**MEDIA CONSUMPTION AND CRIME TREND PERCEPTIONS:**

**A LONGITUDINAL ANALYSIS**

**ABSTRACT**

For over two decades, despite of the downward crime trend, the American public has persisted in believing crime is on the rise. Cultivation theory holds that media is responsible for the public’s crime trend perceptions. Previous cultivation studies heavily rely on cross-sectional data, which may lead to spurious conclusions due to reverse causation and omitted variable bias. This study aims to address these issues by utilizing longitudinal analyses. Drawing on three waves of the 2008-2009 American National Election Survey, we test the cultivation hypothesis using traditional OLS, OLS with lagged crime trend perceptions, fixed effects, and dynamic panel models. Newspaper and TV news consumption are related to crime trend perceptions in traditional OLS models. In other models, media consumption is not related to crime trend perceptions. The results do not support the cultivation hypothesis. It is likely that the cultivation effect of media has been overstated in previous cross-sectional research.

**KEYWORDS**: cultivation theory, crime trend perceptions, longitudinal analysis, dynamic panel models

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**Introduction**

In 2016, seven in ten Americans reported that national crime rates were on the rise (Swift 2016). Yet in reality, since historic highs in the early 1990s, U.S. crime rates have dropped steadily or remained stable (Federal Bureau of Investigation [FBI] 2015; Truman and Morgan 2015). The public’s inaccurate perceptions of crime trends are not new. For the past two decades, most Americans persistently perceive that crime increased over the previous year (McCarthy 2015). Scholars have contended that the public’s misunderstandings about crime trends fuel support for disproportionally punitive criminal justice policies (Enns 2016; Garland, 2001; Roberts 1992).

Examining Americans’ crime trend perceptions, Hough and Roberts (2005: 11, emphasis added) asserted that “the source of the public’s perception of ever-rising crime rate is *the media*.” Researchers suggest that sensationalistic reporting often overemphasizes violence, leading to the public’s over-concern about crime (Thompson 2011). Gerbner and Gross’ (1976) cultivation theory posits that media consumption directly affects individuals’ fear of crime (e.g., see Gerbner et al. 1977; Gerbner et al. 1980). Current empirical evidence corroborates the cultivation theoretical framework and shows that increased exposure to news reports, especially local TV news, is associated with higher levels of fear of crime among respondents (e.g., see Chiricos, Eschholz, and Gertz 1997; Chiricos, Padgett, and Gertz 2000; Weitzer and Kubrin 2004).

Although previous studies are generally supportive of the cultivation hypothesis, virtually all existing empirical analyses of cultivation theory draw on *cross-sectional* samples (Potter 2014), which cannot nor account for the dynamic nature of perception formation processes. This is problematic because in reality people are likely to update their crime trend perceptions constantly based on their previous perceptions (e.g., see Anwar and Loughran 2011; Jennings et al. 2016). People who are anxious about all types of risks and/or criminal victimization in previous time periods may consume more crime news in the current period, and subsequently perceive more crime in the current period. In other words, treating crime trend perceptions as time stable may lead to concerns of reverse causation and omitted variable bias, rendering conclusions from prior cross-sectional cultivation studies spurious. Thus, it is crucial to further examine the cultivation theory using longitudinal analyses (e.g., see Hirsch 1980; Hughes 1980; Morgan and Shanahan 2010).

In the current study, we seek to test the cultivation hypothesis that media consumption is related to the public’s crime trend perceptions using longitudinal analyses. In accordance with previous studies and to provide comparison to our later analyses, we first estimate pooled OLS models. We then estimate OLS models with lagged crime trend perceptions to account for the dynamic nature of crime perception forming processes. We further estimate fixed effects models with lagged crime trend perceptions to control for time invariant unobservables (Allison 2009). Additionally, we compute dynamic panel models, including difference and system generalized method of moments (GMM) estimators, to purge endogeneity in OLS and fixed effects estimates with lagged crime trend perceptions (e.g., see Blundell and Bond 1998, Roodman 2009). Although we utilize a variety of modeling techniques, our goal is not to select the most advanced model to study the cultivation theory nor to draw definitive causal inference from those models. Rather, we investigate if previous cross-sectional works have overstated the influence of media on Americans’ perceptions of crime trends.

**Americans’ Mistaken View on Crime Trends and Its Impact on Criminal Justice Policies**

The popular view of crime in the United States is that “crime rates are always rising and that a high percentage of crimes involve violence” (Roberts and Stalans 1997: 26). This stands in sharp contrast to the actual downward trend in U.S. crime rates over the last twenty years, and the consistently low proportion of all crime that is violent (FBI 2015; Truman and Morgan 2015). According to police-recorded statistics (FBI 2015), violent crime rates have dropped by more than 50% over the past two decades, from 747.1 per 100,000 inhabitants in 1993 to 372.6 per 100,000 inhabitants in 2015. In correspondence with these official crime statistics, violent victimization rates reported by U.S. residents aged 12 or older have declined by 75% from 79.8 per 1,000 persons in 1993 to 20.1 per 1,000 persons in 2015 (Truman and Morgan 2015).

These downward trends in crime, however, have not been reflected in the public’s perceptions. In general, since 1989, when Gallup polls started to record the American public’s perceptions of crime trends, a large majority of respondents consistently reported that crime rates were on the rise (McCarthy 2015). From the early 1990s to 2000, there was a downturn in the popular belief that crime is always increasing (Ramirez 2013). However, after reaching a record low of around 40% in 2001, the majority of people, ranging from over 50% to around 70%, once again began reporting every year that the crime rate in the U.S. was increasing. As shown in Figure 1, both the violent victimization rate and the percent change in violent victimization rate are at odds with the public’s crime trend perceptions. Thus, overall, while the public’s perceptions of crime trends do fluctuate, the majority of Americans almost always believe that crime is rising.

Figure 1 about here

The public’s misperceptions of crime trends may have substantial consequences for Americans’ political behaviors and criminal justice policies. Compared to other policy domains, criminal justice policy decisions are particularly sensitive to public opinion (Canes-Wrone and Shotts 2004). Over-concern about crime is likely to mobilize the public to be more punitive (Enns 2016), thereby fueling support for increased law enforcement spending and harsh sentencing policies (Garland 2001; Simon 2007; Zimring 2003). Public punitiveness is one of the strongest predictors of both federal and state incarceration rates (Enns 2016). Notably, public punitive attitudes might be indirectly influenced by crime framing in the media (e.g., see Enns 2016; Murz and Nir 2010).

**Cultivation Theory and Prior Research Using Cross-sectional Data**

According to cultivation theorists, people who are frequently exposed to media are likely to cultivate a distorted view about crime and criminal justice that mirrors the one depicted by the media (e.g, see Gerbner and Gross 1976; Gerbner et al. 1980). Few Americans have been directly exposed to serious crime or its consequences, either as a victim or an offender. Rather, they ostensibly depend on the media to learn about crime information (Surette 2011), and unfortunately, the image of crimes presented by the media are not “statistically correct” (Roberts et al. 2003: 79). For instance, Chiricos and his colleagues (1997) estimated that mass media coverage on violence increased more than 400% in the mid-1990s while the crime rates declined steadily. In theory, the explosion of crime stories engendered the impression that crime is prevalent (Roberts et al. 2003). The media’s large volume of media coverage very often depicts crime as violent and involving nonwhite male perpetrators (Gilliam and Iyengar 2000; Dixon and Linz 2000). The media also often depicts criminal justice authorities as being unable to address important crime problems (Beckett and Sasson 2004). Thus, exposure to crime reports is theoretically likely to push people to become more anxious about victimization and perceive that crime is increasing (e.g., see Roberts 1992).

Empirical studies suggest that the cultivation effect is dependent on the types of media consumed. Among traditional mass media (TV, newspaper, radio), exposure to television alone has consistently been found to be positively related to anxiety about crime (e.g., see Chiricos et al. 1997; Chiricos et al. 2000; Eschholz, Chiricos, and Gertz 2003). The empirical evidence on exposure to newspapers and radio is mixed. Some studies show that reading newspapers is positively related to fear of crime while others suggest no relationship (Eschholz 1997). Similarly, some research finds listening to the radio increases fear of crime (e.g., see Chiricos et al. 1997) while other research finds no effect (e.g., see Chadee and Ditton 2005). With the increasing popularity of digital news outlets, researchers have begun to investigate the cultivation effect of online news consumption and exposure to social media. Thus far, two studies have found a negative but statistically insignificant relationship between online news consumption and anxiety about crime (Roche, Pickett, and Gertz 2016; Weitzer and Kubrin 2004), while one previous study on social media found that exposure to social media is related to greater fear of crime among young adults (Intravia et al., 2017).

Most American cultivation studies focus on explaining emotional fear of crime and perceived risk of victimization. However, in other developed nations, including Australia, Germany, and Ireland, investigators have expanded the scope of cultivation theory research to explain crime trend perceptions. These studies have found that crime trend perceptions are independent of actual crime rates, and that media exposure is a strong predictor of the public’s perceptions of crime trends (e.g., see Davis and Dossetor 2000; O’Connell and Whelan 1996; Pfeiffer, Windzio, and Kleimann 2005). In the United States, the only study that has examined crime trend perceptions in the context of cultivation theory is Kort-Butler and Hartshorn’s (2011) investigation of the relationship between TV viewing and perceived crime rates. Analyzing data from a telephone survey of 784 Nebraska residents, Kort-Butler and Hartshorn (2011) found that only frequency of viewing local news was related to perceptions of increased local crime rates. While important, the data for this study were collected from a single U.S. state, and did not include a measure of Internet news consumption. Moreover, their data were cross-sectional, which were potentially spurious. Indeed, in testing cultivation theory, researchers have primarily relied on cross-sectional data (Potter 2014).

Although previous studies are important, the results are potentially biased because analyses drawing on cross-sectional data cannot account for the dynamic nature of perception formation processes. The formation process of crime trend perceptions is unlikely to be invariant over time. Rather, perceptions from previous time periods may influence current crime trend perceptions (e.g., see Anwar and Loughran 2011; Jennings et al. 2016). Farrall, Jackson, and Gray (2009) suggested that fear of crime may be an output of individuals’ deeper-seated anxieties about the world generally. It is also possible that people who are already more anxious about crime stay at home and consume more crime-related stories on television (e.g., see Gunter 1987). Accordingly, unobserved factors such as general anxiety may cause people to be more likely to believe crime is becoming worse as well as to self-select into increased media consumption, leading to a spurious and reverse causal relationship between media consumption and crime trend perceptions.

**Current Study**

To our knowledge, no previous studies on crime trend perceptions have utilized longitudinal analyses to strengthen causal inference. In this study, we investigate the cultivation hypothesis that media consumption affects perceptions of crime trends using OLS, fixed effects, and dynamic panel models, including difference and system GMM estimators. We then compare the results from each methodological approach, taking into account the strengths and weaknesses of each methodology.

In accordance with cultivation theory, we test four specific hypotheses: (1) *exposure to* *television news is positively related to perceptions that there is more crime in the United States*; (2) *exposure to news from newspapers* *is positively related to perceptions that there is more crime in the United States; (3) exposure to news on the radio is positively related to perceptions that there is more crime in the United States;* and (4) *exposure to* *online news consumption is positively related to perceptions that there is more crime in the United States.*

We first assess these four hypotheses using traditional OLS models for comparative reasons. To account for the dynamic perception formation processes, we include lagged crime trend perceptions in our subsequent longitudinal analyses. We estimate OLS models with lagged crime trend perception, and fixed effects models to control for time invariant unobservables (Allison 2009). OLS and fixed effects estimates with lags are likely to be biased (Bond 2002; Nickell 1981 1982). We then compute dynamic panel models, including difference GMM that can account for reverse causation (Arellano and Bond 1991), and system GMM dynamic model estimators that can further reduce biases and imprecision associated with the difference GMM estimators (Arellano and Bover 1995; Blundell and Bond 1998). Notably, the dynamic panel models can purge the results from OLS and fixed effects models with lags of potential bias (e.g., see Holtz-Eakin, Newey, and Rosen 1990).

**Data**

The data used in our analysis come from the 2008-2009 panels of the American National Election Studies (ANES). This nationwide study is composed of two cohorts selected via random-digit-dialing (RDD) methods. Beginning in January of 2008 and ending in September of 2009, each cohort was interviewed 21 times, with each participant being asked a series of questions regarding their attitudes towards subjects such as political parties, religion, and crime perceptions. In three of the waves (1, 9, and 11) participants were asked “Compared to 2001, would you say the nation’s crime rate is now (much better, somewhat better, about the same, somewhat worse, or much worse)?” We use this as our measure of crime trend perceptions (1 = much better; 5 = much worse) and treat it as a continuous variable in accordance with previous cultivation studies (e.g., see Chiricos et al. 1997; Eschholz et al. 2003; Roche et al. 2016). One concern that may arise is that since the time periods between the waves, especially between waves 9 and 11, are not very long, respondents’ crime trend perceptions may not have changed sufficiently, and there is not enough variation in the outcome variable. However, as we show below, there is considerable variability over time in crime trend perceptions (see Table 2).

The key independent variables of interest are measures of respondents’ exposure to media per week for each source.[[1]](#footnote-1) For example, regarding exposure to television, respondents were asked “During a typical week, how many days do you watch or read news on TV, not including sports?” Similar questions were asked regarding weekly consumption of news from newspapers, Internet, and radio. This allows us to build a panel dataset of crime trend perceptions and media consumption, composed of three panels. We also control for demographic factors (i.e., age, sex, political ideology, race), and socioeconomic status (i.e., education and income) in the OLS and system GMM models, as cultivation effects may vary depending on audiences’ demographic features and social context (see e.g., Chiricos et al. 1997; Chiricos et al. 2000; Eschholz et al. 2003). After merging we are left with a sample of 3,143 respondents.

Table 1 about here

Table 1 shows descriptive statistics for the sample stratified by sampling wave. We used probability weights provided by the ANES to account for the differential probability of selection into the study and participant non-response. Table 2 presents changes in respondents’ crime trend perceptions over the three waves. Roughly half of the respondents changed their responses to the measure from wave to wave, indicating there is sufficient variation in the outcome variable to conduct further analyses.

Table 2 about here

**Analytic Approach**

The analyses proceed in four stages using a variety of modeling techniques. In the first stage, in accordance with previous cross-sectional studies, we estimate pooled OLS models without lagged crime trend perceptions. We estimate models that include only one type of media consumption (not shown)[[2]](#footnote-2), followed by a comprehensive model that includes exposure to all types of media. The goal here is to obtain results comparable to previous research on cultivation theory. We use robust standard errors as the outcome variable is not perfectly Normally distributed (Acock 2008).

However, the way that individuals form beliefs about crime trend can be conceptualized as a dynamic rather than a static process (e.g., see Anwar and Loughran 2011; Jennings et al. 2016). Subsequently, in the second stage, we compute a dynamic OLS model, including lagged crime trend perceptions. Given our measure of crime trend perceptions “Y” and a set of regressors “X” such media consumption, the model can be formulated as follows for a given individual “i” at time “t”, where the error term is composite in nature and contains an individual specific fixed-effect parameter μi, which is unobservable:

Yit = α \* Yi,t-1 + β \* Xit + ϵit

ϵit = μit+νi

E (μi│yi,t-1,Xit ) ≠ 0

In the third stage, we estimate fixed effects models to purge the bias from any time invariant unobserved effects (e.g., see Allison 2009). Notably, both OLS and fixed effects estimates with lags are potentially biased. The OLS models cannot control for individual specific fixed effects, which are left in the errors. Thus, errors will be correlated with a regressor (lagged crime trend perceptions), leading to positively biased estimates of lags (Nickell, 1981). Although fixed effects models can control for time stable unobservables, lagged crime perceptions will be negatively correlated with the differenced transformed error, leading to negatively biased estimates of laggs (Bond 2002; Nickell 1982). The OLS and fixed effects estimates with lags are not worthless. The biased estimates of lags provide upper and lower bounds as diagnostic statistics for our subsequent dynamic panel estimates.

In the final stage, we compute dynamic panel models, including difference and system GMM estimators, to purge the remaining endogeneity in the OLS and fixed effect models with lags. We choose GMM models as the estimators for the longitudinal data since our dependent variable is dynamic in nature and the data set has the “small T, large N” dynamic panel bias, meaning that we only have three waves of data (small T), and yet a large number of respondents in each panel (large N) (Arellano-Bond 1991; Arellano-Bover 1995; Blundell-Bond 1998).[[3]](#footnote-3) The difference GMM estimator transform repressors by differencing and the system GMM estimator estimates the original and transformed equations simultaneously (Roodman 2009). We start by following the difference GMM methodology (e.g., see Arellano and Bond 1991). We transform the data by taking first-differences, eliminating any time invariant information including the fixed-effects, where “Δ” represents a first-differences transformation:

Yit – Yi,t-1 = α \* (Yi,t-1–Yi,t-2) + β \* (Xit – Xi,t-1) + (ϵit – ϵi,t-1)

Yit – Yi,t-1 = α \* (Yi,t-1 – Yi,t-2) + β \* (Xit – Xi,t-1) + (μi – μi) + (νit – νi,t-1)

ΔYit = α \* ΔYi,t-1 + β \* ΔXit + Δνit

At this point, the fixed effects within individual units have been eliminated. However, as a result, we also introduce correlation between ΔYi,t-1 and Δνit as they are both functions of Yi,t-1, rendering ΔYi,t-1 endogenous. To overcome this limitation, we exploit the panel nature of the data and use deeper lags of Yi,t-1 and lags of Xit as instrumental variables. Yi,t-2 and ΔYi,t-1 are mathematically related as they are both functions of Yi,t-2. In the meantime, Yi,t-2 is unrelated to Δνit, assuming that the errors are not serially correlated.[[4]](#footnote-4) We further rely on Hansen’s J-statistic to assess the validity of the instruments and ensure the instruments are uncorrelated with the errors. The null hypothesis is that our instruments are jointly valid, with a rejection of this hypothesis casting doubt on the validity of the instruments (Hansen 1982). Additionally, we make the assumption of weak exogeneity on the regressors in Xit and allow them to be correlated with past errors, but independent of any shocks[[5]](#footnote-5) that may occur in the future:

E (Xi,t-s ϵit ) = 0,∀s ≥ 0

Thus, we have a set of instrumental variables composed of the second lag of crime trend perceptions and first and second lags of the other regressors and can identify α, which is the coefficient on lagged crime perceptions. One criticism of the difference GMM methodology, pointed out by Blundell and Bond (1998), is that if crime trend perceptions follow a random walk[[6]](#footnote-6), lags will be weak instruments for the transformed variables (Roodman 2009).

To increase efficiency, we estimate a system GMM estimator, which adds to the difference GMM model by instrumenting levels with differences (Blundell and Bond 1998). Two equations (one in levels instrumented by lagged differences, and one in differences estimated by lagged levels) are simultaneously estimated. Introducing the levels equation has the advantage of including time-invariant regressors (i.e., demographic characteristics). The equations are “stacked” and estimated simultaneously, resulting in twice the observations that would be present in the difference GMM specification. Notably, for the system GMM moment conditions to be valid, we must assume stationarity[[7]](#footnote-7) (Roodman 2009). We show that this applies in the present context. As mentioned before, both the difference and system GMM estimates of lagged crime trend perceptions should fall between the positively biased OLS estimate and negatively biased fixed effects estimate of lags.

**Results**

In accordance with previous cultivation theory research, we first estimated traditional pooled OLS regression models without lagged crime trend perceptions. As shown in Model 1 of Table 3, watching TV news was positively related to respondents’ perceptions that crime is worsening (b = .036, p = .002) while reading newspapers showed a negative relationship (b = –.029, p = .001). Browsing news on the Internet news was not related to crime trend perceptions (b = –.012, p = .183), nor was listening to news on the radio (b = –.009, p = .318). The results are generally in accordance with previous cross-sectional research findings (see e.g., Roche et al. 2016).

Table 3 about here

Next, according to Model 2 of Table 3, when lagged crime trend perceptions were included, it became the strongest predictor of crime trend perceptions (b = .557, p < .001). None of the media consumption variables remained statistically significant.

Proceeding to Table 4, our fixed effects specification purged the bias from time invariant unobserved effects (Allison 2009). According to this fixed effects model, changes in exposure to news delivered on different types of media were not associated with changes in crime trend perceptions, suggesting the initial relationship between media consumption and crime trend perceptions may be spurious because of omitted variable bias, including respondents’ broader anxieties about life.

Table 4 about here

Nevertheless, the dynamic panel bias has not yet been eliminated in the fixed effects estimation. Nonetheless, the OLS and fixed effects estimates of lagged crime trend perceptions provided us with the bounds on the coefficient estimates from dynamic panel models, meaning that both the difference and system GMM estimates of lagged crime trend perceptions should lie between –0.467 and 0.557.

To purge endogeneity in the OLS and fixed effects estimators with lags, we estimated the difference GMM and system GMM models. As presented in Model 2 of Table 4, the coefficient estimate of lagged crime trend perceptions is –0.03, which within the acceptable range of –0.467 and 0.557. Utilizing Hansen’s J-statistic we failed to reject the null hypothesis that the instruments were uncorrelated with the error, lending credibility to our chosen instrument set (5.75, p = 0.218). All variables measuring media consumption were not significantly different from zero. These results indicate that, after controlling for unobserved individual specific effects, media consumption had little influence on crime perceptions.

As shown in Model 3 of Table 4, the point estimate of lagged crime perceptions in the system GMM framework was .08, again within the acceptable range and again Hansen’s J-statistic lent credibility to our chosen instrument set (11.17, p = 0.597). All media consumption variables were statistically insignificant. The system GMM model also allowed us to examine the impacts of time invariant regressors that are lost in fixed effects and difference GMM models. Nonwhites were more likely to perceive crime was increasing (b = .235, p = .012). Conservatives, as compared to liberals and independents, were more likely to believe that crime was declining (b = .287, p < .001). While this may seem initially counterintuitive, Kort-Butler and Hartshorn (2011) also found a negative albeit nonsignificant relationship between conservative ideology and crime trend perceptions.

**Discussion**

Throughout the past two decades, the majority of Americans have reported that crime trends are worsening (Swift 2016), despite the fact that crime rates in a variety of contexts have been decreasing (FBI 2014; Truman and Morgan 2015). One of the dominant narratives concerning public’s misunderstanding about crime is cultivation theory, which attributes the discrepancy between perceptions and reality to media coverage (see e.g., Hough and Roberts 2005). Still, the key question of whether media consumption causes crime perceptions remains (see e.g., Potter 2014). In this study, we drew on a nationally representative panel dataset, and used traditional OLS, OLS with lagged crime trend perceptions, fixed effects, and dynamic panel models, to test the hypothesis that media consumption is responsible for the public’s perceptions of worsening crime trends. Below we explore the implications of our results. Limitations and suggestions for future researchers are also discussed.

In the traditional pooled OLS models, our findings are very similar to the results of previous correlational studies (see e.g., Roche et al. 2016). Exposure to news on TV was positively related to views that crime trends were worsening, whereas exposure to newspapers showed a negative relationship. Exposure to news on the radio and Internet had a negative but statistically nonsignificant relationship with crime trend perceptions. However, the pooled OLS results, here and as shown in previous cultivation theory literatures, may not reflect the dynamic processes of crime perception formation, leading to concerns of reverse causation and omitted variable bias.

Indeed, when lagged crime trend perceptions were controlled for in the OLS models and time invariant unobservables were controlled for in the fixed effects model, none of the media consumption variables remained related to crime trend perceptions. This suggests that omitted variables may exist in traditional OLS models. Most importantly, based on our difference GMM dynamic panel model, which accounted for both time invariant unobserved effects and dynamic panel bias, no type of media consumption had a statistically significant effect on respondents’ crime trend perceptions. Our final system GMM model corroborated this result and further reduced biases and imprecisions associated with the difference GMM approach. All the longitudinal analytic strategies yield null finding, which casts doubt on the cultivation hypothesis that media consumption cultivates people’s negative perceptions of crime in audiences.

To understand the differences between the results from correlational and other models, it is vital to explain the role of unobserved individual specific factors. Our results suggest that, after purging the bias from unobserved heterogeneity, media consumption played very little role in shaping perceptions of crime trends. It is likely that unobservable variables drew certain users to certain sources of media and simultaneously shape their views on crime. These unobserved factors may thus be correlated with both media exposure and crime perceptions and potentially lead to inconsistent estimates. Future studies should build on the current study and investigate which specific unobserved variables contribute to the spurious covariance between media exposure and crime perceptions.

Our results imply that cross-sectional studies of media’s effect on dynamic processes like the forming of crime perceptions should be at least cautiously interpreted, if not completely avoided. Exposure to media may have an initial baseline effect on audiences’ understanding of crime. However, increased media consumption is unlikely to explain changes in public’s crime trend perceptions. And our evidence suggests that such perceptions are not stable, but rather vary a great deal over time. We might draw a parallel to the relationship between crime dramas and public punitive attitudes. Although people who are exposed to crime dramas appear to be more punitive (see e.g., Mutz and Nir 2010), public punitiveness is on the rise, while the popularity of crime dramas is declining (Enns 2016).

Our results further raise questions about how to advance the long-standing cultivation paradigm. If the amount of media consumption does not simply cultivate changes in crime perceptions, it might be the quality of media. On one hand, television and online news provide increasingly diverse perspectives and *a la carte* options (Pew Research Center 2016). Different cable news outlets may reflect audiences’ political polarization (Mitchell et al. 2014). Thus, consuming the same amount of conservative-leaning media (e.g., Fox News) and liberal-leaning media (e.g., MSNBC) is likely to lead to differential cultivation effects. On the other hand, the amount of media consumption does not reflect how much *attention* viewers pay to crime in the media, which has been found to be positively related to fear of crime (O’Keefe and Reid-Nash 1987). Future researchers studying cultivation theory should include more nuanced measures of media consumption in accordance with the changing media landscape.

Researchers should also explore alternative theoretical mechanisms for shaping the public’s perceptions of crime and criminal justice issues. Contextual characteristics such as peer networks or neighborhood-level characteristics may influence perceptions of crime. As but one example, extant research suggests that perceptions of disorder and crime may arise from direct interracial contact. For instance, number of Black friends is positively related to Whites’ crime concern (Mears et al. 2009; Mears et al. 2013). Crime perceptions may also be explained by neighborhood-level predictors, or by perceptions of increased societal heterogeneity in general. According to Sampson et al. (1997), perceived violence in a neighborhood depends on concentrated disadvantage (e.g., poverty, high level of unemployment, and low level of public assistance) and immigrant concentration (including Latino and foreign-born) in an area.

The current analysis is not without limitations. In this study, we were only able to conduct a three-period analysis for the difference GMM dynamic panel models and were unable to test for the correlation between the error times. Additionally, the relationship between media consumption and crime trend perceptions may have changed since the interviewing years. Therefore, the conclusions drawn from the current study are not definitive or causal. And it is prudent to point out that our analysis would be strengthened from additional waves of the latest panel data.

To conclude, different from the findings from the previous cross-sectional research, the present longitudinal study suggests that media consumption and changes in crime trend perceptions for 21st century Americans are not related. Future researchers studying cultivation theory using cross-sectional methods should interpret the results cautiously. The results raise questions about causal inferences from cultivation theory and the argument that media is responsible for the public’s distorted view about crime. Moving forward, the evaluation of the dominant and longstanding cultivation paradigm should attempt to leverage longitudinal data and attendant modeling strategies.

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**Figure 1. U.S. Violent Crime Victimization Rate1, Percent Change in Violent Crime Rate2, and Americans’ Perceptions of Crime Rate vs. Year Ago3**

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1 Violent crime victimization rate is the number of victimizations per 1,000 persons that occurred during the year. Violent crime includes murder, rape, sexual assault, robbery, and assault. Source: Bureau of Justice Statistics, National Crime Victimization Survey, 1993 – 2015.

2 Percent change in violent crime victimization rate = (violent crime victimization rate in the current year – violent crime victimization rate in the previous year) / (violent crime victimization rate in the previous year) \* 100%.

3 American’s perceptions of crime rate vs. year ago is the percent of Americans who responded there was more crime than there was a year ago in the U.S. Source: Gallup, 1989 – 2016.

**Table 1. Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |
|  |  | **Wave 1** |  |  | **Wave 2** |  |  | **Wave 3** |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| Variables | Mean | SD | Mean | SD | Mean | SD |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| **Dependent Variable** |  |  |  |  |  |  |
|  National Crime Trend Perceptions | 3.484 | .904 | 3.406 | .902 | 3.470 | .913 |
|  Much Better | .006 | .077 | .013 | .113 | .005 | .071 |
|  Somewhat Better | .118 | .323 | .126 | .331 | .113 | .316 |
|  About the Same | .412 | .492 | .436 | .496 | .399 | .490 |
|  Somewhat Worse | .289 | .453 | .288 | .453 | .314 | .464 |
|  Much Worse | .175 | .380 | .138 | .345 | .169 | .375 |
|  |  |  |  |  |  |  |
| **Independent Variables** |  |  |  |  |  |  |
|  Days of News Exposure |  |  |  |  |  |  |
|  Television | 4.768 | 2.279 | 4.627 | 2.322 | 4.632 | 2.241 |
|  Radio  | 3.151 | 2.475 | 2.959 | 2.451 | 3.058 | 2.506 |
|  Newspaper | 3.310 | 2.800 | 3.096 | 2.701 | 3.043 | 2.685 |
|  Internet | 3.041 | 2.694 | 2.903 | 2.623 | 2.989 | 2.621 |
|   |  |  |  |  |  |  |
| **Control Variables** |  |  |  |  |  |  |
|  Age | 47.331 | 16.858 | 47.308 | 16.831 | 47.341 | 16.855 |
|  Female | .517 | .50 | .518 | .50 | .519 | .50 |
|  Nonwhite | .234 | .424 | .237 | .425 | .237 | .425 |
|  College | .287 | .453 | .288 | .453 | .288 | .453 |
|  Income ≥ $75k | .344 | .475 | .346 | .476 | .345 | .475 |
|  Conservative | .453 | .498 | .446 | .497 | .484 | .50 |
|  South | .361 | .481 | .362 | .480 | .361 | .480 |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| *NOTES:* All control variables other than *Age* are dichotomous.  |
| *ABBREVIATIONS: SD =* standard deviation. |

**Table 2. Changes in Respondents’ Perceptions of Crime Trends Over Time**

|  |  |
| --- | --- |
|  |  |
|  |  | **Wave 1** |  |
|  |  |  |  |
|  |  |  |  |
|  |  | Much Better |  |  | Somewhat Better |  |  | About the Same |  |  | Somewhat Worse |  |  | Much Worse |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| National Crime Trend t1 | *N*(%t1) | *N*(%t1) | *N*(%t1) | *N*(%t1) | *N*(%t1) |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
|  |   |  |  |  |  |
| **Wave 2** |  |  |  |  |  |
|  Much Better  | 1(14.29%) | 5(3.52%) | 4(0.76%) | 1(0.26%) | 0(0.00%) |
|  Somewhat Better | 4(57.14%) | 69(48.59%) | 72(13.69%) | 15(3.87%) | 5(2.72%) |
|  About the Same | 2(28.57%) | 48(33.80%) | 334(63.50%) | 138(35.57%) | 20(10.87%) |
|  Somewhat Worse | 0(0.00%) | 18(12.68%) | 102(19.39%) | 194(50.00%) | 57(30.98%) |
|  Much Worse | 0(0.00%) | 2(1.41%) | 14(2.66%) | 40(10.31%) | 102(55.43%) |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
| **Total** | 7(100.00%) | 142(100.00%) | 526(100.00%) | 388(100.00%) | 184(100.00%) |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
| **Wave 3** |  |  |  |  |  |
|  Much Better  | 2(33.33%) | 3(2.17%) | 1(0.20%) | 0(0.00%) | 1(0.59%) |
|  Somewhat Better | 2(33.33%)) | 58(42.03%) | 66(13.15%) | 16(4.36%) | 6(3.53%) |
|  About the Same | 2(33.33%) | 57(41.30%) | 294(58.57%) | 132(35.97%) | 11(6.47%) |
|  Somewhat Worse | 0(0.00%) | 16(11.59%) | 126(25.10%) | 168(45.78%) | 55(32.35%) |
|  Much Worse | 0(0.00%) | 4(2.90%) | 15(2.99%) | 51(13.90%) | 97(57.06%) |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
| **Total** | 6(100.00%) | 138(100.00%) | 502(100.00%) | 367(100.00%) | 170(100.00%) |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

**Table 3. Pooled OLS Regression Models Predicting Change in Perceptions of National Crime Rate Trends**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Model 1:Traditional OLS | Model 2:OLS with lagged-y |
|  | *b* | RSE | *b* | RSE |
|  |  |  |  |  |
|  Lagged-y | ― | ― | .557\*\*\* |  (.033) |
|  Internet  |  –.012 |  (.011) | –.016 |  (.008) |
|  Radio | –.009 | (.012) | .013 | (.009) |
|  Newspaper | –.029\*\* | (.013) | –.012 | (.010) |
|  Television | .036\*\* | (.015) | .015 | (.012) |
|  Female | .089 | (.067) | .021 | (.043) |
|  Age | .007 | (.011) | –.004 | (.007) |
|  Age2 | –.000 | (.000) | .000 | (.000) |
|  College | –.097 | (.069) | –.047 | (.041) |
|  Nonwhite | .289\*\* | (.095) | .102 | (.062) |
|  Conservative | –.327\*\*\* | (.056) | –.093 | (.049) |
|  Income | –.011 | (.073) | –.032 | (.044) |
|  South | .084 | (.069) | .084 | (.042) |
|  |  |  |  |  |
|  |  |  |  |  |
| ***R*2** | .093 | .365 |
| ***N*** | 3,143 | 2,089 |
|  |  |  |  |  |
| *ABBREVIATIONS: b* = unstandardized coefficient; RSE = robust standard error |
| \*p < .05; \*\*p < .01; \*\*\*p < .001 (two-tailed). |

**Table 4. FE, Difference and System GMM Models Predicting Change in Perceptions of**

 **National Crime Rate Trends**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |
|  |  | Model 3: Fixed Effects |  |  | Model 4: Difference GMM |  |  | Model 5: System GMM |  |
|  |  |  |  |  |  |  |
|  | *b* | RSE | *b* | SE | *b* | SE |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
|  Lagged-*y* | –.467\*\*\* | (.041) | –.030 | (.093) | .080 | (.086) |
|  Internet  | .014 | (.018) | .046 | (.037) | –.014 | (.027) |
|  Radio | –.005 | (.019) | .012 | (.038) | .044 | (.026) |
|  Newspaper | –.032 | (.020) | –.020 | (.055) | –.011 | (.044) |
|  Television | .005 | (.026) | –.015 | (.054) | –.007 | (.037) |
|  Female | ― | ― | ― | ― | .088 | (.073) |
|  Age | ― | ― | ― | ― | –.000 | (.012) |
|  Age2 | ― | ― | ― | ― | .000 | (.000) |
|  College | ― | ― | ― | ― | –.130 | (.076) |
|  Nonwhite | ― | ― | ― | ― | .235\* | (.100) |
|  Conservative | .012 | (.089) | –.101 | (.121) | –.287\*\*\* | (.067) |
|  Income | ― | ― | ― | ― | –.090 | (.072) |
|  South | ― | ― | ― | ― | .092 | (.068) |
|  |  |  | ― | ― |  |  |
|  |  |  |  |  |  |  |
|  ***N*** | 2,089 | 1,041 | 2,089 |
|  ***R*2** |  .324 | ― | ― |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| *NOTES:* Dummy variables for Wave 3 is included but not shown. |
|  |  |  |  |  |  |  |
| *ABBREVIATIONS: b* = unstandardized coefficient; RSE = robust standard error; SE = standard error |
|  |  |  |  |  |  |  |
| \*p < .05; \*\*p < .01; \*\*\*p < .001 (two-tailed). |

1. The media consumption measures were included in waves 1, 9, and 10 of the ANES. For the purposes of our analyses we assume media consumption measures at wave 10 as a proxy for media consumption at wave 11, which is when our last measure of crime trend perceptions was asked. [↑](#footnote-ref-1)
2. Media effects are robust and similar across different OLS models. Findings from OLS models are available upon request. [↑](#footnote-ref-2)
3. As Roodman (2009: 86) summarized, one should consider choosing the GMM estimators are “designed for situations with 1) “small T, large N” panels, meaning few time periods and many individuals; 2) a linear functional relationship; 3) a single left-hand-side variable that is dynamic, depending on its own past realizations; 4) independent variables that are not strictly exogneous, meaning correlated with past and possibly current realizations of the error; 5) fixed individual effects; and 6) heteroskedasticity and autocorrelation within individuals, but not across them.” [↑](#footnote-ref-3)
4. One word of caution must be expressed when interpreting our results. Because our panel is three periods long, we cannot test for autocorrelation of the errors. While we have the minimum requisite time periods to conduct the novel methodology employed here, we cannot test for correlation between the νi,t-1 in Δνi,t-1 and νi,t-2 in Δνi,t-2, since with three periods we only have one vector of residuals for t = 3. [↑](#footnote-ref-4)
5. Shocks are “a surprise one-time or repeated series of increases or decreases in a particular variable (Box-Steffensmeier et al. 2014: 9). [↑](#footnote-ref-5)
6. A random walk is a classic example of a stochastic process, which exhibits “secular movement but do not follow a deterministic path” (Nelson and Plosser 1982: 14). [↑](#footnote-ref-6)
7. A stationary, or a stochastic trend, can be “conceptualized as an outcome of a process operating over time” (Box-Steffensmeier et al. 2014: 25). [↑](#footnote-ref-7)