Journal of Personality and Social Psychology
1985, Vol. 49, No. 5, 1207-1220

0022-3514/85/$00.75

Air Pollution, Weather, and Violent Crimes: Concomitant Time-Series Analysis of Archival Data

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Archival data covering a 2-year period were obtained from three sources in order to assess relations among ozone levels, nine measures of meteorological conditions, day of the week, holidays, seasonal trends, family disturbances, and assaults against persons. Confirming results obtained in laboratory studies, more family disturbances were recorded when ozone levels were high than when they were low. Two-stage regression analyses indicated that disturbances and assaults against persons were also positively correlated with daily temperatures and negatively correlated with wind speed and levels of humidity. Further, distributed lag (Box-Jenkins) analyses indicated that high temperatures and low winds preceded violent episodes, which occurred more often on dry than humid days. In addition to hypothesized relations, it was also found that assaults follow complaints about family disturbances, which suggests that the latter could be used to predict and lessen physical violence. It was concluded that atmospheric conditions and violent episodes are not only correlated but also appear to be linked in a causal fashion. This conclusion, however, was qualified by a discussion of the limitations of archival data and concomitant time-series analysis.

This archival analysis was undertaken to assess the generalizability and real-world relevance (i.e., ecological validity) of results obtained in laboratory studies on the social effects of air pollution. In these studies (Rotton, 1983; Rotton, Barry, Frey, & Soler, 1978; Rotton, Frey, Barry, Milligan, & Fitzpatrick, 1979), undergraduates were exposed to odors produced by ammonium sulfide and other foul-smelling chemicals. Compared with individuals who had not been exposed, students in polluted settings described their moods and emotions in more negative terms, expressed less liking for individuals not sharing their fate, gave lower evaluations of their surroundings, formed more negative attitudes about social stimuli, and spent less time in the setting (an indirect measure of escape). By and large, these results are consistent with predictions derived from models that emphasize the motivating and reinforcing properties of affective states. As Clore and Byrne's (1974) affect–reinforcement model predicts, malodor elicited unpleasant emotional states (e.g., annoyance and irritability) that reinforced negative evaluations. In addition, as Baron's (1978) affect–aggression model predicts, moderately unpleasant odors facilitated aggression, whereas extremely unpleasant ones led to incompatible responses, such as flight, which appeared to inhibit aggressive behavior.

Serious questions have been raised about the external validity of results obtained in laboratory studies on environmental stressors. Although laboratory research (e.g., Baron & Bell, 1976) suggests that violence reaches a peak at moderately high temperatures and then declines, only monotonic (and apparently linear) relations have emerged in archival analyses of violent episodes (Anderson & Anderson, 1984; Cotton, in press; Harries & Stadler, 1983; but cf. Baron & Ransberger, 1978). Kenrick and Johnson (1979) have also raised questions about the generalizability of results obtained in research on malodor and interpersonal attraction. Under conditions of shared stress,

We would like to thank Walter Carr of the Police Department in Dayton, Ohio, and S. Brodshoder and L. Froebe of the Montgomery County, Ohio, Environmental Protection Agency for their help in gaining access to agency files. We are also grateful to Tim Barry, Robert A. Baron, Paul A. Bell, Gary Evans, Charles Kimble, and David R. Mandel for commenting on earlier versions of this report.

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Rotton et al. (1978) found that malodor increased liking for another student. It was only after the possibility of shared stress was eliminated, in a second experiment, that malodor led to negative evaluations. Kenrick and Johnson suggested that results obtained in the first (shared-stress) experiment "are more likely to generalize to actual interpersonal encounters, since attraction would seem to be rarely developed when one is in isolation" (p. 576). However, because one of the defining features of urban life is interaction with strangers, we predicted that more violent episodes would be recorded under high than low levels of outdoor pollution.

Inconsistent results have been obtained in the few studies that have examined relations between outdoor pollution and behavior (for reviews of the literature, see Evans & Jacobs, 1981; Evans, Jacobs, & Frager, 1982). On the one hand, positive correlations between outdoor pollutants and psychiatric disturbances have been reported in three studies (Briere, Downes, & Spensley, 1983; Rotton & Frey, 1985; Strahilevitz, Strahilevitz, & Miller, 1979). On the other hand, Lave and Seskin (1977) obtained nonsignificant results in an epidemiological study that examined relations between two pollutants and social ills (namely, venereal diseases, suicides, homicides, rapes, robberies, assaults, larcenies, burglaries, and auto thefts).

Evans and Campbell (1983) have correctly criticized the common practice of employing catastrophic indices, such as suicide rates, in research on air pollution and behavior. As a stimulus that elicits negative affect, air pollution might be correlated with less serious but more frequent disorders, such as complaints about family disturbances and physical threats. In addition, Lave and Seskin (1977) considered only two types of pollutants (sulfates and suspended particulates). In a study that also obtained nonsignificant results for sulfur and particulate levels, Rotton and Frey (1985) found that psychiatric emergencies were more prevalent when ozone levels were high than when they were low. Ozone is an indicant of photochemical oxidants (or smog), which is a generic term that describes several pollutants (e.g., aldehydes, hydrocarbons, peroxyacetyl nitrate). Epidemiological and laboratory studies have linked oxidants to complaints about headaches, eye irritation, coughing, and chest pains (Coffin & Stokinger, 1977; Goldsmith & Friberg, 1977). On the basis of past research and a model that emphasizes affective states (Clore & Byrne, 1974), it was hypothesized that ozone levels would be correlated with family disturbances and assault rates.

Although Lave and Seskin (1977) controlled for day-to-day variations in weather conditions in their often-cited work on morbidity and mortality rates, they did not include controls for meteorological conditions when they examined relations between air pollution and social ills. In this study, we included controls for temperature and eight other weather variables. We did not formulate a priori hypotheses for meterological variables, however, because contradictory results have been obtained in research on weather and behavior (for reviews of the literature, see Fisher, Bell, & Baum, 1984; Rotton, 1982b). Of the meteorological variables examined in this study, only temperature has consistently emerged as a reliable concomitant of violent behavior. Archival analyses indicate that more violent and aggressive crimes occur on warm than on cool days (e.g., Cotton, in press; Harries, Stadler, & Zdorkowski, 1984).

Because Baron (1978) has suggested that violence declines after reaching a peak at moderately high temperatures, we also assessed quadratic relations between temperature and complaints about violence; however, because temperatures during the period of time covered by this analysis never exceeded 85 °F (29.4 °C), it must be emphasized that our data did not provide a truly fair test of the affect–aggression model, nor were they collected to do so. Instead, our aim was to obtain unbiased estimates of relations between air pollution and violent crime. For this reason, subsidiary analyses were undertaken to determine if our prediction equations should also include quadratic polynomials for barometric pressure, sunshine, and other meteorological variables.

Weather effects are sometimes inferred from seasonal differences in behavior. As Quetelet's thermic law of delinquency (Falk, 1952) predicts, crimes against persons occur more frequently during summer months than other months of the year (Dodge & Lentzner, 1980; Lewis & Alford, 1975). Until quite recently, most criminologists (e.g., Sutherland & Cressey, 1978) and social psychologists (e.g., Rubin, 1979) have followed Durkheim's (1897/1951) lead in attributing seasonal differences to cultural factors, such as the frequency and intensity of social contact. Yet, as surprising as it may seem, it has not been shown that seasonal trends attain significance after day-to-day variations in meteorological conditions are partialed out. In this study, we performed regression analyses to determine if seasonal differences emerge when weather conditions are held constant (i.e., are partialed out statistically).

Finally, although secular trends were tangential to the major aims of this research, we expanded our models to include holidays, day of the week, and linear trend (or drift). This was done because there has been a fairly steady increase in the number of crimes reported to police during the past 50 years (Sutherland & Cressey, 1978), and a disproportionate number of violent crimes occur on weekends and holidays (Anderson & Anderson, 1984; Harries & Stadler, 1983).

Serial Dependencies

Serial dependencies arise whenever observations are correlated over time (i.e., linked in an autoregressive fashion). They are usually assessed by lagging observations (i.e., shifting them back in time) and computing autocorrelation coefficients between observations at each lag. Positive autocorrelations have been reported in past research on weather and behavior (Sanders & Brizzola, 1982; Valentine, Ebert, Oakey, & Ernst, 1975). Their presence increases the probability of Type I errors when traditional (ordinary least squares) procedures are used to assess relations between series (Johnston, 1972, p. 247).

The biasing effects of serial dependencies can be illustrated by tracing paths between a presumed cause and an assumed effect (Cook, Dintzer, & Mark, 1980). In the first diagram in Figure 1, presumed causes are linked by first-order autocorrelation (ϕ), whereas assumed effects are linked by moving averages (θ). Consequently, there is no way that one can assess X's effect on Y. Not only do current values of Y_t depend on concomitant levels of X_t, they also depend on Y's past behavior (Y_{t-k}) and previous values of X. It is only by removing serial dependencies—an operation known as *prewhitening*—that an investigator can determine if two series are related.

After a predictor has been prewhitened, investigators can determine if changes in one series (e.g., air pollution) precede changes in another (e.g., assaults against persons). The second diagram in Figure 1 satisfies one definition (Pierce & Haugh, 1977) of causality. As Catalano, Dooley, and Jackson (1983) have observed, we are more confident that one variable

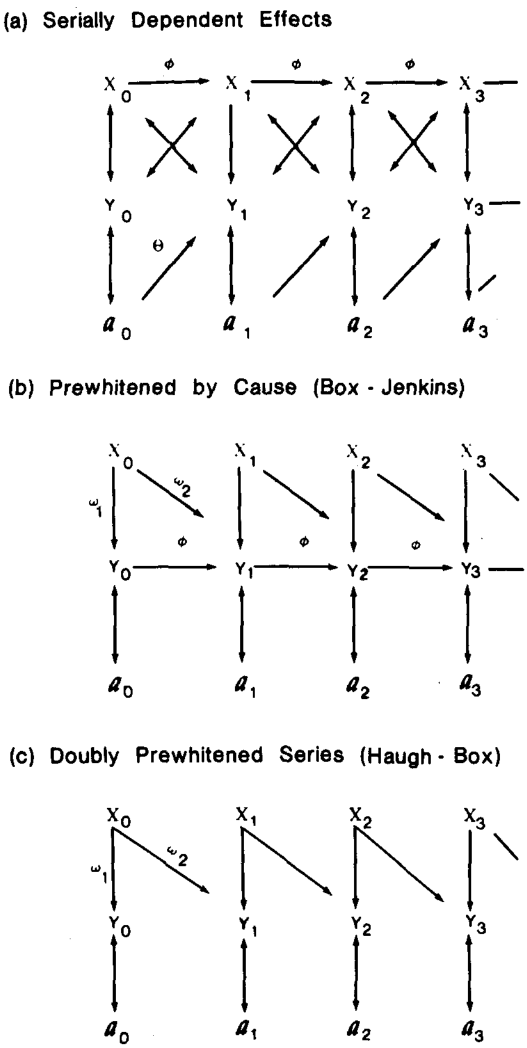

Figure 1. Diagrams of (a) causally ambiguous series, (b) necessary conditions for establishing causality, and (c) independently prewhitened series. (ϕ, θ, and ω represent autoregression coefficients, moving averages, and transfer functions, respectively; a_t = residuals.)

(X) causes changes in another (Y) if the former (X) reduces our uncertainty about future values of Y more than the latter's (Y's) past values. Stating things more simply, temporal precedence is a necessary but not sufficient condition for establishing causality. It goes almost without saying that lagged relations between air pollution and violence might be due to a third variable; for example, automobiles are not only a source of photochemical oxidants, but driving in traffic is also frustrating (Stokols & Novako, 1981), which would facilitate aggressive behavior. Keeping this caveat in mind, however, we can draw *tentative* conclusions about causality if there is a transfer function (ω) that links current values in one series to past values in another (Box & Jenkins, 1976). Although relations can be established after an input (or predictor) variable has been prewhitened, using Box–Jenkins methodology, Haugh and Box (1977) have shown that the task of identifying relations is simplified when dependencies are removed from the criterion as well as predictors. This approach to concomitant time-series analysis, which is illustrated by the third diagram in Figure 1, is usually termed *independent prewhitening* (Cook et al., 1980).

Prewhitening is accomplished by building an ARIMA (autoregressive integrated moving average) model. Procedures for building ARIMA models have been described in recent books written especially for social scientists (e.g., Gottman, 1981; McCleary & Hay, 1980). Although models for individual series are presented in this report, as a means of documenting our results, we were primarily interested in relations between series, and we accordingly focus on transfer functions that link independent and dependent variables.

Method

Data Collection

Between January 1, 1975, and December 31, 1976 (a leap year), dispatchers in the police department in Dayton, Ohio (population = 243,601), logged 108,994 calls for assistance. Of these, 10,765 (9.9%) were classified by police as assaults against persons; another 46,468 (42.6%) were coded as complaints about family and household disturbances. The latter is probably the most common form of violence in the United States (Steinmetz & Straus, 1973). It includes spouse and child abuse as well as family arguments and disputes between members of the same household. These data were obtained as part of a larger study that has also examined atmospheric and temporal correlates of sex crimes (Rotton, 1982a) and psychiatric emergencies (Rotton & Frey, 1985).

Table 1
Daily Means for Predictors

Variable	M	SD
Temperature (°C)	11.11[a]	5.56
Relative humidity	.70	.11
Percentage of sunshine	.55	.36
Barometric pressure (in.)	28.97	.18
Wind (speed in km/hour)	15.16[b]	5.82
Fog (n = 275 days)	.38	.48
Heavy fog (n = 48 days)	.06	.25
Thunderstorms (n = 72 days)	.10	.30
Smoke/haze (n = 366 days)	.53	.50
Ozone (parts per million; n = 712 days)	.06	.03

[a] M = 52 °F; SD = 18.03.
[b] M = 9.43 miles per hour; SD = 3.66.

During the same period of time, a local environmental protection agency obtained 1-hour readings for ozone on 712 days and 24-hour averages for carbon monoxide on 575 days, sulfur dioxide on 459 days, and suspended particulates on 704 days. The agency did not record sulfur dioxide and carbon monoxide levels when ozone and particulate counts were high. Agency records indicated that levels exceeded National Air Quality Standards of 0.08 parts per million (Environmental Protection Agency, 1978) on 155 (or 21.8%) of the days when ozone readings were obtained. On the 19 days when ozone readings were missing, records revealed power outages on 2, Christmas closings on 4, and recalibration of instruments on 13 (consecutive days between November 6 and 18, 1975).

In an effort to avoid some of the problems caused by missing observations, only ozone was retained as a measure of air pollution. In addition, because intervals separating observations in a time series must be equal (Bohrer & Porges, 1982), linear interpolation was used to replace missing ozone readings. As a precaution, we added a dummy variable to our prediction equations to denote days on which observations had been interpolated.

Five continuous and four dichotomous measures of meteorological conditions were obtained from monthly summaries published by the National Oceanic and Atmospheric Administration. The continuous measures were percentage of sunshine and 24-hour averages for temperature, relative humidity, barometric pressure, and wind speed. The dichotomous variables were fog, heavy fog, thunderstorms, and smoke/haze. From the means in Table 1, it can be seen that Dayton's weather during this period was unusually mild; for example, average daily temperatures never fell below 5 °F (-15 °C) nor exceeded 85 °F (29.4 °C). During the following year (1977), winter temperatures dropped below 0 °F on several days, and summer temperatures occasionally rose above 100 °F.

Model Specification

The five continuous measures of meteorological conditions were transformed into deviation scores and then squared in order to assess nonlinear relations. Simple polynomials were also created to estimate and control for linear, secular (holiday, day of the week), and seasonal trends. The first was estimated by assigning numbers from 1 to 731 to each day. Secular trends were estimated by subtracting complaints on Sundays from every other day of the week; this was accomplished by constructing a design matrix composed of 0s and plus and minus 1s (Cohen & Cohen, 1983). Plus 1s were also assigned to the days before, after, and including Easter, Memorial Day, Independence Day, Halloween, Labor Day, Thanksgiving, Christmas, and New Year's Eve. These time periods were expanded to 4 days when a holiday fell on a Friday or Monday. Finally, seasonal trends were estimated by including a sinewave and its complement (cosine) as predictors. These curves had periods of 365 days, and each was aligned so that its 1st day (i.e., initial phase) was the preceding year's winter solstice (December 21).

Results

Three sets of increasingly complex analyses were undertaken to assess relations between atmospheric variables and violence. First, ordinary least squares (OLS) regression analyses were performed to obtain preliminary (or first-stage) estimates of each parameter. This step was also employed to identify variables that accounted for so little variance that they could be dropped from the model. Second, two-stage regression analyses were undertaken to obtain generalized least squares (GLS) estimates of beta weights (Ostrom, 1978). The latter provided guidelines for building distributed lag (Box–Jenkins) models in a third set of analyses.

Only one nonlinear relation attained significance in the first (OLS) analyses. Temperature's quadratic component emerged as a predictor of family disturbances, $F(1, 704) = 42.24$, $p < .01$, but not assaults against persons, $F < 1$. The other polynomials for quadratic trends, whose betas did not attain significance ($ps > .05$), were dropped from the model. In addition, an inspection of scatterplots did not reveal any obvious departures from linearity or homoscedasticity.

Results from first-stage (OLS) analyses are not presented here, because Durbin-Watson's d statistic revealed serious violations of serial independence. For household disturbances, a d statistic of 1.57 was obtained; for assaults against persons, one of 1.78 was obtained. Both are significant ($p < .01$) when compared with values found in tables (King, 1981) for regression equations with seasonal and dummy variables.

Generalized Least Squares

Serial dependencies were removed by lagging residuals from the OLS analyses, pairing lagged and unlagged values, and deriving first-order autocorrelation coefficients (ϕ) for each dependent variable (Ostrom, 1978, pp. 38–42). Although there are procedures for estimating values lost through lagging, they were not employed, because the series began on January 1, an atypical day. Temporal as well as atmospheric variables were transformed to obtain the GLS estimates in Table 2. Although some authors (e.g., Gottman, 1981) have suggested that series should be detrended before correlations between them are estimated, we fol-

Table 2
Generalized Least Squares for Atmospheric and Temporal Variables

	Disturbances		Assaults	
Predictor	β	$t(706)$	β	$t(706)$
Temperature (T)	.592	8.34*	.092	3.30*
T (quadratic)	.010	6.38*	.003	.45
Humidity	3.126	.48	−4.443	−1.69
Sunshine	−1.425	−.85	.917	1.32
Barometer	−.175	−.05	−.870	−.70
Wind speed	−.608	−4.11*	−.061	−1.00
Ozone	3.557	2.67*	7.515	1.39
Fog	−.298	−.27	.387	.71
Heavy fog	2.196	1.16	.380	.48
Storms	−2.358	−1.58	−.382	−.62
Smoke/haze	−.316	−.32	.385	.95
Trend (linear)	.016	5.29*	.001	.95
Missing days	1.966	.65	1.329	1.13
Tuesday–Monday	−5.835	−5.95*	−1.076	−2.62*
Wednesday–Monday	−7.563	−7.79*	−1.086	−2.67*
Thursday–Monday	−5.626	−5.80*	−.317	−.78
Friday–Monday	2.653	2.72*	1.076	2.58*
Saturday–Monday	22.223	22.68*	2.411	5.88*
Sunday–Monday	4.980	5.16*	−.467	−1.18
Holidays	4.465	2.38*	−.343	−.47
Season (sine)	2.833	2.60*	−1.084	−2.63*
Season (cosine)	−6.882	−4.74*	−.432	−.62
Intercept	23.426		32.783	

Note. For family and household disturbances, $R^2 = .695$, $F(22, 706) = 73.25$, $p < .001$, and estimated autocorrelation coefficient = .206. For assaults against persons, $R^2 = .292$, $F(22, 706) = 13.56$, $p < .001$, and estimated autocorrelation coefficient = .108. In both analyses, two degrees of freedom were lost (one from lagging and another for ϕ, the autocorrelation coefficient).
* $p < .05$.

lowed Hibbs (1974, pp. 284–289) and obtained GLS estimates for temporal controls as well as random variables. Also, simultaneous rather than stepwise regression analyses were performed, because second-stage (GLS) estimates depend on residuals obtained in the first (OLS) stage, which in turn depend on every predictor in a regression equation.

Atmospheric variables. As hypothesized, ozone was correlated with family disturbances, GLS $r(727) = .50, p < .01$, and it emerged as a predictor in the simultaneous regression analysis. Although ozone was also correlated with assaults against persons, $r(727) = .37, p < .01$, it was not retained as a predictor when other variables were partialed out. Temperature was selected as a predictor in both sets of analyses. For assaults and family disturbances, OLS correlations were $r(729) = .48$ and .65, respectively; corresponding GLS correlations were $r(727) = .44, p < .01$, for assaults and $r(727) = .58, p < .01$, for family disturbances. Further, as implied by the negative beta weight for temperature's quadratic component, a disproportionate number of complaints about family disturbances were received on warm days. That is, the curve relating disturbances to temperatures was a positively accelerated (or J-shaped) one rather than the inverted U-shaped curve that might have been observed (Baron, 1978) if warmer days had been available for study.

Wind speed was the only other atmospheric variable that attained significance in these analyses. As suggested by the negative beta weight in Table 2, fewer complaints about family and household disturbances were received on windy than calm (or windless) days.

Temporal variables. The positive beta for trend in Table 2 indicates that complaints about family disturbances increased linearly over time. Holidays also attained significance in the analysis of family and household disturbances. Covariate-adjusted and steady-state means for holiday and nonholiday periods were 63.66 and 57.93, respectively.[1] To learn more about this difference, we dropped holidays from the regression equation and inspected the resulting residuals for outliers. A far outlier is one that exceeds a distribution's upper and lower quartiles by two steps, where a step is 1.5 times the interquartile range (Tukey, 1977). More than half (7 of 13) of the far outliers fell during a holiday period. In 1975, a disproportionate number of disturbances occurred on Halloween, Christmas, and New Year's Eve; in 1976, disproportionate numbers occurred during Memorial, Labor, and Independence Day periods.

Table 3
Daily Means for Seasonal Trends

	Disturbances		Assaults	
Season	Actual	Adjusted	Actual	Adjusted
Winter	48.46	66.37_a	11.41	14.02_a
Spring	63.44	66.88_a	13.91	13.75_a
Summer	84.83	72.25	18.07	15.67_b
Fall	57.31	53.65	15.47	15.42_b

Note. Means sharing common subscripts in each column do not differ, $p < .05$ by Fisher's least significant difference test.

Seasonal differences were assessed by dividing each year into quarters (December through February, March through May, etc.). Analyses of variance (ANOVAS) and two-stage regression analyses were performed to obtain OLS and GLS (or adjusted) estimates of seasonal means. From the unadjusted means in Table 3, it can be seen that highly significant seasonal differences were obtained in one-way ANOVAS, $Fs(3, 727) = 143.82$ and 49.06, $p < .01$, for disturbances and assaults, respectively. Further, in each analysis, all pairwise differences between means attained significance, $p < .05$ by Fisher's least significant difference (lsd) procedure.

Seasonal differences were greatly reduced but not eliminated when atmospheric and other temporal variables (e.g., linear trend) were partialed out in second-stage regression analyses, $Fs(3, 705) = 20.64, p < .01$, and 2.67, $p < .05$, for family disturbances and assaults, respectively. From the covariate-adjusted and steady-state means in Table 3, it can be seen police had to deal with more family disturbances during summer than spring or winter months, $p < .05$ by Fisher's lsd procedure; al-

[1] The GLS estimates for holiday and nonholiday means were obtained by first computing a grand mean for all days, excluding holidays, and by adding the beta for holidays (i.e., $b = 4.26$) to the total. The following trasformation was then employed to obtain steady-state means: $M' = M/(1 - \phi)$, where M is the mean obtained from GLS analysis and ϕ is the series' autocorrelation (see Gottman, 1981, p. 372).

Table 4
Daily Means for Secular Trends

	Disturbances		Assaults	
Day	Actual	Adjusted	Actual	Adjusted
Monday	52.61_a	63.58_a	14.18_a	14.72_{ab}
Tuesday	56.86_{ab}	56.23_b	13.83_a	13.51_a
Wednesday	57.86_a	54.05_b	13.70_a	13.50_a
Thursday	58.11_{ab}	56.49_b	14.32_a	14.36_{ab}
Friday	65.98_{bc}	66.92_{ac}	15.66_{ab}	15.92_{bc}
Saturday	85.99	91.57	17.24_c	17.42_c
Sunday	68.21_c	65.53_c	14.15_a	14.17_{ab}

Note. Means sharing common subscripts in each column do not differ, $p < .05$ by Fisher's least significant difference test.

though the latter did not differ, both spring and winter means exceeded the mean for the fall months, $p < .05$. Turning to assaults, adjusted means did not differ during summer and fall months, but both were higher than winter and spring means, $p < .05$, and the latter were not reliably different. In sum, seasonal trends were greatly attenuated when adjustments for day-to-day variations in atmospheric conditions were made; however, as sociologists have suggested, seasonal differences did not depend entirely on weather conditions.

Daily means for family disturbances and assaults are listed in Table 4. As other investigators (e.g., Harries & Stadler, 1983) have found, more violent episodes occurred on Fridays than on other weekdays. They reached a peak on Saturdays and then declined so markedly that means on Sundays were close to means on working days.

Distributed Lag Analysis

Generalized least squares analyses are limited to uncovering synchronous relations between variables. Despite this and other limitations (Cook et al., 1980, p. 107), GLS procedures are useful for screening data before developing more complicated (distributed lag) models. In particular, the preceding results suggested that little was to be gained by retaining binary variables (fog, storms, smoke/haze) as predictors.

Prewhitening. Ordinary least squares procedures were employed to remove linear, secular (i.e., holiday, day of the week), and seasonal trends from the family disturbance, assault, and ozone series. Seasonal but not secular trends were removed from the series for temperature, humidity, sunshine, wind speed, and barometric pressure. An iterative strategy (Box & Jenkins, 1976) was then followed to obtain the ARIMA models in Table 5. To be accepted, each model had to pass two tests (see McCleary & Hay, 1980, pp. 98–99). First, residuals had to be independent on the first and second lag; as indicated by the autocorrelations in Table 5, each set of residuals passed this test. Second, each autocorrelation function had to pass an omnibus test of fit when residuals were lagged 25 time periods. For this test, we computed a Ljung–Box Q, which is distributed as a chi-square statistic with $25 - k$ degrees of freedom, where k is the number of autoregression coefficients and moving averages in one's model (Ljung & Box, 1978). From the rightmost column in Table 5, it can be seen that models passed this test as well.

Cross-correlations. Residuals from the ARIMA models were paired with each other to obtain cross-correlation coefficients for 10 leads and lags. To conserve space, only the first four lead and lag coefficients are listed in Table 6. Although a few investigators (e.g., Persinger, 1975) have suggested that weather exerts delayed effects on behavior, none has postulated lags of more than 3 or 4 days.

Most of the significant cross-correlations in Table 6 are synchronous ones, but temperature and ozone led disturbances by 1 day. Further, wind speed led disturbances by 1 and 4 days, and assaults were also preceded by low winds. On the other hand, a disturbing number of $r(-t)$ or reverse correlations attained significance when atmospheric variables were lagged. For example, disturbances led highs in sunshine by 3 days, and both assaults and disturbances preceded lows in humidity.

Haugh–Box causal models. Reverse correlations are less of a problem when one builds a multiple-input model for each criterion. Although cross-correlation and transfer function analyses lead to identical conclusions when two series are examined (Haugh & Box, 1977), transfer functions (ω) allow one to assess the effects of two or more independent variables. Transfer function identification differs little from regression analysis when cross-correla-

Table 5
ARMA Models for Deseasonalized Series

Variable	Model	Diagnostic test r_1	r_2	df	Q
Disturbances	$(1 - .32B - .15B^2)(1 - .09B^6)(1 - .13B^{30})Y_t = a_t$; $t(689) = 8.73, 4.01, 2.35, 3.46$	.00	.01	21	25
Assaults	$(1 - .14B - .03B^2 + .12B^9)Y_t = a_t$; $t(719) = 3.90, 2.22, -3.36$	.00	.02	22	21
Temperature	$(1 - .86B + .34B^2 - .17B^3)Y_t = a_t$; $t(725) = 23.49, -7.14, 4.58$	.00	.00	22	21
Humidity	$Y_t = (1 + .56B + .15B^2)a_t$; $t(729) = -15.40, -4.07$	.01	.04	23	22
Sunshine	$Y_t = (1 + .25B)a_t$; $t(730) = -6.99$	.00	.01	24	24
Wind	$(1 - .31B - .08B^3 - .10B^5)Y_t = a_t$; $t(719) = 8.81, 2.25, 2.70$	.01	−.05	21	25
Barometric pressure	$(1 - .59B + .21B^2)(1 - .07B^{10} - .08B^{11})Y_t = a_t$; $t(714) = 16.11, -5.81, 1.88, 2.18$	.01	−.02	21	28
Ozone	$(1 - .36B)(1 - .09B^3 - .16B^4 - .11B^6)Y_t = (1 + .09B^9 + .10B^{10})a_t$; $t(713) = 10.30, 2.58, 4.46, 2.87, -2.47, -2.75$	.02	−.04	19	26

Note. ARMA = autoregressive moving average. B is a backshift operator that moves observations back one unit in time; that is, $BY_t = Y_{t-1}$. More generally, $B^kY_t = Y_{t-k}$ so that $B^2Y_t = B(Y_{t-1}) = Y_{t-2}$ (see McCleary & Hay, 1980, pp. 45–48). Q is distributed as a chi-square. All t values are significant, $p < .05$.

Table 6
Cross-Correlation Functions

Variable (X)	Y leads X (in days) −4	−3	−2	−1	0	X leads Y (in days) +1	+2	+3	+4
					Y = disturbances				
Temperature	.01	−.04	.01	.05	.20*	.14*	.05	−.01	.01
Humidity	.08*	−.07*	.07	.06	.01	.02	.03	.03	−.03
Sunshine	−.05	.10*	−.01	.02	.04	.02	.02	−.01	−.02
Wind speed	−.01	−.05	−.06	−.08*	−.09*	−.08*	.00	−.03	−.08*
Air pressure	.00	.04	−.05	−.02	.01	.01	.02	.05	.03
Ozone	−.07	.05	.01	.07	.19*	.09*	.04	.07	.02
					Y = Assaults				
Temperature	.00	.01	.01	.09*	.14*	.07*	.01	.04	−.02
Humidity	.00	−.08*	.04	.06	−.11*	.01	.02	.00	.01
Sunshine	.02	.08*	−.03	.03	.13*	.06	.00	−.03	.00
Wind speed	.02	.05	.05	.06	−.03	−.02	−.10*	−.01	−.02
Air pressure	.01	−.01	−.02	−.07	.00	.00	.03	−.01	.04
Ozone	.02	−.01	.00	.08*	.16*	.06	.01	.08*	.02
Disturbances	−.07	.00	−.03	.06	.12*	.07*	.13*	.04	−.01

Note. No other cross-correlations for assaults attained significance within 10 leads and lags. In addition to values listed, the following cross-correlations with disturbances attained significance for 10 leads and lags: $r(8) = -.07$ for temperature leading, $r(-5) = .07$ for wind speed trailing, $r(7) = -.07$ and $r(8) = -.08$ for ozone leading, and $r(5) = .08$ and $r(8) = .11$ for barometric pressure leading.
* $p < .05$.

Table 7
Transfer Functions (ω) for Distributed Lag Models

	Haugh–Box				Box–Jenkins			
	Disturbances		Assaults		Disturbances		Assaults	
Predictor	ω	$t(724)$	ω	$t(724)$	ω	$t(684)$	ω	$t(709)$
Temperature (t)	.23	4.95	.20	3.78	.23	4.98	.15	3.69
Temperature ($t - 1$)	.22	4.76			.12	2.65		
Wind (t)	−.14	−4.06			−.67	−4.84		
Wind ($t - 2$)			−.11	−2.99			−.08	−2.04
Ozone (t)	.12	3.24			.12	3.32		
Ozone ($t - 3$)					.08	1.97		
Humidity (t)			−.18	−4.31			−.16	−4.24
Disturbances (t)			.09	2.30			.09	2.28
Disturbances ($t - 2$)			.13	3.26			.10	2.69
ϕ_1	.09	2.44			.23	6.16	.11	2.97
ϕ_2			.15	4.14				
ϕ_9							−.09	−2.39
ϕ_6 for $(1 - \phi B^6)^2$					.09	2.53		
ϕ_{30} for $(1 - \phi B^{30})^3$					.14	3.83		

tions drop off (or go to zero) after a few lags (Catalano et al., 1983).

A modification of stepwise (i.e., build-up with deletion) regression procedures was used to obtain the Haugh–Box models in Table 7. After each predictor was added to a model, the latter's residuals were inspected to determine if they passed three tests (see McCleary & Hay, 1980, pp. 242–243). First, residuals had to be independent on the first two lags; second, the residual series as a whole had to be distributed as white noise; and finally, cross-correlations between the model's residuals and prewhitened series had to be close to zero. From the diagnostic tests in Table 8, it can be seen that residuals resembled white noise. Four of 126 cross-correlations attained significance when the prewhitened series and residuals from the model for family disturbances were each lagged 10 days. Only three cross-correlations did so when prewhitened series and residuals from the assault model were lagged 10 days.[2] Since 6 of 126 cross-correlations would attain significance by chance alone, the models in Table 7 would appear to be adequate.

Table 8
Diagnostic Tests for Distributed Lag Models

	Haugh–Box		Box–Jenkins	
Statistic	Disturbances	Assaults	Disturbances	Assaults
r_1	.00	−.03	.00	.00
r_2	−.04	−.03	−.01	.01
Q	26	29	25	28
df	24	25	21	23

Note. Q is distributed as chi-square. All t values are significant, $p < .05$.

The Haugh–Box model for family disturbances indicates that the largest number of complaints about family and household were received on and after warm days when ozone levels were high and wind speeds were low. More complaints about assaults against persons were also received on warm and dry than cool or humid days. In addition, low winds and high ozone levels preceded high assault rates by 2 and 3 days, respectively. Of even greater interest, it was serendipitously found that assaults were also correlated with the other endogenous variable (namely, family distur-

[2] Prewhitened barometric pressure and temperatures led the residuals for disturbances by 8 days, $rs(8) = .10$ and -.08 for barometric pressure and temperature, respectively. Residuals led prewhitened wind speed, $r(-1) = -.12$, and ozone, $r(-4) = .07$, by 1 and 4 days, respectively. Prewhitened temperatures also led the residual series for assaults by 5 and 8 days, $r(5) = .08$ and $r(8) = -.08$, respectively, and ozone led assaults by 7 days, $r(7) = .09$.

bances). As the model for assaults implies, police not only received more complaints about family disturbances and assaults on the same day, but they also had to deal with more assaults 2 days after highs in family disturbances.

Box–Jenkins transfer functions. Haugh–Box procedures suffice when investigators are primarily interested in showing that unpredictable changes in one variable precede changes in another. Procedures developed by Box and Jenkins (1976) allow one to draw conclusions about actual (and not prewhitened) values and forecast trends. It has been our experience that these procedures work best when they are based on initial estimates provided by Haugh–Box models.

The first step in obtaining Box–Jenkins transfer functions is to build an ARIMA model that simultaneously removes dependencies from residuals and estimates transfer functions. That is, we began with a tentative model that included both ARIMA components (see Table 5) and transfer functions from Haugh–Box models (see Table 7). This was the only step that was required to obtain a Box–Jenkins model for family and household disturbances. From the model in Table 7, it can be seen that, once again, low winds and high oxidant/ozone levels, as well as high temperatures on the same and preceding days, were correlated with and could be used to predict family and household disturbances. Only 7 of 120 cross-correlations for this model attained significance when its residuals were paired with the prewhitened series of predictors.[3]

Backward elimination (or teardown with replacement) procedures were followed to obtain the Box–Jenkins model for assaults. That is, nonsignificant terms were dropped from our tentative model, beginning with the one with the smallest t value, until (a) only significant terms remained, (b) the model's residuals resembled white noise, and (c) only a few cross-correlations between residuals and the prewhitened series attained significance. From the Box–Jenkins model in Table 7, it can be seen that ozone was not retained as a predictor; however, as in the previous (Haugh–Box) analysis, more assaults occurred on warm and dry than cool or humid days, and once again, family disturbances and low winds preceded highs in assaults.

Discussion

This study's correlational results confirm predictions derived from laboratory studies (e.g., Rotton, 1983) on malodorous pollution. As was hypothesized, ozone/oxidant levels were correlated with complaints about family disturbances, and Haugh–Box analyses suggested that highs in ozone levels also led assaults by 3 days. However, the latter (delayed) relation is probably a spurious one. Ozone was not selected as a predictor of assaults in more stringent Box–Jenkins analyses. The delayed effect for ozone might be due to other chemicals (e.g., hydrocarbons, aldehydes) found in photochemical oxidants. Although ozone is the principal element in photochemical oxidants (sometimes 90% of total volume), formaldehyde and hydrocarbons are responsible for some of the effects (e.g., eye irritation) attributed to ozone (Jones, 1972). Further, higher levels of nitrogen dioxide and other pollutants are preceded by declines in ozone levels (Goldsmith & Friberg, 1977). Thus, although some faith can be placed in concurrent (or same-day) correlations between ozone and behavior, it is very likely that the lagged relation was due to pollutants associated with earlier increases in ozone levels.

Nevertheless, the overall pattern of correlations in this study suggests that air pollution may be responsible for effects sometimes attributed to weather. For example, without taking air pollution into account, it would be hard to explain why fewer complaints about family disturbances were received on windy days, and delayed relations between wind speed and assaults would also resist easy interpretation. However, these findings are consistent with the well-known fact that high winds disperse pollutants (McCormick & Holzworth, 1972). It is likely that individuals experience less annoyance and irritability on windy than windless days. To take another example, one would expect that individuals would experience more

[3] Prewhitened series for barometric pressure and temperature led residuals for family disturbances by 8 and 9 days, $r(8) = .11$ and $r(9) = -.09$, respectively. The residual series for disturbances led the prewhitened series for sunshine, $r(-3) = .08$; humidity, $r(-4) = .08$; and wind speed, $r(-5) = .07$. Only prewhitened temperatures led the residual series for assaults, $r(8) = -.08$.

discomfort on humid days, especially when temperatures are high (Griffitt & Veitch, 1971), yet in this study, fewer assaults occurred on humid than dry days. This finding makes sense when it is realized that humidity levels are higher before and after a rainfall, which removes pollution from the air.

Although air pollution appears to account for effects often attributed to meteorological variables, temperature emerged as the best predictor of complaints about violent episodes. As several investigators have found, more violent episodes occurred on warm than cool or cold days. Given the fact that high temperatures also preceded complaints about family disturbances, it is tempting to conclude that weather and behavior not only are correlated but some types of weather (e.g., high temperatures and low winds) also cause behavior that requires police intervention. However, even delayed relations may be due to another variable, such as alchohol consumption. Harries et al. (1984) have observed that individuals consume more alchohol on warm than cool days; suffering from hangovers, they might also be more prone to engage in violent behavior on "the day after." One way to deal with this rival hypothesis would be to include surrogate measures of alchohol consumption (e.g., daily sales figures) in future studies.

Discounting rival hypotheses can be distinguished from speculating about factors that may be responsible for relations between weather and behavior. Excluding work done in Europe, which has emphasized thermoregulatory and biochemical processes (e.g., Tromp, 1980), investigators have adopted one of two theoretical approaches in this area. On the one hand, sociologists and criminologists have attributed weather effects, as well as seasonal differences, to the frequency and intensity of social contact. On the other hand, social and environmental psychologists (Baron, 1978; Cunningham, 1979; Fisher et al., 1984) have favored models that emphasize affective states.

As social contact models suggest, seasonal differences attained significance after meteorological variables were partialed out. Social contact also provides a parsimonious explanation for holiday and weekend highs in family disturbances. However, although social contact models can account for relations between weather and assaults against persons, they do not explain why more family disturbances occurred on warm than cool days. In a temperate climate, such as the one studied here, fewer individuals venture outdoors during winter than summer months of the year (Michelson, 1971). As a consequence, contacts among family members should be more frequent and perhaps more intense during winter months and on cold days. However, in this study, we found that family disturbances occurred more frequently on and after warm than cool or cold days.

On the surface, it might be thought that theories emphasizing affective states faired better than theories emphasizing interaction rates. First, the positive correlation between ozone and family disturbances is consistent with a prediction derived from the affect–reinforcement model (Clore & Byrne, 1974). Second, as this and Baron's (1978) model suggest, more violent episodes occurred on and after warm than cool days. However, although temperatures in this locale sometimes reached a low of 5 °F, which is uncomfortable (i.e., elicits negative affect), fewer episodes occurred at cold than temperate or comfortable temperatures. It is possible that discomfort on a moderately cool day is, in part, negated by behavioral adaptations, such as wearing warmer clothes (P. A. Bell, personal communication, August 27, 1982). Another possibility is that the effects of ozone and temperature stem from higher levels of arousal.

As an arousing stimulus (Provins, 1966), heat would be expected to intensify aggressive responses, leading to more violent crimes on warm than cool days. However, low as well as high temperatures are arousing; unless one assumes that individuals are too busy trying to keep warm to engage in aggression, arousal models do not explain why less violence was observed on cold than warm days. There is also some reason to believe that ozone is arousing as well as irritating. It was not too long ago that Huntington (1945) and others (e.g., Peters, 1939) attributed the stimulating effects of some kinds of weather to ozone in the atmosphere. What has been called "Hungtington's ozone hypothesis" (McGregor, 1976) was formulated before biologists linked ozone to pulmonary edema and other respiratory ailments. Given the prevalence of photochemical oxidants in many urban settings and the results obtained in this study, there would seem to be a need to assess the behavioral effects of ozone under laboratory conditions.

However, in speculating about emotional states, we run the risk of committing an ecological fallacy (Firebaugh, 1978; Langbein & Lichtman, 1978). Strictly speaking, on the basis of aggregate data, we can do no more than conclude that the probability of violent episodes is higher when temperatures and levels of air pollution are high than when they are low. It is possible that only a few at-risk (e.g., asthmatic or overweight) individuals are affected by high temperatures and levels of air pollution. For example, on the basis of results obtained in this study, relation between levels of air pollution and violence might be stronger for people living closer to expressways than those living in suburbs or rural areas. One way to explore this possibility would be to follow the lead of epidemiologists who, as a matter of course, disaggregate by type of population. To take another example, our analyses suggest that family disturbances predict and may lead to subsequent highs in assault rates. However, it has yet to be shown that assaults occurred in households whose members were earlier involved in a disturbance. Further research is needed to determine if similar relations emerge when assaults are classifed by locale (e.g., taverns as well as family dwellings).

With further research, it should be possible to determine whether this study's results are generalizable or limited to one geographical locale and period of time. It will be recalled that weather conditions in Dayton were unusually mild. A first step in assessing this study's generalizability would be to see if similar results are obtained in subsequent years. In this regard, it might be noted that Box–Jenkins models are ideally suited for forecasting future trends. A second and even more important step would be to examine correlations between atmospheric variables and crime in other geographical regions. However, it goes almost without saying that relations between predictors and criteria are, in part, dependent on correlations among predictors. Because of the problems that multicollinearity introduces, weaker results might be obtained in regions (e.g., some northeastern cities) where levels of air pollution and meteorological conditions are more highly correlated. At the same time, we would expect that stronger relations would emerge in a region (e.g., southern California) where weather conditions are more stable and levels of air pollution are higher.

Future research in this area also needs to explore the combined (or synergistic) effects of pollutants and different types of weather. For example, one would expect to find that ozone interacts with percentage of sunshine, simply because light is necessary for the production of photochemical oxidants. Past research suggests that the effects of ozone might also be dependent on daily temperatures (Rotton, 1982b) and humidity levels (Graves & Krumm, 1981). In addition, results obtained in one study (Cunningham, 1979) suggest that different sets of correlations might be obtained during summer and winter months.

Unfortunately, serial dependencies place constraints on the number and type of relations that can be examined in a time-series analysis. First, it will be recalled that second-stage estimates in the GLS analyses were derived from simultaneous rather than more conventional (stepwise or hierarchial) regression equations. Adding predictors to our equations to assess interactions would have increased the probability of Type I errors (Cohen & Cohen, 1983) and, at the same time, reduced the power of individual tests of significance (Rotton & Schönemann, 1978). Second, with regard to types of hypotheses, it will also be recalled that serial dependencies had to be removed from each predictor (prewhitening) before transfer functions were estimated. This operation could not have been accomplished if the predictors had been previously transformed to obtain polynomial terms for estimating interactions. At the very least, polynomial transformations would have produced nonstationary predictors (i.e., series whose means and variances change over time). It is for this reason we did not include temperature's quadratic component as a predictor in our distributed lag analyses, even though it accounted for a significant amount of variance in the GLS analysis of family disturbances.

In sum, our findings should be regarded as a first approximation of true and undoubtedly much more complex relations between atmospheric conditions and violent behavior. However, even as a first approximation, they clearly implicate meteorological variables as concomitants and possible causes of violent crimes. Finally, they suggest that cost-benefit analyses of the effects of air pollution should include the social and psychological costs of dealing with violent crimes.

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Received July 24, 1984
Revision received December 10, 1984 ■