Political Language in Economics

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Abstract

Do empirical estimates in economics reflect the political orientation of economists? We show that policy-relevant parameters are correlated with economist partisanship as predicted from the text of published academic papers. Specifically, we predict observed political behavior of a subset of economists using the phrases from their academic articles, obtain good out-of-sample fit, and then predict partisanship for all economists. We show considerable sorting of economists into fields of research by predicted partisanship, and yet can detect differences in partisanship among economists even within a field, even across those estimating the same theoretical parameter. Using policy-relevant parameters collected from previous meta-analyses we then show that imputed partisanship is correlated with estimated parameters, such that the implied policy prescription is consistent with partisan leaning. For example, we find that going from the most left-wing authored estimate of the taxable top income elasticity to the most right-wing authored estimate decreases the optimal tax rate from 84% to 58%.

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1 Introduction

Modern governments incorporate expert opinion into policy analysis via a wide variety of formal and informal mechanisms. Examples from economics include central bank policy, antitrust policy, and 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. The policy relevance of economics partially stems from its ability to combine economic theory (e.g. supply and demand) with parameter estimates (e.g. elasticities) to make prescriptions about optimal policies (e.g. taxes). Expert opinion and judgment are often expected to be non-partisan, and yet experts may have partisan or political preferences of their own. Do the methodological conventions of academic economics successfully filter partisanship from academic, particularly empirical, economics research?

We answer this question using tools from natural language processing applied to a comprehensive corpus of academic economics articles. We draw policy relevant elasticities from Fuchs et al. (1998) and locate available survey papers that compile estimates of these parameters. We collect estimates of the gender gap, returns to job training, labor supply elasticities, minimum wage elasiticities, and union productivity effects. We then predict the ideologies of the authors reporting these estimates by using the text of other papers written by these same authors. We show that empirical results in several key policy relevant fields in economics are correlated with predicted political ideology of the author(s), with predicted liberals reporting elasticities that imply policies consistent with more interventionist ideology.

Measuring ideology implicit in academic economics is another contribution of our paper. Most research economists do not publicly announce any partisan position. Indeed, many of the professional practices and norms of economics are designed to eliminate partisanship from research. We represent academic articles as high-dimensional vectors of phrase counts, and then use machine-learning methods applied to economists' writing linked to observed political behavior, specifically campaign contributions and partisan petition signings. We allow the frequency of a phrase to have a different political valence, depending on the topic (e.g. JEL code) of the paper. If political preferences were irrelevant for academic research in economics, this should be very difficult. Further, it is natural to hypothesize that while detecting partisanship in popular media or politician speech is reasonably easy, doing so in specialized, technical domains may be much harder. Nonetheless our method generates good out-of-sample predictions of economist political behavior based on academic writing alone.

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 among 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, 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, 2014-02).

In his 'The Politics of Political Economists', George Stigler 1959 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 institutionalized incentives and norms for the dissemination of information. "The dominant influence upon the working range of economic theorists is the set of internal values and pressures of the discipline" (Stigler, 1960). Stigler believed that political and policy preferences do not drive economic research, and when they do, it is for the worse.[3] This belief that economics conforms with standard scientific norms[4] is the basis of a working consensus that is widely defended.[5]

Yet, the evidence for the view that scientific practices purge ideology from economics is surprisingly thin, relying upon surveys or subjective coding of political beliefs. The best evidence comes from a comprehensive survey undertaken by Fuchs et al. (1998) who asked a number of labor and public finance economists their views on parameters, policies, and values. They conclude that "one of the

[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 et al. (2014) show that economists are the highest paid of the social scientists, and are the least likely to use interdisciplinary citations.

[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)

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

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

most important empirical results of this study is the strong correlation between economists' positions and their values, but an understanding of this relationship requires further research" (Fuchs et al., 1998, pp 1415). We investigate the role of political preferences, or ideology, in economics with a purely inductive, 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 "groundtruth" 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.[6] 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 to predict out-of-sample economist political leanings. We validate these predictions of political preferences using held-out data, as well as confirming that they are correlated with partisan responses to survey questions from The Initiative on Global Markets' (IGM) Economics Experts Panel (Gordon and Dahl, 2013). Our first result is that it is indeed possible to predict partisan behavior with high-dimensional representations of academic writing, suggesting that distinct academic writing is associated with distinct political preferences.

A series of recent papers investigate empirically the determinants of economic publication and citation patterns (Ellison (2010), Ellison (2011), Önder and Terviö (2015)). Closest to our paper is Gordon and Dahl (2013), who apply clustering techniques to IGM survey responses on a variety of policy questions 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.[7]

Instead of these survey based methods, which may suffer from framing biases as well as selection, our paper uses the correlations between patterns of academic writing and observed political behavior to measure ideology.[8] Ideology extraction from text has received attention from multiple fields including

[6]Groundtruth refers to data that is objectively valid that is used to train a statistical classifier.

[7]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. Another recent paper by Hengel (2016) uses the text of academic papers to document differences in the readability of academic papers written by male and female economists.

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

computer science, political science, and economics. Our tools most closely follow Gentzkow and Shapiro (2010) (see also Jensen et al. (2012)). Grimmer and Stewart (2013) and Gentzkow et al. (2018) provide overviews of many models used in the analysis of text, particularly in the domain of political behavior.

While models predicting ideology from text can show high predictive accuracy, they have not been applied in technical domains where ideology is not immediately apparent. Importantly, detecting ideology in domains where institutions and norms are in place to maintain neutrality is different from predicting ideology in domains where it is overt, such as media or political speech, as all of the papers using text drawn from political actors do (Jelveh et al., 2014). Adjusting for topics may be particularly important in highly specialized domains, where language use is tailored to very narrow audiences of other experts.

2 Model

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

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

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

Suppose individual economists are indexed by ideology θ_i distributed on $U[-1, 1]$. This index corresponds to our "groundtruth" measure of ideology, observed partisan political behavior, which we only observe for a small sample. Economists derive utility from publishing papers with ideology $\theta_{P(i)}$, that is close to their true ideology θ_i as well as from the appearance of objectivity or neutrality, and each source of utility is weighted by Φ and $1 - \Phi$, with $\Phi \in (0, 1)$, respectively. A low Φ corresponds to researchers taking pride in being non-partisan experts, and they derive 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", since the center is merely inferred from the empirical distribution of imputed partisanship. Our metric is the real line bounded by -1 and 1 with the center at 0 (or near 0 depending upon the sample or chosen field). This 0 could correspond to the pivotal American voter, who in a model of party competition would be indifferent between the two parties. The center is not necessarily the truth any more than left or right are "biased" and we consequently avoid the word "bias".

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

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

The optimum choice of ideology will be then given by:

$$\theta_{P(i)} = \lambda\Phi\theta_i + (1-\lambda)\theta_C \tag{2}$$

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 2 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.

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

Empirically, suppose publication ideology is given by:

$$\theta_{P(i)} = X_{P(i)}\beta + \epsilon_i \tag{3}$$

, where $X_{P(i)}$ is a high-dimensional vector of text features of publications $P(i)$ written by author i and

β is an unknown coefficient vector. Then we have the true model:

$$\theta_i = X_{P(i)} \frac{\beta}{\lambda\Phi} - \frac{1-\lambda}{\lambda\Phi}\theta_C \tag{4}$$

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 (4) consistently. However, even if this assumption fails, but θ_C is itself a function only of text $X_{P(i)}$ as well as own ideology θ_i (and noise), we can recover an unbiased prediction. Formally, this can be written in the form of a selection equation:

$$\theta_C = X_{P(i)}\beta_C + \alpha_C\theta_i + \nu_i \tag{5}$$

ν_i uncorrelated with θ_i and $X_{P(i)}$ may be a strong assumption if there are unobserved characteristics of an economist that predict career maximizing expression of ideology independent of own ideology that are not revealed in patterns of writing. For example, having liberal peers may induce an economist to express liberal behavior in order to advance their career even if they are not themselves liberal nor write in liberal manner. However, if we include a rich enough set of features of text, which in practice will be topic-specific phrase frequencies, it may be plausible to assume that we obtain a proxy for even career-maximizing ideology. Note that this assumption works because we are interested in obtaining a good prediction of θ_i and not unbiased coefficients on β. Using (4) and (5) we can estimate the following reduced form equation:

$$\theta_i = X_{P(i)}\gamma + \eta \tag{6}$$

Where $\gamma = \frac{\beta-(1-\lambda)\beta_C}{\phi\lambda+(1-\lambda)\alpha_C}$, and a linear regression would recover the best unbiased linear predictor $\widehat{\gamma}$. Under the assumption of a valid estimate of γ, we can then forecast $\widehat{\theta_j}$, for any economist j, given a document represented by a vector of text features $X_{P(j)}$. This will be the core of our empirical approach. X is a high-dimensional vector, and so we can leverage any number of machine learning tools, such as random forests or LASSO, to obtain a good prediction of $\widehat{\theta_j}$. We 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.

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

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

$$\theta_F = E[\theta_i | i \in F] \tag{7}$$

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: In Appendix A.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.

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

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.

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, 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.

[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.

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

We 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 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.

3.2 Economic Papers Corpus

To create our corpus of academic writings by economists, we also obtained from JSTOR the full text 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.

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 length two (bigram) and three (trigram). We 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

$$\chi^2_{pl} = \frac{(c_{plr}c_{\sim pld} - c_{pld}c_{\sim plr})^2}{(c_{plr} + c_{pld})(c_{plr} + c_{\sim plr})(c_{pld} + c_{\sim pld})(c_{\sim plr} + c_{\sim pld})} \tag{8}$$

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.

3.2.1 Accounting for Topics

Table 2 lists the 40 most slanted bigrams and trigrams ranked by χ^2 values. A quick glance at this table leaves the impression that the top ideological phrases are reflective of ideological sorting into research subfields. For example, stemmed variants of right-leaning terms like 'business cycle', 'money supply', and 'federal reserve' are typically associated with macroeconomics or finance and left-leaning terms 'health insurance', 'birth weight', and 'medical care' are related to health care. While sorting is an interesting phenomenon to document in and of itself, we also wish to investigate whether individual

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

ideology is associated with research results. We attempt to account for field-level sorting by estimating ideology within research area. We map papers to 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 also calculate individual ideology scores without adjusting for topics. Since we do not observe topics for all of the papers in our corpus, we use prediction methods from machine learning to create topic classifications for papers.

Our first method for estimating topics takes advantage of JEL classification codes maintained by the *Journal of Economic Literature*. These codes are hierarchical markers 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*.[12] The per-topic model performances are listed Appendix A.3. We predict codes for the 1st and 2nd levels and refer to these topic mappings as *JEL1* and *JEL2*.

In our second method, we use a variant of the well-known LDA topic model, that provides an unsupervised classification of documents into latent factors, so that each document is given a probability of being in each of a number of latent "topics". One consequence of the Dirichlet prior used in LDA is that topic proportions are assumed independent, which is unlikely to hold in our context. To overcome this, we use a related algorithm, the correlated topic model (CTM) (Lafferty and Blei, 2006) which allows for the presence of one topic to be predictive of the presence of another, thus capturing more realistic latent topic distributions. Mappings were created with 30, 50, and 100 topics (*CTM30*, *CTM50*, and *CTM100*). We use the topic distributions estimated by CTM to assign articles to topics. If there is at least a 10% probability that an article is about a topic, then we assign that article to that topic.

For each topic, it is possible to rank the words or phrases most relevant to that topic. These rankings

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

can be used to qualitatively assess a real-world analogue to the algorithm-generated topics. We can similarly rank phrases within JEL topics by estimating the conditional probability that a word appears in a JEL topic. To compare CTM and JEL topics, Tables A.6 to A.11 display the education topics for each mapping, note that some mappings have more than one topic which refers to education. The left-most column in each table shows the top twenty words associated with that topic while the next two columns show the top left-leaning and right-leaning bigrams for papers in that topic, respectively.

4 Predicting Ideology From Phrases

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

1) A set of economists with known groundtruth ideology derived from campaign contributions and petition signatures

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, CTM30, CTM50, CTM100*, and *NoTopic*.

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

Our topic-adjusted algorithm for ideology prediction works as follows: We first create two sets of individuals, e_{gt} and e_{ngt}, the set of groundtruth and non-groundtruth authors, respectively. We split e_{gt} into five equally sized subsets (folds). We iteratively hold out one fold and build models with the other four folds (training set). This procedure produces out of sample predictions for each person in e_{gt} which will allow us to estimate model performance. The procedure also produces five separate predictions for each person in e_{ngt} which we combine by taking the mean.

For a given a topic mapping, we iterate through each topic t, and, for each topic, select the papers written by e_{gt}. We identify phrases associated with ideology by altering the χ^2 computation from equation 8 and perform it at the topic level. For a given topic, we compute χ^2_{plt} by only considering the set of phrases that appear in papers in t. Certain phrases might pass our ideological filter either by chance or because of author idiosyncrasies in our groundtruth dataset. These scenarios have the effect of both increasing the number phrases that are used for the prediction model and also increasing the noise to signal ratio. To capture phrases that are consistently correlated with our measure of ideology, we additionally partition the training data into five folds. We hold out one fold at a time and apply the χ^2 filter to identify significantly slanted phrases. We take the intersection across the five sets of significant phrases as input into ideology prediction model.

With the filtered phrases in hand, we construct the count matrix $\mathbf{C}_t$ 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. To predict ideology, we then use decision trees, a non-parametric machine learning algorithm which recursively partitions the input space into subspaces that seek to maximize the homogeneity of the outcome variable in each subspace. Partitioning is executed at each step by finding the variable that locally maximizes the increase in homogeneity, as measured by the Gini Index.[13] The advantage of decision trees is that they can model interactions without pre-specification by the analyst and require little data preprocessing.

A short-coming of decision trees is that they can over-fit data, i.e. find signal where there is actually noise. To overcome this, we apply random forest (Breiman, 2001), a model averaging algorithm which combines the output of many decision trees via the application of two 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 same-sized dataset. In our case, we sample with replacement from the rows of $\mathbf{C}_t$. With attribute bagging, a random subset of phrases are drawn from the columns of $\mathbf{C}_t$ at each node within each tree.[14] Each decision tree within a random forest model can be viewed as a vote on whether an author is left- or right-leaning.

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 percentage of right-leaning votes received across topics. 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

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

[14]We sample twice the square root of the number of columns in $\mathbf{C}_t$

$[-1, 1]$ 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 phrases that are good predictors are intuitively plausible. In Appendix Table A.12 we show the phrases that are most predictive without any topic adjustment. The top left-wing predicting bigrams are health insurance, child care, and minimum wages, while the top right-wing bigrams are public choice, business cycle, and gold standard. These are intuitively the patterns of sorting into field by ideology that we would expect. But even within-topic ideological phrases are intuitive. For example, Table A.13 shows phrases within Topic 19 of the CTM-30 topic-adjusted prediction, which clearly corresponds to labor economics. Within that topic, left-wing phrases are oriented towards interventionist policies such as head start (i.e. the federal program for children), affirmative action, and the minimum wage, while right-wing phrases are associated with ability, such as human capital, cognitive skill, and the work of James Heckman. This basic pattern shows up in all the topics that look like labor economics, regardless of which specific topic adjustment is used, as can be seen in tables A.14-A.18.

4.1 Validation

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

Table 3 shows the relative performance for our various topic mappings. The top panel shows results for the full model while the bottom panel shows results from estimating ideology using only the first 50% of papers written by authors.[15] While the *NoTopic* models provides the best performance, most other models perform similarly well. The maximum correlation between predicted and ground truth ideology is 0.474. 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.

[15] If an author only wrote one paper we count it as part of the first 50% of papers.

For further insight into how well our model generalizes, we use data from Gordon and Dahl (2013) to compare our predicted and groundtruth ideologies to responses provided by economists for a survey conducted by the Chicago Booth School of Business through October 30, 2012. The panel sets out to capture a diverse set of views from economists at top 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.[16]. 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 groundtruth ideology of 20 members on the panel and the correlation between groundtruth ideologies and survey responses is also significant. Figure 2 shows binned scatterplots from a linear probability specification, conditional on question fixed effects, for each of our 4 ideology measures. There is a clear correlation between the conservativeness of the predicted ideology scores and the IGM measure of conservativeness.

In order to examine this more formally, Table 5 further presents results from logit and ordered logit regressions of the following form:

$$Pr(response_{i,j} = C) = \Lambda(\beta_1 \widehat{\theta}_i + \delta_j) \tag{9}$$

where Λ is the logistic link function. In the logistic version (columns 1-3), $response_{i,j}$ is a binary variable indicating whether the panelist agreed with the conservative viewpoint or not.[17] In the ordered logistic version (columns 4-6) the response variable is coded with the following order: Strongly Disagree, Disagree, Uncertain, Agree, Strongly Agree.[18] As seen in Table 5, the coefficients between the

[16]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.

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

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

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 groundtruth 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 5 show a significant positive relationship between our ideology variables and the probability of being in an increasingly conservative category. Columns 3 and 6 add the same controls as Gordon and Dahl (2013), which are the years of the awarding of a Ph.D. and the indicator variables for Ph.D. institution, NBER membership, gender, and experience in federal government. 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.[19]

4.2 Sorting by Professional Characteristics

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 across fields of economics as well as school and career characteristics. We collect data from CVs of economists at top 25 departments and top 10 business schools in Spring 2011. We collect year and department of Ph.D. and all subsequent employers, nationality and birthplace where available, and use self-reported field of specialization. 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), international economics, and macroeconomics as determinants of political behavior, as these are among the most policy relevant fields in economics, but we also examine a number of other fields. We classify each department as saltwater or freshwater or neither following Önder and Terviö (2015). An economist is saltwater or freshwater if either went to grad school, had their first job, or had their current job at a saltwater 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

[19] 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. We discuss our performance relative to other political scaling methods more completely in our companion paper Jelveh et al. (2014).

individuals vary independently of topic-adjusted paper ideologies. Secondly, we are interested in institutional affiliations. We construct a variable for being at a business school, a Top 5 department, 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 then look at the correlation between author ideology and various CV characteristics. The estimating equation is:

$$\widehat{\theta_i} = \sum \delta_{Field} Field_i + \gamma X_i + \delta_{DoctoralInstitution \times Year} + \epsilon_i \tag{10}$$

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

Figure 3 summarizes the results from the baseline specification for all measures of predicted ideology used. We see that the fields of finance, macroeconomics and international trade are more conservative, while labor is considerably more liberal than the average. Other fields, such as history and law and economics, show less political valence. We further see that faculty at business schools are more conservative, as are professors affiliated with “freshwater" schools, while “saltwater" schools have a left-wing bent. Professors of European origin also seem to be somewhat more conservative, and there seems to be no effect of Latin American origin, full professor rank or Top 5 department ranking:

Note that these regressions are estimated from topic-adjusted ideologies, so it is not simply selection into area of research. While the significance of field even using topic-adjusted ideology predictions 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.

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 consequently 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 influence) economists with more conservative predicted ideology is interesting in light of the patterns documented in Fourcade et al. (2014), who show that there has been a pronounced increase in economists with business school affiliations as well as in the importance of financial economics as a subfield within economics over the past few decades. These two trends, together with the political preferences documented here, may have contributed to the perception that economics is a “conservative" field. We also test the saltwater-freshwater divide. One natural hypothesis is that saltwater economists are more left wing than freshwater economists, which appears to be borne out in our data.

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 prediction algorithm.

We also find that predicted ideology is persistent within individuals. As documented more fully in Table A.4, we split authors' writings chronologically by their first and second 50% of publications. We then predict ideology separately for each set of publications, and find that the correlation between early predicted ideology and late predicted ideology is quite high. We use this below to isolate “early career" ideology.

5 Ideology And Policy Elasticities

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

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

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

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. Overviews and important examples of this methodology are found in (Chetty, 2009), (Weyl and Fabinger, 2013), and (Costinot and Rodríguez-Clare, 2014). A variety of models incorporate similar fundamental economic intuition, which can then be encoded and quantified in relatively 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 whether 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 that yield elasticities consistent with political beliefs. Of course, there is a possibility of reverse causation, whereby economists who discover elasticities that suggest that market interference is highly costly are moved to contribute to the Republican party or become conservative on other issues as well. It is very difficult to causally identify any effect of political ideology on empirical estimates, as any exogenous shock to political ideology could also influence the decision to be an economist, as well as the selection into what field of economics to work in. Therefore, we limit ourselves to a descriptive analysis. In a robustness exercise below, we mitigate endogeneity concerns by using only ideology estimated from the first 50% of an author’s writing.

We select elasticities drawing on Fuchs et al. (1998) (henceforth FKP). FKP survey labor and public finance economists about their views on policy and parameters. FKP estimate the correlation between policy preferences and beliefs about parameter values. FKP provide a mapping from policy preferences to economic parameters from the fields of labor and public economics that indicates a policy implication by partisan direction. For example, estimates of the empirical effect of unions on productivity might influence preferences towards increased unionization. Similarly, the female labor supply elasticity may influence the desirability of increasing Aid to Families with Dependent Children. The mapping between estimates and policies, as well as the 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 “not-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 each estimates' authors with our predicted slant measures. The list of meta-analyses is also in Table 7. In addition, we obtained a number of other meta-analyses from the meta-analysis archive maintained at Deakin University by Chris Doucougliasis, enabling a placebo exercise, where we check the correlation between author ideology and non-policy relevant parameters.[20] We expect the correlation between predicted ideology of the authors and policy-irrelevant parameters to be insignificant.

Meta-analyses necessarily rely on the judgments of the authors about what to include and what to exclude.[21] 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 show robustness to unweighted estimates below. We adjust

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

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

the sign of each category of estimate so that higher is more conservative, following FKP, and present this in Table 7.

Meta-analyses may have distributions of estimates that are skewed or truncated (as shown in Andrews and Kasy (2017)) and so our primary measure is the rank of the coefficient within the category (multiplied by 100). (Category refers to the policy-relevant literature, e.g. the effect of changing the minimum wage on employment.) We also look at the raw coefficient (with sign aligned with ideology as above), as well as a binary indicator for a coefficient being greater than the median in its category. Finally, in order to give quantitative interpretations to our point estimates, we 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. Let β_{js} denote the elasticity measure (rank, greater than median, or standardized) from paper j in survey paper s. Our baseline regression equation is given by:

$$\beta_{sj} = \gamma\overline{\theta_j} + \delta_s + \epsilon_{sj} \tag{11}$$

where $\overline{\theta_j} = \frac{1}{|N_j|}\sum_{e\in N_j}\theta_e$ is the mean of the authors N_j of paper j ideology predictions from our methodology above. δ_s is a meta-analysis fixed effect, which will be included in all specifications, and ϵ_{sj} is an error term. We illustrate the basic variation using binned scatter plots in Figure 4, which shows that there is a strong correlation between our ideology measures and the coefficient rank, adjusting for meta-analysis fixed effects. This is true across our different topic adjustments, and in fact there is a positive correlation between groundtruth ideology and coefficient estimates.

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

Table 8 shows estimates of γ from equation (11). Panel A shows results for no topic adjustment, Panel B for CTM100 adjustment, and Panel C for JEL1 adjustment. Column 1 shows results with coefficient values as outcome variables, with signs adjusted as described above. Column 2 shows results with the coefficient rank as the outcome variable, while column 3 shows γ when the outcome is the binary indicator variable for a high coefficient. Column 4 shows the standardized coefficient as the outcome (demeaned and divided by standard error within the literature). All estimates are positive and significant. A 1 standard deviation increase in average author conservative ideology results in an increased raw elasticity between .18 and .28, a 14-33 point increase in rank (out of 100), a 24-50 percent increase in the probability that the coefficient is greater than the median in its category, and between .4 and .9 standard deviations within the category.

One way to make sense of these magnitudes is to consider the labor supply elasticity as a particular example. Building on Saez (2001), Diamond and Saez (2011) suggest top tax rates of $\tau^* = \frac{1}{1+1.5\times\epsilon}$, where ϵ is the taxable income elasticity of top income earners. The mean of the Chetty et al. survey on the labor supply elasticity is 0.31, suggesting a top tax rate of 68%. However, the mean ideology among people who estimate taxable income elasticities in this sample is more left than average (e.g. -.22 in JEL1 adjusted ideology), but researchers in this area exhibit a considerable range of ideology, from -0.66 to 0.55. Using our estimates from column 1 row 2 of table 8, moving from the most left wing to the most right wing within this sample would change the elasticity by .35 points, changing the optimal top tax rate from 84% to 58%. Extrapolating to the most liberal ideology of -1 to the most conservative ideology of 1, we end up with optimal tax rates from 96% to 52%. While 52% is still a high tax rate (resulting from the small elasticities uniformly found in the literature, even by conservatives), this result shows that same standard optimal taxation formula may yield quite different prescriptions depending on the ideology of the researcher producing the elasticity.

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

An inevitable feature of our analysis is that there are many decisions about variables and specifications made along the way. Rather than showing a select set of specifications for robustness, Simonsohn et al. (2015) suggests a simple way to check for specification error is to generate estimates for all plausible specifications and to conduct inference on the set of specifications jointly.[22]

Our set of plausible specifications are shown in Table 9 for the coefficient rank and the correlated topic model adjusted ideology prediction. Column 1 in these tables includes fixed effects for category interacted with 5-year bin indicators for publication date, in order to capture observed heterogeneity in methods, data, or simple improvements in estimates over time. Column 2 uses a measure that ignores the standard errors attached to estimates, and instead uses the simple unweighted average of estimates within a paper. Column 3 adds an indicator variable for whether the estimate was obtained on US data. While US estimates seem to be in a more conservative direction, the effect of predicted author ideology remains statistically significant with all three measures (albeit sometimes at only 10% significant).

In column 4 we restrict attention to predictions made using the first 50% of the words written by authors, to minimize reverse causality running from empirical results to predicted ideology. These predictions are necessarily going to have more error, as they use less of the available text for each economist. Indeed, 5 papers (out of 197) in our sample are lost as none of the authors have enough text in the first 50% of their writings to estimate ideology. Nonetheless, the results remain positive and statistically significant, despite the attenuation we would expect from the additional prediction error.

In column 5, we adapt split-sample instrumental variables to deal with possible prediction error in our main estimates. While this instrumental variables strategy does not handle endogeneity, it can address prediction error that is important to the generated nature of our independent regressor. Because our independent variable is a prediction of ideology, it has an error, akin to measurement error that attenuates the true regression slope towards zero. We split each author's writings into 2 random samples, and predict ideology in both. Under the assumption that prediction error is orthogonal to the true

[22]See Steegen et al. (2016) for a similar methodology for exploring the stability of results as a function of the space of reasonable data processing choices and modeling specifications.

ideology, then using the ideology in one sample to instrument for the ideology in the other sample will eliminate the resulting attenuation bias. Formally, if the true second stage equation is 11, but we have prediction error in the main independent variable, we will have:

$$\overline{\theta_j} = \overline{\theta_j^{True}} + \eta_{sj}$$

where η_{sj} is the mean prediction error, $\eta_{sj} = \frac{1}{|N_j|}\sum_{a \in N_j} e_a$, akin to measurement error. And even if η_{sj} is uncorrelated with either the true value of the independent variable or any omitted variable, the estimated coefficient $\widehat{\gamma}$ will be attenuated by the well-known factor $\frac{var(\overline{\theta^{True}})}{var(\overline{\theta^{True}})+var(\eta)} < 1$.[23] Thus our coefficients will be too small, relative to the true value.

Our IV strategy mitigates this problem. We split the words used by each author into 2 samples, and estimate two separate, independent predictions of ideology, $\overline{\theta_j^0}$ and $\overline{\theta_j^1}$. Unsurprisingly, both of these measures are highly correlated with each other. To show that the IV eliminates the influence of prediction error, we write the relationship between the predictions from the subsamples and the true value as:

$$\overline{\theta_j^g} = \overline{\theta_j^{True}} + \eta_{sj}^g, g = 0, 1$$

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

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

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

since ϵ is independent of η^1 and η^0 (which are also independent of each other). We can see the gain from the IV strategy by focusing just on the results for the CTM 100 adjusted models in Table 9. As we hoped to achieve by the IVs, the first-stage F-statistic is unsurprisingly extremely strong, and the coefficients are generally 20% larger than the OLS estimates, with slightly larger standard errors.

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

Finally, in column 6 we conduct an identical exercise using "non-policy-relevant" elasticities, described above. These elasticities are beta convergence in cross-country growth regressions, the value of alternative fuels, the effect of institutions on growth, the value of recreational area, and the labor demand elasticity. We again calculate rank within each category of elasticity and estimate the correlation with mean author ideology. We find no significant correlation between predicted ideology and these elasticities, and the point estimates are an order of magnitude smaller than the same specification estimated on the "policy-relevant" elasticities.

Rather than show tables for every specification and every variant of our dependent and independent variables, we show the specification curve Simonsohn et al. (2015), a procedure to explore the sensitivity of results to modeling choices, in Figure 5. The plot shows the coefficient on γ from all 432 specifications generated by the above 5 specifications, excluding the placebo and including the main specification from Table 9. For each of 6 specifications, we estimate it using 6 different measures of ideology, 4 different outcomes (coefficient, binary, rank, and standardized coefficient) as well as 2 weighting schemes (coefficients within a paper averaged with inverse of standard error where available or not). The 6 specifications include 3 sets of covariates (controlling for category X 5-year fixed effects, an indicator for US estimate, and no covariates except meta-analysis fixed-effects), and 3 additional specifications with fixed effects only (OLS, split-sample IV, and early measure only).

For performing inference, we shuffle the independent variable randomly across observations 100 times to create 100 different datasets. For each data set, we estimate each of the 432 specifications. This procedure gives us the distribution of specification curves under the null hypothesis. We test across all specifications jointly by counting the fraction of the 100 samples for which the estimated coefficient is greater than the median from the truth, the fraction that have more specifications with positive coefficients, and the fraction with more positive and significant coefficients. Across all of these statistics, less than 1% of randomized samples exhibit more evidence than our chosen specifications. While there are some specifications that do not exceed the 95% percentile across the shuffled datasets, these are relatively rare across all the 432 specifications.

Finally, as another check on the general validity of our estimates, in Figure 6 we show results from dropping each category of elasticities one at a time, in order to confirm that no one set of elasticities is driving our result. Across our different ideology measures, the correlation between mean author ideology and average reported elasticity generally remains significant (or nearly so) at 5%, regardless of which category is dropped.

6 Conclusion

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

Our work has two implications. The first is that empirical work, particularly without broad theoretical motivation and credible designs, cannot be assumed to resolve questions of scientific truth if results are politically contestable and economists differ too in their politics. The second implication is that researching the production of economics belongs to economics proper. Academic economics research is a valuable activity that shares the same information and incentive problems seen in other labor markets. It may seem distasteful as hanging the family laundry in the courtyard, but to the contrary, given the importance of science and research to the modern economy, it is natural to consider the forces driving economic research and its contribution to policy and to the economy. As in the literature on self-censorship and political correctness (Loury (1994), Morris (2001)), academic writing does not just reveal the results of research, but also implicit loyalties and beliefs. As academic economic articles have potentially multiple audiences, from specialists to general interest economists to policy makers and journalists, modeling the resulting trade-offs in choosing what to say and how to explain ideas, methods, and results could be a fruitful area of research.

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

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7 Tables

Table 1: Petition signing and contribution patterns for 441 members of the American Economic Association.

	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

This table shows our “groundtruth" sample of economists, comprised of the AEA members with publications we linked to campaign contributions and petition signings.

Table 2: Top Phrases for NoTopic Mapping

Left-leaning Bigrams	Right-leaning Bigrams	Left-leaning Trigrams	Right-leaning Trigrams
health_insur	public_choic	paper_econom_activ	monetari_polici_shock
child_care	busi_cycl	brook_paper_econom	feder_reserv_bank
minimum_wage	gold_standard	public_polici_analys	journal_monetari_econom
health_care	polici_shock	polici_analys_politiqu	real_busi_cycl
medic_care	technolog_shock	post_keynesian_econom	journal_polit_economi
labor_market	feder_reserv	analys_politiqu_vol	impuls_respons_function
mental_health	monetari_polici	industri_labor_relat	busi_cycl_model
heart_attack	money_growth	journal_post_keynesian	classic_gold_standard
post_keynesian	reserv_bank	labor_relat_review	michael_d_bordo
brook_paper	trade_agreement	low_birth_weight	journal_law_econom
food_stamp	median_voter	georg_l_perri	nation_bank_note
paper_econom	time_seri	child_care_subsidi	reserv_bank_minneapoli
nois_trader	bank_failur	sourc_author_calcul	money_credit_bank
head_start	growth_rate	human_resourc_manag	risk_free_rate
birth_weight	human_capit	food_stamp_program	money_growth_rate
employe_ownership	bretton_wood	retire_health_insur	small_open_economi
job_loss	monetari_econom	longterm_care_insur	journal_financi_econom
manag_care	hous_price	incom_tax_credit	journal_money_credit
labor_forc	impuls_respons	earn_incom_tax	michael_r_darbi
singl_mother	polit_economi	labor_forc_particip	anna_j_schwartz
nurs_home	journal_monetari	high_perform_work	bordo_michael_d
insur_coverag	standard_deviat	william_c_brainard	georg_mason_univers
labour_market	forward_premium	journal_econom_issu	american_journal_econom
analys_politiqu	unit_root	journal_human_resourc	journal_econom_sociolog
human_resourc	money_suppli	dual_labor_market	forecast_error_varianc
prenat_care	journal_polit	lawrenc_f_katz	jame_j_heckman
polici_analys	price_level	health_care_system	gold_exchang_standard
labor_relat	return_volatil	jeffrey_d_sach	intermedi_good_produc
politiqu_vol	foreign_countri	heart_attack_patient	review_financi_studi
collect_bargain	gold_reserv	health_care_cost	fanni_mae_freddi
welfar_reform	steadi_state	employerprovid_health_insur	shock_monetari_polici
keynesian_econom	monetari_author	food_stamp_benefit	mae_freddi_mac
east_asian	benchmark_model	mental_health_care	journal_urban_econom
journal_post	new_deal	new_york_state	academ_publish_print
unemploy_rate	tax_rate	health_care_financ	feder_reserv_system
industri_labor	money_credit	editor_scandinavian_journal	r_glenn_hubbard
thi_paper	famili_tie	martin_neil_baili	market_valu_equiti
latin_america	loss_ratio	relat_review_vol	reserv_bank_st
privat_sector	real_busi	rand_journal_econom	bank_st_loui
natur_rate	nation_bank	journal_econom_perspect	balanc_budget_rule

This table presents the 40 bigrams and trigrams most associated with left-leaning and right-leaning ideology as measured by χ^2 values. To determine directionality for a particular phrase p of length l in vocabulary V, we computed separately for each ideology $\frac{c_{p,l}}{\sum_{q \in V} c_{q,l}}$. If this value was higher for left-leaning (right-leaning) authors, then we defined that phrase to be left-leaning (right-leaning).

Table 3: Predictive Performance of Topic-Adjusted Models

Panel A: Full Groundtruth Dataset

(1) Model	(2) Topics	(3) Correlation	(4) AUC	(5) 95% C.I.	(6) Mean Phrases
JEL1	19	0.461	0.773	(0.754, 0.792)	5,144
JEL2	93	0.405	0.742	(0.722, 0.762)	1,526
CTM30	28	0.455	0.770	(0.751, 0.789)	3,655
CTM50	47	0.438	0.761	(0.741, 0.78)	2,077
CTM100	90	0.413	0.749	(0.729, 0.769)	970
No Topic	1	0.474	0.776	(0.757, 0.795)	24,895

Panel B: First 50% of Papers Dataset

(1) Model	(2) Topics	(3) Correlation	(4) AUC	(5) 95% C.I.	(6) Mean Phrases
JEL1	18	0.410	0.741	(0.72, 0.761)	2,316
JEL2	78	0.358	0.710	(0.689, 0.732)	682
CTM30	28	0.400	0.734	(0.713, 0.754)	1,621
CTM50	46	0.387	0.728	(0.707, 0.749)	930
CTM100	84	0.358	0.710	(0.688, 0.731)	421
No Topic	1	0.440	0.753	(0.733, 0.773)	13,035

This table presents the predictive performance of various topic mappings. Listed are (1) the model name (2) the number of topics in the mapping used for prediction (3) the correlation between ground-truth and predicted out-of-sample ideologies (4) the Area Under the Curve (5) the bootstrapped confidence interval for (4), and (6) the average number of phrases per topic that pass the χ^2 filter.

Table 5: Correlation Between Author Ideology and IGM Responses

	(1)	(2)	(3)	(4)	(5)	(6)
Ideology (No Topic)	0.535***	1.240***	1.021***	0.437***	0.590***	0.699***
	(0.154)	(0.415)	(0.387)	(0.137)	(0.201)	(0.145)
Ideology (JEL 1)	0.903***	2.349***	1.619***	0.761***	1.091***	1.084***
	(0.255)	(0.727)	(0.603)	(0.215)	(0.327)	(0.269)
Ideology (CTM 100)	1.216***	3.269***	2.657***	0.988***	1.547***	1.710***
	(0.406)	(1.153)	(0.957)	(0.359)	(0.564)	(0.378)
Groundtruth Ideology	0.274***	0.843***	10.17***	0.266***	0.393***	2.187***
	(0.0681)	(0.220)	(3.100)	(0.0640)	(0.0819)	(0.417)
Question FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Log-Likelihood (No Topic)	-383.2	-138.1	-126.4	-1077.8	-763.2	-744.1
Log-Likelihood (JEL 1)	-383.5	-137.4	-126.4	-1077.9	-762.6	-744.3
Log-Likelihood (CTM 100)	-384.1	-138.1	-126.1	-1078.6	-762.9	-743.8
Log-Likelihood (Groundtruth)	-214.2	-67.63	-57.92	-588.1	-405.8	-395.3
Observations	598	438	438	715	715	715
Individuals	39	39	39	39	39	39
Observations (Groundtruth)	334	199	199	394	394	394
Individuals (Groundtruth)	20	20	20	20	20	20

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

Table 7: Fuchs et al. (1998) Elasticities, Meta-Analyses, and Political Orientations

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

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

Table 6: Correlation Between Author Ideology (CTM100) and CV Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Econ	0.137***	0.116***			0.110***	0.117***	0.115***	0.0879
	(0.0291)	(0.0297)			(0.0288)	(0.0284)	(0.0291)	(0.0645)
Macroeconomics	0.124***	0.108***			0.119***	0.109***	0.121***	0.106**
	(0.0199)	(0.0206)			(0.0203)	(0.0200)	(0.0203)	(0.0502)
Int'l Trade	0.0899***	0.0929***			0.0863***	0.0916***	0.0866***	0.0310
	(0.0249)	(0.0266)			(0.0247)	(0.0248)	(0.0245)	(0.0632)
Labor Econ	-0.0892***	-0.108***			-0.0864***	-0.0962***	-0.0848***	-0.0898
	(0.0204)	(0.0209)			(0.0202)	(0.0201)	(0.0203)	(0.0610)
Public Econ	0.0272	0.0327			0.0225	0.0262	0.0254	0.0711
	(0.0248)	(0.0251)			(0.0245)	(0.0248)	(0.0244)	(0.0558)
Development	-0.0380	-0.0370			-0.0357	-0.0353	-0.0353	-0.0779
	(0.0252)	(0.0245)			(0.0245)	(0.0250)	(0.0245)	(0.0620)
Econometrics	0.0115	0.0111			0.00960	0.00307	0.00850	0.0186
	(0.0268)	(0.0268)			(0.0264)	(0.0261)	(0.0263)	(0.0643)
Micro Theory	-0.0419*	-0.0504**			-0.0452*	-0.0472*	-0.0465*	-0.0815
	(0.0250)	(0.0243)			(0.0250)	(0.0242)	(0.0249)	(0.0654)
Business School			0.0990***	0.0401	0.0666***	0.0477*	0.0673***	0.0926*
			(0.0272)	(0.0290)	(0.0214)	(0.0252)	(0.0216)	(0.0517)
Saltwater Ever			-0.0213	-0.0368	-0.0246	-0.0383	-0.0223	-0.0154
			(0.0451)	(0.0408)	(0.0331)	(0.0362)	(0.0330)	(0.130)
Freshwater Ever			0.110***	0.0939**	0.0780***	0.0758**	0.0778***	0.0392
			(0.0384)	(0.0393)	(0.0300)	(0.0352)	(0.0297)	(0.0715)
Latin Am Origin			0.113*	0.0401	0.0434	0.0327	0.0413	0.131
			(0.0578)	(0.0716)	(0.0680)	(0.0628)	(0.0677)	(0.107)
European Origin			0.0926***	0.0704***	0.0662***	0.0532**	0.0670***	0.0592
			(0.0285)	(0.0271)	(0.0246)	(0.0245)	(0.0245)	(0.0858)
Full Professor			-0.0307	0.000288	-0.000215	-0.0102	-0.000688	-0.0268
			(0.0226)	(0.0219)	(0.0169)	(0.0201)	(0.0169)	(0.0452)
Top 5 Econ Depts			-0.00721	0.0269	-0.0243	0.00326	-0.0239	-0.0719
			(0.0573)	(0.0513)	(0.0194)	(0.0496)	(0.0194)	(0.0435)
Groundtruth Ideo								0.0522**
								(0.0233)
Dept FE	No	Yes	No	No	No	No	No	No
Univ FE	No	No	Yes	Yes	No	Yes	No	No
Field FE	No	No	No	Yes	No	No	No	No
PhD Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	894	894	894	894	894	894	894	262

Robust standard errors in parenthesis. Fields refer to self-reported fields on CVs. Latin Am and European Origin denote undergraduate degree completed in Latin America/Europe respectively. Business School and Top 5 Econ Department indicates current employment at a business school or Top 5 Economics Department. Saltwater and Freshwater are constructed from Tervio and indicate whether the economist was ever employed at a “Freshwater" or “Saltwater" school.

Table 8: Correlation Between Ideology and Policy-Relevant Elasticity Coefficient Rank

Panel A: Ideology (No Topic)

	(1) Coef. Value	(2) Coef. Rank	(3) High Coef. Indicator	(4) Std. Coef.
Mean Pred. Ideology (notopic)	0.180*	0.186**	0.380**	0.460*
	(0.092)	(0.091)	(0.175)	(0.271)
Meta-Analysis FE	Yes	Yes	Yes	Yes
R-squared	0.84	0.04	0.06	0.02
Observations	198	198	198	198
Panel B: Ideology (CTM100)				
Mean Pred. Ideology (CTM100)	0.287***	0.333***	0.499**	0.916***
	(0.107)	(0.106)	(0.216)	(0.326)
Meta-Analysis FE	Yes	Yes	Yes	Yes
R-squared	0.84	0.06	0.07	0.04
Observations	197	197	197	197
Panel C: Ideology (JEL1)				
Mean Pred. Ideology (jel1)	0.291***	0.240**	0.431**	0.681**
	(0.107)	(0.112)	(0.215)	(0.336)
Meta-Analysis FE	Yes	Yes	Yes	Yes
R-squared	0.84	0.04	0.06	0.03
Observations	198	198	198	198
Panel D: Ideology (Groundtruth)				
Mean Pred. Ideology (groundtruth)	0.102	0.141*	0.244***	0.316
	(0.120)	(0.076)	(0.086)	(0.274)
Meta-Analysis FE	Yes	Yes	Yes	Yes
R-squared	0.88	0.50	0.41	0.28
Observations	30	30	30	30

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

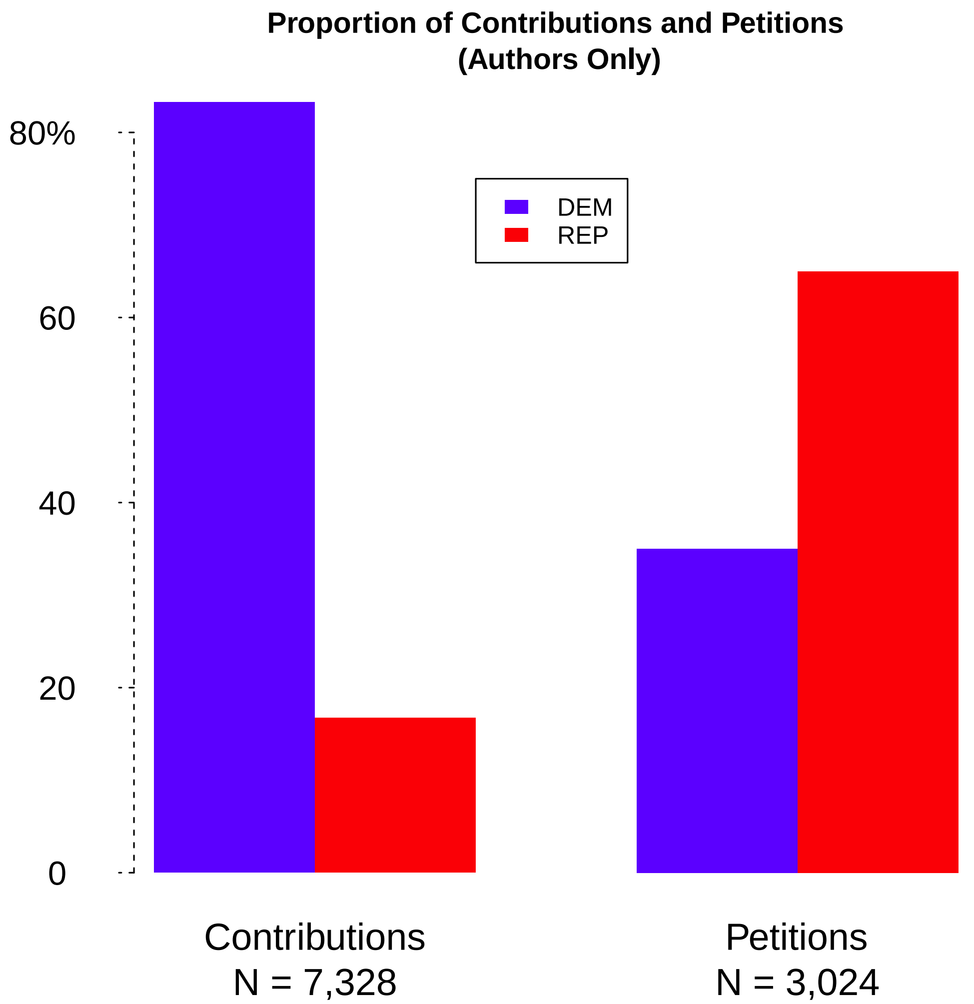
Table 9: Correlation Between Author Ideology and Policy-Relevant Elasticity Coefficient Rank-Robustness (CTM 100)

	(1)	(2)	(3)	(4)	(5)	(6)
	Cat. X 5-Year FE	Unweighted	US control	Early Pred.	IV	Placebo
Mean Pred. Ideology (CTM100)	0.321***	0.301***	0.307***			-0.020
	(0.112)	(0.109)	(0.109)			(0.120)
US Estimate			0.088			
			(0.055)			
Mean Early Pred. Ideology (CTM100)				0.219**		
				(0.092)		
Mean Pred. Ideology (CTM100) Sample 2-IV					0.407***	
					(0.119)	
Meta-Analysis FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.18	0.05	0.08	0.04	0.05	0.00
Observations	197	197	177	192	197	227
Ideology Range	0.96	0.96	0.90	0.96	0.96	1.27
F-stat					960.90	

This table presents the robustness specifications for one outcome (rank) and one topic adjustment (CTM 100). Robust standard errors, clustered by author combination. Outcome variable is coefficient rank within category. Ideology is calculated as the mean ideology of the authors. Column 1 includes Category of estimate X 5-year period fixed effects. Column 2 uses the raw average of estimates reported in a paper, not weighting by the precision of the estimates. Column 3 controls separately for estimates on US data. Column 4 uses ideology estimated from the first 50% of an author's written text (measuring "Early Ideology"). Column 5 presents an IV estimate using a random split of the words for each author to calculate 2 measures of predicted ideology and uses the first to instrument for the second. Column 6 presents a placebo estimate using non-policy relevant elasticities from Deakin University, as described in the text.

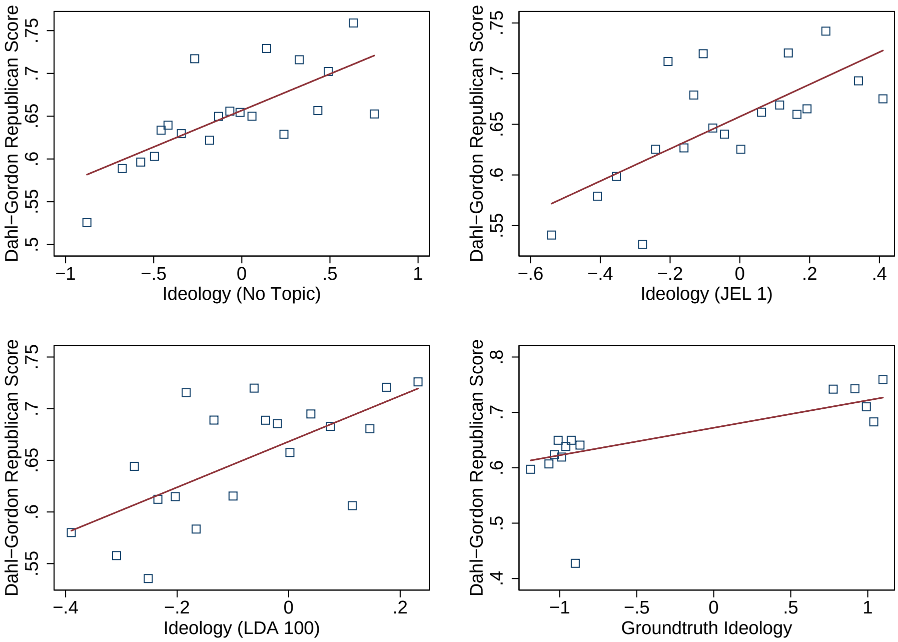
8 Figures

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.

Figure 2: Partial Binned Scatterplots of IGM Responses on Ideology Measures.



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

Figure 3: Regression Coefficients On Economist Characteristics

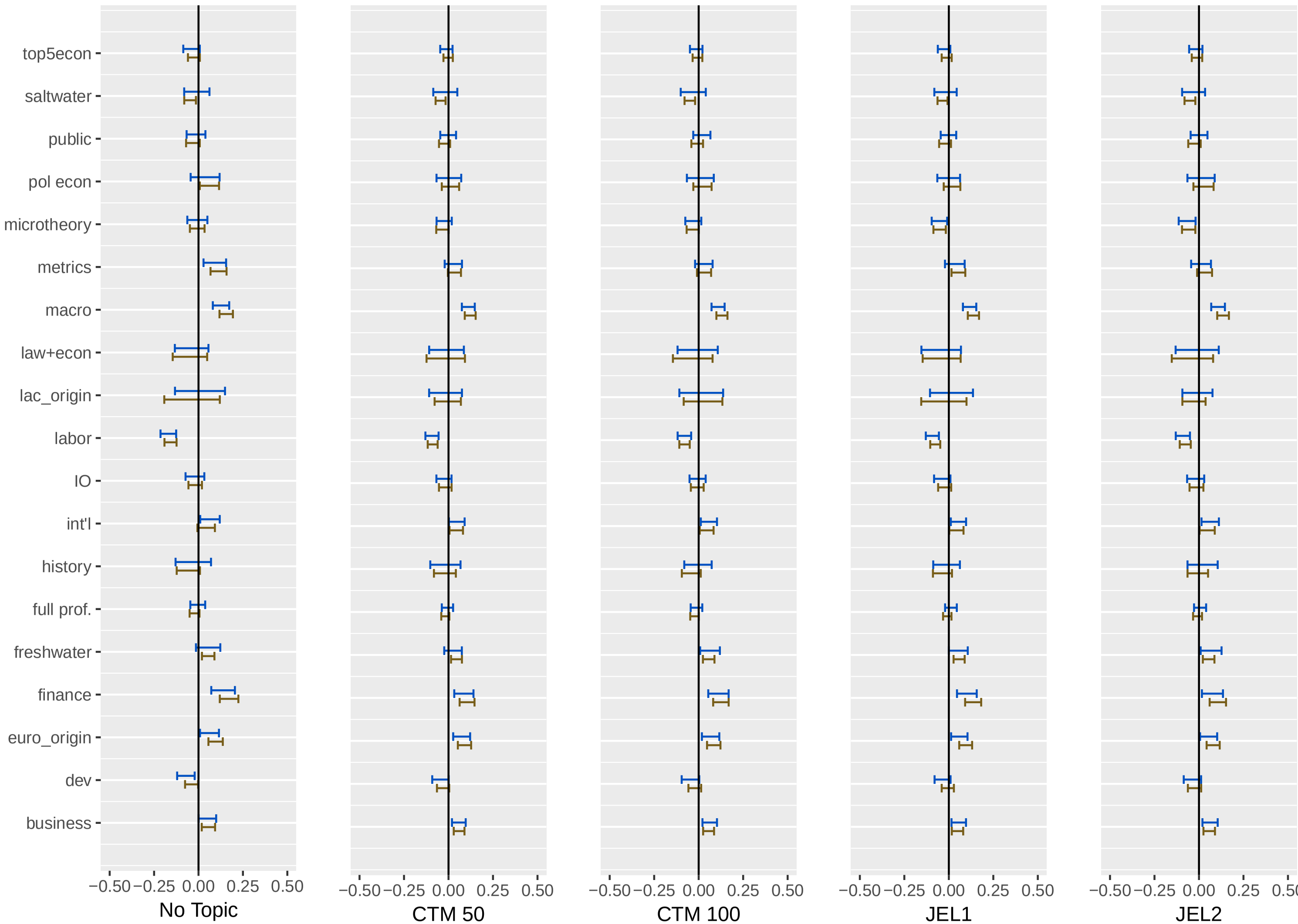
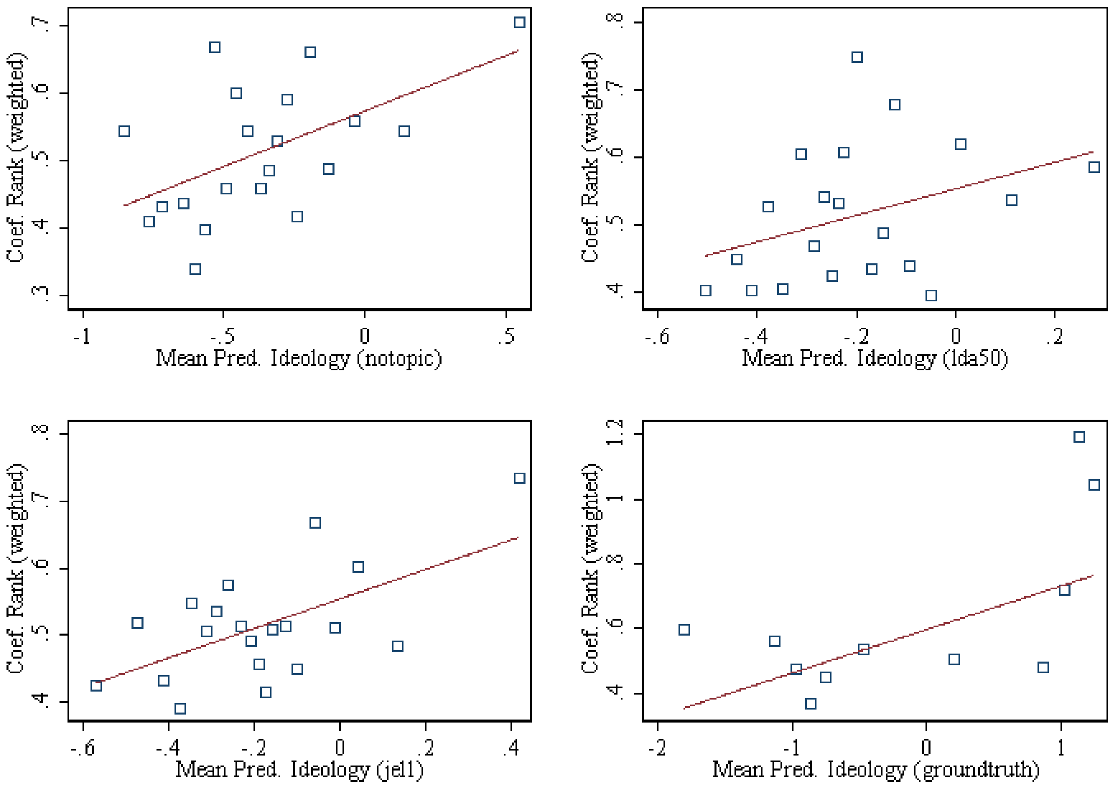


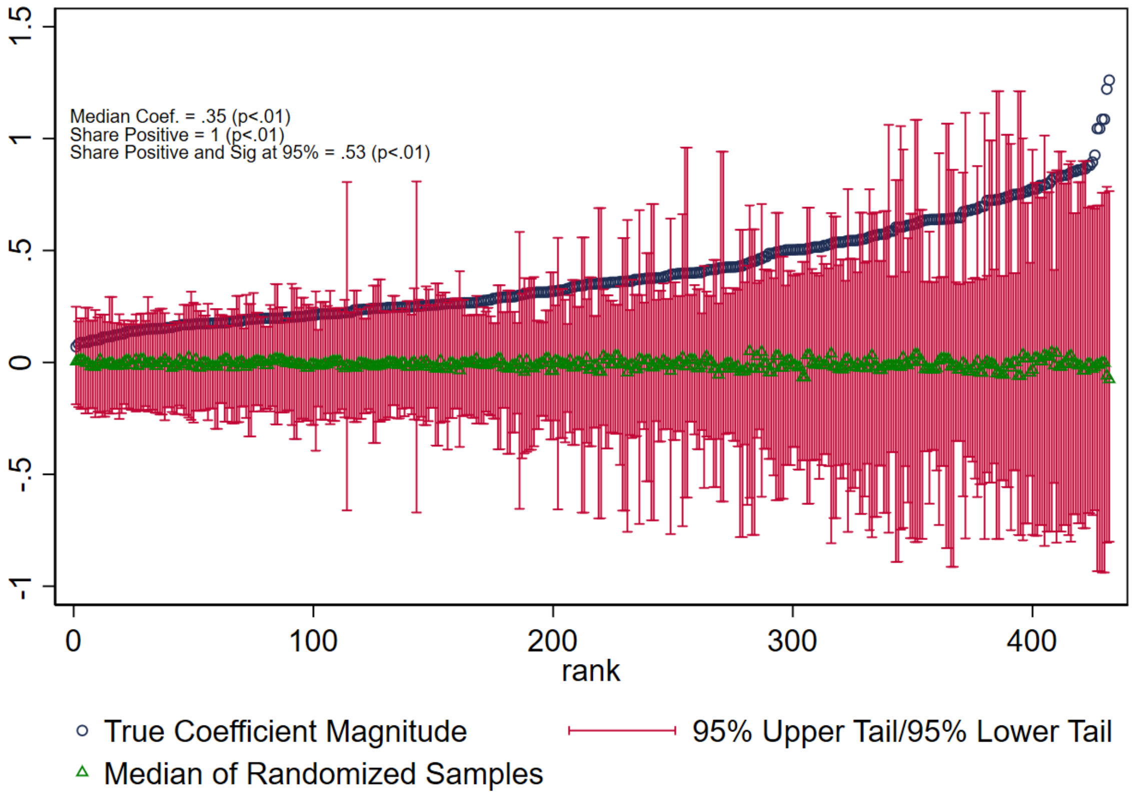
Figure plots coefficients and 95% confidence bands for coefficients on covariates from two regressions. The bottom set of coefficients (brown) include no other controls, the top set of coefficients (blue)controls for 5-year interval when Ph.D. was obtained interacted with Ph.D. institution fixed effects.

Figure 4: Binned Scatterplots of Coefficient Rank Against Predicted Ideology (FKP elasticities).



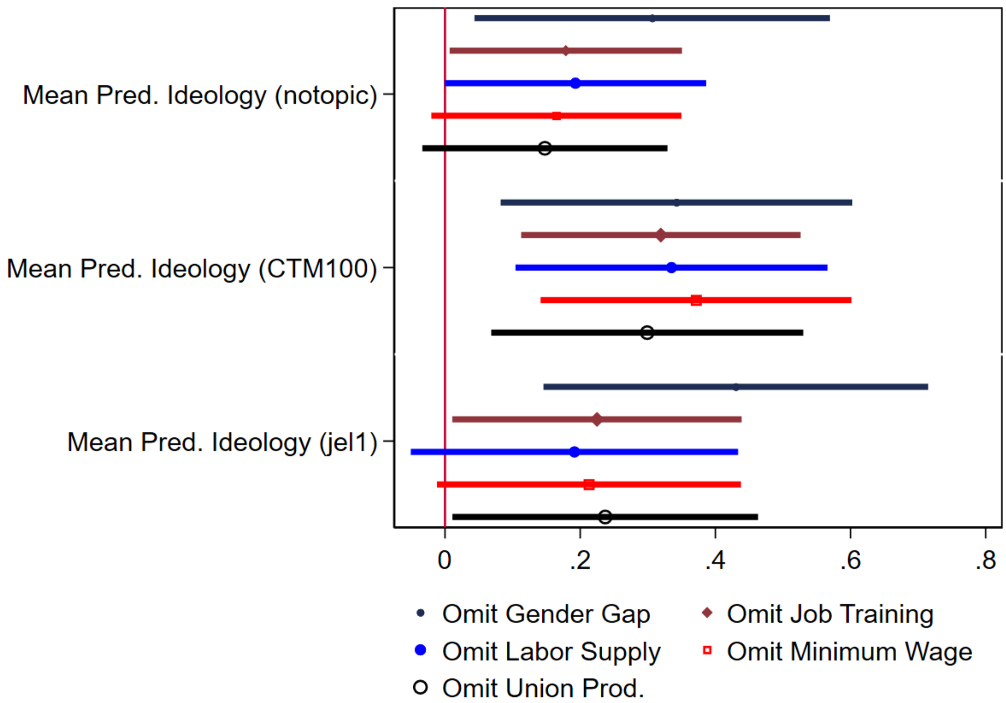
Figures plot mean elasticity rank (within category) by vintiles of predicted author ideology, conditional on meta-analysis fixed effects.

Figure 5: Specification Curve



Coefficients from 432 different specifications shown, ordered by size. Confidence intervals shown constructed from 95% tails from a distribution of 100 samples where predicted ideology is randomly shuffled across authors. Top left corner shows statistics testing a) the probability that the median coefficient from a randomly shuffled sample is greater than the true median coefficient of 0.35, b) the probability that a randomly shuffled sample has at least the same share of positive cofficients as the true sample (which is 1), and c) the probability that a randomly shuffled sample has at least the same share of positive and significant coefficients as the true sample (which is .53). All of these probabilities are below 0.01.

Figure 6: Correlation of Coefficient Rank and Ideology Omitting Each Category of Elasticity



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

9 Appendix

A.1 Model Appendix

Proof Of Proposition 1: 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 $[-1, 0], (0, 1]$.

A.2 Linking Economists to FEC Data

Fuzzy string matching is computationally expensive, so we take the common practical step of creating a candidate set of FEC contributors for each AEA member. We define the candidate set for an

AEA member as those FEC contributions where the contributor's last name starts with the same three characters as that of the AEA member.

For each AEA member and his or her candidate set of FEC contributions, we compute a similarity score between the following variables that appear in both datasets: name, occupation, and employer.[24] We map zip codes to latitude-longitude points and compute the distance from the AEA member's location to each candidate FEC contribution. To reduce the likelihood of a match for people with common names, we compute an additional predictor variable which captures the probability that a person's name is unique (Perito et al., 2011). If a name is more likely to appear in the general population, then its predictive ability in determining whether a match exists is reduced.

We model the likelihood that an AEA-FEC pair is a match as a function of the constructed variables from above. We select 1,300 pairs and manually verify if a match exists. We sample 900 of these pairs and estimate the coefficients to a logistic regression model. We repeat this process with new samples one thousand times and for each sample determine the predictive accuracy of the model on the held out set of 400 AEA-FEC pairs. On average, we make a correct prediction 96.5% (s.e. 0.015) of the time. We take the mean values of the parameter sets generated from the regressions and predict matches for the entire dataset. Using this procedure, we are able to identify 21,409 contributions made by 2,884 AEA members. We drop transactions amounts which are less than zero, leaving us with 21,229 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

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

Democrats, and 236 contributions were made to Club for Growth, a conservative fundraiser.[25] 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. Many of the members in the latter group are in either government or private industry. Table A.1 provides summary statistics on both author and non-author contributors. At the contribution level, 80.0% 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.

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

Table A.1: Campaign Contribution Data. AEA membership rosters from 1993, 1997, and 2002 to 2009 are linked to FEC campaign contribution data, linkage details provided in text. Panel A provides summary statistics on AEA member campaign contributions at the contribution level and Panel B provides summary statistics at the member level. Non-partisan contributions account for the fact that the sum of the shares is less than 1. Among individual contributors, patterns look similar between authors and non-authors.

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: Petitions from Hedengren et al. (2010). The Category columns indicate whether Hendengren classified the survey as liberty augmenting (Augm), reducing (Reduc), or other (Other). The Signature column indicates the number of actual signatures on the petition. The Author column indicates the number that were linked to papers in our corpus. The Political Category column indicates our definition of the political lean of the petition.

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

A.3 Measuring JEL Topic Prediction Accuracy

The tables in this section show the per-model predictive performance of our JEL code classifiers. For each code in *JEL1* and *JEL2*, we iteratively held out 20% of all papers for which groundtruth information on JEL codes existed. We split the remaining 80% of groundtruth papers into training (90%) and validation (10%) sets and ran gradient boosting using the *xgboost* package for *R*. Our predictors were the number of times words appeared in papers.[26] We filtered for words that appeared at least 100 times in each of the holdout, training and validation sets. We trained each model with 250 trees and used the validation set to identify the tree between 1 and 250 which maximized AUC and predicted for the holdout set.[27] By rotating the 20% holdout five times, we generated out-of-sample predictions for each paper and JEL code. The AUCs presented in the tables in this section are computed by stacking all holdout sets within topic.

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

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

Table A.3: Predictive Performance Jel 1st-Level Codes

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

Table A.4: Predictive Performance Jel 2nd-Level Codes

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

J4	Particular Labor Markets	0.949
J5	Labor & Management Relations, Trade Unions, and Collective Bargaining	0.988
J6	Mobility, Unemployment, Vacancies, and Immigrant Workers	0.977
J7	Labor Discrimination	0.988
K1	Basic Areas of Law	0.968
K2	Regulation and Business Law	0.963
K3	Other Substantive Areas of Law	0.904
K4	Legal Procedure, the Legal System, and Illegal Behavior	0.986
L1	Market Structure, Firm Strategy, and Market Performance	0.946
L2	Firm Objectives, Organization, and Behavior	0.941
L3	Nonprofit Organizations and Public Enterprise	0.958
L4	Antitrust Issues and Policies	0.967
L5	Regulation and Industrial Policy	0.956
L6	Industry Studies: Manufacturing	0.954
L7	Industry Studies: Primary Products and Construction	0.941
L8	Industry Studies: Services	0.950
L9	Industry Studies: Transportation and Utilities	0.974
M1	Business Administration	0.964
M2	Business Economics	0.736
M3	Marketing and Advertising	0.927
N1	Macroeconomics and Monetary Economics, Industrial Structure, Growth, Fluctuations	0.973
N2	Financial Markets and Institutions	0.973
N3	Labor and Consumers, Demography, Education, Health, Welfare, Income, Wealth, Religion, and Philanthropy	0.980
N4	Government, War, Law, International Relations, and Regulation	0.954
N5	Agriculture, Natural Resources, Environment, and Extractive Industries	0.983
N6	Manufacturing and Construction	0.967
N7	Transport, Trade, Energy, Technology, and Other Services	0.971
N8	Micro-Business History	0.950
O1	Economic Development	0.964
O2	Development Planning and Policy	0.939
O3	Innovation, Research and Development, Technological Change, Intellectual Property Rights	0.974
O4	Economic Growth and Aggregate Productivity	0.979
O5	Economywide Country Studies	0.935
P1	Capitalist Systems	0.923
P2	Socialist Systems and Transitional Economies	0.980
P3	Socialist Institutions and Their Transitions	0.973
P5	Comparative Economic Systems	0.879
Q1	Agriculture	0.988
Q2	Renewable Resources and Conservation	0.986
Q3	Nonrenewable Resources and Conservation	0.946
Q4	Energy	0.948
R1	General Regional Economics	0.951
R2	Household Analysis	0.944
R3	Real Estate Markets, Spatial Production Analysis, and Firm Location	0.963
R4	Transportation Economics	0.988
R5	Regional Government Analysis	0.890
Z1	Cultural Economics, Economic Sociology, Economic Anthropology	0.954

A.4 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. Table A.5 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. While not shown, the distribution of ideologies across young versus old, as well as assistant versusus associate/full professor, are quite similar. In table A.5 we show this correlation between early and late ideology is robust to a variety of controls, and holds across all of our ideology predictions. This suggests that once early ideology is controlled for, very few professional characteristics are significantly correlated with later ideology. In addition, the coefficients on early ideology are reasonably robust to the inclusion of covariates.

Table A.5: Correlation Between Late and Early Author Ideology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early Paper Ideology (lda50)	0.586***	0.392***	0.403***						
	(0.0576)	(0.0540)	(0.0578)						
Early Paper Ideology (jel1)				0.436***	0.282***	0.313***			
				(0.0547)	(0.0475)	(0.0391)			
Early Paper Ideology (notopic)							0.723***	0.537***	0.544***
							(0.0505)	(0.0323)	(0.0328)
Years Between Undergrad and PhD Degrees			0.000373			-0.00483			-0.00838*
			(0.00402)			(0.00468)			(0.00489)
Latin American Origin			-0.00283			-0.0280			0.0149
			(0.106)			(0.105)			(0.132)
European Origin			0.0480			0.0691**			0.0701
			(0.0351)			(0.0332)			(0.0466)
Full Professor			0.000845			-0.0357			-0.00968
			(0.0223)			(0.0286)			(0.0275)
Groundtruth Sample			-0.00650			-0.0158			-0.0244
			(0.0155)			(0.0225)			(0.0213)
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	824	824	729	823	823	728	824	824	729

Robust standard errors, clustered at the primary field level.

Saltwater and Freshwater are constructed from Tervio and are described in the text.

A.4.1 Phrase Tables

Table A.6: Top Phrases for CTM30 Topic 19

phrases	left	right
school	child_care_2	human_capit_2
educ	head_start_2	cognit_skill_2
student	affirm_action_2	j_heckman_2
colleg	black_student_2	locus_control_2
score	mental_health_2	person_trait_2
year	white_student_2	cognit_noncognit_2
teacher	group_school_2	heckman_j_2
high	school_particip_2	tax_rate_2
effect	test_score_2	metropolitan_area_2
graduat	minimum_wage_2	rate_return_2
grade	compulsori_school_2	school_qualiti_2
test	york_citi_2	sex_educ_2
univers	did_not_2	school_attain_2
program	poverti_rate_2	skill_format_2
qualiti	birth_weight_2	jame_j_2
attend	percentag_point_2	charter_school_2
class	year_old_2	growth_rate_2
enrol	privat_sector_2	princip_compon_2
group	perform_rate_2	special_educ_2
experi	use_comput_2	life_cycl_2

The first column in this table shows the most probable words in Topic 19 from the CTM30 model. The next two columns show the most left-leaning and right-leaning bigrams, respectively, for papers with a higher than 5% probability of containing this topic. The AUC for the ideology prediction model within this topic was 0.675.

Table A.7: Top Phrases for CTM50 Topic 3 AUC = 0.655

phrases	left	right
school	child_care_2	human_capit_2
educ	head_start_2	cognit_skill_2
student	black_student_2	rate_return_2
colleg	white_student_2	locus_control_2
score	group_school_2	cognit_noncognit_2
teacher	school_particip_2	j_heckman_2
year	test_score_2	school_qualiti_2
grade	york_citi_2	tax_rate_2
graduat	compulsori_school_2	skill_format_2
high	minimum_wage_2	school_attain_2
test	automat_enrol_2	metropolitan_area_2
univers	birth_weight_2	life_cycl_2
program	percentag_point_2	person_trait_2
attend	treatment_effect_2	princip_compon_2
enrol	did_not_2	special_educ_2
qualiti	new_york_2	charter_school_2
class	small_class_2	jame_j_2
effect	model_model_2	school_avail_2
econom	group_group_2	growth_rate_2
achiev	assist_professor_2	econom_growth_2

The first column in this table shows the most probable words in Topic 3 from the CTM50 model. The next two columns show the most left-leaning and right-leaning bigrams, respectively, for papers with a higher than 5% probability of containing this topic. The AUC for the ideology prediction model within this topic was 0.655.

Table A.8: Top Phrases for CTM100 Topic 6

phrases	left	right
school	school_particip_2	human_capit_2
educ	higher_educ_2	cognit_skill_2
colleg	compulsori_school_2	metropolitan_area_2
high	group_school_2	sex_educ_2
year	minimum_wage_2	school_attain_2
graduat	percentag_point_2	j_heckman_2
cohort	group_group_2	cognit_noncognit_2
enrol	gi_bill_2	sexual_activ_2
attend	educ_attain_2	tax_rate_2
return	school_attend_2	skill_format_2
higher	treatment_effect_2	locus_control_2
qualiti	black_student_2	option_valu_2
level	volum_indic_2	school_avail_2
abil	labour_market_2	rate_return_2
student	relat_suppli_2	gender_gap_2
attain	did_not_2	special_educ_2
individu	entri_age_2	charter_school_2
complet	goldin_katz_2	jame_j_2
secondari	sat_score_2	intern_rate_2
primari	school_law_2	incom_quartil_2

The first column in this table shows the most probable words in Topic 6 from the CTM100 model. The next two columns show the most left-leaning and right-leaning bigrams, respectively, for papers with a higher than 5% probability of containing this topic. The AUC for the ideology prediction model within this topic was 0.491.

Table A.9: Top Phrases for CTM100 Topic 28

phrases	left	right
black	head_start_2	cognit_skill_2
score	school_particip_2	econom_growth_2
student	black_student_2	special_educ_2
school	white_student_2	charter_school_2
white	high_school_2	oecd_countri_2
teacher	random_assign_2	princip_compon_2
test	affirm_action_2	gdp_capita_2
grade	group_school_2	student_perform_2
race	york_citi_2	develop_countri_2
effect	law_school_2	review_no_2
achiev	black_women_2	gini_coeffici_2
racial	standard_error_2	econom_no_2
discrimin	new_york_2	diagnost_test_2
class	reserv_wage_2	econom_cours_2
district	treatment_effect_2	latin_american_2
minor	birth_weight_2	school_attain_2
differ	group_group_2	human_capit_2
group	small_class_2	technic_effici_2
perform	test_score_2	state_court_2
peer	percentag_point_2	poverti_rate_2

The first column in this table shows the most probable words in Topic 28 from the CTM100 model. The next two columns show the most left-leaning and right-leaning bigrams, respectively, for papers with a higher than 5% probability of containing this topic. The AUC for the ideology prediction model within this topic was 0.569.

Table A.10: Top Phrases for JEL1 Classification I

word	left	right
health	child_care_2	human_capit_2
hospit	mental_health_2	cognit_skill_2
student	heart_attack_2	punit_damag_2
school	health_insur_2	school_qualiti_2
patient	medic_care_2	j_heckman_2
educ	food_stamp_2	subject_wellb_2
drug	head_start_2	gdp_capita_2
poverti	health_care_2	skill_format_2
children	birth_weight_2	locus_control_2
insur	singl_mother_2	person_trait_2
medic	prenat_care_2	rate_return_2
child	manag_care_2	approv_time_2
care	nurs_home_2	product_liabil_2
women	welfar_reform_2	school_attain_2
famili	privat_insur_2	special_educ_2
teacher	insur_coverag_2	cognit_noncognit_2
household	risk_adjust_2	sex_educ_2
physician	tax_credit_2	heckman_j_2
mortal	medic_spend_2	charter_school_2
incom	analys_politiqu_2	social_surplus_2

The first column in this table shows the most probable words in the JEL I classification. The next two columns show the most left-leaning and right-leaning bigrams, respectively, for papers with a higher than 5% probability of containing this topic. The AUC for the ideology prediction model within this topic was 0.675.

Table A.11: Top Phrases for JEL2 Classification I2

word	left	right
student	head_start_2	human_capit_2
school	birth_weight_2	cognit_skill_2
educ	child_care_2	tax_rate_2
teacher	black_student_2	rate_return_2
score	white_student_2	sex_educ_2
grade	york_citi_2	school_qualiti_2
colleg	group_school_2	locus_control_2
enrol	school_particip_2	person_trait_2
children	test_score_2	j_heckman_2
attend	mental_health_2	median_voter_2
parent	famili_structur_2	growth_rate_2
district	law_school_2	time_use_2
child	compulsori_school_2	public_educ_2
graduat	small_class_2	econom_growth_2
cohort	random_assign_2	school_attain_2
famili	minimum_wage_2	metropolitan_area_2
black	sourc_countri_2	charter_school_2
estim	care_subsidi_2	cognit_noncognit_2
math	social_capit_2	special_educ_2
tuition	did_not_2	school_avail_2

The first column in this table shows the most probable words in the JEL I2 classifiation. The next two columns show the most left-leaning and right-leaning bigrams, respectively, for papers with a higher than 5% probability of containing this topic. The AUC for the ideology prediction model within this topic was 0.579.