Strategic roll call vote requests^{*} Fang-Yi Chiou[†] Simon Hug[‡] Bjørn Høyland[§]

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Abstract

Roll call vote analyses used to infer ideal-points of legislators or the cohesiveness of parties all implicitly assume that the data-generating process leading to such votes is random and does not affect MPs' behavior. If roll call votes, however, are requested by party leaders or MPs, this assumption is unlikely to hold. Strategic considerations by the actors requesting roll call votes are likely to influence the inferences we wish to make based on observed voting behavior by legislators. To address this issue we propose the use of a statistical strategic model for simultaneous moves. We present an evaluation of its small sample properties and apply it to data on roll call vote requests in the European parliament. We find that the estimator outperforms competing approaches and demonstrate that strategic considerations play a considerable role in roll call vote requests in the European Parliament.

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The analysis of roll call votes has progressed both in terms of sophistication and scope over the last few decades. On the one hand, new tools make using roll call data easier and theoretically more insightful. On the other, parliaments make available information on parliamentary votes with increasing frequency. Often, however, scholars forget that roll call votes in most parliaments have to be, at least in part, requested by an actor (e.g., Fennell, 1974; Hug, 2010; Crisp and Driscoll, 2012; Hug, Wegmann and Wüest, 2015). So far, we know very little about when, if the standing orders of parliaments permit it, roll call votes are requested. In an early study Fennell (1974) surmises some possible "reasons," while Carrubba, Gabel and Hug (2008*a*) present a game-theoretic analysis of roll call vote requests (see also Ainsley and Maxwell, 2012; Wüest, 2013, 2016).

The few studies that focus on the reasons of roll call votes explicitly emphasize that actors requesting such votes do so for strategic reasons. At the empirical level, however, tests most often focus on evaluating observable implications quite removed from actual roll call vote requests and/or neglect their strategic nature (e.g. Finke, 2015; Thierse, 2016). To our knowledge only Chiou and Yang (2008) offer an empirical analysis that takes into account the strategic nature of roll call vote requests.

In this paper we extend their statistical strategic model by addressing an issue related to characteristics of non-experimental data and make it amenable to a large set of empirical specifications. We demonstrate in Monte Carlo simulations that our estimator recovers well the parameters of the assumed data-generating process, while a commonly used alternative, namely logit models, lead to much more biased estimates. We then illustrate with a replication study focusing on the European parliament how insights change quite dramatically if the strategic context of roll call vote requests is directly integrated in the statistical model. The next section provides the substantive motivation for our contribution. We briefly review work on roll call votes generally and roll call vote requests more specifically. Based on the work discussed we argue that scholars implicitly or explicitly consider requests for roll call votes to be part of a strategic game. In section three we present the estimator which takes into account the strategic nature of roll call vote requests and offer evidence for its performance in a Monte Carlo study in section four. Section five presents the results of a replication study in which we reestimate a model using data from the European Parliament, while applying our proposed estimator.

Substantive motivation

The study of roll call votes in parliaments has seen important developments over the last few decades (for recent reviews, see McCarty, 2011; Hug, 2013; Carroll and Poole, 2014; Godbout, 2014; Hug, 2017). This development has profited on the one hand from methodological developments (for excellent overviews, see Poole, 2005; McCarty, 2011; Armstrong, Bakker, Carroll, Hare, Poole and Rosenthal, 2014) and on the other by the increasing ease with which roll call data can be collected (which is linked in part to the introduction of electronic voting systems in many parliaments, see Middlebrook, 2003; Hug, Wegmann and Wüest, 2015; Wüest, 2016). Having access to datasets on roll call votes from various parliaments also increased the interest in comparative work (e.g., Depauw, 2003; Thames, 2007; Carey, 2009; Depauw and Martin, 2009; Feliú and Onuki, 2014; Godbout, 2014; Coman, 2015; Hix and Noury, 2016). Such work, however, is fraught by difficulties due to differences in the rules under which roll call votes occur. Such differences are also likely to affect the inferences we may draw from roll call data (see Roberts, 2007; Hug, 2010, 2016).

Whether roll call votes are even possible depends in most parliamentary chambers on their standing orders. As several authors have convincingly shown, few chambers envision that all votes are carried out by roll call votes (or open voting, see Saalfeld, 1995; Carrubba, Gabel and Hug, 2008*a*; Hug, 2010; Crisp and Driscoll, 2012; Hug, Wegmann and Wüest, 2015; Wüest, 2016). Equally few chambers envision no circumstances under which roll call votes might be possible. Already these institutional differences are of interest, and Carey (2009) argues that they relate to questions of transparency (for an empirical analysis of voting procedures as defined in the standing orders of European parliaments, see Hug, Wegmann and Wüest, 2015). As many standing orders of parliamentary chambers envision requests for roll call votes, it seems of tantamount importance to understand under what circumstances such requests are made (for information regarding this point for Latin American and European parliamentary chambers, respectively a larger set of countries, see Crisp and Driscoll, 2012; Hug, Wegmann and Wüest, 2015; Wüest, 2016). Only then will we be able to assess the consequences for analyses of roll call vote data.

In an early study Fennell (1974) offers a list of possible reasons why roll call votes might be requested. In a similar vein, focusing on the European parliament Thiem (2009), Finke (2015) and Thierse (2016) offer and evaluate a list of similar hypotheses.¹ At a theoretical level Carrubba, Gabel and Hug (2008*a*) propose a model under the assumption that roll call vote requests are made by leaders of party groups for disciplining purposes. Their model suggests that the location of

¹Relatedly, Trumm (2015) tries to assess through an MP survey whether MPs are likely to vote differently in a roll call vote than in other votes (see also Mühlböck and Yordanova, 2015; Hug, 2016; Hix, Noury and Roland, 2018). Similarly, Thierse (2016) offers some empirical evidence based on interviews in the European parliament. Finally, Stecker (2010), focusing on regional parliaments in Germany, also evaluates what might explain roll call votes (see also Stecker, 2011).

the bill and the status quo, as well as preference heterogeneity in party groups combine in complex ways in explaining roll call vote requests.² Ainsley and Maxwell (2012) focus in their theoretical model mostly on the idea that roll call vote requests are made to signal preferences or unity (resp. disunity) of party groups. Their model implies, however, that if signaling is the motivation behind roll call votes, all votes should be roll called. Finally, Wüest (2013) argues that roll call vote requests must be considered as the result of the interplay of constituency and party preferences and how they relate to MPs' preferences (see also Wüest, 2016). Akin to Ainsley and Maxwell's (2012) approach, MPs may gain electorally if they take a stance in a roll call vote (or do so, invisibly, in a secret vote).

While all these studies either explicitly, by using a game-theoretic approach, or implicitly assume that roll call vote requests are the outcome of a strategic interaction among various actors, the empirical evaluations do only partly, if at all, account for this. To our knowledge the study by Chiou and Yang (2008) on roll call vote requests by the two main parties in the Taiwanese legislature is the only exception. More specifically, based on an extensive data collection the authors assemble detailed measures of various aspects likely to be important in the calculus of parties when deciding to request a roll call vote. Relying on the general ideas of quantal response equilibria proposed by McKelvey and Palfrey (1995, 1998) for analyzing experimental data (see also Goeree, Holt and Palfrey, 2016) and extended to observational data by Signorino (1999) (see also Signorino, 2002; Signorino, 2003; Signorino and Yilmaz, 2003; Signorino and

 $^{^{2}}$ In a preliminary empirical evaluation focusing on the European parliament Carrubba, Gabel and Hug (2008*b*) find considerable evidence in support of their model, while hypotheses proposed by other scholars (Kreppel, 2002; Hix, Noury and Roland, 2006; Thiem, 2009) fare much worse.

Tarar, 2006)³ Chiou and Yang (2008) propose estimators applicable for a sequential and a simultaneous move game. While their game allows for more than two players, their empirical analysis and estimation focuses on roll call vote requests in the Taiwanese legislature where only two major parties existed and requested roll call votes. Their results demonstrate considerable interdependence between parties and show that the latter follow, in part, in their roll call vote requests different logics.⁴ In substance, one of their primary findings is that the two parties have very different incentives to request roll call votes: while the majority party employs roll call requests to discipline members, the minority party's incentives centers on highlighting or embarrassing the unpopular policy stands of its opponent parties.

All other empirical studies that we are aware of consider the strategic interdependence as a nuisance and attempt to control for this lack of independence amongst observations (i.e., roll call vote requests by each party) by employing econometric fixes. These econometric fixes, relying on clustered and/or robust standard errors, are, however, far from being a miracle cure (see, e.g., Angrist and Pischke, 2008; King and Roberts, 2015).

³Note that these recent extensions focus almost exclusively on QRE estimators in sequential games. For simultaneous move games, for which Goeree, Holt and Palfrey (2016), for instance, discuss many applications for experimental data, much less work has focused on observational data. As we discuss below, this raises particular challenges that have, so far, not been acknowledged in the literature.

⁴To our knowledge all other empirical studies of roll call vote requests either assess only losely connected hypotheses (e.g., Fennell, 1974; Thiem, 2009; Stecker, 2010; Finke, 2015; Thierse, 2016) or assess comparative statics results from a game-theoretic model (e.g., Carrubba, Gabel and Hug, 2008*b*).

Theoretical and empirical model

To overcome these statistical difficulties and address the strategic nature of roll call vote requests directly, we apply and slightly extend Chiou and Yang's (2008) game-theoretic model for roll call vote requests.⁵ In their proposed game, there are N players, denoted as player $1, \ldots, N$ ($N \ge 2$). Moreover, the game is independently played for T times. For each time of play $i, i = 1, \ldots, T$, Player j's strategy set is $S_{ij} = \{r, \tilde{r}\}, j = 1, \ldots, N$, where r and \tilde{r} denote requesting a roll call vote and not requesting a roll call vote, respectively.⁶ In terms of game sequence, for each i, each player simultaneously chooses whether or not to request a roll call vote. When at least one player requests a roll call vote, this vote will be recorded. If none of these N players request a roll call, this vote will not be recorded. Only one of these two outcomes can occur in the game. For each i, player j obtains the utility of $U_{ij}(R)$ when a roll call vote occurs, and $U_{ij}(\tilde{R})$ otherwise. $U_{ij}(\tilde{R}) = 0$ is assumed, making $U_{ij}(R)$ standing for player j's net payoff from a recorded vote.

Moreover, for each *i* and each *j*, Chiou and Yang (2008) assume $U_{ij}(R) = \beta'_j x_{ij}$, where x_{ij} is a $k_j \times 1$ vector representing k_j exogenous variables (with the first element equaling to one), $k_j = 1, 2, ...,$ and β_j is a $k_j \times 1$ vector representing the coefficients of the k_j variables, respectively. In words, x_{ij} is a set of k_j exogenous variables influencing player *j*'s net payoff of obtaining a recorded vote R in the *i*th time of play, while β_j denotes the effects of these variables.

To derive player *i*'s expected utility of playing each strategy, $r_{ij} \in [0, 1]$ is

 $^{^{5}}$ Related setups can be found in Goeree, Holt and Palfrey (2016) for a participation game, which relates closely to the volunteer game analyzed by Diekmann (1985).

⁶We use R and \widetilde{R} to denote the outcome of the game, namely whether a roll call vote occurred, while r and \widetilde{r} (without subscripts) denote the pure strategies of requesting or not requesting a roll call vote. Finally, r_{ij} (with subscripts, here i for vote and j for player) denotes the choice probability in mixed strategies.

denoted as the probability that player j will play r in the i^{th} time of play. For $j = 1, \ldots, N$, player i's expected utility of playing each of the two strategies in the i^{th} time of play is⁷

$$EU_{ij}(r) = U_{ij}(R)$$
$$EU_{ij}(\tilde{r}) = U_{ij}(R)(1 - \prod_{h \neq j} (1 - r_{ih}))$$

This means that player j's net expected payoff of requesting a roll call in the i^{th} time of play is

$$EU_{ij}(r) - EU_{ij}(\tilde{r}) = U_{ij}(R) \prod_{h \neq j} (1 - r_{ih}), i = 1, \dots, T, j = 1, \dots, N$$
(1)

To solve for the equilibrium in this game, Chiou and Yang (2008) apply McKelvey and Palfrey's (1995, 1998) Logit quantal response equilibrium (Logit QRE) as their equilibrium concept.⁸ Specifically, McKelvey and Palfrey's (1995, 1998) Logit QRE differs from Nash equilibrium in that the former allows for bounded rationality by incorporating noise in each player's best response function. Under Nash equilibrium of this game, a player will play a pure strategy of r if and

⁷Note that the expected utility for each player only relates to whether or not a roll call vote occurs and not on (possibly additionally) who lodged this request. Below we will offer an extension that allows for a cost parameter, independent of strategic concerns, to affect the choices by the players, which might correspond to participation costs in Diekmann (1985) or Goeree, Holt and Palfrey's (2016, 2007ff) participation game.

⁸This Logit QRE also assumes that the errors made by each of the players are independently and identically (i.i.d.) distributed according to an extreme value distribution. In Signorino's (1999) conceptualization for extensive form games, this would correspond most closely to what he calls agent errors (for a QRE estimator with correlated errors, see Leemann, 2014). Goeree, Holt and Palfrey (2016) elaborate more on this equilibrium concept that, with the assumption of i.i.d. distributed errors, seems quite appropriate for experimental settings. For observational data, one might consider extensions based on relaxing the i.i.d. assumption.

only if the expected payoff of playing it is strictly greater than that of playing \tilde{r} , but a mixed strategy if the expected payoff of playing each strategy is identical. However, under Logit QRE, player j will play r with the following best response function.

$$r_{ij} = \frac{1}{1 + \exp(-\lambda_j (EU_{ij}(r) - EU_{ij}(\tilde{r})))} \\ = \frac{1}{1 + \exp(-\lambda_j (U_{ij}(R) \prod_{h \neq j} (1 - r_{ih})))}$$
(2)

where $\lambda_j \geq 0.9$ This implies that player *i* will always play *r* with a positive probability between zero and one. However, the probability of playing *r* increases as the net expected utility of playing it, as shown in equation (1), becomes larger, if $\lambda_j > 0$. Thus λ_j captures the noise of player *j*'s best response, i.e., how bounded a player's rationality is. A larger λ_j means that when a player's net benefit of playing *r* is positive (negative), this player will play this strategy with a higher (lower) probability, implying less noise that a player has in responding to the other players. At the extreme, when λ_j approaches positive infinity, the best response function in equation (2) corresponds to that in a Nash equilibrium, i.e, no noise in responding.

At the other extreme, however, when λ_j approaches zero, a player randomly plays r with a probability of $\frac{1}{2}$, independent of x_{ij} and β_j . While this setup is quite powerful in capturing noise, the assumption that each plays r and \tilde{r} with equal probability when $\lambda_j = 0$ may not be reasonable in a non-experimental setting, because the probability of each player playing r and \tilde{r} should not be the same and probably depends on data.

 $^{^9 \}mathrm{We}$ assume that each player has a fixed λ over time but could have a different λ from the others.

To overcome the weakness that in Goeree, Holt and Palfrey's (2016) setup the choice probabilities tend toward $\frac{1}{2}$ when λ_j tends toward 0, we propose a slightly different best response function as follows, making our theoretical setting more general than Chiou and Yang's (2008) setup.

$$r_{ij} = \frac{1}{1 + \exp(\tau - \lambda_j (U_{ij}(R) \prod_{h \neq j} (1 - r_{ih})))}$$
(3)

where $\tau \in \mathbb{R}$. The addition of τ in equation (2) relaxes the assumption of equal choice probabilities for r and \tilde{r} when λ_j tends toward 0. Instead, when $\lambda_j = 0$, player j will play R with the probability of $1/(1 + \exp(\tau))$, which can be estimated from data. Seen as a non-strategic cost of playing r, τ does not depend on how the other players will play and how beneficial it is to play this strategy. This implies that τ generally represents the effect that is not explained by strategic consideration or exogenous variables included in the net utility of R.

For each time of play, the Logit QRE in this simultaneous game can be obtained by solving a system of N equations, consisting of equation (2) for j = 1, ..., N. For each i, we solve this system of equations and obtain its solution of $(r_{i1}^*, ..., r_{iN}^*)$, which is the Logit QRE of this game in the i^{th} time of play. Denote $y_{ij} \in \{0, 1\}$ as the observed strategy played by player j in the i^{th} time of play, where y_{ij} equals to 1 if player j plays r and 0 otherwise. For each i, denote $y_i = (y_{i1}, ..., y_{iN})$ as the observed strategy profile played by all players in the i^{th} time of play. Finally, denote $Y = (y_1, ..., y_T)$ as the strategy profiles in T times of play. The likelihood of observing Y is

$$L(\beta, \lambda, \tau | x_1, \dots, x_N, Y) = \prod_{i=1}^T \prod_{j=1}^N (r_{ij}^*)^{y_{ij}} (1 - r_{ij}^*)^{1 - y_{ij}}$$
(4)

where x_j is a $T \times k_j$ matrix containing players j's covariates in these T times of play, and $\beta = (\beta_1, \ldots, \beta_N)$, $\lambda = (\lambda_1, \ldots, \lambda_{N-1})$. as well as τ are parameters to be estimated.¹⁰ We employ a maximum likelihood approach to obtain the maximizer of (β, λ, τ) . The likelihood function to be maximized corresponds to equation 10, but in each iteration, for the current parameter values a non-linear equation solver is used to ensure that for the given parameters the roll call vote request probabilities for each player are mutual best responses, as specified in equation 2.

Before estimating the model, we need to address identification issues. As seen in equation (2), the product of λ_j and $U_{ij}(R)$ implies that not all of the elements in λ and β can simultaneously be identified. For instance, if each player is assumed to have different coefficients even for the same covariates, as assumed in Chiou and Yang (2008), then λ cannot be identified. Thus, the estimated β s comprise also the respective λ s. However, if we assume that all of the players share (some or all of) the same coefficient(s), then N-1 of the elements in λ can be identified, while one of them needs to be set to a particular value (we choose the value of 1). Alternatively, if we assume players share the same λ_j , we need to impose one of the elements in β to be one in order to identify the rest of β . Given the generality of the setup, caution in addressing identification is warranted.

 $^{^{10}}$ In equation we assume that τ is fixed and identical for all players. Letting it vary across players and/or as a function of exogenous variables is also possible.

The properties of the estimator

In this section, we report the results from a series of Monte-Carlo simulations. We report five sets of simulations. First, we compare three actor baseline models with logit models, assuming that the data generating process (DGP) is either the one our model assumes (i.e., strategic) or reflecting three independent logit models. Second, we extend this to models with four actors. Third, we demonstrate the results from a model with seven actors and actor-specific non-strategic costs ($\tau \neq 0$). Fourth, we demonstrate that the estimator is capable of recovering the true parameters reasonably well in cases with many actors through a presentation of results from a model with fifteen actors, actor-specific and common variables for the strategic part of our model and common variables for the (non-strategic) costs. Finally, we demonstrate that our estimator also allows us to capture λ as we present results from a model with five actors and some actor-specific effects for the strategic part of our model and has.

Three players: statistical strategic vs logit model

First, we compare the performance of our estimator with the performance of a series of logit models in two different scenarios. First, we let the underlying DGP be a strategic model in line with the simplest model from the theoretical section above, as such a DGP is closest to a series of logit models. The only difference is that the β parameters are scaled by the probability of no other actor choosing r. We assume three actors, and for each of them we assume that its utility for a roll call vote has two covariates. The covariates are normally distributed with mean zero and standard deviation one. We generated datasets with 1000 observations.

We repeated this 1000 times.

The top half of the table reports the results from the strategic model when the true DGP is strategic and the bottom half reports the results from a strategic model when the true DGP is a set of logit models. The first column state the true parameter. The second column reports the estimated parameters, averaged across the simulations. The third column reports the absolute difference between the true parameter and the estimated parameter. In the fourth column, we report the proportion of simulations where the 95 percent confidence interval of the estimated parameter covered the true parameter. This should be around .95 if the model is correct. Then, in the sixth column we report the root mean squared error (*rmse*), while in the final column appears the number of simulations.

We see from the upper half of Table 1 that our proposed statistical strategic model performs excellently. The estimated parameters are close to the true parameters, with small *rmses* and correct 95 per cent coverage. The statistical implementation of the theoretical model is capable of recovering the true parameters.

	parameters									
	true	estimated	bias	covered	rmse	N_total				
DGP: statistical strategic model										
$Strategic_S(1)$ intercept	-3.00	-3.07	0.07	0.93	0.04	1000.00				
$Strategic_S(1) x1$	0.60	0.58	0.02	0.94	0.02	1000.00				
$Strategic_S(1) x2$	-0.80	-0.77	0.03	0.94	0.02	1000.00				
$Strategic_S(2)$ intercept	-1.50	-1.52	0.02	0.95	0.01	1000.00				
$Strategic_S(2) x1$	-0.40	-0.38	0.02	0.95	0.01	1000.00				
$Strategic_S(2) x2$	0.70	0.66	0.04	0.94	0.01	1000.00				
$Strategic_S(3)$ intercept	-2.25	-2.29	0.04	0.95	0.03	1000.00				
$Strategic_S(3) x1$	0.50	0.48	0.02	0.95	0.01	1000.00				
$Strategic_S(3) x2$	-0.80	-0.77	0.03	0.95	0.01	1000.00				
i	DGP: thr	ee logit models								
Strategic_L(1) intercept	-3.00	-4.33	1.33	0.00	1.84	1000.00				
$Strategic_L(1) x1$	0.60	0.74	0.14	0.89	0.05	1000.00				
$Strategic_L(1) x2$	-0.80	-0.99	0.19	0.83	0.07	1000.00				
Strategic_L(2) intercept	-1.50	-1.79	0.29	0.23	0.10	1000.00				
$Strategic_L(2) x1$	-0.40	-0.34	0.06	0.88	0.01	1000.00				
$Strategic_L(2) x2$	0.70	0.59	0.11	0.73	0.02	1000.00				
Strategic_L(3) intercept	-2.25	-3.00	0.75	0.00	0.59	1000.00				
Strategic_L(3) x1	0.50	0.53	0.03	0.94	0.02	1000.00				
Strategic_L(3) x2	-0.80	-0.85	0.05	0.94	0.02	1000.00				

 Table 1: Performance of statistical strategic

Next, we investigate to what extent the strategic model is capable of recovering the true parameters if the true DGP is a set of logit models. These results are reported in the lower half of the table. Here we see that while the intercepts are too large and have poor coverage, the substantive coefficients are at least partially recovered. The bias is below 25 per cent of the true parameter values and the coverage is between 0.73 and 0.94, while the *rmses* are below 0.7. In sum, while not ideal, one would not do too bad if one were to estimate parameters based on our statistical strategic model in a scenario where the data is generated without any strategic component.

Having demonstrated that our estimator for a statistical strategic model shows excellent performance when the DGP is indeed strategic, and good performance when applied to scenarios where the DGP corresponds to a set of logit specifications, we subject the standard logit estimator to the same test. First, we check that its performance when the DGP is logit before evaluating its performance when the DGP is strategic. These results are reported in Table 2. The logit scenario is reported in the top half of the table, while the strategic scenario is reported in the bottom half of the table.

parameters										
	true	estimated	bias	covered	rmse	N_total				
DGP: staistical strategic model										
$Logit_S(1)$ intercept	-3.00	-1.65	1.35	0.00	1.84	1000.00				
$Logit_S(1) \times 1$	0.60	0.35	0.25	0.18	0.07	1000.00				
$Logit_S(1) x2$	-0.80	-0.48	0.32	0.05	0.11	1000.00				
$Logit_S(2)$ intercept	-1.50	-1.00	0.50	0.00	0.25	1000.00				
$Logit_S(2) \times 1$	-0.40	-0.28	0.12	0.62	0.02	1000.00				
$Logit_S(2) x2$	0.70	0.50	0.20	0.27	0.05	1000.00				
Logit_S(3) intercept	-2.25	-1.34	0.91	0.00	0.83	1000.00				
$Logit_S(3) x1$	0.50	0.32	0.18	0.35	0.04	1000.00				
$Logit_S(3) x2$	-0.80	-0.51	0.29	0.08	0.09	1000.00				
	DGP: tl	nree logit mode	els							
Logit_L(1) intercept	-3.00	-3.02	0.02	0.96	0.03	1000.00				
$Logit_L(1) x1$	0.60	0.60	0.00	0.95	0.02	1000.00				
$Logit_L(1) x2$	-0.80	-0.81	0.01	0.96	0.02	1000.00				
Logit_L(2) intercept	-1.50	-1.51	0.01	0.96	0.01	1000.00				
$Logit_L(2) \ge 1$	-0.40	-0.40	0.00	0.96	0.01	1000.00				
$Logit_L(2) x2$	0.70	0.70	0.00	0.95	0.01	1000.00				
Logit_L(3) intercept	-2.25	-2.26	0.01	0.94	0.02	1000.00				
Logit_L(3) x1	0.50	0.50	0.00	0.95	0.01	1000.00				
$Logit_L(3) x2$	-0.80	-0.81	0.01	0.95	0.01	1000.00				

Table 2: Performance of logit models

We see from the bottom half of Table 2 that logit models perform prefectly, if the DGP is indeed logit. This should not come as a surprise to anyone. The real question is therefore how well it performs if the DGP is not logit, but strategic. This question is addressed in the upper part of the table. Here we see that the logit models perform poorly in the presence of strategic interdependency between actors. The coefficients are biased towards zero and thus off by up to 45 per cent of the true value. The coverage isalso poor. The estimations of the intercept never recovers the true parameter. Moreover, the substantive coefficients do not fare much better. While one of the parameters has a coverage of 0.62, the others have less than 0.35. Two of the parameters have coverages below 0.1. One is hence ill-advised to rely on logit models in scenarios where strategic considerations ny the actors may be present.

Four players: statistical strategic vs logit model

In this subsection, we compare the statistical strategic and logit models with four actors and three covariates per actor. In particular, we add a binary covariate with a mean of .4 for each of the actors. Again we generated 1000 datasets based both on the strategic and logit DGPs. The results from the strategic models are reported in Table 3.

The strategic model is capable of recovering the true parameters with minuscule biases and *rmses*. The 95 per cent coverage is around 95 per cent, as expected. In other words, the strategic model is able to capture effects of strategic considerations in these kind of models. Also, when the DGP is logit, we see that the performance of the strategic model is, by and large, acceptable. While the constants are consistently larger in magnitude than the true parameters, the substantive coefficients are, in general, well recovered, oftentimes similar to the logit models. The biases tend to be small, with only a few exceptions.

In contrast, in Table 4 we see that a different picture emerges in the case of the logit model. As expected, the logit models perform stellar when the DGP

	parameters									
	true	estimated	bias	covered	rmse	N_total				
DGP: staistical strategic model										
$Strategic_S(1)$ intercept	-3.00	-3.03	0.03	0.95	0.07	1000.00				
$Strategic_S(1) x1$	0.60	0.58	0.02	0.94	0.02	1000.00				
$Strategic_S(1) x2$	-0.80	-0.78	0.02	0.93	0.02	1000.00				
$Strategic_S(1) b1$	0.55	0.54	0.01	0.95	0.05	1000.00				
$Strategic_S(2)$ intercept	-2.50	-2.55	0.05	0.96	0.05	1000.00				
$Strategic_S(2) x1$	-0.40	-0.39	0.01	0.94	0.01	1000.00				
$Strategic_S(2) x2$	0.70	0.68	0.02	0.95	0.02	1000.00				
$Strategic_S(2)$ b2	-0.65	-0.62	0.03	0.93	0.06	1000.00				
$Strategic_S(3)$ intercept	-2.25	-2.29	0.04	0.96	0.05	1000.00				
$Strategic_S(3) x1$	0.50	0.48	0.02	0.94	0.01	1000.00				
$Strategic_S(3) x2$	-0.80	-0.77	0.03	0.93	0.02	1000.00				
$Strategic_S(3)$ b3	-0.87	-0.85	0.02	0.95	0.05	1000.00				
$Strategic_S(4)$ intercept	-2.00	-2.02	0.02	0.94	0.04	1000.00				
$Strategic_S(4) x1$	0.55	0.53	0.02	0.94	0.01	1000.00				
$Strategic_S(4) x2$	-0.90	-0.86	0.04	0.93	0.02	1000.00				
$Strategic_S(4)$ b4	0.45	0.43	0.02	0.93	0.04	1000.00				
	DGP: fou	r logit models								
Strategic_L(1) intercept	-3.00	-4.19	1.19	0.00	1.52	1000.00				
$Strategic_L(1) x1$	0.60	0.57	0.03	0.91	0.02	1000.00				
$Strategic_L(1) x2$	-0.80	-0.77	0.03	0.92	0.02	1000.00				
$Strategic_L(1)$ b1	0.55	0.53	0.02	0.93	0.08	1000.00				
Strategic_L(2) intercept	-2.50	-3.76	1.26	0.00	1.66	1000.00				
$Strategic_L(2) x1$	-0.40	-0.40	0.00	0.92	0.02	1000.00				
Strategic_L(2) x2	0.70	0.70	0.00	0.93	0.02	1000.00				
Strategic_L(2) b2	-0.65	-0.67	0.02	0.93	0.11	1000.00				
Strategic_L(3) intercept	-2.25	-3.31	1.06	0.00	1.17	1000.00				
Strategic_L(3) x1	0.50	0.45	0.05	0.91	0.02	1000.00				
$Strategic_L(3) x2$	-0.80	-0.72	0.08	0.89	0.02	1000.00				
Strategic_L(3) b3	-0.87	-0.84	0.03	0.94	0.08	1000.00				
Strategic_L(4) intercept	-2.00	-2.33	0.33	0.43	0.13	1000.00				
Strategic_L(4) x1	0.55	0.35	0.20	0.28	0.05	1000.00				
$Strategic_L(4) x2$	-0.90	-0.57	0.33	0.06	0.11	1000.00				
$Strategic_L(4)$ b4	0.45	0.28	0.17	0.78	0.05	1000.00				

Table 3: Performance of statistical strategic model

is logit. The interesting results appear when the DGP is strategic. Here, the estimates are off. Across the board, the magnitudes of the estimated parameters are less than 0.5 of the magnitudes of the true parameters. It is only in the case of the binary variables that the coverage is not essentially zero, while the rmses are substantial for all of the estimated coefficients.

Hence, we are unlikely to recover the true parameters using a set of logit models if there is a strategic element in the DGP. Having established that logit models are not suitable in situations where the expectations of what other actors will do factor into their decisions. For these situations, researchers should consider models that take strategic interdependencies into account. In the next subsections, we evaluate to what extent our estimator for the statistical strategic model is also capable of recovering the true parameters in more complex situations.

	true	ameters estimated	bias	covered		N_to			
true estimated bias covered rmse N_to DGP: statistical strategic models									
Logit $S(1)$ intercept	-3.00	-1.10	1.90	0.00	3.63	1000.			
Logit $S(1)$ intercept	0.60	0.26	0.34	0.00	0.12	1000.			
Logit $S(1) \times 1$ Logit $S(1) \times 2$	-0.80	-0.34	$0.34 \\ 0.46$	0.01	0.12 0.21	1000.			
Logit $S(1)$ k2 Logit $S(1)$ b1	0.55	0.24	0.40	0.45	0.12	1000			
Logit $S(2)$ intercept	-2.50	-0.87	1.63	0.00	2.65	1000			
$Logit_S(2)$ intercept Logit_S(2) x1	-0.40	-0.18	0.22	0.12	0.06	1000			
Logit $S(2)$ x1 Logit $S(2)$ x2	0.70	0.30	0.40	0.00	0.16	1000			
Logit $S(2)$ k2	-0.65	-0.28	0.37	0.31	0.16	1000			
Logit $S(3)$ intercept	-2.25	-0.80	1.45	0.00	2.10	1000			
Logit $S(3) \times 1$	0.50	0.22	0.28	0.04	0.08	1000			
Logit $S(3) \times 2$	-0.80	-0.35	0.45	0.00	0.21	1000			
Logit $S(3)$ b3	-0.87	-0.38	0.49	0.10	0.26	1000			
Logit $S(4)$ intercept	-2.00	-0.84	1.16	0.00	1.35	1000			
$Logit_S(4) x1$	0.55	0.27	0.28	0.02	0.09	1000			
Logit S(4) x2	-0.90	-0.44	0.46	0.00	0.22	1000			
$Logit_S(4)$ b4	0.45	0.20	0.25	0.58	0.08	1000			
	DGP: f	our logit mode	ls						
$Logit_L(1)$ intercept	-3.00	-3.03	0.03	0.95	0.07	1000			
$Logit_L(1) x1$	0.60	0.58	0.02	0.94	0.02	1000			
$Logit_L(1) x2$	-0.80	-0.78	0.02	0.93	0.02	1000			
$Logit_L(1)$ b1	0.55	0.54	0.01	0.95	0.05	1000			
$Logit_L(2)$ intercept	-2.50	-2.55	0.05	0.96	0.05	1000			
$Logit_L(2) x1$	-0.40	-0.39	0.01	0.94	0.01	1000			
$Logit_L(2) x2$	0.70	0.68	0.02	0.95	0.02	1000			
$Logit_L(2)$ b2	-0.65	-0.62	0.03	0.93	0.06	1000			
$Logit_L(3)$ intercept	-2.25	-2.29	0.04	0.96	0.05	1000			
$Logit_L(3) x1$	0.50	0.48	0.02	0.94	0.01	1000			
$Logit_L(3) x2$	-0.80	-0.77	0.03	0.93	0.02	1000			
$Logit_L(3)$ b3	-0.87	-0.85	0.02	0.95	0.05	1000			
$Logit_L(4)$ intercept	-2.00	-2.02	0.02	0.94	0.04	1000			
$Logit_L(4) x1$	0.55	0.53	0.02	0.94	0.01	1000			
$Logit_L(4) x2$	-0.90	-0.86	0.04	0.93	0.02	1000			
$Logit_L(4)$ b4	0.45	0.43	0.02	0.93	0.04	1000			

Table 4: Performance of logit models

Seven actors and non-strategic costs

In this subsection, we evaluate the performance of the strategic model in a scenario with seven actors and actor-specific non-strategic costs. We estimate models with three continuous variables with mean 0 and a standard deviation of 1 for the strategic part. The strategic part also has two coefficients that are fixed to be identical across all actors. The non-strategic part has actor-specific intercepts and one covariate each for τ . For models with this many actors and covariates, reliable estimates of parameters and uncertainty are obtainable through bootstrapping.¹¹ For the specification discussed, we ran 100 simulations with 100 bootstraps for each estimation. The results for the strategic variables are shown in Figure 1 while the results for the variables related costs (and thus common and non-strategic) are shown in Figure 2.

The main take-away from the figure is that the model can, via bootstrapping, recover the true parameters for models with many actors. We note that there is little variability in the estimates of the parameter values across the bootstraps. There is more variability in the uncertainty estimates. In cases where it is desirable to obtain very precise estimate of the uncertainty, more than 100 bootstraps may be necessary.

Moving on to the common variables and the non-strategic costs, we see that these parameters are also well recovered with the bootstrap approach.

Fifteen actors and common non-strategic costs

As the number of actors increases, the parameters become harder to estimate precisely. We present results from a model with 15 actors, actor-specific and

¹¹With an increasing number of actors obtaining a positive-definite Hessian becomes often a problem.

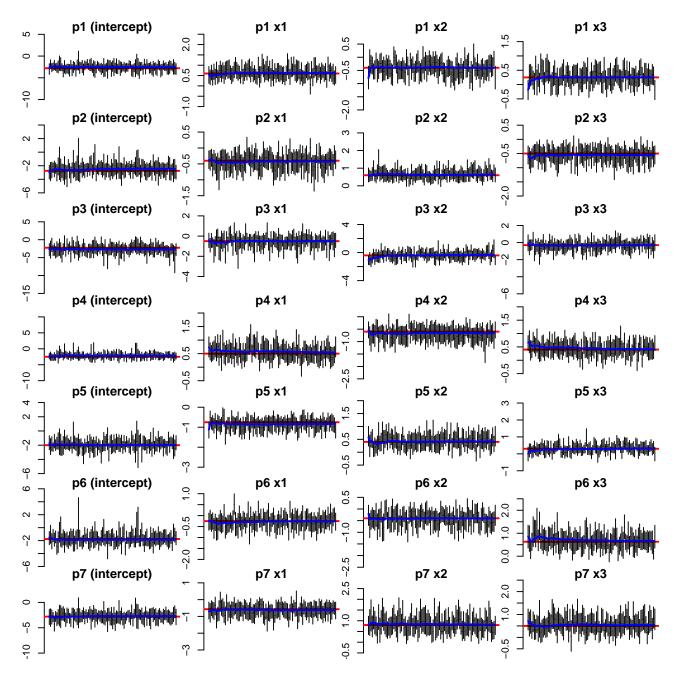


Figure 1: Estimates of strategic model with 7 actors. Red line indicates the true parameter. Blue line indicates cumulative mean. Uncertainty is obtained via bootstrapping. The range on the y-axes indicate the range across the bootstrap estimates.

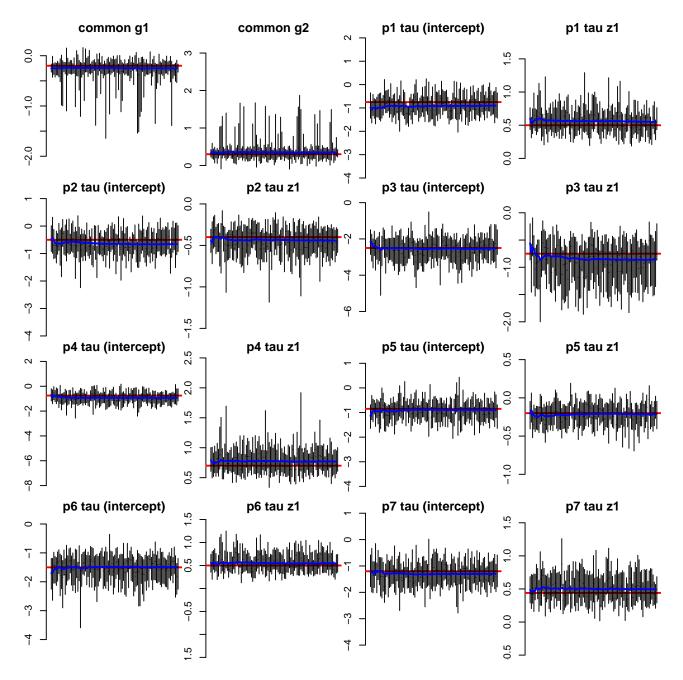


Figure 2: Estimates of strategic model with 7 actors. Red line indicates the true parameter. Blue line indicates cumulative mean. Uncertainty is obtained via bootstrap. The range on the y-axes indicate the range across the bootstrap estimates.

common strategic costs and common non-strategic costs. The results from the simulations are reported in Table 5. The parameters and their uncertainty are calculated on the basis of 100 bootstrap. A higher level of precision may be obtainable through more bootstraps. The results are based on 100 simulations with 100 bootstraps each.

Again, we see that the estimator performs will. Most of the estimated parameters are close to the true parameters. The common parameters, both for the strategic part of the model and non-strategic ones are, perhaps not surprisingly estimated with a higher degree of precision and closer to their true values than the actor-specific parameters. In situations with many actors and not a lot more than 1000 observations per actor, we recommend constraining as many variables as possible to have common effects conditional on it being substantively meaningful.

Five actors, actor-specific non-strategic costs and λ

Finally, we demonstrate that our estimator of the statistical strategic model is able to estimate to what extent actors act strategically relative to the other actors. This is captured by λ and relative to the last actor, in our case, actor 5. To identify these models, it is necessary to constrain some strategic parameters to be common across actors.¹² Here, we also include actor specific non-strategic cost parameters (τ s).

From Table 6 we see that also this model recovers the true parameters, with small biases and low rmses. The coverage of the parameters is close to the theoretically correct level. The only potential exception is with regard to the

 $^{^{12} \}mathrm{In}$ the absence of this constraint, the actor-specific $\lambda \mathrm{s}$ are absorbed by the the slope coefficients.

intercepts, which are less precisely estimated than the other parameters. The estimator is able to capture models with both actor specific costs (τ s), as well as relative rationality (λ).

		par	ameters				
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$\begin{array}{cccc} \mathbf{p1} & \mathbf{p1} & \mathbf{p3} & 0.25 & 0.03 & 0.22 & 0.96 & 0.23 & 100.00 \\ \mathbf{p2} & \mathbf{p1} & -0.40 & -0.77 & 0.13 & 0.99 & 0.11 & 100.00 \\ \mathbf{p2} & \mathbf{p2} & 0.60 & -0.36 & 0.24 & 0.91 & 0.16 & 100.00 \\ \mathbf{p3} & \mathbf{n3} & -0.50 & -0.20 & 0.30 & 0.92 & 0.29 & 100.00 \\ \mathbf{p3} & \mathbf{x1} & -0.50 & -0.33 & 0.17 & 0.91 & 0.15 & 100.00 \\ \mathbf{p3} & \mathbf{x1} & -0.50 & -0.33 & 0.17 & 0.98 & 0.15 & 100.00 \\ \mathbf{p3} & \mathbf{x2} & -0.40 & -0.25 & 0.15 & 0.98 & 0.15 & 100.00 \\ \mathbf{p4} & \mathbf{x1} & 0.50 & -0.33 & 0.17 & 0.98 & 0.12 & 100.00 \\ \mathbf{p4} & \mathbf{x1} & 0.50 & 0.29 & 0.21 & 0.94 & 0.12 & 100.00 \\ \mathbf{p4} & \mathbf{x1} & 0.50 & 0.29 & 0.21 & 0.94 & 0.12 & 100.00 \\ \mathbf{p4} & \mathbf{x2} & -0.60 & -0.35 & 0.25 & 0.91 & 0.18 & 100.00 \\ \mathbf{p4} & \mathbf{x2} & -0.60 & -0.35 & 0.25 & 0.91 & 0.18 & 100.00 \\ \mathbf{p5} & \mathbf{x1} & -0.75 & -0.47 & 0.28 & 0.84 & 0.18 & 100.00 \\ \mathbf{p5} & \mathbf{x2} & 0.40 & 0.29 & 0.11 & 0.98 & 0.12 & 100.00 \\ \mathbf{p5} & \mathbf{x2} & 0.40 & 0.29 & 0.11 & 0.98 & 0.12 & 100.00 \\ \mathbf{p6} & \mathbf{x1} & -0.25 & -0.16 & 0.09 & 0.19 & 0.10 & 100.00 \\ \mathbf{p6} & \mathbf{x1} & -0.25 & -0.16 & 0.09 & 0.19 & 0.10 & 100.00 \\ \mathbf{p6} & \mathbf{x2} & -0.40 & -0.34 & 0.66 & 0.96 & 0.10 & 100.00 \\ \mathbf{p6} & \mathbf{x2} & 0.74 & -0.51 & 0.20 & 0.94 & 0.13 & 100.00 \\ \mathbf{p7} & \mathbf{x1} & 0.57 & -0.37 & 0.20 & 0.94 & 0.13 & 100.00 \\ \mathbf{p7} & \mathbf{x1} & 0.56 & 0.16 & 0.19 & 0.01 & 100.00 \\ \mathbf{p7} & \mathbf{x1} & 0.56 & 0.21 & 0.29 & 0.94 & 0.11 & 100.00 \\ \mathbf{p8} & \mathbf{x1} & 0.56 & 0.23 & 0.27 & 0.98 & 0.25 & 100.00 \\ \mathbf{p9} & \mathbf{p1} & 0.36 & 0.12 & 0.00 & 0.17 & 100.00 \\ \mathbf{p9} & \mathbf{p1} & 0.15 & 0.06 & 0.18 & 0.00 & 0.10 \\ \mathbf{p10} & \mathbf{p1} & 0.56 & 0.74 & 0.88 & 0.99 & 0.11 & 100.00 \\ \mathbf{p1}$							
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p3 (intercept) -2.25 -1.83 0.42 0.82 0.28 100.00 p3 x2 -0.40 -0.25 0.15 0.98 0.15 100.00 p3 x2 -0.40 -0.25 0.15 0.98 0.21 100.00 p4 (intercept) -2.50 -1.96 0.54 0.73 0.41 100.00 p4 x2 -0.60 -0.35 0.25 0.91 0.18 100.00 p4 b3 0.40 0.99 0.31 0.96 0.31 100.00 p5 x1 -0.75 -0.47 0.28 0.84 0.18 100.00 p5 x2 0.40 0.29 0.11 0.98 0.12 100.00 p6 x1 -0.25 -0.16 0.99 0.19 100.00 p6 x2 -0.40 -0.34 0.06 0.10 100.00 p7 x1 -0.57 -0.37 0.20 0.94 0.13 100.00 p7 x1 -0.57 -0.37 0.20 0.							
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$ \begin{array}{ccccc} p3 b3 & -0.30 & -0.13 & 0.17 & 0.98 & 0.21 & 100.00 \\ p4 x1 & 0.50 & 0.29 & 0.21 & 0.94 & 0.12 & 100.00 \\ p4 x2 & -0.60 & -0.35 & 0.25 & 0.91 & 0.18 & 100.00 \\ p4 x2 & -0.60 & -0.35 & 0.25 & 0.91 & 0.18 & 100.00 \\ p5 x1 & -0.75 & -0.47 & 0.28 & 0.84 & 0.18 & 100.00 \\ p5 x2 & 0.40 & 0.29 & 0.11 & 0.98 & 0.12 & 100.00 \\ p5 x3 & 0.30 & 0.21 & 0.09 & 0.99 & 0.19 & 100.00 \\ p5 x3 & 0.30 & 0.21 & 0.09 & 0.99 & 0.19 & 100.00 \\ p6 (intercept) & -0.75 & -0.04 & 0.15 & 0.97 & 0.13 & 100.00 \\ p6 x1 & -0.25 & -0.16 & 0.09 & 1.00 & 0.10 & 100.00 \\ p6 x2 & -0.40 & -0.34 & 0.06 & 0.96 & 0.10 & 100.00 \\ p6 x2 & -0.40 & -0.34 & 0.26 & 0.19 & 100.00 \\ p7 x1 & -0.57 & -0.37 & 0.20 & 0.94 & 0.13 & 100.00 \\ p7 x2 & 0.80 & 0.61 & 0.19 & 0.96 & 0.12 & 100.00 \\ p7 x2 & 0.80 & 0.61 & 0.19 & 0.96 & 0.12 & 100.00 \\ p7 x3 & -0.57 & -0.37 & 0.20 & 0.94 & 0.13 & 100.00 \\ p7 x4 & -0.57 & -0.37 & 0.20 & 0.94 & 0.13 & 100.00 \\ p7 b3 & 0.50 & 0.23 & 0.27 & 0.98 & 0.25 & 100.00 \\ p8 s1 & 0.36 & 0.18 & 0.18 & 0.99 & 0.11 & 100.00 \\ p8 s2 & -0.74 & -0.51 & 0.23 & 0.89 & 0.15 & 100.00 \\ p8 b3 & 0.50 & 0.21 & 0.29 & 0.94 & 0.24 & 100.00 \\ p9 x1 & -0.14 & -0.06 & 0.08 & 0.99 & 0.11 & 100.00 \\ p9 x2 & 0.86 & 0.60 & 0.26 & 0.99 & 0.11 & 100.00 \\ p9 b3 & -0.15 & -0.15 & 0.00 & 0.99 & 0.17 & 100.00 \\ p10 x1 & -0.58 & -0.38 & 0.20 & 0.91 & 0.14 & 100.00 \\ p10 x1 & -0.58 & -0.38 & 0.27 & 1.00 & 0.20 & 100.00 \\ p11 x1 & 0.25 & 0.17 & 0.88 & 0.99 & 0.11 & 100.00 \\ p11 x1 & 0.25 & 0.17 & 0.88 & 0.99 & 0.11 & 100.00 \\ p11 x1 & 0.25 & 0.17 & 0.88 & 0.99 & 0.10 & 100.00 \\ p11 x2 & -0.44 & -0.24 & 0.20 & 0.96 & 0.18 & 100.00 \\ p11 x1 & 0.25 & 0.17 & 0.88 & 0.99 & 0.10 & 100.00 \\ p11 x2 & -0.44 & -0.24 & 0.20 & 0.96 & 0.14 & 100.00 \\ p11 x1 & 0.50 & 0.32 & 0.08 & 0.09 & 0.17 & 100.00 \\ p13 x1 & -0.50 & -0.32 & 0.18 & 0.91 & 0.14 & 100.00 \\ p13 x1 & -0.50 & -0.32 & 0.18 & 0.91 & 0.14 & 100.00 \\ p13 x1 & -0.50 & -0.32 & 0.18 & 0.91 & 0.14 & 100.00 \\ p13 x1 & -0.50 & -0.32 & 0.18 & 0.91 & 0.13 & 100.00 \\ p15 x1 & -0.43 & -0.27 & 0.16 & 0.98 & 0.16 & 100.0$							
p4 (intercept) -2.50 -1.96 0.54 0.73 0.41 100.00 p4 x1 0.50 0.29 0.21 0.94 0.12 100.00 p4 b3 0.40 0.09 0.31 0.96 0.31 100.00 p5 (intercept) -1.75 -1.66 0.19 0.99 0.16 100.00 p5 x1 -0.75 -0.47 0.28 0.84 0.18 100.00 p5 b3 0.30 0.21 0.99 0.99 0.19 100.00 p6 fit -0.25 -0.16 0.99 0.10 100.00 p6 x1 -0.57 -0.37 0.20 0.94 0.13 100.00 p7 x2 0.80 0.61 0.19 0.96 0.12 100.00 p7 x3 0.50 0.23 0.27 0.98 0.17 100.00 p7 x3 0.50 0.23 0.27 0.38 0.11 100.00 p8 x1 0.36 0.18 0.46							
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$\begin{array}{c cccc} p_{5} 5 & 2 & 0.40 & 0.29 & 0.11 & 0.98 & 0.12 & 100.00 \\ p_{6} (ntercept) & 0.75 & -0.90 & 0.15 & 0.97 & 0.13 & 100.00 \\ p_{6} 6 x1 & -0.25 & -0.16 & 0.09 & 1.00 & 0.10 & 100.00 \\ p_{6} 6 x2 & -0.40 & -0.34 & 0.06 & 0.96 & 0.10 & 100.00 \\ p_{7} 6 b 3 & 0.63 & 0.45 & 0.18 & 0.96 & 0.19 & 100.00 \\ p_{7} (ntercept) & -1.80 & -1.54 & 0.26 & 1.00 & 0.17 & 100.00 \\ p_{7} x1 & -0.57 & -0.37 & 0.20 & 0.94 & 0.13 & 100.00 \\ p_{7} x2 & 0.80 & 0.61 & 0.19 & 0.96 & 0.12 & 100.00 \\ p_{8} 8 (ntercept) & -2.30 & -1.82 & 0.48 & 0.74 & 0.36 & 100.00 \\ p_{8} 8 x1 & 0.36 & 0.18 & 0.18 & 0.99 & 0.11 & 100.00 \\ p_{8} b 3 & 0.50 & 0.23 & 0.27 & 0.98 & 0.25 & 100.00 \\ p_{8} b 3 & 0.50 & 0.21 & 0.29 & 0.94 & 0.24 & 100.00 \\ p_{9} p x2 & -0.74 & -0.51 & 0.23 & 0.89 & 0.15 & 100.00 \\ p_{9} p x1 & -0.14 & -0.06 & 0.08 & 0.99 & 0.17 & 100.00 \\ p_{9} p x2 & 0.86 & 0.60 & 0.26 & 0.90 & 0.17 & 100.00 \\ p_{9} p x2 & 0.86 & 0.60 & 0.26 & 0.90 & 0.17 & 100.00 \\ p_{10} x1 & -0.58 & -0.38 & 0.20 & 0.91 & 0.14 & 100.00 \\ p_{10} x1 & -0.58 & -0.38 & 0.20 & 0.91 & 0.14 & 100.00 \\ p_{10} x1 & -0.58 & -0.38 & 0.20 & 0.91 & 0.14 & 100.00 \\ p_{10} x1 & 0.52 & 0.17 & 0.08 & 0.99 & 0.11 & 100.00 \\ p_{11} x2 & -0.44 & -0.24 & 0.20 & 0.96 & 0.14 & 100.00 \\ p_{11} x1 & 0.25 & 0.17 & 0.08 & 0.99 & 0.10 & 100.00 \\ p_{11} x2 & -0.46 & -0.32 & 0.14 & 0.96 & 0.11 & 100.00 \\ p_{11} x2 & -0.46 & -0.32 & 0.14 & 0.96 & 0.11 & 100.00 \\ p_{12} x1 & -0.75 & -0.47 & 0.28 & 0.91 & 0.19 & 100.00 \\ p_{12} h_{3} & 0.73 & 0.30 & 0.43 & 0.86 & 0.43 & 100.00 \\ p_{14} x1 & -0.70 & -0.40 & 0.30 & 0.89 & 0.10 & 100.00 \\ p_{14} x1 & -0.70 & -0.40 & 0.30 & 0.89 & 0.16 & 100.00 \\ p_{15} x2 & 0.84 & 0.27 & 0.16 & 0.96 & 0.11 & 100.00 \\ p_{14} h_{3} & 0.73 & 0.30 & 0.43 & 0.86 & 0.43 & 100.00 \\ p_{15} x1 & -0.43 & -0.27 & 0.16 & 0.96 & 0.11 & 100.00 \\ p_{15} x1 & -0.43 & -0.27 & 0.16 & 0.96 & 0.11 & 100.00 \\ p_{15} x1 & -0.43 & -0.27 & 0.16 & 0.98 & 0.16 & 100.00 \\ common x4 & -0.65 & -0.62 & 0.03 & 1.00 & 0.01 & 100.00 \\ common x4 & -0.65 & -0.62 & 0.03 & 1.00 & 0.01 & 10$							
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$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		0.50	0.23	0.27	0.98	0.25	100.00
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	p8 (intercept)	-2.30	-1.82	0.48	0.74	0.36	100.00
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		0.36	0.18	0.18	0.99	0.11	100.00
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	p8 x2	-0.74	-0.51	0.23	0.89	0.15	100.00
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	p8 b3	0.50	0.21	0.29	0.94	0.24	100.00
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	p9 (intercept)	-2.35	-1.89	0.46	0.77	0.35	100.00
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	p9 x1	-0.14	-0.06	0.08	0.99	0.11	100.00
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	p9 x2	0.86	0.60		0.90	0.17	100.00
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	p9 b3	-0.15	-0.15	0.00	0.99	0.17	100.00
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	p10 (intercept)	-2.00					
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	p10 x1	-0.58					100.00
$\begin{array}{c c c c c c c c c c c c c c c c c c c $			-0.24			0.14	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $							
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$\begin{array}{c} \begin{array}{c} \mbox{common x3} & -0.20 & -0.21 & 0.01 & 1.00 & 0.00 & 100.00 \\ \mbox{common x4} & 0.30 & 0.32 & 0.02 & 1.00 & 0.00 & 100.00 \\ \mbox{common b4} & -0.65 & -0.62 & 0.03 & 1.00 & 0.01 & 100.00 \\ \hline \tau \ \mbox{intercept} & -1.25 & -1.29 & 0.04 & 0.92 & 0.00 & 100.00 \\ \hline \tau \ \ x6 & 0.43 & 0.50 & 0.07 & 0.80 & 0.00 & 100.00 \end{array}$							
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au x6 0.43 0.50 0.07 0.80 0.00 100.00							
-0.11 0.10 0.00 100.00							
	1 00	-0.01	-0.11	0.10	0.03	0.01	100.00

Table 5: 15 actors 1000 observations per actor. Model with actor specific and common strategic variables and common non-strategic variables (τ)

	par	ameters				
	true	estimated	bias	covered	rmse	N_total
p1 (intercept)	-1.75	-1.58	0.17	1.00	0.23	100.00
p1 x1	0.60	0.65	0.05	0.96	0.08	100.00
p1 x2	-0.80	-0.81	0.01	0.99	0.07	100.00
p1 b3	0.55	0.40	0.15	0.93	0.23	100.00
p2 (intercept)	-2.50	-2.45	0.05	0.97	0.98	100.00
p2 x1	-0.40	-0.42	0.02	0.97	0.05	100.00
p2 x2	0.70	0.72	0.02	0.97	0.08	100.00
p2 b3	-0.65	-0.69	0.04	0.97	0.30	100.00
p3 (intercept)	-2.25	-1.93	0.32	0.84	1.11	100.00
p3 x1	0.50	0.49	0.01	0.99	0.07	100.00
p3 x2	-0.80	-0.78	0.02	0.94	0.14	100.00
p3 b3	-0.87	-0.83	0.04	0.97	0.22	100.00
p4 (intercept)	-2.50	-2.80	0.30	0.97	2.21	100.00
p4 x1	0.55	0.62	0.07	0.96	0.16	100.00
p4 x2	-0.90	-1.01	0.11	0.96	0.26	100.00
p4 b3	0.45	0.36	0.09	0.99	0.29	100.00
p5 (intercept)	-2.00	-1.85	0.15	0.86	1.30	100.00
p5 x1	0.48	0.48	0.00	0.93	0.06	100.00
p5 x2	-0.76	-0.76	0.00	0.97	0.13	100.00
p5 b3	-0.32	-0.28	0.04	1.00	0.12	100.00
common g1	-0.75	-0.73	0.02	0.99	0.01	100.00
common g2	0.24	0.21	0.03	0.95	0.02	100.00
p1 τ (intercept)	-0.75	-0.80	0.05	0.97	0.01	100.00
p1 τ z1	-0.33	-0.34	0.01	1.00	0.00	100.00
$p2 \tau$ (intercept)	-0.50	-0.54	0.04	0.99	0.03	100.00
$p2 \tau z1$	0.54	0.57	0.03	0.99	0.01	100.00
p3 τ (intercept)	-0.25	-0.33	0.08	1.00	0.02	100.00
$p3 \tau z1$	0.76	0.80	0.04	0.97	0.01	100.00
p4 τ (intercept)	-1.79	-1.79	0.00	0.98	0.03	100.00
$p4 \tau z1$	-1.40	-1.44	0.04	0.99	0.01	100.00
p5 τ (intercept)	-0.50	-0.56	0.06	0.97	0.02	100.00
$p5 \tau z1$	-0.65	-0.66	0.01	1.00	0.01	100.00
λ 1	0.30	0.45	0.15	0.99	0.06	100.00
λ 2	-0.32	-0.03	0.29	0.94	0.13	100.00
λ 3	0.20	0.32	0.12	0.99	0.07	100.00
$\lambda 4$	-0.24	0.00	0.24	0.94	0.12	100.00

Table 6: Five actors 1000 observations per actor. Model with actor specific and common strategic variables and common non-strategic variables (τ) and relative degree of rationality, (λ).

Application

To illustrate our estimator empirically, we replicate a study of roll call vote requests in the European parliament by Thierse (2016). He relies on the distinction between the logic of requesting roll call votes as a monitoring and disciplining tool vs. roll call requests as a tool for signaling position taking. The paper spends a substantive part discussing different strategic aspects related to the political groups' decision to request a roll call, underscoring the fact that while a group (or 40 MEPs) can obtain a roll call by simply requesting it, there is no way for a group to prevent a roll call vote from occurring, given that some other group may put in a request. This argument provides an excellent motivation for the theoretical setup we have presented above and is underlined by Thierse (2016, 224) quoting Hix, Noury and Roland (2006, 114):

. . . a political party in the European Parliament can decide which issues it would like to see held by a roll-call vote. But a party cannot prevent other parties calling roll-call votes on issues it would prefer to be decided by secret ballot, for example, because its members are divided on the issue.

In his empirical study, Thierse (2016, 226f) aims mainly to adjudicate between the disciplining and signaling logic through three hypotheses focusing on roll call vote (RCV) requests:

- H_1 : EPGs which have lost out cohesively in committee are more likely to sponsor RCV requests.
- H_2 : EPGs which have been in-cohesive in the committee vote are more likely to sponsor RCV requests.

 H_3 : RCV requests are more likely the less consensual the outcome of the preceding vote in the committee responsible for drafting legislation.

In his empirical analysis he finds support for H1, namely a negative coefficient for his variable committee vote, while H3 is rejected as the coefficient for his measure IPP (index of political perturbation, reflecting divisions in the committee vote) is negative as well. This, he concludes, is evidence against the monitoring and disciplining hypothesis. Instead, it counts as support for the signaling account. Roll call vote requests are also more likely on single-authored amendments, according to the empirical results. In addition, he finds that groups are likely to request roll call votes on their own reports and that media attention and the group's policy salience, but not policy position, increase the probability of roll-call requests.¹³ One important issue neglected by Thierse (2016) is that starting with 2008 the IND/DEM party group almost systematically requested roll call votes on all final votes to ensure that the standing orders were changed in favor of more transparency (for an insightful discussion, see Mühlböck and Yordanova, 2015). The consequence of this maneuver was the change in the standing orders requiring roll call votes on all legislative final passage votes (see Mühlböck and Yordanova, 2015; Hug, 2016; Hix, Noury and Roland, 2018).

Thierse's (2016) main analysis is based on a statistical analysis of 6001 votes on 387 proposals and roll call vote requests by seven party groups.¹⁴ He uses a logit model with "crossed-random effects" on political groups and votes, allowing groups to have different baseline probabilities of requesting roll call votes, but holding the effects of covariates fixed across groups. In Table 7 we reproduce the

¹³We have various issues regarding the specification and operationalization of Thierse's (2016) empirical model, but will stick to his setup in the main analysis.

 $^{^{14}}$ Roll call vote requests submitted by at least 40 members of the European parliament were not taken into account in Thierse's (2016) analysis and we proceed likewise.

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	-3.76^{*}	-3.82^{*}	-4.25^{*}	-4.09^{*}	-4.44^{*}
	(0.05)	(0.31)	(0.32)	(0.34)	(0.72)
EPG amendment			2.53^{*}	2.44^{*}	2.40^{*}
			(0.09)	(0.10)	(0.10)
Joint amendment			1.46^{*}	1.44^{*}	1.43^{*}
			(0.10)	(0.10)	(0.10)
Committee amendment			-0.24^{*}	-0.24^{*}	-0.25^{*}
			(0.07)	(0.08)	(0.08)
Final Vote			2.11^{*}	2.31^{*}	2.32^{*}
			(0.10)	(0.11)	(0.11)
EPG committee vote				-0.90^{*}	-0.88^{*}
				(0.08)	(0.40)
IPP				-0.32^{*}	0.11
				(0.14)	(0.59)
Reading				0.81^{*}	0.83^{*}
				(0.09)	(0.09)
Rapporteur				0.59^{*}	0.65^{*}
				(0.09)	(0.09)
# Amendments				0.25	0.32
				(0.18)	(0.18)
Media				0.33^{*}	0.36^{*}
				(0.15)	(0.16)
Policy position				0.14	0.30^{*}
				(0.15)	(0.15)
Policy salience				0.52^{*}	0.34^{*}
				(0.11)	(0.11)
AIC	13847.97	13194.63	11912.90	11331.42	11225.17
BIC	13865.26	13220.57	11973.42	11460.69	11397.52
Log Likelihood	-6921.98	-6594.32	-5949.45	-5650.71	-5592.58
Num. obs.	42007	42007	42007	40863	40863
Num. groups: VoteID	6001	6001	6001	6001	6001
Var: VoteID (Intercept)	1.36	0.78	0.74	0.70	0.73
Num. groups: PG		7	7	7	7
Var: PG (Intercept)		0.65	0.68	0.66	3.27
Var: PG margWin					0.81
Var: PG ipp					2.26
Cov: PG (Intercept) margWin					-1.14
Cov: PG (Intercept) ipp					-2.26
Cov: PG margWin ipp					0.42
$p^* < 0.05$					

Table 7: Replication of Models 1 -4 in Thierse (2016). Model 5 has varying slopes for EPG committee vote and IPP.

results.

There are no substantive differences, once we account for different representation of the party intercepts. Thierse reports the party specific intercepts, but we report the main intercepts and party-specific deviations from that. Note however that this is only a difference in the style of reporting and not a substantive difference in results.

	Model 2 τ		Model 3 τ		Model 4 τ		Model 5 τ	
EPP	0.68	(0.073)	0.07	(0.252)	-0.46	(0.148)	0.78	(0.071)
PSE	-0.15	(0.107)	-0.85	(0.283)	-1.14	(0.155)	-1.87	(0.036)
ALDE	-1.11	(0.158)	-1.78	(0.338)	-2.34	(0.18)	-1.54	(0.04)
GUE	0.46	(0.094)	-0.24	(0.312)	-0.68	(0.13)	-0.12	(0.04)
IND/DEM	1.03	(0.072)	0.56	(0.297)	0.11	(0.131)	1.03	(0.047)
UEN	-1.69	(0.189)	-1.94	(0.336)	-2.15	(0.177)	-4.81	(0.038)
Verts	1.52	(0.057)	0.71	(0.214)	0.32	(0.132)	0.71	(0.036)
EPG amendment			2.60	(0.089)	2.57	(0.069)	2.42	(0.038)
Joint amendment			1.87	(0.141)	1.75	(0.11)	1.70	(0.045)
Committee amendment			-0.31	(0.085)	-0.32	(0.065)	-0.33	(0.044)
Final Vote			3.78	(0.443)	3.84	(0.298)	3.24	(0.395)
EPG committee vote					-0.98	(0.065)		
EPG committee vote EPP							-1.82	(0.042)
EPG committee vote PSE							0.27	(0.038)
EPG committee vote ALDE							-1.85	(0.038)
EPG committee vote GUE							-1.43	(0.038)
EPG committee vote IND/DEM							-0.27	(0.041)
EPG committee vote UEN							2.17	(0.04)
EPG committee vote Verts							-0.84	(0.037)
IPP					-0.44	(0.107)		
IPP EPP							-0.34	(0.045)
IPP PSE							0.29	(0.042)
IPP ALDE							1.56	(0.041)
IPP GUE							0.17	(0.037)
IPP IND/DEM							-2.11	(0.039)
IPP UEN							0.47	(0.393)
IPP Verts							0.01	(0.039)
Reading					1.10	(0.081)	1.03	(0.04)
Rapporteur					0.70	(0.065)	0.72	(0.037)
# Amendments					0.28	(0.12)	0.16	(0.038)
Media					0.95	(0.196)	0.81	(0.091)
Policy position					0.48	(0.093)	0.43	(0.038)
Policy salience					0.67	(0.088)	0.42	(0.037)
$log(\tau)$	1.27	(0.01)	1.24	(0.065)	1.17	(0.022)	1.28	(0.018)
Total observations	42,007		42,007		42,007		42,007	
Votes	6001		6001		6002		6001	
 log-likelihood 								

 Table 8: Strategic models

Results from strategic models

Here, we report the results from the strategic models. We re-estimate models 2 -5 from the previous section, but impute, rather than drop missing observations. We bootstrap standard errors, re-imputing missing data at each bootstrap iteration. We repeat the bootstrap step until the Monte-Carlo errors are less than 6.27% for all coefficients.¹⁵ These results are presented in Table 8. Our main focus is on the two variables of theoretical interest, *EPG Committee Vote* and *IPP*. We see that the non-strategic and the strategic version of Model 4 are in agreement. Both of these variables have negative signs. The strategic model helps to clarify the restrictiveness of the assumption of common effects across actors. It implies that the reaction-function of the parties are equally affected by this variable. By assuming a common effect of *IPP*, one is willing to make the assumption

¹⁵The results reported here are based on fewer iterations, and should as such be considered preliminary.

that all groups react equally to the extent of division within the EP committee, and by extension the EP itself. Also, in the case of *EPG Committee Vote*, this ignores that some groups, such as EPP, ALDE and PES are more often on the winning side than some of the smaller parties that tend to be more permanently in opposition (Kreppel and Hix, 2003).

While both the non-strategic and the strategic versions of Model 5 reveal substantive heterogeneity in these effects, the direction of the effects change in some instances when strategic considerations are taken into account. We first compare *IPP* by group across these two versions of the model. We compare the groups in the order from positive to negative in the non-strategic version of the model. Starting with ALDE. It has a strong positive effect in both versions. This is not the case for UEN. While the effect was almost as strong in the non-strategic model, this effect is not present in the strategic version. In the case of Verts, the non-strategic version did not detect any effect of *IPP*, the strategic version identifies a strong positive effect. In contrast, for GUE, for which we failed to find any effects of *IPP* in the non-strategic version, in the strategic model, we find at best a small positive effect. Now, consider EPP, the non-strategic model suggested a negative effect. In contrast, the strategic version finds a positive effect of division within committees on the utility of roll call requests. In contrast, for PES, the other major party, the negative effect found in the non-strategic model is also supported by the strategic model. This is also the case for IND, the large negative effect hold across both version of the model.

Now, we consider *EPG Committee vote*, the proportion of a group's committee members that voted with the winning side. The original study reported a negative effect. Model 4 also finds a negative effect. Again we contrast the results across the non-strategic and strategic versions of Model 5, going from high to low in the non-strategic version. Note that in this case, we only found effects in the non-strategic case for UEN (positive) and EPP (negative). In the case of both of these groups, these results hold in the strategic case as well. We find effects for several of the other groups as well. In the case of IND, we see a positive effect, where no effect was detectable in the non-strategic case. For Verts, there was no effect in the non-strategic case, but a large negative effect in the strategic model. For PSE, we see, in contrast to the non-strategic case, a clear negative effect. The same is the case for GUE, but here, the negative effect is very large. For ALDE, we also detect a large negative effect. Finally, while the sign of the effect is the same for EPP, the magnitude of the effect is compared to other groups smaller in the strategic version than in the non-strategic case.

Some of the control variables also merit some consideration. For example, the Media coverage effect is positive here as well. In contrast, while policy position, changes from non-significant to significant from Models 4 to 5 in the non-strategic version, the reverse is (almost) the case in the strategic version, where the effect change by almost an order of magnitude. In contrast, policy salience remains fairly stable and positive in model 4 and 5 across both the strategic as well as non-strategic versions. The same is the case when the group has the rapporteur on the legislation. Also, roll calls are more likely on second reading votes.

Models with λ

In Table 9, we report the results from models with λ . Recall that λ is a scaling parameters that capture differences in the degree of actors' rationally given the covariates in the model. Negative values indicate a lower extent of rationality, while positive values indicates a higher extent of rationality. Large differences in the λ may also indicate that the reaction-functions of the actors are poorly

	Model 3 λ		Model 4 λ		Model 5 λ	
EPP	-0.20	(0.11)	-0.48	(0.06)	-0.48	(0.088)
PSE	-0.77	(0.072)	-1.20	(0.119)	-1.16	(0.045)
ALDE	-1.36	(0.105)	-2.27	(0.197)	-2.84	(0.033)
GUE	-0.41	(0.05)	-0.71	(0.05)	-0.76	(0.062)
IND/DEM	-0.23	(0.044)	-0.44	(0.052)	-0.31	(0.054)
UEN	-1.58	(0.095)	-1.86	(0.094)	-1.44	(0.07)
Verts	0.71	(0.101)	0.35	(0.053)	0.15	(0.055)
EPG amendment	1.60	(0.073)	1.90	(0.072)	1.92	(0.044)
Joint amendment	1.07	(0.098)	1.26	(0.072)	1.25	(0.076)
Committee amendment	-0.16	(0.058)	-0.22	(0.038)	-0.19	(0.05)
Final Vote	2.56	(0.159)	2.80	(0.12)	3.21	(0.056)
EPG committee vote			-0.59	(0.052)		
EPG committee vote EPP					-1.05	(0.053)
EPG committee vote PSE n					-0.41	(0.046)
EPG committee vote ALDE					-0.94	(0.045)
EPG committee vote GUE					-0.96	(0.069)
EPG committee vote IND/DEM					-0.44	(0.046)
EPG committee vote UEN					-1.21	(0.051)
EPG committee vote Verts					-0.53	(0.051)
IPP			-0.36	(0.047)		()
IPP EPP				. ,	0.28	(0.059)
IPP PSE					-0.51	(0.084)
IPP ALDE					2.57	(0.122)
IPP GUE					0.33	(0.058)
IPP IND/DEM					-0.87	(0.053)
IPP UEN					0.00	(0.292)
IPP Verts					0.15	(0.052)
Reading			0.69	(0.067)	0.71	(0.06)
Rapporteur			0.43	(0.06)	0.59	(0.053)
# Amendments			-0.04	(0.07)	0.08	(0.044)
Media			0.63	(0.079)	0.44	(0.057)
Policy position			0.50	(0.031)	0.40	(0.053)
Policy salience			0.34	(0.06)	0.18	(0.062)
$log(\lambda)$ EPP	0.38	(0.099)	0.23	(0.049)	0.18	(0.051)
$log(\lambda)$ PSE	0.55	(0.078)	0.32	(0.079)	0.43	(0.051)
$log(\lambda)$ ALDE	0.63	(0.092)	0.14	(0.09)	0.47	(0.074)
$log(\lambda)$ GUE	0.67	(0.062)	0.38	(0.039)	0.28	(0.034)
$log(\lambda)$ IND	0.99	(0.061)	0.90	(0.025)	0.77	(0.023)
$log(\lambda)$ UEN	0.35	(0.103)	0.19	(0.062)	0.20	(0.049)
$log(\tau)$	1.13	(0.03)	1.09	(0.002) (0.015)	1.08	(0.016)
Total observations	42,007	(0.00)	42,007	(0.010)	42,007	(0.0.0)
Votes	6001		6001		6001	
- log-likelihood			0002			

Table 9: Strategic models with λ

specified. For identification, λ_{Verts} is fixed to 1.

Across the models, we see that the differences in λ are decreasing as we move towards the right in the Table. The additional covariates account for some of the differences in λ seen in Model 3. However, one group clearly stands out, IND/DEM. This Euroskeptic group did indeed use roll call requests in order to disrupt the workings of the EP. As mentioned above, they systematically requested roll calls on almost all final passage votes from 2008 onwards.

We also see that the estimating λ s affects the substantive results. We see that *EPG committee vote* is negative across all groups. In line with Thierse's (2016, 231) we also find that EPGs are less likely to request roll calls when their committee members are on the winning side. This in in contrast to the results in Model 5 τ , where we found that positive effects of *EPG committee vote* for PSE and UEN (for UEN only, we also found this positive effect in Model 5).

In contrast, it remains questionable to what extent there are grounds for the

clear rejection of H3, that roll call vote requests are more likely for votes that generated divisions in the committee (*IPP*). While, we also find a negative effect on average, the pattern is mixed when broken down by political groups. Indeed, the reverse is the case for most groups. The EPP, ALDE, GUE and Verts are more likely to request the more contested the committee vote. It is only PSE and IND that have a negative effect. Indeed the overall negative average effect seems to be driven by IND. It is hence premature to reject the hypothesis that most groups in the EP request roll calls on votes that proved divisive in the committee.

Discussion

Overall, we see that the results reported in the original study hold up in the strategic models *only if* we force the effects to be common across parties. But the replication revealed that there was substantive between party variation in the theoretical variables of interests. These findings demonstrate the need to take theory serious in empirical investigations. As there are several problematic issues with regards to both operationalization of key variables and case-selection we refrain from drawing any firm conclusions about logic of roll call vote requests in the European Parliament. Instead, we call for more theoretically informed empirical investigations.

Conclusion

In this paper, we propose a strategic model of roll call requests. While few scholars deny that roll calls are requested for a reason, the strategic feature of roll call requests is rarely taken into account in empirical work on legislative behavior. To our knowledge, the only exception is Chiou and Yang (2008), who model strategic roll call vote requests and apply it empirically to a case with two players in the context of the Taiwanese legislature. We build upon and generalize their statistical strategic model to account also for non-strategic costs.

Monte-Carlo simulations show that the performance of our model is superior to a set of party-specific logit models in terms of parameter coverage and root mean squared errors. Finally, we demonstrate the empirical relevance of our model through a replication study. In the replicated study, the strategic aspects of roll call requests are discussed, but not modeled in the statistical analysis. When the strategic aspects are accounted for, the key findings of this study no longer hold up.

Appendix

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