Field Effects of Consciousness and Reduction in U.S. Urban Murder Rates: Evaluation of a Prospective Quasi-Experiment

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Abstract: Creation of a sustainable society ideally should include promotion of an enhanced overall quality of life, including freedom from crime, violence, and other key indicators of social stress. This study is part of a comprehensive empirical evaluation of the results of a prospective four-year quasi-experiment that sought to reduce rates of homicide and violent crime as well as to improve other measures of the quality of life and public health in the United States. The current research tests the hypothesis that group practice of the Transcendental Meditation® (TM) and TM-Sidhi® program by a group of theoretically predicted size would be sufficient to reduce collective stress in the larger population, as reflected in decreased rates of homicide in a sample of 206 large U.S. urban areas. Time series regression analysis of monthly data for 2002–2010 using a broken-trend intervention model found significant reductions in trend for the urban homicide rate during the 2007–2010 intervention period ($p = 1 \times 10^{-13}$). Controlling for pre-intervention trends, seasonality, and autocorrelation, the estimated total reduction in homicide rate was 28.4% (7.1% annually). The practical significance of these findings is also indicated by an estimated 4,136 murders averted by the reduced trend in murder rate during the intervention. Diagnostic tests are satisfactory and indicate that the results are unlikely due to "spurious regression." The mechanism for these macro-social effects is discussed in the light of possible alternative hypotheses.

Keywords: Quality of Life, Crime Prevention, *Transcendental Meditation* and *TM-Sidhi* Program, Urban Murder Statistics, Intervention Analysis, Quasi-Experiment

1. Introduction

The topic of sustainability is incomplete without consideration of the quality of human life. One aspect of the quality of life that is particularly related to a sustainable society is absence of violence among the members of the society.

Despite long-term declines in murder and other violent crime rates from their peak in the early 1990s, recent increases in U.S. murder and violent crime rates have led to heightened concern among policy makers and the general public. Beginning at historically low levels not experienced since the early 1960s, the national murder rate (murder and non-negligent manslaughter) increased 10.8% in 2015, the largest increase in a quarter century (U.S. Department of Justice, 2016, 2017). The latter increase was marked by highly publicized fatal shootings and street violence in several large U.S. cities (Friedman, Fortier, & Cullen, 2015; Grawert & Cullen, 2016; Williams & Davey, 2016). A report for the U.S. National Institute of Justice found that 10 large cities, with average population of about one million, experienced a disproportionately large surge in the number of homicides during 2015 (Rosenfeld, 2016).

Preliminary data indicate that continued increases in national murder rates in 2016 were being driven by a handful of large U.S. cities (Asher, 2016; Friedman, Grawert, & Cullen, 2016). For example, according to an analysis published in the *New York Times* (Park & Katz, 2016),

"About half of the rise—480 of the 950—occurred in seven cities (Cleveland, Milwaukee, Baltimore, Chicago, Houston, Nashville, Washington). The poverty rate in these cities is higher than the national average. At least three of these cities (Baltimore, Chicago, Cleveland) have also been embroiled in protests after police-involved deaths of black males."

The 2015–2016 increase in U.S. murder and violent crime rates, especially in urban areas, highlights the need to consider new, alternative approaches to reducing violence that might potentially help address this important national issue.

1.1. Review of Previous Empirical Studies

The principle proposed here for reduction of urban violence has been subjected extensively to prior testing at the city, state, and national levels for crime reduction and improvement on other indicators of quality of life. In the following we review studies in which an outcome measure was crime or domestic or international violence, not studies that dealt only with quality of life indices.

The hypothesis tested in these studies may be understood as a *Consciousness-Based* approach to reduced societal violence and improved quality of life. It is long understood that urban violence is a function of a variety of stress-related factors, including poverty (Beasley & Antunes, 1974; Mladenka & Hill, 1976), unemployment (Spector, 1975), lack of education (Quinney, 1966), social instability (Quinney, 1966), and exposure to aggression and stress (Agnew, 2007; Humphrey & Palmer, 1986). What is unique is the proposal that stress and violence can be reduced on the collective level independent of behavioral interaction by a "field-like" effect when a large group of individuals participates in the group practice of the Transcendental Meditation and TM-Sidhi program (Maharishi Mahesh Yogi, 1986, p. 76). That is, although the group of participants is located in one specific area of the society, the effect is seen in the behavior of the whole society; the small size and localized nature of the group is sufficient to rule out behavioral interaction of the participants with the members of the larger society as a cause of these effects. The number of group participants hypothesized to be necessary to create this effect is one per cent of the members of society practicing the Transcendental Meditation technique individually, or the square root of that number participating in the group practice of the TM-Sidhi program (Maharishi Mahesh Yogi, 1986, p. 76).

For example, when a sample of small cities reached 1% of their population instructed in the Transcendental Meditation program, crime rate (FBI Part 1 crime) decreased the following year (F (1,44) = 13.77, p <.001, with effect size (ES) f = –0.559), as did the trend over the next five years (F (1,44) = 5.71, p <.025, f = –0.360) compared to matched control cities, controlling statistically for demographic variables (Dillbeck, Landrith, & Orme-Johnson, 1981). The ES measure f is the square root of Cohen's f^2 for a regression variable (or set of variables), as computed from the outcomes reported in the original papers, with 0.59, 0.39, and 0.14

considered large, medium, and small effects, respectively (Cohen, 1988).

In addition, two studies using cross-lagged panel analysis among random samples of 160 cities and 80 metropolitan areas, controlling for demographic variables, displayed evidence of a causal influence of Transcendental Meditation participation and crime rate decrease—increased participation in the Transcendental Meditation program predicted subsequent crime rate decrease, but not conversely (Dillbeck, Banus, Polanzi, & Landrith, 1988). In all, 15 crime-related urban demographic variables were either considered as candidates for control, but not found to be necessary, or were controlled directly in the three studies described above.

With the introduction of the advanced TM-Sidhi program in 1976, the theoretical requirement for the predicted effect was reduced from 1% of the population to the square root of one percent ($\sqrt{1\%}$) when practiced in a group. This is based on the physical principal that coherent elements create an influence proportional to the square of their number (Hagelin, 1987, p. 65). An example is the superradiance phenomenon that occurs in quantum optics when N emitting elements (atoms) can emit coherently, through their interaction with a common light field; this results in intensity proportional to N^2 rather than the usual N for independent elements (Gross & Haroche, 1982).

The smaller number required for a measurable effect with the TM-Sidhi program permits intervention studies at the national level structured around temporary courses or permanent groups, given that $\sqrt{1\%}$ of even a nation of four million people is only 200. Most of these intervention studies on the TM-Sidhi program used either autoregressive integrated moving average time series (TS) analysis or comparable transfer function methodology (Box & Jenkins, 1976) to control for cycles and trends in the time series data of these studies.

TS intervention studies of crime based on large groups of TM-Sidhi program participants coming together temporarily on courses reported significant reductions in crime rates during such periods in Washington, DC (weekly total homicides, rapes, and assaults, t(39) = –5.47, p <.0001, f = –0.876); in the Union Territory of Delhi in India (daily Indian Penal Code totals, t(260) = –5.12, p <.0001, f = –0.318); in Metro Manila in The Philippines (weekly crime index totals, similar to FBI uniform crime index, t(93) = –2.83, p <.005, f = –0.293); and in Puerto Rico (monthly Type 1 crimes, comparable to FBI uniform crime index, t(160) = –2.02, p <.025, f = –0.160) (Dillbeck, Cavanaugh, Glenn, Orme-Johnson, & Mittlefehldt, 1987; Hagelin et al., 1999).

Stable groups of TM-Sidhi program participants have come together around educational institutions in the U.K. (Maharishi Free School) and the U.S. (Maharishi University of Management), and the effects of these groups have been evaluated. In the U.K., the group, which is not far from Merseyside, expanded over time to exceed the predicted size to influence the Merseyside metropolitan area in March 1988. TS analysis of data from 1979 to 1991 indicated a

significant effect of reduced crime rate by 13.4% ($t(141) = -4.68$, $p <.0001$, $f = -0.394$) (Hatchard, Deans, Cavanaugh, & Orme-Johnson, 1996).

In the U.S., daily participation is recorded for the university and community members at Maharishi University of Management (MUM) who participate in group practice of the Transcendental Meditation and TM-Sidhi program before and after the school or work day. TS analysis from 1982–1985 found that there was a significant leading influence of group participation on reduction in a violence index comprising weekly totals of fatalities due to homicide, suicide, and motor vehicle accidents, using both intervention analysis ($t(136) = -2.47$, $p <.01$, $f = -0.212$) and transfer function methods (Dillbeck, 1990). These transfer function results and intervention results were also replicated for Canada ($t(136) = -2.63$, $p <.005$, $f = -0.226$) when the size of the TM-Sidhi program group at MUM exceeded the $\sqrt{1\%}$ of the combined U.S.-Canada population (Assimakis & Dillbeck, 1995).

Reduction in violence through the group practice of the TM-Sidhi program also has been found to extend to the violence of domestic and international conflict. In 1983 in Israel, a temporary group of TM-Sidhi program participants was brought together in Jerusalem for two months in a prospective experiment monitored by an external advisory group (Orme-Johnson, Alexander, Davies, Chandler, & Larimore, 1988). The authors found significant improvements in multivariate indices of quality of life at the city and national levels (the group varied in size throughout, sometimes enough theoretically for Jerusalem, at other times enough for Israel as a whole, at other times for Israel and Lebanon together, with whom Israel was in conflict at the time). Results were the following: for Jerusalem, $t(55) = 2.85$, $p <.01$, $f = 0.384$; for Israel, $t(54) = 4.00$, $p =.0001$, $f = 0.544$; for content-analysis derived measures of war intensity with Lebanon, ($t(55) = -2.71$, $p <.005$, $f = -0.365$) and war deaths ($t(55) = -2.12$, $p <.02$, $f = -0.286$). In response to critiques indicating possible confounding factors (Fales & Markovsky, 1997; Schrodt, 1990), the authors published several re-analyses of the data supporting their initial findings (Orme-Johnson, Alexander, & Davies, 1990; Orme-Johnson & Oates, 2009).

Even reduction in conflict and violence due to terrorism has been measured at the international level in periods when the size of the group has approached or exceeded the $\sqrt{1\%}$ of the world's population (Orme-Johnson, Dillbeck, & Alexander, 2003).

1.2. The Present Study

This study is part of a comprehensive empirical evaluation of the results of a prospective quasi-experiment intended to help reduce rates of murder and violent crime as well as improve other measures of the U.S. quality of life and public health. Previously published studies have evaluated the impact of this macro-social quasi-experiment using 2002–2010 monthly data on U.S. national homicide rates, motor vehicle fatality rates, fatality rates due to other accidents,

infant mortality rates, and on soaring rates of drug-related death, as well as on monthly violent crime rates in a sample of 206 urban areas (Cavanaugh & Dillbeck, 2017; Dillbeck & Cavanaugh, 2016; Dillbeck & Cavanaugh, in press).

The current study extends the analysis of monthly U.S. homicide rates (*HOMR*) and urban violent crime rates (*VCR*) reported in Dillbeck and Cavanaugh (2016) by reporting detailed results of an analysis of monthly murder rates (*MR*) in a subsample of 206 large U.S. urban areas. Because the urban areas have higher baseline murder rates than the U.S. as a whole and differ demographically from the rest of the U.S., the behavior of urban murder rates during the 2007–2010 intervention period might be expected to differ from that for the national homicide rates analyzed previously. Due to their higher baseline murder rates and demographic characteristics known to be predictive of higher crime rates (higher poverty rates, lower educational levels, higher unemployment, greater social instability, etc.), urban areas may be expected to pose an especially difficult challenge to any proposed initiative to help reduce urban rates of murder and violence.

2. Method

2.1. Dependent Variable

The dependent variable is the monthly murder rate (together with non-negligent manslaughter) for 206 U.S. urban areas as reported by the U.S. Federal Bureau of Investigation (FBI) Uniform Crime Report system. This sample consists of all cities with population of at least 100,000 for which uninterrupted monthly data is available 2001–2010. The murder rate is the most serious and precisely measured of the FBI violent crime categories. Monthly data suitable for time series analysis is not published for the U.S. as a whole by the FBI, but computer files of Return A Master Files, containing all Uniform Crime Report data for each month of a given year for each city or other geographical unit, and the population estimate for that city, was provided by the FBI Multimedia Productions Group. These files were used for each year from 2001 to 2010. The annual population figure for each city was used to derive monthly population estimates for that city by linear interpolation (the listed annual estimate was taken as the April figure, because this listed figure coincided with the official U.S. Census Bureau count published as an April figure for census years; the linear interpolation for 2009–2010 was extended for the latter months of 2010). The 206 cities of this sample were located in 37 states and the District of Columbia and had a total population of 60.17 million in 2010.

The data for all cities were combined into one time series for the murder rate as follows. For each month, the total incidence of murder and non-negligent manslaughter for the 206 cities was divided by the summed monthly population estimate of the cities, multiplied by 100 million (i.e., rate per 100 million population), and divided by the number of days in the month. Thus, the monthly figure represents the mean

daily murder rate for that month per 100 million population in the 206 urban areas. The mean daily murder count was used to control for the possible seasonality that might be introduced by the annual pattern of days in each month.

The analysis of murder rates in the 206 urban areas also permits comparison of results for this subsample of larger urban areas with the results for the analysis of the CDC homicide data for the entire U.S. The two figures are comparable, despite differing terminology. The FBI terminology reflects culpability; the CDC terminology indicates cause of death. The CDC homicide data analyzed in Dillbeck & Cavanaugh (2016) was also expressed in terms of the mean daily rate per 100 million population.

2.2. Design

The current study is based on murder-rate data obtained using a prospective quasi-experimental design (Cook & Campbell, 1979; Shadish, Cook, & Campbell, 2002). The data were analyzed using intervention analysis, or interrupted time series analysis (Box and Tiao, 1975; Chelimsky, Shadish, & Orwin, 1997; Glass, 1997), implemented using time series regression modeling.

2.3. Intervention

To assess the predicted effect on MR, the intervention variable used in this study was a binary indicator based on the size of the largest group of TM-Sidhi participants in North America located at MUM in Fairfield, Iowa.

July 2006 saw the beginning of a concerted effort by University leaders to expand the size of the TM-Sidhi program group (GROUP) from less than 800 to the √1% of the U.S. population (1725 participants based on the U.S. population at that time). Based on previously published theory and empirical research, predictions were lodged in advance with the press and other scientists stating that improved national trends for homicides, violent crime, and accidents would occur when the theoretically predicted threshold was reached.

Starting at an initial average level of 391 participants in June 2006 (average daily afternoon attendance), the average size of the group increased rapidly beginning in mid-July 2006. Several hundred Indian experts joined the group in November 2006 and were hosted on a neighboring campus. This brought the monthly average afternoon size of the GROUP over the √1% target starting in January 2007; the group remained above or near this level through 2010.

The GROUP series approximates a step function, with its size well below threshold prior to the intervention and above or relatively near threshold in the 2007–2010 intervention period. Therefore, in the intervention model for MR, the intervention component is modeled as a binary (0/1) step function that denotes a hypothesized shift in the linear trend function with the onset of the intervention. The intervention variable (I_t) is specified as zero from July 2001 to December 2006, and one from January 2007 to December 2010.

Continuous archival data of the group size was not available prior to July 2001; the 2010 ending date was used to make the results of these studies directly comparable to previous analyses for U.S. homicide and urban violent crime (Dillbeck & Cavanaugh, 2016).

2.4. Plot of Murder Rate

Fig. 1 displays the plot of the monthly MR data in the 206 cities as well as the MR forecast (dotted line) for 2007–2010 based on MR's pre-intervention time series behavior (see section 4.3). From late July to late October 2006 a second TM-Sidhi group was formed in Washington, DC, to add to the effect of daily group practice. Because the two groups were separate and distant, rather than simply adding their sizes, their combined effect was calculated by first squaring each group size separately, adding their squares together, and then taking the square root of that sum. The Washington group was much smaller than the Iowa group, so the effect of the Washington group was small on the total group size for those 3 months, but it was included for the sake of completeness. The sample is November 2002 through December 2010, with effective sample size $N = 98$. This sample was selected in order to give the largest possible effective sample (equivalent for intervention and stationarity tests) after allowing for both first differencing and for 12 lags of first-differenced MR required for diagnostic testing of the statistical assumption of stationarity.

MR exhibits monthly seasonal variation around a relatively flat pre-intervention trend. With the onset of the intervention period in January 2007 (see vertical line in Fig. 1), MR displays a structural shift to a declining trend that continues through the end of the sample period. During the intervention period, MR declines more rapidly than predicted by its prior trend and moves increasingly below the MR forecast, which continues its pre-intervention trend.
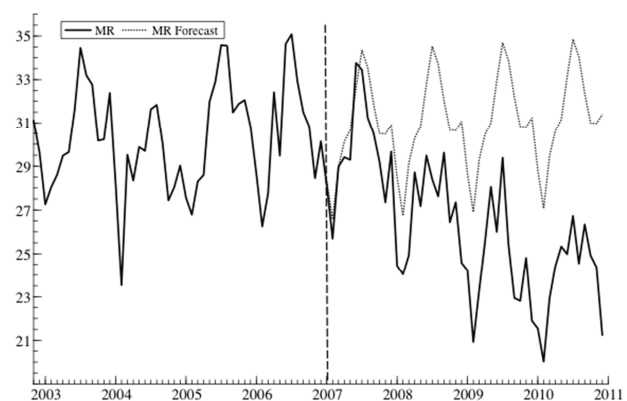
Figure 1. *Plot of monthly mean daily MR. The plot of MR for November 2002 through December 2010 displays monthly seasonal variation and a flat overall pre-intervention trend, shifting to a declining trend during the 2007–2010 intervention period (see vertical line in the plot). During the intervention, MR declines more rapidly than predicted by its prior trend and moves increasingly below the MR forecast, which continues its pre-intervention trend.*
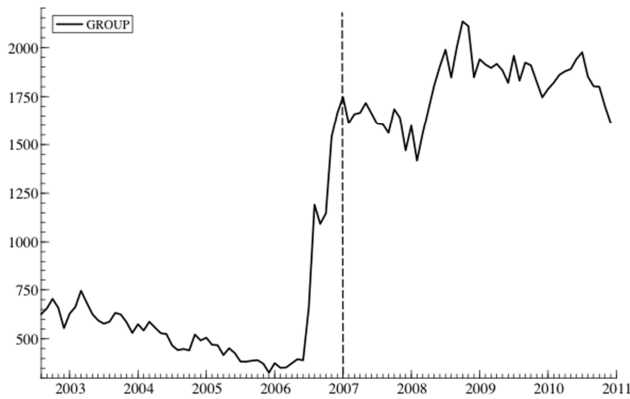
Figure 2 *Plot of monthly average daily group size (GROUP). The plot of the group size rises rapidly starting in July 2006. In January 2007 it exceeds the predicted critical threshold of 1725, the √1% of the U.S. population at that time, and remains near or above that level through 2010. Adapted from "The Contribution of Proposed Field Effects of Consciousness to the Prevention of US Accidental Fatalities: Theory and Empirical Tests," by K. L. Cavanaugh and M. C. Dillbeck, 2017, Journal of Consciousness Studies, 24(1-2), p. 66. Copyright 2017 by Imprint Academic, Ltd.*

2.5. Plot of Group Size

Fig. 2 shows the plot of the *GROUP* series. In January 2007 the monthly average daily size of the group reached 1748, rising for the first time in the sample period above the predicted √1% threshold of 1725, and remained near or above that level through 2010. As noted above, the *GROUP* plot approximates a step function, with an average of 587 participants for the 50-month baseline period compared to 1792 for the 48-month intervention.

3. Data Analysis

3.1. Regression Model

To test the hypothesis of a decrease in trend for *MR* during the intervention period, we estimate the following broken-trend intervention model

$$MR_t = \beta_0 + \beta_1 t + (\beta_2 - \beta_1) DT_t + \sum_j S_{jt} D_j + \varepsilon_t \quad (1)$$

In (1), β_0 is the regression intercept; t is a linear time trend ($t = 1, 2, 3, \ldots, N$), and β_1 is the pre-intervention trend slope for *MR*. The variable DT_t models the change in trend due to the intervention with $DT_t = (t - t_B) I_t$, where t_B is the time of the hypothesized break in the linear trend function (December 2006) and I_t is a binary (0/1) indicator variable (step function) that takes the value 0 for the pre-intervention period and 1.0 for the intervention period ($t > t_B$). The regression coefficient $(\beta_2 - \beta_1)$ for DT_t gives the change in trend slope for *MR* from the pre-intervention value (β_1) to the slope in the intervention period (β_2). The hypothesis of a negative shift in trend for *MR* during the intervention implies $(\beta_2 - \beta_1) < 0$.

The summation term in (1) is a deterministic seasonal component to control for the monthly seasonal variation in *MR*. The seasonal component consists of eleven binary (0/1) seasonal dummy variables D_j (with monthly index $j = 1$,

2, …, 11, where January is denoted by $j = 1$) (Granger & Newbold, 1986). The seasonal regression coefficient for each month is given by S_{jt}. Finally, εt is an independent and identically distributed, serially uncorrelated normal error with mean zero and variance σ^2.

3.2. Hypothesis

The √1% hypothesis predicts a negative shift in trend for *MR* during the 2007–2010 intervention. Thus, as noted above, this hypothesis implies that the estimated change in trend $(\beta_2 - \beta_1)$ in (1) should be negative. Therefore we test the null hypothesis that no trend shift is associated with the intervention, $(\beta_2 - \beta_1) = 0$, versus the alternative hypothesis $(\beta_2 - \beta_1) < 0$. Although our hypothesis is one-sided, to be conservative, two-tailed statistical tests are used to evaluate the null hypothesis.

Table 1. *OLS Regression Results for Monthly Murder Rate in 206 U.S. Cities (MR).*

Parameter	Estimate	SE[a]	t ratio[b]
β_0	29.317	0.849	34.54[***]
β_1	9.326×10^{-3}	1.114×10^{-2}	0.837
$\beta_2 - \beta_1$	-1.793×10^{-1}	2.018×10^{-2}	-8.89[***]
S_{1t}	-2.103	0.686	-3.07[**]
S_{2t}	-3.860	0.685	-5.63[***]
S_{3t}	-1.405	0.685	-2.05[*]
S_{4t}	-0.259	0.685	0.378
S_{5t}	0.823	0.685	1.20
S_{6t}	2.434	0.685	3.55[***]
S_{7t}	3.845	0.685	5.61[***]
S_{8t}	2.377	0.685	3.47[***]
S_{9t}	1.690	0.685	2.47[*]
S_{10t}	0.336	0.685	0.490
S_{11t}	0.417	0.664	0.628

F statistic: $F(13,84) = 38.23$[***]	Mean of $MR = 28.341$
SE of regression = 1.409	SE of $MR = 3.448$
Sum of squared residuals: 166.716	Log-likelihood = -165.091
$R^2 = 0.855$; Adjusted $R^2 = 0.833$	$BIC = 4.024$; $AIC = 3.655$

Diagnostics:

Serial correlation test:	Heteroscedasticity test:
Lags 1–6: $F(6,78) = 1.450$ ($p = 0.207$)	$F(15,82) = 0.908$ ($p = 0.558$)
Lags 1–12: $F(12,72) = 1.452$ ($p = 0.163$)	Test for ARCH:
Normality test: $\chi^2(2) = 1.367$ ($p = 0.505$)	Lags 1–6: $F(6,86) = 0.354$ ($p = 0.906$)
Stationarity test: $z = -1.272$ ($p = 0.898$)	Test of functional form:
Perron unit root test: $\tau_\alpha = -7.284$ ($p < 0.01$)	$F(2,82) = 0.991$ ($p = 0.376$)

Note: Sample is Nov. 2002 to Dec. 2010, $N = 98$. OLS = ordinary least squares; *AIC* = Akaike information criterion; *BIC* = Bayesian information criterion; ARCH = autoregressive conditional heteroscedasticity.
[a] OLS standard errors and *t* ratios. [b] *df* = 84.
[*] $p < 0.05$. [**] $p < 0.01$. [***] $p < 0.001$.

4. Regression Results for Murder Rate

4.1. OLS Regression Results

Table 1 summarizes the ordinary least squares (OLS) regression results for (1) as well as diagnostic tests for model adequacy. The positive, estimated pre-intervention trend for *MR* does not differ significantly from zero, unlike the significant positive trend for the national homicide rate *HOMR* reported in Dillbeck & Cavanaugh (2016). As in the analysis of *HOMR* (Dillbeck & Cavanaugh, 2016), the null hypothesis of no trend shift for *MR* during the intervention period is strongly rejected: the linear trend function displays a highly significant negative shift during 2007–2010 ($t(84) = -8.89$, $p = 1$ x 10^{-13}). Panel (b) of Fig. 3 graphically displays the change in trend (-0.1793) plus 95% confidence interval (-0.2194, -0.1392), and panel (a) shows the *MR* trends for the intervention and pre-intervention periods.
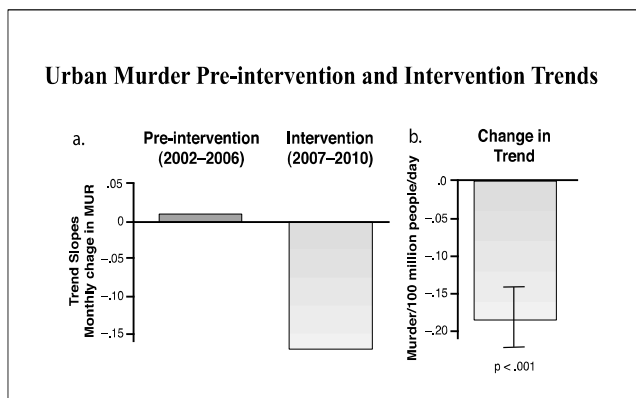
Figure 3. Comparison of MR trends during the pre-intervention and intervention periods. The MR slope is the change per month in MR, the monthly mean daily rate of murder and non-negligent manslaughter per 100 million population. Panel (b) displays the significant negative shift in trend during 2007–2010 with 95% confidence interval.

The effect size for the estimated trend shift is given by Cohen's $f = -0.970$. The absolute value of the effect size measure is the square root of Cohen's f^2 for a regression variable (or set of variables), with 0.59, 0.39, and 0.14 considered large, medium, and small effects, respectively (Cohen, 1988). The effect size f is given by the t ratio (or square root of the F statistic) for the regression coefficient divided by the square root of the residual degrees of freedom (Cohen, 1988; Grissom & Kim, 2012, p. 323). The unsquared effect size metric is used rather than squared because the former is said to better indicate the relative magnitude of effects across variables (Darlington & Hayes, 2017). The guidelines for large, medium, and small values of f mentioned above are the square root of those given by Cohen (1988) for f^2 (0.35, 0.15, and 0.02, respectively).
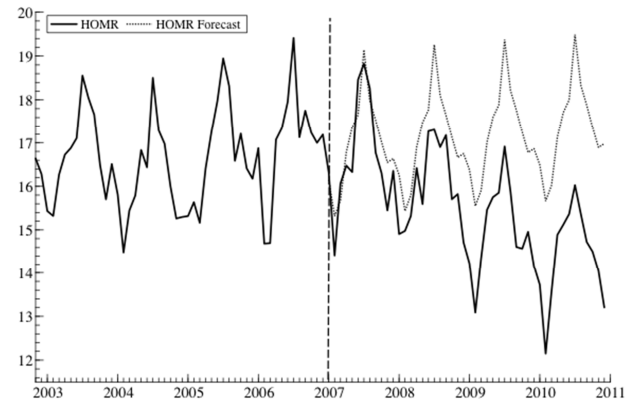

Figure 4. Plot of U.S. monthly homicide rate (HOMR) and its forecast for the intervention period (see dotted line). The plot of HOMR for November 2002 through December 2010 displays strong monthly seasonality, a slightly rising pre-intervention trend, and a shift to a declining trend in the intervention period starting January 2007 (shown by the vertical line in the plot). During the intervention, actual HOMR declines faster than predicted by its baseline trend and moves increasing below its forecasted values, which are based on the pre-intervention data.

4.2. Comparison to Results for the U.S. Homicide Rate

For purposes of comparison, Fig. 4 shows the plot of the U.S. national homicide rate as well as a forecast of its values during the intervention period. As in the case of *MR* in Fig. 1, the *HOMR* forecast is based on pre-intervention data only. Like the *MR* series, *HOMR* exhibits monthly seasonal variation, but around a slightly rising rather than flat pre-intervention trend. During the intervention period *HOMR* shifts to a declining trend, moving increasingly below its forecast, where the forecast continues *HOMR*'s pre-intervention rising trend.

Fig. 5 provides a graphical comparison of the *HOMR* intervention and baseline trends, with panel (b) showing the highly significant shift in trend (-0.07376) ($t(84) = -10.17$, $p = 2.7$ x 10^{-16}) plus 95% confidence interval (-0.0882, -0.0593). (Fig. 5 was not included in Dillbeck and Cavanaugh (2016).) For *HOMR* the effect size for the estimated trend shift is $f = -1.109$ for the trend-shift estimate reported in Table 1 of Dillbeck & Cavanaugh (2016).
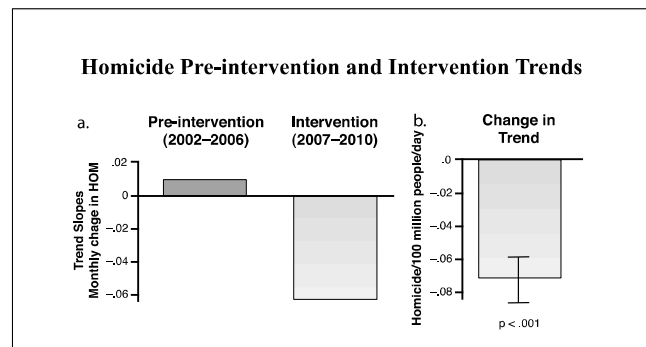
Figure 5. Comparison of trends for the U.S. homicide rate (HOMR) during the pre-intervention and intervention periods. The HOMR slope is the change per month in HOMR, the monthly mean daily rate of homicides per 100 million population. Panel (b) displays the statistically significant, negative shift in trend during 2007–2010 with 95% confidence interval.

The effect size measure for the homicide rate (and also the rate of violent crime) was not reported in the 2016 paper. In that paper, the robust t ratio reported for the change in *HOMR* trend was based on a bandwidth of three Newey-West lags (rather than five as reported in a typo). For the *HOMR* trend shift estimated using standard OLS, the effect size was also large ($f = -1.071$). For the violent crime rate, the negative long-run trend shift of –0.08665 is highly significant ($t(83) = -6.14$, $p = 2.7 \times 10^{-8}$) with 95% confidence interval (–0.1147, –0.0586) and effect size $f = -0.670$, a large effect.

The change in *MR* slope (–0.17933) during the intervention gives the estimated reduction in the expected value of the daily murder rate (per 100 million population) for each month of the intervention period relative to the pre-intervention trend. Multiplying by 48 months gives the cumulative estimated reduction in *MR* for 2007–2010: –8.60784 murders per day per 100 million population. Relative to the pre-intervention mean rate of 30.3052, this is a reduction of 28.40% (average of –7.10% annually).

The corresponding estimated reduction for the overall U.S. homicide rate for the same 2007–2010 period is 21.24% (5.31% annually) relative to the baseline mean of 16.6714 (Dillbeck & Cavanaugh, 2016). Thus the percentage reduction in *MR* is 1.34 times larger than that for *HOMR*. Also, the rate of decline in murder rates for the 206 urban areas during the intervention, as measured by the slope of the 2007–2010 trend, is 2.75 times larger in absolute value than the corresponding rate of decline in homicide rate for the whole U.S. (Note that a typographical error on p. 9 of Dillbeck & Cavanaugh (2016) gives 2.4 rather than 2.75 for the 2007–2010 rate of decline of *MR* relative to that for *HOMR*.)

For these 206 urban areas over 100,000 population, pre-intervention homicide rates were approximately 1.8 times higher (30.30 versus 16.67) than the national average. Thus in the urbanized areas, which experienced higher baseline homicide rates than the national average, murder rates fell substantially faster during the intervention period than in the U.S. as a whole.

4.3. Practical Significance

For the 60.17 million population of the 206 cities in the sample, the estimated change in trend for 2007–2010 implies a total of 4,136 murders and non-negligent homicides averted over 2007–2010 relative to the pre-intervention trend, fatalities that were projected to occur had the pre-intervention trend continued during the intervention period. This projection is based an *ex ante* forecast of *MR* for 2007–2010 calculated from the baseline, pre-intervention data.

The pre-intervention data were used to generate monthly forecasts of *MR* for 2007–2010 based on OLS estimates of (1) after deleting the trend-change variable *DT* from the model. The summed difference between forecast and actual murders for the 48 months of the intervention was calculated as follows:

$$N_{\text{MUR}} = \Sigma_k \left[c \, (\text{forecast } MR_k - \text{actual } MR_k) \, d_k \right],$$

$$k = 1, 2, \ldots, 48, \quad (2)$$

where N_{MUR} is the estimate of total prevented murders, c is a constant defined below, and d_k is the number of days in month k. Because *MR* is the monthly mean rate of daily murders per 100 million people in the 206 urban areas with 60.17 million population, the constant $c = .6017$.

The same forecast-based methodology gives an estimate of 7,385 total U.S. homicides prevented during the intervention. For estimating total U.S. homicides averted, the summed difference between forecast and actual homicides for each month 2007–2010 was calculated as follows:

$$N_{\text{HOM}} = \Sigma_k \left[d_k \, (\text{forecast } HOMR_k - \text{actual } HOMR_k) \, USPOP_k \right],$$

$$k = 1, 2, \ldots, 48, \quad (3)$$

where N_{HOM} is the estimate of total prevented homicides, d_k is the number of days in month k, the forecast and actual monthly values of *HOMR* are rates per 100 million population, and $USPOP_k$ is the estimated U.S. monthly population divided by 100 million.

These projections suggest that the 206 urban areas in the sample with only 19.5% of the total U.S. population accounted for 56.0% of the total estimated U.S. homicide deaths prevented during the intervention. Thus, during 2007–2010, the 206 urban areas—which had substantially higher baseline murder rates than the U.S. as a whole—showed a disproportionately large reduction in prevented homicides and both a faster rate of decline and larger percent reduction in rates compared to the entire U.S.

The projections of 4,136 averted murders in the 206 cities during 2007–2010 and 7,385 total prevented U.S. homicides are broadly similar to those given in Dillbeck & Cavanaugh (2016): 3,865 and 8,157 respectively. The latter estimates were calculated using an alternative method based solely on trend projections. This calculation compared the fatalities that would be predicted by a continuation of the pre-intervention trend with those implied by the reduced trend during 2007–2010. In the 2016 paper, the predicted total number of fatalities averted for crime i during the 48 months of the intervention period, assuming that the pre-intervention trend had continued through 2007–2010, was calculated as follows:

$$N_i = \Sigma_k k \, (\beta_2 - \beta_1) \, c \, d_k, \quad k = 1, 2, \ldots, 48, \quad (4)$$

where N_i gives the fatalities averted, k is the month of the intervention, c is a constant defined below, and d_k is the number of days in month k. The constant c depends on the units of the fatality rate and the size of the population. For *HOMR*, which is the monthly mean of U.S. daily homicides per 100 million people, the constant $c = 3.0874558$, the U.S. population in April 2010 divided by 100 million. The constant $c = .6017$ for *MR*, which is the monthly mean of daily homicides per 100 million people in the sample of 206 cities with 60.17 million total population.

Thus, the trend projections in Dillbeck and Cavanaugh (2016) were based on the change in trend $(\beta_2 - \beta_1)$ for the full

intervention model in (1) as estimated using the complete sample. By contrast, the more intuitive calculation used in the current paper is based on the difference between the monthly observed fatalities during 2007–2010 and the *ex ante* forecast of predicted monthly fatalities during the same period based on the pre-intervention data only. The forecast-based method is also more comprehensive in that the forecasted rates incorporate a projection of both the trend and the seasonal variation, rather than of the trend alone.

4.4. Regression Diagnostics for Analysis of MR

Table 1 reports diagnostic tests to assess whether the key assumptions of the statistical analysis are satisfied. The null hypothesis of serially uncorrelated (white noise) regression residuals at lags 1–6 and 1–12 is not rejected by the Lagrange multiplier (LM) test (Godfrey, 1978). Only one autocorrelation at lags 1–36 is significant at the 5% level (0.225 at lag 2), consistent with the expected number of significant serial correlations for a white noise series. The trend shift also remains significant using robust *SE*s and *t* ratios that are valid (consistent) in the presence of autocorrelation (and heteroscedasticity) of the regression residuals: $t(84) = -8.4870$ ($p < 0.001$) (Newey & West, 1987). Using robust *SE*s and *t* ratios, the pre-intervention trend remains insignificant ($t(84) = 0.00932$, $p = 0.405$). The bandwidth of three Newey-West lags was selected automatically by PcGive 14 software (Doornik & Hendry, 2013) using the integer part of $4(N/100)^{2/9}$.

The residuals from the estimated model appear to be clearly stationary. A time series is defined to be weakly stationary (or covariance stationary) if its mean, variance, and autocorrelations (or, equivalently, its autocovariances) are invariant with respect to time origin (Enders, 2010). A weakly stationary series is said to be integrated of order zero, or I(*d*) with the differencing parameter $d = 0$, where *d* is the number of times the series must be differenced to induce stationarity. For example, a nonstationary series containing a unit root (or random walk) component will require first differencing to transform it from an I(1) to an I(0) series.

A formal test for I(0) (Choi, 2015, p. 126; Harris, McCabe, & Leybourne, 2008) is reported in Table 1 for the residuals from the *MR* intervention model. The test fails to reject the null hypothesis that the residual series is I(0), supporting the conclusion that *MR* is broken-trend stationary, exhibiting weakly stationary fluctuations around a broken trend. The Harris-McCabe-Leybourne (HML) test also indicates that the *HOMR* residuals are stationary ($z = -0.870$, $p = 0.808$). The distribution of the test statistic is asymptotically standard Normal N(0,1). The test was estimated in TSM 4.4.9 software (Davidson, 2016) using the default test settings. The alternate hypothesis for the HML test is $d > 0$, including the unit root case $d = 1$ as well as possible stationary or nonstationary fractional values of the differencing parameter *d* ("fractional integration") (Patterson, 2012, pp. 77–142).

Stationarity of the regression residuals is required for valid statistical inferences regarding the estimated regression parameters in the intervention model (Banerjee, Dolado,

Galbraith, & Hendry, 1993; Enders, 2010; Granger & Newbold, 1986). Broken trend stationarity for *MR* implies that the OLS regression estimates in Table 1 have standard distributions, and thus the observed significant change in trend is unlikely to be the result of "spurious regression" (Banerjee, et al., 1993; Granger & Newbold, 1986). Spurious regressions can arise, for example, when time trends are fitted to nonstationary variables that contain a random walk component ("stochastic trend"). A key signature of such spurious regressions is highly autocorrelated, nonstationary regression residuals, which violate the distributional assumptions underlying statistical inference for time series regression.

Table 1 also reports a formal test for broken-trend stationarity of a time series with a single known (exogenous) structural break (Perron, 1989, 2006). As discussed in Dillbeck and Cavanaugh (2016, p. 12), standard approaches to testing for nonstationarity (unit root tests) such as the augmented Dickey-Fuller test (Dickey & Fuller, 1979; Said & Dickey, 1984) and others have been shown to be biased in favor of concluding that a broken-trend stationary time series is nonstationary.

The Perron unit root test for *MR* rejects the null hypothesis ($p < 0.01$) that the *MR* series contains a nonstationary random walk with drift component (Perron, 1989; Zivot & Andrews, 1992). Following Zivot and Andrews (1992) we test for nonstationarity using the "change in growth" broken-trend model based on equation (15) in Perron (1989, p. 1381), which is model B in Zivot and Andrews (1992, p. 253). The test statistic has a nonstandard distribution tabulated by Perron (1989, Table V. B). The critical value for the test depends on the parameter $\lambda = t_B / N$, the time of the break divided by total sample size. For the variables analyzed in this paper, $\lambda = 0.51$. The alternative hypothesis is that *MR* is broken-trend stationary, displaying stationary fluctuations around a linear trend with a known, one-time break in the trend function in December 2006.

Because of *MR*'s monthly seasonality, a maximum of 12 lags of first-differenced *MR* was considered for inclusion in the regression equation for the Perron test. Because superfluous regressors inflate *SE*s for the regression coefficients, lags that were not significant at the 20% level (lags 1–6 and 11) were deleted from the Perron test regression, substantially increasing the power of the test.

The results of all other diagnostic tests for model adequacy are also satisfactory. The null hypothesis of no autoregressive conditional heteroscedasticity (ARCH) for the regression residuals is not rejected by the LM test for ARCH (Engle, 1982). Likewise, White's general test for heteroscedasticity (White, 1980) fails to reject the null hypothesis that the regression errors are homoscedastic or, if heteroscedasticity is present, it is unrelated to the regressors. The null hypothesis that the functional form of the regression model is correctly specified is not rejected by the regression specification (RESET) test (Ramsey, 1969). Following the recommendation for smaller samples (Harvey, 1990; Kiviet, 1986), the LM test for serial correlation and all other LM tests in Table 1 are reported in their

F-statistic form rather than chi-square.

The omnibus Doornik-Hansen test for normality of the regression errors (Doornik & Hansen, 2008) fails to reject the null hypothesis that the errors are drawn from a normal distribution. No regression residuals exceed 3.5 standard errors, indicating the absence of extreme outliers. Finally, the estimated model tracks the observed data well, as indicated by the squared correlation between the in-sample predictions (fitted values) of *MR* from the model and the actual data values (R^2 = 0.855). Thus the diagnostic tests for model adequacy support statistical conclusion validity for the statistical inferences reported in Table 1.

In sum, the estimated trend shift for *MR* is highly statistically significant and has the predicted negative sign. All diagnostic tests for the estimated model are satisfactory. Thus the null hypothesis of no effect of the intervention on the trend of monthly U.S. urban murder rates during 2002–2007 can be rejected. The statistical analysis summarized in Table 1 suggests that these results cannot be explained by autocorrelation, spurious regression, seasonal variation, or prior trends. The large effect size for the estimated trend-shift in *MR* and the substantial forecast-based estimate of murders prevented during the intervention indicate that the shift in trend for *MR* is practically as well as statistically significant.

5. Discussion

The results of this study indicate that a statistically and practically significant reduction in murder rate was seen in American cities associated with the quasi-experimental intervention. The observed effects were seen at the specific time and in the specific direction hypothesized. The diagnostic tests for this conclusion were suitable for the statistical model. The results of this study are consistent with the hypothesis that a group of participants in the TM-Sidhi program exceeding √1% of the U.S. population is sufficient to measurably reduce the rate of murder in urban areas. A notable feature of these results is that although the 206 urban areas in this study initially had higher murder rates than the country as a whole, they experienced a greater decrease during the experimental period (Dillbeck & Cavanaugh, 2016).

A rejection of the null hypothesis does not itself confirm the specified alternative hypothesis; for time series studies, the most viable alternative hypotheses are those that provide an alternative explanation based on historical change (Shadish, Cook, & Campbell, 2002, p. 179). Therefore, we now analyze the following alternative hypotheses, some of which were considered in Dillbeck and Cavanaugh (2016), and others of which are specific to this study: (a) economic changes, (b) temperature change, (c) change in incarceration, (d) police strategy, (e) police technology, (f) police reporting, and (g) urban demographics

Economic changes. The initial question that might arise is whether the observed changes might be a function of the economic crisis of the recent major recession. The most likely link between these economic changes and crime is unemployment. However, unemployment is generally associated with increased crime (Aaltonen, MacDonald, Martikainen, & Kivivuori, 2013; Cantor & Land, 1985; Spector, 1975). Moreover, U.S. unemployment increased beginning in 2008, as did the trauma of other changes associated with the economic crisis. Unlike all previous major economic downturns since WWII, violent crime failed to rise during the severe recession of December 2007 to June 2009 (Eng, 2012).

Temperature change. Recent research indicates a 4% increase in interpersonal violence with a one standard deviation increase in temperature (Hsiang, Burke, & Miguel, 2013). However, NASA climatologic data (NASA, 2017) indicate that during the intervention period compared to the baseline period, the Global Land-Ocean Temperature Index rose 2.5%, which would also not predict decreased murder rates.

Change in Incarceration. Incarceration rates are negatively associated with crime rates (Marvell & Moody, 1994), but during the intervention period prison admissions were slowing relative to releases, reducing the growth of the U.S. prison population (Guerino, Harrison, & Sabol, 2011; Sabol & West, 2011), which would also predict increased rather than decreased murder rates.

Police Strategy and Police Technology. Improvement in police strategy or police technology may have contributed to reduced rates of murder during the intervention period, but the results found here would have required a large-scale simultaneous implementation of any new strategy or technology beginning at the time of the intervention in order to function as a realistic alternative hypothesis. Moreover, advances in surveillance technology would more likely target property crimes rather than murder; alcohol use would make the latter more intractable to surveillance (Roizen, 1997).

Police Reporting. During the period of this study, smaller cities (population 5–10 thousand) might still be starting to meet the reporting standards of the Federal Bureau of Investigation (FBI) Uniform Crime Reports (UCR), and thus experience some changes in reporting standards. However, the large urban areas of this study would have already met these standards and would have been contributing their data to the FBI UCR system for 30 or 40 years by the beginning of this study. Thus, the count of murders is unlikely to be arbitrarily influenced by reporting standards.

Urban Demographics. The urban demographic factors cited above would not be expected to suddenly change in January 2007 in a way to predict reduced violence. For example, youth (age 18–25) is associated with greater violent crime (Nivette, 2011), but during the period of this study the percentage of young people was gradually increasing (Howden & Meyer, 2011).

Thus, in summary, although in most cases the alternative hypotheses are not viable factors influencing the murder rate, to the degree that they are viable, they would predict a rising rather than falling murder rate during the intervention period.

In contrast, Maharishi Mahesh Yogi, the founder of the Transcendental Meditation program and an exponent in this generation of the Vedic and Vedantic understanding and experience of Transcendental Consciousness, has specifically

proposed the hypothesis that has guided this research, namely a predicted decrease in murder rate during the intervention period. This hypothesis is based on the understanding that consciousness in its pure form, pure consciousness or Transcendental Consciousness, is a universal field shared by all individuals (the innermost self or *Atma* in Vedic terms). As a result, experiencing and enlivening of this field in society by a large group of individuals participating in the TM-Sidhi program will influence all the others in society, leading to development in the same holistic direction as experienced by individuals who begin the practice of Transcendental Meditation.

This conception of consciousness as universal, although missing from contemporary social science, has historically been held by many thinkers in the West (Skrbina, 2005) and currently by some scholars in the physical and life sciences (Goswami, 2001; Hagelin, 1987; Lanza & Berman, 2010; Nader, 2015; Theise & Kafatos, 2016). The present research program is unique in that it tests empirical consequences of this broad assumption.

6. Conclusion

Independent of these theoretical considerations, the findings of the present study suggest both that the intervention studied here—the group practice of the TM-Sidhi program by $\sqrt{1\%}$ of the population—is effective in reducing violence in urban areas, and that this reduction is not mitigated in more violence-prone areas of the U.S. Therefore, we urge those responsible for government and national strength to replicate and subsequently apply these findings. One of the most effective settings for doing so is the military, where large groups of individuals are already supported together for the purpose of national strength.

Acknowledgements

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