Journal of Investigative Psychology and Offender Profiling
J. Investig. Psych. Offender Profil. **6**: 187–211 (2009)
Published online in Wiley InterScience (www.interscience.wiley.com). **DOI**: 10.1002/jip.108

Finding a Serial Burglar's Home Using Distance Decay and Conditional Origin–Destination Patterns: A Test of Empirical Bayes Journey-to-Crime Estimation in The Hague

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Abstract

Can we tell where an offender lives from where he or she commits crimes? Journey-to-crime estimation is a tool that uses crime locations to tell us where to search for a serial offender's home. In this paper, we test a new method: empirical Bayes journey-to-crime estimation. It differs from previous methods because it utilises an 'origin–destination' rule in addition to the 'distance decay' rule that prior methods have used. In the new method, the profiler not only asks 'what distances did previous offenders travel between their home and the crime scenes?' but also 'where did previous offenders live who offended at the locations included in the crime series I investigate right now?'. The new method could not only improve predictive accuracy, it could also reduce the traditional distinction between marauding and commuting offenders. Utilising the CrimeStat software, we apply the new method to 62 serial burglars in The Hague, The Netherlands, and show that the new method has higher predictive accuracy than methods that only exploit a distance decay rule. The new method not only improves the accuracy of predicting the homes of commuters—offenders who live outside their offending area—it also improves the search for marauders—offenders who live inside their offending area. After presenting an example of the application of the technique for prediction of a specific burglar, we discuss the limitations of the method and offer some suggestions for its future development. Copyright © 2009 John Wiley & Sons, Ltd.

Key words: serial offenders; burglary; The Hague; geographic profiling; journey-to-crime; CrimeStat; The Netherlands

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GEOGRAPHIC PROFILING AND JOURNEY-TO-CRIME ESTIMATION: THE PROBLEMS

Can we tell where an offender lives from where he or she commits crimes? Geographic offender profilers claim that we can, or, at least, that we can narrow down the search area considerably. Geographic offender profiling is a combination of good police work, local geographic knowledge, knowledge of suspects, crime scene investigation, and the many other factors that go into investigative activities (Rossmo, 2000). One of the components of geographic profiling is known as 'journey-to-crime estimation'. Journey-to-crime estimation is essentially a mathematical search algorithm that is based on the principle of distance decay. It takes as input the locations of a series of criminal incidents that are attributed to an unidentified offender whose whereabouts are unknown and calculates a risk surface that suggests where the offender is likely and where he or she is unlikely to live. Thus, geographic offender profiling is more general and comprises knowledge, skills, and tools. Journey-to-crime estimation is one of these tools.

Around the turn of the century, geographic profiling gained interest through the works of Rossmo (2000) and Canter, Coffey, Huntley, and Missen (2000), and was generally seen as a useful addition to the police officer's repertoire. In addition to the practical promise of prioritising the search area for a serial offender's home, geographic profiling also had a theoretical appeal. It linked major perspectives on crime such as environmental criminology (Brantingham & Brantingham, 1984, 1999), routine activities (Felson, 2002), and rational choice (Cornish & Clarke, 1986) to a real-life situation.

Only 5 years later, geographic profiling was being questioned on both theoretical and practical grounds. The tools that were developed, for journey-to-crime estimation, only exploited the distance decay function and barely utilised the rich theoretical framework of environmental criminology, routine activities, and rational choice on which it was allegedly based. As a consequence, these tools downplayed environmental characteristics, barriers, and opportunities in the community in which they were searching. Further, very little theory was actually applied in journey-to-crime estimation. In practical applications, the accuracy of the tools was disappointing (Levine, 2005). They were often less accurate than simpler techniques, such as the centre of minimum distance, and did not outperform students and police officers who visually applied one or two heuristic rules (Bennell, Taylor, & Snook, 2007; Bennell, Snook, Taylor, Corey, & Keyton, 2007; Harries & LeBeau, 2007; Paulsen 2006a,b; Snook, Taylor, & Bennell, 2004; Snook, Zito, Bennell, & Taylor, 2005).

Can the early promise of geographic profiling and journey-to-crime estimation be fulfilled? In this paper, rather than compare existing methods with each other and with the heuristics of human actors, we test the accuracy of a new method of journey-to-crime estimation, empirical Bayes journey-to-crime estimation, using data on 62 serial burglars in The Hague, The Netherlands.

The new method is available in version 3.1 of the CrimeStat software (Ned Levine & Associates, Houston, TX, USA, 2007). Currently, two other programs are widely available for journey-to-crime estimation: RIGEL (ECRI, 2002) and Dragnet (Canter, 2003). Each program includes a calculated distance decay function. For a review and comparative test of the three programs, see Paulsen (2006a,b).

The next section expands the principles of journey-to-crime estimation and the rationale behind the new empirical Bayes method already discussed in this issue (Levine, 2009) by analysing the distinction between marauding and commuting offenders. The subsequent

DOI: 10.1002/jip

section provides details on how the new method works, followed by description of the data and the methods used to test the accuracy of the new method, and comparison of its predictions with those of alternative methods. The section that follows presents the results of the comparisons. We then illustrate the method graphically by presenting an individual case, after which the paper concludes with a discussion of the limitations of the new method and some suggestions for its future development.

THE NEW METHOD: EMPIRICAL BAYES JOURNEY-TO-CRIME ESTIMATION

In the introduction to this special issue, Levine outlines the empirical Bayes method demonstrated in this paper. The empirical Bayes method uses not only the distance of the journey to crime, but also exploits our knowledge of origins (where did previous offenders live) and destinations (where did they offend), and the links between them to predict the home of a serial offender. It uses more specific information about past offenders. In contradistinction from previous methods, distance does not completely dictate the outcome of the prediction. If, for example, the police data show that most previous offenders who committed assaults in area B lived in a distant area A, then the new method will prioritise area A, even though there are many other areas located at the same distance or even closer to area B. Thus, given distance, if some destinations have been associated with a particular origin relatively frequently in the past, the new method will identify that particular origin as a likely home area of the offender. Prior methods do not use origin–destination information, and therefore estimate all origins located at the same distance from a destination as equally likely candidates to contain the home of the unknown serial offender.

This characteristic of the new model is particularly relevant for the traditional distinction between two spatial offending patterns: the marauder pattern and the commuter pattern. A marauder is a serial offender whose home or anchor point is bounded by the locations of his or her crimes. A commuter is, by definition, a serial offender who is not a marauder and who thus lives away from the area where he or she committed crimes (technically, a commuter can live close to the crime sites if the angle of his or her journey to crime varies less than 180º). Canter and Larkin (1993) defined an offender as a marauder if his or her anchor point (usually home) was within a circle whose diameter was defined by the distance between the furthest apart incidents attributed to the offender. A commuter was defined as an offender whose anchor point was outside the circle. Warren, Reboussin, Hazelwood, Cummings, Gibbs, and Trumbetta (1998) suggested an additional definition based on a convex hull that includes all of the incidents attributed to an offender (see Figure 1 below). A commuter's anchor point was inside the convex hull and a marauder's anchor point was outside the convex hull.

Some authors recognise that geographic profiling only works, or works best, for marauders (Paulsen, 2007; Rossmo, 2000). However, until an offender's home is identified, a police analyst cannot know whether an offender is a commuter or marauder, an observation that made Paulson write:

> Research into determining marauder offender type before conducting a geographic profile is acutely important given the inability of current geographic profiling software to accurately profile commuter series and the high number of offenders that are commuters (Paulsen, 2007, p. 349).

DOI: 10.1002/jip

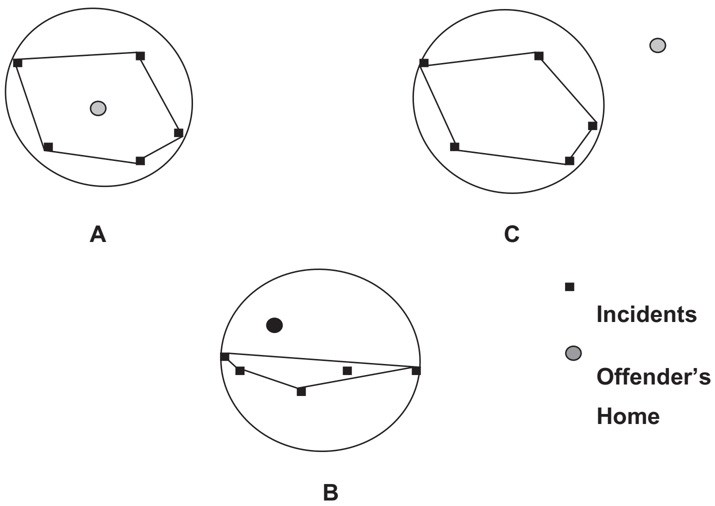

Figure 1. Commuters and marauders. (A) convex and circle marauder, (B) circle marauder convex commuter, and (C) convex and circle commuter.

The new method evaluated in this paper challenges this argument, because it claims to be applicable to both commuters and marauders, and thus, to make the distinction between these two offender types less relevant.

HOW DOES IT WORK?

As outlined by Levine in the introductory paper to this issue, CrimeStat 3.1's new empirical Bayes journey-to-crime estimation method is an extension of its earlier distance-based journey-to-crime estimation method (Levine, 2007). Based on connections between offenders and the incidents they committed, three risk surfaces are calculated.

The first risk surface is the risk surface generated by the regular journey-to-crime/distance decay method in CrimeStat, where it is labelled P(JTC). This surface is based on a distance decay function and the location of incidents attributed to the serial offender whose anchor is being predicted. We will label it the *distance decay* risk surface.

The second is a 'usual suspects' risk surface that implements a rather unsophisticated focus: It prioritises zones where previous offenders lived, independently of where they committed their crimes and independently of the locations of the crimes in the series of the offender that we are searching for. Thus, it does not actually use the locations of the incidents in the series. We will refer to this estimate as the *general* risk surface, whilst CrimeStat labels it P(O).

The third risk surface is based on the origin–destination zone matrix. It is somewhat more complicated than the first two surfaces, but much more sophisticated. It is labelled P(O|JTC) and referred to by CrimeStat as the *conditional* probability risk surface. We will also label it the *conditional* surface. The method selects the zones where the crimes in the current series were committed. Then, conditional on these destinations, it uses the origin–destination zone matrix of the calibration sample to calculate for each zone the likelihood

DOI: 10.1002/jip

that an offender who lived in the reference zone would commit crimes in the selected set of destinations. The ingenuity of this idea is that the method automatically accounts not only for the distance between two zones, but also for travel time, specific attractions, or barriers that impede or facilitate criminal travel between the two zones, whilst the analyst does not need to know what these factors are. For example, in racially segregated cities, racial boundaries may impede travel (Bernasco & Block, 2009). Using the calibration set as an empirical baseline, a conditional probability risk surface will automatically take into account the rarity of offending across racial boundaries (because in the calibration set, we will find few crimes that cross racial boundaries). Therefore, in making the journey-to-crime estimates, *conditional* probability assigns lower probability to origin zones that are racially distinct from the destination zones. This will work, even if the analyst is unaware of the existence of the racial barriers that impede travel. In theory, this risk surface eliminates the distinction between commuters and marauders (for a further discussion, see Levine's introduction to this Journal).

The empirical Bayes journey-to-crime method generates two other risk surfaces by combining the above three risk surfaces. One of these two combination surfaces is the product of P(JTC) and P(O|JTC), the *product* risk surface. This risk surface explicitly recognises both distance decay and the home-to-incident histories of prior offenders. Thus, like the conditional surface, it implicitly acknowledges the target decisions that offenders living in a given neighbourhood make and mirrors the typical barriers, opportunities, travel directions, and transportation modes of these offenders. But it mixes this probability with the probability generated by distance decay logic. The product surface is mathematically the numerator of the other combination surface, the *Bayesian risk* probability.

The *Bayesian risk* surface is calculated by application of the Bayes' formula:

$$\mathrm{P(JTC|O)} = \frac{\mathrm{P(JTC)} \times \mathrm{P(O|JTC)}}{\mathrm{P(O)}}.$$

Thus, in addition to the three basic risk surfaces *distance decay*, *general*, and *conditional*, in this paper, two combination risk surfaces, *product* and *Bayesian risk*, are analysed. In addition, we also analyse the effectiveness of another estimate, the centre of minimum distance (CMD), which is not a surface but a point estimate: It is the location from which the summed distances to all crime locations in the series are minimal. This estimate is popular because it is relatively easy to calculate and interpret.

DATA AND METHOD

In this section, we first present the data. Next, we provide descriptive information on distance decay and origin–destination paths in these data. Following a brief description of the construction of the five risk surfaces, we end by discussing the four measures used to assess the accuracy of the risk surfaces and the statistical tests used to compare accuracy across the risk surfaces and the CMD measure.

Burglary data

From 1996 to 2003, 34,117 household burglaries were recorded by the police in The Hague. Of these, 2158 (6.45%) resulted in the arrest of at least one suspect living in the city. These incident offender pairs are the calibration set: They are used to estimate

DOI: 10.1002/jip

the risk surfaces that are used in the actual search for the serial offender. Following Rossmo (2000), who argues that for an accurate journey-to-crime estimate, at least a series of five offences is required, we selected the 62 offenders who were identified by the police as having been involved in five or more burglaries. These offenders committed 573 household burglaries in total. These incident–offender pairs are in the test set: They are used to assess the accuracy of the risk surfaces that were estimated with the calibration set.

As discussed above, the new method eliminates the need to distinguish commuters and marauders, and should work for both. To test whether or not the method could successfully estimate the home of commuters, the offenders were divided into three categories (see Figure 1). Offenders whose home was within the circle and also within the convex hull of their burglaries were defined as *marauders*. There were 18, and they were involved in 244 burglaries. Offenders whose home was both outside the convex hull and outside the circle were *commuters*. These 24 offenders were involved in 173 burglaries. The remaining offenders were a mixed group. Their home was inside the circle of burglaries but outside the convex hull (see Warren *et al.*, 1998). They were 20 offenders involved in 156 burglaries.

Distance decay

The first step in the empirical Bayes method is the estimation of a distance decay curve. This step is identical to the regular journey-to-crime estimation in CrimeStat. Whilst CrimeStat allows for calibration of a distance decay function through curve fitting, it is simpler and more accurate, given the availability of connected incident offender pairs, to define the function by these connections. Empirical estimation is done using a kernel density function (with a bandwidth of 500 m) passed over the matrix of connections. The result is a distance decay function that is modelled on burglaries in The Hague.

Figure 2A,B display the distance distribution for 'non-serial' burglars who were involved in one to four burglaries (Figure 2A) and for serial burglars who were involved in five or more burglaries (Figure 2B). For both groups, distance decay is clearly evident, as many burglaries occur at or very close to the offender's home and the number of burglaries rapidly decline with distance. Although, generally, the two distributions are similar, the distance decay pattern is somewhat more pronounced for the non-serial group (Figure 2A). Ten per cent of the burglaries occur within 0.01 km, 25% occur within 0.50 km, and 50% take place within 1.73 km from the offender's home. For the serial burglars (Figure 2B), 10% occur within 0.25 km, 25% occur within 0.75 km, and 50% of the serial incidents occur within 1.58 km from the offender's home.

In Figure 3, the distance decay pattern of the serial burglar group—those who were involved in five or more burglaries—is displayed for the *marauders*, the *mixed group*, and the *commuters*. The three subsets have very distinct distance distributions. The distance decay pattern for burglaries by *marauders* is similar to the pattern for non-serial incidents. Distance decay is clearly evident. Many incidents occur close to home. Twenty-five per cent occur within half a kilometre from home. However, burglaries in the *mixed group* have a partial buffer around the burglar's home address. Ten per cent of commuter burglaries occur within 440 m from home. In contrast, 10% of marauder burglaries occur within 170 m from home. Neither distance decay nor a buffer is evident for *commuters*. Ten per cent occur within 770 m from home and 50% within 2.94 km.

DOI: 10.1002/jip

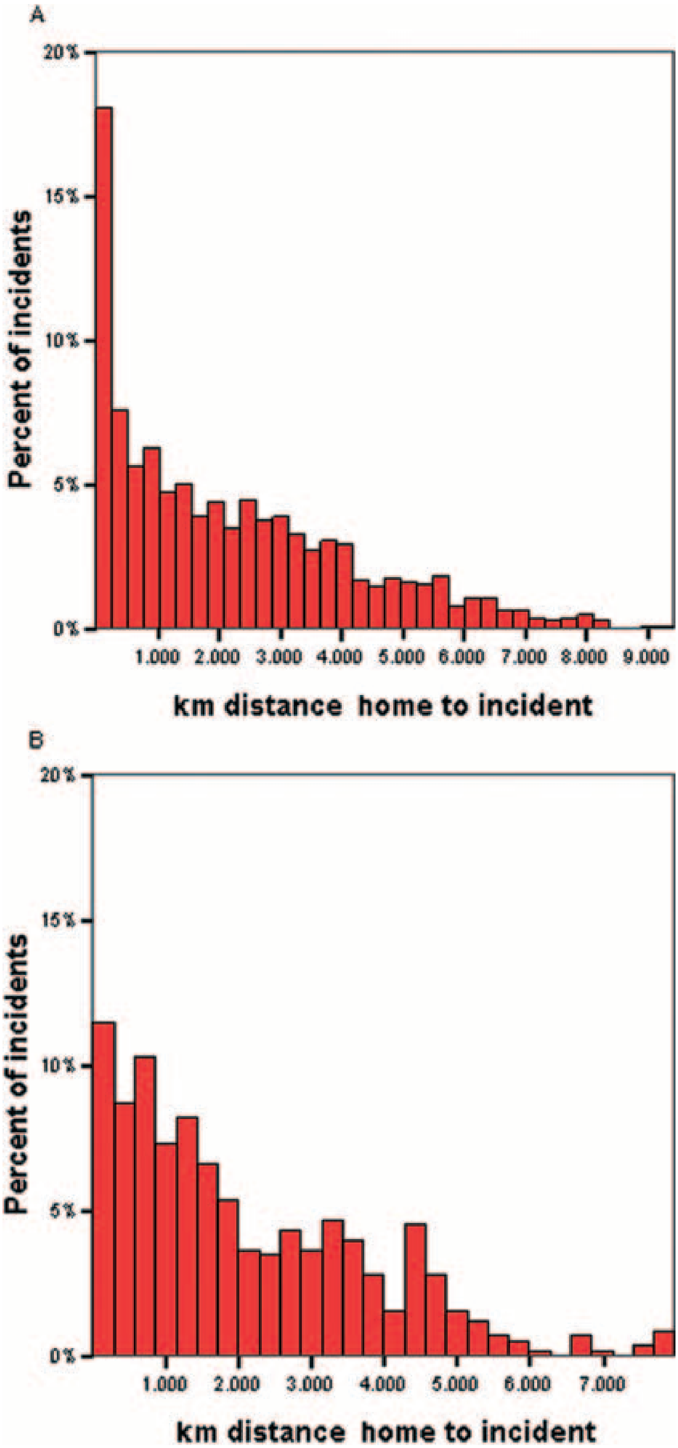

Figure 2. Home-to-burglary distance (A) one to four incidents; (B) serial offenders, five or more incidents.

DOI: 10.1002/jip

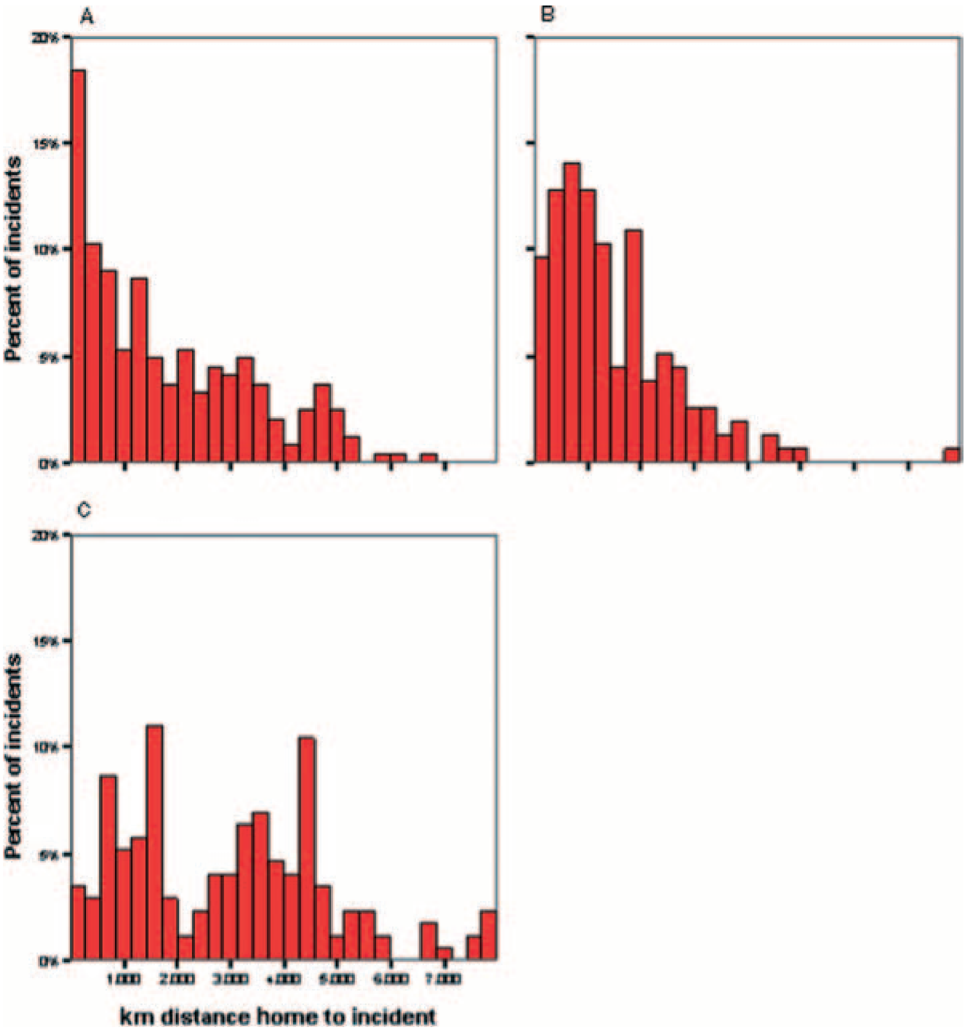

Figure 3. Home-to-burglary distance: marauders and commuters. (A) Convex and circle marauder; (B) circle marauder convex commuter; (C) convex and circle commuter.

The distribution is neither skewed nor peaked. Clearly, the three patterns are quite different.

We show these differences not because this is a spectacular finding in itself (after all, there is circularity involved because the subset definitions themselves are based on individual distance patterns) but because they clearly illustrate that distance decay patterns fit *marauders* quite well, the *mixed group* less well, and *commuters* not at all. A journey-to-crime estimation that only uses the distance decay patterns is likely to be misleading for *commuters*, who are 39% of the sample. The remainder of the paper will not only analyse the total sample of 62 serial offenders, but also the *marauders*, *commuters*, and *mixed group* separately.

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Origin–destination paths

The second step in the empirical Bayes journey-to-crime estimation method is the creation of an origin–destination or 'home–incident' zone matrix. First, 295 uniform zones of about 0.30 sq km were defined by overlaying the The Hague city map with a grid. Next, a 295 by 295 matrix is populated, in which each cell is the number of burglary trips that had their origin (offender home) in the row zone and their destination (incident location) in the column zone. The diagonal represents burglaries committed in the offender's own home zone. This procedure was performed using data on all burglaries involving serial as well as non-serial burglars. In this analysis, the matrix is square because only offenders living in The Hague who committed burglaries in The Hague are analysed.

Of the 87,025 (i.e. 295×295) possible matrix zones, including the diagonal, only 1373 (1.57%) actually have a value other than 0. In other words, there are 1373 origin–destination zone combinations in which at least one offender lived in the zone and/or at least one burglary occurred in the zone. Of the 295 zones, there were 154 zones that included at least one burglar's home and 187 zones that included at least one burglary.

Risk surfaces

The next phase in the empirical Bayes journey-to-crime estimation is the calculation of risk surfaces. Five risk surfaces were calculated. The three basic risk surfaces—*distance decay* P(JTC), *general* P(O), and *conditional* P(O|JTC)—utilise as a calibration sample all burglaries committed by a known offender who lives in The Hague ($n = 2158$). Thus, they include serial offenders as well as the non-serial offenders who were arrested for less than five offences. The other two risk surfaces, *product* and *Bayes*, are combinations of the three basic surfaces.

All five risk surfaces cover the entire city. Some estimation methods use a risk surface that is defined by the extremes of the distribution of offences. This, by definition, excludes commuters. However, the empirical Bayes journey-to-crime estimation should work well for both commuters and marauders. Therefore, the entire area of The Hague was included in the risk surface.

The likelihood that an offender's home will fall into a cell of the risk surface depends on the size of the cell. The larger the size of the cell, the greater the likelihood of the estimate, but the lower its precision. The cells of a risk surface are much smaller than the zones discussed above. The risk surfaces included 4635 cells, each about 15,000 sq m (about 0.015 sq km).

Accuracy measures

In order to test the accuracy of each of the five risk surfaces and the CMD, for each of the 62 serial offenders in the data, we assessed how well his or her actual home zone is predicted by the five risk surfaces that were estimated with data on all offenders. This assessment included four measures that have been used before in the literature.

Three of these measures concentrate on a single cell of the risk surface. Levine (2007) suggests using the estimated probability in the grid cell where the offender actually lived (measure 1). The higher the estimated probability in the home cell, the better is the prediction. Snook *et al.* (2004) measure the distance between the cell of maximum probability and the offender's home (measure 2). The smaller the distance, the better is the prediction. Paulsen (2006a,b) includes a simple dichotomous measure: Is the offender's home within

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1 mi of the maximum probability cell (measure 3). Here, we also calculated the measure for 0.5 mi and 1 km. The larger this percentage, the better is the prediction. The disadvantage of these three measures is that they only focus on a single cell, and thereby completely ignore the variation in estimated probability across all other cells. The risk surface is only marginally used. A possible advantage of these measures is that they can also be used for 'point predictions', such as the CMD and subjective estimates of human subjects, i.e. 'X marks the spot' predictions that indicate the most likely exact location of the offender's home but do not provide a full risk surface.

Arguably, the most robust accuracy measure, and one that is being advocated by the authors of the other two journey-to-crime tools (Canter *et al.*, 2000; Rossmo, 2005) is the search cost measure or 'hit score', which is the percentage of cells that must be searched (if one searches from highest to lowest estimated probability) before arriving at the offender's home (measure 4). The smaller this measure, the better is the prediction. In contrast to the first three measures, measure 4 utilises the entire risk surface. This is an important advantage of this measure, in particular, because the absolute top (maximum probability point) can be a very poor characterisation of the risk surface (which can have multiple local maxima, for example). Furthermore, in real investigations, the police should typically utilise a risk surface that is accurate not only in telling them where to look first, but also in telling them where to look next.

Because the issue of what is the best accuracy measure is still controversial (Rich & Shively, 2004), we will use four measures. They are:

1) The estimated probability in the grid cell where the offender actually lived.
2) The distance between the maximum probability grid cell and the cell where the offender actually lived.
3) Whether the offender's home is within 1 km, 1 mi, and 0.5 mi of the maximum probability cell (these are actually three separate but similar measures).
4) The percentage of the study area that has a higher calculated risk probability than the cell where the offender actually lived, i.e. the percentage of an area that must be searched before arriving at the offender's home.

For each of the four measures, the average accuracy over the 62 burglars is reported in the results section, and they are also calculated separately for *marauders*, *commuters*, and the *mixed group*.

In the results section, in Tables 1–4, the average accuracy levels are reported for the whole sample of the 62 burglars, as well as for *marauders*, *commuters*, and the *mixed group* separately.

Table 1. Estimated probability in the offender's home grid cell (measure 1, larger is better)

Estimation method	Marauders	Mixed group	Commuters	All serial burglars*
Distance decay	0.000568	0.000623	0.000481	0.000553
General	0.000477	0.000426	0.000435	0.000444
Conditional	0.000575	0.000544	0.000510	0.000539
Product	0.001086	0.001103	0.000825	0.000990
Bayes	0.000673	0.000705	0.000542	0.000654
n	18	20	24	62

*Friedman $\chi^2 = 140.4$; $p \leq 0.001$. Because of the small number of observations, significance was not calculated for the three subgroups.

DOI: 10.1002/jip

Table 2. The distance (km) between the maximum probability cell and the grid cell where the offender actually lived (measure 2, smaller is better)

Estimation method	Marauders	Mixed group *n*	Commuters	All serial burglars*
Distance decay	1.24	1.31	2.69	1.82
General	1.35	1.94	1.91	1.76
Conditional	0.68	1.12	1.74	1.23
Product	0.80	1.03	2.18	1.41
Bayes	1.21	0.99	2.61	1.68
CMD	1.26	1.13	2.68	1.77
n	18	20	24	62

*Friedman $\chi^2 = 29.5$; $p \leq 0.001$. Because of the small number of observations, significance was not calculated for the three subgroups.
CMD, centre of minimum distance.

Table 3a. Percentage of serial offenders living within 1 km of the maximum probability cell (measure 3, larger is better)

Estimation method	Marauders	Mixed group	Commuters	All serial burglars*
Distance decay	50.0	60.0	16.7	40.3
General	38.9	30.0	37.5	35.5
Conditional	83.3	75.0	41.7	64.5
Product	66.7	70.0	25.0	51.6
Bayes	55.6	70.0	29.2	50.0
CMD	44.4	50.0	20.8	35.5
n	18	20	24	62

*Cochran Q = 27.3, degrees of freedom = 5, $p \leq 0.001$; Cochran Q of difference between best and second best = 5.4, $p \leq 0.02$. Because of the small number of observations, significance was not calculated for the three subgroups.
CMD, centre of minimum distance.

Table 3b. Percentage of serial offenders living within 1 mi of the maximum probability cell (measure 3, larger is better)

Estimation method	Marauders	Mixed group	Commuters	All serial burglars*
Distance decay	66.7	70.0	37.5	56.5
General	61.1	45.0	37.5	46.8
Conditional	94.4	75.0	62.5	75.8
Product	94.4	80.0	50.0	70.0
Bayes	66.7	80.0	45.8	62.9
CMD	66.7	75.0	37.5	59.7
n	18	20	24	62

*Cochran Q = 24.4, degrees of freedom = 5, $p \leq 0.001$; Cochran Q of difference between best and second best = 0.11, not significant. Because of the small number of observations, significance was not calculated for the three subgroups.
CMD, centre of minimum distance.

DOI: 10.1002/jip

Table 3c. Percentage of serial offenders living within 0.5 mi of the maximum probability cell (measure 3, larger is better)

Estimation method	Marauders	Mixed group	Commuters	All serial burglars*
Distance decay	44.4	50.0	12.5	33.9
General	38.9	30.0	29.2	33.9
Conditional	83.3	70.0	41.7	62.3
Product	61.1	60.0	25.0	46.7
Bayes	50.0	60.0	25.0	43.5
CMD	38.9	50.0	12.5	32.3
n	18	20	24	62

*Cochran Q = 28.8, degrees of freedom = 5, $p \leq 0.001$; Cochran Q of difference between best and second best = 6.25, $p \leq 0.01$. Because of the small number of observations, significance was not calculated for the three subgroups.
CMD, centre of minimum distance.

Table 4. Percentage of the study area that has a higher calculated risk probability than the cell where the offender actually lived, i.e. the percentage of an area that must be searched before arriving at the offender's home (measure 4, smaller is better)

Estimation method	Marauders	Mixed group	Commuters	All serial burglars*
Distance decay	10.51	8.44	33.12	18.60
General	9.53	26.06	21.93	19.67
Conditional	2.27	7.02	12.38	7.72
Product	3.24	6.26	20.54	10.92
Bayes	9.04	5.95	31.88	16.89
n	18	20	24	62

*Friedman $\chi^2 = 49.6$; $p \leq 0.001$. Because of the small number of observations, significance was not calculated for the three subgroups.

To assess performance differences resulting from chance variation, non-parametric tests are used. First, an omnibus test is performed on the existence of overall accuracy differences between all five risk surfaces. With respect to measures 1, 2, and 4, this is done with the Friedman test, a non-parametric alternative to the *t*-test for related samples. For measure 3, where the response is dichotomous, the Cochran test is used. The test statistics are reported in Tables 1–4.

Next, for each measure, 10 pairwise significance tests between all five risk surfaces are conducted using the Wilcoxon signed rank test, a non-parametric test for differences between two related samples. These are reported in Tables A1–A4 in the Appendix.

RESULTS

Overall accuracy of estimation

We first consider the accuracy of the five risk surface estimation methods for all 62 serial burglars, i.e. the last columns of Tables 1–4. According to the outcomes of the Friedman

DOI: 10.1002/jip

and Cochran tests reported at the bottom of the tables, the overall differences for all four measures (including the three distance thresholds used with measure 3) are significant at the 0.001 level.

As Table 1 shows, the *product* risk surface has the highest probability of predicting the exact grid cell of the burglar's home (last column of Table 1). The product risk surface has a significantly ($p < 0.001$) higher probability of predicting the home cell of the offender than each of the four other methods (see Table A1). However, the probabilities are very small because of the size of the cells (15,000 sq m). Similar results have been obtained in Baltimore County (Leitner, 2009), Chicago (Levine & Block, Forthcoming), and Manchester, UK (Levine & Lee, 2009).

According to the other three accuracy measures, reported in the last columns of Tables 2–4, the *conditional* risk surface is more accurate than the other risk surfaces and the CMD. In the Appendix Tables A2–A4 show that the accuracy improvement of the *conditional* surface in comparison to the other estimates is statistically significant in all but two of the pairwise comparisons involved. In the only two exceptions to statistical significance, the *conditional* surface is still more accurate than the next best surface, the *product* risk surface. For burglaries in The Hague, the *conditional* is clearly the first choice risk surface estimate.

It is particularly remarkable that the *conditional* risk surface outperforms the combination surfaces *product* and *Bayes*, which are meant to improve the *conditional* estimate by adding the distance decay principle to it in various ways. The pure *conditional* estimate is more accurate than combinations of it with the poorly performing *distance decay* and *general* estimates. Apparently, because the conditional surface implicitly already takes into account the distance decay phenomenon (because few previous crime trips to a given destination originated from distant origins), further attempts to incorporate it merely introduce noise into the prediction.

The *general* risk surface, the one that is based on where previous offenders lived irrespective of where they committed their crimes, is nearly consistently the least accurate of the five surfaces (it is second worst only on measure 2, the distance measure). Interestingly enough, the *general* risk surface shares its fate with the *distance decay* risk surface that forms the basis of all prior journey-to-crime estimation methods. These two estimates are consistently the least accurate of the five surfaces. The *CMD* does not calculate a risk surface; therefore, its accuracy can only be assessed based on measures 2 and 3. For these, it is not as accurate as the *conditional* or *product* surfaces. It is certainly not a 'gold standard' (Levine, 2005). In summary, the *distance decay* and *general* risk surfaces and the *CMD* are never significantly more accurate than the *conditional*, *product*, or *Bayes* risk surfaces.

Results for marauder, mixed, and commuter patterns

We now turn to a comparison of the *marauders*, *mixed group*, and *commuters*, as presented in the middle three columns of Tables 1–4.With some exceptions, the results within the three subsets *marauders*, *commuters*, and *mixed group* are similar to the results for all 62 serial offenders. However, statistical significance was not calculated because of the limited number of observations.

In all cases, the *product* estimate is most accurate according to measure 1, the estimated probability of the grid cell that includes the offender's home. This is true for *marauders*, for the *mixed group*, and for *commuters*. For measure 3, the *conditional* risk surface

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performs best at all distances for commuters and marauders. For the mixed group, no measure is clearly the most accurate, but the *general* estimate is clearly the least accurate. Much the same is true for measures 2 and 4. The conditional risk surface performs best for commuters and marauders, but no method is clearly more accurate for the mixed group. The *CMD* estimates are in the middle range of accuracy.

In line with the literature on journey-to-crime estimation, the accuracy of all methods is generally better for *marauders* than for *commuters*, and it is also better for the *mixed group* than for *commuters*. In other words: Journey-to-crime estimation is more accurate for marauders than for commuters. This is not only true for the *distance decay* risk surface, but also is true for the *conditional* risk surface and the combination risk surfaces. For example, the average search cost of the *conditional* surface equals 2.3% for *marauders*, 7.0% for the *mixed group*, and 12.4% for *commuters*. Thus, even though the *conditional* estimate does not explicitly take into account distance or other geographical or geometrical relations, the homes of commuters still are more difficult to estimate than those of marauders. Thus, commuters remain a problem for estimation.

SEARCHING THE HOME OF AN UNKNOWN BURGLAR: AN EXAMPLE OF THE EMPIRICAL BAYES APPROACH

In this section, the estimation results for the search of an 'unknown' offender are illustrated. The purpose is to make the preceding analysis more concrete by showing, for a random serial offender from the data, what some of the estimated surfaces look like, and how accuracy is assessed and evaluated by relating these surfaces to the location of the offender's home.

An 'unknown' offender, labelled 'Offender 633', is first excluded from the calibration set, so that the five risk surfaces that are calculated on the calibration set are based on the other 61 burglars. Then, the risk surfaces are compared with the grid cell where Offender 633 actually lived, and the accuracy of the surfaces is assessed for this particular offender.

Offender 633 was responsible for six burglaries. He lived quite close to the centre of concentration for the residence of all The Hague's burglars, but somewhat distant from the commission of his burglaries, which were all to the west (see Figure 4A). Offender 633 is an example of the *mixed group*, as he lived just inside the circle whose diameter is the line that connects his two offences that are furthest apart, but he lived outside the convex hull that surrounds his six offences.

Four maps are used to illustrate the empirical Bayes journey-to-crime estimation of the residence of Offender 633. These maps each apply to one of the following four risk surfaces: *general* (Figure 4A), *distance decay* (Figure 4B), *conditional* (Figure 4C), and *product* (Figure 4D). Each map includes:

- location of the offender's home;
- incidents that he or she committed (three incidents overlap on the map as they occurred very near each other);
- highest probability cell;
- entire risk surface by probability;
- area that would have to be searched before reaching the offender's home; and
- CMD.

DOI: 10.1002/jip

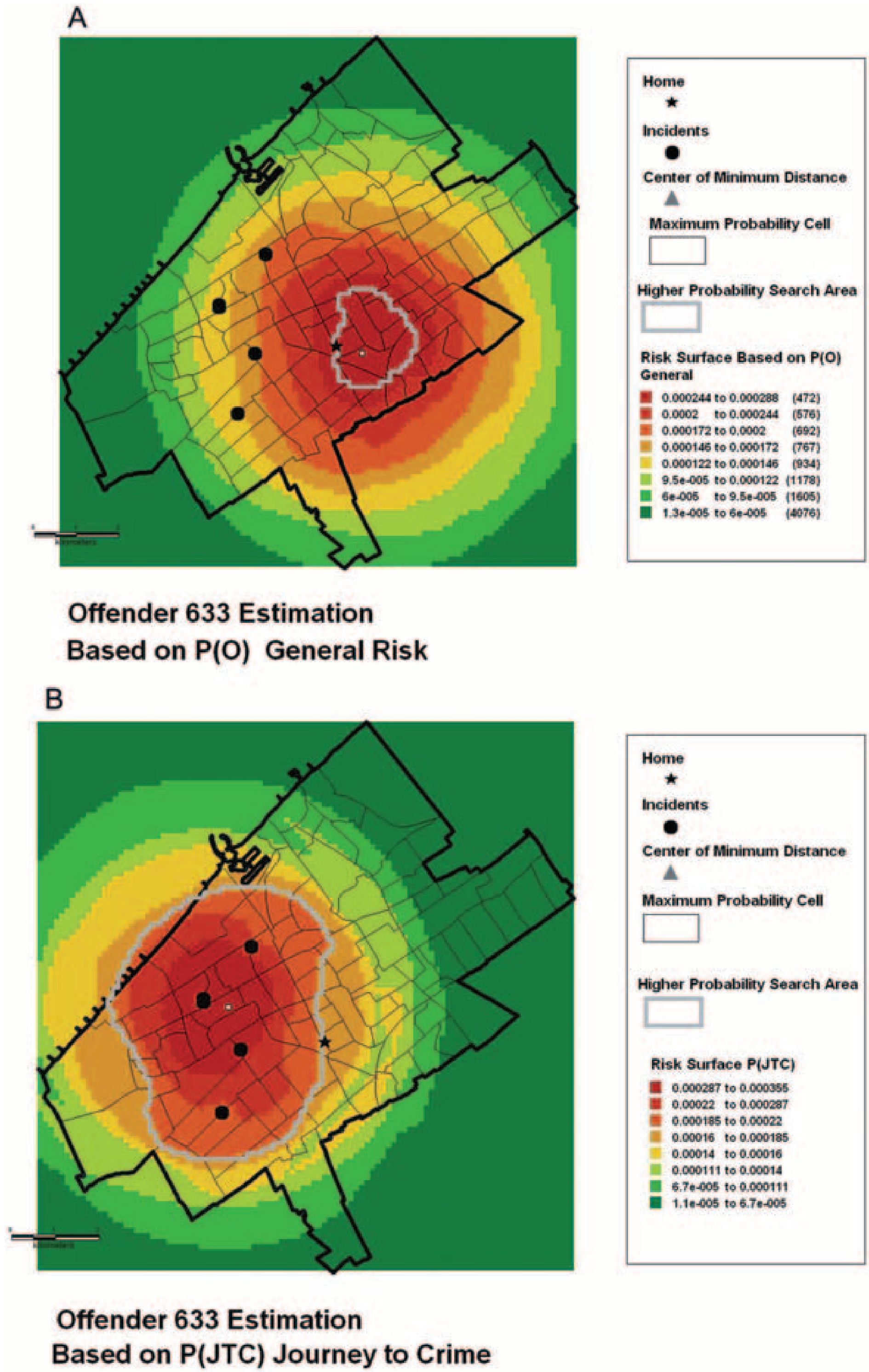

Figure 4. (A) *General* (B) *distance decay*.

DOI: 10.1002/jip

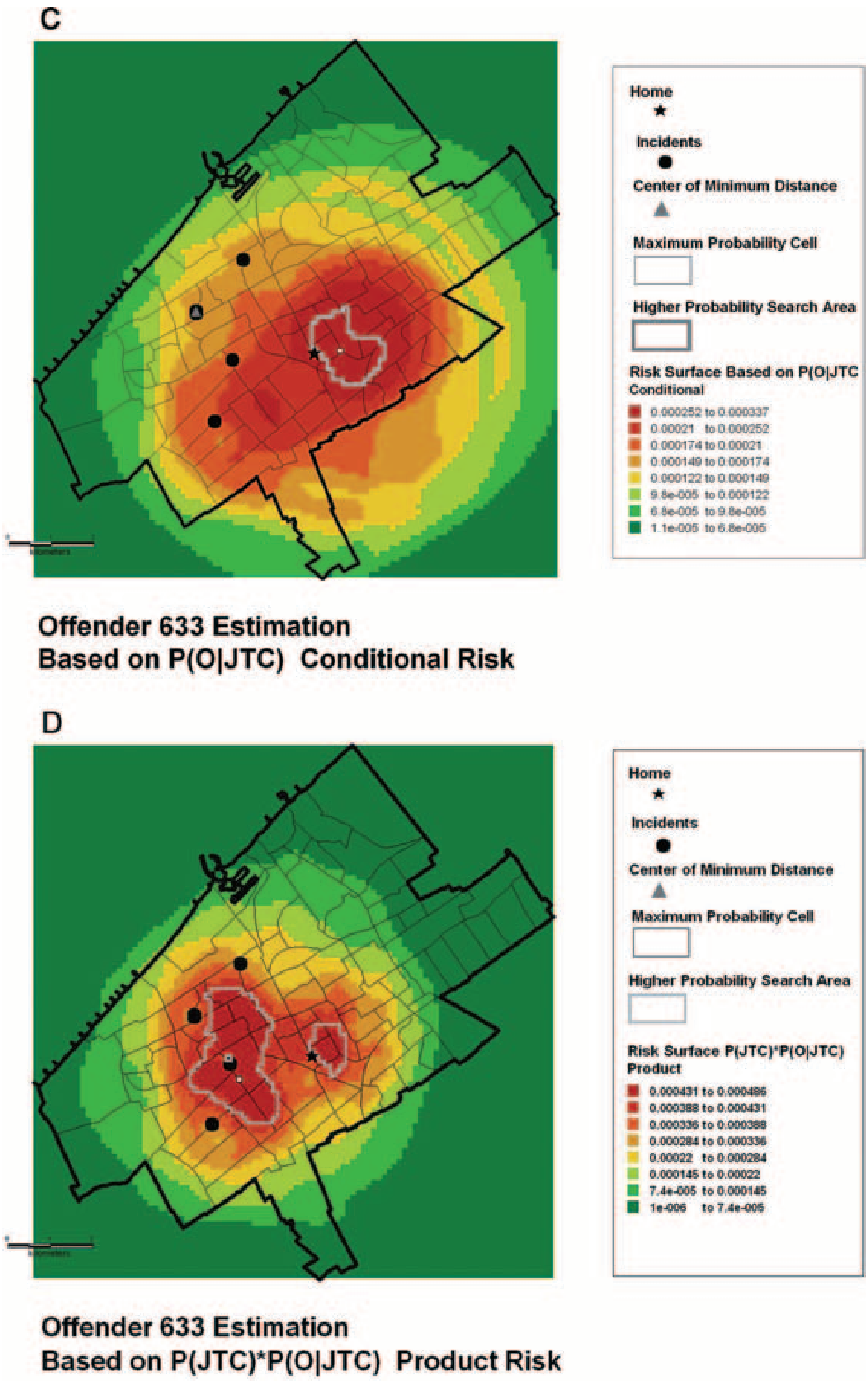

Figure 4. (*Continued*) (C) *Conditional*, and (D) *Product*.

DOI: 10.1002/jip

Figure 4A depicts the *general* risk surface for Offender 633. To repeat, it is based just on the distribution of the home addresses of all known burglars excluding Offender 633 himself. Clearly, Offender 633 lives amongst these burglars. Therefore, the maximum probability cell for this surface is not far from the offender's home (0.61 km.). Beginning at the maximum probability cell, only 4.49% of The Hague would have to be searched before arriving at this offender's home cell.

Figure 4B depicts traditional journey-to-crime estimation based upon an empirically calculated distance decay function. This *distance decay* surface focuses strongly on the crime locations, and as a result of that, it works best if the offender lives within the convex hull and circle of offences. However, Offender 633 does not (to be precise, he does live just within the circle, but he lives outside the convex hull). Therefore, using this surface, over one-third (35.24%) of The Hague would have to be searched before arriving at the offender's resident cell, and the distance between the maximum probability cell and the offender's home is 2.38 km. The *distance decay* surface would not be of much more use to the police than the CMD.

Figure 4C depicts the *conditional* risk surface, which is determined by the history of home-to-offence connections of known offenders who committed burglaries in the same zones as the serial burglar whose home is being estimated. As it is based on the origins and destinations of crime trips, and most of these trips are likely to be close to home, it implicitly incorporates distance decay. The *conditional* risk surface results in a very good estimation of the home of Offender 633. The maximum probability cell is 0.75 km from the offenders home and only 2.69% of The Hague would have to be searched before arriving at the resident cell of the offender.

As shown in Figure 4D, the *product* surface (which is the product of the *conditional* and the *distance decay* surfaces) mostly results in confusion. One good estimate is combined with a weak one. The result is a very complex distribution of high-risk areas. The two estimates barely overlap. The maximum probability cell is 1.79 km from the offender's home and 7.20% of The Hague would have to be searched before arriving at the resident cell of the offender. This is a typical result for many commuters. Distance Decay is often less relevant to commuters than to marauders, and the addition of the *distance decay* risk surface actually makes the estimate less accurate. For commuters, the inclusion of journey-to-crime estimation in a risk surface introduces error in the *product* and *Bayes* risk surfaces.

Table 5 summarises the accuracy results for this offender according to the five measures used here. In line with the general results (see Table 4), for this particular offender, the conditional surface requires the smallest search costs: Following this surface, the police would have to scan 2.69% of the area before having arrived at the grid cell where Offender 633 lived. And, as was previously noted with respect to commuters in general, the traditional JTC risk surface hardly reduces the search area: Starting from the highest probability cell, 35.2% of The Hague would have to be searched before the offender's resident cell was reached (evidently, a random search strategy would yield a 50% score on average).

Three of the incidents occurred very near each other, and the CMD reflects this. The CMD is nearly 3 km from the home of the burglar. Thus, for Offender 633 and others, the CMD and distance decay estimates that the offender's home is near the centre of incidents would result in an inefficient police search. The *conditional* risk surface, which is based on a history of offender trips, is a much better prioritiser.

DOI: 10.1002/jip

Table 5. Accuracy measures of Bayesian journey-to-crime risk surfaces for Offender 633

Estimation method	Measure 1 Estimated probability in home cell	Measure 2 Distance to home (km)	Measure 3 Home < 1 mi of maximum probability cell	Measure 3 Home < 1 km of maximum probability cell	Measure 3 Home < 0.5 mi of maximum probability cell	Measure 4 Search cost (%)
Distance decay	0.000398	2.38	No	No	No	35.24
General	0.000600	0.61	Yes	Yes	Yes	4.49
Conditional	0.000673	0.75	Yes	Yes	Yes	2.69
Product	0.000938	1.79	No	No	No	7.20
Bayes	0.000400	2.51	No	No	No	48.77
CMD	—	2.92	No	No	No	—

CMD, centre of minimum distance.

DOI: 10.1002/jip

CONCLUSIONS AND DISCUSSION

Conclusions from the analysis

The aim of journey-to-crime estimation is to prioritise the search for an unknown serial offender, using as input the locations of the crimes in the series. Based on our study of 62 burglars, the homes of serial burglars were more successfully estimated with the new *conditional* risk surface than with other risk surfaces, including the traditional *distance decay* surface. The latter surface is created by reversing a distance decay function, a procedure that also underlies the surfaces generated by RIGEL and Dragnet. The *conditional* surface is one of three basic risk surfaces calculated in the empirical Bayes procedure, and it was the most successful surface according to three of the four measures used here to assess accuracy in The Hague. According to measure 1 the *product* risk surface appeared optimal.

The commuter marauder distinction proved important. All risk surfaces are most accurate for marauders, and all work less well for offenders who are commuters. The distance decay principle does not apply to commuters and leads to inaccurate predictions. The *conditional* surface stands out as a better estimate for commuters. Apart from the *general* risk surface, which is the only one to completely ignore the locations of the crime series, all other risk surfaces (*distance decay* and the two combination surfaces *product* and *Bayes*) are based directly or indirectly on the distance decay function, which is a poor basis for journey-of-crime estimation in commuters. Whilst not based on distance decay, the *CMD* begins with an assumption that the offender lives within the bounds of his or her incidents. This is not true for commuters. The surprising finding is that the *conditional* surface also generates substantially better predictions for marauders. This is an important result for practical usage, as in real investigations, the police cannot know whether the unknown offender is a marauder or a commuter before he or she is arrested.

Obvious questions and tasks remain. The first is why the conditional surface outperforms other estimates. Our interpretation of the superiority of the *conditional* risk surface is that it implicitly includes in its estimate the distance to the target, as well as many other unmeasured factors that influence local travel patterns, such as physical barriers like railways, parks, and rivers, and the presence or absence of specific crime generators and attractors, e.g. shopping centres, schools, bars, and entertainment establishments. The *conditional* surface implicitly summarises the joint effect of these influences, and any attempt to give additional weight to an inferior estimation instrument—the distance decay function—is more likely to worsen than to improve the prediction.

Another remaining question is our findings differ from those reported elsewhere in this issue. The *conditional* estimates calculated for burglars in The Hague are more accurate than in the other *conditional* estimates presented in this special issue, and the *distance decay* and *product* estimates are less accurate. Why are the results different for The Hague? One possible reason could be that the calibration sample is too small (2158 cases) and includes the serial offenders who are being predicted. Perhaps the only burglar going from one specific neighbourhood to another may be the serial burglar being estimated. If this is true for several destinations for this burglar, then the conditional estimate will be misleadingly accurate. However, this does not explain why the *distance decay* estimate does not work well. The only solution to this problem would be to recalculate the risk surfaces systematically excluding each serial offender from the distance decay function and origin–destination matrix as that offender's residence is estimated. In other words, the analysis

DOI: 10.1002/jip

would have to be redone 62 times. This is probably not practical without CrimeStat being reprogrammed.

Another possible reason for the differences between the The Hague findings and those reported elsewhere in this issue is the existence of size and cultural differences between The Hague and the other cities studied. The Hague is smaller in area, 26.67 sq mi, than Manchester or Baltimore County, densely populated, 475,580 (2006), and has an extensive and relatively cheap public transportation system and a major form of private transportation—bicycles (close to 100% ownership)—that is nearly free of costs except for time. The time costs of biking and driving a car may not be very different in a crowded city, and there is no parking problem. Because of these factors, journey-to-crime estimates based on distance decay may be less relevant than elsewhere. The rate of bicycle theft in The Netherlands is the highest amongst 30 surveyed countries (Van Dijk, Van Kesteren, & Smit, 2007, pp. 62–63), and it is not likely that burglars would bother to buy a bike if they can steal one.

In the analysis, the new technique was only compared with other techniques available in CrimeStat. The results have not been compared with the estimation results by Dragnet or RIGEL, or to the estimates of trained police officers, which is an obvious and urgent task for future enquiries.

Empirical Bayes journey-to-crime estimation as a decision support tool

What is the value of the empirical Bayes method for journey-to-crime estimation as a prioritisation tool? The method demonstrated here may seem complex, but in practice, it need not be. The first step is to develop a geo-coded file of connections between arrested offenders and the crimes they committed. These connections are used to calculate an empirically based distance decay function and an origin–destination (home–offence) matrix of connections. Once developed, these two calibration files can be occasionally updated to reflect more recent spatial offending patterns. As suspected serial incidents occur, the calibration files can be used to estimate the unknown offender's residence. The findings reported here suggest that the *conditional* risk surface is generally the most accurate, and should be the first considered.

Usually, in the practical application of journey-to-crime estimation, after this risk surface is calculated, some areas can be excluded because they are *a priori* unlikely to contain an offender's anchor point (e.g. parks and other areas where no one lives). Typically, these refinements will be hardly necessary for the *conditional* surface, as this surface is calculated on the basis of actual origins and destinations. Therefore, areas where no previous offenders lived (for whatever reason) will already have very low probability values in the *conditional* surface. However, it may be necessary to assess whether there have been major recent changes in residential structures in the study area (either large-scale destruction or construction) as they are likely to change the structure of origin and destination zones.

A possible limitation of the empirical Bayes method is that the connections between origins and destinations that form the basis of the *conditional* risk surface can only be calculated based on a specific area or jurisdiction. These connections implicitly reflect the opportunity structure for offenders living in this specific area and can only be used for journey-to-crime estimation in this particular area. In other words: When using the *conditional* surface for finding the offender responsible for a series, the data file used for calibration must come from the same geographical area. This is different from the *distance*

DOI: 10.1002/jip

decay risk surface. Although not generally recommended, for traditional distance decay journey-to-crime estimation, the calibration data can come from one city and be applied in another, assuming that offenders in both cities can be characterised by similar distance decay functions. This is, by definition, impossible for journey-to-crime estimation that uses the *conditional* surface. Thus, the empirical Bayes journey-to-crime method is truly a tool for local crime investigation. Canter *et al.* (2000) emphasize that geographic profiling is not an expert system, but a decision support tool that allows for a more efficient search for serial offenders in coordination with local knowledge, land use, police investigation, and socio-demographics.

A possible disadvantage of the new method of estimation described is that it requires more data, and a bit more upfront work, than previous techniques. It requires information on a large number of incidents in a specific area and for a specific crime type where the address of the offender is known. A distance decay function can be estimated on the basis of a limited number of crime trips, but the origin–destination matrix, depending on the size of the zones and the required precision, typically requires hundreds of crime trips in the calibration data set. Therefore, the new method may be applied only to relatively common crimes, such as burglary or robbery, or else, it must be assumed that other offenders follow similar spatial patterns.

The new method suffers from many of the same problems that have always limited the applicability of all journey-to-crime estimation, independent of method. First, all prior methods and this one assume that offenders have fixed addresses throughout the series—many do not. Second, the data has all the biases of any police-based incident data. It is filtered by victims and the police, but it is also filtered by the police ability to clear the crimes or arrest an offender. Only a small percentage of incidents result in an arrest. These incidents may be geographically different from incidents where no offender is identified. In addition, only one-fourth of the burglaries analysed for this research were defined by police as a series of five or more crimes, but the defining of a crime series is dependent upon police decision making and available information.

Finally, because the model assumes that an offender from a specific neighbourhood will locate targets in the same way that other offenders have, this method, like all the others, will not be useful to identify the home of an innovative offender, an offender whose home is not his or her anchor point, or an offender who has no home.

Empirical Bayes journey-to-crime estimation as a research tool

The new empirical Bayes model in CrimeStat is more of a tool for police analysts than for researchers. Whilst it may aid in the prioritising of a search area for serial offenders by summarising choices made by other offenders, it does little to explain why these choices are made. How can these choices be made more explicit?

Traditional journey-to-crime estimates and conditional estimates tap different components of burglar's target choice. JTC estimates assume a rational calculation based on the distance or cost of travel. Whilst travel costs remain an important component of conditional estimates, conditional estimates probably are a better measure of the opportunity structure, knowledge space, and choices made by burglars from a specific neighbourhood. However, these choices remain implicit; little is known about how they are made beyond the topography and physical environment of the area under study.

How can these choices be made explicit? Given enough crime trips, risk surfaces can be calculated by crime or offender characteristics. For example, travel patterns for young

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offenders may be quite different from those for older offenders (Levine & Lee, 2009). Second, characteristics of the origin (offender residence) and destination (target) zone could be incorporated into a single regression model that predicts the numbers of crime trips T_{ij} from origin *i* to destination *j*. Such models are known as spatial interaction models or gravity models, and are part of CrimeStat's travel demand tool (for applications of such models to crime trip distributions, see Elffers, Reynald, Averdijk, Bernasco, & Block [2008] and Reynald, Averdijk, Elffers, & Bernasco [2008]). CrimeStat generates Poisson regression equations to explain variation in origin (offender residence) and destination (target) zones. These are then linked in a probabilistic way based on distance, and the connections are compared with the observed connections (the origin–destination links, see above). Whilst this technique will create a calibration layer with explicit measures of the community, it remains based on marginal distributions rather than conditional distributions.

A second technique for explicitly connecting origin and destination zones, based on McFadden's (1973) analysis of discrete choice using a conditional logit regression model, may eventually be tested. In this method, log odds are estimated for every target (destination) zone, conditional on offenders' zone of residence. Whilst distance between origin and destination remains an important component in these regressions, other community and environmental characteristics can be explicitly included. Bernasco and Nieuwbeerta (2005) and Bernasco (2006) applied this model to burglary in The Hague, and Bernasco and Block (2009) applied it to robbery in Chicago. Both studies incorporated offender characteristics, community demography, opportunities, and social barriers. They were able to relatively accurately model overall offence location choices. Bernasco (2007) explains how the model can be reversed and used as an improved method of journey-to-crime estimation. The technique, however, requires complex explicit modelling and extensive data collection on attributes of zones and has not yet been applied to predict the residence of serial offenders. The advantage of the *conditional* surface in the empirical Bayes method is that it does nearly the same thing implicitly, using origin–destination information of prior offenders but without the overhead of an underlying theoretical choice model.

ACKNOWLEDGEMENTS

This research was completed at The Netherlands Institute for the Study of Crime and Law Enforcement (NSCR), whilst the first author was studying under a research leave granted by Loyola University Chicago. The development of CrimeStat and the lead author's research was supported by NIJ grant 2005-IJ-CX-K037, Ned Levine, Principle Investigator. Data were provided by the *Haaglanden* police department.

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APPENDIX

Table A1. Pairwise accuracy comparisons of risk surfaces according to measure 1: estimated probability in the offender's home grid cell

	Distance decay	General	Conditional	Product
General	DistDec***			
Conditional	NS	Condit***		
Product	Prod***	Prod***	Prod***	
Bayes	Bayes***	Bayes***	Bayes**	Prod***

All serial burglars ($n = 62$). The listed measure is more accurate, Wilcoxon signed rank test.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
NS, not significant.

Table A2. Pairwise accuracy comparisons of risk surfaces according to measure 2: distance between maximum probability cell and grid cell where the offender lived ($n = 62$)

	Distance decay	General	Conditional	Product	Bayes
General	NS				
Conditional	Condit***	Condit***			
Product	Prod***	NS	NS		
Bayes	NS	NS	Condit**	Prod**	
CMD	NS	NS	Condit***	Prod***	NS

The listed measure is more accurate, Wilcoxon signed rank test.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
CMD, centre of minimum distance; NS, not significant.

DOI: 10.1002/jip

Table A3a. Pairwise accuracy comparisons of risk surfaces according to measure 3a: percentage of serial offenders living within 1 mi of maximum probability cell (n = 62)

	Distance decay	General	Conditional	Product	Bayes
General	NS				
Conditional	Condit**	Condit***			
Product	Prod***	Prod**	NS		
Bayes	Bayes*	NS	Condit*	Prod**	
CMD	NS	NS	Condit**	Prod***	NS

The listed measure is more accurate, Wilcoxon signed rank test.
*p < 0.05; **p < 0.01; ***p < 0.001.
CMD, centre of minimum distance; NS, not significant.

Table A3b. Pairwise accuracy comparisons of risk surfaces according to measure 3b: percentage of serial offenders living within 1 km of maximum probability cell (n = 62)

	Distance decay	General	Conditional	Product	Bayes
General	NS				
Conditional	Condit***	Condit***			
Product	Prod**	NS	Condit**		
Bayes	NS	NS	Condit*	NS	
CMD	NS	NS	Condit***	Prod**	Bayes**

The listed measure is more accurate, Wilcoxon signed rank test.
*p < 0.05; **p < 0.01; ***p < 0.001.
CMD, centre of minimum distance; NS, not significant.

Table A3c. Pairwise accuracy comparisons of risk surfaces according to measure 3c: percentage of serial offenders living within 0.5 mi of maximum probability cell (n = 62)

	Distance decay	General	Conditional	Product	Bayes
General	NS				
Conditional	Condit***	Condit***			
Product	Prod**	NS	Condit**		
Bayes	Bayes**	NS	Condit**	NS	
CMD	NS	NS	Condit***	Prod**	Bayes*

The listed measure is more accurate, Wilcoxon signed rank test.
*p < 0.05; **p < 0.01; ***p < 0.001.
CMD, centre of minimum distance; NS, not significant.

Table A4. Pairwise accuracy comparisons of risk surfaces according to measure 4: percentage of the study area with higher calculated risk probability than the cell where the offender actually lived

	Distance decay	General	Conditional	Product
General	NS			
Conditional	Condit***	Condit***		
Product	Prod***	Prod*	Condit**	
Bayes	Bayes**	NS	Condit***	Prod***

All serial burglars (n = 62). The listed measure is more accurate, Wilcoxon signed rank test.
*p < 0.05; **p < 0.01; ***p < 0.001.
NS, not significant.

DOI: 10.1002/jip