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Abstract
Researchers who study violence against women often face problems when trying to understand the causes of individual changes in the context of group differences, targeted interventions, and institutional shifts. The authors explore these problems through research on the connections among women’s earnings, welfare, and protection orders. The authors use multigroup, piecewise, latent growth curve models to explore differences in the initial earnings and earnings changes for two groups: welfare recipients who have and who have not petitioned for a restraining order. The authors further examine these differences in the context of institutional change, specifically the implementation of the Personal Responsibility Act of 1996.

Keywords
abuse, battered women, latent growth curves, welfare, earnings

Every year, thousands of women in the United States find themselves trapped by poverty and abuse (Raphael, 2009). The state offers these women two safety nets: the welfare system, specifically the Temporary Assistance for Needy Families (TANF) program for poor mothers, and the criminal or civil courts, where victims can petition for a restraining order. Current political and cultural understandings of battered women tend to be more sympathetic

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and supportive than the stigmatized images of welfare recipients (Berns, 2004; Hancock, 2004). Consequently, the welfare and justice systems offer quite different forms of assistance and remedies for the harms that drive women to seek help. Advocates and policymakers want to understand the mutually reinforcing vulnerabilities to poverty and abuse and are especially concerned with the effectiveness of remedies available through the state safety nets. In particular, it is important to understand the effects of petitioning for a restraining order on welfare recipients’ ability to earn their way out of poverty and abusive relationships.

Unfortunately, researchers’ efforts to track the dynamics of poverty, abuse, work, and welfare are complicated by two methodological problems common in research on violence against women: dealing with selection bias and group differences, and assessing the effects of targeted interventions in the context of institutional shifts. We address these two methodological problems by investigating the connections among welfare, earnings, and petitions for a court order of Protection from Abuse (PFA, known in other jurisdictions as a Personal Protection Order [PPO] or restraining order).

Our data and research design share problems of selection bias and group differences that are widespread in research on violence against women. Many longitudinal methods assume a single underlying model of change across all individuals. Yet true group differences in patterns of change can lead to biased and inconsistent estimates (Bollen & Curran, 2006). We explore the initial earnings and the rates of change in earnings for two groups—welfare recipients who have and who have not petitioned for a PFA—using multigroup latent growth curve (LGC) models. These models employ longitudinal data, enabling comparisons of individuals to themselves over time. They also allow parameters to vary independently for petitioning and nonpetitioning groups and permit exploration of the existence and nature of group differences. We also consider the robustness of our model and sensitivity of our analyses to group selection with data that are censored, or truncated, before or after the observation period.

In 1996, Congress passed and President Clinton signed the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), rescinding 60 years of poor mothers’ entitlement to income support and dramatically altering welfare policy and practice. As a consequence, we face another common problem in research on violence against women: that of determining whether and how large-scale institutional shifts condition the effects of ongoing phenomena. To address this problem, we specify piecewise LGC models, which allow us to test the effects of substantial contextual changes in policy and practice on the relationships among welfare receipt, earnings, and petitioning for a restraining order. In the sections that follow, we provide background and context for our substantive example; discuss, in turn, the two methodological problems we seek to address; introduce our data and methods; and then present the results of our analyses.

Background

Advocates and policymakers urgently need to understand battering—that is, men’s violence and abuse toward their current and former wives and girlfriends—as a factor...
in women’s poverty, in women’s compliance with welfare eligibility requirements, and in women’s progress toward safety and solvency through waged work. Partner-perpetrated physical violence and other abuse can disrupt women’s education and employment (e.g., Corcoran, Danziger, & Tolman, 2004; Honeycutt, Marshall, & Weston, 2001). Battering aggravates women’s homelessness and other hardships associated with poverty (e.g., Brush, 2004; Lindhorst & Mancoske, 2006; Tolman, Danziger, & Rosen, 2002). Abuse can interfere with women’s compliance with welfare eligibility requirements, such as welfare-to-work transition program attendance and job search and employment (e.g., Raphael, 2000; Ridzi, 2009).

Battered women can appeal to the state to support their efforts to navigate or leave abusive relationships through the legal system and the welfare system. One way battered women gain leverage within or safely leave abusive relationships is to petition for a criminal or civil restraining order (in our county, an order of Protection from Abuse or PFA) that restricts an abuser’s access to the petitioner. Research suggests that restraining orders reduce the frequency and severity of subsequent partner-perpetrated abuse (e.g., Holt, Kernic, Wolf, & Rivara, 2003; McFarlane et al., 2004).

To counter the economic dependence that can aggravate abuse and trap women in abusive relationships and to compensate for the loss of access to resources that often comes with leaving an abusive partner, women can apply for public assistance. Since 1996, when Congress rescinded welfare entitlements, imposed time limits on benefits, and mandated work requirements through the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), women now turn to Temporary Assistance for Needy Families (TANF), a means-tested welfare program that subsidizes job search and low-wage employment for poor mothers (e.g., Collins & Mayer, 2010). Research suggests that welfare often does not provide independence from or even leverage against abusive men (e.g., Raphael, 2000; Riger & Staggs, 2004; Scott, London, & Myers, 2002). Nevertheless, economic resources play an important role in women’s safety planning (Goodkind, Sullivan, & Bybee, 2004); women often apply for welfare in the weeks and months around a battering crisis (Brandwein, 1999), and welfare can be a lifeline for battered women (e.g., Davis, 2006). Therefore, it is vital to assess empirically the effects of welfare rescission on the availability and effectiveness of welfare and protection-order petitions.

Methodological Challenges

Researchers hoping to shed light on the connections among poverty, welfare, and battering commonly face two methodological challenges. The first is how to detect and model differences between groups, especially when analyzing observational data (Rosenbaum, 2002). In much research on violence against women, there are reasons to expect that there are multiple distinct groups. For example, women who petition for PFAs are different from women in abusive situations who do not; petitioners report more years of psychological and physical abuse, more negative interactions with friends and family, and more depressive symptoms than nonpetitioners (Duterte et al., 2008; Hutchison & Hirschel, 1998; Macy, Nurius, Kernic, & Holt, 2005; Wolf, Holt, Kernic, & Rivara, 2000). Thus, it is likely that PFA petitioners...
should be modeled as a separate group. The typical strategies for dealing with multiple
groups are separate group analysis (running models independently for each group) or running
fully interactive models, where interactions allow effects to vary across groups. Here, we
posit a third solution: multigroup latent growth curve (LGC) analysis. Multigroup analysis
combines the benefits of separate analysis and interactive models; effects can be estimated
independently, but statistical tests can also indicate when and how groups are different.

The problem remains of properly classifying individuals into groups. When researchers
have observational rather than experimental data, we cannot be sure that we have assigned
groups accurately, and we know they are not assigned randomly. Methodologists
refer to these and similar problems as selection effects, and they are troublesome because
selection bias can lead to errors in estimating both the differences between groups and the
effects of targeted treatment or intervention. Although classifying individuals into groups
based on stable characteristics such as sex category or race/ethnicity is often straightforward,
it is harder to assign individuals to groups on the basis of time-varying characteristics
or actions, as data needed to classify properly individuals may fall outside the study period,
a problem known as “censoring.” In this article, we use additional partial data on PFA peti-
tions in the months directly preceding and following our study period to consider the
potential effects of censoring in the context of multigroup analysis.

A second common group selection issue that we are less able to address given our data
constraints involves the distinction between welfare recipients who are battered and those
who are not. We have no separate measure of battering and cannot distinguish battered from
nonbattered women among the welfare recipients who do not petition for a PFA. As a con-
sequence, our findings speak only to the effects of turning to welfare and petitioning for a
PFA. We cannot address many interesting questions in the literature on the connections
among battering, work, and welfare; we cannot assess the extent to which battering obstructs
work, nor can we estimate the effects of battering on welfare receipt and evaluate the effects
of petitioning for a PFA on the earnings of battered welfare recipients. However, in the
conclusion, we discuss some methods researchers can use to address these kinds of selec-
tion problems, when what selects individuals into groups of interest is not observable.

Another methodological challenge concerns tracking individual changes over time and
accurately assessing outcomes for groups who do and do not participate in a program or
receive a treatment, when life-course changes and targeted interventions coincide with
broader institutional shifts. Are differences in outcomes due to unobserved differences
between individuals, to observed or unobserved differences between groups, to policy
interventions, to processes that occur predictably with the passage of time, to changes in
the broader context, or to chance? We face these questions, trying to understand the rela-
tionships among battering, work, and welfare before and after the implementation of the
PRWORA. In the following, we describe a technique called piecewise latent growth curve
analysis that is well suited to addressing these challenges.

Data and Methods
We collect data on individual earnings, petitions for protective orders (PFAs), and covariates
for the population of welfare recipients in Allegheny County, Pennsylvania, from July 1995
to June 2000. This time period includes data before and after March 1997, when county welfare administrators implemented work requirements and time limits as mandated by the PRWORA. We use partial social security numbers and names to match: (a) all PFA petition records; (b) all Aid to Families with Dependent Children/Temporary Assistance for Needy Families (AFDC/TANF) recipient records, which include time-varying monthly data on welfare receipt and the number of individuals in the household on welfare as well as measures of race/ethnicity, initial age, and sex; and (c) quarterly data on earnings for all women in the first two sets of data. The final data set includes 27,017 women with both earnings and welfare data who were at least 16 years of age in July 1995.

Our dependent variable is quarterly earnings (logged to reduce skewness) modeled every other quarter.2 Earnings data for the fourth quarter of 1996 are missing, which we address using modeling strategies specified below. We include four time-invariant measures as independent variables: (1) age at the start of the study period; (2) household size, proxied using the average number of welfare recipients associated with each individual during all months on welfare; and (3 and 4) two dummy variables measuring race/ethnicity, where Black individuals are the reference category. We also model months of welfare receipt as a time-varying covariate affecting logged earnings in that quarter.

Using data on PFAs, we separate the welfare recipients into two groups: 2,286 women who petition for PFAs and 24,731 women who do not. Because one of our central methodological concerns is the proper classification of welfare recipients into PFA petitioners and nonpetitioners, we also employ supplementary data on 304 petitioners who filed during the 6 months prior to and following (but not during) our 5-year study period. Although we do not have wage information for these time periods, we are able to use these additional data on PFAs in two ways: (1) to aid in proper classification of welfare recipients into the two groups (petitioners and nonpetitioners), and (2) to consider the implications of censoring for assessments of group differences.

First, because we are fundamentally interested in the effects of petitioning for a PFA on earnings trajectories and because petitioning during the 6 months prior to our study period may affect subsequent earnings trajectories, we classify prestudy petitioners in the PFA petitioning group. In contrast, we group individuals known to petition in the 6 months following our study period with nonpetitioners. But because accounting for differences across groups is of central importance to our analysis, we use the supplemental data on petitioning for a second purpose: to test the sensitivity of our group analysis. That is, we move pre- and post-study petitioners into and out of the PFA petitioning group and look for substantive changes to our conclusions about group differences.

We estimate changes in female welfare recipients’ logged earnings using latent growth curve (LGC) models (Bollen & Curran, 2006). LGC models analyze change over time by focusing on intraindividual change, estimating both starting positions (intercepts) and trends (slopes) for each individual’s growth trajectory over time. Furthermore, LGC models do not require observations of the dependent variable to be equally spaced, so we are able to specify the analysis to account for the quarter of data missing in 1996.

Although the simplest models estimate linear change, LGC analysis is flexible enough to estimate a variety of patterns of change over time (e.g., quadratic, cubic). Of particular use to us here is the piecewise, or spline, LGC model, which estimates more than one slope
over the growth trajectory (e.g., Paxton, Painter, & Hughes, 2009). When using splines, the model estimates not only the average rate of change over each “piece” of time but also the effects of covariates (even measures that do not vary over time) separately for each period. We select July 1995-December 1997 and December 1997-June 2000 as two time intervals to capture earnings growth before and after Allegheny County welfare administrators implemented the provisions of the PRWORA, with some lag time to allow for restructuring to take effect. We also consider the robustness of our model and its sensitivity to different transition points, or “knots,” as well as to increasing the number of splines (results not shown). Overall, piecewise LGC models are ideal for assessing whether earnings grew differently among these women pre- and post-welfare rescission, as well as whether the relationships between independent and dependent variables vary over the two time intervals.

Another important advantage of LGC models is that they are able to handle multiple groups with systematically different growth trajectories in a single model. Simultaneously modeling more than one group allows estimating all parameters—for example, intercepts, slopes, and the effects of covariates—individually for each group, while at the same time, it allows testing for statistically significant differences across groups. Multigroup analysis solves one of the selection bias problems common in research on violence against women, in this case by allowing us to consider whether and how earnings changed for welfare recipients who petitioned for a PFA compared to welfare recipients who did not petition.

For a multigroup piecewise (spline) earnings model with two time periods, the individual equation is as follows:

\[
y_{it}^{(g)} = \alpha_{i}^{(g)} + \beta_{1i}^{(g)} \lambda_{1t}^{(g)} + \beta_{2i}^{(g)} \lambda_{2t}^{(g)} + \varepsilon_{it}^{(g)},
\]

where \(y_{it}^{(g)}\) represents logged quarterly earnings for the \(i\)th individual from group \(g\) at time \(t\); \(\alpha_{i}^{(g)}\) is the intercept for individual \(i\) from group \(g\); \(\beta_{1i}^{(g)}\) and \(\beta_{2i}^{(g)}\) are the slopes for individual \(i\) from group \(g\) pre- and post-welfare rescission; \(\lambda_{1t}^{(g)}\) and \(\lambda_{2t}^{(g)}\) are constants manipulated to capture linear change over the two time periods, while accounting for the missing quarter of earnings data in 1996; and \(\varepsilon_{it}^{(g)}\) is an error term for each individual \(i\) from group \(g\) at time \(t\). In this model, each individual, \(i\), has her own intercept and slope, and the superscript, \(g\), signifies group membership, where \(g = 1, 2, 3, \ldots, G\), and \(G\) is the total number of groups.

In addition to analyzing individual-level change, LGC models also estimate the mean intercept and slope for all individuals. Models estimate average initial earnings across all welfare recipients in the fourth quarter of 1995 and the average rate of change in earnings across each of the two time periods of interest. For the multigroup two-piecewise model, this leads to three additional equations:

\[
\alpha_{i}^{(g)} = \mu_{\alpha}^{(g)} + \varepsilon_{\alpha_{i}^{(g)}}
\]

\[
\beta_{1i}^{(g)} = \mu_{\beta_{1i}^{(g)}} + \varepsilon_{\beta_{1i}^{(g)}}
\]

\[
\beta_{2i}^{(g)} = \mu_{\beta_{2i}^{(g)}} + \varepsilon_{\beta_{2i}^{(g)}}
\]
where $\mu^{(\alpha)}_g$ is the mean intercept across all individuals from each group and $\mu^{(\beta_1)}_g$ and $\mu^{(\beta_2)}_g$ are the mean slopes across all individuals from each group across each of the two time periods. The first equation represents a person’s individual intercept ($\alpha^{(\alpha)}_i$) as a function of the average intercept ($\mu^{(\alpha)}_g$) over all individuals from their group and a disturbance term ($\zeta^{(\alpha)}_i$). The second two equations represent the individual slopes pre- and post-welfare rescission ($\beta^{(\beta_1)}_i$ and $\beta^{(\beta_2)}_i$) as a function of the average slopes ($\mu^{(\beta_1)}_g$ and $\mu^{(\beta_2)}_g$) and disturbance terms ($\zeta^{(\beta_1)}_i$ and $\zeta^{(\beta_2)}_i$) over the two time periods. For all models, we assume disturbances are normally distributed with unknown variances and covariances.

By employing multigroup piecewise LGC models, we are able to test whether significant differences exist between model parameters. First, we estimate a fully independent model with no cross-group constraints on model parameters. Then, we constrain model parameters of interest, for example, mean intercepts and slopes, to be the same across the two groups, and test for significant drops in model fit using a chi-square test. A significant chi-square test suggests that at least one of the constrained model parameters is significantly different across the two groups and that the parameters should be allowed to estimate freely. We also use critical ratio tests to consider whether estimates significantly vary pre- and post-welfare rescission.

We estimate all models in AMOS 17. Missing data on race for 22 individuals are accounted for using a maximum likelihood estimation procedure (FIML), an optimal procedure for handling missing data (Allison, 2002). We employ three different statistics to assess model fit: the chi-square test statistic, the Incremental Fit Index (IFI; Bollen, 1989), and the root mean squared error of approximation (RMSEA; Steiger & Lind, 1981). A non-significant chi-square test statistic indicates good fit. For the IFI, values closer to 1 indicate better model fit. Typically, values above 0.90 are considered acceptable and 0.95 considered optimal. In contrast, the RMSEA is scaled so that the closer values are to 0, the better the fit of the model. Values below 0.05 are typically considered to indicate optimal fit (Browne & Cudeck, 1993). Using a range of measures compensates for the limitations of any single fit statistic (Chen, Curran, Bollen, Kirby, & Paxton, 2008).

Our analysis proceeds in three stages. First, we explore differences between welfare recipients who petitioned for one or more PFAs and those who did not petition using descriptive statistics and zero-order correlations. Second, we employ a multigroup unconditional piecewise LGC model to estimate average initial logged earnings and average growth in logged earnings over the two time periods. Third, we add independent variables to estimate a conditional piecewise LGC model, paying particular attention to differences in the effects of months of welfare receipt on logged earnings pre- and post-welfare reform for both groups.

Results

Table 1 reports the means, standard deviations, and correlation coefficients for measures of earnings, welfare receipt, and demographic controls for the welfare recipients who petitioned for one or more PFAs between January 1995 and June 2000 and those who did
<table>
<thead>
<tr>
<th>Variable</th>
<th>PFA</th>
<th>no-PFA</th>
<th>PFA-no-PFA</th>
<th>Zero-order correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Initial earnings</td>
<td>$635.38</td>
<td>$488.53</td>
<td>146.85***</td>
<td>(1) 1.00</td>
</tr>
<tr>
<td></td>
<td>(1331.20)</td>
<td>(1128.70)</td>
<td></td>
<td>(2) −0.41</td>
</tr>
<tr>
<td>(2) Earnings change</td>
<td>$1,222.22</td>
<td>$1,394.53</td>
<td>−172.31**</td>
<td>(3) −0.36</td>
</tr>
<tr>
<td></td>
<td>(2436.50)</td>
<td>(2386.00)</td>
<td></td>
<td>(4) 1.00</td>
</tr>
<tr>
<td>(3) Total months welfare</td>
<td>24.45 (17.41)</td>
<td>17.28 (14.89)</td>
<td>7.17***</td>
<td>(5) −0.18</td>
</tr>
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<td></td>
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<td></td>
<td></td>
<td>(6) −0.06</td>
</tr>
<tr>
<td>(4) Age</td>
<td>27.52 (7.54)</td>
<td>27.33 (7.91)</td>
<td>0.19</td>
<td>(7) 1.00</td>
</tr>
<tr>
<td>(5) Household size</td>
<td>2.96 (1.13)</td>
<td>2.94 (1.20)</td>
<td>0.02</td>
<td>(8) 0.08</td>
</tr>
<tr>
<td>(6) White</td>
<td>0.54 (0.50)</td>
<td>0.45 (0.50)</td>
<td>0.09***</td>
<td>(9) 0.08</td>
</tr>
<tr>
<td>(7) Other race</td>
<td>0.01 (0.12)</td>
<td>0.02 (0.14)</td>
<td>−0.01</td>
<td>(10) −0.01</td>
</tr>
<tr>
<td>(8) Logged quarterly earnings</td>
<td>3.96 (3.72)</td>
<td>3.71 (3.72)</td>
<td>0.25***</td>
<td>(11) −0.02</td>
</tr>
<tr>
<td>(9) Months welfare in quarter</td>
<td>1.22 (1.42)</td>
<td>0.86 (1.29)</td>
<td>0.36***</td>
<td>(12) −0.10</td>
</tr>
</tbody>
</table>

Note: PFA = Protection from Abuse. Numbers in parentheses are standard deviations. Differences between group means are tested using two-tailed t tests. The top-right section of the correlation matrix reports zero-order correlations for the PFA group, whereas the bottom-left section reports correlations for the no-PFA group.

*p < .05, **p < .01, ***p < .001.
not petition for a PFA over the time period. These univariate and bivariate statistics provide an initial picture of differences between these groups.

These descriptive findings suggest that welfare recipients who petition for a PFA have different earnings trajectories than their nonpetitioning counterparts. Petitioners have higher initial quarterly earnings ($635.38) than nonpetitioners ($488.53), a statistically significant difference ($p < .001). Earnings of the PFA group also grow less ($1,222.22) than do earnings of nonpetitioners over the period ($1,394.53), a between-group difference of $172.31 ($p < .01).

The PFA and no-PFA groups are different in other ways. Petitioners spend significantly more total time on welfare over the period than nonpetitioners, a difference of more than 7 months. The racial/ethnic composition of the groups also differs. The majority of petitioners are White (54%), whereas the majority of nonpetitioners during the study period are Black (53%). The groups are similar, however, in terms of age and household size.

The zero-order correlations also suggest salient differences between the PFA and no-PFA groups, in particular the relationships between earnings and welfare receipt. For petitioners, higher initial earnings are more strongly associated with a reduction of the time spent on welfare ($r = -.28$), than for their nonpetitioning counterparts ($r = -.18$). Similarly, higher quarterly earnings are more strongly associated with months on welfare in the quarter for petitioners ($r = -.34$) than for nonpetitioners ($r = -.20$). Informative as they are, these correlations do not account for differences in the relationships between welfare and earnings before and after welfare rescission or control for other characteristics (such as race/ethnicity) that are associated with earnings, welfare receipt, and petitioning for a PFA.

To begin our examination of period differences in the trajectories of welfare recipients’ earnings, we first fit an unconditional piecewise LGC model, represented in Figure 1. Path diagrams such as Figure 1 represent relations between observed (measured) and unobserved (latent) variables. Latent variables are represented with ovals, and observed variables appear as boxes. Straight arrows indicate direction of influence, curved two-headed arrows indicate a covariance between two variables that is unexplained in the model, and measurement error is indicated by δ. In Figure 1 (corresponding to the equations above), the factor loadings for the measures of welfare recipients’ earnings on the latent intercept are fixed to 1 to represent the starting point of the growth trajectory. The loadings on the first latent slope begin at 0 in December 1995, increasing by 1 each two-quarter interval until December 1997, indicating linear growth over the period prior to welfare rescission. The factor loadings for the second latent slope begin at 0 and do not begin to increase until June 1998, when the loadings increase by 1 each interval until the end of the period. For both of the latent slopes, the factor loadings are set to increase as if data were available for December 1996 even though they are missing. This specification of the factor loadings allows LGC models to estimate growth for each period despite unequally spaced data. The latent intercept and the slopes are freely correlated.

Examining the means and variances of the latent intercept and slope terms provides some basic information about the average growth of welfare recipients’ logged earnings during time periods prior to and following welfare rescission. Estimating piecewise earnings growth reveals substantial differences after the shift in welfare policy and practice.
See Figure 2, which graphs predicted logged earnings for the two groups over the two time periods. Using the iterative process of constraining parameters across the groups, we find significant group differences in the intercepts ($\Delta \chi^2 = 53.47, \Delta df = 1, p < .001$). Consistent with the results from Table 1, petitioner have higher earnings, on average, than nonpetitioners. Turning to the slopes, in the first period, the slopes for the two groups are virtually parallel. After the knot, welfare recipients’ predicted average earnings converge. For petitioners, earnings growth postrescission is less than one quarter the size of growth in the earlier time period (0.45 to 0.10, critical ratio [CR] = −10.28, $p < .001$), but see Note 3. For nonpetitioners, the change in earnings growth between the two time intervals is slightly less pronounced but is still more than halved (0.50 to 0.20, CR = −26.45, $p < .001$). Overall, the pattern demonstrates the importance of modeling differences across both groups and time. Even without predictors, the unconditional model fits the data moderately well, with an IFI of 0.92 and RMSEA of 0.06.

We also use the data on 304 petitions for PFAs that occurred during the period 6 months prior to and following our 5-year study period to test the sensitivity of our estimates and conclusions to slight variations in group specification. We find that moving individuals...
Figure 2. Predicted second and fourth quarter logged earnings for PFA and no-PFA groups (December 1995-December 1997 and December 1997-June 2000, piecewise unconditional growth model)

Note: PFA = Protection from Abuse.

potentially misclassified because of right or left censoring between the two groups does not significantly alter either model estimates, fit, or substantive conclusions.

In the final set of models, we incorporate predictors of welfare recipients’ earnings trajectories. In these models, we introduce age, race, and household size as time-invariant covariates that affect the intercepts and slopes of welfare recipients’ earnings trajectories. Months of welfare receipt also enters the model as a time-varying covariate such that the number of months an individual was on welfare during the quarter predicts individual logged earnings in that quarter. Because time on welfare is strongly associated with lower earnings, differences in welfare receipt alone could explain the difference in the earnings trajectories of the two groups. Thus, the introduction of welfare receipt is an important control when assessing the relationship between PFA petitions and earnings. Fit improves markedly once covariates are added to the model. The IFI of 0.95 and RMSEA of 0.04 both indicate optimal fit.

The first panel of Table 2 presents the mean intercepts and slopes, net the effects of the covariates. The estimates further support our findings that petitioners have substantially different earnings trajectories from nonpetitioners. Once covariates are added to the model, petitioners continue to have higher intercepts than their nonpetitioning counterparts ($\Delta \chi^2 = 29.14, \Delta df = 1, p < .001$). In fact, rather than explaining away initial differences, the covariates we add increase the size of the initial gap between the two groups. Furthermore,
Table 2. Results From Conditional Two-Spline Latent Growth Curve Model Comparing Logged Earnings of Welfare Recipients Who Petitioned for a PFA and Those Who Did Not (December 1995-December 1997 and December 1997-June 2000)

<table>
<thead>
<tr>
<th></th>
<th>Intercept (α)</th>
<th>Slope (β₁)</th>
<th>Slope (β₂)</th>
<th>β₂-β₁ Group means Coefficients</th>
<th>SE</th>
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<td>PFA petitioners</td>
<td>4.57***</td>
<td>(0.32)</td>
<td>0.10</td>
<td>(0.10)</td>
<td>0.12</td>
<td>(0.08)</td>
<td>0.02</td>
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<tr>
<td>Nonpetitioners</td>
<td>2.79***</td>
<td>(0.08)</td>
<td>0.38***</td>
<td>(0.03)</td>
<td>0.27***</td>
<td>(0.02)</td>
<td>-0.11*</td>
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<td>PFA–no-PFA</td>
<td>1.78***</td>
<td>—</td>
<td>-0.28**</td>
<td>—</td>
<td>-0.15*</td>
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<td>Effects on intercepts and slopes</td>
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<td>Intercept (α)</td>
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<tr>
<td>PFA petitioners</td>
<td>0.03**</td>
<td>(0.01)</td>
<td>0.00</td>
<td>(0.00)</td>
<td>-0.01***</td>
<td>(0.00)</td>
<td>-0.01</td>
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<tr>
<td>Nonpetitioners</td>
<td>0.01***</td>
<td>(0.00)</td>
<td>0.01***</td>
<td>(0.00)</td>
<td>-0.01***</td>
<td>(0.00)</td>
<td>-0.02***</td>
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<td>PFA–no-PFA</td>
<td>0.02**</td>
<td>—</td>
<td>-0.01*</td>
<td>—</td>
<td>0.00*</td>
<td>—</td>
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<td>Household size</td>
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<tr>
<td>PFA petitioners</td>
<td>-0.37***</td>
<td>(0.06)</td>
<td>0.09***</td>
<td>(0.02)</td>
<td>0.02</td>
<td>(0.02)</td>
<td>-0.07*</td>
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<tr>
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<td>-0.28***</td>
<td>(0.02)</td>
<td>0.07***</td>
<td>(0.01)</td>
<td>0.03***</td>
<td>(0.00)</td>
<td>-0.04***</td>
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<tr>
<td>PFA–no-PFA</td>
<td>-0.09</td>
<td>—</td>
<td>0.02</td>
<td>—</td>
<td>-0.01</td>
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<td>White</td>
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<tr>
<td>PFA petitioners</td>
<td>-0.44***</td>
<td>(0.14)</td>
<td>0.02</td>
<td>(0.04)</td>
<td>-0.05</td>
<td>(0.04)</td>
<td>-0.07</td>
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<tr>
<td>Nonpetitioners</td>
<td>0.02</td>
<td>(0.04)</td>
<td>-0.08***</td>
<td>(0.01)</td>
<td>-0.01</td>
<td>(0.01)</td>
<td>0.07*</td>
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<tr>
<td>PFA–no-PFA</td>
<td>-0.46***</td>
<td>—</td>
<td>0.10*</td>
<td>—</td>
<td>-0.04</td>
<td>—</td>
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<td>Other race</td>
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<tr>
<td>PFA petitioners</td>
<td>-0.13</td>
<td>(0.56)</td>
<td>-0.05</td>
<td>(0.18)</td>
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<td>(0.14)</td>
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<td>-0.74***</td>
<td>(0.14)</td>
<td>0.01</td>
<td>(0.05)</td>
<td>-0.06</td>
<td>(0.04)</td>
<td>-0.07</td>
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<td>PFA–no-PFA</td>
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<td>-0.01</td>
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Table 2. (continued)

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<td>PFA petitioners</td>
<td>-0.72*** (0.04)</td>
<td>-0.83*** (0.04)</td>
<td>-0.86*** (0.03)</td>
<td>-0.58*** (0.04)</td>
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<td>-0.44*** (0.07)</td>
<td>-1.02*** (0.02)</td>
<td>-0.74*** (0.01)</td>
<td>-0.64*** (0.01)</td>
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<td>-0.28*** — —</td>
<td>0.19*** —</td>
<td>-0.12*** —</td>
<td>0.06 —</td>
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<td>PFA petitioners</td>
<td>-0.70*** (0.04)</td>
<td>-0.48*** (0.04)</td>
<td>-0.45*** (0.04)</td>
<td>-0.45*** (0.05)</td>
</tr>
<tr>
<td>Nonpetitioners</td>
<td>-0.69*** (0.01)</td>
<td>-0.59*** (0.01)</td>
<td>-0.60*** (0.01)</td>
<td>-0.56*** (0.01)</td>
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<tr>
<td>PFA–no-PFA</td>
<td>-0.01 — —</td>
<td>0.11*** —</td>
<td>0.15*** —</td>
<td>0.11*** —</td>
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<table>
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<tr>
<th>Months welfare</th>
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<tbody>
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<td>PFA petitioners</td>
<td>-0.55*** (0.05)</td>
</tr>
<tr>
<td>Nonpetitioners</td>
<td>-0.65*** (0.02)</td>
</tr>
<tr>
<td>PFA–no-PFA</td>
<td>0.10*</td>
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Note: PFA = Protection from Abuse. Goodness-of-fit statistics: $\chi^2 = 1127.01, df = 276, p = .000$, Incremental Fit Index (IFI) = .95, root mean squared error of approximation (RMSEA) = .04. This model constrains intercept and slope covariances as well as error variances to be equal across the two groups. Earnings data for December 1996 are missing.

$p < .10$, $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$. 

$^{***}p < .001$. 

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the adjusted slopes for the two groups are quite different. Petitioners no longer experience any underlying growth in earnings over either time period, whereas nonpetitioners do experience wage growth. For nonpetitioners, earnings gains were more substantial during the prerescission period (but see Note 3).

In the second panel of Table 2, we are able to consider whether the time-invariant control variables have different effects on initial earnings or growth for the two groups and for the two time periods. First, comparing across groups, we find significant differences in the effects of the covariates on the intercepts and the slopes, but only for age and race/ethnicity. Key differences across time also emerge. For nonpetitioners, the effects of age, household size, and race/ethnicity vary significantly across the two time periods, whereas for petitioners, only household size has different effects during the pre- and post-rescission time periods.

In the third panel of Table 2, we turn to the effects of welfare receipt. The effects of welfare receipt on earnings vary significantly across the two groups during both time periods, except in two quarters—those immediately prior to and coinciding with the knot (but see Note 3). We also find changes in the effects of welfare receipt across time. For example, for the petitioners, the first three estimated points are significantly different from the last three estimated points (p < .001, tests not displayed). These results imply that welfare rescission changed the context of women’s appeals to the state through both mechanisms—welfare receipt and PFA petitions—and consequently the effect of welfare receipt on earnings. Overall, the results in Table 2 provide strong evidence that researchers studying this complex problem must account for both group differences and contextual shifts.

Conclusion

Researchers face numerous methodological problems while trying to understand the connections between poverty and abuse and to assess PFAs and welfare as remedies for the plight of battered women. In this article, we used longitudinal data and a piecewise multilevel model to explore several of the complexities that arise when assessing the relationships among battering, welfare, and earnings. Multigroup analysis allowed us to model and test differences between what we find to be two distinct groups of women: welfare recipients who do and do not petition for a PFA. The piecewise, or spline, model specification also enabled us to document the effects of shifts in policy and practice. Although in this research we considered the effects of welfare rescission, researchers could easily apply these methods to other significant institutional changes, such as the Violence Against Women Act of 1994.

Even piecewise LGC analysis, a sophisticated data analytic method, could not directly address one of the selection problems that violence against women researchers typically face; that is, our data did not allow us to resolve the selection bias problems arising from modeling battered and nonbattled women together. Researchers needing to account for the effects of unmeasured group differences have two main alternatives: growth mixture modeling or external adjustment methods. Growth mixture modeling allows researchers to model the effects of unobserved classes that give rise to differences in trajectories (Muthen, 2001; Nagin & Tremblay, 2001). However, growth mixture models are relatively new, have
been tested with only limited applications, are complicated, and are prone to problems of model specification and interpretation (Preacher, Wichman, McCallum, & Briggs, 2008). External adjustment methods are appropriate for researchers using event history or analyses producing odds ratios; for such analyses, epidemiologists have developed strategies to test the sensitivity of results to some types of selection bias (see, for example, Greenland, 1998).

Our results demonstrate that petitioners had significantly higher initial earnings than had welfare recipients who did not petition. However, petitioners had slower earnings growth than their nonpetitioning peers, both before and after welfare rescission. Because women who seek help to improve their situations may be different from other women in salient but unpredictable and unobserved ways, researchers should be attentive to selection effects. Combining multigroup analyses and multilevel piecewise models allowed us to consider both group and period differences in the effects of policy change on the relationship between welfare receipt and earnings. We find considerable differences between groups and across periods, reinforcing our methodological recommendations. Our substantive findings about the effects of petitioning for a protective order on the earnings trajectories of welfare recipients suggest that welfare and restraining orders are important safety nets for women seeking to escape the traps of poverty and abuse.

Authors' Note
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Declaration of Conflicting Interests
The authors declared no potential conflicts of interests with respect to the authorship and/or publication of this article.

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Notes
1. Cash assistance for low-income mothers was called AFDC before and TANF after Congress rescinded entitlements with the PRWORA.
2. The fit of LGC models can decline substantially when linearly estimating more than six repeated observations of the dependent variable (Preacher, Wichman, McCallum, & Briggs, 2008). Therefore, we model every other quarter of data, which substantially improves model fit, while not altering substantive conclusions.
3. Auxiliary analyses indicate that there is no significant improvement to model fit and there are no changes to our results about group differences from modeling three splines (pre-reform, transition, postreform) rather than two splines. However, the three-spline model
Hughes and Brush clarifies the timing of earnings growth. In the period before rescission, petitioners and non-petitioners experience negligible earnings growth. In the transition, both groups have steep earnings growth. Postrescission, both groups have lower growth rates, but the petitioners’ growth rate is less than one half that of nonpetitioners. Consistent with the two-spline model, both group differences and changes over time remain. Results are available from the authors upon request.

References


**Bios**

**Melanie M. Hughes** is assistant professor of sociology at the University of Pittsburgh. She takes an intersectional approach to research on women, examining how race/ethnicity, religion, and class affect women’s political and economic power. She also focuses on quantitative methods with an emphasis on measurement and longitudinal analysis. Her work has appeared in numerous peer-reviewed journals, including *American Sociological Review, Politics & Gender, Social Forces*, and *Social Problems*. She is also the coauthor of *Women, Politics, and Power: A Global Perspective* (Pine Forge Press, 2007) with Pamela Paxton.