



Actor-Partner Interdependence Models (APIM) and Voting Behavior: Methodology and Applications

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Abstract

Recently, the social sciences have witnessed a rising interest in dyadic design, as an efficient way to disentangle mechanisms of interpersonal influence. Despite the relevance of this design to political research, few efforts have been made to collect and efficiently analyze dyadic data. In this article, we suggest the Actor-Partner Interdependence Model as a useful tool to test bidirectional effects in dyadic data on political attitudes and behaviors. The model explicitly assumes that members of a dyad (reciprocally identified as actor and partner) involved in political communication are interdependent and influence each other. We apply the model to estimate the effect of partner's party identification on actor's vote choice, using 1996 Indianapolis-St. Louis dyadic data. Results show that partner's party identification is significantly associated with vote choice. Moreover, we show that influence between dyads' members is moderated by their intimacy, and that an increased difference in socio-economic status between dyad's members unbalances the influence effect in favor of the individual with more resources. Our conclusions call for increasing efforts in collecting dyadic data and to develop proper tools for their analysis.

Keywords: political communication, APIM, electoral behavior, multilevel modeling, interpersonal influence

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Introduction

According to a long tradition of electoral studies, discussions on political matters affect voting behavior (Berelson, Lazarsfeld & McPhee, 1954; Huckfeldt & Sprague 1995; Lazarsfeld, Berelson & Gaudet, 1944). Despite a widespread acceptance of this idea, the study of interpersonal political communication remains a challenge because of its interdependent nature. In fact, political communication is not a one-way process and people involved in political discussion influence each other, for instance, reciprocally reinforcing their opinions when they agree or weakening their positions when they disagree (Huckfeldt, Johnson & Sprague, 2004; Huckfeldt & Sprague 1995).

In most of the data used to study the role of political discussion, alters' characteristics are ego-reported, for instance in ANES (Erisen & Erisen, 2007) and GLES (Schmitt-Beck, Bytzeck, Rattinger, Roßteutscher & Weßels, 2009). As pointed out by Huckfeldt and colleagues (Huckfeldt & Sprague 1987), this design is sub-optimal, as respondents' perceptions are potentially affected by cognitive biases that could undermine the validity of such information, especially when referred to alters' political attitudes. Although it has been shown that the main respondent's perceptions of discussant's political preferences are fairly accurate in case of agreement, these perceptions are substantially biased in case of disagreement (Huckfeldt & Sprague 1995, 131). Moreover, the design bears a serious additional limitation, as it is restricted to a limited amount of discussant's information, not allowing to consider the same set of variables for both respondent (the informant) and discussant.

A way to avoid these limitations is to interview both respondents and their discussants, avoiding drawing upon evaluations of proxy informants. Compared to self-reported respondent's perception of discussant's information, such a data collection strategy provides direct and symmetric

information for both the individuals. When confronted with these dyadic data, we are clearly dealing with two agents who can affect each other. As a consequence, the distinction of two different positions in the communication process (respondent and discussant) becomes meaningless (Huckfeldt, Johnson & Sprague, 2004) and we are left with the two roles of actor and partner, those roles being reciprocally played by the two members of the dyad. In recent years, this dyadic design has received increasing attention in social psychology (Badr & Taylor, 2008; Butler, Egloff, Wilhelm, Smith, Erickson, & Gross, 2003; Campbell, Simpson, Kashy & Rholes, 2001), sociology (Butterfield, 2001), and communication studies (Lakey & Canary, 2002). Moreover dyadic datasets have been collected and employed in political studies (Eveland & Hutchens, 2012; Lazer, Rubineau, Chetkovich, Katz & Neblo, 2010, Huckfeldt, Sprague & Levine 2000).

Despite the recent emergence of such data, literature concerning the effects of interpersonal communication on voting behavior still relies on approaches that model the relation between ego and alter in a unidirectional way, namely, it accounts for the effect that characteristics of alters exert on ego, controlling for the ego's individual reported characteristics (see Huckfeldt, Beck, Dalton & Levine, 1995; Huckfeldt & Sprague, 1987). In general, it is possible to identify two major ways in which formal tests of interpersonal influence have been conducted, according to different substantive questions. The first one explains a certain ego characteristic with the same characteristic of alter (e.g. political partisanship or vote choice). In order to avoid simultaneity issues, instrumental variable approaches, two-stage regression models and panel data are usually applied (Fowler, Heaney, Nickerson, Padgett & Sinclair, 2011; Huckfeldt & Sprague, 1987; Huckfeldt & Sprague, 1991; Kenny, 1992; Rogowski & Sinclair, 2012). Other contributions focus on explaining a certain ego characteristic by means of different alter characteristics – assumed as antecedent. We may want, for instance, to explain the respondent's evaluation of a leader with the discussant's partisanship, controlling for respondent's partisanship (a similar design can be found in Huckfeldt, Johnson & Sprague, 2002). This approach allows researchers to employ usual regression models, since the independent variable is exogenous to the outcome. Nonetheless, these analyses have a

major drawback: the interdependence between ego and alter is not considered and the actual interdependent nature of the data is neglected. As a consequence, estimates are biased in terms of both magnitude and statistical significance (Kenny, Kashy & Cook, 2006, Ch. 2).

The aim of this work is to present and apply the Actor-Partner Interdependence Model (Kashy & Kenny, 2000; Kenny, Kashy & Cook, 2006), a technique meant to deal with dyadic data, which explicitly considers interdependence between the two communication agents and allows to estimate the effect of actor and partner characteristics at the same time, dealing simultaneously with the same information for both dyad members. In the following sections, technical details of the model will be presented and applied in order to study the effect of partner's party identification on the propensity to vote for a Presidential Candidate. The data used come from the Indianapolis-St. Louis snowball study, collected in occasion of the 1996 US presidential election, that includes a random sample of main respondents selected among the registered voters in the Indianapolis and St. Louis metropolitan area and a one-stage snowball sample of their political discussion partners (Huckfeldt, Sprague & Levine, 2000, 642). The individuals in the first random sample could name more than one discussant, allowing for more than one dyad per respondent in the final dataset.

To study interpersonal political influence, we first apply a conventional APIM considering only the first discussant indicated by the respondent. We thus show that the results do not change if the discussant is chosen randomly from the set of discussants available for each respondent. We finally generalize the model to the situation in which all the discussants for each respondent are considered. Building on this last model, we test whether the influence between dyad's members is moderated by their intimacy. In addition, we argue that the generalized APIM is useful to study relations where the positions of actor and partner are asymmetric, specifically testing whether an increased difference in socio-economic status unbalances the strength of the influence between dyad's members.

The Actor-Partner Interdependence Model (APIM) and its application to interpersonal political influence

The Actor-Partner Interdependence Model (APIM) has been developed to study interdependent dyadic data in which one partner's characteristics can affect the relevant outcomes on the other partner's side. In particular, the model applies to situations in which the independent variables can vary both between and within dyads. The model allows one to estimate simultaneously *actor* and *partner* effects on the outcome variable: "an actor effect occurs when a person's score on a predictor variable affects that same person's score on an outcome variable; a partner effect occurs when a person's score on a predictor variable affects his or her partner's score on an outcome variable" (Kenny, Kashy & Cook, 2006, 145). Figure 1 shows the effects that can be estimated by means of an APIM. Let us assume that there are two actors influencing each other (actor 1 and actor 2) and the individual property X (independent variable) is an antecedent to the individual output Y (dependent variable).

FIGURE 1 ABOUT HERE

Actor effects, labeled with the letter a , go from X_1 to Y_1 and from X_2 to Y_2 , while partner effects, labeled with the letter p , run from X_1 to Y_2 and from X_2 to Y_1 . In addition, X_1 and X_2 , as well as the errors of the individuals in the dyad's dependent variable, are correlated (Kenny, Kashy & Cook, 2006, 145-147).

There are different options to estimate an APIM (pooled regressions, multilevel analysis or structural equation models), and each of them requires a specific arrangement of data and estimation procedure. In the analyses presented in this article, we follow a multilevel approach, which is to date the most employed in the literature and, compared to the others, has the advantage of allowing to directly control for interaction effects between members' characteristics (e.g. Badr &

Taylor, 2008; Mellon, Kershaw, Northouse & Freema-Gibb, 2007; McMahon, Pouget & Tortu, 2007)¹.

To apply a multilevel model, the data **matrix** should include a row for each member of the dyad. Table 1 exemplifies the data matrix for such an analysis for two dyads. The dependent variable Y reports the individual output for each member of the dyads. The independent variable X must be entered twice for each observation, once for the score associated with respondent (used to estimate the actor effect) and once for the score associated with the respondent's discussant (used to estimate the partner effect). The score on X for each respondent is thus reported twice in the dataset, alternatively appearing for the two members of the dyad as Actor X or Partner X (in Table 1, cells with the same shade of grey).

TABLE 1 ABOUT HERE

The structure of the data presented here clearly violates the assumption of independent observations, as the characteristics of the individuals belonging to a dyad are obviously correlated, preventing the use of OLS models. A solution to this problem is offered by the aforementioned multilevel approach. In particular, random-intercept multilevel models explicitly account for clustered non-independent observations. The structure of the data presented above is in fact hierarchical, with information concerning the individuals (level-1) clustered within dyads (level-2).

The APIM and interpersonal influence: intimate and asymmetric dyads

The APIM and its specific multilevel implementation seem particularly promising in the study of

¹As stressed by Kenny, Kashy and Cook (2006), an APIM estimated with SEM is not easy to implement, especially when one wants to include control variables or test interaction effects. Interaction effects in SEM remain indeed a problematic issue (see, for instance, Cortina, Chen & Dunlap, 2001; Lin, Chen, Marsh & Lin 2010).

interpersonal influence in political matters. Several studies, especially in recent years, have faced the issue of correctly estimating interpersonal influence processes (Klofstad, 2007; Fowler et al., 2011, Bello and Rolfe, 2014). Among these works, little evidence has been produced to assess the simultaneous effect of influence that people can exert one on each other on political matters.

As an example of the potential of the APIM, in this article we study the interdependence between people discussing politics and reciprocally influencing each other's political preferences, focusing on the widely studied relation between party identification and vote choice. Party identification is a crucial psychological orientation (Campbell, Converse, Miller & Stokes, 1960) that largely affects voting behavior. Especially in American politics, party identification of an individual has been found to be consistently associated with her actual vote choice (Campbell, Converse, Miller & Stokes, 1960, Budge, Crewe & Farlie, 2010). However, the relation between party identification and vote choice is not completely straightforward (Green, Palmquist, & Schickler, 2002). Firstly, people who consider themselves as democrats (or republicans) do not deterministically vote for the democrat/republican candidate. Secondly, a number of people perceive themselves as independent and their propensity to vote for the republican/democrat candidates can vary depending on various circumstances, including the influence of other people. Although discussants' partisanship has been seen as a predictor of ego identification (Huckfeldt, Johnson and Sprague, 2002), the association has not been analyzed by taking into account interdependence, being therefore ego the recipient of the influence but not being a source of influence herself. The power of a dyadic model can indeed be found in the possibility to take into consideration the interdependence between pairs of discussants, testing whether *partner's party identification affects actor vote choice*.

In addition, the APIM allows to control whether further characteristics, either belonging to the dyads or to the single members, influence the partner effect. The test is carried out by interacting the variables that operationalize these characteristics with the main partner's independent variable (in our case party identification). This procedure opens a number of interesting opportunities for testing substantive mechanisms of influence.

With reference to the dyads' characteristics, we can consider the example of intimacy. For each dyad, it is possible to indicate different degrees of intimacy, defined by the relation between the two members. This property of the dyad is recognized to play an important role in processes of political influence, as intimate ties within cohesive social groups are expected to lead to higher levels of social pressure and interpersonal influence (e.g. Huckfeldt, Beck, Dalton & Levine, 1995; Mutz and Mondak 2006; Zuckerman, Dasovic & Fitzgerald, 2007). We will thus test whether *a greater degree of intimacy in the relation between actor and partner leads to stronger partner effects*.

Beside the properties that pertain to the dyad as a whole, also member's characteristics can easily be introduced in the model as control variables: as we have stressed above, the APIM - in contrast to non-dyadic analyses - allows to consider the same set of variables for both the dyad' members. However, there is a more interesting situation in which the difference in properties between the members of the dyad is not just a nuisance, but is rather a relevant phenomenon that crucially affects interpersonal influence processes. This is the situation of an asymmetric relation between members of the dyad. The first and most important framework that accounts for asymmetric relations among political discussants (and their effects on political behavior) is undoubtedly the two-step flow of communication model (Katz & Lazarsfeld, 1955). According to this model, the way in which mass media affect public opinion is based on two steps: the first, going from the media to a subset of the population, composed of authoritative individuals particularly sensitive to political messages, namely opinion-leaders; the second, in which opinion-leaders retransmit political messages to the members of their network, the so-called opinion-followers (Katz & Lazarsfeld, 1955; Robinson, 1976). Although the model has mainly been applied to account for media effects on the population, it can be used to deduce hypotheses that concern processes of interpersonal influence. For instance, according to the classical formulation of the model, opinion-leaders, which are seen as more influential than opinion-followers, can be identified by means of different factors, such as life-cycle (namely, age), gregariousness (a scale of individuals' social

interactions)² and socio-economic status, that are asymmetrically distributed in the population.

The APIM can easily accounts for situations in which members do not share the same status on an individual property, generating asymmetric relations. In our case, we can hypothesize that the member with more resources, or a more prominent position, can influence to a greater extent her partner. In particular, we can consider the effect of socio-economic status (SES) asymmetry. We will thus hypothesize that *partner effect will be stronger when partner has a higher socio-economic status compared to the actor*.

Data and methods

The dyadic data employed come from the 1996-1997 Indianapolis-St. Louis Election study (Huckfeldt, Sprague & Levine, 2000), conducted in the counties of Indianapolis and St. Louis before and after the 1996 Presidential Elections. In the following analyses, we use data coming from the post-election sample. The study includes two separate samples: a random sample of main respondents (obtained from a list of registered voters) and a one-stage snowball sample of discussants directly named by the main respondents. The main respondents were not constrained to only one discussant and could name until a maximum of five other people. This represents a further complication in the data structure because each respondent can “generate” multiple dyads, clearly not independent one from the other. Despite the relevance of this variation on the standard dyadic design, the literature concerning APIM has not yet considered it explicitly as, in its original formulation, the APIM has been applied in situations where subjects are naturally arranged in uncorrelated dyads (such as cohabiting couples).

A first option to accommodate the data complexity would be to reduce it artificially, considering only one dyad per respondent. The choice of the discussant to include in the analyses could fall on

² For example, an individual who has a large and heterogeneous network is more likely to be more cosmopolitan (Rogers, 1983), aware of political issues and, in turn, to be able to affect others.

the first person named, assuming that this is the most important. However, this choice can be biased, as intimate relationships may become overrepresented in the sample of dyads. An alternative to avoid this problem is to randomly select for each respondent one of the named discussant.

Neither of these solutions is otherwise able to exploit all the information available. One can thus wonder whether the APIM approach can be generalized in order to include the whole available data simultaneously. The correct structure of the model, in the case of multiple dyads, would thus include a further level, which clusters dyads generated by the same respondent. Such a third level could be seen as the main respondent's network level. The number of dyads within each network would be equal to the number of discussants a respondent has named.

Unfortunately, a full-fledged three-level multilevel model which takes into account dyads, nested within networks, is technically not applicable. In fact, for such a model, the computation of parameters at the network and dyad level exhausts all the available degrees of freedom at the individual level (having each dyad only two actors and being the respondent repeated in all the dyads clustered within one network), leading to null variance at the dyad level.

In the article we thus propose an original solution to this problem, that maintains the two-level dyadic structure of the original model (members nested within dyads), but considers all the available dyads, controlling for their correlation within each network by computing cluster-robust standard errors at the network level.

To show the differences in the outcomes due to model specification, we estimate the APIM following all the three strategies mentioned above:

- a) One dyad for each respondent, selecting the discussant named first;
- b) One dyad for each respondent, selecting randomly the discussant;
- c) All the available dyads for each respondent, computing cluster-robust standard errors at the network level.

In the second option, for each main respondent, a random discussant is sampled from the pool of

people named by the respondent, and a 2-level multilevel regression model is fitted. This random selection of the discussant for each respondent is repeated 1,000 times, producing regression coefficients for 1,000 different combinations of dyads. Thus, the relevant result is not a coefficient computed in a single regression, but the average of the values of that coefficient on the 1,000 repetitions³.

The dependent variable is dichotomous, with 1 indicating a vote for Clinton and 0 a vote for another presidential candidate⁴. The basic formulation of the multilevel APIM (Kenny, Kashy & Cook, 2006) entails a linear dependent variable, which is clearly not our case. Therefore we turn to the logistic version of the multilevel model, where the outcome variable is binary (Gelman & Hill, 2007). By means of a simulation study with fictitious data, it has been demonstrated that a logistic multilevel APIM performs well in estimating fixed coefficients when the number of pairs is sufficiently large: with more than 250 dyads, biases in the fixed portion of the estimation are irrelevant (Spain, Jackson & Edmonds, 2012). The estimation of the random intercept variance is more problematic, thus authors advise caution in interpreting substantively the random variance parameter. Nonetheless, in this study we focus on fixed effect parameters that are considered to be sufficiently reliable for a substantive interpretation (Spain, Jackson & Edmonds, 2012).

As far as the main independent variables are concerned, party identification is measured using the classic 7-points scale where 1 means “Strong Democrat” and 7 means “Strong Republican”. Given that our dependent variable focuses on the vote choice for the Democratic Party presidential candidate, we reverse the party identification scale in order to obtain consistently positive

³ Following this strategy, it is thus possible to produce a distribution of the values of the coefficients for each estimated parameter.

⁴The same analysis was performed considering a dichotomous dependent variable where 1 indicated the vote for Bob Dole and 0 the vote for another candidate. No substantial differences with the results presented here emerged. These results are available on request from the authors.

regression coefficients. Intimacy of the relation between actor and partner presents three categories: spouse, relative or non-relative. Other socio-demographic control variables are: ethnicity (white, black or other), gender, educational level (5 categories from “Less than High School” to “More than a college degree”), income (6 categories, from “Less than 14,000\$” to “More than 75,000\$”), religious denomination (“Protestant”, “Roman Catholic”, “Jewish” and “Other”) and church/temple attendance (“Every week”, “At least once a month”, “A few times a year”, “Never”). For what concerns the test for asymmetric relationships, since the difference in the socio-economic status can be easily expressed in terms of income, we considered a variable based on the comparison of actor and partner income with 5 categories.⁵

The actual number of units at individual and dyad level varies depending on the strategy applied to estimate the model. For strategy *a* (in which we estimate coefficients by employing only the first discussant), we count 435 dyads, for a total of 870 individuals, of which 715 remaining after listwise deletion. For strategy *b* (in which the discussant are chosen randomly, generating 1,000 different combinations of dyads), the number of dyads varies from 428 to 492, accounting for a number of individuals ranging between 664 and 764 after listwise deletion. Finally, for the strategy considering all the available dyads (strategy *c*), the number of dyads amounts to 751, with 1,230 individuals after listwise deletion.⁶

Results

As pointed out above, a generalized version of the APIM applicable to the case of a snowball

⁵ The variable acquires the following values: 1 when actor is placed two or more income categories below the partner, 2 when actor is placed one income category below the partner, 3 when actor and partner are in the same income category, 4 when actor is placed one income category above the partner, 5 when actor is placed two or more income categories above the partner.

⁶ The number of missing cases increases slightly when considering intimacy and income differences. In the first case the number of dyads is 746 with 1,224 individuals. In the second case, the number of dyads is 667 with 1,146 individuals.

sample is not straightforwardly available in the literature. We thus start with results coming from the first two strategies that consider a simplified structure of the data with just one dyad for each main respondent.

In table 2, model 1 presents results for the simplest strategy, which estimates APIM coefficients by selecting only the first discussant. Model 2 presents the results applying the second strategy where the (single) discussant is selected randomly. In this latter model, the figures represent average coefficients and standard errors computed from the 1,000 repetitions with random selection of the discussant. In addition, we give the percentage of times in which the coefficient turned out to be statistically significant at 5% level. As it is possible to see, the results are largely consistent in the two models, and we can thus exclude that the first strategy biases the results due to an excessive number of intimate respondents.

TABLE 2 ABOUT HERE

Table 3 shows results derived from the application of the third strategy, considering all the available dyads for each respondent and computing cluster-robust standard errors at the network level, in order to control for the correlations of the dyads derived from the same respondent. Model 3 (first column) presents exactly the same parameterization of the previous models in Table 2, although a larger number of observations, given by the higher number of discussants for every respondent. Once again, the outcomes on the coefficients of interest are consistent, despite the increased complexity in the data structure. We can thus conclude that the results of the APIM are robust to different strategies of analysis. The third strategy is however the most attractive as it allows to fully exploit the data available. The further steps of the analysis and the interpretation of the outcomes will be therefore built on the basic structure of model 3.

TABLE 3 ABOUT HERE

The first substantial outcome of model 3 is that both actor and partner effects are positive and statistically significant. In other words, both a stronger self-identification as democrat and a stronger partner's identification as democrat lead to higher propensities to vote for Clinton, controlling for socio-demographic variables. How do those effects unfold? Figure 2 shows the predicted probabilities of voting for Clinton as a function of actor self-identification. Moreover, it distinguishes actors in two groups, represented by the two curves in the figure, depending on their partners' identification: the solid line accounts for people who have a strong republican partner, whilst the dashed line represents those who have a strong democrat partner.

FIGURE 2 ABOUT HERE

Firstly, and coherently with our expectations, the probability to vote for Clinton increases for stronger identification as democrat. But in addition, it turns out that the identification of the partner matters especially when actor is placed in the middle of the party identification scale. For example, in the case of an independent actor, the probability to vote for Clinton is 24 percentage points higher for a strong democrat partner compared to a strong republican partner (respectively .73 vs. .49).

Model 4 adds the main effect for intimacy of the relation between the two members of the dyad and its interaction with partner effect. The coefficients are statistically significant for spouses. In this case, as showed by the predicted probabilities in Figure 3, partner effect is stronger: the probability to declare a vote for Clinton by a self-reported independent actor is .86 if the spouse is a strong democrat, against .31 when the spouse is a strong republican.

FIGURE 3 ABOUT HERE

When the partner is a non-relative, the effects are weaker and non-significant. Summarizing, we can

conclude that the APIM applied to the Indianapolis-St. Louis data shows that the partner effect is relevant and significant when the relation between the members of the dyad is more intimate (e.g. spouse), and when the actor is neither a strong democrat nor a strong republican.

Finally, model 5 of table 3 tests the third hypothesis, accounting for asymmetry of socio-economic status (SES) between actor and partner. Figure 4 shows the average marginal effects for partner coefficient, estimated on every category of the variable that indicates the income difference.

FIGURE 4 ABOUT HERE

When actor has a lower SES, the effect of partner is strong and significant. The effect of partner disappears when actor and partner have the same SES, or actor has a higher SES. The third hypothesis is therefore corroborated, as it turns out that individuals who are in a disadvantaged economic position with respect to their dyad's partner are exposed to a stronger influence of these latter.

Discussion

Dyadic data are subject to increasing interest from interpersonal communication scholars (e.g. Eveland & Hutchens, 2012; Huckfeldt, Johnson & Sprague, 2004; Lazer, Rubineau, Chetkovich, Katz & Neblo, 2010), given their potential in unveiling interdependence among people. This article has presented an application of the Actor-Partner Interdependence Model (APIM) that explicitly takes into account the interdependence between the actors in a dyadic relation. We have shown that the APIM offers a straightforward and informative solution to deal with dyadic data. Moreover, the cogent multilevel nature of the proposed model allows the production of unbiased estimates for the dyadic coefficients. The nature of the data employed in the article (extracted from the Indianapolis-St. Louis survey) led us to extend the APIM usually employed in the literature to the situation of

snowball samples, in which the main respondents are allowed to name more than one discussant, which, in turn, are interviewed. Such a generalized model has been compared with two other, simpler, strategies of facing this complex dyadic structure - namely, models in which only one dyad per respondent is considered, being the discussant either the first one named or a discussant selected randomly from those available. Although the three strategies lead to substantively similar results, confirming the robustness of the outcomes, the general multilevel model with cluster-robust standard error has been preferred as it allows to handle all the available data, avoiding any arbitrary choice on the discussant to include in the dyads.

The results obtained by applying this generalized APIM are empirically relevant and bear implications for the theoretical debate on interpersonal influence. Firstly, we showed a significant effect of partner's party identification on actor's vote, in particular when actor does not present a strong party identification. In addition, we tested expectations about the characteristics of the relations, more specifically its intimacy, as well as asymmetry in socio-economic status between members. For what concerns intimacy, it turns out that the effect of partners mainly unfolds when the dyad has a high degree of intimacy (spouses). As far as socio-economic status (SES) is concerned, when partner earns more than actor, partner effect becomes strong and significant. In other words, people with higher SES tend to exert a stronger effect on their partner with respect to people with lower SES. These results are consistent with previous literature on interpersonal influence (see Huckfeldt, Beck, Dalton & Levine, 1995; Zuckerman, Dasovic & Fitzgerald, 2007, Ch. 4; Katz & Lazarsfeld, 1955), but in our analyses the test is formally carried out controlling for the interdependence of the observations, thus producing unbiased estimates.

Summarizing our results, we can say that APIM presents many advantages when researchers have to confront with dyadic data. First of all, APIM offers an easy way to take into account interdependence among people, producing unbiased and straightforward coefficients for both the effect of actor and partner. In addition, by means of the multilevel regression approach illustrated in

this article, it is possible to test whether these effects can be affected by characteristics which are shared by both the members of the dyad - such as in the case of intimacy - or properties that are specific of each dyad's member - such as in the asymmetry case. Finally, the generalization of the model to multiple dyads for each respondent allows to fully exploit data coming from snowball designs with no constraints on the number of discussants to be named. By means of the APIM, the test can be easily extended to a number of other research questions (e.g. one may ask whether geographical distance between discussants or the age of dyad's members affect interpersonal influence).

These advantages come at a price: dyadic data imply high costs and are far from simple to collect. In particular, collecting a snowball sample needs a high level of cooperation by the respondents, who have to communicate to the researcher sensitive information about their relatives, friends and acquaintance. In addition, those mentioned by respondents should also be ready to cooperate, accepting to answer the interview. This is once again not always easy to obtain⁷.

Moreover, even in its generalized form, the APIM still does not allow to take into account some crucial elements that are considered in contemporary political networks research. A straightforward application of a dyadic approach, indeed, limits the possibility to take into account networks' characteristics. In particular, dyadic data analysis can hardly model processes of selection and homophily that resulted to be relevant in the development of political deliberation (Noel & Nyhan, 2011; Bello & Rolfe, 2014). Moreover, in the present form, APIM model makes it hard to account for autoregressive influence processes (namely, the effect that all other members of a network, in addition to the partner, have on the likelihood to vote for a certain party or candidate, see Huckfeldt, Johnson & Sprague, 2004).

A final drawback, which is particularly relevant for generalized APIM model and snowball samples in general, concerns the inferential side of the model: researchers will always be confronted with the

⁷ We can have an idea of the relevance of this issue by noticing that the number of missing cases in our dataset increases when we consider multiple discussants (see the "Data and methods" section).

fact that a complete sampling from a defined population of dyads will be possible only if having information about the complete list of dyadic edges in a certain individuals' population (information that is hard, if not impossible, to gather)⁸.

Being aware of these problems and limitations, we remain confident that the approach illustrated in this article has the potential to improve the study of interpersonal influence in political communication, although more research is required to better understand the theory, methodology and practice of dyadic data collection and analysis. We hope that this contribution will prompt efforts in this direction.

References

Badr, H., & Taylor, C. L. C. (2008). Effects of relationship maintenance on psychological distress and dyadic adjustment among couples coping with lung cancer. *Health Psychology, 27*(5): 616.

Bello, J., & Rolfe, M. (2014). Is influence mightier than selection? Forging agreement in political discussion networks during a campaign. *Social Networks, 36*(1), 134-146.

Berelson, B., Lazarsfeld, P. F., & McPhee, W. N. (1954). *Voting: A study of Opinion Formation in a Presidential Campaign*. Chicago: University of Chicago Press.

Budge, I., Crewe, I., & Farlie, D. (2010), *Party identification and beyond. Representation of voting and party competition*. Colchester: ECPR Press.

Butler, E. A., Egloff, B., Wilhelm, F. H., Smith, N. C., Erickson, E. A., & Gross, J. J. (2003). The

⁸ However, we must stress that limited sets of dyadic data has been collected and we have proven that a proper treatment of this information can lead to relevant results

social consequences of expressive suppression. *Emotion*, 3: 48–67.

Butterfield, R. M. (2001). Health related social control and marital power: A test of two models. *Dissertation Abstracts International: Section B: The Sciences and Engineering*, 61(12-B): 6757.

Campbell, A., Converse, P. E., Miller, W. E., & Stokes, D. E. (1960). *The American voter*. New York: John Wiley & Sons.

Campbell, L., Simpson, J. A., Kashy, D. A., & Rholes, W. S. (2001). Attachment orientations, dependence, and behavior in a stressful situation: An application of the actor–partner interdependence model. *Journal of Social and Personal Relationships*, 18: 821–843.

Cortina, J. M., Chen, G., & Dunlap, W. P. (2001). Testing interaction effects in LISREL: Examination and illustration of available procedures. *Organizational research methods*, 4(4), 324–360.

Erisen, E. & Erisen, C. (2007). *A Report on the Social Network Battery in the 2006 ANES Pilot Study*. 2008. ANES Pilot Study Report n. nes012063.

Eveland Jr, W. P., & Hutchens, M. J. (2012). The Political Coorientation of Young Adults in Voluntary Associations and its Relation with Conversation. Paper presented at the 2012 Political Networks conference in Boulder, CO.

Fowler, J. H., Heaney, M. T., Nickerson, D. W., Padgett, J. F., & Sinclair, B. (2011). Causality in political networks. *American Politics Research*, 39(2), 437–480.

Gelman, A. & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. Cambridge: Cambridge University Press.

Huckfeldt, R., Beck, P. A., Dalton, R. J., & Levine, J. (1995). Political environments, cohesive social groups, and the communication of public opinion. *American Journal of Political Science*, 39(4): 1025-1054.

Huckfeldt, R., & Sprague, J. (1987). Networks in context: The social flow of political information. *The American Political Science Review*: 1197-1216.

Huckfeldt, R., & Sprague, J. (1991). Discussant effects on vote choice: Intimacy, structure, and interdependence. *Journal of Politics*, 53(1), 122-158.

Huckfeldt, R., & Sprague, J. (1995). *Citizens, Politics and Social Communication. Information and Influence in an Election Campaign*. New York: Cambridge University Press.

Huckfeldt, R., Sprague, J., & Levine, J. (2000). The Dynamics of Collective Deliberation in the 1996 Election: Campaign Effects on Accessibility, Certainty, and Accuracy. *American Political Science Review*. 94, (3), 641-651.

Huckfeldt, R., Johnson, P. E. & Sprague, J. (2002). Political Environments, Political Dynamics, and the Survival of Disagreement. *Journal of Politics* 64(1): 1-21.

Huckfeldt, R., Johnson, P. E., & Sprague, J. (2004). *Political disagreement: The survival of diverse opinions within communication networks*. New York: Cambridge University Press.

Kashy, D. A., & Kenny, D.A. (2000). The analysis of data from dyads and groups. In Reis, H. T., & Judd, C. M. (Eds.). (2000). *Handbook of research methods in social and personality psychology*. Cambridge University Press: 451-477.

Katz, E., & Lazarsfeld, P. F. (1955). *Personal Influence, The part played by people in the flow of mass communications*. Piscataway: Transaction Publishers.

Kenny, C. B. (1992). Political participation and effects from the social environment. *American Journal of Political Science*, 36(1): 259-267.

Kenny, D. A., Kashy, D., & Cook, W. L. (2006) *Dyadic data analysis*. New York: Guilford Press.

Klofstad, C. A. (2007). Talk leads to recruitment how discussions about politics and current events increase civic participation. *Political Research Quarterly*, 60(2): 180-191.

Lakey, S. G., & Canary, D. J. (2002). Actor goal achievement and sensitivity to partner as critical factors in understanding interpersonal communication competence and conflict strategies. *Communication Monographs*, 69: 217-235.

Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1944) *The people's choice; how the voter makes up his mind in a presidential campaign*. New York: Free Press.

Lazer, D., Rubineau, B., Chetkovich, C., Katz, N., & Neblo, M. (2010). The coevolution of networks and political attitudes. *Political Communication*, 27(3): 248-274.

Lin, G. C., Wen, Z., Marsh, H. W., & Lin, H. S. (2010). Structural equation models of latent interactions: Clarification of orthogonalizing and double-mean-centering strategies. *Structural*

Equation Modeling, 17(3), 374-391.

McMahon, J. M., Pouget, E. R., & Tortu, S. (2007). Individual and couple-level risk factors for hepatitis C infection among heterosexual drug users: a multilevel dyadic analysis. *Journal of Infectious Diseases*, 195(11), 1572-1581.

Mellon, S., Kershaw, T. S., Northouse, L. L., & Freema-Gibb, L. (2007). A family-based model to predict fear of recurrence for cancer survivors and their caregivers. *Psycho-Oncology*, 16(3): 214-223.

Schmitt-Beck, R., Bytzek, E., Rattinger, H., Roßteutscher, S., & Weßels, B. (2009). *The German Longitudinal Election Study (GLES)*. Vortrag im Rahmen der Jahrestagung der International Communication Association (ICA), Chicago, 21, 25.

Robinson, J. P. (1976). Interpersonal Influence in Election Campaigns: Two Step-flow Hypotheses. *Public Opinion Quarterly*, 40(3): 304-319.

Rogers, E. M. (1983). *Diffusion of innovations*. New York: The Free Press.

Rogowski, J. C., & Sinclair, B. (2012). Estimating the causal effects of social interaction with endogenous networks. *Political Analysis*.

Snijders, T.A.B., & Bosker, R., 1999. *Introduction to multilevel analysis*. London: Sage.

Spain, S. M., Jackson, J. J., & Edmonds, G. W. (2012). Extending the actor-partner interdependence model for binary outcomes: A multilevel logistic approach. *Personal Relationships*, 19(3): 431-444.

Zuckerman, A. S., Dasovic, J., & Fitzgerald, J. (2007). *Partisan families: The social logic of bounded partisanship in Germany and Britain*. Cambridge: Cambridge University Press.

For Review Only

Tables

Table 1: Dataset construction for multilevel APIM model

Dyad	Person	Dep. Var. Y	Actor X	Partner X
1	1	3	4	6
1	2	5	6	4
2	1	6	7	3
2	2	4	3	7

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Table 2: Multilevel APIM logistic regression models (Dependent variable: vote choice for Clinton)

Indep. Variables	Model 1 - Only 1st disc		Model 2 - Random disc.		
	Coef.	S.E.	Avg. Coef.	Avg. S.E.	% p-value <.05
Actor Party ID	1.48***	(0.28)	1.56	(0.30)	100
Partner Party ID	0.22**	(0.09)	0.22	(0.09)	80.9
Gender: Female (ref. Male)	0.46	(0.37)	0.52	(0.38)	4.1
Religious denomination (ref. Protestant)					
Roman Catholic	0.59	(0.42)	0.70	(0.43)	16.8
Jewish	0.88	(1.16)	0.98	(1.17)	0.1
Other	1.34**	(0.57)	1.43	(0.59)	95.5
Church attendance (ref. Every week)					
At least once a month	0.75	(0.48)	0.85	(0.49)	25.7
Few times a year	0.34	(0.50)	0.75	(0.50)	11.9
Never	0.53	(0.59)	0.73	(0.60)	1.3
Income (ref. Less than 15,000\$)					
15,000-24,999	0.75	(1.22)	0.15	(1.16)	0
25,000-34,999	0.36	(1.15)	-0.02	(1.11)	0
35,000-49,999	0.43	(1.15)	0.02	(1.11)	0
50,000-75,000	0.81	(1.13)	0.46	(1.09)	0
More than 75,000	1.25	(1.16)	1.00	(1.11)	0
Educational level (ref. Less than High school)					
High school	-2.77*	(1.68)	-2.65	(1.72)	0
Some college	-2.67	(1.66)	-2.67	(1.71)	0
College degree	-2.20	(1.66)	-2.31	(1.72)	0
More than a college degree	-2.26	(1.68)	-2.14	(1.72)	0
Race (ref. White)					
Black	4.08**	(1.67)	3.19	(1.30)	85.4
Other	-0.62	(1.26)	-0.74	(1.34)	0
Constant	-5.88***	(1.99)	-6.04	(2.06)	0
Ln(level-2)	0.16	(1.31)	0.37	(1.29)	0
Observations	717		(664; 764)		
Number of dyads	437		(428; 492)		

Standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1

Table 3: Generalized multilevel APIM logistic regression models (Dependent variable: vote choice for Clinton)

Indep. Variables	Model 3 - Baseline		Model 4 - With Intimacy		Model 5 - With Asymmetry	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Actor Party ID	1.55***	(0.10)	1.54***	(0.10)	1.61***	(0.10)
Partner Party ID	0.21***	(0.06)	0.15*	(0.08)	0.66***	(0.16)
Gender: Female (ref. Male)	0.83***	(0.31)	0.84***	(0.32)	0.75**	(0.31)
Religious denomination (ref. Protestant)						
Roman Catholic	0.56	(0.39)	0.63	(0.39)	0.38	(0.40)
Jewish	1.52*	(0.86)	1.54*	(0.83)	0.61	(0.70)
Other	1.04**	(0.49)	1.17**	(0.51)	1.06**	(0.51)
Church attendance (ref. Every week)						
At least once a month	0.99**	(0.40)	0.93**	(0.39)	0.98**	(0.40)
Few times a year	0.78	(0.48)	0.77	(0.48)	0.90*	(0.51)
Never	1.04*	(0.54)	1.02*	(0.55)	1.16**	(0.55)
Income (ref. Less than 15,000\$)						
15,000-24,999	-0.56	(0.99)	-0.69	(0.99)	-0.75	(1.00)
25,000-34,999	-0.26	(0.77)	-0.18	(0.80)	-0.23	(0.80)
35,000-49,999	-0.07	(0.84)	-0.02	(0.89)	0.07	(0.89)
50,000-75,000	0.04	(0.81)	0.15	(0.84)	0.32	(0.85)
More than 75,000	0.43	(0.80)	0.55	(0.83)	0.91	(0.91)
Educational level (ref. Less than High school)						
High school	-2.33***	(0.79)	-2.44***	(0.81)	-2.68***	(0.84)
Some college	-2.22***	(0.76)	-2.18***	(0.79)	-2.37***	(0.83)
College degree	-2.00**	(0.78)	-1.97**	(0.80)	-2.10**	(0.85)
More than a college degree	-1.60*	(0.84)	-1.58*	(0.87)	-1.87**	(0.90)
Race (ref. White)						
Black	3.31***	(1.16)	3.17***	(1.17)	4.23***	(1.34)
Other	-0.40	(0.97)	-0.53	(0.99)	-0.24	(1.02)
Relation (ref. Non-relative)						
Spouse			-1.57**	(0.76)		
Relative			-0.15	(0.57)		
Relation: Spouse * Partner Party ID			0.38**	(0.19)		
Relation: Relative * Partner Party ID			0.02	(0.12)		

Continues in the following page...

Indep. Variables	Model 3 - Baseline		Model 4 - With Intimacy		Model 5 - With Asymmetry	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Socio-economic status difference (ref. Actor < partner, 2 or more income cat. difference -)						
Actor < partner (1 income cat. difference)					0.32	(0.90)
Actor = partner					1.43	(0.93)
Actor > partner (1 income cat. difference)					0.45	(1.05)
Actor > partner (2 or more income cat. difference)					0.70	(1.11)
SES – Act. < part. (1 cat.) * Partner Party ID					-0.35	(0.22)
SES – Act. = part. * Partner Party ID					-0.57***	(0.20)
SES – Act. > part. (1 cat.) * Partner Party ID					-0.46**	(0.23)
SES – Act. < part. (2+ cat.) * Partner Party ID					-0.55**	(0.24)
Constant	-6.05***	(0.94)	-5.86***	(1.01)	-7.06***	(1.06)
Ln(level-2)	0.59**	(0.25)	0.58**	(0.26)	0.55**	(0.26)
Observations	1,230		1,224		1,146	
Number of cases	751		746		667	

Robust standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1

Figures

Figure 1: APIM model effects (From Kenny, Cashy and Cook, 2006)

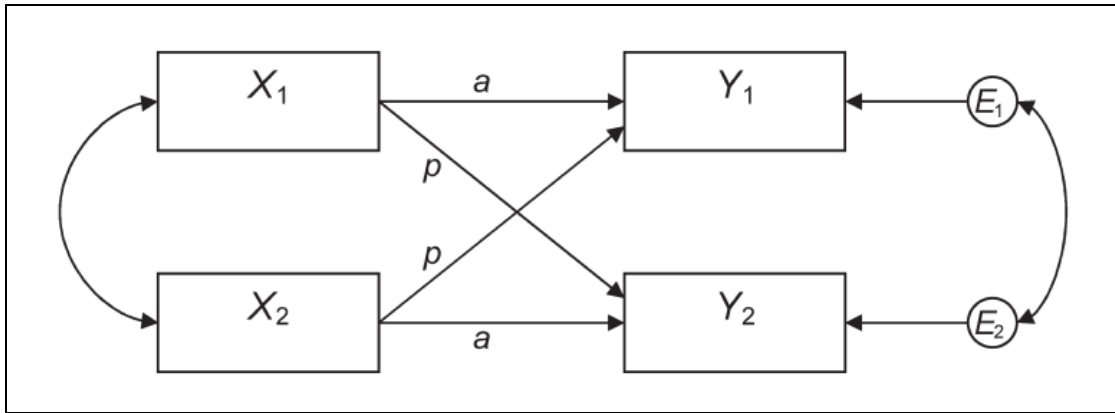


Figure 2: Predicted probabilities (with confidence intervals) for actor and partner party identification (Coefficients from Model 3 – Table 3)

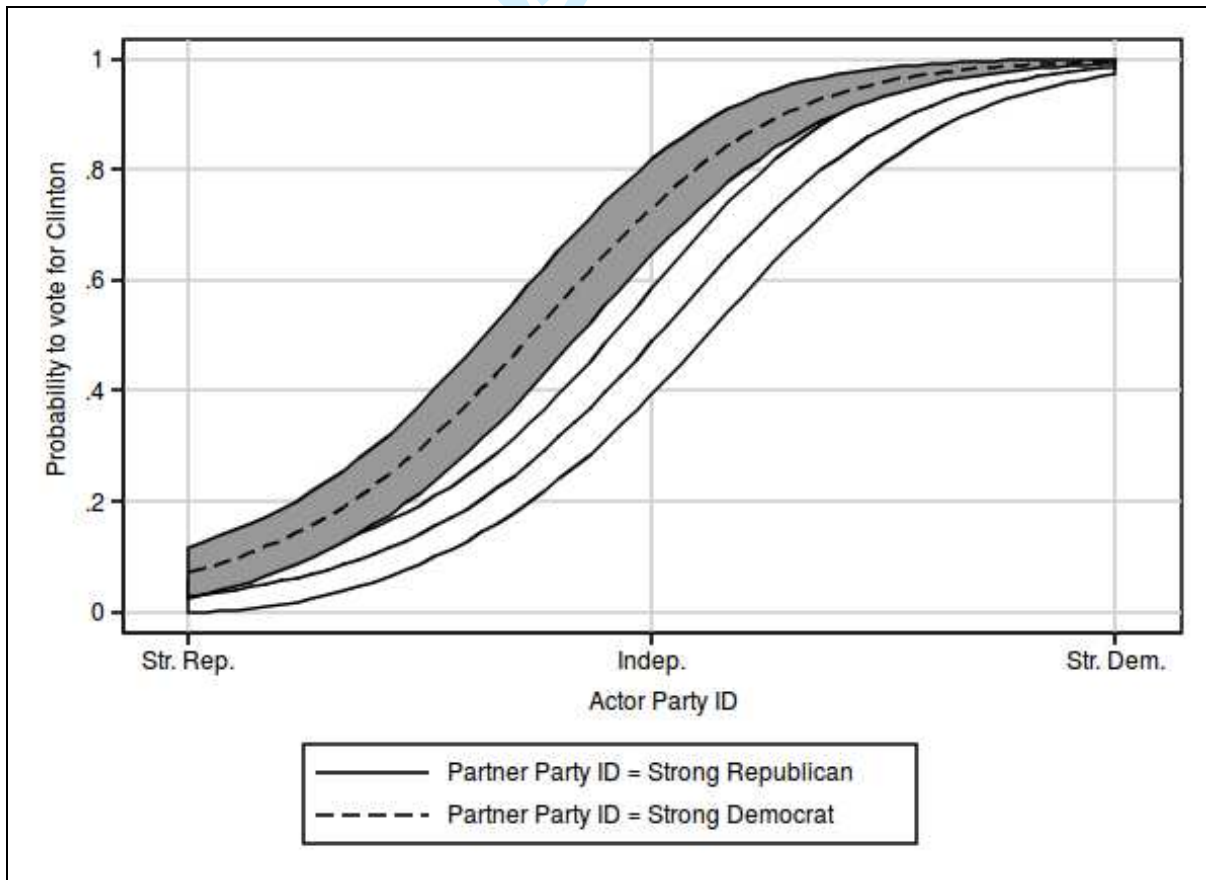


Figure 3: Predicted probabilities (with confidence intervals) for actor and partner party identification at different levels of intimacy (Coefficients from Model 4 – Table 3)

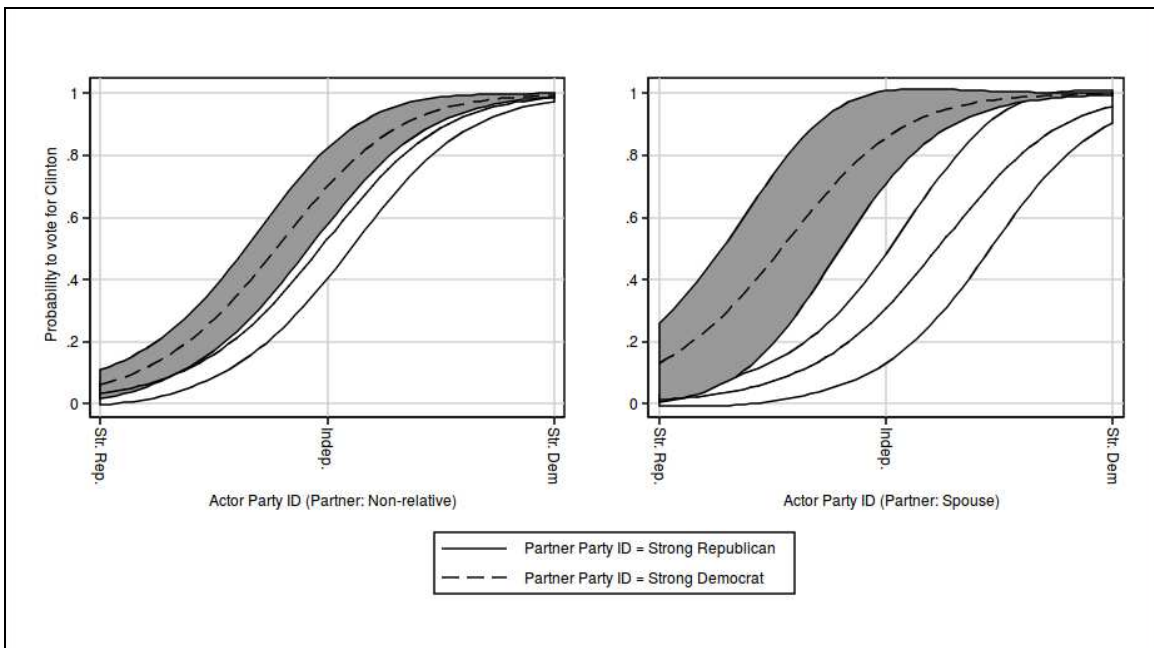


Figure 4: Average Marginal Effects (with confidence intervals) of partner effect at different levels of asymmetry (differences of actor and partner income - Coefficients from Model 5 – Table 3)

