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The rhetoric of de-policing: Evaluating open-ended survey responses from police officers with machine learning-based structural topic modeling

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"[M]uch can be learned about public service by listening to people who perform it" (Brewer Selden, & Facer II, 2000, p. 262).

1. Introduction

Survey research of police officers has increased dramatically over the past several decades (Nix, Pickett, Baek, & Alpert, 2017). Whether examining cynicism, organizational justice, burnout, or other police-related attitudes and perceptions, the vast majority of surveys are conducted with responses to closed-ended questions which offer options along a scale or from pre-established categories. Collection and analysis of open-ended survey data are relatively rare in policing research. Yet, language constitutes the world individuals function within (Weldes, 2014), and textual analysis has always been central to understanding culture (DiMaggio, Nag, & Blei, 2013). To understand the social human, we must understand the language used: "The limits of my language mean the limits of my world" (Wittgenstein, 1921/2013, p. 5.6).

With language being integral to understanding culture, it raises the question of why surveys utilizing open-ended questions in policing research have not been used more often to gain a more informed understanding of police attitudes and beliefs. There are many reasons, and often-cited explanations include prohibitive time allocation, the protracted effort of human coding, and the cost of administration of such surveys (Krosnick, 1999; Roberts et al., 2014; Schuman & Presser, 1996). However, with the advent of machine learning and natural language processing, what was once overly cumbersome has become more practical. With the digitalization of text, new analytical tools are now available that provide scholars with the means of obtaining a richer understanding of behavior than more traditional statistical models derived from surveys with closed-ended questions (Gerrish & Blei, 2012).

We aim to introduce the machine learning-based textual analysis tool of structural topic modeling (STM) to policing research. In doing so, we show that STM analysis allows for a survey instrument that presents officers broad latitude to express and describe their worldview regarding the relationship between the police and the public through open-ended survey responses, facilitating a better understanding of how officers make sense of their realities. Further, we use STM-derived topic scores to test whether officers' expressed attitudes influence their propensity to de-police.

With the above in mind, the primary research question we examine in this study is this: how do officers' attitudes toward the public, *expressed in their own words*, affect their tendency to de-police, or inversely, protect against de-policing? Identifying officers' perceptions through their own words is critical to better understanding the phenomenon of de-policing. To date, research on de-policing has relied on citation, arrest, and crime data (e.g., Pyrooz, Decker, Wolfe, & Shjarback, 2016; Morgan & Pally, 2016; Rosenfeld & Wallman, 2019; Rushin & Edwards, 2017; Shjarback, Pyrooz, Wolfe, & Decker, 2017). Several studies explore police perceptions that lead to de-policing with closed-ended survey items (e.g., Nix et al., 2017; Wolfe & Nix, 2016). While useful, reliance on only closed-ended survey items may not capture the respondents' reality and sense-making of the causes of de-policing, and instead replicate researchers' conceptualization of de-policing (Yanow & Schwartz-Shea, 2014). Moreover, to our knowledge, no other study has attempted to identify police attitudes that protect against de-policing. In this way, this study offers a significant contribution to the literature on both de-policing and analytic strategy in policing surveys.

2. Study aims and structure

The aims of this paper are twofold. First, the introduction and justification of machine-learning-based structural topic modeling (STM) in a policing context. STM provides a flexible platform for leveraging open-ended survey questions (Roberts, Stewart, & Tingley, 2014). Despite advances in other fields, to date, the method has received little attention in the criminology (and adjacent) literature, and to our knowledge, this paper is the first policing study to use STM methods. The second aim is to establish hypothesis validity for the STM technique. This goal is accomplished by testing the association between the derived structural topics and officers' general motivation regarding proactivity (or its absence – de-policing).

With the above aims in mind, we structure the study as follows. The first section provides the foundation for researching de-policing and its relationship to officer-level perceptions of the relationship between police and the public. The second section details the limits of closed-response survey instruments, and the historic reasons open-ended text analysis has been underutilized in quantitative research. In the third

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section, we describe the data collection and our analytic plan. The fourth section presents the study results, including both topic modeling and hypothesis validity testing of those topics. We assess the implications of the findings, and notable limitations, in the fifth section before concluding with a note of potential applications of the presented method for interested scholars.

3. De-policing and the police-public relationship

The term de-policing refers to the idea that police officers withdraw from proactive styles of policing as a way to reduce the likelihood of being involved in controversial incidents (Shjarback et al., 2017). Proactive police work is self-initiated discretionary police action, rather than work initiated by the summoning of police, such as a 911 call. Proactive police work is often associated with so-called public-order, quality-of-life, or 'minor' offenses (MacDonald, 2016; Morgan & Pally, 2016; Rosenfeld & Wallman, 2019), but can also refer to directed patrols and "hot spot" policing (National Academies of Science, Engineering, and Medicine, 2018). Although proactive police work is now seen as an integral part of policing, it has not always been so, and the emphasis placed on proactive policing in the recent past has engendered a significant shift in the practice of policing (MacDonald, 2016).

Evaluations of proactive, targeted enforcement activities such as pedestrian checks, vehicle checks, and directed patrols have shown that proactive police work can reduce crime levels (Braga, Papachristos, & Hureau, 2014; Weisburd, Telep, & Lawton, 2014). Indeed, a large-scale review of proactive policing strategies by the National Academies of Science, Engineering, and Medicine (2018) found that proactive policing in small geographic crime-prone areas ("hot spots") is one of the few proven methods of reducing crime. Further, a decrease in proactive policing has been linked to the increase in levels of violence in Chicago (Arthur & Asher, 2016; Cassell & Fowles, 2018), and a decrease in proactive arrests was identified as a possible explanation for the increase in crime in Baltimore following the death of Freddie Gray (Morgan & Pally, 2016).

In essence, de-policing can be viewed through the lens of motivation. In general, and in policing specifically, motivation affects behavior (Oberfield, 2014). If officers are not motivated to take risks through primarily discretionary activities, then de-policing will likely occur (Mourtgos, Mayer, Wise, & O'Rourke, 2019). Motivation is what drives effortful, effective behavior in organizations (Rainey & Steinbauer, 1999). The question remains: What motivates an officer to engage in de-policing, or in other words, demotivate from proactive police work?

Task motivation speaks to the influence of extrinsic and intrinsic rewards available through an officer's role in the organization. If an officer is tasked with directed patrol in a high crime area, she may be motivated to accomplish this proactive policing in two ways. Either because of the intrinsic reward of accomplishment she feels from completing the task, or because she is motivated by extrinsic rewards of recognition from her agency.

Where one is motivated by internal or external rewards, another may be demotivated by internal or external costs. Specific to the context of de-policing, external costs are a possible avenue of demotivation. Confronting citizens for illegal behavior carries with it several risks, including violence or harm, but just as saliently, potential damage to one's reputation if the incident garners substantial media attention (Adams & Mastracci, 2019; Mourtgos et al., 2019).

When weighed against the risks, discretionary proactive actions may no longer be palatable to some officers. A survey of a nationally representative sample of US police officers conducted by the Pew Research Center lends credence to this possibility. The survey found that 72% of officers have become less willing to stop and question people they think are suspicious (Morin, Parker, Stepler, & Mercer, 2017). Moreover, recent US Department of Justice statistics indicate that police-initiated contacts have fallen substantially in recent years (down 23%, or 8 million contacts; Davis, Whyde, & Langton, 2018).

Several theories regarding the causes of de-policing have been advanced; all incorporate some form of police officers receiving negative attention. Rushin and Edwards (2017) found that de-policing occurs after periods of intense public scrutiny. Oliver (2015) found threats of civil litigation and accusations of racial profiling to be likely causes of de-policing. Shjarback et al. (2017) found that negative attention and increased scrutiny decreased police traffic stops in Missouri after the shooting death of Michael Brown in 2014. Likewise, Morgan and Pally (2016) found that officers in the Baltimore Police Department decreased their arrest rates for crimes generally associated with proactive policing in the two-and-a-half months following the death of Freddie Gray and the attendant negative international attention directed at the police department. Nix and Wolfe (2015) also report that negative publicity led officers in their sample to be less motivated. This line of research points to de-policing as a symptom of the socio-political climate officers find themselves in.

Saunders, Kotzias, and Ramchand (2019) argue that researchers have not paid enough attention to how the socio-political climate affects police officers. They found that officer stress in recent years has revolved more strongly around negative media attention and negative relationships with the community. Officers reported that excessive scrutinization has led to unfair expectations being placed on officers, as well as the belief that policing is being set up for failure by the media. Nix, Wolfe, and Campbell (2018) also recognized the influence of the socio-political climate on police motivation and de-policing. In their study, the majority of command-level officers surveyed believed that there is currently a 'war on cops'. Command officers who felt strongly about the existence of a war on cops were more likely to believe de-policing is common today.

Concerns regarding officer perceptions of the socio-political climate are not easily dismissed. How officers engage in public service is often influenced by their perceptions of public sentiment (Skolnick, 2011). For example, officers who report antagonistic relationships with the public are more likely to use and support physical coercion (Marier & Moule Jr., 2018; Muir, 1977; Terrill, Paoline, & Manning, 2003). Further, officers quickly learn that mistakes, to some degree, are unavoidable in their chaotic work environment, and the public and media will judge them harshly for those mistakes (Van Maanen, 1973). Officers retreat to secrecy (Crank, 2014), as well as isolation from the public (Marier & Moule Jr., 2018; Van Maanen, 1973), thus creating fewer opportunities for meaningful, positive interactions that are the paradigmatic goal of community policing.

An enhanced understanding of officer perceptions of the socio-political climate can be gained by analyzing officers' descriptions of the police-public relationship. That is, by examining a large number of textual responses to open queries (rather than responses to options along a scale or from preestablished categories), we gain better insight into how officers view the police-public relationship. Further, by modeling their responses with a measure of de-policing, one can better understand how officers' sensemaking of the socio-political climate affects their motivation to conduct work that assists in police agencies being successful in accomplishing their missions.

4. Limitations of closed-response survey instruments

Traditional, closed-response survey questions are vulnerable to a large variety of problematic influence and bias (Straits & Singleton, 2018). Using open-ended questions increases confidence that what is being measured is the attitudes of the respondents, rather than respondents' ability to articulate a response to a Likert scale or forced-choice question. Whereas the majority of questions one faces every day in ordinary life are open-ended, "the closed-ended questions that dominate interview schedules put most people in an unnatural position. Individuals are unlikely to ask their coworkers, 'On a scale of 1 to 7, how do you feel about our new boss?'" (Geer, 1988, p. 369). When faced with closed-ended questions, respondents are forced to choose from the available options, even if the best answer is not included (Krosnick, 1999). Presenting respondents with open-ended questions allows for the collection of attitudes that are salient before the question and that remain so afterward (RePass, 1971). Further, the use of open-ended questions mitigates the problem of cueing respondents to think of particular explanations, thus biasing responses and the data obtained from respondents (Iyengar, 1996).

The analysis of text data has been a keystone of qualitative social research for nearly seventy years (Lasswell, 1952). However, in the era of 'big data', for sources found in social media and digitized governmental records, classical hand-coding of corpora is not ideal. Modern computational methods have been rapidly developed to help social science researchers leverage these text sources, and is particularly useful in exploratory studies such as this (Lesnikowski et al., 2019).

A relatively uncommon source of text corpora analyzed with modern text analysis are open-ended survey questions. Written responses to open-ended questions provide a valuable source of data for latent psychological variables (Roberts, Stewart, & Airoldi, 2016). Where typical closed-ended survey items often leave one understanding more about how the researcher conceptualizes the world (Yanow & Schwartz-Shea, 2014), survey texts from open-ended questions allows the exploration of topics from respondents' perspectives (Kwartler, 2017). This inductive paradigm allows the researcher to work upward from empirical data to theory, rather than theory down to data (Ignatow & Mihalcea, 2017). While surveys utilizing scales, inventories, and other types of closed-ended questioning collect clear, 'cleaner', and targeted information that is easier to work with (Ignatow & Mihalcea, 2018), neglecting textual data is an inadequate response for modern scientific inquiry.

Scientific exploration requires myriad sources of information that can explain phenomena (Levy & Franklin, 2014). Triangulating sources of information through the use of new computational techniques is a well-established way of ensuring research does not myopically seek detail only. Triangulation can "capture a more complete, *holistic*, and contextual portrayal of the unit(s) under study" (Jick, 1979, p. 603). Analyzing textual survey data can provide both novel insights and reinforce existing knowledge and theories (Kwartler, 2017).

Utilizing machine learning-based analysis of textual data to better understand police attitudes toward the public is a timely endeavor. While police-community relations consistently ebb and flow over time in the United States, the 2014 police-involved shooting death of Michael Brown in Ferguson, Missouri set off a marked decline in public sentiment toward the police (Jones, 2015). Momentum for this decline only continued to grow in the wake of other controversial police-involved deaths (e.g., Freddie Gray, Laquan McDonald, and Philando Castile). This strain has manifested in public condemnations, protests, and US Department of Justice investigations (Marier & Moule Jr., 2018). As a result, American police are under unprecedented public, media, and governmental scrutiny (Shjarback et al., 2017).

While much of the literature on police-public relations examines the attitudes and beliefs of the public toward the police, understanding police perceptions of the public is just as vital because the relationship between the two entities is reciprocal (Bottoms & Tankebe, 2012; Mourtgos et al., 2019; Sargeant, Murphy, & Madon, 2018). That is, if marked improvement in the relationship between the public and the police is to be accomplished, a better understanding of the attitudes and beliefs of both parties is needed. The process is dynamic, as actions and attitudes of one party affect the actions and attitudes of the other.

A number of classic texts provide an inductive, ethnographic reporting of police attitudes about the public (e.g., Muir, 1977; Van Maanen, 1973; Westley, 1970). More contemporary work, however, tends to use deductive research paradigms, typically utilizing scale-based items applied and collected via surveys (e.g., Bartels & Silverman, 2005; Marier & Moule Jr., 2018; Nalla, Mesko, & Modic, 2018; Pickett & Nix, 2019; Yim & Schafer, 2009). Survey research of this type is crucial and contributes to our knowledge about police attitudes and beliefs. However, a question that is at times left wanting is whether these research designs are capturing the respondents' reality and sense-making of the studied phenomenon, or if they are capturing more of the researchers' conceptualization of the studied phenomenon (Yanow & Schwartz-Shea, 2014).

Qualitative and interpretive work often attempt to address the above described inductive/deductive challenge through the use of interviews and participant-observation; yet work of this kind typically experiences the 'small-n problem' (Kelle, 2006). Utilizing machine learning-based analysis of textual data allows these types of analyses to be accomplished on a much larger scale than what was once possible by removing the necessity of immense amounts of hand coding. This technique allows researchers to better understand respondents' motivations, experiences, assumptions, and emotions through individuals' own words on a larger scale.

In the present study, we bridge the above-outlined gap in police-related survey-based research by employing STM to analyze open-ended survey responses from approximately 400 police officers from across the US. This form of content analysis affords a more direct view of officers' beliefs about the police-public relationship and how that relationship affects officer motivation and de-policing. Critically, the method can account for the effect of covariates on both topic prevalence and topic content, an advantage over less sophisticated algorithmic analysis of textual data. We find three distinct latent topics that officers find salient when speaking about the police-public relationship, offering a more nuanced view than what has previously been analyzed in the literature. Moreover, we find that the three topics have different effects on respondents' propensity to de-police, providing insight into the phenomenon of de-policing, as well as avenues for future research.

5. Data and methods

5.1. Data collection

As part of a larger project examining police perceptions of the public, a survey was conducted of US police officers toward the end of 2015. Emails containing a URL link to the questionnaire were sent to 145 police departments and police organizations within the United States requesting them to distribute the link to their officers. Thirteen organizations responded with a confirmation that they had distributed the survey to their members. Further, officers at one additional police department were solicited in person during their pre-shift meetings. The survey was accessible to respondents for approximately one month in the fourth quarter of the year.

Responses were received from 1305 respondents; 396 responses were retained for this study's analyses (the excluded responses did not provide a textual response to the open-ended prompt). In order to provide anonymity, respondents were not asked to indicate which police department employed them.[1] However, to provide a general view of the agencies that confirmed distribution, we can provide the following information. Regarding region of the United States, 53% of the respondents were employed in the Western United States; 20% were employed in the Midwest; 7.6% were employed in the Northeast; 3.6%

[1] Nix et al. (2017) recognize that to increase participation and honesty in police surveys, precautionary measures to ensure anonymity are of vital importance. Nix et al. elaborate that asking too many demographic questions regarding officers or the departments they work for can compromise respondents' belief in anonymity, and thus participation. Keeping this in mind, we did not inquire about all of the necessary demographic material necessary to be able to report the number of officers invited to participate, the response rate, or the sampling frame. However, we are able to report all of the other suggested standards for police surveys outlined by Nix et al.: the data were collected from November 2, 2015 through December 31, 2015; the survey was administered via email on SurveyMonkey's platform to 13 of the responding organizations, and in-person with paper copies to one of the responding organizations (a number of measures were taken to maintain anonymity with this latter group; see Mourtgos et al. (2019) for details); incentives were not offered; follow-ups were not administered; respondents were told the survey was regarding the "police-public relationship from a police perspective"; 1305 responses were received; 396 responses were retained for this study's analyses (the excluded responses did not provide a response to the open-ended prompt).

were employed in the South; 15.8% did not report their region. The median reported size of respondents' agencies (measured by number of sworn officers) was 500 officers ($M = 952.57$, $Mdn = 500$, $SD = 1139.18$). Of the 396 retained responses, regional composition is as follows: 63.1% of respondents were employed in the Western United States; 24.5% were employed in the Midwest; 9.1% were employed in the Northeast; 3.3% were employed in the South. The median reported size of respondents' agencies was 500 officers ($M = 1045.76$, $Mdn = 500$, $SD = 1266.08$).

Respondents were first asked to answer closed-ended questions. These items were generated after an extensive literature review and consultation with police officers, aiming to assess different ways in which officers were willing to take actions that made them vulnerable to the public (see Mourtgos et al. (2019) for more detail). Among the items were questions specifically intended to measure different facets of de-policing (these items are discussed in further detail below). Prior to data collection, eight police officers reviewed the items for conceptual clarity and face validity, and item wording was adjusted as necessary. The closed-ended items were followed by demographic questions. Additionally, at the end of the questionnaire, respondents were provided an opportunity to write a response to an open-ended prompt. A response to the open-ended prompt and items measuring de-policing were received from 396 respondents.

The sampling design and measure of confidentiality imposes limitations on the data. First, we could not calculate a response rate for the survey. The goal of the survey was not to obtain a nationally representative sample of police officers. Instead, the aim was to obtain a large enough sample to examine the utility of machine learning-based textual analysis to better understand police perceptions related to de-policing and their relationship to the public. Second, and related to response rate, there is no way to assess non-response bias. Police officers are a challenging population of respondents to reach (Nix et al., 2017). Establishing a robust response rate is neither possible nor a fatal flaw for this study. With the long-term trend of decreasing survey response rates in criminological research, scholars "should no longer rely on simplistic response rate rules to evaluate the quality of research" (Pickett, Cullen, Bushway, Chiricos, & Alpert, 2019, p. 7).

Finally, some organizations have historically been unable or unwilling to distribute online-hosted surveys because of information security concerns. It is unknown, but possible, that there is a relationship between this organizational unwillingness and the officer-level perceptions and expressed beliefs that are at the center of this study. While the survey responses offer a valuable look at officer perceptions and proactivity orientations, the limitations discussed above preclude any claim that the police officers studied here are empirically representative of the whole population of police officers within the US. We return to this generalizability threat following the discussion of results below.

5.2. Measures

5.2.1. Text

At the end of the survey, respondents were given the following prompt: "If there is anything else you would like to tell us about the relationship between police officers and the public, from your perspective as an officer, please do so here." Respondents were then given a text box to type open-ended responses to the prompt. The mean number of words per response was 108, with a minimum of 3 words and a maximum of 712 words (see Fig. 1).

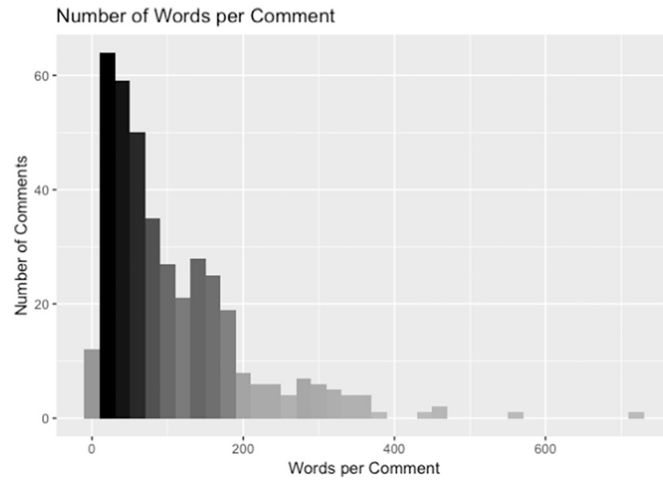

Fig. 1. Number of words per comment

5.2.2. De-policing

Items were developed that measured officers' propensity to de-police. After consultation with police officers, three items encompassing different acts of de-policing were generated. The consultation with police officers was critical to ensure that the scale items had both face validity and external validity. The questionnaire used five-point Likert-type response scales in agree/disagree format with verbal anchors for each response option. The three items addressed the following de-policing actions: 1) willingness to do more proactive police work; 2) willingness to take action on minor offenses; 3) willingness to take action on non-criminal issues, such as dealing with the homeless and the mentally ill.

All three items were highly correlated with one another (0.59, 0.64, and 0.71). Further, Cronbach's alpha was 0.84, well above the accepted threshold (Field, Miles, & Field, 2012). Given the vulnerability of three-item constructs to alpha testing, the high rating found here firmly establishes the latent construct of de-policing. Moreover, though not reported in detail, a variety of exploratory and factor analyses were engaged to establish the robustness of the latent construct (all analyses are available from the corresponding author).

To create a de-policing score for each respondent, responses were summed and averaged. Thus, those with the highest propensity to de-police had a score of 5, and those with the lowest propensity to de-police had a score of 1. The average score was 2.79.

5.3. Machine-assisted textual analysis

As DiMaggio et al. (2013) outline, textual analysis is typically conducted in one of three ways. First is the "virtuoso" method in which a researcher reads texts and produces brilliant interpretations based on their insights. This approach is limited, particularly in generating reproducible results. Second is the thematic/coding method. This conventional approach produces a set of themes via a codebook, based on research questions and theoretical priors. Limitations of this method include impracticality with large corpora, inter-coder reliability, and the presumption that "the researcher knows what is worth finding in the texts before having analyzed them" (p. 577). The third method uses computer programs to search texts for keywords and make comparisons based on the prevalence of those keywords. However, this method requires the researcher to treat each occurrence of a term equally, rather than examining relations among terms.

DiMaggio et al. (2013) outline four essential requirements of rigorous text analysis. First, the analysis must be explicit. In other words, the data must allow for the researcher's testing of their interpretation and enable other researchers to reproduce the analyses. Second, it must be automated to allow for the study of large corpora. Third, it should be inductive, allowing "researchers to discover the structure of the corpus before imposing their priors on the analysis, and to enable different researchers to use the same corpus to pursue different research questions" (p. 577). Fourth, it must treat terms as varying in meaning across contexts. These four requirements are satisfied through the use of STM.

5.3.1. Structural topic modeling

Structural topic modeling identifies underlying latent variables through an unsupervised machine learning process in which themes are inferred from the distribution of words across topics. In comparison, a supervised machine learning process entails an analyst predetermining the topics through manual coding, and then having the machine 'learn' from those pre-established categories. In the unsupervised topic modeling process, topics are learned from the data (Gerrish & Blei, 2012). "Unsupervised methods are valuable because they can identify organizations of text that are theoretically useful, but perhaps understudied or previously unknown" (Grimmer & Stewart, 2013, p. 281).

Topics are distributions over a vocabulary that represent semantically interpretable themes (DiMaggio et al., 2013; Munksgaard & Demant, 2016; Roberts, Stewart, & Tingley, 2014). These distributions are determined by analyzing documents (i.e., a response from a respondent) as vectors of word counts. Within each document, each word belongs to one topic, resulting in each document being represented as a vector of proportions. The vector of proportions denotes what fraction of the words belong to each topic (Roberts, Stewart, Tingley, Lucas, et al., 2014). Thus, topics are mixtures of words, where each word has a probability of belonging to a topic. The topics are generated inductively from the data, utilizing a probabilistic approximation of Bayesian inference. A document is a mixture of topics, resulting in the ability for a single document to encompass multiple topics (Roberts, Stewart, & Tingley, 2014). The ability for a document to be represented as a mixture of topics in topic modeling, rather than each document being restricted to only one topic, refers to a mixed-membership model rather than a single-membership model.

Munksgaard and Demant (2016) provide an intuitive way of understanding how these distributions of words operate within and across topics when discussing their use of topic modeling for examining political discourse around drug distribution in cryptomarket forums. While lengthy, it provides a commonsensical way to understand the probabilistic nature of topic modeling.

> [I]n one topic, 'cannabis' for example, it is likely that there is a higher probability of the terms 'weed' and 'smoke' occurring than the terms 'capital' and 'investment'. 'Weed', for example, may appear in the topic 'gardening' as well as the topic 'cannabis', having entirely different contextual meanings. As the topic is a distribution, 'weed' appears with other high-probability terms such as 'garden', 'nature' and 'flower', in the 'gardening' topic, and with other terms in the 'cannabis' topic such as 'smoke', 'bong' and 'high'…[T]he topics can be understood as if one was to talk about a topic, and when doing so, one is more likely to use some words than others when the topic is 'gardening' as opposed to 'cannabis'. Thus, the preferential vocabularies of individuals can be interpreted as a measure of their meaning-making. Put more simply, if the probability of 'fun' appearing in the same sentence as 'cannabis' is higher than that of 'abuse', this is the ascribing of meaning to cannabis expressed as probabilities (p. 79).

One of the advantages STM has over other topic modeling methods is that it allows for the inclusion of covariates in the prior distributions. During the tokenization and preprocessing steps (explained shortly), each documents' metadata relationship with control variables and independent variables is indexed within each document. As a result, researchers can incorporate covariates over which variance may be expected (Roberts, Stewart, Tingley, Lucas, et al., 2014). That is, rather than assuming topics are constant across all participants, researchers can 1) control for demographics (or other factors) by holding them constant at their sample median; and 2) examine differences between the independent variable(s) being examined. This feature provides a substantial advantage to other topic modeling methods that assume topic constancy across all participants.

In addition to the above, STM provides the advantage of ascertaining topical prevalence, as well as topical content. Topical prevalence refers to how much a document is associated with a topic, while topical content refers to the words used within a topic (Roberts, Stewart, & Tingley, 2014). The ability to examine both of these measures is advantageous to researchers. Not only are we interested in which documents belong to which topics, but we are also interested in what words best describe each topic. This level of analysis is vital because, as described later, it allows the identification of three latent topics from officer responses. We are not only interested in identifying and understanding these topics, but also in how respondents use different words across measurements of de-policing. The latter type of analysis provides a richer understanding of what may drive or protect against de-policing.

6. Analysis and results

6.1. Respondents

On average, respondents had 18 years of law enforcement experience (M = 17.87, SD = 3.54) and were primarily male (n = 81%). The racial composition of the respondents was Caucasian (91.9%), Hispanic (5.8%), African-American (1.3%), Asian-American (1%), and other racial groups (< 1%). Respondents reported the following educational levels: no high school diploma (1%), high school graduate (1.9%), some college but no degree (26.1%), two-year college degree (16.5%), four-year college degree (33.7%), some post-graduate work (5.6%), master's degree (13.9%), and doctoral or law degree (1.3%). The above demographic data (i.e., years of service, sex, race, and educational levels) were controlled for in the topic modeling performed in this study.

Recall that this survey did not seek a nationally representative sample of police officers, but rather a large enough sample to examine the utility of machine learning-based textual analysis in the given context. For completeness sake, however, Table 1 reports the above-listed respondent demographic data in comparison to available national averages as reported in the 2013 Law Enforcement Management and Administrative Statistics (LEMAS) report. Note that while non-whites are underrepresented in our sample, women are overrepresented.

6.2. Structural topic modeling

While many aspects of structural topic modeling are accomplished by a machine (i.e., computer), the full analysis is a blended process requiring human researchers' evaluation and judgment. Since one of the aims of this paper is to promote other researchers' interest in using STM, we identify which processes of STM encompass 'machine learning', and which operations require manual judgment by the researcher. We do this to provide other researchers with an informed view of the STM process. While a number of topic modeling programs are available in the statistical program R, all of the below-described machine learning STM operations are performed by the R package *stm*, authored by Roberts, Stewart, and Tingley (2018).

6.2.1. Preprocessing

In order to allow for machine learning of open-ended responses, the textual data was preprocessed by the *stm* program into a format that a computer could 'read', as well as 'learn' from. STM utilizes the 'bag of words' method. The bag of words method treats every word as a unique feature in a document while retaining word co-occurrence(s). Words within a corpus are then organized into a 'term document matrix', where each document (an individual participant's response) is a column in the matrix, and each word is a row in the matrix (Kwartler, 2017). In order to generate a term document matrix, the text being examined must be tokenized. Tokenization is the process of separating text into pieces that a machine can understand. That is, tokenization refers to the process of identifying and separating each word from other words. This process is typically accomplished by treating white spaces and punctuation as explicit word boundaries (Ignatow & Mihalcea, 2017).

Table 1
Control variables–sample vs. national average

Control variable	Sample	National average
Race		
Caucasian	91.9%	72.8%
Hispanic	5.8%	11.6%
African-American	1.3%	12.2%
Asian-American	1%	2.4%
Other	< 1%	1.1%
Sex		
Male	81%	87.8%
Female	19%	12.2%
Education		
< High School	1%	–
High School	1.9%	–
Some College	26.1%	–
2-Year College	16.5%	–
4-Year College	33.7%	–
Some Post-Grad	5.6%	–
Masters	13.9%	–
PhD/JD	1.3%	–
Years of Service	M = 17.87	–

National average data obtained from 2013 LEMAS

Once a term document matrix is constructed, several additional preprocessing steps must be undertaken by the *stm* program due to the 'noise' that is often present in textual data. That is, not all language is substantively relevant and contains words that are either rare or very common, providing little analytic value (Albert, 2019). Accordingly, several conventional textual analysis techniques were employed to focus attention on meaningful discourse. First, 'stopwords' were removed from the matrix. Stopwords are high-frequency words that do not typically provide additional insight; they are often referred to as function words or closed-class words and include pronouns (e.g., I, it, they), prepositions (e.g., after, at, for), and determiners (e.g., the, a). Second, all letters were converted to lower case. Third, punctuation was removed. Finally, words were stemmed. Stemming removes suffixes and prefixes to obtain words' language root, and allows related words to be shared in the term document matrix (Ignatow & Mihalcea, 2017). For example, *police* and *policing* would be stemmed to *polic*.

Further, as is common in topic modeling and other machine learning-based text analysis methods, low-frequency words were dropped from the analysis. In the current study, a threshold of 1 was used within the *stm* program. This threshold means that words appearing in only one document are dropped from the matrix. The use of this method is advantageous as there is little information added from these words, and the computational cost of including them in the model can be substantial (Roberts et al., 2018). Dropping these low-frequency words resulted in the exclusion of 1382 terms, leaving 15,346 tokens and 1571 terms.

6.2.2. *Topic modeling*

Once the preprocessing steps described above were accomplished, STM was performed to identify substantive latent topics automatically inferred from the text (Roberts, Stewart, & Tingley, 2014). There is no 'correct' answer to the number of topics for a given corpus (Grimmer & Stewart, 2013), and there are no statistical tests for a definitive answer to the optimal number of topics or quality of a solution (DiMaggio et al., 2013). As DiMaggio et al. (2013, p. 582) explain:

> [T]he model is a lens for viewing a corpus of documents. Finding the right lens is different than evaluating a statistical model based on a population sample. The point is not to estimate population parameters correctly, but to identify the lens through which one can see the data most clearly.

With the above in mind, there are many data-driven diagnostic tools to assist in determining the number of topics. These include evaluation of the held-out likelihood, where the dataset is split into two parts, with one part – the test set of unseen documents – evaluated against the training set, after which the log-likelihood of the training set predicting the test set is calculated (Wallach, Murray, Salakhutdinov, & Mimno, 2009); residual analysis (Taddy, 2012); and semantic coherence. All of these diagnostics can be completed within the *stm* program.

Higher levels of semantic coherence are found when the most probable words in a topic frequently appear together. The measure of semantic coherence aligns well with human judgment on topics, but high semantic coherence is easy to obtain when there are only a few topics that are dominated by common words (Mimno, Wallach, Talley, Leenders, & McCallum, 2011). As such, semantic coherence needs to be weighed with held-out likelihood and residual analysis when determining the number of topics within a corpus, as well as the exclusivity of words to topics.

With the above in mind, nine structural topic models were estimated for the corpus with a range of 2 topics to 10 topics. Researchers can instruct the *stm* program to estimate as many, or as few, topics as desired. With a relatively small corpus, we chose to restrict our analysis to nine models, which proved adequate upon evaluation (discussed shortly).

It should be noted that the posterior of structural topic models, as with all mixed-membership topic models, is intractable and non-convex (Roberts, Stewart, & Tingley, 2014). That is, structural topic model solutions suffer from multi-modality, and the solutions one finds can be sensitive to the starting seed. This sensitivity can result in the prevalence of topic usage being unstable across multiple solutions to the model. To remedy this, when estimating the above topic models for evaluation, we instructed the *stm* program to utilize a spectral learning algorithm for the initialization of the models. Spectral learning algorithms offer consistent estimators by identifying an 'anchor' word for each topic. Once the anchor word is identified, the model parameters can be uncovered without iteration, thus removing sensitivity to the starting values of the algorithm. This process side-steps multi-modality concerns and ensures the same results regardless of the seed used (see Roberts, Stewart, & Tingley, 2015 and Arora et al., 2013 for a more technically detailed and lengthy discussion).

After estimating the nine structural topic models, the held-out likelihood, residuals analysis, and semantic coherence were examined for each of the models. Based on the observed diagnostic values, the models with 2 to 6 topics had high levels of held-out likelihood, high levels of semantic coherence, and low residuals. There was a significant deterioration in these measures for the models containing 7 to 10 topics. Thus, the models containing 7 to 10 topics were discarded. While these measures are efficient and interpretable, they cannot replace human judgment. Researchers' investigation of the content of topics by closely reading example documents is paramount in the process of determining the retained model (Roberts, Stewart, Tingley, Lucas, et al., 2014). As such, we performed a manual examination of semantic coherence and the exclusivity of words to topics within the remaining models (described in more detail below), finding the three-topic model to have the best goodness of fit.

With the three-topic model selected, we turned to manually exploring the resulting estimated topics. Fig. 2 provides the expected proportion of the corpus that belongs to each of the three topics, along with the three highest probability words for each topic (proportions and word groupings are generated by the *stm* program). Topic 1 is the most prevalent topic within the corpus, followed by Topic 2 and Topic 3, respectively.

One cannot make substantive judgments about the topics by merely looking at the three highest probability words for each topic. To better interpret the topics, we first examined more complete collections of words associated with them. Second, we reviewed documents that were estimated to be highly associated with each topic.

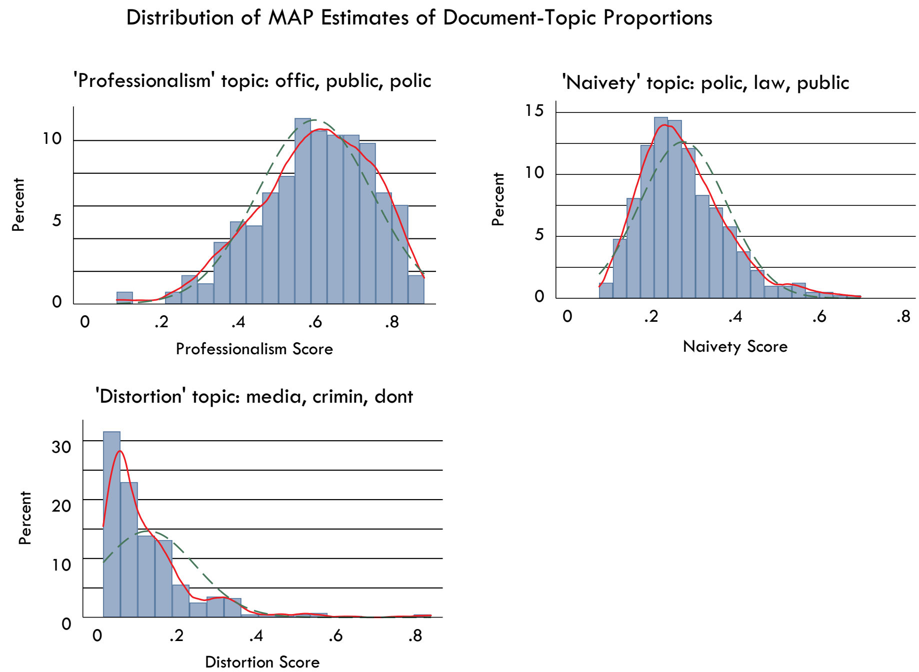

Fig. 2. Distribution of MAP estimates of document-topic proportions
Note: Kernel density denoted by red (solid) line, normal kernel density denoted by green (dash) line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6.2.3. Topic interpretation

Four different types of word profiles were manually examined for each topic, as shown in Table 2. These word profiles include the highest probability words, FREX words, lift words, and score words. FREX words are a category consisting of words weighted by their overall frequency and how exclusive they are to a topic. Lift words give more weight to words that appear less frequently in other topics by dividing their frequency into other topics. Similarly, score words are weighted by dividing the log frequency of the word in the topic by the log frequency in other topics (Roberts, Stewart, & Tingley, 2014). These four categories of word profiles are generated for the researcher by the *stm* program.

While highest probability words are a measure of semantic coherence, recall that semantic coherence is not difficult to achieve when there are only a few topics dominated by common words, which appears to be a possibility when examining the three highest probability words in Topics 1 and 2 (see Fig. 2). Accordingly, when evaluating topics, one must also examine the exclusivity of words to topics.

One can begin to discern meaning in each topic as the above word profiles are manually examined. For example, Topic 3 attends to “media”, race, and “protests”, whereas you see words like “community”, “citizen”, and “thank” in Topic 1. Next, we examined twenty highly associated documents for each topic (supplied by the *stm* program). Through several close readings of the documents, an underlying theme for each topic was identified (Emerson, Fretz, & Shaw, 2011). As outlined with excerpts below, Topic 1 (hereafter referred to as the **Professionalism topic**) was found to express the belief that police departments and police officers must make efforts to interact with the public professionally. Several excerpts from the documents within the Professionalism topic are listed in Table 3.

Topic 2 (hereafter referred to as the **Naivety topic**) expresses the belief that the public does not understand/are not educated about police work; that the public is naive. While the writings in this topic are critical of the public, these criticisms do not appear to be made with animosity. Instead, this topic appears to be expressing the belief that there is an unintentional lack of understanding on the public's part about police work. Excerpts from the documents within the Naivety topic are listed in Table 4 below.

Where the Naivety topic provides more subdued criticism of the public and their understanding of police work, Topic 3 (hereafter referred to as the **Distortion topic**) has a somewhat more indignant tone. Officers' anger is directed at the media, the public, politicians, and police administrators, and emphasizes the idea that false narratives are disseminated about the police. That is, descriptions of police-involved events are being distorted in a way that is untruthful and unfair to officers. Excerpts from documents within the Distortion topic are listed in

Table 2
Topic word profiles

Topic 1 Top Words	Highest Prob:	office, public, polic, peopl, job, believ, work
	FREX:	train, involv, time, year, thank, still, acadmi
	Lift:	approxim, ass, associ, attend, avail, blood, bridg
	Score:	peopl, offic, work, communit, citizen, time, year
Topic 2 Top Words	Highest Prob:	polic, law, public, enforc, one, action, general
	FREX:	great, seem, interact, general, abl, also, portray
	Lift:	accid, driven, mass, perpetu, press, shape, tough
	Score:	mass, interact, general, seem, one, also, great
Topic 3 Top Words	Highest Prob:	media, crimin, dont, will, make, take, minor
	FREX:	black, profession, fuel, ferguson, white, file, movement
	Lift:	assumpt, color, favor, injustic, network, overcom, protest
	Score:	ridicul, black, media, fuel, file, zero, profession

Table 3
Professionalism topic documents

"There needs to be more transparency between the police and the public. Getting people more involved in our job tends to build public confidence and trust."
"Officers should always while at work be professional and respectful to the public and citizens they serve."
"Our profession continues to inbreed paranoid behavior and public mistrust in the name of 'officer safety.' An officer should never compromise his safety, but it does not give him a blank check to do what he wants."

Table 4
Naivety topic documents

"While law enforcement is and should be beholden to the public since law enforcement exists for the public's benefit, the vast majority of the public simply do not have sufficient legal and technical background knowledge to make informed decisions and judgments about police work."
"Sometimes force is used, used because of resistance to the officer's actions. The use of force by law enforcement officers does not look nice, and that appearance seems to be more important than what the officer encountered verbally and physically before the use of force. During the Ferguson riots the media talked about the law enforcement officers being militarized, what I saw were officers wearing helmets to protect against items thrown at them and extra vests that protected them if shot at."
"The public has no idea what constitutes actual policing. Too much of what they think we do is shaped by television and the movies. Law enforcement is not pretty."

Table 5 below.

6.2.4. Model validation

Validation of text models cannot be accomplished in the same manner as more widely used statistical models (i.e., linear regression or factor analysis). Moreover, validating unsupervised models (such as STM) cannot be accomplished in the same manner as text models that use supervised methods. This difference does not relieve the researcher from the obligation of validation (Grimmer & Stewart, 2013), but shifts the burden of determining categories before the analysis to validating the model output afterward (Quinn, Monroe, Colaresi, Crespin, & Radev, 2010).

6.2.4.1. Semantic and exogenous validity. We validate the topic model in our analysis as suggested by Grimmer and Stewart (2013) and Quinn et al. (2010). First, as described previously, we sampled 20 documents from each topic and manually assessed the semantic validity of each.

Table 5
Distortion topic documents

"The public is misinformed as to the duties and struggles of police officers in the country mainly due to social media and news networks who only choose to show the negative incidents to fuel the hatred and negative movements against law enforcement and to boost ratings. The negative propaganda only fuels these movements, putting more law officers in harms way by giving the public and these movements approval to harm law enforcement personnel as if they are not human."
"The public tends to take false information and transform it into a real storyline which gives a false perception of how police do their job. Example, 'hands up' storyline in Ferguson. That simply didn't happen. The current black lives matter agenda goes completely against the truth that the number 1 killer of young black males are other young black males. I don't understand why they don't care about the young blacks being murdered every day."
"The rank and file feel their superiors will throw them under the bus in a ferguson situation in order to appease the clueless masses. The media does zero favors in terms of education of the public, only feeds the stereotype that we at will kill unarmed black men".
"It seems that the media and persons such as Jesse Jackson, Al Sharpton, and President Obama are never interested in the truth when it comes to white on black incidents. A white officer is automatically labeled as racist when there is a black suspect who is injured or killed in an altercation. 'Hands up, don't shoot' was propagated by those listed above and fueled a fire that should have never even been a spark."

That is, we confirmed a common substantive meaning underlying words within each topic. Second, we manually examined topical relationships with exogenous events. The survey was conducted in the Fall of 2015. This period was marked with highly salient events for police officers. It was approximately one year after the shooting of Michael Brown in Ferguson, Missouri, approximately six months after the US Justice Department cleared the shooting officer (Darren Wilson) of any wrongdoing, and during a time when the national climate regarding policing and race was very heated. As such, one would expect to observe mentions of Ferguson, race, and competing narratives about what occurred in Ferguson within the estimated model. This expectation is supported in the excerpts above.

6.2.4.2. Hypothesis validity. Third, and perhaps most importantly, we assess the model's hypothesis validity: Are the model's measurements useful for evaluating theoretical and substantive hypotheses of interest (Quinn et al., 2010)? To test the model's hypothesis validity, we tested each topic's influence across the above-described propensity to de-police scale. When assessing the three topics, we hypothesized that the Professionalism topic would be represented in higher proportions among officers scoring negatively on the de-policing scale (i.e., more willing to be proactive). Recall, this topic conveyed the belief that police officers and police departments should interact with the public positively and professionally. With the topic's emphasis on interacting and engaging with the public in positive ways, we expected de-policing to be an unattractive option for these officers. We further hypothesized that the Naivety topic and Distortion topic would be represented in higher proportions among officers scoring positively on the de-policing scale (i.e., do engage in de-policing). The Naivety topic offers the belief that the public does not understand police work and cannot competently judge police actions. The Distortion topic represents sharp criticism toward the media, public, politicians, and police administrators for propagating false narratives about police and police actions. Previous work has found that both of these beliefs affect officers' proactive work behavior (Mourtgos et al., 2019).

We first plot respondents' topic proportions across their summed score on the propensity to de-police scale. Recall that STM is a mixed-membership model, meaning that each document can be represented as a mixture of topics, rather than each document being restricted to only one topic. As such, topic proportions can be extracted for each respondent. A respondent's topic proportions refer to the proportion of each topic within their textual response. That is, one officer's response may contain 60% of the Professionalism topic, 10% of the Naivety topic, and 30% of the Distortion topic, whereas another officer's response may contain 20% of the Professionalism topic, 30% of the Naivety topic, and 50% of the Distortion topic. By plotting respondents' topic proportions across de-policing scores, we can better understand how each topic affects the propensity to de-police. As shown in Fig. 3, and as posited, there is a well-defined negative linear trend with the Professionalism topic. The Professionalism topic is expressed more prevalently at the lower end of the de-policing scale than at the higher end of the de-policing scale.

Fig. 4 shows that the Naivety topic, while displaying the expected positive relationship with de-policing, does not appear to have a strong influence. However, Fig. 5 shows a clear relationship between the Distortion topic and the de-policing scale. The Distortion topic has a sharp positive linear trend, with the topic being much more prevalent at the higher end of the de-policing scale than at the lower end of the de-policing scale.

To further test the model's hypothesis validity and gain a clearer understanding of significant effects, we analyze topic prevalence between two groups: a high de-policing group and low de-policing group. Recall that the average score on the summed de-policing scale was 2.79. Accordingly, respondents with a de-policing score below 2.79 were assigned to a low de-policing group; respondents with a de-policing score above 2.79 were assigned to a high de-policing group. Fig. 6 plots

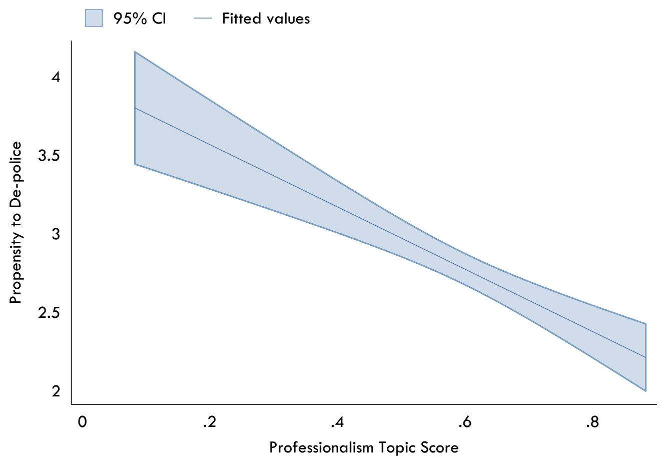

Fig. 3. Linear prediction of professionalism and proactivity.

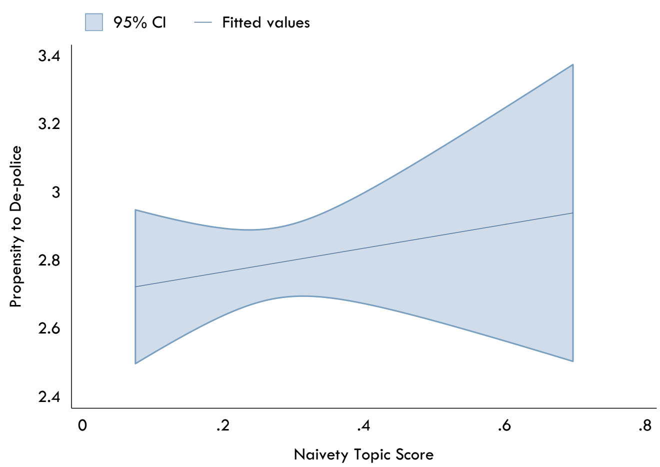

Fig. 4. Linear prediction of naivety and proactivity.

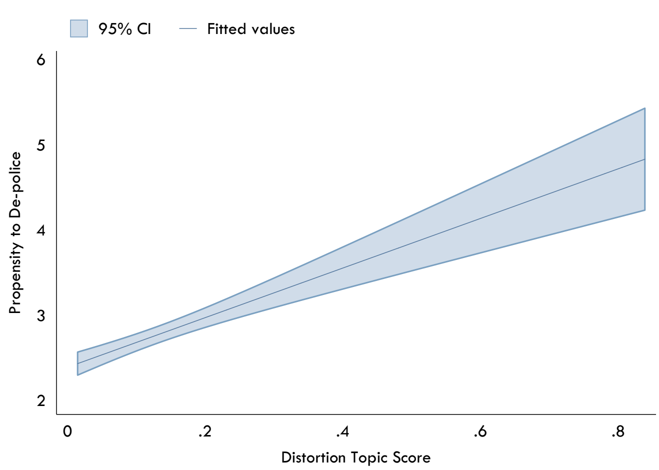

Fig. 5. Linear prediction of distortion and proactivity.

the change in topic proportion shifting from one value to another (i.e., low de-policing to high de-policing).

In Fig. 6, we see that the Distortion topic is strongly expressed by officers in the high de-policing group, while the Professionalism topic is strongly expressed by officers in the low de-policing group. The Naivety topic is close to the center, meaning there is not a significant shift between the use of the Naivety topic among officers in the low de-policing group and officers in the high de-policing group.

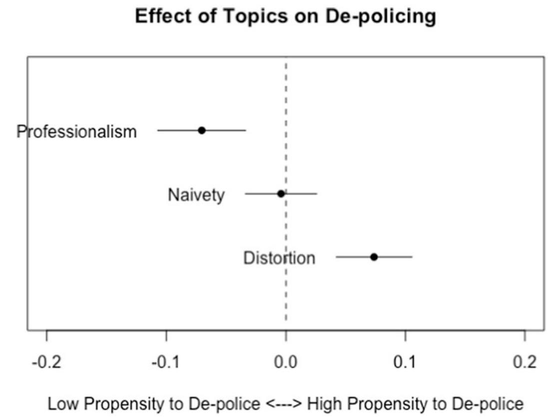

Fig. 6. Effects of topics on De-policing

On the whole, the topics of Professionalism and Distortion have tighter confidence intervals and steeper slopes compared to the Naivety topic. Further, the effects shown in Fig. 6 above indicate the hypothetical effect of Naivety on the De-policing scale is no better than random. Given the analysis, Professionalism and Distortion topics are selected for a further test of hypothesis validity using structural equation modeling.

6.2.4.3. Structural equation modeling with topic proportions. As seen in the linear prediction and categorical analysis figures above, the Professionalism topic and the Distortion topic are expected to have a discernible effect on officer willingness to engage in proactive policing. The Professionalism topic is the most common sentiment identified in the corpus, but most common does not signify most influential. Because the level of analysis is at the individual officer level, we must account for the reality that these constructs are co-occurring. That is, no officer response is entirely encompassed by the Professionalism topic while simultaneously perfectly *not* encompassed by the Distortion topic. This reality gives rise to two related research sub-questions. First, what is the proportional weight of the Professionalism topic versus the Distortion topic? Second, at the individual level, how do these two constructs simultaneously interact with an officer's willingness to engage in proactive policing? Structural equation modeling (SEM) is well suited to answer these questions.

The SEM specification shown in Fig. 7 is testing for the relationship between a latent construction of 'proactive police work' and both the Professionalism topic and the Distortion topic. We expect the two topics to covary to some degree, and so the observed level variables are correlated. When the baseline model is tested against the data the model fit is good: $x^2(2) = 5.42$, $p > x^2 = 0.0666$; TLI = 0.973; CFI = 0.994; SRMR = 0.013; RMSEA = 0.066.[2] Path analysis is straight forward, with the standardized coefficient values indicating that both the Professionalism topic ($p = 0.009$) and the Distortion topic ($p = .0006$) are associated with proactive police work to a statistically significant degree. Despite the greater relative frequency of the Professionalism topic among the officer comment corpus, the Distortion topic has a larger magnitude of effect. As the Professionalism topic score increases, the model predicts a standardized positive effect on proactive police work of 0.17, while the Distortion topic has a negative effect on proactive police work (i.e., de-policing) of −0.21.

7. Discussion

Historically, police culture has been viewed through a monocultural

[2] TLI = Tucker Lewis Index; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation.

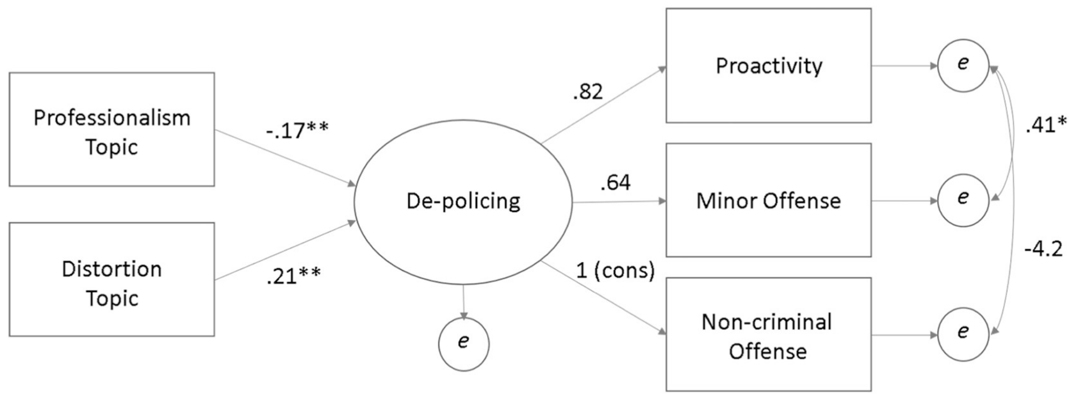

Fig. 7. Confirmatory Model: De-policing Latent Construct (n = 396).
Note: Structural equation model using maximum likelihood estimation. Paths significant at the $p < 0.01$** and 0.05* at the 95% confidence level.

lens (Paoline, 2003). However, the view of a police monoculture has been called into question over the past decade-and-a-half, and researchers have noted heterogeneity in police attitudes at both the individual and workgroup level (Ingram, Paoline, & Terrill, 2013; Paoline, 2004; Paoline & Gau, 2018). This study adds to the growing evidence that police views of the public are not monolithic. There is nuance within how individual officers and groups of officers view their relationship with the public. An enhanced understanding of these nuances is gained by analyzing officers' descriptions of the police-public relationship collected in response to open-ended survey questions.

The preferential vocabularies of the officers are built as topic models, which are then modeled against their propensity to de-police. When asked about their views of the police-public relationship, officers expressed three topics: a responsibility to interact professionally with the public (the Professionalism topic), the belief that the public does not understand their jobs (the Naivety topic), and the belief that false narratives/accusations are made against officers (the Distortion topic). Which topic an officer attended to affected their propensity to de-police. The belief that the public does not understand officers' jobs had little effect on propensity to de-police; those officers who attended more to the responsibility to professionally interact with the public showed less predisposition to de-police; and those that attended to the belief that false narratives were being spread about the police showed more of a predisposition to de-police.

The relationship between the Distortion topic and de-policing supports previous work that hypothesized de-policing occurs when officers are subjected to criticism (Morgan & Pally, 2016; Nix & Wolfe, 2015; Oliver, 2015; Rushin & Edwards, 2017; Shjarback et al., 2017). However, by subjecting this hypothesis to STM, a somewhat more nuanced view of this phenomenon is revealed. It is not merely that officers have a propensity to de-police because they are criticized. Instead, they have a propensity to de-police when they believe that unfair false narratives and false accusations are consistently made against them.

Scholars have long been aware that officers generally believe the public is naive about police work and needs more information on the realities of such work (Bartels & Silverman, 2005; Sparrow, Moore, & Kennedy, 1990; Westley, 1970). However, when Mourtgos et al. (2019) tested officer perceptions of the public's naivety about police work and the public's integrity (encompassing truthfulness and objectivity – i.e., the Distortion topic) against different risk-taking actions, they found that officers' perceptions of the public's integrity generally had a stronger influence on officers than perceptions of the public's naivety. It may be that the consistency of belief in public naivety among officers simply provides too little variability to be a useful predictor. The findings support such an interpretation, but these attitudes have been noted since at least the 1970s in US police, suggesting an attitudinal coherence and low variability that would make naivety a challenging covariate to include in statistical tests.

Our findings give twofold support to the notion that officer perceptions of the public's integrity have a more substantial influence on their work behaviors than the more-often-studied perception of naivety. First, the Distortion topic was associated with de-policing much more strongly than the Naivety topic. Second, although the Distortion topic consisted of a substantially lower proportion of the overall corpus than the Professionalism topic and the Naivety topic, it contributes more influence on officers' propensity to de-police. In other words, de-policing is driven by criticisms officers perceive as unfair or lies, not criticisms based on naivety or ignorance. Further, the fact that the Distortion topic had a more considerable impact than the Professionalism topic, despite its lesser usage, is more evidence of the widely-observed human heuristic to attend more strongly to negative stimuli (Kahneman, 2011).

This finding speaks to the previous description of how the socio-political climate may affect officers. Saunders et al. (2019) find that officer stress in recent years has revolved more strongly around officer perceptions of excessive scrutinization, and Adams and Mastracci (2019) confirm this threat is front-of-mind for officers. Moreover, when de-policing is viewed through the lens of task motivation, the extrinsic cost of being subjected to (whether perceived or real) false criticisms/narratives may demotivate officers to participate in the discretionary work of proactive policing.

The attractiveness of a given task, and the energy invested in it, depends greatly on the expected outcomes (Steers, Mowday, & Shapiro, 2004). That is, if an officer's subjective beliefs regarding the terms of an exchange relationship between the officer and the public are left unfulfilled, there is a feeling of loss of control and predictability. A lack of control and predictability results in avoidance of tasks, which in turn harms efficiency and effectiveness (Schott & Ritz, 2017).

The effect of a non-mutual relationship between officers and the public aligns with the social psychology literature on exchange theory, equity, and reciprocity. Social exchange theory argues that individuals attempt to maximize the benefits to costs ratio in their relationships (Thibaut & Kelley, 1959). An exchange-based model assumes individuals desire relationships in which equity is experienced. Hatfield, Traupmann, Sprecher, Utne, and Hay (1985) describe equity as a state of affairs in which the benefits and costs of the relationship are proportional to the benefits and costs incurred by the other half of the relationship. If officers fail to obtain equity in their relationship with the public, this may reduce their motivation to interact with the public in ways that increase their chances of experiencing negative costs (i.e., conducting discretionary proactive police work). These external negative costs can include damage to one's reputation if the incident garners substantial attention (Mourtgos et al., 2019). Our findings with the relationship between propensity to de-police and the Distortion topic supports this idea.

On the other hand, it should also be recognized that the

Professionalism topic is associated with a decrease in the propensity to de-police. Officers who attend more strongly to this topic emphasize their responsibility to interact with the public professionally. This emphasis may be a function of the style of policing within a department (i.e., community policing), a factor of individual differences, or some mix of both. Regardless, based on our findings, departments should pay attention to the attitudes of officers within their department. If officers are especially upset by popular media stories, political statements, or other popular narratives that they perceive as deceitful, department leadership should address these negative perceptions. Department leadership should also continually be reinforcing an ethos of professionalism, which may act as a guard against decreased task motivation.

The above discussion helps identify why STM (and other machine learning-based textual analytical techniques) can provide significant advantages to policing, and other criminal justice, scholars. In order to identify the more nuanced perception among officers between the Naivety topic and the Distortion topic, as well as identify the protective factor encompassed in the Professionalism topic, officers had to be allowed to provide their own thoughts in an open-ended manner. Of course, it is possible a researcher could have conceptualized the nuance between the Naivety and Distortion topic on their own and administered closed-ended survey items to measure those two attitudes, as well as the protective attitude of the Professionalism topic. But relying on the possibility that a researcher will conceptualize these attitudes on their own can unnecessarily delay theoretical and scientific advancement, and may ultimately still miss idiosyncrasies that only the subjects being studied can provide. STM side-steps these disadvantages, as well as allows for researchers to test the hypothesis validity of the results.

Moreover, STM allows for the analysis of large corpora, beyond what is typically feasible for qualitative studies. From a machine learning perspective, 396 observations are not computationally challenging. STM and other machine learning-based textual analytical techniques can be used on datasets containing thousands, even tens-of-thousands or hundreds-of-thousands, of observations, opening the possibility for large-scale studies using textual data.

Finally, STM, and other similar unsupervised machine learning methods, provide a sort of validity check on researcher presuppositions. That is, methods such as STM not only allow researchers to uncover new insights into respondents' views, attitudes, and beliefs, they also allow researchers to test if their theories and derived scales align with the views of the subjects they are studying. In this way, STM offers exciting opportunities for researchers to revisit widely used, but long ago established, scalar instruments in a variety of contexts.

8. Limitations

The findings reported here provide additional context for understanding police perceptions about their relationship with the public, and how those perceptions affect an officer's de-policing propensity. However, this study is not without limitations, and with those limitations the findings should not be over-interpreted. Perhaps most importantly, this study does not engage with the behavioral aspects of de-policing. The gap between intent, feelings, and behavior is well known throughout social science. As a general matter, and in the specific case of de-policing, we should be wary of attributing a propensity to de-police with an actual reduction in proactivity. Nonetheless, while research findings provide mixed evidence on the effects of de-policing (Rosenfeld & Wallman, 2019), evidence for the act of de-policing itself has been documented (Morgan & Pally, 2016; Mourtgos et al., 2019; Oliver, 2015; Rushin & Edwards, 2017).

We provide convincing though preliminary evidence that a propensity to de-police can be derived from the words of officers themselves. Despite the novelty of the technique and saliency of the finding, the study does not claim that an actual de-policing effect has occurred – to do so would be well outside the scope or interest of this report. We caution restraint in making the inferential leap from propensity and belief to behavioral outcomes. Future research should consider the role of officer perceptions as scholars seek to clarify the empirical base in other de-policing studies.

There are several additional notes that limit the generalizability of the findings. First, because this study did not have a representative sample of US police officers, the results may not generalize across unaccounted variables such as regions of the country, size of police departments, and department policing styles. This limitation also applies to other potentially transitory factors that may affect police perceptions of the public. Adverse events of this nature might include a recent occurrence of a police shooting and protests directed against the police. Alternatively, positive public stories with a more heroic flavor could result in a short-term benefit to perception. Accordingly, additional research is needed to assess if the results from the present study are replicable.

Second, respondents were asked about the police relationship with ‘the public’. Police officers may define ‘the public’ in different ways: as individuals they encounter while working, members of the community they serve, or even all individuals in the US. In the end, rather than defining what ‘the public’ meant *a priori*, we allowed respondents to define the term for themselves. However, this allowance for personal meaning-making warrants further parsing of officers' different conceptualizations of ‘the public’.

Third, there are often concerns about common source bias when using a self-reported instrument to measure both the independent and dependent variables. It is argued that this practice may inflate correlations and result in biased findings. While these concerns should not be wholly disregarded, they have been recently shown to be overstated (George & Pandey, 2017).

Finally, while STM is an innovative approach to investigating large amounts of textual responses from police officers, in the end, it is a probabilistic model. By transforming words and word co-occurrences into probabilities, some of the context and meaning is unavoidably lost. Researchers wishing to utilize this method should keep in mind that probabilistic models of text cannot replace human judgment and understanding, but rather augment it and allow for new insights (Grimmer & Stewart, 2013). Interpretation of the generated models still requires informed analysis and judgment by researchers (Ignatow & Mihalcea, 2017).

9. Conclusion

This study introduced the use of STM to police survey research. By utilizing STM, and other machine learning-based textual analysis tools, we believe a richer understanding of policing culture, attitudes, and beliefs can be discovered. Allowing police officers broad latitude to express and describe their worldview about areas of interest allows researchers to better understand how officers make sense of their realities. Using machine learning tools allows researchers to explore these attitudes on a much larger scale than more traditional textual analysis allows. Future studies should continue to leverage topic modeling, as well as other machine learning-based tools, to further explore their usefulness in this field.

An additional benefit demonstrated here is the importation urged for quantitative criminology, the “adoption of statistical approaches from other fields” (Weisburd et al., 2015, p. 352). We concur and advance precisely that: a unique quantitative approach that has to date not been applied in a policing study. Such an advance has specific contributions for researchers. Through careful application of STM, researchers gain an opportunity to revisit their datasets. Survey researchers commonly include open-response questions within their instruments. However, given the difficulties of traditional text analysis, much of this data is left fallow. New methods bring new opportunities to harvest.

Finally, this study provides an improved understanding of officer perceptions of the police-public relationship, and how different attitudes based on these perceptions affect officers' propensity to de-police. This improved understanding can provide better tools to police administrators by identifying problematic and advantageous officer attitudes regarding task motivation, and also officer well-being as related to interacting with the public.

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