Political Language in Economics

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Abstract

Does academic writing in economics reflect the political orientation of economists? We use machine learning to measure partisanship in published academic economics articles. We predict observed political behavior of a subset of economists using the phrases from their academic articles, show good out-of-sample predictive accuracy, and then predict partisanship for all economists. We then use these predictions to examine patterns of political language in economics. We estimate journal-specific effects on predicted ideology, controlling for author and year fixed effects, that accord with other measures. We show considerable sorting of economists into fields of research by predicted partisanship. We also show that partisanship is detectable even within fields, even across those estimating the same theoretical parameter. Using policy-relevant parameters collected from previous meta-analyses, we then show that imputed partisanship is correlated with estimated parameters, such that the implied policy prescription is consistent with partisan leaning. For example, we find that going from the most left-wing authored estimate of the taxable top income elasticity to the most right-wing authored estimate decreases the optimal tax rate from 84% to 58%.

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1 Introduction

Modern governments incorporate academic economists' research findings into policy analysis via a wide variety of formal and informal mechanisms. For example, economists inform central bank policy, antitrust policy, and the design of taxes and regulation. The policy relevance of economics partially stems from its ability to combine economic theory (e.g. supply and demand) with parameter estimates (e.g. elasticities) to make prescriptions about optimal policies (e.g. taxes). Among social scientists, economists have a great deal of weight as government officials and public commentators. Their academic opinions and judgments are often expected to be non-partisan, but these experts may have partisan or political preferences of their own. This leads naturally to the question of how partisan is academic economics? Do the methodological conventions of academic economics, such as formal modeling, quantitative analysis, and peer-review successfully filter partisanship from academic economics research? We answer this question by applying tools from natural language processing (Gentzkow and Shapiro, 2010) to a comprehensive corpus of academic economics articles. We link academic economist political behavior, measured from campaign contributions and political petition signing, with the plain text of academic articles. We then train a machine learning algorithm to predict political behavior of authors within this linked sample, both unconditionally and within detailed fields of research. We show that our classifier achieves out-of-sample predictive performance comparable to many other social science applications (Zeng et al. (2017); Berg et al. (2020)), and that the predicted ideologies (or predicted partisanship, which we use interchangeably in this paper) are correlated with responses from the Initiative for Global Markets survey of leading economists scored as liberal or conservative by Gordon and Dahl (2013).

We show patterns of predicted ideology (or partisanship) across economics journals, measured as journal fixed-effects, are consistent with measures from other work. We also show economists exhibit substantial sorting on predicted ideology by field and department. Our main application of these predicted ideologies is to examine their relationship with published empirical papers. We draw policy relevant elasticities from Fuchs et al. (1998) and locate available survey papers that compile estimates of these parameters. We collect estimates of the gender gap, returns to job training, labor supply elasticities, minimum wage elasticities, and union productivity effects. We show that empirical results in several policy relevant fields in economics are correlated with the predicted political ideology of the author(s), with predicted liberals (conservatives) reporting elasticities that imply policies consistent with more interventionist (laissez-faire) ideology. While we are unable to rule out all sources of omitted variable bias, these specifications are robust to numerous alternative measures and sets of control variables, which we summarize using specification curves (Simonsohn et al., 2020).

Our paper contributes a methodology for measuring ideology in academic economics, that could be extended to other technical or putatively nonpartisan domains of writing. Most research economists do not publicly announce any partisan position. Indeed, many of the professional practices and norms of economics are designed to eliminate partisanship from research. For example, the National Bureau of Economic Research does not allow explicit endorsements of policy in its working paper series. In order to extract a measure of partisan ideology from academic research, we extend supervised learning methods from natural language processing (benchmarked against other methods in our companion short paper (Jelveh et al., 2014)). Our approach is novel in that it allows the frequency of a phrase to have a different political valence, depending on the topic (e.g. JEL code) of the paper. This flexible and rich representation of academic language allows us to disentangle the partisanship of an author from the partisanship of their article's research field.

While models predicting ideology from text can show high predictive accuracy, they have not been applied in technical domains where partisanship is not immediately apparent. Importantly, detecting ideology in domains where institutions and norms are in place to maintain neutrality is different from predicting ideology in domains where it is overt, such as media or political speech.[1] Adjusting for topics may be particularly important in highly specialized domains, where language use is tailored to very narrow audiences of other experts.

If political preferences were irrelevant for academic research in economics, predicting political behavior from academic writing should be very difficult. Further, it is natural to hypothesize that while detecting partisanship in popular media or politician speech is reasonably easy, doing so in specialized, technical domains may be much harder. Nonetheless, our method generates good out-of-sample predictions of economist political behavior based on academic writing alone. Further, by using written language as the set of features for prediction, we can also produce article- and journal-specific predictions of ideology, and we show the latter accord with other measures produced in the literature. Methods

[1] Vafa et al. (2020) show that unsupervised methods of text classification work extremely well in measuring partisanship in a sufficiently rich text model.

like ours may be useful for extracting ideology from highly specialized, yet also partisan, fields like climate science, public health (particularly during COVID-19), and many engineering disciplines that are of immediate relevance to policy makers.

Why focus on economics to study political preferences in academic research? One is the simple lack of Republicans in other social sciences, reducing the power of statistical methods to detect partisan differences.[2] Economics also influences policy more than any other social science, with economists accounting for almost 70% of all PhD social scientists testifying before Congress (Maher et al., 2020), and cited more than any other discipline in both the New York Times and The Congressional Record (Wolfers, 2015).[3] In the United States, the Council of Economic Advisors has no analogue in the other social sciences, and the representation of economists in institutions such as the Congressional Budget Office, the Federal Reserve, the Federal Trade Commission, the Department of Justice, and other agencies is far larger than that of any other social science. Empirical work in economics informs policy proposals and evaluations, and economists often testify before Congress. More broadly, economic ideas are important for shaping economic policy by influencing the public debate and setting the range of expert opinion on various economic policy options (Rodrik, 2014-02).

Despite their importance in shaping policies, economists share a long-standing self-conception as apolitical. In his 'The Politics of Political Economists', Stigler (1959) argued that while professional economics was averse to sudden, large, changes in its orientation, advances in economic science were non-partisan due to institutionalized incentives and norms for the dissemination of information. "The dominant influence upon the working range of economic theorists is the set of internal values and pressures of the discipline" (Stigler, 1960). Stigler believed that political and policy preferences do not drive economic research, and when they do, it is for the worse.[4] This belief that economics conforms

[2]Economics has more registered Republicans than any other social science, although they still are a minority. Cardiff and Klein (2005) use voter registration data in California to rank disciplines by Democrat to Republican ratios. They find that economics is the most conservative social science, with a Democrat to Republican ratio of 2.8 to 1. This can be contrasted with sociology (44 to 1), political science (6.5 to 1) and anthropology (10.5 to 1). Consequently, there is more ideological diversity in economics. Langbert (2020) finds that the highest positions in the American Economics Association are overwhelmingly filled by registered Democrats and, among contributors, Democratic contributors.

[3]Fourcade et al. (2014) show the high status of economists is reflected in being the highest paid of the social scientists and the least likely to use interdisciplinary citations.

[4]Stigler continues "Often, of course, the explicit policy desires of economists have had a deleterious effect upon the theory itself.... the effect of policy views on the general theory .... has stemmed from a feeling that the theory must adapt to widely held humanitarian impulses." (Stigler, 1960)

with standard scientific norms[5] is the basis of a working consensus that is widely defended.[6]

Yet, the evidence for the view that scientific practices purge ideology from economics is surprisingly thin, relying upon surveys or subjective coding of political beliefs. The best evidence comes from a comprehensive survey undertaken by Fuchs et al. (1998) who asked a number of labor and public finance economists their views on parameters, policies, and values. They conclude that "one of the most important empirical results of this study is the strong correlation between economists' positions and their values, but an understanding of this relationship requires further research" (Fuchs et al., 1998, pp 1415). Closest to our paper is Gordon and Dahl (2013), who apply clustering techniques to the Institute for Global Markets (IGM) survey responses from prominent economists on a variety of policy questions to assess whether economists are divided over policy issues.

Instead of survey-based methods, our paper uses the correlations between patterns of academic writing and observed political behavior to forecast ideology.[7] Ideology extraction from text has received attention from multiple fields including computer science, political science, and economics. Gentzkow et al. (2018) provide overviews of many models used in the analysis of text, particularly in the domain of political behavior. While our text-and-behavior based measure may mitigate some of the non-response and social desirability bias that may affect surveys, the selected nature of our political behavior data may introduce other biases, which we discuss below.

Several papers investigate the determinants of economic publication and citation patterns (Card and DellaVigna (2020); Ellison (2010, 2011); Önder and Terviö (2015)). None of these papers look at predicted political ideology of economics articles, and none use the text of economics articles themselves as data. Instead, they analyze citation patterns or publication counts alone.[8]

Our paper is also the first to show correlations between predicted political ideologies and empirical results. We build on the policy-relevant classification of empirical estimates done by Fuchs et al. (1998), who classify a range of empirical parameters into implied liberal and conservative directions. Using

[5]For example, norms as articulated for example by the sociologist Merton (1942).

[6]For example, see http://www.nytimes.com/2013/10/21/opinion/yes-economics-is-a-science.html(Chetty, 2013-10-20)

[7]Fuchs et al. (1998) only survey economists at top 40 schools, and have only a 50% response rate. The IGM survey only looks at a small sample of "top" economists, and tends to be more Democratic than average by our measure, as we show below.

[8]Zingales (2014) looks at papers in managerial compensation, and finds that top journals are more likely to publish papers that suggest that managerial pay increases are optimal and that IGM-surveyed economists who serve on boards are more likely to disagree with the statement that CEOs are paid more than their marginal productivity.

collections of these estimates analyzed by published meta-analyses, we show there is a significant and robust correlation of our predicted ideology scores with empirical results. While we lack the data and the empirical design to establish causality, we think these correlations are informative and worthy of further research.

2 Data and Methodology

Our methodology is straightforward, and we preview it now. We begin by linking economists to two measures of political behavior: campaign contributions and petition signings, to measure economists as conservative (+1) or liberal (-1) on a binary scale. Appendix A.5 discusses results from using each measure separately, and confirms that while they are correlated, there is independent information in each measure. We next link these authors to a corpus of academic economics articles obtained from JSTOR and NBER. We then use random forests to predict ideology from academic economics text, adjusting for unsupervised topics (via a correlated topic model) as well as imputed Journal of Economic Literature codes. We then show that our prediction varies primarily at the author-level, and has good out-of-sample performance within the sample of authors for whom we measure behavior. We detail each of these steps below.

2.1 Linking Economists to Their Political Activity

To define our set of economists, we obtained the member directory of the American Economics Association (AEA) for the years 1993, 1997, and 2002 to 2009. From these lists, we extracted over 53,000 potential authors, along with their name, location, email address, education, employer, and occupation.[9] We then link the AEA member directory to two datasets with observed political behavior: political campaign contributions and petition-signing activity.

We obtain campaign contribution data from the Federal Election Commission's website for the years 1979 to 2012. Campaign committees are required to publicly disclose information about individuals who have contributed more than $200. These disclosures contain the contributor's name, employer, occupation, state, city, zip code, transaction date, and transaction amount. We match the AEA roster to

[9]Since AEA members are drawn not only from academia, but government and the business world, not all of these individuals have produced academic research.

these individual contributions of which there are about 20 million. Since a person's information is often recorded differently across the AEA and FEC datasets, we apply a fuzzy string matching algorithm (Navarro, 2001; Tahamont et al., 2021) to member and contributor attributes. We describe the methodology and the results in full detail in Appendix A.2. Summary statistics on the campaign contributions are provided in Table A.1.

Besides campaign contributions, we also proxy economist partisan behavior with petition signings. Our data comes from Hedengren et al. (2010) who collected 35 petitions signed principally by economists. We use fuzzy string matching and manual inspection to match the signatories to our economists. Hedengren et al. (2010) classify petitions according to whether they advocate for or against individual freedoms. Similarly, many of the petitions exhibit viewpoints that are aligned with the political left or right, particularly on economic issues. Examples include petitions for and against federal stimulus following the 2008 financial crisis and for and against tax increases. Appendix Table A.2 reproduces the list of petitions from Hedengren et al. (2010) which includes their classification on the liberty scale along with an additional column indicating our classification. We drop petitions classified as neutral.

We take a simple approach to assigning an ideology $\theta_{i,combined}$ to an economist based on their campaign contribution and petition signing behavior. Let $pet_{k,i}$ be the number of petitions signed by economist i aligned with partisanship k taking on values d (left-leaning), r (right-leaning), or u (undetermined). A similar definition applies to $contrib_{k,i}$ which is the number of campaign contributions. The following logic is then applied to assigning ideologies.

- For each economist i and ideology labels $x, y \in \{d,\ r\}$, $x \neq y$:
    - If $pet_{x,i} \ > \ pet_{y,i}$ and $contrib_{x,i} \ > \ contrib_{y,i}$ then $\theta_{i,combined} \ = \ x$
    - If $pet_{x,i} \ > \ pet_{y,i}$ and $contrib_{x,i} \ = \ contrib_{y,i} \ = \ 0$ then $\theta_{i,combined} \ = \ x$
    - If $pet_{x,i} \ = \ pet_{y,i} \ = \ 0$ and $contrib_{x,i} \ > \ contrib_{y,i}$ then $\theta_{i,combined} \ = \ x$
    - Otherwise $\theta_{i,combined} = u$

If an economist has given more times to Democrats (Republicans) and signed more left-leaning (right-leaning) petitions, the assigned ideology is left-leaning (right-leaning). In the cases where the economist has zero contributions (or signed no petitions), then we only consider signed petitions (contributions). If there is disagreement between the signals, or one of them is indeterminate but nonzero (e.g same number of Republican and Democrat contributions), we treat the ideology as undetermined. For notational brevity we drop reference to $combined$ in $\theta_{i,combined}$ for the rest of the paper.

We choose a simple and interpretable binary measure because there seems to be no natural scale on which to measure intensity of partisanship in the data across the two measures. Both the frequency of petition signing and magnitude of contributions could be driven by professional networks and income/wealth, respectively, in addition to partisanship. Putting these very different continuous quantities on a single scale would require more assumptions. See Appendix A.5 to see results separately for $\theta_{i,contributions}$ and $\theta_{i,petitions}$, as well as evidence that combining both sources produces at least weakly better predictions than using each separately.

There is an extremely high level of agreement across the two binary versions of these signals when considering authors who have signed petitions and made contributions. Prior to dropping authors who have undetermined ideology, there are 238 authors that made left- or right-leaning contributions *and* signed left- or right-leaning petitions. Table 1 shows the level of agreement between the two signals. We see that there are zero economists who are assigned opposing ideologies across the two measures, and only one economist who is assigned an undetermined ideology by the contribution measure and hence dropped from our sample of groundtruth authors.

A natural concern is that the two signals are picking up different dimensions of political ideology, for example cultural vs economic liberalism. When examining Table A.2, we see that the petitions are overwhelmingly about economic policies, except for two that are just for or against John Kerry for president. Campaign contributions, especially those to candidates or parties, are significantly harder to categorize as being motivated by particular social or fiscal concerns alone. However, the high degree of overlap between the petitions and the campaign contributions indicates that there are few partisan Democrat (Republican) economists who are conservative (liberal) on economic policy, so partisanship in this sample seems unlikely to be driven by social issues alone.

2.2 Economic Papers Corpus

To create our corpus of academic writings by economists, we obtained the full text of 62,888 research articles published in 93 journals in economics for the years 1991 to 2008 from JSTOR. We also collected 17,503 working papers from the website of the National Bureau of Economic Research covering June 1973 to October 2011, dropping any duplicates that also appear in JSTOR. These papers were downloaded in PDF format and optical character recognition software was applied to extract text.

We remove common words and capitalization from the raw text and use a stemmer (Porter, 1980) to replace words with their morphological roots.[10] For example, a stemmer will resolve the words 'measures', 'measuring', and 'measured' to their common root 'measur'. After dropping words or phrases that appear fewer than 10 times and more than 100,000 times, we are left with 98,479 single- and multi-word phrases which will serve as predictors for our algorithm. We extract 33,579 one-word phrases (also referred to as unigrams), 56,807 two-words phrases (bigrams), and 8,093 phrases with three or more words.[11]

To further focus our attention on the phrase sequences that are most likely to contain ideological valence, we follow (Gentzkow and Shapiro, 2010) and rank phrases by Pearson's χ^2 statistic. Table 2 lists the phrases that are most consistently associated with left- or right-leaning ideology in our groundtruth sample of economists.[12] As we would expect from a technical corpus with peer review, the table exhibits none of the phrases often associated with partisanship by research looking at media or political text, suggesting that for writing by academics, partisanship is likely to be encoded in much more specialized language. For example, right-leaning terms include stemmed variants of 'stock return', 'median voter', and 'rent seeking', which are typically associated with finance or political economy, and left-leaning terms include 'health insurance', 'welfare reform', and 'food stamps', which are related to health care and welfare.

These are clearly words associated with broad areas of research rather than particular policy stances or political ideologies. That they are predictive of author political behavior is suggestive of sorting of

[10]These common words include terms not likely to be correlated with author partisanship such as 'a', 'the', and 'to'.

[11]We extract multi-word phrases automatically using a modified version of the method from Mikolov et al. (2013) and implemented by the *gensim* module for the Python programming language. The method scores multi-word phrases by computing the normalized pointwise mutual information (NPMI), a measure of association ranging from -1 to 1. Multi-word phrases that have NPMI values closer to one are more likely to appear together than with other words.

[12]The method for ranking the phrases in Table 2 are further described in Section 2.4.

researchers into fields on the basis of characteristics associated with partisan leanings. But as the model in Appendix A.1 shows, if publications have to satisfy peer reviewers who are also sorted into fields based on partisan leanings, then the partisanship revealed by a paper will be a combination of an author's partisanship and that of the audience for the paper (peer reviewers and editors). Fortunately, many economists write in a variety of research fields, allowing an individual's partisan leaning to be expressed independently of the research field.

2.3 Accounting for Topics

To investigate the extent to which sorting may explain the relationship between text and ideology, we construct measures of research areas, or "topics". Since we do not observe topics for all of the papers in our corpus, we use prediction methods from machine learning to predict topics for all papers. We map papers to topics using both unsupervised and supervised methods from machine learning, and then we predict authors' ideologies using phrase counts weighted by topic prevalence. For example, the correlation between political behavior and the phrase "transaction cost" is allowed to vary depending on whether the phrase is used in a labor economics or a macroeconomics topic.[13] These within-topic predictions are combined to form a final estimate of an author's political leaning. For robustness, we also predict author ideology without adjusting for topics, and show results with and without topic adjustment throughout.

If sorting into fields was driving the relationship between language and ideology, then it should be more difficult to predict ideology within fields. As we show below, not only are we able to predict ideology accurately within fields, but our topic-adjusted predicted ideologies (which are comprised of weighted averages of the topic-specific predicted ideologies) have greater accuracy than an algorithm which does not take topics into account. This points to another utility for our topic adjustments: If the relationship between language and ideology changes across fields, then accounting for those shifts can lead to more accurate predictions of ideology.

Our first method for estimating topics takes advantage of classification codes maintained by the *Journal of Economic Literature*. These codes are hierarchical markers of an article's subject area. For

[13]For example, we see that the stemmed version of "transaction cost" is the top right-leaning two-word phrase in Journal of Economic Literature (JEL) code J7 (Labor Discrimination) and the top left-leaning bigram in JEL code E6 (Macroeconomic Policy, Macroeconomic Aspects of Public Finance, and General Outlook). See online appendix for the full list of top-leaning terms by topic.

example, the code C51 can be read, in increasing order of specificity, as Mathematical and Quantitative Methods (C), Econometric Modeling (C5), Model Construction and Estimation (C51). Our JSTOR dataset did not include JEL codes so we obtain classifications for 539,572 published articles and the 1.4 million JEL codes assigned to them by the *Journal of Economic Literature*.[14] The per-topic model performances are listed Appendix A.3. We predict codes for the 1st and 2nd levels and refer to these topic mappings as *JEL1* and *JEL2*.

In our second method, we use a variant of the well-known Latent Dirichlet Allocation (LDA) topic model, which provides an unsupervised classification of documents into latent factors, so that each document is given a probability of being in each of a number of latent "topics". One consequence of the Dirichlet prior used in LDA is that topic proportions are assumed independent, which is unlikely to hold in our context. To overcome this, we use a related algorithm, the correlated topic model (CTM) (Lafferty and Blei, 2006) which allows for the presence of one topic to be predictive of the presence of another, thus capturing more realistic latent topic distributions. Topic mappings were created with 30, 50, and 100 topics (*CTM30*, *CTM50*, and *CTM100*).

For each topic, it is possible to rank the words or phrases most relevant to that topic. These rankings can be used to qualitatively assess a real-world analogue to the algorithm-generated topics. We can similarly rank phrases within JEL topics by estimating the conditional probability that a word appears in a JEL topic. Tables A.9 to A.11 display the education topics for each mapping, note that some mappings have more than one topic which refers to education. The left-most column in each table shows the top twenty words associated with that topic while the next two columns show the top left-leaning and right-leaning bigrams for papers in that topic, respectively.

[14] We were able to match and assign JEL codes to 37,364 of our JSTOR articles. The average paper was assigned to 1.90, 2.31, and 2.68 first-, second- and third-level JEL codes, respectively. We then predict codes for the set of papers that fall outside of the EconLit data. To do so, we take a "one-vs-all" (Bishop, 2006) approach to construct a series of binary classification models, in this case gradient boosting (Friedman, 2002), a decision-tree based classifier. For each JEL code, we take the set of papers for which we know the actual JEL codes and construct a training set where we define outcome $y_{p,j}$ as one if paper p was assigned code j and zero otherwise. We also construct a matrix of predictive features $\mathbf{C}$ where the (p, w)-th element is the count of the number times word w appeared in paper p. We estimate a series of prediction models for each JEL code that generates $\hat{y}_{p,j}$, the probability that paper p is about topic t. The models perform well with an average area under the curve (AUC) of 0.96. We provide further details on AUC below.

2.4 Predicting Ideology From Phrases

In this section we describe our algorithm for predicting political leanings. To recap, we have created a dataset which contains 2,471 economists who have both known groundtruth ideology as well papers in our corpus. These authors have written 20,029 papers from which we have extracted 98,479 phrases and associated counts for each paper. We have also created six mappings from papers to topics: *JEL1, JEL2, CTM30, CTM50, CTM100*, and *NoTopic*. The *NoTopic* mapping refers to pooling all papers without regard to topic.

The steps for our prediction algorithm proceed as follows. We first split our sample of 2,471 groundtruth authors into five partitions, or folds. We iteratively hold out one fold, which we call the *test set*, and build models on the dataset that is created by combining the four other folds, which we refer to as the *training set*. To avoid obtaining an optimistic measure of out-of-sample predictive performance, we remove co-authored papers from the training set where at least one of the coauthors is also in the test set. We then create F^{train}, a matrix where the rows represent each paper written by a groundtruth author in the training set and the columns represent phrases. The (r, p)-th element in F^{train} is the number of times phrase p was used in the paper associated with row r. The mapping of rows to papers is referred to as $g(r)$. We also construct F^{test} in a similar fashion but for test set authors.

For a topic mapping m, we iterate through each topic t, and, within a topic, we multiply each row in F^{train} by the probability that $g(r)$ was about topic t.[15] We then aggregate up to the author level by summing the weighted phrase counts within author and call the resulting matrix E^{train}.[16] Specifically, for topic t and author i, we set

$$E_{i,\cdot}^{train} = \sum_{\{r|g(r)\in G(i)\}} \omega_{r,t,m} \cdot F_{r,\cdot}^{train}$$

where $G(i)$ returns the set of papers written by author i and $\omega_{r,t,m}$ is the probability that paper $g(r)$ is about topic t under mapping m. This produces a matrix where the rows are each groundtruth author in the training set and the columns are the weighted sums of phrase counts across the papers written by each author. We also construct E^{test} in a similar fashion.

[15] As a reminder, these probabilities are generated from the three unsupervised Correlated Topic Models and the two supervised JEL prediction models.

[16] If a paper is written by multiple authors, then that paper's phrase counts are repeated in $F^{(\cdot)}$ in as many rows as there are coauthors.

Next, we follow Gentzkow and Shapiro and filter out phrases in E^{train} that are not likely to be predictive of ideology. We create a ranking of phrases by partisanship by computing Pearson's χ^2 statistic for each phrase:

$$\chi^2_{p,t,m} = \frac{(c_{p,t,m,r}\, c_{\sim p,t,m,d} - c_{p,t,m,d} c_{\sim p,t,m,r})^2}{(c_{p,t,m,r} + c_{p,t,m,d})(c_{p,t,m,r} + c_{\sim p,t,m,r})(c_{p,t,m,d} + c_{\sim p,t,m,d})(c_{\sim p,t,m,r} + c_{\sim p,t,m,d})}$$

where $c_{p,t,m,\cdot}$ is the weighted counts of the number of times phrase p in topic t of mapping m was used by all economists with particular partisan behavior (d or r) and $c_{\sim p,t,m,\cdot}$ is the number of times phrases in topic t that are not p were used. We calculate p-values from the χ^2 statistics and keep only those phrases where this value is ≤ 0.05.

To further limit the noise that may exist in the predictors, we only keep phrases that are consistently associated with partisan behavior. We partition the training set into 5 folds and hold out one fold at a time. We apply the χ^2 filter to the other four folds to identify significantly slanted phrases. We repeat this process for each possible holdout fold which produces five sets of significant phrases. We then take the intersection across the five sets and the resulting phrases are used as input into the ideology prediction model. In other words, if a phrase is not significantly predictive of partisanship in any of these folds, it is not used in the predictive model in a particular topic and mapping.

The phrases that are good predictors are intuitively plausible. In Table 2, we show the phrases that are most predictive without any topic adjustment. We keep proper names because they convey information about intellectual influences (e.g. Friedman, Keynes) and schools of thought, these are also quite a small share of our tokens (e.g. among the top 100 left-leaning bigrams only 4 are proper names, and among the top 100 right-leaning bigrams only 7 are proper names). The top left-wing predicting bigrams are stemmed versions of child care, post Keynesian, and labor market, while the top right-wing predicting bigrams are stemmed versions of public choice, rent seeking, stock returns. These are intuitively the patterns of sorting into field by predicted ideology that we would expect. But even predictive phrases within topic are intuitive. For example, the first table in Appendix A.6 shows phrases within Topic 19 of the CTM30 topic-adjusted prediction, which clearly corresponds to education. Within that topic, left-wing phrases are oriented towards interventionist policies such as Head Start (i.e. the federal program for children), affirmative action, and the minimum wage, while right-wing phrases are associated with ability, such as human capital, cognitive skill, and school attainment. This basic pattern shows up in all the topics associated with education, regardless of which specific topic adjustment is used, as can be seen in the other four tables in Appendix A.6.

After the phrases have been selected, we then build a model to predict authors' ideologies. Specifically we use decision trees, a non-parametric machine learning algorithm which recursively partitions the input space into regions that seek to maximize the homogeneity of the outcome variable in each region. Partitioning is executed at each step in the tree by finding the variable that locally maximizes the increase in homogeneity, as measured by the Gini impurity.[17] The advantage of decision trees is that they can model interactions without pre-specification by the analyst. A short-coming of decision trees is that they can overfit data, i.e. find signal where there is actually noise. To overcome this, we apply gradient boosting (Friedman, 2002), a model averaging algorithm which combines the output of a large number of trees.[18]

For a topic mapping m and an economist i, the procedure above produces a series of probabilities we call $\zeta_{i,t,m}$ which are the topic-specific probabilities that author i is a right-leaning economist. To produce a final prediction for an author, we aggregate across these topic-specific probabilities by taking a weighted average:

$$\widehat{\theta}_i = \frac{\sum_t P_m(Topic = t|author = i)\,\zeta_{i,t,m}}{\sum_t P_m(Topic = t|author = i)}$$

where the weights are $P_m(Topic = t|author = i)$, or the probability that author i writes about topic t under topic mapping m. We estimate $P_m(Topic = t|author = i) = \frac{1}{|G(i)|}\sum_{\{q|q\in G(i)\}} P_m(Topic = t|Paper = q, author = i)$ for all papers written by an author.

Predicted ideology values closer to zero are associated with a left-leaning ideology and values closer to one are associated with a rightward lean. To get back to the $[-1, 1]$ range, we transform $\widehat{\theta}_i$ by multiplying by two and subtracting by one. For example, if $\widehat{\theta}_i$ = .5, we multiple this number by 2 and subtract 1, returning the value of 0. Thus, our ideology scores are centered in theory at 0 with a maximum value of 1 and minimum value of -1.

[17]The Gini impurity is computed as $1 - \sum_j p_j^2$, where p is the proportion of economists of ideology j. The index is minimized when a variable perfectly splits economists into two different subspaces.

[18]We use the *lightgbm* package for the Python programming language and tune the following hyperparameters: number of trees, learning rate, and maximum depth.

3 Validation

We assess the performance of our prediction model by computing the area under the receiver operating curve or the AUC (Fawcett, 2006) which can be interpreted as the probability that our classifier will rank a randomly chosen right-leaning author higher on our partisan scale than a randomly chosen left-leaning author. An AUC of one indicates that the classifier can perfectly separate left- from right-leaning authors, an AUC of 0.5 means the classifier does no better than random guessing, and AUCs below 0.5 imply the model actually does worse than random guessing.

Table 3 shows that all topic adjustment specifications are able to predict ideology better than random chance with AUCs ranging from 0.718 ($JEL1$) to 0.690 ($NoTopic$). We also find that topic adjustments improve predictive accuracy, likely due to the ability to pickup changes in the sign of the correlation between language and ideology across fields.[19] The maximum correlation between predicted and groundtruth ideology is 0.368. For comparison, the out-of-sample correlation reported by Gentzkow and Shapiro between their ideology measure and one obtained from another source of newspaper slant was 0.40.

For further insight into how well our model generalizes, we use data from Gordon and Dahl (2013) to compare our predicted and groundtruth ideologies to responses provided by economists for a survey conducted by the Chicago Booth School of Business through October 30, 2012. The panel sets out to capture a diverse set of views from economists at top-ranked departments in the United States. Each question asks for an economist's opinion on a particular statement. The questions reflect issues of contemporary and/or long-standing importance such as taxation, minimum wages, or the debt ceiling. Valid responses are: Did Not Answer, No Opinion, Strongly Disagree, Disagree, Uncertain, Agree, Strongly Agree.[20] Of importance here is that Gordon and Dahl (2013) categorize a set of questions where agreement with the statement implies belief in 'Chicago price theory' and disagreement implies concern with market failure. The former of these also implies a rightward lean while the latter is consistent with left-leaning beliefs. While Gordon and Dahl (2013) found no evidence of a conservative/liberal divide in the survey responses, we find a significant correlation between the responses and

[19] Across all topic mappings and topics, there were 24,390 phrases that made it past the χ^2 significance filter. Of these, 15,672 appeared in multiple topics. When we look at these multi-topic phrases, we see that 32.3% (5,070) were correlated with right-leaning ideology in one topic and correlated with left-leaning ideology in another topic.

[20] For further details on the data see Gordon and Dahl (2013) and Sapienza and Zingales (2013). The latter show that the IGM panel answers to the questions are different from the answers of a random sample of the public.

our predicted ideologies. We also know the groundtruth ideology of 20 members on the panel and the correlation between groundtruth ideologies and survey responses is also significant. Figure 1 shows binned scatterplots, following recent methods proposed by (Cattaneo et al., 2022a), from a linear probability specification, conditional on question fixed effects, for each of our 4 ideology measures. There is a clear correlation between the predicted ideology scores and the IGM-based measure of partisanship.

In order to examine this more formally, Table 4 further presents results from logit and ordered logit regressions of the following form:

$$Pr(response_{i,j} = C) = \Lambda(\beta_1 \widehat{\theta}_i + \delta_j) \tag{1}$$

where Λ is the logistic link function. In the logistic version (columns 1-3), $response_{i,j}$ is a binary variable indicating whether the panelist agreed with the conservative viewpoint or not.[21] In the ordered logistic version (columns 4-6), the response variable is coded with the following order: Strongly Disagree, Disagree, Uncertain, Agree, Strongly Agree.[22] As seen in Table 4, the coefficients between our predicted ideology variable and the conservative viewpoint are all in the expected directions and all are significant. Across all the different topic adjustments, the logit and ordered logit results in Table 4 show a significant positive relationship between our predicted ideology variables and the probability of being in an increasingly conservative category. Columns 3 and 6 add the same controls as Gordon and Dahl (2013), which are the years of the awarding of a Ph.D. and the indicator variables for Ph.D. institution, NBER membership, gender, and experience in federal government.[23]

Finally, we present evidence that our predicted ideologies are primarily a function of individuals, not journals or time. We rerun our prediction model to produce predicted ideologies for each paper rather than each author.[24] We then decompose the variation across these paper-level predicted ideologies for each author into an author fixed effect, a journal fixed effect, and a time fixed effect, following recent work using matched worker-firm data. For each article (co-)written by author i, in journal j, published in year t we model ideology θ as additively separable, estimating:

[21] Uncertain, No Opinion, and Did Not Answer responses where dropped for the binary logistic analysis.

[22] No Opinion and Did Not Answer responses were dropped for ordered logit analysis.

[23] As an additional validation exercise, we run our algorithm on a corpus of editorials written by Israeli and Palestinian authors and show that we can achieve high prediction accuracy in classifying who wrote them. We discuss our performance relative to other political scaling methods more completely in our companion paper Jelveh et al. (2014).

[24] The paper-level prediction algorithm uses paper-level phrase counts, F^{train}, to predict paper-level ideologies.The

$$\widehat{\theta}_{ijt} = \delta_i + \delta_j + \delta_t + \epsilon_{ijt} \tag{2}$$

We restrict attention to articles published in journals with at least 50 articles, and include indicators for each co-author for co-authored articles. Under this additive separable assumption on the determinants of article slant, the variance of predicted ideology can be decomposed into the share explained by individual authors, the share explained by journals, and the share explained by time, along with covariances across these terms. Figure 2 shows that across measures of θ, the variance is most explained by individual author fixed effects. We also show while explained variance is less than 50%, journals only explain 10-15 percent, while individual authors explain 20-25%, and the rest is explained by the covariance of authors and journals, which suggests sorting of authors to journals along predicted ideology. The fact that individual authors explain the majority of what can be explained raises our confidence that we are recovering an individual measure of ideology, given that our original training data was individual political behavior.

We can also use this specification to examine the contribution of journals to predicted article ideology. Figure 3 shows the resulting estimates of δ_j correspond to existing estimates of political ideology across journals. Davis et al. (2011) survey economists and ask them their favorite journal along with a assessment of their free-market orientation, and then score journals by the mean free-market orientation of the economists that rank them as favorite. On the sample of our journals that overlaps with theirs, their measure of “free-market orientation" largely agrees with our predictions of conservative ideology, with a Spearman correlation of 0.87. For example, our most left wing journal fixed effect comes from “The Journal of Post-Keynesian Economics", and our most right wing journal is “Public Choice", which is exactly the lowest and highest free-market score, respectively, assigned by Davis et al. (2011).[25] The Journal of Political Economy is the most conservative out of the “Top 5" journals, and the Journal of Law and Economics (a generally conservative field historically, see Ash et al. (2022)) is among the most right wing journals. Labor and development economics journals, and non-English-language journals, on the other hand, tend to be more left-wing. These fixed effects could be reflecting either sorting of authors to journals or causal effects of journals, and we do not attempt to disentangle

[25] The “Journal of Feminist Economics" has the lowest free-market score assigned by Davis et al. (2011) but it is not in our sample.

them here, but just note that the journal fixed effects are intuitively plausible and accord with prior research, raising confidence in our methodology.

Most relevant for the rest of the paper, the fact that individual authors fixed effects explain the bulk of the variation in predicted article ideology, rather than year or journal, suggest that our predicted ideology is primarily determined by authors, rather than secular changes over time or journals.

4 Sorting by Professional Characteristics

We link CVs of economists to our predictions and document cross-sectional patterns of predicted ideology. We start by first describing these descriptive patterns of ideology across fields of economics as well as school and career characteristics. We collect data from CVs of economists at top 25 departments and top 10 business schools in Spring 2011. We collect year and department of Ph.D. and all subsequent employers, nationality and birthplace where available, and use self-reported field of specialization. Looking at self-declared primary fields, we examine labor economics, public economics, financial economics (including corporate finance), international economics, and macroeconomics as determinants of political behavior, as these are among the most policy relevant fields in economics, but we also examine a number of other fields. We classify each department as saltwater or freshwater or neither following Önder and Terviö (2015). An economist is saltwater or freshwater if either went to grad school, had their first job, or had their current job at a saltwater school (i.e.situated on the west or east coast) or at freshwater school (i.e. situated in a city by one of the Great Lakes). A saltwater school is likely to be more liberal than a freshwater school.

We are interested to see if there are significant correlations between predicted political ideology and field of research. Note that while our ideology predictions account topics, self-reported fields of individuals vary independently of topic-adjusted predicted paper ideologies. Secondly, we are interested in institutional affiliations. We construct a variable for being at a business school, a Top 5 department (Harvard, MIT, Stanford, Chicago, and Princeton), as well as our indicator for “freshwater" and “saltwater" schools. Finally, we consider a set of demographic and professional characteristics such as Latin American origin (measured by undergraduate institution), European origin (measured by European undergraduate institution), and doctoral degree year, years between undergraduate degree and economics Ph.D., and number of different employers per year since obtaining a Ph.D.

We then look at the correlation between predicted author ideology and various CV characteristics. The estimating equation is:

$$\widehat{\theta_i} = \sum_F \delta_F F_i + \gamma X_i + \delta_{phd(i)\times Year} + \epsilon_i \tag{3}$$

Here $\widehat{\theta_i}$ denotes predicted ideology, F_i is a set of indicator variables for different fields of economics, X_i is a vector of other economist characteristics. We also include fixed effects for Ph.D. institution of economist i interacted with year, to see if the correlations remain robust within Ph.D. cohorts. Standard errors are clustered at the department level. We vary this specification with different sets of controls, including department fixed effects, university fixed effects (there are 15 business schools in the same university as economics departments in our sample).

Figure 4 summarizes the results from the baseline specification for the CTM100 measure of ideology, although as we show in Appendix A.7 results are extremely similar for all the other topic adjustments. We see that the fields of finance, macroeconomics and industrial organization are more conservative, while labor is considerably more liberal than the average. Other fields, such as history and international trade, show less political valence. We further see that faculty at business schools are more conservative, as are professors affiliated with “freshwater" schools, while “saltwater" schools have a left-wing bent. Professors of European origin also seem to be somewhat more conservative, and there seems to be no association with Latin American origin, full professor rank or Top 5 department ranking.

The finding that both the finance subfield and business schools tend to attract (or influence) economists with more conservative predicted ideology is interesting in light of the patterns documented in Fourcade et al. (2014), who show that there has been a pronounced increase in economists with business school affiliations as well as in the importance of financial economics as a subfield within economics over the past few decades. These two trends, together with the political preferences documented here, may have contributed to the perception that economics is a “conservative" field.

The magnitudes of all these coefficients should be interpreted as changes in the predicted probability of an economist being right-leaning. For example, a coefficient of 0.2 indicates that the author was 10 percentage points (20 divided by the 2 that we rescale all the ideology scores by) more likely to be classified as a Republican by our prediction algorithm.

We also find that predicted ideology is persistent within individuals. As documented more fully in Table A.9, we split authors' writings chronologically by their first and second 50% of publications. We then predict ideology separately for each set of publications, and find that the correlation between early predicted ideology and late predicted ideology is quite high. We use this below to isolate “early career" ideology as less likely to be influenced by the results of research.

5 Ideology and Policy Elasticities

Part of economists‘ influence on policy is arguably its quantitative precision. Economic theory identifies important empirical estimates that in turn imply particular optimal policies. Introductory microeconomics teaches thousands of students every semester about supply and demand elasticities, and how knowing the magnitude of the relevant elasticity tells you about the economic incidence of various policies. Economic literatures have thus developed around key empirical estimates of behavioral responses to policy. These elasticities are then used to argue, either formally or informally, for various policies. For example, the labor demand elasticity for low-wage workers can tell policy makers what are the costs and benefits of the minimum wage and empirical fiscal multipliers gauge the efficacy of government stimulus spending. Various government agencies, such as the Congressional Budget Office, the Federal Reserve, and the Federal Trade Commission actively incorporate empirical economic research into policy evaluations.

This marriage of economic theory and data is well-articulated, again, by Stigler:

“In general there is no position, to repeat, which cannot be reached by a competent use of respectable economic theory. The reason this does not happen more often than it does is that there is a general consensus among economists that some relationships are stronger than others and some magnitudes are larger than others. This consensus rests in part, to be sure, on empirical research." (Stigler, 1959).

An important question, therefore, is whether predicted author political ideology predicts the magnitude of an elasticity reported in a published paper in these policy relevant literatures. If it does, it may suggest that economists are selecting into methods or implementations of methods (e.g. p-hacking, see Brodeur et al. (2020)) that yield elasticities consistent with political beliefs. Of course, there is a possibility of reverse causation, whereby economists who discover elasticities that suggest that market interference is highly costly are moved to contribute to the Republican party or become conservative on other issues as well. It is very difficult to causally identify any effect of predicted political ideology on empirical estimates, as any exogenous shock to partisanship could also influence the decision to be an economist, as well as the selection into what field of economics to work in. Therefore, we limit ourselves to a descriptive analysis, and discuss mechanisms below. In a robustness exercise below, we mitigate endogeneity concerns by using only ideology predicted from the first 50% of an author's papers.

We select policy-relevant elasticities drawing on Fuchs et al. (1998) (henceforth FKP). FKP survey labor and public finance economists about their views on politically salient policies and parameters. FKP estimate the correlation between policy preferences and beliefs about relevant economic parameter values. For example, estimates of the empirical effect of unions on productivity might influence preferences towards increased unionization. Similarly, the female labor supply elasticity may influence the desirability of increasing Aid to Families with Dependent Children. The mapping between estimates and policies, as well as the partisan leaning, is provided in Table 5. There is one elasticity, the labor demand elasticity, that FKP did not assign to a clear policy, and consequently we denote it as "not-policy" relevant.

We focus on estimated rather than calibrated or simulated parameters, which are mostly from the labor economics literature, as these are more comparable and studied in meta-analyses. We then looked through the literature for meta-analyses of these parameters, obtained the data from the authors where available, and then merged each estimate's authors with our predicted slant measures. The list of meta-analyses is also in Table 5. In addition, we obtained a number of other meta-analyses from the meta-analysis archive maintained at Deakin University by Chris Doucougliasis, enabling a placebo exercise where we check the correlation between predicted author ideology and non-policy relevant parameters.[26] We expect the correlation between predicted ideology of the authors and policy-irrelevant parameters to be insignificant.

Meta-analyses necessarily rely on the judgments of the authors about what to include and what to exclude.[27] With such diverse literatures, we take the datasets of estimates as they are, and do not

[26] At http://www.deakin.edu.au/buslaw/aef/meta-analysis/, accessed March 6, 2016.

[27] Andrews and Kasy (2017) examines the econometrics of meta-analyses rigorously, and develop tests for publication bias, finding that publication bias in the minimum wage literature cannot be rejected.

process them extensively. One exception is the female gender gap, where the literature reports both the total gender gap as well as the unexplained gender gap. We construct the measure of gender wage discrimination to be the ratio of the unexplained gender wage gap to the total gender wage gap, to better account for idiosyncracies in choices of control variables.

There are often many estimates from a single paper. When standard errors are provided, we weight estimates by the inverse of the standard error, otherwise we take the simple average of estimates. These give a single estimate from each paper. We show robustness to unweighted estimates below. We adjust the sign of each estimate so that higher is more conservative, following FKP, and present these adjustments in Table 5.

Meta-analyses may have distributions of estimates that are skewed, multi-modal, or truncated (as shown in Andrews and Kasy (2017)) and so our primary measure is the rank of the coefficient within the category (multiplied by 100). Category refers to the policy-relevant literature (e.g., the effect of changing the minimum wage on employment). We also look at a binary indicator for a coefficient being greater than the median in its category. Finally, in order to give quantitative interpretations to our point estimates, we also normalize each paper-level estimate within the survey paper, taking the Z-score of its value using the mean and the standard deviation of the elasticities reported in the survey paper.

As many estimates have multiple coauthors, we average the predicted author ideology, only for the authors for whom we are able to predict ideology (i.e. they have enough papers in our JSTOR and NBER corpus), to construct an estimated average author ideology for each paper. Unfortunately, this means that for some papers we only have predicted ideology for a subset of the authors, but Appendix Table A.14 shows that this missing predicted ideology does not seem correlated with either average predicted ideology of the coauthors we do have in our sample or with the magnitude of the FKP parameter estimates. Let β_{ps} denote the elasticity measure (rank, greater than median, or standardized) from paper p in survey paper s. Our baseline regression equation is given by:

$$\beta_{sp} = \gamma\overline{\theta_p} + \delta_s + \epsilon_{sp} \tag{4}$$

where $\overline{\theta_p} = \frac{1}{|N_p|}\sum_{i \in N_p} \widehat{\theta}_i$ is the mean predicted ideology of the N_p authors of paper p from our methodology above. δ_s is a meta-analysis fixed effect, which will be included in all specifications, and

ϵ_{sp} is an error term. We illustrate the basic variation using binned scatter plots in Figure 5, which shows that there is a strong correlation between our ideology measures and the coefficient rank, adjusting for meta-analysis fixed effects. This is true across our different topic adjustments, and in fact there is a positive correlation between groundtruth ideology and coefficient estimates.

One piece of evidence that our topic adjustments are indeed picking up fields of research is that the correlation between the topic-adjusted slants (JEL1 or CTM100) and the coefficients is larger than without topic-adjustments; if our results were driven solely by sorting across subfields then the coefficient would shrink.

An issue arises from the generated nature of our independent variable, which, at a minimum, could bias our standard errors downwards (Murphy and Topel, 2002) and also could attenuate the coefficient towards 0. As is common in high-dimensional prediction, our algorithm does not yield a straightforward standard error on the prediction. While a standard solution would be to bootstrap the whole procedure, the computationally costly prediction algorithm makes the bootstrap impractical. We instead examine robustness to a split-sample instrumental variables procedure discussed below that will account for biases due to prediction error in both the coefficient as well as the standard error. The bias of OLS vs IV in this case depends on an untestable assumption on whether the prediction error is uncorrelated with the truth (classical error requiring IV) or uncorrelated with the mismeasured variable (in which case OLS is unbiased, but the standard errors are too small). That our estimates are qualitatively similar in both cases is thus reassuring.

Table 6 shows estimates of γ, the coefficient on mean predicted author ideology, from equation (4). Panel A shows results for the CTM30 adjustment, Panel B for CTM100 adjustment, and Panel C for JEL1 adjustment. Column 1 shows results with coefficient values as outcome variables, with signs adjusted as described above. Column 2 shows results with the coefficient rank as the outcome variable, while column 3 shows γ when the outcome is the binary indicator variable for a high coefficient. Column 4 shows the standardized coefficient as the outcome (standardized to be a unit normal within the meta-analysis). All estimates are positive and significant.

One way to make sense of these magnitudes is to consider tax policy and the taxable income elasticity as a particular example. Building on Saez (2001), Diamond and Saez (2011) suggest top tax rates of $\tau^* = \frac{1}{1+1.5\times\epsilon}$, where ϵ is the taxable income elasticity of top income earners. The mean of the Chetty et al. survey on the labor supply elasticity is 0.31, suggesting a top tax rate of 68%. However, the mean ideology among people who estimate taxable income elasticities in this sample is more left than average (e.g. -.22 in JEL1 adjusted ideology), but researchers in this area also exhibit a considerable range of ideology, from -0.66 to 0.55. Using our estimates from column 1 row 2 of table 6, moving from the most left wing to the most right wing within this sample would change the elasticity by .35 points, changing the optimal top tax rate from 84% to 58%. Extrapolating to the most liberal ideology of -1 to the most conservative ideology of 1, we end up with optimal tax rates from 96% to 52%. While 52% is still a high tax rate (resulting from the small elasticities uniformly found in the literature, even by conservatives), this result shows that same standard optimal taxation formula may yield quite different prescriptions depending on the estimate, and so if partisanship is correlated with estimates, the implied policy prescription will depend on the researcher producing the elasticity.

For comparison, Panel D shows results with the groundtruth measure of ideology. While all the coefficients are positive and comparable in magnitude to the results in Panel A, the sample of elasticities is, at N=31, quite small, and the resulting standard errors make the estimates insignificant at conventional levels. This shows the utility of our text-based measure: with only the groundtruth measure constructed from campaign contributions and petition signings we would not be able to predict the ideology of very many economists, but using the groundtruth measure together with academic text allows us to predict ideology for many more economists, and thus expand the sample used in this regression considerably.

We examine robustness to a variety of specifications, shown in Table 7 for the coefficient rank and the correlated topic model adjusted ideology prediction. Column 1 in these tables includes fixed effects for each category of estimate (e.g., labor supply elasticity) interacted with 5-year bin indicators for publication date, in order to capture observed heterogeneity in methods, data, or simple improvements in estimates over time. Column 2 uses a measure that ignores the standard errors attached to estimates, and instead uses the simple unweighted average of estimates within a paper. Column 3 adds an indicator variable for whether the estimate was obtained on US data. While US estimates seem to be in a more conservative direction, the effect of predicted author ideology remains statistically significant with all three measures (albeit sometimes at only 10% significance).

In column 4, we restrict attention to predictions made using the first 50% of papers written by authors to minimize reverse causality running from empirical results to predicted ideology. These predictions are necessarily going to have more error, as they use less of the available text for each economist. Indeed, 5 papers (out of 197) in our sample are lost as none of the authors have enough text in the first 50% of their writings to estimate ideology. Nonetheless, the results remain positive and statistically significant despite the attenuation we would expect from the additional prediction error. In column 5, we omit any papers that have an author that is in the groundtruth sample, and the similarity of this coefficient to the rest of the table indicates that our results are not driven by the groundtruth subsample.

In column 6, we adapt split-sample instrumental variables to deal with possible prediction error in our main estimates. As discussed above, while this instrumental variables strategy does not handle endogeneity, it can address prediction error that is important to the generated nature of our independent regressor. Because our independent variable is a prediction of ideology, it has an error, akin to measurement error that attenuates the true regression slope towards zero. We split each author's writings into two random samples and predict ideology in both. Under the assumption that prediction error is orthogonal to the true ideology, then using the ideology in one sample to instrument for the ideology in the other sample will eliminate the resulting attenuation bias. Formally, if the true second stage equation is (4), but we have prediction error in the main independent variable, we will have:

$$\overline{\theta_p} = \overline{\theta_p^{True}} + \eta_{sp}$$

where η_{sp} is the mean prediction error, $\eta_{sp} = \frac{1}{|N_p|}\sum_{i \in N_p} \eta_i$, akin to measurement error. And even if η_{si} is uncorrelated with either the true value of the independent variable or any omitted variable, the estimated coefficient $\widehat{\gamma}$ will be attenuated by the well-known factor $\frac{var(\overline{\theta^{True}})}{var(\overline{\theta^{True}})+var(\eta)} < 1$.[28] Thus our coefficients will be too small, relative to the true value.

Our IV strategy mitigates this problem. We split the words used by each author into two equally-sized random samples, and estimate two separate, independent predictions of ideology, $\overline{\theta_p^0}$ and $\overline{\theta_p^1}$, where 0 and 1 refer to the 2 random samples. Unsurprisingly, these measures are highly correlated with each other. To show that the IV eliminates the influence of prediction error, we write the relationship

[28] Even though our groundtruth measure is a binary measure, our prediction is continuous, so the measurement error can still be classical, which would not be the case if our prediction was binary.

between the predictions from the subsamples and the true value as:

$$\overline{\theta_p^g} = \overline{\theta_p^{True}} + \eta_{sp}^g, g = 0, 1$$

where η_{sp}^1 is independent of η_{sp}^0. We then use the $g = 1$ prediction as an instrument for the $g = 0$ prediction. Keeping the covariates δ_s implicit, this results in an IV coefficient given by:

$$\gamma^{IV} = \frac{Cov(\beta_{sp}, \overline{\theta^0})}{Cov(\overline{\theta^0}, \overline{\theta^1})}$$

$$= \frac{Cov(\gamma(\overline{\theta^{True}}) + \epsilon, \overline{\theta^0})}{Cov(\overline{\theta^0}, \overline{\theta^1})} = \gamma \frac{Var(\overline{\theta^{True}}))}{Var(\overline{\theta^{True}})} = \gamma$$

since ϵ is independent of η^1 and η^0 (which are also independent of each other). We can see the gain from the IV strategy by focusing just on the results for the CTM 100 adjusted models in Table 7. As we hoped to achieve by the IVs, the first-stage F-statistic is unsurprisingly extremely strong, and the coefficients are generally 20% larger than the OLS estimates, with slightly larger standard errors. This serves as additional confirmation that the error in our prediction is random rather than systematically correlated with observable or unobservable variables.

Finally, in column 7 we conduct an identical exercise using “non-policy-relevant" elasticities, described above. These elasticities are beta convergence in cross-country growth regressions, the value of alternative fuels, the effect of institutions on growth, the value of recreational area, and the labor demand elasticity. We again calculate rank within each category of elasticity and estimate the correlation with mean author ideology. We find no significant correlation between predicted ideology and these elasticities, and the point estimates are an order of magnitude smaller than the same specification estimated on the “policy-relevant" elasticities.

While these robustness results are reassuring, they by no means exhaust the space of specifications and measures. Rather than show tables for every specification and every variant of our dependent and independent variables, we show the specification curve (Simonsohn et al., 2020), a procedure to explore the sensitivity of results to modeling choices, in Figure 6. For each of 9 specifications, we estimate the specification using 6 different measures of ideology, 4 different outcomes (coefficient, binary, rank, and standardized coefficient) as well as 2 weighting schemes (coefficients within a paper averaged with inverse of standard error where available or not). The 9 specifications include 3 sets of covariates (controlling for category X 5-year fixed effects, an indicator for US estimate, and no covariates except meta-analysis fixed-effects), crossed with 3 identification strategies, OLS, split-sample IV, and the early measure of ideology only). The solid plot shows the coefficient on γ from all 324 specifications generated by the above 5 specifications, excluding the placebo and including the main specification from Table 7, ordered by magnitude.

For performing inference, we shuffle the independent variable randomly across observations 100 times to create 100 different datasets. For each data set, we estimate each of the 324 specifications. This procedure gives us the distribution of specification curves under the null hypothesis. The bars on Figure 6 show the 5% confidence intervals for each specification. We test across all specifications jointly by counting the fraction of the 100 samples for which the estimated coefficient is greater than the median from the truth, the fraction that have more specifications with positive coefficients, and the fraction with more positive and significant coefficients. Across all of these statistics, less than 1% of randomized samples exhibit a higher coefficient than our chosen specifications. While there are some specifications that do not exceed the 95% percentile across the shuffled datasets, these are sufficiently rare across all the 432 specifications that the tests of joint significance can rule out misspecification at 99% confidence.

Finally, as another check on the general validity of our estimates, in Figure 7 we show results from dropping each category of elasticities one at a time, in order to confirm that no one set of elasticities is driving our result. Across our different ideology predictions, the correlation between mean author predicted ideology and average reported elasticity generally remains significant (or nearly so) at 5%, regardless of which category is dropped.

5.1 Assessing Mechanisms and Threats to Validity

The evidence supplied in this section, as we have stressed, is correlational. In this subsection, we assess the evidence for various interpretations of the correlation between elasticities and predicted partisanship.

Reverse Causality: A natural concern is that our estimates are driven by reverse causality, in that economists' personal political views are influenced by the results of their research. Our results above on gender point against this, although they may be contaminated, as discussed by omitted variables bias. Further, our results show the same correlation when ideology is predicted only from early papers. More tellingly, as Appendix Figure A.11 shows, predicted partisanship is remarkably consistent across estimates using the first 50% of an authors' papers and those using the second 50%. Consistent with a wide variety of evidence from political behavior (e.g. Sears and Funk, 1999; Kaplan and Mukland, 2011) , although see Peltzman (2019) for evidence that people become more Republican with age), this result suggests that very few economists have their predicted partisanship change over their lifecycle, suggesting that there is little evidence of researchers being “surprised" and changing their views.

Selection via Methodology: Another interpretation is that the choice of methodology is rationally a result of researcher priors. Imagine a researcher knows that journals only publish significant results, and must choose a methodology that is most likely to generate a publication. The researcher will choose a methodology most likely to generate a significant estimate, and this estimate will be correlated with their prior. While we cannot rule this out definitely, the robustness of our estimates to adjusting for topics suggests that this is not an immediate control. We examined results from the one elasticity in our sample that is estimated using a variety of methodologies, the labor supply elasticity. However, the sample is still too small to yield conclusive results.

Spurious Prediction: One concern is that the small number of economists who give contributions or sign petitions themselves sort into fields, topics, and methodologies that support those views, and that this induces predicted partisanship of the language used by all other economists. The strong correlation between predicted partisanship and the IGM scores done by Gordon and Dahl, and the fact that our scores reflect the same gender differences in partisanship found in survey data, suggest that our predictions are informative even for economists that do not contribute or sign petitions. A variant of this concern is that the language economists use in discussing results that may support left or right wing policies mirror the language of advocates for those policies, generating correlations between academic writing and career trajectories or empirical results that are spurious. However, we present all of our results using only our groundtruth data: the contributions or petition signings. The coefficient on predicted partisanship remains significant in these specifications despite a much smaller set of observations, suggesting that there is a correlation between political behavior and empirical estimates, independent of any text-based prediction.

Editor Political Preferences: Our results may be an outcome of the publishing process driven by the political preferences of editors rather than authors. In a previous version of this paper, we showed that even though predicted journal ideology and predicted editor ideology are highly correlated, once journal fixed effects are included, there is little correlation between predicted editor partisanship and predicted journal partisanship. This finding indicates that either authors themselves adapt their language, or a strong selection process that induces sorting jointly across editors, journals, and authors, as the source of the correlation between research findings and predicted partisanship.

Author Political Preferences: Our tentatively favored explanation is that many economists have political preferences that, consciously or not, may lead to particular empirical findings. At the end of the day, the lack of any clear exogenous variation in a highly persistent variable (e.g. predicted author ideology) makes it difficult to find a clean test. For example, any exogenous shock to lifetime partisanship is unlikely to be excludable, as it would likely affect many different professional choices, including the decision to become an economist in the first place. Further, we do not know to what extent the preferences are driven by personal preferences, versus preferences amplified by sorting into fields and methodologies. We leave the disentangling of these issues to future work.

6 Conclusion

There is a robust correlation between patterns of academic writing and political behavior. If in fact partisan political behavior was completely irrelevant to academic economic writing, then academic writing would be a very poor predictor of political ideology. However, our within-topic ideological phrases are not only intuitive, they also predict political behavior well out-of-sample, and even predict the partisanship calculated from completely unrelated Gordon and Dahl IGM survey data. The patterns of individual ideology we document are also of interest, as they suggest that there are in fact professional patterns of ideology in economics, across universities and subfields. Finally we show that predicted ideology is correlated with empirical results on policy-relevant elasticities. We cannot claim causal identification, however we believe our methodology for measuring ideology and the correlations we show between predicted ideology and academic outcomes are informative.

Our paper suggests that empirical results, particularly without credible and transparent research designs, cannot be assumed to resolve questions of economic interest if results are politically contestable and economists differ too in their politics. As in the literature on self-censorship and political correctness (Loury (1994), Morris (2001)), policy-relevant academic writing does not just reveal the results of research, but also implicit loyalties and beliefs. As academic economic articles have potentially multiple audiences, from specialists to general interest economists to policy makers and journalists, modeling the resulting trade-offs in choosing what to say and how to explain ideas, methods, and results could be a fruitful area of research (Andrews and Shapiro, 2021).

We have illustrated above how “ideological adjustments" can, as a first pass, be flagged by considering the sensitivity of implied elasticities to ideological preferences. More ambitiously, one potential route for combining theory with the empirical approach in this paper is to develop methods for “ideological adjustments" that incorporate the effects of sorting into summaries of parameter estimates, such as weighting results counter to a field’s average ideology more highly. One simple observation is that Bayesian updating of parameters will be slower if there is known ideologically driven reporting of estimates. However, we are skeptical that any purely technical solution to this fundamentally political problem can be found. Debates in economics about the extent of intervention in the market or the merits of various policies will not be resolved by better methodologies alone. A simpler alternative is to understand partisanship in economic arguments as part of the democratic process of policy making, and acknowledge that economics itself as not outside of politics.

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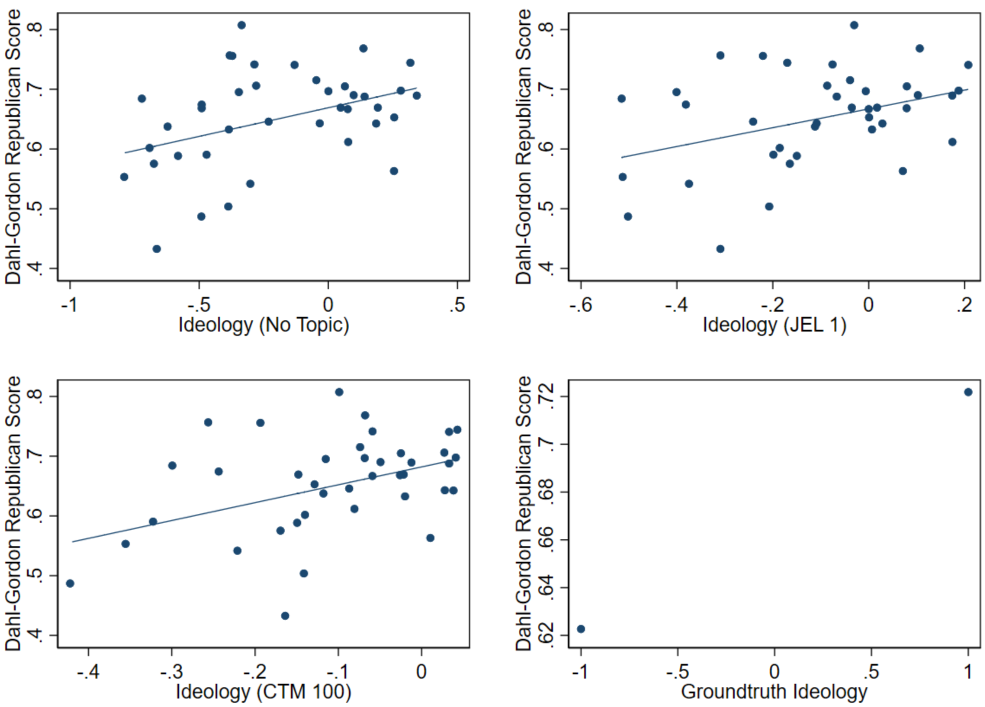
7 Figures

Figure 1: Partial Binned Scatterplots of Institute for Global Markets Responses on Predicted Ideology Measures.



Figures plot mean IGM conservative answers by ventiles of predicted author ideology, conditional on question fixed effects.

Figure 2: Variance Decomposition of Article-Level Predicted Ideologies

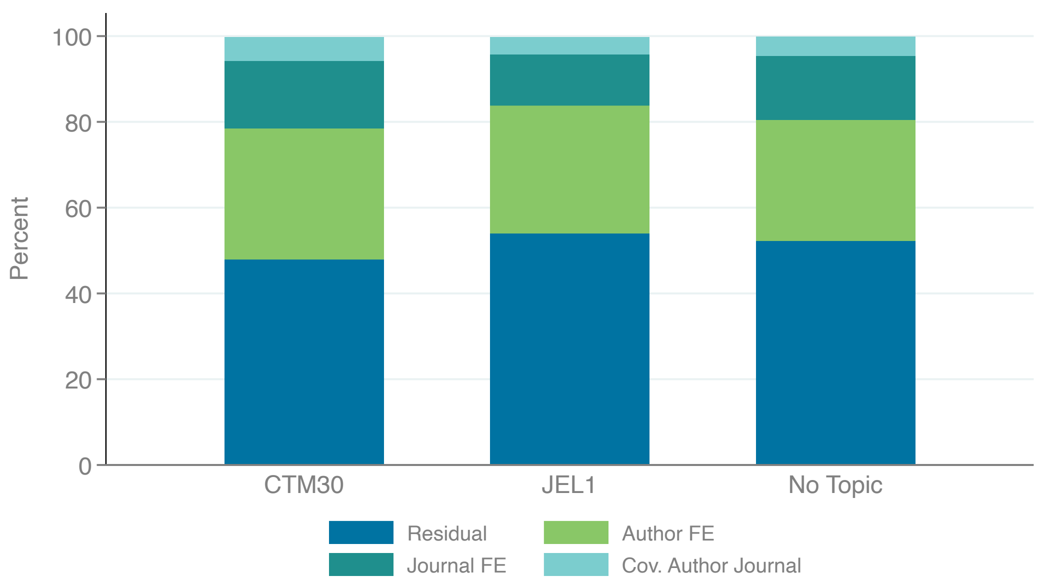


Figure shows variance decomposition of article-level predicted CTM-30 ideology under various topic adjustment into author, journal, and year components, together with covariances and the residual unexplained variation. Covariances between year and author and year and journal are too small to visualize and so are not labelled. Co-authored papers have each author fixed effect included.

Figure 3: Journal Fixed Effects on CTM-30 Predicted Slants

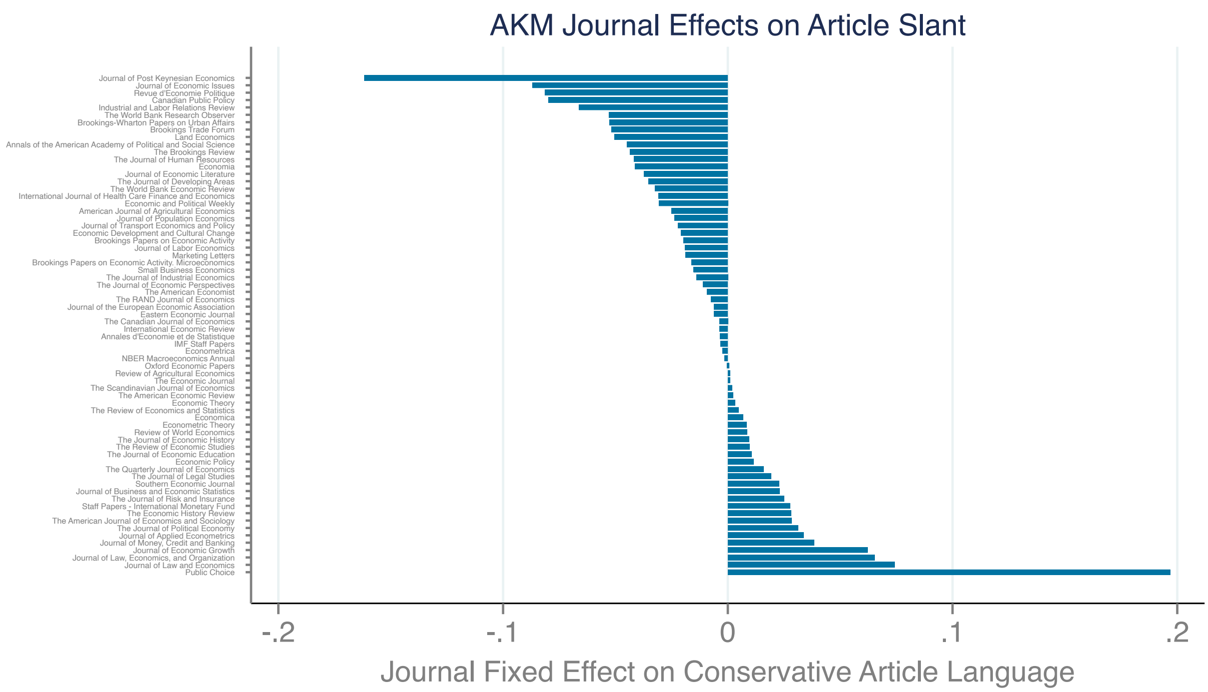


Figure plots journal fixed effects from regression of predicted article ideology using the $CTM-30$ topic adjustment on author, journal, and year fixed effects.

Figure 4: Regression Coefficients On Economist Characteristics

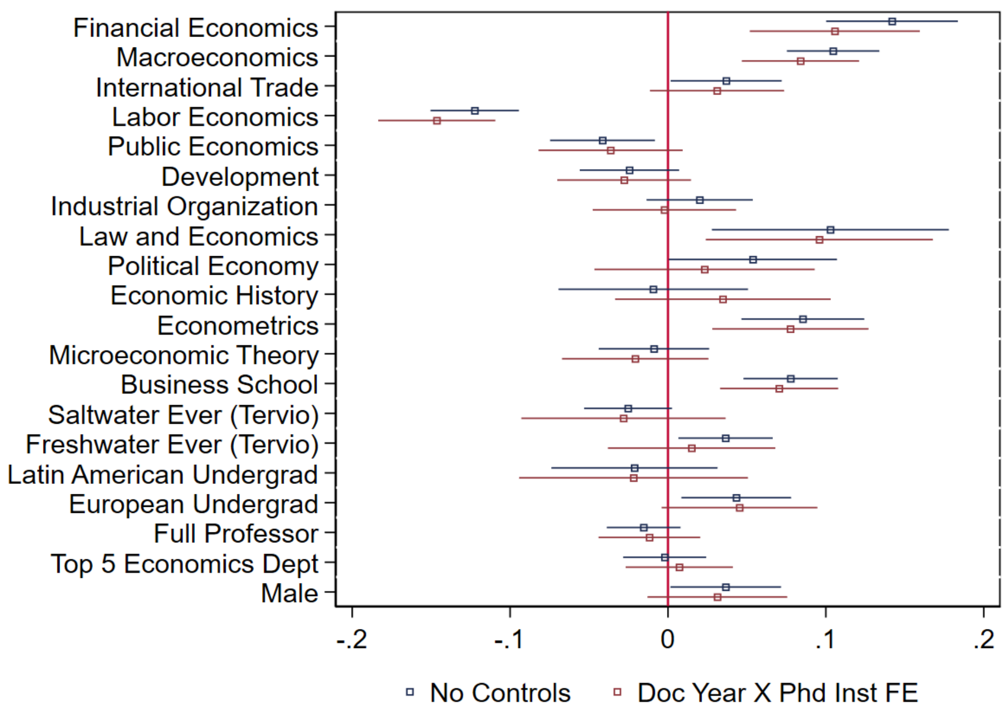
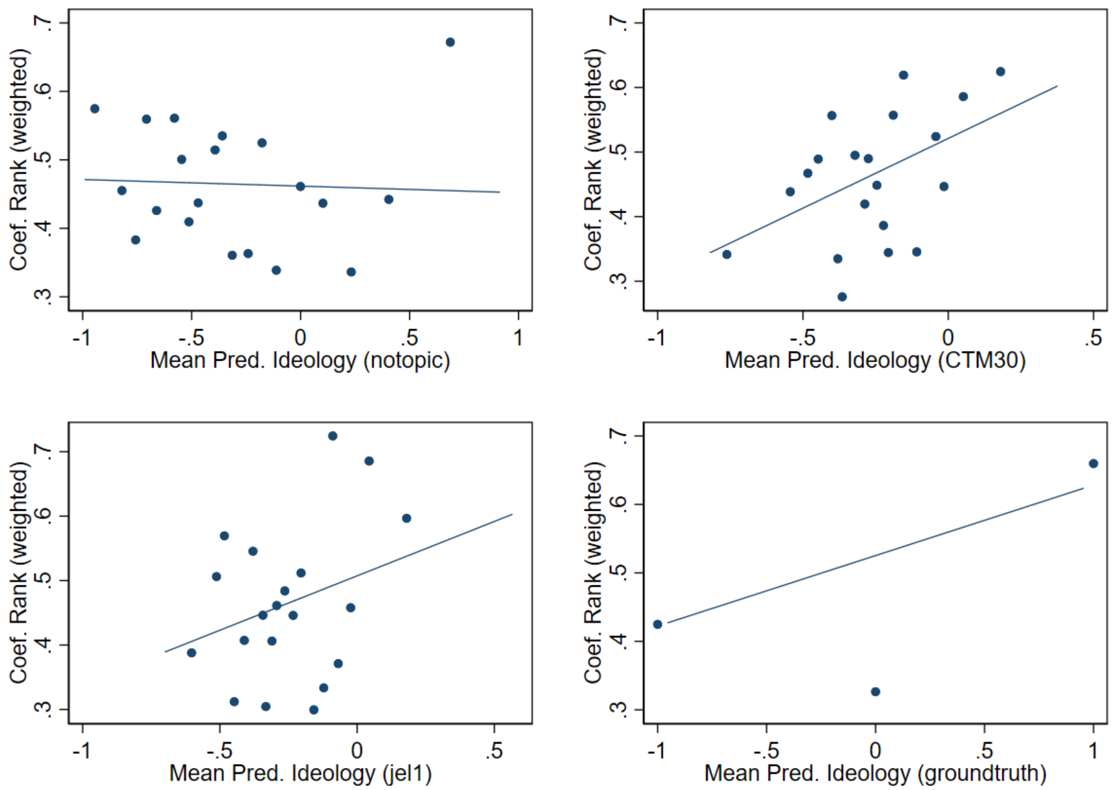


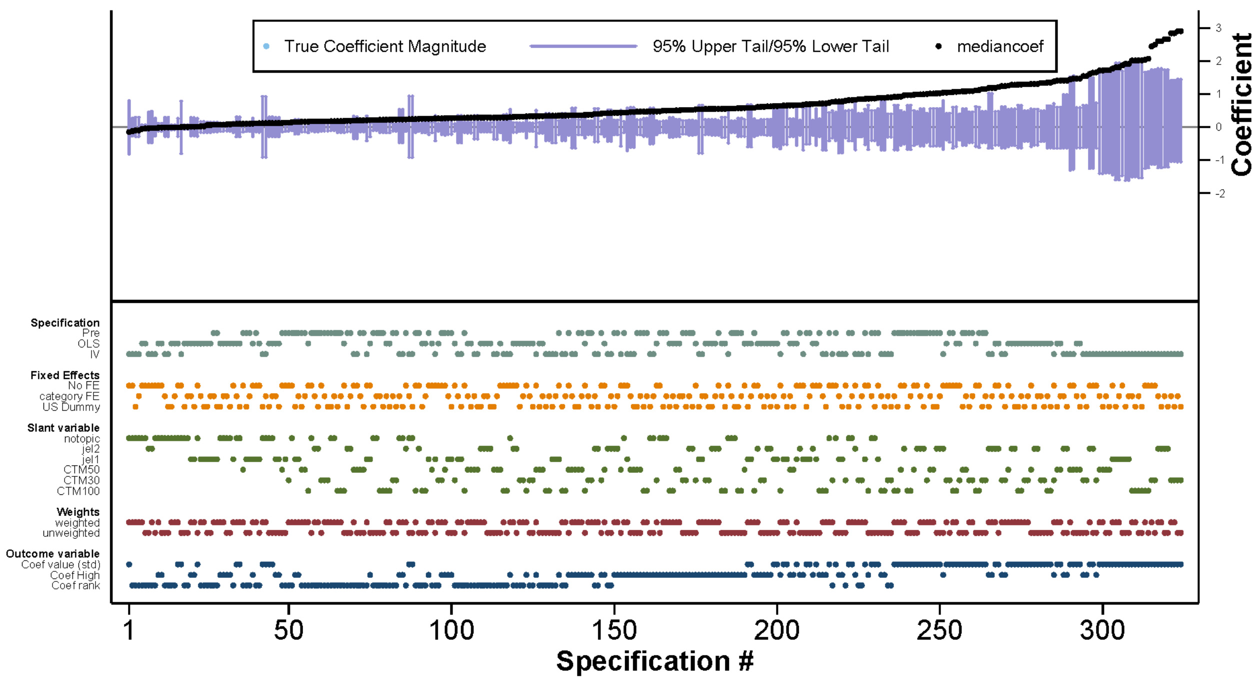
Figure plots coefficients and 95% confidence bands for coefficients on covariates from two regressions using the CTM-30 ideology scores as the outcome. Coefficients are similar for all other ideology measures. The bottom set of coefficients (brown) include no other controls, the top set of coefficients (blue)controls for 5-year interval when Ph.D. was obtained interacted with Ph.D. institution fixed effects.

Figure 5: Binned Scatterplots of Coefficient Rank Against Predicted Ideology (FKP elasticities).



Figures plot mean elasticity rank (within category) by vintiles of predicted author ideology, conditional on meta-analysis fixed effects.

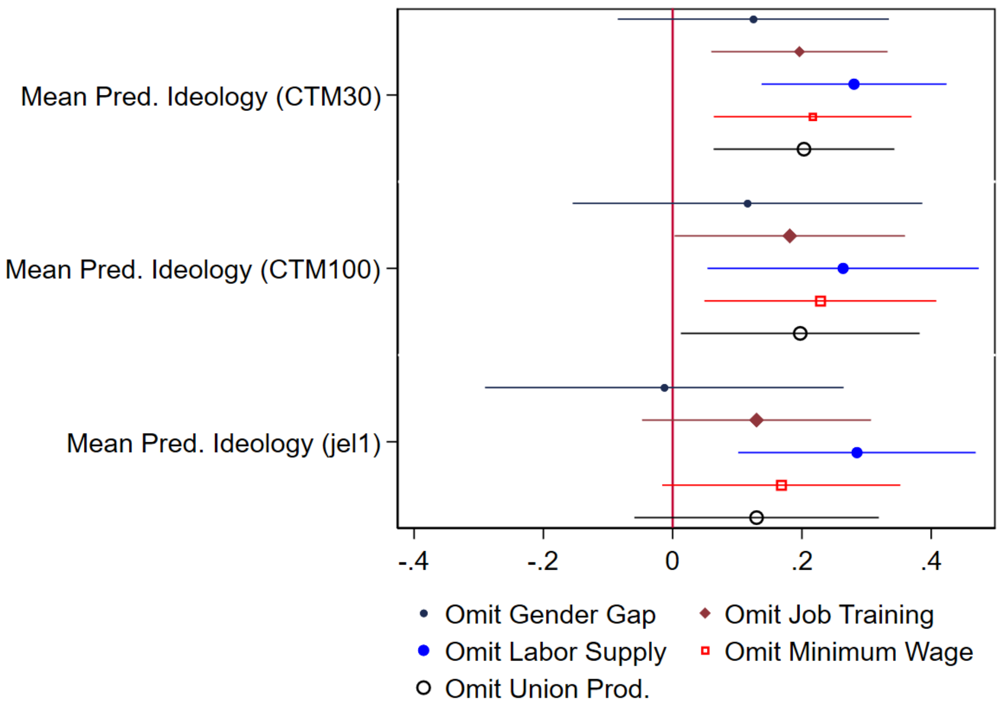
Figure 6: Specification Curve



Median Coef. = .47 (p<.01)
Share Positive = .95 (p<.02)
Share Positive and Sig at 95% = .39 (p<.01)

Coefficients from 324 different specifications shown, ordered by size. Bottom left corner shows statistics testing a) the probability that the median coefficient from a randomly shuffled sample is greater than the median coefficient, b) the probability that a randomly shuffled sample has at least the same share of positive coefficients as the true sample, and c) the probability that a randomly shuffled sample has at least the same share of positive and significant coefficients as the true sample.

Figure 7: Correlation of Coefficient Rank and Ideology Omitting Each Category of Elasticity



Each estimate shows correlation between predicted ideology measure and coefficient rank, omitting a category of elasticity. 95% confidence windows are shown, together with a vertical line at 0.

8 Tables

Table 1: Petition signing and campaign contribution patterns

		Petitions	
Contributions	Left-Leaning (-1)	Undetermined	Right-Leaning (+1)
Left-Leaning (-1)	164	0	0
Undetermined	0	0	0
Right-Leaning (+1)	0	1	73

This table shows the overlap between between our two “groundtruth" measures of ideology for the sample of economists with papers in our corpus who both signed petitions and made campaign contributions.

Table 2: Top Left- and Right-Leaning N-grams

Left-Leaning			Right-Leaning		
Unigram	Bigram	Other	Unigram	Bigram	Other
women	child_care	journal_post_keynesian_econom	vote	public_choic	unit_root_test
employ	post_keynesian	journal_econom_issu	hayek	rent_seek	public_choic_kluwer_academ
work	labor_market	labor_market_outcom	senat	stock_return	publish_print_netherland
wage	social_capit	public_polici_analys_politiqu	incumb	social_secur	journal_polit_economi
care	singl_mother	review_intern_polit_economi	tullock	path_depend	southern_econom_journal
famili	health_insur	minimum_wage_increas	rule	unit_root	london_school_econom_polit
social	low_wage	long_term_care	cartel	bond_price	journal_financi_econom
train	african_american	capit_account_liber	cigarett	life_expect	journal_monetari_econom
poverti	welfar_reform	singl_parent_famili	candid	median_voter	ludwig_von_mise
canada	minimum_wage	cambridg_journal_econom	grower	cite_note	cobb_dougla_product_function
mother	food_stamp	canadian_public_polici_analys	measur	major_parti	close_end_fund
forest	labor_forc	african_american_women	disclosur	child_labor	blackwel_publish_ltd
keyn	low_incom	earn_incom_tax_credit	tariff	pressur_group	journal_law_econom
union	industri_relat	human_resourc_practic	cattl	privat_properti	wall_street_journal
children	work_forc	labor_relat_review	legislatur	bank_japan	american_polit_scienc_review
global	poverti_line	child_care_subsidi	court	human_capit	test_unit_root
unemploy	treatment_group	meet_associ_evolutionari	voter	stock_price	springer_public_choic
caregiv	health_care	journal_human_resourcest	contract	properti_right	american_journal_econom_sociolog
manag	white_men	work_hour_week	politician	child_support	univers_texa_dalla
poor	low_skill	journal_post_keynesian	advertis	network_extern	impuls_respons_function
need	collect_bargain	industri_labor_relat	litig	life_insur	copyright_john_wilei_son
site	welfar_recipi	nation_research_council	dissip	brown_williamson	bid_ask_spread
hospit	sexual_orient	foreign_direct_invest	size	null_hypothesi	ltd_appl_econ
provinc	wage_inequ	dual_labor_market	rank	time_seri	social_secur_benefit
veblen	white_women	low_incom_famili	return	insid_trade	monetari_polici_shock
gender	labor_relat	labor_forc_particip	insur	journal_financ	line_item_veto
interview	work_er	long_term_care_insur	sport	henri_georg	journal_intern_monei_financ
arrear	rel_wage	monthli_review_press	legisl	sampl_period	journal_risk_insur
sector	race_gender	canada_unit_state	price	par_valu	review_financi_studi
plan	emploi_ment	brook_trade_forum	index	bond_rate	secur_exchang_commiss
cohort	new_orlean	tight_labor_market	hoover	signific_level	capit_labor_ratio
respond	food_expenditur	live_wage_ordin	elect	buchanan_tullock	digit_sic_industri
cent	cge_model	food_stamp_program	model	friedman_schwartz	overlap_gener_model
girl	statist_canada	journal_human_resourc	artist	congression_district	spot_exchang_rate
household	high_perform	treatment_control_group	payoff	firm_s	journal_polit_economi_august
employe	travel_cost	brook_paper_econom_activ	bond	gordon_tullock	smoot_hawlei_tariff
adult	live_wage	high_school_degre	shock	excess_return	journal_econom_dynam_control
migrat	worker_compens	sourc_author_calcul	contest	journal_law	brigham_young_univers
marx	black_women	health_care_financ	kodak	win_percentag	major_leagu_basebal
woman	critic_think	annal_the_american	beta	state_legislatur	journal_polit_economi_june

This table shows the top 40 unigrams, bigrams, and phrases with 3 or more words (Other) that are most associated with left-leaning and right-leaning ideology as measured by χ^2 values. To determine the directionality of a particular phrase, we computed the correlation between phrase counts and ideology. If this value was positive (negative), we defined that phrase to be right-leaning (left-leaning).

Table 3: Predictive performance of topic-adjusted prediction algorithm

Topic Map	Num Topics	AUC	95% C.I.	Correlation	95% C.I.
JEL1	19	0.718	(0.697, 0.736)	0.368	(0.333, 0.400)
JEL2	99	0.698	(0.677, 0.720)	0.332	(0.294, 0.367)
CTM30	30	0.714	(0.694, 0.734)	0.364	(0.330, 0.396)
CTM50	50	0.707	(0.688, 0.729)	0.354	(0.322, 0.390)
CTM100	100	0.704	(0.683, 0.723)	0.347	(0.312, 0.378)
NoTopic	1	0.690	(0.671, 0.712)	0.326	(0.293, 0.362)

This table presents the predictive performance of various topic mappings. Listed are (1) the topic mapping, (2) the number of topics in the mapping used for prediction, (3) the Area Under the Curve, (4) the bootstrapped confidence interval for (3), (5) the correlation between groundtruth and predicted ideology and (6) the bootstrapped confidence interval for (5). The number of bootstrap iterations to estimate the confidence intervals was 1,000.

Table 4: Correlation Between Predicted Author Ideology and Institute for Global Markets (IGM) Responses

	(1)	(2)	(3)	(4)	(5)	(6)
Groundtruth Ideology	0.274***	0.843***	15.61**	0.266***	0.393***	3.186***
	(0.0681)	(0.220)	(4.917)	(0.0640)	(0.0819)	(0.712)
JEL 1	0.961*	2.265*	2.387	0.727*	1.214*	1.071*
	(0.376)	(1.081)	(1.302)	(0.333)	(0.506)	(0.442)
JEL 2	1.372**	3.168**	4.327**	1.118**	1.901**	3.230***
	(0.453)	(1.223)	(1.671)	(0.406)	(0.621)	(0.604)
CTM 30	1.502**	3.270*	2.818	1.145**	1.607**	1.268*
	(0.493)	(1.370)	(1.579)	(0.399)	(0.593)	(0.546)
CTM 50	1.781***	3.960**	3.954*	1.430***	2.032***	2.060**
	(0.445)	(1.401)	(1.601)	(0.352)	(0.568)	(0.634)
CTM 100	1.915***	4.202**	4.276*	1.496**	2.212**	1.822*
	(0.553)	(1.562)	(1.958)	(0.464)	(0.738)	(0.718)
	(1)	(2)	(3)	(4)	(5)	(6)
No Topic	0.574***	1.393**	1.025*	0.572***	0.824***	0.866***
	(0.206)	(0.573)	(0.578)	(0.173)	(0.263)	(0.227)
Question FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	598	438	414	715	715	673
Individuals	39	39	37	39	39	37

Standard errors are clustered by economist. Controls include year of Ph.D., and binary indicators for gender, Ph.D. university, and any Federal government experience. Columns 1-3 are logit regressions predicting the author as conservative as coded by Gordon and Dahl (2013) (which omits neutral answers), while Columns 4-6 are ordered logit regressions using the 5 different levels of agreement with statements coded by Gordon and Dahl (2013) conservative (which includes neutral answers, hence the larger sample size). * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Fuchs et al. (1998) Elasticities, Meta-Analyses, and Political Orientations

Labor/Public	Type of elasticity	Surveys found	Usable data?	Policy Relevant	Political Orientation
Labor	Job Training	Card. et al. 2015	No	Yes	-
Labor	Job Training	Heckman et al. 1999	Some	Yes	-
Labor	Labor Supply	Bargain & Peichl 2013	Some	Yes	+
Labor	Labor Supply	Chetty et al. 2011	Yes	Yes	+
Labor	Labor Supply	McClelland & Mok 2012	Some	Yes	+
Labor	Labor Supply	Reichling & Whalen 2012	No	Yes	+
Labor	Minimum Wage	Neumark & Wascher 2006	Yes	Yes	-
Labor	Minimum Wage	Belman & Wolfson 2014	Yes	Yes	-
Labor	Union Productivity	Belman & Voos 2004	No	Yes	-
Labor	Union Productivity	Hirsch 2004	No	Yes	-
Labor	Union Productivity	Jarrell & Stanley 1990	No	Yes	-
Labor	Union Productivity	Doucouliagos &Laroche 2000	Yes	Yes	-
Labor	Gender Wage Gap	Stanley & Jarrell 1998	No	Yes	-
Labor	Gender Wage Gap	Stanley & Jarrell 2003	No	Yes	-
Labor	Gender Wage Gap	Weichselbaumer et al. 2005	Some	Yes	-
Labor	Labour Demand	Lichter et al. 2014	Yes	No	
Public	Elasticity of Gasoline Demand	Brons et al. 2008	No	Yes	+
Public	Elasticity of Gasoline Demand	Espey 1996	Yes	Yes	+
Public	Elasticity of Gasoline Demand	Espey 1998	Yes	Yes	+

This table shows the set of meta-analyses of elasticities identified by Fuchs et al. (1998). Usable data indicates that the data was available from the authors. Policy relevant denotes whether the elasticity was relevant to a policy identified by FKP. Political Orientation denotes whether or not the coefficient magnitude is associated with “conservative" or “liberal" policy choices (again as identified by Fuchs et al. (1998).)

Table 6: Correlation Between Predicted Ideology and Policy-Relevant Elasticity Coefficient Rank

	(1)	(2)	(3)	(4)
Mean Predicted Ideology (CTM30)	0.285***	0.216**	0.366**	0.848***
	(0.102)	(0.086)	(0.141)	(0.292)
Meta-Analysis FE	Yes	Yes	Yes	Yes
R-squared	0.88	0.09	0.06	0.04
Observations	238	238	266	238
Ideology Range	1.22	1.22	1.32	1.22
	(1)	(2)	(3)	(4)
Mean Pred. Ideology (CTM100) strong	0.388***	0.237**	0.454**	1.137***
	(0.144)	(0.107)	(0.187)	(0.408)
Meta-Analysis FE	Yes	Yes	Yes	Yes
R-squared	0.88	0.08	0.06	0.05
Observations	238	238	266	238
Ideology Range	0.94	0.94	0.94	0.94
	(1)	(2)	(3)	(4)
Mean Predicted Ideology (JEL1)	0.228*	0.169	0.254	0.755**
	(0.131)	(0.103)	(0.174)	(0.369)
Meta-Analysis FE	Yes	Yes	Yes	Yes
R-squared	0.88	0.08	0.04	0.03
Observations	238	238	266	238
Ideology Range	1.30	1.30	1.30	1.30
	(1)	(2)	(3)	(4)
Mean Pred. Ideology (groundtruth)	0.101	0.103	0.127	0.182
	(0.099)	(0.070)	(0.094)	(0.217)
Meta-Analysis FE	Yes	Yes	Yes	Yes
R-squared	0.91	0.44	0.45	0.24
Observations	46	46	47	46
Ideology Range	2.00	2.00	2.00	2.00

Robust standard errors, clustered by author combination, reported in parenthesis. Ideology is calculated as the mean ideology of the authors, using ideology predicted from papers written prior to the published estimate. Coefficient rank is the rank of the average elasticity reported in the paper in the set of elasticities of the same category. High coefficient is an indicator variable for the paper elasticity being higher than the median elasticity within the same category. Standardized coefficient value is the paper's elasticity normalized by the mean and standard deviation within category. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Correlation Between Author Ideology and Policy-Relevant Elasticity Coefficient Rank-Robustness (CTM 30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cat. X 5-Year FE	Unweighted	US control	Early Pred.	No GT	IV	Placebo
Mean Pred. Ideology (CTM30)	0.277***	0.217**	0.184**		0.195**		-0.008
	(0.088)	(0.086)	(0.084)		(0.097)		(0.097)
US Estimate			0.084*				
			(0.047)				
Mean pred. Ideology (CTM30) - Early				0.173**			
				(0.076)			
Mean pred. Ideology (CTM30) - IV						0.576**	
						(0.241)	
Meta-Analysis FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.23	0.09	0.10	0.08	0.12	0.05	0.00
Observations	238	238	211	232	192	195	265
F-stat						12.84	

This table presents the robustness specifications for one outcome (rank) and one topic adjustment (CTM 30). Robust standard errors, clustered by author combination. Outcome variable is coefficient rank within category. Ideology is calculated as the mean ideology of the authors for whom we are able to predict ideology. Column 1 includes Category of estimate X 5-year period fixed effects. Column 2 uses the raw average of estimates reported in a paper, not weighting by the precision of the estimates. Column 3 controls separately for estimates on US data. Column 4 omits any estimate where any author has a groundtruth observation. Column 5 uses ideology estimated from the first 50% of an author's written text (measuring “Early Ideology"). Column 6 presents an IV estimate using a random split of the words for each author to calculate 2 measures of predicted ideology and uses the first to instrument for the second. Column 7 presents a placebo estimate using non-policy relevant elasticities from Deakin University, as described in the text. * p<0.1, ** p<0.05, *** p<0.01.

9 Appendix

A.1 Model Appendix

In this section we provide a simple analytic framework to clarify what our methodology is estimating and under what assumptions it recovers individual ideology. We consider ideology to be a scalar variable indexing economists from left to right that captures any correlation between partisan political behavior and patterns in academic writing. The model also can be used to shed light on how the professional incentives of academic economists interact with personal ideology to generate ideology measured in academic articles. In our model, economists choose the ideology revealed in their academic papers in order to optimize a combination of ideological preferences, professional incentives, and a preference for being neutral or centrist.

The model illustrates the assumptions needed to recover ideology from our empirical strategy. Importantly, our empirical strategy requires that there be no omitted variables that are correlated with both academic text as well as political behavior (like campaign contributions) besides ideology. An important potential omitted variable is field of economics, which we incorporate as an extension.

When economists are allowed to sort into fields, we have multiple equilibria. An important set of equilibria involve agents sorting into distinct fields based on similar ideologies. We model fields as composed of peers, and success in a field is more likely when papers are aligned with the average ideology within the field. In the simple 2-subfield model in the appendix, professional incentives push agents to sort into fields where they express their ideology in a language used in academic articles that conforms to the expectations of reviewers and peers. We show that equilibria can consequently arise where all agents left of the median sort into one field, and all agents right of the median sort into the other field. Besides illustrating the identification assumptions, the conceptual framework stresses the importance of adequately controlling for field, and motivates our use of both JEL codes and topic models to categorize papers.

Suppose individual economists are indexed by ideology θ_i distributed on $U[-1, 1]$. This index corresponds to our "groundtruth" measure of ideology, observed partisan political behavior, which we only observe for a small sample. Economists derive utility from publishing papers with ideology $\theta_{P(i)}$, that is close to their true ideology θ_i as well as from reporting the truth about the economy, and each source of utility is weighted by Φ and $1 - \Phi$, with $\Phi \in (0, 1)$, respectively. A low Φ corresponds to researchers taking pride in being non-partisan experts, and they derive more utility from reporting what they find than their ideology.

We will use the word "centrist" below to mean the political ideology score close to 0. We do not denote any particular view as "unbiased" or "ideology-free", since the center is merely inferred from the empirical distribution of imputed partisanship. Our metric is the real line bounded by -1 and 1 with the center at 0 (or near 0 depending upon the sample or chosen field). This 0 could correspond to the pivotal American voter, who in a model of party competition would be indifferent between the two parties. The center is not necessarily the truth any more than left or right are "biased" and we consequently avoid the word "bias".

In addition, researchers derive utility not only from "researcher objectives" but they also care about professional or career concerns. If ideology (or neutrality) matters for publication, letters of recommendation, or future government and consulting opportunities, then economists may alter the tone and content of their research to be closer to one that is optimal for these pecuniary career outcomes. If academic and publication incentives are paramount, we might expect θ_C to reflect the ideology of editors, senior colleagues, and peer-reviewers. We also allow economists to sort into fields. Fields are important because they are the source of randomly drawn peers for ones publications and promotion, and ideology expressed in text may get amplified by the process of peer review within a field. We do not take a stand on which of these is most important, nor do we model how the market extracts information about ideology from written work, and instead simply represent the career-optimizing ideology as θ_C, which we weight by $1 - \lambda$ with $\lambda \in (0, 1)$. Combining these three forces, we have total utility given by:

$$V(\theta_{P(i)}, \theta_i) = -\lambda\Phi(\theta_{P(i)} - \theta_i)^2 - \lambda(1 - \Phi)\theta_{P(i)}^2 - (1 - \lambda)(\theta_{P(i)} - \theta_C)^2 \tag{5}$$

The optimum choice of ideology will be then given by:

$$\theta_{P(i)} = \lambda\Phi\theta_i + (1 - \lambda)\theta_C \tag{6}$$

Generally, if $0 < \lambda < 1$ and $\Phi > 0$, then the economist will choose the ideology of their paper

$\theta_{P(i)}$ as a point between their personal ideology and their career maximizing ideology. Equation 6 describes how the ideology observed in a paper is a function of own ideology, as well as the strength of preferences for truth (Φ) and career/pecuniary incentives λ. As Φ or λ approaches 0, $\theta_{P(i)}$ approaches θ_C, so that external field norms dominate own ideology, leading the economist to converge on the level of partisanship in their field, department, or other professionally important source. As λ approaches 1 publication ideology will reflect own preferred ideology, which could be 0 if either $\theta_i = 0$, so that the economist is actually centrist, or Φ small, in which case the economist cares about being politically neutral in their work despite having own ideology possibly different from 0. If $\theta_C = 0$ and λ is small, then the institutions are “Mertonian": substantial incentives are provided for even ideological economists to be centrist.

The difference between Φ and a θ_i captures the difference between being centrist ($\theta_i = 0$) versus wishing to be centrist in published academic work despite being non-centrist ($\Phi = 0, \theta_i \neq 0$), which are potentially two different motivations. If $\theta_C \neq 0$ then it implies that there is a level of partisanship that optimizes professional or career objectives.

Empirically, suppose publication ideology is given by:

$$\theta_{P(i)} = X_{P(i)}\beta + \epsilon_i \tag{7}$$

, where $X_{P(i)}$ is a high-dimensional vector of text features of publications $P(i)$ written by author i and β is an unknown coefficient vector. Then we have the true model:

$$\theta_i = X_{P(i)}\frac{\beta}{\lambda\Phi} - \frac{1-\lambda}{\lambda\Phi}\theta_C \tag{8}$$

We do not observe θ_C, so we need an assumption to recover an unbiased predictor of θ_i as a function of $X_{P(i)}$ alone. The first assumption we could make is that θ_C is uncorrelated with $X_{P(i)}$, so we can estimate equation (8) consistently. However, even if this assumption fails, but θ_C is itself a function only of text $X_{P(i)}$ as well as own ideology θ_i (and noise), we can recover an unbiased prediction. Formally, this can be written in the form of a selection equation:

$$\theta_C = X_{P(i)}\beta_C + \alpha_C\theta_i + \nu_i \tag{9}$$

ν_i uncorrelated with θ_i and $X_{P(i)}$ may be a strong assumption if there are unobserved characteristics of an economist that predict career maximizing expression of ideology independent of own ideology that are not revealed in patterns of writing. For example, having liberal peers may induce an economist to express liberal behavior in order to advance their career even if they are not themselves liberal nor write in liberal manner. However, if we include a rich enough set of features of text, which in practice is topic-specific phrase frequencies, it may be plausible to assume that we obtain a proxy for even career-maximizing ideology. Note that this assumption works because we are interested in obtaining a good prediction of θ_i and not unbiased coefficients on β. Using (8) and (9) we can estimate the following reduced form equation:

$$\theta_i = X_{P(i)}\gamma + \eta \tag{10}$$

Where $\gamma = \frac{\beta-(1-\lambda)\beta_C}{\phi\lambda+(1-\lambda)\alpha_C}$, and a linear regression would recover the best unbiased linear predictor $\widehat{\gamma}$. Under the assumption of a valid estimate of γ, we can then forecast $\widehat{\theta_j}$, for any economist j, given a document represented by a vector of text features $X_{P(j)}$. This is the core of our empirical approach. X is a high-dimensional vector, and so we can leverage any number of machine learning tools, such as random forests or LASSO, to obtain a good prediction of $\widehat{\theta_j}$. We also use the IGM subsample of economists for whom we observe rich demographic covariates to check whether omission of demographic and professional characteristics introduces important biases in our predicted ideology.

We can extend this framework to examine how peer-review and sorting may generate a correlation between fields and methodologies and political preferences. Peer-review provides a natural mechanism. If peers act as gatekeepers for publication and promotion within a field or methodology, and peers have ideological preferences, then economists will sort into those fields and methodologies where peers are ideologically sympathetic.

To fix ideas suppose there are two fields F that partition the set of economists, P_L and P_M. Researchers can choose a field prior to publishing a paper. Editors invite peer reviewers at random from the set of economists who have chosen that field. We assume that when peers referee a paper they reject papers that are too far from the ideological mean of researchers in that field. So formally this yields for $F \in \{L, M\}$:

$$\theta_F = E[\theta_i | i \in F] \tag{11}$$

This is a reduced-form way of capturing the pressure towards conformity with the other researchers in a field that peer-review induces. Referees are anonymous, and generally sampled from the population of scholars who have previously worked in that field.

We further assume that the career concerns of researchers are purely determined by field, so that $\theta_C = \theta_F$. An equilibrium in this model is a partition of $-1, 1$ into L and F such that no researcher wishes to change fields. Clearly, from equation 1, each researcher would like to sort into the field that is closest to them in ideology, which is not identical to own ideology only to the extent there is a taste for political neutrality or non-partisanship, i.e. $\Phi \approx 0$. This results in the following proposition.

Proposition: If $\Phi \neq \frac{1}{2}$, there are two classes of equilibria in this model:

1. Degenerate equilibria: ideologies are evenly distributed within each field so both fields have mean ideology 0.

2. Full Sorting equilibria: One field has all economists with ideology < 0, and so the mean ideology of the field is $-\frac{1}{2}$, while the other field has all economists with ideology > 0 and so has mean ideology $\frac{1}{2}$.

Proof: We first show that each of these is an equilibrium.
Suppose there is a partition P_L, P_M such that $P_M \cap P_L = 0$ and $P_M \cup P_L = [-1, 1]$ and $E[\theta_i | i \in P_j] = 0$. Then every researcher gets the same utility in each field, and so is indifferent between fields. Thus no researcher wishes to switch fields and this is an equilibrium.

Now suppose there is a partition P_L, P_M such that $E[\theta_i | i \in P_M] = \frac{1}{2}$ and $E[\theta_i | i \in P_L] = \frac{-1}{2}$. Then researchers with ideology $\theta_i < 0$ will choose whichever is close to $\Phi\theta_i$, which is L and researchers with ideology $\theta > 0$ will similarly choose M. For all $\theta_i \in M$ we have $\Phi\theta_i \in M$ and $\theta_i \in L$ implies $\Phi\theta_i \in L$. Thus $L = [-1, 0)$ and $F = (0, 1]$ and the partition is an equilibrium.

We next show there can't be any other equilibria. Assume a partition P_M, P_L is an equilibrium where at least one partition P_s has $E[\theta | \theta \in P_s] \neq 0$. We first show that all such partitions must be a pair of intervals $[-1, x], (x, 1]$ (WLOG one closed and one open could be reversed) and then show that $x = 0$ is the only equilibrium. Suppose this equilibrium is not a pair of intervals. Then there is a set x, y, z, such that $x < y < z$, and $x, z \in P_M$ and $y \in P_L$. However, then $|\Phi x - E[\theta|P_M]| \leq |\Phi x - E[\theta|P_L]|$ and $|\Phi z - E[\theta|P_M]| \leq |\Phi z - E[\theta|P_L]|$, but $y \in P_M$ implies $|\Phi y - E[\theta|P_M]| \leq |\Phi y - E[\theta|P_L]|$. This implies that $x, z \leq \frac{\theta_M + \theta_L}{2\Phi}$ while $y \geq \frac{\theta_M + \theta_L}{2\Phi}$ which contradicts $x < y < z$.

Now suppose $[-1, x], (x, 1]$ is an equilibrium. If, WLOG, $x > 0$, then $\theta_L = \frac{x-1}{2}$ and $\theta_M = \frac{x+1}{2}$. Now, for all y such that $\Phi y \leq \frac{1}{2}(\theta_L - \theta_M) = \frac{x}{2}$, we will have $|\Phi y - \theta_L| \leq |\Phi y - \theta_M|$, and so all such y will choose P_L. Similarly y such that $\Phi y \geq \frac{x}{2}$ will choose P_M.

Since $\Phi \neq \frac{1}{2}$ then either $\Phi x < \frac{x}{2}$ and there exists an ϵ such that $\frac{x}{2} > \Phi(x + \epsilon) > 0$ and thus $x + \epsilon$ would choose P_L. Similarly if $\Phi x > \frac{x}{2}$ there is an ϵ such that $\Phi(x - \epsilon) > \frac{x}{2}$ and so $x - \epsilon$ would choose P_M. Thus this cannot be an equilibrium, and so $x \leq 0$. A similar argument shows that $x < 0$ cannot be an equilibrium and hence the only equilibrium partitions are $[-1, 0), [0, 1]$ or $[-1, 0], (0, 1]$.

This model implies that revealed ideology $\theta_{P(i)}$ will in fact be a mix of own ideology θ_i and field ideology θ_L or θ_M. Sorting implies different fields have distinct political preferences. But while there is sorting, it is not perfect, which motivates including topic-adjusted (with correlations allowed between topics) frequencies in $X_{P(i)}$ as it allows us to use within-field differences in language as predictors for θ_i. Since self-reported fields do not correspond perfectly to paper topics, we can still estimate effects of fields on ideology recovered from within-topic predictions of ideology. While not explicit in our model, sorting additionally implies that ideology does not change much over the career, and that changes in ideology are not predicted by field.

“Field" in this model could easily be replaced with “Methodology", as long as the peer-review process remains the same. This is of course plausible, as editors will choose referees also on the basis of shared methodology. This is how empirical work, while estimating the same parameter, could still have ideological sorting. If there is selection into methodology that is granular enough (e.g. structural vs reduced-form, micro versus macro estimates), then even estimates of the same parameter could be vulnerable to the same forces of sorting that lead to ideology being correlated with field. A message of this very simple model is that peer-review, together with sorting, may in fact make academic institutions less-Mertonian.

This framework has implications for empirical work, particularly where there are many degrees of researcher freedom. Suppose there is an empirical estimate that has political or partisan implications, so that the preferred reported β is a monotonic function of ideology $\beta^p(\theta)$. For example, a very conservative analyst may prefer a low tax rate τ, which would be implied by a standard optimal taxation model together with a high taxable income elasticity estimate β^p. Suppose further that there is a design or specification choice that influences the observed estimate, which we denote β^O. If economists report their ideologically preferred estimates, there will be a correlation between reported estimates β^O reported by economist i and i's measured ideology θ^i.

A.2 Linking Economists to FEC Data

Fuzzy string matching is computationally expensive, so we take the common practical step of creating a candidate set of FEC contributors for each AEA member. We define the candidate set for an AEA member as those FEC contributions where the contributor's last name starts with the same three characters as that of the AEA member.

For each AEA member and his or her candidate set of FEC contributions, we compute a similarity score between the following variables that appear in both datasets: name, occupation, and employer.[29] We map zip codes to latitude-longitude points and compute the distance from the AEA member's location to each candidate FEC contribution. To reduce the likelihood of a match for people with common names, we compute an additional predictor variable which captures the probability that a person's name is unique (Perito et al., 2011). If a name is more likely to appear in the general population, then its predictive ability in determining whether a match exists is reduced.

We model the likelihood that an AEA-FEC pair is a match as a function of the constructed variables from above. We select 1,300 pairs and manually verify if a match exists. We sample 900 of these pairs and estimate the coefficients to a logistic regression model. We repeat this process with new samples one thousand times and for each sample determine the predictive accuracy of the model on the held out set of 400 AEA-FEC pairs. On average, we make a correct prediction 96.5% (s.e. 0.015) of the time. We take the mean values of the parameter sets generated from the regressions and predict matches for the entire dataset. Using this procedure, we are able to identify 21,409 contributions made by 2,884 AEA members. We drop transactions amounts which are less than zero, leaving us with 21,226 contributions from 2,882 members.

The FEC data indicates if a candidate or committee is associated with a particular party. Of the contributions that could be mapped directly to a party, 97% went to either Democrats or Republicans, so we only keep track of three types of recipients: Democrats, Republicans, and Others. Examining the list of committees in the Others category, it is apparent that a subset of the recipients have known political affiliations. For example, 659 contributions went to ActBlue, which funds Democrats, and

[29] We use Python's *difflib* module that incorporates a version of the Ratcliff-Obershelp pattern matching algorithm (Ratcliff and Metzener, 1988) The algorithm works by finding the number of matching characters in the longest common subsequence between two strings. This number is multiplied by two and divided by the total number of characters in the two strings. For example, the distance between 'abcdef' and 'adbecf' is $\frac{2}{3}$ since the longest common subsequence is 'abcf'.

236 contributions were made to Club for Growth, a conservative fundraiser.[30] To assign parties to these types of committees in the Others category, we tallied their contributions in a similar manner as above. Our decision rule was that if the committee gave more than 80% to Democrats (Republicans), then we classify its party affiliation as Democrat (Republican). According to this assignment, AEA members made 13,892 contributions to Democrats, 4,670 to Republicans, and 2,667 to Others.

Of these contributions, 7,374 were made by economists who have written a paper in our dataset while 13,852 were made by other AEA members. Many of the members in the latter group are in either government or private industry. Table A.1 provides summary statistics on both author and non-author contributors. At the contribution level, 80.9% go to left-leaning PACs while 15.4% go to right leaning ones. For non-authors these figures are 61.5% and 27.2%, respectively. Of the contributors who have written a paper in our dataset, 11.6% gave to both left-leaning and right-leaning committees compared with 20.3% for non-authors.

[30] See http://www.opensecrets.org/orgs/summary.php?id=D000021806 and http://www.opensecrets.org/orgs/summary.php?id=D000000763

Table A.1: Campaign Contribution Data.

	N AEA Members	N Contri-butions	Dem. Share	Rep. Share	Total Amount	Amount per Con-tribution
Authors	1,084	7,374	80.9%	15.4%	$5,917,430	$802
Non-Author	1,798	13,852	61.5%	27.2%	$11,891,448	$885

AEA membership rosters from 1993, 1997, and 2002 to 2009 are linked to FEC campaign contribution data, linkage details provided in text. The table provides summary statistics on AEA member campaign contributions. Non-partisan contributions account for the fact that the sum of the shares is less than 1.

Table A.2: List of Petitions

Petition	Year	Organizer or Sponsor	Category	Political Category
Support Market Oriented Health Care Reform	1994	The Independent Institute	+	R
Oppose Antitrust Protectionism	1999	The Independent Institute	+	R
Support Market Oriented Health Care Reform	2000	The Independent Institute	+	R
Economists for Sweatshops	2000	Academic Consortium on Int'l Trade	+	/
Oppose Death Tax	2001	National Taxpayers Union	+	R
Scholars Against Sweatshop Labor	2001	PERI	-	/
Oppose Bush Tax Cuts	2003	Economic Policy Institute	-	D
Oppose Tax Increase	2004	National Taxpayers Union	+	R
Endorse John Kerry for President	2004		/	D
Oppose John Kerry for President	2004		/	R
Warning Future of Social Security	2005	Cato Institute	+	R
Increase Immigration	2006	The Independent Institute	+	/
Support Raising the Minimum Wage	2006	The Economic Policy Institute	-	D
Oppose Marijuana Prohibition	2006	Marijuana Policy Project	+	/
Oppose Government Regulation of Internet	2007	AEI-Brookings Joint Center	+	R
Statement on Prediction Markets	2007	AEI-Brookings Joint Center	+	/
Economists Against Protectionism	2007	The Club for Growth	+	/
Oppose "Windfall Taxes"	2007	National Taxpayers Union	+	R
Support John McCain Economic Plan	2008		/	R
Concerns about Government Bail Out	2008	John Cochrane	/	R
Support Government Bail Out for Mortgages	2008	Unknown	-	D
Concerned about Climate Change	2008	Nancy Olewiler	-	D
Support Federal Recovery Act	2008	CEPR	-	D
Oppose Federal Recovery Act	2009	Cato Institute	+	R
Oppose Budget Reduction in Washington State	2009	Wash. State Budget & Policy Center	-	D
Support Employee Free Choice Act	2009	The Economic Policy Institute	-	D
Support Cap and Trade	2009	Southern Alliance for Clean Energy	-	/
Replace Federal Income Tax with FairTax	2009	FairTax.org	/	R
Support Using Procurement Auctions	2009	Paul Milgrom	/	/
Support Government Intervention on Biofuels	2009	Union of Concerned Scientists	-	D
Oppose Green Protectionism	2009	Atlas Global Initiative	+	R
Fed Independence Petition	2009	Wall Street Journal	/	/
Support Tax Increase	2009	Oregon Center for Public Policy	-	D
Government Oriented Health Care Reform 2009	2009	Unknown	-	D
Support for a Financial Transactions Tax	2009	CEPR	-	D

List from Hedengren et al.. The Category columns indicate whether Hendengren classified the survey as liberty augmenting (+), reducing (-), or other (/). The Signature column indicates the number of actual signatures on the petition. The Author column indicates the number that were linked to papers in our corpus. The Political Category column indicates our definition of the political lean of the petition.

A.3 Measuring JEL Topic Prediction Accuracy

The tables in this section show the per-model predictive performance of our JEL code classifiers. For each code in *JEL1* and *JEL2*, we iteratively held out 20% of all papers for which groundtruth information on JEL codes existed. We split the remaining 80% of groundtruth papers into training (90%) and validation (10%) sets and ran gradient boosting using the *xgboost* package for *R*. Our predictors were the number of times words appeared in papers.[31] We filtered for words that appeared at least 100 times in each of the holdout, training and validation sets. We trained each model with 250 trees and used the validation set to identify the tree between 1 and 250 which maximized AUC and predicted for the holdout set.[32] By rotating the 20% holdout five times, we generated out-of-sample predictions for each paper and JEL code. The AUCs presented in the tables in this section are computed by stacking all holdout sets within topic.

[31] https://cran.r-project.org/web/packages/xgboost/

[32] The following parameter settings were used: max_depth=1, objective='binary:logistic', eval_metric='auc', subsample=.5, colsample_bytree=.5, nrounds=250

JEL Code	Description	AUC
A	General Economics and Teaching	0.981
B	History of Economic Thought, Methodology, and Heterodox Approaches	0.977
C	Mathematical and Quantitative Methods	0.966
D	Microeconomics	0.882
E	Macroeconomics and Monetary Economics	0.947
F	International Economics	0.974
G	Financial Economics	0.966
H	Public Economics	0.936
I	Health, Education, and Welfare	0.971
J	Labor and Demographic Economics	0.966
K	Law and Economics	0.967
L	Industrial Organization	0.927
M	Business Administration and Business Economics, Marketing, Accounting, Personnel Economics	0.938
N	Economic History	0.980
O	Economic Development, Innovation, Technological Change, and Growth	0.945
P	Economic Systems	0.958
Q	Agricultural and Natural Resource Economics, Environmental and Ecological Economics	0.983
R	Urban, Rural, Regional, Real Estate, and Transportation Economics	0.949
Y	Miscellaneous Categories	0.969
Z	Other Special Topics	0.941

Table A.3: Predictive Performance JEL 1st-Level Codes: This table shows the performance as measured by Area Under Curve (AUC) when predicting whether a particular paper was assigned a particular JEL code. The first column shows the second-level JEL code, the second column shows the description, and the last column shows the AUC. The prediction was performed by – for each JEL code – iteratively holding out 20 percent of articles and with the remaining 80 percent predicting whether an article was assigned to that JEL code. By repeating this procedure five times, out of sample predictions were generated for each article. All out of sample predictions were combined across the five sets and a single AUC value was calculated. The features used for the prediction where the count of the number of times a particular word appeared in an article.

JEL Code	Description	AUC
A1	General Economics	0.967
A2	Economic Education and Teaching of Economics	0.996
B1	History of Economic Thought through 1925	0.978
B2	History of Economic Thought since 1925	0.968
B3	History of Economic Thought: Individuals	0.984
B4	Economic Methodology	0.962
B5	Current Heterodox Approaches	0.901
C1	Econometric and Statistical Methods and Methodology: General	0.974
C2	Single Equation Models, Single Variables	0.986
C4	Econometric and Statistical Methods: Special Topics	0.956
C5	Econometric Modeling	0.956
C6	Mathematical Methods, Programming Models, Mathematical and Simulation Modeling	0.957
C7	Game Theory and Bargaining Theory	0.986
C8	Data Collection and Data Estimation Methodology, Computer Programs	0.944
C9	Design of Experiments	0.945
D0	General	0.907
D1	Household Behavior and Family Economics	0.939
D2	Production and Organizations	0.914
D3	Distribution	0.963
D4	Market Structure, Pricing, and Design	0.965
D5	General Equilibrium and Disequilibrium	0.966
D6	Welfare Economics	0.928
D7	Analysis of Collective Decision-Making	0.969
D8	Information, Knowledge, and Uncertainty	0.948
D9	Micro-Based Behavioral Economics	0.937
E1	General Aggregative Models	0.944
E2	Consumption, Saving, Production, Investment, Labor Markets, and Informal Economy	0.935
E3	Prices, Business Fluctuations, and Cycles	0.966
E4	Money and Interest Rates	0.960
E5	Monetary Policy, Central Banking, and the Supply of Money and Credit	0.982
E6	Macroeconomic Policy, Macroeconomic Aspects of Public Finance, and General Outlook	0.950
F0	General	0.960
F1	Trade	0.981
F2	International Factor Movements and International Business	0.968
F3	International Finance	0.982
F4	Macroeconomic Aspects of International Trade and Finance	0.961
G1	General Financial Markets	0.972
G2	Financial Institutions and Services	0.981
G3	Corporate Finance and Governance	0.964
H1	Structure and Scope of Government	0.888
H2	Taxation, Subsidies, and Revenue	0.963
H3	Fiscal Policies and Behavior of Economic Agents	0.908
H4	Publicly Provided Goods	0.950
H5	National Government Expenditures and Related Policies	0.951
H6	National Budget, Deficit, and Debt	0.960
H7	State and Local Government, Intergovernmental Relations	0.964
H8	Miscellaneous Issues	0.857
I1	Health	0.986
I2	Education and Research Institutions	0.985
I3	Welfare, Well-Being, and Poverty	0.972
J1	Demographic Economics	0.969
J2	Demand and Supply of Labor	0.952
J3	Wages, Compensation, and Labor Costs	0.971
J4	Particular Labor Markets	0.949

J5	Labor & Management Relations, Trade Unions, and Collective Bargaining	0.988
J6	Mobility, Unemployment, Vacancies, and Immigrant Workers	0.977
J7	Labor Discrimination	0.988
K1	Basic Areas of Law	0.968
K2	Regulation and Business Law	0.963
K3	Other Substantive Areas of Law	0.904
K4	Legal Procedure, the Legal System, and Illegal Behavior	0.986
L1	Market Structure, Firm Strategy, and Market Performance	0.946
L2	Firm Objectives, Organization, and Behavior	0.941
L3	Nonprofit Organizations and Public Enterprise	0.958
L4	Antitrust Issues and Policies	0.967
L5	Regulation and Industrial Policy	0.956
L6	Industry Studies: Manufacturing	0.954
L7	Industry Studies: Primary Products and Construction	0.941
L8	Industry Studies: Services	0.950
L9	Industry Studies: Transportation and Utilities	0.974
M1	Business Administration	0.964
M2	Business Economics	0.736
M3	Marketing and Advertising	0.927
N1	Macroeconomics and Monetary Economics, Industrial Structure, Growth, Fluctuations	0.973
N2	Financial Markets and Institutions	0.973
N3	Labor and Consumers, Demography, Education, Health, Welfare, Income, Wealth, Religion, and Philanthropy	0.980
N4	Government, War, Law, International Relations, and Regulation	0.954
N5	Agriculture, Natural Resources, Environment, and Extractive Industries	0.983
N6	Manufacturing and Construction	0.967
N7	Transport, Trade, Energy, Technology, and Other Services	0.971
N8	Micro-Business History	0.950
O1	Economic Development	0.964
O2	Development Planning and Policy	0.939
O3	Innovation, Research and Development, Technological Change, Intellectual Property Rights	0.974
O4	Economic Growth and Aggregate Productivity	0.979
O5	Economywide Country Studies	0.935
P1	Capitalist Systems	0.923
P2	Socialist Systems and Transitional Economies	0.980
P3	Socialist Institutions and Their Transitions	0.973
P5	Comparative Economic Systems	0.879
Q1	Agriculture	0.988
Q2	Renewable Resources and Conservation	0.986
Q3	Nonrenewable Resources and Conservation	0.946
Q4	Energy	0.948
R1	General Regional Economics	0.951
R2	Household Analysis	0.944
R3	Real Estate Markets, Spatial Production Analysis, and Firm Location	0.963
R4	Transportation Economics	0.988
R5	Regional Government Analysis	0.890
Z1	Cultural Economics, Economic Sociology, Economic Anthropology	0.954

Table A.4: Predictive Performance JEL 2nd-Level Codes: Table shows performance as measured by Area Under Curve (AUC) when predicting whether a particular paper was assigned a JEL code. The columns show the second-level JEL code, the associated description, and the AUC, respectively. For each JEL code, we held out 20 percent of articles and trained a model with the remaining 80 percent to predict whether an article belonged to that JEL code. By repeating this procedure five times, out of sample predictions were generated for each article. All out of sample predictions were combined across the five sets and a single AUC value was calculated. The features used for the prediction where the count of the number of times a particular word appeared in an article.

A.4 Predictive Performance by Topic

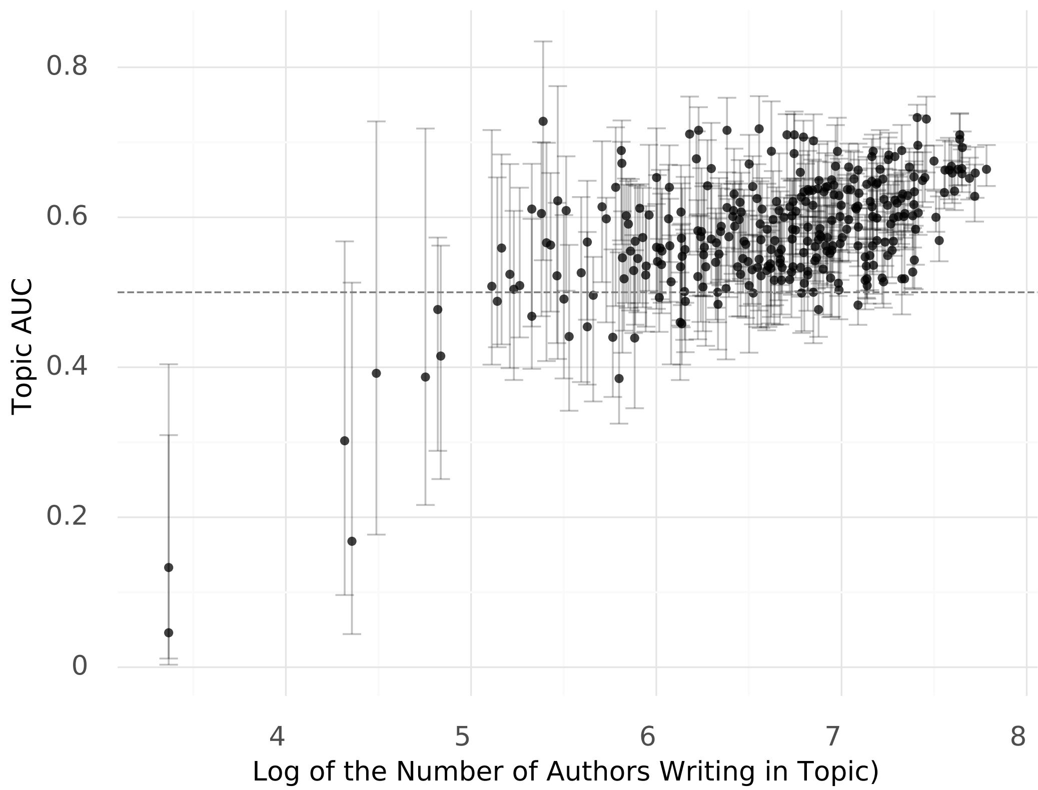
In this Appendix section we report the predictive performance of five topic-adjusted models at the individual topic level. We compute AUC within topic and by weighting economists by their probability of writing in that topic.

Table A.5 shows the performance of these models across five topic mappings. The columns respectively show the topic mapping, the topic, the top three most probable words in that topic, the number of groundtruth authors with papers in the topic[33], the AUC, and the bootstrapped 95% confidence interval for the AUC. These bootstrap estimates are based on 1,000 replicates. Overall, 60.0% of topics have AUCs that are significantly higher than 0.5 as estimated from our bootstrap confidence intervals. Figure A.1 shows that significance is associated with the number of authors writing in a topic. The x-axis shows the log of the number of authors writing in a topic while the y-axis shows the AUC for a topic.

Lower interest in a topic, as measured by economists' chance of writing in the topic, is associated with lower accuracy of our topic-adjusted ideology predictors. We may be concerned that non-groundtruth authors show different topic prevalence patterns, meaning that models built on groundtruth authors may not be directly generalizable to non-groundtruth authors. In Figure A.2 we compare the probability that authors write about a particular topic across groundtruth and non-groundtruth authors. The x-axis in Figure A.2 shows the probability that groundtruth authors write about a topic while the y-axis shows the same for non-groundtruth authors. The points are colored by topic mapping. We see that the points fall nearly exactly on the 45 degree line, showing that the topic prevalence across groundtruth and non-groundtruth authors is highly correlated.

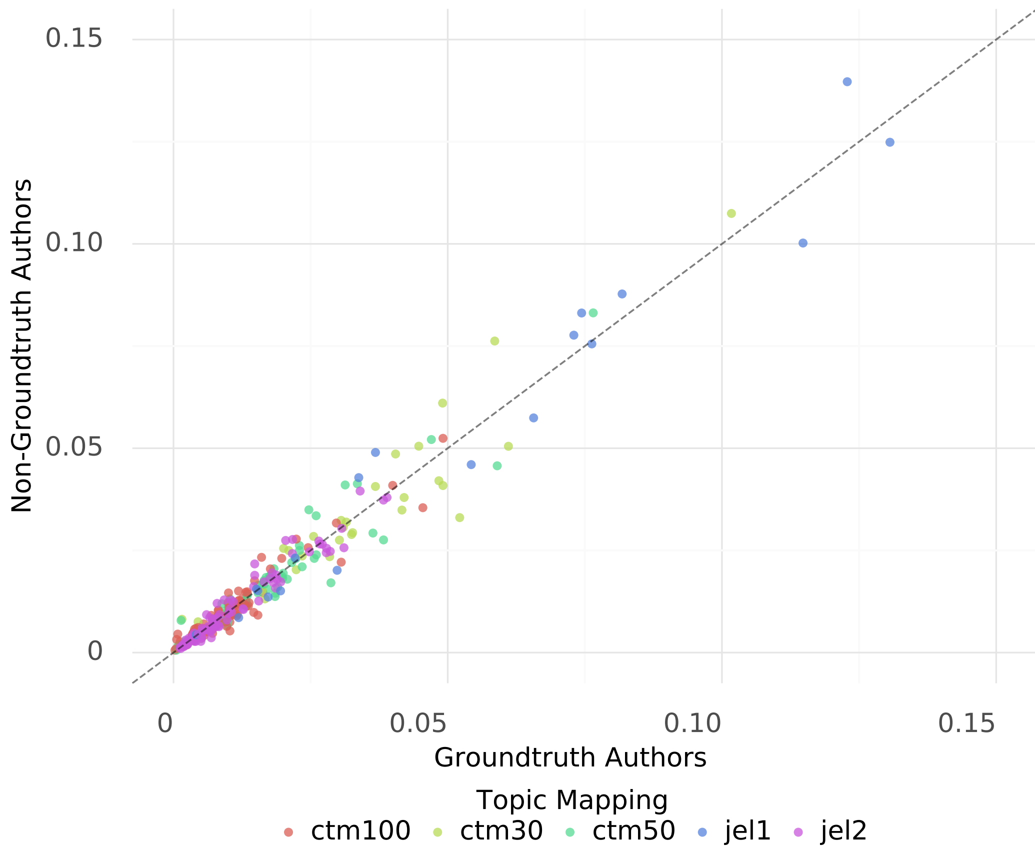
[33] Specifically, we remove authors who had a less than one percent chance of writing in a particular topic.

Figure A.1: Relationship Between Sample Size and AUC by Topic



This shows the log of the number of authors writing in a topic (x-axis) versus the AUC for a topic (y-axis). Each of the 298 points in the figure represent one of the topics across five topic mappings. With each point is the associated 95% bootstrapped confidence interval.

Figure A.2: Comparing Topic Distributions Across Groundtruth and Non-Groundtruth Authors



This chart compares the propensity that authors write about a particular topic across groundtruth and nongroundtruth authors. For each topic mapping, the probability that an author writes about a topic was aggregated and normalized to sum to one separately for groundtruth- and nongroundtruth-authors. The x-axis shows these computed topic proportions for groundtruth authors. The y-axis shows the same for non-groundtruth authors. The colors represent the five topic mappings. The dashed $45\deg$ line represents equal topic proportions across the two groups of authors.

Table A.5: AUCs by Topic: This table lists the performance of models predicting ideology in each topic of five topic mappings. The columns respectively show the topic mapping, the topic, the top three most probable words in that topic, the number of groundtruth authors that had a probably greater than 1% of writing in that topic, the AUC, and the bootstrapped 95% confidence interval for the AUC. These bootstrap estimates are based on 1,000 replicates.

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
ctm100	1	shock, model, cycl	844	0.621	(0.527, 0.649)
ctm100	2	citi, hous, local	857	0.608	(0.55, 0.652)
ctm100	3	cient, erent, erenc	334	0.689	(0.569, 0.701)
ctm100	4	american, york, nation	1650	0.733	(0.66, 0.75)
ctm100	5	agricultur, land, farm	459	0.460	(0.383, 0.526)
ctm100	6	school, educ, colleg	830	0.614	(0.534, 0.652)
ctm100	7	polici, public, privat	1411	0.677	(0.627, 0.706)
ctm100	8	countri, develop, world	792	0.557	(0.515, 0.617)
ctm100	9	children, famili, child	591	0.613	(0.536, 0.66)
ctm100	10	como, politica, mayor	29	0.046	(0.012, 0.31)
ctm100	11	forecast, model, varianc	697	0.533	(0.454, 0.576)
ctm100	12	invest, foreign, domest	749	0.532	(0.482, 0.601)
ctm100	13	chang, year, increas	1807	0.675	(0.637, 0.696)
ctm100	14	retir, pension, plan	644	0.545	(0.499, 0.629)
ctm100	15	experi, respond, subject	1030	0.552	(0.527, 0.627)
ctm100	16	crime, crimin, polic	416	0.555	(0.486, 0.638)
ctm100	17	cent, india, indian	183	0.524	(0.399, 0.671)
ctm100	18	drug, birth, abort	236	0.522	(0.432, 0.619)
ctm100	19	month, time, probabl	1041	0.596	(0.545, 0.637)
ctm100	20	social, polit, econom	849	0.685	(0.629, 0.737)
ctm100	21	health, mortal, life	519	0.507	(0.448, 0.58)
ctm100	22	debt, borrow, loan	562	0.500	(0.46, 0.598)

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Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
ctm100	23	centuri, histori, british	472	0.488	(0.42, 0.578)
ctm100	24	household, consumpt, wealth	884	0.499	(0.446, 0.548)
ctm100	25	immigr, migrat, migrant	336	0.546	(0.419, 0.608)
ctm100	26	insur, risk, coverag	616	0.588	(0.515, 0.648)
ctm100	27	develop, manag, system	1464	0.623	(0.58, 0.656)
ctm100	28	black, score, student	707	0.591	(0.532, 0.648)
ctm100	29	pour, sont, nous	116	0.387	(0.216, 0.718)
ctm100	30	servic, network, comput	796	0.533	(0.499, 0.61)
ctm100	31	money, monetari, polici	626	0.534	(0.468, 0.58)
ctm100	32	agent, incent, effort	829	0.517	(0.501, 0.604)
ctm100	33	econom, journal, model	2102	0.658	(0.633, 0.69)
ctm100	34	china, japan, japanes	505	0.582	(0.495, 0.623)
ctm100	35	incom, poverti, distribut	1007	0.562	(0.527, 0.633)
ctm100	36	industri, manufactur, product	983	0.574	(0.525, 0.615)
ctm100	37	financi, credit, market	772	0.621	(0.521, 0.64)
ctm100	38	test, statist, hypothesi	969	0.477	(0.441, 0.542)
ctm100	39	tion, ment, tive	2019	0.635	(0.61, 0.664)
ctm100	40	price, market, consum	1366	0.519	(0.485, 0.57)
ctm100	41	estim, model, distribut	1278	0.549	(0.503, 0.596)
ctm100	42	return, stock, price	732	0.529	(0.449, 0.58)
ctm100	43	valu, period, model	1611	0.527	(0.506, 0.586)
ctm100	44	wage, labor, worker	1053	0.630	(0.59, 0.682)
ctm100	45	contract, cost, bargain	879	0.533	(0.494, 0.591)
ctm100	46	asset, fund, equiti	793	0.516	(0.47, 0.572)
ctm100	47	program, particip, benefit	920	0.635	(0.601, 0.706)

Continued on next page

Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
ctm100	48	mexico, argentina, latin	248	0.609	(0.502, 0.681)
ctm100	49	technolog, innov, patent	662	0.541	(0.482, 0.602)
ctm100	50	polit, vote, parti	677	0.530	(0.484, 0.629)
ctm100	51	firm, market, profit	1303	0.536	(0.498, 0.6)
ctm100	52	function, theorem, condit	958	0.546	(0.505, 0.608)
ctm100	53	energi, capac, power	515	0.581	(0.496, 0.665)
ctm100	54	regul, environment, pollut	543	0.571	(0.511, 0.642)
ctm100	55	union, employe, worker	563	0.484	(0.424, 0.551)
ctm100	56	para, esta, entr	29	0.133	(0.003, 0.404)
ctm100	57	advertis, trader, market	612	0.609	(0.515, 0.637)
ctm100	58	pour, economiqu, plus	75	0.302	(0.096, 0.568)
ctm100	59	employ, unemploy, worker	842	0.584	(0.528, 0.626)
ctm100	60	capit, growth, economi	1088	0.601	(0.542, 0.635)
ctm100	61	smoke, alcohol, youth	351	0.555	(0.476, 0.651)
ctm100	62	equilibrium, good, model	1254	0.535	(0.493, 0.573)
ctm100	63	data, tabl, sampl	1911	0.633	(0.612, 0.667)
ctm100	64	rate, real, interest	1451	0.568	(0.549, 0.617)
ctm100	65	bond, market, reserv	681	0.499	(0.457, 0.577)
ctm100	66	demand, elast, suppli	1387	0.567	(0.535, 0.607)
ctm100	67	court, case, legal	556	0.540	(0.464, 0.612)
ctm100	68	choic, risk, prefer	1082	0.503	(0.464, 0.556)
ctm100	69	firm, compani, manag	734	0.584	(0.53, 0.645)
ctm100	70	product, output, input	1260	0.509	(0.485, 0.571)
ctm100	71	care, health, hospit	464	0.548	(0.483, 0.639)
ctm100	72	right, govern, member	1301	0.688	(0.618, 0.71)

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Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
ctm100	73	bank, deposit, loan	573	0.588	(0.517, 0.645)
ctm100	74	variabl, effect, estim	1826	0.600	(0.581, 0.635)
ctm100	75	polit, african, militari	433	0.640	(0.54, 0.696)
ctm100	76	food, commod, product	460	0.534	(0.456, 0.59)
ctm100	77	auction, buyer, seller	388	0.603	(0.502, 0.697)
ctm100	78	ofth, effect, inth	410	0.493	(0.447, 0.571)
ctm100	79	will, even, make	2189	0.652	(0.624, 0.68)
ctm100	80	earn, work, hour	893	0.707	(0.61, 0.729)
ctm100	81	region, area, locat	942	0.500	(0.432, 0.529)
ctm100	82	trade, export, import	804	0.600	(0.525, 0.626)
ctm100	83	govern, spend, expenditur	1040	0.650	(0.572, 0.673)
ctm100	84	welfar, optim, social	1328	0.599	(0.555, 0.637)
ctm100	85	game, equilibrium, player	763	0.516	(0.457, 0.563)
ctm100	86	inflat, polici, target	695	0.625	(0.555, 0.671)
ctm100	87	countri, european, germani	654	0.564	(0.466, 0.609)
ctm100	88	cultur, social, communiti	301	0.614	(0.514, 0.701)
ctm100	89	exchang, currenc, foreign	631	0.597	(0.534, 0.645)
ctm100	90	canada, canadian, provinc	278	0.454	(0.377, 0.58)
ctm100	91	state, unit, feder	1198	0.615	(0.587, 0.663)
ctm100	92	incom, percent, gain	1014	0.555	(0.509, 0.616)
ctm100	93	econom, economi, transit	382	0.535	(0.454, 0.615)
ctm100	94	firm, busi, small	710	0.522	(0.452, 0.574)
ctm100	95	women, femal, male	597	0.574	(0.494, 0.624)
ctm100	96	student, univers, econom	882	0.627	(0.574, 0.683)
ctm100	97	inform, type, signal	1078	0.512	(0.495, 0.582)

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Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
ctm100	98	transport, cost, vehicl	521	0.550	(0.495, 0.641)
ctm100	99	peopl, polit, govern	404	0.560	(0.478, 0.618)
ctm100	100	water, resourc, forest	412	0.559	(0.491, 0.663)
ctm30	1	health, insur, care	1006	0.640	(0.595, 0.686)
ctm30	2	cent, india, rural	648	0.568	(0.511, 0.637)
ctm30	3	variabl, estim, data	2106	0.693	(0.659, 0.714)
ctm30	4	chang, period, rate	1526	0.631	(0.59, 0.659)
ctm30	5	land, agricultur, farm	1095	0.616	(0.554, 0.649)
ctm30	6	trade, countri, export	1132	0.637	(0.573, 0.665)
ctm30	7	women, famili, children	965	0.638	(0.57, 0.675)
ctm30	8	benefit, program, retir	1371	0.651	(0.6, 0.691)
ctm30	9	model, shock, consumpt	610	0.601	(0.525, 0.645)
ctm30	10	pour, plus, sont	237	0.622	(0.411, 0.775)
ctm30	11	bank, financi, debt	1205	0.632	(0.585, 0.677)
ctm30	12	rate, polici, inflat	1380	0.624	(0.583, 0.665)
ctm30	13	equilibrium, function, model	1625	0.543	(0.504, 0.589)
ctm30	14	incom, household, consumpt	1660	0.606	(0.577, 0.662)
ctm30	15	para, como, esta	89	0.392	(0.177, 0.728)
ctm30	16	price, cost, market	1859	0.569	(0.541, 0.628)
ctm30	17	polit, vote, parti	1082	0.629	(0.574, 0.678)
ctm30	18	return, market, stock	1246	0.547	(0.502, 0.603)
ctm30	19	school, educ, student	1296	0.562	(0.524, 0.624)
ctm30	20	model, estim, test	1611	0.602	(0.56, 0.636)
ctm30	21	contract, inform, will	1481	0.619	(0.577, 0.657)
ctm30	22	firm, industri, product	1544	0.605	(0.557, 0.633)

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Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
ctm30	23	capit, growth, product	1699	0.649	(0.613, 0.687)
ctm30	24	state, citi, region	1625	0.634	(0.6, 0.675)
ctm30	25	countri, develop, econom	1200	0.663	(0.616, 0.698)
ctm30	26	econom, social, theori	2076	0.704	(0.666, 0.738)
ctm30	27	centuri, histori, british	1173	0.651	(0.6, 0.687)
ctm30	28	govern, state, public	1985	0.668	(0.629, 0.701)
ctm30	29	wage, worker, employ	1416	0.683	(0.631, 0.713)
ctm30	30	polit, peopl, also	638	0.607	(0.518, 0.659)
ctm50	1	state, region, citi	1452	0.599	(0.57, 0.648)
ctm50	2	tion, ment, tive	2100	0.665	(0.643, 0.695)
ctm50	3	school, educ, student	1101	0.573	(0.54, 0.644)
ctm50	4	countri, growth, develop	974	0.577	(0.539, 0.635)
ctm50	5	health, care, hospit	714	0.611	(0.537, 0.652)
ctm50	6	model, consumpt, rate	1535	0.601	(0.573, 0.648)
ctm50	7	experi, choic, prefer	1431	0.591	(0.556, 0.643)
ctm50	8	centuri, histori, british	782	0.552	(0.489, 0.612)
ctm50	9	canada, canadian, provinc	365	0.545	(0.473, 0.642)
ctm50	10	variabl, effect, estim	1994	0.659	(0.619, 0.676)
ctm50	11	case, right, court	1324	0.644	(0.594, 0.681)
ctm50	12	countri, european, unit	839	0.602	(0.551, 0.649)
ctm50	13	save, retir, pension	913	0.568	(0.503, 0.618)
ctm50	14	technolog, innov, patent	950	0.542	(0.499, 0.608)
ctm50	15	pour, plus, sont	219	0.728	(0.543, 0.835)
ctm50	16	capit, invest, asset	1281	0.621	(0.567, 0.642)
ctm50	17	cient, erent, speci	357	0.529	(0.446, 0.576)

Continued on next page

Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
ctm50	18	firm, compani, manag	1199	0.562	(0.522, 0.612)
ctm50	19	test, model, seri	1089	0.565	(0.517, 0.619)
ctm50	20	cost, polici, environment	1293	0.614	(0.584, 0.665)
ctm50	21	function, condit, follow	1199	0.483	(0.457, 0.56)
ctm50	22	year, rate, percent	2056	0.664	(0.642, 0.697)
ctm50	23	risk, expect, valu	1188	0.611	(0.553, 0.637)
ctm50	24	polit, vote, parti	904	0.621	(0.564, 0.671)
ctm50	25	para, como, esta	78	0.168	(0.044, 0.513)
ctm50	26	firm, market, cost	1406	0.616	(0.58, 0.664)
ctm50	27	wage, worker, labor	1292	0.681	(0.621, 0.705)
ctm50	28	manag, organ, work	1622	0.654	(0.616, 0.687)
ctm50	29	crime, polic, crimin	437	0.514	(0.404, 0.576)
ctm50	30	bank, debt, credit	971	0.649	(0.6, 0.698)
ctm50	31	insur, union, coverag	788	0.544	(0.51, 0.635)
ctm50	32	work, hour, earn	1183	0.613	(0.564, 0.658)
ctm50	33	price, demand, consum	1636	0.584	(0.537, 0.609)
ctm50	34	model, estim, distribut	1541	0.518	(0.497, 0.591)
ctm50	35	servic, cost, transport	1034	0.519	(0.467, 0.587)
ctm50	36	product, industri, manufactur	1407	0.549	(0.512, 0.596)
ctm50	37	polici, inflat, monetari	1140	0.667	(0.597, 0.698)
ctm50	38	agricultur, land, farm	703	0.544	(0.476, 0.597)
ctm50	39	rate, exchang, currenc	850	0.710	(0.603, 0.741)
ctm50	40	women, children, famili	758	0.597	(0.548, 0.662)
ctm50	41	trade, export, countri	997	0.634	(0.547, 0.65)
ctm50	42	rate, revenu, incom	1046	0.562	(0.526, 0.616)

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Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
ctm50	43	econom, social, theori	1734	0.731	(0.66, 0.761)
ctm50	44	return, market, stock	915	0.587	(0.539, 0.642)
ctm50	45	polit, nation, state	943	0.702	(0.594, 0.737)
ctm50	46	incom, household, welfar	1291	0.648	(0.583, 0.694)
ctm50	47	govern, polici, public	1656	0.696	(0.662, 0.736)
ctm50	48	black, immigr, white	840	0.571	(0.497, 0.603)
ctm50	49	contract, inform, agent	1328	0.569	(0.528, 0.635)
ctm50	50	cent, india, indian	126	0.415	(0.251, 0.562)
jel1	A	student, teach, instructor	1017	0.641	(0.593, 0.701)
jel1	B	veblen, keyn, marx	878	0.660	(0.586, 0.706)
jel1	C	player, theorem, asymptot	1376	0.514	(0.479, 0.583)
jel1	D	vote, equilibrium, voter	2399	0.664	(0.642, 0.696)
jel1	E	inflat, monetari, shock	1962	0.663	(0.624, 0.706)
jel1	F	export, countri, trade	1518	0.689	(0.627, 0.723)
jel1	G	bank, insur, asset	1720	0.653	(0.62, 0.696)
jel1	H	incom, pension, revenu	1917	0.663	(0.633, 0.703)
jel1	I	health, hospit, student	1621	0.617	(0.58, 0.67)
jel1	J	wage, worker, women	2077	0.710	(0.674, 0.739)
jel1	K	crime, court, plaintiff	1062	0.668	(0.614, 0.723)
jel1	L	firm, price, industri	2251	0.628	(0.594, 0.67)
jel1	M	firm, advertis, entrepreneur	1298	0.601	(0.561, 0.654)
jel1	N	centuri, bank, gold	1140	0.597	(0.542, 0.652)
jel1	O	patent, countri, growth	2258	0.659	(0.626, 0.694)
jel1	P	china, russia, russian	1257	0.644	(0.571, 0.68)
jel1	Q	agricultur, farm, land	1512	0.625	(0.564, 0.663)

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Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
jel1	R	citi, hous, urban	1491	0.601	(0.56, 0.654)
jel1	Z	muslim, cultur, religi	787	0.539	(0.457, 0.594)
jel2	A1	economist, citat, student	751	0.688	(0.592, 0.755)
jel2	A2	student, instructor, teach	375	0.573	(0.48, 0.639)
jel2	B1	veblen, marx, smith	228	0.563	(0.474, 0.659)
jel2	B2	veblen, keyn, institutionalist	501	0.678	(0.554, 0.715)
jel2	B3	veblen, keyn, marx	543	0.665	(0.567, 0.726)
jel2	B4	scienc, philosophi, scientif	269	0.526	(0.38, 0.627)
jel2	B5	veblen, institutionalist, firm	558	0.566	(0.479, 0.605)
jel2	C1	asymptot, theorem, bootstrap	187	0.504	(0.383, 0.609)
jel2	C2	asymptot, estim, theorem	513	0.574	(0.46, 0.602)
jel2	C3	cointegr, asymptot, matrix	206	0.611	(0.454, 0.671)
jel2	C4	index, malmquist, price	124	0.477	(0.289, 0.573)
jel2	C5	forecast, estim, model	897	0.512	(0.448, 0.557)
jel2	C6	theorem, proof, lemma	206	0.468	(0.398, 0.598)
jel2	C7	player, game, payoff	415	0.537	(0.472, 0.632)
jel2	C8	softwar, data, cent	359	0.439	(0.345, 0.556)
jel2	D0	game, player, axiom	193	0.509	(0.44, 0.639)
jel2	D1	household, consumpt, incom	1441	0.556	(0.52, 0.632)
jel2	D2	firm, input, output	1246	0.516	(0.477, 0.564)
jel2	D3	inequ, incom, wealth	679	0.641	(0.554, 0.682)
jel2	D4	auction, bidder, seller	765	0.569	(0.483, 0.616)
jel2	D5	equilibrium, agent, theorem	330	0.385	(0.325, 0.553)
jel2	D6	incom, agent, altruism	993	0.531	(0.47, 0.579)
jel2	D7	vote, voter, elect	1351	0.664	(0.615, 0.716)

Continued on next page

Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
jel2	D8	agent, player, equilibrium	1258	0.518	(0.491, 0.612)
jel2	D9	consumpt, bequest, save	738	0.535	(0.454, 0.588)
jel2	E1	keynesian, keyn, shock	703	0.718	(0.602, 0.762)
jel2	E2	unemploy, wage, consumpt	1331	0.646	(0.585, 0.672)
jel2	E3	inflat, shock, monetari	1073	0.688	(0.605, 0.733)
jel2	E4	money, bank, monetari	894	0.553	(0.502, 0.601)
jel2	E5	inflat, monetari, bank	614	0.631	(0.554, 0.692)
jel2	E6	fiscal, deficit, debt	914	0.528	(0.502, 0.6)
jel2	F0	global, countri, trade	324	0.640	(0.482, 0.72)
jel2	F1	export, trade, tariff	856	0.583	(0.519, 0.629)
jel2	F2	foreign, export, firm	636	0.524	(0.468, 0.604)
jel2	F3	exchang, currenc, foreign	817	0.710	(0.568, 0.738)
jel2	F4	exchang, countri, trade	571	0.581	(0.509, 0.639)
jel2	G1	portfolio, stock, volatil	976	0.585	(0.512, 0.625)
jel2	G2	bank, insur, loan	1128	0.584	(0.556, 0.657)
jel2	G3	firm, merger, debt	951	0.561	(0.515, 0.627)
jel2	H1	govern, voter, parti	343	0.602	(0.486, 0.652)
jel2	H2	incom, taxat, revenu	915	0.637	(0.579, 0.689)
jel2	H3	incom, taxat, taxabl	527	0.534	(0.429, 0.554)
jel2	H4	public, good, provis	483	0.711	(0.55, 0.761)
jel2	H5	pension, retir, secur	1052	0.643	(0.542, 0.652)
jel2	H6	deficit, debt, fiscal	369	0.612	(0.486, 0.644)
jel2	H7	local, fiscal, voter	566	0.551	(0.513, 0.652)
jel2	I1	health, hospit, patient	837	0.527	(0.466, 0.598)
jel2	I2	student, school, educ	666	0.671	(0.576, 0.71)

Continued on next page

Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
jel2	I3	poverti, afdc, children	783	0.609	(0.541, 0.685)
jel2	J1	women, children, child	1463	0.681	(0.605, 0.698)
jel2	J2	wage, worker, labor	1582	0.667	(0.618, 0.692)
jel2	J3	wage, worker, pension	1152	0.637	(0.592, 0.689)
jel2	J4	wage, worker, unemploy	940	0.616	(0.535, 0.65)
jel2	J5	union, wage, worker	404	0.653	(0.537, 0.719)
jel2	J6	immigr, unemploy, worker	844	0.534	(0.516, 0.62)
jel2	J7	discrimin, black, women	381	0.523	(0.448, 0.608)
jel2	K1	court, liabil, plaintiff	463	0.458	(0.404, 0.591)
jel2	K2	firm, court, sharehold	968	0.570	(0.534, 0.652)
jel2	K3	court, patent, worker	360	0.568	(0.457, 0.643)
jel2	K4	crime, crimin, plaintiff	507	0.716	(0.604, 0.747)
jel2	L1	firm, price, profit	1519	0.518	(0.47, 0.581)
jel2	L2	firm, industri, smes	1016	0.573	(0.506, 0.599)
jel2	L3	privat, privatis, enterpris	461	0.607	(0.463, 0.669)
jel2	L4	antitrust, merger, firm	278	0.567	(0.463, 0.649)
jel2	L5	regul, regulatori, firm	634	0.620	(0.558, 0.676)
jel2	L6	drug, firm, patent	1201	0.587	(0.535, 0.631)
jel2	L7	price, gasolin, firm	339	0.518	(0.449, 0.644)
jel2	L8	internet, retail, team	1041	0.556	(0.467, 0.594)
jel2	L9	airlin, carrier, electr	666	0.509	(0.419, 0.568)
jel2	M1	firm, entrepreneur, entrepreneurship	471	0.557	(0.486, 0.654)
jel2	M3	advertis, brand, consum	287	0.496	(0.354, 0.547)
jel2	M5	worker, employe, wage	431	0.598	(0.514, 0.67)
jel2	N1	gold, bank, centuri	470	0.501	(0.437, 0.584)

Continued on next page

Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
jel2	N2	bank, gold, loan	335	0.672	(0.564, 0.729)
jel2	N3	women, slave, centuri	523	0.560	(0.495, 0.645)
jel2	N4	land, india, centuri	532	0.642	(0.558, 0.703)
jel2	N5	land, farm, agricultur	217	0.605	(0.468, 0.7)
jel2	N6	cotton, industri, textil	175	0.559	(0.43, 0.684)
jel2	N7	tariff, trade, export	252	0.441	(0.342, 0.563)
jel2	N8	compani, firm, cent	171	0.488	(0.427, 0.653)
jel2	O1	india, countri, cent	1568	0.629	(0.582, 0.662)
jel2	O2	countri, bank, exchang	434	0.562	(0.487, 0.625)
jel2	O3	patent, innov, firm	914	0.523	(0.475, 0.589)
jel2	O4	growth, capit, countri	895	0.634	(0.552, 0.652)
jel2	O5	cent, growth, export	319	0.440	(0.36, 0.557)
jel2	P1	capitalist, marx, social	591	0.716	(0.629, 0.759)
jel2	P2	china, russia, soviet	505	0.521	(0.437, 0.602)
jel2	P3	china, russia, enterpris	406	0.541	(0.499, 0.656)
jel2	Q1	agricultur, farm, crop	747	0.538	(0.458, 0.582)
jel2	Q2	forest, environment, pollut	938	0.636	(0.557, 0.677)
jel2	Q3	extract, resourc, environment	166	0.508	(0.404, 0.716)
jel2	Q4	energi, emiss, fuel	245	0.491	(0.385, 0.603)
jel2	Q5	emiss, environment, pollut	308	0.598	(0.46, 0.626)
jel2	R1	citi, region, urban	750	0.557	(0.467, 0.593)
jel2	R2	migrat, immigr, citi	710	0.570	(0.5, 0.626)
jel2	R3	hous, citi, locat	588	0.505	(0.41, 0.56)
jel2	R4	transport, road, traffic	223	0.566	(0.408, 0.699)
jel2	R5	land, citi, urban	347	0.591	(0.479, 0.648)

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Table A.5: AUCs by Topic

Topic Mapping	Topic	Top 3 Words	Num Authors	AUC	AUC CI
jel2	Z1	religi, cultur, religion	462	0.572	(0.453, 0.645)

A.5 Comparing Petitions and Contributions

In this Appendix section we compare our two measures of ground-truth ideology and reproduce our main results separately for both measures. To generate $\hat{\theta}_{e,contributions}$, the predicted ideology derived from $\theta_{e,contributions}$, our contributions measure of groundtruth ideology, we train our algorithm from Section 2.4 but limit to the 1,054 authors who have made contributions and using $\theta_{e,contributions}$ as the outcome. We repeat the same process to obtain $\widehat{\theta_{e,petitions}}$, the predicted ideology derived from the 1,650 authors who signed petitions in our data.

We first show that predictive performance of the model is highest when both measures of ideology are combined, justifying combining them. We then conduct a further check that the two sources of groundtruth measurement are yielding similar text-based predictors of ideology by calculating correlations between n-grams selected as significant correlates of each source separately, and that the author-level predicted ideologies are very highly correlated between the two sources of groundtruth. We then reproduce the correlations with the IGM-survey measures as well as the specification curves for each of the petitions, contributions, and combined measures, showing that the results are qualitatively quite similar across different groundtruth measures.

A.5.1 Predictive performance

Figure A.4 shows the AUCs for the full combination of training and evaluation outcomes. The rows show the AUCs when evaluating on the contributions, petitions, and combined measures of groundtruth ideology, respectively. In each row, the AUCs are grouped by topic mapping. Within each group, AUCs are reported separately for models that are trained on the contributions, petitions, and combined measures of groundtruth ideology, respectively.

We see that while all combinations are more accurate than random noise since AUCs are significantly greater than 0.50, models trained on contributions have lower AUCs regardless of the outcome. This suggests that the relationship between campaign contribution patterns and the text of papers is noisier than it is for petitions or for the combined measures. One potential explanation is that the share of right-leaning authors in the contribution data is much smaller than it is in the petitions data. Of the 1,054 authors with contributions, only 17% are classified as right-leaning, as compared with 60% of the 1,650 authors who signed petitions. Prediction problems involving class-imbalance (a.k.a. low base rates) generally lead to lower performance estimates.

We also see from the first row in Figure A.4 that models trained on petitions have higher AUCs than models trained on contributions, when evaluating contributions. The best performance when evaluating on campaign contributions comes from the model trained on the combined measure of ideology. We see a similar pattern in the third row when evaluating on the combined measure in that the models trained on the combined measure outperform models trained only on contributions or only on petitions. The second row of Figure A.4 shows that the combined model does not improve performance on the petition measure of ideology.

These patterns show the utility of combining the petitions and contributions into a single measure of ideology. These are both imperfect measures of political behavior, as the ideal measure would be observed for a random subsample economists. However, given that combining the two measures weakly improves prediction for each of the measures independently, and that our elasticity results are robust to each ideology measure, we elect to present the combined measure in the main text.

A.5.2 Phrase-level

We next examine the extent to which the contribution and petition measures pick up on the same signal of ideology. Since our prediction models are driven by the relationship between ideology and text patterns, we first measure the level of agreement between the phrases that passed the χ^2 filter.

When we focus on the *NoTopic* mapping, that 2,564 n-grams were shared across the two measures. That represents 20.3% of 12,575 significant phrases under the petitions model, and 52.3% of the 4,906 significant phrases under the contribution model. Of the phrases that were shared, there was agreement 63.9% of the time in the sign of the correlation between phrase usage and ideology. We examine agreement systematically by estimating the following regression for each topic mapping

$$\rho_{p,t}^{cont} = \beta_0 + \beta_1 \rho_{p,t}^{pet} + \beta_2 Topic_t$$

where $\rho_{p,t}^{cont}$ is the correlation between the contribution measure of groundtruth ideology for phrase p in topic t. We define $\rho_{p,t}^{pet}$ in a similar manner but for the petitions measure of ideology. Both sets of correlations are standardized to have mean zero and variance one within topic mapping. A β_1 greater than zero indicates that the average change in correlation is in the same direction between the contribution and petition specifications. As seen in Table A.6, there is a moderately strong relationship between the two sets of correlations across topic mapping. For example, in the unconditional specification for *CTM100* a one standard deviation increase in correlations when petitions are the ground truth measure is associated with a .473 increase in standard deviation in correlations for the same phrases when contributions are the ground truth measure. Controlling for topics reduces the relationship somewhat but there is still on average agreement in the direction of the relationship between phrase usage and ideology across the two groundtruth measures.

A.5.3 Author-level

We next turn to the relationship between economist-level ideologies estimated from the contributions and petitions data. Figure A.6 shows the mean predicted ideology, controlling for topic mapping fixed effects, from the model trained on petitions by bins of predicted author ideology from a model trained on contributions. The binned scatter plots are shown separately by groundtruth author status. We follow the methodology proposed in Cattaneo et al. (2022b). We see that while the measures are noisy, there is general agreement at the level of predictions for authors between the two measures despite a completely different ideology measure and a different set of groundtruth authors.

A.5.4 Validation on IGM Surveys

Tables A.7 and A.8 show the relationship between IGM survey responses and the petition and contribution prediction of ideology, respectively. Consistent with the results from Appendix A.5.1, the relationship between predicted ideology and survey responses is stronger for the petitions measure than the contributions measure.

A.5.5 Specification Curves

Figures A.7, A.8, and A.9 show specification curves for the contribution, petition, and combined measures of ideology when we limit it to ordinary least squares specifications.

Table A.6: Patterns of phrase usage across two measures of ideology

Outcome: ρ^{cont}	*NoTopic*	*JEL1*	*JEL2*	*CTM30*	*CTM50*	*CTM100*
ρ^{pet}	0.3521***	0.4887***	0.4080***	0.4394***	0.4504***	0.473 ***
	(0.020)	(0.015)	(0.016)	(0.015)	(0.018)	(0.020)
ρ^{pet} w/ Topic FE		0.3191***	0.2218***	0.3478***	0.3266***	0.2867***
		(0.023)	(0.020)	(0.022)	(0.023)	(0.022)
Observations	2,564	3,006	3,725	2,312	2,325	2,022
Adj R^2	0.124	0.239	0.166	0.193	0.203	0.223
Adj R^2 w/ Topic FE		0.432	0.498	0.425	0.530	0.601

Results from regression of the correlation between phrase usage and contributions (ρ^{cont}) and phrase usage and petitions (ρ^{pet}) across six topic mappings. Standard errors are robust.

Table A.7: Correlation Between Author Ideology and IGM Responses - Petitions only

Ideology	(1)	(2)	(3)	(4)	(5)	(6)
JEL 1	0.804***	2.156**	2.153**	0.792***	1.200***	1.139**
	(0.283)	(0.897)	(1.087)	(0.220)	(0.334)	(0.457)
JEL 2	1.397***	3.694***	4.195***	1.049***	1.630***	2.574***
	(0.366)	(1.086)	(1.615)	(0.344)	(0.529)	(0.652)
CTM 30	1.431***	3.762***	3.880***	1.161***	1.550***	1.462***
	(0.352)	(1.117)	(1.266)	(0.295)	(0.448)	(0.553)
CTM 50	1.381***	3.284***	4.798***	1.110***	1.421***	1.535**
	(0.332)	(1.078)	(1.521)	(0.288)	(0.443)	(0.657)
CTM 100	1.190**	3.129**	3.828**	1.054***	1.490**	2.008***
	(0.466)	(1.382)	(1.891)	(0.406)	(0.626)	(0.761)
No Topic	0.662***	1.998***	2.141***	0.577***	0.773***	0.620*
	(0.183)	(0.537)	(0.669)	(0.131)	(0.209)	(0.322)
Question FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	598	598	598	715	715	715
Individuals	39	39	39	39	39	39

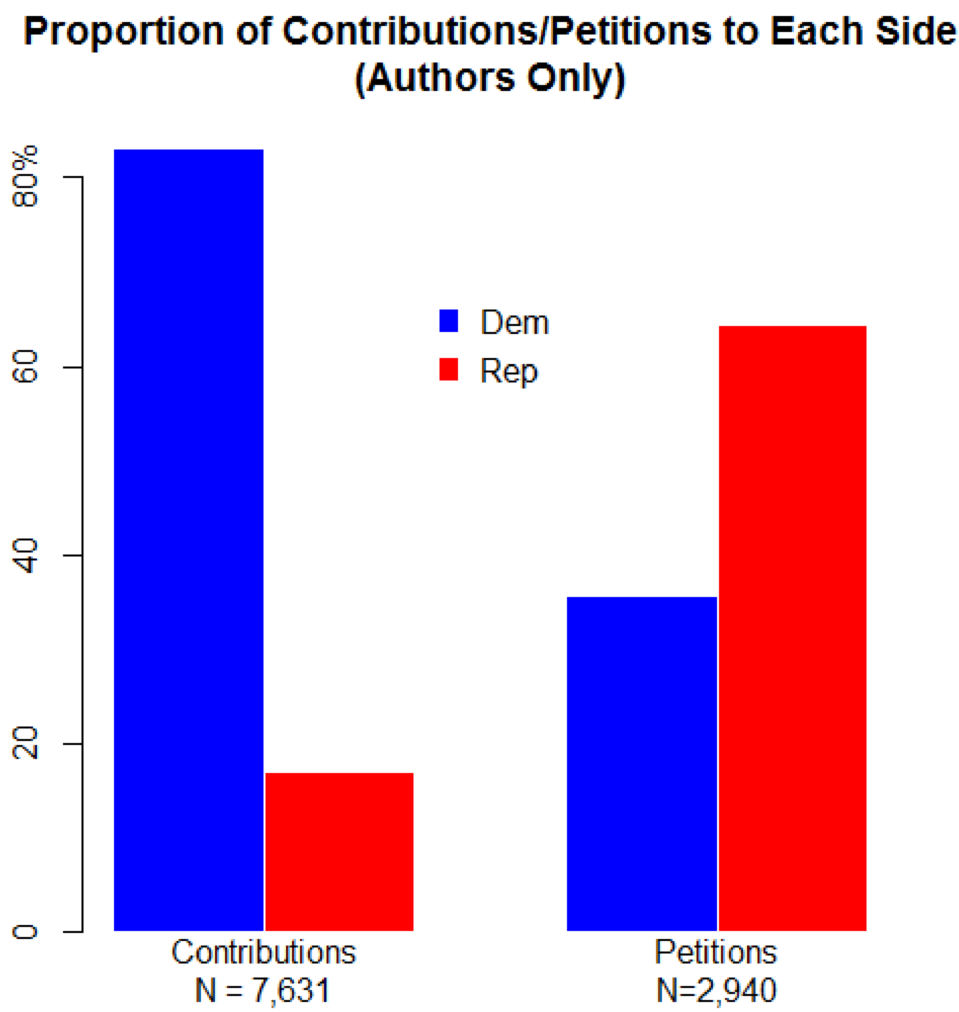
Standard errors are clustered by economist. Controls include year of Ph.D., and binary indicators for gender, Ph.D. university, and any Federal government experience. Columns 1-3 are logit regressions predicting the author as conservative as measured by Gordon and Dahl (2013), while Columns 4-6 are ordered logit regressions using the 5 different levels of agreement with statements coded by Gordon and Dahl (2013) conservative.

Table A.8: Correlation Between Author Ideology and IGM Responses - Contributions only

Ideology	(1)	(2)	(3)	(4)	(5)	(6)
JEL 1	2.624***	3.612	7.552	1.826**	2.565**	-0.562
	(1.011)	(2.259)	(6.735)	(0.875)	(1.296)	(2.774)
JEL 2	3.581***	6.250*	1.293	2.864**	4.236**	3.668**
	(1.318)	(3.539)	(3.728)	(1.157)	(1.662)	(1.458)
CTM 30	1.184	-0.593	-10.28**	1.309	2.439	1.561
	(1.321)	(3.439)	(4.883)	(1.327)	(2.076)	(2.363)
CTM 50	2.558*	3.922	6.210	1.189	2.261	5.420*
	(1.447)	(3.842)	(6.274)	(1.394)	(2.215)	(2.904)
CTM 100	3.780**	5.909	11.25*	2.720	5.197**	13.30***
	(1.845)	(4.857)	(6.342)	(1.660)	(2.610)	(2.537)
No Topic	-0.00558	-0.974	-1.199	-0.106	-0.209	0.241
	(0.578)	(1.043)	(0.786)	(0.437)	(0.573)	(0.486)
Question FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Observations	598	598	598	715	715	715
Individuals	39	39	39	39	39	39

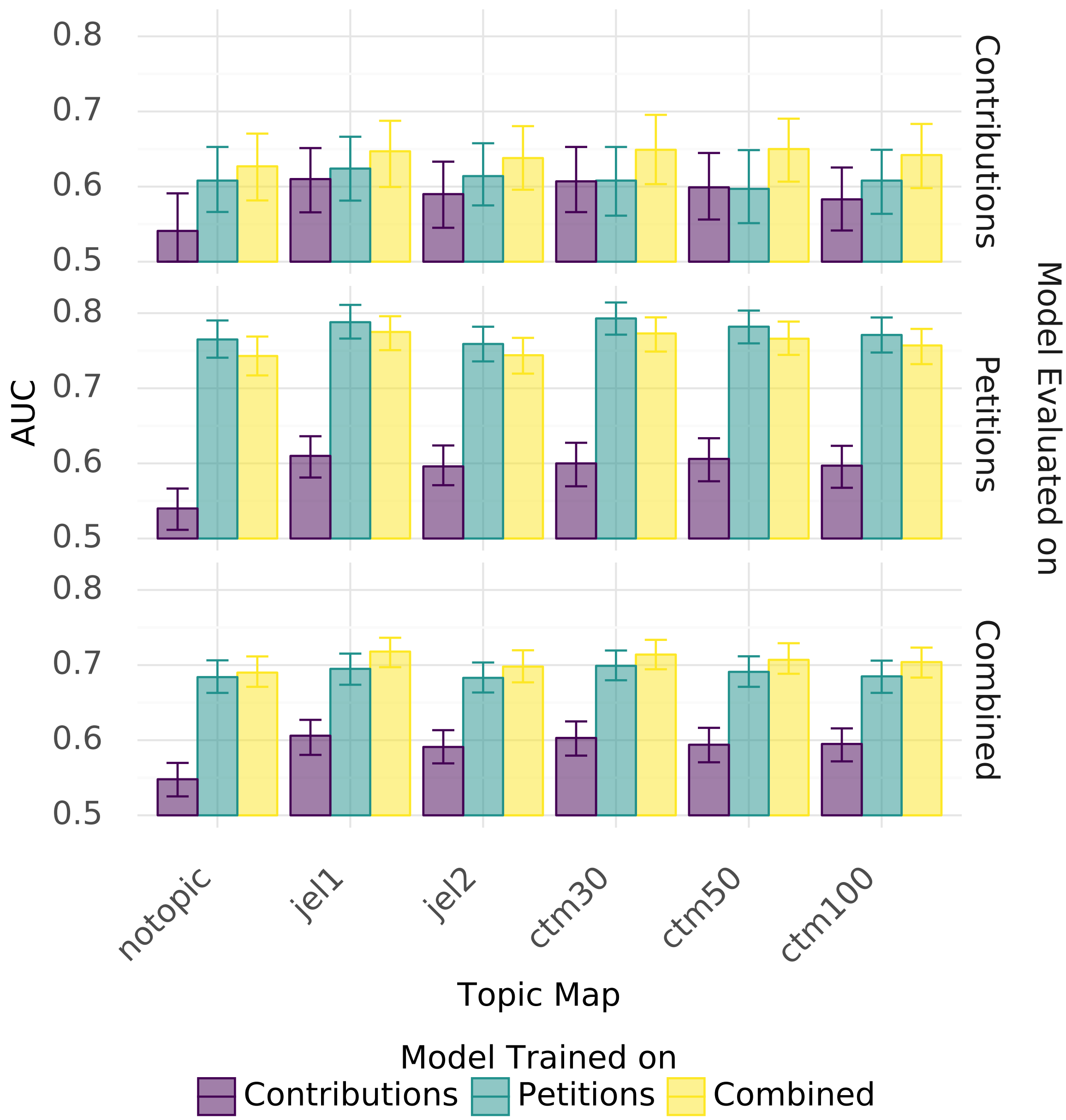
Standard errors are clustered by economist. Controls include year of Ph.D., and binary indicators for gender, Ph.D. university, and any Federal government experience. Columns 1-3 are logit regressions predicting the author as conservative as measured by Gordon and Dahl (2013), while Columns 4-6 are ordered logit regressions using the 5 different levels of agreement with statements coded by Gordon and Dahl (2013) conservative.

Figure A.3: Patterns of Economist Political Behavior



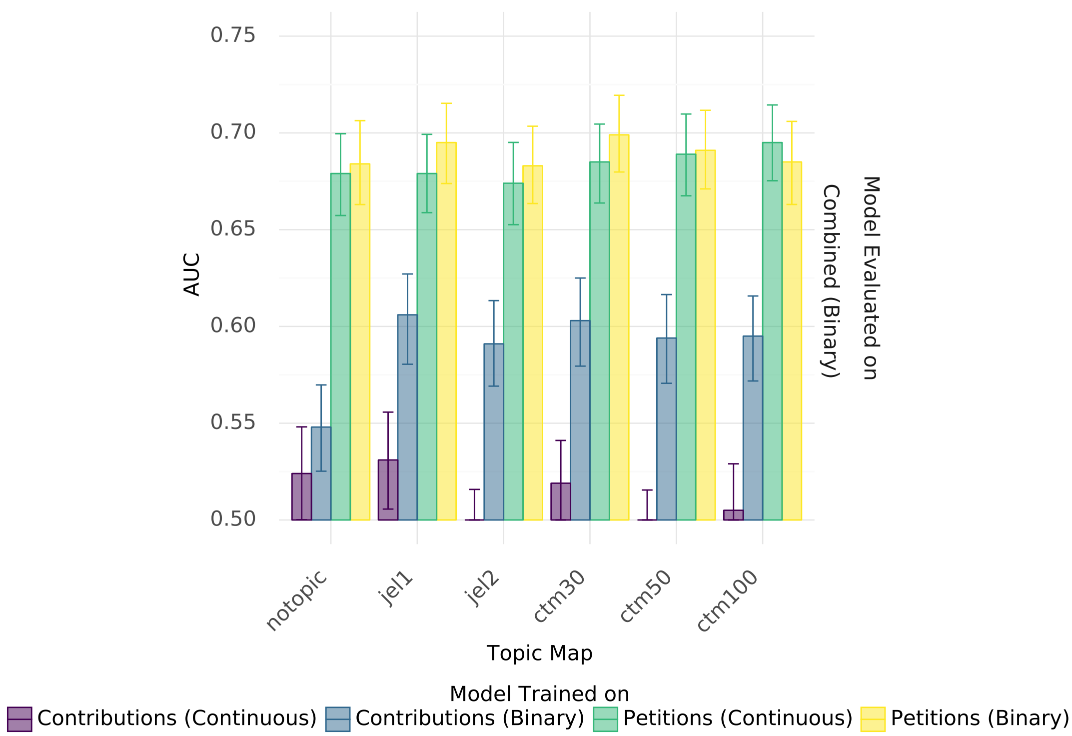
The proportion of campaign contributions to each party is shown on the left and the proportion of signatures on left- and right-leaning petitions is on the right. There were 1,101 authors making contributions and 1,456 signing petitions.

Figure A.4: Predictive Performance of Three Groundtruth Models



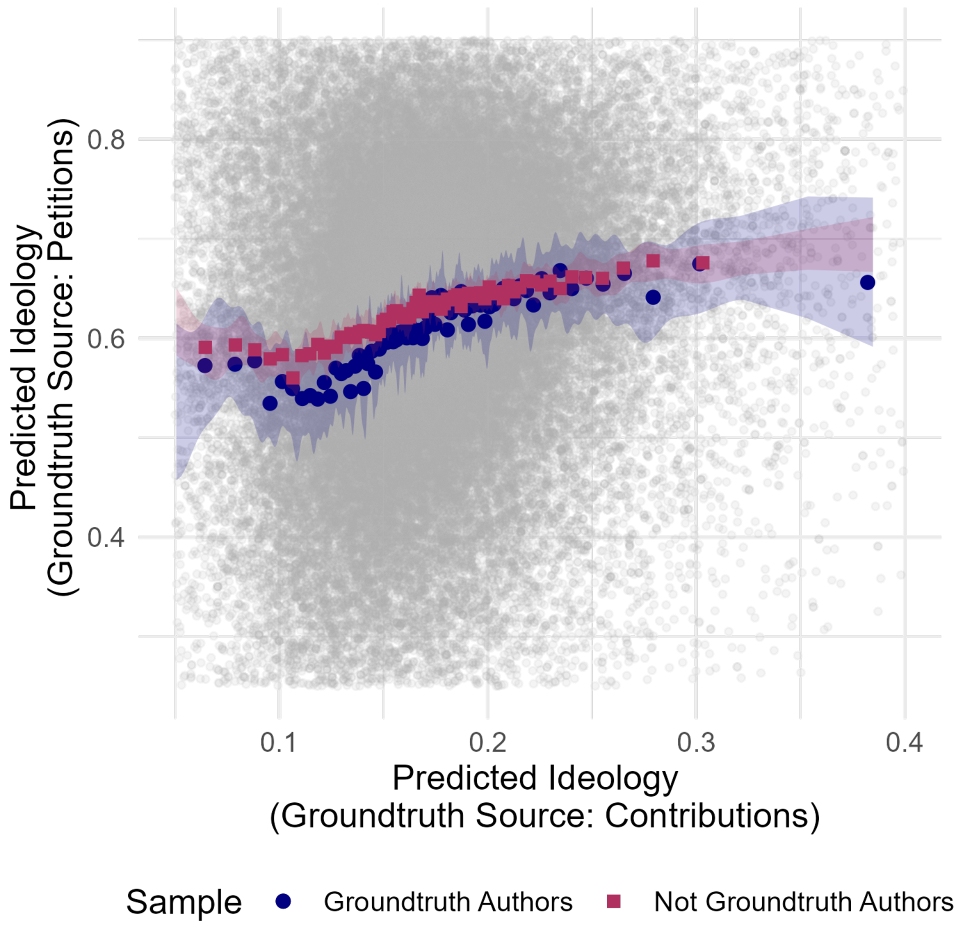
This figure shows the AUC and bootstrapped 95% confidence intervals (with 1,000 replicates) when evaluating accuracy on $\theta_{i,combined}$, the groundtruth measure of ideology drawn from both the petitions and contributions. The models being evaluated are optimized to predict the binary versions of $\theta_{i,pet}$, the petitions-derived measure of ideology, $\theta_{i,cont}$, the contributions-derived measure of ideology, and $\theta_{i,combined}$, respectively.

Figure A.5: Predictive Performance of Continuous Groundtruth Models



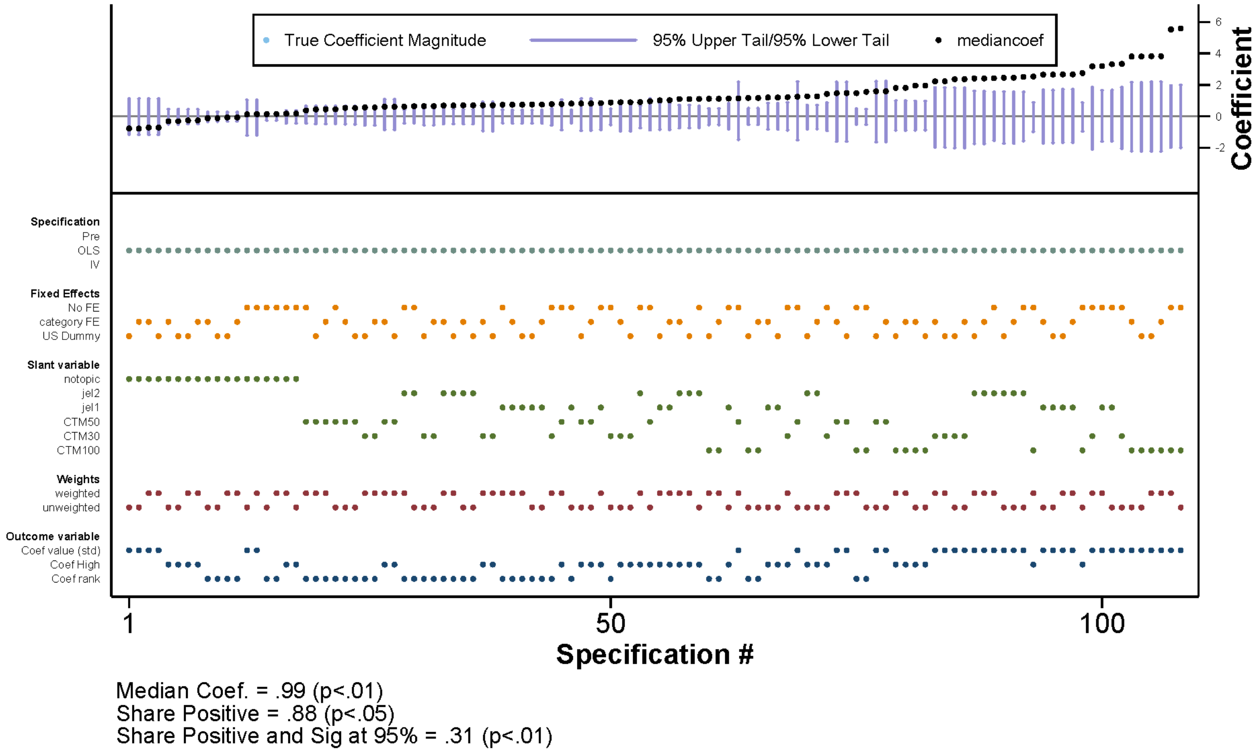
This figure shows the AUC and bootstrapped 95% confidence intervals (with 1,000 replicates) when evaluating accuracy on $\theta_{i,combined}$, the groundtruth measure of ideology drawn from both the petitions and contributions. The models being evaluated are optimized to predict the binary and continuous versions of $\theta_{i,pet}$, the petitions-derived measure of ideology and $\theta_{i,cont}$, the contributions-derived measure of ideology, respectively.

Figure A.6: Partial Binned Scatterplot of $\hat{\theta}_{e,petitions}$ on $\hat{\theta}_{e,contributions}$



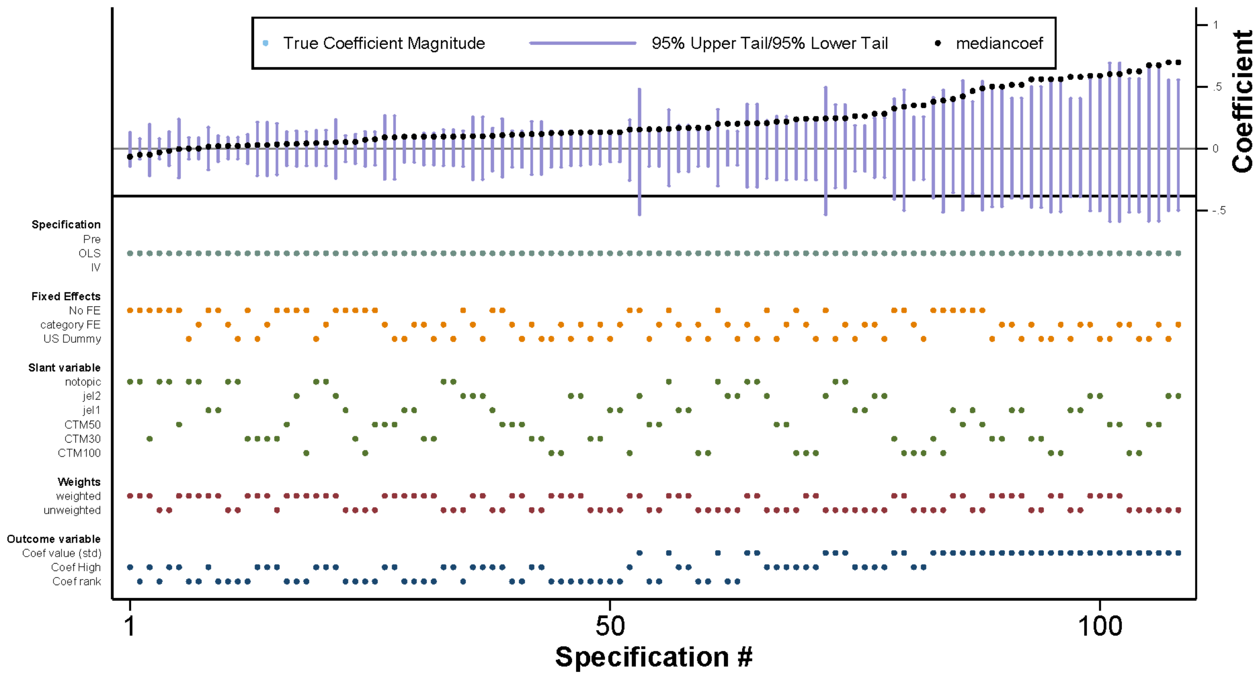
This figure shows the binned scatter plot (controlling for topic mapping fixed effects) for the relationship between predicted ideology from the petitions model by bins of predicted ideology from the contributions model. The binned scatter plots are shown separately by groundtruth author status. We follow the methodology proposed in Cattaneo et al. (2022b).

Figure A.7: Specification Curve: Contributions-based measure of ideology.



Coefficients from 108 different specifications shown, ordered by size. Bottom left corner shows statistics testing a) the probability that the median coefficient from a randomly shuffled sample is greater than the true median coefficient, b) the probability that a randomly shuffled sample has at least the same share of positive coefficients as the true sample, and c) the probability that a randomly shuffled sample has at least the same share of positive and significant coefficients as the true sample.

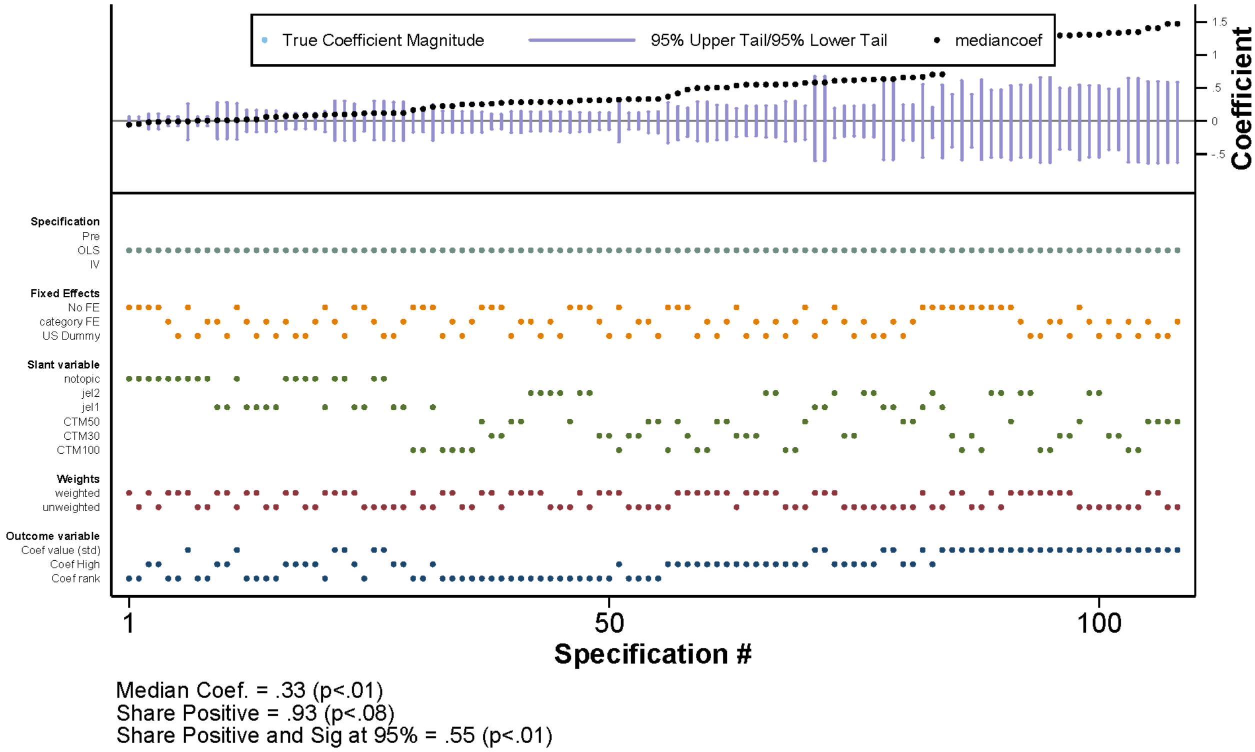
Figure A.8: Specification Curve: Petitions-based measure of ideology



Median Coef. = .15 (p<.05)
Share Positive = .92 (p<.13)
Share Positive and Sig at 95% = 0 (p<.05)

Coefficients from 108 different specifications shown, ordered by size. Bottom left corner shows statistics testing a) the probability that the median coefficient from a randomly shuffled sample is greater than the true median coefficient, b) the probability that a randomly shuffled sample has at least the same share of positive coefficients as the true sample, and c) the probability that a randomly shuffled sample has at least the same share of positive and significant coefficients as the true sample.

Figure A.9: Specification Curve: Combined



Coefficients from 108 different specifications shown, ordered by size. Bottom left corner shows statistics testing a) the probability that the median coefficient from a randomly shuffled sample is greater than the median coefficient, b) the probability that a randomly shuffled sample has at least the same share of positive coefficients as the true sample, and c) the probability that a randomly shuffled sample has at least the same share of positive and significant coefficients as the true sample.

A.6 Comparing Predictive Phrases Across Topic Mappings

In this Appendix section we show the set phrases that were most predictive of the left- and right-leaning ideology across five topics in four topic mappings related to the economics of education. The caption in each table show the topic mapping, the particular topic in the mapping, and the topic-specific AUCs.[34] The first column in each table shows the top 20 most probable words in the topic. The CTM models estimate these probabilities directly. For the JEL models, we estimate these probabilities empirically using papers with known JEL codes. The next three columns show the top 20 left-leaning one-word, two-word, and three-or-more-word phrases, respectively. The last three columns show the same but for right-leaning phrases. See the supplementary material for the full list of such tables covering all topic mappings.

[34] The computation of topic-specific AUCs weights economists by the probability of writing in the topic.

Table A.9: Topic Mapping = ctm30, Topic = 19, AUC = 0.568

Topic Word	Unigram	Bigram	Other	Unigram	Bigram	Other
school	women	head_start	pupil_teacher_ratio	athlet	public_choic	grade_point_averag
educ	earn	grade_standard	canadian_public_polici_analys	credit	school_district	journal_econom_educ
student	train	qualiti_adjust	public_polici_analys_politiqu	hope	financi_aid	southern_econom_journal
colleg	employ	child_care	australian_bureau_statist	sport	faculti_member	privat_school_enrol
score	work	minimum_wage	politiqu_vol_xxxiv	season	athlet_particip	american_journal_econom_sociolog
year	children	labor_market	implicit_price_deflat	load	alumni_give	-
teacher	univers	nation_account	sourc_author_compil	student	student_perform	-
high	volum	gender_gap	high_school_dropout	alumni	final_exam	-
effect	disciplin	primari_school	labor_market_outcom	journal	fall_spring	-
graduat	famili	critic_think	bureau_econom_analysi	class	letter_grade	-
grade	canadian	men_women	labor_forc_particip	lachmann	growth_rate	-
test	household	test_score	-	cheat	academ_year	-
univers	group	quantil_regress	-	test	causal_impact	-
program	teacher	primari_secondari	-	instructor	public_educ	-
qualiti	polici	teach_staff	-	truste	intermedi_microeconom	-
attend	differenti	higher_educ	-	summer	clemson_univers	-
class	canada	labour_market	-	articl	summer_school	-
enrol	immigr	african_american	-	tullock	fixed_effect	-
group	outcom	quantiti_index	-	semest	fund_rais	-
experi	pupil	affirm_action	-	scholarship	student_enrol	-

Table A.10: Topic Mapping = ctm50, Topic = 3, AUC = 0.59

Topic Word	Unigram	Bigram	Other	Unigram	Bigram	Other
school	school	head_start	pupil_teacher_ratio	hope	public_choic	journal_econom_educ
educ	train	qualiti_adjust	canadian_public_polici_analys	credit	school_district	privat_school_enrol
student	earn	grade_standard	public_polici_analys_politiqu	load	alumni_give	grade_point_averag
colleg	women	test_score	australian_bureau_statist	alumni	faculti_member	southern_econom_journal
score	univers	minimum_wage	politiqu_vol_xxxiv	instructor	intermedi_microeconom	journal_human_resourc
teacher	children	nation_account	implicit_price_deflat	journal	final_exam	journal_polit_economi
year	employ	child_care	high_school_graduat	scholarship	behavior_respons	-
grade	famili	labor_market	sourc_author_compil	summer	summer_school	-
graduat	volum	critic_think	socio_econom_statu	cheat	univers_georgia	-
high	enrol	colleg_attend	bureau_econom_analysi	prerequisit	student_perform	-
test	grade	year_old	-	class	econom_depart	-
univers	princip	primari_secondari	-	sport	resid_nonresid	-
program	skill	higher_educ	-	athlet	intertempor_substitut	-
attend	educ	teach_staff	-	withdraw	depart_econom	-
enrol	wage	colleg_educ	-	tullock	technic_effici	-
qualiti	polici	colleg_graduat	-	nonresid	academ_year	-
class	standard	quantiti_index	-	major	tax_rate	-
effect	disciplin	secondari_school	-	articl	student_learn	-
econom	district	log_wage	-	state	hous_price	-
achiev	household	post_keynesian	-	section	fall_spring	-

Table A.11: Topic Mapping = jel2, Topic = I2, AUC = 0.655

Topic Word	Unigram	Bigram	Other	Unigram	Bigram	Other
student	univers	qualiti_adjust	pupil_teacher_ratio	alumni	school_district	privat_school_enrol
school	district	class_size	australian_bureau_statist	credit	alumni_give	southern_econom_journal
educ	earn	minimum_wage	implicit_price_deflat	load	south_carolina	human_capit_accumul
teacher	award	head_start	canadian_public_polici_analys	athlet	technic_effici	percentag_point_like
score	volum	nation_account	public_polici_analys_politiqu	truste	human_capit	attend_privat_school
grade	share	child_care	bureau_econom_analysi	season	fund_rais	-
colleg	children	higher_educ	-	donat	median_voter	-
enrol	measur	grade_standard	-	hope	public_educ	-
children	chang	primari_secondari	-	sport	fix_effect	-
attend	educ	year_old	-	hour	privat_school	-
parent	salari	teach_staff	-	gift	fixed_effect	-
district	student	school_financ	-	georgia	technic_ineffici	-
child	rate	singl_mother	-	asset	board_truste	-
graduat	number	enrol_rate	-	diploma	school_choic	-
cohort	govern	quantiti_index	-	nurs	colleg_major	-
famili	price	quantil_regress	-	scholarship	public_school	-
black	percent	low_incom	-	religios	athlet_particip	-
estim	faculti	real_output	-	farrel	clemson_univers	-
math	enrol	financi_aid	-	summer	pre_program	-
tuition	index	primari_school	-	donor	fall_spring	-

Table A.12: Topic Mapping = ctm100, Topic = 6, AUC = 0.603

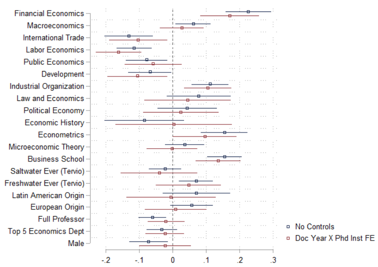
Topic Word	Unigram	Bigram	Other	Unigram	Bigram	Other
school	earn	minimum_wage	high_school_graduat	hope	human_capit	-
educ	train	higher_educ	pupil_teacher_ratio	alumni	causal_impact	-
colleg	school	qualiti_adjust	colleg_high_school	credit	social_secur	-
high	work	labor_market	-	home	median_voter	-
year	effect	colleg_graduat	-	truste	school_district	-
graduat	children	nation_account	-	vote	school_attain	-
cohort	women	colleg_educ	-	happi	econom_growth	-
enrol	chang	men_women	-	voter	-	-
attend	colleg	public_school	-	load	-	-
return	employ	financi_aid	-	scholarship	-	-
higher	rate	colleg_attend	-	nurs	-	-
qualiti	wage	educ_attain	-	summer	-	-
level	black	rate_return	-	journal	-	-
abil	percent	cohort_size	-	nonresid	-	-
student	volum	male_femal	-	withdraw	-	-
attain	differ	gender_gap	-	citat	-	-
individu	continu	attend_colleg	-	expenditur	-	-
complet	enrol	primari_school	-	athlet	-	-
secondari	district	return_school	-	input	-	-
primari	famili	class_size	-	-	-	-

Table A.13: Topic Mapping = ctm100, Topic = 28, AUC = 0.594

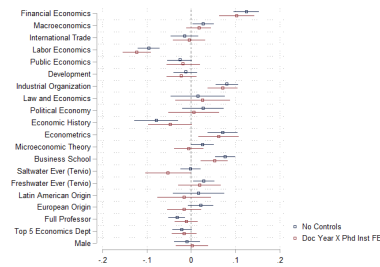
Topic Word	Unigram	Bigram	Other	Unigram	Bigram	Other
black	school	test_score	high_school_graduat	student	poverti_rate	standard_error_cluster
score	earn	black_student	black_white_test_score	district	black_player	journal_legal_studi
student	black	african_american	pupil_teacher_ratio	test	school_district	-
school	effect	labor_market	canadian_public_polici_analys	athlet	median_famili	-
white	estim	black_men	-	season	home_ownership	-
teacher	work	white_student	-	team	fix_effect	-
test	grade	low_incom	-	sport	fixed_effect	-
grade	percent	white_men	-	instructor	transact_cost	-
race	employ	class_size	-	basebal	win_percentag	-
effect	children	black_enrol	-	load	cognit_achiev	-
achiev	averag	e_ect	-	award	public_school	-
racial	teacher	head_start	-	perform	labor_earn	-
discrimin	women	qualiti_adjust	-	juri	older_sibl	-
class	discrimin	student_s	-	incent	median_voter	-
district	wage	standard_deviat	-	game	academ_year	-
minor	famili	grade_standard	-	bond	-	-
differ	white	black_worker	-	happi	-	-
group	educ	health_insur	-	loan	-	-
perform	model	visibl_minor	-	firm	-	-
peer	chang	black_white	-	judg	-	-

A.7 Sorting by CV characteristics for different topic adjustments

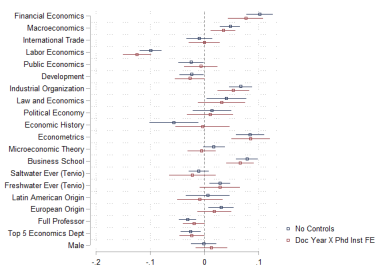
In this Appendix we present the results from section 4 for all the topic adjustments in the Figures below.



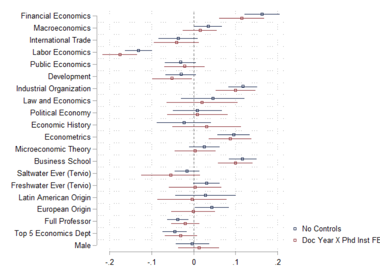
No topic



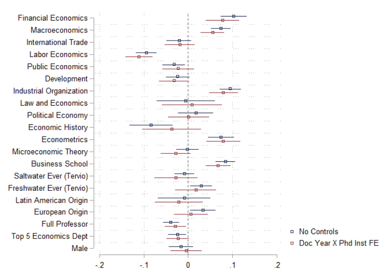
CTM-50



CTM-100



JEL1



JEL2

Figure A.10: CV regressions for various topic adjustments.

A.8 Selection into elasticity data

Table A.14: Sample selection into matching with prediction data

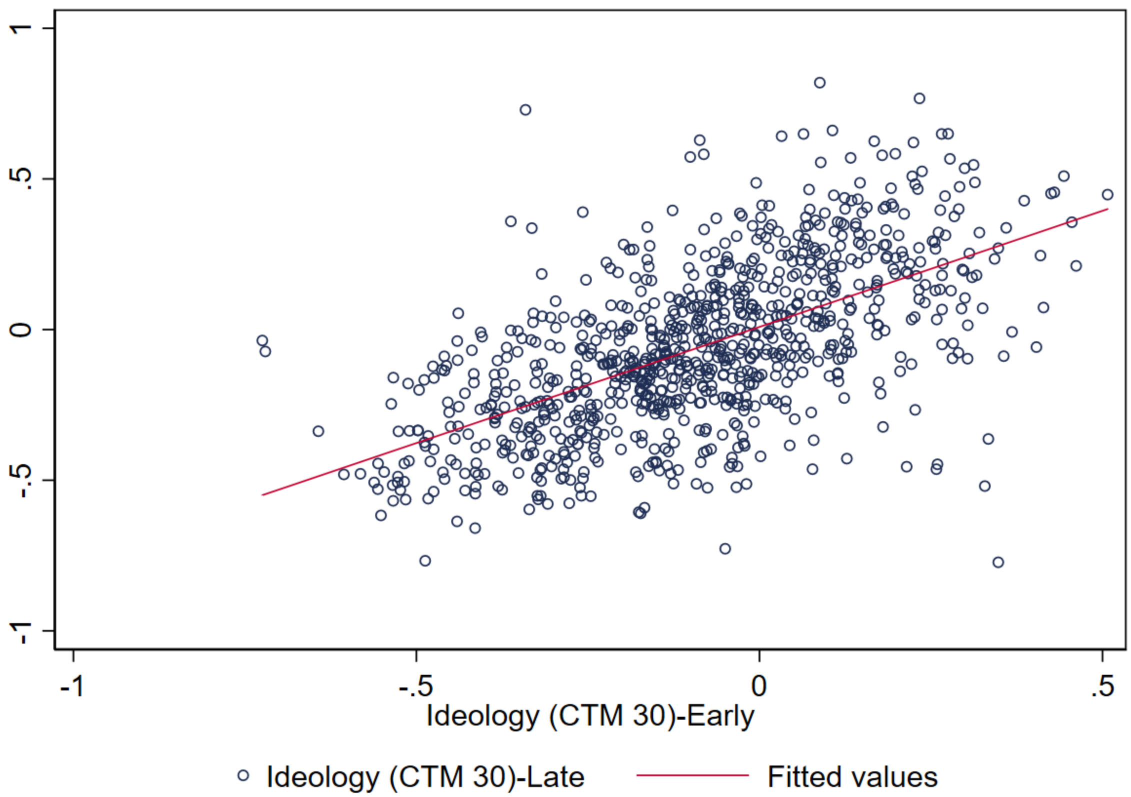
	(1) Pred. Ideo. (CTM30)	(2) Pred. Ideo. (CTM30)	(3) Coef. Rank	(4) Coef. Rank
Number Unmatched	0.006	0.028	0.018	0.027
	(0.029)	(0.021)	(0.024)	(0.026)
Meta-Analysis FE	No	Yes	No	Yes
R-squared	0.00	0.10	0.00	0.07
Observations	240	240	212	212
Mean Unmatched	0.65	0.65	0.67	0.67

Standard errors are clustered by author group.

A.9 Stability of Ideology Predictions

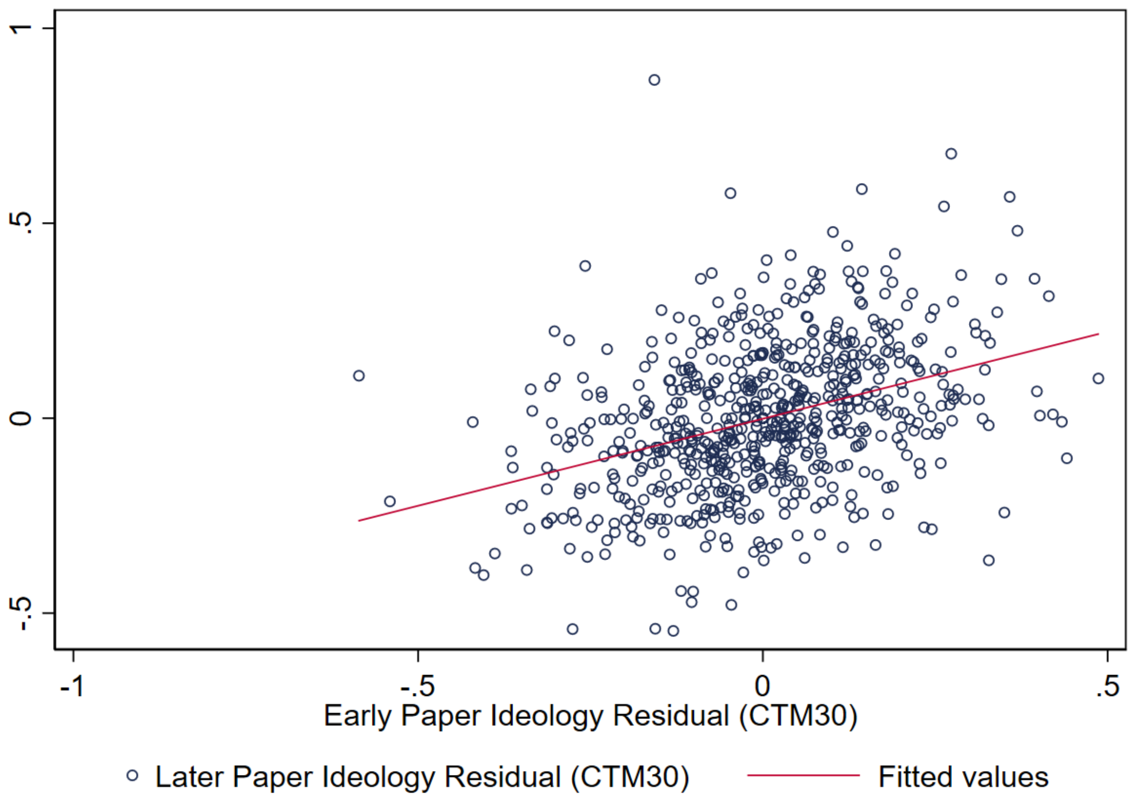
In this Appendix section we look at whether our ideology scores exhibit changes over the careers of economists. We proceed by forming two predictions of ideology: $Ideology_i^{Pre}$, from the first 50% of an economist i's academic writing by words, and $Ideology_i^{Post}$ from the last 50%. We only show results for the $CTM50$ measure of ideology, as others are quite similar. Figure A.11 shows the scatterplot between $Ideology_i^{Pre}$ and $Ideology_i^{Post}$ for all the AEA economists in our sample. A.12 shows the scatterplot for the CV sample, with saltwater/freshwater, business school, Ph.D. completion year fixed effects, subfield fixed effects, rank, presence in groundtruth sample, region of origin, and years between undergrad and Ph.D. all partialled out. As discussed in the main text, the correlation is quite strong in both figures.

Figure A.11: Stability of Predicted Ideology for Full Sample



This Figure shows the scatterplot of CTM-30 slants estimated using the first 50% of an author's words against those estimated from the second 50% for our full sample of economists.

Figure A.12: Stability of Predicted Ideology Residuals for CV Sample



This Figure shows the scatterplot of CTM-30 slants estimated using the first 50% of an author's words against those estimated from the second 50% for the sample of economists for which we have CV data.