

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 if Brexit in the following year than other forecasters. The 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.

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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 advantage to influence the voting process. Our approach combines a simple theoretical framework, which shows how forecasting 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 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 complete information about the potential states of the economy after a referendum and therefore rely on professional forecasters to form beliefs. 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 potential states of the economy depend on published forecasts rather than on the states themselves. 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 measured by the forecast

¹The 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 casting the decisive vote to swing the election outcome is negligible.

error, whereas the information asymmetry 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 are more likely to release incorrect forecasts than other forecasters, and the size of the propaganda bias is increasing in both parameters. After the vote, forecasters face a trade-off between accuracy and consistency of their estimates, so that the propaganda bias is observable in the subsequent releases after the vote.

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 0.60 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 results confirm the theoretical prediction of increasingly more pessimistic forecasts when either stakes or influence increase. The empirical setup at hand does not allow to estimate the impact of the propaganda bias on the voters' decision, that would require the comparison with a counterfactual world in which forecasters release unbiased estimates. This exercise is possible within the theoretical model, which according to our baseline calibration suggests that the probability of Brexit has been reduced by 9 percentage points.

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 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, in line with the trade-off between accuracy and consistency after the vote postulated in the theoretical model.

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. \(2011\)](#), [DellaVigna et al. \(2014\)](#) and [Qin et al. \(2018\)](#)) 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 ([Martin and Yurukoglu \(2017\)](#) and [Durante et al. \(2019\)](#)). Our theoretical model and empirical results suggest that macroeconomic forecasters also exploit their information oligopoly 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.

²The 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.

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.

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 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 “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.

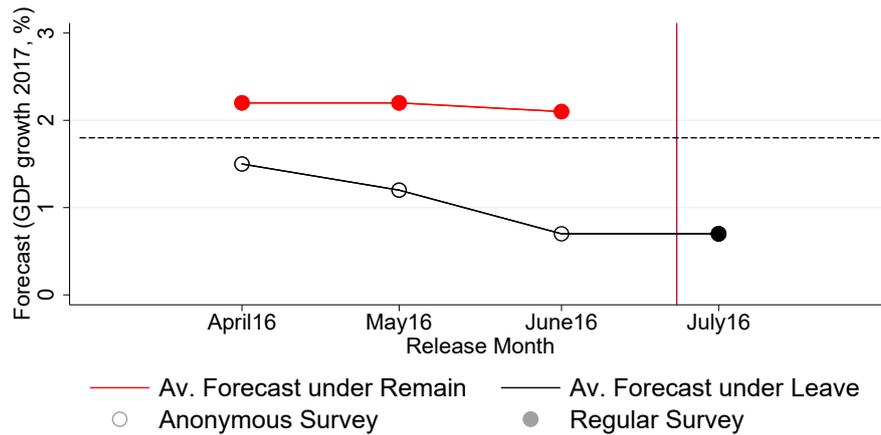


Figure 1: Consensus Forecasts for Leave and Remain around the Referendum

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).

Forecasters were heterogeneous in their estimates approaching the vote, as reported in Giles (2019), who detects that the think tank of pro-Leave economists *Economists for Brexit* was the most optimistic about the potential effects of Brexit on the economy, while the HM Treasury, lead by a pro-Remain minister, has been among the most pessimistic and incorrect forecasters.

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 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. 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 need professional forecasters to form beliefs before voting. Forecasters have the opportunity to exploit the asymmetry of information if they have an economic interest to defend that is at stake during the referendum.

We start by presenting a simplified version of our theoretical model, in which we assume that voters correctly observe y^R while they do not have perfect information on y^L , and gather information from only one forecaster. This simple version is helpful to follow the intuition behind the model, to familiarize with the notation and to get an intuitive solution. In the next subsection, we extend the model in several dimensions and solve it with the help of numerical methods: first, we assume that voters do not have perfect information on y^R either; second, we consider several forecasters that are heterogeneous in stakes and influence; third, we extend the timing of the model allowing forecasters to release multiple updates before and after the vote to follow the dynamic evolution of the propaganda bias; fourth, we extend the objective function of macroeconomic forecasters. While in the basic model the forecaster trades-off accuracy with the attempt of influencing the referendum results, in the extended version forecasters care also about the consistency over time of the forecasts that they release.

In the versions of the model presented in this section, we assume that voters are naive since they do not expect forecasts to be potentially biased. We relax this simplifying assumption in the model presented in Section A.2 in the Appendix, which yields qualitatively the same predictions.

⁴According 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 future relationships. The procedure ruled by Article 50 started on March 29, 2017. The timeline of key dates and events before and after the referendum are summarized in Table A1 in the Appendix.

3.1 Basic Model

3.1.1 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 and their ideological preferences.

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

$$y^L \geq y^R + \sigma_i, \quad (1)$$

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

We assume that voters do not observe y^L , although they know that $y^L \sim \mathcal{N}(\mu, \tau_L^{-1})$ and use a forecast, F^L , to update their beliefs before casting the vote. Voters observe a noisy measure of F^L from the forecaster:

$$\widehat{F}^L = F^L + \varepsilon \quad (2)$$

where $\varepsilon \sim \mathcal{N}(0, \tau^{-1})$ is a transition error capturing the friction between the information released by the forecaster and the signal received by voters. The intuition behind this transition error comes from the observation that voters tend to receive incomplete information about macroeconomic forecasts through mass media, policy makers or other individuals.

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

$$\mathbb{E}\left(y^L | \widehat{F}^L\right) \geq y^R + \sigma_i. \quad (3)$$

where $\mathbb{E}\left(y^L | \widehat{F}^L\right)$ is the posterior belief about y^L consistent with Bayesian updating. Formally,

$$\mathbb{E}\left(y^L | \widehat{F}^L\right) = \frac{\tau}{\tau_L + \tau} \widehat{F}^L + \left(1 - \frac{\tau}{\tau_L + \tau}\right) \mu^L = \gamma \widehat{F}^L + (1 - \gamma) \mu^L. \quad (4)$$

The parameter $\gamma = \frac{\tau}{\tau_L + \tau}$ captures the relative influence of the forecaster on the posterior belief

⁵In the case of the Brexit referendum, examples of σ_i are the different preferences that voters have on migration issues.

formed by voters.

Voters that are indifferent between the two alternatives are denoted swing voters. According to (3), they are defined by the relationship

$$\tilde{\sigma} = \mathbb{E}\left(y^L | \hat{F}^L\right) - y^R.$$

By ranking voters according to their ideological parameter, all individuals with $\sigma_i \in \left[-\frac{1}{2\phi}, \tilde{\sigma}\right]$ 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

$$\pi^L = \int_{-\frac{1}{2\phi}}^{\tilde{\sigma}} \phi \, di = \phi \left(\tilde{\sigma} + \frac{1}{2\phi} \right) = \frac{1}{2} + \phi \left[\gamma \left(F^L + \varepsilon \right) + (1 - \gamma) \mu^L - y^R \right],$$

while the probability that L wins is given by

$$p^L = P\left(\gamma\varepsilon > y^R - \gamma F^L - (1 - \gamma)\mu^L\right) = 1 - G\left(y^R - \gamma F^L - (1 - \gamma)\mu^L\right), \quad (5)$$

where $G(\cdot)$ is the cumulative distribution function of the gaussian random variable $\gamma\varepsilon$. In political equilibrium, the probability that L wins depends on F^L instead on the true y^L , providing the incentive to the forecaster to influence the voting outcome if it has economic interests at stake during the vote.

3.1.2 Forecaster

Assume a forecaster has perfect information on y^L and y^R and can either face an economic loss under L or be indifferent between the two states.⁶ The forecaster minimizes the following loss function with respect to F^L , given y^L and voters' strategies:

$$\min_{F^L} \mathcal{L} = p^L \left[\eta C + \frac{1 + \gamma}{2} \left(F^L - y^L \right)^2 \right], \quad (6)$$

where $F^L \in \left[\underline{F}^L, \overline{F}^L \right]$ represents the forecast released under state L, $C > 0$ represents a cost associated with state L, p^L is the probability of leaving the status quo and the parameter $\eta \geq 0$

⁶The theoretical predictions derived from the theoretical model do not depend on the assumption that the forecaster is perfectly informed about y^L and y^R . The same theoretical predictions would be derived assuming that the forecaster receives noisy signals about y^L and y^R , as long as the signal is not systematically biased. The assumption of perfect information has been formulated solely to simplify the notation.

captures the stakes of the forecaster on the referendum outcome.^{7,8} 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. If the forecaster faces a loss in the event that L wins, then it has a direct economic interest in the referendum result and hence has stakes, while if the forecaster is indifferent between the two states, then it has no stakes on the referendum result, and only aims to minimize the forecast error.

This simple loss function, which entails a linear incentive for bias and a quadratic incentive for accuracy, shows that the problem at hand is not as straightforward as it seems. First, the forecaster is able to influence both the probability of paying the cost attached to L, ηC , and the probability of paying the accuracy cost, $\frac{1+\gamma}{2}(F^L - y^L)^2$, which is endogenous to the referendum outcome. Second, higher influence increases the marginal impact of F^L on p^L , but also the cost that the forecaster pays if she releases incorrect estimates.

Assuming an interior solution, the first-order condition with respect to F^L takes the form

$$\begin{aligned} & \gamma g\left(y^R - \gamma F^L - (1 - \gamma)\mu^L\right) \left[\eta C + \frac{1 + \gamma}{2} (F^L - y^L)^2\right] + \\ & (1 + \gamma) (F^L - y^L) \left[1 - G\left(y^R - \gamma F^L - (1 - \gamma)\mu^L\right)\right] = 0, \end{aligned} \quad (7)$$

where $g(\cdot)$ is the probability density function of the random variable $\gamma\varepsilon$ with cumulative distribution function equal to $G(\cdot)$. From (7), we derive the following proposition.

Proposition 1. Existence of political equilibrium with unbiased forecasts

Under the assumptions of the model, $F^L = y^L$ is part of a political equilibrium if and only if $\eta = 0$ or $\gamma = 0$.

Proposition 1 predicts that the forecaster releases its best estimate for y^L approaching the referendum only if it has no stakes or no influence. This result is not surprising since a forecaster who does not prefer one state over the other or cannot influence voting behavior because voters are perfectly informed over y^L does not face a trade-off between accuracy and the referendum outcome, and only aims to minimize the forecast error.

The optimal bias, for any $\eta > 0$, $\gamma > 0$ is implicitly determined by (7) and takes the form

$$F^L - y^L = -f\left(\eta, \gamma, C, \mu^L, y^R\right) < 0. \quad (8)$$

⁷In the occasion of a referendum, forecasters may either have stakes in support of a state or in support of the other or being indifferent between the two alternatives. We assume for simplicity that $\eta \geq 0$ so that forecasters can either have preferences in support of R or being indifferent between the two states in order to derive theoretical predictions consistent with the types of forecasters observed in our sample. See Section 4.1 for details.

⁸The sign of η determines the sign of the propaganda bias at the individual level, but not its presence.

The optimal bias derived in (8) implies the following proposition.⁹

Proposition 2. Existence of political equilibrium with a propaganda bias

Under the assumptions of the model, necessary and sufficient conditions for $F^L \in \left[\underline{F^L}, y^L \right)$ to be part of a political equilibrium are $\eta > 0$ and $\gamma > 0$.

Proposition 2 predicts that in a political equilibrium a forecaster with stakes ($\eta > 0$) and influence ($\gamma > 0$) will 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. This model is consistent with the findings in Giles (2019), who documents that the HM Treasury, lead by a pro-Remain minister, released very pessimistic forecasts approaching the vote and that, conversely, the pro-Leave *Economists for Brexit* released very optimistic forecasts prior to the referendum.

3.1.3 Intuition and Mechanisms

This basic theoretical framework is simple and tractable, but nevertheless provides sufficient insights about the incentives that the asymmetry of information gives to the forecaster in this strategic game. A forecaster who releases biased estimates solves the trade-off between accuracy and the attempt to influence the outcome of the voting process by taking double advantage of its strategy. The optimal choice of F^L takes into account that if 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 $\frac{1+\gamma}{2}(F^L - y^L)^2$. The strategic manipulation of the forecast is very appealing for the forecaster, who can take the opportunity to 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, a reduction in its exogenous component $1 - G(y^R - \gamma y^L - (1 - \gamma)\mu^L)$ increases the magnitude of the bias for any $y^L < y^R$. 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 the probability of leaving is relatively high, then higher expected

⁹The forecasters' objective function is cubic in F^L and hence is convex only in a subset of its domain. Among the two solutions of (7), we select the one satisfying the second-order conditions with respect to F^L .

marginal cost of propaganda bias attenuates it.

The equilibrium propaganda bias reduces the voters' welfare in the case of both naive and rational voters (presented in Section A.2 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 forecaster has fewer stakes than the average, and become more prone to vote for R if the forecaster instead has more stakes than the average. In the case of rational voters, the propaganda bias also reduces the welfare of the forecaster since it reduces its accuracy without influencing the expected referendum result, and hence represents a case of inefficiency in this market.

3.2 Extended Model

In this version, we model the announcement periods, the referendum campaign, and the post-referendum periods. At the beginning of the game, the political economy is subject to a status-quo with an associated economic outcome, and J forecasters and voters are informed that a referendum will take place between the status quo and an alternative. During the campaign period k , the two alternatives are discussed, and voters have to choose between two states, $S \in \{L, R\}$, each of them associated with an economic outcome y^S . As in the basic version, L represents the decision of leaving the status quo for the alternative, while R is the decision of remaining.

Here we assume that voters do not observe y^S , although they know that $y^S \sim \mathcal{N}(\mu^S, \tau_S^{-1})$, such that $\tau_L = \rho\tau_R$ with $\rho \in (0, 1)$ and use forecasters to update their beliefs over y^L and y^R before casting the vote. The parameter ρ indicates that voters have better knowledge about the current state R than they do on the alternative L. Forecasters have economic preferences over the alternative states and observe perfectly y^R and y^L . During periods 1 to $k - 1$, each forecaster releases a forecast for y^R , denoted $F_{j,t}^R$. During the campaign period k , each forecaster releases both $F_{j,k}^R$ and $F_{j,k}^L$. After the vote, forecasters will release only the forecast subject to the state winning the referendum.

Forecasters release strategically their forecasts to the public based on three competing incentives. First, they have incentives in minimizing the forecast error (i.e. the difference between the forecast and the ex-post realization of the economic outcome subject to the same state); second, forecasters aim to influence voters' beliefs over the referendum by manipulating the released forecasts; third, forecasts subject to the same state need to be consistent over time for the forecaster to preserve its credibility.

3.2.1 Voters

The voters' decision rule follows (1). Differently from the basic model, we assume now that in each period, they observe a noisy measure of $F_{j,t}^S$ from each forecaster

$$\widehat{F}_{j,t}^S = F_{j,t}^S + \varepsilon_{j,t} \quad (9)$$

where the transition error $\varepsilon_{j,t} \sim \mathcal{N}(0, \tau_{j,t}^{-1})$ such that $\tau_{j,t}^{-1} = \beta \tau_{j,t-1}^{-1}$ where $\beta \in (0, 1)$ captures the heterogeneity over time in the precision of the signal that forecasters send to voters. The assumption that the variance of the transition error is reduced every period by a constant reduction reflects the idea that forecasts become more precise the shorter is the time horizon before the realization of the outcome.¹⁰ We define $\tau_j := \tau_{j,0}$ such that $\tau_{j,t}^{-1} = \beta^t \tau_j^{-1}$.

Voters aggregate information coming from different forecasters using Bayesian updating, and form posterior beliefs about the alternative states of the economy before casting a vote. Formally,

$$\begin{aligned} \mathbb{E}\left(y^L | \widehat{F}_{1,k}^L, \dots, \widehat{F}_{J,k}^L\right) &= \frac{\tau_L}{\tau_L + \left(\frac{1}{\beta}\right)^k \sum_{j=1}^J \tau_j} \mu^L + \left(\frac{1}{\beta}\right)^k \sum_{j=1}^J \frac{\tau_j}{\tau_L + \left(\frac{1}{\beta}\right)^k \sum_{j=1}^J \tau_j} \widehat{F}_{j,k}^L \\ &= m \mu^L + \left(\frac{1}{\beta}\right)^k \sum_{j=1}^J \gamma_j \widehat{F}_{j,k}^L := \widetilde{F}^L, \end{aligned} \quad (10)$$

and

$$\begin{aligned} \mathbb{E}\left(y^R | \widehat{F}_{1,1}^R, \dots, \widehat{F}_{J,k}^R\right) &= \frac{\tau_R}{\tau_R + \sum_{j=1}^J \sum_{t=1}^k \left(\frac{1}{\beta}\right)^t \tau_j} \mu^R + \sum_{j=1}^J \sum_{t=1}^k \frac{\left(\frac{1}{\beta}\right)^t \tau_j}{\tau_R + \sum_{j=1}^J \sum_{t=1}^k \left(\frac{1}{\beta}\right)^t \tau_j} \widehat{F}_{j,t}^R \\ &= \nu \left[\frac{1}{\rho} m \mu^R + \sum_{j=1}^J \gamma_j \sum_{t=1}^k \left(\frac{1}{\beta}\right)^t \widehat{F}_{j,t}^R \right] := \widetilde{F}^R, \end{aligned} \quad (11)$$

where $m := \frac{\tau_L}{\tau_L + \left(\frac{1}{\beta}\right)^k \sum_{j=1}^J \tau_j}$, $\gamma_j := \frac{\tau_j}{\tau_L + \left(\frac{1}{\beta}\right)^k \sum_{j=1}^J \tau_j}$ and $\nu := \frac{\tau_L + \left(\frac{1}{\beta}\right)^k \sum_{j=1}^J \tau_j}{\frac{1}{\rho} \tau_L + \frac{1 - \left(\frac{1}{\beta}\right)^k}{\beta - 1} \sum_{j=1}^J \tau_j}$, so that

$\left(\frac{1}{\beta}\right)^k \sum_{j=1}^J \gamma_j = 1 - m$.¹¹ Consistently with the basic version of the theoretical framework, the parameter γ_j is a sufficient statistics to determine the influence of each forecaster on the voters' posterior belief.

¹⁰See e.g. [Andersson et al. \(2017\)](#) for an analysis of the expected size of forecast errors at different horizons.

¹¹Notice that the final step of (11) comes from the application of the formula for the geometric series $\sum_{x=1}^n x^n = \frac{x - x^{n+1}}{1 - x}$.

Naive voters do not expect forecasters to release biased $F_{j,t}^L$, and hence vote based on

$$\tilde{F}^L \geq \tilde{F}^R + \sigma_i. \quad (12)$$

Following the same steps as in the basic model, the probability that state L wins is

$$p^L = 1 - G\left(m\left(\frac{\nu}{\rho}\mu^R - \mu^L\right) - \sum_{j=1}^J \gamma_j \left[\left(\frac{1}{\beta}\right)^k F_{j,k}^L - \nu \sum_{t=1}^k \left(\frac{1}{\beta}\right)^t F_{j,t}^R\right]\right), \quad (13)$$

where $G(\cdot)$ is the cumulative distribution function of the gaussian random variable $\sum_{j=1}^J \gamma_j \left[\left(\frac{1}{\beta}\right)^k \varepsilon_{j,k} - \nu \sum_{t=1}^k \left(\frac{1}{\beta}\right)^t \varepsilon_{j,t}\right]$. Also in this version of the model, forecasters have the leverage to influence the voting result and to favor the most preferred outcome. The allocation of the propaganda bias between $F_{j,t}^L$ and $F_{j,t}^R$ depends on the number of pre-referendum time periods during which forecasters released a forecast for y^R , the relative precision of voters' prior ρ and on the variation over time in the precision of forecaster's signal determined by β .

3.2.2 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.¹² Each forecaster minimizes the following expected loss function with respect to $F_{j,t}^L$ and $F_{j,t}^R$, given y^S as well as other forecasters' and voters' strategies:

$$\begin{aligned} \min_{F_{j,t}^L, F_{j,t}^R} \mathcal{L}_j = & \left(1 - p^L\right) \sum_{t=1}^k \left(\frac{1}{\beta}\right)^t \left(1 + \gamma_j^R\right) \left[\frac{\alpha}{2} \left(F_{j,t}^R - y^R\right)^2 + \frac{1 - \alpha}{2} \left(F_{j,t}^R - F_{j,t-1}^R\right)^2\right] \\ & + p^L \left[\left(\frac{1}{\beta}\right)^k \left(1 + \gamma_j^L\right) \frac{\alpha}{2} \left(F_{j,k}^L - y^L\right)^2 + \eta_j C\right] \\ & + \sum_{S \in \{L, R\}} p^S \sum_{t=k+1}^T \left(\frac{1}{\beta}\right)^t \left(1 + \gamma_j^S\right) \left[\frac{\alpha}{2} \left(F_{j,t}^S - y^S\right)^2 + \frac{1 - \alpha}{2} \left(F_{j,t}^S - F_{j,t-1}^S\right)^2\right], \quad (14) \end{aligned}$$

where $F_{j,t}^S \in [\underline{F}_j^S, \overline{F}_j^S]$ represents the forecast released by institution j in period t subject to 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.¹³ Moreover, $\alpha \in [0, 1]$ indicates

¹²The theoretical predictions derived from the theoretical model do not depend on the assumption that forecasters are perfectly informed about y^L and y^R . The same theoretical predictions would be derived assuming that forecasters receive noisy signals about y^L and y^R , as long as the signal is not systematically biased. The assumption of perfect information has been formulated solely to simplify the notation.

¹³ $\eta_j \geq 0$ 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.

Table 1: Calibration of parameters

Parameter	Calibration
T	12
k	6
J	44
y^L	1.8
y^R	2.1
μ^L	1.8
μ^R	2.1
C	40
β	.99
α	.5
ρ	.001
τ_L	.1
η_j	$\sim \mathcal{U}[0, 1]$
τ_j	$\sim \mathcal{U}[0, .1]$

Notes: Calibration of the exogenous parameters introduced in the extended model presented in Section 3.2. See Section 3.2.3 for a discussion of the parameters and see Section A.1 in the Appendix for details on how we solve the model numerically.

the relative weight of the incentive for accuracy compared to the incentive for consistency. In this version of the model, forecasters trade-off accuracy with the will of favoring the preferred outcome in the referendum, as well as the consistency of released estimates over time.

3.2.3 Calibration

This version of the theoretical framework is solved numerically to take into account the recursivity in the forecasters' problem generated by the dynamics and by their strategic interaction, which also introduces a common pool problem among forecasters in the economy.

We calibrate the parameters of the extended model with the aim of being consistent with the main intuitions behind the theoretical framework and the application of the model predictions to the Brexit referendum. In Section 3.2.5, we perform a number of comparative dynamics exercises to show how the predictions of the model vary as a function of exogenous parameters.

As shown in Table 1, the number of forecasters in the economy is set to 44 to reproduce the data collection *Forecasts for the UK economy*, collected and released by the HM Treasury on a monthly basis. Consequently, we calibrate the number of time periods T to 12, hence imposing that the forecasters in the model release a new estimate each month for a full year. We set $k = 6$, so that between January and May forecasters only release $F_{j,t}^R$, while they start publishing forecasts subject to state L from June onwards. The measure of stakes η_j is drawn at the individual forecaster level from a uniform distribution between 0 and 1, while τ_j , from which the measure of influence γ_j is generated, is drawn from a uniform distribution between 0 and 0.1.

y^L and y^R are respectively calibrated to 1.8 and 2.1. The former figure replicates the actual GDP growth observed in the UK in the year 2017, after the victory of Leave in the occasion of

the Brexit referendum, while the latter replicates the average forecast for GDP growth in 2017 reported in the latest release before the referendum of *Forecasts for the UK economy*. We make this choice since we cannot observe ex-post what the GDP growth in 2017 would have been had the UK voters decided not to leave the European Union. We also calibrate voters' prior μ^S to be correct, so that $\mu^S = y^S \forall S \in \{L, R\}$.

The parameter α , which represents the relative weight of accuracy and consistency in the cost structure of forecasters, is calibrated to 0.5, while β is imposed equal to 0.99 to represent that the quality of the signal that forecasters send to voters does not change substantially in precision over time in the short run.

τ_L and ρ are set respectively to 0.1 and to 10^{-3} in order to represent that voters have a very precise prior subject to R, while their prior information about the alternative state L is of much lower precision.

Lastly, C is calibrated to 40 with the aim of calculating an expected probability of Brexit consistent with [Consensus Economics \(2016a\)](#) and the bookmakers' odds (see Figure A2 in the Appendix). It is worth to notice that the calibration of other parameters defines acceptable bounds for C .

3.2.4 Predictions

The numerical solution of the extended model provides additional insights beyond the prediction of a propaganda bias in the estimates released by macroeconomic forecasters with influence over voters and economic interest at stake during the referendum. More specifically, this version of the model allows us to predict three additional facts that we are able to test in the data. First, the relative allocation of the propaganda bias between forecasts subject to R and L when voters do not have complete information about any of the states; second, whether there exists also an intensive margin of propaganda bias; third, the dynamic evolution of forecasts after the vote, when forecasters do not have any electoral incentives. The extended model allows also to predict how voters reacted to the presence of the propaganda bias in the occasion of the Brexit referendum, both in terms of beliefs about GDP growth and in terms of the probability of leaving the European Union. According to our model calibration, voters' posterior belief about the GDP growth in 2017 following Brexit has been 0.2 percentage point lower than in a counterfactual economy in which forecasters do not release biased estimates, resulting in a reduction of the probability of Brexit by around 9 percentage points.

In Figure 2, we report how the bias in $F_{j,k}^L$ and $F_{j,k}^R$ vary as a function of η_j (stakes) and γ_j (influence). In both heatmaps, the red areas represent the cases of largest bias, whereas the

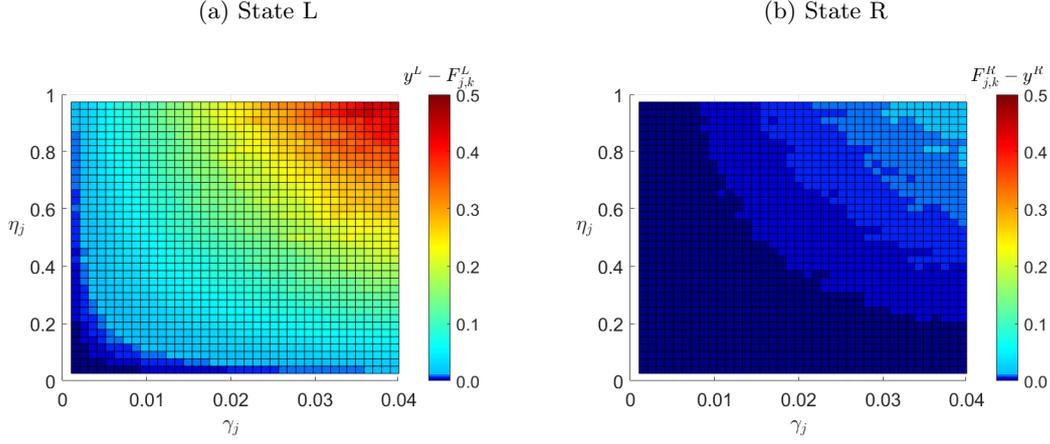


Figure 2: Propaganda Bias in period k

Notes: The figure reports at the individual forecaster level the bias in $F_{j,k}^L$ and $F_{j,k}^R$ as a function of the individual parameters η_j and γ_j . The parameters are reported on the axes of the graph, whereas different values of the bias are reported with different marker colors, as summarized in the legend. Dark blue markers represent $F_{j,k}^S = y^S$, whereas red markers represent the relatively most biased forecasts. Note that we have adjusted the sign of the bias to have the same color scale in both graphs. All other parameters have been calibrated as described in Section 3.2.3.

combination of parameters for which the model does not predict any bias are reported in dark blue.¹⁴ The figure shows that, in equilibrium, forecasters with stakes and influence do not allocate equally the propaganda bias across states. In the left panel, the estimates released by forecasters with highest values of stakes and influence are substantially different from y^L , while the right panel shows that the propaganda bias is, albeit present, very small to what concerns forecasts subject to state R.

The intuition behind this result comes from the trade-off that forecasters with stakes and influence face at time k . Forecasters choose optimally the propaganda bias at the level that equalizes the marginal benefit (i.e. the impact on p^L scaled by the level of stakes) and the marginal cost. In terms of marginal benefit, (13) implies that a propaganda bias on $F_{j,k}^L$ is more profitable because voters weight more the signals subject to L observed in period k than the ones subject to state R. The influence of $F_{j,k}^R$ on the posterior belief is mitigated by all signals sent in the previous periods by forecasters, as well as by the much more precise prior that voters have about on R than they do on L. Marginal costs of a propaganda bias, according to (14), are instead higher under state R because forecasters would have to pay an additional cost for a large revision from the previous release and because p^L is lower than 0.5, making it relatively more profitable to release a biased forecast subject to the less likely state.

Figure 2 clarifies also that there exists an intensive margin of propaganda bias, in terms of both stakes and influence. Among institutions with $\eta_j > 0$ and $\gamma_j > 0$, indeed, there is a monotonic

¹⁴Note that the bias is defined with different signs in order to be on the same color scale.

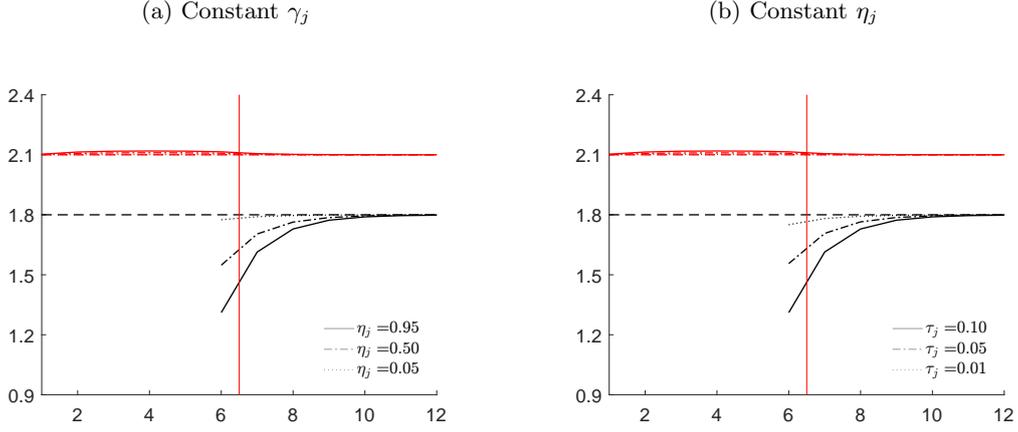


Figure 3: Evolution of propaganda bias over time

Notes: The figure reports the evolution of $F_{j,t}^L$ and $F_{j,t}^R$ over time. Dashed lines represent y^L and y^R , while solid lines as well as dotted and dashed-dotted represent forecasts. Black lines represent variables referring to state L, while red lines represent variables referring to state R. In the left graph, τ_j is held constant at 0.1, so that γ_j is on average equal to 0.04. In the right graph, η_j is held constant at 0.95. All other parameters have been calibrated as described in Section 3.2.3.

relationship between each of the two and the size of the bias. Forecasters with relatively higher stakes (influence) released more biased estimates than their colleagues with positive but lower levels of η_j or γ_j , holding the other individual parameter constant. While it is not surprising that higher stakes lead to a more pronounced propaganda bias, influence increases the marginal benefit, as well as the marginal cost of a biased forecast and hence its impact on the size of the propaganda bias, was ambiguous at first sight.

Figure 3 shows how $F_{j,t}^L$ and $F_{j,t}^R$ evolve over time before and after the referendum for forecasters of different levels of η_j and γ_j . In the left graph, we hold constant γ_j and compare forecasters with different values of η_j , while in the right panel we hold constant η_j and compare forecasters with different values of γ_j . In both graphs, the solid lines, as well as the dotted and dashed-dotted lines, represent forecasts, while the dashed lines represent respectively the true y^R and y^L . All variables referring to state R are reported in red, while variables referring to state L are shown in black.

Figure 3 confirms the predictions presented in Figure 2 and highlights the convergence of $F_{j,t}^L$ after the referendum. Even if forecasters with stakes and influence do not have any electoral incentives after the vote, the presence of an incentive for the consistency over time of the estimates implies that the propaganda bias generates pessimistic forecasts subject to state L for some periods after k .

3.2.5 Comparative Dynamics

In Figure A3 in the Appendix, we show how the main predictions of the theoretical model are affected by the calibration of parameters. These comparative dynamics exercises, on the one hand, show the robustness of the theoretical predictions, and on the other hand, provide additional insights useful to understand in depth the incentives that macroeconomic forecasters with stakes and influence face in connection with an important referendum.

Panel (a) in Figure A3 shows the comparative dynamics with respect to C , which in the model represents the economic cost that forecasters face in the event state L prevails during the referendum. Unsurprisingly, an increase in C is associated with a more pronounced propaganda bias, both in period k and in the subsequent periods.

Panel (b) reports the effect of the variation in α on the size and evolution over time of the propaganda bias. In the theoretical model, α represents the weight that forecasters attach to the accuracy cost relative to the weight attached to the revision cost. For values of α approaching 1, the propaganda bias is attenuated compared to forecasters which trade-off accuracy and consistency. In addition, for high values of α , the forecaster adjusts the estimates sharply after the referendum to the unbiased target y^S , while forecasters with lower α show a dynamic transition after the vote that lasts for some periods.

The effect of a variation in β on the dynamic evolution of the propaganda bias is presented in Panel (c). β represents the variation over time in the precision of the signal that voters receive from forecasters. For β approaching 1, voters put similar weights on forecasts released at different points in time, while lower values of β imply that voters are more influenced by the most recent releases. In the forecasters' loss function, β implies that the accuracy and consistency costs for forecasters are higher close to the realization of the economic outcomes than in the first periods in which forecasters release an estimate subject to a state. The graph shows that the largest propaganda bias is predicted when the quality of the signal that voters receive from forecasters does not vary over time, while the model predicts an attenuated bias in the cases in which voters put a higher weight on the most recent releases.

In Panel (d), we plot the effect of a variation in ρ on the allocation of the propaganda between $F_{j,t}^R$ and $F_{j,t}^L$. In the theoretical model, ρ captures the ratio between the precision of voters' prior on y^L compared to their prior on y^R . When voters are very well informed about y^R , then the propaganda bias is sizable only subject to L. Conversely, if voters are also uninformed about y^R , then forecasters with stakes and influence take advantage of both sources of asymmetric information and release both biased $F_{j,t}^R$ and biased $F_{j,t}^L$.

Panel (e) shows how the number of forecasters J modifies the propaganda bias. In the theoretical model, forecasters face a common pool problem which deflects the propaganda bias, as each of them can take advantage of biased estimates released by the other forecasters. When the number of forecasters decreases, the common pool problem is attenuated and forecasters release a relatively more pessimistic $F_{j,k}^L$.

In panels (f) and (g), we show that the number of time periods in the model influences the size of the propaganda bias, although it neither influences its presence nor its dynamics. The numerical solution to our theoretical model predicts that an increase in T reduces the propaganda bias since the marginal cost of releasing biased forecasts increases with the number of periods, while the marginal benefit is static. A reduction in k , instead, reduces voters' weight on the signals received by forecasters before the referendum compared to the weight that voters assign to their prior and hence is predicted to reduce the size of the propaganda bias.

Lastly, we report in panel (h) and in panel (i) the effects of an exogenous variation to p^L on the propaganda bias. A reduction in y^L , as well as an increase in μ^R , generate a reduction in p^L . The former parameter reduces the probability of leaving because the economy is going to perform relatively worse in the event that L wins the referendum, while the latter induces voters to be incorrectly optimistic about the future economy in the event that the society decides not to leave the status-quo. According to our theoretical model, these variations lead to a relatively larger propaganda bias, following the prediction that the marginal cost of propaganda bias is lowest when p^L approaches zero.

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 in connection to 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 fore-

casters 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. The sample mainly contains financial institution and research companies, which are also the forecasters updating their estimates most frequently, but we observe also some international institutions.¹⁵ At the beginning of each month, each forecaster in the sample is surveyed and the results are quickly released online.¹⁶

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 $t + 1$.¹⁷ Table [A2](#) in the Appendix provides descriptive statistics of the relevant forecasts. The use of short-term forecasts allows us to evaluate the ex-post accuracy of the released forecast on the basis of the actual GDP growth rates.¹⁸

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, so that in each period we can only observe one of the two conditional forecasts.¹⁹ We observe conditional forecasts under the Remain state (i.e. $F_{j,t}^R$ 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 $F_{j,t}^L$.

Figure [4](#) clarifies our empirical strategy to estimate the propaganda bias even if $F_{j,t}^L$ is unobservable. In Figure [4](#), dotted lines represent the model predictions, whereas solid lines represent

¹⁵This data source it is largely equivalent to the Consensus Economics forecasts report, although it reports information from more forecasters. 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 sample.

¹⁶Not 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.

¹⁷All data refer to the changes in annual figures expressed in percent. For the January collection, the forecasts refer to the year t .

¹⁸Short-term forecasts are nevertheless very informative also about the potential effects of Brexit in the subsequent years. Figure [A5](#) in the Appendix shows that forecasts for GDP growth in the year $t + 1$ and forecasts for GDP growth in the year $t + 3$ are highly correlated in the subsample of institutions releasing medium-term forecasts on a quarterly basis. A regression controlling for time and individual fixed effects yields an R^2 of 0.55.

¹⁹Table [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 is affected the most, with forecasts falling from above 4 to -1.2 percent.

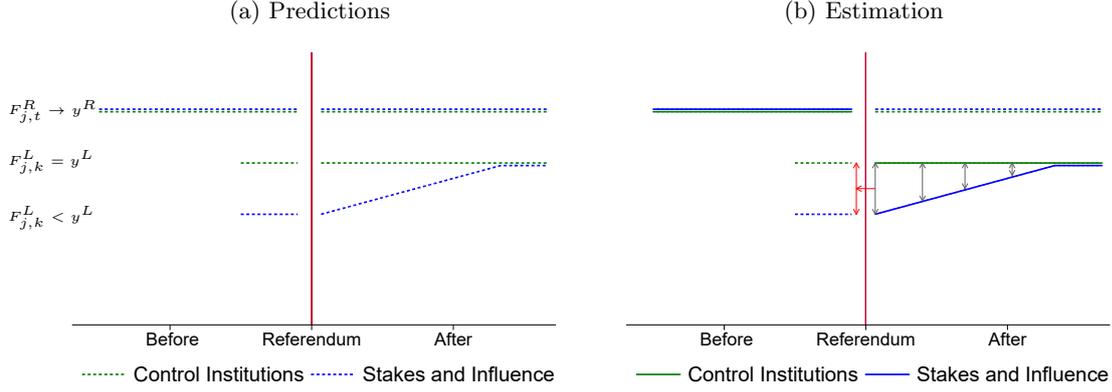


Figure 4: Theoretical Predictions and Empirical Analysis

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.

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 very similar forecasts under the state R (see Figure 4a).

In Figure 4b, we add to the predictions what is observable in the data at the forecaster level: $F_{j,t}^R$ prior to the referendum and $F_{j,t}^L$ 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 released 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). 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 began the survey for the July release of the collection.²⁰ 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.

Second, it is costly for forecasters to revise their estimates subject to the same state in the

²⁰The 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.

very short run. A large revision from a forecast under the state Remain to a forecast under 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 forecasters' loss function in the extended model, as well as 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).^{21,22}

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 on growth components is in line with the predictions of standard macroeconomic theory.

4.1 Measures of Stakes and Influence

In our 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. Ramiah et al. (2017) estimates 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.

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.3 in the Appendix for details). Forecasters have been very differently exposed to the immediate effects of Brexit, as reported in Figure 5, which shows stock market losses ranging between 1.8 percent and 31 percent.²³

²¹The anonymity of the Consensus Economics survey does not rule out credibility concerns. Forecasters are held accountable by Consensus Economics, internal users and customers.

²²If forecasters cared about consistency and have had time to adjust their estimates between the referendum and the July survey, then our empirical strategy would estimate a lower bound of propaganda bias.

²³The 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.

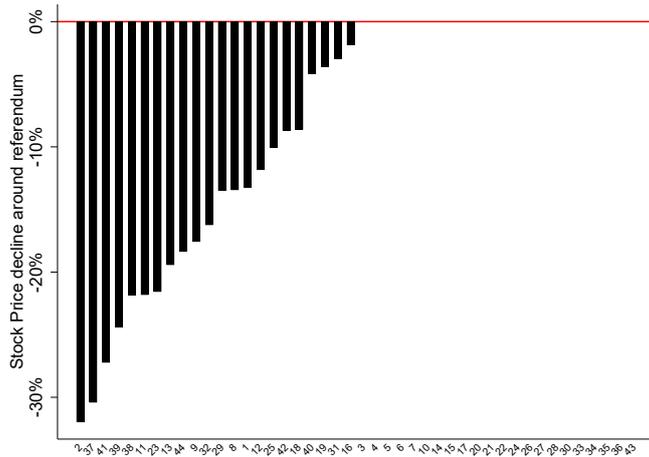


Figure 5: Stock Price

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.

It is not obvious how to measure influence. In the model, influence represents the weight that each individual forecaster has in the formation of voters’ posterior beliefs. We propose proxies that aim at capturing 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 of the public. We use Google Trends to measure how often the users search for an individual forecaster on the web.²⁴ The second approach aims at capturing media coverage. We retrieve the number of times in which each institution is mentioned in a Google News search during 2015.²⁵ 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.²⁶

4.2 Estimation

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

$$F_{j,m} = \theta_j + \delta_m + \mathbb{1}(\eta_j \gamma_j > 0) \sum_{k=-5}^4 \beta_k \mathbb{1}(m = k) + \varepsilon_{j,m}, \quad (15)$$

²⁴Google 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.

²⁵Google News search reports the total number of entries in the news for a given search item. We defined the threshold as having 7,000 citations during 2015, such that the indicator takes value 1 for half of the forecasters and 0 for the other institutions.

²⁶See the Data Appendix (Section A.3) for details on the group assignment and how the different definitions are correlated (see Table A4 in the Appendix).

where θ_j represents the forecaster fixed effects, δ_m represents the survey time effects and $k = -5, \dots, 4$ 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 β_1, \dots, β_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 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.²⁷ 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

²⁷The 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 a 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 the 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.

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 influence. 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 2.²⁸ In column (1) we suppress the forecaster-specific fixed effects, and columns (2)–(4) report results from estimating the model in equation (15) using different measures of stakes and influence. In 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 2, 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 -0.745 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 strongly 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,

²⁸For simplicity, in the table we limit ourselves to showing coefficients β_0, \dots, β_4 , whereas Table A5 in the appendix reports the estimation results with the anticipated coefficients $\beta_{-1}, \dots, \beta_{-5}$.

Table 2: Estimation of Propaganda Bias in GDP Growth Forecasts

	Stakes x Influence			Stakes	Influence	
	(1)	(2)	(3)	(4)	(5)	(6)
Group x Referendum	-0.526*** (0.183)	-0.638*** (0.171)	-0.745*** (0.185)	-0.601*** (0.173)	-0.755*** (0.204)	-0.766*** (0.166)
Group x Ref. (+1)	-0.711*** (0.140)	-0.753*** (0.172)	-0.529*** (0.177)	-0.751*** (0.171)	-0.743*** (0.146)	-0.578*** (0.170)
Group x Ref. (+2)	-0.456*** (0.148)	-0.445*** (0.144)	-0.471*** (0.148)	-0.484*** (0.142)	-0.536*** (0.155)	-0.488*** (0.145)
Group x Ref. (+3)	-0.420*** (0.158)	-0.483*** (0.150)	-0.473*** (0.154)	-0.451*** (0.150)	-0.479*** (0.151)	-0.447*** (0.152)
Group x Ref. (+4)	-0.121 (0.145)	-0.126 (0.122)	-0.157 (0.120)	-0.125 (0.122)	0.001 (0.149)	-0.377*** (0.127)
Observations	1,643	1,643	1,643	1,643	1,643	1,643
R ²	0.679	0.776	0.776	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 (15). Standard errors robust to two-way clustering at the forecaster and the survey levels are in parentheses. *, **, *** represent the 10%, 5%, 1% significance levels.

up to 50 percent of the forecast error at the time of the referendum.²⁹ 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.³⁰

²⁹Figure 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.

³⁰The two groups of forecasters converge release equal forecasts starting from one year prior to the target (i.e. 2017), making it unlikely that the convergence is completely due to the approaching horizon.

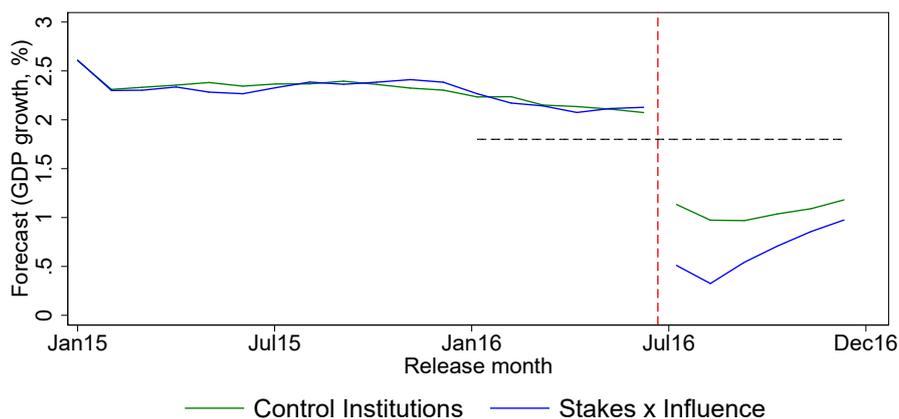


Figure 6: Pre-Referendum Trends

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 in section 4.2, while the green line represents the remaining institutions. The black dashed line represents the actual GDP growth rate in 2017.

5.1 Robustness Checks

Evidence in support of the parallel trends assumption is presented in Figure 6, 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. This evidence is in line with the calibration of our theoretical model, which predicted a negligible propaganda bias subject to R . In addition, we perform a number of robustness checks to validate our empirical strategy and exclude that our estimates are driven by chance or large variability in a relatively small sample.

First, we estimate the same regression model as in equation (15) 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

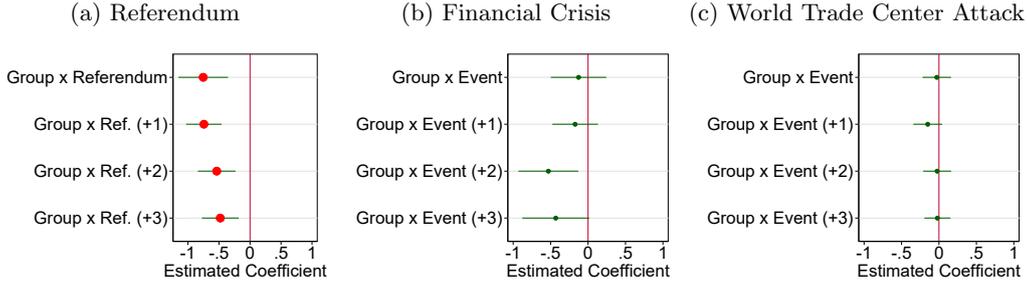


Figure 7: Effect during the EU Referendum and in the Occasion of Other Events

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 (15), 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.

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 2 do not represent extreme estimates.

Fourth, we replicate the main results using alternative measures from Google News that disentangle the general knowledge of each institutions from their influence in the forecasting activity. The measure used in Table 2 captures the overall media coverage of each forecaster, thus pooling cases in which each institution was mentioned in the UK news for several possible reasons.³¹ In Table A7, we show that the results hold when we refine the Google News measure by requiring the words “GDP” and “forecast” to be part of the same newspaper article as the name of the forecasting institutions.³²

Fifth, 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

³¹For instance, consider that *Barclays* has been title sponsor of the soccer’s Premier League between 2011 and 2016.

³²See Section A.3 in the Appendix for details.

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 (15) in which we compare financial institutions and other forecasters before and after the unexpected beginning of the 2008 financial crisis and the 2001 attack on the World Trade Center in New York.^{33,34} The results in Table A6, summarized in Figure 7, 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.³⁵ 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 (15). 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 2 lie. Our results, as expected, always lie in the lower parts of the distribution, which is symmetric and centered in zero.³⁶

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 con-

³³We identify the unexpected beginning of the financial crisis with the bankruptcy of the Lehman Brothers Holdings Inc. on September 15, 2008.

³⁴We investigate forecasters' behavior around the time of the 2001 terrorist attack by estimating equation (15), assuming that everyone is influential, in a sample between the year 1998 and the year 2003, while we explore the reaction to the financial crisis restricting the sample to observations between the year 2004 and the 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.

³⁵In 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.

³⁶Other checks, that we do not include for brevity, include the estimation of equation (15) 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.

sumption does not react as much and the government expenditure usually increases as a response to economic crises.

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

$$Y = C + I + G + (X - M) \tag{16}$$

so that GDP growth rate can be expressed as

$$g_Y = g_C \varepsilon_C + g_I \varepsilon_I + g_G \varepsilon_G + (g_X \varepsilon_X - g_M \varepsilon_M), \tag{17}$$

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 8 we plot results of estimating equation (15) for each component. The symbols report the estimated propaganda bias at the time of the referendum (β_0 in equation (15)) for each of the specifications used in Table 2.

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 coefficients on export, of similar magnitude as the growth of investments, 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 (17).

This exercise shows that forecasters with stakes and influence conducted their propaganda

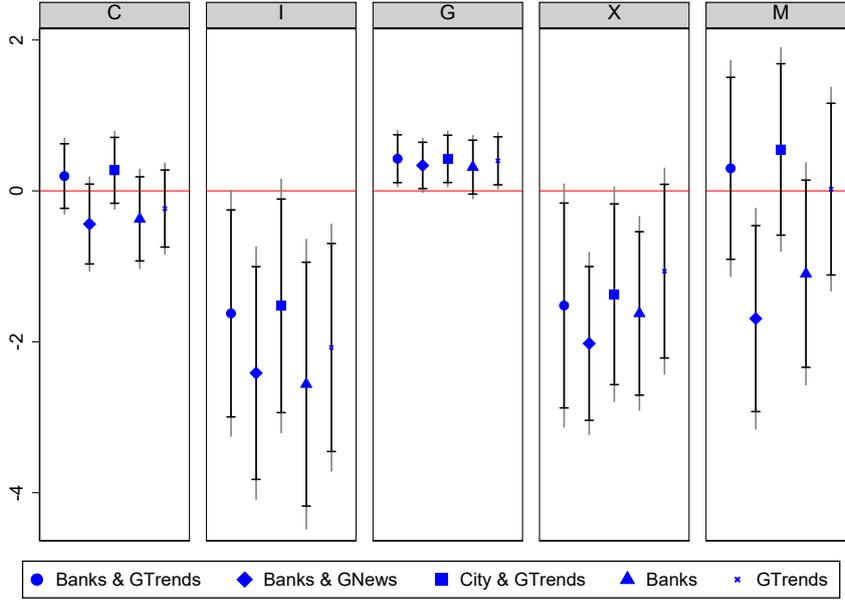


Figure 8: Estimation of Propaganda Bias in GDP Growth Components Forecasts

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 (15), 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.

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 3, we estimate Difference-in-Differences models of the form

$$F_{j,m} = \theta_j + \delta_m + \beta_1 \eta_j \mathbb{1}(\eta_j \gamma_j > 0) \mathbb{1}(m = 0) + \beta_2 \gamma_j \mathbb{1}(\eta_j \gamma_j > 0) \mathbb{1}(m = 0) + \varepsilon_{j,m}, \quad (18)$$

Table 3: Estimation of Propaganda Bias at the Intensive Margin in GDP Growth Forecasts

	Stakes x Influence			Stakes	Influence
	(1)	(2)	(3)	(4)	(5)
Group x Ref. x Stock Price	-0.361*** (0.094)		-0.316*** (0.102)	-0.330*** (0.098)	
Group x Ref. x log(Trend)		-0.252*** (0.093)	-0.067 (0.084)		-0.308*** (0.092)
Observations	1,643	1,643	1,643	1,643	1,643
R ²	0.770	0.769	0.770	0.770	0.769
Fixed Effects	✓	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓	✓
Measure of Stakes	Banks	Banks	Banks	Banks	
Measure of Influence	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. Stock Price and log(Trend) have been standardized to have mean 0 and variance 1. 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 (18). Standard errors robust to two-way clustering at the forecaster and the survey levels are in parentheses. *, **, *** represent the 10%, 5%, 1% significance levels.

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 3 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 $F_{j,k}$ 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 (18), 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 statistically significant.

In columns (4) and (5), we repeat the exercise interacting the continuous measures of stakes and influence with the groups defined in columns (5) and (6) of Table 2, detecting large and statistically significant negative coefficients.

Additional evidence is presented in Table A8 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 $F_{j,k}^L - F_{j,k}^R$ and the continuous measures of stakes and influence.

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 oligopoly 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 they have to rely on scenarios published by professional forecasters to form beliefs before the referendum. 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 competitions (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 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 more uncertain 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 Details on the Numerical Solution of the Model

We solve the model numerically using the parameters reported in Table 1 as the base calibration. Given the parameters, we solve the model by supplying an initial guess of forecasts for all forecasters and allowing all forecasters to update their forecasts to minimize the individual loss given the guess on the forecast of others.³⁷ We then update our guess using the resulting forecasts from the optimization problem performed by all individuals and allow all forecasters to re-optimize given the updated guess. We repeat this process until the forecasters no longer wish to change their forecasts given the forecasts of others. Due to the randomness of the draws of η_j and τ_j , we always simulate multiple economies in order to find the model solution in expectations.

We assume unbiased forecast as the initial guess but we performed a robustness check in which we allowed for different initial guesses. More specifically, we perturbed the initial guess by adding a random number drawn from a normal distribution. The model was solved 100 times and the obtained equilibrium solution is the same in all cases.

The graphs in Figure 2 are based on 500 simulated economies. In the baseline calibration, we obtain a p^L of 0.22 with voter posteriors that are $\tilde{F}^L = 1.6$ and $\tilde{F}^R = 2.1$. When we calibrate $C = 0$, such that all forecasters provide unbiased forecasts, p^L is equal to 0.31 while voters' posteriors are $\tilde{F}^L = 1.8$ and $\tilde{F}^R = 2.1$. Hence, the bias in the baseline calibration reduced p^L by 9 percentage points.

In the graphs in Figures 3 and A3, we report the mean of 100 simulated economies for each parameter case. In all graphs we keep the base calibration reported in Table 1 and only vary the parameter of interest. We fix the η_j and τ_j values for one forecaster to be $\eta_j = 0.95$ and $\tau_j = 0.1$. Hence, we show the forecasts for a forecaster with high levels of stake and influence. A τ_j of 0.1 corresponds to an expected γ_j of 0.04.

Figure A4 reports the forecasts of a forecaster with $\eta_j = 0.95$ and $\tau_j = 0.1$ in the baseline economy. The solid line reports the median forecast based on 100 simulated economies while the dotted lines report the 1st and 99th percentiles. This illustrates how the bias varies depending on the random draw of the other forecasters' individual parameters η_j and γ_j in the economy.

³⁷We use the Nelder-Mead simplex algorithm as described in Lagarias et al. (1998) in order to minimize the loss function.

A.2 Model with Fully Rational Voters

In this section, we modify the framework presented in Section 3 and allow voters to perform Bayesian updating taking into account that there is a positive probability that the forecaster has stakes, and hence may strategically release biased estimates.

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 $\varepsilon \sim \mathcal{N}(0, \tau^{-1})$ between the information sent by the forecaster and the signal received by voters, so voters receive

$$\widehat{F}^L = F^L + \varepsilon \tag{A1}$$

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 $y^L \sim \mathcal{N}(\mu^L, \tau_L^{-1})$ 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.2.1 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

$$y^L \geq y^R + \sigma_i. \tag{A2}$$

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

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

$$\mathbb{E}(y^L | \widehat{F}^L) = \gamma(\widehat{F}^L + qb) + (1 - \gamma)\mu^L, \tag{A3}$$

where $\gamma = \frac{\tau}{\tau + \tau_L}$ represents the optimal weighting. Therefore, the voters' decision rule (A2) changes to

$$\gamma(\widehat{F}^L + qb) + (1 - \gamma)\mu^L \geq y^R + \sigma_i. \tag{A4}$$

Following the same steps as in Section 3, then

$$\pi^L = \frac{1}{2} + \phi\left[\gamma(F^L + \varepsilon + qb) + (1 - \gamma)\mu^L - y^R\right] \tag{A5}$$

and

$$p^L = 1 - G\left(y^R - \gamma(F^L + qb) - (1 - \gamma)\mu^L\right) \tag{A6}$$

where $G(\cdot)$ is the cumulative distribution function of the gaussian random variable $\gamma\varepsilon$.

A.2.2 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

$$\min_{F^L} \mathcal{L} = p^L \left[\eta C + \frac{1 + \gamma}{2} (F^L - y^L)^2 \right], \quad (\text{A7})$$

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

The first-order condition with respect to F^L yields

$$\begin{aligned} & \gamma g(y^R - \gamma(F^L + qb) - (1 - \gamma)\mu^L) \left[\eta C + \frac{1 + \gamma}{2} (F^L - y^L)^2 \right] + \\ & (1 + \gamma)(F^L - y^L) \left[1 - G(y^R - \gamma(F^L + qb) - (1 - \gamma)\mu^L) \right] = 0. \end{aligned} \quad (\text{A8})$$

Equation (A8) implies that it is optimal for a forecaster with no stakes (i.e. $\eta = 0$) or no influence (i.e. $\gamma = 0$) 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. $\eta > 0$ and $\gamma > 0$), equation (A8) 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,

$$\begin{aligned} & \gamma g(y^R + \gamma[b^*(1 - q) - y^L] - (1 - \gamma)\mu^L) \left[\eta C + \frac{1 + \gamma}{2} b^{*2} \right] - \\ & (1 + \gamma)b^* \left[1 - G(y^R + \gamma[b^*(1 - q) - y^L] - (1 - \gamma)\mu^L) \right] = 0, \end{aligned} \quad (\text{A9})$$

where $g(\cdot)$ is the probability density function of the random variable $\gamma\varepsilon$ with the cumulative distribution function equal to $G(\cdot)$. The optimal bias is implicitly determined by

$$b^* = b(\eta, \gamma, C, y^L, y^R, \mu^L). \quad (\text{A10})$$

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.³⁸ 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.

³⁸The 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 (A9) is satisfied identifies an interior minimum of the objective function since the second-order conditions are positive in equilibrium.

A.3 Data

A.3.1 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 A6a). 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. We record the number of mentions in a Google News search in the United Kingdom during 2015. Then, the binary measure of influence is constructed based on a threshold of 7,000 citations, so that half of the forecasters are above and half are below (see Figure A6b).

In Table A7, we consider alternative measures from Google News that corroborate the robustness of our findings. First, we span several time periods using the Archive settings of the search engine in order not to restrict the research to only the calendar year 2015.³⁹ Second, we restrict the news search such that we only consider media releases in which the name of each forecaster is accompanied either by the word “GDP” or by the words “GDP” and “forecast”. This allows us to separate the cases in which an institution is reported in the media because of its forecasting activity from the cases in which the institution is mentioned for other reasons. In all cases, the binary measure of influence is constructed based on thresholds dividing the sample in two groups of equal size.

A.3.2 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 5). 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](#).

³⁹The Google News search for Archive settings enlarges the research from the oldest article that the search engine is able to retrieve up to the date of the current research. The last access to this research was on December 7, 2017.

A.4 Figures and Tables

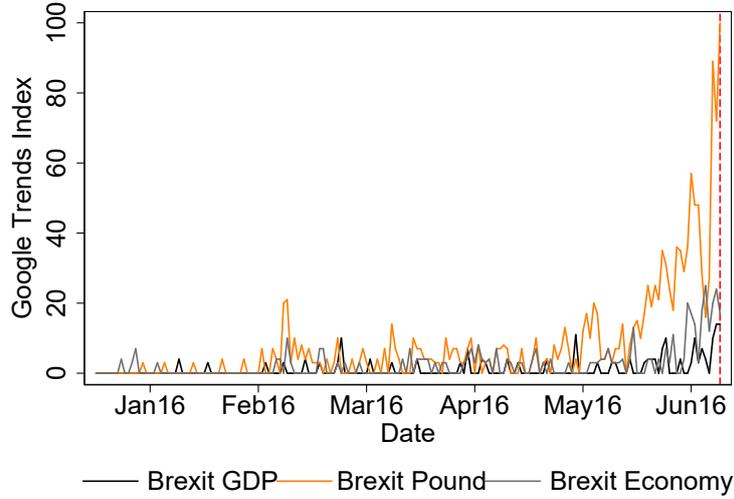


Figure A1: Brexit and the Economy Approaching the Referendum

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](#).

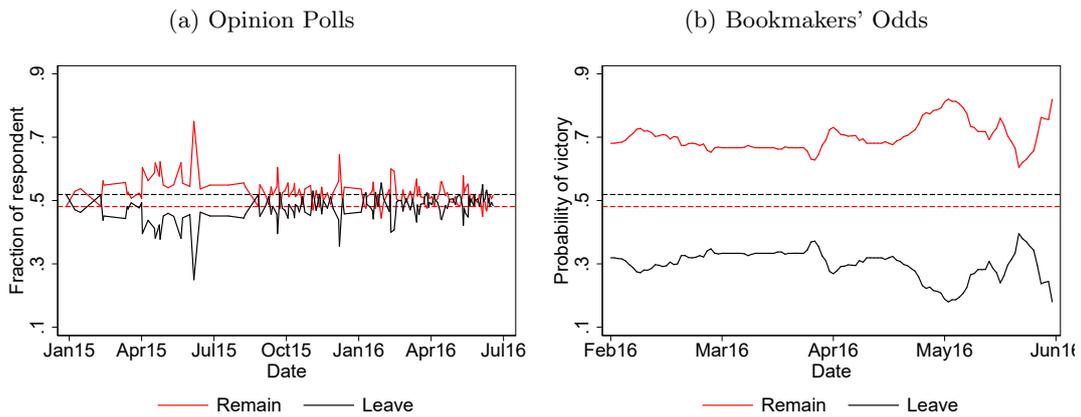


Figure A2: Opinion Polls and Bookmakers’ Odds Approaching the Referendum

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.

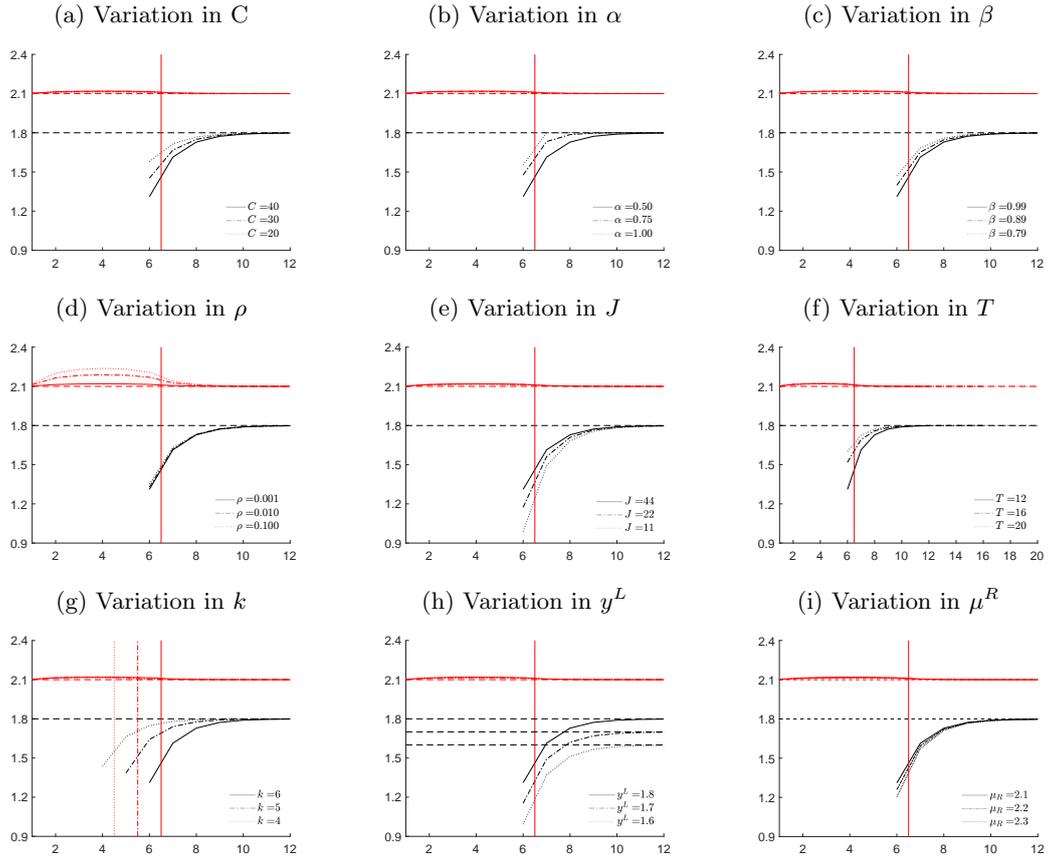


Figure A3: Comparative Dynamics with respect to the Exogenous Parameters

Notes: The figure reports the evolution of $F_{j,t}^L$ and $F_{j,t}^R$ over time. Dashed lines represent y^L and y^R , while solid lines as well as dotted and dashed-dotted represent forecasts. Black lines represent variables referring to state L, while red lines represent variables referring to state R. In each graph, one parameter at the time is allowed to vary according to the values reported in the legends. τ_j is held constant at 0.1, so that γ_j is on average equal to 0.04, and η_j is held constant at 0.95. All other parameters have been calibrated as described in Section 3.2.3.

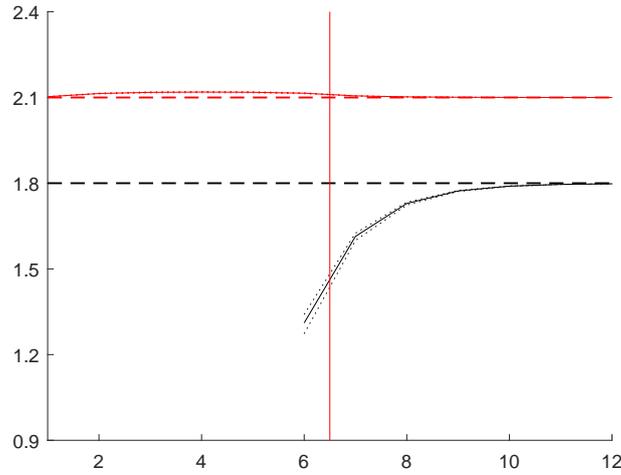


Figure A4: Baseline Calibration

Notes: The figure reports the evolution of $F_{j,t}^L$ and $F_{j,t}^R$ over time. Dashed lines represent y^L and y^R , while solid line report the median forecast based on 100 simulated economies while the dotted lines report the 1st and 99th percentiles. Black lines represent variables referring to state L, while red lines represent variables referring to state R. τ_j is held constant at 0.1, so that γ_j is on average equal to 0.04, and η_j is held constant at 0.95. All other parameters have been calibrated as described in Section 3.2.3.

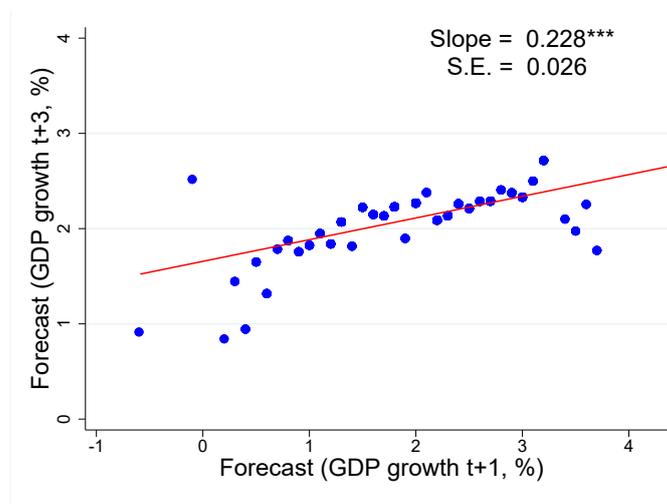


Figure A5: Correlation between short-term and medium-term forecasts for GDP growth

Notes: All forecasters surveyed by HM Treasury between January 2012 and June 2016 which reported within the same release both short-term and medium-term forecasts. The figure reports the bivariate regression $F_{j,t}^{t+3} = \alpha + F_{j,t}^{t+1} + \varepsilon_{j,t}$. Heteroskedasticity-robust standard errors are reported. *, **, *** represent the 10%, 5%, 1% significance levels. Blue markers represent the sample average of $F_{j,t}^{t+3}$ within bins of 0.1 percentage points of $F_{j,t}^{t+1}$.

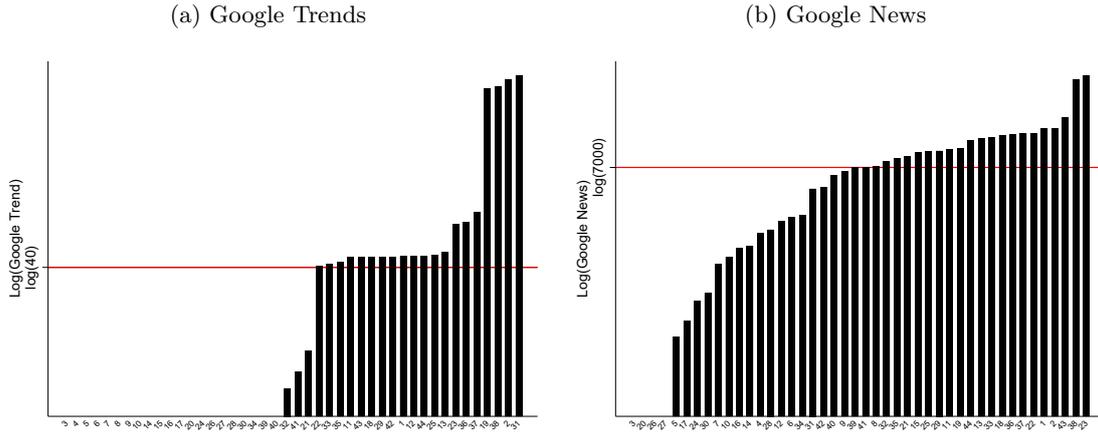


Figure A6: Google Measures

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.

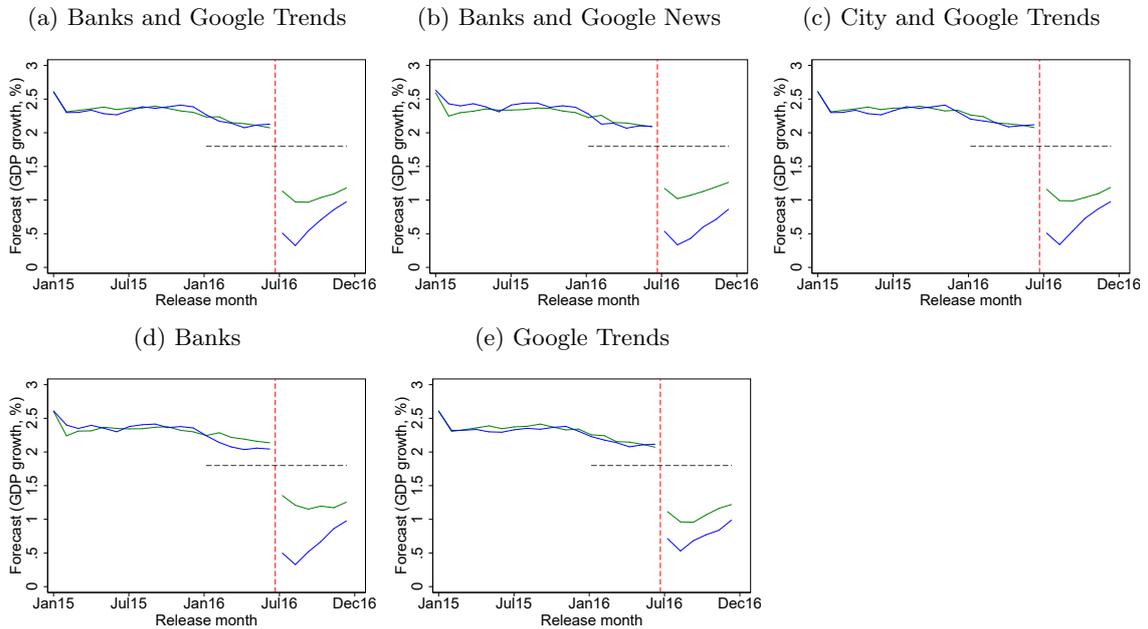


Figure A7: Pre-Referendum Trends for all Measures of Stakes and Influence

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 in Section 4.2, while green lines represent the remaining institutions. Black dashed lines represent the realization of GDP growth rate in 2017.

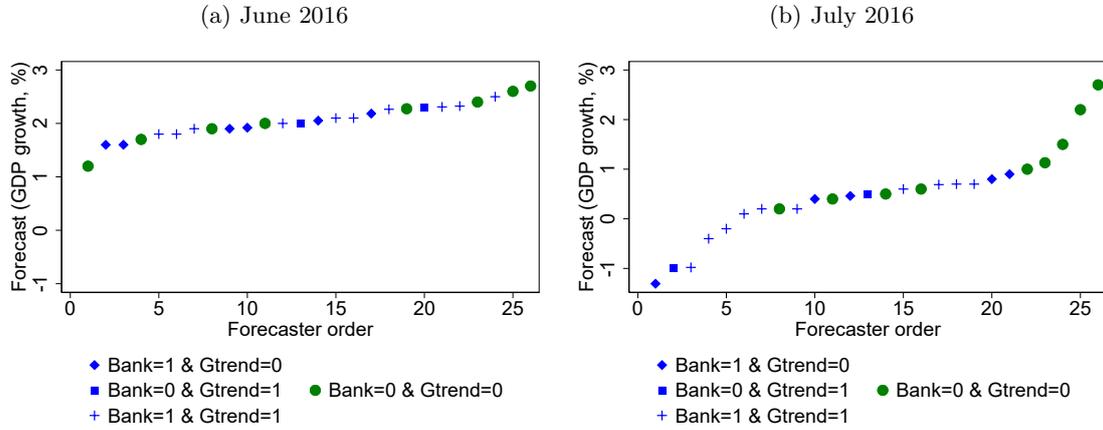


Figure A8: Forecast for the GDP Growth Rate in 2017 Before and After the Referendum

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.

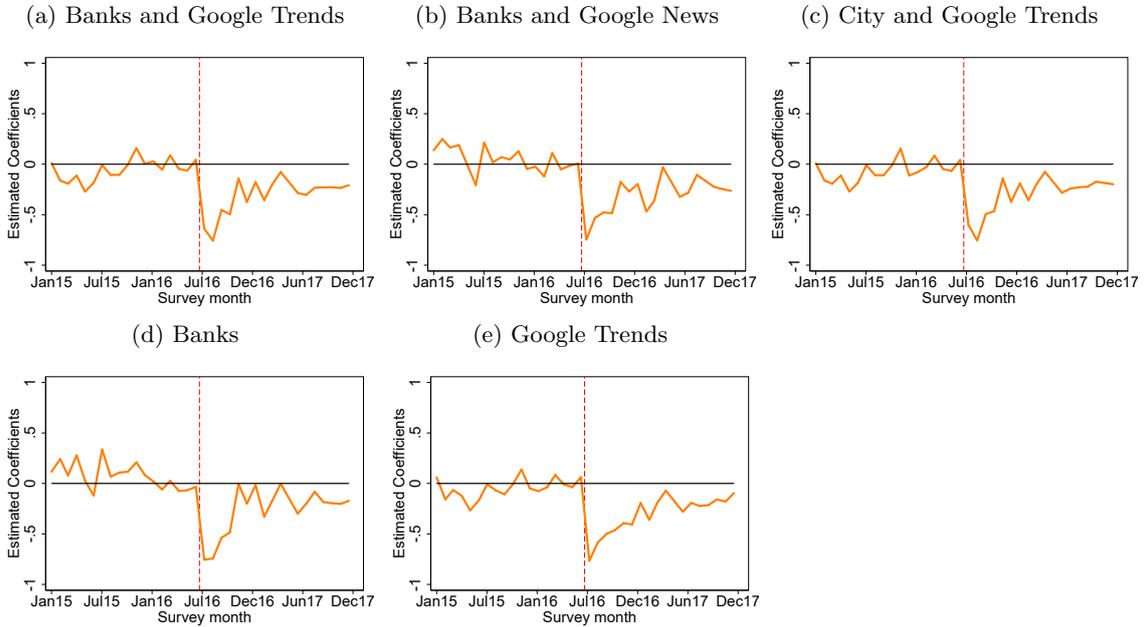


Figure A9: Estimated Propaganda Bias at Different Points in Time

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. In each graph, we replicate the results in Table 2, 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 .

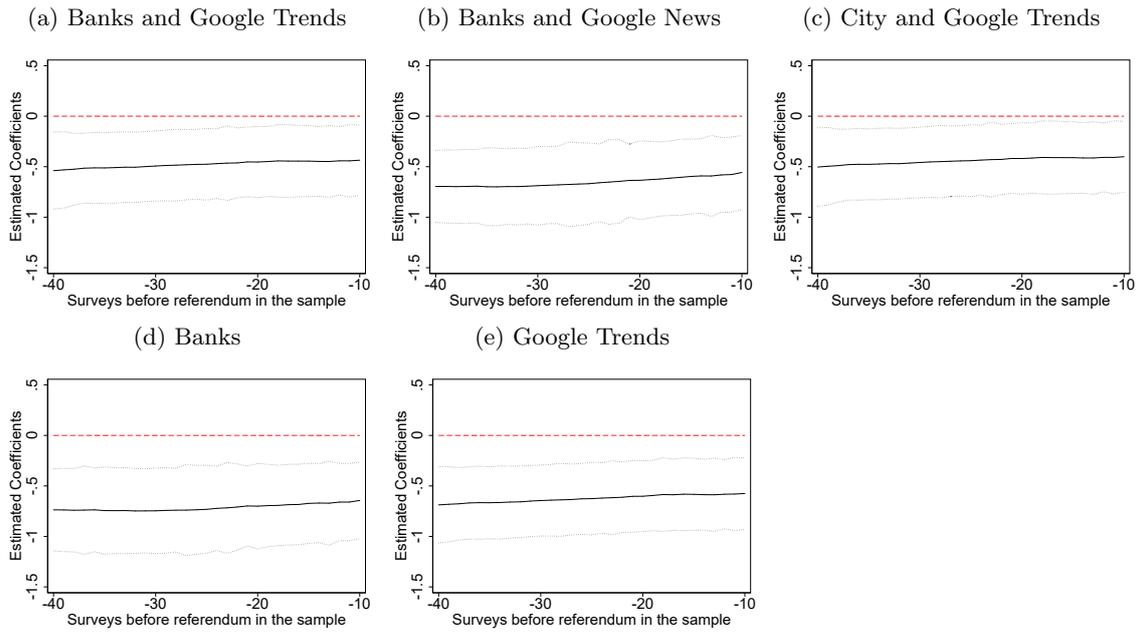


Figure A10: Sensitivity to Changes in the Time Span

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 2, 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.

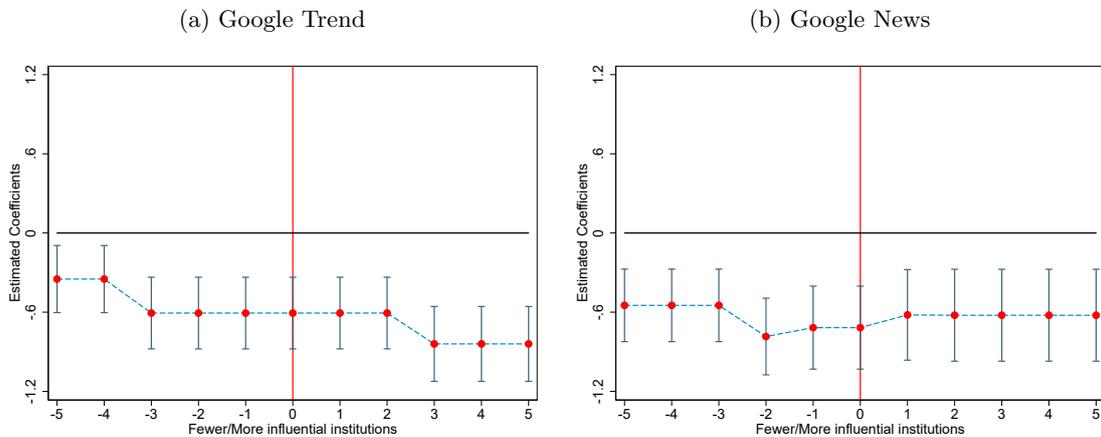


Figure A11: Sensitivity to the Definitions of Influence

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 (15) 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.

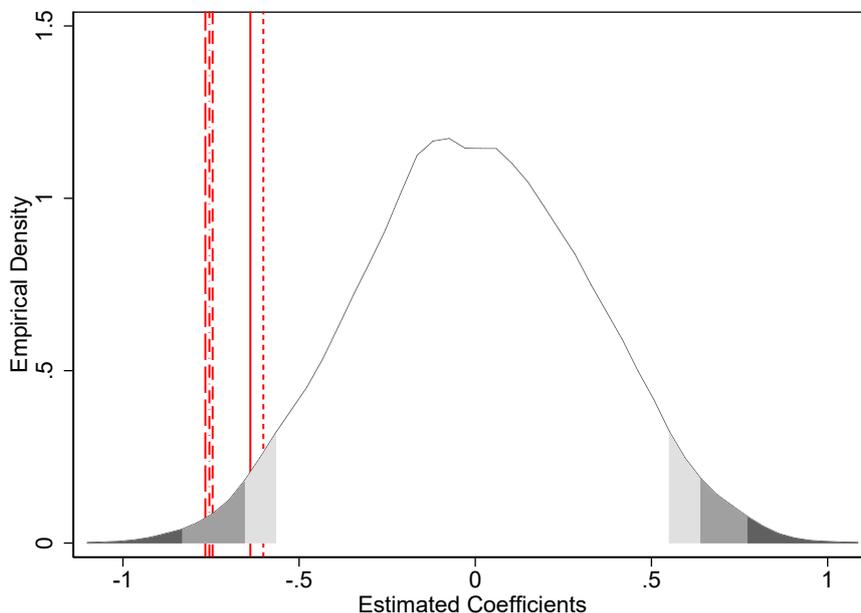


Figure A12: Monte Carlo Simulation: Random Assignment to Groups

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 (15). 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 2. The areas shaded in gray show the 1%, 5% and 10% tails of the distribution.

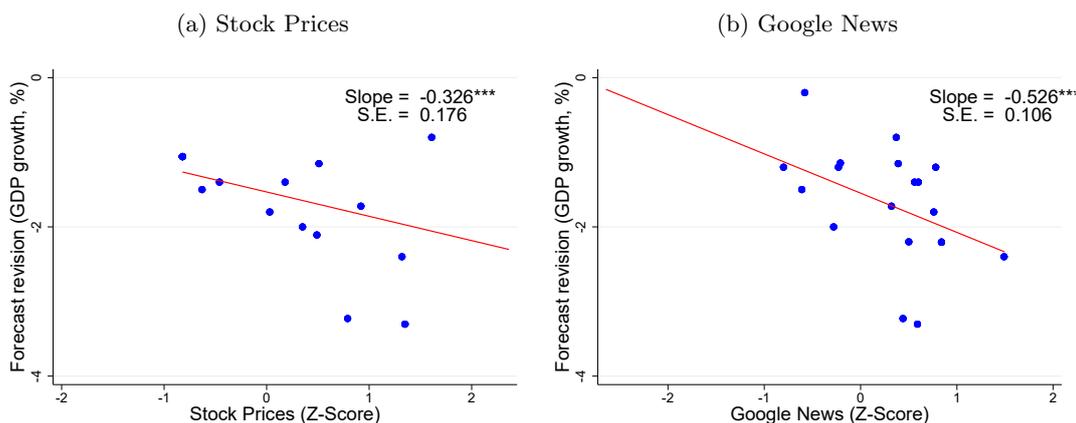


Figure A13: $F_{j,k}^L - F_{j,k}^R$ as a Function of Stakes and Influence

Notes: Panel (a) reports the bivariate regression $F_{j,k}^L - F_{j,k}^R = \alpha + \beta StockPrice_j + u_{j,k}$. Panel (b) reports the bivariate regression $F_{j,k}^L - F_{j,k}^R = \gamma + \delta GoogleNews_j + v_{j,k}$. In both panels, $F_{j,k}^L$ represents the forecast published in July 2016 by each institution and $F_{j,k}^R$ the forecast published in June 2016. Heteroskedasticity-robust standard errors are reported. *, **, *** represent the 10%, 5%, 1% significance levels. Blue markers represent the sample average of $F_{j,k}^L - F_{j,k}^R$ within bins of 0.04 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. 29, 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

Variable	June 2016	July 2016
	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	0.36	0.50	0.55	0.79
City	0.82	1.00	0.47	0.37	0.49	0.58	0.71
GTrends	0.46	0.47	1.00	0.64	0.90	0.64	0.38
GNews	0.36	0.37	0.64	1.00	0.59	0.74	0.46
Log(Trend)	0.50	0.49	0.90	0.59	1.00	0.62	0.43
Log(News)	0.55	0.58	0.64	0.74	0.62	1.00	0.53
Stock Price	0.79	0.71	0.38	0.46	0.43	0.53	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 A6a and 0 otherwise. GNews is an indicator taking the value 1 if the institution has a score above the threshold value reported in Figure A6b, 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)	(6)	
Group x Referendum	-0.526*** (0.183)	-0.638*** (0.171)	-0.745*** (0.185)	-0.601*** (0.173)	-0.755*** (0.204)	-0.766*** (0.166)
Group x Ref. (+1)	-0.711*** (0.140)	-0.753*** (0.172)	-0.529*** (0.177)	-0.751*** (0.171)	-0.743*** (0.146)	-0.578*** (0.170)
Group x Ref. (+2)	-0.456*** (0.148)	-0.445*** (0.144)	-0.471*** (0.148)	-0.484*** (0.142)	-0.536*** (0.155)	-0.488*** (0.145)
Group x Ref. (+3)	-0.420*** (0.158)	-0.483*** (0.150)	-0.473*** (0.154)	-0.451*** (0.150)	-0.479*** (0.151)	-0.447*** (0.152)
Group x Ref. (+4)	-0.121 (0.145)	-0.126 (0.122)	-0.157 (0.120)	-0.125 (0.122)	0.001 (0.149)	-0.377*** (0.127)
Group x Ref. (-1)	0.089 (0.112)	0.041 (0.096)	0.005 (0.093)	0.042 (0.096)	-0.033 (0.111)	0.056 (0.093)
Group x Ref. (-2)	-0.050 (0.115)	-0.077 (0.096)	-0.026 (0.098)	-0.074 (0.094)	-0.077 (0.113)	-0.051 (0.091)
Group x Ref. (-3)	0.045 (0.115)	-0.066 (0.088)	-0.067 (0.090)	-0.064 (0.088)	-0.092 (0.097)	-0.032 (0.089)
Group x Ref. (-4)	0.085 (0.147)	0.053 (0.101)	0.081 (0.097)	0.055 (0.099)	-0.004 (0.127)	0.050 (0.099)
Group x Ref. (-5)	-0.065 (0.135)	-0.104 (0.112)	-0.168 (0.110)	-0.075 (0.110)	-0.116 (0.113)	-0.091 (0.111)
Observations	1,643	1,643	1,643	1,643	1,643	1,643
R ²	0.679	0.776	0.776	0.776	0.778	0.777
Fixed Effects		✓	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓	✓	✓
Measure of Stakes	Banks	Banks	Banks	City	Banks	
Measure of Influence	G'Trends	G'Trends	G'News	G'Trends		G'Trends

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 (15). 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 (0.189)	-0.092 (0.194)	-0.029 (0.097)	-0.009 (0.106)
Group x Event (+1)	-0.173 (0.155)	-0.179 (0.154)	-0.150 (0.098)	-0.105 (0.098)
Group x Event (+2)	-0.530*** (0.204)	-0.456** (0.213)	-0.025 (0.095)	-0.031 (0.100)
Group x Event (+3)	-0.431* (0.228)	-0.320 (0.237)	-0.021 (0.089)	-0.060 (0.095)
Group x Event (-1)	-0.104 (0.191)	-0.031 (0.201)	0.042 (0.114)	0.054 (0.124)
Group x Event (-2)	-0.375* (0.198)	-0.390* (0.204)	0.224** (0.111)	0.270** (0.109)
Group x Event (-3)	-0.204 (0.191)	-0.308 (0.193)	-0.024 (0.077)	-0.082 (0.081)
Group x Event (-4)	-0.108 (0.175)	-0.114 (0.178)	0.122 (0.090)	-0.006 (0.088)
Group x Event (-5)	-0.034 (0.163)	-0.096 (0.174)	0.026 (0.101)	0.025 (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 (15), 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: Estimation of Propaganda Bias in GDP Growth Forecasts – Alternative Google News Measures

	Stakes x Influence			
	(1)	(2)	(3)	(4)
Group x Referendum	-0.745*** (0.185)	-0.413** (0.193)	-0.745*** (0.188)	-0.753*** (0.215)
Group x Ref. (+1)	-0.529*** (0.177)	-0.654*** (0.174)	-0.656*** (0.177)	-0.209 (0.206)
Group x Ref. (+2)	-0.471*** (0.148)	-0.511*** (0.143)	-0.514*** (0.144)	-0.401*** (0.151)
Group x Ref. (+3)	-0.473*** (0.154)	-0.484*** (0.149)	-0.473*** (0.155)	-0.388** (0.156)
Group x Ref. (+4)	-0.157 (0.120)	-0.064 (0.129)	-0.157 (0.122)	-0.409*** (0.129)
Group x Ref. (-1)	0.005 (0.093)	-0.010 (0.098)	0.044 (0.096)	0.071 (0.093)
Group x Ref. (-2)	-0.026 (0.098)	-0.137 (0.098)	-0.026 (0.098)	0.090 (0.097)
Group x Ref. (-3)	-0.067 (0.090)	-0.117 (0.090)	-0.017 (0.092)	0.074 (0.088)
Group x Ref. (-4)	0.081 (0.097)	-0.008 (0.112)	0.081 (0.098)	0.175* (0.099)
Group x Ref. (-5)	-0.168 (0.110)	-0.112 (0.114)	-0.114 (0.116)	-0.080 (0.111)
Observations	1,643	1,643	1,643	1,643
R ²	0.776	0.774	0.777	0.775
Fixed Effects	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓
Measure of Stakes	Banks	Banks	Banks	Banks
Measure of Influence	GNews	Gnews Archive	Gnews + GDP	GNews + GDP Forecast

Notes: All forecasters surveyed by HM Treasury between January 2012 and April 2018. The dependent variable is GDP growth rate in period $t + 1$. The relevant group assignment is Stakes x Influence. In Column (1), the measure of influence is the Google News measure as described in Section 4.1. In Column (2), we extend the search to Archive settings. In Column (3), we require the media release to contain the word “GDP”, while in column (4), we require the media release to contain both the words “GDP” and “forecast”. All specifications include survey fixed effects. The estimated equation is (15). 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 A8: Propaganda Bias at the Intensive Margin in GDP Growth Forecasts – Google News

	Stakes x Influence			Stakes	Influence
	(1)	(2)	(3)	(4)	(5)
Group x Ref. x Stock Price	-0.431*** (0.096)		-0.319*** (0.107)	-0.330*** (0.098)	
Group x Ref. x log(News)		-0.602*** (0.152)	-0.253 (0.155)		-0.833*** (0.146)
Observations	1,643	1,643	1,643	1,643	1,643
R ²	0.771	0.770	0.771	0.770	0.772
Fixed Effects	✓	✓	✓	✓	✓
Survey Month Effects	✓	✓	✓	✓	✓
Measure of Stakes	Banks	Banks	Banks	Banks	
Measure of Influence	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. Stock Price and log(News) have been standardized to have mean 0 and variance 1. 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 (18). Standard errors robust to two-way clustering at the forecaster and the survey levels are in parentheses. *, **, *** represent the 10%, 5%, 1% significance levels.