Table 2.2 Model comparison of the estimation results explaining the crime rate

	OLS	SAR	SEM	SLX	SAC	SDM	SDEM	GNS
Intercept	0.686**	0.451**	0.599**	0.750**	0.478**	0.428**	0.735**	0.509
	(14.49)	(6.28)	(11.32)	(11.32)	(4.83)	(3.38)	(8.37)	(0.75)
Income	−1.597**	−1.031**	−0.942**	−1.109**	−1.026**	−0.914**	−1.052**	−0.951**
	(−4.78)	(−3.38)	(−2.85)	(−2.97)	(−3.14)	(−2.76)	(−3.29)	(−2.16)
House value	−0.274**	−0.266**	−0.302**	−0.290**	−0.282**	−0.294**	−0.276**	−0.286**
	(−2.65)	(−3.01)	(−3.34)	(−2.86)	(−3.13)	(−3.29)	(−3.02)	(−2.87)
W * Crime rate		0.431**			0.368*	0.426**		0.315
		(3.66)			(1.87)	(2.73)		(0.33)
W * Income				−1.371**		−0.520	−1.157**	−0.693
				(−2.44)		(−0.92)	(−2.00)	(−0.41)
W * House value				0.192		0.246	0.112	0.208
				(0.96)		(1.37)	(0.56)	(0.73)
W * Error term			0.562**		0.166		0.425**	0.154
			(4.19)		(0.56)		(2.69)	(0.15)
R^2	0.552	0.652	0.651	0.609	0.651	0.665	0.663	0.651
Log-Likelihood	13.776	43.263	42.273	17.075	43.419	44.260	44.069	44.311

**Significant at 5 %; *Significant at 10 %; T-values in parentheses, W = Binary contiguity matrix LR test $= -2*(\log L_{restricted} - \log L_{unrestricted})$

Advice for model selection: Pick a model that is both statistically and economically significant. Find a balance between fit, flexibility and interpretability

On the basis of these robust LM tests the SAR model is more appropriate.

The SDM appears to outperform the SLX model (LR-test 54.370, 2 df, critical value 5.99), but not the SAR model (LR-test 1.994, 1 df, critical value 3.84) and the SEM model (LR-test 3.974, 2 df, critical value 5.99).

The SDEM model also appears to outperform the SLX model (LR-test 53.998, 1 df, critical value 3.84) but not the SEM model (LR-test, 3.592, 1 df, critical value 3.84).

Whether it is the SDM model or the SDEM model that better describes the data is difficult to say, since these two models are not nested

Unfortunately, estimation of the GNS model which nests these two models does not provide an answer. The increase of the log-likelihood function value when estimating this model is so small that it is impossible to draw any conclusion as to whether it is SDM, SDEM or GNS that best describes the data.

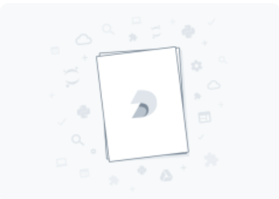
Table 2.3 Model comparison of the marginal effects of the explanatory variables on the crime rate

	OLS	SAR	SEM	SLX	SAC	SDM	SDEM	GNS
Direct effects								
Income	−1.597**	−1.086**	−0.942**	−1.109**	−1.063**	−1.024**	−1.052**	−1.032**
	(−4.78)	(−3.44)	(−2.85)	(−2.97)	(−3.25)	(−3.19)	(−3.29)	(−3.28)
House value	−0.274**	−0.280**	−0.302**	−0.290**	−0.292**	−0.279**	−0.276**	−0.277
	(−2.65)	(−2.96)	(−3.34)	(−2.86)	(−3.10)	(−3.13)	(−3.02)	(0.32)
Indirect or spatial spillover effects								
Income		−0.727*		−1.371**	−0.560	−1.477*	−1.157**	−1.369
		(−1.95)		(−2.44)	(−0.18)	(−1.83)	(−2.00)	(0.02)
House value		−0.188*		0.192	−0.154	0.195	0.112	0.163
		(−1.71)		(0.96)	(−0.39)	(0.66)	(0.56)	(−0.03)

**Significant at 5 %; *Significant at 10 %; T-values in parentheses, W = Binary contiguity matrix

- An evaluation of the direct and indirect effects can also help us chose the best model
- The spillover effects of SEM are zero by construction
- In this dataset, differences between direct effects and coefficient estimates are relatively small. Thus, feedback effects are relatively small
- In this dataset, differences in direct effects across models are small.
- In this dataset, differences in the indirect effects across models are large
- In this dataset, the spillover effects produced by SLX, SDM, SDEM, and GNS are more or less comparable to each other.
- The SAR (and SAC) suffers from a flexibility problem: The IE/DE ratio has to be same for each explanatory variable. The model is TOO rigid model spillover effects adequately. It can produce wrong signs
- The GNS is usually overparameterized. As a result, significance levels are usually low
- In this dataset, only SDM and SDEM produce acceptable results. This is a challenge because these two models have different interpretation

SDM implies global spillovers while SDEM imply local spillovers.



[STATA] Spatial cross-section models: Columbus example

Deepnote