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Crime and divorce. Can one lead to the other? Using Multilevel Mixed Models

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Cross-sectional and time-series studies of the influence of divorce on crime and the reverse are few in developing and developed countries. Questions arise as to whether divorce causes crime, the reverse, or both effects exist in Jordan. The objectives are to investigate the relationship between divorce and crime, determining whether the clustering in divorce and in crime within governorates exist and whether divorce and crime increase or decrease over time. The study design was a cross-sectional time-series analysis. Several Jordanian statistical yearbooks and surveys issued by the Jordanian Statistics Department provided the data of 12 governorates over 14 years (2000-2013). After calculating the divorce rate (DR) and crime rate (CR), multilevel mixed-effects linear regression was performed, estimating three models each for divorce and crime. Comparison between these models was explained in intraclass correlation, the proportional change in the variance of the response variable, and the deviation. The statistical and social epidemiological concepts of contextual phenomena confirm that the rates of divorce and crime in the same governorate are more similar to each other than to those from different governorates. Using the CR as a predictor for the DR reduced the within-governorate variance more than four times the between-governorates variance. Using the DR as a predictor for the CR reduced the within-governorate variance and inflated the between-governorates variance. Using time as a predictor for the DR reduced the within-governorate variance dramatically higher than the between-governorates variance and as a predictor for the CR reduced the within-governorate variance but inflated the between-governorates variance a small amount. Thus, both divorce and crime lead to the other.

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keywords: multilevel modeling, divorce, crime, time, governorate, intra-class correlation.

1 Introduction

Researchers use a multilevel mixed-effects linear regression model when they group the data in more than one category, for example the governorates in the current study. However, using multilevel modeling allows researchers simultaneously to investigate the effect of individual-level and group-level predictors on the response variable of interest. A multilevel model is a hierarchical model that contains variables measured at different hierarchical levels. Because the multilevel model acknowledges hierarchical data, researchers should not move to a single model in studying aggregated or disaggregated variables (Hox, 1995). Thus, statistical and conceptual advantages accrue in choosing this methodology.

Data from the same governorate are usually more similar to each other than data from different governorates. If they are, one cannot use statistical methods on these data that assume independence, because estimates of variance, and therefore p-values, will be incorrect. Thus, multilevel mixed models not only account for the correlation among data in the same governorate, they provide an estimate of that correlation.

In the present study, I highlighted the importance of the context for understanding that social and security differences may differ over time with different characteristics. I obtained panel data for divorce and crime variables across 12 governorates in Jordan over the 14 years of (2000-2013). Panel data allow researchers to control for variables they cannot observe or measure like cultural factors or difference in business practices across companies; or variables that change over time but not across governorates (i.e., national policies, federal regulations, international agreements, country rules, and legislation). This is, panel data account for governorate heterogeneity.

The real relationship between the two social phenomena of divorce and crime follow. One may assume that if parents' divorce in a family with a small boy or girl, the probability that this child will later commit a crime could be higher than a child in a family without divorce. If such couple gets divorced, the probability exists that at least one of them will commit a crime could be higher than for members of a couple without divorce due to instability, depression, and stress that can affect both adults. A third example is a family where husband or wife committed a crime; after that, the probability of divorce could be higher in this family than in a family where no crime was committed.

The objectives of the current study were to investigate the rates of divorce and crime and their descriptive statistics in Jordan over time, measured by years, and across space, measured by governorates. The purpose was to identify the relationship between divorce and crime. Here, I introduce multilevel regression modeling (MRM) in a way that is easy to understand by statisticians and non-statisticians alike, using simple details to compare variables. Many previous studies applied the MRM only in a way that could be used by researchers in their studies. Several advantages ensue from this technique of MRM use, such as dependency among observations that are not permitted in familiar regression modeling. Here, I determine intraclass correlations (ICC) among observations in the same governorate to explain the statistical and non-statistical meaning of ICC among observations in the same governorate.

Several questions arose in the present study. What is the average of 12 regression equations for 12 governorates? What is the average of the intercept and the slope of these equations? How much do regression equations vary from governorate to governorate? Can one infer that divorce leads to crime, the reverse, or both? Which the crime or the divorce changes more changed over time and in what direction? Do time, crime, and divorce predict within-governorate slopes? How much variation in the intercepts and the slopes is explained by time, crime, and divorce? Thus, I am interested in investigating how individual divorce rate (DR) and crime rate (CR) differences partition in variability between rates from the same governorate and between governorates.

Mednick et al. (1987) explored the long-term effects of parental divorce on young adult male crime from a longitudinal perspective in Denmark. They found an initial significant relationship between divorce and young adult crime based on the results of analyses of variance; the effects of divorce disappeared when further path analysis controlled for the effects of social class and father's criminality. Evidence suggested that the negative relationship between women education and divorce was weaker when marriages involve abuse than when they do not in the United States (Kreager et al., 2013). Education appears to benefit women by maintaining stable marriages and dissolving violent ones. Bishop et al. (2015) examined differences in self-reported dispositional forgiveness types among older male prison inmates who experienced parental separation/divorce earlier in life in Oklahoma. In their examination, they used mean differences across forgiveness of self, situation, and others; the disposition to forgive among older prison inmates depended on criminal-offender type as well as whether the older inmate experienced parental dissolution earlier in life. Bourne et al. (2014) evaluated the role of divorce and marital relationships on murders in Jamaica, where they used regression analyses and curve estimations in their analysis. Bourne et al. found that logged marriage rate and DR are factors in MR and these factors positively correlate with the murder rate, with the DR accounting for most of the variance in the murder rate.

The current study is quite important for several reasons. First, increasing the DRs even with small values in any society has dramatically negative effects on overall children live and on the mental health of all family members. Second, as a consequence, divorce will destroy society because building a strong family is the basis for having a concrete and healthy society. Third, divorce may expose divorced people and their family members to hard conditions, making them suffer psychologically and mentally, which may lead them to perpetrate crimes. The reverse of this relationship may happen: criminals could face many social and economic troubles with their partners, leading to divorce. Fourth, to my knowledge, no study has investigated DR and CR together over a relatively long time period and across all Jordanian governorates. Fifth, findings from the current study will provide useful social and security information that policymakers and researchers can use in increasing social awareness.

2 Materials and Methods

2.1 Data

I selected Jordan because of its importance in the Middle East region and the availability of good-quality data. Jordan has faced several socioeconomic and demographic challenges, one of which is a large numbers of immigrants and refugees from neighboring countries. I obtained data from 12 governorates over 14 years (2000-2013) from several Jordanian statistical yearbooks and surveys issued by the Jordanian Statistics Department. Although divorce is a largely simple and measurable procedure, crime is not. Crime varies from petty theft to murder. Crime in the present study includes all types of crime, based on the definitions in collected crime data. I calculated the DR and CR for the ith governorate as follows:

$$rate_i = (O_i/n_i)1000,\ i = 1, 2, ..., 12 \tag{1}$$

where:
O_i = Observed number of the indicator (divorces or crimes) in the ith governorate,
n_i = Population size of the ith governorate.

Historically, in Jordan, the CR decreased slightly in most governorates over the period (2000-2013), whereas the DR increased slightly in all governorates over this period. The average CRs of all governorates decreased dramatically from 11.65 in 2000 to 4.49 in 2013. The average DRs of all governorates increased from 1.41 in 2000 to 2.58 in 2013. I used no other variables to control for confounding changes and moderate variables; the type of relationships in the current study should be multivariate, due to other variables either being unavailable or missed for most years.

2.2 Analysis

I investigated measures of variance in DRs and CRs between-governorates, within-governorates, and ICC within-governorates to understand the distribution of some common social and security problems in the Jordanian population. The research design was a multilevel mixed regression and time-series analysis. Consideration of multilevel modeling at the study-design stage may help researchers to select theoretically and statistically sound research method in most fields. I conducted six steps of analysis. In Step 1, I tested the variables to discern if they follow a normal distribution using the Kolmogorov-Smirnov test. They followed approximately a normal distribution. Step 2 involved descriptive statistics for each variable across governorates and over time. In

Step 3, I estimated six multilevel mixed models of DR and CR using Stata Software. In Step 4, the ICC, I calculated the proportional change in the variance (PCV) of the response variable between-governorates (PCVBG) and within-governorate (PCVWG), Akaike's information criterion (AIC), and the deviance for each model. In Step 5, I compared and explained the estimated models for ICC, PCV, AIC, and deviance, discussed in some detail. In Step 6, I calculated the forecasted values of DR and CR in each governorate for the years 2014, 2015, 2016, 2017, and 2018.

2.2.1 Multilevel Linear Regression Analysis

The linear mixed models (LMMs) procedure expands the general linear model so the error terms and random effects are permitted to exhibit correlated and nonconstant variability. The LMM, therefore, provides the flexibility to model not only the mean of a response variable, but its covariance structure as well. Researchers can use a multilevel model to study the effects that vary by governorates and can estimate governorate-level averages. Scholars use LMMs when the data include some sort of clustering. Observations from the same cluster are usually more similar to each other than observations from different clusters. If they are, one cannot use statistical methods on these data to assume independence, because estimates of variance, and therefore p-values, will be incorrect. Mixed models not only account for the correlation among observations in the same cluster, they provide an estimate of that correlation.

LMM is called multilevel modeling because one can study the variance and clustering in the response variable at multiple levels of analysis. Here, Level-1 and Level-2 explain the variation in DRs and CRs within-governorates and between-governorates, respectively. Regular regression ignores the average variation between-governorates and individual regression may face sample problems and lack of generalization. The variation across governorates is assumed to be random and uncorrelated with the covariates. Figure 1 shows the structure of a multilevel proposition. I included the explanatory variables - time, DR, and CR - in the models as fixed and random effects due to changes in these variables occurring between- and within- governorates that may affect the proposed response variable.

Models were fitted using the maximum likelihood method. I explain the details of just one model Model-3 of the six models; the details of the other models are similar and easy for readers to understand. In the combined Model-3, I investigated the Level-1 model to examine variations within-governorates and explain these variations over time and crime. Level-2 of Model-3 examined the differences between-governorates and explained these differences in governorate characteristics of CR and time. The combined LMM contains fixed and random effects, such that the predictors of time and CR affect the LMM for the DR response, shown as follows:

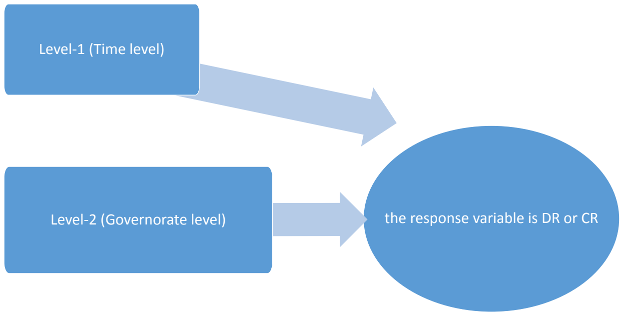

Figure 1: Shows the structure of a multilevel proposition

$$DR_{ij} = \beta_o + \beta_1 time_{ij} + \beta_2 CR_{ij} + u_{oj} + u_{1j} time_{ij} + u_{2j} CR_{ij} + \epsilon_{ij}, \qquad (2)$$

i=1,2,...,14 years, j=1,2,...,12 governorates

where:
DR_{ij} represents an outcome of DR for the ith observation in the jth governorate,
CR_{ij} represents an explanatory variable of CR for the ith observation in the jth governorate,
β_o represents an intercept term (overall mean intercept) of all governorates,
β_1 represents a regression coefficient of time (the overall mean slope of time) of all governorates,
β_2 represents a regression coefficient of crime (the overall mean slope of crime) of all governorates,
u_{oj} is the random intercept for the jth governorate. It is really a residual term that measures the distance from each subject's intercept around the overall intercept, β_o. Rather than calculating an estimate for each distance, the model is able to merely estimate a single variance, σ_o^2,
u_{1j} is the random slope of time for the jth governorate,
u_{2j} is the random slope of crime for the jth governorate,
ϵ_{ij} is the overall error term (Level-1 errors) of the DR for the ith observation in the jth governorate.

Researchers may use fixed-effects to model averages of regression coefficients whereas they may use random-effects to model differences in governorate-variance. The fixed portion of the above model, $\beta_o + \beta_1 time_{ij} + \beta_2 CR_{ij}$, states that one overall regression line representing the population average is required. Fixed-effects are important in studying the impact of variables over time. The random effect, u_{oj}, shifts the regression line up or down according to each governorate, and the random effects, $u_{1j} time_{ij} + u_{2j} CR_{ij}$ explain the effect of time and CR, respectively, on the DR across governorates. The random effects occur at the governorate-level (Level-2). Random-effects are very important in studying the impact of variables across governorates. The $u \sim N(0, \Sigma_u)$ independently of $\epsilon \sim N(0, \sigma_\epsilon^2 I)$. The errors, ϵ_{ij}, are assumed to be homoscedastic and not correlated. The within-governorates variance, σ_ϵ^2, represents how far each ijth observation of DR is to the governorate specific mean. Covariance structure was not specified for the Level-2 u-terms due to the covariance estimates between u_{oj}, u_{1j}, and u_{2j}; $(\widehat{\sigma}_{o1}, \widehat{\sigma}_{o2}, \text{and } \widehat{\sigma}_{12})$ were not found to be significant. Thus, the variance-covariance matrix of $\begin{pmatrix} u_{oj} & u_{1j} & u_{2j} \end{pmatrix}'$ can be shown as follows:

$$\Sigma_u = Var \begin{pmatrix} u_{oj} \\ u_{1j} \\ u_{2j} \end{pmatrix} = \begin{pmatrix} \sigma_o^2 & & \\ & \sigma_1^2 & \\ & & \sigma_2^2 \end{pmatrix} \tag{3}$$

where, σ_o^2 represents the between-governorates variance in the DR, that is, how far each jth mean of DR is to the overall governorates mean, and the σ_1^2 and σ_2^2 represent the between-governorates variances in the DR due to the time and CR respectively.

Table 1 shows six equations of multilevel models under investigation. Models 1 and 4 are called empty models because they do not include explanatory variables; rather, they estimate the governorate response variable (RV) mean and the governorate- and individual-level differences in the RV. In these models, I assumed variations in the RV between-governorates are of similar magnitude for each observation. In using these models, the aim was to identify a possible contextual phenomenon that can be quantified by clustering of RV within-governorates. Models 1 and 4 expand to Models 2 and 5 respectively by including the time variable as fixed- and random-effects. Models 2 and 5 expand to Models 3 and 6 respectively by including CR and DR variables, respectively, as fixed- and random-effects.

Table 1: Six equations of multilevel models to be estimated

Model	Statistical equation combining both levels	Notes
1	$DR_{ij} = \beta_o + u_{oj} + \epsilon_{ij}$	empty model
2	$DR_{ij} = \beta_o + \beta_1 time_{ij} + u_{oj} + u_{1j} time_{ij} + \epsilon_{ij}$	adding time variable
3	$DR_{ij} = \beta_o + \beta_1 time_{ij} + \beta_2 CR_{ij} + u_{oj} + u_{1j} time_{ij} + u_{2j} CR_{ij} + \epsilon_{ij}$	adding crime variable
4	$CR_{ij} = \beta_o + u_{oj} + \epsilon_{ij}$	empty model
5	$CR_{ij} = \beta_o + \beta_1 time_{ij} + u_{oj} + u_{1j} time_{ij} + \epsilon_{ij}$	adding time variable
6	$CR_{ij} = \beta_o + \beta_1 time_{ij} + \beta_2 DR_{ij} + u_{oj} + u_{1j} time_{ij} + u_{2j} DR_{ij} + \epsilon_{ij}$	adding divorce variable

2.2.2 Intraclass correlation (ICC)

ICC measures similarity among the DRs or CRs over time in the same governorate and therefore can be used to operationalize the concept of contextual phenomena (Merlo, 2003). Individuals who live in the same governorate may be more similar to each other than individuals who live in other governorates, as they share a number of socioeconomic and demographic characteristics that may condition similar social and security statuses (Merlo, 2003). Statistically, the ICC can be interpreted as the proportion of variance in the response variable accounted for or explained by clustering. However, the ICC helps to determine whether an LMM is necessary. The ICC can be calculated, for instance, for Model 3 or 6 as follows (Merlo, 2003):

$$ICC = \frac{VAR_{2nd.level}}{VAR_{2nd.level} + VAR_{1st.level}} = \frac{\sigma_o^2 + \sigma_1^2 + \sigma_2^2}{\sigma_o^2 + \sigma_1^2 + \sigma_2^2 + \sigma_\epsilon^2} \quad (4)$$

2.2.3 Proportional change in variance (PCV)

The PCV of RV between-governorates (PCVBG) and within-governorates (PCVWG) explains the variance in the RV between-governorates and within-governorates, respectively, by differences in the explanatory variables. The differences between governorates in the DR and CR may be attributable to contextual influences or to differences in the individual composition of governorates in time, CR, DR, and other individual characteristics, such as socioeconomics, not considered in the current study. By adjusting for individual characteristics, I consider some part of the compositional differences and explain some of the governorate variance detected in the empty model. The PCVBG and PCVWG can be calculated respectively as follows:

$$PCVBG = \frac{\hat{\sigma_o^2} \text{ in the empty model} - \hat{\sigma_o^2} \text{ in the model including the characteristic}}{\hat{\sigma_o^2} \text{ in the empty model}} \quad (5)$$

$$PCVWG = \frac{\hat{\sigma_\epsilon^2} \text{ in the empty model} - \hat{\sigma_\epsilon^2} \text{ in the model including the characteristic}}{\hat{\sigma_\epsilon^2} \text{ in the empty model}} \quad (6)$$

3 Results

The current study rests on real data; therefore, the results should be used as empirical evidence. Tables 2 and 3 show descriptive statistics across governorates and over time, respectively. As shown in Table 2, the highest and lowest means of CR emerged in Aqaba and Ajlun, respectively, and of DR in Zarqa and Tafiela, respectively. Highest and lowest variations in CR emerged in Ajlun and Mafraq, respectively, and in DR, in Tafiela and Zarqa, respectively based on the coefficient of variation (CV). As shown in Table 3, the highest and lowest means of CR emerged in 2000 and 2011, respectively, and of DR, in 2013 and 2003 respectively. The highest and lowest variations in the CR emerged in 2005 and 2008, respectively, and in DR, in 2003 and 2008, respectively, based on CV.

Table 2: Descriptive Statistics for the Rates of Crime and Divorce of Each Governorate over the Period (2000-2013)

	Mean		SD		CV(%)	
Governorate	CR	DR	CR	DR	CR	DR
Irbid	5.27	1.93	2.19	0.41	41.60	21.18
Ajlun	4.36	1.26	2.19	0.38	50.38	30.52
Jarash	5.15	1.61	1.98	0.49	38.49	30.33
Mafraq	7.65	2.06	1.89	0.42	24.68	20.24
Balqa	5.65	1.86	2.10	0.52	37.13	28.12
Zarqa	6.38	2.76	2.55	0.40	39.99	14.58
Amman	8.52	2.36	2.67	0.48	31.37	20.16
Madaba	5.72	2.15	2.43	0.50	42.41	23.20
Karak	4.61	1.29	2.06	0.37	44.63	29.08
Tafiela	4.90	1.10	2.40	0.35	49.03	31.89
Ma'an	5.88	1.96	2.28	0.48	38.82	24.69
Aqaba	13.40	2.21	5.42	0.48	40.42	21.94

Note: CR=crime rate; DR=divorce rate; CV=coefficient of variation

Figure 2 shows a comparison between the DR and CR of each governorate over the period (2000-2013) using a line chart. As shown in this figure, the trend in DR and CR over time was approximately the same in all governorates except Aqaba, where the variation between the DR and CR was larger in the period (2000-2010). Figures 3 and 4 show line charts for the DR and CR, respectively, of each governorate. As shown from these figures, fluctuations in the DR trend between-governorates was slightly larger than in the CR. Also, the DR slightly increased over time whereas the CR slightly deceased.

Tables 4 and 5 show estimates of fixed- and random- effects of DR models and CR models, respectively, their standard errors, and their 95% confidence intervals (CI). The $p < .0001$ of Wald-χ^2 was found highly significant in all models. Given the 95% CI, the fixed and random effects in all models were significant. When performing statistical modeling, the researcher can measure the goodness of fit using different statistical techniques. One very common technique, used in the current study, is a reduction in the deviance (goodness of fit). Researchers use this technique to evaluate the fit of consecutive models

Table 3: Descriptive Statistics for the Rates of Crime and Divorce of Each Year for all Governorates

	Mean		SD		CV(%)	
Year	CR	DR	CR	DR	CR	DR
2000	11.65	1.41	5.03	.47	43.14	33.64
2001	11.60	1.54	3.95	.49	34.05	31.95
2002	5.79	1.45	2.23	.45	38.49	31.05
2003	5.29	1.40	2.44	.53	46.17	37.55
2004	5.24	1.51	2.70	.48	51.61	31.66
2005	5.25	1.58	2.79	.50	53.16	31.50
2006	4.77	1.70	1.99	.58	41.70	34.02
2007	6.97	1.83	2.74	.47	39.25	25.51
2008	7.27	2.06	1.79	.44	24.57	21.37
2009	7.18	2.28	2.64	.52	36.73	22.89
2010	6.47	2.27	2.50	.53	38.62	23.37
2011	4.16	2.24	1.75	.51	42.13	22.78
2012	4.39	2.44	1.93	.55	43.89	22.33
2013	4.49	2.58	2.03	.63	45.18	24.36

Note: CR=crime rate; DR=divorce rate; CV=coefficient of variation

with additional terms. The deviance cannot be interpreted directly; rather it is compared between models that fit the same data set. Suppose that two models, Model-1 and Model-2, have deviances by D_1 and D_2 with k_1 and k_2 parameters, respectively. The difference of the deviance $(D_1 - D_2)$ can be a test statistic having a χ^2-distribution with $(k_2 - k_1)$ degrees of freedom (Cho, 2003). For instance, compared to Model-1, Model-2 shows much better fit, having $(D_1 - D_2 = 269.645)$ with $(k_2 - k_1 = 2)$, and $p < .001$. Compared to Model-2, Model-3 shows much better fit, having $(D_2 - D_3 = 55.231)$ with $(k_3 - k_2 = 2)$, and $p < .001$. Compared to Model-4, Model-5 shows much better fit, having $(D_4 - D_5 = 57.256)$ with $(k_5 - k_4 = 2)$, and $p < .001$. Compared to Model-5, Model-6 shows much better fit, having $(D_5 - D_6 = 40.871)$ with $(k_6 - k_5 = 2)$, and $p < .001$. Compared with the empty model, every consecutive model significantly decreases the deviance and improves the goodness of fit of the model. Also, to search for the best model, I compared the AIC of Models 1, 2, and 3, where Model-3 had the smallest AIC compared with Models 1 and 2. Model 3 is, therefore, the best model of the three. From the comparison between Models 4, 5, and 6, using AIC, Model-6 is the best model of the three because its AIC is smallest. Thus, I used Models 3 and 6 for forecasting.

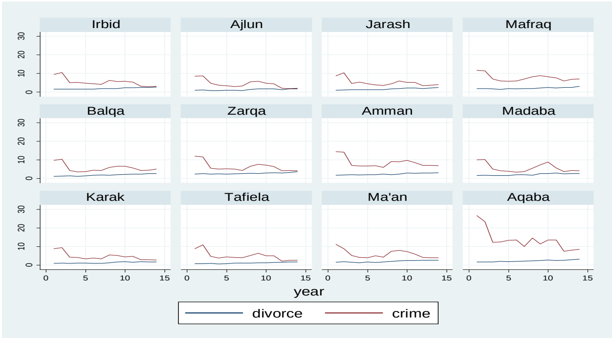

Figure 2: Line charts for the DR and CR of each governorate over the time period (2000-2013)

Figure 3: Shows line chart for the DR of each governorate over the time period (2000-2013)

Estimates of fixed-effects indicated that predictors have a significant influence on the response variable. The fixed effects of predictors in Models 3 and 6 can be explained as follows: For a given jth governorate, as crime increases by one rate, the DR increases on average by $\hat{\beta}_2 = .05$ and as DR increases by one rate, CR increases on average by $\hat{\beta}_2 = 5.39$. Although both effects are significant, the effect of DR on CR is dramatically higher than the effect of CR on DR. For a given jth governorate, as time increases by 1 year, the DR increases on average by $\hat{\beta}_1 = .11$ and as time increases by 1 year, the CR decreases on average by $\hat{\beta}_1 = .87$. Although the effect of time is significant for DR and CR in different directions, the effect of time on the CR is dramatically higher than the effect of time on the DR. The fixed-effect of the time predictor in Models 2 and 5 can be explained as follows: For a given jth governorate, as the time increases by 1 year, the DR increases on average by $\hat{\beta}_1 = .10$, almost the same found for Model-3, and the CR decreases on average by $\hat{\beta}_1 = .35$, less than half found for Model-6. Although the

Table 4: Estimates of Fixed- and Random-Effects of DR Models, their standard errors (SE), their 95% confidence interval (CI); proportional change in the variance (PCV); ICC = intraclass correlation; and AIC = Akaike's information criterion

Statistic		Model-1 (Number of parameters=3)			Model-2 (Number of parameters=5)			Model-3 (Number of parameters=7)		
		Estimate	SE	95% CI	Estimate	SE	95% CI	Estimate	SE	95% CI
Fixed	$\hat{\beta}_o$	1.878	.136	(1.612,2.144)	1.157	.132	(.897,1.416)	.713	.139	(.439,.986)
	$\hat{\beta}_1$				.096	.005	(.087,.105)	.113	.004	(.105,.121)
	$\hat{\beta}_2$							.053	.009	(.036,.070)
Random	$\hat{\sigma_o}$	.454	.099	(.297,.698)	.446	.094	(.295,.676)	.440	.100	(.281,.688)
	$\hat{\sigma_1}$				.010	.005	(.004,.027)	.009	.005	(.003,.026)
	$\hat{\sigma_2}$							.021	.007	(.011,.041)
	$\hat{\sigma_\epsilon}$	.444	.025	(.398,.496)	.184	.011	(.164,.620)	.149	.009	(.132,.168)
PCVBG		Reference			4%			6%		
PCVWG		Reference			83%			89%		
ICC		.51	.113	(.302,.718)	.85	.054	(.714,.933)	.90	.044	(.775,.957)
Deviance		237.140			-32.505			-87.736		
AIC		243.14			-22.50			-73.74		

Note: Model-1 is empty, model-2 is a function of time, and model-3 is a function of time and CR

Table 5: Estimates of Fixed- and Random-Effects of CR Models, their standard errors (SE), their 95% confidence interval (CI); proportional change in the variance (PCV); ICC = intraclass correlation; and AIC = Akaike's information criterion

		Model-1 (Number of parameters=3)			Model-2 (Number of parameters=5)			Model-3 (Number of parameters=7)		
Statistic		Estimate	SE	95% CI	Estimate	SE	95% CI	Estimate	SE	95% CI
Fixed	$\hat{\beta_o}$	6.465	.690	(5.113,7.818)	9.119	.760	(7.629,10.610)	2.887	1.245	(.448,5.327)
	$\hat{\beta_1}$				-.354	.043	(-.437,-.270)	-.872	.090	(-1.049,-.695)
	$\hat{\beta_2}$							5.388	.752	(3.914,6.861)
Random	$\hat{\sigma_o}$	2.282	.512	(1.471,3.541)	2.316	.504	(1.512,3.548)	2.901	.721	(1.783,4.720)
	$\hat{\sigma_1}$				1.5e-09	1.1e-08	(6.4e-16,.004)	.143	.062	(.061,.336)
	$\hat{\sigma_2}$							3.2e-07	2.7e-06	(3.0e-14,3.311)
	$\hat{\sigma_\epsilon}$	2.671	.151	(2.390,2.984)	2.223	.126	(1.990,2.484)	1.853	.122	(1.630,2.108)
PCVBG		Reference			-3%			-62%		
PCVWG		Reference			31%			52%		
ICC		.42	.113	(.227,.645)	.52	.113	(.309,.725)	.71	.109	(.465,.873)
Deviance		835.86			778.60			737.73		
AIC		841.86			788.60			751.73		

Note: Model-1 is empty, model-2 is a function of time, and model-3 is a function of time and DR

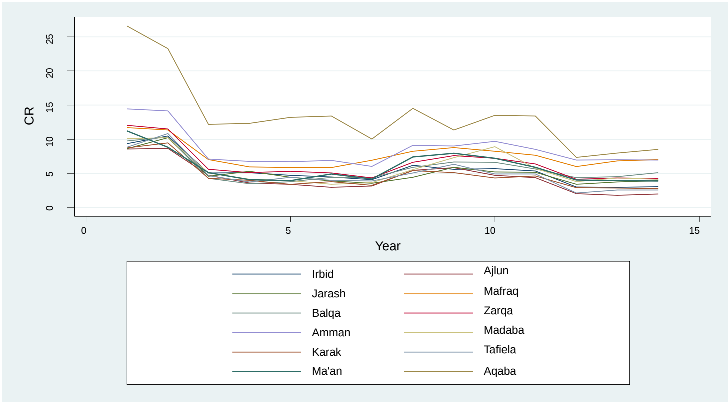

Figure 4: Line Chart for the CR of Each Governorate over the Time Period (2000-2013)

effect of time is significant for both DR and CR in different directions, the effect of time on the CR is dramatically higher than the effect of time on the DR. The fixed effect of intercept, $\hat{\beta_o}$ in Models 2 and 3 and indicates that for DRs in the range of the values observed, .71 and 1.16 is the portion of the DR not explained by time and CR, and not explained by time, respectively. The $\hat{\beta_o}$ in Models 5 and 6 indicates that for CRs in the range of values observed, 2.89 and 9.12 is the portion of the CR not explained by time and DR, and not explained by time, respectively.

In Model-3, the total variance, $\hat{\sigma_o^2} + \hat{\sigma_\epsilon^2}$, in the DR that is not explained by time and CR was 22.58%. Variances $\hat{\sigma_1^2}$ and $\hat{\sigma_2^2}$ in the DR that are explained by time and CR were .01% and .04%, respectively. In Model-6, the total variance, $\hat{\sigma_o^2} + \hat{\sigma_\epsilon^2}$ in the CR that is not explained by the DR and time was 11.85. Variances, $\hat{\sigma_1^2}$ and $\hat{\sigma_2^2}$ in the CR that are explained by time and DR were 2.04% and almost 0%, respectively. However, comparing the results for Models 3 and 6, the CR can explain the between-governorates variance in the DR slightly more than the DR in its explanation the between-governorates variance in the CR. The reverse was found for the time variable, confirmed by visual inspection in Figures 2-4. The total variance, $\hat{\sigma_o^2} + \hat{\sigma_\epsilon^2} = 11.85$ in the CR in Model-6 that is not explained by the DR and time was dramatically higher than the DR in Model-3, which is not explained by the CR and time.

As shown in Table 4, PCVBG=4% of the DR variance between-governorates in empty Model-1 was attributable to the time indicator. The PCVBG=6% of the DR variance between-governorates in empty Model-1 was attributable to time and CR compositional indicators. This means that 6%-4%=2% of the DR variance between-governorates in empty Model-1 was attributable to the CR indicator. As shown in Table 4, PCVWG=83% of the DR variance within-governorates in the empty Model-1 was attributable to the time indicator. The PCVWG=89% of the DR variance within-governorates in the empty

Model-1 was attributable to time and CR compositional indicators. This means that 89%-83%=6% of the DR variance within-governorates in the empty Model-1 was attributable to the CR indicator. However, using the CR as a predictor for the DR reduced the within-governorates variance by 6% and the between-governorates variance by 2%. Using time as a predictor for the DR reduced the within-governorate variance by 83% and the between-governorates variance by 4%.

Adding explanatory variables in the model may increase the governorate-level variance. In cases in which differences between governorates are hidden by their within-governorates composition, the total variance may decrease (as found in the crime models) but the governorate component of the variance increases (Merlo et al., 2004). As shown in Table 5, PCVBG=-3% of the CR in the empty Model-1 was attributable to the time indicator. The PCVBG=-62% of the CR in the empty Model-1 was attributable to time and the DR compositional indicators. This means that -62%-(-3%)=59% of the CR variance between-governorates in the empty Model-1 was attributable to the DR indicator. As shown in Table 5, PCVWG=31% of the CR in the empty Model-1 was attributable to the time indicator. The PCVWG=52% of the CR in the empty Model-1 was attributable to time and the DR compositional indicators. This means that 52%-31%=21% of the CR variance within-governorates in the empty Model-1 was attributable to the DR indicator. However, using the DR as a predictor for the CR reduced the within-governorate variance by 21% and inflated the between-governorates by 59%. Using time as a predictor for the CR reduced the within-governorates variance by 31% and inflated the between-governorates variance by 3%.

I sought to know if the ICC was statistically different from zero. Due to the estimated variance, $\hat{\sigma_o^2}$, was found significant in all models, providing justification for computing the ICC (Goldstein, 2011). An ICC 0% suggests that the governorates are important determinants for social and security statuses, as the observations are nested within-governorates. However, the ICC was significant in all models based on 95% CI. This outcome supports and confirms the role and importance of the within-governorate clustering, mentioned in studies conducted in other countries. Table 4 shows that about 51%, 85%, and 90% of observation residual differences in the DR in Models 1, 2, and 3, respectively, related to the governorate level and might be attributable to contextual factors. Table 5 shows that about 42%, 52%, and 71% of observation residual differences in the CR in Models 4, 5, and 6, respectively, related to the governorate level and might be attributable to contextual factors. Alternatively, this clustering might be attributable to the different composition of governorates. Thus, these ICC results indicate that clustering in the DR is greater than clustering in the CR.

Tables 6 and 7 show the estimated models for each governorate found from Model-3 and Model-6 with forecasted values of DR and CR, respectively, for the years 2014, 2015, 2016, 2017, and 2018. I calculated the forecasted values for additional years, but the further the forecast, the lower the accuracy. However, results showed a steady increase in the DR. The change in the CR is different: the CR increases slightly for the next years in the following governorates: Irbid, Ajlun, Madaba, Karak, and Ma'an. In other governorates, the decrease in the CR is approximately steady, but with different rates. As seen in Table 7, the random coefficients of time seem the same, whereas they are actually not, due to rounding to four digits.

4 Discussion

I partitioned the differences in the DRs and CRs between time and governorate in Jordan to provide relevant social and demographic information. The number of divorce and crime cases with respect to the size of each governorate population was considered by using the rate of the variable. All people living in the same governorate share a common level of socioeconomic and demographic characteristics that differ from the governorate mean in an amount that corresponds to the governorate residual. It makes sense that observations collected from the same governorate will be more similar to each other in relation to at least one characteristic than to observations from other governorates. However, people with similar characteristics may have different degrees of social and security problems according to whether they live in one governorate or another, due to differing economic, political, and environmental circumstances. These contextual indicators cluster in some way by individual information within governorates (Merlo et al., 2005). That is, if the divorce and crime rates differ among time periods in the present study, the quotient may be attributable to the governorates in which these data were collected. Some part of the total differences in DRs and CRs between years might result from the differences between governorates. One objective of the current study was to answer the question of which part of total differences in DRs and CRs is greater: the variation between years (within-governorates) or between governorates themselves?

The suggested relationship between the DR and CR in the current study is conservative. A majority of crimes could happen by unmarried people and the majority of divorces are among those who do not commit crimes. Therefore, conclusions should be drawn carefully and conservatively. Results show a high possibility of family members of a divorced couple committing crimes and a high possibility that people who commit crimes will divorce.

Imagine one collects precise data for particular families. Then, if a divorce takes place in a given year, the crime of their already grown child would not happen immediately but several years afterward, as a consequence of a hard childhood; this possibility is quite limited because over time, the child will forget the hard conditions of divorce, the child will understand the divorce in time as the child's mind grows, and later the grown child will be busy with many activities such as study and marriage. Thus, the possibility of committing a crime will be higher by the parents who suffered directly from the stress of divorce and depression.

Table 6: Estimated Models Found from Model-3 for Each Governorate with Forecasted Values of DR for the Years, 2014, 2015, 2016, 2017, and 2018

Governorate	Estimated model	2014	2015	2016	2017	2018
Irbid	$\hat{DR} = .713 + .113time + .053CR + .084 - .0001time + .0001CR$	3.41	3.49	3.81	3.75	3.86
Ajlun	$\hat{DR} = .713 + .113time + .053CR - .605 + .026time - .005CR$	2.29	2.33	2.59	2.71	2.85
Jarash	$\hat{DR} = .713 + .113time + .053CR - .239 - .004time + .005CR$	2.33	2.39	2.44	2.66	2.77
Mafraq	$\hat{DR} = .713 + .113time + .053CR - .004 + .019time - .006CR$	3.01	3.08	3.19	3.41	3.54
Balqa	$\hat{DR} = .713 + .113time + .053CR + .038 - .015time + .007CR$	2.52	2.53	2.52	2.82	2.92
Zarqa	$\hat{DR} = .713 + .113time + .053CR + .849 + .003time - .001CR$	3.52	3.68	3.75	3.87	3.98
Amman	$\hat{DR} = .713 + .113time + .053CR + .439 - .014time + .003CR$	3.02	3.07	3.12	3.32	3.42
Madaba	$\hat{DR} = .713 + .113time + .053CR + .257 + .001time + .003CR$	2.91	2.91	3.04	3.25	3.36
Karak	$\hat{DR} = .713 + .113time + .053CR - .510 + .011time - .008CR$	2.19	2.18	2.38	2.56	2.68
Tafiela	$\hat{DR} = .713 + .113time + .053CR - .620 - .007time - .008CR$	1.79	1.84	1.94	2.11	2.22
Ma'an	$\hat{DR} = .713 + .113time + .053CR - .018 + .014time + .003CR$	2.82	2.88	3.04	3.20	3.33
Aqaba	$\hat{DR} = .713 + .113time + .053CR + .328 - .034time + .008CR$	2.75	3.10	3.12	2.99	3.07

Note 1. DR = divorce rate; CR = crime rate.

Table 7: Estimated Models Found from Model-6 for Each Governorate with Forecasted Values of CR for the Years, 2014, 2015, 2016, 2017, and 2018

Governorate	Estimated model	2014	2015	2016	2017	2018
Irbid	$\hat{CR} = 2.887 - .872time + 5.388DR - 1.250 - .0001time - .013DR$	2.53	6.46	7.32	0.08	0.96
Ajlun	$\hat{CR} = 2.887 - .872time + 5.388DR + .695 + .0001time + .070DR$	0.02	2.34	2.89	2.83	3.71
Jarash	$\hat{CR} = 2.887 - .872time + 5.388DR + .207 + .0001time - .009DR$	2.93	1.98	1.41	0.31	0.56
Mafraq	$\hat{CR} = 2.887 - .872time + 5.388DR - .692 + .0001time + .124DR$	5.65	5.22	4.97	3.04	2.17
Balqa	$\hat{CR} = 2.887 - .872time + 5.388DR - .784 + .0001time + .009DR$	3.60	1.82	0.90	0.98	0.11
Zarqa	$\hat{CR} = 2.887 - .872time + 5.388DR - 4.638 - .0001time - .012DR$	5.06	4.09	3.57	2.44	1.57
Amman	$\hat{CR} = 2.887 - .872time + 5.388DR - .437 - .0001time - .010DR$	3.02	3.07	3.12	3.42	2.55
Madaba	$\hat{CR} = 2.887 - .872time + 5.388DR - 2.288 - .0001time - .019DR$	2.12	2.38	2.20	0.50	1.37
Karak	$\hat{CR} = 2.887 - .872time + 5.388DR + .697 + .0001time + .083DR$	0.01	1.55	1.79	2.81	3.68
Tafiela	$\hat{CR} = 2.887 - .872time + 5.388DR + 2.189 + .0001time + .050DR$	1.24	1.14	0.82	1.37	2.25
Ma'an	$\hat{CR} = 2.887 - .872time + 5.388DR - 1.189 + .0001time + .029DR$	2.70	3.35	3.36	0.09	0.79
Aqaba	$\hat{CR} = 2.887 - .872time + 5.388DR + 7.490 - .0001time - .339DR$	12.95	12.06	11.31	10.33	9.46

Note 1. DR = divorce rate; CR = crime rate.

Note 2. It is noticed that the estimated values, ignoring the sign, of random coefficient for time are the same due to these values were rounded to 4 decimals.

The MRMs applied in previous studies used individual observations; however, in the current study, I used observation rates across years. Statistically, it is necessary to use multiple linear regression analysis, which considers the dependence of the outcome variable between the observations from the same governorate. If this assumption is violated, results of the regression analysis are biased. However, clustering in the DRs and CRs over time within-governorates is not a statistical nuisance that only needs to be considered to obtain correct statistical estimations (Merlo et al., 2005) but a key concept in social and security fields that itself yields important information (Merlo et al., 2001; Petronis and Anthony, 2003). The more the people characteristics in a governorate are alike, as compared with people in other governorates, the more probable it is that the determinants of individual characteristics directly relate to the contextual environment, or that the social processes of geographical segregation are taking place. That is, similar types of people choose or are forced to reside in a given governorate (Merlo et al., 2005). Those aspects are of great significance to reduce inequalities in social and security fields in certain geographical areas rather than for specific people only.

When ICC equals zero, the suitability of performing a multilevel analysis is questionable (Snijders and Bosker, 1999). This is one of the several reasons that lead to the application of MRM, where, in the current study, the ICC results in all models were more than 40%. The correlation results between the random intercept and the random slopes in Models 2, 3, 5 and 6 were not significant; thus, I did not show them in the results section. The same was found for the correlation results between the random slopes in Models 3 and 6.

Using the CR as a predictor for the DR reduced the within-governorate variance more than four times, compared with between-governorates variance. Using the DR as a predictor for the CR reduced the within-governorate variance but inflated the between-governorates variance. The CR variance within-governorate attributable to the DR was more than double the DR variance within-governorate attributable to the CR. Using time as a predictor for the DR reduced the within-governorate variance more than the between-governorates variance. Using time as a predictor for the CR reduced the within-governorate variance but slightly inflated the between-governorates variance. Both divorce and crime can lead to each other, but divorce affects crime more in terms of fixed-effects and the PCVWG, and crime affects divorce more in the random-effects and deviance. The increase in the DR was relatively stable for the next forecasted years when the CR decreases in most governorates at a relatively stable rate.

That the CR has decreased significantly in Jordan in all governorates for the last 14 years is strangely peculiar; everywhere experienced an uptick in crime around (2008-2009), and then crime declined again. It is quite difficult to explain why because related data are unavailable. The present study may help provide greater insight into the importance of the statistical measures of clustering that are appropriate for quantifying contextual phenomena. The current study can be extended in some ways. For instance, researchers might use more covariates and levels to provide greater depth and insight to the results if they can find the data. However, the present study supports the use of multilevel analysis when addressing variables measured at different hierarchical levels.

5 Conclusions and Recommendations

Statistical measures of multilevel variations can effectively quantify contextual effects in different governorates, which is a relevant issue for understanding divorce and crime inequalities. I can summarize the conclusions in at least six aspects: First, the positive fixed effect of the DR on the CR was higher than the positive fixed effect of the CR on the DR. Second, the negative fixed effect of time on the CR was higher than the positive fixed effect of time on the DR. Third, the moderate to large results of ICC explained the total variance in the DRs and CRs, accounted for by clustering in the same governorate. This clustering could be attributable to the same composition of governorates, where DR clustering was stronger than CR clustering. Fourth, the large results of ICC explain that the governorates are very important in understanding the differences in DRs and CRs. Fifth, the random effect of the CR can explain the between-governorates variance in the DR a bit more than the random effect of the DR in between-governorate variances in CR. Sixth, the random effect of time on the DR emerged more than that on the CR.

Although the present paper could not study all covariates and their relationship to divorce and crime, it was possible to highlight important issues raised in social, epidemiological, and public health analyses. Because ICC results were moderate to large, focusing interventions on governorates may be an efficient strategy to evaluate the relative importance of the governorate level and can promote countrywide resources for specific governorate interventions for those social and security outcomes that are largely determined by the governorate. Thus, a major recommendation is to focus on creating social and awareness programs and services for divorced and married people, especially for those who are going to be divorced, to improve their living conditions and that of their families and, consequently, their communities. Also, the government should help divorced people refrain from becoming criminals. Adopting government and private training strategies corresponding to social-awareness needs and providing guidance can create social awareness and improvement. Further studies should examine more explanatory variables such as age and socioeconomic status, which may cause divorce and crime. Also, more levels of analysis, such as municipality-level, could provide information about which level of analysis would better discern the problems of divorce and crime, thereby saving country resources and time to address these problems. Finally, policies to improve social and security awareness need to be monitored in all times and places.

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