their absolute values, or by absolute value scaled by the standard deviation of the associated covariate, or perhaps by the order in which they first become nonzero in a lasso

path of decreasing penalties. Alternatively, see Gentzkow, Shapiro, and Taddy (2016) for application-specific term rankings.

Inspection of fitted parameters is generally more informative in the context of a generative model. Even there, some caution is in order. For example, Taddy (2015a) finds that for MNIR models, getting an interpretable set of word loadings requires careful penalty tuning and the inclusion of appropriate control variables. As in text regression, it is usually worthwhile to look at the largest coefficients for validation but not take the smaller values too seriously.

Interpretation or story building around estimated parameters tends to be a major focus for topic models and other unsupervised generative models. Interpretation of the fitted topics usually proceeds by ranking the tokens in each topic according to token probability, θ_{lj} , or by token lift θ_{lj}/\bar{p}_j with $\bar{p}_j = (1/n)\sum_i c_{ij}/m_i$. For example, if the five highest lift tokens in topic l for a model fit to a corpus of restaurant reviews are *another.minute*, *flag.down*, *over.minute*, *wait.over*, *arrive.after*, we might expect that reviews with high v_{il} correspond to negative experiences where the patron was forced to wait for service and food (example from Taddy 2012). Again, however, we caution against the overinterpretation of these unsupervised models: the posterior distributions informing parameter estimates are often multimodal, and multiple topic model runs can lead to multiple different interpretations. As argued in Airolidi and Bischof (2016) and in a comment by Taddy (2017a), the best way to build interpretability for topic models may be to add some supervision (i.e., to incorporate external information on the topics for some set of cases).

4. Applications

We now turn to applications of text analysis in economics and related social sciences.

Rather than presenting a comprehensive literature survey, the goal of this section is to present a selection of illustrative papers to give the reader a sense of the wide diversity of questions that may be addressed with textual analysis and to provide a flavor of how some of the methods in section 3 are applied in practice.

4.1 Authorship

A classic descriptive problem is inferring the author of a document. While this is not usually a first-order research question for social scientists, it provides a particularly clean example, and a good starting point to understand the applications that follow.

In what is often seen as the first modern statistical analysis of text data, Mosteller and Wallace (1963) use text analysis to infer the authorship of the disputed *Federalist Papers* that had alternatively been attributed to either Alexander Hamilton or James Madison. They define documents i to be individual *Federalist Papers*, the data features \mathbf{c}_i of interest to be counts of function words such as “an,” “of,” and “upon” in each document, and the outcome v_i to be an indicator for the identity of the author. Note that the function words the authors focus on are exactly the “stop words” that are frequently excluded from analysis (as discussed in section 2 above). The key feature of these words is that their use by a given author tends to be stable regardless of the topic, tone, or intent of the piece of writing. This means they provide little valuable information if the goal is to infer characteristics such as political slant or discussion of policy uncertainty that are independent of the idiosyncratic styles of particular authors. When such styles are the object of interest, however, function words become among the most informative text characteristics. Mosteller and Wallace (1963) use a sample of *Federalist Papers*, whose authorship by either Madison or Hamilton is

undisputed, to train a naive Bayes classifier (a supervised generative model, as discussed in section 3.2) in which the probabilities $p(c_{ij}|v_i)$ of each phrase j are assumed to be independent Poisson or negative binomial random variables, and the inferences for the unknown documents are made by Bayes’ rule. The results provide overwhelming evidence that all of the disputed papers were authored by Madison.

Stock and Trebbi (2003) apply similar methods to answer an authorship question of more direct interest to economists: who invented instrumental variables? The earliest known derivation of the instrumental variables estimator appears in an appendix to *The Tariff on Animal and Vegetable Oils*, a 1928 book by statistician Philip Wright. While the bulk of the book is devoted to a “painfully detailed treatise on animal and vegetable oils, their production, uses, markets and tariffs,” the appendix is of an entirely different character, with “a succinct and insightful explanation of why data on price and quantity alone are in general inadequate for estimating either supply or demand; two separate and correct derivations of the instrumental variables estimators of the supply and demand elasticities; and an empirical application” (Stock and Trebbi 2003, p. 177). The contrast between the two parts of the book has led to speculation that the appendix was not written by Philip Wright, but rather by his son Sewall. Sewall Wright was an economist who had originated the method of “path coefficients” used in one of the derivations in the appendix. Several authors including Manski (1988) are on record attributing authorship to Sewall; others including Angrist and Krueger (2001) attribute it to Philip.

In Stock and Trebbi’s (2003) study, the outcome v_i is an indicator for authorship by either Philip or Sewall. The data features $\mathbf{c}_i = [\mathbf{c}_i^{func} \ \mathbf{c}_i^{gram}]$ are counts of the same function words used by Mosteller and

Wallace (1963) plus counts of a set of grammatical constructions (e.g., “noun followed by adverb”) measured using an algorithm due to Mannion and Dixon (1997). The training sample \mathbf{C}^{train} consists of forty-five documents known to have been written by either Philip or Sewall, and the test sample \mathbf{C}^{test} in which v_i is unobserved consists of eight blocks of text from the appendix plus one block of text from chapter 1 of *The Tariff on Animal and Vegetable Oils* included as a validity check. The authors apply principal components analysis, which we can think of as an unsupervised cousin of the topic modeling approach discussed in section 3.2.1. They extract the first four principal components from \mathbf{c}_i^{func} and \mathbf{c}_i^{gram} respectively, and then run regressions of the binary authorship variable on the principal components, resulting in predicted values \hat{v}_i^{func} and \hat{v}_i^{gram} .

The results provide overwhelming evidence that the disputed appendix was in fact written by Philip. Figure 3 plots the values $(\hat{v}_i^{func}, \hat{v}_i^{gram})$ for all of the documents in the sample. Each point in the figure is a document i , and the labels indicate whether the document is known to be written by Philip (“P” or “1”), known to be written by Sewall (“S”), or of uncertain authorship (“B”). The measures clearly distinguish the two authors, with documents by each forming clear, nonoverlapping clusters. The uncertain documents all fall squarely within the cluster attributed to Philip, with the predicted values $\hat{v}_i^{func}, \hat{v}_i^{gram} \approx 1$.

4.2 Stock Prices

An early example analyzing news text for stock price prediction appears in Cowles (1933). He subjectively categorizes the text of editorial articles of Peter Hamilton, chief editor of the *Wall Street Journal* from 1902–29, as “bullish,” “bearish,” or “doubtful.” Cowles then uses these classifications

to predict future returns of the Dow Jones Industrial Average. Hamilton’s track record is unimpressive. A market-timing strategy based on his *Wall Street Journal* editorials underperforms a passive investment in the Dow Jones Industrial Average by 3.5 percentage points per year.

In its modern form, the implementation of text-based prediction in finance is computationally driven, but it applies methods that are conceptually similar to Cowles’s approach, seeking to predict the target quantity \mathbf{V} (the Dow Jones return, in the example of Cowles) from the array of token counts \mathbf{C} . We discuss three examples of recent papers that study equity return prediction in the spirit of Cowles: one relying on a preexisting dictionary (as discussed at the beginning of section 3), one using regression techniques (as discussed in section 3.1), and another using generative models (as discussed in section 3.2).

Tetlock’s 2007 paper is a leading dictionary-based example of analyzing media sentiment and the stock market. He studies word counts \mathbf{c}_i in the *Wall Street Journal*’s widely read “Abreast of the Market” column. Counts from each article i are converted into a vector of sentiment scores $\hat{\mathbf{v}}_i$ in seventy-seven different sentiment dimensions based on the Harvard IV-4 psychosocial dictionary.²² The time series of daily sentiment scores for each category ($\hat{\mathbf{v}}_i$) are condensed into a single principal component, which Tetlock names the “pessimism factor” due to the component’s especially close association with the “pessimism” dimension of the sentiment categories.

The second stage of the analysis uses this pessimism score to forecast stock market

²²While it has only recently been used in economics and finance, the Harvard dictionary and associated General Inquirer software for textual content analysis dates to the 1960s and has been widely used in linguistics, psychology, sociology, and anthropology.

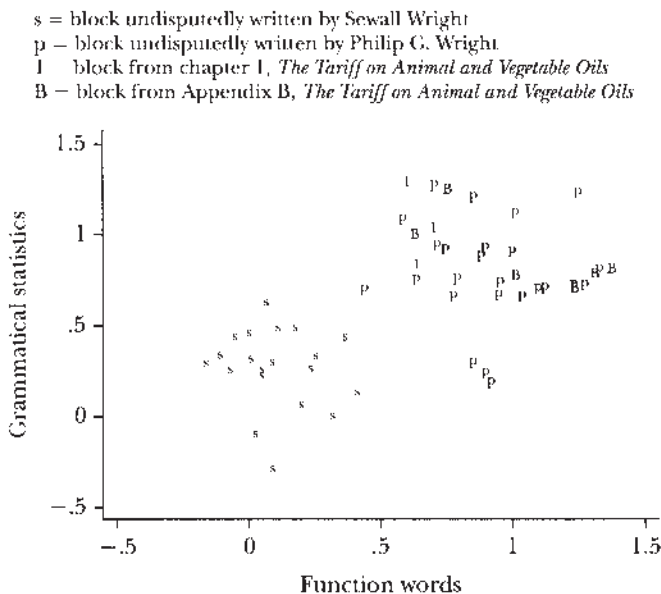


Figure 3. Scatterplot of Authorship Predictions from PCA Method

Source: Stock and Trebbi (2003). Copyright American Economic Association; reproduced with the permission of the *Journal of Economic Perspectives*.

activity. High pessimism significantly negatively forecasts one-day-ahead returns on the Dow Jones Industrial Average. This effect is transitory, and the short-term index dip associated with media pessimism reverts within a week, consistent with the interpretation that article text is informative regarding media and investor sentiment, as opposed to containing fundamental news that permanently impacts prices.

The number of studies using dictionary methods to study asset pricing phenomena is growing. Loughran and McDonald (2011) demonstrate that the widely used Harvard dictionary can be ill-suited for financial applications. They construct an alternative, finance-specific dictionary of positive and negative terms and document its improved predictive power over existing sentiment dictionaries. Bollen, Mao, and Zeng (2011)

document a significant predictive correlation between Twitter messages and the stock market using other dictionary-based tools such as OpinionFinder and Google's Profile of Mood States. Wisniewski and Lambe (2013) show that negative media attention of the banking sector, summarized via *ad hoc* pre-defined word lists, Granger-causes bank stock returns during the 2007–2009 financial crisis and not the reverse, suggesting that journalistic views have the potential to influence market outcomes, at least in extreme states of the world.

The use of text regression for asset pricing is exemplified by Jegadeesh and Wu (2013). They estimate the response of company-level stock returns, v_i , to text information in the company's annual report (token counts, \mathbf{c}_i). The authors' objective is to determine whether regression techniques

offer improved stock return forecasts relative to dictionary methods.

The authors propose the following regression model to capture correlations between occurrences of individual words and subsequent stock return realizations around regulatory filing dates:

$$v_i = a + b \left(\sum_j w_j \frac{c_{ij}}{\sum_j c_{ij}} \right) + \varepsilon_i.$$

Documents i are defined to be annual reports filed by firms at the Securities Exchange Commission. The outcome variable v_i is a stock's cumulative four-day return beginning on the filing day. The independent variable c_{ij} is a count of occurrences of word j in annual report i . The coefficient w_j summarizes the average association between an occurrence of word j and the stock's subsequent return. The authors show how to estimate w_j from a cross-sectional regression, along with a subsequent rescaling of all coefficients to remove the common influence parameter b . Finally, variables to predict returns are built from the estimated weights, and are shown to have stronger out-of-sample forecasting performance than dictionary-based indices from Loughran and McDonald (2011). The results highlight the limitations of using fixed dictionaries for diverse predictive problems, and that these limitations are often surmountable by estimating application-specific weights via regression.

Manela and Moreira (2017) take a regression approach to construct an index of news-implied market volatility based on text from the *Wall Street Journal* from 1890–2009. They apply support vector machines, a nonlinear regression method that we discuss in section 3.1.3. This approach applies a penalized least squares objective to identify a small subset of words whose frequencies are most useful for predicting outcomes—in this case, turbulence in financial markets. Two important findings

emerge from their analysis. First, the terms most closely associated with market volatility relate to government policy and wars. Second, high levels of news-implied volatility forecast high future stock market returns. These two facts together give insight into the types of risks that drive investors' valuation decisions.²³

The closest modern analog of Cowles's study is Antweiler and Frank (2004), who take a generative modeling approach to ask: how informative are the views of stock market prognosticators who post on internet message boards? Similar to Cowles's analysis, these authors classify postings on stock message boards as “buy,” “sell,” or “hold” signals. But the vast number of postings, roughly 1.5 million in the analyzed sample, makes subjective classification of messages infeasible. Instead, generative techniques allow the authors to automatically classify messages.

The authors create a training sample of one thousand messages, and form \mathbf{V}^{train} by manually classifying messages into one of the three categories. They then use the naive Bayes method described in section 3.2.2 to estimate a probability model that maps word counts of postings \mathbf{C} into classifications $\hat{\mathbf{V}}$ for the remaining 1.5 million messages. Finally, the buy/sell/hold classification of each message is aggregated into an index that is used to forecast stock returns. Consistent with the conclusions of Cowles, message board postings show little ability to predict stock returns. They do, however, possess significant and economically meaningful

²³While Manela and Moreira (2017) study aggregate market volatility, Kogan et al. (2009) and Boudoukh et al. (2016) use text from news and regulatory filings to predict firm-specific volatility. Chinco, Clark-Joseph, and Ye (2017) apply lasso in high frequency return prediction using preprocessed financial news text sentiment as an explanatory variable.

information about stock volatility and trading volume.²⁴

Bandiera et al. (2017) apply unsupervised machine learning—topic modeling (LDA)—to a large panel of CEO diary data. They uncover two distinct behavioral types that they classify as “leaders” who focus on communication and coordination activities, and “managers” who emphasize production-related activities. They show that, due to horizontal differentiation of firm and manager types, appropriately matched firms and CEOs enjoy better firm performance. Mismatches are more common in lower income economies, and mismatches can account for 13 percent of the labor productivity gap between firms in high- and middle/low-income countries.

4.3 Central Bank Communication

A related line of research analyzes the impact of communication from central banks on financial markets. As banks rely more on these statements to achieve policy objectives, an understanding of their effects is increasingly relevant.

Lucca and Trebbi (2009) use the content of Federal Open Market Committee (FOMC) statements to predict fluctuations in Treasury securities. To do this, they use two different dictionary-based methods (section 3)—Google and Factiva semantic orientation scores—to construct $\hat{\mathbf{v}}_i$, which quantifies the direction and intensity of the i th FOMC statement. In the Google score, \mathbf{c}_i counts how many Google search hits occur when searching for phrases in i plus one of the words from a list of antonym pairs signifying positive or negative sentiment (e.g., “hawkish” versus “dovish”). These counts are mapped into $\hat{\mathbf{v}}_i$ by differencing the frequency

of positive and negative searches and averaging over all phrases in i . The Factiva score is calculated similarly. Next, the central bank sentiment proxies $\hat{\mathbf{v}}_i$ are used to predict Treasury yields in a vector autoregression (VAR). They find that changes in statement content, as opposed to unexpected deviations in the federal funds target rate, are the main driver of changes in interest rates.

Born, Ehrmann, and Fratzscher (2014) extend this idea to study the effect of central bank sentiment on stock market returns and volatility. They construct a financial stability sentiment index $\hat{\mathbf{v}}_i$ from Financial Stability Reports (FSRs) and speeches given by central bank governors. Their approach uses a sentiment dictionary to assign optimism scores to word counts \mathbf{c}_i from central bank communications. They find that optimistic FSRs tend to increase equity prices and reduce market volatility during the subsequent month.

Hansen, McMahon, and Prat (2018) research how FOMC transparency affects debate during meetings by studying a change in disclosure policy. Prior to November 1993, the FOMC meeting transcripts were secret, but following a policy shift transcripts became public with a time lag. There are potential costs and benefits of increased transparency, such as the potential for more efficient and informed debate due to increased accountability of policy makers. On the other hand, transparency may make committee members more cautious, biased toward the status quo, or prone to group-think.

The authors use topic modeling (section 3.2.1) to study 149 FOMC meeting transcripts during Alan Greenspan’s tenure. The unit of observation is a member-meeting. The vector \mathbf{c}_i counts the words used by FOMC member m in meeting t , and i is defined as the pair (m, t) . The outcome of interest, \mathbf{v}_i , is a vector that includes the proportion of i ’s language devoted to the K different topics (estimated from the fitted topic model),

²⁴Other papers that use naive Bayes and similar generative models to study behavioral finance questions include Buehlmaier and Whited (2018), Li (2010), and Das and Chen (2007).

the concentration of these topic weights, and the frequency of data citation by i . Next, a difference-in-differences regression estimates the effects of the change in transparency on \hat{v}_i . The authors find that, after the move to a more transparent system, inexperienced members discuss a wider range of topics and make more references to data when discussing economic conditions (consistent with increased accountability); but also speak more like Chairman Greenspan during policy discussions (consistent with increased conformity). Overall, the accountability effect appears stronger, as inexperienced members' topics appear to be more influential in shaping future deliberation after transparency.

4.4 *Nowcasting*

Important variables such as unemployment, retail sales, and GDP are measured at low frequency, and estimates are released with a significant lag. Others, such as racial prejudice or local government corruption, are not captured by standard measures at all. Text produced online such as search queries, social media posts, listings on job websites, and so on can be used to construct alternative real-time estimates of the current values of these variables. By contrast with the standard exercise of forecasting future variables, this process of using diverse data sources to estimate current variables has been termed “nowcasting” in the literature (Bańbura et al. 2013).

A prominent early example is the Google Flu Trends project. Zeng and Wagner (2002) note that the volume of searches or web hits seeking information related to a disease may be a strong predictor of its prevalence. Johnson et al. (2004) provide an early data point suggesting that browsing influenza-related articles on the website healthlink.com is correlated with traditional surveillance data from the Centers for Disease Control (CDC). In the late 2000s, a group of Google engineers built on this idea

to create a product that predicts flu prevalence from Google searches using text regression.

The results are reported in a widely cited *Nature* article by Ginsberg et al. (2009). Their raw data \mathcal{D} consist of “hundreds of billions of individual searches from 5 years of Google web search logs.” Aggregated search counts are arranged into a vector \mathbf{c}_i , where a document i is defined to be a particular US region in a particular week, and the outcome of interest v_i is the true prevalence of flu in the region-week. In the training data, this is taken to be equal to the rate measured by the CDC. The authors first restrict attention to the fifty million most common terms, then select those most diagnostic of an outbreak using text regression (section 3.1), specifically a variant of partial least squares regression. They first run fifty million univariate regressions of $\log(v_i/(1-v_i))$ on $\log(c_{ij}/(1-c_{ij}))$, where c_{ij} is the share of searches in i containing search term j . They then fit a sequence of multivariate regression models of v_i on the top n terms j as ranked by average predictive power across regions for $n \in \{1, 2, \dots\}$. Next, they select the value of n that yields the best fit on a hold-out sample. This yields a regression model with $n = 45$ terms. The model produces accurate flu rate estimates for all regions approximately 1–2 weeks ahead of the CDC’s regular report publication dates.²⁵

²⁵A number of subsequent papers debate the longer-term performance of Google Flu Trends. Lazer et al. (2014), for example, show that the accuracy of the Google Flu Trends model—which has not been recalibrated or updated based on more recent data—has deteriorated dramatically, and that in recent years it is outperformed by simple extrapolation from prior CDC estimates. This may reflect changes in both search patterns and the epidemiology of the flu, and it suggests a general lesson that the predictive relationship mapping text to a real outcome of interest may not be stable over time. On the other hand, Preis and Moat (2014) argue that an adaptive version of the model that more flexibly accounts for joint dynamics in flu incidence and search volume significantly improves real-time influenza monitoring.

Related work in economics attempts to nowcast macroeconomic variables using data on the frequency of Google search terms. In Choi and Varian (2012) and Scott and Varian (2014, 2015), search term counts are aggregated by week and by geographic location, then converted to location-specific frequency indices. They estimate spike and slab Bayesian forecasting models, discussed in section 3.1.4 above. Forecasts of regional retail sales, new housing starts, and tourism activity are all significantly improved by incorporating a few search term indices that are relevant for each category in linear models. Their results suggest a potential for large gains in forecasting power using web browser search data.

Saiz and Simonsohn (2013) use web search results to estimate the current extent of corruption in US cities. Standard corruption measures based on surveys are available at the country and state level, but not for smaller geographies. The authors use a dictionary approach in which the index \hat{v}_i of corruption is defined to be the ratio of search hits for the name of a geographic area i plus the word “corruption” divided by hits for the name of the geographic area alone. These counts are extracted from search engine results. As a validation, the authors first show that country-level and state-level versions of their measure correlate strongly with established corruption indices and covary in a similar way with country- and state-level demographics. They then compute their measure for US cities and study its observable correlates.

Stephens-Davidowitz (2014) uses the frequency of racially charged terms in Google searches to estimate levels of racial animus in different areas of the United States. Estimating animus via traditional surveys is challenging because individuals are often reluctant to state their true attitudes. The paper’s results suggest Google searches provide a less filtered, and therefore more accurate, measure. The author uses a dictionary approach in which the index \hat{v}_i of racial

animus in area i is the share of searches originating in that area that contain a set of racist words. He then uses these measures to estimate the impact of racial animus on votes for Barack Obama in the 2008 election, finding a statistically significant and economically large negative effect on Obama’s vote share relative to the Democratic vote share in the previous election.

4.5 Policy Uncertainty

Among the most influential applications of text analysis in the economics literature to date is a measure of economic policy uncertainty (EPU) developed by Baker, Bloom, and Davis (2016). Uncertainty about both the path of future government policies and the impact of current government policies has the potential to increase risk for economic actors and so potentially depress investment and other economic activity. The authors use text from news outlets to provide a high-frequency measure of EPU and then estimate its economic effects.

Baker, Bloom, and Davis (2016) define the unit of observation i to be a country-month. The outcome v_i of interest is the true level of economic policy uncertainty. The authors apply a dictionary method to produce estimates \hat{v}_i based on digital archives of ten leading newspapers in the United States. An element of the input data c_{ij} is a count of the number of articles in newspaper j in country-month i containing at least one keyword from each of three categories defined by hand: one related to the economy, a second related to policy, and a third related to uncertainty. The raw counts are scaled by the total number of articles in the corresponding newspaper-month and normalized to have standard deviation one. The predicted value \hat{v}_i is then defined to be a simple average of these scaled counts across newspapers.

The simplicity of the manner in which the index is created allows for a high amount of

flexibility across a broad range of applications. For instance, by including a fourth, policy-specific category of keywords, the authors can estimate narrower indices related to Federal Reserve policy, inflation, and so on.

Baker, Bloom, and Davis (2016) validate \hat{v}_i using a human audit of twelve thousand articles from 1900–2012. Teams manually scored articles on the extent to which they discuss economic policy uncertainty and the specific policies they relate to. The resulting human-coded index has a high correlation with \hat{v}_i .

With the estimated \hat{v}_i in hand, the authors analyze the micro- and macro-level effects of EPU. Using firm-level regressions, they first measure how firms respond to this uncertainty and find that it leads to reduced employment, investment, and greater asset price volatility for that firm. Then, using both US and international panel VAR models, the authors find that increased \hat{v}_i is a strong predictor of lower investment, employment, and production.

Hassan et al. (2017) measure political risk at the firm level by analyzing quarterly earnings call transcripts. Their measure captures the frequency with which policy-oriented language and “risk” synonyms co-occur in a transcript. Firms with high levels of political risk actively hedge these risks by lobbying more intensively and donating more to politicians. When a firm’s political risk rises, it tends to retrench hiring and investment, consistent with the findings of Baker, Bloom, and Davis (2016) at the aggregate level. Their findings indicate that political shocks are an important source of idiosyncratic firm-level risk.

4.6 *Media Slant*

A text analysis problem that has received significant attention in the social science literature is measuring the political slant of media content. Media outlets have long been seen as having a uniquely important role in

the political process, with the power to potentially sway both public opinion and policy. Understanding how and why media outlets slant the information they present is important to understanding the role media play in practice, and to informing the large body of government regulation designed to preserve a diverse range of political perspectives.

Groseclose and Milyo (2005) offer a pioneering application of text analysis methods to this problem. In their setting, i indexes a set of large US media outlets, and documents are defined to be the complete news text or broadcast transcripts for an outlet i . The outcome of interest v_i is the political slant of outlet i . To give this measure content, the authors use speeches by politicians in the US Congress to form a training sample, and define v_i within this sample to be a politician’s Americans for Democratic Action (ADA) score, a measure of left-right political ideology based on congressional voting records. The predicted values \hat{v}_i for the media outlets thus place them on the same left-right scale as the politicians, and answer the question “what kind of politician does this news outlet’s content sound most similar to?”

The raw data are the full text of speeches by congresspeople and news reports by media outlets over a period spanning the 1990s to the early 2000s.²⁶ The authors dramatically reduce the dimensionality of the data in an initial step by deciding to focus on a particularly informative subset of phrases: the names of two hundred think tanks. These think tanks are widely viewed as having clear political positions (e.g., the Heritage Foundation on the right and the NAACP on the left). The relative frequency

²⁶For members of Congress, the authors use all entries in the *Congressional Record* from January 1, 1993 to December 31, 2002. The text includes both floor speeches and documents the member chose to insert in the record but did not read on the floor. For news outlets, the time period covered is different for different outlets, with start dates as early as January 1990 and end dates as late as July 2004.

with which a politician cites conservative as opposed to liberal think tanks turns out to be strongly correlated with a politician's ideology. The paper's premise is that the citation frequencies of news outlets will then provide a good index of those outlets' political slants. The features of interest \mathbf{c}_i are a (1×50) vector of citation counts for each of forty-four highly cited think tanks plus six groups of smaller think tanks.

The text analysis is based on a supervised generative model (section 3.2.2). The utility that congress member or media firm i derives from citing think tank j is $U_{ij} = a_j + b_j v_i + e_{ij}$, where v_i is the observable ADA score of a congress member i or unobserved slant of media outlet i , and e_{ij} is an error distributed type-I extreme value. The coefficient b_j captures the extent to which think tank j is cited relatively more by conservatives. The model is fit by maximum likelihood with the parameters (a_j, b_j) and the unknown slants v_i estimated jointly. This is an efficient but computationally intensive approach to estimation, and it constrains the authors' focus to twenty outlets. This limitation can be sidestepped using more recent approaches such as Taddy's (2013b) multinomial inverse regression.

Figure 4 shows the results, which suggest three main findings. First, the media outlets are all relatively centrist: they are all to the left of the average Republican and to the right of the average Democrat with one exception. Second, the ordering matches conventional wisdom, with the *New York Times* and *Washington Post* on the left, and *Fox News* and the *Washington Times* on the right.²⁷ Third, the large majority of outlets fall to the left of the average in congress,

which is denoted in the figure by "average US voter." The last fact underlies the authors' main conclusion, which is that there is an overall liberal bias in the media.

Gentzkow and Shapiro (2010) build on the Groseclose and Milyo (2005) approach to measure the slant of 433 US daily newspapers. The main difference in approach is that Gentzkow and Shapiro (2010) omit the initial step that restricts the space of features to mentions of think tanks, and instead consider all phrases that appear in the 2005 *Congressional Record* as potential predictors, letting the data select those that are most diagnostic of ideology. These could potentially be think tank names, but they turn out instead to be politically charged phrases such as "death tax," "bring our troops home," and "war on terror."

After standard preprocessing—stemming and omitting stop words—the authors produce counts of all 2-grams and 3-grams by speaker. They then select the top one thousand phrases (five hundred of each length) by a χ^2 criterion that captures the degree to which each phrase is diagnostic of the speaker's party. This is the standard χ^2 -test statistic for the null hypothesis that phrase j is used equally often by Democrats and Republicans, and it will be high for phrases that are both used frequently and used asymmetrically by the parties.²⁸ Next, a two-stage supervised generative method is used to predict newspaper slant v_i from the selected features. In the first stage, the authors run a separate regression for each phrase j of counts (c_{ij})

features and estimate a much more conservative slant for the *Wall Street Journal*.

²⁸The statistic is

$$\chi_j^2 = \frac{f_{jr}f_{\sim jd} - f_{jd}f_{\sim jr}}{(f_{jr} + f_{jd})(f_{jr} + f_{\sim jd})(f_{\sim jr} + f_{jd})(f_{\sim jr} + f_{\sim jd})}$$

where f_{jd} and f_{jr} denote the number of times phrase j is used by Democrats or Republicans, respectively, and $f_{\sim jd}$ and $f_{\sim jr}$ denote the number of times phrases other than j are used by Democrats and Republicans, respectively.

²⁷ The one notable exception is the *Wall Street Journal*, which is generally considered to be right-of-center but which is estimated by Groseclose and Milyo (2005) to be the most left-wing outlet in their sample. This may reflect an idiosyncrasy specific to the way they cite think tanks; Gentzkow and Shapiro (2010) use a broader sample of text

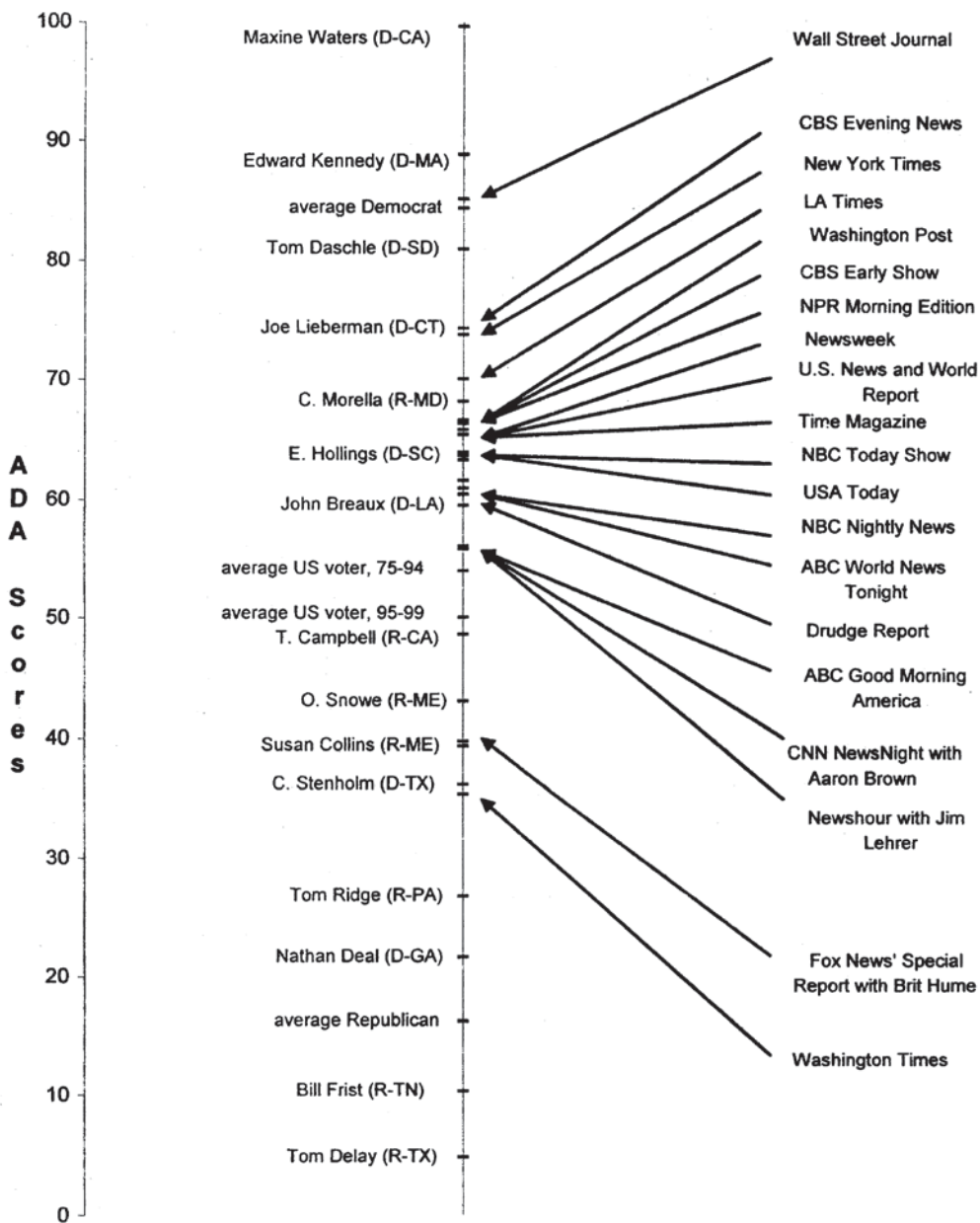


Figure 4. Distribution of Political Orientation: Media Outlets and Members of Congress

Source: Groseclose and Milyo (2005). Reprinted with permission from the *Quarterly Journal of Economics*.

on speaker i 's ideology, which is measured as the 2004 Republican vote share in the speaker's district. They then use the estimated coefficients $\hat{\beta}_j$ to produce predicted slant $\hat{v}_i \propto \sum_{j=1}^{1,000} \hat{\beta}_j c_{ij}$ for the unknown newspapers i .

The main focus of the study is characterizing the incentives that drive newspapers' choice of slant. With the estimated \hat{v}_i in hand, the authors estimate a model of consumer demand in which a consumer's utility from reading newspaper i depends on the distance between i 's slant v_i and an ideal slant v^* which is greater the more conservative the consumer's ideology. Estimates of this model using zipcode-level circulation data imply a level of slant that newspapers would choose if their only incentive was to maximize profits. The authors then compare this profit-maximizing slant to the level actually chosen by newspapers, and ask whether the deviations can be predicted by the identity of the newspaper's owner or by other nonmarket factors such as the party of local incumbent politicians. They find that profit maximization fits the data well, and that ownership plays no role in explaining the choice of slant. In this study, \hat{v}_i is both an independent variable of interest (in the demand analysis) and an outcome of interest (in the supply analysis).

Note that both Groseclose and Milyo (2005) and Gentzkow and Shapiro (2010) use a two-step procedure where they reduce the dimensionality of the data in a first stage and then estimate a predictive model in the second. Taddy (2013b) shows how to combine a more sophisticated generative model with a novel algorithm for estimation to estimate the predictive model in a single step

²⁹As Taddy (2013b) notes, this method (which Gentzkow and Shapiro 2010 derive in an ad hoc fashion) is essentially partial least squares. It differs from the standard implementation in that the variables v_i and c_{ij} would normally be standardized. Taddy (2013b) shows that doing so increases the in-sample predictive power of the measure from 0.37 to 0.57.

using the full set of phrases in the data. He shows that this substantially increases the in-sample predictive power of the measure.

Greenstein, Gu, and Zhu (2016) analyze the extent of bias and slant among Wikipedia contributors using similar methods. They find that contributors tend to edit articles with slants in opposition to their own slants. They also show that contributors' slants become less extreme as they become more experienced, and that the bias reduction is largest for those with the most extreme initial biases.

4.7 Market Definition and Innovation Impact

Many important questions in industrial organization hinge on the appropriate definition of product markets. Standard industry definitions can be an imperfect proxy for the economically relevant concept. Hoberg and Phillips (2016) provide a novel way of classifying industries based on product descriptions in the text of company disclosures. This allows for flexible industry classifications that may vary over time as firms and economies evolve, and allows the researchers to analyze the effect of shocks on competition and product offerings.

Each publicly traded firm in the United States must file an annual 10-K report describing, among other aspects of their business, the products that they offer. The unit of analysis i is a firm-year. Token counts from the business description section of the i th 10-K filing are represented in the vector \mathbf{c}_i . A pairwise cosine similarity score, s_{ij} , based on the angle between \mathbf{c}_i and \mathbf{c}_j , describes the closeness of product offerings for each pair i and j in the same filing year. Industries are then defined by clustering firms according to their cosine similarities. The clustering algorithm begins by assuming each firm is its own industry, and gradually agglomerates firms into industries by grouping a firm to the cluster with its nearest neighbor according to s_{ij} . The

algorithm terminates when the number of industries (clusters) reaches three hundred, a number chosen for comparability to Standard Industrial Classification and North American Industrial Classification System codes.³⁰

After establishing an industry assignment for each firm–year, \hat{v}_i , the authors examine the effect of military and software industry shocks to competition and product offerings among firms. As an example, they find that the events of September 11, 2001, increased entry in high-demand military markets and pushed products in this industry toward “non-battlefield information gathering and products intended for potential ground conflicts.”

In a similar vein, Kelly et al. (2018) use cosine similarity among patent documents to create new indicators of patent quality. They assign higher quality to patents that are *novel* in that they have low similarity with the existing stock of patents and are *impactful* in that they have high similarity with subsequent patents. They then show that text-based novelty and similarity scores correlate strongly with measures of market value. Atalay et al. (2017) use text from job ads to measure task content and use their measure to show that within-occupation task content shifts are at least as important as employment shifts across occupations in describing the large secular reallocation of routine tasks from humans to machines.

4.8 Topics in Research, Politics, and Law

A number of studies apply topic models (section 3.2.1) to describe how the focus of attention in a specific text corpus shifts over time.

A seminal contribution in this vein is Blei and Lafferty’s (2007) analysis of topics in *Science*. Documents i are individual articles,

the data \mathbf{c}_i are counts of individual words, and the outcome of interest \mathbf{v}_i is a vector of weights indicating the share of a given article devoted to each of one hundred latent topics. The authors extend the baseline LDA model of Blei, Ng, and Jordan (2003) to allow the importance of one topic in a particular article to be correlated with the presence of other topics. They fit the model using all *Science* articles from 1990–99. The results deliver an automated classification of article content into semantically coherent topics such as evolution, DNA and genetics, cellular biology, and volcanoes.

Applying similar methods in the political domain, Quinn et al. (2010) use a topic model to identify the issues being discussed in the US Senate over the period 1997–2004. Their approach deviates from the baseline LDA model in two ways. First, they assume that each speech is associated with a single topic. Second, their model incorporates time-series dynamics that allow the proportion of speeches generated by a given topic to gradually evolve over the sample, similar to the dynamic topic model of Blei and Lafferty (2006). Their preferred specification is a model with forty-two topics, a number chosen to maximize the subjective interpretability of the resulting topics.

Table 1 shows the words with the highest weights in each of twelve fitted topics. The labels “Judicial Nominations,” “Constitutional,” and so on are assigned by hand by the authors. The results suggest that the automated procedure successfully isolates coherent topics of congressional debates. After discussing the structure of topics in the fitted model, the authors then track the relative importance of the topics across congressional sessions and argue that spikes in discussion of particular topics track, in an intuitive way, the occurrence of important debates and external events.

Sim, Routledge, and Smith (2015) estimate a topic model from the text of amicus

³⁰Best, Hjort, and Szakonyi (2017) use a similar approach to classify products in their study of public procurement and organizational bureaucracy in Russia.

TABLE 1
CONGRESSIONAL RECORD TOPICS AND KEY WORDS

Topic (Short Label)	Keys
1. Judicial nominations	nomine, confirm, nomin, circuit, hear, court, judg, judici, case, vacanc
2. Constitutional	case, court, attorney, supreme, justic, nomin, judg, m, decis, constitut
3. Campaign finance	campaign, candid, elect, monei, contribut, polit, soft, ad, parti, limit
4. Abortion	procedur, abort, babi, thi, life, doctor, human, ban, decis, or
5. Crime 1 [violent]	enforc, act, crime, gun, law, victim, violenc, abus, prevent, juvenil
6. Child protection	gun, tobacco, smoke, kid, show, firearm, crime, kill, law, school
7. Health 1 [medical]	diseas, cancer, research, health, prevent, patient, treatment, devic, food
8. Social welfare	care, health, act, home, hospit, support, children, educ, student, nurs
9. Education	school, teacher, educ, student, children, test, local, learn, district, class
10. Military 1 [manpower]	veteran, va, forc, militari, care, reserv, serv, men, guard, member
11. Military 2 [infrastructure]	appropri, defens, forc, report, request, confer, guard, depart, fund, project
12. Intelligence	intellig, homeland, commiss, depart, agenc, director, secur, base, defens

Source: Quinn et al. (2010). Reprinted with permission from John Wiley and Sons.

briefs to the Supreme Court of the United States. They show that the overall topical composition of briefs for a given case, particularly along a conservative–liberal dimension, is highly predictive for how individual judges vote in the case.

5. Conclusion

Digital text provides a rich repository of information about economic and social activity. Modern statistical tools give researchers the ability to extract this information and encode it in a quantitative form amenable to descriptive or causal analysis. Both the availability of text data and the frontier of methods are expanding rapidly, and we expect the importance of text in empirical economics to continue to grow.

The review of applications above suggests a number of areas where innovation should proceed rapidly in coming years. First, a large share of text analysis applications continue to rely on ad hoc dictionary methods rather than deploying more sophisticated

methods for feature selection and model training. As we have emphasized, dictionary methods are appropriate in cases where prior information is strong and the availability of appropriately labeled training data is limited. Experience in other fields, however, suggests that modern methods will likely outperform ad hoc approaches in a substantial share of cases.

Second, some of the workhorse methods of text analysis such as penalized linear or logistic regression have still seen limited application in social science. In other contexts, these methods provide a robust baseline that performs similarly to or better than more complex methods. We expect the domains in which these methods are applied to grow.

Finally, virtually all of the methods applied to date, including those we would label as sophisticated or on the frontier, are based on fitting predictive models to simple counts of text features. Richer representations, such as word embeddings (3.3), and linguistic models that draw on natural language processing

tools have seen tremendous success elsewhere, and we see great potential for their application in economics.

The rise of text analysis is part of a broader trend toward greater use of machine learning and related statistical methods in economics. With the growing availability of high-dimensional data in many domains—from consumer purchase and browsing behavior, to satellite and other spatial data, to genetics and neuro-economics—the returns are high to economists investing in learning these methods and to increasing the flow of ideas between economics and fields such as statistics and computer science, where frontier innovations in these methods are taking place.

REFERENCES

- Airolidi, Edoardo M., and Jonathan M. Bischof. 2016. "Improving and Evaluating Topic Models and Other Models of Text." *Journal of the American Statistical Association* 111 (516): 1381–403.
- Airolidi, Edoardo M., Elena A. Erosheva, Stephen E. Fienberg, Cyrille Joutard, Tanzy Love, and Suyash Shringarpure. 2010. "Reconceptualizing the Classification of PNAS Articles." *Proceedings of the National Academy of Sciences of the United States of America* 107 (49): 20899–904.
- Akaike, H. 1973. "Information Theory and an Extension of the Maximum Likelihood Principle." In *Proceedings of the 2nd International Symposium on Information Theory*, edited by B. N. Petrov and F. Csaki, 267–81. Budapest: Akademiai Kiado.
- Angrist, Joshua D., and Alan B. Krueger. 2001. "Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments." *Journal of Economic Perspectives* 15 (4): 69–85.
- Antweiler, Werner, and Murray Z. Frank. 2004. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards." *Journal of Finance* 59 (3): 1259–94.
- Armagan, Artin, David B. Dunson, and Jaeyong Lee. 2013. "Generalized Double Pareto Shrinkage." *Statistica Sinica* 23 (1): 119–43.
- Atalay, Enghin, Phai Phongthientham, Sebastian Sotelo, and Daniel Tannenbaum. 2017. "The Evolving U.S. Occupational Structure." Washington Center for Equitable Growth Working Paper 12052017.
- Athey, Susan, and Guido Imbens. 2016. "Recursive Partitioning for Heterogeneous Causal Effects." *Proceedings of the National Academy of Sciences of the United States of America* 113 (27): 7353–60.
- Bai, Jushan, and Serena Ng. 2008. "Forecasting Economic Time Series Using Targeted Predictors." *Journal of Econometrics* 146 (2): 304–17.
- Baker, Scott R., Nicholas Bloom, and Steven J. Davis. 2016. "Measuring Economic Policy Uncertainty." *Quarterly Journal of Economics* 131 (4): 1593–636.
- Bañbura, Marta, Domenico Giannone, Michele Modugno, and Lucrezia Reichlin. 2013. "Now-Casting and the Real-Time Data Flow." In *Handbook of Economic Forecasting*, Vol. 2A, edited by Allan Timmermann and Graham Elliot, 195–237. Sebastopol: O'Reilly Media.
- Bandiera, Oriana, Stephen Hansen, Andrea Prat, and Raffaella Sadun. 2017. "CEO Behavior and Firm Performance." NBER Working Paper 23248.
- Belloni, Alexandre, Victor Chernozhukov, and Christian B. Hansen. 2013. "Inference for High-Dimensional Sparse Econometric Models." In *Advances in Economics and Econometrics: Tenth World Congress*, Vol. 3, 245–95. Cambridge: Cambridge University Press.
- Best, Michael Carlos, Jonas Hjort, and David Szakonyi. 2017. "Individuals and Organizations as Sources of State Effectiveness." NBER Working Paper 23350.
- Bickel, Peter J., Ya'acov Ritov, and Alexandre B. Tsybakov. 2009. "Simultaneous Analysis of Lasso and Dantzig Selector." *Annals of Statistics* 37 (4): 1705–32.
- Bishop, Christopher M. 1995. *Neural Networks for Pattern Recognition*. Oxford: Oxford University Press.
- Bishop, Christopher M. 2006. *Pattern Recognition and Machine Learning*. Berlin: Springer.
- Blei, David M. 2012. "Probabilistic Topic Models." *Communications of the ACM* 55 (4): 77–84.
- Blei, David M., and John D. Lafferty. 2006. "Dynamic Topic Models." In *Proceedings of the 23rd International Conference on Machine Learning*, edited by W. Cohen and A. Moore, 113–20. New York: Association for Computing Machinery.
- Blei, David M., and John D. Lafferty. 2007. "A Correlated Topic Model of Science." *Annals of Applied Statistics* 1 (1): 17–35.
- Blei, David M., and Jon D. McAuliffe. 2007. "Supervised Topic Models." *Proceedings of the 20th International Conference on Neural Information Processing Systems*, edited by J. C. Platt, D. Koller, Y. Singer, and S. T. Roweis, 121–28. Red Hook: Curran Associates.
- Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. "Latent Dirichlet Allocation." *Journal of Machine Learning Research* 3: 993–1022.
- Bollen, Johan, Huina Mao, and Xiaojun Zeng. 2011. "Twitter Mood Predicts the Stock Market." *Journal of Computational Science* 2 (1): 1–8.
- Bolukbasi, Tolga, Kai-Wei Chang, James Y. Zou, Venkatesh Saligrama, and Adam T. Kalai. 2016. "Man Is to Computer Programmer as Woman Is to Homemaker? Debiasing Word Embeddings." In *Proceedings of the 29th International Conference on Neural Information Processing Systems*, edited by D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, 4349–57. Red Hook: Curran Associates.
- Born, Benjamin, Michael Ehrmann, and Marcel

- Fratzschler. 2014. "Central Bank Communication on Financial Stability." *Economic Journal* 124 (577): 701–34.
- Boudoukh, Jacob, Ronen Feldman, Shimon Kogan, and Matthew Richardson. 2016. "Information, Trading, and Volatility: Evidence from Firm-Specific News." Available on SSRN at 2193667.
- Breiman, Leo. 2001. "Random Forests." *Machine Learning* 45 (1): 5–32.
- Breiman, Leo, Jerome H. Friedman, Richard A. Olshen, and Charles J. Stone. 1984. *Classification and Regression Trees*. Routledge: Taylor and Francis.
- Buehlmaier, Matthias M., and Toni M. Whited. 2018. "Are Financial Constraints Priced? Evidence from Textual Analysis." *Review of Financial Studies* 31 (7): 2693–728.
- Bühlmann, Peter, and Sara van de Geer. 2011. *Statistics for High-Dimensional Data*. Berlin: Springer.
- Candès, Emmanuel J., Michael B. Wakin, and Stephen P. Boyd. 2008. "Enhancing Sparsity by Reweighted ℓ_1 Minimization." *Journal of Fourier Analysis and Applications* 14 (5–6): 877–905.
- Carvalho, Carlos M., Nicholas G. Polson, and James G. Scott. 2010. "The Horseshoe Estimator for Sparse Signals." *Biometrika* 97 (2): 465–80.
- Chen, Danqi, and Christopher Manning. 2014. "A Fast and Accurate Dependency Parser Using Neural Networks." In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing*, 740–50. Stroudsburg: Association for Computational Linguistics.
- Chernozhukov, Victor, et al. 2018. "Double/Debiased Machine Learning for Treatment and Structural Parameters." *Econometrics Journal* 21 (1): C1–C68.
- Chinco, Alexander M., Adam D. Clark-Joseph, and Mao Ye. 2017. "Sparse Signals in the Cross-Section of Returns." NBER Working Paper 23933.
- Choi, Hyunyoung, and Hal Varian. 2012. "Predicting the Present with Google Trends." *Economic Record* 88 (S1): 2–9.
- Cook, R. Dennis. 2007. "Fisher Lecture: Dimension Reduction in Regression." *Statistical Science* 22 (1): 1–26.
- Cowles, Alfred. 1933. "Can Stock Market Forecasters Forecast?" *Econometrica* 1 (3): 309–24.
- Das, Sanjiv R., and Mike Y. Chen. 2007. "Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web." *Management Science* 53 (9): 1375–88.
- Deerwester, Scott, Susan T. Dumais, George W. Furnas, Thomas K. Landauer, and Richard Harshman. 1990. "Indexing by Latent Semantic Analysis." *Journal of the Association for Information Science* 41 (6): 391–407.
- Denny, Matthew J., and Arthur Spirling. 2018. "Text Preprocessing for Unsupervised Learning: Why It Matters, When It Misleads, and What to Do about It." *Political Analysis* 26 (2): 168–89.
- Efron, B. 1979. "Bootstrap Methods: Another Look at the Jackknife." *Annals of Statistics* 7 (1): 1–26.
- Efron, B. 2004. "The Estimation of Prediction Error: Covariance Penalties and Cross-Validation." *Journal of the American Statistical Association* 99 (467): 619–32.
- Efron, B. 2012. "Bayesian Inference and the Parametric Bootstrap." *Annals of Applied Statistics* 6 (4): 1971–97.
- Engelberg, Joseph E., and Christopher A. Parsons. 2011. "The Causal Impact of Media in Financial Markets." *Journal of Finance* 66 (1): 67–97.
- Evans, James A., and Pedro Aceves. 2016. "Machine Translation: Mining Text for Social Theory." *Annual Review of Sociology* 42: 21–50.
- Fan, Jianqing, and Runze Li. 2001. "Variable Selection via Nonconcave Penalized Likelihood and Its Oracle Properties." *Journal of the American Statistical Association* 96 (456): 1348–60.
- Fan, Jianqing, Lingzhou Xue, and Hui Zou. 2014. "Strong Oracle Optimality of Folded Concave Penalized Estimation." *Annals of Statistics* 42 (3): 819–49.
- Flynn, Cheryl J., Clifford M. Hurvich, and Jeffrey S. Simonoff. 2013. "Efficiency for Regularization Parameter Selection in Penalized Likelihood Estimation of Misspecified Models." *Journal of the American Statistical Association* 108 (503): 1031–43.
- Foster, Dean P., Mark Liberman, and Robert A. Stine. 2013. "Featurizing Text: Converting Text into Predictors for Regression Analysis." <http://www-stat.wharton.upenn.edu/~stine/research/regressor.pdf>.
- Friedman, Jerome H. 2002. "Stochastic Gradient Boosting." *Computational Statistics and Data Analysis* 38 (4): 367–78.
- Gentzkow, Matthew, and Jesse M. Shapiro. 2010. "What Drives Media Slant? Evidence from U.S. Daily Newspapers." *Econometrica* 78 (1): 35–71.
- Gentzkow, Matthew, Jesse M. Shapiro, and Matt Taddy. 2016. "Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech." NBER Working Paper 22423.
- George, Edward I., and Robert E. McCulloch. 1993. "Variable Selection via Gibbs Sampling." *Journal of the American Statistical Association* 88 (423): 881–89.
- Ginsberg, Jeremy, Matthew H. Mohebbi, Rajan S. Patel, Lynnette Brammer, Mark S. Smolinski, and Larry Brilliant. 2009. "Detecting Influenza Epidemics Using Search Engine Query Data." *Nature* 457 (7232): 1012–14.
- Goldberg, Yoav. 2016. "A Primer on Neural Network Models for Natural Language Processing." *Journal of Artificial Intelligence Research* 57 (1): 345–420.
- Goldberg, Yoav, and Jon Orwant. 2013. "A Dataset of Syntactic-Ngrams over Time from a Very Large Corpus of English Books." In *Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 1: Proceedings of the Main Conference and the Shared Task: Semantic Textual Similarity*, edited by Mona Diab, Tim Baldwin, and Marco Baroni, 241–47. Stroudsburg: Association for Computational Linguistics.
- Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. 2016. *Deep Learning*. Cambridge: MIT Press.
- Greenstein, Shane, Yuan Gu, and Feng Zhu. 2016.

- "Ideological Segregation among Online Collaborators: Evidence from Wikipedians." NBER Working Paper 22744.
- Griffiths, Thomas L., and Mark Steyvers. 2004. "Finding Scientific Topics." *Proceedings of the National Academy of Sciences of the United States of America* 101 (S1): 5228–35.
- Grimmer, Justin. 2010. "A Bayesian Hierarchical Topic Model for Political Texts: Measuring Expressed Agendas in Senate Press Releases." *Political Analysis* 18 (1): 1–35.
- Grimmer, Justin, and Brandon M. Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* 21 (3): 267–97.
- Groseclose, Tim, and Jeffrey Milyo. 2005. "A Measure of Media Bias." *Quarterly Journal of Economics* 120 (4): 1191–237.
- Hans, Chris. 2009. "Bayesian Lasso Regression." *Biometrika* 96 (4): 835–45.
- Hansen, Stephen, Michael McMahon, and Andrea Prat. 2018. "Transparency and Deliberation within the FOMC: A Computational Linguistics Approach." *Quarterly Journal of Economics* 133 (2): 801–70.
- Hassan, Tarek A., Stephan Hollander, Laurence van Lent, and Ahmed Tahoun. 2017. "Firm-Level Political Risk: Measurement and Effects." NBER Working Paper 24029.
- Hastie, Trevor, Robert Tibshirani, and Jerome Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York: Springer.
- Hastie, Trevor, Robert Tibshirani, and Martin Wainwright. 2015. *Statistical Learning with Sparsity: The Lasso and Generalizations*. New York: Taylor and Francis.
- Hoberg, Gerard, and Gordon Phillips. 2016. "Text-Based Network Industries and Endogenous Product Differentiation." *Journal of Political Economy* 124 (5): 1423–65.
- Hoerl, Arthur E., and Robert W. Kennard. 1970. "Ridge Regression: Biased Estimation for Nonorthogonal Problem." *Technometrics* 12 (1): 55–67.
- Hoffman, Matthew D., David M. Blei, Chong Wang, and John Paisley. 2013. "Stochastic Variational Inference." *Journal of Machine Learning Research* 14 (1): 1303–47.
- Hofmann, Thomas. 1999. "Probabilistic Latent Semantic Indexing." In *Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 50–57. New York: ACM.
- Horowitz, Joel L. 2003. "The Bootstrap in Econometrics." *Statistical Science* 18 (2): 211–18.
- Iyyer, Mohit, Peter Enns, Jordan Boyd-Graber, and Philip Resnik. 2014. "Political Ideology Detection Using Recursive Neural Networks." In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, Vol. 1, edited by Kristina Toutanova and Hua Wu, 1113–22. Stroudsburg: Association for Computational Linguistics.
- Jegadeesh, Narasimhan, and Di Wu. 2013. "Word Power: A New Approach for Content Analysis." *Journal of Financial Economics* 110 (3): 712–29.
- Joachims, Thorsten. 1998. "Text Categorization with Support Vector Machines: Learning with Many Relevant Features." In *10th European Conference on Machine Learning*, edited by Claire Nédellec and Céline Rouveirol, 137–42. Berlin: Springer.
- Johnson, Heather A., et al. 2004. "Analysis of Web Access Logs for Surveillance of Influenza." *Studies in Health Technology and Informatics* 107 (2): 1202–06.
- Jurafsky, Daniel, and James H. Martin. 2009. *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. 2nd ed. London: Pearson.
- Kass, Robert E., and Larry Wasserman. 1995. "A Reference Bayesian Test for Nested Hypotheses and Its Relationship to the Schwarz Criterion." *Journal of the American Statistical Association* 90 (431): 928–34.
- Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy. 2018. "Measuring Technological Innovation over the Long Run." NBER Working Paper 25266.
- Kelly, Bryan, and Seth Pruitt. 2013. "Market Expectations in the Cross-Section of Present Values." *Journal of Finance* 68 (5): 1721–56.
- Kelly, Bryan, and Seth Pruitt. 2015. "The Three-Pass Regression Filter: A New Approach to Forecasting Using Many Predictors." *Journal of Econometrics* 186 (2): 294–316.
- Knight, Keith, and Wenjiang Fu. 2000. "Asymptotics for Lasso-Type Estimators." *Annals of Statistics* 28 (5): 1356–78.
- Kogan, Shimon, Dmitry Levin, Bryan R. Routledge, Jacob S. Sagi, and Noah A. Smith. 2009. "Predicting Risk from Financial Reports with Regression." In *Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, 272–80. Stroudsburg: Association for Computational Linguistics.
- Lazer, David, Ryan Kennedy, Gary King, and Alessandro Vespignani. 2014. "The Parable of Google Flu: Traps in Big Data Analysis." *Science* 343 (6176): 1203–05.
- Le, Quoc, and Tomas Mikolov. 2014. "Distributed Representations of Sentences and Documents." *Proceedings of Machine Learning Research* 32: 1188–96.
- LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. 2015. "Deep Learning." *Nature* 521 (7553): 436–44.
- Li, Feng. 2010. "The Information Content of Forward-Looking Statements in Corporate Filings—A Naïve Bayesian Machine Learning Approach." *Journal of Accounting Research* 48 (5): 1049–102.
- Loughran, Tim, and Bill McDonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance* 66 (1): 35–65.
- Lucca, David O., and Francesco Trebbi. 2009. "Measuring Central Bank Communication: An Automated Approach with Application to FOMC Statements." NBER Working Paper 15367.

- Manela, Asaf, and Alan Moreira. 2017. "News Implied Volatility and Disaster Concerns." *Journal of Financial Economics* 123 (1): 137–62.
- Manning, Christopher D., Prabhakar Raghavan, and Hinrich Schütze. 2008. *Introduction to Information Retrieval*. Cambridge: Cambridge University Press.
- Mannion, David, and Peter Dixon. 1997. "Authorship Attribution: The Case of Oliver Goldsmith." *Journal of the Royal Statistical Society, Series D* 46 (1): 1–18.
- Manski, Charles F. 1988. *Analog Estimation Methods in Econometrics*. New York: Chapman and Hall.
- Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. "Distributed Representations of Words and Phrases and Their Compositionality." In *Proceedings of the 26th International Conference on Neural Information Processing Systems*, edited by C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, 3111–19. Red Hook: Curran Associates.
- Morin, Frederic, and Yoshua Bengio. 2005. "Hierarchical Probabilistic Neural Network Language Model." In *Proceedings of the Tenth International Workshop on Artificial Intelligence and Statistics*, 246–52. New Jersey: Society for Artificial Intelligence and Statistics.
- Mosteller, Frederick, and David L. Wallace. 1963. "Inference in an Authorship Problem." *Journal of the American Statistical Association* 58 (302): 275–309.
- Murphy, Kevin P. 2012. *Machine Learning: A Probabilistic Perspective*. Cambridge: MIT Press.
- Ng, Andrew Y., and Michael I. Jordan. 2001. "On Discriminative versus Generative Classifiers: A Comparison of Logistic Regression and Naive Bayes." In *Proceedings of the 14th International Conference on Neural Information Processing Systems: Natural and Synthetic*, edited by T. G. Dietterich, S. Becker, and Z. Ghahramani, 841–48. Cambridge: MIT Press.
- Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan. 2002. "Thumbs up? Sentiment Classification Using Machine Learning Techniques." In *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 79–86. Stroudsburg: Association for Computational Linguistics.
- Park, Trevor, and George Casella. 2008. "The Bayesian Lasso." *Journal of the American Statistical Association* 103 (482): 681–86.
- Pennington, Jeffrey, Richard Socher, and Christopher Manning. 2014. "GloVe: Global Vectors for Word Representation." In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, edited by Alessandro Moschitti, Bo Pang, and Walter Daelemans, 1532–43. Stroudsburg: Association for Computational Linguistics.
- Politis, Dimitris N., Joseph P. Romano, and Michael Wolf. 1999. *Subsampling*. Berlin: Springer.
- Polson, Nicholas G., and Steven L. Scott. 2011. "Data Augmentation for Support Vector Machines." *Bayesian Analysis* 6 (1): 1–24.
- Porter, M. F. 1980. "An Algorithm for Suffix Stripping." *Program* 14 (3): 130–37.
- Preis, Tobias, and Helen Susannah Moat. 2014. "Adaptive Nowcasting of Influenza Outbreaks Using Google Searches." *Royal Society Open Science* 1 (2): Article 140095.
- Pritchard, Jonathan K., Matthew Stephens, and Peter Donnelly. 2000. "Inference of Population Structure Using Multilocus Genotype Data." *Genetics* 155 (2): 945–59.
- Quinn, Kevin M., Burt L. Monroe, Michael Colaresi, Michael H. Crespin, and Dragomir R. Radev. 2010. "How to Analyze Political Attention with Minimal Assumptions and Costs." *American Journal of Political Science* 54 (1): 209–28.
- Rabinovich, Maxim, and David M. Blei. 2014. "The Inverse Regression Topic Model." *Proceedings of Machine Learning Research* 32: 199–207.
- Roberts, Margaret E., Brandon M. Stewart, Dustin Tingley, and Edoardo M. Airoldi. 2013. "The Structural Topic Model and Applied Social Science." Paper presented at the Advances in Neural Information Processing Systems Workshop on Topic Models: Computation, Application, and Evaluation, Lake Tahoe.
- Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams. 1986. "Learning Representations by Back-Propagating Errors." *Nature* 323 (6088): 533–36.
- Saiz, Albert, and Uri Simonsohn. 2013. "Proxying for Unobservable Variables with Internet Document-Frequency." *Journal of the European Economic Association* 11 (1): 137–65.
- Schwarz, Gideon. 1978. "Estimating the Dimension of a Model." *Annals of Statistics* 6 (2): 461–64.
- Scott, Steven L., and Hal R. Varian. 2014. "Predicting the Present with Bayesian Structural Time Series." *International Journal of Mathematical Modeling and Numerical Optimisation* 5 (1–2): 4–23.
- Scott, Steven L., and Hal R. Varian. 2015. "Bayesian Variable Selection for Nowcasting Economic Time Series." In *Economic Analysis of the Digital Economy*, edited by Avi Goldfarb, Shane M. Greenstein, and Catherine E. Tucker, 119–35. Chicago: University of Chicago Press.
- Sim, Yanchuan, Bryan R. Routledge, and Noah A. Smith. 2015. "The Utility of Text: The Case of Amicus Briefs and the Supreme Court." In *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2311–17. Palo Alto: AAAI Press.
- Stephens-Davidowitz, Seth. 2014. "The Cost of Racial Animus on a Black Candidate: Evidence Using Google Search Data." *Journal of Public Economics* 118 (C): 26–40.
- Stock, James H., and Francesco Trebbi. 2003. "Retrospectives Who Invented Instrumental Variable Regression?" *Journal of Economic Perspectives* 17 (3): 177–94.
- Stock, James H., and Mark W. Watson. 2002a. "Forecasting Using Principal Components from a Large Number of Predictors." *Journal of the American Statistical Association* 97 (460): 1167–79.
- Stock, James H., and Mark W. Watson. 2002b. "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business and Economic Statistics* 20 (2):

- 147–62.
- Sutskever, Ilya, Oriol Vinyals, and Quoc V. Le. 2014. “Sequence to Sequence Learning with Neural Networks.” In *Advances in Neural Information Processing Systems*, Vol. 27, edited by Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, 3104–12. La Jolla: Neural Information Processing Systems Foundation.
- Taddy, Matt. 2012. “On Estimation and Selection for Topic Models.” In *Proceedings of the 15th International Conference on Artificial Intelligence and Statistics*, 1184–93. New York: Association for Computing Machinery.
- Taddy, Matt. 2013a. “Measuring Political Sentiment on Twitter: Factor Optimal Design for Multinomial Inverse Regression.” *Technometrics* 55 (4): 415–25.
- Taddy, Matt. 2013b. “Multinomial Inverse Regression for Text Analysis.” *Journal of the American Statistical Association* 108 (503): 755–70.
- Taddy, Matt. 2013c. “Rejoinder: Efficiency and Structure in MNIR.” *Journal of the American Statistical Association* 108 (503): 772–74.
- Taddy, Matt. 2015a. “Distributed Multinomial Regression.” *Annals of Applied Statistics* 9 (3): 1394–414.
- Taddy, Matt. 2015b. “Document Classification by Inversion of Distributed Language Representations.” In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing*, Vol. 2, edited by Chengqing Zong and Michael Strube, 45–49. Stroudsburg: Association for Computational Linguistics.
- Taddy, Matt. 2017a. “Comment: A Regularization Scheme on Word Occurrence Rates That Improves Estimation and Interpretation of Topical Content.” <https://github.com/TaddyLab/reuters/raw/master/comment/comment-AirolldiBischof.pdf>.
- Taddy, Matt. 2017b. “One-Step Estimator Paths for Concave Regularization.” *Journal of Computational and Graphical Statistics* 26 (3): 525–36.
- Taddy, Matt, Chun-Sheng Chen, Jun Yu, and Mitch Wyle. 2015. “Bayesian and Empirical Bayesian Forests.” *Proceedings of Machine Learning Research* 37: 967–76.
- Taddy, Matt, Matt Gardner, Liyun Chen, and David Draper. 2016. “A Nonparametric Bayesian Analysis of Heterogeneous Treatment Effects in Digital Experimentation.” *Journal of Business and Economic Statistics* 34 (4): 661–72.
- Teh, Yee Whye, Michael I. Jordan, Matthew J. Beal, and David M. Blei. 2006. “Hierarchical Dirichlet Processes.” *Journal of the American Statistical Association* 101 (476): 1566–81.
- Tetlock, Paul C. 2007. “Giving Content to Investor Sentiment: The Role of Media in the Stock Market.” *Journal of Finance* 62 (3): 1139–68.
- Tibshirani, Robert. 1996. “Regression Shrinkage and Selection via the Lasso.” *Journal of the Royal Statistical Society, Series B (Methodological)* 58 (1): 267–88.
- Tong, Simon, and Daphne Koller. 2001. “Support Vector Machine Active Learning with Applications to Text Classification.” *Journal of Machine Learning Research* 2 (1): 45–66.
- Tran, Dustin, Matthew D. Hoffman, Rif A. Saurous, Eugene Brevdo, Kevin Murphy, and David M. Blei. 2017. “Deep Probabilistic Programming.” Paper presented at the 5th International Conference on Learning Representations, Toulon.
- Tran, Dustin, Alp Kucukelbir, Adji B. Dieng, Maja Rudolph, Dawen Liang, and David M. Blei. 2016. “Edward: A Library for Probabilistic Modeling, Inference, and Criticism.” Available on arXiv at 1610.09787.
- Vapnik, Vladimir N. 1995. *The Nature of Statistical Learning Theory*. Berlin: Springer.
- Wager, Stefan, and Susan Athey. 2018. “Estimation and Inference of Heterogeneous Treatment Effects Using Random Forest.” *Journal of the American Statistical Association* 113 (523): 1228–42.
- Wager, Stefan, Trevor Hastie, and Bradley Efron. 2014. “Confidence Intervals for Random Forests: The Jackknife and the Infinitesimal Jackknife.” *Journal of Machine Learning Research* 15 (1): 1625–51.
- Wainwright, Martin J. 2009. “Sharp Thresholds for High-Dimensional and Noisy Sparsity Recovery Using ℓ_1 -Constrained Quadratic Programming (Lasso).” *IEEE Transactions on Information Theory* 55 (5): 2183–202.
- Wainwright, Martin J., and Michael I. Jordan. 2008. “Graphical Models, Exponential Families, and Variational Inference.” *Foundations and Trends in Machine Learning* 1 (1–2): 1–305.
- Wisniewski, Tomasz Piotr, and Brendan Lambe. 2013. “The Role of Media in the Credit Crunch: The Case of the Banking Sector.” *Journal of Economic Behavior and Organization* 85 (C): 163–75.
- Wu, Yonghui, et al. 2016. “Google’s Neural Machine Translation System: Bridging the Gap between Human and Machine Translation.” Available on arXiv at 1609.08144.
- Yang, Yun, Martin J. Wainwright, and Michael I. Jordan. 2016. “On the Computational Complexity of High-Dimensional Bayesian Variable Selection.” *Annals of Statistics* 44 (6): 2497–532.
- Zeng, Xiaoming, and Michael Wagner. 2002. “Modeling the Effects of Epidemics on Routinely Collected Data.” *Journal of the American Medical Informatics Association* 9 (6): S17–22.
- Zou, Hui. 2006. “The Adaptive Lasso and Its Oracle Properties.” *Journal of the American Statistical Association* 101 (476): 1418–29.
- Zou, Hui, and Trevor Hastie. 2005. “Regularization and Variable Selection via the Elastic Net.” *Journal of the Royal Statistical Society, Series B (Methodological)* 67 (2): 301–20.
- Zou, Hui, Trevor Hastie, and Robert Tibshirani. 2006. “Sparse Principal Component Analysis.” *Journal of Computational and Graphical Statistics* 15 (2): 265–86.
- Zou, Hui, Trevor Hastie, and Robert Tibshirani. 2007. “On the ‘Degrees of Freedom’ of the Lasso.” *Annals of Statistics* 35 (5): 2173–92.

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2. Kotaro Miwa. 2023. Informational role of analyst and investor days. *Global Finance Journal* 56, 100812. [[Crossref](#)]
3. Jianhao Lin, Ziwei Mei, Liangyuan Chen, Chuanqi Zhu. 2023. Is the People's Bank of China consistent in words and deeds?. *China Economic Review* 78, 101919. [[Crossref](#)]
4. Shuang (Sophie) Zhai, Zhu (Drew) Zhang. 2023. Read the News, Not the Books: Forecasting Firms' Long-term Financial Performance via Deep Text Mining. *ACM Transactions on Management Information Systems* 14:1, 1-37. [[Crossref](#)]
5. Peter S. Lee, Ishita Chakraborty, Shrabastee Banerjee. Artificial Intelligence Applications to Customer Feedback Research: A Review 169-190. [[Crossref](#)]
6. Nancy Kong, Uwe Dulleck, Adam B. Jaffe, Shupeng Sun, Sowmya Vajjala. 2023. Linguistic metrics for patent disclosure: Evidence from university versus corporate patents. *Research Policy* 52:2, 104670. [[Crossref](#)]
7. Katharina Baur, Markus Rosenfelder, Bernhard Lutz. 2023. Automated real estate valuation with machine learning models using property descriptions. *Expert Systems with Applications* 213, 119147. [[Crossref](#)]
8. Marcel Garz, Ferenc Szucs. 2023. Algorithmic selection and supply of political news on Facebook. *Information Economics and Policy* 62, 101020. [[Crossref](#)]
9. Diego García, Xiaowen Hu, Maximilian Rohrer. 2023. The colour of finance words. *Journal of Financial Economics* 147:3, 525-549. [[Crossref](#)]
10. Mohammed Qorich, Rajae El Ouazzani. 2023. Text sentiment classification of Amazon reviews using word embeddings and convolutional neural networks. *The Journal of Supercomputing* 57. . [[Crossref](#)]
11. Siwei Wang, Xin Li, Zibiao Li, Yongwei Ye. 2023. The effects of government support on enterprises' digital transformation: Evidence from China. *Managerial and Decision Economics* 15. . [[Crossref](#)]
12. Asmus Leth Olsen, Anders Woller. 2023. Citizens' economic recovery models for a pandemic. *PLOS ONE* 18:2, e0266531. [[Crossref](#)]
13. Austin van Loon, Jeremy Freese. 2023. Word Embeddings Reveal How Fundamental Sentiments Structure Natural Language. *American Behavioral Scientist* 67:2, 175-200. [[Crossref](#)]
14. Hans Christian Schmitz, Bernhard Lutz, Dominik Wolff, Dirk Neumann. 2023. When machines trade on corporate disclosures: Using text analytics for investment strategies. *Decision Support Systems* 165, 113892. [[Crossref](#)]
15. Marcel Garz, Jonna Rickardsson. 2023. Ownership and media slant: Evidence from Swedish newspapers. *Kyklos* 76:1, 18-40. [[Crossref](#)]
16. Milan Miric, Nan Jia, Kenneth G. Huang. 2023. Using supervised machine learning for large-scale classification in management research: The case for identifying artificial intelligence patents. *Strategic Management Journal* 44:2, 491-519. [[Crossref](#)]

17. Dong Ding, Bin Liu, Millicent Chang. 2023. Carbon Emissions and TCFD Aligned Climate-Related Information Disclosures. *Journal of Business Ethics* **182**:4, 967-1001. [[Crossref](#)]
18. Johannes Jakubik, Abdolreza Nazemi, Andreas Geyer-Schulz, Frank J. Fabozzi. 2023. Incorporating financial news for forecasting Bitcoin prices based on long short-term memory networks. *Quantitative Finance* **23**:2, 335-349. [[Crossref](#)]
19. Andrea Bellucci, Alexander Borisov, Gianluca Gucciardi, Alberto Zazzaro. 2023. The reallocation effects of COVID-19: Evidence from venture capital investments around the world. *Journal of Banking & Finance* **147**, 106443. [[Crossref](#)]
20. Maximilian Andres, Lisa Bruttel, Jana Friedrichsen. 2023. How communication makes the difference between a cartel and tacit collusion: A machine learning approach. *European Economic Review* **152**, 104331. [[Crossref](#)]
21. Christian Eggenberger, Uschi Backes-Gellner. 2023. IT skills, occupation specificity and job separations. *Economics of Education Review* **92**, 102333. [[Crossref](#)]
22. Tobias Schultheiss, Curdin Pfister, Ann-Sophie Gnehm, Uschi Backes-Gellner. 2023. Education expansion and high-skill job opportunities for workers: Does a rising tide lift all boats?. *Labour Economics* **111**, 102354. [[Crossref](#)]
23. Jiaxuan Lu. 2023. Leadership rotations and the convergence of subnational economic policies in China: evidence from provincial government work reports. *The Journal of Law, Economics, and Organization* **67**. . [[Crossref](#)]
24. Steven J. Hyde, Eric Bachura, Joseph S. Harrison. Garbage in, Garbage out: A Theory-Driven Approach to Improve Data Handling in Supervised Machine Learning 101-132. [[Crossref](#)]
25. Matthieu Ballandonne, Igor Cersosimo. 2023. TOWARDS A “TEXT AS DATA” APPROACH IN THE HISTORY OF ECONOMICS: AN APPLICATION TO ADAM SMITH’S CLASSICS. *Journal of the History of Economic Thought* **15**, 1-23. [[Crossref](#)]
26. Allen H. Huang, Hui Wang, Yi Yang. 2023. FinBERT : A Large Language Model for Extracting Information from Financial Text*. *Contemporary Accounting Research* **68**. . [[Crossref](#)]
27. Colin Harris, Andrew Myers, Adam Kaiser. 2023. The humanizing effect of market interaction. *Journal of Economic Behavior & Organization* **205**, 489-507. [[Crossref](#)]
28. Bryan Seegmiller, Dimitris Papanikolaou, Lawrence D.W. Schmidt. 2023. Measuring document similarity with weighted averages of word embeddings. *Explorations in Economic History* **87**, 101494. [[Crossref](#)]
29. Francesco Bianchi, Roberto Gómez-Cram, Thilo Kind, Howard Kung. 2023. Threats to central bank independence: High-frequency identification with twitter. *Journal of Monetary Economics* **3**. . [[Crossref](#)]
30. Sebastiano Manzan. Big Data and Computational Social Science for Economic Analysis and Policy 231-242. [[Crossref](#)]
31. Piet Daas, Blanca de Miguel, Maria de Miguel. 2023. Identifying Drone Web Sites in Multiple Countries and Languages with a Single Model. *Journal of Data Science* **11**, 1-14. [[Crossref](#)]
32. Christopher Carroll, Tao Wang. Epidemiological expectations 779-806. [[Crossref](#)]
33. Argimiro Arratia. What to Do with Your Sentiments in Finance 25-37. [[Crossref](#)]

34. Sergio Consoli, Marco Colagrossi, Francesco Panella, Luca Barbaglia. On the Development of a European Tracker of Societal Issues and Economic Activities Using Alternative Data 38-43. [[Crossref](#)]
35. Pascal Frömel, Severin Kolmeder, Dominik Wagner. 2023. Where prices are not lazy: Evidence from REITs and the financial sector. *Finance Research Letters* 5, 103601. [[Crossref](#)]
36. Brian J. Kokensparger. Visualizing the Roles of Frequent Terms in LTEs Following Two Economic Crisis Trigger Articles 247-276. [[Crossref](#)]
37. Joseph S. Harrison, Matthew A. Josefy, Matias Kalm, Ryan Krause. 2022. Using supervised machine learning to scale human-coded data: A method and dataset in the board leadership context. *Strategic Management Journal* . [[Crossref](#)]
38. Alison Watts. 2022. Contests with gender bias: evidence from a culinary competition. *Applied Economics* 54:60, 6875-6886. [[Crossref](#)]
39. Yuchen Chai, Juan Palacios, Jianghao Wang, Yichun Fan, Siqu Zheng. 2022. Measuring daily-life fear perception change: A computational study in the context of COVID-19. *PLOS ONE* 17:12, e0278322. [[Crossref](#)]
40. Maiting Zhuang. 2022. Intergovernmental Conflict and Censorship: Evidence from China's Anti-Corruption Campaign. *Journal of the European Economic Association* 20:6, 2540-2585. [[Crossref](#)]
41. Hannes Mueller, Christopher Rauh. 2022. The Hard Problem of Prediction for Conflict Prevention. *Journal of the European Economic Association* 20:6, 2440-2467. [[Crossref](#)]
42. Nobuyuki Hanaki, Ali I. Ozkes. 2022. Strategic environment effect and communication. *Experimental Economics* 111. . [[Crossref](#)]
43. Chris Florackis, Christodoulos Louca, Roni Michaely, Michael Weber. 2022. Cybersecurity Risk. *The Review of Financial Studies* 36:1, 351-407. [[Crossref](#)]
44. David Ardia, Keven Bluteau, Kris Boudt, Koen Inghelbrecht. 2022. Climate Change Concerns and the Performance of Green vs. Brown Stocks. *Management Science* 3. . [[Crossref](#)]
45. Khrystyna Bochkay, Stephen V. Brown, Andrew J. Leone, Jennifer Wu Tucker. 2022. Textual Analysis in Accounting: What's Next?*. *Contemporary Accounting Research* 33. . [[Crossref](#)]
46. Salomé Do, Étienne Ollion, Rubing Shen. 2022. The Augmented Social Scientist: Using Sequential Transfer Learning to Annotate Millions of Texts with Human-Level Accuracy. *Sociological Methods & Research* 3, 004912412211345. [[Crossref](#)]
47. Siddharth Sachdeva, Angel Hsu, Ian French, Elwin Lim. 2022. A computational approach to analyzing climate strategies of cities pledging net zero. *npj Urban Sustainability* 2:1. . [[Crossref](#)]
48. David A. Hyman, Jing Liu, Bernard S. Black. 2022. Should patients use online reviews to pick their doctors and hospitals?. *Journal of Empirical Legal Studies* 19:4, 897-935. [[Crossref](#)]
49. Guoxing Zhang, Yang Gao, Jiexun Li, Bin Su, Zhanglei Chen, Weichun Lin. 2022. China's environmental policy intensity for 1978-2019. *Scientific Data* 9:1. . [[Crossref](#)]
50. Brooke Scoles, Catia Nicodemo. 2022. Doctors' attitudes toward specific medical conditions. *Journal of Economic Behavior & Organization* 204, 182-199. [[Crossref](#)]
51. Hendrik Hüning. 2022. Schools' We-mentality and Students' Civic Engagement – A Text-based Approach. *Child Indicators Research* 15:6, 2215-2241. [[Crossref](#)]

52. Sami Diaf, Jörg Döpke, Ulrich Fritsche, Ida Rockenbach. 2022. Sharks and minnows in a shoal of words: Measuring latent ideological positions based on text mining techniques. *European Journal of Political Economy* **75**, 102179. [[Crossref](#)]
53. Tobias Schultheiss, Uschi Backes-Gellner. 2022. Does updating education curricula accelerate technology adoption in the workplace? Evidence from dual vocational education and training curricula in Switzerland. *The Journal of Technology Transfer* **220**. . [[Crossref](#)]
54. Jianhao Lin, Jiacheng Fan, Yifan Zhang, Liangyuan Chen. 2022. Real-time macroeconomic projection using narrative central bank communication. *Journal of Applied Econometrics* **120**. . [[Crossref](#)]
55. Yunhe Lu. 2022. Detecting Imperfect Substitution between Comparably Skilled Immigrants and Natives: A Machine Learning Approach. *International Migration Review* **28**, 019791832211264. [[Crossref](#)]
56. Ennio E. Piano, Louis Rouanet. 2022. The calculus of american indian consent: the law and economics of tribal constitutions. *Public Choice* **43**. . [[Crossref](#)]
57. Natalie A. Carlson. 2022. Differentiation in microenterprises. *Strategic Management Journal* **38**. . [[Crossref](#)]
58. Phil Magness, Michael Makovi. 2022. The Mainstreaming of Marx: Measuring the Effect of the Russian Revolution on Karl Marx's Influence. *Journal of Political Economy* **1**. . [[Crossref](#)]
59. Gaurab Aryal, Federico Ciliberto, Benjamin T Leyden. 2022. Coordinated Capacity Reductions and Public Communication in the Airline Industry. *The Review of Economic Studies* **89**:6, 3055-3084. [[Crossref](#)]
60. Sasan Mansouri, Paul P. Momtaz. 2022. Financing sustainable entrepreneurship: ESG measurement, valuation, and performance. *Journal of Business Venturing* **37**:6, 106258. [[Crossref](#)]
61. Hiroyuki Kawakatsu. 2022. Parliamentary debate as electoral signaling. *Journal of Computational Social Science* **5**:2, 1235-1255. [[Crossref](#)]
62. Mikhail Stolbov, Maria Shchepeleva, Alexander Karminsky. 2022. When central bank research meets Google search: A sentiment index of global financial stress. *Journal of International Financial Markets, Institutions and Money* **81**, 101692. [[Crossref](#)]
63. Austin van Loon. 2022. Three families of automated text analysis. *Social Science Research* **108**, 102798. [[Crossref](#)]
64. Ana Macanovic. 2022. Text mining for social science – The state and the future of computational text analysis in sociology. *Social Science Research* **108**, 102784. [[Crossref](#)]
65. Jason Lennard, Finn Meinecke, Solomos Solomou. 2022. Measuring inflation expectations in interwar Britain. *The Economic History Review* **39**. . [[Crossref](#)]
66. Gabriela Czarnek, David Stillwell. 2022. Two is better than one: Using a single emotion lexicon can lead to unreliable conclusions. *PLOS ONE* **17**:10, e0275910. [[Crossref](#)]
67. Fabienne Kiener, Ann-Sophie Gnehm, Simon Clematide, Uschi Backes-Gellner. 2022. IT skills in vocational training curricula and labour market outcomes. *Journal of Education and Work* **35**:6-7, 614-640. [[Crossref](#)]
68. Yongheng Deng, Lina Meng, Yinggang Zhou. 2022. The effectiveness and costs of nonpharmaceutical interventions for COVID-19 containment: A border discontinuous difference-in-difference approach. *China Economic Review* **75**, 101849. [[Crossref](#)]

69. Zhimin (Jimmy) Yu. 2022. Financial Report Readability and Accounting Conservatism. *Journal of Risk and Financial Management* 15:10, 454. [[Crossref](#)]
70. Dan Claudiu Neagu, Andrei Bogdan Rus, Mihai Grec, Mihai Augustin Boroianu, Nicolae Bogdan, Attila Gal. 2022. Towards Sentiment Analysis for Romanian Twitter Content. *Algorithms* 15:10, 357. [[Crossref](#)]
71. Dennis W. Campbell, Ruidi Shang. 2022. Tone at the Bottom: Measuring Corporate Misconduct Risk from the Text of Employee Reviews. *Management Science* 68:9, 7034-7053. [[Crossref](#)]
72. Yan Xu, Jian Ni. 2022. Entrepreneurial Learning and Disincentives in Crowdfunding Markets. *Management Science* 68:9, 6819-6864. [[Crossref](#)]
73. Laura Abrardi, Carlo Cambini, Laura Rondi. 2022. Artificial intelligence, firms and consumer behavior: A survey. *Journal of Economic Surveys* 36:4, 969-991. [[Crossref](#)]
74. Massimo Ferrari Minesso, Frederik Kurcz, Maria Sole Pagliari. 2022. Do words hurt more than actions? The impact of trade tensions on financial markets. *Journal of Applied Econometrics* 37:6, 1138-1159. [[Crossref](#)]
75. Bhargav Srinivasa Desikan, James Evans. 2022. Misalignment Between Skills Discovered, Disseminated, and Deployed in the Knowledge Economy. *Journal of Social Computing* 3:3, 191-205. [[Crossref](#)]
76. Venky Nagar, Jordan Schoenfeld. 2022. Measuring weather exposure with annual reports. *Review of Accounting Studies* 33. . [[Crossref](#)]
77. Anna-Carolina Haensch, Bernd Weiß, Patricia Steins, Priscilla Chyrva, Katja Bitz. 2022. The semi-automatic classification of an open-ended question on panel survey motivation and its application in attrition analysis. *Frontiers in Big Data* 5. . [[Crossref](#)]
78. David B. Audretsch, Erik E. Lehmann. 2022. Narrative entrepreneurship: bringing (his)story back to entrepreneurship. *Small Business Economics* 19. . [[Crossref](#)]
79. Qiang Wang, Wen Zhang, Jian Li, Feng Mai, Zhenzhong Ma. 2022. Effect of online review sentiment on product sales: The moderating role of review credibility perception. *Computers in Human Behavior* 133, 107272. [[Crossref](#)]
80. Yoontae Jeon, Thomas H. McCurdy, Xiaofei Zhao. 2022. News as sources of jumps in stock returns: Evidence from 21 million news articles for 9000 companies. *Journal of Financial Economics* 145:2, 1-17. [[Crossref](#)]
81. SASKIA TER ELLEN, VEGARD H. LARSEN, LEIF ANDERS THORSRUD. 2022. Narrative Monetary Policy Surprises and the Media. *Journal of Money, Credit and Banking* 54:5, 1525-1549. [[Crossref](#)]
82. MIKAEL APEL, MARIANNA BLIX GRIMALDI, ISAAH HULL. 2022. How Much Information Do Monetary Policy Committees Disclose? Evidence from the FOMC's Minutes and Transcripts. *Journal of Money, Credit and Banking* 54:5, 1459-1490. [[Crossref](#)]
83. David Kohns, Arnab Bhattacharjee. 2022. Nowcasting growth using Google Trends data: A Bayesian Structural Time Series model. *International Journal of Forecasting* 40. . [[Crossref](#)]
84. Jason M. Baik, Thet H. Nyein, Sepideh Modrek. 2022. Social Media Activism and Convergence in Tweet Topics After the Initial #MeToo Movement for Two Distinct Groups of Twitter Users. *Journal of Interpersonal Violence* 37:15-16, NP13603-NP13622. [[Crossref](#)]

85. Andrii Babii, Eric Ghysels, Jonas Striaukas. 2022. High-Dimensional Granger Causality Tests with an Application to VIX and News. *Journal of Financial Econometrics* **33**. . [[Crossref](#)]
86. Sergio Consoli, Luca Barbaglia, Sebastiano Manzan. 2022. Fine-grained, aspect-based sentiment analysis on economic and financial lexicon. *Knowledge-Based Systems* **247**, 108781. [[Crossref](#)]
87. Ben Cormier, Mark S. Manger. 2022. Power, ideas, and World Bank conditionality. *The Review of International Organizations* **17**:3, 397-425. [[Crossref](#)]
88. Jae Yeon Kim, Yee Man Margaret Ng. 2022. Teaching Computational Social Science for All. *PS: Political Science & Politics* **55**:3, 605-609. [[Crossref](#)]
89. Richard Frankel, Jared Jennings, Joshua Lee. 2022. Disclosure Sentiment: Machine Learning vs. Dictionary Methods. *Management Science* **68**:7, 5514-5532. [[Crossref](#)]
90. A.M. Oosthuizen, R. Inglesi-Lotz. 2022. The impact of policy priority flexibility on the speed of renewable energy adoption. *Renewable Energy* **194**, 426-438. [[Crossref](#)]
91. Yong Shi, Yuan An, Xiumei Zhu, Fuwei Jiang. 2022. Better to hear all parties: Understanding the impact of homophily in online financial discussion. *Electronic Commerce Research and Applications* **54**, 101159. [[Crossref](#)]
92. Alessandro Marra, Cristiano Baldassari. 2022. Using text data instead of SIC codes to tag innovative firms and classify industrial activities. *PLOS ONE* **17**:6, e0270041. [[Crossref](#)]
93. Rabah Arezki, Oussama Belmejdoub, Bilal Diab, Samira Kalla, Ha Nguyen, Abdulla Saif, Ivan Yotzov. From #Hashtags to Legislation: Engagement and Support for Economic Reforms in the Gulf Cooperation Council Countries **3**, . [[Crossref](#)]
94. Necmi Gürsakal, Sadullah Çelik, Serkan Özdemir. 2022. High-frequency words have higher frequencies in Turkish social sciences article. *Quality & Quantity* **6**. . [[Crossref](#)]
95. Adam Hale Shapiro, Moritz Sudhof, Daniel J. Wilson. 2022. Measuring news sentiment. *Journal of Econometrics* **228**:2, 221-243. [[Crossref](#)]
96. Ishita Chakraborty, Minkyung Kim, K. Sudhir. 2022. Attribute Sentiment Scoring with Online Text Reviews: Accounting for Language Structure and Missing Attributes. *Journal of Marketing Research* **59**:3, 600-622. [[Crossref](#)]
97. Yiming He, Meng Chen. 2022. Do Urbanization and Energy-environment Policies Affect Housing Values? Evidence From Spatial Textual Analysis. *Applied Spatial Analysis and Policy* **15**:2, 365-395. [[Crossref](#)]
98. Daniel Levy, Tamir Mayer, Alon Raviv. 2022. Economists in the 2008 financial crisis: Slow to see, fast to act. *Journal of Financial Stability* **60**, 100986. [[Crossref](#)]
99. Eugénie Dugoua, Marion Dumas, Joëlle Noailly. 2022. Text as Data in Environmental Economics and Policy. *Review of Environmental Economics and Policy* **16**:2, 346-356. [[Crossref](#)]
100. Ece A Özçelik, Cédric Doucet, Hyunjin Kang, Noémie Levy, Isabelle Feldhaus, Tiago Cravo Oliveira Hashiguchi, Aliénor Lerouge, Michele Cecchini. 2022. A comparative assessment of action plans on antimicrobial resistance from OECD and G20 countries using natural language processing. *Health Policy* **126**:6, 522-533. [[Crossref](#)]
101. Julian Ashwin, Vijayendra Rao, Monica Biradavolu, Arshia Haque, Afsana Khan, Nandini Krishnan, Nagy Peer. Qualitative Analysis at Scale: An Application to Aspirations in Cox's Bazaar, Bangladesh **38**, . [[Crossref](#)]

102. Luca Barbaglia, Sergio Consoli, Sebastiano Manzan. 2022. Forecasting with Economic News. *Journal of Business & Economic Statistics* **15**, 1-12. [[Crossref](#)]
103. Joey Blumberg, Gary Thompson. 2022. Nonparametric segmentation methods: Applications of unsupervised machine learning and revealed preference. *American Journal of Agricultural Economics* **104**:3, 976-998. [[Crossref](#)]
104. Karsten Müller. 2022. German forecasters' narratives: How informative are German business cycle forecast reports?. *Empirical Economics* **62**:5, 2373-2415. [[Crossref](#)]
105. Mark Egan, Gregor Matvos, Amit Seru. 2022. When Harry Fired Sally: The Double Standard in Punishing Misconduct. *Journal of Political Economy* **130**:5, 1184-1248. [[Crossref](#)]
106. Beatrice Ferrario, Stefanie Stantcheva. 2022. Eliciting People's First-Order Concerns: Text Analysis of Open-Ended Survey Questions. *AEA Papers and Proceedings* **112**, 163-169. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
107. Lea-Rachel Kosnik. 2022. Who Are the More Dismal Economists? Gender and Language in Academic Economics Research. *AEA Papers and Proceedings* **112**, 592-596. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
108. Valentina Aprigliano, Simone Emiliozzi, Gabriele Guaitoli, Andrea Luciani, Juri Marcucci, Libero Monteforte. 2022. The power of text-based indicators in forecasting Italian economic activity. *International Journal of Forecasting* **191**. . [[Crossref](#)]
109. Victor Murinde, Efthymios Rizopoulos, Markos Zachariadis. 2022. The impact of the FinTech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis* **81**, 102103. [[Crossref](#)]
110. Peter Grajzl, Peter Murrell. 2022. Using Topic-Modeling in Legal History, with an Application to Pre-Industrial English Case Law on Finance. *Law and History Review* **40**:2, 189-228. [[Crossref](#)]
111. Bernhard Lutz, Nicolas Pröllochs, Dirk Neumann. 2022. Are longer reviews always more helpful? Disentangling the interplay between review length and line of argumentation. *Journal of Business Research* **144**, 888-901. [[Crossref](#)]
112. Pierre-Philippe Combes, Laurent Gobillon, Yanos Zylberberg. 2022. Urban economics in a historical perspective: Recovering data with machine learning. *Regional Science and Urban Economics* **94**, 103711. [[Crossref](#)]
113. Valeria Fanghella, John Thøgersen. 2022. Experimental evidence of moral cleansing in the interpersonal and environmental domains. *Journal of Behavioral and Experimental Economics* **97**, 101838. [[Crossref](#)]
114. Dario Caldara, Matteo Iacoviello. 2022. Measuring Geopolitical Risk. *American Economic Review* **112**:4, 1194-1225. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
115. Daniel Borup, Bent Jesper Christensen, Nicolaj Søndergaard Mühlbach, Mikkel Slot Nielsen. 2022. Targeting predictors in random forest regression. *International Journal of Forecasting* **9**. . [[Crossref](#)]
116. Gloria Gennaro, Elliott Ash. 2022. Emotion and Reason in Political Language. *The Economic Journal* **132**:643, 1037-1059. [[Crossref](#)]
117. Ashani Amarasinghe. 2022. Diverting domestic turmoil. *Journal of Public Economics* **208**, 104608. [[Crossref](#)]

118. Euntack Im, Dukjin Kim, Minhye Jwa, Gwangyong Gim. 2022. The Detection of Brand Identity and Image Using Semantic Network Analysis. *International Journal of Software Innovation* **10**:2, 1-13. [[Crossref](#)]
119. Andrea Bastianin, Paolo Castelnovo, Massimo Florio, Anna Giunta. 2022. Big science and innovation: gestation lag from procurement to patents for CERN suppliers. *The Journal of Technology Transfer* **47**:2, 531-555. [[Crossref](#)]
120. David Pastoriza, Thierry Warin. 2022. Dataset of two decades of Tiger Woods press conferences and tournament performance. *Data in Brief* **41**, 107955. [[Crossref](#)]
121. Tim Loughran, Bill McDonald, James R. Otteson. 2022. How Have Corporate Codes of Ethics Responded to an Era of Increased Scrutiny?. *Journal of Business Ethics* **29**. . [[Crossref](#)]
122. Luma Ramos, Kevin P. Gallagher, Corinne Stephenson, Irene Monasterolo. 2022. Climate risk and IMF surveillance policy: a baseline analysis. *Climate Policy* **22**:3, 371-388. [[Crossref](#)]
123. Gabjin Oh. 2022. Multifractal analysis of social media use in financial markets. *Journal of the Korean Physical Society* **80**:6, 526-532. [[Crossref](#)]
124. Roberto Gómez-Cram, Marco Grotteria. 2022. Real-time price discovery via verbal communication: Method and application to FedSpeak. *Journal of Financial Economics* **143**:3, 993-1025. [[Crossref](#)]
125. Leonardo Cei, Edi Defrancesco, Gianluca Stefani. 2022. What topic modelling can show about the development of agricultural economics: evidence from the Journal Citation Report category top journals. *European Review of Agricultural Economics* **49**:2, 289-330. [[Crossref](#)]
126. Andrey Simonov, Justin Rao. 2022. Demand for Online News under Government Control: Evidence from Russia. *Journal of Political Economy* **130**:2, 259-309. [[Crossref](#)]
127. Gianluca Stefani, Mario Biggeri, Lucia Ferrone. 2022. Sustainable Transitions Narratives: An Analysis of the Literature through Topic Modelling. *Sustainability* **14**:4, 2085. [[Crossref](#)]
128. Franz Ulrich Ruch, Temel Taskin. Demand and Supply Shocks: Evidence from Corporate Earning Calls . [[Crossref](#)]
129. Vijayendra Rao. Can Economics Become More Reflexive? Exploring the Potential of Mixed-Methods **6**, . [[Crossref](#)]
130. Colin Harris, Andrew Myers, Christienne Briol, Sam Carlen. The Binding Force of Economics 69-103. [[Crossref](#)]
131. Daniel Borup, Erik Christian Montes Schütte. 2022. In Search of a Job: Forecasting Employment Growth Using Google Trends. *Journal of Business & Economic Statistics* **40**:1, 186-200. [[Crossref](#)]
132. Brian J. Fogarty, David C. Kimball, Lea-Rachel Kosnik. 2022. The media, voter fraud, and the U.S. 2012 elections. *Journal of Elections, Public Opinion and Parties* **32**:1, 46-66. [[Crossref](#)]
133. Vincenzo Alfano, Massimo Guarino. 2022. A Word to the Wise Analyzing the Impact of Textual Strategies in Determining House Pricing. *Journal of Housing Research* **31**:1, 88-112. [[Crossref](#)]
134. Jacopo Perego, Sevgi Yuksel. 2022. Media Competition and Social Disagreement. *Econometrica* **90**:1, 223-265. [[Crossref](#)]
135. Sergio Consoli, Matteo Negri, Amirhossein Tebbifakhr, Elisa Tosetti, Marco Turchi. Forecasting the IBEX-35 Stock Index Using Deep Learning and News Emotions 308-323. [[Crossref](#)]

136. Annika SH Isfeldt, Thyge R Enggaard, Anders Blok, Morten A Pedersen. 2022. Grøn Genstart : A quali-quantitative micro-history of a political idea in real-time. *Big Data & Society* **9**:1, 205395172110703. [[Crossref](#)]
137. Yiming He. Do Agricultural Population Urbanization and Energy-Environment Policy Affect Housing Values? Evidence from China 165-195. [[Crossref](#)]
138. Jon Ellingsen, Vegard H. Larsen, Leif Anders Thorsrud. 2022. News media versus FRED-MD for macroeconomic forecasting. *Journal of Applied Econometrics* **37**:1, 63-81. [[Crossref](#)]
139. Alessandra Amendola, Walter Distaso, Alessandro Grimaldi. TPPI: Textual Political Polarity Indices. The Case of Italian GDP 7-12. [[Crossref](#)]
140. Zhigang Qiu, Xiaolin Huo, Yue Dai. Development of FinTech in Academia 71-84. [[Crossref](#)]
141. Sven Grüner. Fake News 1-5. [[Crossref](#)]
142. Benjamin Bluhm, Jannic Alexander Cutura. 2022. Econometrics at Scale: Spark up Big Data in Economics. *Journal of Data Science* **49**, 413-436. [[Crossref](#)]
143. Vincent Grégoire, Noah Jepson. Alternative Data 13-33. [[Crossref](#)]
144. Max Nathan, Anna Rosso. 2022. Innovative events: product launches, innovation and firm performance. *Research Policy* **51**:1, 104373. [[Crossref](#)]
145. Vijayendra Rao. Can Economics Become More Reflexive? Exploring the Potential of Mixed Methods 1-27. [[Crossref](#)]
146. Matthias Pöferlein. 2021. Sentiment Analysis of German Texts in Finance: Improving and Testing the BPW Dictionary. *Journal of Banking and Financial Economics* **2021**:2(16), 5-24. [[Crossref](#)]
147. Malte Schierholz, Matthias Schonlau. 2021. Machine Learning for Occupation Coding—A Comparison Study. *Journal of Survey Statistics and Methodology* **9**:5, 1013-1034. [[Crossref](#)]
148. Peter Sheridan Dodds, Joshua R. Minot, Michael V. Arnold, Thayer Alshaabi, Jane Lydia Adams, Andrew J. Reagan, Christopher M. Danforth. 2021. Computational timeline reconstruction of the stories surrounding Trump: Story turbulence, narrative control, and collective chronopathy. *PLOS ONE* **16**:12, e0260592. [[Crossref](#)]
149. Alex Coad. 2021. Econometrics and the Growth of Firms: Perspectives from Evolutionary Economics. *Strategy Science* **6**:4, 338-352. [[Crossref](#)]
150. Luís Madureira, Aleš Popovič, Mauro Castelli. 2021. Competitive intelligence: A unified view and modular definition. *Technological Forecasting and Social Change* **173**, 121086. [[Crossref](#)]
151. Mehran Azimi, Anup Agrawal. 2021. Is Positive Sentiment in Corporate Annual Reports Informative? Evidence from Deep Learning. *The Review of Asset Pricing Studies* **11**:4, 762-805. [[Crossref](#)]
152. Thomas Laloux, Tom Delreux. 2021. The origins of EU legislation: agenda-setting, intra-institutional decision-making or interinstitutional negotiations?. *West European Politics* **44**:7, 1555-1576. [[Crossref](#)]
153. Paul M. Anglin, Yanmin Gao. 2021. Value of Communication and Social Media: An Equilibrium Theory of Messaging. *The Journal of Real Estate Finance and Economics* **87**. . [[Crossref](#)]
154. Sergio Consoli, Luca Tiozzo Pezzoli, Elisa Tosetti. 2021. Emotions in macroeconomic news and their impact on the European bond market. *Journal of International Money and Finance* **118**, 102472. [[Crossref](#)]

155. FNU Shweta, Andrea Belz. Computational Linguistic Analysis of Submitted SEC Information (CLASSI) 1132-1137. [[Crossref](#)]
156. Kevin W. Capehart. 2021. Expensive and Cheap Wine Words Revisited. *Journal of Wine Economics* 16:4, 411-418. [[Crossref](#)]
157. Gregory Ferguson-Cradler. 2021. Narrative and computational text analysis in business and economic history. *Scandinavian Economic History Review* 57, 1-25. [[Crossref](#)]
158. Amir Amel-Zadeh, Martin Glaum, Thorsten Sellhorn. 2021. Empirical Goodwill Research: Insights, Issues, and Implications for Standard Setting and Future Research. *European Accounting Review* 12, 1-32. [[Crossref](#)]
159. Ji Ma, Islam Akef Ebeid, Arjen de Wit, Meiying Xu, Yongzheng Yang, René Bekkers, Pamala Wiepking. 2021. Computational Social Science for Nonprofit Studies: Developing a Toolbox and Knowledge Base for the Field. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations* 29. . [[Crossref](#)]
160. Stelios Michalopoulos, Melanie Meng Xue. 2021. Folklore. *The Quarterly Journal of Economics* 136:4, 1993-2046. [[Crossref](#)]
161. Marianne Bertrand, Matilde Bombardini, Raymond Fisman, Brad Hackinen, Francesco Trebbi. 2021. Hall of Mirrors: Corporate Philanthropy and Strategic Advocacy. *The Quarterly Journal of Economics* 136:4, 2413-2465. [[Crossref](#)]
162. Matthew C. Harding, Carlos Lamarche. 2021. Small Steps with Big Data: Using Machine Learning in Energy and Environmental Economics. *Annual Review of Resource Economics* 13:1, 469-488. [[Crossref](#)]
163. Sanjiv R. Das, Michele Donini, Muhammad Bilal Zafar, John He, Krishnaram Kenthapadi. 2021. FinLex: An Effective Use of Word Embeddings for Financial Lexicon Generation. *The Journal of Finance and Data Science* 59. . [[Crossref](#)]
164. Nicholas Crafts. 2021. Artificial intelligence as a general-purpose technology: an historical perspective. *Oxford Review of Economic Policy* 37:3, 521-536. [[Crossref](#)]
165. Alexander Mee, Elmina Homapour, Francisco Chiclana, Ofer Engel. 2021. Sentiment analysis using TF-IDF weighting of UK MPs' tweets on Brexit. *Knowledge-Based Systems* 228, 107238. [[Crossref](#)]
166. Gloria Hristova. 2021. Text Analytics in Bulgarian: An Overview and Future Directions. *Cybernetics and Information Technologies* 21:3, 3-23. [[Crossref](#)]
167. Gloria Hristova. 2021. Text Analytics in Bulgarian: An Overview and Future Directions. *Cybernetics and Information Technologies* 21:3, 3-23. [[Crossref](#)]
168. Seokkyun Woo, Jan Youtie, Ingrid Ott, Fenja Scheu. 2021. Understanding the long-term emergence of autonomous vehicles technologies. *Technological Forecasting and Social Change* 170, 120852. [[Crossref](#)]
169. Nina Rizun, Aleksandra Revina, Vera G. Meister. 2021. Analyzing content of tasks in Business Process Management. Blending task execution and organization perspectives. *Computers in Industry* 130, 103463. [[Crossref](#)]
170. Julian Freitag, Anna Kerkhof, Johannes Münster. 2021. Selective sharing of news items and the political position of news outlets. *Information Economics and Policy* 56, 100926. [[Crossref](#)]
171. J. Daniel Aromi, Adam Clements. 2021. Facial expressions and the business cycle. *Economic Modelling* 102, 105563. [[Crossref](#)]

172. Claire S.H. Lim, James M. Snyder. 2021. What Shapes the Quality and Behavior of Government Officials? Institutional Variation in Selection and Retention Methods. *Annual Review of Economics* 13:1, 87-109. [[Crossref](#)]
173. Tiffany Jiang. 2021. Using Machine Learning to Analyze Merger Activity. *Frontiers in Applied Mathematics and Statistics* 7. . [[Crossref](#)]
174. Max Besbris, Ariela Schachter, John Kuk. 2021. The Unequal Availability of Rental Housing Information Across Neighborhoods. *Demography* 58:4, 1197-1221. [[Crossref](#)]
175. Mikko Moilanen, Stein Østbye. 2021. Doublespeak? Sustainability in the Arctic—A Text Mining Analysis of Norwegian Parliamentary Speeches. *Sustainability* 13:16, 9397. [[Crossref](#)]
176. Bryan Kelly, Asaf Manela, Alan Moreira. 2021. Text Selection. *Journal of Business & Economic Statistics* 1-61. [[Crossref](#)]
177. Cuong V. Nguyen, Sanjiv R. Das, John He, Shenghua Yue, Vinay Hanumaiah, Xavier Ragot, Li Zhang. Multimodal Machine Learning for Credit Modeling 1754-1759. [[Crossref](#)]
178. Paulo Mourao. 2021. Health by Words—A Content Analysis of Political Manifestos in the Portuguese Elections of 1975. *International Journal of Environmental Research and Public Health* 18:13, 7119. [[Crossref](#)]
179. Carsten Herrmann-Pillath, Luís Otávio Bau Macedo. 2021. Narratives and Economic Policy: Theoretical Explorations and the Case of Central Bank Communication in Brazil. *Journal of Contextual Economics – Schmollers Jahrbuch* 141:3, 243-272. [[Crossref](#)]
180. Kai Li, Feng Mai, Rui Shen, Xinyan Yan. 2021. Measuring Corporate Culture Using Machine Learning. *The Review of Financial Studies* 34:7, 3265-3315. [[Crossref](#)]
181. Itay Goldstein, Chester S Spatt, Mao Ye. 2021. Big Data in Finance. *The Review of Financial Studies* 34:7, 3213-3225. [[Crossref](#)]
182. Sean Shun Cao, Vivian W. Fang, Lijun (Gillian) Lei. 2021. Negative peer disclosure. *Journal of Financial Economics* 140:3, 815-837. [[Crossref](#)]
183. Vegard Høghaug Larsen. 2021. COMPONENTS OF UNCERTAINTY. *International Economic Review* 62:2, 769-788. [[Crossref](#)]
184. Maximilian Andres, Lisa Bruttel, Jana Friedrichsen. 2021. The leniency rule revisited: Experiments on cartel formation with open communication. *International Journal of Industrial Organization* 76, 102728. [[Crossref](#)]
185. Janna Axenbeck, Patrick Breithaupt. 2021. Innovation indicators based on firm websites—Which website characteristics predict firm-level innovation activity?. *PLOS ONE* 16:4, e0249583. [[Crossref](#)]
186. Jose M. Fernandez, Erin A. Yetter, Kim Holder. 2021. What do economic education scholars study? Insights from machine learning. *The Journal of Economic Education* 52:2, 156-172. [[Crossref](#)]
187. Heidi Kühnemann. 2021. Anwendungen des Web Scraping in der amtlichen Statistik. *AStA Wirtschafts- und Sozialstatistisches Archiv* 15:1, 5-25. [[Crossref](#)]
188. Paweł Baranowski, Wirginia Doryń, Tomasz Łyziak, Ewa Stanisławska. 2021. Words and deeds in managing expectations: Empirical evidence from an inflation targeting economy. *Economic Modelling* 95, 49-67. [[Crossref](#)]
189. Anestis Antoniadis, Sophie Lambert-Lacroix, Jean-Michel Poggi. 2021. Random forests for global sensitivity analysis: A selective review. *Reliability Engineering & System Safety* 206, 107312. [[Crossref](#)]

190. Achim Ahrens, Christopher Aitken, Mark E. Schaffer. Using Machine Learning Methods to Support Causal Inference in Econometrics 23-52. [[Crossref](#)]
191. Monique Reid, Pierre Siklos, Timothy Guetterman, Stan Du Plessis. 2021. The role of financial journalists in the expectations channel of the monetary transmission mechanism. *Research in International Business and Finance* **55**, 101320. [[Crossref](#)]
192. Sergio Consoli, Luca Tiozzo Pezzoli, Elisa Tosetti. Information Extraction From the GDELT Database to Analyse EU Sovereign Bond Markets 55-67. [[Crossref](#)]
193. Luca Barbaglia, Sergio Consoli, Sebastiano Manzan. Exploring the Predictive Power of News and Neural Machine Learning Models for Economic Forecasting 135-149. [[Crossref](#)]
194. Massimo Minesso Ferrari, Frederik Kurcz, Maria Sole Pagliari. 2021. Do Words Hurt More Than Actions? The Impact of Trade Tensions on Financial Markets. *SSRN Electronic Journal* . [[Crossref](#)]
195. Fredy Nehme, Keith Feldman. 2021. Evolving Role and Future Directions of Natural Language Processing in Gastroenterology. *Digestive Diseases and Sciences* **66**:1, 29-40. [[Crossref](#)]
196. Peter Grajzl, Peter Murrell. 2021. Characterizing a legal–intellectual culture: Bacon, Coke, and seventeenth-century England. *Cliometrica* **15**:1, 43-88. [[Crossref](#)]
197. Ekaterina Prytkova. 2021. ICT's Wide Web: a System-Level Analysis of ICT's Industrial Diffusion with Algorithmic Links. *SSRN Electronic Journal* . [[Crossref](#)]
198. Itay Goldstein, Chester S. Spatt, Mao Ye. 2021. Big Data in Finance. *SSRN Electronic Journal* **5** . [[Crossref](#)]
199. Sascha O. Becker, Jared Rubin, Ludger Woessmann. Religion in economic history: a survey 585-639. [[Crossref](#)]
200. Anjali Adukia, Alex Eble, Emileigh Harrison, Hakizumwami Birali Runesha, Teodora Szasz. 2021. What We Teach About Race and Gender: Representation in Images and Text of Children's Books. *SSRN Electronic Journal* **59** . [[Crossref](#)]
201. Nicola Amoroso, Loredana Bellantuono. From complex to neural networks 137-154. [[Crossref](#)]
202. Sergio Consoli, Luca Barbaglia, Sebastiano Manzan. 2021. Fine-Grained, Aspect-Based Sentiment Analysis on Economic and Financial Lexicon. *SSRN Electronic Journal* **50** . [[Crossref](#)]
203. Tara M. Sinclair, Zhoudan Xie. 2021. Sentiment and uncertainty about regulation. *SSRN Electronic Journal* **60** . [[Crossref](#)]
204. Renato Faccini, Rastin Matin, George Skiadopoulos. 2021. Dissecting Climate Risks: Are they Reflected in Stock Prices?. *SSRN Electronic Journal* . [[Crossref](#)]
205. Sasan Mansouri, Paul P. Momtaz. 2021. Financing Sustainable Entrepreneurship: ESG Measurement, Valuation, and Performance in Token Offerings. *SSRN Electronic Journal* . [[Crossref](#)]
206. David A. Hyman, Jing Liu, Bernard S. Black. 2021. Should Patients Use Online Reviews to Pick Their Doctor? Lessons from Illinois and Indiana. *SSRN Electronic Journal* **105** . [[Crossref](#)]
207. Raffaele Dell'Aversana, Edgardo Bucciarelli. Approaching Natural Language as a Business Game from the Bottom Up: A Cognitive Real-Effort Lab Experiment 56-69. [[Crossref](#)]
208. Francesco Bianchi, Roberto Gomez Cram, Howard Kung. 2021. Using Social Media to Identify the Effects of Congressional Partisanship on Asset Prices. *SSRN Electronic Journal* **29** . [[Crossref](#)]
209. Jiaxuan Lu. 2021. Leadership Rotations and the Convergence of Subnational Economic Policies in China: Evidence from Provincial Government Work Reports. *SSRN Electronic Journal* . [[Crossref](#)]

210. Sophie Hatte, Etienne Madinier, Ekaterina Zhuravskaya. 2021. Reading Twitter in the Newsroom: How Social Media Affects Traditional-Media Reporting of Conflicts. *SSRN Electronic Journal* **130**. . [\[Crossref\]](#)
211. Sophia Kazinnik, Cooper Killen, Daniela Scida, John Wu. 2021. News and Networks: Using Text Analytics to Assess Bank Networks During COVID-19 Crisis. *SSRN Electronic Journal* **38**. . [\[Crossref\]](#)
212. Florian Popp, Bernhard Lutz, Dirk Neumann. Where NeuroIS Helps to Understand Human Processing of Text: A Taxonomy for Research Questions Based on Textual Data 1-8. [\[Crossref\]](#)
213. Jikhan Jeong. 2021. Identifying Consumer Preferences From User-Generated Content on Amazon.Com by Leveraging Machine Learning. *IEEE Access* **9**, 147357-147396. [\[Crossref\]](#)
214. Justin Case, Adam Clements. The Impact of Sentiment in the News Media on Daily and Monthly Stock Market Returns 180-195. [\[Crossref\]](#)
215. Finn Müller-Hansen, Max W. Callaghan, Jan C. Minx. 2020. Text as big data: Develop codes of practice for rigorous computational text analysis in energy social science. *Energy Research & Social Science* **70**, 101691. [\[Crossref\]](#)
216. Piet J.H. Daas, Suzanne van der Doef. 2020. Detecting innovative companies via their website. *Statistical Journal of the IAOS* **36:4**, 1239-1251. [\[Crossref\]](#)
217. Kimmy Wa Chan, Stella Yiyang Li, Jian Ni, John JianJun Zhu. 2020. What Feedback Matters? The Role of Experience in Motivating Crowdsourcing Innovation. *Production and Operations Management* **76**. . [\[Crossref\]](#)
218. Philipp Adämmmer, Rainer A Schüssler. 2020. Forecasting the Equity Premium: Mind the News!*. *Review of Finance* **24:6**, 1313-1355. [\[Crossref\]](#)
219. Tim Loughran, Bill McDonald. 2020. Textual Analysis in Finance. *Annual Review of Financial Economics* **12:1**, 357-375. [\[Crossref\]](#)
220. Ulrich Kaiser, Johan M. Kuhn. 2020. The value of publicly available, textual and non-textual information for startup performance prediction. *Journal of Business Venturing Insights* **14**, e00179. [\[Crossref\]](#)
221. Michael P. Clements, J. James Reade. 2020. Forecasting and forecast narratives: The Bank of England Inflation Reports. *International Journal of Forecasting* **36:4**, 1488-1500. [\[Crossref\]](#)
222. Dooruj Rambaccussing, Andrzej Kwiatkowski. 2020. Forecasting with news sentiment: Evidence with UK newspapers. *International Journal of Forecasting* **36:4**, 1501-1516. [\[Crossref\]](#)
223. Sergio Consoli, Luca Barbaglia, Sebastiano Manzan. Fine-grained, aspect-based semantic sentiment analysis within the economic and financial domains 52-61. [\[Crossref\]](#)
224. Heidi Kühnemann, Arnout van Delden, Dick Windmeijer. 2020. Exploring a knowledge-based approach to predicting NACE codes of enterprises based on web page texts. *Statistical Journal of the IAOS* **36:3**, 807-821. [\[Crossref\]](#)
225. Andres Algaba, David Ardia, Keven Bluteau, Samuel Borms, Kris Boudt. 2020. ECONOMETRICS MEETS SENTIMENT: AN OVERVIEW OF METHODOLOGY AND APPLICATIONS. *Journal of Economic Surveys* **34:3**, 512-547. [\[Crossref\]](#)
226. JANNIS BISCHOF, HOLGER DASKE, CHRISTOPH J. SEXTROH. 2020. Why Do Politicians Intervene in Accounting Regulation? The Role of Ideology and Special Interests. *Journal of Accounting Research* **58:3**, 589-642. [\[Crossref\]](#)

227. Stephen Michael Impink, Andrea Prat, Raffaella Sadun. 2020. Measuring Collaboration in Modern Organizations. *AEA Papers and Proceedings* **110**, 181-186. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
228. Enghin Atalay, Phai Phongthientham, Sebastian Sotelo, Daniel Tannenbaum. 2020. The Evolution of Work in the United States. *American Economic Journal: Applied Economics* **12**:2, 1-34. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
229. Samuel Bowles, Wendy Carlin. 2020. What Students Learn in Economics 101: Time for a Change. *Journal of Economic Literature* **58**:1, 176-214. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
230. Julia Litofcenko, Dominik Karner, Florentine Maier. 2020. Methods for Classifying Nonprofit Organizations According to their Field of Activity: A Report on Semi-automated Methods Based on Text. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations* **31**:1, 227-237. [[Crossref](#)]
231. Luca Barbaglia, Sergio Consoli, Sebastiano Manzan. Monitoring the Business Cycle with Fine-Grained, Aspect-Based Sentiment Extraction from News 101-106. [[Crossref](#)]
232. Jian Ni, Yi Xin. 2020. Financing Micro-entrepreneurship in Online Crowdfunding Markets: Local Preference versus Information Frictions. *SSRN Electronic Journal* . [[Crossref](#)]
233. Hasan A Fallahgoul. 2020. Inside the Mind of Investors During the COVID-19 Pandemic: Evidence from the StockTwits Data. *SSRN Electronic Journal* . [[Crossref](#)]
234. Zheng Ke, Bryan T. Kelly, Dacheng Xiu. 2020. Predicting Returns with Text Data. *SSRN Electronic Journal* . [[Crossref](#)]
235. Ashani Amarasinghe. 2020. Diverting Domestic Turmoil. *SSRN Electronic Journal* . [[Crossref](#)]
236. Thomas Niebel, Patrick Breithaupt, Reinhold Kesler, Christian Rammer. 2020. Intangible Capital Indicators Based on Web Scraping of Social Media. *SSRN Electronic Journal* . [[Crossref](#)]
237. Michael Ryan. 2020. A Narrative Approach to Creating Instruments with Unstructured and Voluminous Text: An Application to Policy Uncertainty. *SSRN Electronic Journal* . [[Crossref](#)]
238. Chris Florackis, Christodoulos Louca, Roni Michaely, Michael Weber. 2020. Cybersecurity Risk. *SSRN Electronic Journal* . [[Crossref](#)]
239. Francesco D'Acunto, Jin Xie, Jiaquan YAO. 2020. Trust and Contracts: Empirical Evidence. *SSRN Electronic Journal* . [[Crossref](#)]
240. Kai Li, Xing Liu, Feng Mai, Tengfei Zhang. 2020. The Role of Corporate Culture in Bad Times: Evidence from the COVID-19 Pandemic. *SSRN Electronic Journal* . [[Crossref](#)]
241. Alan Zhang. 2020. Uncovering Mutual Fund Private Information with Machine Learning. *SSRN Electronic Journal* **33** . [[Crossref](#)]
242. Sergio Consoli, Luca Tiozzo Pezzoli, Elisa Tosetti. Using the GDELT Dataset to Analyse the Italian Sovereign Bond Market 190-202. [[Crossref](#)]
243. Luca Barbaglia, Sergio Consoli, Sebastiano Manzan. 2020. Forecasting with Economic News. *SSRN Electronic Journal* **133** . [[Crossref](#)]
244. Emerson Escolar, Yasuaki Hiraoka, Mitsuru Igami, Yasin Ozcan. 2020. Mapping Firms' Locations in Technological Space: A Topological Analysis of Patent Statistics. *SSRN Electronic Journal* **31** . [[Crossref](#)]

245. Daniel Levy, Tamir Mayer, Alon Raviv. 2020. Academic Scholarship in Light of the 2008 Financial Crisis: Textual Analysis of NBER Working Papers. *SSRN Electronic Journal* 25. . [[Crossref](#)]
246. Daniel Borup, Bent Jesper Christensen, Nicolaj Mühlbach, Mikkel Slot Nielsen. 2020. The Effects of Targeting Predictors in a Random Forest Regression Model. *SSRN Electronic Journal* 9. . [[Crossref](#)]
247. Tarek Alexander Hassan, Stephan Hollander, Laurence van Lent, Ahmed Tahoun. 2020. Firm-level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1. *SSRN Electronic Journal* 107. . [[Crossref](#)]
248. Matthieu Ballandonne, Igor Cersosimo. 2020. Toward a “Text as Data” Approach in the History and Methodology of Economics: An Application to Adam Smith’s Classics. *SSRN Electronic Journal* 34. . [[Crossref](#)]
249. Murillo Campello, Gaurav Kankanhalli, Pradeep Muthukrishnan. 2020. Corporate Hiring under COVID-19: Labor Market Concentration, Downskilling, and Income Inequality. *SSRN Electronic Journal* 9. . [[Crossref](#)]
250. Roberto Gomez Cram, Marco Grotteria. 2020. Real-time Price Discovery via Verbal Communication: Method and Application to FedSpeak. *SSRN Electronic Journal* 108. . [[Crossref](#)]
251. Andrii Babii, Eric Ghysels, Jonas Striaukas. 2020. Inference for High-Dimensional Regressions With Heteroskedasticity and Auto-correlation. *SSRN Electronic Journal* 33. . [[Crossref](#)]
252. Diego Garcia, Xiaowen Hu, Maximilian Rohrer. 2020. The Colour of Finance Words. *SSRN Electronic Journal* 59. . [[Crossref](#)]
253. Tim Loughran, Bill McDonald. 2020. Measuring Firm Complexity. *SSRN Electronic Journal* 143. . [[Crossref](#)]
254. Manish Jha, Hongyi Liu, Asaf Manela. 2020. Does Finance Benefit Society? A Language Embedding Approach. *SSRN Electronic Journal* 56. . [[Crossref](#)]
255. Gleb Kurovskiy. 2019. Using Textual Information to Predict In Macroeconomics. *Moscow University Economics Bulletin* 2019:6, 39–58. [[Crossref](#)]
256. Tarek A. Hassan, Laurence van Lent, Stephan Hollander, Ahmed Tahoun. 2019. The Global Impact of Brexit Uncertainty. *Institute for New Economic Thinking Working Paper Series* 1–60. [[Crossref](#)]
257. Vincent P. Crawford. 2019. Experiments on Cognition, Communication, Coordination, and Cooperation in Relationships. *Annual Review of Economics* 11:1, 167–191. [[Crossref](#)]
258. Peter Grajzl, Peter Murrell. 2019. Estimating a Culture: Bacon, Coke, and Seventeenth-Century England. *SSRN Electronic Journal* . [[Crossref](#)]
259. Philipp Adümmer, Rainer Alexander Schüssler. 2019. Forecasting the Equity Premium: Mind the News!. *SSRN Electronic Journal* . [[Crossref](#)]
260. Tim Loughran, Bill McDonald. 2019. Textual Analysis in Finance. *SSRN Electronic Journal* . [[Crossref](#)]
261. Daniel Borup, Erik Christian Montes Schütte. 2019. In Search of a Job: Forecasting Employment Growth Using Google Trends. *SSRN Electronic Journal* . [[Crossref](#)]
262. Ali Ozkes, Nobuyuki Hanaki. 2019. Talkin' Bout Cooperation. *SSRN Electronic Journal* . [[Crossref](#)]
263. Andres Algaba, David Ardia, Keven Bluteau, Samuel Borms, Kris Boudt. 2019. Econometrics Meets Sentiment: An Overview of Methodology and Applications. *SSRN Electronic Journal* . [[Crossref](#)]

264. Janna Axenbeck, Patrick Breithaupt. 2019. Web-Based Innovation Indicators – Which Firm Website Characteristics Relate to Firm-Level Innovation Activity?. *SSRN Electronic Journal* . [[Crossref](#)]
265. Mikael Apel, Marianna Blix Grimaldi, Isaiah Hull. 2019. How Much Information Do Monetary Policy Committees Disclose? Evidence from the FOMC's Minutes and Transcripts. *SSRN Electronic Journal* . [[Crossref](#)]
266. Johannes Kriebel, Jörn Debener. 2019. Measuring the Effect of Digitalization Efforts on Bank Performance. *SSRN Electronic Journal* . [[Crossref](#)]
267. Sudheer Chava, Wendi Du, Nikhil Paradkar. 2019. Buzzwords?. *SSRN Electronic Journal* . [[Crossref](#)]
268. Jinfei Sheng. 2019. Asset Pricing in the Information Age: Employee Expectations and Stock Returns. *SSRN Electronic Journal* **68**. . [[Crossref](#)]
269. Sean S. Cao, Vivian W. Fang, Lijun Lei. 2019. Negative Peer Disclosure. *SSRN Electronic Journal* **29**. . [[Crossref](#)]
270. Venky Nagar, Jordan Schoenfeld. 2019. Measuring Corporate Weather Exposure using Computational Linguistics. *SSRN Electronic Journal* **33**. . [[Crossref](#)]
271. Leland Bybee, Bryan T. Kelly, Asaf Manela, Dacheng Xiu. 2019. The Structure of Economic News. *SSRN Electronic Journal* **24**. . [[Crossref](#)]
272. Joseph Kalmenovitz. 2019. Regulatory Intensity. *SSRN Electronic Journal* **11**. . [[Crossref](#)]
273. Francesco Bianchi, Thilo Kind, Howard Kung. 2019. Threats to Central Bank Independence: High-Frequency Evidence with Twitter. *SSRN Electronic Journal* **4**. . [[Crossref](#)]
274. Yan Xu, Jian Ni. 2019. Asymmetric Information and Entrepreneurial Disincentives in Crowdfunding Markets. *SSRN Electronic Journal* **14**. . [[Crossref](#)]
275. Leonid Kogan, Dimitris Papanikolaou, Lawrence Schmidt, Bryan Seegmiller. 2019. Technological Change and Occupations over the Long Run. *SSRN Electronic Journal* **4**. . [[Crossref](#)]
276. Benjamin Bluhm. 2018. Time Series Econometrics at Scale: A Practical Guide to Parallel Computing in (Py)Spark. *SSRN Electronic Journal* . [[Crossref](#)]
277. Mehran Azimi, Anup Agrawal. 2018. Is the Sentiment in Corporate Annual Reports Informative? Evidence from Deep Learning. *SSRN Electronic Journal* . [[Crossref](#)]
278. Mark Egan, Gregor Matvos, Amit Seru. 2018. Arbitration with Uninformed Consumers. *SSRN Electronic Journal* . [[Crossref](#)]
279. Gaurab Aryal, Federico Ciliberto, Benjamin T. Leyden. 2018. Public Communication and Collusion in the Airline Industry. *SSRN Electronic Journal* **34**. . [[Crossref](#)]
280. Gaurab Aryal, Federico Ciliberto, Benjamin T. Leyden. 2018. Public Communication and Collusion in the Airline Industry. *SSRN Electronic Journal* **34**. . [[Crossref](#)]
281. Jannis Bischof, Christoph J. Sextroh. 2017. Why Did Politicians Intervene in the Fair Value Debate? The Role of Ideology and Special Interests. *SSRN Electronic Journal* . [[Crossref](#)]
282. Andrey Simonov, Justin M. Rao. 2017. Demand for (Un)Biased News: Government Control in Online News Markets. *SSRN Electronic Journal* . [[Crossref](#)]
283. Juha Joensuu, Cristian Ioan Tiu. 2017. Hedge Fund Flows and Name Gravitas. *SSRN Electronic Journal* **501**. . [[Crossref](#)]