Political Language in Economics

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Abstract

Does political ideology influence economic research? We rely upon purely inductive methods in natural language processing and machine learning to examine patterns of implicit political ideology in economic articles. Using observed political behavior of economists and the phrases from their academic articles, we construct a high-dimensional predictor of political ideology by article, economist, school, and journal. In addition to field, journal, and editor ideology, we look at the correlation of author ideology with magnitudes of reported policy relevant elasticities. Overall our results suggest that there is substantial sorting by ideology into fields, departments, and methodologies, and that political ideology influences the results of economic research.

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1 Introduction

Modern governments incorporate expert opinion into policy analysis via a wide variety of formal and informal mechanisms. Examples from economics include central bank policy, anti-trust policy, the design of taxes and regulation. Beyond economics, expertise in climate science, medicine and public health, and many engineering disciplines are of immediate relevance to policy makers. Expert opinion and judgement is often expected to be non-partisan, and yet experts may have partisan or political preferences of their own.

Whether expert opinion includes political beliefs is difficult to empirically assess. While diagnosing partisanship in media or speech is relatively straightforward, specialized technical languages may make it difficult for outsiders to distinguish partisan beliefs from expert judgement. In addition, political opinions may be shaped by expertise rather than vice-versa, or there might be unobserved experiences that shape both expert views as well as political preferences.

In this paper, we provide a purely inductive method for assess the importance of political preferences to professional sorting in economics and to the substance of economic research using a purely inductive approach. We predict out-of-sample individual political behavior with the language from that individual's academic research papers, even adjusting for field of research. If political preferences were irrelevant for academic research in economics, this should be very difficult. Nonetheless our method generates good out-of-sample predictions of economist political behavior based on academic writing alone. We use this methodology to predict the ideology of economics papers and individual economists, and as our main application, we document a robust correlation between predicted ideology of authors and empirical estimates in policy relevant literatures.

Why focus on economics to study political preferences in research? Economics has more partisan diversity than any other social science.[1] Economics has more direct policy influence than other social sciences, and economists are the most highly paid and confident in their methodology.[2] 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,

[1] 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).

[2] Fourcade, Ollion, and Algan (2014) argue that economists are the highest paid of the social scientists, and are the most insular in terms of interdisciplinary citations.

the Federal Trade Commission, the Department of Justice, and other agencies is far larger again 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).

In his 'The Politics of Political Economists', George Stigler argued that while professional economics was conservative (in the sense of hostile to radical changes) in its orientation, advances in economic science were non-partisan due to its 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 pg 40). Stigler believed that political and policy preferences do not drive economic research, and when they do, it is for the worse.[3] This belief that economics conforms with scientific norms, often identified with the work of the sociologist Robert Merton (1942), is the basis of the working consensus that is widely defended.[4]

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. We investigate the role of political preferences, or ideology, in economics with a data-driven approach. We extend methods of machine learning and of natural language processing introduced to economics by Gentzkow and Shapiro (2010). Data on individual campaign contributions and on petition signings establish a ground-truth sample of economists' ideologies, which, linked to the text of academic articles, allows us to identify word phrases whose frequency is correlated with individual partisan political behavior. These "partisan" phrases look intuitively plausible, and are identified within a given topic of research, ensuring that we are not simply picking up different language patterns across fields of economics. We use the correlations of these phrases with partisan political behavior together with the phrase frequency of other economists' economics papers to predict paper, journal, and economist ideology. We validate these predictions of political preferences using held-out data, as well as confirming that they are correlated with partisan IGM responses (Gordon and Dahl 2013). Our first result is that it is indeed possible to

[3] 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 pg 43)

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

predict partisan behavior with high-dimensional representations of academic writing.

The possibility of a completely apolitical economic science remains contested. In their book "the Making of an Economist", Colander and Klamer (1990) argued that graduate training in economics induced conservative political beliefs, with Colander (2005 pg 177) writing that: "10 percent of first-year students considered themselves conservative; by the fourth and fifth year, this number had risen to 23 percent. There was also a large drop by year in students who considered themselves radical; that percentage fell from 13 percent of first year students to only 1 percent of fourth-year and higher students". Or consider the view of a venerable, aptly named, magazine: "People drawn to the economics profession do tend to favour the market mechanism to allocate resources instead of the government".[5] Countering this view of economics as intrinsically libertarian, Klein and Stern (2005) use a survey of AEA members to argue that only 8% of economists are "truly free-market". The best evidence comes from a comprehensive survey undertaken by Fuchs, Krueger, and Poterba, 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, Krueger, and Poterba 1998 pg 1415). A series of recent papers investigate empirically the determinants of economic publication and citation patterns (Ellison 2000, 2004, Terviö 2013, Önder and Terviö 2013). Closest to our paper is the recent article by Gordon and Dahl (2013), who use the IGM survey responses to assess whether economists are divided over policy issues. None of these papers look at political ideology of economics articles, and none use the text of economics articles themselves as data, and instead analyze citation patterns or publication counts alone.[6]

Instead of these survey based methods, which may suffer from framing biases as well as selection[7], our paper uses the correlations between patterns academic writing and observed political behavior to measure ideology. Ideology extraction from text has received attention from multiple fields including computer science, political science, and economics. Our tools most closely follow Gentzkow and

[5]The Economist http://www.economist.com/blogs/freeexchange/2010/08/fiscal_policy

[6]A recent paper by 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.

[7]Fuchs, Krueger and Poterba (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 left than average by our measure, as we show below.

Shapiro (2010) (see also Jensen et al 2013). Grimmer and Stewart (2013) provide an overview of many models used in the analysis of the text of political actors like politicians and bureaucrats.[8] Recent research in natural language processing has focused on unsupervised topic models that jointly model lexical variation due to topics and other factors such as ideology (Mei et al. (2007); Lin et al. (2008); Ahmed and Xing (2010); Paul and Girju (2010); Eisenstein et al. (2011); Wang et al. (2012)). While the these models can show high predictive accuracy, they are unlikely to be effective in domains where expressions of ideology are 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, as all of the papers using text drawn from political actors do (Jelveh et al., 2014a). Adjusting for topics may be particularly important in highly specialized domains, where language use is tailored to very narrow audiences of other experts. Other domains with similar politics embedded in technical language could include climate science, law, or human genetics and evolution.

As an application of the usefulness of our methodology, we turn to empirical results in several key policy relevant fields in economics. The power of economics partially derives 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). From a variety of published survey papers, we collect estimates of taxable income elasticities, labor supply elasticities, minimum wage employment elasticities, intergenerational mobility elasticities, and fiscal multipliers. Using ideology predicted from papers by authors written before the reported elasticity, we find a significant correlation of ideology with reported estimates of various policy relevant parameters, with predicted liberals reporting elasticities that imply policies consistent with more interventionist ideology.

2 Conceptual Framework

In the Appendix, we provide a formal framework to interpret our estimation and prediction strategy in terms of the political preferences and professional incentives, including sorting into subfields, facing economists. In our model, economists are indexed by a latent left-right political ideology variable. The

[8]Unsupervised modeling is a machine learning technique which tries to uncover patterns in data without using auxiliary data (e.g. cluster analysis or hidden Markov models).

extent of preferences for being “neutral" in academic writing are parameterized, as are the importance of professional incentives. These professional incentives can include conforming with the ideology expressed in a subfield of economics. Economists choose the degree of their political preferences to reveal in their academic writing according to their tastes, trading this off against their desire for professional success.

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 many equilibria. But 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. Indeed, in the simple 2-subfield model in the Appendix, where professional incentives push agents to sort into fields where they can express their ideology in academic articles and reviewers and peers will accept them, equilibria can 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.

3 Data

3.1 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 where for each member we have his or her name, location, email address, education, employer, and occupation.[9] These data are used to match members across years. We then link the AEA member directory to two datasets with observed political behavior: political campaign contributions and petition signing activity.

[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.

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 to them. These disclosures contain the contributor's name, employer, occupation, state, city, zip code, transaction date, and transaction amount. Our goal is to match the AEA roster to these individual contributions of which there are about 20 million. This is an example of a typical record linkage or data matching problem and has been studied extensively in the science of informational retrieval.[10] Ideally, we would like to compare each AEA member with each FEC contributor to determine if there is an identity match while taking into account that, in a significant proportion of matches, a person's information will be recorded differently in the two databases. To address this, we apply a fuzzy string matching algorithm (Navarro, 2001) to member and contributor attributes. We describe the methodology and the results in full detail in Appendix A.2, and summary statistics on the campaign contributions are provided in Table A.1. Besides campaign contributions, we also proxy economist ideology through 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 on whether they advocate for or against individual freedoms. Similarly for our purposes, many of the petitions exhibit viewpoints that are aligned with the political left or right. Examples include petitions for and against federal stimulus following the 2008 financial crisis and petitions endorsing or opposing John Kerry's 2004 presidential campaign. 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. Figure 1 compares the ratios of contributions to Democrats vs. Republicans against the ratio of signatures for left- and right- leaning petitions. Surprisingly, left-leaning authors make more political contributions while right-leaning authors sign more petitions.

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

[10] A general probabilistic approach was formalized by Fellegi and Sunter (1969). For more recent developments, see Winkler (2006).

logic is then applied to assigning ideologies, θ_e.

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

If an economist has given more times to Democrats (Republicans) and signed more left-leaning (right-leaning) petitions, then 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), then we treat the ideology as undetermined.

Revealed ideology through campaign contributions and petition signatures is largely consistent. Table 1 displays the pattern exhibited by 441 AEA members who both signed partisan petitions and contributed to Democrats and/or Republicans. Of these, 83.4% showed agreement between their petition signatures and campaign contributions. However, these rates mask some heterogeneity. When viewed from the perspective of contributions, 76.7% of AEA members who contributed more to Democrats also signed more left-leaning petitions while 98.7% of members who contributed more to Republicans signed more right-leaning petitions. When viewed from the petition signing perspective, 98.7% of members who signed more left-leaning petitions also contributed more to Democrats while only 69.5% of members who signed more right-leaning petitions gave more times to Republicans. Economists who contribute more times to Republicans or sign more left-leaning petitions have greater consistency in their ideologies.

3.2 Economic Papers Corpus

To create our corpus of academic writings by economists, we also obtained from JSTOR the fulltext of 62,888 research articles published in 93 journals in economics for the years 1991 to 2008. We also collected 17,503 working papers from the website of the National Bureau of Economic Research covering June 1973 to October 2011. These papers were downloaded in PDF format and optical character recognition software was applied to extract text. Figures A.5 and A.4 show the number of JSTOR and NBER papers per year, respectively, and Table A.13 lists the individual JSTOR journals.

We remove common words and capitalization from the raw text and use a stemmer (Porter, 1980) to replace words with their morphological roots.[11] For example, a stemmer will resolve the words 'measures', 'measuring', and 'measured' to their common root 'measur'. We construct predictors for our algorithm by combining adjacent words to create phrases of varying length. These sequences are commonly referred to as n-grams. Typically, only two- and three-word phrases are constructed (which are referred to as bigrams and trigrams, respectively), however Margolin et al. (2013) demonstrate that ideological word choice can be detected by longer phrase sequences, so we capture all consecutive sequences out to a length of eight.

The previous steps leave us with more than a billion unique n-grams, the vast majority of which only appear a few times in the corpus. We therefore drop phrases that occur less than five times. To further focus our attention on the phrase sequences that are most likely to contain ideological valence, we follow Gentzkow and Shapiro and compute Pearson's χ^2 statistic for each remaining phrase. More explicitly, we create a ranking of phrases by partisanship by computing

$$\chi^2_{pl} = \frac{(c_{plr}c_{\sim pld} - c_{pld}c_{\sim plr})^2}{(c_{plr} + c_{pld})(c_{plr} + c_{\sim plr})(c_{pld} + c_{\sim pld})(c_{\sim plr} + c_{\sim pld})} \tag{1}$$

where $c_{pl\cdot}$ is the count for the number of times phrase p of length l was used by all economists of a particular ideology (d or r) and $c_{\sim pl\cdot}$ is the number of times phrases of length l 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. This results in about 267,549 unique n-grams.

3.2.1 Accounting for Topics

Table 2 lists the 40 most conservative bigrams and trigrams sorted by χ^2 scores. A quick glance at this table leaves the impression that the top ideological phrases are related to specific research subfields. For example, right-leaning terms like 'bank_note', 'money_suppli', and 'feder_reserv' are typically asso-

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

ciated with macroeconomics and left-leaning terms 'mental_health', 'medic_care', and 'mental_ill' are related to health care. This observation leads us to ask if the association is spurious. In other words, are the phrases that are more right-leaning (or left-leaning) merely a by-product of an economist's research interest rather than reflective of true ideology?

If this were the case, then the phrases we have identified primarily reflect the relative distribution of Republicans or Democrats in different fields. This sorting would not then be informative as to whether the research results are influenced by individual ideology or by conforming to field ideology. We control for this sorting by estimating ideology within research area. We map papers to different topics and predict authors' ideologies using topic-specific phrase counts. These predictions are combined to form a final estimate of an author's political leaning. We are consequently removing the effect of field ideology by estimating individual ideology within field. For purposes of comparison, we also calculate individual ideology scores without correcting for topics; these are called the 'no topic' ideology scores.

Since we do not observe topics for all of the papers in our corpus, we use two methodologies from statistical natural language processing to create topic classifications for papers.

3.2.2 JEL Codes as Topics

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

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 use the relationship between language and topic codes to predict JELs for the set of papers that fall outside of the EconLit data. We predict codes for the 1st and 2nd levels and refer to these topic mappings as *JEL1* and *JEL2*.

Our method for predicting JEL codes is a variation of the k-nearest neighbors algorithm (Hastie et al., 2001b). In order to predict the codes for a target paper, we look at the codes for the k closest papers in the EconLit dataset where closeness is measured by similarity in language use and k is a positive integer. Let $p_{econlit}$ be the set of papers with EconLit-assigned JEL codes and p_{other} be the set of papers without codes. We construct matrix $\mathbf{E}_{econlit}$ from the papers in $p_{econlit}$ where the (i, j)-th element is the number of times bigram j was used in paper i. We construct a similar matrix $\mathbf{E}_{other}$ from the papers in p_{other}. We include bigrams that appeared at least 100 times in the corpus leaving us with about 300,000 bigrams. We convert both $\mathbf{E}_{econlit}$ and $\mathbf{E}_{other}$ into term-frequency inverse document frequency (TF-IDF) matrices. TF-IDF is a weighting scheme which assigns greater values to terms that appear less frequently across documents. The intuition is that these terms are better able to aid in discriminating between different topics.[12]

To capture similarity in language use between two papers, we compute the cosine similarity between each row in $\mathbf{E}_{other}$ and all rows in $\mathbf{E}_{econlit}$.[13] For each paper in p_{other}, we create a ranking of papers in $p_{econlit}$ by cosine similarity. For each ranking, we count the number of times different JEL codes are assigned to the top k most similar papers. Each paper in p_{other} is associated with two vectors jel_{1st} and jel_{2nd}, where each vector keeps track of the percentage of times each 1st- and 2nd-level code, respectively, appears in the set of k closest papers. If elements in jel_{1st} and jel_{2nd} are above a cutoff value c, then the paper is assigned those JELs.

For example, the three closest papers to "The Impact of Employee Stock Options on the Evolution of Compensation in the 1990s" are

- "The Trouble with Stock Options" with 1st-level JEL code M and second-level codes M1 and M5
- "Are CEOS Really Paid Like Bureaucrats?" with 1st-level codes D and M and second-level codes D8, M1 and M5
- "Stock Options and Managerial Optimal Contracts" with 1st-level code M and second-level code

[12]The TF-IDF for phrase i in paper j is calculated by multiplying the frequency of i in j by the logarithm of the number of papers in the matrix divided by the number of papers containing i. A phrase that is contained in many documents will get a lower weighting.

[13]The cosine distance between $paper_i$ and $paper_j$ over N phrases is the dot product between the normalized vectors of phrase counts and can be computed as: $\frac{\sum_{k=1}^{N} paper_{i,k} \cdot paper_{j,k}}{\sqrt{\sum_{k=1}^{N} paper_{i,k}^2 \sum_{k=1}^{N} paper_{j,k}^2}}$

M1

The potential 1st-level codes for this paper are M and D and potential second-level codes are M1, M5 and D8. In this example, the element in jel_{1st} associated with JEL code M would be set to 0.75 and the element associated with D would be 0.25. All other elements would remain zero. If our cutoff c was 0.3, then the paper would be assigned 1st-level code M and second-level codes M1 and M5. We experimented with different values for k and c and found that predictive performance was maximized with $k = 30$ and $c = .20$. In cases where no JEL is greater than c we assign the paper only to the single code with the highest value. We describe our prediction assessment in Appendix A.3.

3.2.3 Latent Dirichlet Allocation

In the previous section we described a method which relied on a pre-labeled set of topics in order to assign topics to new papers. We also construct a topic mapping using an algorithm which does not rely on pre-labeled data but learns topics based on patterns of co-occurring words across documents. This method, Latent Dirichilet Allocation (LDA) (Blei et al., 2003), is a popular hierarchical Bayesian machine learning algorithm that defines a probabilistic model for the joint distribution of observed data and the latent factors generating the data.[14] In common practice, the observed data are text from documents and the latent factors are unobserved topics. A key assumption behind LDA is that documents can be about more than one topic. For example, some of the topics present in this paper are economics, political ideology, and text mining.

The model underlying LDA assumes that words in a document are generated by the following process:

- For each topic t, a distribution over words in the vocabulary is generated: β_t
- For each document d, a distribution over topics is randomly sampled: η_d
    - For each word in the document, a topic is sampled from η_d
    - Given the topic t sampled in the previous step, sample a word from the corresponding word distribution β_t

[14]Generative models have a similar flavor as structural models in econometrics. A generative model can be seen as a relaxed version of a structural model in the sense that the data generating process need not be tied to an underlying behavioral theory.

The only observed variables are words within documents. The unobserved parameters – the distribution over words for each topic (β_t) and the distribution over topics for each document (η_d) – are estimated using Bayesian techniques such as Gibbs sampling or variational estimation. The researcher must specify the number of topics to be learned beforehand. We ran LDA on the set of papers used in the analyses below which accounts for 57,742 papers. Mappings were created with 30, 50, and 100 topics (*LDA30*, *LDA50*, and *LDA100*). 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. For example, the left-most column of Tables 3 and 4 shows the top twenty bigrams for two of the topics generated by running LDA with 50 topics on the economic papers corpus and our qualitative descriptions for those topics.[15]

We use the topic distributions estimated by LDA to assign articles to topics. If there is at least a 5% probability that an article is about a topic, then we assign that article to that topic. While 5% might seem to be a lower threshold, the topic distributions estimated by LDA tend to be sparse. For example, even with 50 topics to 'choose' from in LDA50 and a threshold of 5%, 99.5% of the papers would be assigned to five or fewer topics.

3.2.4 Selecting Ideological Phrases Within Topics

With the mapping of papers to topics in hand, we now alter the χ^2 computation from equation 1 and perform it at the topic level. For a given topic t, we compute χ^2_{plt} by only considering the set of phrases that appear in papers about t.

Since text data is inherently noisy, certain phrases might pass our ideological filter either by chance or because of author idiosyncrasies in our ground-truth dataset. To capture phrases that are consistently correlated with ideology, we perform stratified 10-fold cross validation, a machine learning technique which aims to improve model generalizability. In general k-fold cross validation, a dataset is broken up into k mutually exclusive subsamples of equal size and the analysis is then performed k times leaving out one of the k subsamples in each iteration. Depending on the particular analysis, the results from cross validation are then combined across the k iterations. With stratified cross validation, each fold is created such that the subsamples have the same characteristics as the overall sample. In our case each

[15]The top phrases and partisan phrases for all the topics, both *JEL1* and *LDA50*, are available online at www.santafe.edu/~snaidu/topics.pdf.

fold has the same ratio of left-leaning to right-leaning economists, $3:2$. In our analyses below, we will be predicting the ideologies of economists whose ideologies we know. To avoid contamination, we do not include these authors in our cross-validation filtering procedure and perform this filtering on 1,814 economists (1,106 left-leaning, 708 right-leaning).

For each topic, we collected authors and the set of papers they wrote in t. This sample is then split into 10 folds and the χ^2 filter is applied. Phrases are selected based on two criteria: that they pass the p-value filter at least γ percent of the time and that they are always slanted in the same direction. This latter criteria would filter out phrases that are left-leaning in one fold and right leaning in another. We set γ at 10, 60, and 100. The filter is the most permissive at 10%, meaning that if a phrase is slanted once across the ten folds, then it is not dropped. The filter is most restrictive at 100% (what we call “strong"), meaning that a phrase must be slanted in each fold. The predictive performance of our method is similar across different filters, however, the number of phrases that pass the filter is significantly smaller for the most restrictive filter. For example, when all topics are pooled, the most permissive filter finds about 140,000 slanted phrases while the most restrictive finds only 10% that amount. Since the smaller set of phrases with the restrictive filter allows for faster runtime without loss of accuracy, we only report results from this strong filter below.

4 Predicting Ideology From Phrases

In this section, we describe how the gathered and constructed data described above are used in our prediction algorithm. To recap, we have created a dataset which contains the following:

1) A set of economists with known ground-truth ideology

2) A set of economists with unknown ideology

3) The set of papers written by these economists

4) The n-grams and associated counts for each paper

5) Six mappings from papers to topics: *JEL1, JEL2, LDA30, LDA50, LDA100*, and *NoTopic*.

The *NoTopic* mapping refers to pooling all papers without regard to topic.

Our topic-adjusted algorithm for ideology prediction works as follows: Given a topic mapping, we iterate through topics and, for each topic, select the papers written by ground-truth authors.[16] We filter the papers by the significant phrases in that topic and construct the frequency matrix $\mathbf{F}_t$ where the (e, p)-th entry is the number of times economist e used partisan phrase p. For papers with multiple authors, each author gets the same count of phrases. We transform each row by taking the norm, meaning that the sum of the squares of the resultant row equals one. Columns of $\mathbf{F}_t$ are then standardized to have unit variance. Our analysis is at the author-level so economists' phrases are aggregated across their papers in a topic. We then use partial least squares (PLS) to estimate the relationship between ideology and word choice and to predict the ideology of other authors.

PLS is useful when data array is 'wide', that is, when the number of predictors (n-grams) is much greater than the number of cases (authors) and when prediction is the goal. PLS finds latent orthogonal factors (or directions) that capture the covariance structure between both the predictors and the response (ideology).[17] Ideology predictions from PLS are computed as follows. For the set of economists with known ground-truth ideology, Let $\mathbf{y}$ be the vector of imputed political ideology scores:

1) Set $\mathbf{v}_0 = \mathbf{y}$ and $m = 1, ..., M$

1) Compute $\mathbf{w}_{m,t} = Corr(\mathbf{F}_t, \mathbf{v}_{m-1})$, the correlations between each phrase and ideology

2) Project phrases down to one dimension: $\mathbf{z}_{m,t} = \mathbf{F}_t \mathbf{w}_{m,t}$

3) Calculate the new response $\mathbf{v}_m = \mathbf{v}_{m-1} - \frac{\mathbf{z'}_{m,t}\mathbf{v}_{m-1}}{\mathbf{z'}_{m,t}\mathbf{z}_{m,t}}\mathbf{z}_{m,t}$

4) After M iterations, regress $\mathbf{y}$ onto the set of the constructed PLS directions.

5) To predict ideology for a new economist, use the coefficients estimated in previous step and the new author's scaled frequency vector

We found that prediction accuracy was maximized by setting $M = 3$. Prediction accuracy can further be improved by combining the output of different models (Maclin and Opitz (2011) and Varian

[16] As previously mentioned, in subsequent analyses we will be predicting the ideologies of some ground-truth authors, so they are not included in this step.

[17] We view PLS as a drop-in classifier in our algorithm which could be replaced by other appropriate classifiers such as regularized logistic regression or support vector machines. In unreported results we found PLS to slightly outperform these other methods.

(2014)) , a procedure known as ensemble learning.[18]

We repeatedly perform PLS within each topic and create a new dataset by sampling with replacement from the rows of $\mathbf{F}_t$ and sampling without replacement from the columns of $\mathbf{F}_t$ where the number of phrases to be sampled is set to twice the square root of the number of columns in $\mathbf{F}_t$ to reduce over-fitting. Each PLS iteration can be viewed as a vote on whether an author is left- or right-leaning. We calculate the vote as follows. Run PLS on the ground-truth data and use the estimated model to predict the ideology in-sample (i.e. on the *ground-truth data*). Let f_i be the optimal threshold that maximizes the accuracy of this prediction for the current iteration i. This threshold is determined by finding the value which minimizes the euclidean distance between the true positive and negative rates for the current model and that of the perfect classifier (i.e. (1.0, 1.0)).[19] An author in the test set is voted right-leaning if the predicted ideology value is greater than f_i.

Our algorithm results in a three-dimensional array with the (e, t, c)-th entry representing the number of votes economist e received in topic t for ideology c. A final prediction is computed as the weighted average of the percentage of right-leaning votes received in each topic:

$$\widehat{\theta}_e = \sum_{t=1}^{T} w_{e,t} \frac{r_{e,t}}{r_{e,t} + d_{e,t}}$$

where $r_{e,t}$ and $d_{e,t}$ are the number of right- and left-leaning votes economist e received in topic t, respectively, and $w_{e,t}$ is the topic- and economist-specific weight. We let $w_{e,t}$ equal the share of all votes e received in t

$$w_{e,t} = \frac{r_{e,t} + d_{e,t}}{\sum_{t=1}^{T} r_{e,t} + d_{e,t}}$$

which simplifies predicted ideology to

[18] We apply this methodology through the use of two model averaging techniques: bootstrap aggregation (also referred to as bagging) and attribute bagging. With bagging, samples of the original data are drawn with replacement to form a new dataset. In our case, one bagged dataset would be created by sampling authors and their associated phrases within a topic. With attribute bagging, the sampling is done at the level of the predictor (i.e. attribute). In our case, the resulting dataset would be created by sampling without replacement from the columns of $\mathbf{F}_t$. In both bootstrap aggregation and attribute bagging, models are estimated for each constructed dataset and the results are combined when a prediction is made for a new data point.

[19] The true positive (negative) rate is the number of correctly predicted right-leaning (left-leaning) authors divided by the actual number of right-leaning (left-leaning) authors.

$$\widehat{\theta}_e = \frac{\sum_{t=1}^{T} r_{e,t}}{\sum_{t=1}^{T} r_{e,t} + d_{e,t}}.$$

Topics with more votes have a greater say in determining the final prediction. 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 $\widehat{\theta}_e$ by multiplying by two and subtracting by one. For example, if $\widehat{\theta}_e$ = .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. The empirical mean will deviate from 0 depending on the sampling.

4.1 Validation

Our analysis in subsequent sections involves studying attributes of academic economists at American colleges and universities. We know the ground-truth ideology for a subset of these economists and use this information to evaluate the predictive ability of the algorithm presented in the previous section. In terms of our model, we are comparing observed θ_i to predicted $\widehat{\theta}_e$. We stress here that the information from this group of economists is never used as a predictor in our algorithm (i.e. it is held out) so we are not contaminating our estimate of $\widehat{\theta}_e$ with θ_i itself. This means that the to-be-analyzed authors phrase counts are not used in the χ^2 filter step or as input into the prediction algorithm. Additionally, we also elimimate the contamination from the case where we predict the ideology of an economist who has coauthored a paper with someone in the ground-truth dataset. When we construct the vector of phrase counts for this author, we do not include the phrase counts from the coauthored paper.[20]

We assess the performance of our algorithm by employing a summary statistic that is commonly used in binary prediction problems: the area under the receiver operating curve (AUC) (Fawcett, 2006). To see how this curve is constructed, note that our algorithm produces a probability that an author is right- or left-leaning. We translate these probabilities to binary predictions by setting a threshold (e.g. 25%, 50%, etc.) and assigning an author to be right-leaning if their predicted ideology is above this threshold and left-leaning otherwise. From each possible threshold, we compute and plot the true positive rate (the proportion of correctly predicted right-leaning authors) and the true negative rate (the

[20]We also ran a version of the algorithm where these types of coauthored papers were dropped from the dataset but our results were unaffected.

proportion of correctly predicted left-leaning authors). By connecting these points, a Lorenz-like curve is created. The area under this curve can range from zero to one and tells us about the predictive accuracy of our algorithm. An AUC of one means the classifier can perfectly separate positive from negative cases, 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. The AUC is equivalent to the probability that a binary classifier will rank a randomly chosen right-leaning author higher than a randomly chosen left-leaning author, where the rank is based on the percentage of right-leaning votes received.

There are two primary benefits to employing AUC as a performance metric. First, the AUC is less sensitive to asymmetry in the outcome distribution than a simple measure of accuracy. To see this, imagine the extreme case where we had 90 left-leaning and 10 right-leaning economists in the test set. If all authors were predicted to be left-leaning, our accuracy would be a seemingly strong 90% even though the algorithm itself was quite dumb. The second benefit is that algorithm performance is not a function of just one threshold but many. For example, a naive way of converting the predicted probabilities to ideology assignments would be to assign authors as right-leaning if their predicted probability is greater 50% and left-leaning otherwise. But it may be the case that the best separation between left- and right-leaning authors occurs at some other threshold.

Figure 2 shows the AUC plots and Table 5 the relative performance for our various topic mappings. While *LDA50* provides the best performance, many of the models show similar results in terms of AUC and correlation with ground truth ideology. The maximum correlation between predicted and ground truth ideology is 0.412. 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.

We can also see from Table 5 that a model without an ensemble component performs worse than all other models except for *JEL2*. The likely reason for the under-performance of *JEL2* is that the combination of a large number of topics and a low number of topics assigned to each paper lead to a small dataset size by which to estimate PLS in each *JEL2* topic. There are about two topics assigned to each paper in the *JEL2* mapping. For comparison, the LDA topic mappings have about four topics per paper. *JEL1* also has about two papers per topic, but since the number of *JEL1* topics is about 15% of the size of *JEL2* topics, each *JEL1* topic still has many papers.

Adjusting for topics does not appear to provide a performance improvement versus the unadjusted model. But this result may be due to the 4-fold increase in the number of authors used to construct the prediction algorithm for the *No Topics* mapping. For comparison, we also constructed a reduced version of the *No Topics* mapping by down-sampling the number of authors to mimic that of the topic-adjusted mappings. To do so, we constructed the *No Topics* version by sampling 400 of the 1,812 available authors and computing the prediction metrics. We repeated this 30 times by taking a different sub-sample of 400 authors and averaging the results. As shown in Table 5, the predictive performance declines in this scenario, suggesting that the larger sample size on which the full *No Topics* version is built is driving some of its accuracy and that adjusting for topics does provide some performance gains.

For further insight into how well our model generalizes, we use data from Gordon and Dahl (2013) to compare our predicted and ground-truth 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 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.[21]. 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 our predicted ideologies. We also know the ground-truth ideology of 20 members on the panel and the correlation between ground-truth ideologies and survey responses is also significant. Table 7 Panels A-D all present results from logit and ordered logit regressions of the following form

$$Pr(response_{i,j} = C) = \Lambda\left(\tau_j - X_{ij}\right) - \Lambda\left(\tau_{j-1} - X_{ij}\right), \tag{2}$$

[21]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 far away from the answers of a random sample of the public.

where Λ is the logistic cumulative distribution function, τ represents cut points dividing the density into regions corresponding to survey responses, and $X_{ij} = \beta_1 \widehat{Ideology}_i + \beta_2 question_j$. Hats denote predicted values. 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.[22] In the ordered logistic version (columns 4-6) the response variable is coded with the following order: Strongly Disagree, Disagree, Uncertain, Agree, Strongly Agree.[23] As seen in Table 6, the coefficients between the ideology variable and the conservative viewpoint are all in the expected directions and all are significant. The magnitude of the relationship varies between the models. For the ground-truth model, the probability of switching from liberal to conservative increases by about 5% when a person's ideology switches from far left to far right. Other models put the probability at between 14% to 48%. Across all the different topic adjustments, the logit and ordered logit results in Table 6 show a significant positive relationship between our ideology variables and the probability of being in an increasingly conservative category. Columns 3 and 6 in each panel 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. Figure 3 shows linear probability residual scatterplots, conditioning on the question and individual controls. It is worthwhile to note the small increase in log-likelihood when controls are added, suggesting that our ideology scores are much better predictors of IGM responses than demographic and professional controls.[24]

4.2 Descriptive Patterns of Ideology

Since topic adjustment of the ideological score is central to the analysis, it is instructive to validate that ideologies varies by field and topic and even by institutional affiliation. We link CVs of economists to our ideology prediction and document cross-sectional patterns of ideology. We start by first describing these descriptive patterns of ideology, which are of independent interest, leaving a more complete documenation to the Appendix to conserve space.

We collect data from CVs of economists at top 50 departments and business schools in Spring 2011. The list of schools, the number of economists, and mean ideology is provided in Table A.7. We collect

[22] Uncertain, No Opinion, and Did not answer responses where dropped for the binary logistic analysis.

[23] No Opinion and Did not answer responses were dropped for ordered logit analysis.

[24] 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. See Appendix A.4 for details.

year and department of Ph.D. and all subsequent employers, nationality and birthplace where available, and use self-reported field of specialization. As Proposition 1 suggests above, we are interested in the political behavior of economists by subfield. In particular, looking at self-declared primary fields, we examine labor economics, public economics, financial economics (including corporate finance), and macroeconomics as determinants of political behavior, as these are among the most policy relevant fields in economics. We classify each department as saltwater or freshwater or neither following Önder and Terviö (2012). An economist is saltwater or freshwater if either went to grad school, had their first job, or had their current job at a saltwater or freshwater school.

We are interested to see if there are significant correlations between political ideology and field of research. Note that even though our ideology scores are adjusted for topic, self-reported fields of individuals vary independently of topic-adjusted paper ideologies. So it very well could be that financial economists who write on monetary policy adopt conservative language within that topic. Secondly, we are interested in institutional affiliations. We construct a variable for being at a business school, 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, European origin, and doctoral degree year, years between undergraduate degree and economics phd, and number of different employers per year since obtaining the Ph.D. We present summary statistics in the appendix Table **.

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

$$\widehat{Ideology}_i = X_i\beta + \epsilon_i \tag{3}$$

Here $\widehat{Ideology}$ denotes predicted ideology and X_i is a vector of economist characteristics. Standard errors are clustered at the department level. We augment this specification with a variety of fixed effects, including department fixed effects, university fixed effects (there are 15 business schools in the same university as economics departments in our sample), field fixed effects, and year of Ph.D. effects.

We show results for the LDA-50 ideology measure in Table A.8 with the *Notopic* and *JEL1* adjusted ideology scores shown in Appendix tables A.10 and A.9. Column 1 shows the basic regression with no fixed effects. We find robust evidence of differential political behavior in two self-reported fields: finance and labor. Perhaps unsurprisingly, economists who work in finance tend to contribute to

Republicans and sign right-wing petitions, while labor economists, while not significantly differing in their contribution behavior, are predicted to be left wing. Note that this is estimated from topic-adjusted ideologies, so it is not simply selection into area of research. While this could indicate that our topic adjustment strategy is performing poorly, it could also imply that self reported fields are a significant predictor of ideology even within a field. It could very well be that a financial economist who writes on monetary policy adopts conservative language within the field of monetary economics. While not reported to save space, there is no robust evidence of significant ideology for economists who declare their primary fields as microeconomic theory, econometrics, development, or economic history.

It is natural to hypothesize that faculty in business schools lean conservative, as sympathy with business interests is either induced or selected on by institutions that educate business leaders. Our methodology finds more conservative ideology for economists at business schools. This is true controlling for both self-reported field as well as controlling for university fixed effects, and so suggests that there is some professional affinity between business schools and conservative ideology.

The finding that both the finance subfield and business schools tend to attract (or produce) 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.

We also test the saltwater-freshwater divide. One natural hypothesis is that saltwater economists are more left wing than freshwater economists. While this appears to be the case, it is only because there is no significant correlation between freshwater economists and ideology, so the saltwater-freshwater methodological divide, insofar as it is political, appears to be one sided. When we interact this variable with an indicator for an economist being in macroeconomics, we obtain qualitatively similar results in that saltwater macroeconomists are significantly more left wing, while freshwater macroeconomics is not significantly more right wing (results not shown to save space).

The magnitudes of all these coefficients should be interpreted as effects on the expected ideology of the economist. 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 ensemble methodology.

Results are quite similar for other ideology measures such as JEL1 or even with no topic adjustment, although the coefficients are smaller in the latter case. However, when we restrict attention to our ground truth sample in Table A.11 for whom we have CVs, we see the same left-right divide between finance and labor, but the results for macroeconomics and public economics become statistically insignificant, although the signs and magnitudes are similar to the notopic ideology measure. There is however no significant effect of business schools. The saltwater-freshwater divide becomes quite salient, with saltwater economists behaving much more left-wing and freshwater economists behaving much more right wing. Interestingly, some of the personal background variables become significant, with younger economists (higher doctoral degree year) *more* likely to contribute to the Republicans or sign conservative petitions. Finally, there is some evidence that economists with a Latin American origin behave in a more liberal or Democratic manner.

We also find that ideological is persistent within individuals. As documented fully in A.1, we split authors by their first 50% of publications and their second 50%. 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. [25]

5 Ideology And Policy Elasticities

Part of economists‘ influence on policy is arguably its 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 the costs and benefits of the

[25] In a previous version of the paper, we examined the relationship between journal editors and journal ideology, measured as the mean ideology of the articles. While predicted editor ideology is strongly correlated with journal ideology in both the cross-section and the pooled panel data, this relationship disappears once journal fixed effects are controlled for, with reasonably precise standard errors. While this may suggest that editors have no effect on journal ideology, it may also suggest that the ideological matching between editors and journals is quite assortative, and so there is little variation in ideology across editorial changes within a journal.

minimum wage are, and empirical fiscal multipliers gauge the efficacy of government stimulus spending. Various government agencies, such as the Congressional Budget Office, along with policymakers, actively incorporate empirical economic research into policy proposals.

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 pg 531).

Recently, the focus on key behavioral elasticities as sufficient for optimal policy has been reinvigorated in applied fields such as public finance, labor economics, industrial organization, and trade. (Chetty 2009, Weyl and Fabinger 2013, Costinot and Rodriguez-Clare 2014). This approach suggests that a variety of models incorporate similar fundamental economic intuition, which can then be encoded in a few empirical estimates. The magnitudes of these estimates, together with formulas yielded by economic theory, discipline the policy prescriptions of economists.

An important question, therefore, is if 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 methodologies and variation that yield elasticities consistent with political beliefs. However, 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. We mitigate this by using only ideology estimated from papers published *before* the paper containing the reported ideology.

5.1 Fuchs-Krueger-Poterba Elasticities and Meta-Analyses

We select elasticities drawing on Fuchs, Krueger and Poterba (1998) (henceforth FKP). FKP survey labor and public finance economists about their views on policy and parameters. In a section of the paper, they estimate the correlation between policy preferences and beliefs about parameter values. They provide a mapping from policy preferences to economic parameters from labor and public that implicitly gives each parameter estimate a policy implication that is easy to map into a partisan direction. For example, beliefs about the empirical effect of unions on productivity might influence preferences towards increased unionization. Similarly, the female labor supply elasticity may influence beliefs about the desirability increasing Aid to Families with Dependent Children. The mapping between estimates and policies, as well as the implicit partisan leaning, is provided in table 7. There is one elasticity, the labor demand elasticity, that FKP did not assign to a clear policy, and so we denote it non-“policy-relevant". Indeed one can imagine a high labor demand elasticity being both favored by (conservative) skeptics of labor market interventions such as the minimum wage, as well as (liberal) skeptics about welfare reform.

We focus on estimated rather than calibrated or simulated parameters, which are mostly from the labor economics literature. We then looked through the literature for meta-analyses of these parameters, obtained the data from the authors where available, and then merged the authors of each estimate in each meta-analysis to our predicted slant measures. The list of meta-analyses is also in 7. In addition, we obtained a number of other meta-analyses from Chris Doucougliasis, enabling a placebo exercise.

Meta-analyses necessarily rely on the judgements of the authors about what to include and what to exclude.[26] With such diverse literatures, we take the datasets as they are, and do not 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 transform this to be the ratio of the unexplained to the total, 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 gives a single estimate from each paper. We further 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 to construct an estimated average author ideology for each paper. Formally, we use $\widetilde{elasticity}_{sj}$ to denote the normalized elasticity from paper j in survey paper s, calculated as $\frac{elasticity_{sj}-\overline{elasticity_{sj}}}{\sigma_s}$ and sign adjusted so that higher is more conservative. The sign adjustments are given in Table 7.

$$\widetilde{elasticity}_{sj} = \gamma \overline{AuthorIdeology_j} + \delta_s + \epsilon_{sj} \tag{4}$$

[26] A recent paper by Andrews and Kasy (2017) examines the econometrics of meta-analyses rigorously.

Table 10 shows estimates of γ from 4. Panel A shows results for no topic adjustment, Panel B for LDA50 adjustment, and Panel C for JEL1 adjustment. The coefficients in columns 1 through 4 can be interpreted as standardized regression coefficients, since both the independent and dependent variables are normalized to mean 0 and unit variance. Column 1 shows the estimate of γ from 5, and can be interpreted as saying that moving 1 standard deviation in predicted ideology is associated with an increase in the reported elasticity of almost 2 standard deviations. Column 2 controls for survey paper fixed effects, and finds a similar magnitude. Columns 3 and 4 estimate the same specifications for the set of “tax-relevant" elasticities, which are the labor supply elasticities from Keane and Chetty, and the taxable income elasticities from Mathur et al., again normalized within paper. The larger coefficients here suggest that partisan ideology is particularly important for parameters that are relevant for determining the optimal tax. As the debate over taxes is where partisanship in American economics has been particularly salient, it is interesting to note that the empirical magnitude of these parameters does in fact correlate with author ideology.

5.2 More Recent Elasticities

As discussed above, meta-analyses are quite suspect as an econometric exercise. As an alternative strategy, we use our own judgement and look at the recent literature in labor and public finance. Again, we pick estimates that have a clear partisan policy implication. The literatures we examine are the taxable income elasticity (Feldstein 1998, Chetty 2009) and the labor supply elasticity (Chetty 2012), both of which are key inputs to the design of optimal taxes. If the taxable income elasticity is large, then the optimal income tax is small; if the labor supply elasticity is large, then the deadweight loss from labor income taxes is higher. The intergenerational mobility elasticity has been argued to be a diagnostic of the extent of equality of opportunity in a society. Thus estimates of the intergenerational elasticity reveal the degree of mobility in a market economy. The higher this estimate, the less mobile a market economy is. Finally, we examine fiscal multipliers, which measure the extent to which government spending can boost income during recessions.

We collect a number of survey papers on these policy relevant parameters. Thus we use estimates of the taxable income elasticity compiled by Mathur, Slavov and Strain (2012), estimates of the labor supply elasticity compiled by Keane (2011) and Chetty (2012), fiscal multiplier estimates from Ramey

(2011) and estimates of the intergenerational income elasticity compiled by Corak (2006). We also use estimates of labor demand elasticities from the minimum wage literature compiled by Neumark and Wascher (2006).

We also adjust author ideologies in two ways. We take only the ideology estimated from papers written by the author before the estimated elasticity, to minimize reverse causality. Second we average all the resulting ideologies across the authors for coauthored papers. Let $Authors(j)$ denotes the set of authors of elasticity in paper j (in survey article s), and $Pre\widehat{AuthorI}deology_i$ denote the ideology estimated from papers published by author i before publishing j. Therefore we can write $\overline{PreAuthorIdeology_j} = \sum_{i \in Authors(j)} \frac{Pre\widehat{AuthorI}deology}{|Authors(j)|}$. Figure 6 shows the pooled scatterplot of the normalized elasticity and the ideology of the authors for each different ideology measure, including the ground truth measure. In all of these scatters, a clear upward sloping relationship can be seen, suggesting that elasticities are in fact correlated with both predicted and ground truth ideology. We present this basic fact more systematically by estimating the following equation:

$$el\widetilde{asticit}y_{sj} = \gamma \overline{PreAuthorIdeology_j} + \delta_s + \epsilon_{sj} \tag{5}$$

Table 10 shows estimates of γ from 5. Panel A shows results for no topic adjustment, Panel B for LDA50 adjustment, and Panel C for JEL1 adjustment. The coefficients in columns 1 through 4 can be interpreted as standardized regression coefficients, since both the independent and dependent variables are normalized to mean 0 and unit variance. Column 1 shows the estimate of γ from 5, and can be interpreted as saying that moving 1 standard deviation in predicted ideology is associated with an increase in the reported elasticity of almost 2 standard deviations. Column 2 controls for survey paper fixed effects, and finds a similar magnitude. Columns 3 and 4 estimate the same specifications for the set of “tax-relevant" elasticities, which are the labor supply elasticities from Keane and Chetty, and the taxable income elasticities from Mathur et al., again normalized within paper. The larger coefficients here suggest that partisan ideology is particularly important for parameters that are relevant for determining the optimal tax. As the debate over taxes is where partisanship in American economics has been particularly salient, it is interesting to note that the empirical magnitude of these parameters does in fact correlate with author ideology.

Columns 5 through 9 estimate a version of equation 5 separately for each survey paper. We do not normalize these elasticities, and instead report the mean and standard deviation of the elasticity from the survey paper, estimating the following regression:

$$elasticity_{sj} = \gamma \overline{PreAuthorIdeology_j} + \epsilon_{sj} \tag{6}$$

While the small sample in each of these regressions means that many are not significant, the signs on the coefficients are generally in the expected direction. Conservative (liberal) economists consistently report larger (smaller) labor supply and taxable income elasticities as well as larger disemployment effects of the minimum wage. The effects on fiscal multipliers are noisier, but are generally consistent with smaller multipliers being found by more conservative writers than by liberal economists. The mobility correlation, is negative when it is significant, so more conservative authors report greater intergenerational mobility (lower persistence). The variation perhaps reflects how low mobility estimates can be consistent with both conservative (genetic talent determines earnings) and liberal (more needs to be done to promote equality of opportunity) viewpoints.

For completeness, Panel D shows the correlation between our “ground-truth" measure of ideology and the elasticities. Despite the much smaller sample sizes, we obtain significant results on the pooled sample, and in the minimum wage and multiplier samples. This panel shows a significant correlation between partisan political behavior (campaign contributions and petition signings) and empirical results in academic publications. Given that we see these correlations even without ideology predicted from academic text, it suggests that the results in Panels A-C are not artifacts of our text-based methodology.

The R^2 in panels A-C of Table 10 is relatively low, between .06 and .14, depending on whether fixed effects are included. This could be due to that our independent variable is measured with error (given the 74% chance of correct classification in our best predictor this is almost certainly a contributor), but then this would also imply that our coefficients are biased towards 0 and the true effect is in fact larger. In addition, we are pooling elasticities across multiple papers, estimated with different methods on different data sets. These are likely to be different for a large number of reasons, most of which are independent of political ideology. Predicted ideology does not explain the bulk of the variation across estimates, even within papers.

Table 11 examines robustness to outliers, with even numbered columns including survey paper fixed effects. Columns 1-2 winsorize the elasticity outcome variable, setting values greater than the

95th and less than the 5th percentile equal to those values, respectively. This eliminates any outliers in the outcome variable. Columns 3-4 discard observations with Cook's distance greater than $4/N$, which eliminates observations that have a lot of leverage in the regression. Finally, columns 5-6 estimate a median regression, which is robust to outliers. Results are quite similar across all these variants of the main specification, and show that our coefficients are not fragile or driven by outliers.

What to make of the estimates? One answer is that policymakers looking to cater to the median American voter could "re-center" the parameter estimates put forth by economists. For example, when scoring tax changes, minimum wages, or fiscal policy, the Congressional Budget Office often compiles a diverse range of estimates from the academic literature. Sometimes these estimates map directly into policy prescriptions, as with the optimal taxation literature. Building on Saez (2001), Saez and Diamond (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 AEI taxable income elasticity is .96, suggesting a top tax rate of 41%. However, the mean (JEL1) ideology among people who estimate taxable income elasticities is -0.16, slightly more left than average. Increasing *LDA50* ideology from the lowest (-0.35) to the highest (.03) would increase the elasticity by 0.95, and would imply an optimal tax going from 31% to 57%. The optimal tax at 0 ideology is 33%, but if the most conservative economist (with ideology of +1) estimated a taxable income elasticity, extrapolating our results implies they would find an elasticity of 4, implying an optimal top tax rate of 14%. If ideology is associated with sorting into fields and methodologies, then policy makers may wish to consider the sensitivity of parameters to partisanship. Following Manski (2003), one might consider constructing "ideological bounds" around an estimate, adjusting for the sorting by ideology into particular fields.

These estimates do not imply that economists are deliberately altering empirical work in favor of preconceived political ideas. Firstly, these correlations could be driven by omitted variables. While we have used ideology measured using previously published papers, if past research findings drive both measured ideology as well as current research results then that would confound these estimates. However, given the stability of our ideology scores over careers, we think it more likely that ideology is driving selection into methodologies that generate particular estimates. Economists with predetermined policy preferences could select into methodologies that yield parameter estimates that justify those policy preferences. Or it could be other, omitted factors that determine both political behavior and parameter estimates. For example, our results could be driven by methodology or field-specific human capital. If particular skill-sets and cognitive abilities yield comparative advantages in the use of certain methodologies, and if they are also associated with different worldviews and political beliefs, then the sorting of political ideology across research findings could be relatively efficient in the context of that literature. Attempting to alter patterns of political ideology across fields could in fact worsen research productivity.

Our estimates are robust to all of our different methods of adjusting for topics (including LDA30, LDA100, and JEL1, which we omit for brevity), as well as within empirical literatures that are trying to estimate the same parameter, leading us to believe that it is not simply selection into broad fields that are driving our results. Instead, we conjecture that it is more likely that decisions about methodology and (sometimes implicit) models of how the economy works are driving this correlation. Indeed, it is possible that methodological innovation is in fact driven by economists looking to overturn results that are contrary to their political priors. Empirical work in economics, even with careful identification, are still subject to numerous decisions about implementation, interpretation, and generalizability. If these decisions are correlated with both political beliefs and research outcomes, then even literatures with a strong commitment to credible research designs, such as the minimum wage, could exhibit correlations between politics and point estimates.

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. While we cannot claim causal identification, we believe our methodology for measuring ideology and the correlations we have uncovered are informative.

Of course, economists may not know themselves if their work is partisan. The advantage of our approach is that we do not need to rely solely on direct expert advice to discriminate phrases by ideological orientation. A drawback is that we instead use variation in observed political behavior among economists, which may be both a coarse projection of complex underlying beliefs, as well as missing ideological beliefs that do not vary across economists in our sample.

Theoretical research on the determinants of ideology in academic research would be welcome. A promising place to start could be the literature on self-censorship and political correctness (Loury 1994, Morris 2001), where 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, modelling the resulting trade-offs in choosing what to say and how to explain ideas, methods, and results could be a fruitful area of research.

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 an author’s ideology more highly. 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 economics itself as not above politics.

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7 Tables

Table 1: Petition and contribution patterns for 441 AEA members present in both datasets.

	Petitions		
Contributions	Left-Leaning (+1)	Undetermined (-)	Right-Leaning (-1)
Left-Leaning (+1)	220	5	62
Undetermined (-)	1	0	3
Right-Leaning (-1)	2	0	148

Table 2: Top 50 bigrams and trigrams by strength of χ^2 correlation with no topic adjustment.

Left-Leaning Bigrams	Right-Leaning Bigrams	Left-Leaning Trigrams	Right-Leaning Trigrams
mental_health	public_choic	post_keynesian_econom	yes_yes_yes
post_keynesian	stock_return	public_polici_analys	journal_law_econom
child_care	feder_reserv	polici_analys_politiqu	journal_financi_econom
labor_market	yes_yes	analys_politiqu_vol	anna_j_schwartz
health_care	market_valu	journal_post_keynesian	initi_public_offer
work_time	journal_financi	paper_econom_activ	polit_scienc_review
keynesian_econom	bank_note	brook_paper_econom	american_polit_scienc
high_school	money_suppli	industri_labor_relat	money_credit_bank
polici_analys	free_bank	mental_health_care	journal_monetari_econom
analys_politiqu	liquid_effect	journal_econom_issu	monetari_gold_stock
politiqu_vol	journal_financ	low_birth_weight	american_journal_polit
birth_weight	median_voter	high_perform_work	georg_mason_univers
labor_forc	law_econom	high_school_graduat	journal_polit_scienc
journal_post	vote_share	mental_health_servic	under_bretton_wood
latin_america	war_spend	labor_relat_review	academ_publish_print
mental_ill	journal_law	canadian_public_polici	resal_price_mainten
medic_care	money_demand	intern_labor_market	journal_money_credit
labour_market	gold_reserv	labor_market_outcom	springer_public_choic
social_capit	anna_j	politiqu_vol_xxix	kluwer_academ_publish
singl_mother	switch_cost	econom_issu_vol	literatur_vol_xxxvi
brook_paper	mutual_fund	robust_standard_error	southern_econom_journal
human_resourc	polit_scienc	health_servic_research	yes_no_yes
paper_econom	financi_econom	vol_xxix_no	bank_hold_compani
substanc_abus	transact_cost	health_care_system	rate_tax_rate
african_american	price_level	labor_forc_particip	financi_statist_yearbook
wage_inequ	insid_trade	labor_product_growth	jame_m_buchanan
statist_canada	j_schwartz	capit_account_liber	risk_free_rate
men_women	money_credit	cambridg_ma_nber	vol_xxxvi_decemb
hazard_wast	rent_seek	journal_human_resourc	gold_standard_period
psychiatr_disord	note_issu	current_account_balanc	money_suppli_shock
cohort_size	monetari_econom	labor_forc_growth	voter_ideal_point
unemploy_rate	supra_note	incom_tax_schedul	studi_public_choic
minimum_wage	custom_union	econom_polici_institut	yes_yes_no
welfar_reform	initi_public	live_wage_ordin	buchanan_jame_m
industri_labor	fiat_money	low_incom_famili	aggreg_demand_shock
labour_suppli	pecuniari_extern	journal_econom_perspect	month_quarter_annual
reserv_wage	stock_price	effect_child_care	review_financi_studi
new_keynesian	journal_polit	high_school_dropout	uniform_state_law
labor_relat	abnorm_return	institut_intern_econom	secur_exchang_commiss
labor_suppli	base_money	signif_percent_level	monetari_polici_shock

Table 3: Phrases from LDA-50 Topic 34: Wages

Topic Phrases	Left-Leaning Phrases	Right-Leaning Phrases
minimum_wage	child_care	overtim_pay
hour_work	work_time	school_year
child_care	lone_mother	overtim_hour
food_stamp	singl_mother	public_hous
labor_suppli	labour_market	hous_program
work_hour	new_orlean	year_employ
welfar_reform	mental_health	overtim_premium
wage_increas	welfar_reform	voucher_program
control_group	welfar_recipi	peopl_disabl
comparison_group	polici_analys	hous_assist
welfar_benefit	analys_politiqu	opportun_cost
child_support	live_wage	incom_limit
effect_minimum	politiqu_vol	support_payment
welfar_recipi	labour_suppli	administr_data
time_limit	public_assist	great_depress
wage_rate	singl_parent	work_council
singl_mother	marri_mother	effect_school
hour_week	fix_cost	hous_subsidi
journal_human	center_care	work_overtim
estim_effect	public_polici	substitut_effect

Table 4: Phrases from LDA-50 Topic 49: Business cycles

Topic Phrases	Left-Leaning Phrases	Right-Leaning Phrases
steadi_state	post_keynesian	social_secur
busi_cycl	keynesian_econom	period_t
journal_econom	labor_market	fiat_money
doe_not	journal_post	laissez_fair
adjust_cost	new_keynesian	money_hold
valu_function	effect_demand	public_choic
econom_review	long_run	capit_stock
american_econom	fiscal_polici	pecuniari_extern
technolog_shock	general_theori	public_good
gener_equilibrium	firm_size	price_path
decis_rule	real_wage	tax_rate
econom_theori	aggreg_demand	price_distort
journal_polit	keynesian_theori	monetari_econom
consumpt_good	industri_relat	tax_system
econom_studi	market_power	hold_period
dynam_model	labor_demand	durabl_good
polit_economi	keyn_p	govern_debt
review_econom	labor_forc	factor_input
equilibrium_model	modern_technolog	rate_return
market_clear	gross_invest	wealth_transfer

Table 5: Predictive Performance on Held Out Data.

Model (1)	Topics (2)	Correlation (3)	AUC (4)	Authors (5)	Papers (6)	Phrases (7)
LDA30	30	0.387	0.717	564.5	1,346.5	1,467.5
LDA50	50	0.412	0.741	396.0	811.5	747.0
LDA100	100	0.388	0.726	223.9	423.4	365.6
JEL1	19	0.393	0.732	327.1	733.5	597.8
JEL2	96	0.256	0.653	80.0	137.6	134.2
No Topics	1	0.391	0.726	1,812	8,490	14,639
No Topics, Reduced	1	0.363	0.707	400	1,883	727.0
No Topics, No Ensemble	1	0.357	0.679	1,812	8,490	14,639

This table compares predictive performance between topic mappings. Listed are (1) the model name (2) the number of topics in the mapping (3) the correlation between ground-truth and predicted ideologies (4) the Area Under the Curve (5) the average number of authors per topic (6) the average number of papers per topic (7) the average number of significant phrases per topic. The No Ensemble version of *No Topics* does not use the ensemble methodology. The Reduced version of *No Topics* down-samples the number of authors.

Table 6: Correlation Between Author Ideology and IGM Responses

Panel A: Ideology (No Topic) Correlation with IGM Responses

Ideology (No Topic)	0.608***	1.473***	1.185*	0.524***	0.659***	0.824***
	(0.126)	(0.402)	(0.702)	(0.108)	(0.161)	(0.248)
Question FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Log-Likelihood	-381.2	-134.2	-122.1	-1075.3	-760.5	-741.0
Observations	598	438	438	715	715	715
Individuals	39	39	39	39	39	39

Panel B: Ideology (JEL 1) Correlation with IGM Responses

Ideology (JEL 1)	1.472***	4.757***	3.022**	1.450***	2.128***	1.799***
	(0.392)	(1.227)	(1.273)	(0.285)	(0.431)	(0.438)
Question FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Log-Likelihood	-382.8	-132.0	-121.6	-1075.3	-757.4	-740.5
Observations	598	438	438	715	715	715
Individuals	39	39	39	39	39	39

Panel C: Ideology (LDA-50) Correlation with IGM Responses

Ideology (LDA-50)	1.821***	5.316***	4.481**	1.814***	2.457***	2.243***
	(0.409)	(1.487)	(1.854)	(0.352)	(0.557)	(0.674)
Question FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Log-Likelihood	-382.5	-133.4	-120.8	-1075.0	-758.7	-740.6
Observations	598	438	438	715	715	715
Individuals	39	39	39	39	39	39

Panel D: groundtruth Correlation with IGM Responses

Ideology (Groundtruth)	0.274***	0.843***	0.704	0.266***	0.393***	0.0840**
	(0.0681)	(0.220)	(0.437)	(0.0640)	(0.0819)	(0.0334)
Question FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Log-Likelihood	-214.2	-67.63	-59.98	-588.1	-405.8	-395.2
Observations	334	199	199	394	394	394
Individuals	20	20	20	20	20	20

Standard errors are clustered by economist. Controls include year of Ph.D., indicators for gender, phd university, and washington 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 7: Fuchs, Krueger Poterba (1998) Elasticities and Meta-Analyses

Labor/Public	Type of elasticity	Surveys found	Usable data?	Policy Relevant
Labor	job training	Card. et al. 2015	No	Yes
Labor	job training	Heckman et al. 1999	Some	Yes
Labor	labour supply	Bargain & Peichl 2013	Some	Yes
Labor	labour supply	Chetty et al. 2011	Yes	Yes
Labor	labour supply	McClelland & Mok 2012	Some	Yes
Labor	labour supply	Reichling & Whalen 2012	No	Yes
Labor	minimum wage	Neumark & Wascher 2006	Yes	Yes
Labor	minimum wage	Belman & Wolfson 2014	Yes	Yes
Labor	unions	Belman & Voos 2004	No	Yes
Labor	unions	Hirsch 2004	No	Yes
Labor	unions	Jarrell & Stanley 1990	No	Yes
Labor	unions	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	Espey1998	Yes	Yes height

Table 8: Correlation Between Predicted Ideology And Mean Elasticities (Labor & Policy Relevant)

	FKP	FKP	FKP	FKP	FKP	FKP	FKP
Ideology (LDA 50)	1.022** (0.486)						
Early Paper Ideology (lda50)		1.329** (0.531)					
Ideology (JEL 1)			0.687 (0.422)				
Early Paper Ideology (jel1)				1.309*** (0.425)			
Ideology (No Topic)					0.694** (0.277)		
Early Paper Ideology (notopic)						0.787** (0.323)	
Ideology (Groundtruth)							0.456 (0.301)
Survey Paper FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.04	0.07	0.03	0.10	0.06	0.07	0.16
Observations	124	108	124	108	124	108	26
Mean Elasticity	0.00	0.01	0.00	0.01	0.00	0.01	-0.13
SD Elasticity	0.98	1.03	0.98	1.03	0.98	1.03	1.54
Ideology Range	1.20	1.20	1.35	1.25	1.94	1.94	2.00

Robust Standard Errors, clustered by author set. Ideology is calculated as the mean ideology of the authors, using ideology predicted from papers written prior to the published estimate. Elasticities are the set examined Krueger, Fuchs, and Poteba (1998), with meta-analyses detailed, along with ideological sign, in the previous table.

Table 9: Correlation Between Predicted Ideology And Placebo Mean Elasticities

	Placebo Estimates						
Ideology (LDA 50)	0.412						
	(0.330)						
Early Paper Ideology (lda50)		0.394					
		(0.372)					
Ideology (JEL 1)			0.543^{**}				
			(0.270)				
Early Paper Ideology (jel1)				0.132			
				(0.249)			
Ideology (No Topic)					0.135		
					(0.180)		
Early Paper Ideology (notopic)						0.276	
						(0.227)	
Ideology (Groundtruth)							-0.480
							(0.404)
Survey Paper FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.01	0.01	0.02	0.00	0.00	0.01	0.64
Observations	227	185	227	184	227	185	6
Mean Elasticity	-0.00	0.02	-0.00	0.02	-0.00	0.02	-0.22
SD Elasticity	0.99	0.97	0.99	0.98	0.99	0.97	0.69
Ideology Range	1.35	1.24	1.38	1.24	1.78	1.24	2.00

Robust Standard Errors, clustered by author set. Ideology is calculated as the mean ideology of the authors, using ideology predicted from papers written prior to the published estimate. Elasticities include water income elasticities, recreational time-use values, institutions and growth.

Table 10: Correlation Between Author Ideology and Reported Elasticities

Panel A: Ideology (No Topic) Correlation with Reported Elasticities

	All	All	Tax	Tax	AEITax	LS	LSStructural	Minwage	Mobility	Multiplier
Ideology (No Topic), strong	0.674**	0.978***	0.824*	0.877	1.226*	0.225	0.0935	-0.876**	-0.0435	-0.194**
	(0.262)	(0.339)	(0.421)	(0.519)	(0.485)	(0.169)	(0.433)	(0.306)	(0.105)	(0.0592)
Survey Paper FE	No	Yes	No	Yes	No	No	No	No	No	No
R-squared	0.10	0.14	0.12	0.13	0.61	0.13	0.01	0.27	0.01	0.14
Observations	67	67	32	32	5	19	8	19	10	6
Mean Elasticity	-0.00	-0.00	-0.00	-0.00	0.96	0.33	0.14	-0.15	0.29	0.95
SD Elasticity	0.96	0.96	0.97	0.97	0.64	0.28	0.39	0.56	0.14	0.20
Ideology Range	1.82	1.82	1.62	1.62	0.94	1.62	0.86	1.18	1.02	1.18

Panel B: Ideology (LDA50) Correlation with Reported Elasticities

	All	All	Tax	Tax	AEITax	LS	LSStructural	Minwage	Mobility	Multiplier
Ideology (LDA 50), strong	1.134**	1.346***	1.040	1.197	-0.0708	0.633*	-0.0964	-1.135**	-0.0198	-0.970
	(0.482)	(0.491)	(0.761)	(0.843)	(1.299)	(0.313)	(0.515)	(0.438)	(0.146)	(0.975)
Survey Paper FE	No	Yes	No	Yes	No	No	No	No	No	No
R-squared	0.04	0.05	0.03	0.03	0.00	0.11	0.00	0.13	0.00	0.07
Observations	99	99	51	51	9	24	18	24	12	12
Mean Elasticity	-0.00	-0.00	-0.00	-0.00	0.78	0.33	0.07	-0.23	0.30	1.19
SD Elasticity	0.97	0.97	0.98	0.98	0.60	0.30	0.27	0.57	0.13	0.51
Ideology Range	0.85	0.85	0.60	0.60	0.41	0.58	0.32	0.58	0.78	0.42

Panel C: Ideology (JEL1) Correlation with Reported Elasticities

	All	All	Tax	Tax	AEITax	LS	LSStructural	Minwage	Mobility	Multiplier
Ideology (JEL 1), strong	1.129***	1.362**	0.606	0.761	2.535**	0.153	0.121	-1.198**	-0.270*	0.0928
	(0.392)	(0.526)	(0.536)	(0.761)	(0.855)	(0.210)	(0.684)	(0.466)	(0.122)	(0.452)
Survey Paper FE	No	Yes	No	Yes	No	No	No	No	No	No
R-squared	0.09	0.11	0.03	0.03	0.50	0.02	0.00	0.34	0.16	0.00
Observations	67	67	32	32	5	19	8	19	10	6
Mean Elasticity	-0.00	-0.00	-0.00	-0.00	0.96	0.33	0.14	-0.15	0.29	0.95
SD Elasticity	0.96	0.96	0.97	0.97	0.64	0.28	0.39	0.56	0.14	0.20
Ideology Range	0.95	0.95	0.95	0.95	0.45	0.95	0.63	0.85	0.73	0.34

Panel D: Ideology (groundtruth) Correlation with Reported Elasticities

	All	All	Tax	Tax	AEITax	LS	LSStructural	Minwage	Mobility	Multiplier
Ideology (Ground Truth)	0.490**	0.467***	0.366	0.337	0.508*	0.0811	0.0163	-0.538**	0.0274	-0.443***
	(0.189)	(0.173)	(0.310)	(0.267)	(0.203)	(0.135)	(0.0348)	(0.207)	(0.0635)	(0.115)
Survey Paper FE	No	Yes	No	Yes	No	No	No	No	No	No
R-squared	0.16	0.30	0.10	0.33	0.76	0.05	0.01	0.41	0.04	0.48
Observations	44	44	20	20	4	10	6	7	5	12
Mean Elasticity	-0.09	-0.09	0.01	0.01	1.16	0.41	-0.14	0.17	0.28	1.19
SD Elasticity	1.14	1.14	1.12	1.12	0.67	0.34	0.21	0.82	0.15	0.51
Ideology Range	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Robust Standard Errors, clustered by author set. Tax-relevant elasticities include the AEITax, LS, and LS Structural estimates, all normalized within survey paper. Ideology is calculated as the mean ideology of the authors, using ideology predicted from papers written prior to the published estimate.

Table 11: Correlation Between Author Ideology and Reported Elasticities:Robustness to Outliers.

Panel A: Ideology (No Topic) Correlation with Reported Elasticities

	Winsor DV	Winsor DV	Cook D	Cook D	Med. Reg.	Med. Reg.
Ideology (No Topic), strong	0.691***	1.022***	0.704***	1.317***	0.588**	0.654*
	(0.205)	(0.286)	(0.190)	(0.303)	(0.250)	(0.331)
Survey Paper FE	No	Yes	No	Yes	No	Yes
R-squared	0.09	0.13	0.09	0.22	0.09	0.05
Observations	99	99	94	89	99	99
Mean Elasticity	0.02	0.02	0.02	-0.00	-0.00	-0.00
SD Elasticity	0.84	0.84	0.84	0.80	0.97	0.97
Ideology Range	1.46	1.46	1.43	1.43	1.46	1.46

Panel B: Ideology (LDA50) Correlation with Reported Elasticities

	Winsor DV	Winsor DV	Cook D	Cook D	Med. Reg.	Med. Reg.
Ideology (LDA 50), strong	0.955**	1.146***	0.995**	1.290***	1.311**	1.160**
	(0.401)	(0.419)	(0.379)	(0.424)	(0.509)	(0.477)
Survey Paper FE	No	Yes	No	Yes	No	Yes
R-squared	0.04	0.05	0.03	0.08	0.04	0.02
Observations	99	99	95	94	99	99
Mean Elasticity	0.02	0.02	0.04	0.04	-0.00	-0.00
SD Elasticity	0.84	0.84	0.87	0.83	0.97	0.97
Ideology Range	0.85	0.85	0.83	0.85	0.85	0.85

Panel C: Ideology (JEL1) Correlation with Reported Elasticities

	Winsor DV	Winsor DV	Cook D	Cook D	Med. Reg.	Med. Reg.
Ideology (JEL 1), strong	1.286***	1.415***	1.115***	1.290***	1.434***	1.343**
	(0.347)	(0.406)	(0.328)	(0.402)	(0.492)	(0.585)
Survey Paper FE	No	Yes	No	Yes	No	Yes
R-squared	0.08	0.09	0.06	0.11	0.08	0.05
Observations	99	99	95	93	99	99
Mean Elasticity	0.02	0.02	0.01	0.02	-0.00	-0.00
SD Elasticity	0.84	0.84	0.84	0.82	0.97	0.97
Ideology Range	0.95	0.95	0.95	0.95	0.95	0.95

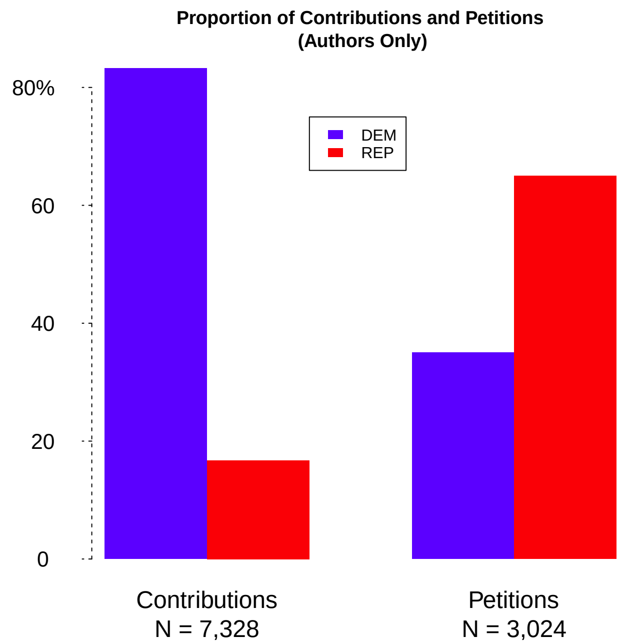
Panel D: Ideology (groundtruth) Correlation with Reported Elasticities

	Winsor DV	Winsor DV	Cook D	Cook D	Med. Reg.	Med. Reg.
Ideology (Ground Truth)	0.402**	0.386**	0.485***	0.518***	0.685**	0.461*
	(0.166)	(0.151)	(0.147)	(0.149)	(0.267)	(0.249)
Survey Paper FE	No	Yes	No	Yes	No	Yes
R-squared	0.17	0.30	0.24	0.42	0.16	0.26
Observations	44	44	40	41	44	44
Mean Elasticity	-0.01	-0.01	-0.09	-0.03	-0.09	-0.09
SD Elasticity	0.92	0.92	0.91	0.97	1.14	1.14
Ideology Range	2.00	2.00	2.00	2.00	2.00	2.00

Robust standard errors, clustered by authors. Ideology is calculated as the mean ideology of the authors, using ideology predicted from papers written prior to the published estimate. Winsor means normalized elasiticities greated than the 95 or less than 5 are assigned the 95th or 5th percentile value, respectively. Cook's distance restricts sample to observations with Cook's distance $> 4/N$ ($= .04$ in the full sample). Med. Reg. means median regressions, estimated on the full sample.

8 Figures

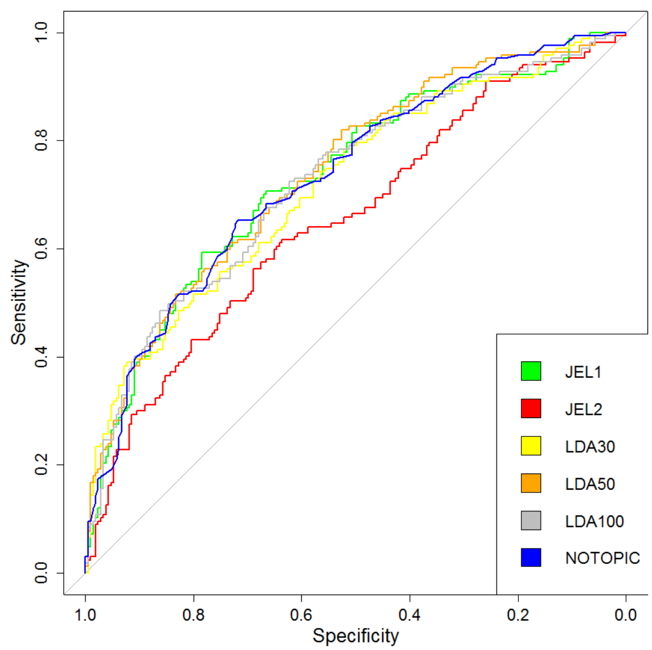
Figure 1: Patterns of Economist Political Behavior



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.

Placebo Categories: recreation use values,labour demand, , beta convergence, capital tax competition,driving car range, institutions and growth

Figure 2: Receiver Operating Curves.



Plots of the true negative rates (also known as specificity) against the true positive rates (also known as the sensitivity) for various topic mappings.

Figure 3: Partial Scatterplots of IGM Responses on Ideology Measures.

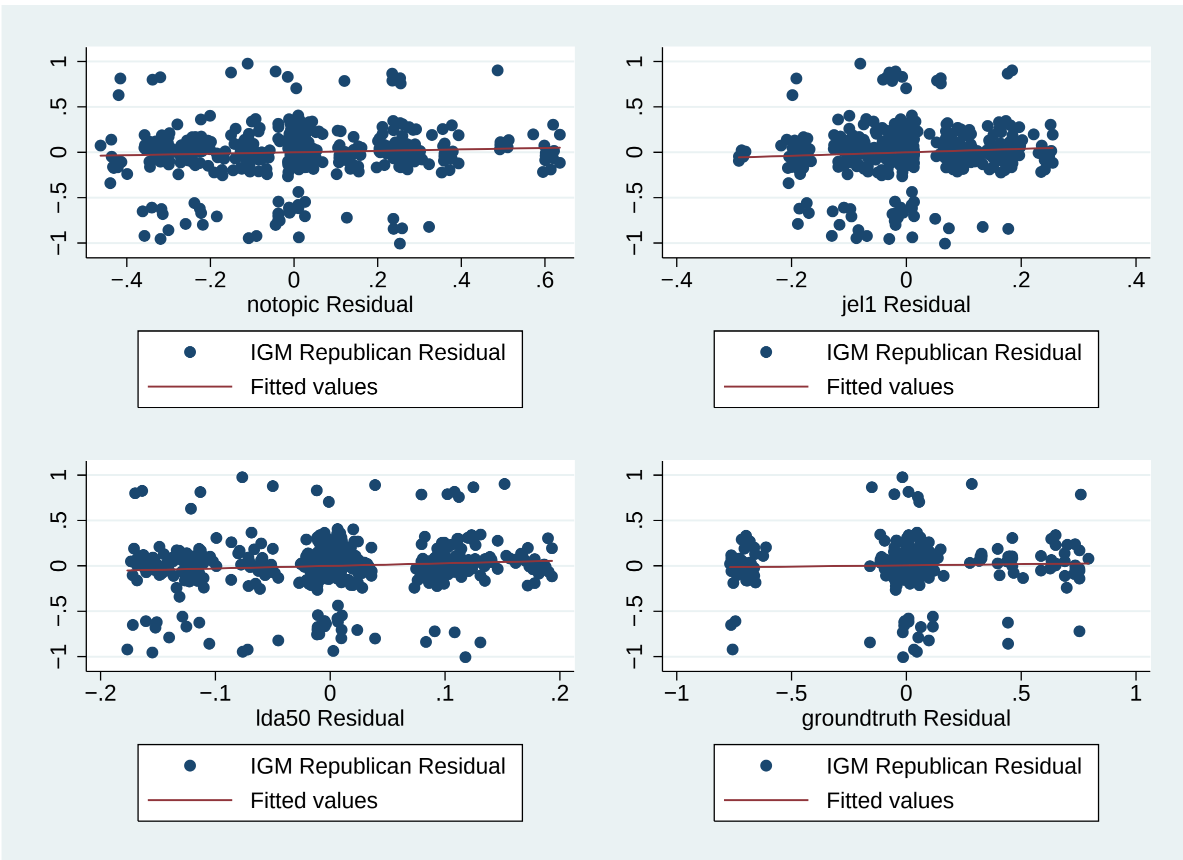


Figure 4: Scatterplots of Pooled (Normalized) Elasticities Against Predicted Ideology (FKP elasticities).

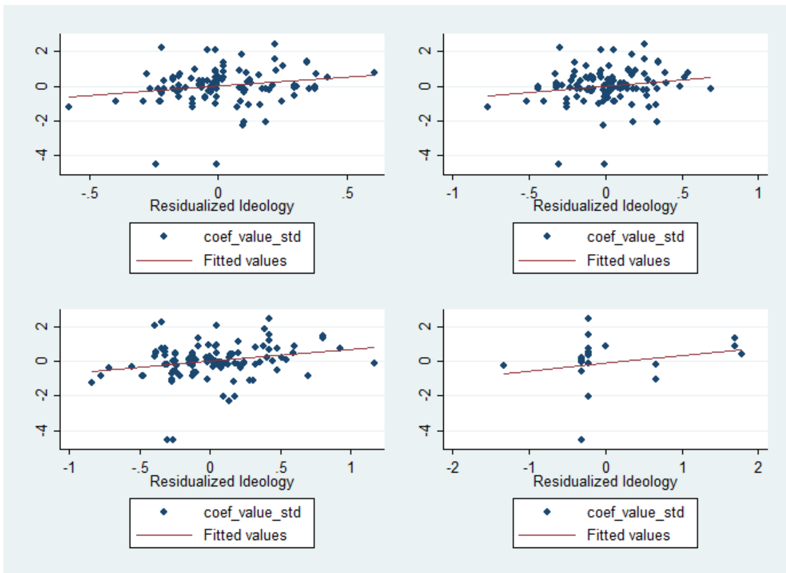


Figure 5: Scatterplots of Pooled (Normalized) Elasticities Against Predicted Ideology (Placebo elasticities).

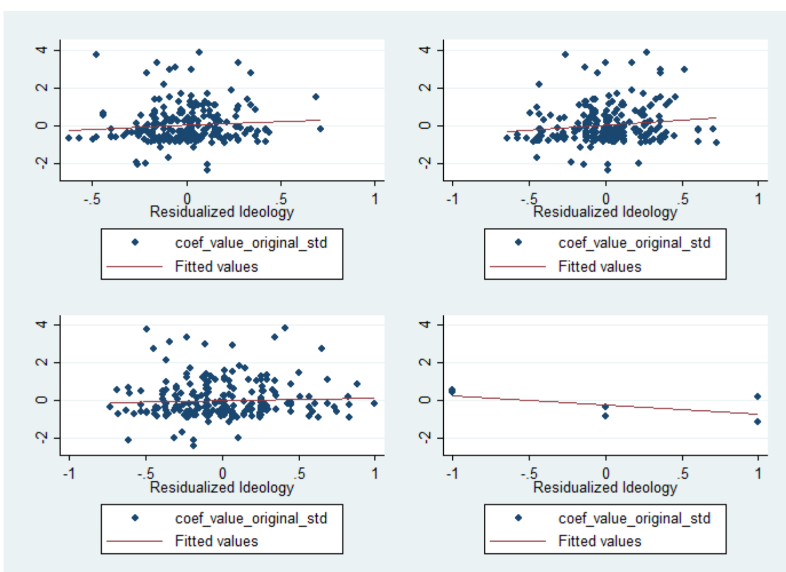
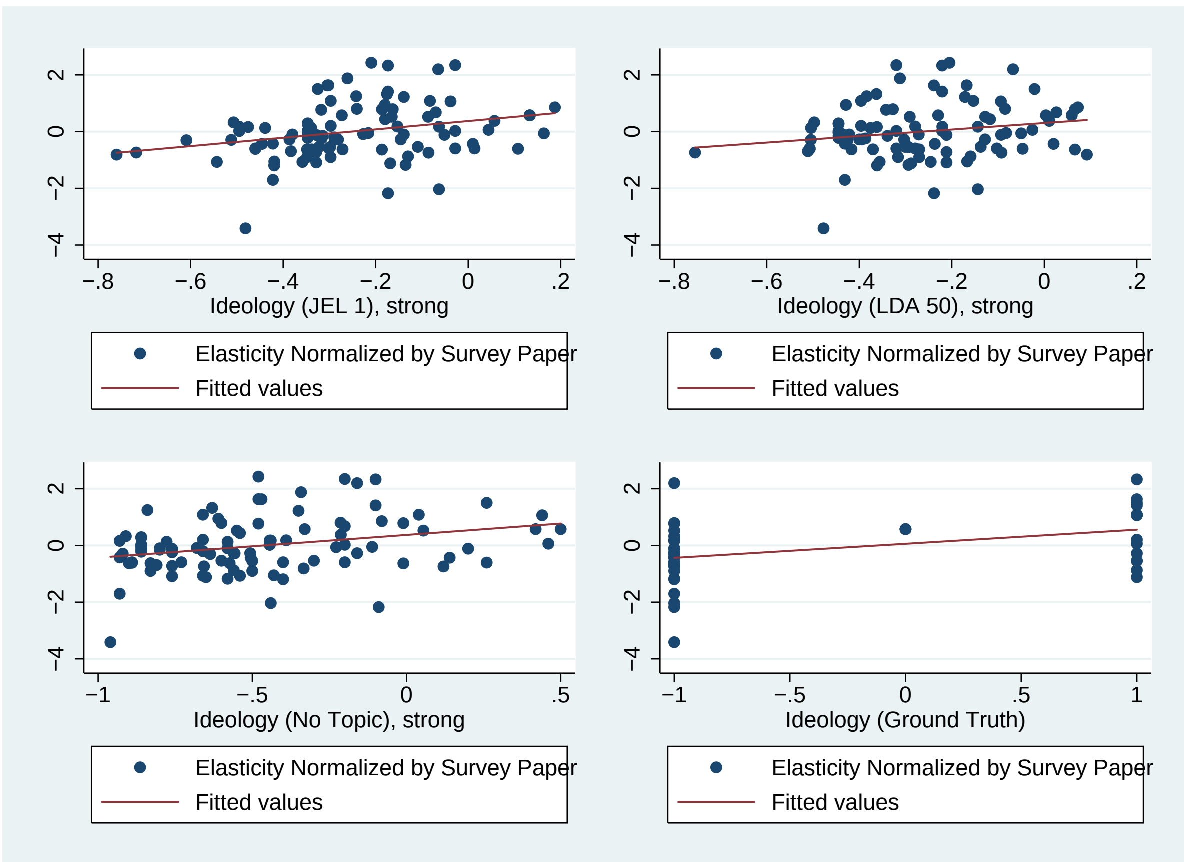


Figure 6: Scatterplots of Pooled (Normalized) Elasticities Against Predicted Ideology.



9 Appendix

A.1 Sorting, Peer-review and Partisan Science

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.[27]

Suppose individual economists are indexed by ideology θ_i distributed on $U[-1,1]$. This index corresponds to our “Ground-Truth" 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 not only to their true ideology θ_i, but to political neutrality, which is given a weight $1-\Phi$, with $\Phi \in (0,1)$. A low Φ corresponds to researchers taking pride in being non-partisan experts, and they derive utility from being difficult to pigeonhole politically.

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”. 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 median American voter, who theoretically should 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”. Other approaches may wish to pick different points in our ideological spectrum.

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.[28] 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:

$$V(\theta_{P(i)}, \theta_i) = -\lambda\Phi(\theta_{P(i)} - \theta_i)^2 - \lambda(1-\Phi)\theta_{P(i)}^2 - (1-\lambda)(\theta_{P(i)} - \theta_C)^2 \tag{7}$$

If $\lambda = 1$, then there are no professional incentives to be close to career-optimizing θ_C, and so a researcher's revealed partisanship would be given by $\theta_{P(i)} = \Phi\theta_i$. If $\lambda = 1$ *and* $\theta_i = 0$ *or* if $\Phi = 0$, so that the researcher is politically neutral and has no incentives to express ideology, then the economist

[27] We do not interpret “centrist" as “unbiased" or more accurate, however, as being non-partisan or centrist could in fact be another form of bias.

[28] In Appendix A.1, we present an extension of this model where we allow economists to sort into fields. Fields are important because they are the source of randomly drawn peers for ones publications and promotion. This results in an equilibrium where fields are completely partitioned, where all left-wing economists are in one field and all right-wing economists are in another. Ideology in this case imperfectly correlates with field.

will choose $\theta_{P(i)} = 0$ in their writing. 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.

$$\theta_{P(i)} = \lambda\Phi\theta_i + (1-\lambda)\theta_C \tag{8}$$

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 8 describes how the ideology observed in a paper is a function of own ideology, as well as the strength of preferences against partisanship (Φ) and career/pecuniary incentives λ. As Φ or λ approaches 0, $\theta_{P(i)}$ approaches θ_C, so that career concerns 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 centered.

Empirically, suppose publication ideology is given by:

$$\theta_{P(i)} = X_{P(i)}\beta + \epsilon \tag{9}$$

, where $X_{P(i)}$ is a 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:

$$\theta_i = X_{P(i)}\frac{\beta}{\lambda\Phi} - \frac{1-\lambda}{\lambda\Phi}\theta_C \tag{10}$$

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 (10) consistently. However, even if this assumption fails, there are slightly weaker assumptions under which we can still proceed to recover a valid predictor of θ_i without necessarily having to identify separately the correct structural coefficients β, λ, Φ.

The second assumption is that career-maximizing ideology is a linear combination of text features of publications and own ideology. Formally, this can be written:

$$\theta_C = X_{P(i)}\beta_C + \alpha_C\theta_i + \nu \tag{11}$$

This may be a strong assumption if there are unobserved characteristics of an economist that predict ideological incentives independent of own ideology that are not revealed in their writing. However, if we include a rich enough set of features of text, which in practice will be topic-specific phrase frequencies, it may be plausible to assume that we absorb the field-specific ideology. The assumption expressed in (11) says that there are enough professional niches so that economists sort into fields, methodologies, or departments according to closeness of ideology, and any remaining ideology that is due to constraints and not preferences are captured by $X_{P(i)}$. Then, using (10) and (11) we can estimate the following reduced form equation:

$$\theta_i = X_{P(i)}\gamma + \eta \tag{12}$$

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 $\widehat{\theta_j}$, given a document represented by a vector of text features $Z_{P(j)}$. This will be the core of our empirical approach. The main technical issue is that the length of the vector X is larger than the number of observations i, which rules out OLS and requires us to use a dimension-reduction methodology such as partial least squares. We will 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.

What are possible determinants of θ_C? We can use 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 $F \in \{L, M\}$:

$$\theta_F = E[\theta_i | i \in F] \tag{13}$$

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 will have distinct political preferences. In this model, while there is sorting, it is not perfect. This motivates including topic-adjusted 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 explicitly 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 fine 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".

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 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

[29] We use Python's *difflib* module that incorporates a version of the Ratcliff-Obershelp pattern matching algorithm (Ratcliff

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 21,229 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. Besides parties that are neither Democrat or Republican, the Other category includes cases where the party affiliation is blank or listed as unknown or none. According to this assignment, AEA members made 12,508 contributions to Democrats, 4,420 to Republicans, and 4,301 to Others between 1979 and 2012.

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 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). After this step we counted 13,892 contributions to Democrats, 4,670 to Republicans, and 2,667 to Others.

Of these contributions, 7,631 were made by economists who have written a paper in our dataset while 13,595 were made by other AEA members. Based on a visual inspection of the employee and occupation fields in the FEC data, it appears that many of the members in the latter group are either from the government or private industry. Table A.1 provides summary statistics on both author and non-author contributors. At the contribution level, 80.0% go to left-leaning PACs while 16.1% go to right leaning ones. For non-authors these figures are 61.6% and 27.0%, 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.

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'.

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

A.3 Measuring JEL Topic Prediction Accuracy

We assess our methodology for predicting JEL codes through three standard accuracy measures from information retrieval. For a given paper, let $jel_{econlit}$ be the set of JEL codes from EconLit and $jel_{predict}$ the set of predicted codes. The recall of the Econlit set is defined as

$$\text{recall}_{\text{econlit}} = \frac{|jel_{econlit} \cap jel_{predict}|}{|jel_{econlit}|}$$

which is the fraction of EconLit JELs that appear in the prediction set. The precision of the prediction set is defined as

$$\text{precision}_{\text{predict}} = \frac{|jel_{econlit} \cap jel_{predict}|}{|jel_{predict}|}$$

which is the fraction of the predicted JELs that appear in the EconLit set. A high recall can be obtained by including more JELs in $jel_{predict}$, but this may decrease the precision if many of the items in $jel_{predict}$ are not in $jel_{econlit}$. For example, if we predicted that each paper belongs to all JELs, then our recall would be perfect but our precision would be quite low. Similarly, it is possible to obtain high precision by including fewer items in $jel_{predict}$, but this may decrease recall if many items in $jel_{econlit}$ are not in $jel_{predict}$. To balance these countervailing forces, precision and recall can be combined into the F-measure which is the weighted harmonic mean of the two:

$$F_\beta = \left(1 + \beta^2\right) \frac{\text{precision} \cdot \text{recall}}{\beta^2 \cdot \text{precision} + \text{recall}}$$

Setting β to one weights precision and recall equally while a higher (lower) β gives more importance to precision (recall). We set β equal to one for our comparisons. We compute the precision, recall, and $F1$ score for each pair of EconLit and predicted JELs and take the average. As another comparison to our methodology, we exploit the fact that 1,256 of the papers in the NBER database are working paper versions of published works in the JSTOR set for which we have EconLit-assigned codes. Many of these NBER papers have JEL codes that are author-assigned and do not perfectly match up with the EconLit-assignments. We treat the author-assigned codes as predictions for the final codes. We compare how well our predictions overlapped with the EconLit-assigned codes versus the overlap between NBER and EconLit codes. Table A.4 shows that our methodology is better aligned than NBER author self-assignments with EconLit JEL codes.

A.4 Predicting Editorial Authorship

We compare the performance of our algorithm to TAM2/12 (Paul and Girju, 2010) and mview-LDA (Ahmed and Xing, 2010) on the bitterlemons corpus which consists of editorials written by Palestinian and Israeli authors. Both of these are unsupervised topic models which jointly model topic and ideology. We also show results from predicting using a support vector machine, which is a supervised learning model similar to ours but does not account for topics. For more information on the bitterlemons dataset see Lin et al. (2008). We sample 80% of the editorials for the training set and produce predictions with and without topic adjustments (*LDA10*, a topic mapping with 10 topics and *No Topics*). Table A.5 shows how well our model predicts if a test set author is Israeli or Palestinian compared with results from TAM2/12 and mview-LDA.[31] Our algorithm performs on par. Additionally, it does not appear that accounting for topic is necessarily helpful in improving ideology prediction accuracy. We discuss the performance of our prediction algorithm more in our companion paper (Jelveh, Kogut, and Naidu 2014).

[31]The TAM2/12 and mview-LDA values are taken from the respective papers. In the case of mview-LDA, the value is an estimate from a figure in the paper.

Table A.1: Campaign Contribution Data: Panel A provides summary statistics on AEA member campaign contributions at the contribution level and Panel B provides summary statistics at the member level.

Panel A: Contribution-Level

	N	Dem. Share	Rep. Share	Total Amount	Amount per Contribution	Amount Share to Dem.	Amount Share to Rep.
Authors	7,631	80.0%	16.1%	$6,151,074	$806	76.3%	19.4%
Non-Author	13,595	61.6%	27.0%	$11,657,804	$858	64.5%	26.6%

Panel B: Individual-Level

	N	Contrib. per Person	Contrib. per Person to Dem.	Contrib. per Person to Rep.	Amount Contrib. per Person	Dem Contrib. per Person	Rep. Contrib. per Person
Authors	1,125	6.78	5.42	1.09	$5,468	$4,172	$1,059
Non-Author	1,757	7.74	4.77	2.08	$6,635	$4,277	$1,761

Table A.2: The 35 petitions from Hedengren et al. (2010). The last column is the categorization applied in this paper.

Petition	Date	Organizer or Sponsor	Category	Signatures	Authors	Political Category
Support Market Oriented Health Care Reform 1994	03/16/94	The Independent Institute	Augm	637	224	Rep
Oppose Antitrust Protectionism	06/02/99	The Independent Institute	Augm	240	101	Rep
Support Market Oriented Health Care Reform 2000	03/01/00	The Independent Institute	Augm	538	226	Rep
Economists for Sweatshops	07/29/00	Academic Consortium on International Trade	Augm	252	80	Other
Oppose Death Tax	05/21/01	National Taxpayers Union	Augm	279	119	Rep
Scholars Against Sweatshop Labor	10/22/01	Political Economy Research Institute	Reduc	435	98	Other
Oppose Bush Tax Cuts	02/01/03	Economic Policy Institute	Reduc	464	273	Dem
Oppose Tax Increase	01/14/04	National Taxpayers Union	Augm	116	10	Rep

Endorse John Kerry for President	08/25/04	John Kerry Campaign (Not Sure)	Other	10	10	Dem
Oppose John Kerry for President	10/13/04	George W. Bush Campaign (Not Sure)	Other	367	148	Rep
Warning Future of Social Security	05/11/05	Cato Institute	Augm	454	155	Rep
Increase Immigration	06/19/06	The Independent Institute	Augm	523	183	Other
Support Raising the Minimum Wage	09/27/06	The Economic Policy Institute	Reduc	659	317	Dem
Oppose Marijuana Prohibition	11/30/06	Marijuana Policy Project	Augm	554	108	Other
Oppose Government Regulation of Internet ("Network Neutrality")	03/28/07	AEI-Brookings Joint Center	Augm	17	10	Rep
Statement on Prediction Markets	05/01/07	AEI-Brookings Joint Center	Augm	25	10	Other
Economists Against Protectionism	08/01/07	The Club for Growth	Augm	1028	320	Other
Oppose "Windfall Taxes"	10/17/07	National Taxpayers Union	Augm	234	82	Rep
Support John McCain Economic Plan	05/11/08	John McCain Campaign (Not Sure)	Other	326	132	Rep
Raising Some Concerns about Government Bail Out for Mortgages	09/24/08	John Cochrane	Other	230	124	Rep
Support Government Bail Out for Mortgages	10/01/08	Unknown	Reduc	76	47	Dem
Concerned about Climate Change	10/07/08	Nancy Olewiler	Reduc	254	112	Dem
Support Federal Recovery Act	11/19/08	Center for Economic and Policy Research	Reduc	387	138	Dem
Oppose Federal Recovery Act	01/27/09	Cato Institute	Augm	203	105	Rep
Oppose Budget Reduction in Washington State	02/19/09	Washington State Budget & Policy Center	Reduc	7	4	Dem
Support Employee Free Choice Act	02/24/09	The Economic Policy Institute	Reduc	40	34	Dem
Support Cap and Trade	03/04/09	Southern Alliance for Clean Energy	Reduc	601	142	Other
Replace Federal Income Tax with FairTax	03/29/09	FairTax.org	Other	80	24	Rep

Support Using Procurement Auctions Over Grant Submissions	04/13/09	Paul Milgrom	Other	64	24	Other
Support Government Intervention to Promote Biofuels	04/21/09	Union of Concerned Scientists	Reduc	16	11	Dem
Oppose Green Protectionism	05/08/09	Atlas Global Initiative for Free Trade Peace and Prosperity	Augm	1215	230	Rep
Fed Independence Petition	07/15/09	Wall Street Journal	Other	183	62	Other
Support Tax Increase on Corporations and High Income Persons	10/07/09	Oregon Center for Public Policy	Reduc	36	10	Dem
Government Oriented Health Care Reform 2009	11/17/09	Unknown	Reduc	23	19	Dem
Support for a Financial Transactions Tax	12/03/09	Center for Economic and Policy Research	Reduc	204	73	Dem

Table A.3: Correlation Between Indicator for Groundtruth Sample and Author Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Financial Economics	0.168***	0.178***	0.172***	0.179***	0.161***		
	(0.0288)	(0.0272)	(0.0348)	(0.0284)	(0.0287)		
Labor Economics	0.0392	0.0676**	0.0615	0.0606	0.0442		
	(0.0361)	(0.0315)	(0.0387)	(0.0383)	(0.0366)		
Macroeconomics	0.0641**	0.0715***	0.0763***	0.0790***	0.0855**		
	(0.0268)	(0.0238)	(0.0290)	(0.0279)	(0.0410)		
Public Economics	0.117***	0.139***	0.145***	0.144***	0.118***		
	(0.0301)	(0.0316)	(0.0280)	(0.0297)	(0.0353)		
Business School	0.0358	0.0309		-0.00987	-0.0200	-0.0244	-0.00587
	(0.0343)	(0.0353)		(0.0424)	(0.0383)	(0.0348)	(0.0437)
Saltwater Ever (Tervio)	0.138***	0.134***	0.0966**	0.109***	0.0757**	0.0478	0.0552
	(0.0359)	(0.0347)	(0.0466)	(0.0367)	(0.0324)	(0.0377)	(0.0394)
Freshwater Ever (Tervio)	0.0286	0.0175	0.0143	0.0478	0.0344	0.0116	0.00396
	(0.0423)	(0.0427)	(0.0651)	(0.0419)	(0.0408)	(0.0486)	(0.0509)
Doctoral Degree Year	-0.962***	-0.961***	-0.990***	-0.978***			
	(0.111)	(0.152)	(0.116)	(0.109)			
Years Between Undergrad and PhD Degrees		-0.00937					-0.00764
		(0.00673)					(0.00822)
Latin American Origin		-0.0490					-0.0926
		(0.103)					(0.146)
European Origin		0.00577					0.0268
		(0.0548)					(0.0643)
Full Professor		0.00392					0.0347
		(0.0321)					(0.0435)
Department FE	No	No	Yes	No	No	No	No
University FE	No	No	No	Yes	Yes	Yes	Yes
Field FE	No	No	No	No	No	Yes	Yes
PhD Year FE	No	No	No	No	Yes	Yes	Yes
Observations	891	843	891	891	962	962	843

Standard errors in parentheses
Robust Standard Errors. Clustered at the primary field level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Metrics for assessing the accuracy of predicted EconLit-assigned JEL codes.

Panel A: First-Level JELS

	NBER Authors	Our Method
F_1	0.752	0.769
Recall	0.673	0.709
Precision	0.788	0.816

Panel B: Second-Level JELS

	NBER Authors	Our Method
F_1	0.630	0.669
Recall	0.477	0.479
Precision	0.589	0.768

Table A.5: Predictive performance (%) on bitterlemons dataset using 80% of the data for training.

Model	No. Topics	Accuracy (%)
TAM2/12	12	87.5
mview-LDA	10	94
SVM	0	94
LDA10	10	91.0
No Topics	0	94.4

A.1 Other Descriptive Results

A.1 Robustness of Patterns of Individual Ideology

In this section we document professional patterns of predicted ideology of economists. We are interested in how our predicted measure of political ideology is correlated with field of research, employment and educational history, and national origin. We hypothesize that sorting, perhaps driven by the process of peer-review and evaluation, results in politically similar economists systematically located in particular fields and departments.

As noted in section *, we collected CV data. We reported in A.7 that ideological scores show that there is sorting by fields and institutions. These results support the reasoning to adjust the ideological scores by field in the empirical analysis, including that of the influence of ideology on elasticities.

It is possible that these results from the CV reflect nevertheless how we constructed the topic-adjusted ideology variables. Consequently, along with the demographic and professional variables we include here a control for whether or not the author appears in the ground truth sample. We do this to assess the importance of selection into the ground truth sample. Our estimates rely on the assumption that the relationship between n-grams and ideology is the same among the population that contributes and the population that doesn't contribute. Previous work evaluating the problem of non-representative samples in large prediction exercises like ours have generally found the bias to be quite low, on the order of 2%. If the parameters on other coefficients change substantially when this control is included, it would suggest that our sample of campaign contributors and petition signers are different in terms of their relationship between ideology predicted from text and individual characteristics. However, our coefficients are quite similar regardless of whether we control for the ground truth sample indicator or not, and the ground truth variable is always insignificant. While we do not show them here, none of our ideology predictions are correlated with being in the ground truth sample in simple bivariate regressions either. While the ground truth sample is different on observables from the other economists in our CV sample, as shown in Appendix Table A.3, differential selection of economists into the ground truth sample does not seem to be an important for predicting political preferences.[32]

A natural concern is that our predicted ideology scores are in fact driven by reverse causality, where research findings are driving support for particular political ideologies. If this were true, then we might expect predicted ideology to change over an economists' career, and ideological differences to narrow over time. We first check the stability of predicted ideology within a given individual economist. To do this, we split each economist's published work into the first and second 50% of their published words and look at the stability of ideology over time. The raw correlation is 0.55. Appendix A.1 shows that ideology is highly correlated over time, even conditional on all the professional variables we have used in this section. Secondly, we check if the distributions of ideologies look different for young, old, tenured, and untenured faculty, and find that the distributions are remarkably similar between old and young faculty (both faculty above and below median age in our sample have variance of 0.21 in the LDA-50 ideology prediction) as well as untenured and tenured faculty (0.21 and 0.22 variance, respectively, also with LDA50 ideology). Thus we believe our ideology scores are not reflecting transient political behavior that responds to available evidence, but instead a more durable characteristic of an individual.

While we have focused on predicting the ideology of individual economists, one might worry how much our results are affected by selection into publication. We can examine this by predicting the ideology of individual articles, and running a parallel analysis at the article level, controlling for journal and year of published article fixed effects. All of our results remain in this specification, and are omitted for space reasons. We can also decompose predicted ideology into journal, year, and individual economist components. We find that authors explain 30% of the total variation, while journals explain 6% and year explains 0.2%. In addition the journal and year variation is largely orthogonal to the author variation. Together, these results suggest that selection by authors of articles into journal or timing of publication is not important for the patterns of predicted individual political preferences we document here.

[32]We also found little robust evidence of peer-effects at either the Ph.D. cohort-grad school or cohort-grad school-field level. We did find some evidence of advisor-advisee correlation in ideology, but this was sensitive to the inclusion of advisor field controls.

Table A.6: CV Summary Statistics

	mean	sd
Ideology (LDA 50), strong	-0.15	0.21
Ideology (JEL 1), strong	-0.13	0.25
Ideology (No Topic), strong	-0.070	0.47
Groundtruth	-0.15	0.99
Financial Economics	0.14	0.35
Labor Economics	0.15	0.35
Macroeconomics	0.15	0.35
Public Economics	0.067	0.25
Business School	0.23	0.42
Saltwater Ever (Tervio)	0.64	0.48
Freshwater Ever (Tervio)	0.25	0.43
Doctoral Degree Year	19.9	0.12
Years Between Undergrad and PhD Degrees	6.24	2.10
Latin American Origin	0.012	0.11
European Origin	0.11	0.31
Full Professor	0.48	0.50
Groundtruth Sample	0.29	0.45
Observations	962	

Table A.7: Department Level CV Summary Statistics

	mean	sd	count
boston_college			
Ideology (LDA 50), strong	-0.14	0.21	12
Ideology (JEL 1), strong	-0.15	0.25	12
boston_u			
Ideology (LDA 50), strong	-0.21	0.23	26
Ideology (JEL 1), strong	-0.18	0.20	26
brown			
Ideology (LDA 50), strong	-0.25	0.12	6
Ideology (JEL 1), strong	-0.12	0.23	6
caltech			
Ideology (LDA 50), strong	-0.14	0.20	12
Ideology (JEL 1), strong	-0.13	0.25	12
carnegie_mellon			
Ideology (LDA 50), strong	-0.16	0.22	8
Ideology (JEL 1), strong	-0.097	0.20	8
carnegie_mellon_tepper			
Ideology (LDA 50), strong	0.12	0.18	10
Ideology (JEL 1), strong	0.18	0.35	10
columbia			
Ideology (LDA 50), strong	-0.22	0.19	44
Ideology (JEL 1), strong	-0.18	0.21	44
columbia_business_school			
Ideology (LDA 50), strong	-0.091	0.21	10
Ideology (JEL 1), strong	-0.033	0.22	10
cornell			
Ideology (LDA 50), strong	-0.13	0.24	24
Ideology (JEL 1), strong	-0.17	0.27	24
cornell_johnson			
Ideology (LDA 50), strong	-0.32	0.045	3
Ideology (JEL 1), strong	-0.45	0.21	3
dartmouth			
Ideology (LDA 50), strong	-0.23	0.17	20
Ideology (JEL 1), strong	-0.26	0.18	20
dartmouth_tuck			
Ideology (LDA 50), strong	-0.040	0.29	5
Ideology (JEL 1), strong	0.025	0.33	5
duke			
Ideology (LDA 50), strong	-0.16	0.24	40
Ideology (JEL 1), strong	-0.10	0.31	40
duke_fuqua			
Ideology (LDA 50), strong	-0.072	0.11	5
Ideology (JEL 1), strong	0.0092	0.20	5
harvard			
Ideology (LDA 50), strong	-0.20	0.17	40
Ideology (JEL 1), strong	-0.17	0.19	40
harvard_business_school			
Ideology (LDA 50), strong	-0.058	0.26	26
Ideology (JEL 1), strong	-0.021	0.23	26
lse			

Ideology (LDA 50), strong	-0.21	0.17	20
Ideology (JEL 1), strong	-0.15	0.25	20
mit			
Ideology (LDA 50), strong	-0.21	0.19	29
Ideology (JEL 1), strong	-0.17	0.20	29
mit_sloan			
Ideology (LDA 50), strong	-0.062	0.15	16
Ideology (JEL 1), strong	-0.016	0.23	17
northwestern			
Ideology (LDA 50), strong	-0.22	0.19	29
Ideology (JEL 1), strong	-0.20	0.29	29
northwestern_kellogg			
Ideology (LDA 50), strong	0.13	0.10	6
Ideology (JEL 1), strong	-0.078	0.13	6
nyu			
Ideology (LDA 50), strong	-0.14	0.18	25
Ideology (JEL 1), strong	-0.094	0.17	25
nyu_stern			
Ideology (LDA 50), strong	-0.073	0.18	35
Ideology (JEL 1), strong	-0.054	0.25	35
ohio_state			
Ideology (LDA 50), strong	-0.064	0.21	20
Ideology (JEL 1), strong	-0.082	0.27	20
princeton			
Ideology (LDA 50), strong	-0.14	0.21	30
Ideology (JEL 1), strong	-0.10	0.18	30
stanford			
Ideology (LDA 50), strong	-0.20	0.14	31
Ideology (JEL 1), strong	-0.20	0.17	31
stanford_gsb			
Ideology (LDA 50), strong	-0.093	0.27	22
Ideology (JEL 1), strong	-0.082	0.30	22
u_chicago			
Ideology (LDA 50), strong	0.038	0.41	2
Ideology (JEL 1), strong	-0.081	0.23	2
u_chicago_booth			
Ideology (LDA 50), strong	-0.035	0.23	39
Ideology (JEL 1), strong	0.048	0.25	39
u_illinois			
Ideology (LDA 50), strong	-0.11	0.18	13
Ideology (JEL 1), strong	-0.100	0.30	13
u_maryland			
Ideology (LDA 50), strong	-0.10	0.23	25
Ideology (JEL 1), strong	-0.084	0.24	25
u_michigan			
Ideology (LDA 50), strong	-0.23	0.17	36
Ideology (JEL 1), strong	-0.26	0.17	36
u_michigan_ross			
Ideology (LDA 50), strong	-0.10	0.27	6
Ideology (JEL 1), strong	-0.097	0.23	6
u_minnesota			
Ideology (LDA 50), strong	-0.17	0.11	16

Ideology (JEL 1), strong	-0.13	0.18	16
u_penn			
Ideology (LDA 50), strong	-0.19	0.14	19
Ideology (JEL 1), strong	-0.18	0.22	19
u_penn_wharton			
Ideology (LDA 50), strong	0.0035	0.23	22
Ideology (JEL 1), strong	-0.024	0.28	22
u_rochester			
Ideology (LDA 50), strong	-0.31	0.091	6
Ideology (JEL 1), strong	-0.29	0.24	6
u_southern_california			
Ideology (LDA 50), strong	-0.17	0.18	8
Ideology (JEL 1), strong	-0.15	0.21	8
u_wisconsin			
Ideology (LDA 50), strong	-0.18	0.19	19
Ideology (JEL 1), strong	-0.19	0.21	19
uc_berkeley			
Ideology (LDA 50), strong	-0.22	0.18	49
Ideology (JEL 1), strong	-0.18	0.23	50
uc_berkeley_haas			
Ideology (LDA 50), strong	-0.069	0.23	18
Ideology (JEL 1), strong	-0.034	0.33	18
uc_davis			
Ideology (LDA 50), strong	-0.22	0.24	18
Ideology (JEL 1), strong	-0.23	0.27	18
uc_san_diego			
Ideology (LDA 50), strong	-0.19	0.21	26
Ideology (JEL 1), strong	-0.19	0.24	26
ucla			
Ideology (LDA 50), strong	-0.20	0.20	27
Ideology (JEL 1), strong	-0.18	0.23	27
vanderbilt			
Ideology (LDA 50), strong	-0.049	0.22	23
Ideology (JEL 1), strong	-0.032	0.39	23
washington_u_st_louis			
Ideology (LDA 50), strong	-0.057	0.18	14
Ideology (JEL 1), strong	-0.15	0.15	14
yale			
Ideology (LDA 50), strong	-0.22	0.15	19
Ideology (JEL 1), strong	-0.19	0.22	19
yale_school_of_management			
Ideology (LDA 50), strong	-0.068	.	1
Ideology (JEL 1), strong	0.16	.	1
Total			
Ideology (LDA 50), strong	-0.15	0.21	960
Ideology (JEL 1), strong	-0.13	0.25	962
Observations	962		

Table A.8: Correlation Between Author Ideology (lda50) And CV Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Financial Economics	0.170***	0.175***	0.180***	0.177***	0.170***		
	(0.0256)	(0.0289)	(0.0216)	(0.0254)	(0.0253)		
Labor Economics	-0.129***	-0.128***	-0.132***	-0.132***	-0.125***		
	(0.0325)	(0.0309)	(0.0333)	(0.0347)	(0.0289)		
Macroeconomics	0.0946***	0.0933***	0.102***	0.0952***	0.0760***		
	(0.0211)	(0.0217)	(0.0174)	(0.0204)	(0.0214)		
Public Economics	0.0354	0.0442	0.0335	0.0357	0.0362*		
	(0.0260)	(0.0271)	(0.0217)	(0.0248)	(0.0215)		
Business School	0.0678***	0.0693***		0.0653***	0.0669***	0.0452**	0.0360*
	(0.0171)	(0.0182)		(0.0207)	(0.0198)	(0.0188)	(0.0212)
Saltwater Ever (Tervio)	-0.0522***	-0.0461***	-0.0284*	-0.0426***	-0.0453***	-0.0414**	-0.0346**
	(0.0149)	(0.0150)	(0.0149)	(0.0144)	(0.0151)	(0.0161)	(0.0152)
Freshwater Ever (Tervio)	-0.0108	-0.0128	0.0251	-0.0193	-0.00935	-0.000836	-0.00640
	(0.0125)	(0.0138)	(0.0230)	(0.0146)	(0.0143)	(0.0159)	(0.0171)
Doctoral Degree Year	-0.0874*	-0.105	-0.0565	-0.0876*			
	(0.0493)	(0.0663)	(0.0538)	(0.0475)			
Years Between Undergrad and PhD Degrees		-0.00489					-0.00646
		(0.00331)					(0.00451)
Latin American Origin		0.0469					0.0848
		(0.0704)					(0.0729)
European Origin		0.0194					0.0340
		(0.0262)					(0.0333)
Full Professor		0.00680					0.0122
		(0.0167)					(0.0186)
Groundtruth Sample		-0.0275					-0.0362*
		(0.0225)					(0.0204)
Department FE	No	No	Yes	No	No	No	No
University FE	No	No	No	Yes	Yes	Yes	Yes
Field FE	No	No	No	No	No	Yes	Yes
PhD Year FE	No	No	No	No	Yes	Yes	Yes
Observations	890	842	890	890	960	960	842

Standard errors in parentheses
Robust Standard Errors. Clustered at the primary field level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Correlation Between Author Ideology (jel1) And CV Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Financial Economics	0.222***	0.226***	0.231***	0.227***	0.222***		
	(0.0247)	(0.0256)	(0.0226)	(0.0231)	(0.0255)		
Labor Economics	-0.117***	-0.123***	-0.117***	-0.117***	-0.116***		
	(0.0307)	(0.0288)	(0.0318)	(0.0317)	(0.0313)		
Macroeconomics	0.118***	0.111***	0.120***	0.112***	0.0935***		
	(0.0196)	(0.0192)	(0.0178)	(0.0186)	(0.0225)		
Public Economics	0.0410	0.0373	0.0420	0.0415	0.0490**		
	(0.0276)	(0.0294)	(0.0265)	(0.0268)	(0.0221)		
Business School	0.0703***	0.0722***		0.0646***	0.0612***	0.0400	0.0348
	(0.0208)	(0.0214)		(0.0218)	(0.0213)	(0.0257)	(0.0298)
Saltwater Ever (Tervio)	-0.0211	-0.0177	0.0122	-0.00695	-0.00631	-0.00691	-0.00164
	(0.0174)	(0.0199)	(0.0182)	(0.0186)	(0.0187)	(0.0194)	(0.0218)
Freshwater Ever (Tervio)	0.00390	0.00488	0.0515*	0.0102	0.0132	0.0137	0.0116
	(0.0172)	(0.0171)	(0.0289)	(0.0197)	(0.0176)	(0.0166)	(0.0178)
Doctoral Degree Year	-0.0471	-0.0538	-0.0257	-0.0567			
	(0.0467)	(0.0574)	(0.0513)	(0.0511)			
Years Between Undergrad and PhD Degrees		-0.00243					-0.00283
		(0.00464)					(0.00521)
Latin American Origin		0.0716					0.138**
		(0.0676)					(0.0670)
European Origin		0.00723					0.0160
		(0.0322)					(0.0391)
Full Professor		-0.0125					-0.00303
		(0.0142)					(0.0170)
Groundtruth Sample		-0.00691					-0.0327*
		(0.0232)					(0.0195)
Department FE	No	No	Yes	No	No	No	No
University FE	No	No	No	Yes	Yes	Yes	Yes
Field FE	No	No	No	No	No	Yes	Yes
PhD Year FE	No	No	No	No	Yes	Yes	Yes
Observations	891	843	891	891	962	962	843

Standard errors in parentheses
Robust Standard Errors. Clustered at the primary field level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Correlation Between Author Ideology (notopic) And CV Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Financial Economics	0.460***	0.463***	0.491***	0.481***	0.465***		
	(0.0410)	(0.0431)	(0.0405)	(0.0397)	(0.0380)		
Labor Economics	-0.424***	-0.422***	-0.426***	-0.424***	-0.415***		
	(0.0836)	(0.0759)	(0.0845)	(0.0881)	(0.0719)		
Macroeconomics	0.240***	0.228***	0.237***	0.227***	0.173***		
	(0.0403)	(0.0401)	(0.0401)	(0.0418)	(0.0382)		
Public Economics	-0.101	-0.102	-0.0986	-0.0914	-0.101		
	(0.0720)	(0.0789)	(0.0644)	(0.0724)	(0.0697)		
Business School	0.163***	0.179***		0.148***	0.141***	0.0922***	0.0892***
	(0.0402)	(0.0396)		(0.0398)	(0.0386)	(0.0288)	(0.0326)
Saltwater Ever (Tervio)	-0.0626**	-0.0493*	-0.0468*	-0.0464*	-0.0558**	-0.0463**	-0.0259
	(0.0251)	(0.0254)	(0.0239)	(0.0243)	(0.0215)	(0.0210)	(0.0273)
Freshwater Ever (Tervio)	0.0249	0.0303	0.0198	0.00606	0.0199	0.0335	0.0317
	(0.0278)	(0.0269)	(0.0322)	(0.0268)	(0.0297)	(0.0331)	(0.0327)
Doctoral Degree Year	-0.0681	-0.120	-0.0123	-0.0578			
	(0.119)	(0.121)	(0.117)	(0.108)			
Years Between Undergrad and PhD Degrees		-0.0139*					-0.0118
		(0.00714)					(0.00771)
Latin American Origin		0.105					0.203*
		(0.114)					(0.111)
European Origin		0.0862					0.0819
		(0.0738)					(0.0874)
Full Professor		0.0180					0.0176
		(0.0289)					(0.0360)
Groundtruth Sample		-0.0508					-0.0638**
		(0.0373)					(0.0314)
Department FE	No	No	Yes	No	No	No	No
University FE	No	No	No	Yes	Yes	Yes	Yes
Field FE	No	No	No	No	No	Yes	Yes
PhD Year FE	No	No	No	No	Yes	Yes	Yes
Observations	891	843	891	891	962	962	843

Standard errors in parentheses
Robust Standard Errors. Clustered at the primary field level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Correlation Between Author Ideology (groundtruth) And CV Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Financial Economics	0.705***	0.658***	0.630***	0.617***	0.336		
	(0.157)	(0.161)	(0.194)	(0.171)	(0.203)		
Labor Economics	-0.303**	-0.345**	-0.211	-0.334**	-0.381**		
	(0.147)	(0.154)	(0.155)	(0.145)	(0.168)		
Macroeconomics	0.336***	0.277**	0.258**	0.184*	0.123		
	(0.0889)	(0.119)	(0.118)	(0.0982)	(0.129)		
Public Economics	-0.00385	0.0422	0.110	-0.0357	-0.147		
	(0.133)	(0.125)	(0.114)	(0.109)	(0.162)		
Business School	0.132	0.149		-0.0158	0.0764	-0.0809	-0.0601
	(0.135)	(0.153)		(0.118)	(0.202)	(0.254)	(0.273)
Saltwater Ever (Tervio)	-0.308	-0.280	-0.181	-0.286	-0.258	-0.394	-0.484
	(0.215)	(0.202)	(0.207)	(0.218)	(0.216)	(0.282)	(0.298)
Freshwater Ever (Tervio)	0.355**	0.352**	0.418	0.321*	0.377**	0.512***	0.428**
	(0.158)	(0.157)	(0.286)	(0.161)	(0.162)	(0.188)	(0.178)
Doctoral Degree Year	1.140	0.953	1.336*	1.222*			
	(0.742)	(0.801)	(0.705)	(0.718)			
Years Between Undergrad and PhD Degrees		-0.0170					-0.0230
		(0.0186)					(0.0359)
Latin American Origin		-1.214***					-1.749***
		(0.181)					(0.568)
European Origin		0.458*					0.370
		(0.246)					(0.431)
Full Professor		0.182*					0.116
		(0.0967)					(0.190)
Department FE	No	No	Yes	No	No	No	No
University FE	No	No	No	Yes	Yes	Yes	Yes
Field FE	No	No	No	No	No	Yes	Yes
PhD Year FE	No	No	No	No	Yes	Yes	Yes
Observations	256	245	256	256	279	279	245

Standard errors in parentheses
Robust Standard Errors. Clustered at the primary field level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.1.1 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 $LDA50$ measure of ideology, as others are quite similar. Figure A.1 shows the scatterplot between $Ideology_i^{Pre}$ and $Ideology_i^{Post}$ for all the AEA economists in our sample. A.2 shows the scatterplot for the CV sample, with saltwater/freshwater, business school, Ph.D. copletion 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. Table A.12 shows that the correlation between early ideology and late ideology is robust to all of the controls mentioned above for all three of our predictions.

Figure A.3 shows the distribution of ideologies by young and old, and full professors and associate/assistant professors for each of our three predicted ideologies. The distributions are quite similar, suggesting that little narrowing or widening of views is taking place as economists get older or more professionally secure.

Figure A.1: Stability of Predicted Ideology for Full Sample

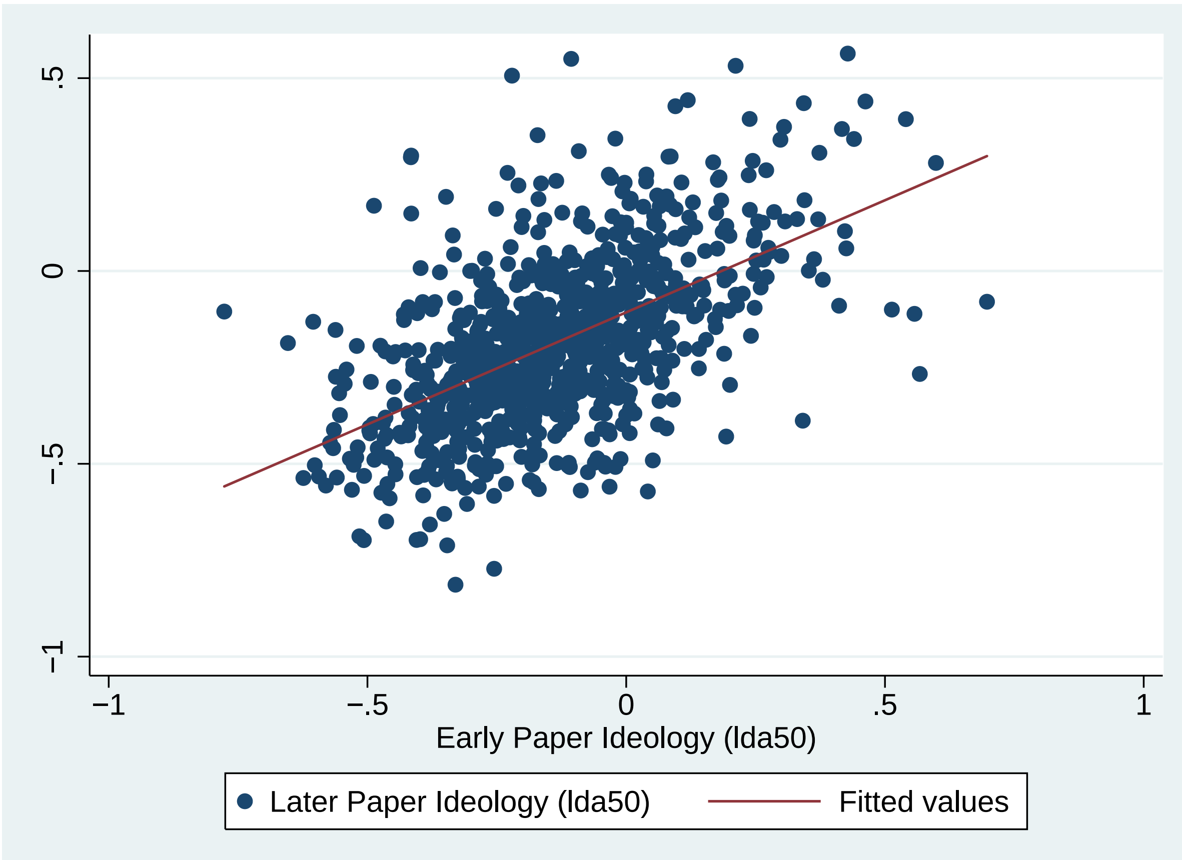


Figure A.2: Stability of Predicted Ideology Residuals for CV Sample

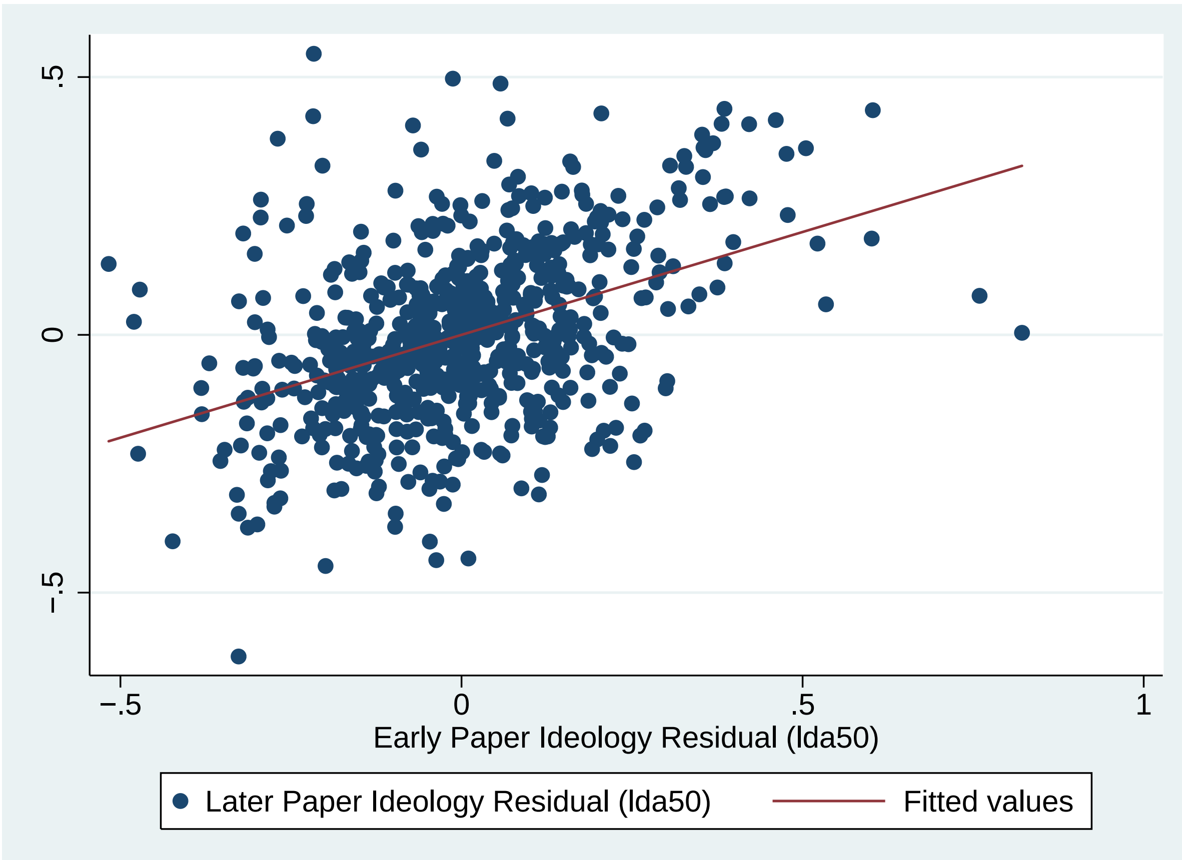
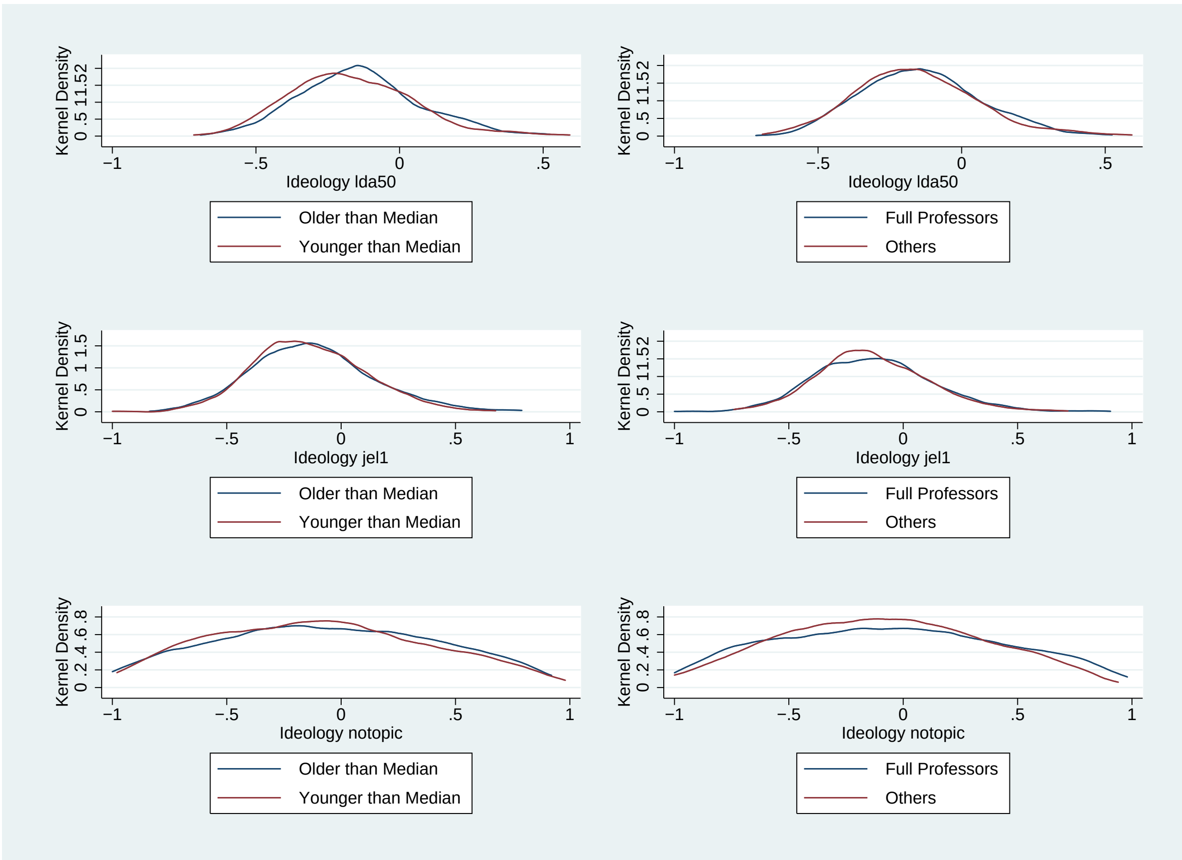


Table A.12: Correlation Between Late and Early Author Ideology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early Paper Ideology (lda50)	0.581***	0.388***	0.399***						
	(0.0581)	(0.0532)	(0.0574)						
Early Paper Ideology (jel1)				0.433***	0.279***	0.311***			
				(0.0567)	(0.0494)	(0.0397)			
Early Paper Ideology (notopic)							0.721***	0.533***	0.540***
							(0.0512)	(0.0330)	(0.0332)
Years Between Undergrad and PhD Degrees			0.000242			-0.00471			-0.00827*
			(0.00406)			(0.00469)			(0.00495)
Latin American Origin			-0.00428			-0.0298			0.0140
			(0.107)			(0.106)			(0.134)
European Origin			0.0483			0.0695**			0.0703
			(0.0352)			(0.0333)			(0.0468)
Full Professor			0.00412			-0.0314			-0.00688
			(0.0223)			(0.0274)			(0.0273)
Groundtruth Sample			-0.00931			-0.0196			-0.0270
			(0.0163)			(0.0229)			(0.0219)
University FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Field FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
PhD Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	821	821	727	820	820	726	821	821	727

Standard errors in parentheses
Robust Standard Errors. Clustered at the primary field level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.3: Distributions of Predicted Ideology by Age and Rank



A.1.2 Journal Sample and Journal Ideology

Figure A.4: The Number of NBER Working Papers by Year.

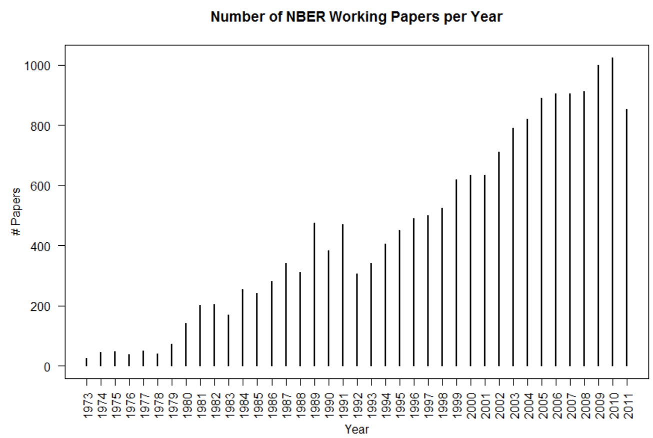


Figure A.5: The Number of Published Papers in JSTOR by Year.

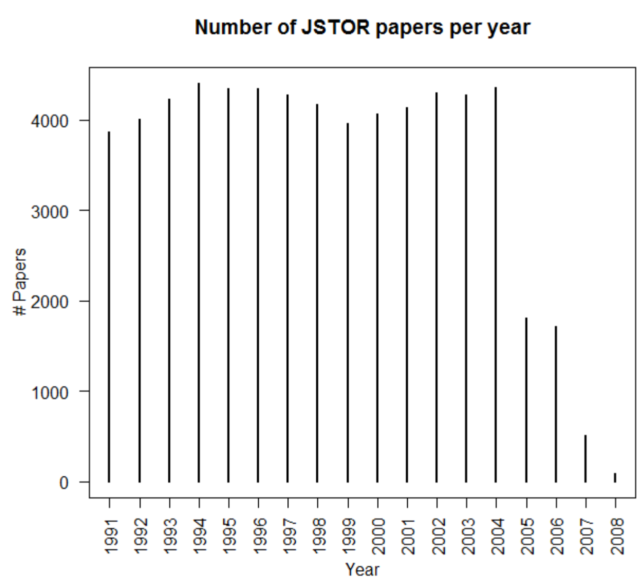


Table A.13: Journal Summary Statistics

Journal	Count	LDA50	JEL1
African Economic History	104	-0.038	0.021
American Journal of Agricultural Economics	2046	0.030	-0.054
Annales d'Economie et de Statistique	596	-0.345	-0.169
Annals of the American Academy of Political and Social Science	1220	-0.395	-0.249
Brookings-Wharton Papers on Urban Affairs	42	-0.212	-0.154
Brookings Papers on Economic Activity	253	-0.505	-0.425
Brookings Papers on Economic Activity. Microeconomics	62	-0.287	-0.217
Brookings Trade Forum	81	-0.331	-0.296
Canadian Journal of Political Science	383	-0.060	0.110
Canadian Public Policy	616	-0.586	-0.603
Desarrollo Econ	475	-0.628	-0.543
Eastern Economic Journal	544	-0.055	-0.070
Eastern European Economics	304	-0.255	-0.259
Econom	67	-0.352	-0.279
Econometric Theory	1045	-0.073	0.110
Econometrica	1019	-0.267	-0.166
Economic and Political Weekly	15288	-0.279	-0.173
Economic Development and Cultural Change	503	0.103	0.275
Economic Geography	273	-0.516	-0.458
Economic Policy	170	-0.145	-0.159
Economic Theory	1188	-0.181	-0.250
Economica	452	-0.102	-0.101
Emerging Markets Finance & Trade	65	-0.279	-0.232
Estudios Econ	190	-0.085	-0.076
Health Economics in Prevention and Care	29	-0.397	-0.636
IMF Staff Papers	192	-0.220	-0.147
Indian Journal of Industrial Relations	449	-0.301	-0.263
Industrial and Labor Relations Review	599	-0.246	-0.195
Innovation Policy and the Economy	43	-0.401	-0.276
International Economic Review	729	-0.189	-0.181
International Journal of Health Care Finance and Economics	97	-0.336	-0.222
Journal of Applied Econometrics	511	0.043	0.037
Journal of Business & Economic Statistics	694	0.002	0.137
Journal of Economic Growth	163	-0.158	-0.137
Journal of Economic Issues	1043	-0.546	-0.554
Journal of Economic Literature	303	-0.203	-0.288
Journal of Labor Economics	446	-0.202	-0.037
Journal of Law and Economics	352	0.420	0.461
Journal of Law, Economics, & Organization	162	0.094	0.164
Journal of Money, Credit and Banking	874	0.281	0.407
Journal of Population Economics	471	-0.259	-0.144
Journal of Post Keynesian Economics	551	-0.547	-0.612
Journal of the Economic and Social History of the Orient	203	-0.408	0.080
Journal of the European Economic Association	273	-0.185	-0.131
Journal of Transport Economics and Policy	332	-0.096	0.004
Land Economics	659	-0.092	-0.208
Marketing Letters	444	-0.144	-0.049
MIR: Management International Review	256	-0.236	-0.116
NBER International Seminar on Macroeconomics	31	-0.260	-0.176
NBER Macroeconomics Annual	370	-0.198	-0.120

Table A.13 (continued)

New Labor Forum	328	-0.418	-0.194
Oxford Economic Papers	296	-0.168	-0.118
Public Choice	1406	0.561	0.606
Review (Fernand Braudel Center)	250	-0.384	-0.344
Review of African Political Economy	894	-0.275	-0.253
Review of Agricultural Economics	545	0.132	0.184
Review of International Political Economy	343	-0.327	-0.065
Review of World Economics	128	-0.306	-0.213
Revue	1188	-0.701	-0.259
Russian and East European Finance and Trade	227	-0.187	-0.215
Science & Society	335	-0.384	-0.452
Small Business Economics	708	-0.175	-0.143
Southern Economic Journal	1111	0.095	0.102
Soviet and Eastern European Foreign Trade	19	-0.104	-0.442
Staff Papers - International Monetary Fund	256	-0.078	-0.031
Supreme Court Economic Review	61	0.200	0.238
Tax Policy and the Economy	94	-0.281	-0.290
The American Economic Review	3031	-0.167	-0.155
The American Economist	320	-0.020	-0.022
The American Journal of Economics and Sociology	604	0.168	0.177
The Brookings Review	799	-0.302	-0.215
The Business History Review	198	-0.348	-0.303
The Canadian Journal of Economics	1065	-0.178	-0.112
The Economic History Review	415	-0.175	-0.224
The Economic Journal	1311	-0.130	-0.178
The European Journal of Health Economics	297	-0.267	-0.306
The Journal of Developing Areas	250	-0.138	-0.069
The Journal of Economic Education	520	0.090	0.011
The Journal of Economic History	617	-0.089	-0.113
The Journal of Economic Perspectives	921	-0.230	-0.202
The Journal of Human Resources	610	-0.352	-0.250
The Journal of Industrial Economics	379	-0.116	-0.144
The Journal of Legal Studies	353	0.132	-0.082
The Journal of Political Economy	720	0.019	0.022
The Journal of Risk and Insurance	498	0.065	-0.078
The Quarterly Journal of Economics	618	-0.139	-0.128
The RAND Journal of Economics	712	-0.236	-0.351
The Review of Economic Studies	643	-0.246	-0.203
The Review of Economics and Statistics	1108	-0.045	-0.011
The Scandinavian Journal of Economics	602	-0.176	-0.210
The World Bank Economic Review	259	-0.297	-0.233
The World Bank Research Observer	152	-0.376	-0.522
Weltwirtschaftliches Archiv	435	-0.039	0.047

The list of 93 journals obtained from the JSTOR archive, the number of research articles in each journal, and the average JEL1 and LDA50 predicted ideologies across papers (the correlation between JEL1 and LDA50 is 0.862).