

# Does Electronic Monitoring Home Detention Program Work? Evaluating Program Suitability Based on Offenders' Post-Program Recidivism Status



Avdi S. Avdija<sup>1</sup> and JiHee Lee<sup>2</sup>

Justice Policy Journal • Volume 11, Number 1 (Fall)

© Center on Juvenile and Criminal Justice 2014 • [www.cjcj.org/jpj](http://www.cjcj.org/jpj)

## Abstract

*The main purpose of this study is to investigate the impact of Electronic Monitoring Home Detention (EMHD) program on post-program recidivism status of those who have participated in the program. The second objective of this study is to determine what factors best predict post-EMHD program recidivism. A binary logistic regression analysis was performed on a fourteen-variable model attempting to predict post-program recidivism status for the subjects who have been sentenced in the EMHD program. The analyses of the data in this study are based on a total of 293 subjects. A significant, yet interesting finding that emerged from this study is that EMHD program, measured as the "exit status" (successful completion vs. unsuccessful) had no effect on reducing post-program recidivism for the subjects that participated in the program. The data show that the odds of one recidivating after their release were two times higher for those who had successfully completed the EMHD program compared to the subjects who did not complete the program.*

---

<sup>1</sup> Department of Criminology and Criminal Justice, Indiana State University.

<sup>2</sup> Department of Justice Administration, University of Louisville.

Corresponding author: Avdi S. Avdija, Ph.D. Assistant Professor of Criminology and Criminal Justice, Indiana State University Email: [avdi.avdija@indstate.edu](mailto:avdi.avdija@indstate.edu)

## Introduction

In the United States, intermediate sanctions have been used as alternative means of punishment for more than three decades. Depending on the sentencing guidelines of the jurisdictions, these sanctions are imposed by the courts at either pre-trial or post-trial stage (Roy, 2010; Lilly & Ball, 1993). Intermediate sanctions such as electronic monitoring home detention (EMHD) provide more restrictive control compared to traditional probation, but it is a form of less harsh punishment than imprisonment (Caputo, 2004; Lilly & Ball, 1993). Non-imprisonment sanctions include a continuum of eight different sentencing options. This includes intensive probation supervision, victim restitution, community service, substance abuse treatment, day reporting, electronically monitored home detention, halfway houses, and boot camps (Caputo, 2004; Clear & Dammer, 1999; Lilly & Ball, 1993). These sanctions provide the court with a wide spectrum of sentencing options matching sanctions according to the severity of the offense. Having been conceptualized as punishments, situated in a continuum between traditional probation and imprisonment, intermediate sanctions have built their credibility and diversity based on a mixture of political, judicial and fiscal needs, which divide the objects of intermediate sanctions into two exclusive but interrelated purposes: administrative and correctional (Clear & Dammer, 1999; Lilly & Ball, 1993). The administrative purpose of intermediate sanctions is primarily designed to reduce jail and prison overcrowding.

The number of incarcerated inmates in the U.S. has been increasing consistently since the 1980s. In 2009, more than 1,000,000 offenders were incarcerated in state and federal prisons, which marked an increase by 0.2 % compared to the numbers of 2008 (Bureau of Justice Statistics, 2010). This given fact has required more government funding to build new prison facilities and to manage overpopulation behind bars more effectively so as to protect the communities from future threats (Yeh, 2010; Padgett, Bales, & Blomberg, 2006; Renzema & Mayo-Wilson, 2005). Thus, rapid growth in the imprisonment rate has not only resulted in prison overcrowding, but also caused a great deal of public and political concern regarding over-expenses and reduced effectiveness of imprisonment. Consequently, these multifaceted issues have convinced the criminal justice agencies to look for community-based alternatives to incarceration, specifically intermediate sanctions. These sanctions make it possible for the correctional agencies, mainly federal and state agencies, to save expenses of building new detention facilities and hiring more correctional staff with an already limited budget (Finn & Muirhead-Steves, 2002; Lilly & Ball, 1993).

The issue of cost-effectiveness has accelerated the implementation of alternatives to formal penitentiary settings, and by doing so, both the criminal justice system and the selected offenders have benefitted from the modified sentencing options. In theory, intermediate sanctions work as a diversion, which allows certain categories of offenders an opportunity to avoid unnecessary prosecution or prison sentence, while maintaining a greater level of offenders' accountability and agency's surveillance (Roy, 2010). As opposed to the negative impact of imprisonment (e.g., maladapted prison subculture), the advantages of intermediate sanctions are multi-faceted: (a) less punitive control on selected offenders, (b) less expense to the taxpayer, and (c) more rehabilitative (Padgett et al., 2006).

Of the eight different types of intermediate sanctions mentioned earlier, Electronic Monitoring Home Detention (EMHD) is one that is being increasingly used in the United States since its establishment by the Palm Beach County Sheriff's Department in Florida in 1984 (Gainey & Payne, 2003; Roy, 2010). Across the country, a wide variety of offenders are placed under supervision of EMHD. Utilizing continuous transmission of electronic signals from an electronic device, the application of EMHD has greatly increased in the U.S. criminal justice system, comprising approximately 20 percent of community-based sanctions (Barton & Roy, 2008; Gable & Gable, 2005; Roy, 2010). Despite its utilization, from a research perspective, the biggest question that needs to be addressed is its effectiveness in terms of reducing re-offending. In other words, does EMHD have an impact on recidivism among those who are sentenced to the program?

## **The Impact of Electronic Monitoring on Recidivism**

Fewer research studies have actually evaluated the outcome of EMHD program in term of its effectiveness in reducing recidivism. Most prior studies have been focused primarily on evaluating the process; that is, whether or not offenders successfully complete the program (Di Tella & Schargrotsky, 2013; Baumer et al., 1993; Brown & Roy, 1995;; Enos et al., 1992; Kuplinski, 1990; Maxfield & Baumer, 1990; Renzema & Skelton, 1990). Of those studies that have evaluated the outcome, on the other hand, not all of them produced the same empirical results. A number of research studies show that Electronic Monitoring (EM) reduces recidivism (Bales, Mann, Blomberg et al., 2010; Marklund & Holmberg, 2009; Padgett et al., 2006; Stanz & Tewksbury, 2000; Dodgson, Goodwin, Howard, et al., 2001) and therefore it has a deterrent effect on crime. However, this conclusion is not universally supported by researchers. Some research studies show that EM does not reduce re-arrest rates. Stanz and Tewksbury's (2000) study, for example, shows that of the

85% of offenders who successfully completed the program, 69% of them were re-arrested shortly after they were released. Moreover, other researchers have also voiced their concerns in regards to ineffectiveness of EMHD compared to other available intermediate sanctions (Gable & Gable, 2005; Renzema & Mayo-Wilson, 2005).

While there are some studies that have produced common results, either in favor of electronic monitoring or against it, there are studies that have produced mixed results or results from which conclusions cannot be drawn (Finn & Muirhead-Steeves, 2002; Jolin & Stipak, 1992; Jones & Ross, 1997). The prior research findings overall imply in their analysis that studies of the post-program recidivism outcome of EMHD proved that placement to this given program may not convincingly represent a true alternative to imprisonment fulfilling a deterrence purpose (Bonta, Wallace-Capretta, & Rooney, 2000).

In summary, there are two extreme ends when it comes to evaluating the effectiveness of EMHD program. At one end, there is empirical evidence suggesting that electronic monitoring has a deterrent effect on crime – it reduced recidivism. At the other end of the spectrum, there is empirical evidence that suggests otherwise. Yet, there is a gray area in between the two extremes that suggests no conclusions can be drawn about its effectiveness because of the mixed results; thus suggesting more research is needed in this area. The current study is designed to fulfill some of those gaps by adding to the existing literature some empirical evidence to help researchers draw evidence-based conclusions.

## **The Current Study**

The main purpose of this study is to investigate the impact of EMHD program on post-program recidivism status of those who have participated in the program. To measure the impact of EMHD on post program recidivism, we used the “exit status” outcome of the program. In this study, two groups of offenders represent the “exit status;” those who have successfully completed the EMHD, and those who have not successfully completed the program. Thus, in this study we attempt to find out whether there is a significant difference between the two groups of participants in terms of exit status and post-program recidivism. Additionally, we have included thirteen other contributing factors that we use as control variables in this study. We

started the analysis by examining the suitability of the data first. To accomplish that, we computed the correlation matrix for all variables together and variance inflation factor (VIF) values for each variable to determine whether or not we have multicollinearity issues within the data.

## Methods

The dependent variable of interest in this study is post-program recidivism status of offenders who have participated in the EMHD program. The dependent variable was coded as a "Yes/No" dichotomous indicator of recidivism. Individuals who have committed any crimes within one full year after they had exited the program are classified as "recidivated," coded 1 otherwise coded 0. The binary nature of the dependent variable in this study necessitated the use of logistic regression model to analyze whether the likelihood of recidivism among offenders who have participated in the EMHD program would be affected by successful completion of the program. In other words, the post-program status is used to evaluate whether or not the EMHD program has an impact on recidivism. Logistic regression estimates the probability that an event will occur, and identifies the statistically significant predictors of that event (Pallant, 2011). The probability of an event occurring (coded 1) is made in reference to another event (coded 0).

The main independent variable or predictor of recidivism in this study is the exit status; coded dichotomously with "Yes/No" binary response categories. Individuals who have successfully completed the EMHD program were classified as "successful" coded 1, otherwise coded 0. Subjects that were classified as "unsuccessful" were individuals that, for various reasons, did not complete the entire program (e.g., were removed from the program for violations, were re-arrested while in the program, etc.). Of the 293 subjects, 112 (38.2%) had successfully completed the program and 181 (61.8%) of them failed to complete it. Other independent variables that we used in this study include age at the time of placement in the EMHD program, race (non-whites coded 1; whites coded 0), gender (female coded 0; male coded 1), marital status (not married coded 0; married coded 1), education (less than high school/GED coded 0; more than high school/GED, coded 1), employment status (unemployed code 0; employed coded 1), type of offense (misdemeanor code 0; felony coded 1), drunk driving offense (*No* coded 0; *Yes* coded 1), prior placement in counseling (*No* coded 0; *Yes* coded 1), sentence length (i.e. the numbers of days each subject spent under EMHD supervision), prior offense (*No* code 0; *Yes* coded 1), the number of prior offenses, prior drunk driving offense (*No* coded 0; *Yes* coded 1), and the number of prior drunk driving offenses.

## *Data Source*

This study used administrative data that were collected by the Vigo County Community Corrections Office in Indiana, USA. The subjects in this study include all offenders who were sentenced to the EMHD program and completed their sentences, regardless of success in the program, from January 2006 through December 2009. The post-program recidivism data were collected from January through the end of December of 2010, as part of post-release follow-up. The recidivism data were gathered from the State of Indiana criminal history information system. Any new recorded offenses that were committed by the same subjects that went through the EMHD program were classified as “recidivism.” This included re-arrests for committing any misdemeanor and/or felony offenses. It is noteworthy that most offender participants in the EMHD in Vigo County, Indiana, were nonviolent offenders and all participants that were sentenced to the program over the four year period were convicted of nonviolent offenses. In terms of human subject protection, the confidentiality of all subjects in this study is maintained by using identification numbers for each subject instead of their names.

## *Subjects in This Study*

The analyses of the data in this study are based on a total of 293 program subjects. The subjects who participated in the EMHD program were very diverse in terms of age, gender, and race. The age distribution of the subjects in these data ranged from 18 to 71. The average age of the subjects was 34 years old ( $SD = 10.50$ ). Among the subjects, 246 (84%) were whites, 47 (16%) were non-whites. In terms of gender, 16% of the subjects were females and 84% were males. Moreover, the descriptive analysis shows that only 19.8% of them were married, whereas 80.2% were not married at the time when they were sentenced to the EMHD program. As for the educational level, 70% had achieved high school or higher level of education and 30% of them had less than high school/GED. More than two thirds of the subjects (71%) were employed, and 29% were unemployed at the time of program participation. Furthermore, 81.9% of the subjects were sentenced to the EMHD program because they had committed some type of felony crimes, whereas 18.1% had committed misdemeanors. The distribution of the sentence length indicated that the sentence length ranged from 12 days to 331 days, with an average of about 211 days. About 64% of the subjects were sentenced to up to 180 days, while 36% of them were involved in the program more than six months (181+), but no more

than 331 days. The majority of participants (82%) had never been placed in the Vigo County Community Corrections prior to the current admission.

## Results

To investigate the effects that the successful completion of Electronic Monitoring Home Detention program (variable: exit status) and other independent variables on the post-program recidivism status, we computed a logistic regression model. In the first stage of the analysis, however, we computed the Spearman correlation coefficients (see Table 1) and the Variance Inflation Factor (VIF) values to make sure there were no issues with multicollinearity. The Spearman correlation matrix shows that there was one pair of independent variables that had a high correlation. The prior placement in counseling (variable: prior counseling) and the number of prior drunk driving offenses (variable: number of D. D. offenses) had a high correlation,  $r_s=.737$ ,  $n = 293$ ,  $p < .01$ . Also the exit status and sentencing length showed a moderate to high correlation,  $r_s=.608$ ,  $n = 293$ ,  $p < .01$ . Nonetheless, these moderately high correlated sets of variables did not rise to the level of concern with the multicollinearity. Besides the correlation matrix, the data can be inspected by looking at the variance inflation factor (VIF) values. Thus, to make sure that the two sets of variables discussed above did not violate the multicollinearity assumption, we computed the VIF values also. The analyses show that the tolerance value for each independent variable was greater than .604, which exceeded the suggested criteria of below .1 (Pallant, 2011). "Tolerance [value] is an indicator of how much of the variability of the specified independent [variable] is not explained by the other independent variables" (Pallant, 2011, p. 158). The tolerance value less than .10 is an indication of multicollinearity problem. On the other hand, the tolerance value greater than .10 indicates there are no issues with multicollinearity. The tolerance value for each independent variable in this study was greater than .1; thus multicollinearity assumption was not violated. Also the variance inflation factor (VIF) values were well below the cut-off value of 10. They ranged from 1.042 to 1.653. The suggested cut-off value for the VIF is 10 (Pallant, 2011; Field, 2009). This means that VIF values below 10 do not violate multicollinearity assumption.<sup>3</sup> In light of the

---

<sup>3</sup> To rule out the issues with multicollinearity in a given data set, the tolerance values should be above .1; whereas the variance inflation factor values (VIF) should be below 10 (see Pallant, 2011; Field, 2009). As mentioned above, the tolerance value for each independent variable that was included in this study was greater than .604, which indicates that 60% of the variability for each independent variable remains unexplained by other variables. Thus, there is enough variation for each independent variable that is not shared with other variables in the model. Less shared

above statistical results, we concluded that there were no issues with the multicollinearity in this fourteen-variable model. After the preliminary analysis of the data, to address the objectives of this study, we computed the binary logistic regression coefficients.

The results of logistic regression analysis show that the full model was statistically significant,  $\chi^2(14, N = 293) = 44.699, p < .001$ , indicating that the model was able to distinguish between those who recidivated and those who did not recidivate after participating in the EMHD program. The model as a whole explained between 14% (Cox and Snell R squared) and 19% (Nagelkerke R squared) of the variance in the post-program recidivism status for the offenders who participated in the EMHD program, and correctly classified approximately 75% of the cases.

	7	8	9	10	11	12	13	14
----								
.041	----							
.109	.013	----						
-.091	.105	.176**	----					
.070	.063	.128*	.161*	----				
.	-.019	.063	.151*	.045	----			
.045	.737**	.061	.096	.129*	-.015	----		
.059	.012	.608**	.081	.194**	-.004	.077	----	
.119*	.088	.024	.094	.132*	-.146*	.076	.112	----

variation between independent variables indicates that there would be no problems with multicollinearity.



**Table 1** Spearman Correlation Matrix

Variables	1	2	3	4	5	6
1. Age	----					
2. Gender	-.047	----				
3. Race	-.048	.064	----			
4. Marital Status	.203**	-.016	-.030	----		
5. Education	.071	.099	-.119*	-.011	----	
6. Employment	.022	.192*	-.089	-.003	.041	----
7. Type of Offense	.010	-.060	.036	.011	-.056	-.105
8. Prior	.092	-.004	-.045	.056	.035	.056
9. Sentence	.043	.001	-.113	.048	.015	.064
10. Prior Offense	.056	-.020	-.113	-.139*	.008	.039
11. Number of	.029	.067	.022	-.086	-.070	-.023
12. Drunk Driving	.174**	.045	-.141*	-.024	.099	.145*
13. Number of D.	.043	.034	-.051	-.013	.043	.087
14. Exit Status	.034	.038	-.038	.015	-.006	.039
15. RECIDIVISM	-.210	-.018	-.056	-.085	-	-.060

Notes: \*p= <.05; \*\*p= <.01 (2-tailed). Post-program recidivism is the dependent variable.

The main independent variable in this study was the “exit status,” measuring the effect of the EMHD on post-program recidivism status of those who have successfully completed the program and those who have not successfully completed the program. The analyses in Table 2 show that the exit status has the odds ratio of 2.001. This indicates that offenders who successfully completed the EMHD program (coded 1) in fact were two times more likely to recidivate after completing the program compared those who did not successfully complete the program. Thus, if the program’s success is measured based on the post-program recidivism status of those who have participated in the program, this study indicates that the program does not work.

Two other variables (age and education) were statistically significant in predicting post-program recidivism. Age recorded an odds ratio of .956. This indicates that the odds of an offender recidivating again decreased by a factor of .956 for every unit increase in age, holding all other variables constant. In other words, the odds of an offender committing another crime after released decreased by 4.4% for each year increase in age. Among other statistically significant variables in the model was education. Education recorded an odds ratio of .507, which indicates that offenders who had completed high school or more were 49.3% less likely to recidivate compared to those who had less than high school level of education (odds ratio = .507), holding all other variables constant. In other words, the higher the education, the less likely to recidivate. Race, marital status, employment status, whether or not an offender was placed in counseling, sentence length, types of offense (misdemeanor vs. felony), and prior drunk driving offenses were statistically insignificant in predicting post-program recidivism status for those who participated in the EMHD program.

**Table 2** Logistic Regression: Predicting Offender's Post-Program Recidivism Status

Variables	B	S.E.	Wald	Sig.	Exp(B)	95.0% C.I. for EXP(B)	
Age	-.045	.014	11.213	.001	.956	.931	.981
Gender (male)	.007	.356	.000	.984	1.007	.502	2.022
Race (non-white)	-.639	.376	2.879	.090	.528	.252	1.104
Marital Status (married)	-.227	.341	.442	.506	.797	.409	1.555
Education	-.679	.285	5.697	.017	.507	.290	.886
Employment (employed)	-.205	.290	.501	.479	.815	.462	1.437
Type of Offense	.541	.355	2.319	.128	1.718	.856	3.449
Placed in Counseling	.599	.450	1.772	.183	1.820	.754	4.398
Sentence Length	-.145	.112	1.666	.197	.865	.694	1.078
Prior Offense	.618	.395	2.448	.118	1.855	.855	4.024
Number of Prior Offenses	.416	.258	2.593	.107	1.515	.914	2.514
Drunk Driving Offenses	-.445	.285	2.431	.119	.641	.367	1.121
Number of Drunk D/ Offen.	-.129	.253	.262	.609	.879	.536	1.442
Exit Status	.693	.340	4.145	.042	2.001	1.026	3.897
Constant	1.016	.813	1.562	.211	2.762	----	----

Note: Dependent Variable – Post Program Recidivism

## Discussion

The main purpose of this study was to investigate the impact of EMHD program on post-program recidivism status of those who have participated in the program. The logistic model that we employed in this study explained 19% of the variance in recidivism, and correctly classified 75% of the cases. Needless to say, of the fourteen variables we included in the model, only three of them provided a significant contribution in predicting recidivism. The main independent variable (the variable of interest) in this study was the exit status of the offenders who were sentenced to EMHD program.

Overall, the results of this study show that Electronic Monitoring Home Detention program does not reduce recidivism. In fact, this research indicates that

the likelihood of re-offending for those who have successfully completed the program increases compared to those who have not successfully completed it. Needless to say, based on the results of this study, we do not conclude that EMHD does not work, unless its success is measured based on its impact on recidivism. Considering that the entire model explains only a small portion of variation (19%) in recidivism status of the offenders who have participated in the program, the current study provides only a piece of evidence that shows electronic monitoring does not reduce recidivism. This significant finding contradicts prior research studies that found empirical evidence showing electronic monitoring reduced recidivism (Di Tella & Schargrotsky, 2013; Bales et al., 2010; Marklund & Holmberg, 2009; Padget et al., 2006; Dodgson et al., 2001; Stanz & Tewksbury, 2000).

Furthermore, the fourteen-variable model that we tested in this study shows that offenders who are less likely to recidivate are older in age, and more educated. Thus, the results of this study imply that removing younger offenders and those with less than high school education from the program may improve the success rate of EMHD program. This study shows that age and education have a positive and statistically significant impact on reducing recidivism.

As with any research study, this study has its own limitations. One of the limitations that should be taken into account when interpreting the results is the number of participants in this study. A study with a larger number of cases may produce different results. Thus, the readers are advised to interpret the results with this limitation in mind. Also the level of supervision during the program is unknown. In other words, we do not know whether or not individuals who recidivated after completing the program received the same type of supervision as others. Additionally, it is noteworthy that EMHD program has multiple objectives, and only one of them includes reducing recidivism. Other objectives include assisting offenders in terms of correctional services, reducing costs of criminal justice agencies, to provide offenders who do not need the security of prison settings with the opportunity to maintain employment, etc. In short, just because it does not have a desirable effect on recidivism, it does not mean it should be discontinued. Recidivism can be used as one among many measuring units to measure its effectiveness. Perhaps, cost-effectiveness (i.e., keeping someone in prison vs. at home, correctional expenditures, avoiding construction and operation costs of new jails and prisons, etc.) can be used to measure the necessity of this program in the criminal justice system. Another limitation to consider is that in this study, we do not examine the types of crimes offenders commit after exiting the EMHD. We test only the overall effect of EMHD on recidivism. Recidivism in this study includes any misdemeanor or felony offenses, regardless of the type of offense (e.g., property

crimes vs. crimes against persons). Also, readers should keep in mind that offenders who are sentenced in the EMHD program do not live in the same area. Thus, recidivism could be as a result of factors beyond the influence of EMHD program; factors such as changes in the lifestyle, monetary needs, environmental factors, or other co-existing conditions that may affect the generalizability of the results of this study.

## References

- Bales, W., Mann, K., Blomberg, T., Gaes, G., Barrick, K., Dhungana, K., & McManus, B. (2010). *A quantitative and qualitative assessment of electronic monitoring*. Washington D.C: National Institute of Justice.
- Baumer, T., Maxfield, M., & Mendelsohn, R. (1993). A comparative analysis of three electronically monitored home detention programs. *Justice Quarterly*, 10(1), 121-142.
- Barton, S., & Roy, S. (2008). Convicted drunk drivers in an electronic monitoring program: An exploratory study. *International Journal of Criminal Justice Sciences*, 3(1), 28-43.
- Bonta, J., Wallace-Capretta, S., & Rooney, J. (2000). Can electronic monitoring make a difference? An evaluation of three Canadian programs. *Crime & Delinquency*, 46(1), 61-75.
- Brown, M. P., & Roy, S. (1995). Manual and Electronic House Arrest: An Evaluation of Factors Related to Failure, in J.O. Smykla & W.L. Selke (eds.) *Intermediate Sanctions: Sentencing in the 90s* (pp. 1-20), Cincinnati, OH: Anderson Publishing.
- Bureau of Justice Statistics. (2010). *Prisoners in 2009*. Washington D.C: U.S. Department of Justice, Bureau of Justice Statistics.
- Caputo, G. A. (2004). *Intermediate sanctions in corrections*. Denton, TX: University of North Texas Press.
- Clear, T. R., & Dammer, H. R. (1999). *The offender in the community*. Belmont, CA:Wadsworth/Thomson learning.
- Di Tella, R., & Schargrodsky, E. (2013). Criminal recidivism after prison and electronic monitoring. *Journal of Political Economy*, 121 (1), 28-73.
- Dodgson, K., Goodwin, P., Howard, P., Llewellyn-Thomas, S., Mortimer, E., Russell, N., et al. (2001). *Electronic monitoring of released prisoners: An evaluation of the*

- home detention curfew scheme* (Home Office Research Study No. 222). London: Home Office Research Development and Statistics Directorate.
- Enos, R., C.M. Black, J.F. Quinn, & J.E. Holman (1992). *Alternative sentencing: Electronically monitored correctional supervision*. Bristol, IN: Wyndham Hall Press.
- Field, A. (2009). *Discovering Statistics Using SPSS*(3<sup>rd</sup> ed.). London, England: Sage Publications, Inc.
- Finn, M. A. & Muirhead-Steves, S. (2002). The effectiveness of electronic monitoring with violent male parolees. *Justice Quarterly*, 19(2), 293-312.
- Gable, R. K., & Gable, R. G. (2005). Electronic monitoring: Positive intervention strategies. *Federal Probation*, 69(1), 21-15.
- Gainey, R. R. & Payne, B. K. (2003). Changing attitudes toward house arrest with electronic monitoring: The impact of a single presentation? *International Journal of Offender Therapy and Comparative Criminology*. 47(2), 196-209.
- Jolin, A., & Stipak, B. (1992). Drug treatment and electronically monitoring home confinement: An evaluation of a community-based sentencing option. *Crime and Delinquency*, 38(2),158-170.
- Jones, M. & Ross, D. L. (1997). Electronic house arrest and boot camp in North Carolina: Comparing recidivism. *Criminal Justice Policy Review* 8 (4), 383-404.
- Kuplinski, J. (1990). *Electronic offender monitoring in Virginia: Evaluation report*. Richmond, VA: Department of Criminal Justice Services.
- Lilly, J. R., & Ball, R. A. (1993). Selling justice: Will electronic monitoring last?. *Northern Kentucky Law Review*,20, 505-512.
- Marklund, F., & Holmberg, S. (2009). Effects of early release from prison using electronic tagging in Sweden. *Journal of Experimental Criminology*, 5(1), 41-61.
- Maxfield, M. G., & Baumer, T. L. (1990). Home detention with electronic monitoring: Comparing pretrial and post-conviction programs. *Crime and Delinquency*, 36 (4),521-536.
- Padgett, K. G., Bales, W. D., & Blomberg, T. G. (2006). Under surveillance: An empirical test of the effectiveness and consequences of electronic monitoring. *Criminology and Public Policy*, 5 (1), 61–91.
- Pallant, J. (2011): *SPSS: Survival manual* (4<sup>th</sup> ed.). Crows Nest, Australia: Allen & Unwin.

- Renzema, M., & Mayo-Wilson, E. (2005). Can electronic monitoring reduce crime for moderate to high-risk offenders? *Journal of Experimental Criminology*, 1, 215-237.
- Renzema, M. & Skelton, D. (1990). Trends in the use of electronic monitoring. *Journal of Offender Monitoring*, 3(3), 12-19.
- Roy, S. (2010). *Convicted drunk drivers in an electronically monitored home detention program: A three-year study on exit status and subsequent recidivism*. Manuscript submitted for publication.
- Stanz, R., & Tewksbury, R. (2000). Predictors of success and recidivism in home incarceration program. *The Prison Journal*, 80 (3), 326-344.
- Yeh, S. S. (2010). Cost-benefit analysis of reducing crime through electronic monitoring of parolees and probationers

## About the Authors

**Avdi S. Avdija, Ph.D.**, is an assistant professor of criminology and criminal justice at the Indiana State University. His research interests include community policing policy, problems related to the implementation of evidence-based policing, crime prevention strategies and tactics, and methods of criminal investigation, including techniques of interviewing and interrogation. Dr. Avdija has published nineteen research articles in various academic journals and two books. His current research interests are on testing the effectiveness of eyewitness identification methods, and evaluation of correctional programs. Email: [avdi.avdija@indstate.edu](mailto:avdi.avdija@indstate.edu)

**Jihee Lee, M.S.** is a graduate student in the Department of Justice Administration at the University of Louisville pursuing her Ph.D. in Justice Administration. Ms. Lee has completed her M.S. degree in criminology and criminal justice, a BA in English and Literature, and a BA in Human Justice. She is a special agent in the Foreign Affairs Division of the South Korean National Police Agency. Her research interests include evaluation of electronic monitoring home detention programs and their effect on recidivism, and police culture across international police agencies. Email: [jlee88@sycamores.indstate.edu](mailto:jlee88@sycamores.indstate.edu)