Poisson-Normal Dynamic Generalized Linear Mixed Models of U.S. House Campaign Contributions

by

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and

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Abstract

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We develop generalized linear mixed models to analyze itemized contributions to U.S. House campaigns. Our basic model is a system of Poisson processes that have means that are log-linear functions of normally distributed random effects. Our model permits multiple random effects, including serially correlated effects. The mixed model specification involves an integration over the random effects that is analytically intractable. When there is only one, serially independent random effect, the model may be estimated using quadrature to evaluate the integral. With multiple random effects, quadrature is infeasible but the model may be estimated using the Monte Carlo EM (MCEM) algorithm proposed by McCulloch (1997). We illustrate these various estimation methods. The system we analyze includes contributions to Democratic and Republican candidates from different sources, including individuals and PACs. We estimate dynamic effects both within and across contributions series. The cross-series dynamics measure how contributions to one candidate react to contributions to the other. The cross-series dynamics also measure how contributions to a candidate from one source can mobilize contributions from other sources. We use a combination of observed variables and random effects to test the hypothesis of dynamic mobilization against several hypotheses that imply constant differences between candidates and between districts. One such hypothesis is that some candidates received persistently higher contributions from all sources because of PAC endorsements. Another is that some candidates are simply better at raising money than others. We also test how national expectations about presidential election outcomes affect contributions. We apply our model to itemized contributions data for open seat races in the 1984 election.

Introduction

The large positive correlation between money and electoral outcomes among non-incumbent U.S. House candidates and the recent easy availability of Federal Election Commission (FEC) itemized contributions data has sparked the search for adequate models of how some candidates are able to raise money and others fail. There is increasing attention to the analysis of fundraising and its evolution through an election cycle (Biersack, Herrnson and Wilcox 1993, Krasno, Green and Cowden 1994, Box-Steffensmeier 1996, Himmelberg and Wawro 1998, Wand and Mebane 1999). Previous work has generally focused on either total amounts of money or a single type of contribution, ignored unobserved heterogeneity across districts and candidates, excluded national-level factors, and made unrealistic assumptions about the distributions of the data generating process. To estimate a more general model of contributions that allows for contributions from multiple sources, unobserved heterogeneity, and a more plausible data generating process, we adopt the framework of generalized linear mixed models (GLMMs). Our basic model is a system of Poisson processes that have means that are log-linear functions of fixed effects and normally distributed random effects. The model includes effects of lagged and cross-lagged dependent variables. Our model permits multiple random effects, including serially correlated effects. To estimate the model we use the Monte Carlo EM (MCEM) algorithm proposed by McCulloch (1997).

In the remaining part of this introduction we outline some of the substantive issues pertaining to contributions that we address in the current analysis. In the following sections we outline the motivation for modeling contributions as a count process and present the statistical model. Finally, we present a detailed account of the models we estimate and the results.

Fundraising is a dynamic process, with a sequence of opportunities for a candidate to appeal to potential contributors during an election campaign. In particular, acquiring money from one type of contributor may affect a candidate's ability to raise money from other sources. Many PACs are known to use a candidate's past success in raising individual contributions in deciding whether to contribute. Similarly, the actions of one PAC may affect the behavior of other PACs, as well as of individual contributors: an endorsement by a PAC may help coordinate targeted contributions to particular candidates. Even if individuals and PACs are not overtly conditioning their contributions on the past behavior of others, money from any source can pay for direct mailing lists, professional campaign staff, and other instruments that facilitate raising money from different sources. In addition, successful fundraising efforts by a candidate's opponent may also encourage greater effort by a candidate and provide extra leverage in requesting additional donations from the candidate's supporters. An adequate model therefore needs to allow for a system of processes for contributions from different sources and to the various candidates.

Some candidates have greater skill and fortune than others at raising contributions from different sources, or have more resources with which to do so. Some districts reside within more expensive media markets, and therefore have greater need to raise money. Ignoring such variations among candidates induces an artificially high appearance of serial correlation in the contribution series, as does ignoring district-specific effects that persist throughout the campaign. Consequently the effects of lagged and cross-lagged contributions will be overstated. One should therefore take into account district-specific and candidate-specific effects that may persistently increase or decrease the ability of the candidate to raise money.

Other reasons for heterogeneity among candidates may also be important. Historical electoral returns in a district can play a central role both in attracting a particular type of candidate and in setting up expectations for the possibility of a candidate's success. Historical returns are generally time-invariant within a campaign in that they play an important initial role in influencing what types of candidates will contest a district's election. The effect of previous returns may be diminished by unexpectedly good performance in polling or fund-raising by a traditionally disadvantaged party. One should also directly take into account the quality of the candidates as this has been highly correlated with fund-raising success. For non-incumbents, previous experience in elected office has been used effectively to measure candidate quality

(Jacobson 1990). Ideological positions are another source of candidate heterogeneity. An endorsement by a PAC suggests that the candidate is predisposed to a cluster of issues promoted by the PAC and, more importantly for the current analysis, may signal the attractiveness and viability of a candidate to like minded groups and individuals.

In addition to local effects, there is also reason to believe that contributions are influenced by national considerations. In a previous paper (Wand and Mebane 1999) we analyzed aggregate individual contributions using a model that implies moderating behavior by individual contributors. We found support for the hypothesis that individuals use expectations about the Presidential election outcome when deciding whether to donate money to a House candidate.

Generalized Linear Mixed Models for Contributions

A primary methodological challenge for modeling campaign contributions is to specify a reasonable approximation to the data generating process. The itemized data contain a record for each distinct contribution that a campaign committee reported to the FEC. For contributions from individuals, the recorded value of each contribution has a positive lower bound because small contributions are not itemized: a contribution of less than \$500 from an individual is not reported as an itemized record in FEC data. For all contributions the recorded values have an upper bound due to legal limits on how much an individual or PAC may contribute. The legal limits specify restrictions both on the amount someone may contribute to a single campaign and on the total the person may contribute to all campaigns during an election cycle. Moreover, contributions most often occur in one of a few distinct, "round figure" amounts. Such special features of the recorded values make it doubtful that an assumption that contributions are normally distributed is correct. Also doubtful is the modified assumption that the distribution of contributions is normal except for censoring or truncation at the bottom and at the top. Table 1 shows that during the 1984 campaign cycle most contributions from PACs occurred in one of three amounts: \$200, \$500 or \$1,000. Seventy percent of PAC contributions were of one of those sizes. Including other "round figure" amounts—\$100, \$200, \$300, \$750, \$1,500,

\$2,000, \$2,500 and \$5,000—covers 88 percent percent of PAC contributions. The concentration of contributions on a few distinct values is even more stark for contributions from individuals. Two sizes of contributions, \$500 and \$1,000, account for 93 percent of all donations of \$500 or more.

—Table 1 about here—

The results in Table 1 are only suggestive. A better test of the hypothesis that contributions have an additive normal disturbance is to regress the dollar amount of contributions on plausible sets of regressors and then test the distribution of the residuals. We regressed both dollar amounts and logarithms of dollar amounts of contributions on the same variables used in the GLMM specifications that are presented below. For both individual and PAC contributions, tests such as the Kolmogorov-Smirnov test resoundingly reject that the ordinary least squares residuals have normal distributions.

We propose that a decision to contribute to a candidate is best modeled as a discrete choice among categories of donation levels. For instance, for contributions from individuals, the idea is to specify distinct count processes for large ($>$ \$750) and medium (\$500–\$750) contributions. Though the processes are distinct, they are not independent. Many variables affect contributions of all sizes in essentially the same way, and the specifications we propose take that into account. Note that although we do not have itemized records for small contributions ($<$ \$500) from individuals, we do know the total amount of the small contributions. With some adjustments we can include the small contributions in our model.

Our treatment of contributions as counts leads to a notable difference in how to interpret the absence of a contribution during a period of time. A model based on a normal data generating process for the amount of a contribution would suggest that when zero contributions are observed, all potential contributors would rather have taken money away from the candidate. In contrast, zero contributions are a natural result of a count process. In a count process, a zero implies no more than that no one wished to make a contribution to the candidate.

To model the number of contributions, we adopt the GLMM framework. In the preceding discussion of factors that affect contribution decisions we suggested that accounting for heterogeneity in the mean across candidates and districts is important. Some variables that affect the mean may not be observed by a researcher. In a GLMM specification for a Poisson process, the mean is a log-linear function of the unobserved effects, which are treated as random variables. For a single observed count y_i, the Poisson mean given observed vectors $\mathbf{x}_i$ and $\mathbf{z}_i$, a fixed effect parameter vector β and a vector of unobserved random effects $\mathbf{u}$ is

$$\mu_i = \exp(\mathbf{x}_i'\beta + \mathbf{z}_i'\mathbf{u}) \ .$$

The conditional density for observation y_i is

$$f_{y|u}(y_i \mid \mathbf{u}, \mathbf{x}_i, \mathbf{z}_i, \beta) = e^{-\mu_i}\mu_i^{y_i}/y_i! \ .$$

For a sample of n observations we have the conditional joint density

$$f_{y|u}(\mathbf{y} \mid \mathbf{u}, \mathbf{X}, \mathbf{Z}, \beta) = \prod_{i=1}^{n} f_{y|u}(y_i \mid \mathbf{u}, \mathbf{x}_i, \mathbf{z}_i, \beta) \ , \tag{1}$$

where $\mathbf{y}$ is the vector of all the observed counts, and $\mathbf{X}$ and $\mathbf{Z}$ are the matrices of variables $\mathbf{x}_i$ and $\mathbf{z}_i$. The specification says that conditional on all observed and unobserved effects, the counts are independently distributed Poisson random variables. To complete the GLMM specification one integrates (1) with respect to the distribution assumed for the random effects. When that distribution has a density f_u that is a function of parameters $\mathbf{D}$, $\mathbf{u} \sim f_u(\mathbf{u} \mid \mathbf{D})$, we have the likelihood

$$L(\beta, \mathbf{D} \mid y, \mathbf{X}, \mathbf{Z}) = \int f_{y|u}(\mathbf{y} \mid \mathbf{u}, \mathbf{X}, \mathbf{Z}, \beta)\, f_u(\mathbf{u} \mid \mathbf{D})\, d\mathbf{u} \ . \tag{2}$$

In general (2) has no closed form solution.

The difficulty of the integral has motivated a number of approaches that involve estimation of models that loosely approximate (2). The generalized estimating equations (GEE) approach (Liang and Zeger 1986, Zeger, Liang and Albert 1988) is based on estimating moments that roughly approximate moments derived from (2). Breslow and Clayton (1993) derive a penalized likelihood method by truncating a Laplace transform of (2). Neither the GEE nor the penalized likelihood methods give consistent estimates for the fixed effects, and both have exhibited substantial bias in sampling experiments (Breslow and Clayton 1993, Kuk 1995, McCulloch 1997, Jiang 1998). Lee and Nelder (1996) propose a hierarchical likelihood model that avoids the integral in (2) altogether. Under conditions that they specify, their method gives consistent estimates of fixed effects and asymptotically best unbiased estimates of random effects. But the method suffers certain deficiencies in terms of bias and robustness.

Estimates from the MCEM algorithm of McCulloch (1997) are maximum likelihood (ML) estimates that are consistent for the parameters of (2). MCEM estimates have not exhibited substantial bias in sampling experiments. The most important novelty in McCulloch's proposal is use of a Metropolis algorithm to simulate a good sample of draws from the distribution of the random effects. The simulated sample allows (2) to be evaluated in a straightforward way: by Monte Carlo integration. We outline the MCEM algorithm in the Appendix.

For what we refer to as a GLMM Poisson-Normal (GLMM-PN) specification, the density $f_u(\mathbf{u} \mid \mathbf{D})$ is a product of densities for normally distributed variables. When there is a single random effect, it is possible to use quadrature to evaluate the integral in (2).[1] In that case it is possible to estimate the parameters of (2) by ML without introducing the simulation error that the Monte Carlo estimation part of the MCEM algorithm entails. But even with the recent vast increases in readily available computing resources, quadrature evaluation of (2) is not feasible for more than one random effect, nor for random effects that are not independently distributed. MCEM is feasible in cases where quadrature-based ML estimation is not.

It is also feasible to move beyond GLMM-PN specifications in cases where the conditional Poisson density of (1) is not plausible. In the data on contributions, omitting relevant measures of district and candidate heterogeneity would produce overdispersion in a Poisson regression. Overdispersion would also result if individuals and PACs contribute in a coordinated fashion in ways that the Poisson model ignores. In the models we have estimated for this paper, we

[1]SAS V7 includes the experimental procedure NLMIXED that performs such estimation.

have included observed variables in order to take such potential sources of misspecification into account. Our inclusion of lagged counts, in addition to being of substantive theoretical interest for the question of whether contributions are reactive, is also important to take into account a potential source of contagion across observations. But the counts of contributions exhibit clustering of a kind that may be beyond the scope of a simple Poisson model. For example, in the record of contributions from individuals we frequently observe spouses on the same day contributing identical amounts to a candidate. Also frequent in the record of individual contributions are apparent clusters in which several individuals who work for the same employer contribute to a candidate on the same day. In light of such apparent clustering it would be better to use a conditional compound-Poisson density, or perhaps a conditional negative binomial density, in place of (1). For the illustrative analysis reported in this paper, we ignore such clustering and proceed with GLMM-PN specifications.

A System of Poisson Processes

We define a model in which, conditional on a set of observed and unobserved variables, each count of contributions has an independent Poisson distribution. The model describes separate counts for each of several sources of contributions, sets of candidates of each party who receive the contributions, sizes of contributions, congressional district and epochs of time (e.g., each day or week) during a two-year election cycle. The counts are conditionally independent, but correlated in their joint unconditional distribution because of exogenous observed and unobserved variables that commonly affect their conditional Poisson means. The counts are also correlated because the conditional Poisson mean of each count is affected by contributions received at earlier times. The conditional Poisson mean of the count of contributions received from each source by each party's set of candidates in each district is, in general, affected by the counts of contributions received in previous time periods from all sources by all candidates in the same district. In this way the count processes for all kinds of contributions in each district form a system of processes that interact dynamically and evolve together over time. In the current formulation we assume that the parameters that characterize each system's dynamics are the same in every district.

A key point about the systems is that their dynamics are not in general stationary. The model specification allows for explosive changes in contributions to one or more of the sets of candidates in a district. Such explosive changes need not occur, even when the model's parameters describe nonstationary system behavior. But the model can describe cases in contributions to one party's candidates suddenly increase dramatically while contributions to the other party remain level or even decline. The model can also describe cases in which contributions to all parties' candidates blow up in a reactive frenzy.

Let y_{hkijt} be the count of contributions to a set of House candidates, where the indices are used as follows,

$h \in H = \{h_1, \ldots, h_{m_H}\}$ source of contribution: individual, PAC, party, etc.

$k \in K = \{k_1, \ldots, k_{m_K}\}$ size class of contribution

$i \in I = \{i_1, \ldots, i_{m_I}\}$ party (for major parties, Democrat and Republican, $m_I = 2$)

$j \in J = \{j_1, \ldots, j_{m_J}\}$ congressional district (to cover all districts, $m_J = 435$)

$t \in T = \{t_1, \ldots, t_{m_T}\}$ epoch within a single election cycle (for weeks, $m_T = 104$)

A more complete model may include data from multiple elections. Here we omit an index for the election cycle, to reduce notational clutter.

The daily count of contributions of each size class from each source to the candidates of each party in each district is independently Poisson distributed, conditional on a set of exogenous variables, previous counts, fixed effect parameters and random effects. Define

$$\eta_{hkijt} = \mathbf{x}'_{hkijt}\beta + \left(\sum_{\bar{h}\in H} \sum_{\bar{k}\in K} \sum_{\bar{i}\in I} \sum_{t-q^{\bar{h}\bar{k}}_{hk} \leq \bar{t} < t} y_{\bar{h}\bar{k}\bar{i}j\bar{t}} \alpha^{\bar{h}\bar{k}\bar{i}}_{hki,t-\bar{t}} \right) + b_{hj} + c_{ij} + d_{hjt} + e_{hkij} \qquad (3)$$

$$\mu_{hkijt} = \exp(\eta_{hkijt}) \,.$$

The variables in the vector $\mathbf{x}_{hkijt}$ are assumed to be exogenous. β is a vector of fixed effect parameters. The set

$$\mathbf{y}_{hkj,<t} = \bigcup_{\bar{h}\in H} \bigcup_{\bar{k}\in K} \bigcup_{\bar{i}\in I} \bigcup_{t-q_{hk}^{\bar{h}\bar{k}} \le \bar{t} < t} y_{\bar{h}\bar{k}\bar{i}j\bar{t}}$$

contains the lagged contributions pertinent for y_{hkijt} from all sources, size classes and parties included in the system. The nonnegative integers $q_{hk}^{\bar{h}\bar{k}}$ specify the maximum order up to which lagged counts from source $\bar{h}$ of size class $\bar{k}$ may affect the mean of counts from source h of size class k. Each $\alpha_{hki,t-\bar{t}}^{\bar{h}\bar{k}\bar{i}}$ is a scalar fixed effect parameter. Let

$$\alpha_{hki} = \bigcup_{\bar{h}\in H} \bigcup_{\bar{k}\in K} \bigcup_{\bar{i}\in I} \bigcup_{t-q_{hk}^{\bar{h}\bar{k}} \le \bar{t} < t} \alpha_{hki,t-\bar{t}}^{\bar{h}\bar{k}\bar{i}}$$

denote the set of such parameters that pertain to y_{hkijt}. The parameters in α_{hki} characterize the system's dynamics. In general, the system has nonstationary dynamics if all the values in α_{hki} are positive and stationary dynamics if all the values in α_{hki} are negative. If some values in α_{hki} are positive and some are negative, the stationarity of the overall dynamics depends on the exact combination of the parameter values. α_{hki} is the same for all epochs $t \in T$ and all districts $j \in J$. Let

$$\alpha = \bigcup_{h\in H} \bigcup_{k\in K} \bigcup_{i\in I} \alpha_{hki}$$

denote the set of all such parameters. Any values in the set $\{y_{\bar{h}\bar{k}\bar{i}j\bar{t}} \in \mathbf{y}_{hkj,<t} : \bar{t} < t_1\}$ are predetermined initial conditions. Let

$$\mathbf{y}_{<} = \bigcup_{h\in H} \bigcup_{k\in K} \bigcup_{j\in J} \bigcup_{t\in T} \{y_{\bar{h}\bar{k}\bar{i}j\bar{t}} \in \mathbf{y}_{hkj,<t} : \bar{t} < t_1\}$$

denote the set of all such initial conditions. The effects b_{hj}, c_{ij}, d_{hjt} and e_{hkij} are random. Defining

$$u_{hkijt} = (b_{hj}, c_{ij}, d_{hjt}, e_{hkij})' \ ,$$

we have a conditional Poisson density for each observed count y_{hkijt}:

$$f_{y|u}(y_{hkijt} \mid u_{hkijt}, \mathbf{x}_{hkijt}, \mathbf{y}_{hkj,<t}, \beta, \alpha_{hki}) = \exp\{-\mu_{hkijt} + y_{hkijt}\eta_{hkijt} - \log(y_{hkijt}!)\} \ .$$

Defining the vector of the realizations of all the random effects as

$$\mathbf{u} = (b_{j_1}, \ldots, b_{j_{m_J}}, c_{i_1 j_1}, \ldots, c_{i_{m_I} j_{m_J}}, d_{h_1 j_1 t_1}, \ldots, d_{h_{m_H} j_{m_J} t_{m_T}},$$
$$e_{h_1 k_1 i_1 j_1}, \ldots, e_{h_{m_H} k_{m_K} i_{m_I} j_{m_J}})'$$

implicitly defines $\mathbf{Z}$ of (1) to index the random effects: $\mathbf{z}'_{hkijt}\mathbf{u} = b_{hj} + c_{ij} + d_{hjt} + e_{hkij}$. The conditional joint density of all the observed counts is

$$f_{y|u}(\mathbf{y} \mid \mathbf{u}, \mathbf{X}, \mathbf{Z}, \mathbf{y}_<, \beta, \alpha) =$$
$$\prod_{h\in H} \prod_{k\in K} \prod_{i\in I} \prod_{j\in J} \prod_{t\in T} f_{y|u}(y_{hkijt} \mid u_{hkijt}, \mathbf{x}_{hkijt}, \mathbf{y}_{hkj,<t}, \beta, \alpha_{hki}) \,. \quad (4)$$

We assume all the random effects are normal with zero mean. Each of the effects b_{hj}, c_{ij} and e_{hkij} is identically and independently distributed with variance, respectively, ϕ^2, σ^2 and τ^2. The effect d_{hjt} is identically distributed but serially correlated. For simplicity here, we assume it to be first-order autoregressive with innovation variance ψ^2 and autoregression parameter ρ. In formal terms,

$$b_{hj} \sim f_b(b_{hj} \mid \phi^2) = (2\pi\phi^2)^{-1/2} \exp\{-b_j^2/(2\phi^2)\}$$
$$c_{ij} \sim f_c(c_{ij} \mid \sigma^2) = (2\pi\sigma^2)^{-1/2} \exp\{-c_{ij}^2/(2\sigma^2)\}$$
$$e_{hkij} \sim f_e(e_{hkij} \mid \tau^2) = (2\pi\tau^2)^{-1/2} \exp\{-e_{hkij}^2/(2\tau^2)\}$$

and using $\mathbf{d}_{hj} = (d_{hjt_1}, \ldots, d_{hjt_{m_T}})'$,

$$\mathbf{d}_{hj} \sim f_d(\mathbf{d}_{hj} \mid \psi^2, \rho) = (2\pi\psi^2)^{-m_T/2} |\mathbf{R}|^{-1/2} \exp\{-\mathbf{d}'_{hj}\mathbf{R}^{-1}\mathbf{d}_{hj}/(2\psi^2)\}$$

where $\mathbf{R}$ is the autocorrelation matrix for a first-order autoregressive process:

$$\mathbf{R} = \begin{bmatrix} 1 & \rho & \cdots & \rho^{m_T} \\ \rho & 1 & \cdots & \rho^{m_T-1} \\ \vdots & \vdots & \ddots & \vdots \\ \rho^{m_T} & \rho^{m_T-1} & \cdots & 1 \end{bmatrix} .$$

With $\mathbf{D} = (\phi^2, \sigma^2, \tau^2, \psi^2, \rho)'$, the joint density of the realizations of all the random effects is

$$f_u(\mathbf{u} \mid \mathbf{D}) = \left[\prod_{h \in H} \prod_{j \in J} f_b(b_{hj} \mid \phi^2)\right] \left[\prod_{i \in I} \prod_{j \in J} f_c(c_{ij} \mid \sigma^2)\right] \\ \times \left[\prod_{h \in H} \prod_{j \in J} f_d(\mathbf{d}_{hj} \mid \psi^2, \rho)\right] \left[\prod_{h \in H} \prod_{k \in K} \prod_{i \in I} \prod_{j \in J} f_e(e_{hkij} \mid \tau^2)\right] .$$

The GLMM-PN model likelihood takes the form

$$L(\beta, \alpha, \mathbf{D} \mid y, \mathbf{X}, \mathbf{Z}, \mathbf{y}_<) = \int f_{y|u}(\mathbf{y} \mid \mathbf{u}, \mathbf{X}, \mathbf{Z}, \mathbf{y}_<, \beta, \alpha)\, f_u(\mathbf{u} \mid \mathbf{D})\, d\mathbf{u} . \tag{5}$$

The source-and-district-specific effect b_{hj} induces correlation between the counts of contributions to both parties within each district from each source. Correlation is induced among all size classes over the whole span of a campaign cycle, but not across sources or across districts. For example, if a House race is designated by pundits as some kind of bellwether district, both parties may receive increased contributions as partisan or ideological contributors may exert particular effort in order to raise expectations for friendly candidates in other districts. Because the data we use do not include measures of advertising cost within a district, this random effect may also capture the relative difference in the basic need for raising money.

The party-and-district-specific effect c_{ij} induces correlation between the counts of contributions to one party within a district. The effect induces correlation among all sources of contributions and all size classes, over the whole span of a campaign cycle. Parties in some districts may simply be better than other parties at raising money.

For small contributions from individuals we observe only the total amount contributed to each party in a district. Such contributions require special handling that we do not describe here.

Data and Detailed Model Specification

The campaign contributions data for individuals and PACs are drawn from the Federal Election Commission (FEC) Itemized Contributions files for 1984. For comparability with our previous aggregate analysis, we restrict the data to include contributions only during the 42-week period from mid-January 1984 until just before the general election. For computational convenience in this preliminary analysis, we further limit our sample to twenty open seat races. We aggregate the counts of contributions to the level of parties within districts and to the frequency of weeks. More details on the dataset used for this paper are presented in the appendix. We define separate series for each party and each type of contribution by district. Figures 1 to 4 plot the values of the counts of weekly contributions we analyze. The first week begins January 16, 1984, and the last begins October 29, 1984.

—Figures 1 to 4 about here—

The variables in $\mathbf{X}$ are as follows.

I(district) In some of our model specifications we use dummy variables to estimate district-specific fixed effects, omitting the dummy for AL06 (which therefore determines the intercept). In a model that included many more than twenty open seat races, the use of dummy variables would become unattractive for reasons of both statistical consistency and computational stability as number of districts increased. In such a situation, accounting for district heterogeneity by random effects would become much more attractive.

$\mathbf{count}_{t-\tau}$ Lagged counts are constructed from the dependent count variable for each of the series. Currently we have simply allowed three lagged weeks of counts. Note that for this and the other lagged variables, we use data available prior to the period analyzed in this paper as initial conditions.

opp. $\mathbf{count}_{t-\tau}$ We allow for a candidate and her supporters to react to fund-raising successes of the opposing party by also including as regressors the lagged count of the opponents series.

opp./own IND/PAC $\mathbf{count}_{t-\tau}$ In the model where we pool individual and PAC itemized contributions, we allow a variety of reactions. In addition to the two previous types of lagged effects, individual contributors may also react separately to PAC contributions to each party. Similarly, PAC contributors may react to receipts in each of the individual contribution series. "Own" and "opp" indicate simply whether the contributions are to the same party as that of the dependent variable ("own"), or to the opposing party ("opp"). This designation is not meant to suggest any judgment about the preference of the contributors, in terms of defining which party is perceived as the opposition. Individuals and PACs are at liberty to contribute to both parties, and we do not attempt to take into account this type of behavior.

HQ We seek to measure the quality of the candidates, since this is likely to be related both to the beliefs potential contributors have about the candidate's prospects and the candidate's organizational ability to raise money. Quality is a dichotomous variable based solely on whether a candidate has previously held elected office. A non-incumbent who has done so is deemed high quality. The quality dataset was collected by Gary Jacobson; see Jacobson (1990). Because Jacobson's data only indicate the quality of the general election candidates, our classification of some parties as having a high quality open seat candidate is actually an approximation. A candidate who did not survive to the general election may have been of high quality. If a party's general election candidate in a district is designated as high quality in Jacobson's data, then we designate the entire aggregate contributions Poisson process for that party in the district as having the high quality dummy variable equal to one. The HQ dummy is zero otherwise.

Primary$_t$ is a dummy variable indicating whether the district had a contested primary prior to time t.[2] This variable captures the impact of resolving uncertainty over which candidate will compete in the general election for each party. Once a candidate has won the primary, individuals may be more likely to contribute to that candidate's campaign. But in our analysis of the total number of contributions to all candidates from each party in a district, the dominant effect of this variable is most likely to be negative, as there are fewer viable candidates to whom to contribute after the primary.

[2] We collated the dates of all contested House primaries during 1984 from Scammon and McGillivray (1985).

No Primaries is a dummy variable for a party that did not have a contested primary in that district.

Party We allow the Republican and Democratic parties to have different means on average across the different open seat races by including a dummy variable, Party, which is equal to one if the dependent variable of the series is for contributions to Republicans and zero otherwise.

f(Dem vote 1982) Past Vote measures the level of support for the Democratic House candidate in the 1982 general election. We specify the basic variable as the difference of the two-party vote proportion for the Democrat from 0.5. To allow for opposite, but equal effects, for each party, we multiply the basic variable by -1 for Democratic series and 1 for Republicans.

I(PAC) We include dummies for endorsements from six of the most influential PACs in 1984: Americans for Democratic Action (ADA), AFL-CIO, Committee on Political Education (COPE), National Committee for an Effective Congress (NCEC), Americans for Constitutional Action (ACA), Business-Industry PAC (BIPAC), and National Conservative PAC (NCPAC).[3] Since the timing of the endorsements in currently unavailable to us, we cannot comment on whether these endorsements instigated higher contribution levels. Rather, the measure is aimed at accounting for differences in ideology and interests of the general election candidates.

$(\theta_{Dt} - \theta_{Rt})$ is the difference in the expected policy location of the two major parties' presidential candidates. Each policy location is mapped onto the $[0, 1]$ interval, with 0 being most liberal position and 1 being the most conservative. θ_{Dt} is the weighted sum of the locations of each of the Democratic party presidential primary candidates, the weights being each candidate's expected probability of nomination. Both the candidate positions and the candidate's probabilities of winning are derived from data taken from the American National Election

[3]The source of the endorsement data is Congressional Quarterly Weekly Report summary of general election endorsements in 1984 (Nov 17, pp. 2971–76).

Study (ANES) 1984 Continuous Monitoring Study (Miller and the National Election Studies 1985). The Continuous Monitoring Study performed daily interviews of random cross-sections of individuals from 11 January 1984, through 31 December 1984. θ_{Rt} is the policy location of President Ronald Reagan, the de facto Republican candidate throughout the 1984 primary season; we treat θ_{Rt} as constant throughout the entire year. See Wand and Mebane (1999) for more details about θ_{Dt} and θ_{Rt}.

$\bar{P}_t$ is the average subjective probability of Reagan winning the general election. The expected probability of winning data for Reagan are also derived from the Continuous Monitoring Study. Details regarding the construction of the national-level variables and their analytical motivation within a policy moderating theory of campaign contributions are described in Wand and Mebane (1999). The key predictions from the policy moderating model concern the effects of $(\theta_{Dt} - \theta_{Rt})$ and $\bar{P}_t$. We show in Wand and Mebane (1999) that a policy moderating model predicts that during 1984 the effect of $(\theta_{Dt} - \theta_{Rt})$ on the number of contributions should be positive, likewise the effect of $\bar{P}_t$.

Estimation and Results

For the analysis in this paper we have not separated the contributions by size class. The counts we analyze are the number of contributions of \$500 or larger to all candidates of each party (Democrats and Republicans only) in each district in each week, counting separately contributions from individuals and contributions from PACs. In the specification of (3), and hence (5), all indexing by k (for size class) is removed, as are any effects specific to size class.

We begin with the series of contributions from individuals. Table 2 presents results from a plain Poisson model and a GLMM-PN model that has one random effect estimated using quadrature. The random effect is the party-and-district-specific effect denoted c_{ij} in (3). The effect takes 40 distinct values in the data, one for each party in each district. In the models of Table 2, the source-and-district-specific effects b_{hj} of (3) are reduced to district-specific effects,

b_j. In the models of Table 2 we estimate b_j as fixed effects, by including a dummy variable for each district.

—Table 2 about here—

The models include all of the presumed-exogenous variables described above, except for candidate quality. The models also include three weeks of lagged counts for the party and for the opposition party; in terms of (3), $q_h^{\bar{h}} = 3$. We have imposed symmetry conditions on the parameters of the dynamic relations: for i_1 = Democrat and i_2 = Republican, we impose the equalities $\alpha_{hi_1,t-\bar{t}}^{\bar{h}i_2} = \alpha_{hi_2,t-\bar{t}}^{\bar{h}i_1}$ and $\alpha_{hi_1,t-\bar{t}}^{\bar{h}i_1} = \alpha_{hi_2,t-\bar{t}}^{\bar{h}i_2}$. The first equality assumes that contributions to both parties candidates react to previous fundraising by the opposing parties' candidates with exactly the same effect. The second equality assumes that contributions to both parties' candidates are influenced by their own previous fundraising with exactly the same effect. The first assumption is dubious if one believes that one party is better able to counter-mobilize resources quickly.

Comparing the Poisson model and the GLMM-PN estimates, we observe that the estimated effects of the lagged count variables are of slightly smaller magnitude in the GLMM-PN model. The standard errors (SEs) are the same and inferences about the effects would be substantively the same in both models, however. In both models, the greater the number of contributions a party's candidates received in each of the previous three weeks, the greater the mean number of contributions the party's candidates will receive during the current week. Contributions to one party's candidates during the previous week do not have a significant effect on the mean number of contributions to the other party during the current week. But contributions a party's candidates received two weeks previously significantly increase the current mean number of contributions to the other party's candidates. Contributions a party's candidates received three weeks previously significantly decrease the current mean of the other party's candidates. Thus contributions to one party's candidates uniformly enhance the chances for future contributions to those candidates, but induce an oscillation in the prospects for contributions to the other party. These results suggest that local reactivity is an important feature of individuals' contributing behavior.

The estimates for the effects of the national time-series variables, $(\theta_{Dt} - \theta_{Rt})$ and $\bar{P}_t$, are nearly identical in the two models. The mean number of contributions increases significantly with an increase in either variable. Individuals' decisions to contribute react to national political conditions.

The two models have noticeably different estimates for the fixed effects of many of the variables that do not vary over time. The SEs of the GLMM-PN model estimates for those effects are larger than the SEs for those same effects in the Poisson model. Several of the GLMM-PN SEs are nearly three times larger than the Poisson model SEs. The larger SEs of the GLMM-PN estimates is a consequence of the fact that the c_{ij} random effect in the GLMM-PN model varies over districts but does not vary over time. The GLMM-PN model averages over all possible values those effects might take; viz. the integral in (2). The uncertainty about those unobserved values causes the effects of the observed time-invariant variables to be estimated with less precision. The greater the variation in the random effects, the less precise are the inferences one may make about fixed effects associated with observed variables that vary over the same indices as the random effects. If the random effects actually exist, then the estimates from the Poisson model are overstating the precision with which the effects of time-invariant variables may be estimated using the observed data.

Even with all the fixed effects that are included in the GLMM-PN model, the variance estimated for the random effect is significant according to normal-theory confidence intervals (MLE $\pm\, z_{1-\alpha/2}$SE for a $100(1-\alpha)\%$ interval) constructed using the SE from the GLMM-PN model estimates.

In Table 3 we contrast the results of plain Poisson with both the quadrature and MCEM estimators of the GLMM-PN model using a specification that simply adds a dummy variable for candidate quality to the set of variables with fixed effects. The addition of this variable reduces the variance of the random effect by nearly 66 percent—from 0.046 to 0.016 according to the quadrature estimates—but it remains statistically significant. Estimates of the fixed effects of variables that vary over time are virtually identical to those reported in Table 2. For the fixed effects of the time-invariant variables, the differences between the GLMM-PN model estimates and those of the Poisson model are not as great in Table 3 as in Table 2. The GLMM-PN model SEs are still larger than the Poisson model SEs, but the discrepancy is less than in Table 2. This is because the variance of the random effect c_{ij} is smaller with the candidate quality variable included. Adding the candidate quality variable increased the SEs of the estimates of the time-invariant variables' effects in the Poisson model, but decreased the SEs of such estimates in the GLMM-PN model. The increase in the Poisson model SEs reflects the consumption of one degree of freedom to estimate the fixed effect of candidate quality. The decreases in the GLMM-PN model SEs reflects the reduction in the variance of the random effect.

—Table 3 about here—

The GLMM-PN MCEM estimates and standard errors are generally intermediate in value between those of the Poisson model and quadrature-estimated GLMM-PN, and where they agree so does MCEM. The parameter estimates most invariant under the different estimators are those for the effects of the lagged counts and the effects of the national time-series variables. This may suggest that these estimates are more reliable than are estimates for the effects of the time-invariant variables, such as those for endorsements. One of the major differences in parameter estimates between Table 2 and Table 3 are the significantly negative estimates for Party in Table 3. The negative estimates suggesting that, all else equal, Republican candidates attract fewer individual contributions (of $500 or larger) than Democratic candidates do.

With the candidate quality variable included, the variance component c_{ij} may seem small enough to ignore. One may therefore reasonably ask whether accounting for the district-specific and party-and-district-specific effects has produced the equality between mean and variance that characterizes a Poisson distribution. To test this equality against a negative binomial variance, we follow Cameron and Trivedi (1998, 78) and use the artificial regression

$$\frac{(y-\hat{\mu})^2 - y}{\hat{\mu}} = \alpha\hat{\mu} + u$$

where the t-statistic for α is asymptotically standard normal under the null hypothesis of no over-dispersion of the quadratic negative binomial form. We can soundly reject the null with $t = 8.314$. Clearly we need to augment the model to handle the additional clustering that we strongly suspect exists based on inspection of the raw FEC data files.

Continuing with the model with the quality variable included, we replace the fixed effects for unobserved district effects b_j with a random effect. We present estimates from the two random effect model in Table 4. We find that the MCEM estimation of the model with the two random effects, for both b_j and c_{ij}, provides generally the same inferences for the lagged count and national time-series variables as in the model that includes a random effect only for c_{ij}. The major difference is in inferences regarding the effects of the time-invariant variables, namely the Party, No Primary and endorsement variables. In the absence of the district dummies, most of the time-invariant parameters are estimated with much smaller standard errors, suggesting the efficiency loss of treating the b_j values as fixed effects in the estimates in Table 3. In addition to becoming more precise, several of the estimates of the effects of endorsements are reduced in magnitude. Some are larger in Table 4 than in Table 3, however. We note that the estimated variance of the b_j random effects in Table 4 ($\phi^2 = 0.32$) is much smaller than the variance of the b_j fixed effects in Table 3 ($\mathrm{var}(b_j) = 0.64$).

—Table 4 about here—

Finally we estimate a system of Poisson processes that includes both individual and PAC contributions. Two main advantages result from this joint analysis. If the unobserved district and candidate qualities that affect individual and PAC receipts are drawn from the same distribution, then we should get better estimates of these parameters by pooling the data. Second, there are important substantive implications for understanding how contributions from one source affect contributions from another. Do contributions from PACs mobilize individuals to contribute? Do contributions from individuals frighten away PACs? The results of the pooled model are summarized in Table 5.

—Table 5 about here—

We allow most of the parameters to have different values for each of the series. The estimates suggest that there are a number of parameters that could be further pooled. We have constrained the effects of previous contributions to a party's candidates from one source on current contributions from the same source to be the same for both individual and PAC contributions ($\alpha^{h_1 i}_{h_1 i, t-\bar{t}} = \alpha^{h_2 i}_{h_2 i, t-\bar{t}}$). As in the separate analysis of contributions from individuals, the greater the number of contributions a party's candidates received from a type of source in each of the previous three weeks, the greater the mean number of contributions the party's candidates receive from that type of source during the current week. In other respects there are stark differences in the ways the two sources of contributions react to previous contributions. The mean of contributions to a party's candidates from PACs uniformly increases with greater numbers of previous contributions to those candidates from individuals. But the mean of contributions to a party's candidates from individual exhibits a complex oscillation in response to greater numbers of previous contributions to the candidates from PACs: the mean of contributions from individuals increases in response to more contributions from PACs one week and three weeks previously, but decreases in response to PAC contributions from two weeks previously. Contributions to a party's candidates from individuals react strongly to contributions that candidates of the opposing party receive from both individuals and PACs. Here there is a pattern of oscillation similar to that observed in the separate analysis of individual's contributions, except that contributions to the opposition from PACs during the previous week increase the mean number of contributions from individuals in the current week. But contributions from PACs do not respond significantly to contributions to the opposing party's candidates from PACs, and they respond only relatively weakly—the mean increases—to the previous week's contributions to the opposing party's candidates from individuals. PAC contributions do not respond significantly to contributions from individuals to the opposing party's candidates during the preceding two or three weeks.

The national time-series variables have large and significant effects in both series. The policy difference variable $(\theta_{Dt} - \theta_{Rt})$ has a larger effect on the mean number of PAC contributions that it does on the mean number of contributions from individuals. The effect of subjective expectations that Reagan would win the general election $(\bar{P}_t)$ affects the mean number of contributions from both types of sources equally.

The electoral history of the district plays a large role in individual contributions, but not PAC. With a negative coefficient, this means that the larger the Democratic victory in 1982, the more money the Democrats are likely to raise from individuals in each week during 1984. The Party variable also suggests that Democrats tend to be more successful in individual contributions, while Republicans fare better in attracting PAC money. The conclusion of a contested primary, or the absence of a primary altogether, greatly reduces individual contributions to both parties, while these factors have significant effect for the PAC decision to contribute.

Endorsement effects also vary across the two sources. The liberal organizations had the largest effect on PAC contributions, with COPE being associated with low contribution candidates and NCPAC supporting those who ultimately raised more money. The right-wing PAC endorsements were associated more strongly with individual contributions, although primarily in a negative manner.

Discussion and Conclusions

The primary contribution this paper is the general and flexible framework for analyzing campaign contributions data. Specifically, we are able to account for unobserved heterogeneity and dynamic effects within a system of Poisson processes. Substantively, the current results show that even using the available observable measures of candidate and district effects, there are still significant unobserved party-district and district specific effects. Failing to account for such unobserved effects would lead a researcher to overstate the significance of observed time-invariant variables. The dynamics of lagged and cross-lagged contributions are highly significant and robust to changes in estimation technique. The interpretation of these dynamic coefficients, particularly those that suggest oscilation in the combined PAC-individual system, will be better understood with forthcoming simulations. In particular, the simulations will provide a better understanding of which series demonstrate explosively nonstationary dynamics.

A limitation of the current analysis is our inability to distinguish between changes in candidate effort and changes in contributor receptivity when an opponent successfully raises contributions. For example, with an increase in the number of contributions to one party and a positive coefficient on an opponent lagged count variable, there are at least two possible interpretations for an increase in the current contribution to the opposing party. First, the increase in contributions leads the other party's candidates to increase their effort to solicit funds. Alternatively, potential contributors may be more receptive to existing solicitations when the opposition is successfully mobilizing funds. With the limited information available to individual contributors, candidates would nevertheless have to make the effort to inform individuals and solicit contributions under the second scenario. We can only estimate the net effect of these changes, with each scenario being partially true.

More generally, this analysis demonstrates the potential usefulness of GLMMs. Political scientists are increasingly taking into account unobserved heterogeneity, particularly in the context of linear panel models. The use of models with non-normal data has a longer tradition in the discipline. GLMMs provide a method for combining these two strands of research methods, allowing for the consistent estimation of panel models for non-normal data.

Appendix: MCEM

We outline the MCEM algorithm we use to estimate our models. The MCEM algorithm proper, from McCulloch (1997), comprises steps 2 and 3.

1. We choose starting values for β in one of two ways: by ML estimation of a negative binomial model, which provides consistent slope parameters in the presence of some kinds of heterogeneity; or by a GLMM-PN model using the SAS procedure NLMIXED. The first approach does not directly model the random effects, but does allow for the overdispersion from all of the unspecified sources. The later approach assumes that there is no overdispersion once the single random effect is estimated. When starting from Negative Binomial starting values, we undertake a search algorithm based on a set of initial values of $\mathbf{D}$. Alternatively, we used the scalar $\mathbf{D}$ estimated from NLMIXED.

2. The MCEM algorithm uses a Metropolis algorithm to get random draws from the conditional distribution of $\mathbf{u} \mid \mathbf{y}$. Iteration m of the MCEM algorithm begins with the generation of N replications of the random effects, $\tilde{\mathbf{u}}^{(1)}, \ldots, \tilde{\mathbf{u}}^{(N)}$, from the candidate distribution $f_u(\mathbf{u} \mid \mathbf{D}^{(m-1)})$. The Metropolis step compares each element of the newly generated replications to the corresponding element of the set of simulated values from the previous iteration, namely, $\mathbf{u}^{(1)}, \ldots, \mathbf{u}^{(N)}$. The Metropolis algorithm probabilistically replaces the previous element with the new element, using probabilities determined by an acceptance function, A_k. Let $\tilde{u}_k^{(j)}$ denote the kth element of the jth replication $\tilde{\mathbf{u}}^{(j)}$ in the newly generated values. Define $\mathbf{u}^{(j)*} = (u_1^{(j)}, u_2^{(j)}, \ldots u_{k-1}^{(j)}, \tilde{u}_k^{(j)}, \ldots, u_q^{(j)})$. One accepts $\tilde{u}_k^{(j)}$ (and replaces u_k within the jth replication) with probability,

$$A_k(\mathbf{u}^{(j)}, \mathbf{u}^{(j)*}) = \min\left\{1, \frac{f_{y|u}(\mathbf{y} \mid \mathbf{u}^{(j)*}, \mathbf{X}, \mathbf{Z}, \beta)}{f_{y|u}(\mathbf{y} \mid \mathbf{u}^{(j)}, \mathbf{X}, \mathbf{Z}, \beta)}\right\} .$$

   A special virtue of A_k is that it depends only on the conditional distribution of $\mathbf{y} \mid \mathbf{u}^{(j)}$. Repeating this acceptance/rejection step for each of the q elements of each $\mathbf{u}^{(j)}$, $j = 1, \ldots, N$, produces the set of simulations of the random effects to be used in the maximization step of iteration m.

(a) Choose $\beta^{(m)}$ to maximize the empirical expectation of the conditional log-likelihood of $\mathbf{y}$:

$$\frac{1}{N}\sum_{j=1}^{N}\log f_{y|u}(\mathbf{y} \mid \mathbf{u}^{(j)}, \mathbf{X}, \mathbf{Z}, \beta)$$

(b) Choose $\mathbf{D}^{(m)}$ to maximize the empirical expectation of the log-likelihood of $\mathbf{u}$:

$$\frac{1}{N}\sum_{j=1}^{N}\log f_{u}(\mathbf{u}^{(j)} \mid \mathbf{D})$$

(c) Set $m = m + 1$.

3. Iterate until $\beta^{(m)}$ and $\mathbf{D}^{(m)}$ converge. The converged values are the MLEs $\hat{\beta}$ and $\hat{\mathbf{D}}$ (unless convergence has been to a local maximum). McCulloch (1997) discusses convergence issues.

4. Using the MLEs, the variance of the estimates may be estimated using a standard result for random variables w and v:

$$\mathrm{var}(w) = \mathrm{E}_v[\mathrm{var}(w \mid v)] + \mathrm{var}_v[\mathrm{E}(w \mid v)]\ .$$

Setting $w = \hat{\beta}$ and $v = \mathbf{u}$, the asymptotic covariance matrix of $\hat{\beta}$ may be estimated by

$$\mathrm{var}(\hat{\beta}) = \frac{1}{N}\sum_{j=1}^{N}\mathrm{var}\left(\hat{\beta}^{(j)}\right) + \frac{1}{N}\sum_{j=1}^{N}\left(\hat{\beta}^{(j)} - \hat{\beta}\right)\left(\hat{\beta}^{(j)} - \hat{\beta}\right)'$$

where $\hat{\beta}^{(j)}$ is the conditional ML estimate for the jth replication $\mathbf{u}^{(j)}$. The asymptotic variance of the estimated variance component for an identically and independently distributed random effect with q clusters (i.e., an effect that takes q distinct values in the data) may be estimated similarly. Using σ^2 to denote the variance component,

$$\mathrm{var}(\hat{\sigma}^2) = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{q}\left[\frac{1}{q}\sum_{k=1}^{q}\left(u_k^{(j)}\right)^4 - \left(\hat{\sigma}^{2(j)}\right)^2\right] + \frac{1}{N}\sum_{j=1}^{N}\left(\hat{\sigma}^{2(j)} - \hat{\sigma}^2\right)^2$$

where

$$\hat{\sigma}^{2(j)} = \frac{1}{q}\sum_{k=1}^{q}\left(u_k^{(j)}\right)^2\ .$$

Appendix. Data definitions and selection criteria

We obtained the raw itemized contributions data files from the FEC by anonymous ftp from ftp.fec.gov:/FEC/. In combination with the Committee Master files and Candidate Master files, we extracted for each election cycle all new contributions for candidates competing in the upcoming election. Contributions are defined as those with transaction code 15 from individuals and either code 24K or 24Z from PACs. The itemized individual contributions are observed only for amounts of \$500 or more. Since we are interested in the act of contribution, we exclude refunds which are indicated by new negative contributions. Since we do not currently estimate small individual contributions as part of our system of Poisson processes, we make the magnitude of observed PAC and individual contributions comparable by treating small PAC contributions ($<$ \$500) as a separate series and exclude them from the current analysis.

Our selection includes all contributions to a candidate in the current cycle who has raised or spent \$5,000 toward the current election and any individual who appears on a ballot or who has registered with the FEC but has not yet raised \$5,000.

We selected districts which were reported to be open seat races early in 1984 by Congressional Quarterly Weekly Report (24 Feb, p.344), and were in fact open seat races at the time of election. Therefore we exclude those open seat races where the incumbent dies during 1984 or lost in the primary. The included districts are: AL01, AR02, CO03, IA05, IL13, IL14, IL22, KS03, MA05, NC09, NH01, NY20, NY30, TN06, TX06, TX19, TX22, UT02, VA07, WA01. We aggregate the counts of contributions to the level of parties within districts and to the frequency of weeks. The time span of our analysis starts during the week of January 16th and the ends with the week of October 29th, 1984. Lagged variables for initial weeks of the series (used as the initial conditions) are drawn from weeks prior to the beginning of this time span.

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Table 1: Most Frequent Itemized Contribution Levels (in Dollars) to House Candidates by Source in the 1984 Election Cycle

PAC

Contribution level	N	Percentage
100	3876	3.0
200	4799	3.7
250	40871	31.5
300	5116	3.9
500	34256	26.4
1000	15764	12.2
2000	3142	2.4

Individual

Contribution level	N	Percentage
500	27518	53.5
1000	20526	39.9

Table 2: Poisson and Poisson-Normal Models omitting High Quality variable: Itemized Individual Contributions

	Poisson		GLMM-PN Quadrature	
	Est.	SE	Est.	SE
Intercept	1.142	0.790	1.234	0.810
I(AR02)	0.454	0.102	0.557	0.304
I(CO03)	−0.920	0.130	−1.047	0.332
I(IA05)	−1.265	0.133	−1.261	0.284
I(IL13)	−1.908	0.161	−2.412	0.383
I(IL14)	−1.782	0.160	−2.144	0.380
I(IL22)	−0.810	0.134	−0.633	0.313
I(KS03)	−0.618	0.092	−0.556	0.281
I(MA05)	0.396	0.122	0.515	0.323
I(NC09)	−0.244	0.078	−0.344	0.244
I(NH01)	−0.000	0.152	0.298	0.348
I(NY20)	0.192	0.102	0.323	0.286
I(NY30)	−0.432	0.193	−0.137	0.419
I(TN06)	−0.239	0.113	−0.192	0.319
I(TX06)	−0.449	0.100	−0.446	0.288
I(TX19)	−0.091	0.084	−0.268	0.264
I(TX22)	−0.338	0.091	−0.517	0.267
I(UT02)	−0.482	0.113	−0.327	0.285
I(VA07)	0.157	0.168	0.528	0.405
I(WA01)	−0.514	0.116	−0.583	0.302
count_{t-1}	0.023	0.002	0.021	0.002
count_{t-2}	0.023	0.002	0.020	0.002
count_{t-3}	0.021	0.002	0.018	0.002
opp. count_{t-1}	−0.004	0.003	−0.001	0.003
opp. count_{t-2}	0.015	0.002	0.018	0.002
opp. count_{t-3}	−0.019	0.003	−0.015	0.003
$\theta_{Dt} - \theta_{Rt}$	14.772	1.918	14.742	1.918
P_t	6.088	0.987	6.172	0.987
f(Dem vote 1982)	−1.922	0.274	−2.719	0.709
Primary_t	−0.458	0.045	−0.488	0.046
No Primary	−0.909	0.093	−1.172	0.211
Party	0.222	0.151	0.362	0.403
I(ADA)	−0.238	0.090	−0.371	0.219
I(COPE)	−0.355	0.092	−0.689	0.247
I(NCEC)	0.219	0.105	0.453	0.258
I(ACA)	0.184	0.098	0.191	0.227
I(BIPAC)	−0.114	0.100	−0.380	0.271
I(NCPAC)	−0.639	0.076	−0.781	0.187
I(Apr)	−0.012	0.051	−0.011	0.051
I(May)	−0.112	0.061	−0.102	0.061
I(Jun)	0.219	0.060	0.238	0.060
I(Jul)	0.121	0.060	0.146	0.061
I(Aug)	0.093	0.072	0.113	0.072
I(Sep)	0.031	0.082	0.051	0.082
I(Oct)	0.233	0.088	0.252	0.088
σ^2	—		0.046	0.015
−2 Loglikelihood	6622.96		8917.1	

Note: $m_H = 1$, $m_I = 2$, $m_J = 20$, and $m_T = 42$, therefore total number of observations is 1680.

Table 3: Poisson and Poisson-Normal Models with High Quality variable: Itemized Individual Contributions

	Poisson		GLMM-PN Quadrature		GLMM-PN MCEM	
	Est.	SE	Est.	SE	Est.	SE
Intercept	0.969	0.790	0.987	0.797	0.966	0.788
I(AR02)	1.252	0.133	1.334	0.239	1.377	0.166
I(CO03)	−0.166	0.155	−0.152	0.268	−0.087	0.194
I(IA05)	−0.900	0.140	−0.857	0.212	−0.840	0.165
I(IL13)	−1.567	0.170	−1.707	0.279	−1.616	0.213
I(IL14)	−1.469	0.169	−1.564	0.273	−1.491	0.208
I(IL22)	0.010	0.161	0.162	0.262	0.187	0.195
I(KS03)	0.139	0.121	0.256	0.234	0.279	0.154
I(MA05)	0.594	0.130	0.674	0.221	0.695	0.162
I(NC09)	−0.130	0.080	−0.126	0.159	−0.107	0.102
I(NH01)	0.703	0.172	0.814	0.266	0.825	0.209
I(NY20)	0.979	0.134	1.049	0.231	1.088	0.163
I(NY30)	0.318	0.216	0.474	0.322	0.504	0.260
I(TN06)	0.520	0.141	0.643	0.257	0.689	0.177
I(TX06)	0.106	0.117	0.140	0.215	0.177	0.145
I(TX19)	0.223	0.089	0.242	0.182	0.269	0.116
I(TX22)	−0.309	0.094	−0.331	0.174	−0.308	0.120
I(UT02)	0.094	0.125	0.193	0.216	0.206	0.155
I(VA07)	1.038	0.200	1.288	0.320	1.320	0.242
I(WA01)	−0.236	0.126	−0.167	0.215	−0.116	0.156
count_{t-1}	0.022	0.002	0.021	0.002	0.021	0.002
count_{t-2}	0.021	0.002	0.020	0.002	0.020	0.002
count_{t-3}	0.018	0.002	0.018	0.002	0.018	0.002
opp. count_{t-1}	−0.002	0.003	−0.001	0.003	−0.001	0.003
opp. count_{t-2}	0.017	0.002	0.018	0.002	0.018	0.002
opp. count_{t-3}	−0.016	0.003	−0.015	0.003	−0.015	0.003
$\theta_{Dt} - \theta_{Rt}$	14.716	1.918	14.714	1.918	14.725	1.912
P_t	6.135	0.987	6.146	0.987	6.151	0.984
f(Dem vote 1982)	−1.862	0.277	−2.259	0.488	−2.154	0.345
Primary_t	−0.456	0.046	−0.481	0.046	−0.477	0.046
No Primary	−1.041	0.098	−1.115	0.150	−1.110	0.117
Party	−0.494	0.172	−0.546	0.303	−0.626	0.216
I(ADA)	−0.100	0.094	−0.063	0.162	−0.066	0.118
I(COPE)	−1.023	0.117	−1.230	0.209	−1.231	0.147
I(NCEC)	0.122	0.120	0.244	0.181	0.228	0.135
I(ACA)	0.194	0.103	0.223	0.159	0.253	0.125
I(BIPAC)	−0.013	0.103	−0.072	0.185	−0.034	0.130
I(NCPAC)	−0.389	0.082	−0.409	0.142	−0.376	0.103
HQ	0.601	0.063	0.650	0.114	0.656	0.078
I(Apr)	−0.010	0.051	−0.010	0.051	−0.011	0.051
I(May)	−0.103	0.061	−0.099	0.061	−0.101	0.060
I(Jun)	0.228	0.060	0.238	0.060	0.236	0.060
I(Jul)	0.130	0.060	0.144	0.060	0.142	0.060
I(Aug)	0.098	0.072	0.111	0.072	0.109	0.072
I(Sep)	0.035	0.082	0.050	0.082	0.047	0.082
I(Oct)	0.233	0.088	0.250	0.088	0.247	0.088
σ^2	—		0.016	0.007	0.012	0.004
−2 Loglikelihood	6719.0		8892.2		8835.503	

Note: $m_H = 1$, $m_I = 2$, $m_J = 20$, and $m_T = 42$, therefore total number of observations is 1680.

Table 4: GLMM-PN with District and Candidate Random Effects: Itemized Individual Contributions

	Est.	SE
intercept	0.563	0.786
count_{t-1}	0.021	0.002
count_{t-2}	0.021	0.002
count_{t-3}	0.018	0.002
opp. count_{t-1}	-0.001	0.003
opp. count_{t-2}	0.019	0.002
opp. count_{t-3}	-0.015	0.003
$\theta_{Dt} - \theta_{Rt}$	14.674	1.914
$\bar{P}_t$	6.145	0.985
f(Dem vote 1982)	-3.260	0.341
Primary_t	-0.479	0.046
No Primary	-0.572	0.062
Party	-0.328	0.116
I(ADA)	-0.135	0.076
I(COPE)	-0.611	0.074
I(NCEC)	0.070	0.079
I(ACA)	-0.096	0.062
I(BIPAC)	0.173	0.079
I(NCPAC)	-0.283	0.059
HQ	0.378	0.049
I(Apr)	-0.014	0.051
I(May)	-0.104	0.061
I(Jun)	0.234	0.060
I(Jul)	0.137	0.060
I(Aug)	0.107	0.072
I(Sep)	0.046	0.082
I(Oct)	0.239	0.088
σ^2	0.048	0.0002
ϕ^2	0.325	0.072
-2 Loglikelihood		

Note: $m_H = 1$, $m_I = 2$, $m_J = 20$, and $m_T = 42$, therefore total number of observations is 1680.

Table 5: GLMM-PN with District and Candidate Random Effects: Pooled Itemized PAC and Individual Contributions

Individual Series Parameters:

	Est.	SE
own PAC count$_{t-1}$	0.047	0.005
own PAC count$_{t-2}$	−0.028	0.006
own PAC count$_{t-3}$	0.011	0.005
opp IND count$_{t-1}$	−0.005	0.003
opp IND count$_{t-2}$	0.015	0.003
opp IND count$_{t-3}$	−0.014	0.003
opp PAC count$_{t-1}$	0.012	0.006
opp PAC count$_{t-2}$	0.034	0.006
opp PAC count$_{t-3}$	−0.019	0.006
$\theta_{Dt} - \theta_{Rt}$	12.735	1.935
$\bar{P}_t$	4.400	0.994
f(Dem vote 1982)	−2.579	0.341
Primary$_t$	−0.488	0.049
No Primary	−0.508	0.073
Party	−0.194	0.146
HQ	0.330	0.062
I(ADA)	0.017	0.103
I(COPE)	−0.495	0.115
I(NCEC)	−0.070	0.102
I(ACA)	−0.170	0.069
I(BIPAC)	0.138	0.097
I(NCPAC)	−0.217	0.071
I(Apr)	−0.052	0.051
I(May)	−0.105	0.061
I(Jun)	0.226	0.061
I(Jul)	0.060	0.064
I(Aug)	0.000	0.074
I(Sep)	−0.024	0.084
I(Oct)	−0.139	0.108

PAC Series Parameters:

	Est.	SE
own IND count$_{t-1}$	0.014	0.003
own IND count$_{t-2}$	0.009	0.003
own IND count$_{t-3}$	0.014	0.003
opp PAC count$_{t-1}$	0.004	0.005
opp PAC count$_{t-2}$	−0.003	0.006
opp PAC count$_{t-3}$	0.007	0.005
opp IND count$_{t-1}$	0.006	0.003
opp IND count$_{t-2}$	−0.002	0.003
opp IND count$_{t-3}$	−0.000	0.003
$\theta_{Dt} - \theta_{Rt}$	19.778	3.191
$\bar{P}_t$	4.126	1.079
f(Dem vote 1982)	0.036	0.374
Primary$_t$	0.026	0.058
No Primary	−0.005	0.074
Party	0.433	0.161
HQ	0.065	0.071
I(ADA)	−0.175	0.110
I(COPE)	−0.579	0.111
I(NCEC)	0.916	0.111
I(ACA)	−0.110	0.076
I(BIPAC)	−0.117	0.089
I(NCPAC)	−0.047	0.065
I(Apr)	0.168	0.087
I(May)	0.210	0.094
I(Jun)	0.355	0.094
I(Jul)	0.361	0.094
I(Aug)	0.565	0.107
I(Sep)	0.987	0.113
I(Oct)	0.900	0.123

Common Parameters:

	Est.	SE
Intercept	1.869	1.083
I(Individual)	−0.708	1.340
count$_{t-1}$	0.028	0.002
count$_{t-2}$	0.023	0.002
count$_{t-3}$	0.018	0.002
σ^2	0.022	0.006
ϕ^2	0.223	0.052
−2 Loglikelihood	14710.57	

Note: $m_H = 2$, $m_I = 2$, $m_J = 20$, and $m_T = 42$, therefore total number of observations is 3360.

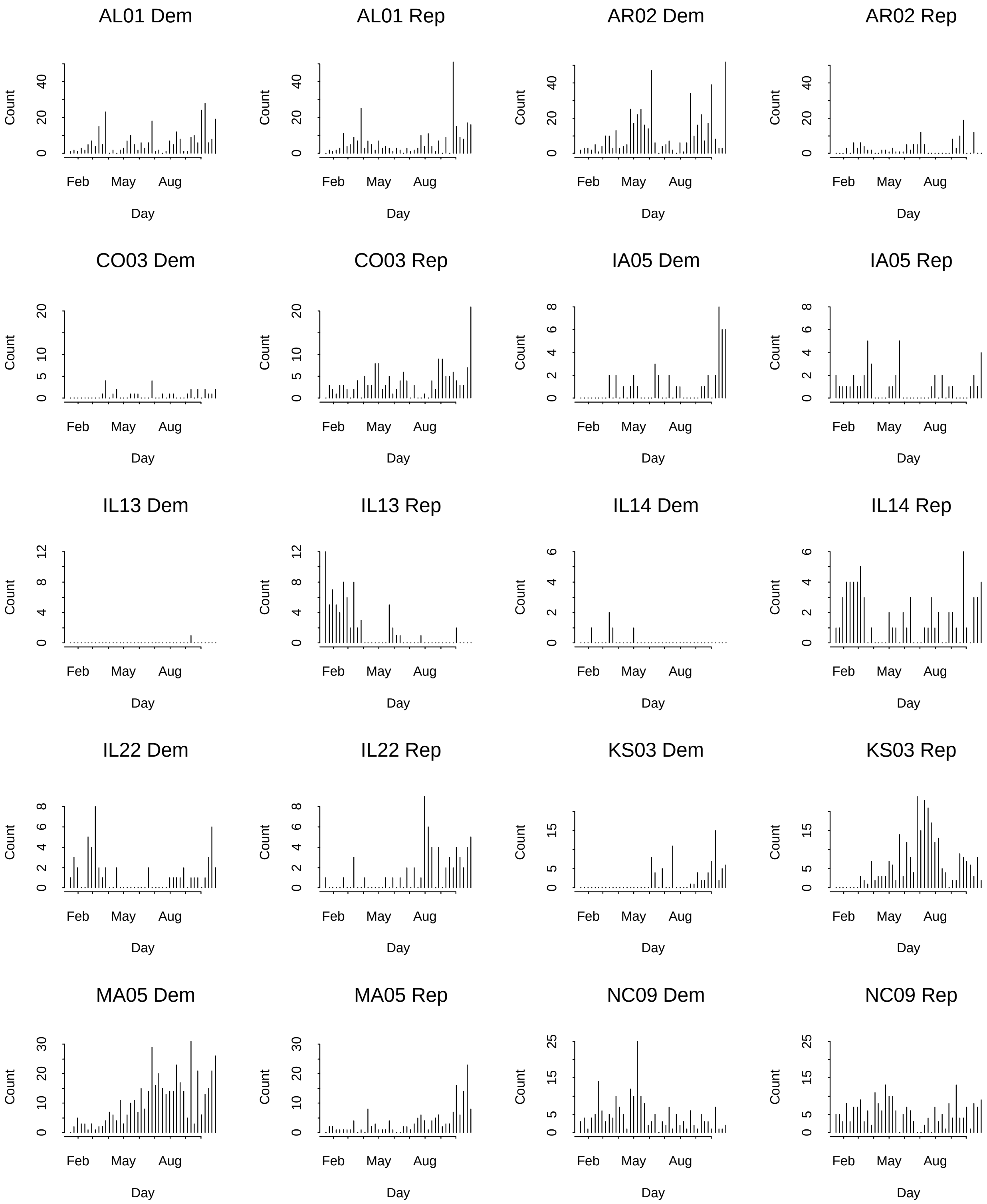

Figure 1: Weekly Total Counts of Contributions to House Candidates: Individuals

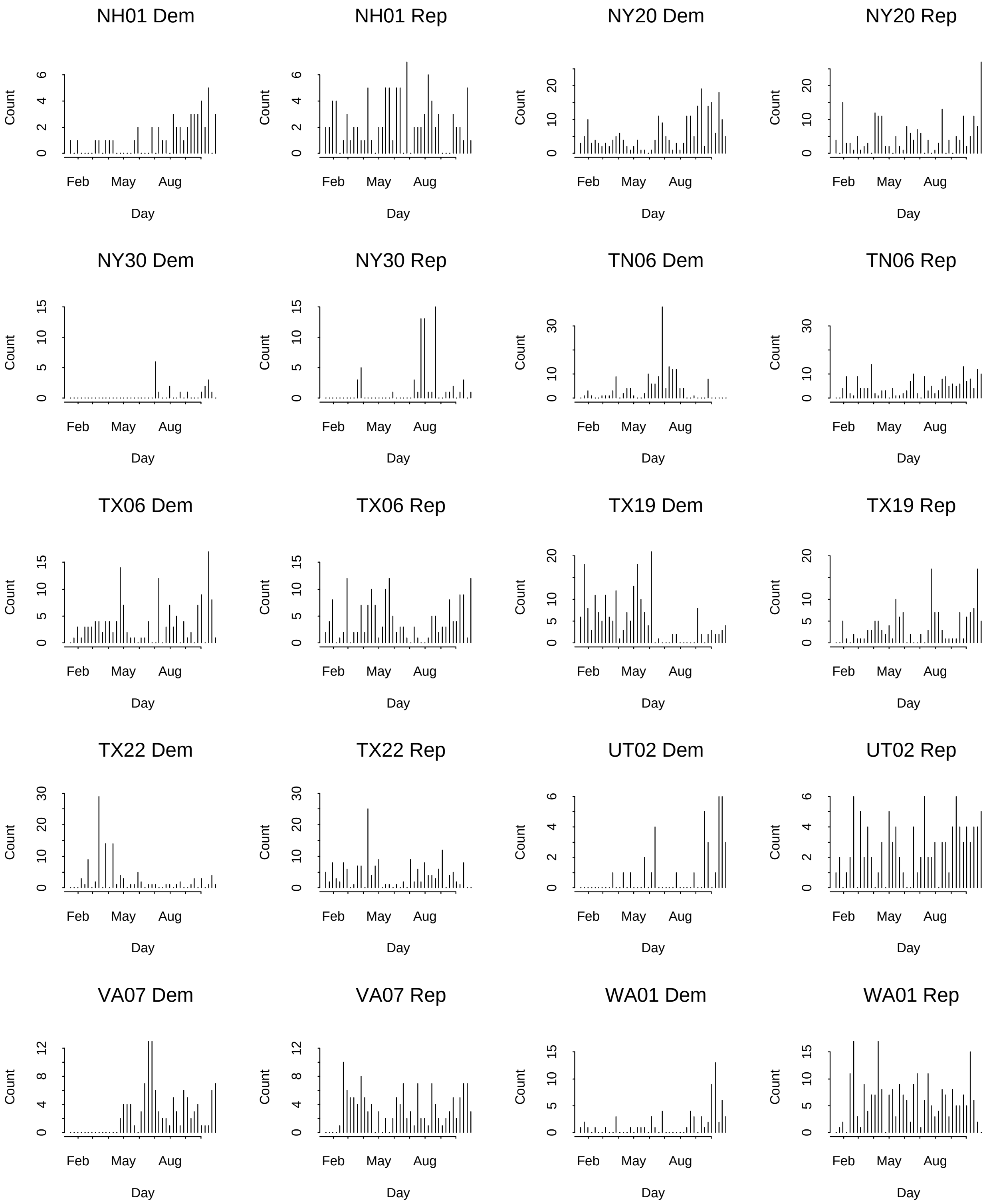

Figure 2: Weekly Total Counts of Contributions to House Candidates: Individuals

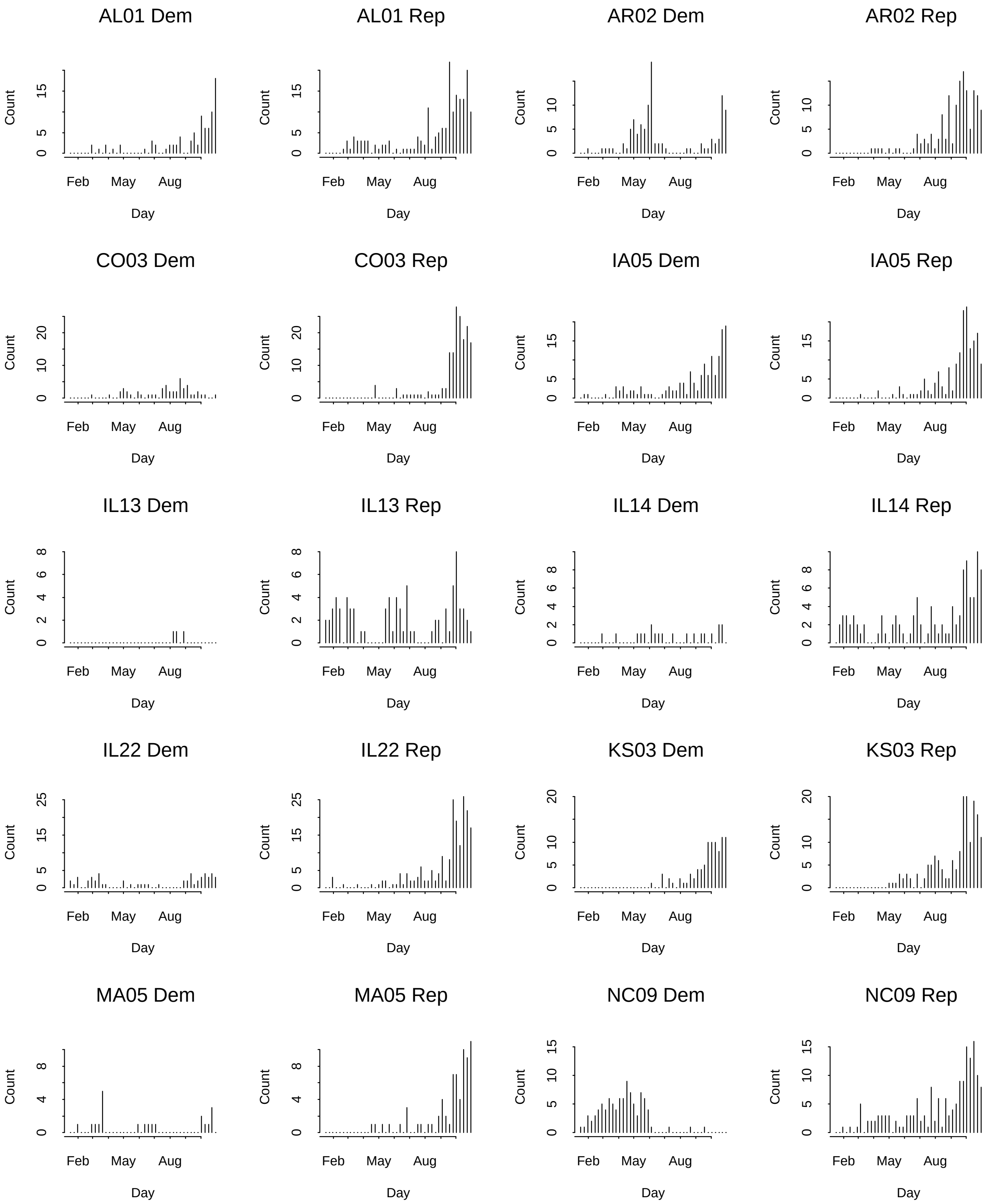

Figure 3: Weekly Total Counts of Contributions to House Candidates: PACs

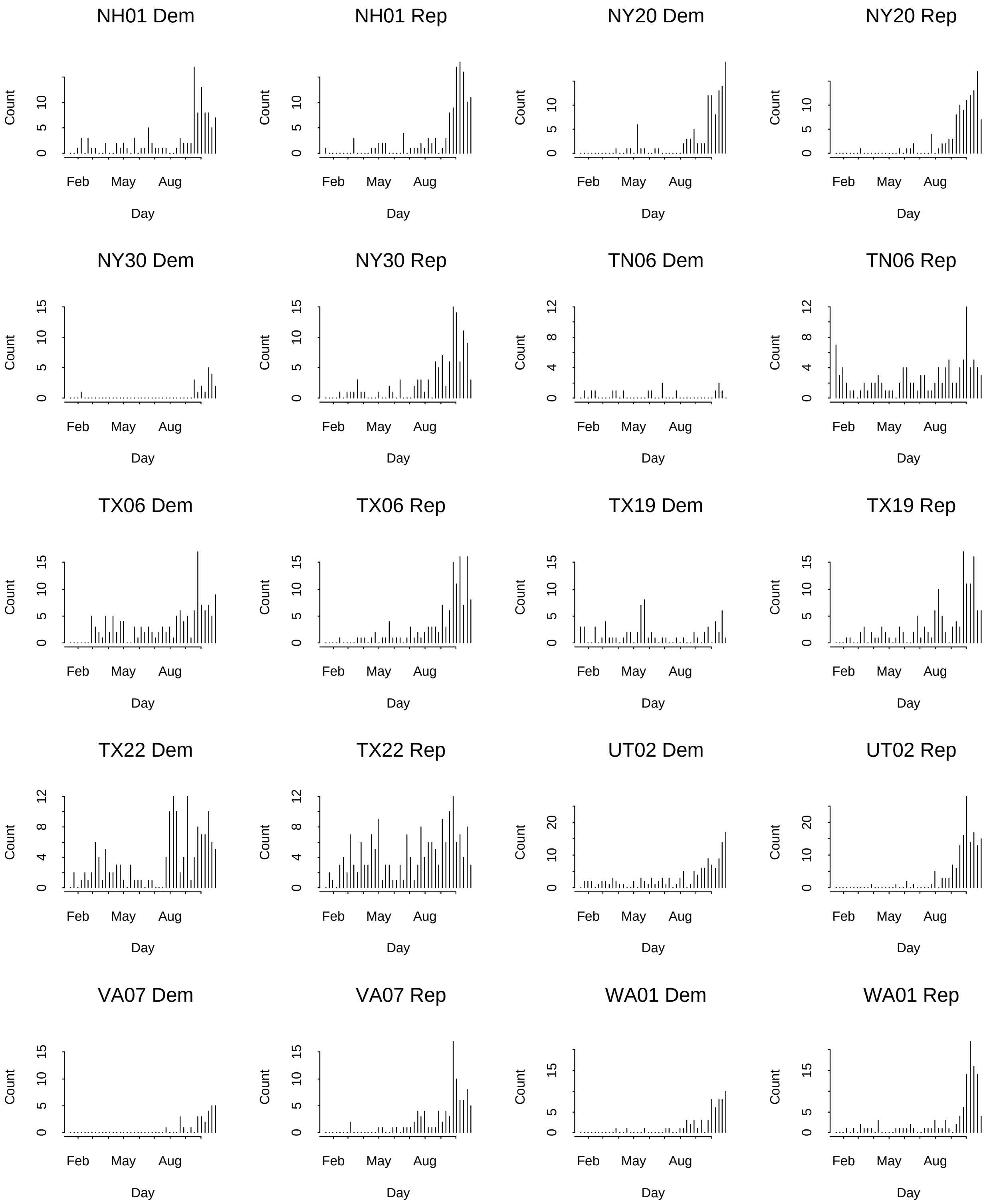

Figure 4: Weekly Total Counts of Contributions to House Candidates: PACs