An Actuarial Analysis of Crime Data with Applications to Subscription Patrol and Restitution[1]

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Abstract

Data from the US Federal Bureau of Investigation's Uniform Crime Reports and the US Department of Justice's National Crime Victimization Survey are reviewed and analyzed for expected values and variances over time and geography. The locale of Montgomery County, Texas is chosen to particularize the results. Considering insurance against the perils of murder, rape, robbery, assault, burglary, larceny, and motor vehicle theft, insurance premia are calculated for each peril, the effect of insurance caps and other coverage modifications are explored, and ruin theory is applied to estimate cash flow requirements for a subscription patrol and restitution startup that would cover these perils.

[1] Please do not quote this paper without permission from the corresponding author.

Introduction

Subscription-based patrol and restitution (SPR) services were suggested by Molinari,[2] the Tannehills,[3] Rothbard,[4] and Friedman.[5] Alternative arrangements have been suggested by Barnett[6] and Murphy.[7] Criticism has come from Nozick.[8]

The business model for such a firm, in brief, is subscription services (residential subscribers pay ~$35/mo). The services rendered are: patrol of premises and environs, first-response for home monitoring systems or other calls, monthly crime reports to the subscriber, crime resolution, and crime indemnification. By *crime resolution* is meant: should a crime occur, the business investigates, attempts to locate the perpetrator, and facilitates engaging the perpetrator in mediation or arbitration to obtain restitution for the victim-subscriber. By *crime indemnification* is meant that should crime resolution fail to make the subscriber whole,[9] the business will pay the subscriber directly to make him chrematistically whole. Legally, the business stands as surety for the civil liability of the direct (special) damages[10] caused by the perpetrator.

We have written two papers in this area, which appear to be the only serious, detailed, written treatments of this business model from a practical perspective.

In our *On the Viability of Subscription Patrol and Restitution Services*,[11] we explored the business model's viability by looking at whether the elements of the business model (patrol, insurance, first-response, premium services, crime reports, mediation, and arbitration) are essential. We explored the questions of whether an SPR company should also adjudicate disputes and whether it should have arrest powers or search powers (contractual or otherwise). We addressed the challenges of potential free riding in a subscription environment, multiple-firm interaction, optimum firm size, and cooperation

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[2] "De la production de la sécurité," in *Journal des Economistes* (Feb, 1849), pp. 277-90. Webbed at http://praxeology.net/GM-PS.htm
[3] *The Market for Liberty* by Linda and Morris Tannehill, Fox and Wilkes, San Francisco, 1993(1970).
[4] *Power and Market* by Murray Rothbard, Sheed Andrews and McMeel , Kansas City, 1977. Webbed as part of *Man, Economy, and State with Power and Market* at http://www.mises.org/rothbard/mes.asp
[5] *The Machinery of Freedom* by David Friedman, Harper and Row, 1971.
[6] *The Structure of Liberty* by Randy Barnett, Oxford University Press, 1998.
[7] *Chaos Theory: Two Essays on Market Anarchy* by Robert Murphy, RJ Communications, New York, 2002. Webbed at http://www.mises.org/books/chaostheory.pdf
[8] *Anarchy, State, and Utopia* by Robert Nozick, Basic Books, New York, 1974.
[9] *Making the victim whole* means that the victim and the perpetrator come to a mutually agreed solution which could include payments of money, performance of services, and/or other arrangements. The key element is that the victim agrees to the arrangement as a suitable remedy for the tort. In the absence of a mediated agreement, *making the victim whole* is only a loose term, unless qualified.
[10] That is, it does not stand for surety for general damages. Examples of special damages include: extra costs, repair or replacement of damaged property, lost earnings (both historically and in the future), loss of irreplaceable items, and additional domestic costs. Examples of general damages include physical or emotional pain and suffering, loss of companionship, loss of consortium, disfigurement, loss of reputation, loss or impairment of mental or physical capacity, and loss of enjoyment of life.
[11] Presented at the Association of Private Enterprise Education Annual Conference, April 2006 and webbed at http://gil.guillory.googlepages.com/

problems. We reported on secondary market research on the home monitoring market and we reported on our primary marketing research pilot.

In our *The Legal Landscape for Subscription Patrol and Restitution in Texas*,[12] we reviewed the laws of Texas as they apply to the business model. We determined the taxes and regulations it would be bound by, the required involvement of state agents, and the legal duties to report certain crimes to the police. We explored the legality of and possible civil liability due to the novel practice of issuing *Notices of Refusal to Arbitrate*.

The present paper explores the narrow topic of the surety component of the business model. An outline of the investigation follows:

1. Time Variation of US Incident Rates. Aggregate data for US crime perils over time from the UCR are shown and explored. Time series are fit with ARIMA models.
2. Geographic Variation of Incident Rates. UCR data for 2005 and 2006 are shown in statistical summaries at the state and county level.
3. Time Variation of Incident Rates of Selected Counties. Montgomery County, Texas and surrounding counties are chosen for special study. Time series for each county is graphed.
4. Absolute Incident Rates. NCVS data are compared to UCR data.
5. Predicted Incident Rates. ARIMA model for Montgomery and correction factors are used to predict incident rates in 2008.
6. Effects of Clearance Rates and Mediated and Arbitrated Settlements. UCR clearance rates are reported for 1995-2006.
7. Severity Data from NCVS and Models. For each peril, severity data are taken from the NCVS and a model is proposed and its parameters estimated.
8. Actuarial Loss Models. The loss models are built up from the information in preceding sections. Expected losses and variances are tabulated, and a shortcut reserving estimate is calculated.
9. Diffusion of Subscriptions. A model for diffusion of subscriptions is proposed.
10. Monte Carlo Simulation. A full Monte Carlo simulation is performed on the actuarial model to suggest reserving and contribution policy.
11. Conclusions.

[12] Presented at the Austrian Scholar's Conference, March 2007 and webbed at http://gil.guillory.googlepages.com/

1. Time Variation of US Incident Rates

The US Federal Bureau of Investigation collects and publishes a number of statistics on crimes in the United States named the Uniform Crime Reports. A useful summary of crime volume and rates excerpted from the 1995 and 2006 reports[13] is reproduced below as Tables 1 and 2. Figure 1 shows relative rates of each crime category.

Table 1. Crime Volume Over Time in the US as Reported in the Uniform Crime Reports of the United States Federal Bureau of Investigation

Year	Population	Murder and nonnegligent manslaughter	Forcible rape	Robbery	Aggravated assault	Burglary	Larceny-theft	Motor vehicle theft
1976	214,659,000	18,780	57,080	427,810	500,530	3,108,700	6,270,800	966,000
1977	216,332,000	19,120	63,500	412,610	534,350	3,071,500	5,905,700	977,700
1978	218,059,000	19,560	67,610	426,930	571,460	3,128,300	5,991,000	1,004,100
1979	220,099,000	21,460	76,390	480,700	629,480	3,327,700	6,601,000	1,112,800
1980	225,349,264	23,040	82,990	565,840	672,650	3,795,200	7,136,900	1,131,700
1981	229,146,000	22,520	82,500	592,910	663,900	3,779,700	7,194,400	1,087,800
1982	231,534,000	21,010	78,770	553,130	669,480	3,447,100	7,142,500	1,062,400
1983	233,981,000	19,310	78,920	506,570	653,290	3,129,900	6,712,800	1,007,900
1984	236,158,000	18,690	84,230	485,010	685,350	2,984,400	6,591,900	1,032,200
1985	238,740,000	18,980	88,670	497,870	723,250	3,073,300	6,926,400	1,102,900
1986	241,077,000	20,610	91,460	542,780	834,320	3,241,400	7,257,200	1,224,100
1987	242,288,918	20,096	91,111	517,704	855,088	3,236,184	7,499,851	1,288,674
1988	244,498,982	20,675	92,486	542,968	910,092	3,218,077	7,705,872	1,432,916
1989	246,819,230	21,500	94,504	578,326	951,707	3,168,170	7,872,442	1,564,800
1990	249,464,396	23,438	102,555	639,271	1,054,863	3,073,909	7,945,670	1,635,907
1991	252,153,092	24,703	106,593	687,732	1,092,739	3,157,150	8,142,228	1,661,738
1992	255,029,699	23,760	109,062	672,478	1,126,974	2,979,884	7,915,199	1,610,834
1993	257,782,608	24,526	106,014	659,870	1,135,607	2,834,808	7,820,909	1,563,060
1994	260,327,021	23,326	102,216	618,949	1,113,179	2,712,774	7,879,812	1,539,287
1995	262,803,276	21,606	97,470	580,509	1,099,207	2,593,784	7,997,710	1,472,441
1996	265,228,572	19,645	96,252	535,594	1,037,049	2,506,400	7,904,685	1,394,238
1997	267,783,607	18,208	96,153	498,534	1,023,201	2,460,526	7,743,760	1,354,189
1998	270,248,003	16,974	93,144	447,186	976,583	2,332,735	7,376,311	1,242,781
1999	272,690,813	15,522	89,411	409,371	911,740	2,100,739	6,955,520	1,152,075
2000	281,421,906	15,586	90,178	408,016	911,706	2,050,992	6,971,590	1,160,002
2001	285,317,559	16,037	90,863	423,557	909,023	2,116,531	7,092,267	1,228,391
2002	287,973,924	16,229	95,235	420,806	891,407	2,151,252	7,057,379	1,246,646
2003	290,788,976	16,528	93,883	414,235	859,030	2,154,834	7,026,802	1,261,226
2004	293,656,842	16,148	95,089	401,470	847,381	2,144,446	6,937,089	1,237,851
2005	296,507,061	16,740	94,347	417,438	862,220	2,155,448	6,783,447	1,235,859
2006	299,398,484	17,034	92,455	447,403	860,853	2,183,746	6,607,013	1,192,809

[13] UCR/NIBRS statistics are available on the UCR website: http://www.fbi.gov/ucr/ucr.htm

Table 2. Crime Rates per 100,000 Population Over Time, calculated from Table 1

Year	Murder and nonnegligent manslaughter	Forcible rape	Robbery	Aggravated assault	Burglary	Larceny-theft	Motor vehicle theft
1976	8.75	26.6	199	233	1,448	2,921	450
1977	8.84	29.4	191	247	1,420	2,730	452
1978	8.97	31.0	196	262	1,435	2,747	460
1979	9.75	34.7	218	286	1,512	2,999	506
1980	10.22	36.8	251	298	1,684	3,167	502
1981	9.83	36.0	259	290	1,649	3,140	475
1982	9.07	34.0	239	289	1,489	3,085	459
1983	8.25	33.7	217	279	1,338	2,869	431
1984	7.91	35.7	205	290	1,264	2,791	437
1985	7.95	37.1	209	303	1,287	2,901	462
1986	8.55	37.9	225	346	1,345	3,010	508
1987	8.29	37.6	214	353	1,336	3,095	532
1988	8.46	37.8	222	372	1,316	3,152	586
1989	8.71	38.3	234	386	1,284	3,190	634
1990	9.40	41.1	256	423	1,232	3,185	656
1991	9.80	42.3	273	433	1,252	3,229	659
1992	9.32	42.8	264	442	1,168	3,104	632
1993	9.51	41.1	256	441	1,100	3,034	606
1994	8.96	39.3	238	428	1,042	3,027	591
1995	8.22	37.1	221	418	987	3,043	560
1996	7.41	36.3	202	391	945	2,980	526
1997	6.80	35.9	186	382	919	2,892	506
1998	6.28	34.5	165	361	863	2,729	460
1999	5.69	32.8	150	334	770	2,551	422
2000	5.54	32.0	145	324	729	2,477	412
2001	5.62	31.8	148	319	742	2,486	431
2002	5.64	33.1	146	310	747	2,451	433
2003	5.68	32.3	142	295	741	2,416	434
2004	5.50	32.4	137	289	730	2,362	422
2005	5.65	31.8	141	291	727	2,288	417
2006	5.69	30.9	149	288	729	2,207	398

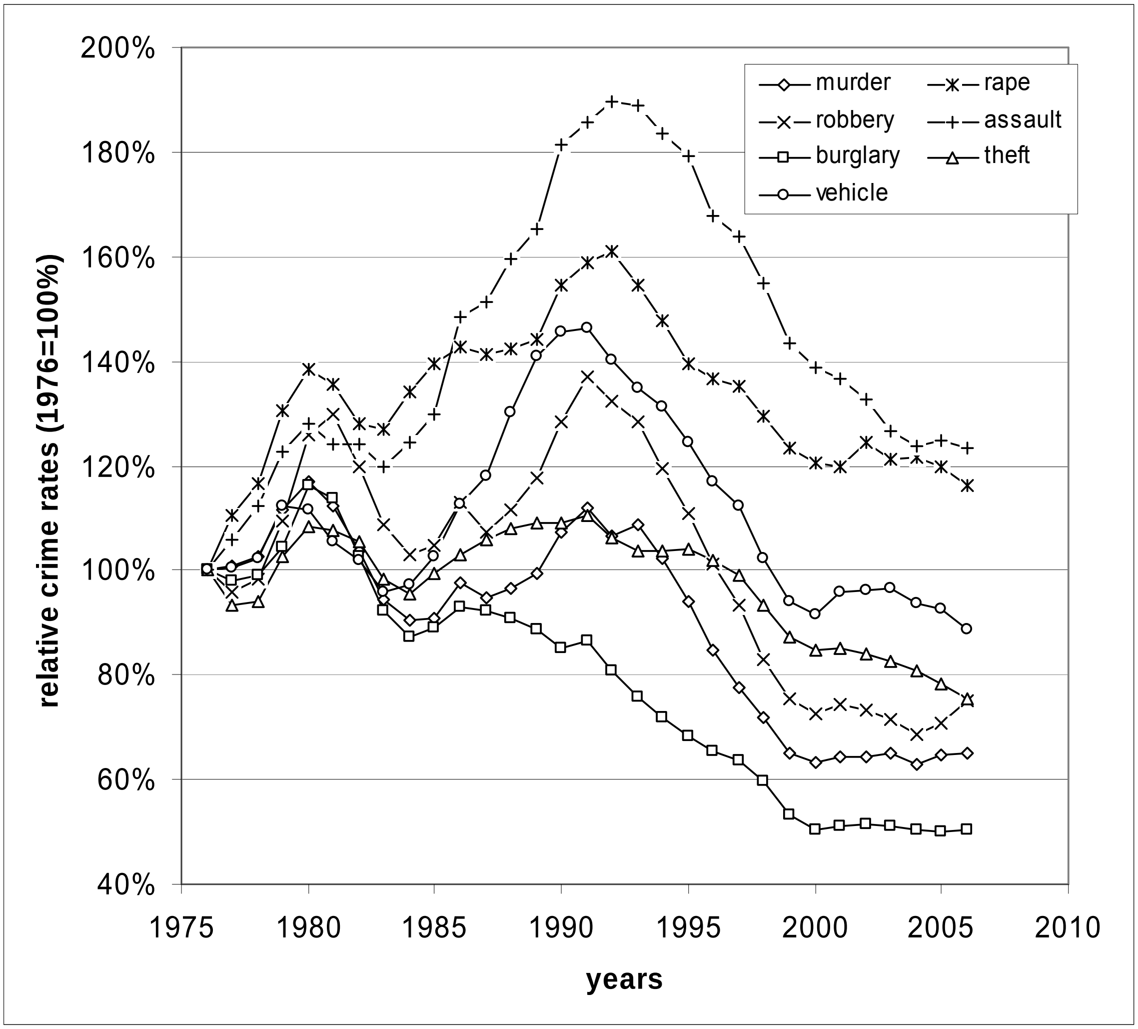

Figure 1. Relative Crime Rates from Table 2

Using standard econometric techniques,[14,15] we found that the time series in Table 2 are all best fit[16] with ARIMA(1,1,0) models.[17] In Table 3 we have reproduced the data from Table 2, and extended the data 2 years by using the ARIMA models. Also reported in Table 3 are the standard errors for the predictions and the fitted autoregressive

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[14] Our tool was R (see r-project.org), a freely-available statistical computing and graphing package.
[15] Our main reference was *Econometric Models and Economic Forecasts* by Pindyck and Rubinfeld, McGraw Hill, 4th international edition, 1998.
[16] Besides the obvious metrics of log likelihood and AIC, we consulted the very good set of rules of thumb webbed by Robert F. Nau at http://www.duke.edu/~rnau/411arim.htm
[17] What is the commonsense meaning of a good fit of an ARIMA(1,1,0)? Like most things in life, the crime rate does not stay constant. It is either going up or going down. ARIMA(1,1,0) fitting well means that the rate of change in the crime rate tends to have some degree of "momentum". If the crime rate is going up, it tends to keep going up, and vice versa. This is clear from Figure 1, which has long periods of crime rate increases and decreases. With the autoregressive parameters (see Table 3) all hovering around 50%, we can loosely say that the crime rate prediction is a 50-50 blend of what the crime rate was last year (keeping the crime rate constant) and what the trend has been from the last 2 years.

parameters. Note that true to AR form, if the crime rate went up from 2005 to 2006, the model predicts a continued upward trend (murder, robbery, burglary) and if the crime rate went down from 2005 to 2006, the model predicts a continued downward trend.

Table 3. Crime Rates per 100,000 Population Over Time from Table 2, and Predicted Rates for 2007 and 2008 with Std Err and AR Coeff.

Year	Murder and nonnegligent manslaughter	Forcible rape	Robbery	Aggravated assault	Burglary	Larceny-theft	Motor vehicle theft
1976	8.75	26.6	199	233	1,448	2,921	450
1977	8.84	29.4	191	247	1,420	2,730	452
1978	8.97	31.0	196	262	1,435	2,747	460
1979	9.75	34.7	218	286	1,512	2,999	506
1980	10.22	36.8	251	298	1,684	3,167	502
1981	9.83	36.0	259	290	1,649	3,140	475
1982	9.07	34.0	239	289	1,489	3,085	459
1983	8.25	33.7	217	279	1,338	2,869	431
1984	7.91	35.7	205	290	1,264	2,791	437
1985	7.95	37.1	209	303	1,287	2,901	462
1986	8.55	37.9	225	346	1,345	3,010	508
1987	8.29	37.6	214	353	1,336	3,095	532
1988	8.46	37.8	222	372	1,316	3,152	586
1989	8.71	38.3	234	386	1,284	3,190	634
1990	9.40	41.1	256	423	1,232	3,185	656
1991	9.80	42.3	273	433	1,252	3,229	659
1992	9.32	42.8	264	442	1,168	3,104	632
1993	9.51	41.1	256	441	1,100	3,034	606
1994	8.96	39.3	238	428	1,042	3,027	591
1995	8.22	37.1	221	418	987	3,043	560
1996	7.41	36.3	202	391	945	2,980	526
1997	6.80	35.9	186	382	919	2,892	506
1998	6.28	34.5	165	361	863	2,729	460
1999	5.69	32.8	150	334	770	2,551	422
2000	5.54	32.0	145	324	729	2,477	412
2001	5.62	31.8	148	319	742	2,486	431
2002	5.64	33.1	146	310	747	2,451	433
2003	5.68	32.3	142	295	741	2,416	434
2004	5.50	32.4	137	289	730	2,362	422
2005	5.65	31.8	141	291	727	2,288	417
2006	5.69	30.9	149	288	729	2,207	398
			Predicted Rates				
2007	5.71	30.4	154	286	730	2,163	385
2008	5.72	30.0	157	285	731	2,139	377
			Standard Errors of Predicted Rates				
2007	0.38	1.2	11	13	56	90	20
2008	0.70	2.3	22	25	102	166	38
			Autoregressive Parameters				
Φ	0.54	0.61	0.60	0.60	0.54	0.54	0.67

For clarity, please note that the ARIMA(1,1,0) models used here have the following equation form: $y_t = \phi \cdot y_{t-1}$, where y_t is the differenced series and x_t is the original series: $y_t = x_t - x_{t-1}$. Combining these yields: $x_t = x_{t-1} + \phi \cdot (x_{t-1} - x_{t-2})$.

We are fully aware that this analysis is elementary and even naïve, when considered as a sociological model of crime or as a robust econometric model. Surely, there are other factors at play in the determination of crime rates, such as changes introduced by the Supreme Court by Mapp v. Ohio (exlusionary rule), Gideon v. Wainwright (legal representation in the courtroom), and Miranda v. Arizona (the so-called Miranda rights): Atkins and Rubin have done a superb job exploring the impact of these with the datasets available.[18] The impact of gun laws has been explored extensively,[19] and other exogenous factors have been proferred[20] as explanations for variations in crime rates.

Our defense of using such a gross tool is that we are attempting to make a reasonable business estimation of crime rates for the upcoming year conditioned upon what has happened to date. Since it is a 1-2 period "look-ahead", it does not have to account for all manner of demographic and institutional change. It only has to account for small changes that may occur over the course of 1-2 years.

[18] *Effects of Criminal Procedure On Crime Rates: Mapping Out the Consequences of The Exclusionary Rule*, Raymond A. Atkins and Paul H. Rubin, The Journal of Law and Economics, volume 46 (2003), pages 157–179.
[19] John Lott's work on this is indispensible, including his *More Guns, Less Crime: Understanding Crime and Gun Control Laws*, John R. Lott, Jr., The University of Chicago Press, 2nd edition, 2000.
[20] *Understanding Why Crime Fell in the 1990s: Four Factors that Explain the Decline and Six that Do Not*, Steven D. Levitt, Journal of Economic Perspectives, Volume 18, Number 1, Winter 2004, pages 163–190.

2. Geographic Variation of Incident Rates

UCR data are aggregated and reported at the national, state, and county level, as well as by the individual reporting entity (usually a sheriff's department or police department).[21] We now examine the geographic variation of incident rates within a given year. We analyze the state-by-state data in Table 4.

Table 4. Basic Statistical Metrics of Crime Rates per 100,000 Population in 2006 When Aggregated by State (50 plus DC and PR), Plus Tabulation of Texas and Top-Five and Bottom-Five States Ranked by Total Property Crimes

metric	murder	rape	robbery	assault	burglary	theft	vehicle
min	0.99	3.0	11	59	311	711	92
max	29.06	76.0	658	789	1,213	2,949	1,259
median	4.92	31.3	108	219	652	2,271	324
mean	5.51	32.7	122	267	689	2,185	361
sd	4.61	11.6	98	152	236	496	228
TEXAS	5.89	35.6	158	316	917	2,758	406
DISTRICT OF COLUMBIA	29.06	31.8	658	789	659	2,735	1,259
ARIZONA	7.54	31.5	150	313	925	2,813	889
WASHINGTON	2.97	42.9	100	200	912	2,851	718
SOUTH CAROLINA	8.31	40.8	137	580	990	2,873	380
NEVADA	8.98	43.2	282	408	995	2,014	1,080
NEW YORK	4.77	16.4	179	235	355	1,531	166
NORTH DAKOTA	1.26	30.4	11	85	376	1,465	159
NEW HAMPSHIRE	0.99	26.2	32	79	331	1,434	108
SOUTH DAKOTA	1.15	43.0	15	112	339	1,189	92
PUERTO RICO	18.81	3.0	134	72	424	711	219

Texas tends to fall in the middle of the crime rate distributions among states for crime categories, except for larceny-theft, where it is near the upper end. Aggregating murder, rape, and assault as "violent crime" and robbery, burglary, larceny-theft, and vehicle theft as "property crime", we show the distribution of crime rates when crime is aggregated by state in Figures 2 and 3.

[21] There is also the NIBRS, the National Incident-Based Reporting System, where crimes are reported at the incident level. These data will not be examined in this paper.

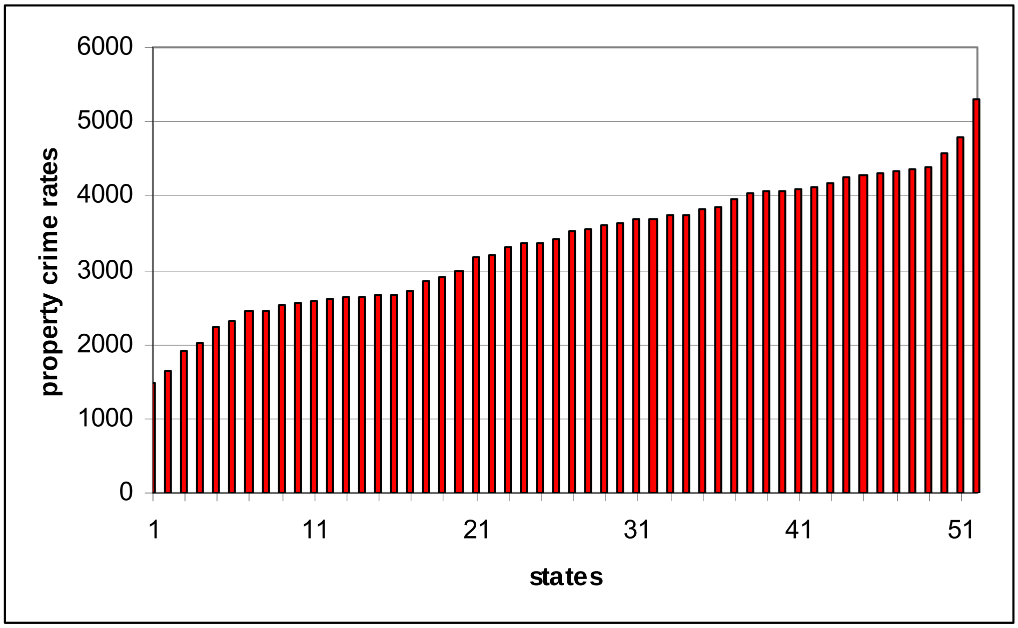

Figure 2. Total Property Crime Rate in States of the US in 2006 (50 + DC + PR)

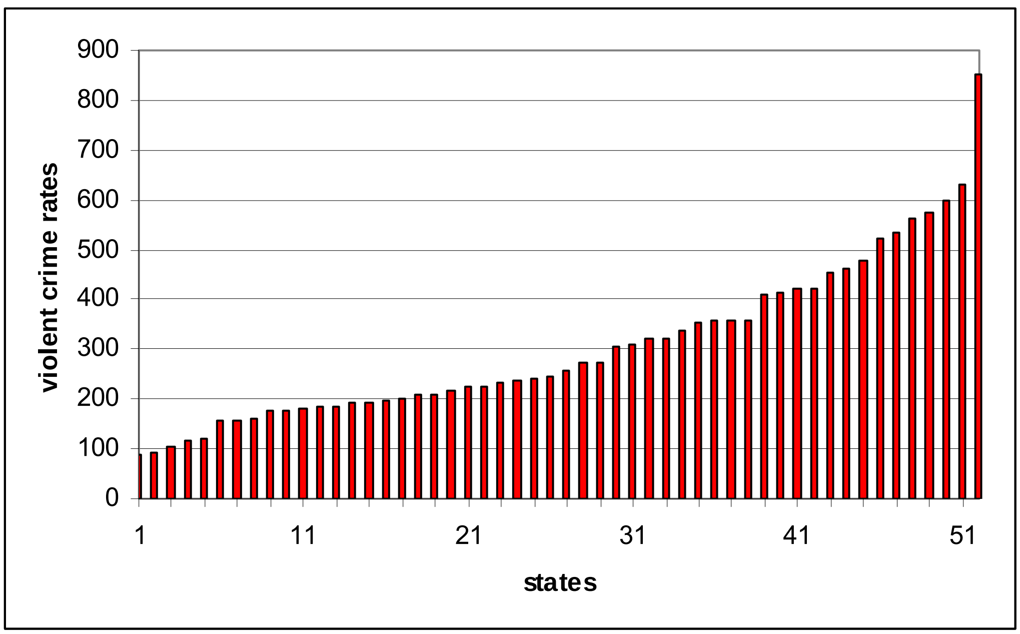

Figure 3. Total Violent Crime Rate in States of the US in 2006 (50 + DC + PR)

Our study centers on Montgomery County, Texas. See the map below for an understanding of the geographical relations between Montgomery and surrounding counties.

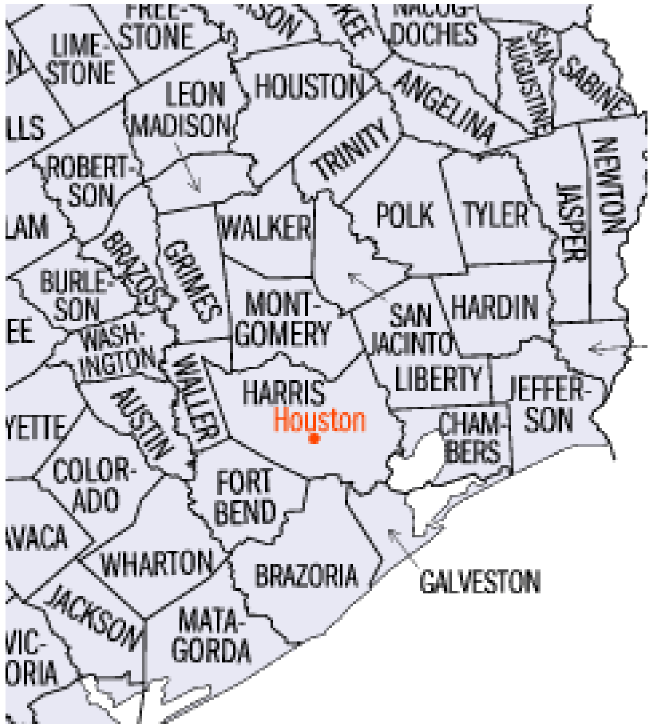

Figure 4. Map of Montgomery and Surrounding Counties (near Houston, Texas)

County-level data are not readily available for 2006, so we have used county-level data for 2005 to compare the geographical variation in crime rate. See Table 5.

Table 5. Basic Statistical Metrics of Crime Rates per 100,000 Population for Entire US in 2005 When Aggregated by Counties, Plus Tabulation of Selected Texas Counties

metric/county	murder	rape	robbery	assault	burglary	theft	vehicle
min	0.00	0.0	0.0	0	0	0	0
max	79.11	361.4	856.9	1,576	2,776	14,447	2,354
median	0.49	22.3	17.3	156	513	1,508	134
mean	3.50	26.9	42.1	209	587	1,678	181
sd	6.29	26.2	70.0	194	375	1,120	186
montgomery	2.71	22.3	62.7	281	634	1,774	219
	Adjacent counties clockwise from southernmost:						
harris	11.04	36.8	359.7	462	1,113	2,976	714
waller	2.83	8.5	67.9	204	1,067	1,701	238
grimes	3.90	7.8	54.6	203	943	2,081	117
walker	0.00	15.8	49.0	231	691	2,065	177
san jacinto	3.99	0.0	23.9	191	742	1,068	247
liberty	10.52	26.3	27.6	189	756	1,604	233
	Counties bordering above counties, clockwise from southernmost:						
brazoria	2.90	31.6	38.1	123	716	1,658	135
fort bend	4.90	28.3	124.6	231	630	1,668	241
austin	7.63	26.7	19.1	191	683	1,472	99
washington	6.30	22.0	47.2	327	963	1,499	135
brazos	5.67	57.3	85.6	414	1,264	3,733	218
madison	0.00	52.2	37.3	358	805	1,483	238
houston	0.00	16.9	16.9	160	532	1,267	76
trinity	6.86	0.0	41.1	199	542	940	110
polk	6.36	27.6	17.0	187	825	1,346	184
hardin	5.86	0.0	11.7	117	596	1,102	201
jefferson	9.91	55.1	191.8	391	1,445	3,560	371
chambers	3.49	7.0	45.3	209	1,035	1,767	164
galveston	5.43	70.6	118.0	230	1,058	2,713	333

Montgomery is a county that is almost a perfect example of the national average with regard to crime rates. However, it borders Harris county, which is home to the large city of Houston (not to be confused with Houston county listed above, which is rural). Discontinuities in crime rates such as murder, assaults, and virtually all property crime categories raise uncertainties in using Montgomery county statistics as representative of households that live near the Montgomery-Harris border.

The variation in violent crime rate and property crime rate across US counties is shown below.

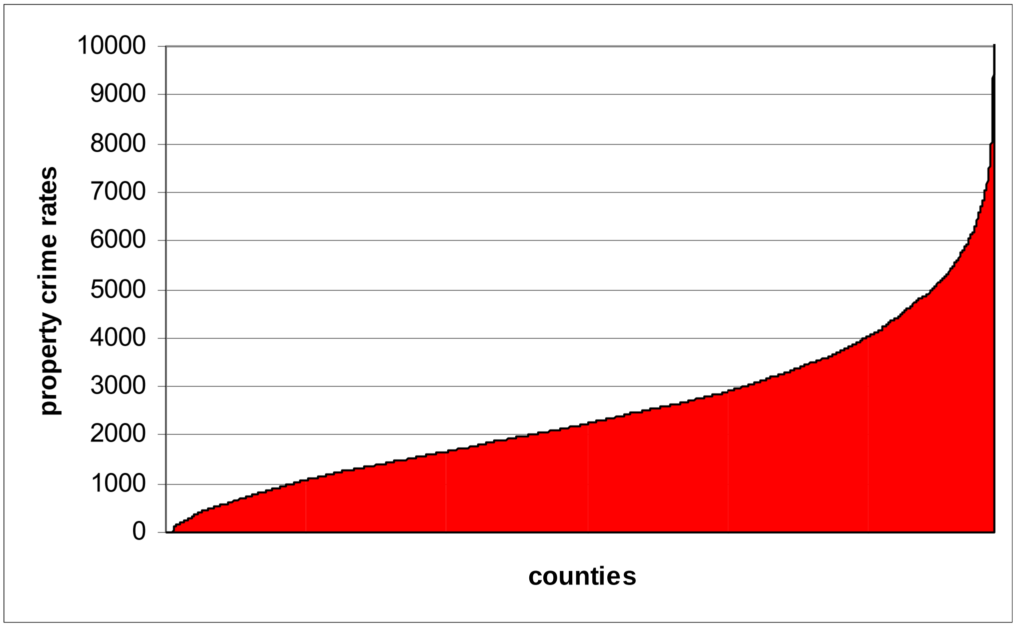

Figure 5. Total Property Crime Rate in Counties in the US in 2005

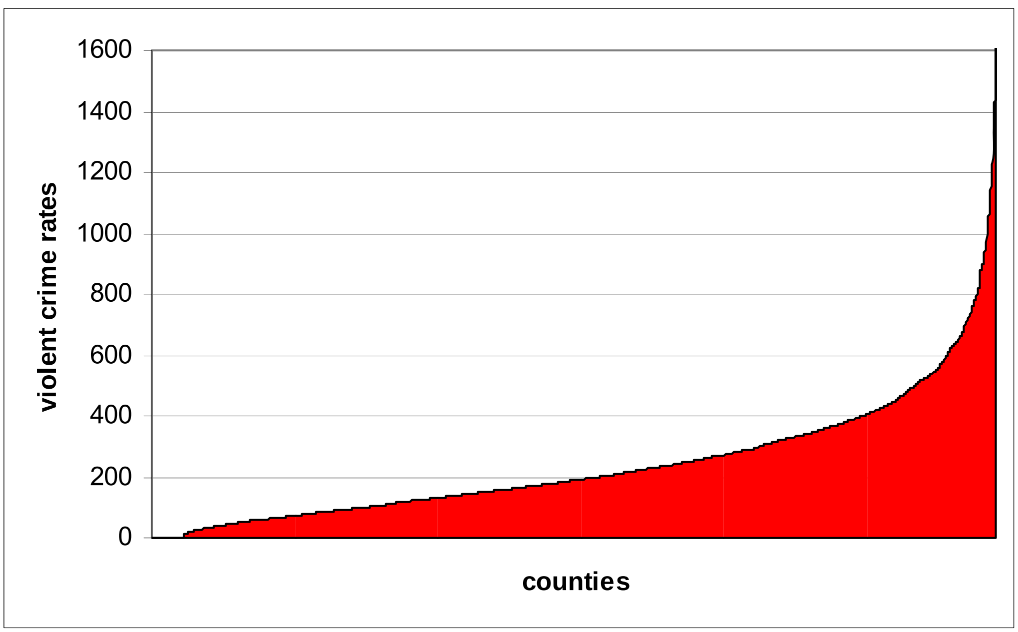

Figure 6. Total Violent Crime Rate in Counties in the US in 2005

3. Time Variation of Incident Rates of Selected Counties

We now consider how crime rates vary over time for Montgomery, Texas and the 6 immediately surrounding counties. This is easily presented as Figures 7-13, below. The data presented are for 1977-2004, years for which UCR data are available as statistical data files. The data for 1993 were corrupted, so the averages for years 1992 and 1994 are used for 1993. We also present in Table 6 summary statistics on the population and averages and standard deviations for crime perils of each of these counties.

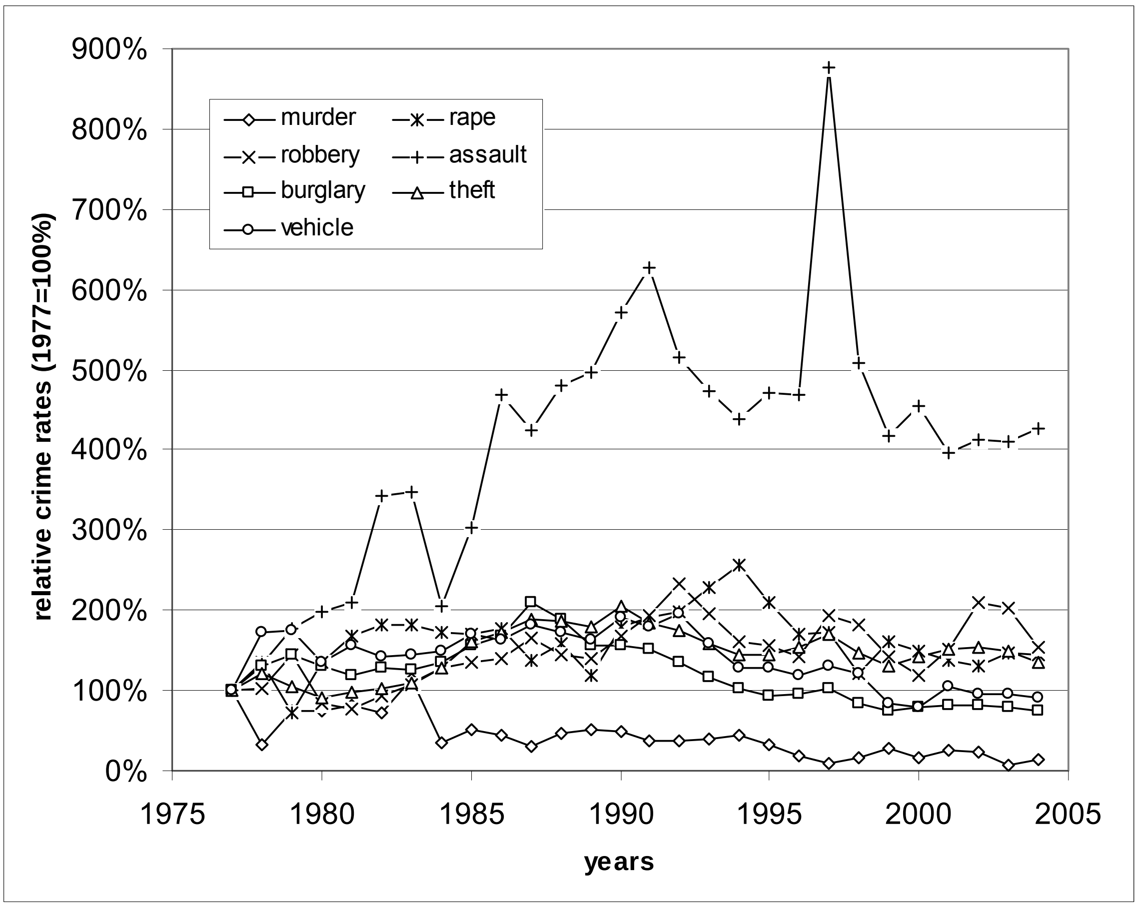

Figure 7. Relative Crime Rates in Montgomery County, Texas

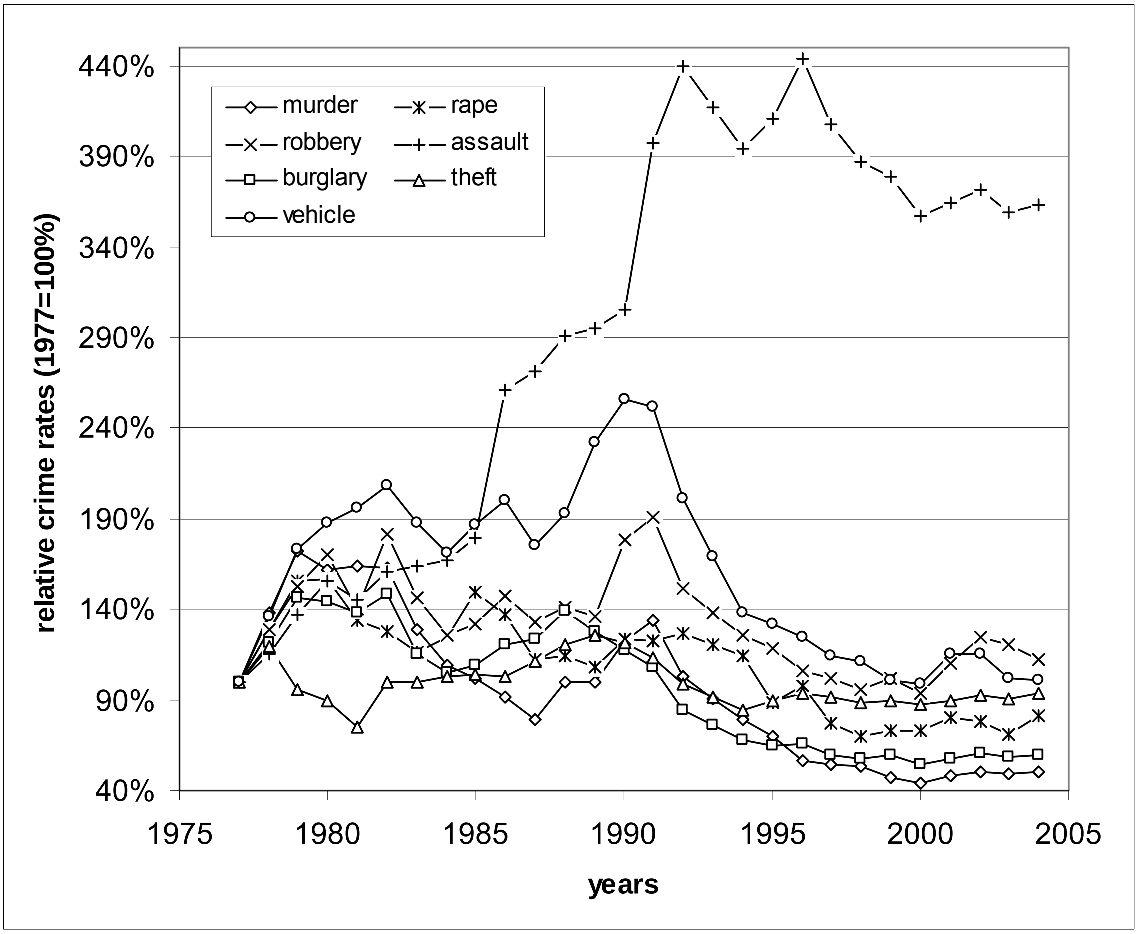

Figure 8. Relative Crime Rates in Harris County, Texas

Table 6. Population in 2004 and Average Crime Rates per 100,000 Population for 1977-2004 and Standard Deviations for Same, Selected Texas Counties

county	harris	montgomery	liberty	walker	waller	grimes	san jacinto
population	3,656,478	350,490	75,362	63,080	35,160	25,382	24,319
murder	18.05	8.73	9.10	7.39	10.22	10.62	7.73
sd	7.74	5.44	5.36	7.34	8.79	10.89	6.50
rape	53.8	28.7	26.9	31.2	36.2	13.6	15.0
sd	13.1	6.8	16.2	14.1	20.2	9.7	13.0
robbery	398	60	50	61	56	29	25
sd	79	16	17	24	24	17	13
assault	389	270	293	311	287	238	145
sd	150	108	119	50	145	102	121
burglary	1,768	1,103	1,118	928	1,102	1,025	1,141
sd	613	327	192	251	355	208	395
theft	3,277	2,177	1,956	2,204	1,880	1,602	1,124
sd	413	461	337	561	847	383	357
vehicle	1,199	328	278	199	284	202	185
sd	362	81	57	64	89	70	105

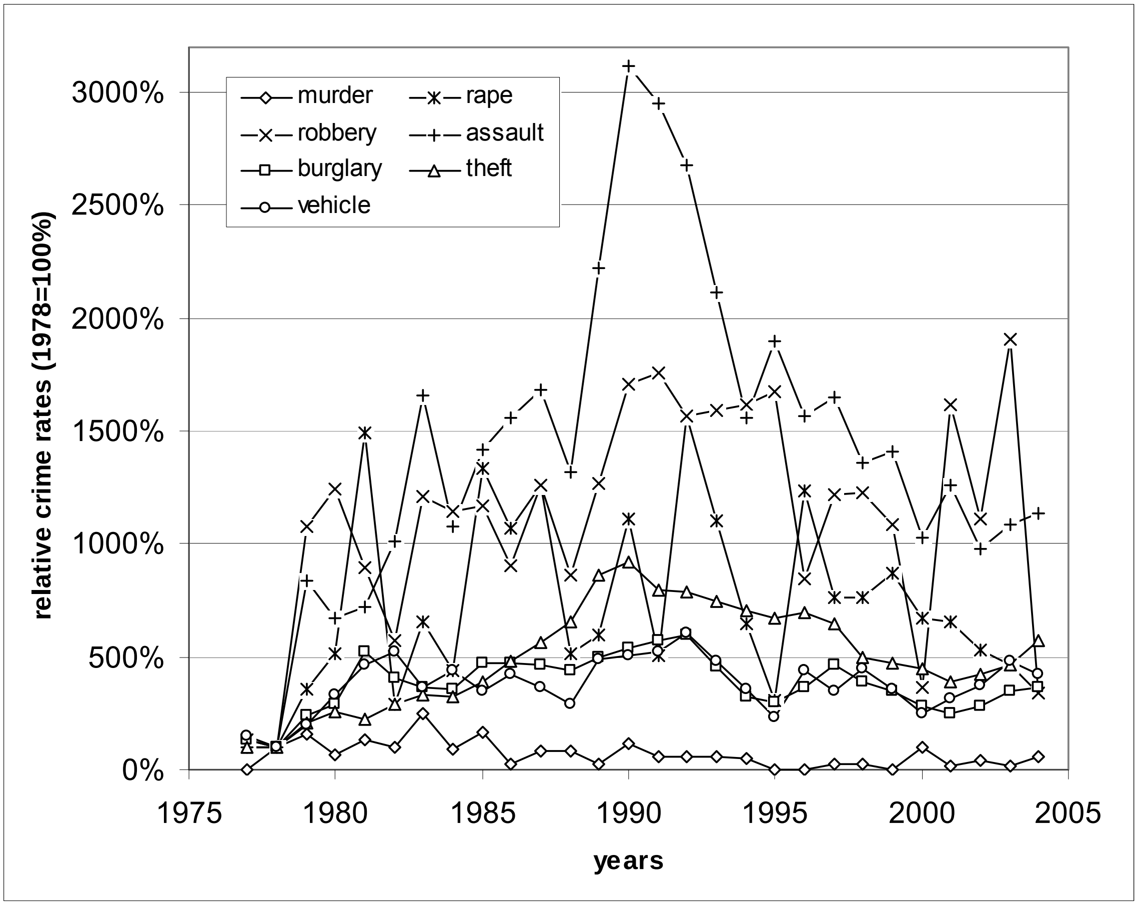

Figure 9. Relative Crime Rates in Waller County, Texas

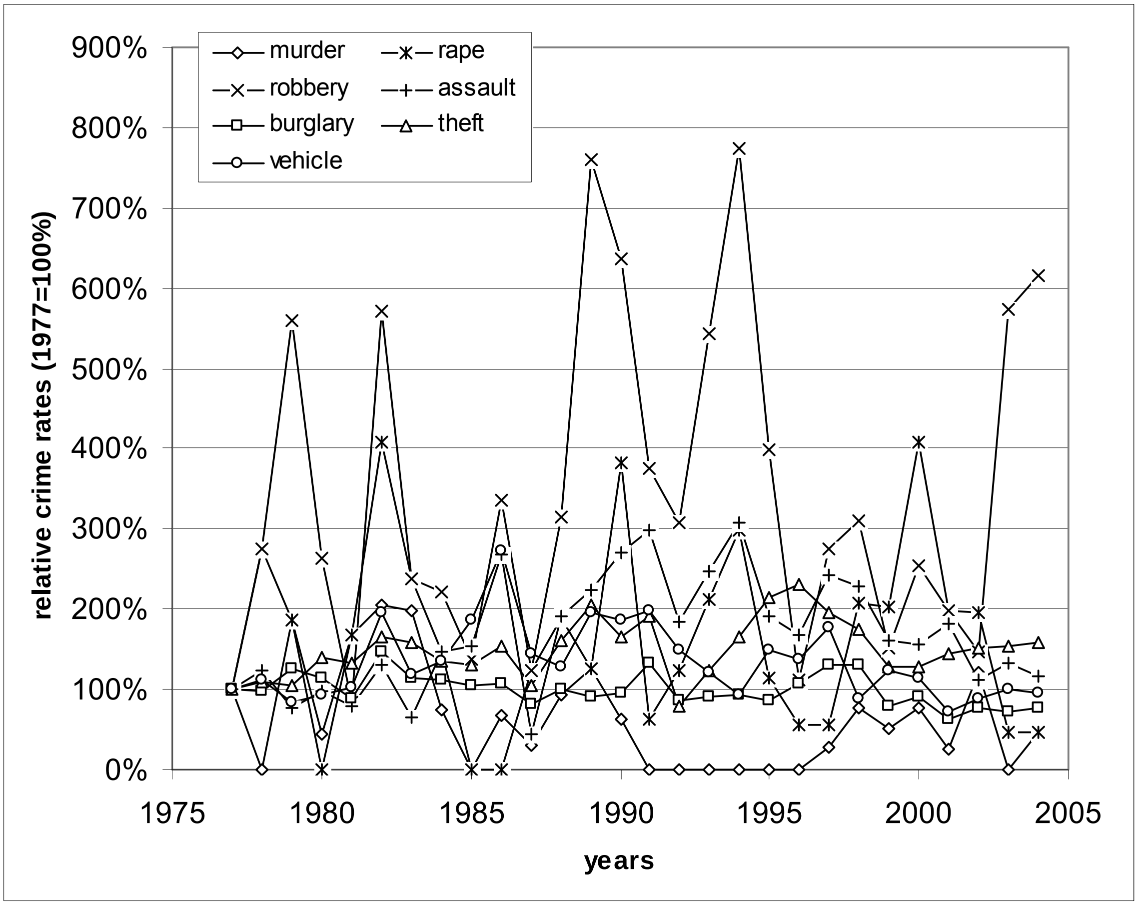

Figure 10. Relative Crime Rates in Grimes County, Texas

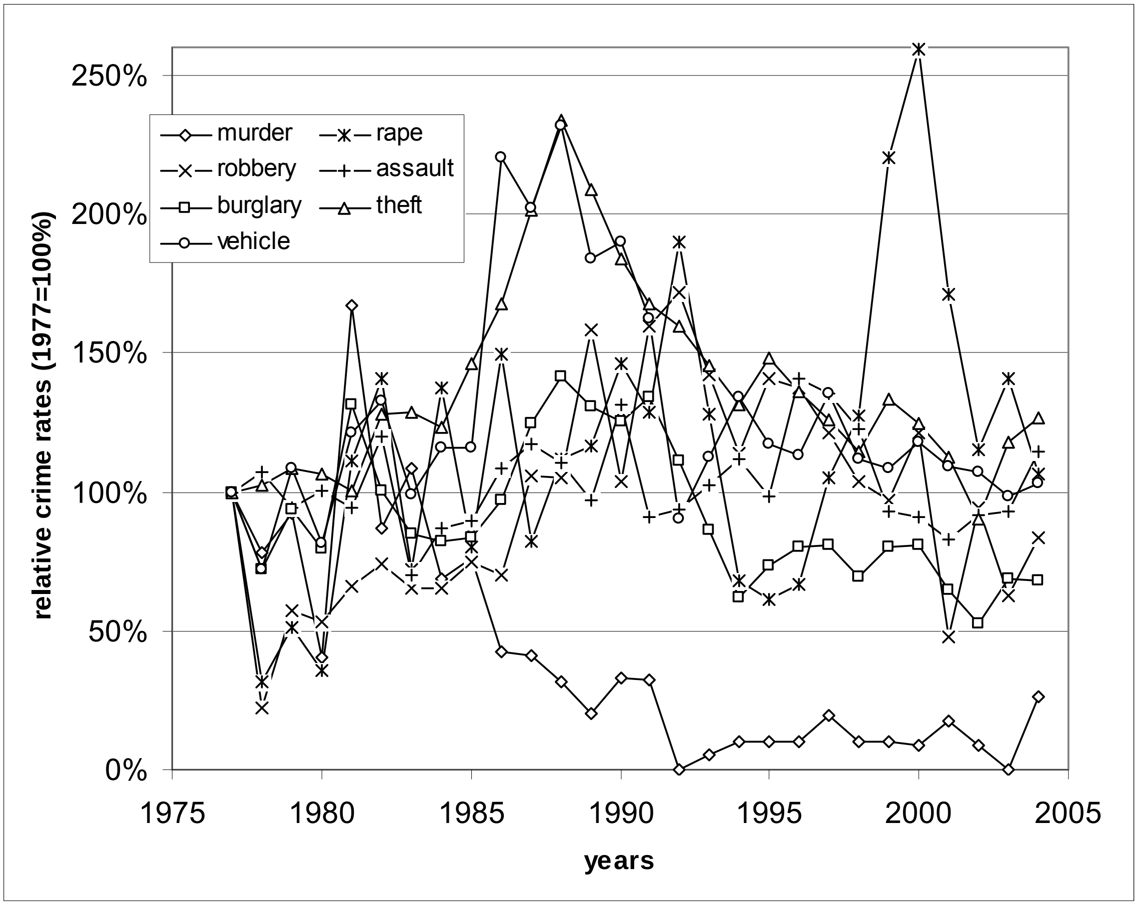

Figure 11. Relative Crime Rates in Walker County, Texas

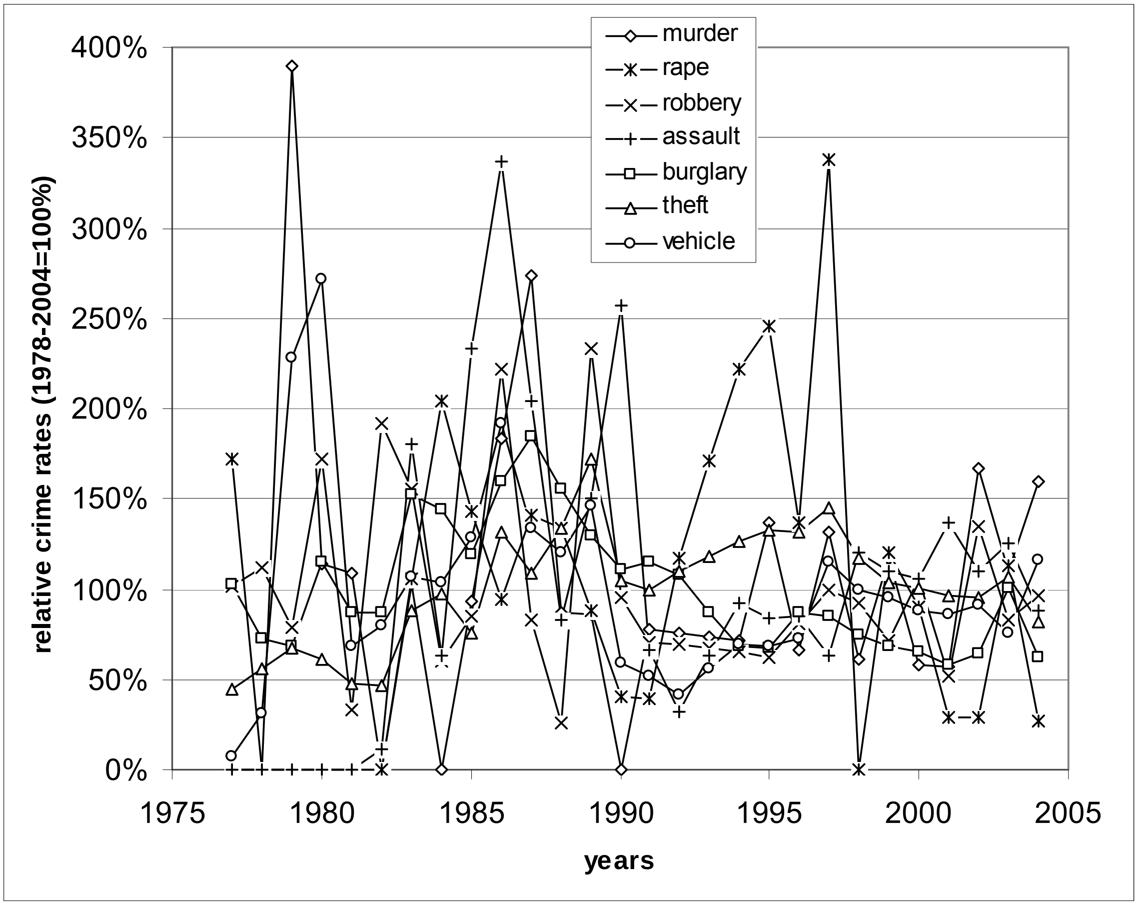

Figure 12. Relative Crime Rates in San Jacinto County, Texas

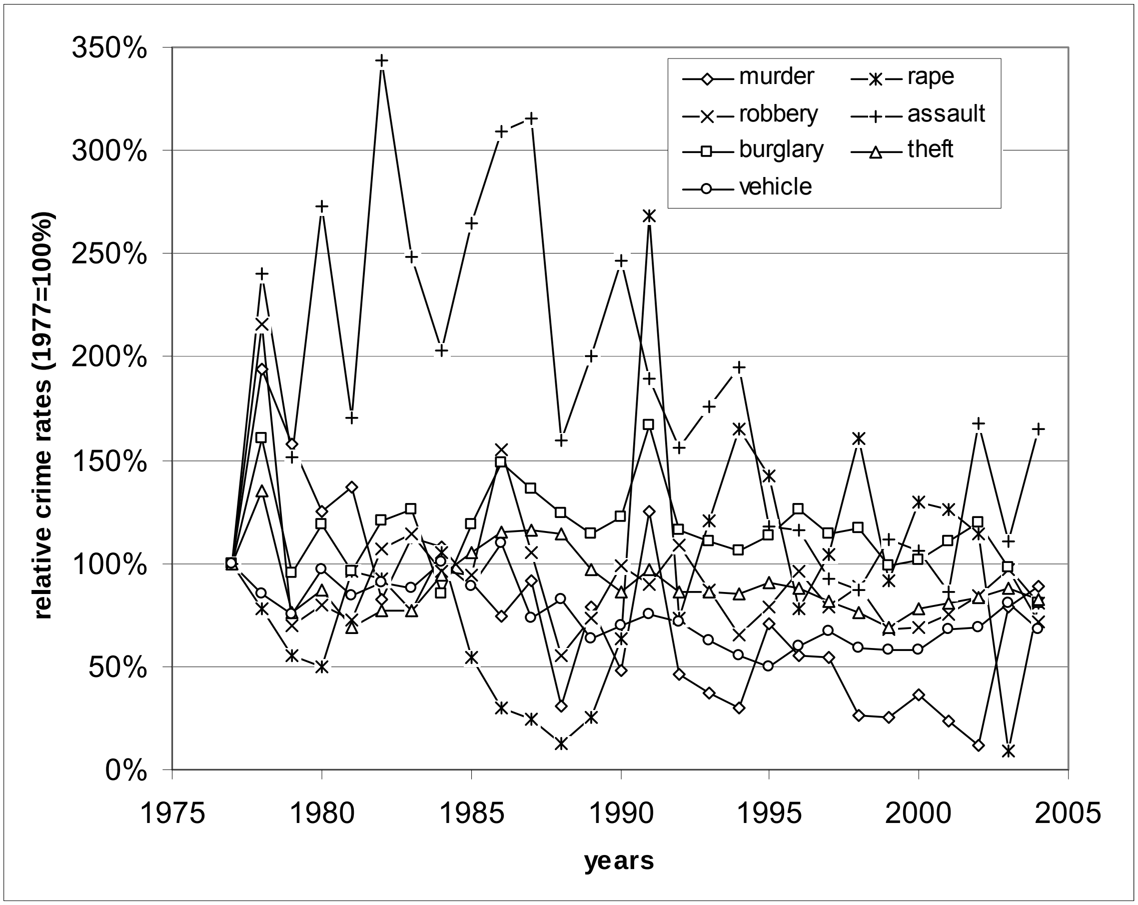

Figure 13. Relative Crime Rates in Liberty County, Texas

From Table 6 (and Table 5, and Figures 8-13) it is clear that the principal threat of crime rate "diffusion" is from Harris County. This fear has failed to materialize when we consider Figures 7 and 8 and the social context. Montgomery County experienced significant population growth from 1977 (84,200) to 2004 (350,490) as it became one of many burgeoning suburban areas of Houston. Notwithstanding this history, crime rates in Montgomery county seem not to have been affected by this – while carefully noting the broader secular trends found nationally (Figure 1) and also the permanent change in assault rates that is characteristic of Montgomery, Harris, and Waller (Figures 7-9). Furthermore, crime rates in Montgomery and Harris have been very stable for the last 5 years.

4. Absolute Incident Rates: NCVS vs. UCR data

The US Department of Justice's National Crime Victimization Survey uses a wholly different research methodology from the Federal Bureau of Investigation's Uniform Crime Reports. The UCR's count crime reported to the police. The NCVS interviews a nationally representative sample of people and asks whether and how they have been victimized in the past year.[22] The result is that there is geographic richness in the UCR data, but the rates are consistently lower than reported by the much more reliable NCVS data. The richness in the NCVS data have to do with victim and offender characteristics and relationships, location of crime, and other factors. The NCVS program started in 1973, with a significant redesign in 1992. The Bureau of Justice Statistics has published a very usable set of tables of the NCVS results for 1996-2005,[23] which we will use here.

In this section, we will develop two modification factors that can be applied to the UCR ARIMA models developed in Sections 1 and 5. First, the real vs. reported crime rates factor; second, the at-home vs. away-from-home crime factor. This latter factor is necessary to adjust for the fact that in an SPR business model, crime perils at the home are indemnified, but crime perils elsewhere are not indemnified.

First, we tabulate national NCVS crime incidence side-by-side with national UCR crime incidence.[24] The NCVS data also contain reporting rates (that is, victims are asked whether they reported the crime to police). These are also tabulated for comparison. See Table 7. Murders are not reported in the NCVS, so these are not tabulated. Motor vehicle thefts are not compared here since the numbers in the UCR tend to be higher than those reported in the NCVS – we will use the UCR data. For the most part, the NCVS reporting rates agree with the ratio of NCVS incidents to UCR incidents. The only discrepancy is for the crime of assault. This is because the UCR rates are for aggravated assault and the NCVS rates are for all assaults, both simple and aggravated. We choose to capture the total rate and handle the severity separately.

Second, we reproduce data from the NCVS detailing the location of the crime.[25] We count our "at-home" factor to be the sum of the reported NCVS categories of "inside home or lodging" and "near respondent's home". We exclude all other NCVS categories, including "don't know or not available". Here, burglaries are omitted (all are "at home"), but motor vehicle thefts are included. Murders are not reported in the NCVS, so we propose to use 25% as the proportion of murders that would be covered by an SPR business model, if coverage were extended to this peril. We base this upon a presentation

[22] The methodology is actually more complex than this, with quarterly interviews, information about all people within the household 12 years of age and older, the time scales are overlapping, and the representativeness of the sample is an especially tricky part of the NCVS analysis. However, we will take the NCVS data at face value for the purposes of this paper.
[23] See http://www.ojp.usdoj.gov/bjs/abstract/cvusst.htm
[24] We use data from Table 91 of the NCVS and Table 1 of the UCR for each year.
[25] From Table 65 of the NCVS for each year.

by Groff and McEwen,[26] which states, based upon a geostatistical analysis of about 4000 homocides over a 10-year period in the Washington, D.C. area, that "25% of victims [were] killed within one block [of their homes]."

We recognize that an additional discounting of crime rate could be given, since the SPR business model will not recognize claims for crime committed within a household; however, NCVS data are not reported for percent of property crimes committed by other householders. And, if the household violence data[27] are any indication, this rate of incidence compared to the overall rate is less than about 10%.

[26] *Disaggregating the Journey to Homicide*, by Elizabeth R. Groff, presented at The Seventh Annual International Crime Mapping Research Conference, Boston, 2004. See http://www.ojp.usdoj.gov/nij/maps/boston2004/

[27] See Table 34 of the NCVS for each year.

Table 7. NCVS vs. UCR Crime Incidents Plus NCVS Reporting Rates, 1996-2005

Year	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	mean	sd
Rape												
UCR	96,252	96,153	93,144	89,411	90,178	90,863	95,235	93,883	95,089	94,347		
NCVS	307,100	311,000	332,500	333,000	260,950	248,250	247,730	198,850	209,880	191,670		
ratio	31.3%	30.9%	28.0%	26.9%	34.6%	36.6%	38.4%	47.2%	45.3%	49.2%	36.8%	8.1%
NCVS report rate	30.7%	30.5%	31.6%	28.3%	48.1%	38.6%	53.7%	38.5%	35.8%	38.3%	37.4%	8.1%
Robbery												
UCR	535,594	498,534	447,186	409,371	408,016	423,557	420,806	414,235	401,470	417,438		
NCVS	1,134,330	944,000	886,490	886,000	731,780	630,690	512,490	596,130	501,820	624,850		
ratio	47.2%	52.8%	50.4%	46.2%	55.8%	67.2%	82.1%	69.5%	80.0%	66.8%	61.8%	13.2%
NCVS report rate	53.9%	55.8%	62.0%	61.2%	56.3%	60.5%	71.2%	60.5%	61.1%	52.4%	59.5%	5.3%
Assault												
UCR	1,037,049	1,023,201	976,583	911,740	911,706	909,023	891,407	859,030	847,381	862,220		
NCVS	7,683,540	7,359,000	6,897,250	6,897,000	5,330,010	4,864,890	4,581,190	4,606,740	4,470,960	4,357,190		
ratio	13.5%	13.9%	14.2%	13.2%	17.1%	18.7%	19.5%	18.6%	19.0%	19.8%	16.7%	2.7%
NCVS report rate	41.6%	43.7%	44.5%	42.6%	46.7%	48.5%	45.7%	46.3%	49.4%	47.1%	45.6%	2.5%
Burglary												
UCR	2,506,400	2,460,526	2,332,735	2,100,739	2,050,992	2,116,531	2,151,252	2,154,834	2,144,446	2,155,448		
NCVS	4,844,690	4,635,000	4,054,170	4,054,000	3,443,700	3,139,700	3,055,720	3,395,620	3,427,690	3,456,220		
ratio	51.7%	53.1%	57.5%	51.8%	59.6%	67.4%	70.4%	63.5%	62.6%	62.4%	60.0%	6.5%
NCVS report rate	50.6%	51.8%	49.4%	49.3%	50.7%	53.7%	57.9%	54.1%	53.0%	56.3%	52.7%	2.9%
Theft												
UCR	7,904,685	7,743,760	7,376,311	6,955,520	6,971,590	7,092,267	7,057,379	7,026,802	6,937,089	6,783,447		
NCVS	21,120,480	19,749,000	17,702,790	17,703,000	14,915,900	14,135,090	13,494,750	14,198,290	14,211,940	13,605,590		
ratio	37.4%	39.2%	41.7%	39.3%	46.7%	50.2%	52.3%	49.5%	48.8%	49.9%	45.5%	5.5%
NCVS report rate	28.4%	27.9%	29.2%	27.1%	29.5%	30.1%	32.8%	31.8%	32.3%	32.3%	30.1%	2.0%

Table 8. Selected NCVS Data Detailing Location by Crime Type, 1996-2005

Year	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	mean	sd
Rape												
inside home	34.8%	34.4%	44.0%	27.9%	38.7%	30.0%	30.0%	33.6%	31.0%	38.0%	34.2%	4.9%
near home	7.1%	7.8%	5.1%	4.8%	11.5%	12.3%	6.3%	8.6%	3.7%	1.5%	6.9%	3.4%
sum	41.9%	42.2%	49.1%	32.7%	50.2%	42.3%	36.3%	42.2%	34.7%	39.5%	41.1%	5.7%
Robbery												
inside home	12.1%	15.1%	23.2%	16.6%	14.4%	20.9%	21.8%	19.7%	20.9%	13.7%	17.8%	3.9%
near home	13.6%	10.5%	12.8%	13.6%	14.9%	11.3%	15.0%	15.9%	13.3%	16.2%	13.7%	1.9%
sum	25.7%	25.6%	36.0%	30.2%	29.3%	32.2%	36.8%	35.6%	34.2%	29.9%	31.6%	4.1%
Assault												
inside home	13.7%	14.6%	15.9%	12.8%	15.0%	14.9%	15.2%	15.7%	16.1%	14.0%	14.8%	1.0%
near home	15.0%	16.5%	14.0%	16.2%	16.8%	15.2%	17.8%	15.5%	16.0%	18.7%	16.2%	1.4%
sum	28.7%	31.1%	29.9%	29.0%	31.8%	30.1%	33.0%	31.2%	32.1%	32.7%	31.0%	1.5%
Theft												
inside home	9.9%	9.7%	10.2%	9.8%	9.9%	9.5%	9.8%	9.1%	9.2%	8.7%	9.6%	0.5%
near home	41.1%	41.2%	41.0%	40.4%	41.6%	44.2%	46.6%	46.8%	49.4%	49.4%	44.2%	3.6%
sum	51.0%	50.9%	51.2%	50.2%	51.5%	53.7%	56.4%	55.9%	58.6%	58.1%	53.8%	3.2%
Vehicle												
inside home	0.7%	0.6%	1.9%	1.2%	1.3%	2.2%	1.3%	1.4%	1.0%	1.0%	1.3%	0.5%
near home	59.6%	61.5%	59.1%	62.9%	61.4%	58.1%	63.1%	62.2%	64.0%	66.6%	61.9%	2.5%
sum	60.3%	62.1%	61.0%	64.1%	62.7%	60.3%	64.4%	63.6%	65.0%	67.6%	63.1%	2.3%

5. Predicted Incident Rates.

In this section, we combine insights from the previous 4 sections to predict incident rates for each crime category for the ZIP codes of 77380, 77381, and 77382 in Montgomery County, Texas. These ZIP codes have population-to-household ratios[28] for owner-occupied housing of 2.75 (with 12708 owner-occupied housing units), 3.07 (31152), and 3.14 (13353) for the respective ZIP codes. This is a weighted average of 3.015 people per household. This factor will be applied to the UCR rates, since UCR rates are in crimes per population, and the relevant unit of analysis for the SPR business model is per (subscribing) household.

As in section 1, we use standard econometric techniques to forecast crime rates in Montgomery County out to 2008 based upon UCR data readily available (1977-2004 in statistical files plus 2005 from a separate spreadsheet tabulation). Unlike section 1, the models are not all ARIMA(1,1,0). Instead, some are ARIMA(0,1,1) and some are ARIMA(1,1,1). Unlike the national data (Figure 1), Montgomery county data (Figure 7) are characterized by up and down movements along a secular trend. This is most apparent in the assault rate, which climbs from 67 to 281, but with lots of scatter around this trend. The secular trend results in a need to difference the series to achieve stationarity, and the mean-reverting behavior around the trend results in a moving average term. The autoregressive character of the differenced Montgomery time series was significantly less than in the national data, resulting in many of the crime categories not even meriting inclusion of an autoregressive parameter.

Table 9. Crime Rates per 100,000 Population Over Time for Montgomery County, Texas, Predicted Rates, Econometric Parameters, and Other Adjustments

year	murder	rape	robbery	assault	burglary	theft	vehicle
1977	20.20	17.8	40	67	909	1,494	234
1978	6.60	24.1	42	89	1,194	1,800	402
1979	14.90	13.0	59	117	1,307	1,570	411
1980	14.90	24.3	34	132	1,182	1,345	318
1981	16.50	30.1	31	139	1,087	1,470	365
1982	14.60	32.2	37	228	1,156	1,516	330
1983	23.30	32.5	43	231	1,153	1,652	338
1984	7.10	30.8	52	137	1,223	1,906	347
1985	10.40	30.5	54	202	1,414	2,392	399
1986	9.00	31.7	56	312	1,531	2,561	383
1987	6.30	24.4	67	282	1,898	2,818	427
1988	9.50	28.4	59	319	1,709	2,773	403
1989	10.50	21.0	57	330	1,425	2,667	383
1990	9.90	31.8	68	380	1,420	3,053	445
1991	7.50	33.9	79	417	1,371	2,762	419
1992	7.40	35.4	95	343	1,221	2,622	456
1993	8.20	40.9	79	315	1,066	2,377	373
1994	9.00	45.8	65	291	927	2,158	299

[28] According to US Census 2000, data set Summary File 1, Quick Table QT-H3. Household Population and Household Type by Tenure. See http://factfinder.census.gov/

1995	6.60	37.6	63	314	839	2,163	300
1996	3.90	30.3	58	312	859	2,296	280
1997	1.70	30.6	78	584	938	2,532	305
1998	3.40	21.7	73	339	759	2,206	281
1999	5.80	28.7	58	278	669	1,937	197
2000	3.40	26.6	48	303	727	2,119	188
2001	5.00	24.6	62	263	749	2,250	245
2002	4.60	23.5	85	274	752	2,284	223
2003	1.50	26.1	82	273	724	2,221	222
2004	2.90	25.7	63	284	681	2,021	213
2005	2.71	22.3	63	281	634	1,774	219
Raw Predicted Rates							
2006	3.08	23.1	65	280	622	1,694	218
2007	3.08	23.1	64	280	625	1,741	218
2008	3.08	23.1	65	280	624	1,713	218
Standard Errors of Raw Predicted Rates							
2006	4.01	5.5	12	76	129	203	52
2007	4.26	6.9	18	87	225	346	63
2008	4.49	8.0	22	97	282	418	73
Parameters							
Φ			-0.60		-0.29	-0.59	
θ	-0.65	-0.25	0.81	-0.45	0.72	1.00	-0.29
ARIMA	0,1,1	0,1,1	1,1,1	0,1,1	1,1,1	1,1,1	0,1,1
Factor to account for UCR under-reporting (from Table 7)							
ratio	100.0%	36.8%	59.5%	16.7%	52.7%	30.1%	100.0%
factor	1.000	2.717	1.681	5.988	1.898	3.322	1.000
Factor to account for at-home location only (from Table 8)							
factor	25.0%	41.1%	31.6%	31.0%	100.0%	53.8%	63.1%
Factor to account for "per household" instead of "per person of population" (see paragraph above)							
factor	3.015	3.015	3.015	3.015	3.015	3.015	3.015
Predicted Rates = Raw Rates multiplied by factors tabulated above							
2006	2.32	77.8	104	1,570	3,559	9,127	415
2007	2.32	77.8	102	1,570	3,578	9,383	415
2008	2.32	77.8	103	1,570	3,572	9,232	415
Standard Errors of Predicted Rates							
2006	3.03	18.5	19	425	737	1,093	98
2007	3.21	23.2	30	486	1,289	1,865	120
2008	3.38	27.0	36	540	1,611	2,254	139

6. Clearance Rates and Mediated and Arbitrated Settlements.

When a covered crime is committed under the SPR business model, the SPR business performs the following functions: investigates the scene, including conducting an adjuster's estimate of losses; investigates any leads to find the perpetrator; if the perpetrator is found, attempt to engage the perpetrator in victim-offender mediation (if he admits culpability); failing that, attempt to engage the perpetrator in binding arbitration (if he disputes culpability); failing that, the SPR will make the subscriber chrematistically whole with an indemnity.

It is clear that not all covered crimes committed will result in payment of an indemnity. But how many crimes will be cleared? The FBI's UCR data include clearance statistics. In the UCR, a cleared crime means: when at least one person is arrested, charged with the commission of the offense, and is turned over to the court for prosecution (whether following arrest, court summons, or police notice). There are reasons to think that a private SPR company's clearance rate will be better than that reported in the UCR, and there are reasons to think it will be worse. The UCR clearance rates for property crimes, the most practical and immediate concern of the SPR company, are quite low. So, even if these rates are not accurate, their low values ensure that the error is not a great one.

For the purposes of this paper, we will assume that the clearance rates shown in Table 10 are the percentage of crimes for which the indemnity paid is zero. For clarity, we present our "final" hazard rates in Table 11. These hazard rates are the input to the actuarial models discussed in sections 8, 10, and 11.

Table 10. Clearance Rates by Crime Type Reported in the UCR, Average of All Agencies in the US

Year	murder	rape	robbery	assault	burglary	theft	vehicle
1995	64.8%	51.1%	24.7%	55.7%	13.4%	19.6%	14.1%
1996	66.9%	51.9%	26.9%	58.0%	13.8%	20.3%	14.0%
1997	66.1%	50.8%	26.3%	58.5%	13.8%	19.8%	14.0%
1998	68.7%	49.9%	28.4%	58.5%	13.6%	19.2%	14.2%
1999	69.1%	49.5%	28.5%	59.2%	13.7%	19.1%	14.9%
2000	63.1%	46.9%	25.7%	56.9%	13.4%	18.2%	14.1%
2001	62.4%	44.3%	24.9%	56.1%	12.7%	17.6%	13.6%
2002	64.0%	44.5%	25.7%	56.5%	13.0%	18.0%	13.8%
2003	62.4%	44.0%	26.3%	55.9%	13.1%	18.0%	13.1%
2004	62.6%	41.8%	26.2%	55.6%	12.9%	18.3%	13.0%
2005	62.1%	41.3%	25.4%	55.2%	12.7%	18.0%	13.0%
2006	60.7%	40.9%	25.2%	54.0%	12.6%	17.4%	12.6%
mean	64.7%	46.5%	26.4%	57.0%	13.3%	18.7%	13.8%
sd	2.7%	3.8%	1.2%	1.4%	0.4%	0.9%	0.6%

Table 11. Hazard Rates for Payment Events

	murder	rape	robbery	assault	burglary	theft	vehicle
Predicted Incident Rates, 2008 (from Table 9)	2.32	77.8	103.4	1,570	3,572	9,232	415
Standard Errors of Predicted Incident Rates, 2008 (from Table 9)	3.38	27.0	36.0	540	1,611	2,254	139
Clearance Rates (from Table 10)	64.7%	46.5%	26.4%	57.0%	13.3%	18.7%	13.8%
Hazard Rates for Payment Events	0.82	41.6	76.1	674	3,098	7,511	358
Standard Errors of Hazard Rates	1.19	14.5	26.5	232	1,397	1,834	120

7. Severity Data from NCVS and Models

When a crime occurs, the victim suffers a loss. In order to estimate payments to subscribers for their losses, we must develop a severity distribution for each crime peril. These are amounts that the perpetrator would have to pay to the victim. For the peril of murder, we posit a constant severity of $1,000,000. For the peril of rape, we posit a constant severity of $50,000.[29]

For other perils, we use data from NCVS Table 83 to compute severity distributions. These tables only give values for direct monetary losses, which is consistent with our objective of indemnifying only chrematistic losses. A portion of NCVS Table 83 from 2004 is reproduced below as Table 12 to demonstrate the type of data available. We have chosen to tabulate attempted vehicle thefts and completed vehicle thefts separately, since their distributions are drastically different. We model vehicle theft severity thusly: 80% are completed and 20% are attempted (this is the approximate average according to the NCVS data for 2000-2005). For the completed thefts, we use a constant severity of $8000. For the attempted vehicle thefts, keep reading.

Table 12. Loss Distribution by Peril Extracted from 2004 NCVS Table 83

	robbery	assault	burglary	vehicle completed	vehicle attempted	theft
No monetary value	0.7%	4.3%	2.5%	0.3%	5.3%	2.9%
Less than $50	22.4%	21.0%	9.9%	0.0%	1.7%	26.0%
$50-$99	7.2%	11.6%	9.0%	0.0%	7.9%	13.2%
$100-$249	29.3%	18.0%	16.0%	0.5%	10.2%	20.6%
$250-$499	9.8%	4.5%	11.0%	1.0%	19.4%	10.2%
$500-$999	7.0%	2.7%	9.2%	2.8%	4.9%	7.1%
$1000 or more	6.9%	4.1%	25.0%	87.0%	12.9%	7.3%
Not known and not available	16.7%	33.8%	17.5%	8.4%	37.7%	12.8%
Number of victimizations	323,790	419,960	2,952,280	779,220	153,330	13,780,810

We distributed the "not known and not available" percentages in the same proportion as the known percentages. We computed the weighted average losses in each cell shown in Table 12 from NCVS data from 2000-2005. Using the resulting data, we fit each crime's data to four probability distributions (gamma, Pareto, Weibull and lognormal) by minimizing four independent objective functions. So, each crime dataset was fit 16 times. See Table 13 for results. The objective functions were as follows:

$$Q = \sum_{i=1}^{n} W_i \left(P_i^{\exp} - P_i^{act}\right)^2 \qquad \text{(Type 1)}$$

$$Q = \sum_{i=1}^{n} W_i P_i^{act} \left(P_i^{\exp} - P_i^{act}\right)^2 \qquad \text{(Type 2)}$$

[29] These are somewhat arbitrary, round figures used to give a sense of the magnitude of premia and reserving required.

$$Q=\sum_{i=1}^{n}W_i\left(\ln\frac{P_i^{\exp}}{P_i^{act}}\right)^2 \qquad \text{(Type 3)}$$

$$Q=\sum_{i=1}^{n}W_iP_i^{act}\left(\ln\frac{P_i^{\exp}}{P_i^{act}}\right)^2 \qquad \text{(Type 4)}$$

Where Q = objective function to be minimized
W_i = monetary weight assigned to loss band i
P_i^{act} = actual probability of a loss in band i, and
$P_i^{\exp}$ = expected probability of a loss in band i according to the chosen probability distribution.

Table 13. Severity Modelling Objective Function Results

distribution model	robbery	assault	burglary	attempted vehicle	theft
			Objective Function Type 1		
Gamma	2.547	1.740	1.078	4.926	2.078
Pareto	0.323	0.132	0.073	1.961	0.046
Weibull	1.552	0.815	0.628	3.985	1.021
Lognormal	0.694	0.177	0.095	0.858	0.157
			Objective Function Type 2		
Gamma	0.368	0.243	0.185	0.910	1.942
Pareto	0.045	0.021	0.011	0.446	0.045
Weibull	0.229	0.124	0.111	0.796	0.955
Lognormal	0.094	0.030	0.017	0.150	0.156
			Objective Function Type 3		
Gamma	141.161	83.189	45.311	161.235	109.004
Pareto	19.267	7.062	3.175	60.399	1.305
Weibull	80.363	30.798	24.027	125.921	45.978
Lognormal	39.642	5.632	3.094	33.238	7.207
			Objective Function Type 4		
Gamma	19.319	12.730	7.510	26.147	15.302
Pareto	2.349	0.881	0.472	9.493	0.245
Weibull	11.501	5.459	4.147	20.680	7.105
Lognormal	5.265	1.049	0.560	4.832	1.100

For all perils, and all objective function types, the Pareto and lognormal forms fit much better than either the gamma or Weibull forms. Some of the fitted Pareto distributions resulted in parameters that fit well as specified above, but whose expected values were infinite, since the α parameter was less than 1. The lognormal distribution is more robust, and not much is lost in accuracy compared to the Pareto distribution, so we have chosen lognormal distributions for all perils, and have chosen the parameters consistent with minimizing objective function type 4. These results are in Table 14. The functional form of the lognormal cumulative probability distribution is $\Pr(X \le a) = \Phi\left(\frac{(\ln a) - \mu}{\sigma}\right)$, where $\Phi(\cdot)$ is the standard normal distribution function, and μ and σ are parameters (be warned, they are not the mean and standard deviation).

Table 14. Lognormal Distribution Modelling Results

	robbery		assault		burglary		attempted vehicle		theft	
mu[30]		4.97		4.54		5.83		5.45		4.60
sigma		2.14		1.70		1.90		1.21		1.67
E[X]		1,425		398		2,089		483		398
sd		14,055		1,647		12,648		878		1,550
skewness		988.8		83.5		240.1		11.5		70.5
	actual	model	actual	model	actual	model	actual	model	actual	model
Less than $50	0.2891	0.3110	0.3551	0.3570	0.1453	0.1570	0.0586	0.1018	0.3265	0.3405
$50-$99	0.1018	0.1217	0.1424	0.1592	0.0995	0.1031	0.1344	0.1408	0.1543	0.1613
$100-$249	0.2164	0.1692	0.2300	0.2024	0.1965	0.1755	0.3255	0.2814	0.2352	0.2084
$250-$499	0.1260	0.1178	0.1109	0.1193	0.1389	0.1443	0.2327	0.2129	0.1223	0.1237
$500-$999	0.0801	0.0977	0.0787	0.0803	0.1329	0.1342	0.1289	0.1495	0.0765	0.0831
$1000 or more	0.1867	0.1826	0.0829	0.0818	0.2869	0.2858	0.1199	0.1137	0.0851	0.0829

A portion of NCVS Table 82 from 2004 is reproduced below as Table 15. These data, along with information about the demographics of the 3 ZIP codes of interest (see section 5) allow us to adjust our severity models for income distribution. This adjustment is small, and is shown in Table 16.

[30] Note that the "true" severity model input parameters must be scaled in accordance with the results of the calculation shown in Table 16.

Table 15. Mean and median losses by peril extracted from 2004 NCVS Table 82

	All crimes				Crimes involving loss of $1 or more				
Type of crime	Gross loss ($M)	Total crimes	Mean dollar loss	Median dollar loss	Total crimes	Mean dollar loss	Median dollar loss	Crimes involving loss-no monetary value specified	Crimes involving no loss
Robbery	236	501,820	471	140	302,470	782	160	42,050	157,300
Assault	878	4,470,960	196	75	413,470	2,124	200	443,330	3,614,160
Household burglary	3,888	3,427,690	1,134	250	2,546,570	1,527	300	414,150	466,970
Motor vehicle theft	6,058	1,014,770	5,969	3,500	811,650	7,463	4,120	120,900	82,220
Theft	4,762	14,211,940	335	80	12,279,220	388	100	1,501,600	431,120
Household Income of Victim									
Less than $7,500	551	1,431,720	385	90	972,640	566	120	164,040	295,040
$7,500-$14,999	1,035	2,223,460	465	80	1,385,110	747	110	282,810	555,540
$15,000-$24,999	1,579	2,667,650	592	100	1,822,370	866	150	288,750	556,530
$25,000-$34,999	1,555	2,493,030	624	100	1,754,820	886	150	259,930	478,280
$35,000-$49,999	1,856	3,198,450	580	100	2,237,000	830	130	323,550	637,900
$50,000-$74,999	2,698	3,350,690	805	80	2,260,100	1,194	100	317,800	772,790
$75,000 or more	3,393	4,502,570	754	100	3,229,810	1,051	120	432,350	840,410

Table 16. Severity Scale Factor for Income Distribution of 3 ZIP Codes of Interest

	Household Income Distributions from US Census				Crime Data from NCVS, 2004					
	Households within 3 ZIP's	% Total	Households, Nationally	% Total	Gross Loss in income band ($M)	Number of Crimes in income band	Number of Crimes resulting in monetary loss	% No-Loss	Mean Loss	Mean Loss for Crimes with Losses
Less than $14,999	1,874	7.6%	16,724,255	15.8%	1,988	4,426,701	2,859,413	23.3%	449	695
$15,000-$24,999	1,467	5.9%	13,536,965	12.8%	1,980	3,230,727	2,210,119	25.0%	613	896
$25,000-$34,999	1,462	5.9%	13,519,242	12.8%	1,950	3,019,249	2,128,197	20.9%	646	916
$35,000-$49,999	2,415	9.8%	17,446,272	16.5%	2,327	3,873,566	2,712,971	19.2%	601	858
$50,000-$74,999	3,756	15.2%	20,540,604	19.5%	3,383	4,057,941	2,740,986	19.9%	834	1,234
$75,000 or more	13,697	55.5%	23,771,784	22.5%	4,254	5,452,955	3,917,023	23.1%	780	1,086
Totals	24,671		105,539,122		15,881	24,061,140	16,568,710			
Average Income	105,325		55,644				weighted national averages:	21.8%	670	969
							weighted 3-ZIP averages:	22.2%	728	1,035
								ratios	**1.086**	**1.068**

The lognormal distribution is scaled by adjusting the μ parameter thusly: $\mu_{scaled} = \mu + \ln\alpha$, where α is the scaling factor (here, 1.068). The σ parameter is not affected by scaling a lognormal distribution.

8. Actuarial Loss Models

The actuarial loss model for a book of subscribers is built up in this section. We remind the reader that we follow the conventions of probability mathematics: a capital letter designates a random variable whose realization is modeled with a probability distribution, a realization of a random variable is designated with a corresponding lowercase letter, the symbol "~" is read "modeled as" or "distributed as", etc.

$N_i =$ number of payment events[31] in the current year for a single subscriber household for crime type i

$N_i \sim Poisson(\lambda_i)$ for all crime types

$X_i =$ severity of a single payment event of crime type i

$X_i \sim Lognormal(\mu_i, \sigma_i)$ for most crime types

$X_i = \alpha_i$ (constant) for 3 crime types

$Y_i =$ total severity of payment events of crime type i for a single subscriber household[32]

$$Y_i = X_{i1} + X_{i2} + \cdots + X_{iN_i}$$

The total severity for a crime type, Y_i, is an example of a compound model for aggregate claims.[33] The choice of models for X_i and N_i do not allow for analytical solutions of the probability distribution of Y_i. It must be computed numerically. However, it is possible to analytically calculate the expectation and variance of Y_i:

$$E[Y_i] = E[X_i]E[N_i]$$

$$Var(Y_i) = E[N_i]Var(X_i) + Var(N_i)(E[X_i])^2$$

[31] A payment event is an uncleared crime event.
[32] Multiple payment events of the same crime type in a single subscriber household are possible.
[33] *Loss Models: From Data to Decisions* by Klugman, Panjer, and Willmot, John Wiley & Sons, Second Edition, 2004, pp. 140-161.

Table 17. Parameters and Moments for N_i's, X_i's, and Y_i's

	murder	rape	Robbery	assault	burglary	theft	attempted vehicle	completed vehicle
i	1	2	3	4	5	6	7	8
λ_i (from Table 11 and Section 7)	8.18E-06	4.16E-04	7.61E-04	6.74E-03	3.10E-02	7.51E-02	7.16E-04	2.87E-03
α_i (from Section 7)	$1,000,000	$50,000	-	-	-	-	-	$8,000
μ_i (from Tables 14 and 16)	-	-	5.03	4.60	5.90	4.66	5.51	-
σ_i (from Table 14)			2.14	1.70	1.90	1.67	1.21	
$E[N_i]$	8.18E-06	4.16E-04	7.61E-04	6.74E-03	3.10E-02	7.51E-02	7.16E-04	2.87E-03
$Var(N_i)$	8.18E-06	4.16E-04	7.61E-04	6.74E-03	3.10E-02	7.51E-02	7.16E-04	2.87E-03
$E[X_i]$	$1,000,000	$50,000	$1,522	$425	$2,231	$426	$515	$8,000
$Var(X_i)$	0.00E+00	0.00E+00	2.25E+08	3.10E+06	1.82E+08	2.74E+06	8.78E+05	0.00E+00
$E[Y_i]$	$8.18	$20.81	$1.16	$2.86	$69.13	$31.96	$0.37	$22.92
$Var(Y_i)$	8.18E+06	1.04E+06	1.73E+05	2.21E+04	5.81E+06	2.19E+05	8.20E+02	1.83E+05

Continuing with the model development,

$Z =$ total severity of payment events of all crime types for a single subscriber household

$$Z = \sum_{i=1}^{8} Y_i$$

Even with analytical expressions for the Y_i's, there is no analytical solution to Z. But, again, we can compute the expectation and variance of the sum:

$E[Z] = \sum_{i=1}^{8} E[Y_i] = \$157$ for all crimes, = $126 for property crimes only

$Var(Z) = \sum_{i=1}^{8} Var(Y_i) = 1.56E7$ for all crimes, = 6.38E6 for property crimes only

There are two proposed coverage modifications. The first one is a “money-back guarantee”. To reduce reserve requirements, encourage pre-payment of subscriptions, to discourage subscription lapses, and to buttress its legal case against the prospect of insurance regulation, the SPR could adopt a policy that the stop-loss per subscriber is equal to the sum of subscription payments the subscriber has made. If the subscriber has paid for 10 months at $35/mo, then indemnity payments would be capped at $350 for that subscriber. Since the distribution of tenure of subscribers affects the calculation, we must make assumptions about subscriber behavior. The limiting case is that every subscriber has full tenure. If new subscriptions are had at a constant rate with no subscribers lapsing, then the most elegant distribution to capture this is a uniform distribution with mean equal to $\$35n/2$, where n is the number of months in business.

$T =$ household tenure cap for moneyback guarantee

$T \sim Uniform(35t)$, $t =$ age of the business in months

The second proposed coverage modification is to limit the SPR's liability per incident to the amount of the subscriber's homeowners' insurance deductible. This serves several purposes. First, it is equitable, in that the SPR is not required to reimburse the subscriber for losses for which he will be reimbursed anyway (and by doing so reduces the moral hazard associated with such double indemnity). Second, it limits the risk faced by the SPR, and makes the business much more financially predictable. Finally, it brings the cost of coverage down to a small portion of the total SPR fees.

$H =$ homeowner's insurance deductible

$H \sim Step$

- 35% of subscribers have a \$250 deductible
- 45% of subscribers have a \$500 deductible
- 20% of subscribers have a \$1,000 deductible

With the coverage modifications defined, we can define the payment model for a single household.

$W =$ total payments made to a single household in a year

$$W = \min(Z, T, H)$$

Alternatively, we can consider $W = \min(Z, T)$ or $W = \min(Z, H)$ for only one of the two coverage modifications. Continuing with the main line of development of the model, note that choosing the minimum random variable from among many is equivalent to taking the product of the survival functions of the random variables:[34]

$$S_W = S_Z S_T S_H$$

If Z, T, and H are analytical, then S_W is analytical, but the calculation of f_W , E[W], and Var(W) requires numerical calculations. Finally, we come to:

$L =$ loss model for m subscribers

$$L = \sum_{j=1}^{m} W$$

[34] See Bean, Michael A., *Probability: The Science of Uncertainty with Applications to Investments*, Insurance, and Engineering, China Machine Press, 2001, p. 311-312.

Yet again, even with an analytical expression for W, there is no analytical solution to L but there is a simple calculation for the first and second moments of L:

$$E[L] = m \cdot E[W]$$

$$Var(L) = m \cdot Var(W)$$

Besides the parameters shown in Table 17, we note that two additional parameters have been introduced in this section, both of which vary over time:

$m =$ the number of subscribers

$n =$ age of the business

These will be discussed in section 9.

Analytical Exploration

Before we explore more deeply, we will take an "analytical" shot at understanding the premium requirements. First, we use $E[Z]$ and $Var(Z)$ calculated above, and posit $Z \sim Lognormal$ fitting these moments.[35] Then, we specify m=500, n=12, and calculate $E[W]$. Three versions were calculated:

$$W_1 = \min(Z, T)$$

$$W_2 = \min(Z, H)$$

$$W_3 = \min(Z, T, H)$$

Then, we posited $L \sim Normal\left(\mu_L = mE[W], \sigma_L^2 = mVar(W)\right)$ and required that the total of payments into the reserve fund equal the 95th percentile of the cumulative distribution function of L:

$$p = E[W] + \frac{\Phi(0.95) \cdot \sigma_W}{\sqrt{m}}$$

where $p =$ yearly contribution to the reserve fund for each subscriber

[35] Z is essentially a sum of lognormal distributions, plus some very high-severity point masses (murder, rape, completed vehicle theft), so fitting the tail with a skewed distribution such as the lognormal is appropriate here, realizing that the tail will be cut off by the coverage modifications. Wu, Mehta, and Zhang have shown that using the method of moments to fit a sum of lognormal distributions to a single lognormal distribution fits the tail portion closely. See Wu, J., Mehta, N., and Zhang, J., *A Flexible Lognormal Sum Approximation Method*, IEEE Global Telecommunications Conference (GLOBECOM), vol. 6, pp. 3413-3417, November 2005.

These calculations are shown in Table 18 for all crimes and for property crimes only.

Table 18. Shortcut Results for Premium Contributions

all crimes

	E[W]	Var(W)	p	theta[36]	p per mo
W1	$34.22	4.61E+03	$36.73	7%	$3.06
W2	$52.15	1.50E+04	$56.69	9%	$4.72
W3	$33.45	4.20E+03	$35.85	7%	$2.99
	E[L]	Var(L)			
L1	$17,108	2.31E+06			
L2	$26,074	7.52E+06			
L3	$16,726	2.10E+06			

property crimes

	E[W]	Var(W)	p	theta	p per mo
W1	$32.63	4.27E+03	$35.05	7%	$2.92
W2	$48.72	1.35E+04	$53.02	9%	$4.42
W3	$31.95	3.90E+03	$34.26	7%	$2.86
	E[L]	Var(L)			
L1	$16,314	2.13E+06			
L2	$24,359	6.73E+06			
L3	$15,973	1.95E+06			

This shortcut method suggests (since theta is low) that the initial reserve need not be large, and the contributions to the reserve fund can be very close to the expected value of the losses. These are tentative conclusions, since two critical assumptions were made (Z~Lognormal and L~Normal) and m, which determines T's probability distribution, varies over time.

[36] Theta, called the *relative security loading* or *premium loading factor* in actuarial literature, is the percentage by which the contribution to the reserve fund is greater than the expectation of the loss. Here, $\theta = \frac{p}{E[W]} - 1$.

9. Diffusion of Subscriptions

Every new product or service experiences the marketing challenge of the relevant market understanding and then adopting the new offering. Most of this process of adoption proceeds by word-of-mouth of the consumers, and is best modeled as a diffusion-like process. The landmark paper describing the technique[37] considered the history of the adoption of 11 consumer durables in the US from 1920 to 1961, and reliably predicted the future sales of color televisions for the years 1966-1970. A useful review of the literature of diffusion of innovation was recently published.[38] A recent, detailed and highly successful approach[39] to forecasting the adoption of a subscription service focused upon DIRECTV sales, and we shall follow it closely for our calculations.

The basic model is this: $\dfrac{f(t)}{1-F(t)} = p + qF(t)$

where

p = the coefficient of innovation;
q = the coefficient of imitation;
f(t) = the adoption rate density function; and
F(t) = the fraction that has adopted by time t.

If m is the number of ultimate adopters, the number that will not have adopted by time t is $m(1-F(t))$, and letting $mF(t) = Y(t)$ and $mf(t) = S(t)$, the equation above may be used to obtain $S(t) = m(1-F(t))(p+qF(t)) = pm + (q-p)Y(t) - (q/m)[Y(t)]^2$ where S(t) = sales at t (adopters at t); and Y(t) = cumulative adopters at t.

This equation is clearly a differential equation that may be solved analytically to find either S(t) or Y(t). The solutions are:

$$S(t) = \frac{m}{p}\frac{(p+q)^2 e^{-(p+q)t}}{(1+(q/p)e^{-(q+p)t})^2} \text{ and } Y(t) = \frac{m(1-e^{-(p+q)t})}{1+(q/p)e^{-(p+q)t}}$$

For this paper, we will assume that the field of potential subscribers is those who live in single family dwellings or duplexes in the ZIP codes of 77380, 77381, and 77382 and whose household incomes exceed $20K/year. These ZIP codes are wholly within Montgomery County, Texas. Using US Census data for 2000, we estimate this to be 18,225 households. Using an ultimate adoption rate of 20%, which is supported by our

[37] Bass, Frank M. 1969, "A new product growth model for consumer durables," Management Science, vol. 15, no. 5 (January), pp. 215-227. Reprinted in Management Science vol. 50, no. 12 supplement, December 2004, pp. 1825-1832.
[38] Meade, Nigel and Islam, Towhidul, "Modelling and forecasting the diffusion of innovation – A 25-year review," International Journal of Forecasting, vol. 22, issue 3, 2006, pp. 519-545.
[39] Bass, Frank M.; Gordon, Kent; Ferguson, Teresa L.; and Githen, Mary Lou, "DIRECTV: Forecasting Diffusion of a New Technology Prior to Product Launch," Interfaces, vol. 31, issue 3, Part 2 of 2, May-June 2001, pp. S82-S93.

secondary market research on home monitoring and marketing research pilot,[40] this means that m=3645 households.

The coefficient of innovation, p, can be augmented by marketing efforts: giveaways, trial subscriptions, and local publicity.[41] This will be the major focus of the marketing efforts, and so we choose a moderately aggressive value of p=0.01.[42,43]

The coefficient of imitation, q, is not easily influenced by marketing, but is inherent in the nature of the offering and the interaction dynamics of the adopters. An award-winning survey[44] of a large dataset covering diverse products such as online banking, hybrid corn, CAT scanners, and educational innovations have shown that q tends to a value[45] of about 0.38.[46] Our choices of p=0.01 and q=0.38 hold up to additional scrutiny in light of the revisionist database of p and q data recently published:[47]

Table 19. Subscription Services Data and Parameters from Jiang, Bass, and Bass

subscription service	year introduced	data period	p	q
AOL	1989	1993-1997	0.02051	1.1624
Cable TV	1948	1953-1971	0.00001	0.5013
Cell phones (analog)	1983	1984-1995	0.00074	0.4132
Satellite TV	1994	1994-1998	0.04693	0.3346

With these data in hand, we stand ready to estimate the number of subscribers per year over the startup years. As is clear from Figure 14 below, assuming no initial “seed” of subscriptions, speed of subscription is low until around year 5. The intent is to offer a large number of free and trial subscriptions to fast-forward the base of subscribers upon which the imitation rate can act. We assume for this paper that 500 free and trial subscriptions can be given away within the first year, and that the number of subscriptions will grow according to the model from that point. See Figure 15 for a

[40] Guillory and Drake, ibid.
[41] Personal conversation with Portia Bass of Bass Model Institute and basseconomics.com, 10 May 2007.
[42] Compare p values of room air conditioners 1946-1961 (0.0104), automatic coffee makers 1948-1961 (0.0171), and black-and-white televisions 1946-1961 (0.0279). These values are from Bass, Frank M, ibid.
[43] The units of p are fraction adopting (without being influenced by those who have already adopted) in the course of a year among those that will ultimately adopt but have not yet done so. Note that yr^{-1} is part of the unit of measure.
[44] Sultan, Fareena; Farley, John U.; and Lehmann, Donald R., “A meta-analysis of applications of diffusion models,” Journal of Marketing Research, Vol. 27 (February 1990), pp. 70-77.
[45] Sultan, Fareena; Farley, John U.; and Lehmann, Donald R., “Reflections on ‘A meta-analysis of applications of diffusion models,’” Journal of Marketing Research, Vol. 33 (May 1996), pp. 247-249.
[46] The units of q are fraction of those who have already adopted that result in an imitation (a purchase) in the course of a year among those that will ultimately adopt but have not yet done so. Note that yr^{-1} is part of the unit of measure.
[47] Jiang, Zhengrui; Bass, Frank M.; and Bass, Portia Isaacson, “Virtual Bass Model and the left-hand data-truncation bias in diffusion of innovation studies,” International Journal of Research in Marketing, vol. 23, Issue 1, March 2006, pp. 93-106.

shifted subscription growth curve. This sort of shifting is not usually possible, since the relevant markets for products studied is usually large. These assumptions should be explored in a later marketing study.

Note that the rate of subscriptions is the net rate of subscriptions, implicitly taking into account subscription lapse rates. For the purposes of this paper, we will consider these data accurate, and explore the actuarial models with these subscriber rates and counts in mind.

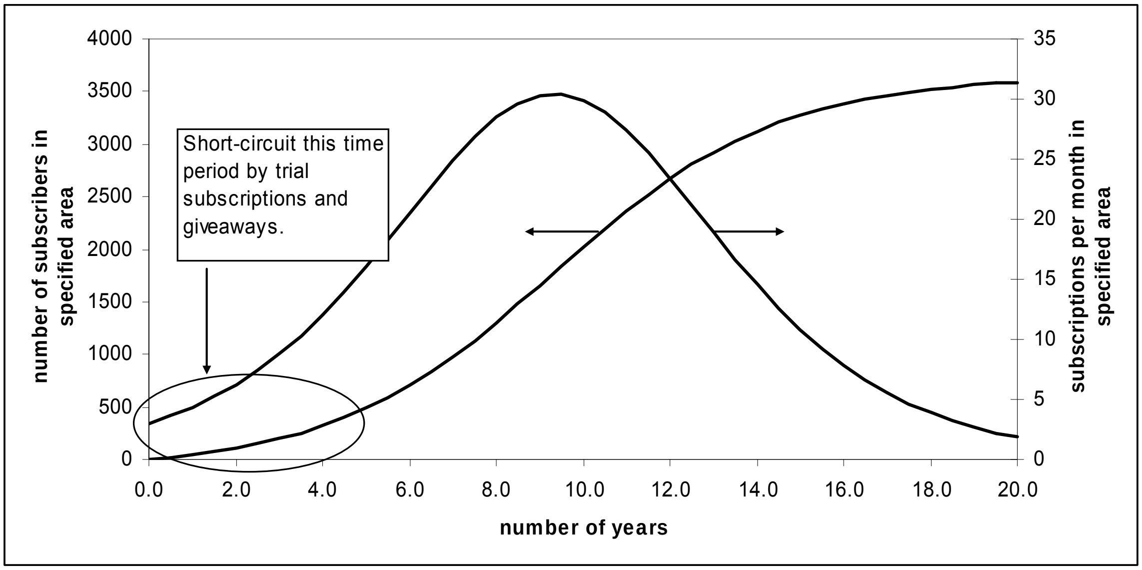

Figure 14. Predicted Subscriptions and Rate of Subscriptions Over Time with Initial Number of Subscriptions Equal to Zero

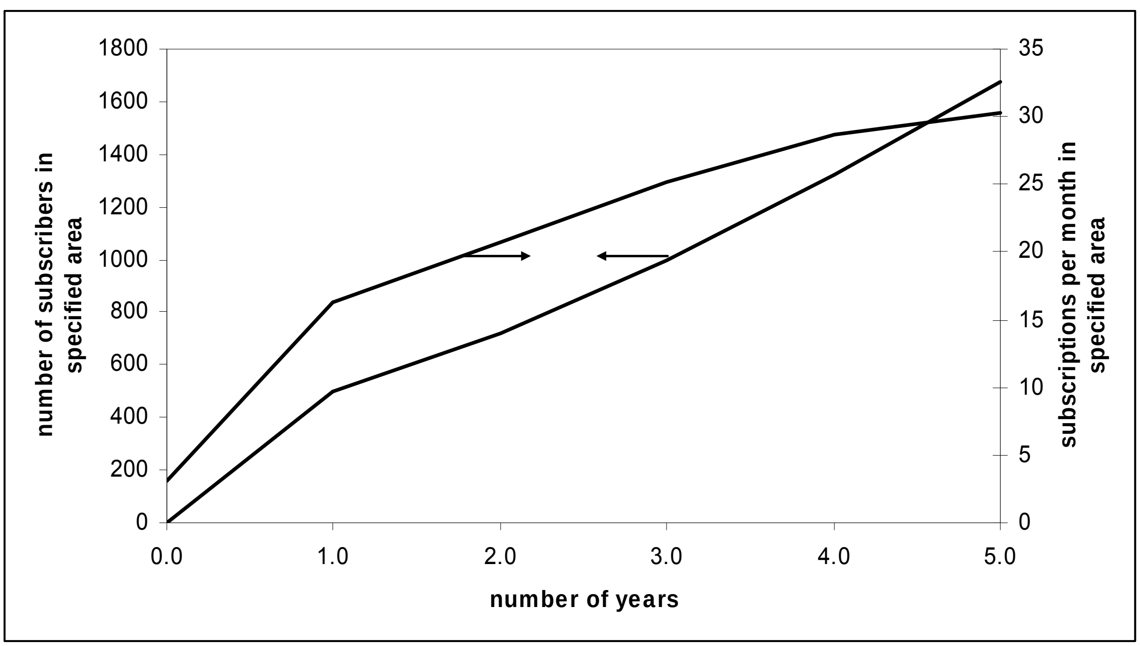

Figure 15. Predicted Subscriptions and Rate of Subscriptions Over Time with Marketing Efforts to Raise Subscriptions to 500 Within First Year

10. Monte Carlo Simulation

There are a number of complexities that recommend a simulation of this actuarial model. The number of subscribers varies over time, the tenure distribution T varies over time, and simulation is a good way to apply ruin theory in setting a reserving policy.

Discrete, finite-time ruin theory considers a Markov process of the reserve fund. In each increment of time, contributions and deductions from the reserve fund are considered, and the probability that the reserve will be depleted (ruin) can be calculated. Simulation by pseudo-random number generation and calculation period by period (here, we simulated by months) accomplishes the same result, with the advantages of being able to simulate a complex model such as this one.

With the loss model outlined in section 8 and the time-varying number of subscribers shown in Figure 15, we simulated four scenarios:[48]

1. No coverage modifications: $W = Z$
2. Homeowners' insurance deductible cap: $W = \min(Z, H)$
3. Money-back guarantee cap: $W = \min(Z, T)$
4. Combined cap: $W = \min(Z, T, H)$

For each scenario, a Monte Carlo approach was used to simulate the indemnity portion of the SPR business. The following assumptions were used:

1. Per-household incidence and severity distributions were independent of all other variables, as described in sections 6-8.
2. A 20 year (240 month) horizon was assumed.
3. In all scenarios, a \$5,000 initial reserve fund balance and a constant interest rate of 4.0% were assumed.

The simulation process was as follows:

1. For each month of operation, $m =$ the number of subscribers predicted by the diffusion model (Figure 15). A count of losses was generated randomly from the specified Poisson distributions for the entire book of insureds.
2. For each loss simulated in step 1, an unmodified loss amount was randomly generated according to the models in section 8.
3. According to the scenario being simulated, a cap was applied to the unmodified loss amount to determine the SPR's expected liability for the event.
4. Total monthly losses were generated for the entire 240 month simulation horizon (the "loss history profile").

[48] The parameters in Table 17 were not the exact values used in the Monte Carlo simulations. The Monte Carlo simulation results are therefore somewhat conservative. The Monte Carlo simulations are programmed in Excel files downloadable from http://gil.guillory.googlepages.com/ . We encourage you to download them and try them out with your own parameters.

5. A reserve fund was simulated, assuming a $5,000 starting amount, a 4% annual return on any amounts in the fund, and an undetermined target amount to be contributed to the reserve fund on a per-contract-per-month (PCPM) basis. For each loss history profile, this amount was solved for numerically as the minimum amount necessary to maintain a positive surplus in the reserve fund throughout the 20-year horizon (technically, the minimum amount to avoid ruin). The target reserve contribution was stored as the main output of the simulation. An example of such a reserve fund simulation is shown in Figure 16.

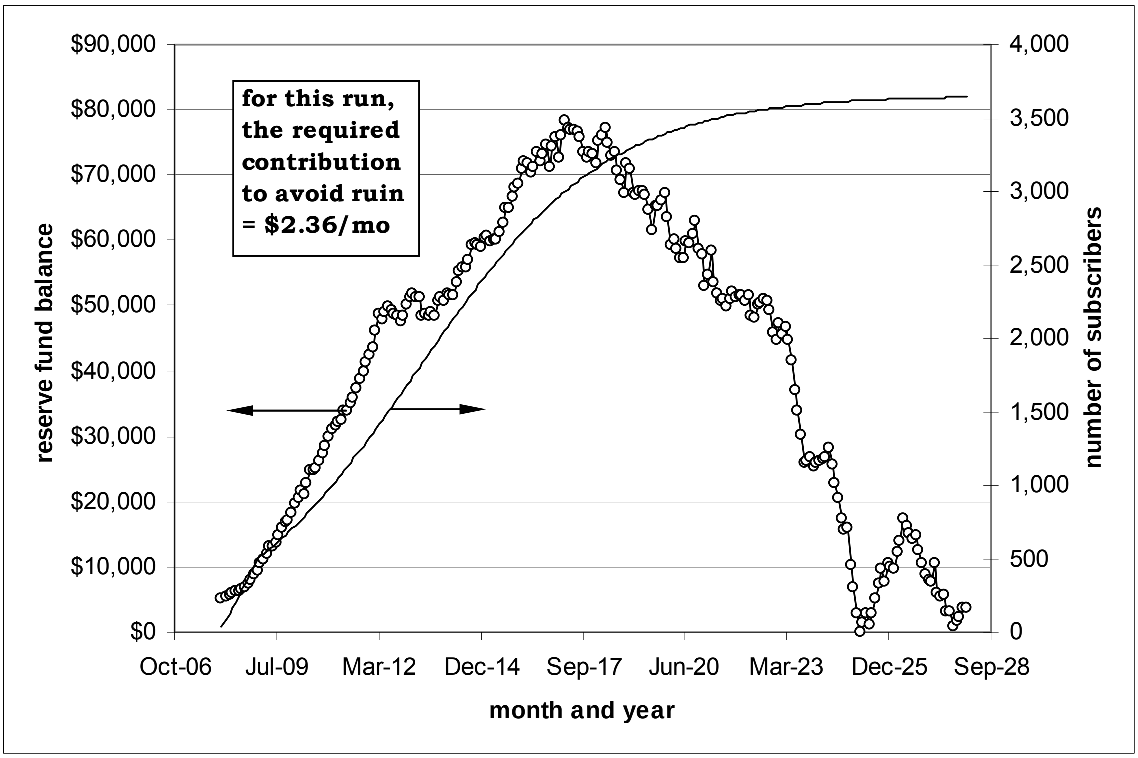

Figure 16. Example Simulation of Reserve Fund Over 20-year Period

6. Steps 1-5 were repeated 1,000 times for each of the 4 scenarios. The distributions of the required PCPM amounts for each scenario are shown in Table 20.

Table 20. PCPM Required Reserve Fund Contributions to Avoid Ruin With Initial Reserve of $5000

	Scenario 1: No cap	Scenario 2: H cap	Scenario 3: T cap	Scenario 4: Both caps
Minimum	$9.18	$2.34	$4.89	$2.21
Maximum	$445.32	$2.63	$5.75	$2.44
Mean	$15.25	$2.49	$5.29	$2.32
50th percentile	$11.47	$2.49	$5.28	$2.32
90th percentile	$18.98	$2.55	$5.46	$2.38
95th percentile	**$26.54**	**$2.57**	**$5.50**	**$2.40**
99th percentile	$76.71	$2.60	$5.64	$2.41

As can be seen in Table 20, the required PCPM contributions for scenario 1 (unmodified coverage) are large, highly variable, and are distributed with a long tail, since the SPR is not insulated in any way from large losses in the early years of operation.

Scenario 2 limits the SPR's liability per incident to the amount of the subscriber's homeowners' insurance deductible. This clearly brings the cost of coverage down to a small portion of the total SPR fees.

The premium refund (or money-back guarantee) of scenario 3 also has relatively large required PCPM contributions. However, this is due not to early-year exposure (which is sharply limited by the restriction of payment to $35 per month of contract duration), but to the later exposure to large liabilities for long-term clients who have accrued a sizable refundable premium pool.

The final scenario tested the combined long-term risk limitation of scenario 2 with the short-term risk limitation of scenario 3. This scenario has the smallest required PCPM contribution, as well as the lowest variance of the four scenarios.

Returning to Figure 16, you will notice a mountain shape, characteristic of the simulation runs. The reason for this characteristic is from 4 related factors:

1. the reserve starts with more than 150 subscriber-months of expected losses and no subscribers
2. the tenure cap distribution grows continuously throughout the life of the simulation, shifting the expected losses higher and higher
3. relatedly, the contributions are fixed over the simulation period, but the expected losses grow. Over the course of the simulation, the contributions are first higher than, and then lower than, the expected losses.
4. interest on the reserve fund magnifies the preceding effects. When the reserve fund reaches $50,000, interest accounts for a contribution to the account of more than $150/month with subscribers at about 1500, so each subscriber's contribution is being "subsidized" by about a dime.

This mountain characteristic is found in reserve funds where premiums exceed losses in the near term, and then losses exceed premiums in the long term. Level term life insurance is an example where this characteristic is also found. The assumed distribution of T was conservative and perhaps unrealistic. As an SPR business gains experience in the tenure behavior of subscribers, it can adjust its reserving policy.

Simulation of the reserve fund

Once the PCPM reserve contribution amounts had been determined, another series of simulations were performed, holding the PCPM contribution fixed. This second round of simulations was intended to estimate the overall risk associated with the reserve fund at the specified contribution level. The same general simulation process was used, except that the reserve contribution was held fixed, even if the reserve fund went into a deficit.[49] The contribution used for each scenario was the 95th percentile from Table 20.

We simulated 200 iterations of the loss history profile for each of scenarios 2, 3 and 4. Figures 17 and 18 show the results for scenario 4, the scenario of primary interest.

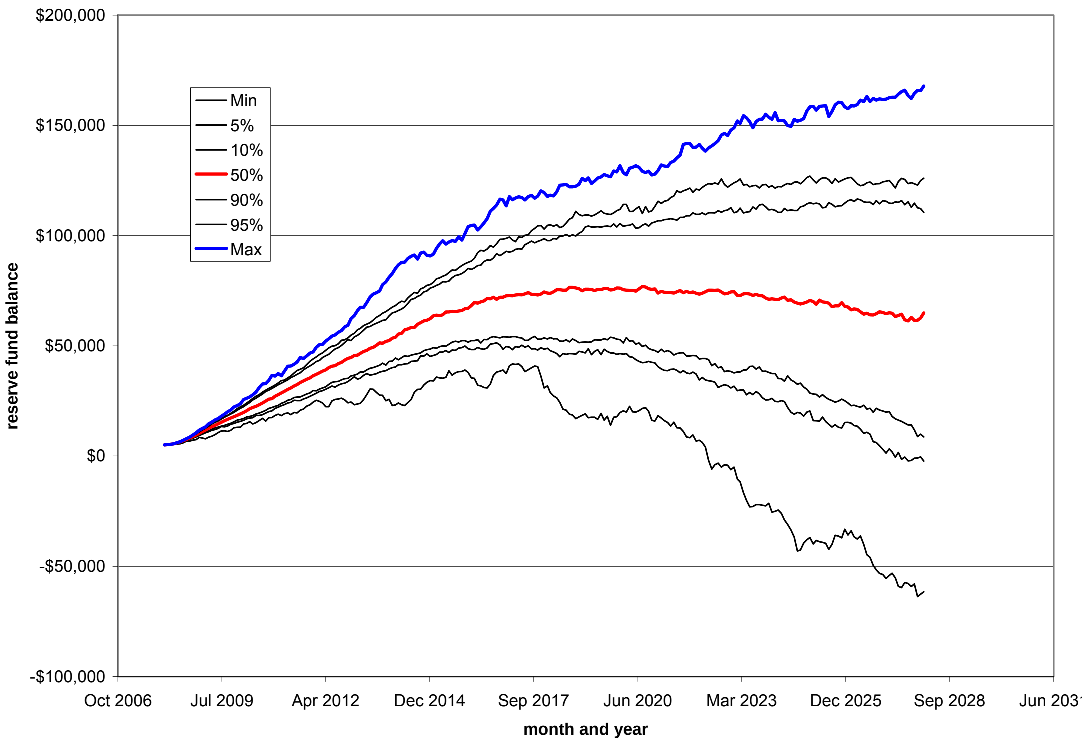

Figure 17. Percentiles of 200 Simulations of Reserve Fund History Over 20-year Period with $5000 Starting Reserves and PCPM=$2.40

[49] Note that "ruin" (a deficit position in the reserve fund) is *not* equivalent to insolvency. In actual practice, any impending deficits could be foreseen to at least some extent, and hopefully averted by increasing the PCPM contribution or by making *ad hoc* lump-sum contributions to the fund. An appropriate reinsurance contract could also mitigate ruin risk.

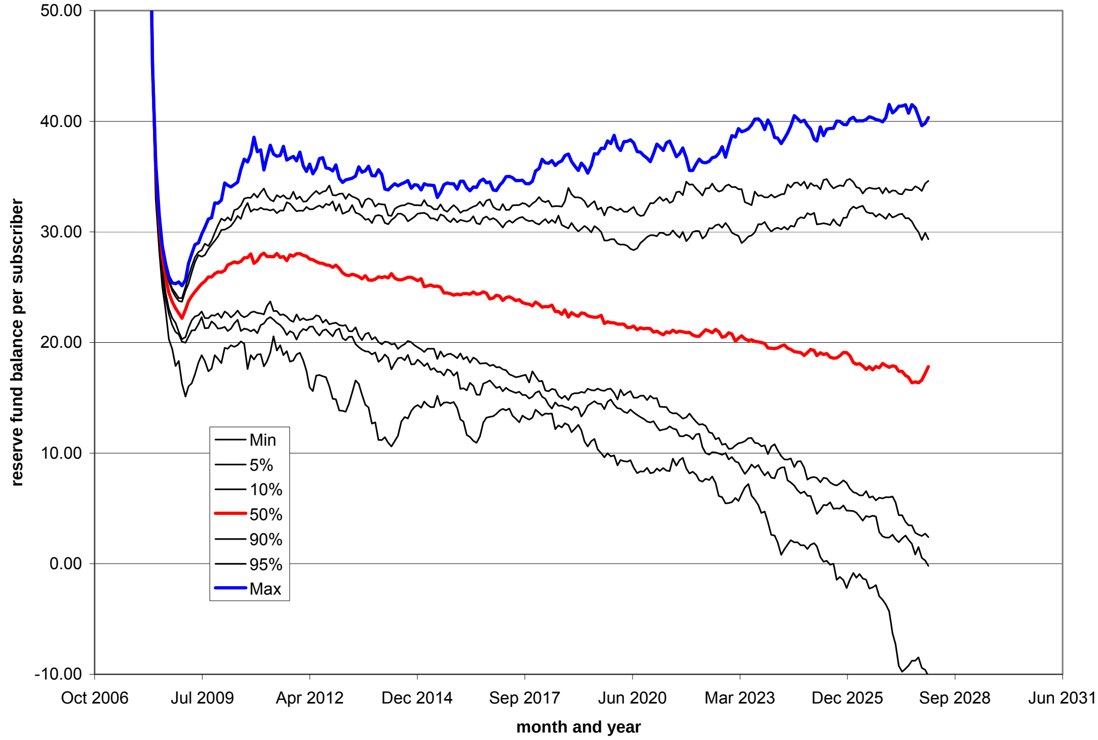

Figure 18. Percentiles of 200 Simulations of Reserve Fund Balance per Subscriber, History Over 20-year Period with $5000 Starting Reserves and PCPM=$2.40

11. Conclusions

Insuring against the perils of murder, rape, robbery, assault, burglary, larceny theft, and motor vehicle theft under the business model of subscription patrol and restitution is relatively cheap to implement. Our calculations indicate that for an SPR startup, if it starts with reserves of $5000, prudent contributions for the locale of Montgomery County, Texas in the year 2008 is $2.40 per month per subscriber.

This is significantly lower than the anticipated monthly fee of $35/month. This contribution amount could be lowered by starting with a higher reserve amount or considering lesser coverage, such as only property crimes (robbery, burglary, larceny theft, and motor vehicle theft) or changing the coverage modifications.

A number of approaches and tools have been developed in this paper which will allow an entrepreneur to calculate new reserving and contribution policies for different conditions. We invite the public to download them at http://gil.guillory.googlepages.com/.

Future Work

The SPR will collect incident-level data as part of its other duties. Equations and tools must be developed to take a database of incident data[50] and robustly and reliably calculate crime rate and severity probabilities as functions of time and place. This sort of tool could be used to determine the effect of patrols on crime rates, severities, and clearances; and, would inform operational policies on patrol and reserving. This sort of actuarial model is much more complex, and preliminary research indicates no extant publication of such geostatistical models.

[50] Incident data should be as rich as possible, including lat-long, time/date, crime type, crime severity, clearance (yes/no), clearance date, pointer to reports, perpetrator characteristics, victim characteristics, home characteristics, etc. Of course, obtaining data has costs, so we cannot expect a full Christmas list.