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Biased Forecasts to Affect Voting Decisions? The Brexit Case

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Abstract

This paper introduces macroeconomic forecasters as political agents and suggests that they use their forecasts to influence voting outcomes. We develop a probabilistic voting model in which voters do not have complete information about the future states of the economy and have to rely on macroeconomic forecasters. The model predicts that it is optimal for forecasters with economic interest (stakes) and influence to publish biased forecasts prior to a referendum. We test our theory using high-frequency data at the forecaster level surrounding the Brexit referendum. The results show that forecasters with stakes and influence released much more pessimistic estimates for GDP growth in the following year than other forecasters. Actual GDP growth rate in 2017 shows that forecasters with stakes and influence were also more incorrect than other institutions and the propaganda bias explains up to 50 percent of their forecast error.

Keywords: Brexit, Interest Groups, Forecasters Behavior, Voting

JEL Classification: D72, D82, E27, H30

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1 Introduction

Several issues of great economic relevance have recently been addressed using referenda: the referendum held in the United Kingdom to leave the European Union, the referendum held in Greece on the agreements with the EU institutions to solve the debt crisis, the referendum held in Italy on a major change to the national Constitution, and the referendum held in Catalonia on the independence from Spain. Many of the debates leading up to those referenda focused on the potential effects on economic growth, using estimates published by professional macroeconomic forecasters. Economic forecasts can be easily communicated to and understood by voters even if advanced competence, modeling and equipment are required to produce a forecast. Voters can use the forecasts to obtain information about economic variables, such as GDP growth, before turning to the ballot.[1] In many public debates, economic forecasts are taken as a given, without considering that the institutions publishing the forecasts may be promoting their own interests.

In this paper, we introduce macroeconomic forecasters as political agents and argue that they may exploit their information monopoly to influence the voting process. Our approach combines a simple theoretical framework, which shows how forecast institutions can profit from the asymmetry of information in relation to voters, and an empirical analysis, which uses a panel of forecasters surveyed on a monthly basis before and after the Brexit referendum. Different forecasters face different incentives. First, a forecaster has incentives to favor one of the outcomes at the expense of the other if it has an economic interest to defend or maintain and this interest is threatened by the referendum. Second, a forecaster can have an impact on the outcome of the decision-making process only if it is influential enough. The model predicts, and the empirical results confirm, that forecasters with stakes in and influence over the referendum decision released more pessimistic and more incorrect estimates of GDP growth rate than the other institutions.

We set up a probabilistic voting model in which voters do not have information about one of the potential states of the economy after a referendum and therefore have to rely on professional forecasters. In the model, the voters' decision rule is to support the outcome that yields them the highest utility (Lindbeck and Weibull, 1987), but their beliefs on the state of the economy under the unobserved alternative depend on published forecasts rather than on the state itself. Forecasters' economic interests (stakes) in the outcome are heterogeneous, and some can influence voters' beliefs more than others. Forecasters with stakes and influence face a trade-off between the accuracy of their forecast and the attempt to influence the referendum result. Accuracy is

[1] The relationship between voters and macroeconomic forecasters can be understood in the light of Downs (1957). Rational agents lack incentives to invest in collecting costly information before voting because the probability of being the decisive voter for the election outcome is negligible.

measured by the forecast error, whereas the information monopoly provides the opportunity to influence the voters. In equilibrium, forecasters with stakes and influence release intentionally biased forecasts in order to make swing voters change their voting decision. The model predicts the presence of an extensive as well as an intensive margin of propaganda bias. Forecasters with positive stakes and influence will release more incorrect forecasts than other forecasters, and the size of the propaganda bias is increasing in both parameters.

We test our theory using high-frequency data at the forecaster level collected in connection with the EU membership referendum (also known as the Brexit referendum) held in 2016 in the United Kingdom. In the empirical analysis, we compare the forecasts for GDP growth published by forecasters with stakes and influence to those released by other institutions. We define the financial institutions in our sample and the forecasters located in the City of London's financial district to be the ones with the highest stakes, and we use Google Trends and Google News data to proxy for the influence of each forecaster.

The Brexit referendum is ideal to test our theory for at least two reasons. First, no country had previously experienced a retreat from the EU and thus the economic consequences are difficult to predict for voters; second, several forecasters have economic interests that are threatened by Brexit.

We document that forecasters with stakes and influence released short run GDP growth rate estimates subject to Brexit that were between 0.41 and 0.77 percentage points lower than the estimates released by other institutions. The actual outcome for GDP growth in 2017 shows that these forecasters were more incorrect than other institutions and that the propaganda bias explains up to 50 percent of the forecast error. We also find that the difference between the groups of forecasters comes primarily from pessimistic forecasts on investments and trade exposure. In addition, we test the implications of our model at the intensive margin. The empirical results confirm the prediction of increasingly more pessimistic forecasts when either stakes or influence increase.

The propaganda bias is estimated in proximity to the referendum, while forecasts released by different institutions converge within few months after the vote, ruling out the presence of alternative mechanisms related to behavioral biases.[2] Nevertheless, the convergence is consistent with a two-fold interpretation; first, after the result was realized, there was still scope for forecasters

[2] The concept of propaganda bias among macroeconomic forecasters differs substantially from behavioral biases of either agents or information sources. In our model, forecasters neither have their own ideological preferences (see e.g. Sethi and Yildiz (2016) for a rationalization of motivated reasoning), which in turn would worsen the accuracy of their previsions, nor exploit the customers' aptitude to be more trusting of the sources that confirm their previous priors (Gentzkow and Shapiro (2006) and Gentzkow et al. (2018)). The propaganda bias comes as a consequence of economic gains and the asymmetry of information between forecasters and voters, and it is predicted only at the time at which individuals are called upon to vote.

to influence the implementation of a *hard* or *soft* Brexit, and second, they might have decided to adjust their forecasts slowly to preserve their credibility.

This paper extends two strands of literature. First, earlier literature has shown that special interest groups (see, for example, Baron (1994), Grossman and Helpman (1996) and Besley and Coate (2001)) and media (see, for example, Enikolopov et al. (2011) and DellaVigna et al. (2014)) are active players in the political economy and may release biased pieces of information in order to affect individuals' beliefs and, in turn, voting behavior. Our theoretical model and empirical results suggest that macroeconomic forecasters also exploit their information monopoly to influence the voters' beliefs. Second, on the strategic behavior of forecasters, Laster et al. (1999) develop a theoretical model in which forecasters' payoffs are based on two criteria: their accuracy and their ability to generate publicity. There is a trade-off between the two as efforts to attract publicity compromise accuracy (see also Croushore (1997), Ottaviani and Sørensen (2006) and Marinovic et al. (2013)).[3] Our theoretical model proposes an alternative trade-off and shows that the strategic behavior of macroeconomic forecasters can also be generated by a propaganda bias coming from the attempt to influence voters.

The propaganda bias reduces the welfare of voters, who in equilibrium may not cast a vote for the preferred choice, compared to a world with unbiased forecasters. Naive voters are predicted to make systematic voting errors in line with the outcome preferred by macroeconomic forecasters, while sophisticated voters make the correct choice in expectations but are incorrect for particular realizations of stakes and influence. If voters are rational, the propaganda bias generates an inefficient equilibrium in this information market since forecasters in expectations pay an accuracy cost without systematically influencing the referendum result.

The paper proceeds as follows. The next section discusses the relevant details about the Brexit referendum. Section 3 introduces the theoretical framework and derives testable predictions. Section 4 outlines the choices that we make to take the model to data and the estimation details. Section 5 presents the estimation results and rules out alternative interpretations. Finally, Section 6 concludes.

2 The Brexit Referendum

In January 2016, the UK Prime Minister David Cameron announced a referendum on the EU membership that would take place on June 23 of the same year. The referendum was formally non-binding since the Parliament maintained the right to make the final decision on the issue, but

[3] Deb et al. (2018) show in an infinitely repeated game that strategic forecasters need to be correct a minimum number of times to maintain their credibility and not lose customers.

the Government clarified before the vote its willingness to commit to the voters' preference.

During the campaign, which started in mid-April, the economic effects of the eventual withdrawal from the European Union, and, potentially, from the Single European Market (see Dhingra et al. (2015) and Kierzenkowski et al. (2016)), were a major argument against Brexit. Governmental agencies, forecasters, media and European and international public institutions warned the British citizens about a large economic downturn, especially due to a drop in investments (Dhingra et al., 2016a) and exports (Dhingra et al., 2016b), if the UK withdrew from the EU. The voters themselves seemed to be concerned about the future state of the economy. According to Google Trends summary reports, the number of online searches for economic keywords such as "Brexit GDP", "Brexit pound" and "Brexit economy" increased substantially (from 10 to 100 times on a relative scale) in the weeks approaching the referendum date (see Figure A1 in the Appendix).

Macroeconomic forecasters were asked in a special survey by Consensus Economics about the effects of the Brexit vote in the short run. Each forecaster reported the central forecast (i.e. the Remain forecast prior to the referendum and the Leave forecast after) and, anonymously prior to the referendum, the forecast in the event of Leave. The surveyed institutions highlighted that the victory of the Leave would lead to "uncertainty in the transition process" and cause "a loss of foreign direct investments and trading opportunities with Eurozone countries" (see Consensus Economics (2016a)). Figure 1 shows that professional forecasters were predicting Brexit to have a substantial impact on GDP growth in the short run and that the forecasts conditional on Leave became on average more pessimistic approaching the referendum date. These forecasts remained the same in the first survey after the vote. In the June survey, forecasters predicted a GDP growth rate in 2017 of 0.7 percentage points in the case of Leave, compared to 2.1 in case of Remain. The dashed line in the figure represents the actual GDP growth in 2017. Its distance to the forecasts conditional on Leave shows that the more pessimistic scenarios released approaching the referendum were more incorrect, as the forecast error increased on average between the April and the June releases.

The Remain side was leading according to 66 percent of the opinion polls released in the weeks approaching the referendum, and often with a winning margin of at least 5 percentage points. Macroeconomic forecasters as well as bookmakers were predicting the victory of the Remain side. According to Consensus Economics (2016a), forecasters were assigning a probability of 63 percent to Remain, whereas the bookmakers assigned Remain a probability around 85 percent in the final days before the vote (see Figure A2 in the Appendix).

The referendum results reversed all predictions. On June 23, a majority (51.9%) of the voters decided to leave the European Union. Prime Minister David Cameron, who had campaigned to

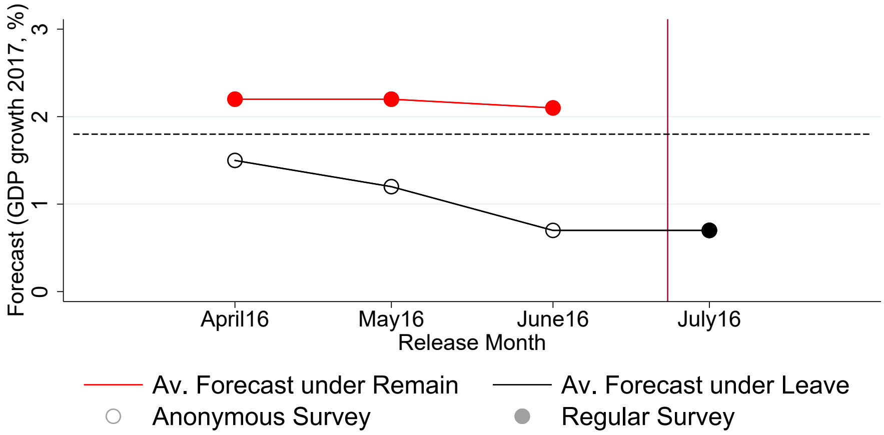

Figure 1: Consensus Forecasts for Leave and Remain around the Referendum

Notes: The graph reports the average forecast for the 2017 GDP growth rate conditional on Remain (red) and Leave (black), published by Consensus Economics in June and July 2016. The red vertical line represents the referendum date, while the dashed line represents the actual GDP growth rate in 2017. Source: Authors' elaboration on data from Consensus Economics (2016a) and Consensus Economics (2016b)).

remain in the EU despite the opposition of several ministers and party colleagues, announced his resignation the day after the referendum.

The Conservative party had to choose its new candidate for PM in the days that followed. Within the party, two factions were competing for the position of party leader. On the one hand, the strongest supporters of Brexit asked for a *hard* Brexit (namely, to quit the Single European Market as well). On the other hand, those who had not played a primary role during the campaign were willing to pursue the withdrawal in a much milder way. The latter position prevailed in the party, and the Home Secretary Theresa May was formally declared the party leader on July 11, two days before being appointed the new Prime Minister.[4]

3 Theoretical Framework

We consider two types of agents: voters and forecasters. Voters have to choose between two states, $S \in \{L, R\}$, each of which is associated with an economic outcome y^S. L represents the decision of leaving the status quo and R the decision of remaining. Voters only observe y^R and use information from professional forecasters to form beliefs about the unobserved y^L. Forecasters have complete information about the economic outcomes, but each of them can choose strategically whether to reveal this information with a bias. This framework represents a standard model of asymmetric information: voters are prospective and care about the economy in the future, but professional

[4] According to Article 50 of the Treaty of European Union, a country is allowed to leave the EU after two years from the first notification. In the meanwhile, the country and the EU partners have to make agreements to rule the transition period and the future relationships. The procedure ruled by Article 50 started on March 28, 2017. The timeline of key dates and events before and after the referendum are summarized in Table A1 in the Appendix.

forecasters have the information monopoly over y^L and voters use their estimates to form beliefs before voting.

In this version of the model, we assume that voters are naive since they do not expect forecasts to be potentially biased. Also, we assume that voters do not have any information about y^L and can only rely on estimates released by professional forecasters. We relax these simplifying assumptions in the version of the model presented in Section A.3 in the Appendix, which yields qualitatively the same predictions.

The timing is as follows: in the first period, a referendum is announced with associated states of the economy y^L and y^R; in the second period, each forecaster releases a forecast under each state of the economy and in the third period, voters observe an aggregate signal from forecasters and the status quo economy y^R, and they cast their vote.

3.1 Voters

Consider a continuum of voters with total mass 1, with linear preferences over policy outcomes represented by $W(y) = y$. Following the well-established probabilistic voting model (Lindbeck and Weibull, 1987), we assume that voters make their decision based on the state of the economy, their ideological preferences and the relative popularity of the two alternatives.

Individual i prefers alternative L over alternative R if and only if

$$y^L \geq y^R + \delta + \sigma_i, \tag{1}$$

where the ideology parameter σ_i captures all preferences at the individual level in support of R that are orthogonal to $W(\cdot)$, and δ captures the aggregate popularity shocks in support of R. We assume that σ_i is uniformly distributed over the interval $\left[-\frac{1}{2\phi}, \frac{1}{2\phi}\right]$ with density $\phi > 0$ and that δ is uniformly distributed in the interval $\left[-\frac{1}{2\psi}, \frac{1}{2\psi}\right]$ with density $\psi > 0$.[5]

3.2 Forecasters

Assume a discrete number of J forecasters who have information on y^L and y^R and can face an economic loss under L or be indifferent between the two states. Each forecaster minimizes the following loss function with respect to F_j^L and F_j^R, given y^S as well as other forecasters' and

[5] In the case of the Brexit referendum, examples of σ_i are the different preferences that voters have on migration issues, whereas δ represent shocks that shift all the voters' distribution, e.g. the assault and murder of MP Jo Cox just one week prior to the vote.

voters' strategies:

$$\min_{F_j^L, F_j^R} \mathcal{L} = p^L(F^L, F^R)\Big[\eta_j C + \frac{1}{2}(F_j^L - y^L)^2\Big] + [1 - p^L(F^L, F^R)]\Big[\frac{1}{2}(F_j^R - y^R)^2\Big], \tag{2}$$

where $F_j^S \in [\underline{F_j^S}; \overline{F_j^S}]$ represents the forecast released by institution j under state S, $C > 0$ represents a cost associated with state L, p^L is the probability of leaving the status quo and the parameter $\eta_j \geq 0$ captures the stakes of each forecaster.[6] We model the loss function of forecasters in the spirit of Laster et al. (1999), modifying their trade-off between accuracy and publicity into a trade-off between the accuracy of the released estimate and the will of favoring the preferred outcome in the referendum. Forecasters facing a loss if L wins have a direct economic interest in the referendum result and hence have stakes, while forecasters without stakes are indifferent between the two states.

We assume that voters do not directly observe individual forecasts but only a joint signal F^S, defined as the weighted average

$$F^S = \sum_{j=1}^{J} \gamma_j F_j^S, \tag{3}$$

where the parameter $\gamma_j \geq 0$, such that $\sum_{j=1}^{J} \gamma_j = 1$ captures the relative influence of each individual forecaster. This assumption represents a simple and tractable way to model the fact that average voters in general do not have access to the full distribution of published forecasts, as other entities e.g. mass media and summary reports usually refer to aggregate consensus measures or to a restricted number of forecasters.[7]

3.3 Political Equilibrium

We solve this dynamic game by backward induction, starting by solving the voters' problem given forecasters' optimal behavior.

Naive voters do not expect forecasters to release biased F^L, hence their decision rule in (1) can be expressed as

$$F^L \geq y^R + \delta + \sigma_i. \tag{4}$$

[6] $\eta_j \geq 0$ implies that we assume forecasters do not have a strict preference in support of L. The sign of η_j determines the sign of the propaganda bias at the individual level, but not its presence.

[7] Figure 1 is an example of the empirical motivation behind this assumption, as conditional forecasts subject to Leave were in general not available to the public at the forecaster level. Nevertheless, equation (3) can also be derived by assuming that voters observe individual forecasts. In that case, the heterogeneity in influence would be generated by the variation in the precision of the signal that individuals receive.

Voters that are indifferent between the two alternatives are denoted swing voters. According to (4), they are defined by the relationship

$$\tilde{\sigma} = F^L - y^R - \delta.$$

By ranking voters according to their ideological parameter, all individuals with $\sigma_i \in \Big[-\frac{1}{2\phi}, \tilde{\sigma}\Big]$ will then vote in favor of alternative L.

We define π^L to be the share of votes in society in support of L, and $p^L = P(\pi^L > \frac{1}{2})$ is, by extension, the probability that L wins in a binary competition. The share of votes that L receives in the population is

$$\pi^L = \int_{-\frac{1}{2\phi}}^{\tilde{\sigma}} \phi \; di = \phi\Big[\tilde{\sigma} + \frac{1}{2\phi}\Big] = \frac{1}{2} + \phi\Big(F^L - y^R - \delta\Big),$$

while the probability that L wins is given by

$$p^L(F^L, F^R) = p^L(F^L) = P(\pi^L > \frac{1}{2}) = P\Big(\delta < F^L - y^R\Big),$$

which can be rewritten as

$$p^L(F^L) = \int_{-\frac{1}{2\psi}}^{F^L - y^R} \psi \; di = \frac{1}{2} + \psi\Big[F^L - y^R\Big]. \tag{5}$$

In political equilibrium, the probability that L wins does not depend on F^R since voters correctly observe y^R. However, it depends on F^L since voters do not have information about y^L.

We now move to the forecasters' problem, given $p^L(\cdot)$. In equilibrium, each forecaster minimizes (2) subject to (3), (5) and other forecasters' rational behavior at the time of the referendum. Assuming an interior solution, the first-order conditions in an equilibrium in which forecasters behave optimally given voters' strategies and each other forecasters' behavior are

$$\frac{\partial \mathcal{L}}{\partial F_j^L}\Big|_{p^L = p^{L*}} = \psi\gamma_j\Big(\frac{1}{2}(F_j^L - y^L)^2 + \eta_j C - \frac{1}{2}(F_j^R - y^R)^2\Big) + (F_j^L - y^L)p^{L*} = 0 \tag{6}$$

and

$$\frac{\partial \mathcal{L}}{\partial F_j^R}\Big|_{p^L = p^{L*}} = F_j^R - y^R = 0. \tag{7}$$

From (7), we have that $F_j^R = y^R$ for every value of η_j and γ_j, whereas (6) collapses to

$$\psi\gamma_j\left(\frac{1}{2}(F_j^L - y^L)^2 + \eta_j C\right) + (F_j^L - y^L)p^{L*} = 0 \tag{8}$$

so that all forecasters release unbiased forecasts under the state R, whereas F_j^L depends on η_j, γ_j and ψ.[8]

3.4 Predictions

From (7) and (8), we derive the following propositions.

Proposition 1. ***Existence of political equilibrium with unbiased forecasts***
Under the assumptions of the model, $F_j^L = y^L$ and $F_j^R = y^R$ are part of a political equilibrium $\forall\ p^{L*} \in (0,1)$ if and only if $\eta_j = 0$ or $\gamma_j = 0$.

Proof. See Appendix A.1 ■

Proposition 1 predicts that forecasters without stakes ($\eta_j = 0$) or influence ($\gamma_j = 0$) release unbiased estimates under both states approaching a referendum. This result is not surprising since a forecaster who does not prefer one state over the other or cannot influence voting behavior does not face a trade-off and only aims to minimize the forecast error.

Proposition 2. ***Existence of political equilibrium with a propaganda bias***
Under the assumptions of the model, necessary and sufficient conditions for $F_j^L \in \left[\underline{F}^L, y^L\right)$ and $F_j^R = y^R$ to be part of a political equilibrium $\forall\ p^{L*} \in (0,1)$ are $\eta_j > 0$ and $\gamma_j > 0$.

Proof. See Appendix A.1 ■

Proposition 2 predicts that in a political equilibrium it is optimal for forecasters with stakes ($\eta_j > 0$) and influence ($\gamma_j > 0$) to publish biased estimates for state L approaching a referendum. The bias appears in the form of pessimistic forecasts for state L as forecasters with stakes are assumed to prefer state R.[9]

We have solved the model numerically to investigate whether there is also an intensive margin of propaganda bias; namely, whether, among forecasters with stakes and influence, a larger value

[8]The forecasters' objective function is cubic in F_j^L and hence is convex only in a subset of its domain. However, it is possible to show that the unique point in which (8) is satisfied identifies an interior minimum of the objective function since the second-order conditions are positive in equilibrium.

[9]All forecasters release an unbiased F_j^R because voters are assumed to correctly observe the status quo economy y^R. The prediction of a propaganda bias in F_j^L does not rest on this assumption, which nevertheless clarifies the intuition of a large asymmetry of information between forecasters and voters. Assuming instead that voters do not have perfect information about y^R, then forecasters with stakes and influence would bias both F_j^R and F_j^L. Forecasters would strategically decide how much to bias each of the two based on p^{L*} and on the quality of information that voters get about y^R. The assumption that y^R is observed correctly while y^L is unobservable is a particular case.

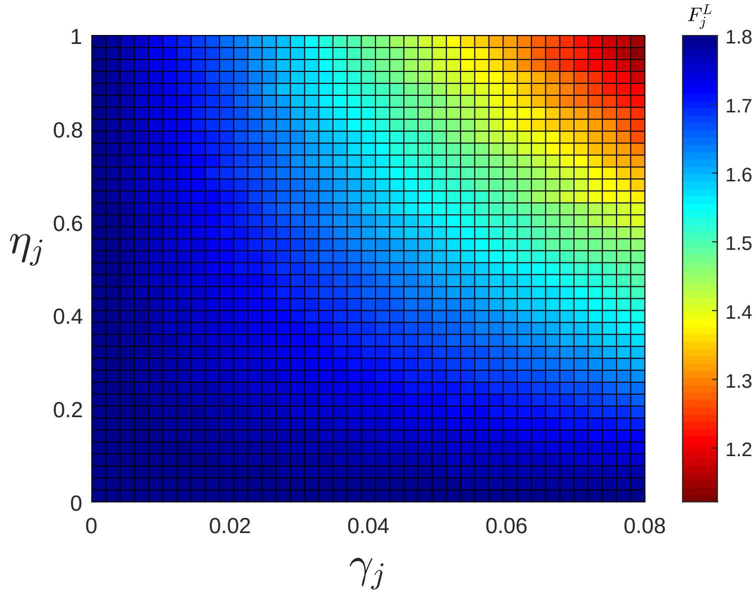

Figure 2: Intensive Margin of the Propaganda Bias

Notes: The figure reports at the individual forecaster level F_j^L as a function of the exogenous parameters η_j and γ_j. The parameters are reported on the axes of the graph, whereas different values of F_j^L are reported with different marker colors, as summarized in the legend. Dark blue markers represent $F_j^L = y^L$, whereas red markers represent the relatively most biased forecasts. The exogenous parameter ψ has been calibrated to take the value 0.3.

of the two parameters is associated with a more pronounced propaganda bias. We summarize the main results of this numerical exercise in Figure 2, while all technical details are reported in Section A.2 in the Appendix. In Figure 2, we report how F_j^L varies as a function of η_j (stakes) and γ_j (influence). In the heatmap the red areas represent the cases of largest bias, whereas the combination of parameters for which the model does not predict any bias are reported in dark blue. The graph shows that there exists an intensive margin of propaganda bias, both in terms of stakes and influence. Among institutions with $\eta_j > 0$ and $\gamma_j > 0$, indeed, there is a monotonic relationship between each of the two and the size of the bias.

3.5 Intuition and Mechanisms

The theoretical framework presented in the above section is simple and tractable, but nevertheless provides sufficient insights about the incentives that the asymmetry of information provides to forecasters in this strategic game.

Forecasters who release biased estimates solve the trade-off between accuracy and the attempt to influence the outcome of the voting process by taking double advantage of their strategy. The optimal choice of F_j^L takes into account that if the outcome preferred by forecasters with stakes

(R) prevails, the propaganda bias is costless in terms of ex-post accuracy. Indeed, the bias reduces the probability of paying the economic cost C in the event state L wins, but it also reduces the probability of paying the accuracy cost $(F_j^L - y^L)^2$. The strategic manipulation of the forecasts is very appealing for forecasters, who can potentially influence the voters at no cost. Voters, instead, face a utility loss compared to a world with unbiased forecasts if the propaganda bias is decisive to swing the referendum result.

The relationship between the probability that state L wins and the magnitude of the bias is bijective. A larger bias decreases p^{L*}. In addition, an exogenous reduction in p^{L*} (increase in ψ as reported in Figure A3a) also increases the magnitude of the bias for any $y^L < y^R$ (see Figure A3b). The intuition for this insight is as follows. Although the marginal impact that forecasters have on the referendum result is maximized when p^{L*} approaches 0.5, in this case there is a large probability that forecasters would pay the accuracy cost. If the probability attached to the state that forecasters dislike is instead low, a very large bias would reduce it even more and would be almost costless in expectations. When instead ψ is low, so that p^{L*} approaches 0.5 and the relative weight that voters put on the economic outcomes when casting their vote is low, the relationship between F_j^L and the stakes and influence parameters is attenuated (see Figure A4).

The equilibrium propaganda bias reduces the voters' welfare in the case of both naive and rational voters (presented in Section A.3 in the Appendix). If voters are naive and do not expect forecasters to bias their publications, marginal voters change the voting strategy systematically towards R. Rational voters, who completely internalize the bias of the *average* forecaster, in expectations cast the correct vote, but become more prone to vote for L if the drawn forecasters have fewer stakes than the average, and become more prone to vote for R if the drawn forecasters instead have more stakes than the average. In the case of rational voters, the propaganda bias also reduces the welfare of forecasters since it reduces accuracy without influencing the referendum result in expectations, and hence represents a case of inefficiency in this market.

4 Taking the Model to Data

We test the predictions of our theoretical model using the EU membership referendum, known as Brexit, held in June 2016 in the United Kingdom. Several reasons make the Brexit referendum ideal for empirically testing the model. First, some forecasters would have been exposed to substantial losses in the event of a withdrawal from the European Union. Second, it was difficult for voters to anticipate the effects of their choice on the economy since no country had previously withdrawn from the European Union. Third, the probability of leaving the European Union was considered low prior to the vote.

The model predicts the presence of a propaganda bias approaching a referendum due to the stakes parameter η_j and the influence parameter γ_j. The predictions are confirmed empirically if significantly different forecasts released by institutions with and without stakes and influence are observed. To test the model in the data, it is necessary to bear in mind that macroeconomic forecasters usually release forecasts to their customers and mass media that are not always comparable across institutions since they are based on different timing, frequencies, horizons and scenarios. Surveys in which professional forecasters are asked for their central forecast relative to the same setting make comparisons possible, but they are only subject to the most likely realization of the future, given present information.

We use the data collection *Forecasts for the UK Economy* from the HM Treasury (the UK government's ministry for economics and finance). The dataset is a monthly survey of independent forecasters collected by the Treasury that is publicly available. The collection covers 44 forecasters from January 2012 to April 2018. At the beginning of each month, each forecaster in the sample is surveyed and the results are quickly released online.[10]

The data contain short-term forecasts for GDP growth and its components: private and government Consumption, Investments, Imports and Exports. Our focus is on the forecasts for GDP growth rate and its components in the year $t+1$.[11] Table A2 in the Appendix provides descriptive statistics of the relevant forecasts.

From an empirical point of view, we have a standard problem of missing counter-factual (Imbens and Rubin, 2015) because, as mentioned before, each forecast is subject to the most likely realization of the future, given present information.[12] We observe conditional forecasts under the Remain state (i.e. F_j^R according to the notation of the model) prior to the referendum. After the referendum and the victory of the Leave side, we observe the conditional forecasts F_j^L.

Figure 3 clarifies our empirical strategy to estimate the propaganda bias even if F_j^L is unobservable. In Figure 3, dotted lines represent the model predictions, whereas solid lines represent what is observable in the data. Forecasters with stakes and influence are predicted to release more pessimistic forecasts under the state L than the ones without, while the two groups of forecasters are predicted to release the same forecasts under the state R (see Figure 3a).

[10]Not all forecasters release new predictions every month, but we observe when the latest available prediction was released so that we exclude the ones that were not updated in the occasion of a new survey from the empirical analysis.

[11]All data refer to the changes in annual figures expressed in percent. For the January collection, the forecasts refer to year t.

[12]Table A3 in the Appendix shows by comparing the June and July 2016 surveys how the sample averages changed substantially at the time of the referendum. More specifically, forecasts for GDP growth decreased from 2 percent to less than 1 percent, together with a large increase in standard deviation. All GDP components, apart from government consumption, show the same pattern. Investments are the component that are affected the most, with forecasts falling from above 4 to -1.2 percent.

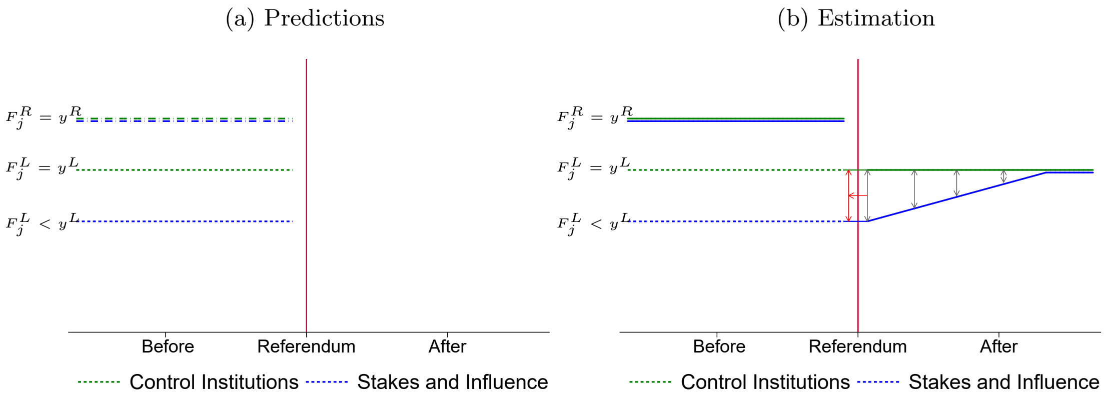

Figure 3: Theoretical Predictions and Empirical Analysis

Notes: Panel (a) reports the theoretical predictions on the extensive margin derived in Propositions 1 and 2, while Panel (b) adds to the predictions the information that is observable in the data. Dotted lines represent theoretical predictions, while solid lines represent what it is observable in the data. Blue lines represent an institution with stakes and influence, while green lines represent an institution in the *control* group.

In Figure 3b, we add to the predictions what is observable in the data at the forecaster level: F_j^R prior to the referendum and F_j^L once the result is realized.

We measure the difference between the forecasts released by institutions with stakes and influence and the other institutions in the sample just after the referendum (gray arrows in the figure) under the assumption that the first observation collected after the referendum reflects the forecast subject to the Leave state that an institution was releasing just before the vote. If the assumption holds and the difference between the two groups disappears moving away from the referendum date, the results of this empirical exercise can be interpreted as an estimate of propaganda bias, already in place prior to the referendum (red arrow). We believe this assumption to be reasonable, and the following arguments help in validating the assumption.

First, forecast institutions had only seven calendar days between the referendum and the day in which the HM Treasury started collecting the July survey.[13] In this limited window of time, it is unlikely that they updated the estimates or got new information about the economy in the event of Brexit, other than the referendum result. In fact, Figure 1 shows that our assumption is confirmed as least on average since the conditional forecasts subject to Leave did not vary between the last survey prior to the vote and the first after.[14]

Second, it is costly in terms of credibility for a forecaster to revise the estimates in the absence of a change of state. A large revision from a forecast under the state Remain to a forecast under

[13]The July 2016 edition of *Forecasts for the UK Economy* was published on July 20 and contained information from forecasters surveyed between July 1 and July 13.

[14]It should be noted that not all institutions surveyed by Consensus Economics are also surveyed by the HM Treasury's *Forecasts for the UK Economy* and vice versa, but the two samples are basically the same. Specifically, six institutions surveyed by the HM Treasury have not been surveyed by Consensus Economics, and Consensus Economics instead surveyed three institutions not included in our original sample.

Leave is justified and does not affect credibility, whereas the publication of a significantly different estimate from the one previously released that is subject to the same state would reduce credibility substantially. This argument is consistent with the empirical results in Nordhaus (1987), who motivates that forecasters move away slowly from the last period's consensus to an emerging reality, and the concept of consistency developed in Deb et al. (2018).[15]

Our identifying assumption, on the contrary, would be violated if forecasters with stakes respond irrationally to negative shocks to the economy that affect their profits. In Section 5.1 we address and rule out this possibility by comparing the results of our empirical analysis to their counterparts estimated before and after the 2008 financial crisis and the 2001 attacks to the World Trade Center in New York. We further strengthen our case against an irrational response in Section 5.2, where a GDP decomposition exercise shows that the propaganda bias is consistent with the predictions of standard macroeconomic theory.

4.1 Measures of Stakes and Influence

In our theoretical model, stakes represent the economic loss that a forecaster faces in the event the United Kingdom leaves the European Union. We argue that Brexit is likely to damage financial institutions and the institutions located in the City of London financial district, more than other forecasters. Hence, we measure stakes with an indicator equal to 1 if the forecast is a financial institution and 0 otherwise, and alternatively with an indicator capturing whether the institution is located in the City of London's financial district.[16] Among financial institutions, we use the percentage decline in stock market prices in the two banking days after the referendum to obtain a variation in stakes at the intensive margin (See Section A.4 in the Appendix for details). Forecasters have been very differently exposed to the immediate effects of Brexit, as reported in Figure A6 in the Appendix, which shows stock market losses ranging between 1.8 percent and 31 percent.[17]

It is not obvious how to measure influence. In the model, influence represents the weight that each individual forecaster has in the formation of the aggregate forecast that voters observe. We propose proxies that aim at understanding how known each institution is and whether it is established in the UK public debate. The first approach measures influence from the point of view

[15] The anonymity of the Consensus Economics survey does not rule out credibility concerns. Forecasters are held accountable by Consensus Economics, internal users and customers. We do not have credibility concerns in our model, which can be easily extended by adding a revision cost. This addition would not change the theoretical predictions.

[16] Ramiah et al. (2017) estimate that the victory of Leave has reduced the stock market prices of the banking sector by 15.37 percent in the very short run compared to baseline. Our data show that the financial institutions in our sample have faced on average a reduction in stock market prices of 16.37 percent in the two days after the referendum.

[17] The stock market loss in the very short run excludes the possibility of reverse causality since it is computed before any evaluation of the quality of published forecasts.

of the public. We use Google Trends to measure how often the users search for an individual forecaster on the web.[18] The second approach aims at capturing the media coverage. We use a simple web-scraping algorithm to retrieve the number of times in which each institution is mentioned in a Google News search.[19] In both cases, we create an indicator equal to 1 if the institution scores above a threshold and 0 otherwise to investigate the extensive margin, while we use the full support of the Google Trends and Google News measures (in logs) to proxy for influence at the intensive margin.[20]

4.2 Estimation

We investigate the existence of a propaganda bias by estimating the following baseline regression model

$$F_{j,m} = \theta_j + \delta_m + \mathbb{1}(\eta_j \gamma_j > 0) \sum_{k=-5}^{4} \beta_k \mathbb{1}(m = k) + \varepsilon_{j,m}, \tag{9}$$

where θ_j represents the forecaster fixed effects, δ_m represents the survey time effects and $k = -5, ..., 4$ measures the distance in months from the first survey after the vote. The indicator function $\mathbb{1}(\eta_j \gamma_j > 0)$ allows us to compare forecasters with stakes (η_j) and influence (γ_j) to the other institutions in the sample.

The dependent variable is the forecasts for GDP growth rate in the next year, where $F_{j,m}$ is the central forecast released by institute j in survey month m. β_0 estimates the propaganda bias around the date of the referendum, while $\beta_1, \dots, \beta_4$ capture the eventual persistence of the effect after the vote and $\beta_{-1}, \dots, \beta_{-5}$ reflect different judgments across groups between the announcement of the referendum and the vote. A negative β_0 would be consistent with the theoretical prediction that forecasters with stakes and influence have intentionally released pessimistic forecasts to influence voter behavior.

In the model, η_j and γ_j are treated as exogenous parameters, but empirically they are potentially correlated with omitted variables that also affect the published forecasts. For instance, influential forecasters might have become such because they have had better accuracy in the past or forecasters with stakes might be more pessimistic than others at any time period. The panel structure of our data allows us to control for all time-unvarying characteristics that are determinant

[18] Google Trends releases a normalized score on a weekly basis, such that the value 100 is assigned to the most-visited forecaster in the week of the largest number of visits. We then aggregate all summary reports for the year 2015 and assign the value 1 to those that scored at least 40. All institutions above the threshold have been visited in 2015 at least the 1% of the times of the most visited institution.

[19] Google News reports the total number of entries in the news archives for a given search item. We defined the threshold as having 20,000 citations in the archive, so the indicator takes value 1 for half of the forecasters and 0 for the other institutions.

[20] See the Data Appendix (Section A.4) for details on the group assignment and how the different definitions are correlated (see Table A4 in the Appendix).

of published forecasts and potentially correlated with stakes or influence in a dynamic difference-in-differences setup under the parallel trends assumption, where the treatment (i.e. the referendum result) is at least partially unexpected by the forecasters and only changes the central forecast from state R to state L.[21] In order to corroborate that our estimates are not due to omitted confounders or selection, we also show results using a specification excluding the forecaster-specific fixed effects as well as several robustness checks (see Section 5.1).

Economic forecasts are serially correlated due to persistence and the structure of annual horizons, and they are potentially correlated across different institutions within the same survey date since institutions share information and models at least partially (see e.g. Davies and Lahiri (1995) and Andersson et al. (2017)). For this reason, we use standard errors robust to two-way clustering (Cameron et al. (2011) and Cameron and Miller (2015)) at the forecaster and the survey levels.

Our measures of stakes and influence defined in Section 4.1 identify which forecasters have higher stakes and greater influence in the sample, but they do not guarantee that the remaining institutions have no stakes or no influence. If some forecasters with positive stakes and influence turned out to be in the *control* group, then our estimates would suffer an attenuation bias. First, all the forecasters that the HM Treasury reports in the survey might be influential. In that case, it should be assumed that $\gamma_j > 0$ for all institutions. Second, if all forecasters have stakes, then it should be assumed that $\eta_j > 0$ for all. We limit this potential concern by proposing two additional specifications in which we compare separately institutions with and without stakes and institutions with and without infuence. We expect to detect a larger coefficient in absolute terms in the event of an attenuation bias or conversely an attenuated coefficient.

5 Results

We report the estimation results for the extensive margin of propaganda bias in Table 1.[22] In column (1) we suppress the forecaster-specific fixed effects, and columns (2)–(4) report results from estimating the model in equation (9) using different measures of stakes and influence.[23] In

[21] The literature investigating correlations and plausible causal relationships between socioeconomic, historic and demographic characteristics of UK districts and the referendum results has been constantly increasing in the past few months. For instance, Viskanic (2017) finds that areas with higher concentration of Polish migrants are associated with a larger vote share of the Leave. On the contrary Becker et al. (2017) do not find any correlation between migration, trade exposure and the variation across-districts in the support for the Leave side, while individual characteristics such as per-capita income in the district and education have a much larger explanatory power and a negative effect. Alabrese et al. (2019) find using a large individual-level survey that support for Leave is associated with personal characteristics like age, ethnicity, education, use of smartphones and the internet and life satisfaction. See also Liberini et al. (2017) for a comprehensive literature review as of September 2017.

[22] For simplicity, in the table we limit ourselves to showing coefficients $\beta_0, ..., \beta_4$, whereas Table A5 in the appendix reports the estimation results with the anticipated coefficients $\beta_{-1}, ..., \beta_{-5}$.

[23] The combinations "Banks and Google News" and "City and Google News" are multicollinear. Hence, we do not report "City and Google News" in the table.

Table 1: Estimation of Propaganda Bias in GDP Growth Forecasts

	Stakes x Influence				Stakes	Influence
	(1)	(2)	(3)	(4)	(5)	(6)
Group x Referendum	-0.526***	-0.638***	-0.413**	-0.601***	-0.755***	-0.766***
	(0.183)	(0.171)	(0.193)	(0.173)	(0.204)	(0.166)
Group x Ref. (+1)	-0.711***	-0.753***	-0.654***	-0.751***	-0.743***	-0.578***
	(0.140)	(0.172)	(0.174)	(0.171)	(0.146)	(0.170)
Group x Ref. (+2)	-0.456***	-0.445***	-0.511***	-0.484***	-0.536***	-0.488***
	(0.148)	(0.144)	(0.143)	(0.142)	(0.155)	(0.145)
Group x Ref. (+3)	-0.420***	-0.483***	-0.484***	-0.451***	-0.479***	-0.447***
	(0.158)	(0.150)	(0.149)	(0.150)	(0.151)	(0.152)
Group x Ref. (+4)	-0.121	-0.126	-0.064	-0.125	0.001	-0.377***
	(0.145)	(0.122)	(0.129)	(0.122)	(0.149)	(0.127)
Observations	1,643	1,643	1,643	1,643	1,643	1,643
R^2	0.679	0.776	0.774	0.776	0.778	0.777
Fixed Effects		✓	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓	✓	✓
Measure of Stakes	Banks	Banks	Banks	City	Banks	
Measure of Influence	GTrends	GTrends	GNews	GTrends		GTrends

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variable is GDP growth rate in period $t+1$. For each column, the column title defines the relevant group assignment. All specifications include survey fixed effects. The estimated equation is (9). Standard errors robust to two-way clustering at the forecaster and the survey levels are in parentheses. *,**,*** represent the 10%, 5%, 1% significance levels.

column (5), we compare institutions with stakes and forecasters without, while in Column (6) we compare influential and non-influential forecasters. The difference in forecasts released by the two groups of forecasters in the first survey after the referendum is reported in the first row of the table, while coefficients labeled with (+1)...(+4) estimate the eventual persistence of the difference in the subsequent months.

In column (2) of Table 1, we estimate that forecasters with stakes and influence published a GDP growth rate forecast that was 0.638 percentage points lower than the other institutions. The result is larger in magnitude than the coefficient in column (1), suggesting that the potential selection bias at work without accounting for the unobserved heterogeneity would have underestimated the propaganda bias of forecasters with stakes and influence. In columns (3) and (4) we estimate coefficients of -0.413 and -0.601, respectively, showing that results are robust to changes in the measures of stakes and influence. In columns (5) and (6), we estimate a coefficient of -0.755 percentage points for the forecasters with stakes compared to their competitors and of -0.766 percentage points for the institutions with influence.

All specifications clearly confirm the predictions of our theoretical model about the presence of a propaganda bias, namely that forecasters with stakes and influence released more pessimistic forecasts for GDP growth around the Brexit referendum. The estimated propaganda bias is very large, statistically significant and precisely estimated. It explains, depending on the specification,

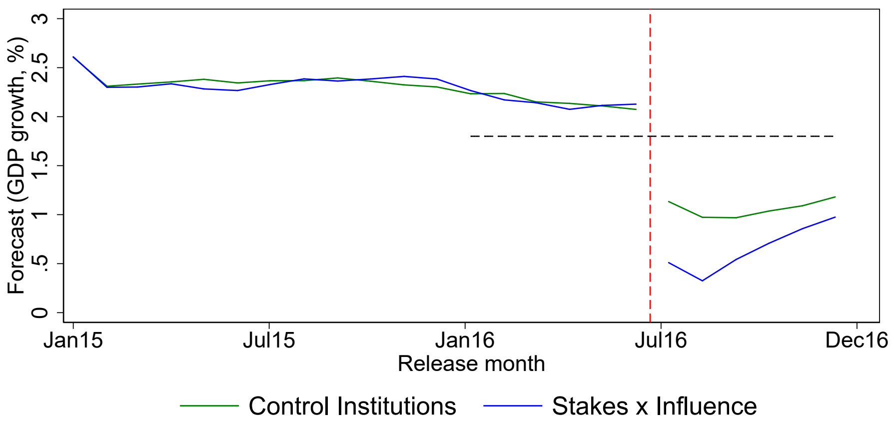

Figure 4: Pre-Referendum Trends

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The relevant measure of stakes is to be a financial institution (Banks). The relevant measure of influence is Google Trends (see Section 4.1 for details). The graph plots the average GDP growth rate forecast for the next year among forecasters belonging to different levels of stakes and influence between January 2015 and December 2016. Specifically, the blue line represents the group with stakes and influence as defined is section 4.2, while the green line represenst the remaining institutions. The black dashed line represents the actual GDP growth rate in 2017.

up to 50 percent of the forecast error at the time of the referendum.[24] In all specifications, we find that in the subsequent surveys the two groups converge in their forecasts as point estimates approach zero after four months for five out of six specifications. This additional evidence is consistent with a two-fold interpretation: first, the decision-making process leading to the withdrawal of the UK from the European Union did not end with the realization of the referendum result. Indeed, the victory of the Leave side opened new discussions among policymakers about the terms of the negotiation with the EU partners, the opportunity of remaining or not in the Single European Market (*soft* or *hard* Brexit) and the choice of the new prime minister after the immediate resignation of PM David Cameron. Second, even when the forecasters who were trying to influence the policy-making process no longer have had incentives to pursue their objectives, it might have taken time to converge back to their competitors' forecast so as not to lose credibility compared to their competitors. Crucially, the convergence after the referendum of the forecasts released by different institutions rules out alternative mechanisms orthogonal to the referendum and in line with behavioral biases (Sethi and Yildiz (2016), Gentzkow and Shapiro (2006) and Gentzkow et al. (2018)), which would have required the two groups to behave differently from each other in the subsequent months after the vote as well.

[24]Figure A8 reports the distribution of released forecasts just before and just after the referendum. It shows that in the first survey after the referendum there was a clear cluster of forecasters with stakes and/or influence in the bottom of the distribution of published scenarios, whereas this evidence was not in place in the June survey.

5.1 Robustness Checks

Evidence in support of the parallel trends assumption is presented in Figure 4, in which we plot the average GDP growth rate forecast for the following year released by the two groups of institutions. The figure shows that for many time periods prior to the referendum, forecasters with stakes and influence and those without released on average the same GDP growth rate forecasts (see Figure A7 in the Appendix for the other group specifications). This corroborates the results in Table A5 in the Appendix in which we document that anticipated coefficients are never distinguishable from zero. In addition, we perform a number of robustness checks to validate our empirical strategy and exclude that our estimates are driven by chance or a large variability in a relatively small sample.

First, we estimate the same regression model as in equation (9) at different points in time to assess whether there is evidence of similar estimates in other periods. Figure A9 in the Appendix reports the coefficients of propaganda bias estimated every month from 2015 to 2017. There is a large jump in the estimates at the referendum and in the months just following, while the pre-referendum estimates are centered at zero. Moreover, forecasters both with and without stakes and influence publish very similar estimates throughout the year 2017, confirming that our results are not consistent with alternative behavioral biases.

Second, we reduce the number of surveys included in the sample to the months much closer to the referendum. Figure A10 in the Appendix reports the estimated coefficients and confidence intervals for β_0 estimated with the support of several different windows of time. Estimated coefficients are stable for all specifications and are not sensitive to the time span of the data.

Third, we show that our results do not depend on the arbitrary thresholds chosen to determine the most influential institutions in the sample. Specifically, we move the thresholds used to separate influential and non-influential forecasters in order to alter the composition of the two groups. The results of this exercise as presented in Figure A11 show that a large propaganda bias is estimated using other thresholds as well, and that the coefficients reported in Table 1 do not represent extreme estimates.

Fourth, we address the possibility that our estimates may be inflated by the irrational response of institutions with stakes to large and negative economic shocks. In the time span of our data (from January 2012 to April 2018), we do not identify any negative event that can be comparable to the withdrawal from the European Union. Therefore, we digitalize the older publications of the *Forecasts for the UK Economy* collection from The National Archives online, enlarging the sample back in time until the year 1998. Then, we estimate a version of equation (9) in which we compare financial institutions and other forecasters before and after the unexpected beginning of

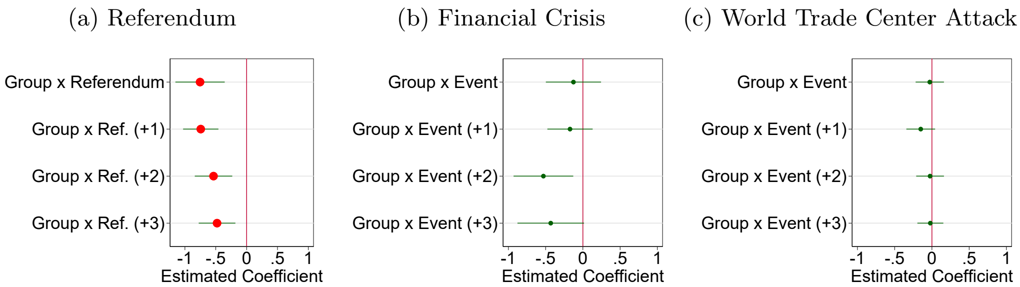

Figure 5: Effect during the EU Referendum and in the Occasion of Other Events

Notes: All forecasters surveyed by HM Treasury between January 1998 and April 2018 (2011 excluded). The relevant measure of stakes is to be a financial institution (Banks). The graphs report estimated coefficients and 95% confidence intervals from estimating (9), assuming that everyone is influential, in the occasions of the EU membership referendum on June 23, 2016; of the bankruptcy of the Lehman Brothers Holdings Inc. on September 15, 2008 and of the attacks to the World Trade Center on September 11, 2001. Sample restrictions: results in panel (a) are estimated in the time window between January 2012 and April 2018; results in panel (b) are estimated in the time window between January 2004 and December 2010; results in panel (c) are estimated in the time window between January 1998 and December 2003. The dependent variable is the GDP growth rate in the period $t+1$. Standard errors are robust to twoway clustering at the forecaster and the survey levels. Confidence intervals represent the 5% significance level.

the 2008 financial crisis and the 2001 attack on the World Trade Center in New York.[25,26] The results in Table A6, summarized in Figure 5, show that in the first survey after each event there is no evidence of a different behavior of institutions with stakes compared to their competitors. Coefficients are never distinguishable from zero in the first and second survey after the event, and they are much smaller in magnitude compared to the ones estimated in proximity to the EU membership referendum.[27] Moreover, we do not observe a significant revision of the forecasts in the first survey after the events, confirming that forecasters are unlikely to adjust their forecasts during a very limited window of time after an unexpected shock.

As a final check, we perform a Monte Carlo simulation with 10,000 draws, in each of which we randomly assign half of the institutions to a placebo treatment group, and estimate equation (9). Figure A12 shows the empirical density of the coefficient estimated at every draw, as well as where in the distribution the coefficients reported in Table 1 lie. Our results, as expected, always lie in the lower parts of the distribution, which is symmetric and centered in zero.[28]

[25] We identify the unexpected beginning of the financial crisis with the bankruptcy of the Lehman Brothers Holdings Inc. on September 15, 2008.

[26] We investigate forecasters' behavior around the time of the 2001 terrorist attack by estimating equation (9), assuming that everyone is influential, in a sample between year 1998 and year 2003, while we explore the reaction to the financial crisis restricting the sample to observations between year 2004 and year 2010. Compared to the sample used in the main empirical analysis and described in Section 4.1, a slightly different group of forecasters has been surveyed in the less recent publications.

[27] In the event of the financial crisis forecasters of both groups released more optimistic forecasts than the observed realization of the outcome, an eventual overreaction of institutions with stakes should be interpreted as a better forecast, rather than a low-quality one driven by panic.

[28] Other checks, that we do not include for brevity, include the estimation of equation (9) using forecasts for the inflation rate in the next year to address the possibility that the effect we observe is due to a merely nominal response. Results show that there is no evidence of different forecasts across groups when it turns to inflation forecasts.

5.2 GDP Decomposition

The empirical results show that the forecasters with stakes and influence predicted a larger downturn in the economy than their competitors. We proceed by decomposing the effect on GDP growth rate in its components. This contributes to the interpretation of the forecasters' behavior around the time of the referendum, as it highlights whether biased forecasts were published based on a precise rationale consistent with the voters' beliefs on the potential economic effects of Brexit. If forecasters conducted the propaganda bias in a rational manner, we expect to detect heterogeneous effects in line with the supposed economic effects of Brexit and consistent with predictions from standard macroeconomic models. Investments and trade are volatile and pro-cyclical, while consumption does not react as much and the goverment expenditure usually increases as a response to economic crises.

According to the expenditure approach, the GDP can be decomposed as follows:

$$Y = C + I + G + (X - M) \tag{10}$$

so that GDP growth rate can be expressed as

$$g_Y = g_C \varepsilon_C + g_I \varepsilon_I + g_G \varepsilon_G + (g_X \varepsilon_X - g_M \varepsilon_M), \tag{11}$$

where C is household consumption, I is investments, G is government consumption, X is exports and M is imports, while g and ε represent respectively the growth rate of each component and its share of GDP. In Figure 6 we plot results of estimating equation (9) for each component. The symbols report the estimated propaganda bias at the time of the referendum (β_0 in equation (9)) for each of the specifications used in Table 1.

The results show that the propaganda bias in investments is very pronounced, as estimated coefficients are around -2 percentage points, significant at least at the 10 percent level for most specifications. Consistent with the stylized evidence that investments are usually much more volatile than GDP, and that they are supposed to be among the major driving channels of the economic effects of Brexit (Dhingra et al., 2016b), the estimated coefficients are much larger than the ones estimated for GDP growth. In addition, our data forecast the short-term effects of the referendum result, and investments usually react immediately to changes in the political or economic environment.

Trade is expected to be another major channel of the effect of Brexit on economic growth (Dhingra et al., 2016a). Looking at the trade components of GDP, we find large and negative

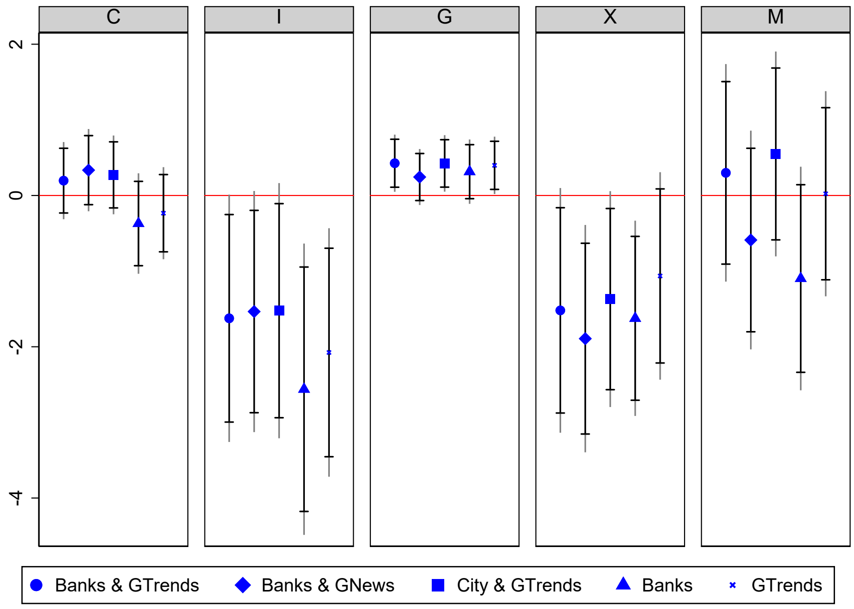

Figure 6: Estimation of Propaganda Bias in GDP Growth Components Forecasts

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variables are Household consumption, Investments, Government consumption, Exports and Imports in period $t+1$. All specifications include individual fixed effects and survey fixed effects. The estimated equation is (9), and the reported coefficient is β_0. Standard errors robust to two-way clustering at the forecaster and the survey levels. Gray lines represent 5% significance level while black lines represent 10% significance level.

coefficients on export, of similar magnitude as the investments growth, while estimated coefficients on imports are not distinguishable from zero. Overall, the institutions which released biased forecasts for GDP growth also predicted lower trade activity than their competitors due to a pessimistic forecast on export growth.

As expected, the coefficients on household consumption are never statistically different from zero at conventional significance levels. We detect small positive coefficients on government consumption, which translate into more pessimistic forecasts released by institutions with stakes and influence, even if generating the opposite effect on GDP growth according to equation (11).

This exercise shows that forecasters with stakes and influence conducted their propaganda bias by reporting much more negative views on investments and export growth, together with an excessive increase in government consumption to counteract part of the downturn.

5.3 Intensive Margin

The numerical solution of the theoretical model predicts that the propaganda bias is also present at the intensive margin. Namely, forecasters with more stakes, influence or both are predicted to release more biased forecasts than those having smaller values of these parameters. The result is intuitive. If one forecaster has a more relevant economic interest to maintain or has the opportunity to influence voters' beliefs more substantially, the incentive to conduct the propaganda bias is larger all else equal. As described in Section 4.1, we measure stakes using the short-run percentage decline in the stock market prices, and proxy for influence using a continuous version of the Google Trends and Google News variables described earlier (in logs). In Table 2, we estimate Difference-in-Differences models of the form

$$F_{j,m} = \theta_j + \delta_m + \beta_1 \eta_j \mathbb{1}(\eta_j\gamma_j > 0)\mathbb{1}(m = 0) + \beta_2 \gamma_j \mathbb{1}(\eta_j\gamma_j > 0)\mathbb{1}(m = 0) + \varepsilon_{j,m}, \qquad (12)$$

where the terms $\eta_j \mathbb{1}(\eta_j\gamma_j > 0)\mathbb{1}(m = 0)$ and $\gamma_j \mathbb{1}(\eta_j\gamma_j > 0)\mathbb{1}(m = 0)$ represent the interaction between the group indicator with the intensive margin variables γ_j and η_j at the time of the referendum.

The results in Table 2 strongly confirm the predictions about the existence of an intensive margin of propaganda bias. In columns (1) and (2), where we estimate the coefficients β_1 and β_2 in two separate regressions, we detect a large and negative correlation between the continuous measures of stakes and influence and the released forecast at the time of the referendum. Specifically, a one-standard deviation increase in the stock price loss after the referendum is associated with more pessimistic forecasts of 0.361 percentage points, while a one standard deviation increase in influence is associated with a lower F_j of 0.252 percentage points. In column (3), we estimate the parameters β_1 and β_2 in the same regression, as stated in equation (12), and confirm that both variables are negatively correlated with the forecast for GDP growth rate in the next year, although the coefficient attached to the continuous measure of influence is not significant.

In columns (4)–(6), we repeat the exercise interacting the continuous measures of stakes and influence with the groups defined in columns (5) and (6) of Table 1. These results also confirm the theoretical predictions about the existence of an intensive margin of propaganda bias. Specifically, column (6) in which the two coefficients are estimated simultaneously shows the negative and significant impact of stakes and influence on the published forecast.

Additional evidence is presented in Table A7 in the Appendix, where we repeat the exercise using Google News instead of Google Trends as the measure of influence, and in Figure A13 in the Appendix, where we show the negative relationship between the distance $F_j^L - F_j^R$ and the continuous measures of stakes and influence.

Table 2: Estimation of Propaganda Bias at the Intensive Margin in GDP Growth Forecasts

	Stakes x Influence			Stakes	Influence	
	(1)	(2)	(3)	(4)	(5)	(6)
Group x Ref. x Stock Price	-0.361***		-0.316***	-0.330***		-0.246**
	(0.094)		(0.102)	(0.098)		(0.098)
Group x Ref. x log(Trend)		-0.252***	-0.067		-0.308***	-0.197**
		(0.093)	(0.084)		(0.092)	(0.087)
Observations	1,643	1,643	1,643	1,643	1,643	1,643
R^2	0.770	0.769	0.770	0.770	0.769	0.770
Fixed Effects	✓	✓	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓	✓	✓
Measure of Stakes	Banks	Banks	Banks	Banks		Banks
Measure of Influence	GTrends	GTrends	GTrends		GTrends	GTrends

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variable is GDP growth rate in period $t+1$. For each column, the column title defines the relevant group assignment. In column (6), the group defined by institutions with stakes and the group defined by institutions with influence are included separately in the regression. In all specifications, continuous measures of stakes and influence have been standardized to have zero mean and unit variance. All specifications include forecaster fixed effects and survey fixed effects. The estimated equation is (12). Standard errors robust to two-way clustering at the forecaster and the survey levels are in parentheses. *,**,*** represent the 10%, 5%, 1% significance levels.

6 Concluding Remarks

Voters are seldom completely aware of different political platforms and the economic consequences of their choices before casting a vote since they lack incentives to invest in gathering costly information. Traditionally, we think of special interest groups and media as having some monopoly power, and releasing biased pieces of information in order to affect individuals' beliefs and in turn their voting behavior.

In this paper, we have introduced macroeconomic forecasters as political agents and suggested that they exploit their information monopoly over the future states of the economy to influence the policy-making process. First, we have analyzed theoretically a framework of asymmetric information between forecasters and voters approaching a referendum. Forecasters know the future state of the economy under each of the potential outcomes of a referendum. Voters care about the economy in the future, but since they do not know the consequences of leaving the status quo, they have to rely on scenarios published by professional forecasters. Under the assumptions of our model, it is optimal for forecasters with stakes and influence to publish biased scenarios instead of their best estimate. Second, we have tested the predictions of the model in the occasion of the EU membership referendum, also known as the Brexit referendum, held in the UK in 2016.

The results show that forecasters with stakes and influence released GDP growth forecasts in the case of Leave that were more pessimistic than the forecasts released by other institutions. Under the assumption that forecasts reported just after the referendum reflect the forecasts released prior to the vote, these results confirm the theoretical predictions about the presence of a propaganda bias in macroeconomic forecasts released by institutions with stakes and influence. We also find that the propaganda bias is present at the intensive margin, which is consistent with the predictions from the model, and that it is generated prevalently by biased forecasts on investment and trade exposure.

The predictions of biased forecasts in equilibrium differ from the lobbying models of campaign expenditures in electoral competition (e.g. Baron (1994)), despite the very similar setup, because of the institutional nature of referenda. In the models of electoral competition, policy convergence implies that, in equilibrium, organized groups face no incentives to favor one candidate over another, as the two are going to implement the same platform after the vote. The policy outcome is affected by the presence of special interest groups, but the voting is not. Instead, in a referendum, policy outcomes are given ex-ante and are divergent. In equilibrium, forecasters may have a preference for one over the other.

The propaganda bias might impact the welfare of both voters and forecasters. In the case of the Brexit referendum, in which the Leave side won, the realization of individual and aggregate shocks to preferences was determinant in generating the outcome that forecasters did not prefer. In that case, voters did not face any welfare loss compared to a world of unbiased forecasters, although the race was closer because of the bias. Forecasters with stakes and influence, on the contrary, ended up paying a large accuracy cost due to the bias, as well as facing the economic loss attached with the Brexit. In addition to those presented in the model, the propaganda bias might generate additional welfare reductions because of general equilibrium effects if consumers and investors make consumption and investment decisions based on the forecasts. If forecasts are biased, then economic agents may make incorrect decisions that could in turn reduce GDP.

Our results contribute to the political economics literature, by proposing economic forecasters as an additional player, and to the forecast evaluation literature, by highlighting an additional strategic behavior underlying forecasts errors. According to our theoretical predictions and empirical results, macroeconomic forecasters may use their information advantage to influence the decision-making process and favor the realization of their most preferred outcome. We recommend that voters and policymakers take this into account when forming their beliefs to avoid systematic mistakes.

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A Appendix

A.1 Proofs

A.1.1 Proof of Proposition 1

Equation (7) implies that $F_j^R = y^R \ \forall \ \eta_j \geq 0 \ \& \ \forall \gamma_j \geq 0$. We proceed by showing sufficient and necessary conditions for releasing $F_j^L = y^L \ \forall \ p^{L*} \in (0,1)$.

Proof. **Sufficiency**:
Suppose $\gamma_j = 0$. Then (8) implies that $F_j^L = y^L \ \forall \ \eta_j \geq 0$.
Suppose instead that $\eta_j = 0$. Then (8) requires either $F_j^L = y^L$ or $\psi\gamma_j = 0$. If $\gamma_j = 0$, then the previous part of the proof applies. Also, $\psi > 0$ by assumption. Hence, $F_j^L = y^L \ \forall \ \gamma_j \geq 0$. ■

Proof. **Necessity**:
Suppose that, to get a contradiction, $\gamma_j > 0$ and $\eta_j > 0$. (8) implies that

$$p^{L*}(F_j^L - y^L) = -\psi\gamma_j\Big(\frac{1}{2}(F_j^L - y^L)^2 + \eta_j C\Big) \leq 0, \tag{A1}$$

$\forall \ p^{L*} \in (0,1)$. $F_j^L - y^L = 0$ requires the RHS to be zero. Hence, $\gamma_j = 0$ or $\frac{1}{2}(F_j^L - y^L) - \eta_j C = 0$, which contradicts $\gamma_j > 0$ and $\eta_j > 0$. ■

A.1.2 Proof of Proposition 2

Equation (7) implies that $F_j^R = y^R \ \forall \ \eta_j \geq 0 \ \& \ \forall \ \gamma_j \geq 0$. We proceed by showing sufficient and necessary conditions for releasing $F_j^L < y^L \ \forall \ p^{L*} \in (0,1)$.

Proof. **Sufficiency**:
Suppose $\eta_j > 0$ and $\gamma_j > 0$. According to (A1),

$$\frac{1}{2}(F_j^L - y^L)^2 + \eta_j C \geq 0. \tag{A2}$$

Also, Proposition 1 applies. Hence, $F_j^L < y^L \ \forall \ p^{L*} \in (0,1)$. ■

Proof. **Necessity**:
Suppose that, to get a contradiction, $\eta_j = 0$. Then, Proposition 1 applies. Also, suppose that, to get a contradiction, $\gamma_j = 0$. Then, Proposition 1 also applies. ■

A.2 Details on the Numerical Solution of the Model

We solve the model numerically by calibrating the number of forecasters to 44 (to match our data) and impose equation (7). Hence, we solve a system of 44 individual versions of equation (8), plus (3) and (5), which pin down p^{L*} and close the political equilibrium.

Each forecaster is assigned an ID number, $j = \{1 : 44\}$. Forecasters 1 to 22 are assigned $\eta_j = 0$ and/or $\gamma_j = 0$. More specifically, we assign values such that seven forecasters have $\eta_j = 0$ but $\gamma_j > 0$, seven forecasters have $\gamma_j = 0$ but $\eta_j > 0$. We also ensure that eight forecasters have both $\eta_j = 0$ and $\gamma_j = 0$. We then randomly assign values between 0 and 1 to the remaining 22 forecasters with unassigned η_j and γ_j values. The γ_j values are then normalized so they sum to 1. With this assignment scheme, Proposition 1 and Proposition 2 predict that forecasters 1 to 22 should release an unbiased F_j^L while forecasters 23 to 44 should publish biased forecasts.

y^R is calibrated to 2.1 to match the average forecast conditional on Remain prior to the referendum, while y^L is set to 1.8 to match the actual GDP growth in 2017 (source UK Office for National Statistics). C takes the value 10 and ψ is randomly drawn from a uniform distribution between 0 and 1. The calibration of C and ψ modifies the level of the bias, but not its sign. Moreover, the value of C constrains the values of ψ for which the model has a solution.

The system of 46 equilibrium conditions is solved numerically using a Levenberg–Marquardt algorithm with an initial guess of no bias for all forecasters. The results are stored if a valid solution is found. We repeat the exercise, randomizing ψ at every iteration until 10,000 valid solutions are obtained (for some parameter draws, a solution could not be found).

The numerical exercise confirms Propositions 1 and 2, namely that a forecaster needs both stakes ($\eta_j > 0$) and influence ($\gamma_j > 0$) to release a biased F_j^L. As described in Section 3, this exercise also shows that there is a monotonic relation between F_j^L and both η_j and γ_j. Figure A3 shows the role of ψ. Figure A3a shows that there is a negative relation between ψ and the equilibrium value of p^{L*}. Figure A3b reports that there is also a negative relation between ψ and F_j^L so the bias is larger when ψ increases. Finally, Figure A4 shows how F_j^L altogether depends on η_j, γ_j and ψ.

A.3 Model with Bayesian Voters and Noisy Forecast

In this section, we modify the framework presented in Section 3 and allow voters to perform Bayesian updating taking into account that (i) voters know the distribution from which y^L is drawn; (ii) a share of forecasters have stakes, and hence may strategically release biased estimates; and (iii) voters observe a noisy signal for what forecasters publish.

For simplicity, we assume that voters are exposed to one forecaster, drawn at random. The forecaster has stakes ($\eta = 1$) with probability $q \in (0, 1)$ and has no stakes ($\eta = 0$) with probability $1 - q$. Also, assume that there is a transition error $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ between the information sent by the forecaster and the signal received by voters, so voters receive

$$\hat{F}^L = F^L + \varepsilon \tag{A3}$$

if the forecaster releases F^L. We assume that voters correctly observe y^R, but do not have complete information on y^L. Specifically, assume that voters know that y^L is drawn from the Gaussian distribution

$$y^L \sim \mathcal{N}(\mu, \sigma_L^2) \tag{A4}$$

and use the information gathered by the forecaster to update their prior μ.

Voters have the belief that if the forecaster has stakes, it will intentionally release a biased forecast so that $y^L = F^L + b$, whereas if the forecaster has no stakes, it will release $F^L = y^L$.

All other assumptions are the same as in the model presented in Section 3.

A.3.1 Voters

Consider a continuum of voters with total mass 1, with linear preferences over policy outcomes represented by $W(y) = y$. Consistent with the assumptions of the model in Section 3, individual i prefers alternative L over alternative R if and only if

$$y^L \geq y^R + \delta + \sigma_i. \tag{A5}$$

A.3.2 Forecaster

Consider one forecaster, drawn at random from a population of forecasters, a share q of which has stakes and a share $1 - q$ of which does not have stakes. The forecaster observes its type and releases F^L to minimize the loss function

$$\min_{F^L} \mathcal{L} = p^L(F^L)\Big[\eta C + \frac{1}{2}(F^L - y^L)^2\Big], \tag{A6}$$

where $\eta = 1$ if the forecaster has stakes and 0 otherwise and $C > 0$ is a fixed cost associated with the state L.[29]

A.3.3 Political Equilibrium

Voters anticipate that the signal they receive from the forecaster, $\hat{F}^L$, is potentially biased since the forecaster to which they are exposed has stakes with probability q.

[29]In this version of the model, we abstracted for simplicity from the trivial choice of $F^R = y^R$.

Voters perform Bayesian updating on their prior μ given the signal $\hat{F}^L$, taking into account that it is noisy and biased with probability q. Hence,

$$\mathbb{E}(y^L|\hat{F}^L) = m(\hat{F}^L + qb) + (1-m)\mu, \tag{A7}$$

where $m = \frac{\sigma_L^2}{\sigma_L^2+\sigma_\varepsilon^2}$ represents the optimal weighting.

Therefore, the voters' decision rule (A5) changes to

$$m(\hat{F}^L + qb) + (1-m)\mu \geq y^R + \delta + \sigma_i. \tag{A8}$$

Following the same steps as in Section 3, then

$$\pi^L = \frac{1}{2} + \phi\big(m(\hat{F}^L + qb) + (1-m)\mu - y^R - \delta\big) \tag{A9}$$

and

$$p^L = \frac{1}{2} + \psi\big[m(\hat{F}^L + qb) + (1-m)\mu - y^R\big]. \tag{A10}$$

Plugging (A10) and (A3) into (A6) and re-arranging, the forecaster minimizes

$$\min_{F^L} \Big\{\frac{1}{2} + \psi\big[m(F^L - y^L) + m(\varepsilon + qb + y^L) + (1-m)\mu - y^R\big]\Big\}\Big[\eta C + \frac{1}{2}(F^L - y^L)^2\Big] \tag{A11}$$

with the first-order condition

$$\begin{aligned}&(F^L - y^L)\Big\{\frac{1}{2} + \psi\big[m(F^L - y^L) + m(\varepsilon + qb + y^L) + (1-m)\mu - y^R\big]\Big\}\\&+ \psi m\Big[\eta C + \frac{1}{2}(F^L - y^L)^2\Big] = 0.\end{aligned} \tag{A12}$$

Equation (A12) implies that it is optimal for a forecaster with no stakes (i.e. $\eta = 0$) to release the unbiased forecast $F^L = y^L$. This is also a Perfect Bayesian Equilibrium (PBE) since the voters' belief that forecasters with no stakes released an unbiased forecast for y^L is consistent given optimal strategies. For a forecaster with stakes (i.e. $\eta = 1$), (A12) predicts that it is optimal to release a biased forecast. Also in this case, in a PBE voters' belief $y^L = F^L + b$ must be consistent given optimal strategies. Therefore,

$$-b^*\Big\{\frac{1}{2} + \psi\big[-mb^* + m(\varepsilon + qb^* + y^L) + (1-m)\mu - y^R\big]\Big\} + \psi m\Big[C + \frac{1}{2}b^{*2}\Big] = 0, \tag{A13}$$

where $y^L = F^L + b^*$ implicitly closes the model.

Therefore, Propositions 1 and 2 are also satisfied when voters have an unbiased prior on y^L and expect forecasters with stakes and influence to be biased in support of R.[30] The presence of an equilibrium propaganda bias, though internalized better by rational than by naive voters, does not rest on the non-rationality of some of the players and hence differs substantially from the behavioral biases introduced in the literature. The propaganda bias can be detected only in proximity to a voting decision.

[30] The forecasters' objective function is cubic in F^L and hence is convex only in a subset of its domain. However, it is possible to show that the unique point in which (A13) is satisfied identifies an interior minimum of the objective function since the second-order conditions are positive in equilibrium.

A.4 Data

A.4.1 Google News and Google Trends

Google Trends allows us to retrieve, for each institution, a measure of the number of Google searches from the public, relative to the most searched forecaster. We restrict to the UK and only consider searches in the 2015 calendar year (prior to the announcement of the referendum). After downloading weekly data in which the most searched institution scores 100, we aggregate on a yearly level and assign the binary measure of influence based on a threshold of 40, so that the forecasters above have been searched at least 1 percent of the times of the most searched institution (see Figure A5a). The same variable is also used for the analysis of the intensive margin.

The number of search results on Google News gives an indication of how influential an institution is according to the media. If it is frequently mentioned in the news, then the institution is more influential than if it were very rarely mentioned. To record the number of mentions, we perform for each institution a web-scraping exercise narrowing the search to the United Kingdom with archive settings. From the scraped website, we store the Google printed estimate of the number of search results. Then, the binary measure of influence is constructed based on a threshold of 20,000 citations, so that half of the forecasters are above and half are below (see Figure A5b).

A.4.2 Banks, City and Stock Price

We determine whether a forecaster is a financial institution by referring to each forecaster's official web page and relying on how the institution describes herself. We label those which best can be described as a financial institution as Banks. We also assert that all the institutions labeled as Banks are quoted on international financial markets. We also propose an alternative measure of stakes based on the geographical location of each forecaster. Specifically, we make use of the group assignment to City or Non-City made by HM Treasury in its data collection *Forecast for the UK Economy* under the assumption that forecasters located in the City of London's financial district have higher stakes than the others.

For the investigation of the intensive margin, we have computed for each institution the percentage decline in the stock market price after the referendum. Specifically, between the referendum date (since both the London and the New York stock markets closed before the announcement of the referendum results) and the second banking day after the referendum results (see Figure A6). We make this choice based on the stylized fact that the decline in market prices has been continuous not only on the very first day after the vote (a Friday), but also on the subsequent Monday. The data source for this analysis is Thomson Reuters Eikon.

A.5 Figures and Tables

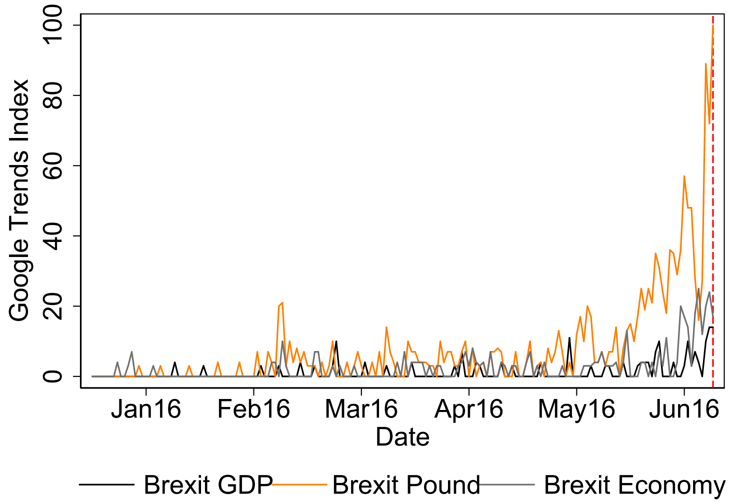

Figure A1: Brexit and the Economy Approaching the Referendum

Notes: The figure shows the Google Trends summary reports for the search entries “brexit GDP”, “brexit pound” and “brexit economy” on a daily basis before the referendum. Source: Authors’ elaboration on data from Google Trends.

(a) Opinion Polls

(b) Bookmakers’ Odds

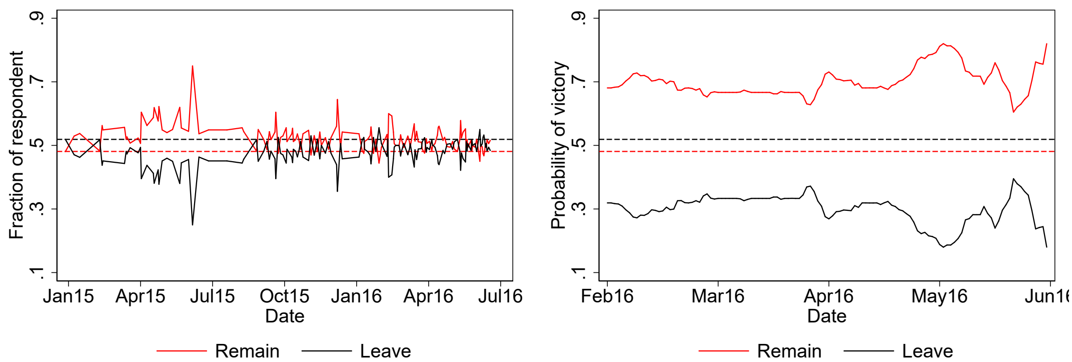

Figure A2: Opinion Polls and Bookmakers’ Odds Approaching the Referendum

Notes: Panel (a) reports the daily averages of all opinion polls recorded by the Financial Times between January 2015, before the official announcement of the referendum, and June 22, 2016. Source: Authors’ elaboration on data from the FT Research. Panel (b) reports the daily average of the odds released by all bookmakers recorded by the portal Betdata.io from the announcement of the referendum date until June 22, 2016. Source: Authors’ elaboration on data from BetData. In both panels, dashed lines represent the referendum result.

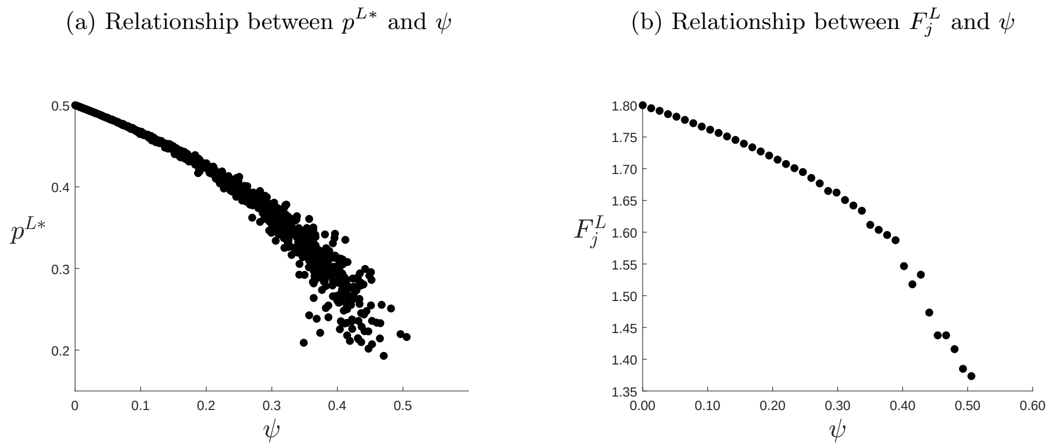

Figure A3: The Role of the Exogenous Parameter ψ

Notes: Graph (a) shows the equilibrium relationship between p^{L*} and ψ while graph (b) shows the relationship between F_j^L and ψ for a typical forecaster with $\eta_j = 0.5$ and $\gamma_j = 0.0345$.

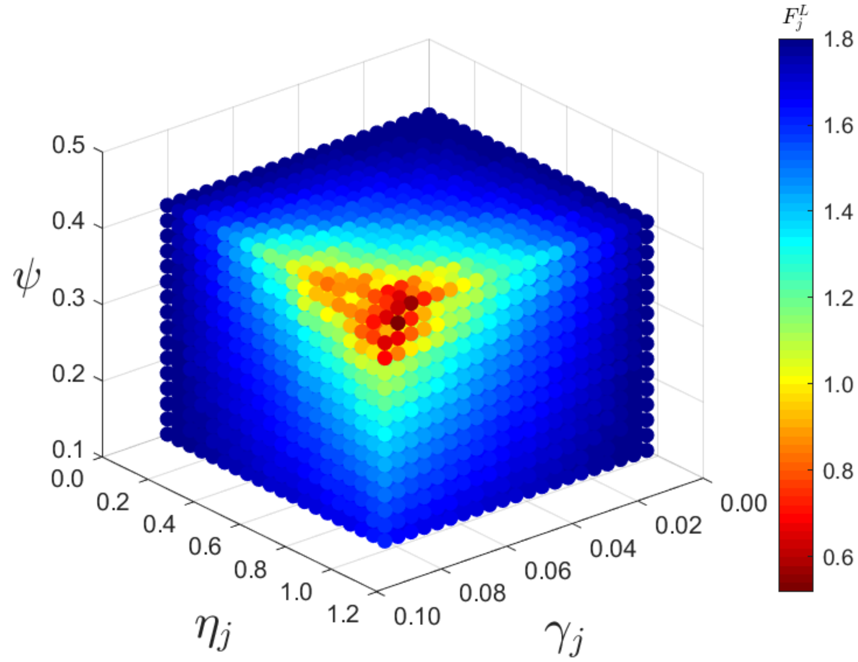

Figure A4: Results of the Numerical Solution to the Model

Notes: The figure reports, at the individual forecaster level, F_j^L as a function of the parameters η_j, γ_j and ψ. The F_j^L values are reported with different marker colors, as reported in the legend. Dark blue markers represent $F_j^L = y^L$, whereas red markers represent the relatively most biased forecasts.

(a) Google Trends (b) Google News

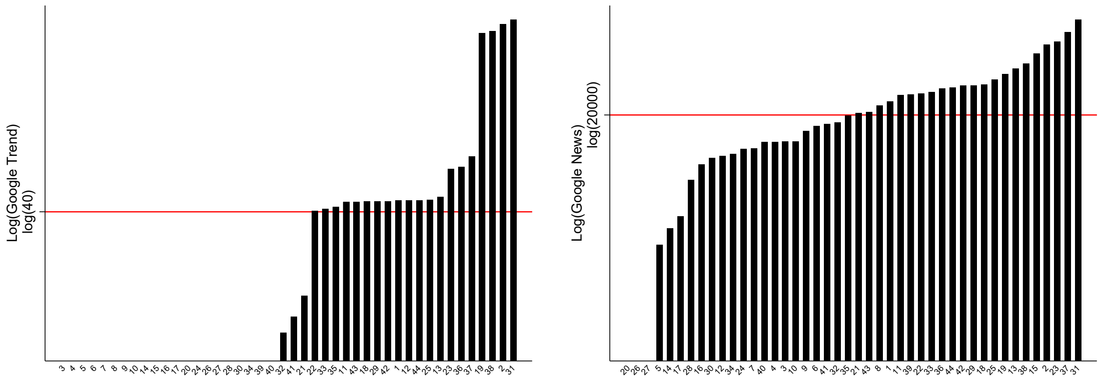

Figure A5: Google Measures

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The horizontal axis shows a forecaster ID. Panel (a) plots the number of searches (in logarithms) that the general public has done for each institution according to Google Trends. Panel (b) plots the number of citations (in logarithms) that each institution has reported in Google News. In both panels, the red horizontal line represents the threshold used to assign binary measures of influence used in the extensive margin analysis.

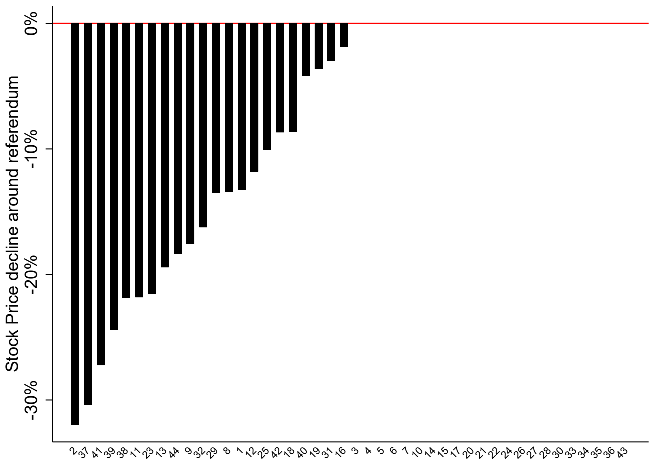

Figure A6: Stock Price

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The horizontal axis shows a forecaster ID. The figure reports for each financial institution the percentage variation in stock market prices between the referendum date and the second market day after the vote.

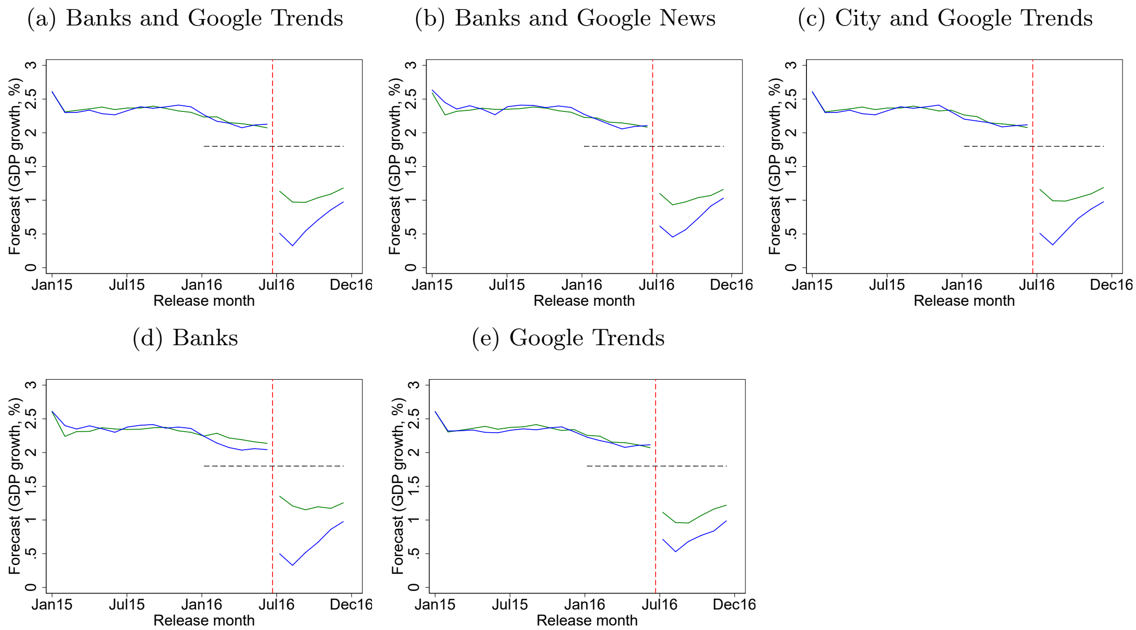

Figure A7: Pre-Referendum Trends for all Measures of Stakes and Influence

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. Each graph plots the average GDP growth forecast for period $t+1$ among institutions belonging to each of the different groups under investigation between January 2015 and December 2016. Specifically, blue lines represent the group under investigation as defined is Section 4.2, while green lines represent the remaining institutions. Black dashed lines represent the realization of GDP growth rate in 2017.

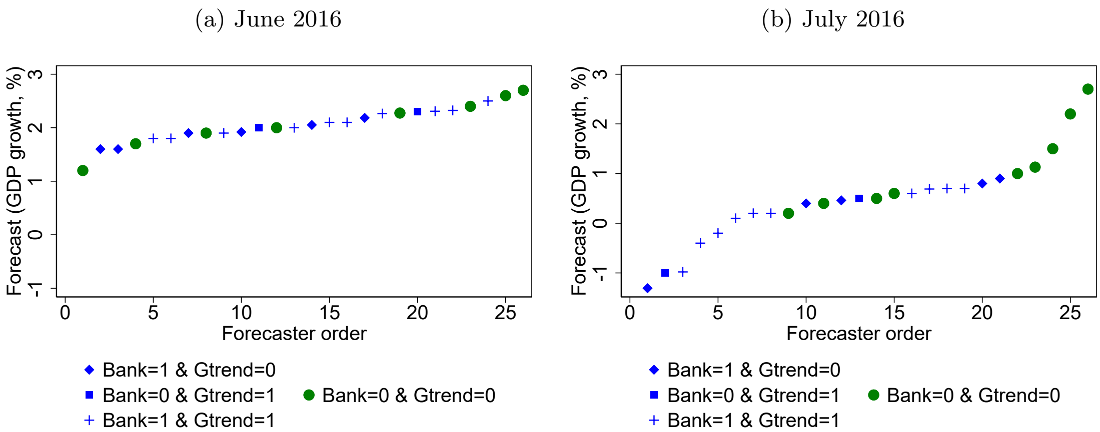

Figure A8: Forecast for the GDP Growth Rate in 2017 Before and After the Referendum

Notes: All forecasters surveyed by HM Treasury in June and July 2016. The relevant measure of stakes is to be a financial institution (Banks). The relevant measure of influence is Google Trends (see Section 4.1 for details). Each marker represents an individual GDP growth forecast for period $t+1$. Blue markers represent forecasters with stakes or influence, while green markers represent the control institutions.

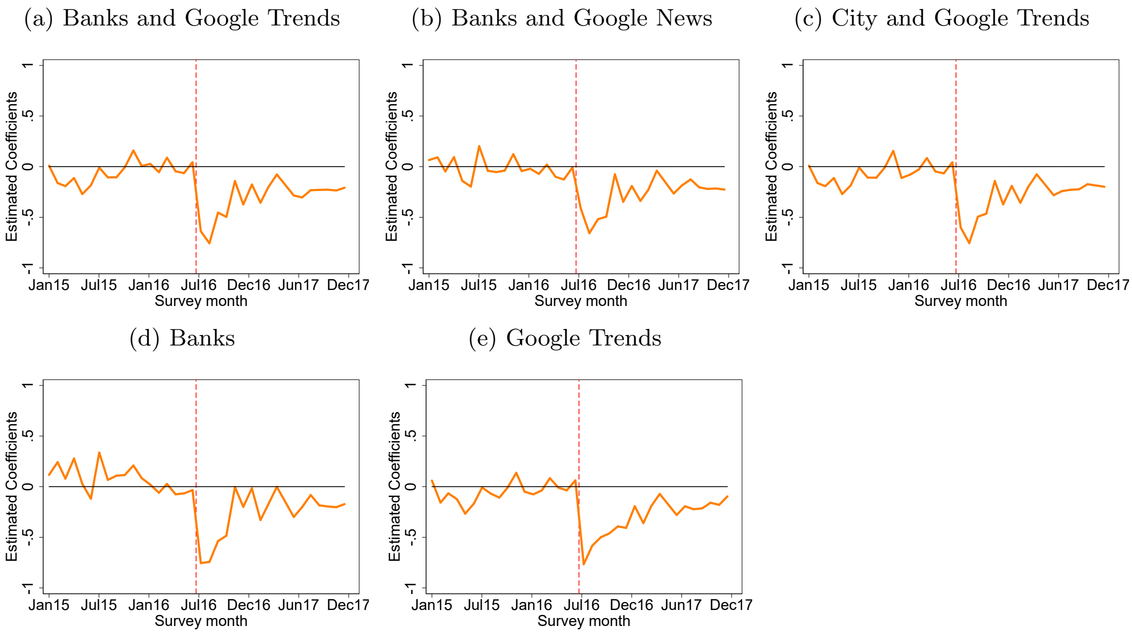

Figure A9: Estimated Propaganda Bias at Different Points in Time

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. In each graph, we replicate the results in Table 1, columns (2)–(6) by assuming a placebo referendum at every month between January 2015 and April 2018. All specifications include forecasters' fixed effects and survey fixed effects. The dependent variable is GDP growth rate in period $t + 1$. The orange line represents the estimated coefficient for β_0.

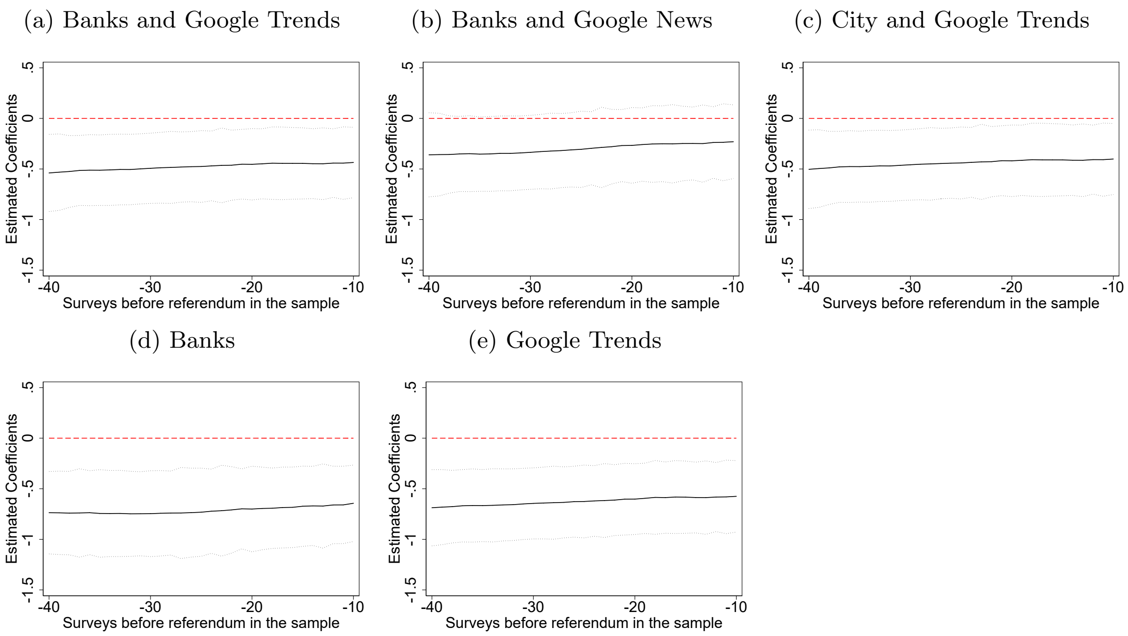

Figure A10: Sensitivity to Changes in the Time Span

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variable is GDP growth rate in period $t + 1$. In each graph, we replicate the results in Table 1, columns (2)–(6) by estimating with the support of sample that spans a different number of months. The black solid line represents estimated coefficients, while dotted lines represent the 95% confidence intervals. All specifications include forecasters' fixed effects and survey fixed effects.

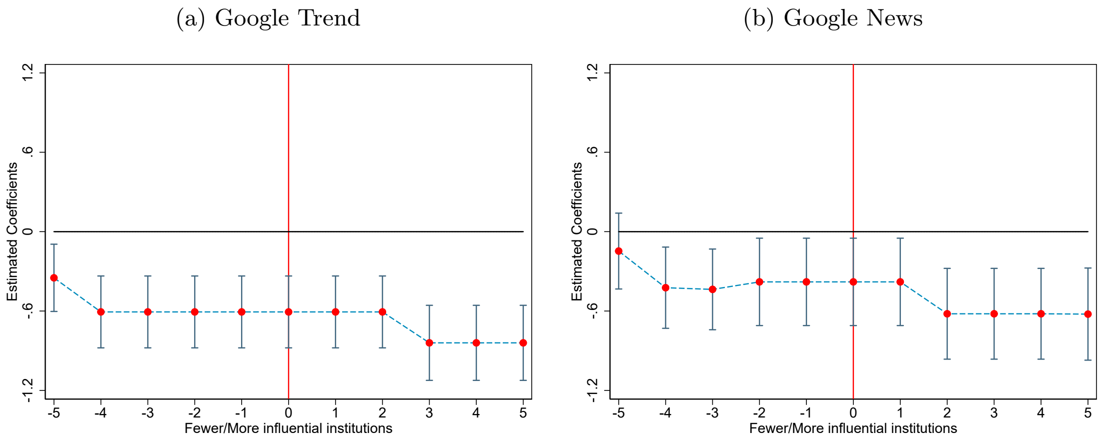

Figure A11: Sensitivity to the Definitions of Influence

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variable is GDP growth rate in period $t + 1$. In each panel, we estimate (9) by including in or excluding from the group of institutions with influence up to five forecasters before interacting with the stakes measure (Banks). All specifications include forecasters' fixed effects and survey fixed effects. Standard errors are robust to two-way clustering at the forecaster and the survey levels. For all regressions, graphs report estimated coefficients and 95% confidence intervals.

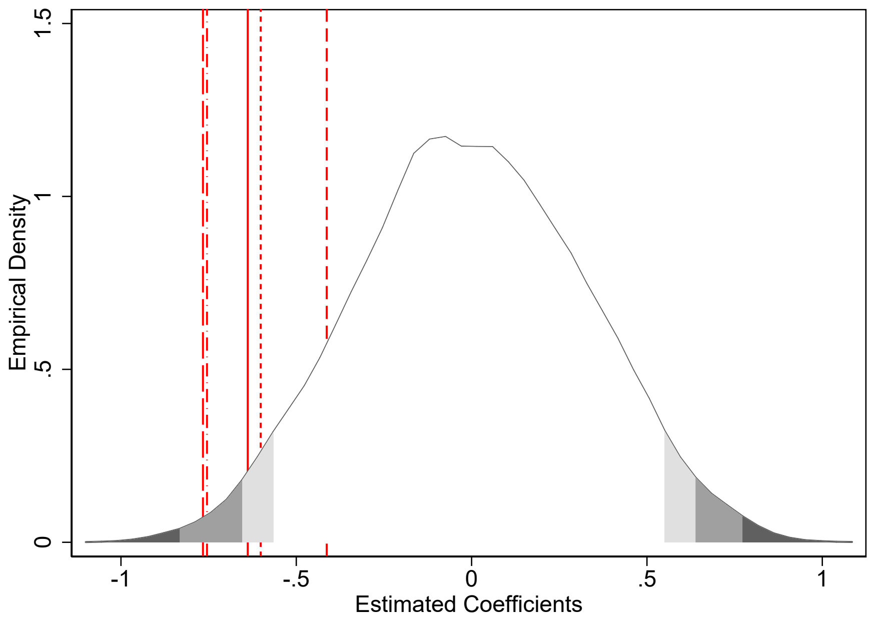

Figure A12: Monte Carlo Simulation: Random Assignment to Groups

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variable is GDP growth rate in period $t + 1$. We perform a Monte-Carlo simulation with 10,000 draws, in each of which we randomly assign half of the institutions to one group and the other half to another group. At each draw, we then estimate equation (9). All specifications include forecasters' fixed effects and survey fixed effects. We then plot the empirical density of estimated coefficients. Red lines represent the estimated coefficient obtained in columns (2)–(6) of Table 1. The areas shaded in gray show the 1%, 5% and 10% tails of the distribution.

(a) Stock Prices (b) Google News

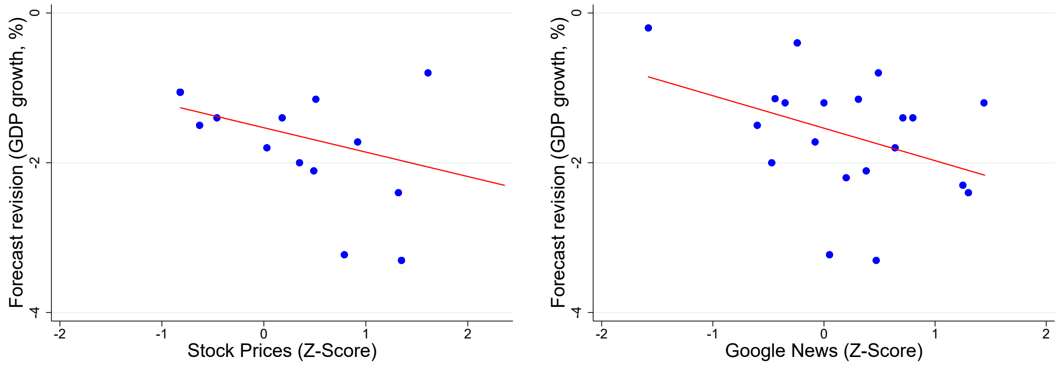

Figure A13: $F_j^L - F_j^R$ as a Function of Stakes and Influence

Notes: Panel (a) reports the bivariate regression $F_j^L - F_j^R = \alpha + \beta StockPrice_j + u_j$. Panel (b) reports the bivariate regression $F_j^L - F_j^R = \gamma + \delta GoogleNews_j + v_j$. In both panels, F_j^L represents the forecast published in July 2016 by each institution and F_j^R the forecast published in June 2016. Blue markers represent the sample average of $F_j^L - F_j^R$ within bins of 0.01 standard deviation units of $StockPrice$ and $GoogleNews$.

Table A1: Timeline of the United Kingdom European Union Membership Referendum

Jan. 22, 2013	•	Prime Minister David Cameron announced that a referendum on EU membership would be held before the end of 2017, on a renegotiated package, if elected in 2015
May 22, 2014	•	The UK Independence Party (UKIP) gets 26 percent of the vote in European elections and becomes the largest UK party in the European Parliament
May 7, 2015	•	The Conservative Party won the majority in 2015 general elections
May 27, 2015	•	The European Union Referendum Act 2015 (c. 36) was unveiled in the Queen's Speech
Dec. 17, 2015	•	The Act is given Royal Assent
Jan. 5, 2016	•	PM Cameron says ministers are free to campaign on either side
Feb. 20, 2016	•	PM Cameron announced the referendum date (23 June 2016)
Apr. 15, 2016	•	Start of the official campaign period
June 23, 2016	•	The United Kingdom European Union membership referendum
June 24, 2016	•	PM Cameron announces resignation after vote for Brexit
July 9, 2016	•	A petition calling for a second referendum was rejected by the Government
July 11, 2016	•	Theresa May formally declared leader of the Conservative Party
July 13, 2016	•	Theresa May appointed Prime Minister by Queen Elizabeth II
Jan. 24, 2017	•	The Supreme Court: the Government needs parliamentary approval to trigger Article 50
Mar. 28, 2017	•	Prime Minister Theresa May triggers Article 50, which starts the clock on the process of the UK leaving the EU

Notes: This table reports the key dates of the UK membership referendum, before and after the vote. Source: Authors' elaboration on information from https://www.bbc.com/news/politics.

Table A2: Descriptive Statistics

Variable	Mean	St. Dev.	Obs.
GDP	1.792	0.721	1,643
Private consumption	1.724	0.853	1,620
Fixed investment	3.429	3.225	1,626
Government consumption	0.208	1.087	1,618
Total exports	3.556	1.785	1,520
Total imports	2.984	2.044	1,518

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. All variables represent yearly growth rates (%) and refer to year $t+1$.

Table A3: Aggregate Views around the Referendum

	June 2016	July 2016
Variable	Mean (St. Dev.)	Mean (St. Dev.)
GDP	2.092 (0.339)	0.926 (1.041)
Private consumption	2.187 (0.399)	1.004 (1.370)
Fixed investment	4.234 (1.396)	-1.288 (4.608)
Government consumption	0.705 (0.706)	0.830 (0.758)
Total exports	3.436 (1.619)	2.808 (1.685)
Total imports	3.269 (1.503)	1.278 (2.610)

Notes: All forecasters surveyed by HM Treasury in June and July 2016. All variables represent yearly growth rates (%) and refer to year $t+1$.

Table A4: Correlation Matrix of the Assignment to Groups

	Banks	City	GTrends	GNews	Log(Trend)	Log(News)	Stock Price
Banks	1.00	0.82	0.46	0.45	0.50	0.51	0.79
City	0.82	1.00	0.47	0.37	0.49	0.52	0.71
GTrends	0.46	0.47	1.00	0.73	0.90	0.59	0.38
GNews	0.45	0.37	0.73	1.00	0.71	0.68	0.43
Log(Trend)	0.50	0.49	0.90	0.71	1.00	0.61	0.43
Log(News)	0.51	0.52	0.59	0.68	0.61	1.00	0.47
Stock Price	0.79	0.71	0.38	0.43	0.43	0.47	1.00

Notes: Correlation between the groups described in Section 4.1. All forecasters surveyed by HM Treasury between January 2012 and April 2018. Banks is an indicator taking the value 1 if the institution self-reports itself as a financial institution on the official website, and 0 otherwise. City is an indicator taking the value 1 if the institution is located in the City of London according to HM Treasury information, and 0 otherwise. Google Trend is an indicator taking the value 1 if the institution has a score above the threshold value reported in Figure A5a and 0 otherwise. GNews is an indicator taking the value 1 if the institution has a score above the threshold value reported in Figure A5b, and 0 otherwise. Log(Trend) and Log(News) are the continuous measures of influence associated with GTrends and GNews. Stock Prices is a continuous variable representing the drop in capitalization of each company between the referendum day and two days after.

Table A5: Estimation of Propaganda Bias in GDP Growth Forecasts – Pre-Referendum Coefficients

	Stakes x Influence				Stakes	Influence
	(1)	(2)	(3)	(4)	(5)	(6)
Group x Referendum	-0.526***	-0.638***	-0.413**	-0.601***	-0.755***	-0.766***
	(0.183)	(0.171)	(0.193)	(0.173)	(0.204)	(0.166)
Group x Ref. (+1)	-0.711***	-0.753***	-0.654***	-0.751***	-0.743***	-0.578***
	(0.140)	(0.172)	(0.174)	(0.171)	(0.146)	(0.170)
Group x Ref. (+2)	-0.456***	-0.445***	-0.511***	-0.484***	-0.536***	-0.488***
	(0.148)	(0.144)	(0.143)	(0.142)	(0.155)	(0.145)
Group x Ref. (+3)	-0.420***	-0.483***	-0.484***	-0.451***	-0.479***	-0.447***
	(0.158)	(0.150)	(0.149)	(0.150)	(0.151)	(0.152)
Group x Ref. (+4)	-0.121	-0.126	-0.064	-0.125	0.001	-0.377***
	(0.145)	(0.122)	(0.129)	(0.122)	(0.149)	(0.127)
Group x Ref. (-1)	0.089	0.041	-0.010	0.042	-0.033	0.056
	(0.112)	(0.096)	(0.098)	(0.096)	(0.111)	(0.093)
Group x Ref. (-2)	-0.050	-0.077	-0.137	-0.074	-0.077	-0.051
	(0.115)	(0.096)	(0.098)	(0.094)	(0.113)	(0.091)
Group x Ref. (-3)	0.045	-0.066	-0.117	-0.064	-0.092	-0.032
	(0.115)	(0.088)	(0.090)	(0.088)	(0.097)	(0.089)
Group x Ref. (-4)	0.085	0.053	-0.008	0.055	-0.004	0.050
	(0.147)	(0.101)	(0.112)	(0.099)	(0.127)	(0.099)
Group x Ref. (-5)	-0.065	-0.104	-0.112	-0.075	-0.116	-0.091
	(0.135)	(0.112)	(0.114)	(0.110)	(0.113)	(0.111)
Observations	1,643	1,643	1,643	1,643	1,643	1,643
R^2	0.679	0.776	0.774	0.776	0.778	0.777
Fixed Effects		✓	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓	✓	✓
Measure of Stakes	Banks	Banks	Banks	City	Banks	
Measure of Influence	GTrends	GTrends	GNews	GTrends		GTrends

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variable is GDP growth rate in period $t + 1$. For each column, the column title defines the relevant group assignment. All specifications include survey fixed effects. The estimated equation is (9). Standard errors robust to two-way clustering at the forecaster and the survey levels are in parentheses. *,**,*** represent the 10%, 5%, 1% significance levels.

Table A6: Reaction to Negative Economic Events

	Stakes			
	Financial Crisis		Terrorist Attacks	
	(1)	(2)	(3)	(4)
Group x Event	-0.127	-0.092	-0.029	-0.009
	(0.189)	(0.194)	(0.097)	(0.106)
Group x Event (+1)	-0.173	-0.179	-0.150	-0.105
	(0.155)	(0.154)	(0.098)	(0.098)
Group x Event (+2)	-0.530***	-0.456**	-0.025	-0.031
	(0.204)	(0.213)	(0.095)	(0.100)
Group x Event (+3)	-0.431*	-0.320	-0.021	-0.060
	(0.228)	(0.237)	(0.089)	(0.095)
Group x Event (-1)	-0.104	-0.031	0.042	0.054
	(0.191)	(0.201)	(0.114)	(0.124)
Group x Event (-2)	-0.375*	-0.390*	0.224**	0.270**
	(0.198)	(0.204)	(0.111)	(0.109)
Group x Event (-3)	-0.204	-0.308	-0.024	-0.082
	(0.191)	(0.193)	(0.077)	(0.081)
Group x Event (-4)	-0.108	-0.114	0.122	-0.006
	(0.175)	(0.178)	(0.090)	(0.088)
Group x Event (-5)	-0.034	-0.096	0.026	0.025
	(0.163)	(0.174)	(0.101)	(0.103)
Observations	1,954	1,954	1,632	1,632
R^2	0.885	0.885	0.717	0.717
Fixed Effects	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓
Measure of Stakes	Banks	City	Banks	City
Measure of Influence				

Notes: Columns (1) and (2): All forecasters surveyed by HM Treasury between January 2004 and December 2010. Columns (3) and (4): All forecasters surveyed by HM Treasury between January 1998 and December 2003. The dependent variables is the GDP growth rate in period $t+1$. For each column, the column title defines the relevant group assignment. All specifications include forecaster fixed effects and survey fixed effects. The estimated equation is (9), assuming that everyone is influential. Columns (1) and (2): $k = 0$ on the occasion of the first survey after the bankruptcy of the Lehman Brothers Holdings Inc. on September 15, 2008. Columns (3) and (4): $k = 0$ on the occasion of the first survey after the attack to the World Trade Center in New York on September 11, 2001. Standard errors robust to two-way clustering at the forecaster and the survey levels are in parentheses. *,**,*** represent the 10%, 5%, 1% significance levels.

Table A7: Propaganda Bias at the Intensive Margin in GDP Growth Forecasts – Google News

	Stakes x Influence			Stakes	Influence	
	(1)	(2)	(3)	(4)	(5)	(6)
Group x Ref. x Stock Price	-0.245**		-0.176	-0.330***		-0.292**
	(0.100)		(0.115)	(0.098)		(0.122)
Group x Ref. x log(News)		-0.364***	-0.143		-0.436***	-0.093
		(0.136)	(0.147)		(0.133)	(0.166)
Observations	1,643	1,643	1,643	1,643	1,643	1,643
R^2	0.769	0.769	0.769	0.770	0.769	0.770
Fixed Effects	✓	✓	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓	✓	✓
Measure of Stakes	Banks	Banks	Banks	Banks		Banks
Measure of Influence	GNews	GNews	GNews		GNews	GNews

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variable is GDP growth rate in period $t + 1$. For each column, the column title defines the relevant group assignment. In column (6), the group defined by institutions with stakes and the group defined by institutions with influence are included separately in the regression. In all specifications, continuous measures of stakes and influence have been standardized to have zero mean and unit variance. All specifications include forecaster fixed effects and survey fixed effects. The estimated equation is (12). Standard errors robust to two-way clustering at the forecaster and the survey levels are in parentheses. *,**,*** represent the 10%, 5%, 1% significance levels.