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Data Distortions and the Quantification of Fear

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ABSTRACT

The explosion of data in the digital age has provided new possibilities for policy creation, the development of knowledge, and societal innovations. In this way, data becomes an essential tool in personal decision-making, legal change, and policy creation as we leverage new forms of data to understand social phenomena. But along with the massive increase in digital data and data storage come new consequences and potential for data to be biased, intentionally misleading or completely false. I take this work one step further to investigate what can go wrong even when the data at hand is all technically true and not clearly maliciously misleading. I call this phenomenon a data distortion.

I define a data distortion as when sociological processes inject bias and assumptions into data that in turn shapes how society responds to perceived threats. In other words, how people absorb and understand different data available to them as they make decisions. Importantly, I propose that these data distortions can be located by interrogating new digital forms of data rather than relying solely on traditional custom-made data by social scientists. This dissertation reveals data distortions in news coverage, legal blameworthiness, and online housing markets and seeks to reconceptualize and reconstitute those distorted data to understand how changing the projections of true information changes the way people make fear-related decisions.

This dissertation unfolds in three empirical chapters, preceded by an introduction to the foundational concepts therein. In chapter 1, I interrogate the foundations of newsworthiness in homicide news coverage to demonstrate how distortions in homicide news create a universe of homicide that simply does not match reality, to the detriment of specific groups of homicide victims. In chapter 2, I go beyond the simple existence of news coverage to test how the contents of the news affects readers' perceptions of legal and moral blameworthiness. In chapter 3, I test

how a distorted data projection has economic consequences for consumer decision-making in online housing markets. Finally, I conclude with a look at the combined utility of these empirical projects and with an assessment of directions for future work.

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INTRODUCTION

DATA DISTORTIONS, DECISION-MAKING, AND FEAR

This dissertation explores the interrelatedness of three concepts interpreted through a sociological lens: data distortions, decision-making, and fear. In the form of three empirical chapters, I investigate different dimensions of these concepts to demonstrate the power of data and data projections in society. I introduce these three foundational concepts here as a means of demonstrating how the chapters of this work contribute to the larger project of developing a data-informed sociology of fear. I conclude this introduction with a conceptual question about how we can measure fear-related data distortions without directly asking 'are you scared?'

Data Distortions

The quantity of digital information has exploded in the last twenty years and shows no signs of slowing down (Figure 1). This mass of information leaves us with huge amounts of data, both in traditionally recognized and newer digital forms. Just because we have more data and can use it to for a myriad of purposes, does not mean that all of that data is equally good or equally well understood. Consequently, researchers have conducted rigorous analysis of how bad data matters including data that is biased, misleading, or just entirely false (Greene and Murphy 2020; Redman 2016; Robinson 1966; Slota et al. 2020). 'Bad data' is important, but here I want to muddy the concept of bad data by arguing that the dividing line between true and false data is often not so clear-cut and can result in what I call 'data distortions.'

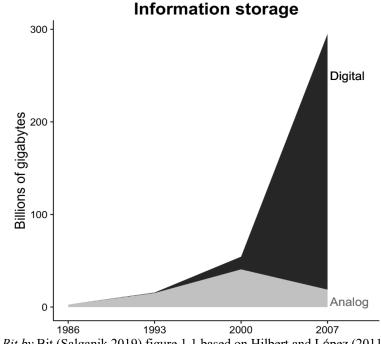


Figure 1: Information Storage in the Digital Age

Bit by Bit (Salganik 2019) figure 1.1 based on Hilbert and López (2011)

I use the term data distortion to describe what happens when sociological processes inject bias and assumptions into the way that data itself is projected. I argue that these distortions, which are sometimes even more insidious because they are not easily discernible as false or as bad data, can affect the way people understand the world around them and how they make decisions. Importantly, I argue that we can find and dissect (and perhaps even reconstruct) these data distortions by investigating the digital trace data of the new information age rather than relying solely on traditional custom-made data by social scientists.

In this dissertation I deal with several examples of data distortions that characterize different ways that data distortions matter, including newsworthiness, blameworthiness, and personal decision-making. In the first two chapters of my dissertation, I begin this investigation of data distortions by considering how the institution of the news serves as a source of data about crime and society for its readers. The news is an especially important creator of data because the news is a living, breathing institution that responds to and changes the social world around it. In this way, the shared universe of readers, journalists, and subjects of the news are intertwined in the creation of the news itself (Fishman 1988; Pan and Kosicki 1993). Importantly, this is not to suggest that the news is purely fabricated, but rather suggests that the news itself is the outcome of sociological work (Schudson 2011).

An example of a canonical data distortion created by the news is the 1976 crime wave against the elderly analyzed by Fishman (1988). This crime wave was not fictional, each of the criminal incidents reported was true, but it also did not mark a quantitative increase or pattern in crime that would constitute a crime wave. Rather, the news was able to seize upon a usual (or even decreased) supply of incidents as fitting a theme that was salient to society at the time (Fishman 1988) to actually create the perception of a crime wave through news reporting. This crime wave was not just a news phenomenon, it resulted in proposed changes to laws about elder crime (see Fishman 532:1988).

In chapter 1 of this dissertation I explore data distortions in news using the existing concept of newsworthiness. Newsworthiness is the process by which reporters and other news stakeholders decide what becomes news (Surette 1992). I use this concept to contextualize the difference between the way homicides appear in the news and the actual underlying patterns of homicide. In this chapter, I use three measures of newsworthiness (dichotomous presence of any coverage, a count of total articles, and a dichotomous measure of enduring interest) to demonstrate how data distortions operate differently in different homicide data markets.

In chapter 2 of this dissertation I transition from analyzing the presence of news to measuring the impact of specific news content using perceptions of blameworthiness. In this

way, I use perceived blameworthiness to measure the salience of specific pieces of information because of the relationship between morality and punishment. In criminal law, blameworthiness is codified into law by a set of standards and heightened punishments through the vehicle of mens rea, or guilty mind. Theories of blameworthiness postulate that punishment should reflect the individual's degree of moral blameworthiness rather than being based merely on the degree of resulting harm (Edwards and Simester 2019). When evaluating wrongs and harmful acts, people care about what kind of person the actor is: who that person is and not just what they have done (Nadler 2012; Nadler and McDonnell 2012). Certain acts are viewed as highly informative of character: these include animal cruelty, racist speech, and to some extent in recent decades, drunk driving, especially when it results in injury or death. I leverage this concern about morality to test how including specific pieces of true information in news vignettes change perceptions of appropriate punishment – further demonstrating how data that is not intentionally 'bad data' can have consequences.

Decision-Making

Focus on news characterizes much of this dissertation, but I do not mean to suggest that data distortions do not happen in other spaces in society, too. Therefore, I use chapter 3 of this dissertation to focus directly on how data distortions around crime data can affect every day decision-making outside of news media. Decision-making is a logical extension of the analysis of data distortions because it gives us the opportunity to quantify why data distortions matter at scale.

I begin with the premises that that meaning-making of crime data is polysemic and that distorted or missing information can be effective, regardless of its veracity. As put by Thomas and Thomas (1928), "If men define situations as real they are real in their consequences" (527).

In accordance with the Thomas Theorem it may not matter if information is actually true, as long consumers believe it is true (Merton 1995). A polysemic phenomenon is one is that is filtered through the lens of the individual, allowing them to draw specific meanings based on their own specific context (Dahlgren 1988; Fiske 1986). Crime researchers have found support for this characterization of crime as polysemic, finding that local crime news is more emotionally affective, specifically because of the relatedness to personal context (Chiricos, Eschholz, and Gertz 1997).

In chapter 3, I look specifically at personal decision-making in light of a different type of data distortion: data projections. Taken literally, here I argue that the way we chose to project the same true information can have substantial consequences for decision-making, especially if the specific consequences of the chosen projection are not clear to the end user. When I refer to a data projection distortion, I am not claiming that it is always easy to tell which of a number of possible data projections is the 'correct' projection, only that choices about projections can affect people who did not have agency in making the original choice. In chapter 3, I use the example of housing markets to test how projecting true crime data in different ways affects consumer decisions to purchase or not purchase a property and how much money people think the property is worth.

Research has shown that crime has tangible effects on housing prices (Thaler 1978; Troy and Grove 2008; Wentland, Waller, and Brastow 2014), but it is unclear how specific translations of information might be contributing to these effects. Crime has generally been found to have the effect of lowering home prices. This is likely because few people want to live in areas where they are more likely to be victims of crime or will be more exposed to crime. Here I take this literature consensus and use it as a fertile testing ground for how this data distortion in particular can change decisions.

Fear

A central project of this dissertation is also to consider the building blocks of a sociology of fear and how it entangles with crime data distortions. As put by Tudor in his canonical work on fear "Fearfulness in varying degrees is part of the very fabric of everyday social relations. Any sociology, therefore, must find ways of conceptualizing fear and examining its social causes and consequences" (Tudor 238:2003). Here I briefly consider why sociology should be concerned with the study of fear and suggest possibilities for measuring fear in new ways.

The study of emotions is not new to sociologists, many of whom consider emotions necessary to explain fundamentals of social behavior and the patterns of relationships that link individuals to other people, institutions, groups, and environments (Barbalet 2001; Burkitt 2002). Kemper (1987) provides a useful framework to consider emotions as the product of 2 social dimensions of power and status. Kemper (1987) specifically defines fear as the outcome of an interaction in which an actor is subject to a power greater than their own.

Sociologists have spoken less on the topic fear than one might expect, with some scholars chalking this up to the heightened study of fear as an individualized emotion in psychology (Tudor 2003). Popular means of measuring fear, like the Chapman University Survey of American Fears or the Fear Survey Schedule (I-III) take a very psychological approach in asking individuals directly if they are personally afraid of a specific thing (Arrindell and Emmelkamp 1984; Chapman University 2018). For example, the Fear Survey Schedule III asks respondents to indicate if they are afraid of 'dirt' or 'bats' on a scale of 1-5 with no further clarification. That said, a smaller body of sociological work has considered how topics can be conceptualized as fearful in media (Glassner 1999) or how moral climates of fearfulness can pervade society in general (Furedi 1997; Skoll and Korstanje 2013). Tudor (2003) offers the clearest sociological framework for a study of fear using a 6-part classification system (Figure 2 below).





MACRO (structure)

Tudor (2003) explains that there are both micro and macro level structures that range from the physical to the social. Tudor describes macro structures as containing three parameters: environments (natural and built), cultures, and social structures. Tudor's conceptualization of social structure concerns both the nature of social structures and changes to them. Tudor describes micro structures as containing the last three parameters: bodies, personalities, and social subjects. Most interesting here is the concept of social subjects because here Tudor describes them as having both positions within the social system and social circumstances. Using this set of 6 parameters Tudor creates a useful unifying theory of how fear can be both constituted and negotiated in society (2003). What this theory of fear does not do, however, is lay out exactly how sociologists might go about measuring and creating a unified sociology of fear.

Fear of Crime

While perhaps sociologists have spent less time studying fear as a social emotion, a robust field of work in criminology has specifically studied fear of crime. While a specific trajectory of fear, fear of crime does give us a useful starting place to begin the project of building a broader sociology of fear outwards.

Turning our attention to the carefully negotiated relationship between truth and social importance, fear of crime does not correlate well with the actual crime rate – remaining relatively stable even as crime declines (Rader 2017). There are many possible explanations for how fear of crime can remain stable or increasing without a corresponding rise in crime including perceptions of vulnerability or differences across groups. It is important to note though, that it is not just fear of crime is not the only perception concern with crime data. Perceptions of how much actual crime occurs are also divorced from reality. In 1983, 37% of respondents in a Gallup Poll said there was more crime in their area than there was a year ago (Dugan 2014). In 2013, 41% of respondents said there was more crime in their area than there was a year ago (2014). However, crime had been declining over the period (Gramlich 2020; LaFree 1999; Levitt 2004).

In general, researchers do find some variation in fear of crime by demographic group. Researchers conclude that women fear crime more than men, despite lower rates of victimization (Braungart, Braungart, and Hoyer 1980; LaGrange and Ferraro 1989; Stanko 1985). Theories behind this disconnect range from perceptions of vulnerability, gender norms in society, male socialization to not admit to fear crime, hidden or under-reported female victimization, or female fear around specific types of crime like sex crimes (Rader 2017; Reid and Konrad 2004; Riger and Gordon 1981; Sutton and Farrall). Research also finds that the elderly fear crime more than their younger counterparts (Braungart et al. 1980), though some researchers argue this is actually due to measurement error (LaGrange and Ferraro 1989). Research on racial/ethnic and social class correlates of fear of crime are sparser, though some studies have concluded that poorer people are more afraid of crime and that fear of crime does vary by racial group (Boulahanis and Heltsely 2004; Ortega and Myles 1987; Pantazis 2000). Residents of racially heterogeneous neighborhoods often reported a higher fear of crime, but this is not necessarily related to actual increases in crime (Chiricos et al. 1997).

The fear of crime literature intentionally distinguishes between victimization risk and emotional fear. Rader (2017) identifies four fundamental problems 1) questions about feelings of safety that actually measure perceptions of the likelihood of victimization rather than the emotional fear of a crime happening to oneself, 2) not being specific about the type of crime, 3) not including location specific cues, 4) not using a measure (like a Likert scale) that is capable of measuring the magnitude of fear of crime. Consequently, there has been a concentrated effort in recent decades to be more intentional about how fear-related concepts are measured by criminologists, specifically asking how fearful individuals are of specific crimes in specific geographic contexts with scalable responses (Boulahanis and Heltsley 2004; Chiricos, Padgett, and Gertz 2000).

How to Measure Social Fear

Gains in specificity around question wording help ensure conceptual clarity but are still limited to certain types of data collection in social sciences that can consequently limit our ability to measure fear in the larger social context described by Tudor (2003). Salganik (2019) describes data in two ways that are helpful here: custom-made data and ready-made data. Custom-made data is the traditional type of data used by social scientists, where you create a survey or interview guide and intentionally collect data customized to your needs. This has a lot of advantages in collecting maximal information, measuring very specific concepts, and creating easier causal pathways. A lot of research about fear has been conducted in this way (Boulahanis and Heltsely 2004; Chiricos et al. 2000; Shi 2021), with very specific questions literally asking 'are you afraid?'' However, Salganik also describes ready-made data as data that exists as digital trace data or data generated for another purpose that can be repurposed to study various social phenomenon (Salganik 2019). What I attempt to do in this dissertation is to consider a combination of both: looking at ready-made data in society and creating custom-made data when useful to test specific facets of that ready-made data.

What that means is that I never once ask the question "how scared are you" of any of the participants or data in this dissertation. Instead, I seek to begin understanding a sociology of fear by examining the intersections of institutions, data distortions, and fear. In this way I hope to start the project of measuring fear as broadly related to data distortions, decision-making, and social complexity rather than as a separate and personal emotion for each individual.

CHAPTER 1

THE EFFECTS OF LOCAL CONTEXT ON NEWSWORTHINESS

Acknowledgments

Thank you to Lydia Wuorinen for her valuable assistance with data collection related to this chapter.

Introduction

Criminologists have spent considerable time and effort studying crime news because it tells us more than counts of crimes, it tells us how the American public thinks and feels about crime. This is particularly important for crimes like homicide that have a relatively low rate of occurrence relative to their social impact. Consequently, a robust criminological literature has studied the impact of homicide news using the concept of newsworthiness (Chermak 1995; Chermak 199; Gruenewald et al. 2009, Johnstone, Hawkins, and Michener 1994; Lundman 2003; Schildkraut and Donley 2012; and others).

Newsworthiness is the process by which reporters and other news stakeholders decide what becomes news (Surette 1992). Generally, scholars have investigated this by looking at the demographic characteristics of victims and offenders (things like age, race or gender) and effectively counting up the amount of reporting about a homicide case. This method is used to figure out how many words of news coverage (or number of articles) are written about different groups of people. For example, Gruenewald et al. (2009) found that there are more words of news coverage written when the offender belongs to a minority racial group. This universe of findings gives us some important descriptive information, but often does not make meaning of it relative to the social (or demographic) contexts where the crime occurred. Therefore, I argue that this understanding of crime news is oversimplified and therefore will continue producing inconsistent results.

In this article, I make several significant advances to the understanding and importance of newsworthiness in homicide reporting. First, I seek to alleviate the concern that differential findings in the newsworthiness literature are due to differing data collection/analysis methods of varying time points. Second, I will demonstrate that disparate findings are not only possible but expected – if we consider the nuance of varying context. Third, I make substantive meaning of these findings to describe the effects of substantial data distortions of the 'true' patterns of homicide in various cities.

I do this by conducting a rigorous study of how seasonal, situational, and victim factors predict multiples types of news coverage in three intentionally different US cities: Chicago, Philadelphia, and San Antonio. Using a comparative structure, I run predictive models in each city to predict whether victims of homicide receive any news coverage, any follow-up news coverage, and how much news coverage they receive. I then make sense of a seemingly disparate universe of findings using the descriptive context of homicide in each city, predictive models with interactions that allow for victims to be intersectional actors, and by conducting an exploratory look at how homicide news coverage can vary even within the geography of a single city. I conclude with a discussion of why a distorted perception of homicide in the news constitutes a data distortion that is more broadly important to societal perceptions of safety and victimization.

The Importance of News

Crime news is one of the most prevalent types of reported news, but numerous studies have concluded that news reports about crime do not correlate with actual crime rates (Boulahanis and Heltsley 2004). In Fishman's fictitious crime wave, 29% of news stories were about elder homicide compared to a 1% incidence of elder homicide (1988). In fact, the elder murder rate had actually dropped 19% compared to the same period the year prior (1988). Examples of this phenomena abound outside the conception of unusual crimes waves as well. For example, a 2001 study of crime in the LA Times concluded that 80% of murders received some news coverage, but only 2% of physical and sexual assaults received any news coverage

(Dorfman, Thorson, and Stevens 2001). This might create a perception that there are far more murders in LA than assaults when the opposite is true.

Newspapers are created for and read by an audience who themselves exist in the social world, and newspapers themselves can change things about that social world. Importantly, the flow of information from news media is not uni-directional; rather it is a socio-cognitive relationship involving multiple actors including journalists, readers, and the worlds they inhabit. Pan and Kosicki (1993) describe the shared cultural universes of sources, journalists and audiences in the dissemination of news media with particular emphasis on the role of the audience as both readership and financial life-force for the institution of news. These tensions are not about fabricating news, but instead characterize news as the outcome of sociological work (Schudson 2011). Here we can transcend the logistical process of reporting news and instead intuit value from its actual construction (see Berkowitz 1997; Lu 2012). Fishman (1988) argues that the news is in fact socially constructed, employing the example of a 1976 crime wave against elderly New Yorkers. This particular crime wave, while made up of real criminal incidents – was not actually an increase in crime from the same period in the previous year. Fishman explained that reporters did not fabricate the news, rather "they gave a determinate form and content to the incidents they report[ed]" (10-11). In this way, reporters are not transcribers of objective fact, instead they interpret and ascribe meaning to events in the way that they report them.

Researchers have also connected crime news to particular negative consequences including racial stereotyping and the generation of faux mythology like the juvenile superpredator (Barlow, Barlow, and Chiricos 1995; Boulahanis and Heltsley 2004; Gilliam Jr. et al. 1996; Sorenson, Manz, and Berk 1998; Thorson 2001). Crime news has a robust history of being used to inspire fear and cue racial stereotypes in the United States. Notably, George Bush's 1988 presidential campaign used the imagery and story of Willie Horton to inspire fear of crime – but also to cue race-based fears (Jamieson 1992). Cronin, Cronin and Milakovich (1981) explain that this alleged fear of crime actually transcended a fear of crime alone and was a fear of disorder, fear of riots, and a fear of Black people in the United States. Barlow et al. (1995) translates this into a broader finding about crime news being ideological and political. Simon (1999) explains this directly in the Willie Horton case, writing that "The image of a dangerous killer being released from prison to prey on an unsuspecting family was used by Dukakis opponents to cast the Democratic Party as out of touch with the fears of ordinary law-abiding citizens and unable to inflict the punishments supported by such citizens" (855). Other studies have also found that media portrayal of crime can inspire fear that is closely connected to racial stereotypes. Peffley, Shields and Williams (1996) found that even briefly showing a black suspect on televised crime news would activate fear responses and racial stereotyping responses in white audiences, both findings confirmed by Gillam et al. (1996) that same year.

Researchers have also proposed that news itself might be responsible for creating fear and panic around certain types of crime that might not actually exist. Unlike Fishman's (1988) crime wave that was made of real incidents that were interpreted through the news as a novel crime event, the creation of the juvenile superpredator myth exemplifies a case where the news (assisted by a number of criminologists) instilled panic and legal consequences around a crime wave that simply did not exist (Boulahanis and Heltsely 2004). In the 1990s criminologists and political and local leaders, influenced strongly by the work of John Diluilo and James Fox, predicted a rise in juvenile crime due to an expanding juvenile population (Miller, Potter, and Kappeler 2006). However, this was no ordinary juvenile crime. Diluilo wrote that this juvenile crime wave would be comprised of vicious, predatory, youths operating with no remorse: superpredators (DiIulio 1995). As the media frenzy reached its zenith, juvenile homicide rates began what would be their largest drop in history – and DiIuilo's crime juvenile crime wave simply never happened (Zimring 2013). The suprepredator panic was not without consequences, as it is believed that it contributed directly to policy measures that levied more punitive punishments onto youth and resulted in an overrepresentation of Black or African American youth in the juvenile justice system (Department of Justice Juveniles Justice and Delinquency Prevention 1999; Zimring 1998).

Newsworthiness and Homicide News

The importance of crime news has not gone un-noticed by criminologists, who have studied crime news primarily using the concept of newsworthiness and homicide reporting. Surette (1992) usefully defined the process by which newspapers decide what to report on as newsworthiness, writing that newsworthiness is essentially "...the criteria by which news producers choose which of all known events are to be presented to the public as news events (60)." Chermak (1995) presented some of the earliest evidence that news reporters consciously select crime stories for reporting based on how newsworthy they were. Importantly, Chermak noted that not only are not all crimes newsworthy, even some extreme crimes like homicide were deemed 'not interesting enough' to be covered by the media (1998).

While there are many types of crime and violence reported in the news, studies of newsworthiness most often focus on homicide reporting for a variety of substantive and methodological reasons. First, despite the relative infrequency of its occurrence, a disproportionate number of Americans worry about homicide. In 2018, 0.005% of the population or 5 in 100,000 individuals in the United States were murdered (FBI 2018). However, polls in the same year found that 17% of Americans occasionally or frequently worried about being murdered – a rate of 17,000 per 100,000 individuals (Gallup 2019).

Second, the burdens of homicide in the United States are felt very unequally. Victims of violent crime more generally are disproportionately likely to be African American or Native American. In some years close to 50% of homicide victims are African American, even though only 13% of the U.S. population is African American (Harrell 2011). Expanding the scope of impact to the neighborhood at large, research has also found that the impact of homicide on life expectancy for black males is a loss of 2.1 years, and in some low-income neighborhoods that impact was as high as a loss of 5 years (Redelings, Lieb, and Sorvillo 2010).

Third, while the true rate of crime is unobservable, we can do the best job of counting homicides (Weaver 2007). This is because we can count victims, without knowing who the offender was and without relying on victims to self-report like other types of violent crime. This naturally makes it easier to study homicide reporting relative to homicide rates, since the sampling frame is more likely to be known.

Despite the large body of work around newsworthiness and homicide, the literature is plagued with inconsistent and incompatible findings (see Table 1). Some studies point to increased news coverage of minority offenders (Gruenewald et al. 2009). Others found less coverage of black and Hispanic victims (Johnstone, Hawkins, and Michener 1994). Others pointed to increased reporting on female victims killed by male perpetrators (1994). In direct contradiction, other studies conclude that there is no consistency across racial or gendered reporting at all (Schildkraut and Donley 2012). Some studies emphasize the importance of salacious circumstances in creating the news (Chermak 1998) while still others emphasize that salacious circumstances alone are insufficient to understand newsworthiness (Lundman 2003).

This leaves the literature of newsworthiness as a mess of disparate findings that are very difficult

to interpret in combination.

	lore or Less News Coverag More	Less	Inconsistent
Salacious			
Circumstances	Chermak 1998	-	Lundman 2003
Gender (female)	Boulahanis and Heltsley 2004, Bucker and Travis 2005, Paulsen 2003, Pritchard and Hughes 1997, Sorenson, Manz and Berk 1998	-	Johnstone et al. 1994, Schildkraut and Donley 2012
Age (young)	Boulahanis and Heltsley 2004, Jewkes 2004, Gruenewald et al. 2009	-	Schildkraut and Donley 2012, Sorenson, Manz and Berk 1998
Age (old)	Gruenewald et al. 2013, Schildkraut and Donley 2012	-	Schildkraut and Donley 2012, Sorenson, Manz and Berk 1998
Minority (victim)	-	Johnstone, Hawkins, and Michener 1994, White et al. 2020	Schildkraut and Donley 2012
Minority (offender)	Bucker and Travis 2005, Gruenewald et al. 2009, Lin and Phillips 2012, Lundman 2003	-	Schildkraut and Donley 2012

Table 1: Who Gets More or Less News Coverage?

Notes: Importantly, these are the significant findings, meaning that most studies found that most of the other variables were not significant.

The Limitations of Newsworthiness

Some scientists have criticized measures of newsworthiness as insufficient to understand crime news in the United States. Notably, Shoemaker (2006) writes that "Underlying the general understanding of what, within a culture, will become news is a long list of factors and influences, and newsworthiness is only one of these... We should no longer use the prominence with which events are covered as a measure of the event's newsworthiness, and our theories should not use newsworthiness as the sole (or even an important) predictor of what becomes news" (111). That leaves us with the problem of what to use instead, or what to add to newsworthiness to more completely understand the news.

One possibility for improving newsworthiness constructs is by improving our understanding of contextual factors that operate in tandem with newsworthiness in the cities where homicide news is reported. Research has already made the connection between engagement with local news and individual and community participation (Paek, Yoon, and Shah 2005) as well as drawing the connection between crime, culture, and the neighborhood or community. Importantly, studies have found that when exposed to crime news stories, the cultural context of where someone lives predicts increased stereotyping and advocacy for more punitive punishments. Gillam, Valentino, Beckmann (2002) found that whites living in homogenous neighborhoods responded with these stereotypes and punitive recommendations when exposed to racially biased crime news, whereas whites in heterogenous neighborhoods did not, even if they were exposed to racially biased crime news. Scholars have also characterized television news media as polysemic, meaning that the meaning of the news will vary as it's transmitted through the context of the receivers' own lived experience (Dahlgren 1988; Fiske 1986). Chiricos et al. (2000) also finds that the locality of the news changes the effect it has on consumers of news. That is, that local crime news is more effective at instilling fear than national news (2000). This demonstrates the importance of studying the local context as well as the local news in order to understand how they work together to describe the culture of crime in local contexts.

The Importance of Distorted News

I take inspiration from cultivation theory to theorize around the importance of crime news as a data distortion. Cultivation theorists argue that the intentional framing of crime news as violent and fear-inducing cultivates increased fear of crime in its readers (Beckett and Sasson 2004; Gerbner et al. 1980; Shi 2021). For example, Shi (2021) finds that international college students who paid attention to crime news in the United States perceived they had a higher likelihood of victimization and reported higher rates of fear of crime. This cultivation effect is predicated on a series of foundational claims that I adapt here to be specific to homicide news.

Foundational Claim 1: The media mediates many peoples' contact with the reality of homicide Foundational Claim 2: Homicide news is intentionally framed as violent and frightening Foundational Claim 3: This framing can create data distortions surrounding homicide

Most people lack direct contact with homicide and therefore learn about homicide via the news or other people (Sacco 1995; Surette 1992). Hertz, Prothrow-Stith, and Chery (2012) estimate that 5 million adults have experienced the murder of a family member, 6.6 million more have experienced the murder of a relative, and 4.8 million have experienced the murder of a firiend for a total of 16.4 million people directly affected by homicide. While a substantial number, with a total population over 300 million people, that means a vast majority of US

residents have not directly experienced a homicide. Therefore, if we accept the claim that individuals are then left to indirect channels like media and stories from other people to understand the reality of homicide, then the content of that media becomes even more important.

As Fishman (1988) describes, reporters give determinate form to the events of society when they create news. Scholars have found that homicide news in particular is intentionally written to be more violent and more frightening (Beckett and Sasson 2004). Baranauskas 2020 finds that this phenomenon is even more extreme in disadvantaged Black neighborhoods where crime is described more intensely and as 'normal' than in affluent white neighborhoods where it is described as shocking. This leaves us with a category of media that is heavily reported, described in ways to intentionally evoke emotion, and is targeted at a majority of the population who has not experienced the underlying phenomenon directly.

Therefore, cultivation theorists argue, heavy consumption of homicide news may lead to distorted perceptions of crime (Gerbner et al. 1977). I take this concept one step further and postulate that the distorted perception may rise to the elevated social problem of a society-wide data distortion that varies based on social context. I define a data distortion as somewhere where sociological processes inject bias and assumptions into data that in turn shapes how society responds to perceived threats. In other words, how people absorb and understand different fear-related data available to them as they make decisions. Importantly, I propose that these data distortions can located by interrogating the data itself rather than relying solely on traditional custom-made data by social scientists. As such, I take an opportunity in this project to attempt to disentangle the confusing myriad of scholarly findings around newsworthiness in homicide news while also considering fully how this media might produce specific data distortions in different directions.

Hypotheses

My goal in this project is to try to make sense of the current mass of disparate findings in the newsworthiness literature, investigate the potential benefits of integrating different measures of news coverage and underlying context into the newsworthiness framework, and to consider the implications of homicide news as a data distortion on society more broadly. In order to do this, I have laid out a series of 4 empirical hypotheses that build upon each other methodologically and substantively to drive my analysis and discussion of results.

H1: Variance in data collection methodology and studied time periods will not explain the disparate findings in what causes a homicide victim to be more newsworthy

H2: The underlying patterns of homicide and news reporting, even in the same year, are highly variable based on specific context of the city in which the news is reported

H3: Even within cities, news coverage is far from homogeneous across geographical space

H4: The difference between homicide in the news and the reality of homicide is substantial enough to create a media-driven data distortion around the true picture of homicide in the United States

Methods

To analyze the consistency of newsworthiness predictors across different contexts, I intentionally select dramatically different markets of homicide that are plausibly dissimilar in their news coverage of killings. For the purposes of this project, I intentionally maximize variation across several dimensions including region, number of killings, and population racial demographics. Regional location was intentionally varied to lessen the likelihood of overlapping local news coverage. While related, number of killings and population are not completely collinear, therefore I sought out cities that ranged both in size and relative numbers of homicides. Finally, to analyze the effects of different demographic contexts, I selected one demographic category to intentionally vary across the sample. Taking cues from Johnstone et al. (1994) and Schildkraut and Donley (2012), I focused my sampling variation on victim racial demographics, since they vary more widely across cities in the United States than age or gender.

The analysis in this article is intentionally constrained to the year 2007, due to the restricted world of digital news in the mid-2000s. Put another way, 2007 is one of the most recent years that social media platforms (like Facebook, Twitter, Instagram) etc. did not serve as hubs of digital news that can further complicate the way news is spread in digital space. The goal of this project is to interrogate the news itself rather than digital spread of news, so 2007 serves as an optimal more closed-world for this analysis. That is not to say that spread of news is unimportant to the understanding of newsworthiness and data distortions, only that it is necessary to begin with a strong foundation in the originating discourse before expanding the world of analysis.¹

The resultant sample included three cities: Chicago, Philadelphia, and San Antonio (see Table 2). Chicago is the largest of the three cities, with a population of ~2.7 million at the time of analysis and has the most homicide of the 3 cities, seeing 454 killings in 2007. Philadelphia and San Antonio were more similar in size, with populations of ~1.5 million and ~1.3 million respectively (Census 2010). Despite being more similar in size, the number of homicides in Philadelphia (392) and San Antonio (126) were dramatically different in 2007. All three cities vary by racial demographics. Chicago's population is roughly split into thirds across white, black, and Hispanic residents (Census 2010).² Philadelphia has a similar number of white

¹ Data lists of homicides in each city were also prepared for 2008-2015, such that this analysis could be easily extended in the future.

² These population figures do not total 100 because there is a smaller proportion of the population that identifies under a different racial/ethnic category. I do not focus on these other racial/ethnic identities here due to their low representation in the homicide victim pool across these three specific cities.

residents but has substantially more Black or African American residents (42.1%) and a much smaller population of Hispanic residents (14.7%) (Census 2010). San Antonio differs from both Chicago and Philadelphia by having a substantially lower percentage of white (24.7%) and black (7%) residents and having a simple majority Hispanic or Latino population (64.2%). This left me with three cities with different local contexts that are well-suited to this analysis.

	Number of		%	%	%
	Killings	Population	White	Black	Hispanic
Chicago	454	2,695,598	33.3	29.6	28.8
Philadelphia	392	1,525,006	34.5	42.1	14.7
San Antonio	126	1,327,407	24.7	7.00	64.2

Table 2: Homicide by City, 2007

Notes: Population estimates from 2010 US Census

The sampling frame for this analysis was constructed using complete lists of homicides in each city. It was particularly important to have source lists outside of a specific newspapers' content in order for the possibility of 'no coverage' to exist in the data set. Articles were gathered manually, using a small sample of newspapers from each location. In accordance with findings from (Chiricos et al. 2000) about the resonance of local news and my ultimate interest in the local social contexts of homicide news, I restricted my analysis to local news sources, as described below in Table 3.³ I conducted my article searches in the San Antonio Express News, the Philadelphia Inquirer and Philadelphia Daily News, the Chicago Sun Times and the Daily

³ This means that analysis from Chicago intentionally excluded the Chicago Tribune. This decision maintains the narrowness of the sampling frame on local news, which aligns with the principal research question, but comes with significant limitations. The Chicago Tribune is the largest newspaper in Chicago with a daily circulation of over 500,000 (BurrellesLuce 2009) which means that a large amount of the news in Chicago is simply not included here. However, the Chicago Tribune caters also to a non-local audience which differently characterizes its coverage of non-local news.

Herald. My goal was to use the largest local newspapers possible to obtain total coverage over the regions where homicides took place. In San Antonio this was possible with one newspaper but required multiple newspapers in the other locations.

	City	Circulation	Articles Selected
The Chicago Sun Times	Chicago	313,176	629
The Daily Herald	Chicago	138,186	02)
Philadelphia Inquirer	Philadelphia	300,674	1190
Philadelphia Daily News	Philadelphia	97,694	1180
San Antonio Express News	San Antonio	206,933	549

Table 3: Newspaper Descr	iptives
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Notes: Numbers calculated from 2009 circulation⁴

Using the external lists of homicides, articles were collected manually from each newspapers' archive following a rigorous Boolean search procedure.⁵ I used the most general Boolean search criteria possible and manually screened the results for relevant articles. I started with the name of victim, and this often returned a small enough number of results (<100) to screen manually. In cases where the victim's name was very common (e.g. Michael Johnson) I added a string of words related to homicide (murder* OR kill* OR homicide*). In the rare incidents where this was not sufficient, I added quotation marks around the victim's name to force an exact match. This search process yielded 2,358 valid articles across the 5 samples newspapers.

⁴ A cached copy of the 2009 BurrellesLuce Report was obtained using WayBack Machine. This was the nearest neighbor year of high-quality circulation data available at the time of writing.

⁵ Articles were accessed from the central hub of Access World News, at which time the corpus was restricted to each newspaper in the sample.

In this analysis I conceptualize newsworthiness as increased news coverage of homicide victims relative to other homicide victims. I provide multiple measures of news coverage to understand how different operationalizations of coverage might affect the cohesiveness of newsworthiness factors. First, I take a crude approach to measuring news coverage by treating coverage as a dichotomous variable (Table 4). In this measure a victim either receives news coverage (59.16% of the total sample) or does not (40.84% of the total sample).

Table 4: Coverage (Dichotomous %)

	Full Sample	Chicago	Philadelphia	San Antonio
No Coverage	40.84	56.39	30.36	17.46
Coverage	59.16	43.61	69.64	82.54
Total	972	454	392	126

The percentage of cases that receive news coverage varies across each city. Chicago, which has the largest number of homicides, also has the lowest percentage of victims that are covered by the news (~44%). In contrast, San Antonio, which has over 3x times fewer homicides has the highest percentage of covered cases at nearly 83%. This dichotomous measure is advantageous in its simplicity and ability to draw a stark contrast between victims who are never mentioned at all and those who are but lacks the ability to demonstrate any level of difference across covered victims.

To account for this problem, I include a second measure of news coverage as a count variable indicating the number of articles that mention a given victim of homicide. As shown in Figure 3, a vast majority of homicides receive 2 or fewer articles of news coverage. In addition to the 40.84% of victims that received no coverage, a further 26.85 percent received 1 article of news coverage and 11.42 received 2 articles of news coverage. A much smaller set of 38 victims (3.91%) received much more coverage than average, ranging from 10-111 articles.

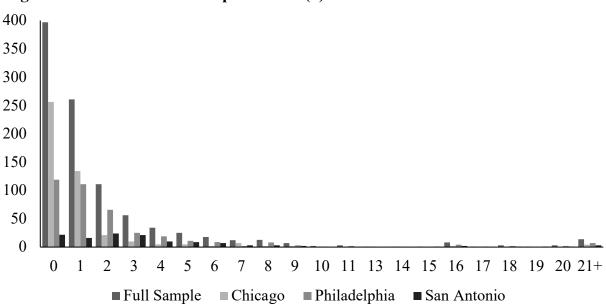


Figure 3: Number of Articles per Victim (#)

Like the dichotomous measure of news coverage, article counts also varied widely by city. Chicago homicide victims received an average of 1.38 articles of news coverage with a range from 0 - 81. Philadelphia homicide victims received an average of 3.01 articles of news coverage with a range from 0 - 111 and a substantial standard deviation of 8.34. San Antonio homicide victims received the most news coverage on average with a mean of 4.36 articles and a range from 0 - 50. While this count measure provides necessary contextual information about the magnitude of newsworthiness, it is inflated by its extreme tails (the 3.91 percent of cases that see substantially elevated coverage).

Rather that dismiss the count measure due to the behavior on the extreme tails, since removing it would also remove many articles (and therefore news reporting) from the sample, I

instead introduce a third measure of news coverage that addresses the gap between the dichotomous and count measures. This measure, a dichotomous indicator, reports whether a case received any follow-up coverage after the initial article. Therefore, this measure serves as a measure of enduring newsworthiness for each victim, giving me additional leverage to see any similar or differing patterns within the data.

	Full Sample	Chicago	Philadelphia	San Antonio
Follow-up articles	32.3	14.1	41.33	69.84
No follow-up articles	67.7	85.9	58.67	30.19
Total	972	454	392	126

Table 5: Coverage Follow-Up (Dichotomous %)

The results in Table 5 clearly indicate that follow-up news coverage is even more variable than the other coverage indicators. In Chicago, a very small number of victims received follow-up news coverage (14.1%) compared to 41.33% in Philadelphia and 69.84% in San Antonio. Notably, the likelihood of follow-up coverage overall correlates with the number of homicides in each location.

Measuring Victim Demographic Variables

In line with previous work, I extract some situational and demographic characteristics for each victim in order to see how they differently predict coverage. I included seasonality due to the well-studied relationship between seasonality and increases in crime (Andresen and Malleson 2013) in case the cycle of news coverage mirrored this seasonal relationship. I also included a dichotomous variable indicating whether the victim had been killed by a gunshot. I included this information on the type of killing to tap into the sensational/salacious circumstances findings noted elsewhere in the literature (Chermak 1998, Lundman 2003). I had intended to construct a more nuanced breakdown of type of killing information but found that the samples were relatively homogenous in modes of killing, such that the simple dichotomy of gunshot/no gunshot was reasonably good for splitting the sample. Specifically, after firearms the most common method of killing was stabbings (~10% in the full sample), so further breakdowns of the category would be statistically tenuous.

I then included victim characteristic variables including age, sex, and race, which each required different cleaning procedures to include into the data. Age was reported in each version of the source data, so required no imputation or cleaning. Sex, however, was not reported in any of the original source data. While it would be possible to read each article and note pronoun or word use to code sex (ex: Man shot, Woman stabbed), instead I use the publicly available API Genderize.io to quickly estimate gender across the entire sample of 972 cases.⁶ Racial/ethnic information was available from the source data for homicides from Philadelphia and San Antonio, but not Chicago. In order to estimate race for Chicago homicides. I used the Wall Street Journal Race Calculator. This tool uses surname and geographic location data from the US Census to predict race by offering a percentage likelihood of racial/ethnic group membership for each surname. The WJS Calculator estimated that 71% of the Chicago victim sample were most likely Black or African American. This percentage is highly plausible since from 2003-2011, 75% of murder victims in Chicago were Black or African American (Hoston 2014).

Analytic Strategy & Results

⁶ Genderize.io contains a database of over 250,000 first names and uses this database to generate the most likely gender for each name fed into the API. This means that it is plausible that some names are not coded correctly, however, since I am looking for significant effects, a small number of non-systematic error is unlikely to greatly impact the final models. More information on the API can be found here: https://genderize.io/

I conduct my analysis in four stages: 1) a series of logistic and linear regression models to predict each type of news coverage in each city and the larger sample, 2) an analysis of the underlying descriptive differences in homicide in each location, 3) a series of exploratory logistic regression models with interactions to model intersectional victim characteristics, and 4) an exploratory look at across-city variation in Chicago to more fully capture the coverage disparity across geography in the city.

I structure the majority of my results comparatively, showing results from each city alongside the full sample results. I do this as a consistent test of how the locations vary and as a representation of what nuance is lost if the cities are not considered independently. The reference categories for all models are gun-related killings, fall seasonality, white race, female sex, and adult age. In the latter phases of the analysis, the results become sparser and more exploratory as the project of measuring context becomes more difficult.

Predicting News Coverage with Victim Characteristics

Table 6 (below) depicts the results of a logistic regression using seasonal, situational, and victim characteristics to predict dichotomous coverage in the full sample and across all three cities. The model demonstrates substantial variability across studied contexts, despite the utilization of identical data collection methods.

Table 6: The Effects of Victim Characteristics on Dichotomous Coverage

	Full Sample	San Antonio	Chicago	Philadelphia
	b/(se)	b/(se)	b/(se)	b/(se)
Season				
Spring	-0.04	0.8	-0.93**	0.92**
	(0.19)	(0.95)	(0.28)	(0.34)
Summer	0.08	0	-0.32	0.79*
	(0.18)	(0.74)	(0.26)	(0.32)
Winter	-0.22	-0.37	-1.14***	0.44
	(0.2)	(0.79)	(0.32)	(0.33)
Shooting	0.24	0.91	-0.31	0.67*
	(0.17)	(0.61)	(0.25)	(0.33)
Race				
Black	-0.49*	-0.31	-0.34	0.15
	(0.21)	(0.87)	(0.38)	(0.32)
Hispanic	-0.46	-0.11	-0.57	0.29
	(0.26)	(0.64)	(0.44)	(0.84)
Other	-0.41	0	0.04	0.11
	(0.41)	(.)	(0.58)	(0.72)
Age				
Juvenile	0.90***	0	1.07***	0.75
	(0.25)	(.)	(0.32)	(0.55)
Elderly	0.85*	-0.91	0.87	2.27*
	(0.43)	(1.13)	(0.60)	(1.09)
Sex				
Male	-0.44*	-2.12	-0.74*	0.35
	(0.20)	(1.14)	(0.30)	(0.35)
Unknown	-0.31	0	-0.67	0.59
	(0.43)	(.)	(0.66)	(0.72)
Constant	0.91**	2.99*	1.29**	-0.81
	(0.30)	(1.24)	(0.48)	(0.53)
BIC	1354.5	127.6	650.1	527.6

* p<0.05, ** p<0.01, *** p<0.001

The model indicates that there are virtually no consistent predictors of dichotomous news coverage across the 3 cities. Some seasonal effects in news coverage were significant in Chicago

and Philadelphia, but they moved in opposite directions with less coverage for victims killed in the spring or winter months in Chicago (compared to fall) and more coverage for victims killed in spring or summer in Philadelphia. There was a significant increase in coverage for juveniles in Chicago, but a significant increase in news coverage for the elderly in Philadelphia. There were also some low-level effects of gender that indicated that coverage for male victims was less likely in Chicago.

Many of these significant findings and the general directions of the betas change when the method of measuring news coverage changes. Table 7 (below) depicts the results for predicting the number of articles of news coverage per victim. The seasonal effects are no longer significant in the model, though gunshot homicides remain weakly significant in Philadelphia. Interestingly, the coefficient of every race/ethnic group (relative to white) is negative in the linear model, including strongly significant negative relationships between minority race/ethnicity in Philadelphia and the sample at large. The betas for juvenile age are also consistently positive, rising to the level of statistically significant in Chicago and San Antonio. Elderly age continues to be positive and significantly predictive only in Philadelphia.

Table 7: The Effects of Victim Characteristics on Number of News Articles

Full Sample	San Antonio	Chicago	Philadelphia
b/(se)	b/(se)	b/(se)	b/(se)

Season				
Spring	-0.22	3.00	-0.75	-0.75
	(0.64)	(1.98)	(0.72)	(1.22)
Summer	0.05	0.40	-1.12	1.56
	(0.61)	(1.82)	(0.67)	(1.19)
Winter	-0.87	-0.66	-1.55	-0.70
	(0.68)	(1.92)	(0.8)	(1.27)
Shooting	0.47	-0.55	-0.18	2.57*
	(0.57)	(1.42)	(0.63)	(1.23)
Race				
Black	-3.34***	-1.94	-0.32	-5.15***
	(0.68)	(1.95)	(0.97)	(1.16)
Hispanic	-2.72**	-0.01	-0.88	-6.49*
	(0.84)	(1.54)	(1.11)	(3.14)
Other	-2.81*	-4.46	-0.11	-3.24
	(1.35)	(7.53)	(1.5)	(2.62)
Age				
Juvenile	3.33***	7.22***	2.28**	2.96
	(0.76)	(2.01)	(0.8)	(1.72)
Elderly	1.58	-1.93	-0.77	7.19**
	(1.28)	(3.10)	(1.46)	(2.51)
Sex				
Male	-1.25	-1.48	-2.49**	1.00
	(0.66)	(1.65)	(0.76)	(1.29)
Unknown	-0.8	-4.92	-3.28	2.79
	(1.41)	(4.46)	(1.71)	(2.49)
Constant	5.72***	4.94*	4.59***	3.67
	(0.96)	(2.14)	(1.21)	(1.97)
R-sqr	0.05	0.19	0.06	0.1
dfres	953	110	441	378
BIC	6549	865.3	2873.7	2792.6

Finally, I ran the same model to predict coverage endurance (i.e. the presence of followup coverage), as depicted in Table 8 (below). These findings were again slightly different than either of the previous models, again emphasizing the importance of clear conceptualization and operationalization about the type of media coverage. Seasonal effects were once again significant in the model for Philadelphia, but not Chicago. Gun-involved killings received more follow-up coverage than non-gun-involved killings in San Antonio and Philadelphia. Coefficients for all races and ethnicities (compared to white) remained negative, reaching statistical significance in the overall sample and in Chicago. Juvenile age significantly predicted news coverage in Chicago and Philadelphia, while elderly age continued to predict increased news coverage in Philadelphia. Males received less coverage than females in every market, with statistically significant results in both San Antonio and Chicago.

Table 8: The Effects of Victim Characteristics on Follow-Up Coverage

Full Sample	San Antonio	Chicago	Philadelphia
b/se	b/se	b/se	b/se

Season				
	0.29	0.23	-0.54	0.74*
Spring	(0.22)	(0.68)	(0.42)	(0.34)
	0.58**	-0.01	-0.27	1.37***
Summer	(0.2)	(0.61)	(0.38)	(0.33)
	0.45*	0.08	-0.35	0.71*
Winter	(0.22)	(0.67)	(0.44)	(0.36)
Shooting	0.40*	1.20*	-0.40	0.96**
	(0.18)	(0.48)	(0.33)	(0.36)
Race				
Black	-1.11***	-0.15	-1.14**	-0.54
	(0.21)	(0.71)	(0.44)	(0.31)
Hispanic	-0.63*	-0.35	-0.92	-1.40
	(0.26)	(0.54)	(0.53)	(1.16)
Other	-1.04*	0	-0.63	-0.34
	(0.43)	(.)	(0.71)	(0.72)
Age				
Juvenile	1.02***	1.19	1.50***	1.20*
	(0.23)	(0.87)	(0.35)	(0.48)
Elderly	0.37	-1.79	0.03	2.24**
	(0.40)	(1.10)	(0.72)	(0.79)
Sex				
Male	-0.82***	-1.47*	-1.23***	-0.39
	(0.20)	(0.70)	(0.36)	(0.35)
Unknown	-0.25	-1.73	-0.99	0.35
	(0.43)	(1.60)	(0.88)	(0.67)
Constant	0.02	1.58	0.36	-1.31*
	(0.30)	(0.81)	(0.55)	(0.56)
BIC	1217	177.3	396.7	553

Taken in sum, these three sets of models demonstrate that there is no single predictor class that predicts increased news coverage in every scenario. However, there are some patterns of significance and common directions in coverage relationships that characterize the sample. In general, I conclude that coverage can vary by season, perhaps indicating a need to study the cycle of news itself in relation to newsworthiness in homicides. In 8/9 city specific models, Black or African American victims received less news coverage compared to white victims, with this difference reaching the level of statistical significance in 2 models in two different cities (Chicago and Philadelphia). Hispanic or Latino ethnicity predicted less news coverage compared to white victims in 8/9 models, with this difference reaching the level of statistical significance once in Philadelphia. Juvenile age was generally associated with more news coverage while elderly age consistently predicted elevated coverage in Philadelphia alone. In general, male victims received less news coverage than their female counterparts (8/9 models) and this difference reached the level of statistical significance in 4 city-specific models.

Descriptives of Homicide

In order to investigate why some relationships were variable across the sample or were unlikely to attain statistical significance in traditional logistic/linear modelling, I turn to the underlying descriptive data of homicides in each city. In crux, the results I have already reported demonstrate that predictors of newsworthiness are not the same in each city, but now I look at the underlying patterns of homicide to see if we really should expect those predictors to be the same at all.

Beginning with seasonality data, it becomes immediately clear that there is substantial variation in the sample at the foundational level. Across the whole sample, killings are more likely to occur in the summer (30.86%) and less likely to occur in the winter (20.47%). However, this pattern does not hold across each city, rather it is driven primarily by Chicago and to a lesser extent Philadelphia. It makes sense then, that San Antonio and Chicago would present differently in the regression models on seasonality and news coverage when they diverge so strongly in the foundational data.

	Full Sample	Chicago	Philadelphia	San Antonio
Fall	24.38	26.21	22.96	22.22
Spring	24.28	24.45	25.77	19.05
Summer	30.86	31.5	29.59	32.54
Winter	20.47	17.84	21.68	26.19
N	972	454	392	126

Table 9: Season of Killing (%)

	Full Sample	Chicago	Philadelphia	San Antonio
Gunshot	75.41	72.03	84.44	59.52
Other	24.59	27.97	15.56	40.48
Total	972	454	392	126

 Table 10: Type of Killing (%)

Table 10 above also demonstrates substantial variability in types of killing in each location, lending credence to the theory that there are important underlying differences in the patterns of homicide even before trying to predict newsworthiness. A vast majority (84.44%) of homicide victims in Philadelphia were killed by gunshots, whereas 40.48% of victims in San Antonio were killed by something other than a firearm. In fact, a full 28.57% of San Antonio victims were killed by blunt force trauma or stabbings (see Appendix C).

The racial breakdown of homicide victims is also highly variable across the sample (Table 11), perhaps unsurprisingly, since racial heterogeneity was initially maximized in site selection. In both Chicago and Philadelphia, a large majority of homicide victims are Black or African American (70.71% and 79.28%) respectively. However, the next largest group of victims in Chicago is Hispanic (16.52%) and is white in Philadelphia (16.6%). San Antonio had a majority Hispanic or Latino victims (53.23%), followed by a substantial proportion of white

victims (27.42%). This shows that not only are the underlying demographic make-ups of the three cities different – but the demographic make-up of their homicide victims are still different from that. This makes it easier to understand why findings by race are more or less likely to come out as significant when considering the number of cases available in the actual sample. It also shows the challenge of using the same set of demographic measures to draw inferences about dramatically different contexts.

	Full Sample	Chicago	Philadelphia	San Antonio
White	13.52	7.93	15.6	27.42
Black	67.49	70.71	79.28	18.55
Hispanic	15.38	16.52	2.05	53.23
Other	3.61	4.85	3.07	0.81
Total	969	454	391	124

The remaining demographic categories of sex and age were less variable, though some differences were still present in the sample. San Antonio had a higher percentage of female victims compared to Chicago and Philadelphia. Philadelphia also had fewer youth homicide victims as a percentage of total homicide compared to Chicago and San Antonio.

Table 12: Sex of Victims (%)

	Full Sample	Chicago	Philadelphia	San Antonio
Female	14.92	15.2	11.73	23.81

Male	81.89	82.16	84.18	73.81					
Unknown	3.19	2.64	4.08	2.38					
Total	972	454	392	126					
Table 13: Age Categories (%)									
	Full Sample	Chicago	Philadelphia	San Antonio					
Adult	86.34	84.77	90.03	80.33					

6.91

3.07

391

14.75

4.92

122

11.92

3.31

453

Exploratory Models to Demonstrate Nuanced Context

10.25

3.42

966

Juvenile

Elderly

Total

The univariate descriptives clearly indicate that there are highly differentiated contexts within each city that were not captured by the original predictive models. In order to explore more nuanced contexts of victim coverage I conducted two brief exploratory analyses using interactions and neighborhood context.

First, I ran a series of models that allowed for interactions between the predictor variables. I ran each model using only the dichotomous coverage measure in an effort to simplify the interpretation of the model. Based on the intentional racial variation and consistent age-related findings in the preliminary regressions, I prioritized a series of models that interacted race and age in each city and the larger sample, keeping main effects in the models.⁷ The results of these models are reported in Table 14 below.

⁷ I also ran a series of exploratory models of raceXgender interactions and ageXinteractions that I report in Appendix D, but do not analyze in detail here as they do not align with the most central variables of interest in the project.

Coverage, Interacteu				
	Full	San		
	Sample	Antonio	Chicago	Philadelphia
	b/se	b/se	b/se	b/se
Season				
Spring	-0.22	3.98*	-0.76	-0.75
	(0.64)	(1.94)	(0.72)	(1.22)
Summer	0.05	0.44	-1.15	1.40
	(0.61)	(1.74)	(0.68)	(1.19)
Winter	-0.85	-0.61	-1.63*	-0.73
	(0.68)	(1.84)	(0.80)	(1.27)
Shooting	0.29	-1.05	-0.05	2.24
8	(0.57)	(1.42)	(0.64)	(1.24)
Race/ethnicity				
Black	-3.11***	-1.38	-0.38	-4.38***
Didek	(0.73)	(2.04)	(1.09)	(1.21)
Hispanic	-2.90**	-1.54	-0.56	-5.29
mspunie	(0.92)	(1.56)	(1.25)	(3.32)
Other	-3.10*	9.96	0.01	-3.49
0	(1.43)	(8.58)	(1.60)	(2.74)
A as Catagony	()	(0.00)	()	()
Age Category Juvenile	3.38	-7.38	2.52	14.99*
Juvenne				(5.82)
Elderly	(2.55) 2.65	(5.18) -2.59	(2.91) -0.66	9.34**
Lideny	(2.06)	(4.17)	(2.91)	(3.54)
	(2.00)	(4.17)	(2.91)	(3.34)
Interactions				
Black x Juvenile	-0.96	7.8	0.41	-13.22*
51 1 511 1	(2.71)	(6.52)	(3.07)	(6.08)
Black x Elderly	-2.16	-0.85	-0.02	-5.90
TT' ' T '1	(2.83)	(8.07)	(3.50)	(5.38)
Hispanic x Juvenile	2.16	19.18***	-2.02	0
II	(2.97)	(5.56)	(3.34)	(.)
Hispanic x Elderly	-3.31	0.62	0.52	-7.42
Oth	(3.79)	(6.36)	(4.88)	(9.28)
Other # Juvenile	0.78		$\begin{pmatrix} 0 \\ \end{pmatrix}$	
Other # Elderly	(7.53) 4.68	(.) 0	(.) -1.67	(.) 6.38
Other # Elderry				
_	(5.49)	(.)	(6.32)	(9.16)
Sex				
Male	-1.15	-2.34	-2.51**	1.02
	(0.66)	(1.64)	(0.77)	(1.30)
Unknown	-0.51	-4.72	-3.42*	3.22
	(1.42)	(4.29)	(1.73)	(2.48)

Table 14: The Effects of Victim Characteristics on DichotomousCoverage, Interacted

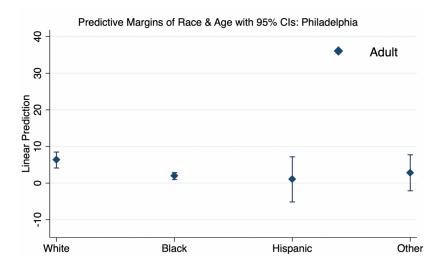
Constant	5.65*** (1.00)	6.42** (2.13)	4.52*** (1.29)	3.35 (2.00)			
R-sqr	0.06	0.29	0.06	0.12			
dfres	947	106	436	374			
BIC	6584.7	867.5	2902.4	2809.1			
* p<0.05, ** p<0.01, *** p<0.001							

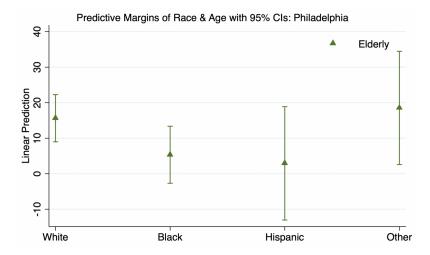
This exploratory interaction, using white and adult as base outcomes, reveals some significant results among specific interacted conditions including predicting decreased coverage for Black youth in Philadelphia (main effects remain significant in the model) and elevated news coverage for Hispanic juveniles in San Antonio (main effects are not significant in the model). Once again, there do not appear to be consistent findings across cities.

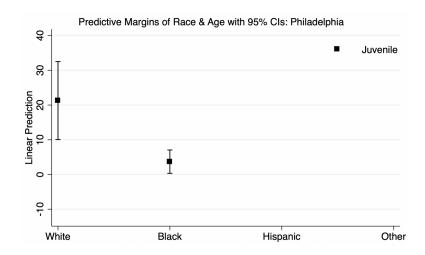
Main Effects in Philadelphia

Figure 4 visualizes the simple main effects in the Philadelphia model, visually depicting less news coverage for black victims compared to white victims in every age condition, most notably in the comparison of black juveniles to their white counterparts. The plot also visualizes the expected wide confidence intervals for Hispanic and 'Other' victims, which are very infrequent in the Philadelphia data.

Figure 4: Predictive Margins of Race and Age in Philadelphia







These results suggest that perhaps interacted models may provide some additional leverage in some questions and facets of newsworthiness, but they do not ultimately produce sets of uniform predictor variables that predict news coverage across all cities either. These results also help make meaning of how wide the confidence intervals of prediction really are in the model.

Exploratory Analysis of Chicago Community Areas

In an attempt to explore more fine-grained city context, I also conduct a brief exploratory analysis of geographic disparity of news coverage within Chicago. I re-shape the data to place homicide victims in the neighborhood context in which they were killed, totaling the number of victims in each of Chicago's 77 community areas. The number of killings ranged from 0 - 36, with an average of 7 killings per community area. The 5 community areas with the most killings were Austin (36), Greater Grand Crossing (25), Humboldt Park (21), Englewood (20), and South Lawndale and Roseland with (19). It was immediately evident that the impact of homicide is not equally felt across Chicago.

Simple pairwise correlations revealed a strong correlation between neighborhoods with majority Black residents and the number of victims of homicide in the community area (0.37) and a strong negative correlation between neighborhoods with majority white residents and the number of homicide victims in the community area (-0.26), indicating that majority black neighborhoods are bearing the brunt of homicide victimization in Chicago.⁸ I also found a negative correlation between news coverage and majority Black neighborhoods (-0.15) and a

⁸ Majority neighborhoods were determined by simple racial majority, i.e. a neighborhood was coded as a Black majority neighborhood if 50.01% or more of residents were Black (using 2010 Census data). Using this simple classification system, I classified 27 neighborhoods in Chicago as majority Black and 11 as majority white.

positive correlation between news coverage and majority white neighborhoods (0.05) demonstrating that coverage is also unequally allocated by geography and race in Chicago.

Indeed, in majority Black neighborhoods there was an average of 10.15 victims of homicide compared to an average 2.82 homicide victims in majority white neighborhoods. In majority Black neighborhoods, 39.02% of homicide victims received any news coverage. In majority white neighborhoods, 48.49% of homicide victims received any news coverage. This disparity reveals that there is substantial local variation in news coverage that is collapsed into the larger regression models. In the original dichotomous coverage predictive model (Table 7), race did not appear to be a significant driver of news coverage in Chicago. However, a more contextualized look at the data within the city demonstrates that a more complex pattern of coverage.

Discussion

What we are left with after this investigation, is no easy answer to the solution of improving models of newsworthiness, but with some promising leads in making sense of a seemingly disparate literature and reconceptualizing context in modelling homicide news. I started with the postulation that homicide news is very important, but with a vast array of potential answers about what actually makes a homicide more newsworthy than any other homicide.

First, I predicted that this disparate universe of findings was not solely due to different scholars using different methods or different moments in time to study homicide news. I attempted to control for this possibility by selecting three vastly different cities and conducting the same Boolean logic search, data cleaning, and modeling procedure on all three cities in the same year. I found support for my hypothesis and that despite efforts to treat all three cities the same way, I could not easily pin-point a set of individual features of newsworthiness that were equally significant in predicting news coverage in every city. I did find, however, some evidence to support the theory that differential conceptualizations and operationalizations of news coverage itself can have a substantial effect on the data. My three measures of coverage: the dichotomous presence of any coverage or not, the number of articles of news coverage, and the presence of follow-up coverage intentionally tapped into three different elements of newsworthiness: baseline existence, magnitude of coverage, and endurance of coverage. Depending on which variation of coverage I used, I found different significant predictors of that type of coverage. I do not mean to suggest that this is an error necessarily, more to suggest that it indicates that precision with which we define the questions at the core of the newsworthiness argument is crucial. That is, why do we want to know if something is newsworthy? Here I agree with Shoemaker (2006) that newsworthiness for the sake of newsworthiness is not sufficient conceptualization and instead the goal of measuring newsworthiness needs to be supplemented with additional features.

Second, my conclusion that no stable set of features universally predicts news coverage may seem discouraging, but perhaps it really is exactly what we would expect. I predicted that the underlying patterns of homicide and news reporting itself would be so highly variable that we might not reasonably expect the same set of predictors to successfully measure coverage. I found substantial support for this hypothesis by going back to basics and really dissecting patterns of variation in the underlying homicide data. What I found was that homicide does not look the same in Chicago, Philadelphia, and San Antonio – and nor does news coverage look the same in Chicago, Philadelphia, and San Antonio. So why then, would we expect to be able to predict different contexts and different outcomes using the same set of predictors at all.

It would be tempting then to declare that the disparate world of newsworthiness findings is not a problem at all, but this would be the exact type of oversimplification of news that Shoemaker (2006) warns against. Rather than producing a world of findings, perhaps one article for every city in the United States re-written every so often to update with the times, that remains intentionally disjointed, we can turn to the specific context of homicide and localities to extract larger meanings from newsworthiness concepts. The goal of studies of newsworthiness is not simply to quantify the news, rather it is to understand the determinate forms and sociological work being conducted by the news (Fishman 1988; Schudson 2011). We know that the burdens of homicide are disproportionately inflicted upon Black and African American communities in the United States (Harrell 2011) and that the news can serve as a vehicle that exacerbates inequality (Baranauskas 2020; Boulahanis and Heltsely 2004; Peffley et al. 1966). Therefore, we can take up the study of newsworthiness in the same vein and conduct more careful analyses of how the context of newsworthiness in a specific place breeds and reifies inequality.

Third, I predicted that even my city-by-city modeling of newsworthiness, informed through the lens of the foundational data, would continue to be insufficient to model the complexities of homicide news coverage with appropriate attention to context. I attempted two methods of increasing nuance and in the second found some support for my prediction that there would be substantial within-city variation in news coverage that is reduced by traditional models of newsworthiness. Attempts to run interacted models were only marginally successful – likely a function of the small cell size produced by interacting multiple conditions within a rare phenomenon (for example, San Antonio only has 126 homicides in the study year to begin with, even before interacting conditions in the data that might be uncommon). More successful was my look within Chicago at the way coverage systematically varied by geographic and neighborhood composition. The larger regressions of Chicago found the general relationship (in terms of the direction of the coefficient and one statistically significant beta in the follow-up coverage condition), but could not provide insights about how the news actually varied within the city itself. Given the resonance of local news compared to larger aggregates of news (Chiricos et al. 2000) it is worth considering, then, the limits of aggregate measures of newsworthiness in understanding phenomena that we know vary locally.

Taking these first three considerations as a collective, I recommend that scholars of newsworthiness spend substantial time analyzing the foundational descriptive data in a given context, use those conclusions to target specific geographic aggregates and measures of coverage, and then place those conclusions more directly into the context of the city where the news is produced. Pushing the sociological-meaning making of newsworthiness research to the forefront will help the literature transition from a series of descriptive findings about relevant predictors to contextually informed conclusions about how news matters in different contexts.

Fourth and finally, I predicted that there would be a substantial data distortion between the reality of homicide and the world of homicide news. Cultivation theorists proposed a process by which news comes to inform perceptions of homicidal reality by being the most direct connection between the people and crime and by intentionally framing crime stories as more violent or frightening (Baranauskas 2020; Beckett and Sasson 2004; Sacco 1995; Surette 1992). What I found was the consistent presence of data distortions: but in inconsistent directions. There were some conclusions drawn from the data that were more universal, like the consistent negative coefficients of coverage for homicides with Black or Hispanic victims, the relatively consistent increase in coverage for juveniles, and the general trend of male homicide victims receiving less news coverage, but they varied in strength and sometimes even in direction across different models. This makes the problem of quantifying and disentangling data distortions substantially more difficult.

Data distortions in homicide news might be more important than we think for a number of reasons. In addition to understandings of homicide, even if they are incorrect, affecting perceptions of fear and safety (Shi 2021), understandings of crime and the normalization of crime can have compounding political, legal, and social consequences for communities. For example, I found that Chicago homicide victims in majority white neighborhoods were more likely to receive news coverage than Chicago homicide victims in majority black neighborhoods. This data distortion might increase fear of homicide in neighborhoods that statistically do not have a lot of homicide or it might obfuscate the extent of the crime crises in majority Black neighborhoods in Chicago. Even more simply, it creates a world of homicide in the news that does not match what homicide looks like in real life. If the news, as Schudson (2011) puts it, is the outcome of sociological work, then we must more fully analyze what these distortions say about society more broadly.

Limitations & Directions for Future Work

While this study makes substantial gains in establishing consistent methodology and studying the role of context, it is not without limitations that should be considered in future research. While there are numerous directions for future work, I describe three in brief here.

First, this study uses only victim characteristics rather than allowing for the dyadic relationship of victim and offender characteristics. This is potentially problematic for determining the 'true' universe of news coverage as previous scholarship has found that minority offenders can affect levels of news coverage (Buckler and Travis 2005, Gruenewald et al. 2009, Lin and Phillips 2012, Lundman 2003) though not all scholars replicate these findings (Schildkraut and Donley 2012). While this is surely a limitation, not including offender information also has some interesting potential benefits to simplifying the research, since every homicide case has a victim but not necessarily a known offender. This means that increased coverage might be due from discovery of an offender, or court information about an offender, or another type of enduring interest in the case that is not applicable when an offender is not known. Future research should consider dissecting this terrain of potential reasons perhaps with attention paid to disaggregating structural reporting factors and the influence of demographic characteristics.

A second limitation of this work is the time period of inquiry: 2007. While this time period was strategically chosen, it does only give us a year-long snapshot of homicide across the three cities. However, data was collected for the period of 2008-2015 so that future research could extract additional articles and extend the analysis, making it sensitive to population-level changes over time and making sample sizes more robust.

A third potential limitation is in the measures of news coverage. This study was principally concerned with the existence of news coverage in multiple forms rather than the contents of that news coverage. Future work could continue the project of measuring and unpacking nuance by looking inward to the context of the articles (perhaps in the spirit of Baranauskas 2020) to analyze differential patterns of rhetoric and characterizations of victims/offenders as innocent or blameworthy.

CHAPTER 2

ASSIGNING PUNISHMENT: READER RESPONSES TO CRIME NEWS

Acknowledgements

Thank you to Dr. Janice Nadler for her mentorship, advice, and assistance on this chapter. This data collection was funded by the American Bar Foundation.

Introduction

The content and construction of crime news provides an important resource for examining social inequality. American media produces a large quantity of news about crime, and this reporting resonates with Americans (Boulahanis and Heltsley 2004; Norman 2008). Importantly, the news is not a monolith; instead, it is a site of interactive creation, allowing us to digest information from the world around us and extract value from it at the same time (Berkowitz 1997; Byers 2004; Lu 2012; Pan and Kosicki 1993). News shapes our perception of the world -- not by providing an objective reflection of facts, but rather by filtering information through the lens of the reporters and institutions that create the news (Schudson 2011). By studying the filtering process through which information becomes news stories, we can understand how readers form beliefs and opinions about guilt and innocence in crime news.

In this study we analyzed how the construction of news stories can change the perceptions of news readers. Specifically, we tested how altering both the quantity and the nature of the information presented can change perceptions of blameworthiness. First, we conducted a detailed content analysis of homicide news articles in Minnesota to develop three news vignettes that cue different levels of moral culpability of vehicular homicide offenders. Next, we conducted a survey experiment using the news vignettes to measure blameworthiness, measured as deserved years of prison time. We observed differing punishment recommendations that varied according to political views and other demographic factors. The results suggest a link between news and the current political climate, specifically invoking beliefs about morality as guiding belief in punishment.

The Importance of Crime News

Crime news does not just report crimes as rote fact, rather the process of crime news reporting and reading can create new fears about crime that are unfounded, sometimes even generating crime conspiracies that never really happened. An example of this is the so-called 'Creepy Clown Conspiracy' of 2016. In 2016, sightings of creepy clowns committing crimes or stalking people were reported across small towns in the United States, eventually becoming a nationwide panic that resulted in schools being closed due to clown threats and even the implementation of some local laws banning clowns (Roth 2016). One thing that was never discovered during the Creepy Clown Conspiracy? Creepy clowns. Instead, there was a fervor of reporting about these sightings that generated a fictious panic that had no underlying true events, perhaps even originating as a viral marketing stunt for a clown movie called "Gags the Clown" (Hay 2016).⁹

This example demonstrates how newspapers do not exist in a vacuum; they are created for and digested by an audience who themselves exist in the social world. Thus, the flow of information from news media is not uni-directional; rather it is a socio-cognitive relationship involving multiple actors. Pan and Kosicki (1993) describe the shared cultural universes of sources, journalists and audiences in the dissemination of news media with particular emphasis on the role of the audience as both readership and financial life-force for the institution of news. Shoemaker (2006) explains the logistics of this system of news and the interactive roles of its constituents.

"News is a commodity. It can be bought, sold, and traded. Journalists manufacture the news. Public relations firms manipulate the news. The audience consumes the news. Advertisers pay to place their products next to the news. News travels by word of mouth, across the Internet and other mass media. Professional associations focus on the

⁹ See Appendix A for some original research figures (created by this Author) showing the spread of the Creepy Clown Conspiracy through the news.

production of news and on social science research about news. Televised news shouts at us in airport waiting rooms. News is ubiquitous" (106).

These tensions are not about fabricating news, but rather characterize news as a social institution shaped by economics, technology, politics, culture, and organizational structures (Schudson 2011). This perspective helps us transcend the logistical process of reporting news and instead intuit value from its actual construction (see Berkowitz 1997; Lu 2012). This explanation gives reporters greater status than inscribers of rote fact -- instead they interpret and ascribe meaning to events in the way that they report them. Indeed, reporters are quite cognizant of the social meaning of the events they report about even though news is very subjective (Gieber 1964). The shaping of news is important because of its influence in the everyday lives of consumers. 93% of Americans say they follow the news at least occasionally, a large majority of them reporting that they do so for reasons that are primarily due to social interactions and civic responsibility (Purcell et al. 2010). In this way, the very circulation of news is dependent on the same society it reports about.

Crime news is one of the most prevalent types of reported news, but numerous studies have concluded crime news does not correlate with actual crime rates (Boulahanis and Heltsley 2004; Dorfman, Thorson and Stevens 2001; Garber 1979). The prevalence and construction of crime news matters because of its connection to negative consequences on attitudes, including racial stereotyping, public mis-perceptions of certain people as super-predators, and fostering fear of crime that does not accurately reflect the real spatial/demographic picture of crime (Barlow et al. 1995; Boulahanis and Heltsley 2004; Gilliam Jr et al. 1996; Sorenson et al. 1998; Thorson 2001). These effects are attributable not only to the simple dichotomy of which cases are covered and which ones are not, but also to the way in which cases are covered and constructed. In one study, researchers found that the way news is reported implies that minority persons, unemployed persons, and male youths are more often members of deviant social groups (Dixon 2006; Humphries 1981; Meyers 2004).

One theory about variation in reporting focuses on the concept of newsworthiness and efforts to make content newsworthy. Surette (1998) usefully defined newsworthiness as essentially "...the criteria by which news producers choose which of all known events are to be presented to the public as news events (60)." Chermak (1995) presented some of the earliest evidence that news reporters consciously select crime stories for reporting based on how newsworthy they were. Importantly, Chermak noted that not only are not all crimes newsworthy, even some extreme crimes like homicide were deemed 'not interesting enough' to be covered by the media (1998). This further illustrates the shared space of journalist and reader where anticipated reader response can help drive reporting decisions.

Katz (2007) proposes that for something to be newsworthy it must transgress a moral boundary as internalized by society. Increased attention to crime news can produce harsher blameworthiness evaluations for Black suspects compared to White suspects (Dixon 2008), demonstrating that boundaries of morality are subject to and derivative of other biases in society. This poses difficult and important questions for why certain victims are more sympathetic and certain offenders are perceived as guiltier. We explore these questions here through the lens of criminal law, using vignettes designed to trigger moral judgments, such as drunk driving and illegal immigration.

Blameworthiness and Criminal Law

In criminal law, blameworthiness is codified into law by a set of standards and heightened punishments through the vehicle of mens rea, or guilty mind. Historically derived from Christianity, generally immoral conduct was sufficient to prove mens rea (Robinson 2002). By the middle of the 13th century it was well established that "justifiable punishment is premised on and proportional to moral guilt" (Gardener 1993:655). Historically, punishment was thus intrinsically connected to moral blameworthiness. While current systems of criminal law have developed into a less explicitly normative inquiry into the offender's state of mind, even contemporary conceptions of mens rea reflects the attachment of moral blame and the offender's state of mind at the time of the offense (Gardener 1993).

Blameworthiness continues to influence our justice system not only in assigning guilt, but also in proscribing punishment. Theories of blameworthiness postulate that punishment should reflect the individual's degree of moral blameworthiness rather than being based merely on the degree of resulting harm (Edwards and Simester 2019). Robinson (1994) explains that a deserved sentence would be proportionate to the sentences of others with similar amounts of blameworthiness. This would allow, for example, some murderers to be punished less severely than others – even if the outcome of death is the same. We see this frequently in the contemporary justice system where we distinguish justifiable and non-justifiable killings, but also divide non-justifiable killings into degrees that call for less punishment based on less intent and mitigating circumstances.

While clearer in its legal and philosophical applications, blameworthiness can be very difficult to measure in practice. Studies of blameworthiness have shown that people struggle to objectively calculate fault and instead use more holistic process to ascribe blame, or that they occasionally make errors in determining blameworthiness (Feigenson et al. 1997; Shaver 2012). Studies of crime news and violent crime indicate that laypeople are prone to see certain groups as more blameworthy. Emile Durkheim proposes an explanation for this saying, "Crime is an action

which offends certain collective feelings which are especially strong and clear-cut" ([1893] 1984:71). In other words, something is a crime because it violates the collective consciousness. Therefore, if racial, ethnic, gendered, or other forms of bias were deeply ingrained into American society, we should expect to see certain groups of people elevated in blameworthiness even if their actions are comparable. Indeed, Peffley et al. (1996) found that even just a brief image of a black man in a crime news story activated racial stereotypes that caused participants to rate black suspects as more guilty, and more deserving of punishment. In the studies reported here, we test the effect of small changes in news reporting on punishment more broadly by operationalizing blameworthiness under the law as years of prison time for a vehicular manslaughter crime. By controlling the information communicated to the participant, we predict that we will be able to activate different assessments of blameworthiness. We do this by cuing morality in vignettes about drinking and driving and illegal immigration. First, we present a brief synopsis of how morality is thought to be entangled with both drinking and driving and illegal immigration.

The Morality of Drinking and Driving

Fifty years ago, the decision to get behind the wheel of a car after drinking alcohol was considered mostly a matter of personal preference. In the ensuing years, the issue of driving while impaired by alcohol underwent a radical change and moved into the domain of morality. During the 1980s, activists grew the number of local anti-drunk-driving groups from a few dozen to over 400. Their goal was to reduce drunk driving in their respective communities (McCarthy and Wolfson 1996). Aided by national umbrella organizations, local activists focused on moralization of the issue with the message "You can make a difference" – a slogan plainly designed to appeal to the American ethic of individual responsibility. At the same time, the success of the effort to move drunk driving into the consciousness of the public and into the

domain of the moral depended on tapping into and managing intense emotions, like fear. Mothers Against Drunk Driving (MADD) is the highest profile organization of its kind in the U.S., and its very name evokes the tragic image of a mother grieving for a dead child, "a threat to something sacred in society: the relationship of mother and child..." (Schmidt 2014).

The fear of a drunk driving crash in the future presents the looming potential of losing one's own life, losing a loved one, or taking another person's life (Schmidt 2014). Drunk driving injuries and deaths are shaped into narratives involving a binary moral discourse involving immoral, anti-civil perpetrators acting upon innocent victims. Collectively the acts performed by these individual perpetrators – driving vehicles while under the influence of alcohol – represent a challenge to the moral foundations of society (Schmidt 2014). At the same time, because drunk driving is a behavior that is ongoing and strikes randomly, there is the possibility that any one of us could become a victim in the future.

Perpetrators of drunk driving accidents are framed as individuals who make a choice: they put the key in the ignition. By choosing to insert the key, the individual is portrayed as choosing not to care about others and instead to put them at risk – a fundamental lack of compassion. The MADD narrative presses us to empathize with the anguish of a mother whose young adult child's life has suddenly ended. The individual who chooses to insert the key after drinking is portrayed as displaying a complete disregard for that anguish. By disregarding this pain and sorrow, the drunk driver is perceived as rejecting this sacred value of motherhood, and is rendered a moral monster.

Strong moral reactions can result from harm that is diagnostic of the actor's moral character. For example, a CEO who spent company funds redecorating his office while the company was cutting thousands of jobs provoked public scorn not because the act of

redecorating was particularly harmful but because in context the act was seen as indicative of the CEO's character (Tannenbaum, Uhlmann, and Diermeier 2011). When evaluating wrongs and harmful acts, people care about what kind of person the actor is: who that person is and not just what they have done (Nadler 2012; Nadler and McDonnell 2012). Certain acts are viewed as highly informative of character: these include animal cruelty, racist speech, and to some extent in recent decades, drunk driving, especially when it results in injury or death.

The Morality of Illegal Immigration

In the past few decades, immigration patterns in the U.S. shifted such that immigrants now live in communities throughout the nation, rather than being concentrated in a handful of regions. Many Americans have negative attitudes toward immigrants as a group – most commonly that immigrants cause problems and should be kept out of the country. At the same time many people hold positive attitudes toward immigrants, including the belief that they are hard-working and enrich American culture. Sometimes these conflicting negative and positive views are held by the same individuals (Ostfeld 2017). White Americans' attitudes toward immigrants tend to track with their racial attitudes, and individuals who hold more ethnocentric views are more hostile toward immigrants who come from countries outside of Europe (Hainmueller and Hopkins 2014). Racially resentful whites would like to see restrictions on the flow of immigrants as well as government services denied to immigrants (Kinder and Sanders 1996:123). Immigrants who entered the country without authorization are viewed negatively, especially by ideological conservatives (Hainmueller and Hopkins 2014).

Racial resentment among whites increases when the presence of non-whites is perceived to affect their own community. "In the view of many Whites, Blacks in the neighborhood threaten property values and safe schools; Blacks at church violate definitions of community; Blacks at work stir up apprehensions about lost jobs and promotions.... At the same time, distance from Blacks allows Whites the luxury of expressing racial tolerance" (Kinder and Mendelberg (1995:404). Experimental work has demonstrated that whites are less comfortable with immigrants living near them, working with them, and marrying into their family when those immigrants are depicted as darker skinned compared to when they are depicted as lighter skinned (Ostfeld 2017). This finding was independent of whether the individual immigrants in question were more assimilated or less assimilated in American culture.

There is a significant literature discussing the morality of immigration, with a particular emphasis on illegal immigration. Importantly, scholars argue that illegal immigration is not always morally wrong depending on the larger belief structures and the incompatibility of multiple legal, social, and protective obligations. For example, if a country limits immigration more than it morally should, the illegal immigration may be a legitimate response rather than a moral breach (Risse 2008; Taylor 2008). Many of these writings in law and philosophy tie the moral obligation back to the state, but there is less work analyzing how a layperson in America might interpret the morality of illegal immigration. We do know that Americans are divided on the issue of illegal immigration and that ways of framing illegal immigration as an issue vary across the country. Discourse in border adjacent regions tends to focus on illegality in immigration (as opposed to immigration more broadly) and to be significantly racialized (Branton and Dunaway 2009; Merolla, Ramakrishnan, Haynes 2013; Ramakrishnan et al. 2010). Much of this framing plays out in the news, with different rhetoric and framing characterizing liberal/progressive versus conservative news sources (Merolla et al. 2013), though the changes in laypeople's decision making as a result of those frames is less studied.

Site of the Research

In this study, we survey readers in the state of Minnesota in the United States of America due to a confluence of salient situational factors and a more general need for increased homicide research outside the largest urban settings.¹⁰ First, we prioritized a location with a relatively high rate of occurrence of vehicular homicides, but that had varied sentencing outcomes. According to the Minnesota Sentencing Commission, while the recommended sentencing guidelines under MN Statute 609.2112 recommend up to 10 years in prison for all vehicular homicide offenders, a substantial portion of vehicular homicide offenders receive stayed sentences or local confinement for a relatively short period (MSGC 2016/2017). This primed readers with the realistic ability to make varied choices in punishment outcomes. Second, we wanted to choose a location with a standardized type of media coverage, i.e. one main news outlet that covers criminal news across the region. This increases the likelihood that participants will have seen news disseminated in a similar format.

Hypotheses

We lay out a set of three intertwined hypotheses that make sense of exposure to different amounts of information, assignment of blameworthiness, and resultant duration of punishment. First, we predict that respondents will assign blameworthiness differently across different news vignettes based on the amount and type of information revealed by the article. Second, we predict that cues that correspond with legal status or criminal conduct will prompt differential assignment of blameworthiness. Third, we predict that duration of punishment will vary by the respondents' demographic categories.

¹⁰ Studies often focus instead on cities that have the most homicide, ostensibly to get a robust picture of homicides overall (see Lattimore 1997). In our case, we are less interested in homicide as a nationwide phenomenon, so we take this opportunity to focus on an understudied context.

Data/Methods

This study had two phases of data collection: the purpose of the first phase was to understand the standard formulation of news articles about Minnesota homicides, and in the second we constructed and deployed a vignette experiment on Amazon Mechanical Turk. The survey experiment was designed to assess how readers assign punishment to hypothetical perpetrators given in the presence or absence of information regarding the driver's immigration status and alcohol impairment. The phase 1 results necessarily informed the specifications of the vehicular manslaughter vignettes used in the MTurk experiment.¹¹

Phase 1: Constructing the Experimental Vignettes

Using the Minneapolis Star Tribune, the largest newspaper in Minnesota,¹² we gathered 600 articles that met our criteria for potentially being about a homicide.¹³ We screened the articles for relevance and established a 3-month cut point for analysis, leaving us with a final corpus of 177 test articles. In our examination of a recent three-month period (March 18, 2019 – June 18, 2019) we coded 110,250 words of text in 177 articles, covering 83 separate cases and 93 victims (7 cases involved multiple victims) of homicide.

We collected metadata about each article including date of publication, article title, author, and total wordcount. We also collected case-level information about the number of actors, the type of killing, any specific homicide-related charges, and the location of murderous

¹¹ Not all vignette-based work requires as much content analysis and adherence to real-world scenarios as we conducted here. However, in this case, the localized nature of the research required us to replicate reality as closely as possible to approximate news articles with appropriate verbiage, content, and tone. Notably, 66.7% of participants reported reading crime news from Minnesota (the context modelled in the vignettes) sometimes, often, or always, demonstrating the likely familiarity of the participant pool with a particular type of crime news.

¹² The Star Tribune has a daily circulation of 288,315, a Sunday circulation of 581,063, and a digital subscription rate of 50,000.

¹³ Using the World Access News Database, we used one inclusive Boolean search function gather articles [kill* OR homicid* OR slay* OR murder*]

assault. Finally, we also collected victim-level and offender-level information like age, gender, race, and the relationship between victim and offender.

We used the information gleaned from the corpus of 177 news articles to design our experimental murder vignettes. In our population of articles, victim and offender gender were mentioned a vast majority of the time (86.44% and 85.31% of the articles respectively). The age of the offender was also usually mentioned (79.66% of articles), though the age of victims was reported only about half the time (53.11% of articles). It was much less common for race to be mentioned in the article with offender race mentioned around 17.51% of the time and victim race mentioned 18.64% of the time. Consequently, in our manufactured vignette we opted to report both victim and offender gender, offender age and one victim's age, and no race information.

The most common type of killings reported in this period were shootings (42) and vehicular manslaughter (24). While we considered selecting shootings for our vignettes, we instead chose vehicular manslaughter because it lacks many confounding characteristics of other homicide types. For example, there are less frequently pre-existing relationships between parties, neighborhood effects, or complicated motives that might not be clear from a news article in vehicular homicide cases. The fact that nearly ¼ of homicides in the 3-month period were vehicular indicated that this time of crime would be plausible in the Minnesotan context. Importantly, vehicular manslaughter can also be framed as purely accidental or as accidental with compounding factors which gave us more flexibility in designing the vignettes.

In conducting a close code of all 177 articles we were also able to familiarize ourselves with the verbiage used in reporting about vehicular manslaughter. It was very important for us to replicate actual news stories as closely as possible. To further this end, we selected two articles for further inspiration in the wording of our experimental vignettes (see Appendix E). We designed three vignettes derivative of the same vehicular manslaughter scenario (see Appendix E). The scenarios are as similar as possible in wording and keep victim and offender characteristics constant excluding the key experimental manipulations. In the first scenario, we offered very little information about the criminal event and use this as our control scenario. In the second scenario, we added information about the perpetrator having an elevated blood-alcohol content level and history of drunk driving. In the final scenario, we removed the alcohol related information, but instead informed the reader that the perpetrator was an immigrant who had entered the country illegally 10 years prior and was set to be deported.¹⁴ Our goal in choosing these three experimental vignettes was to cue different amounts of blameworthiness and resultant punishment by offering different amounts and types of information about the perpetrator.

Phase 2: Deployment on Amazon Mechanical Turk

We conducted our survey on Amazon Mechanical Turk, requiring the 191 participating Turkers to have above a 95% HIT rating and to be located in Minnesota.¹⁵ We further confirmed their presence in the state of Minnesota by collecting the first 3 digits of each participants zip code at the end of the survey. While not a perfect proxy for residency, restricting the geography of participants makes it substantially more likely that participants would have been exposed to Minnesota crime media. We confirmed this by asking if participants had ever read news stories

¹⁴ Note that while this detail may seem far afield from the vehicular manslaughter incident, it is actually inspired by an actual case in Minnesota (see Appendix E). In this case, Jose O. Vasquez-Guillen was later deported and a stream of mainstream and partisan media described Vassquez-Guillen in various ways that highlighted his immigration status including referring to him as 'Salvadoran man,' 'undocumented', and an 'illegal alien with deportation order' in news headlines. Interestingly, other headlines referred to him more generally as a 'St. Paul resident'.

¹⁵ In order to ensure data quality, we included a short series of questions asking participants about their familiarity with a real-life case, then them to explain what happened in that case in words, and then asked them to evaluate the outcome as fair/unfair/not sure. 9 participants were removed from the final analysis because they provided incompatible or nonsensical responses.

about crime in Minnesota, to which only 2.84% of respondents indicated that they never had (see Table 15). Participants were asked to read 1 of the 3 randomly assigned experimental vignettes and respond to questions about punishment, news consumption, and demographics.

	Read News	Read MN Crime News	Watch TV News
Never	0.57	2.84	14.2
Rarely	10.8	20.45	30.11
Sometimes	36.36	39.2	22.73
Often	38.07	27.27	23.86
Always	14.2	10.23	9.09
Ν	176	176	176

 Table 15: News Engagement Descriptives (%)

Independent Variables

The key manipulated variable was the potential blameworthiness of the vehicular homicide offender. We used three scenarios to re-design the news vignettes: control, driving under the influence (DUI), and immigration. In each scenario we altered only the blameworthiness information, holding all other facts about the incident constant. In the control vignette, we gave very little information about the criminal incident, aside from the nature of the accident and the outcome. In the DUI condition, we included information about the elevated blood alcohol content (BAC) level of the offender. In the immigration vignette, we included information about the immigration history of the perpetrator, specifically that they immigrated to the United States illegally as a minor many years ago.

We controlled for a variety of demographic and related variables in this analysis including gender, educational attainment, income, age, race, Hispanic ethnicity, and political views. Participants in our study were more likely to be male (56.02%) than female (43.43%). Nearly half had a bachelor's degree (46.59%) and 85.14% of them described themselves as white. Around 60% of the participants made between 35,000-100,000 dollars per year and were between the ages of 25 and 44 (full descriptives can be found in Appendix F). Importantly, we also asked participants to indicate their political views using a sliding scale from 0 to 100, with 0 being very conservative and 100 being very liberal. The sample skewed slightly liberal with a mean response of 59.3, though the standard deviation was large (29.73).

Key Dependent Variable

The key dependent variable in this analysis is the number of years of punishment assigned to the hypothetical offender. Each participant was shown a slider and asked to assign a number of years of punishment between 0 and 10. While the numbers may be conceptually meaningful, we also want to focus on the behavior inherent to the response pattern. That is, a selection of '10' means something beyond just 10 years of punishment, it means the maximum punishment allowable. We use duration of punishment as a measurable proxy for the idea of blameworthiness, that is, the idea that some perpetrators deserve more punishment than others even if the outcome of the criminal act is the same. In this study, we keep the outcome of the scenario constant, only varying factors that might affect the level of culpability on the part of the perpetrator.

Results

Punishment duration varied greatly by vignette, suggesting that exposure to different amounts and kinds of information did change respondent decision-making (see Table 16). In the control vignette, where we gave very little information, respondents chose a punishment duration of 5.37 years on a scale of 0 to 10. This regression to the mid-point makes sense, given the limited information. However, when exposed to the DUI vignette the respondents assigned the driver a more punitive 9.19 years of prison on average. Interestingly, participants assigned 7.54 years of prison in the illegal immigration condition, striking a high mid-point between the other two vignettes.

88			
	N	Mean	Standard Deviation
Control	55	5.37	3.47
DUI	62	9.19	1.52
Immigrant	75	7.54	3.06

Table 16: Suggested Punishment Duration

DUI629.191.52Immigrant757.543.06We estimated separate linear regression models for each vignette type in order to

understand how demographic factors and self-identified political views may impact punishment evaluations (Table 17). We found that none of the demographic factors predicted punishment duration in the control vignette, which is consistent with the effects of having very little information to potentially evoke a response. In the DUI vignette we saw that political views had some directional effects that approached significance, but none of the provided demographic variables significantly predicted punishment duration. This is consistent with literature suggesting the drunk driving is unanimously disparaged. Finally, in the immigration vignette, we found that only self-identified political views had a significant impact on punishment duration (p < 0.01). As self-identified political views became more conservative, suggested punishment duration went up.

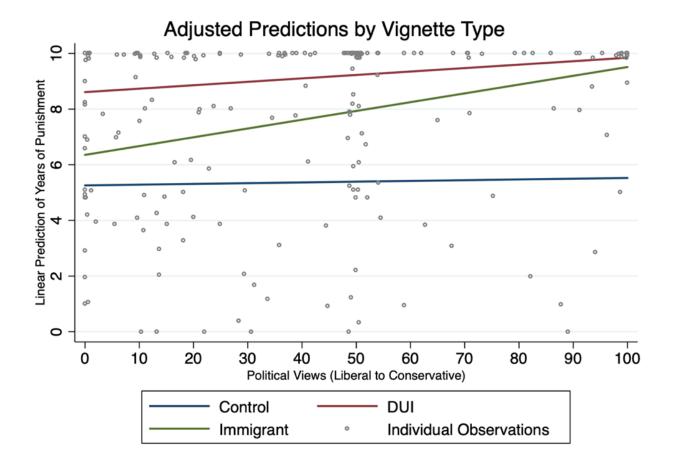
Variables	Control	DUI	Immigrant
Political Views	-0.01 (0.02)	-0.02+ (0.01)	-0.04** (0.02)
Income	()	(0.0-)	((***=)
Less than 10,000	-0.13	-1.18	-1.63
	(5.26)	(1.21)	(2.89)
200,000 or more	-0.79	-0.28	3.58
	(7.58)	(1.43)	(2.68)
Education			
High school/GED	-0.03	1.68	3.41
C C	(2.36)	(0.72)	(1.82)
Some college	-0.91	0.17	1.60
C C	(1.32)	(0.50)	(1.03)
Gender	× ,		× ,
Male	-1.03	-0.43	-0.56
	(1.22)	(0.41)	(0.94)
Race	`	· · ·	
Black	-4.07	2.09	4.01
	(5.38)	(1.95)	(2.42)
White	-5.06	0.51	1.05
	(4.52)	(1.36)	(1.92)
Ethnicity			
Hispanic	5.24	0.62	-0.42
	(3.82)	(1.61)	(2.56)
Age			
20 to 24	-2.17	1.29	-1.48
	(3.64)	(1.26)	(3.84)
60 to 64	-1.27	0.40	1.23
	(5.14)	(2.20)	(4.63)
Constant	12.02	0.54	0 40
Constant	12.02	9.54	8.40
	(7.82)	(1.67)	(3.20)
# of Observations	54	60	73

 Table 17: Regression Predicting Years of Punishment by Vignette Type

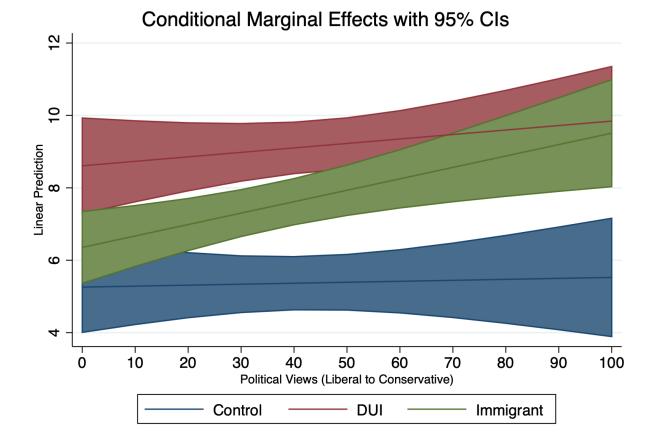
+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001Reported as regression coefficients with standard errors in parentheses Insignificant values redacted for visual clarity, see Appendix G

In Figure 5, we plot the adjusted linear prediction of years of punishment by vignette type with a specific focus on political views, reversing the scale so that the left side of the x axis represents liberal identification and the right side represents conservative, for ease of visualization. We find that the slope of punishment across the control condition is extremely flat for all ranges of political views. Consistent with our regression results, we see some effects of conservative political views on increased punishment in the DUI condition, but find that suggested punishment in this condition is much higher all along the spectrum of self-identified political views. Also consistent with the regression results is the much larger slope in the immigration condition. In fact, at the furthest tail of self-identified conservative views, the predicted punishment duration scores in the immigration vignette and DUI vignette are not statistically different from each other. This means that the participants who self-identified as the most conservative perceived that an immigrant driver unlawfully present in the country who caused death deserved the same punishment enhancement as a drunk driver who caused death.





We also plot the conditional marginal effects of political views on linear predictions of punishment duration with a 95% confidence interval, confirming the results above (Figure 6). In this visual depiction behavior at the tails of the distribution is shown to be highly differentiated, with self-identified liberal views assigning punishment in the control and immigration conditions very similarly, while respondents with self-identified conservative views seemed to assign punishment more similarly between the DUI and immigration conditions.





Discussion

Our results show that readers will indeed assign blameworthiness differently for the same criminal incident when we vary information about the scenario, lending support to our first hypothesis. When we presented readers with the control vignette, which included no cues about immigration status or impaired driving, respondents selected punishment durations of a little over 5 years. We argue that this relatively lower amount of punishment is reflective of that lack of moral cuing. In the absence of any detail about circumstances, readers conceptualized the death as closer to an accident, because the perpetrator culpability is not specified. When we used predictive modelling, we found no significant demographic patterns in reader responses. This

lack of influence of demographic characteristics suggests that we successfully retracted any cuing information from the control vignette that would prompt differential decision-making.

In contrast, in the DUI vignette, where we specify deviant behavior that has been entrenched as immoral (Schmidt 2014) we see mean punishment substantially increased to more than 9 years of prison time. We want to stress that participants were not just choosing a particular number of years, rather they were selecting within a given range. That means that participants on average assigned close to the maximum amount of punishment allowed in this scenario. Once again, we do not find that any particular demographic characteristic is predictive of recommended punishment. This second set of null findings again conforms to findings in the literature indicating that drunk driving gives rise to moral outrage, and this response has become culturally pervasive enough to nullify potential group differences.

In the immigration vignette, we see something different, where there is substantial variation across participants regarding punishment and moral blameworthiness. As we demonstrate in Figure 5, readers with more liberal political views (closer to 0) selected a punishment duration much closer to the control condition, where readers with conservative views (closer to 100) selected a punishment duration much closer to the DUI condition. There are several components that we think might help explain this difference in punishment assignment. First, the issue of illegal immigration in the United States is in many ways a partisan issue with research postulating that this political entrenchment has grown in recent years (Dionne Jr. and Suro 2008). Therefore, differential assignment of punishment by political views on a polarizing political issue is not altogether surprising. What is more interesting is the particular context in which it occurs. Importantly, there was nothing different about the conduct of the driver in the

control vignette and immigrant vignette, yet the proscribed punishments were very different.¹⁶ This implies that the same offense committed by someone without legal immigration status is perceived as more blameworthy than the same crime committed by someone who is not identified as lacking legal immigration status. This difference represents a very tangible consequence to differing interpretations of morality. This finding in particular merits future study to understand how political views may impact ultimate consequences for defendants in the criminal justice system, especially lawyers, judges, and laypeople involved in the justice system (i.e. juries) may bring their political ideologies into the courtroom.

Importantly, we did not assign an ethnicity to the driver, but rather only noted that he immigrated illegally as a minor many years ago. This likely presents a race cue of some kind, so the immigration could be proxying for racial resentment which has been shown to impact beliefs about illegal immigration (Hainmueller and Hopkins 2014). Another possibility is that the difference in punishment is measuring the distinct but related concept of xenophobia.

These possibilities are especially salient in the Minnesotan context. The largest two immigrant communities in Minnesota are from Mexico (about 64,500 foreign-born Minnesotans) and Somalia (about 33,500 foreign-born Minnesotans) (MSDC 2019). So, the blameworthiness differences we observe might result from anti-Mexican racism and/or a version of anti-Black racism. We have some evidence that our Minnesota participants were conscious of race and national origin around the time they participated in this survey.

To get a sense of how participants understood crime and culpability in their community, after responding to the experiment vignette we asked them if they were familiar with the recent

¹⁶ It is feasible that participants were concluding that someone without legal immigration status would not have a driver's license, making their criminal circumstances worse. However, we feel it is unlikely that this consideration explains the large amount of increased punishment assigned primarily by self-identified conservatives.

case of Mohamed Noor and Justine Damond. This case made headlines when Noor, an immigrant Somali police officer, mistakenly shot the unarmed Australian native Justine Damond who had called 911 to report a suspected sexual assault. Noor was found guilty of third-degree murder and manslaughter and sentenced to 12.5 years in prison, a marked difference in criminal justice outcomes compared to other police officers who killed civilians (Jackson 2019). Notably, one year earlier, Minneapolis officer Jeronimo Yanez was acquitted of the killing of Philando Castile (Jackson 2019). When asked if they were familiar with the Noor case, 58.12% of participants said they were at least a little familiar. When asked about whether or not the verdict was fair participants were divided (34.74% believed it was fair, 12.11% believed it was not fair, and 53.16% were not sure) and themselves brought up the issues of race and immigration status. One respondent wrote:

"The facts in that case were not significantly different than other cop involved shootings in which the cop was exonerated. There was a feeling of racial undertones to the conviction."

This represents a common theme among respondents: not necessarily a belief that Noor was innocent, but rather than inequality in the criminal justice based on race led to an unfair overall outcome. Participants struggled to choose a dichotomous marker of 'fair' but were able to articulate agreement with a guilty verdict – without endorsing the broader system of punishment. Another respondent compared the Damond case directly to the case of Castile saying:

"I think he should do SOME time, but not that much. Yes, he killed her. He didn't listen to her. He didn't follow training or protocol. However, other cops in the TCs [Twin Cities] have shot black, Hmong, Indian people etc. and were not sentenced. If this cop is getting 12.5, the one that shot Philando Castile should have gotten 25."

This respondent carefully articulates a disparity in blameworthiness relative to other cases that they conceptualize as similar. That is not to say that respondents were all in agreement. Many focused-on Noor as 'trigger-happy' or articulated a belief that police officers should be

held to a higher standard. Specific mentions of race or immigration status were generally avoided by participants who positively endorsed the outcome of the case, excluding one participant who suggested that:

"In my opinion he should have been deported back to his country with no chance of reentry."

These responses demonstrate patterns in assessing blameworthiness mentally – but also in articulating blameworthiness around race. Further testing with a similar vignette design could more directly test these possibilities.

This study is also limited in its generalizability to vehicular homicides in the state of Minnesota. Future research should expand crime types and social contexts to see if these patterns are reproducible in other places in the United States. Additionally, this analysis also only makes use of varying information about the offender (driver). Future work should consider varying the victim characteristics to more effectively measure the dyadic bias potentials between victim and offender.

Finally, we argue that this advances knowledge about the role of news media in constructing popular perceptions of moral guilt. All of the scenarios we presented here were derivative of the same set of base facts. Moreover, both of the two blameworthiness conditions might have been true, simultaneously, about the actual incident, and the decision about whether and how to include these aspects of the story would be in the discretion of the writer. ,. In other words, just because a driver had an elevated BAC level does not guarantee a news article reports on it, which may change the guilt perception of the perpetrator in that case. Evoking Schudson (2011), we do not mean to suggest that reporters' lying causes distorted perceptions. Rather, a different portrayal of the truth for any number of reasons (unknown facts, facts perceived to be uninteresting or not newsworthy, limits on length etc.) can change the contents of news

unbeknownst to news readers. In the case of our sample, nearly all had read crime news before and a vast majority in the specific context of Minnesota. This ubiquity further explains the amplified importance of context in crime news. Even if news readers are not called to make direct decisions about a particular crime they read about in the news, the cumulative consequences of news can lead to racial stereotyping, fostering inaccurate fear of crime, and reifying mis-perceptions of who commits crime do affect everyone in society (Barlow et al. 1995; Boulahanis and Heltsley 2004; Gilliam Jr et al. 1996; Sorenson et al. 1998; Thorson 2001).

Conclusion

The construction of news stories can substantially influence readers' judgments about blame and punishment for vehicular homicide offenders. By varying moral cues from neutral to negative in the same scenario, we demonstrate that readers select punishments around the midpoint when they lack information and select higher levels of punishment for universally condemnable moral behavior like drinking and driving. When faced with a morally controversial piece of information, like immigration status, we find that readers with differing political views assign different amounts of punishments. This finding underscores the importance of how news writing and presentation matters and how its influence can vary sharply according to pre-existing moral and political commitments of the reader.

CHAPTER 3

CRIME DOESN'T PAY:

QUANTIFYING THE COST OF DISTORTED DATA ON HOUSING MARKETS

Acknowledgements

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Introduction

In a newly digital marketplace, millions of people are no longer solely reliant on real estate agents or personal connections: they now can look for housing online. Two of the most popular online real estate websites, Zillow.com and Trulia.com record 73.5 million and 33.4 million unique users respectively each month (Feeney 2016). Some of these sites, like Trulia, use filters to project different types of data over the map area where consumers browse for potential homes for rent or for sale, giving searchers the option to view the results of different filters like school quality, the number of restaurants in the neighborhood, or even neighborhood crime data. Some of Trulia's filters have changed a little over time. Notably Trulia has changed the color ramp of their data (see Figure 7 below to compare earlier the earlier Trulia color ramp to today's iteration). For the purposes of this analysis, I focus on the crime filter provided by Trulia due to specific data collection and projection decisions that present an ideal opportunity to test the power of data projections.¹⁷

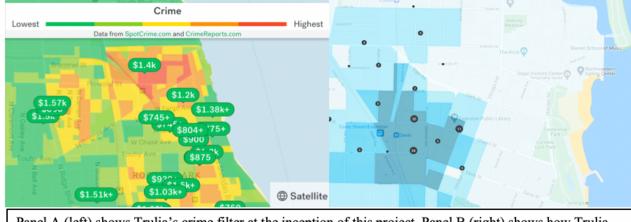


Figure 7: Sample Crime Maps from Trulia (before/after)

Panel A (left) shows Trulia's crime filter at the inception of this project, Panel B (right) shows how Trulia has altered the color ramp for the crime filter (as of May 2021).

¹⁷ In this study I take color cues from Trulia's older scheme because that was the color ramp in use at the time of data collection.

Trulia's crime filter plots crime as 'lowest to highest' using color ramps over a relative search area as specified by the user. According to Trulia's customer support page this data comes from places like CrimeReports.com. CrimeReports.com mines data from over 1000 participating agencies, however, they report on their website that "Each agency controls their data flow to CrimeReports, including how often they send data, which incidents are included." As a result, the crime maps on Trulia might match other institutionally derived crime maps or they might not simply due to data input.

However, even if we presume the underlying data is indistinguishable from other sources of crime data (which themselves are imperfect), Trulia also makes very specific choices in how they project the underlying data across the map. Critics of Trulia's filter say that by not weighting crime data by population, some highly populated areas might appear more dangerous or artificially appear to be criminal hotspots (Lucido 2011). Further Trulia does not distinguish between types of crime or specific geo-location when composing aggregate color labels, perhaps further clouding perceptions of what crime is happening where (Del Coronado Realty Group 2016). The current iteration of Trulia filters allows users to see individual criminal incidents but only for four categories of crime: theft, assault, vandalism, and burglary. This gives users an incomplete picture of both index and property crimes. Notably, these categories include crime against commercial entities like shoplifting (Trulia 2021).

Other crime data maps like Walk Score project their data differently, instead using estimates of population density and day-time population. A spokesman for Walk Score remarked that this change is essential because consumers would rather know the likelihood of victimization instead of a raw number of crimes in a given area (Smith 2014). Trulia is aware of the criticism, but has gone on record saying, "We believe engaged house hunters care more about what's actually happening in a neighborhood in regards to crime, not how likely they will be a victim of a crime given the population" (Wiggin 2014). While these projections differ substantially, there is no way for an average consumer to understand the impacts of the differing projection using Trulia.com. That is, there is no way to tell if a neighborhood would be equally dangerous under both projections of the same, presumably true, data. I predict that the differences in these projections could be substantial enough to affect consumer decision-making.

In this study, I use this use case scenario of online real-estate or housing websites and analyze how crime data projections in these contexts might have tangible financial consequences. Specifically, I will analyze how potentially distorted crime data projections might impact consumer decisions to purchase a home or perceptions of home value. In doing so, I will calculate a 'price of crime' that compares the financial costs of decisions made by consumers exposed to distorted crime data to consumers making decisions with differently projected crime data. I do this using a multi-stage experimental survey design on Amazon Mechanical Turk that invites study participants to evaluate hypothetical homes in the presence of different types of data distortion. I will briefly contextualize the study in relevant economic and fear of crime literature before turning to an extended analysis of the pre-survey testing done at the front-end of the project (N=100). Following this extended methodology, I introduce and analyze the main sample for the project (N=500) with a discussion of the results and their implications on decision-making, data distortions, and fear to follow.

The Importance of Information

Data is a powerful tool in individual decision-making and the creation of public policy. Data allow us to draw seemingly objective conclusions about the world around us and attempt to understand phenomena. Researchers analyze what happens when data is misleading, biased, or just false in studies of fake news, artificial intelligence, criminal justice and everything in between (Green 2020, Redman 2016, Robinson 1966, Slota et al. 2020). Of course, data are valuable sources of information that helps shape behavior and that can have concrete economic consequences regardless of its veracity, but these consequences can get even more insidious when the data is true. That is, the world of data cannot be so simply defined as 'intentionally false or poor quality' and 'true' data, rather there is a substantial gray area within the data distortion where decisions about how to project the same true data can be just as effective in changing decision-making. Because these projections are not fully known or interrogated by the consumers of data, they can become even more difficult to disentangle than data that is clearly dubious.

Circulation of information has undeniable economic outcomes. We can conceptualize some of these economic outcomes in a consumer-driven context using the Efficient Markets Hypothesis (EMH). EMH argues that market prices can reflect all available information about an asset, communicating to consumers and investors everything they need to know about that asset (Carruthers 2017; Fama 1970; Market Technicians Associations 2017). This would imply that markets manage to self-regulate (to an extent) and that this regulation and information is able to be gauged using prices as a sort of crude indicator.

EMH has not gone unchallenged, principally due to criticism about the lack of human nuance baked into the theory. For example, in his review of EMH Malkiel (2003) notes that economists have protested that psychological and behavioral elements are left unaccounted for. Additionally, econometricians argued that various features of the economy are actually more predictable than EMH would have us believe.

Moreover, EMH does not neatly account for the realistic situation in which information is not evenly distributed throughout a market or a society. Fama (1970) notes this distortion, but minimizes its effect asserting that freely available and agreed upon information is ideal, but not necessary for an efficient market. In contrast, Rothschild and Stiglitz (1978) lament this lack of focus on information, noting that such mundane matters are even relegated to footnotes. They argue for the importance of information in economic models, even suggesting that many important economic conclusions do not hold up in situations of imperfect information. Information discrepancy occurs when one party in a marketplace knows a lot and another party knows very little. Akerlof (1970) notably explains this uncertainty through a metaphor of a lemon car. In this case, the seller of the car knows it is a lemon, but the buyer is none the wiser. As such, the purchaser faces direct economic consequences as a result of unequal information. Akerlof uses this scenario to determine the economic costs of dishonesty. Carruthers (2017) concludes that these differences in information are especially important in labor and credit markets, even contributing to the recent financial crash. What this leaves us with is an imperfect information-sphere where distorted or missing information can still become the basis for decision-making.

How Information Becomes Data

Distorted or missing information can be effective, regardless of its veracity. As put by Thomas and Thomas (1928), "If men define situations as real they are real in their consequences" (527). In accordance with the Thomas Theorem it may not matter if information is actually true, as long consumers believe it is true (Merton 1995). It is this belief that drives decision-making that produces very real consequences. Manifestations of worry and fear in the stock market constitute a useful example of this phenomena. Summa (2008) details how fear about changes in stock, futures, and options markets can drive decisions. This and other similar analyses focus on how investors attach emotions to the financial landscape. For example, if they worry that a particular stock is going to plummet in value they might sell off that stock. In this instance, the financial consequence could be 1) profit 2) loss or 3) breaking even with intervening variables such as time and stress. The consequences of this fear response can exist even if the basis of that worry turns out to be false. Zhang, Fuehures, and Gloor (2011) explore a more direct pathway between fear and investor behavior with a study of twitter users and the stock market. By monitoring emotional tweets, Zhang et al. concludes that emotion on twitter can act as a predictor of stock market behavior (2011). This demonstrates how concern or fear might have an effect on market decisions. In this study I propose to push this idea one step further and engage the concept of fear in housing markets as a direct response to potentially distorted crime data. I propose that criminal data can act as a mechanism for emotional responses or risk calculations that may trigger behavior with economic consequences.

Applications in Housing Markets

The claim that misleading crime data might prompt decisions due to fear of victimization might seem radical. However, grounding this theory in the practical world of housing markets will demonstrate the plausible chain of logic. Information asymmetries are acutely felt in the housing market. Germaise and Moskowitz (2004) propose that housing markets can also present a unique opportunity to actually measure asymmetric information. Using property taxes, they find evidence that information itself is a significant consideration for consumers. One particular site of informational inequality is the relationship between real estate agents and individuals. Levitt and Syverson (2008) assert that real estate agents use their informational advantages to sell houses more quickly and cheaply than they treat their own homes. Homes owned by real estate agents sold at higher prices and were given more time on the market demonstrating how different information led to different behaviors and outcomes. I posit that these asymmetries are even more acute with the digitization of real estate markets.

Effects of Crime on Housing

Research has shown that crime has tangible effects on the price of housing (Thaler 1978; Troy and Grove 2008; Wentland, Waller, and Brastow 2014). Crime has the effect of lowering home prices. This is likely because few people want to live in areas where they are more likely to be victims of crime or will be more exposed to crime. Past criminal offending, or the presence of former offenders, in a neighborhood can also have substantial negative effects on home prices. Wentland, Waller and Brastow (2014) found this to be especially salient for sex crimes. Troy and Grove (2008) find that even positive features of a neighborhood can become negative features in the presence of crime. In cities, parks are generally considered a neighborhood positive unless the amount of crime surpasses a certain threshold. Beyond this threshold parks lose their status as safe community structures and become further threats of victimization (2008).

The big question is if people are actually willing to pay more to live in a neighborhood with less crime. Previous research indicates that they are, even when accounting for other preferences (Thaler 1978). This finding seems to indicate support for the same theoretical chain I described earlier but applied to housing markets (see Table 18). However, this research does not apply to the world of digital research and is not sensitive to questions about crime data projection, making my survey project a useful addition to the housing literature and the emerging literature on digital markets.

Theory	Housing Application		
1. Information asymmetries can affect decisions	1. Information asymmetries can cause some prospective buyers and renters to rely more on data presented on online housing websites when they do not have access to realtors or other local contacts		
2. Data can provide information	2. Crime data can provide information that changes how prospective buyers and renters evaluate potential homes or home prices		
3. Fear can contribute to decision- making	 Fear of crime can contribute to the decision to purchase a home by changing willingness to purchase or the price of a home 		
4. Decisions have tangible economic outcomes	 Homes in neighborhoods that appear safer cost more 		

Table 18: How Crime Data Leads to Economic Consequences

Fear of Crime

Crime is more than a facet of decision-making, it also has a unique power to inspire fear that may become important as homebuyers or renters decide what neighborhoods to invest in. A robust field of literature undergirds the importance of fear of crime, demonstrating the necessity for understanding how crime data in particular affects decision-making. Echoing the core message of the Thomas Theorem, fear of crime is characterized by what seems like a great paradox. Fear of crime does not correlate well with the actual crime rate – remaining relatively stable even as crime declines (Rader 2017). There are many possible explanations for how fear of crime can remain stable or increasing without a corresponding rise in crime including perceptions of vulnerability or differences across groups. It is important to note though, that it is not just fear of crime that stays stable. Perceptions of how much actual crime occurs are also divorced from reality. In 1983, 37% of respondents in a Gallup Poll said there was more crime in their area than there was a year ago (Dugan 2014). In 2013, 41% of respondents said there was more crime in their area than there was a year ago (2014). However, crime had been declining over the period (Gramlich 2020; LaFree 1999; Levitt 2004). In this way we find ourselves in a complex situation where perceptions of the base phenomena are distorted along with fear responses directed toward that phenomenon.

In general, researchers do find some variation in fear of crime by demographic group. Researchers conclude that women fear crime more than men, despite lower rates of victimization (Braungart et al. 1980; LaGrange and Ferraro 1989; Stanko 1985). Theories behind this disconnect range from perceptions of vulnerability, gender norms in society, male socialization to not admit to fear of crime, hidden or under-reported female victimization, or female fear around specific types of crime like sex crimes (Rader 2017; Reid and Konrad 2004; Riger and Gordon 1981; Sutton and Farrall 2005). Research also finds that the elderly fear crime more than their younger counterparts (Braungart et al. 1980), though some researchers argue this is actually due to measurement error (LaGrange and Ferraro 1989). Research on racial/ethnic and social class correlates of fear of crime are sparser, though some studies have concluded that poorer people are more afraid of crime and that fear of crime does vary by racial group (Boulahanis and Heltsely 2004; Ortega and Myles 1987; Pantazis 2000). Residents of racially heterogeneous neighborhoods often reported a higher fear of crime, but this is not necessarily related to actual increases in crime (Chiricos, Eschholz, and Gertz 1997).

Criminologists studying fear of crime historically agreed that fear of crime is a way of understanding perceived risk, with updates to understand that generally, precautionary behaviors and likelihood of risk can be taken together to predict fear of crime (LaGrange and Ferraro 1987; LaGrange, Ferraro, and Supancic 1992; Mesch 2000). However, scholars like Liska, Sanchirico, and Reed (1988) and Rader (2004) argue that the emotional component of fear should not be reduced out of that definition. Liska et al. (1988) posits that changes in behavior, for example, could be both a cause and a consequence of fear crime. Taking a security system as an example, do you get a security system because you're already afraid of crime? Or does interacting with the system that was at your house when you moved in over and over make you more afraid? In this way, there is perhaps a reciprocal feedback loop between the two concepts.

The distinction between victimization risk and emotional fear becomes methodologically important because something as simple as survey question wording can cue different elements of fear of crime (Rader 2017). Further, the conceptual cloudiness surrounding fear of crime can render the actual fear phenomenon unmeasurable (Ferraro and LaGrange 1987). Rader (2017) identifies four fundamental problems 1) questions about feelings of safety that actually measure perceptions of the likelihood of victimization rather than the emotional fear of a crime happening to oneself, 2) not being specific about the type of crime, 3) not including location specific cues, 4) not using a measure (like a Likert scale) that is capable of measuring the magnitude of fear of crime. This methodological critique pays particular attention to the relationship between individuals and their neighborhoods. This type of conceptualization about the safety within neighborhoods provides a pathway for considering how fear crime can be reflected in housing decision-making.

A number of scholars have recently paid great attention to the methodology of measuring fear, including the neighborhood component. Chiricos et al. (2000) included two banks of Likert scale questions that asked respondents how fearful they were of certain crimes on a scale of 1 - 1

10 and how safe they felt in their neighborhood on a scale of 1-4 in an effort to separate the constructs, provide geographical context, specify crime types, and estimate magnitude of fear. Shi (2021) separated the constructs slightly differently by asking respondents how afraid or unafraid they were of crime and how likely or unlikely they think they are to become a victim, which very intentionally estimated fear and likelihood of victimization as separate. Boulahanis and Heltsely (2004) were similarly specific, using 14 Likert scale questions to measure just the fear of crime and its potential effects on housing decisions are challenges inherent to crime data and crime itself.

Challenges with Criminal Data

Crime data can be difficult to work with due to complexities within the data and how we interpret that data (Baumer 1985; Neapolitan 1996; Potter and Kappeler 2006). Crime data is usually built using information from multiple agencies who have different personnel, standards, and reporting policies. Of particular difficulty are cross-national/cross-regional and multi-year trends that inform perceptions of criminality. In his study of cross-national crime data Neapolitan (1996) found that choice of data sources directly affects relationships with independent variables. Additionally, this did not just vary by data source, but also by the type of crime that was studied. Here in the United States even main bastions of usable crime data, like the UCR, are voluntary and contain large amounts of imputed data (Maltz 1999).

These challenges call into question the validity of the data that researchers and consumers use to make decisions and formulate accurate understandings of crime. Beyond logistical trouble with the data, we also encounter difficulties in interpreting and disseminating that data. As Baumer (1985) points out, research on the fear of crime to this point has assumed that fear is a rational response to potential victimization. This belief was drawn out of data almost entirely from urban neighborhoods. When testing this theory Baumer found that the current models only held for urban neighborhoods, challenging widely-held assumptions in criminal data. Potter and Kappeler (2006) argue that misleading media packaging of crime actively increases fear and changes perception about who perpetrates crime and their motives. Additionally, media outlets do not exist in a vacuum. The flow of framed information is not uni-directional; rather it is a socio-cognitive relationship involving multiple actors. Pan and Kosicki (1993) describe the shared cultural universes of sources, journalists and audiences in the creation of news media. This creates a cycle of information that feeds appetites for sensationalism and intrigue, but also reinforces perceptions that such events are visible and frequent. Applied to crime data in particular, this can lead to distorted perceptions on how often crime actually occurs. Violent crimes like homicide are among the most sensationalized (Schildkraut and Donley 2012; Soothill et al. 2002). In this sense, crime data becomes a source of information that contributes to the emotional state of consumers. In this way, crime data can provoke fear that may impact future decision-making or behavior.

Hypotheses

This project is driven by three main hypotheses that serve to collectively progress our understanding about how a projection-based data distortion could have financial consequences on consumer decision-making. In order to accomplish this I need to test multiple facets of the use-case including: if crime data is important to potential renters/buyers relative to other types of available information, whether or not a change in data projection substantially changes crime maps, whether or not this change is enough to change purchasing or valuation decisions, exploring different potential magnitudes of projection distortion, and finally exploring potential reasons why consumers care about different pieces of information. In theorizing this project, I

generate three main hypotheses that I unfold in order below.

H1: Homebuyers over-rely on crime data (compared to other information) to help them make decisions.

H2: Distorting these crime data can effectively change the perceived value of the house and the perceived likelihood to purchase the house.

H3: These decisions are rooted in fear of crime.

Methods

I use a 2-part survey design to create a housing game that asks participants to view hypothetical houses and estimate their monetary value and comment on their willingness to purchase. The experiment begins with a text-based pilot survey to prove out the underlying mechanics of the game and then I launched the larger game/survey on a larger sample.

Pilot Survey

The pilot survey was conducted with principle aims designed to alleviate some methodological assumptions in the final sample. First, I wanted to determine whether participants can assign a monetary value to a home given a relatively small amount of information, a hypothetical scenario, and limited time. Further, I needed to test if it was possible to get meaningful price variation with changing characteristics of hypothetical houses. Second, I wanted to test whether or not participants were able to naturally separate the related concepts of monetary value and willingness to purchase a home or if the hypothetical nature of the scenario would render these responses indistinguishable. Third, I needed to test whether or not crime is as salient of a feature in purchasing decisions as previous literature implies. In order to accomplish these aims, I launched a test survey of 99 individuals on Amazon Mechanical Turk that described a hypothetical house, presented a purchasing scenario, and asked participants how much they think the house costs, whether they would buy it, and how confident they were in their purchasing decision. Participants were compensated at a rate of \$12 per hour.

Participants were given the following hypothetical purchasing scenario for each of 5 hypothetical properties: "Imagine you have all the resources you need to buy a home. The text below describes a home that is currently for sale. You are given information about the house and the surrounding neighborhood. Carefully read and consider the information before answering the questions." This scenario was designed to release as many constraints as possible. Participants were instructed to read all of the information provided in a text-based figure about each house. An example of the text provided for each house is given below in Figure 8.¹⁸ Houses were intentionally constructed to vary widely, ranging in number of bedrooms, bathrooms, and interior style. I also selected several variables to vary on a spectrum of low to high, representative of the variety of filters provided by Trulia. These included crime, foreclosure, schools, retail availability, and average neighborhood home value. I printed these features in colors ranging from red – yellow – green to match the type of information provided by Trulia filters.

¹⁸ See Appendix I for a complete list of the features for houses 1-5.

Figure 8: Sample Survey Text, Pilot

Number of Bedrooms: 3 Number of Bathrooms: 1 Description: This house is furnished in a Classic style. The house itself is in renovated condition. Crime: High Foreclosure: Low School Districts: Above average Amount of Restaurants/Shopping Nearby: Average Average Neighborhood Home Value: Low-priced

Participants were then asked to input how much they thought the described home would cost in an open-text box with no context. This was intentionally difficult, compared to providing a benchmark or slider, to see how well participants could achieve variability without additional assistance. I then asked participants to self-report their confidence in their valuation using a 5-point Likert scale before having them answer a dichotomous question about willingness to purchase the home (asked as: would you buy this home? Yes/No). Participants were then given a set of housing and demographic debrief questions to contextualize their responses.¹⁹

Participants reported being familiar with online housing websites like Trulia, with 92.93% reporting that have visited an online housing website. Further, 56.57% report using an online housing website with the intent to rent or buy a home, further asserting the general familiarity of the participant sample with the use-case.

¹⁹ I did not attempt to balance valuations across participants from different housing markets, since every participant rated every house. That is, even if two participants came from wildly different housing markets (say an average home value of 200,000 vs. 1.5 million) their valuations are represented across all 5 houses and do not inhibit me from calculating percent differences across the population of houses.

	Counts	(%)
Visiting online housing websites	Counts	(70)
Have visited an online housing website	92	92.93
Have not visited an online housing	/_	,_,,,
website	7	7.07
Reasons for visiting online housing sites		
Looking with intent to rent or buy	56	56.57
Helping someone else who had intent to		
rent or buy	9	9.09
Just looking	27	27.27
Have not visited an online housing		
website	7	7.07
Total	99	100.00

Table 19: Familiarity with Online Housing Websites, Pilot

The pilot results in Table 20 (below) demonstrates that participants were able to assign variable monetary values to different houses, even in the absence of constraints. Assigned home values ranged substantially, with averages from ~148k (House 2) to ~228k (House 3), indicating that participants were assigning different monetary values to different combinations of information.

Table 20: Costs of Houses (USD), Pilot Survey

	Mean	Median	Std. Deviation
House 1	216,743.40	175,000	227085.6
House 2	148,072.70	140,000	84793.57
House 3	227,554	200,000	122485.6
House 4	213,604	200,000	121832.4
House 5	184,219.30	162,000	108958.2

To further evaluate whether assigning monetary values so quickly was difficult for participants, I also asked them to self-report their level of confidence in their valuation for each house. Across the entire sample, approximately 27.48% of participants reported being somewhat or very unconfident meaning that a substantial proportion of the sample felt neutral or confident in their ability to provide a valuation (Table 21).

Table 21: Average Confidence in Valuation Across All 5 Houses, Pilot

	(%)
Very confident	3.43
Somewhat confident	46.67
Neither confident nor unconfident	22.42
Somewhat unconfident	20.40
Very unconfident	7.08
Total	99

Table 22: Willingness to Purchase, Pilot

	Yes (%)	No (%)	Ν
House 1	5.05	94.95	99
House 2	6.12	93.88	98
House 3	27.55	72.45	98
House 4	53.06	46.94	98
House 5	22.45	77.55	98

The pilot study also verified the usefulness of posing monetary valuation and willingness to purchase as separate questions (Table 22). For example, participants valued houses 1 and 4 very similarly (a difference of about \$3,000), but reported vastly different willingness to purchase each home. 5.05% of participants said they would

purchase House 1, but 53.06% of participants said they would purchase House 4, demonstrating that there is a decision-making schema for price evaluation that is at least somewhat different that the decision-making schema for willingness to purchase. Notably, participants were generally unwilling to purchase, but this is likely due to the intentional construction of the hypothetical houses at various extremes to prompt response variation.²⁰

The final goal of the pilot sample was to test what pieces of information were most salient to participants in their decision-making process. Table 23 (below) lists all the tested characteristics in order of importance, based on the percentage of participants that indicated that each feature was important. As predicted, crime rose to the top as the single most important piece of information. To follow were unchangeable elements of the home like bedrooms and bathrooms, followed by schools, average neighborhood value, and the description of the house. Participants were split on the value of schools, with some (22.22%) deeming it unimportant, which reasonably follows the differing usefulness of schools to individuals (i.e. people who have no interest in children or who plan to homeschool might not be invested in school quality). Participants found the availability of restaurants less important (27.55%) and the amount of foreclosure to be the least important by a substantial margin (14.29% deeming it important). This is particularly interesting as crime and foreclosure rates are often conceptualized as related to each other, though Kirk and Hyra (2012) find that this correlation is spurious and instead similar neighborhood processes give rise to both elevated crime and foreclosure. Nevertheless, crime

²⁰ The maximization of variation was done intentionally because if there was no visible effect in extreme scenarios, it would be unlikely that a more nuanced effect in the full sample would produce any meaningful results.

and foreclosure often are elevated in similar locations, so the perception that foreclosure information is not important is worth investigating in the future.

	Important (%)	Neutral (%)	Unimportant (%)
Crime	90.82	7.14	2.04
Bedrooms	87.76	11.78	1.02
Bathrooms	76.53	19.39	4.08
Schools	59.6	18.18	22.22
Average Value	52.04	40.82	7.14
Description	50	35.71	14.29
Restaurants	27.55	47.96	24.49
Foreclosure	14.29	45.92	39.8

Table 23: Importance of Different Pieces of Information, Pilot

Notes: N=98

Finally, I conducted an exploratory linear regression using collected demographic conditions (age, sex, race, ethnicity, education) to crudely test whether or not specific demographic characteristics were driving differences in decision-making. Table 24 demonstrates that demographic characteristics do not explain differences in valuation, aside from a weak negative relationship between white race and price estimation.

	Pilot Sample
	b/se
Age	
30s	10498.06
	(26272.27)
40s	33642.14
	(29242.79)
50 or older	45190.03
	(30770)
Male	36194.44
	(20588.88)
College Degree	-32974.49
	(20038.89)
White	-68321.77*
	(27325.83)
Hispanic	7256.02
	(46544.18)
Constant	239520.55***
	(32361.84)
R-sqr	0.14
dfres	91
BIC	2586.0

 Table 24: Effect of Demographics on Average Price Valuation, Pilot

Reference groups = 20s, female, non-white, not Hispanic

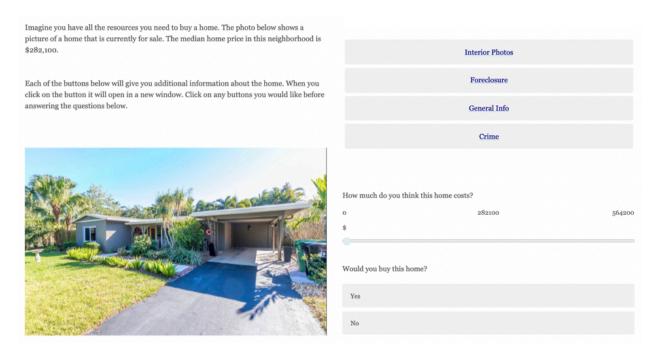
Overall, the pilot survey successfully demonstrated that participants are able to assign varied monetary values to hypothetical houses given specific information about related features. I also determined that valuation and willingness to purchase are indeed separate, but related, concepts. I also confirmed that crime is the most important feature to participants, along with establishing a sort of benchmark for the salience of other features. Using the insight gleaned from the pilot survey, I designed a survey experiment for the main sample, with the goal of constructing a tight design that would allow for parsimonious analysis. I launched a 500-person survey on Amazon Mechanical Turk to test how a data projection distortion like the one used on Trulia would affect consumer decision-making. I designed two aims to replicate the conditions of the website, where users can opt into using crime information and see the surrounding area. The 3rd aim was to calculate any difference resulting from the data projection distortion to see how much these projection decisions matter.

- *Aim 1*: To test if giving participants the option to use only certain pieces of information changes how they make decisions
- *Aim 2*: To test if visual information about the surrounding area of a house is salient in decision-making,
- *Aim 3*: To calculate any 'cost' of a data distortion by taking true crime information and projecting it differently.

I accomplished this by creating a sort of 'housing game' that used identical mechanics for both the treatment and control groups. Participants were compensated with \$7.50 and the survey took 10-15 minutes to complete.

Figure 9 below visually depicts a sample housing scenario (1 of 5) from the main survey. Once again, the purchasing scenario was given without constraints on personal resources across the 5 homes. This time, participants were shown a photograph of the home, provided with a median home price, and were invited to click on any of the buttons they choose (on the right) to open a pop-up window with additional information about the home.²¹ I chose 4 information features based on the results of the pilot survey: crime, general information, description, and foreclosure and projected the four buttons in a random order.²² I once again asked participants to provide a monetary valuation for the home, this time on a sliding scale with a labelled median, and to state whether or not they would buy the home. Each participant was asked to decide on 5 houses and to respond to some debrief and demographic questions at the conclusion of the survey.

Figure 9: Sample Survey Text, Main Sample



To participants, it was not distinguishable whether they were in the control or

experimental survey group, but the participants were divided into equal groups based on

²¹ Photographs of the home were taken from MLS listings.

²² I decided in this case to choose the most important features (crime, bedrooms, bathrooms (the latter two subsumed under the general information category), interior photos as a more polarizing description feature, and foreclosure as an unimportant feature that is nevertheless correlated with crime. A sample of these images is available in Appendix J.

differential data projection. To do this I first gathered 'true' source data to undergird the data distortion. I collected crime data, population data, and foreclosure data from the state of Florida for each county within the state.²³ I then created crime and foreclosure maps for real geographies in Florida, taking a snapshot of a focal county and the area the around it. Focal counties included: Lake, Miami Dade, Palm Beach, and Osceola.²⁴

Each crime and foreclosure map was projected in two ways: 1) as a simple count of the number of foreclosures or the number the crimes as a replication of how Trulia projects crime, 2) as a foreclosure rate or violent crime rate that takes population and the salience of certain types of crime into account. An example of the projections is given in the map visualization below (Figure 10).



Figure 10: Example Crime Map Projection, Counts (left) and Rates (right)

²³ Population data from the US Census, crime data from Florida Department of Law Enforcement, foreclosure data from Attom Data Services DLP 3.0 Foreclosure data set.

²⁴ In the survey, no labelling or zoomed out map images were provided in order to lessen the chance that participants were familiar with Florida geography. The maps are visualized in this manuscript in Figures X to X.

Because I opted to use real data, I had less control in designing an ideal typology of changes in projection, but I was able to obtain sample variation in both crime and foreclosure across several conditions as shown in Tables 25 and 26 below. I report each change in several ways using the counts projection as the baseline to which I compare the projection change (i.e. when I project violent crime or foreclosure rates instead of raw counts). First, I report the change as a color change in the county the house is located in, literally transcribing the change to the color ramp in each map visualization. Next, I report the change directionally (increasing or decreasing) and as a magnitude (a number) that shows how much higher or lower on the color ramp the new projection is. Finally, I report a general trajectory measure of how crime or foreclosure changed in the area surrounding the house (i.e. adjacent counties).

	Local Crime (color change)	Local Crime (qual. change)	Area Crime (qual. change)
House 1	Green to orange	Substantial increase (+3)	Increased
House 2	•	•	•
House 3	Red to orange	Small decrease (-1)	Increased
House 4	No change	No change (0)	Increased
House 5	Green to red	Substantial increase (+4)	Increased

Table 25: Changes in Crime from Counts to Rates, Main Sample

Table 26: Changes in	Foreclosure from (Counts to Rates	, Main Sample

	Local foreclosure (color change)	Local foreclosure. (qual. change)	Area foreclosure (qual. change)
House 1	Green to light green	Small decrease (-1)	No change
House 2	Light green to red	Substantial increase (+3)	Decreased
House 3	•		
House 4	Red to orange	Small decrease (-1)	No change
House 5	No change	No change (0)	No change

I then looked up median home prices on Zillow for a 3-bedroom, 2-bathroom singlefamily house in each county to establish a realistic benchmark for home value. All of the houses used in the main sample were constructed to be as similar as possible. Number of bedrooms, number of bathrooms, square footage, nature of the interior photos etc. were all controlled to be within a very narrow window of variation. A small pilot survey was disseminated to a nonrandom sample of individuals to test if the houses were comparable.

The success of this survey design hinges on whether the survey groups, those that received the data projected as simple counts (hereafter referred to as counts) or population and crime-adjusted rates (hereafter referred to as rates), are comparable. Initially, 250 participants had been assigned to each group, but several responses were dropped due to data quality concerns so the final counts sample was 237 participants and the final rates sample was 231, meaning that 93.6% of the collected data was deemed suitable for analysis. Table 27 lays out the main demographics of the sample, demonstrating that the two groups are largely comparable.

Both groups were very similar by age, with the majority of respondents reporting being in their 20s and 30s. The counts group was slightly more female (44.92%) compared to the rates group (38.53%). A majority of participants across both groups made \$25,000 - \$49,000 per year. Both groups reported being highly educated, with ~54% of each group reporting that they hold a bachelor's degree or higher. Both groups were vast majority white, with 83.05 of the counts group identifying as white and 84.42% of the rates group identifying as white. Approximately 90% of each group also indicated that they were not Hispanic or Latino. While this sample is not representative of the United States it does provide distinct advantages for studying individuals who make decisions online. That is, Turkers are a known population of digital decision-makers who may be uniquely likely to use something like an online housing website.

	Counts (%)	Rates (%)
Age		
< 20	0.84	0.43
20s	31.22	27.71
30s	43.46	42.86
40s	11.82	19.48
50 or older	12.65	9.53
Gender		
Female	44.92	38.53
Male	54.66	61.47
Other	0.42	0
Income		
< 15,000	10.22	11.74
15,000 - 24,999	10.21	11.74
25,000 - 34,999	17.45	14.78
35,000 - 49,999	22.55	21.74
50,000 - 74,999	23.4	20.43
75,000 - 99,999	7.66	11.74
> 100,000	8.52	7.82
Education		
Less than high school diploma	0.42	0.87
High school diploma/GED	13.5	14.29
Some college or vocational school	32.49	31.17
Bachelor's degree	45.99	45.45
Post-baccalaureate degree	7.59	8.23
Race		
White	83.05	84.42
Black	4.24	4.33
Asian	8.47	5.63
American Indian/Alaskan Native	1.27	0.87
Other	2.97	4.75
Ethnicity		
Hispanic/Latino	10.17	9.21
Not Hispanic/Latino	89.83	90.79
Ν	237	231

Table 27: Demographics Main Sample

Levels of reported familiarity with online housing websites was very similar to the pilot sample with 89.87% of participants reporting having visited online housing websites in the past (Table 28). 56.54% of participants report using online housing websites practically – either to look for housing for themselves or to help someone else.

	Counts	(%)
Visiting online housing websites		
Have visited an online housing website	213	89.87
Have not visited an online housing website	27	11.39
Reasons for visiting online housing sites		
Looking with intent to rent or buy	112	47.26
Helping someone else who had intent to rent or buy	22	9.28
Just looking	79	33.33
Have not visited an online housing website	27	11.39
Total	237	100.00

Table 28: Familiarity with Online Housing Websites, Main Sample

Results

Participants continued to find crime information to be important after playing the housing game (86.08 - 87.45%), but it was no longer the most important decision-making feature. In the main sample, I used photographs of the interior and exterior of each home rather than text-based description to describe décor style and condition. Participants in both conditions agreed that photos were important (95.32% in counts and 89.61% in rates). General home information, which included square footage and number of bedrooms and bathrooms was also generally considered important (74.03 - 80.43%). Foreclosure was the least likely to be indicated as

important, with a relative majority of participants in both conditions considering foreclosure data to be a neutral piece of information (Table 29).

	Counts			Rates		
	Important (%)	Neutral (%)	Unimportant (%)	Important (%)	Neutral (%)	Unimportant (%)
Photos	95.32	4.26	0.43	89.61	8.23	2.16
Crime	86.08	10.55	3.38	87.45	9.09	3.46
General Information	80.43	15.74	3.83	74.03	21.65	4.33
Foreclosure	26.16	48.52	25.32	23.81	40.69	35.5

Notes: Counts 237, Rates 231

Reasonably satisfied that the two survey groups were comparable, I next did two calculations to compare the group that received the counts data and the group that received the rates data for each house (Tables 30 and 31). Table 30 shows a calculated monetary difference and percent difference for each house using the average price estimate provided by participants in the full sample and in each separate group. The results show that there was some variation between the two groups, but the percent difference in price valuation was relatively small except perhaps in the case of House 5.

	Full sample (av \$)	Counts (av \$)	Rates (av \$)	Difference	% Difference
House 1	246,362.9	241,276.9	251,298.7	- 10,021.8	4.07
House 2	228,114.2	221,258	234,796.8	- 13,538.8	5.94
House 3	248,841.3	254,517.1	243,309.1	11,208	4.5
House 4	258,712.5	266,732.5	250,895.5	15,837	6.12
House 5	279,084.4	261,664.7	296,063	34,398.3	12.34

Table 30: Costs of Houses by Experimental Group (USD), Main Sample

What changed more substantially across survey groups was willingness to purchase each home. I replicated the percent difference calculation for each home (Table 31) to see how widely the group that received the counts data and the group that received the rates data varied for each house. Here the difference was much more substantial with percentage differences ranging from 9.31% to 84.44%. Participants in the main sample were much more willing to purchase homes than the pilot sample, with 4/5 homes receiving majority likelihood to purchase in at least one condition. In the case of two homes, House 1 and House 4, majority opinion actually flipped in the presence of the data distortion. In the counts group 60.34% of participants were willing to purchase House 1 compared to only 33.91% of participants in the rates group. For House 5, 74.58% of participants were willing to purchase in the counts group compared to 30.3% in the rates group. These results support my hypothesis that, all other things equal, data distortions of true crime data can affect consumer decision-making. However, in order to fully make meaning of these distortions, we must evaluate each House individually and more qualitatively since the distortions themselves can be complex and move in different directions.

	C	Counts	I	Rates	% Difference
	Purchase (%)	No Purchase (%)	Purchase (%)	No Purchase (%)	
House 1	60.34	39.66	33.91	66.09	(-) 56.09
House 2	62.87	37.13	52.38	47.62	(-) 18.2
House 3	31.22	68.78	41.99	58.01	29.42
House 4	60.34	39.66	66.23	33.77	9.31
House 5	74.58	25.42	30.3	69.7	(-) 84.44

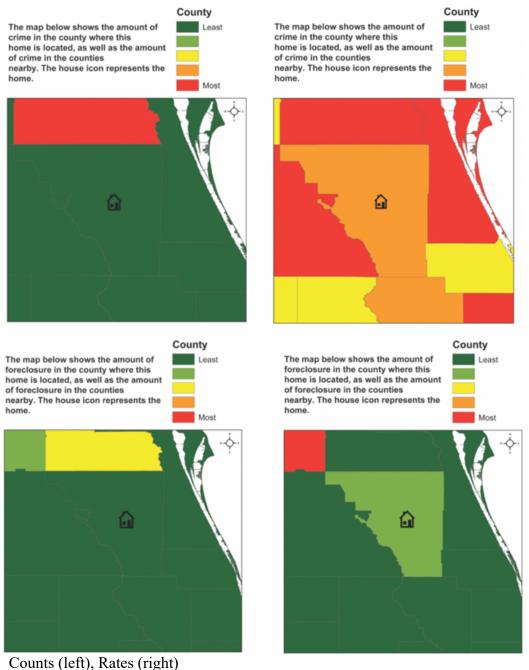
Table 31: Willingness to Purchase, Main Sample

Notes: Counts 237, Rates 231

Map Analysis

In the section that follows, I visualize each set of maps and provide some qualitative evaluation of the visual change in the data to compare against the calculated difference in price and purchase likelihood. Because participants reported finding the crime information more important by a substantial margin, I will constrain my analysis here mostly to crime-related findings.

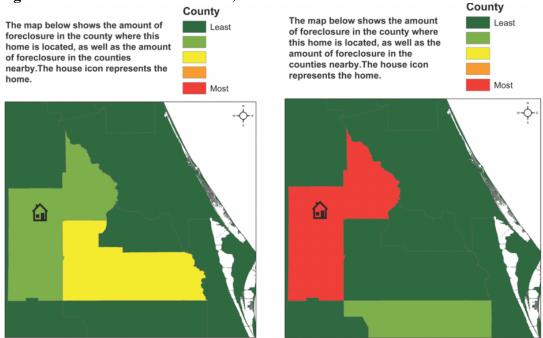
Figure 11: Crime and Foreclosure, House 1



House 1 was subject to a substantial projection change in crime - where a change in data projection from counts to rates would dramatically increase the visual appearance of crime, but leave foreclosure rates only minimally decreased (Figure 11). In this case, the crime in the local area of the house and surrounding geographies increased substantially using the rate of violent crime projection. The price valuation change between experimental groups was negative \$10,021.8 suggesting that participants found the house less monetarily valuable in the rates condition, though the percentage difference was relatively small at only 4.07%. However, House 1 saw a substantial change in willingness to purchase. 60.34% of participants were willing to purchase the house in the counts condition (Figure 11 left), but only 33.91% were willing to purchase the same house in the rates condition (Figure 11 right) comprising a percentage difference of 56.09%.

House 2 did not feature crime information at all, in part to test whether, in the absence of crime data, foreclosure data dramatically worsening would have any effect on willingness to purchase of monetary valuation (Figure 12). There was some movement, with a valuation change of negative \$13,538.8 and a percentage change of 5.94%. Interestingly, while the change in price valuation was larger than for House 1, willingness to purchase changed substantially less between groups with a percentage difference of -18.2%. This provides some early evidence that foreclosure may have less impact on willingness to purchase (further supported by participants indicating that foreclosure rates were less important to them when choosing a home), but may still have similar implications to crime for perceptions of monetary value.

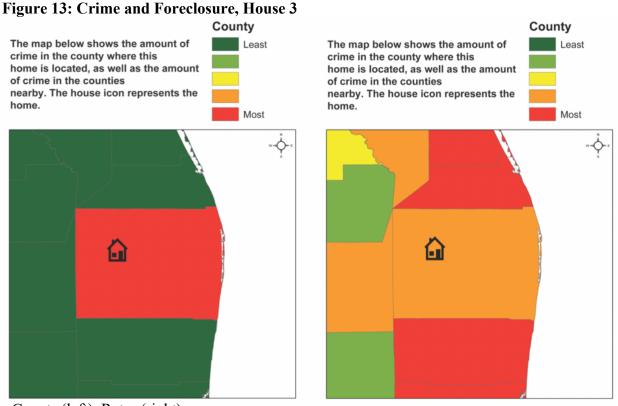




Counts (left), Rates (right)



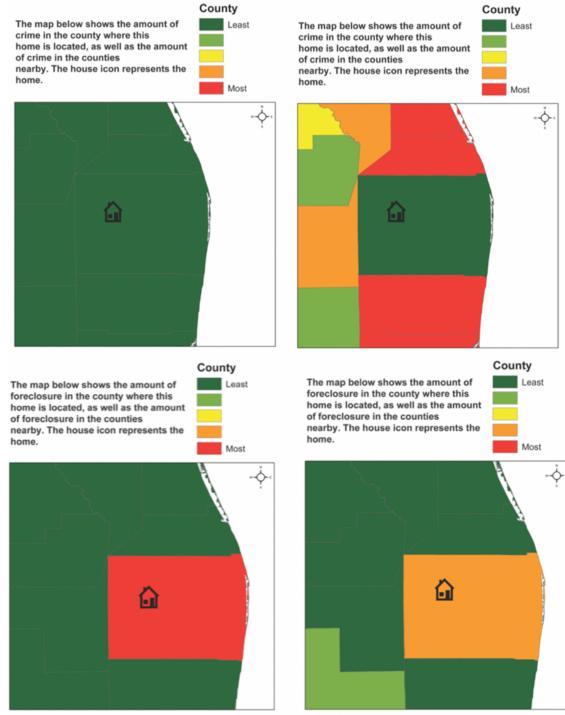
For House 3 (Figure 13 below) I did the opposite and redacted information about foreclosure, only projecting crime map data for both survey groups. The rate projection featured a slightly lower local crime rate, but a much higher amount of crime in the surrounding counties. Interestingly, participants valued the rate projected house (Figure 7 right) \$11,208 higher than the count project house, for a percentage difference of about 4.5%. Participants were also more willing to purchase the house in the rate projected condition, despite seemingly higher crime rates in the surrounding area (percent difference of 29.42%). There are several interesting possible explanations for this phenomenon, perhaps that the house in the count projected map looks worse because crime is so much lower in its neighbors or perhaps area crime is simply not as salient to prospective home buyers as crime in the immediate area.



Counts (left), Rates (right)

For House 4 (Figure 14), I manipulated the area crime projection, leaving the immediate area crime projection unchanged and the foreclosure rate only minimally improved. Respondents indicated that the house was more valuable in the rate projection (+ \$15,837) with a percentage difference of 6.12%. But participants did not respond to the projection with any strong differentiated signals about willingness to purchase. Willingness to purchase increased, but with a more modest percentage difference of 9.31%.

Figure 8: Crime and Foreclosure, House 4

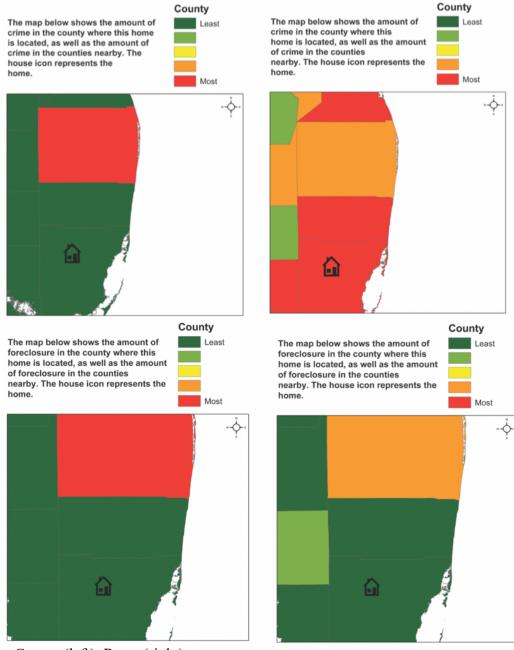


Counts (left), Rates (right)

There are several possibilities here that should be explored more in future work about the interaction of the regional crime compared to the localized crime rate. It is plausible that participants may have been relating that the rate projected house would be more expensive relative to the areas around it due to increased crime in the surrounding area. However, it would be equally plausible that a house may have less monetary value if it were surrounded by crime-heavy areas. Future work should specifically prove out this distinction.

Finally, House 5 (Figure 15) was the most dramatically different in the crime data projection. House 5 went from Dark Green to Red, indicating a move from the lowest crime to the highest crime. Crime in the surrounding area also increased while foreclosure remained unchanged. House 5 experienced the most dramatic monetary valuation change of negative \$34,398.30 and a percentage change of 12.34%. Even more dramatic was the change in willingness to purchase across survey groups. The count projected group was strongly in favor of purchasing (74.58%) whereas the rate projected group was strongly against purchasing (30.3% said they would purchase). This constituted a percentage difference of negative 84.44%. This lends credence to the theory that a change in the projection of true crime data could greatly sway consumer decision-making and provides some evidence that it might even have monetary consequences.

Figure 15: Crime and Foreclosure, House 5



Counts (left), Rates (right)

Taken in sum, all houses that experienced substantial (+3 or +4 color changes) changes in their projections saw some decrease in monetary valuation and willingness to purchase. This was true in the case of distorted foreclosure (House 2) to a smaller extent, but was dramatically true in substantial crime distortions (Houses 1 and 5). There was also some evidence that surrounding area effects matter, though the specific direction of those effects is less clear as worsening adjacent area crime seemed to make houses slightly more desirable.

Discussion

This study diverges from previous work in an important way: all the distorted data is true. Rather than simply suggesting that bad data is bad or that misleading data is misleading, this work suggests that data distortions can also arise from intentional decisions about how to project data. Projecting data in any given way is not in and of itself a distortion, however, when the stakeholder that relies upon that data has no agency to easily ascertain the consequences of that projection, data distortions can still be present. This becomes especially important in something like housing markets, that are already plagued by information asymmetries (Levitt and Syverson 2008). Data distortions via differential data projection can become particularly insidious when the data itself is subject to fear and misperception. Substantial research demonstrates that fear of crime is not well correlated with crime itself (Rader 2017) and that even the data we have about crime is likely incomplete and difficult to interpret (Baumer 1985; Neapolitan 1996; Potter and Kappeler 2006). This puts consumers in a situation where they are facing compounding information asymmetries as they make high stakes decisions about purchasing or renting housing. Importantly, it is consumers with less resources and insider knowledge who must logically rely more on whatever data is available to them, therefore creating an incubator where distorted data projections can act to exacerbate or reify existing inequality.

Over the course of this work I found support for all 3 of my layered hypotheses. I predicted that homebuyers would over-rely on crime data compared to other information as they

made decisions. Support for this hypothesis can be found in two places: 1) participant selfreports about the broad importance of crime as a selection feature across the pilot survey and main sample, and 2) the results of the data projection analysis that showed that the two houses (House 1 and 5) with the strongest crime projection change also had the most substantial change in willingness to purchase and/or price valuation.

My related second hypothesis predicted that distorting crime data through differential projection could yield consequences for price estimation and willingness to purchase. This hypothesis was also supported by the calculations provided in Tables 30 and 31. Results indicated that increases in crime (and to a lesser extent foreclosure) in the local area of the house yielded lower value estimations and substantially decreased odds of purchasing. At a larger geographic aggregate increasing crime seemed to have the opposite effect and increase both valuation and willingness to purchase the home, given that the crime level in the local vicinity of the house remained unchanged or improved.

Finally, I turn to hypothesis 3, where I predicted that respondent decisions are rooted in fear of crime. Admittedly, the relationship between decision-making and crime data as I have described it so far is not necessarily due to fear. It could be based on a perception of properties in more dangerous areas being suboptimal investments. It is also unclear from the set-up of the housing game how I could parse likelihood of victimization for emotional fear of crime. What I did to start exploring this concept was provide an open text response question in both the pilot and main survey, right before asking participants to rank the study features by importance.²⁵ This question asked participants to state what they thought was the single most important thing to

²⁵ This was done in an effort to not guide participants to crime as the 'correct' answer. Indeed, not all participants responded that crime was their most substantial concern. The most common answer besides crime was location, a factor not able to be tested in this study due to the necessity of unrecognizable geographies and general scenarios.

consider when buying a home, besides the price of the home. Crime was the most common response from participants in all conditions and iterations of the survey. One participant elaborated writing,

"I want a safe neighborhood where I'm not worried about locking doors or walking outside at night."

This response indicates more than concern about 'crime' as a general concept. Instead, it specifically refers to both safety and worry. Another participant echoed these concerns and specified that part of their motivation was,

" [That they] have a family and kids to look out for."

This implies an externalization of fear of crime or perception of risk that is less studied in both the fear of crime literature and housing markets. This response though, still not explicitly advance emotional fear as a motivating concept. One participant did so directly, writing that

"The crime rate near my surrounding area has to be very low because my house being broken into is one of my biggest fears."

This response suggests that at least for some respondents, there may have been fearrelated motivations embedded in their decision. While not firm and unshakable evidence in support of my third hypothesis, these open code responses do suggest that future work seeking to connect the emotional fear concept to housing decisions has some basis in reality.

Limitations

While I believe this article makes significant advances in all three fundamental hypotheses, it is not without limitations, some of which I review in brief here conceptualized as

directions for future work. Future work should more carefully replicate the actual browsing experience of online housing websites, ideally placing participants in an interactive space that allows the researcher to analyze click patterns, attention patterns, and less intrusive means of information synthesis. Future work might also carefully create a more rigorously controlled combination of data distortions such that a threshold for distortion could be established – i.e. to determine exactly how much crime is needed to prompt changes in monetary valuations and willingness to purchase. Finally, in my own future work I intend to more strategically analyze the difference between emotionally evocative fear and potential victimization calculations so that this work can sit more directly in conversation with the body of work on fear of crime.

Conclusion

At the opening of this article I considered the case of Trulia's data projection and asked a fundamental question: "are people actually willing to pay more to live in a neighborhood with less crime?" The results from this study indicate that participants are willing to pay more money, but more importantly, that they are substantially more willing to purchase a home in an area with lower crime. My findings show that this finding is persistent in online housing markets, that crime data is extremely important in consumer decision-making compared to other features, and that the way we project the same true data can substantially change how people make choices around housing. These findings are more than of academic interest, rather, they are important for understanding how asymmetries in housing markets can function to exacerbate inequalities – even if all the data is true.

CONCLUSION

Taken in sum, this dissertation represents the beginning steps of a larger trajectory of work that seeks to identify and disentangle data distortions that affect fear and decision-making. Using three separate examples and their corresponding data distortions, I demonstrate that fear is 1) socially constructed, 2) measurable, and 3) malleable.

In chapter 1, I demonstrated that sensationalized homicide news serves as a mechanism of data distortions: presenting very different pictures of homicide in different locations. This news-generated distortion of reality demonstrates the power of data distortions in society more broadly, but also helps explain why social science finds different conclusions about newsworthiness and different levels of distortion in different contexts.

In chapter 2, I use a vignette-style survey experiment to demonstrate how the same case can be presented in different ways in realistic news articles to change reader decision-making. In this chapter I asked participants to make high-stakes judgements about levels of deserved punishment in a vehicle manslaughter scenario, finding that including information in a news article unrelated to the active offense can prompt some participants to assign a significantly higher punishment.

In chapter 3, I directly quantify the cost of crime for hypothetical homebuyers and renters by testing how decisions to project true data in a certain way can become another form of data distortion. I find that simply changing a projection (without transparently explaining the effect of this projection change) can substantially change willingness to purchase property.

Importantly, as I interrogated a series of data distortions in this dissertation, I never asked participants 'how scared are you?' In doing this I endeavored to separate this work from more

traditional psycho-social work on individualized fear. Instead, I used fear of crime, and the robust criminological literature behind it, to consider fear as a sociological and society-wide project rather than a personal and emotional one. This presents some limitations in being absolutely confident that the concept being measured is actually fear. In my future work, I plan to combine some of the traditional survey methods of fear research with my theories surrounding data as something broader (like news) or available in ready-made form (like housing data). This will allow me to more concretely match the data distortions I am measuring to fear concepts, even if I test those fear concepts on small, similar populations before using other forms of digital trace data.

Another limitation of this dissertation as a whole is that it does not seek to create a coherent ontology of data distortions. Such an ontology could be extremely useful in more clearly elucidating what types of distortions I deem important and could even assist in more clearly defining what a data distortion is in the first place. In my future work I will endeavor to create such an ontology that might be widely applied across multiple fields and even outside the fear-specific context.

That said, this dissertation is a crucial first step to developing these career-sized research trajectories. It does so in a series of three empirical papers that each stand on their own, but also comprise building blocks of this larger project work that I will continue in the next phase of my career.

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APPENDICES

Appendix A: Creepy Clown Conspiracy Informational Tables



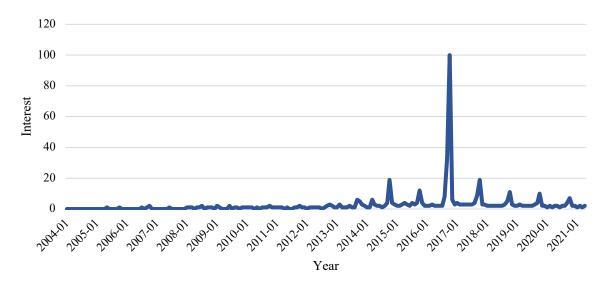


Figure A1 was generated using Google Trends data to show relative interest in creepy clowns (and related terms) over time. The spike in October 2016 is the zenith of the Creep Clown Conspiracy.

Figure A2: Creepy Clown Coverage in the United States, 2000-2021

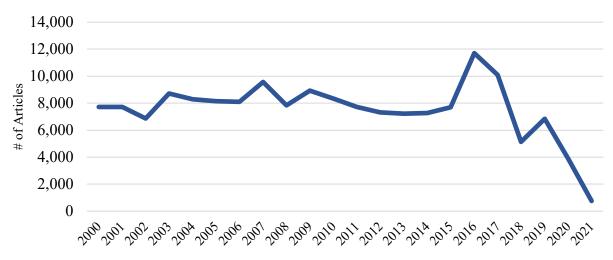


Figure A2 visualizes this data as actual news coverage, showing a spike in the number of articles about creepy clowns in 2016, with approximately 12,000 articles in the US. Figure A2 and A3 (below) were generated using data from Access World News.

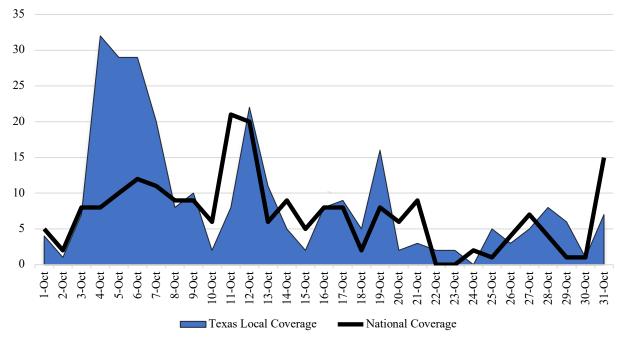


Figure A3: Local vs. National Creepy Clown Coverage, October 2016

Figure A3 plots two trendlines, inspired by Fishman (1988) to show the difference in creepy clown coverage by local news in a given location and national news. Looking at this example of Texas, we see that Texas local coverage dwarfed National coverage in early October, but that National news coverage seems to have reinvigorated local news coverage by early/mid-October.

Appendix B: Supplemental News Coverage Tables (as counts)

	Full Sample	Chicago	Philadelphia	San Antonio
No Coverage	397	256	119	22
Coverage	575	198	273	104
Total	972	454	392	126

Table B1: Coverage (Dichotomous Counts)

Table B2: Coverage (Number of Articles)					
	Full Sample	Chicago	Philadelphia	San Antonio	
0	397	256	119	22	
1	261	134	111	16	
2	111	21	66	24	
3	56	10	25	21	
4	34	5	19	10	
5	25	5	11	9	
6	18	2	9	7	
7	12	7	2	3	
8	13	2	8	3	
9	7	2	3	2	
10	2	1	1	0	
11	3	1	2	0	
13	1	1	0	0	
14	1	1	0	0	
15	1	0	0	1	
16	8	2	4	2	
17	1	0	1	0	
18	3	0	2	1	
19	1	0	0	1	
20	3	0	2	1	
21+	14	4	7	3	
Total	972	454	392	126	

(N]----0 **b**

	Full Sample	Chicago		Philadelphia	San Antonio	
Yes	314		64	162		88
No	658		390	230		38
Total	972		454	392		126

Table B3: Coverage Follow-Up (Dichotomous Counts)

Appendix C: Supplemental Demographics Tables (as counts)

	Full Sample	Chicago	Philadelphia	San Antonio
Fall	237	119	90	28
Spring	236	111	101	24
Summer	300	143	116	41
Winter	199	81	85	33
Total	972	454	392	126

Table C1: Season of Killing (Counts)

Table C2: Type of Killing (Counts)

	Full Sample	Chicago	Philadelphia	San Antonio
Gunshot	733	327	331	75
Other	239	127	61	51
Total	972	454	392	126

Table C3: Type of Killing (All Counts)

	Full Sample	Chicago	Philadelphia	San Antonio
Abuse	8	8	0	0
Arson	5	5	0	0
Asphyxia	39	18	16	5
Assault	17	17	0	0
Auto	4	1	0	3
Blunt force	20	0	0	20
Child abuse	1	1	0	0
Dismembered	1	0	0	1
Drowning	1	1	0	0
Gunshot	733	327	331	75
Other	35	15	15	5
Stabbing	92	47	29	16
Unknown	16	14	1	1
Total	972	454	392	126

	Full Sample	Chicago	Philadelphia	San Antonio
Abuse	0.82	1.76	0	0
Arson	0.51	1.1	0	0
Asphyxia	4.01	1.85	4.08	3.97
Assault	1.75	3.75	0	0
Auto	0.41	0.22	0	2.38
Blunt force	2.06	0	0	15.87
Child abuse	0.1	0.22	0	0
Dismembered	0.1	0	0	0.79
Drowning	0.1	0.22	0	0
Gun	75.41	72.03	84.44	59.52
Other	3.6	3.3	3.83	3.97
Stabbing	9.47	10.35	7.4	12.7
Unknown	1.65	3.08	0.26	0.79
Total	972	454	392	126

Table C4: Type of Killing (All %)

Table C5: Race/Ethnicity of Victims (Counts)

	Full Sample	Chicago	Philadelphia	San Antonio
White	131	36	61	34
Black	654	321	310	23
Hispanic	149	75	8	66
Other	35	22	12	1
Total	969	454	391	124

Table C6: Gender of Victims (Counts)

	Full Sample	Chicago	Philadelphia	San Antonio
Female	145	69	46	30
Male	796	373	330	93
Unknown	31	12	16	3
Total	972	454	392	126

	Full Sample	Chicago	Philadelphia	San Antonio
Adult	834	384	352	98
Juvenile	99	54	27	18
Elderly	33	15	12	6
Total	966	453	391	122

Table C7: Age Categories (Counts)

Appendix D: Additional Interacted Models

	Full Sample	San Antonio	Chicago	Philadelphia
	b/se	b/se	b/se	b/se
Season				
Spring	-0.21	3.2	-0.7	-0.77
	(0.64)	(2.01)	(0.72)	(1.22)
Summer	0.04	0.34	-1.11	1.45
	(0.61)	(1.84)	(0.68)	(1.19)
Winter	-0.92	-0.74	-1.59*	-0.71
	(0.68)	(1.95)	(0.80)	(1.28)
Shooting	0.69	-0.55	-0.16	2.71*
	(0.57)	(1.45)	(0.65)	(1.24)
Race				
Black	-3.48***	-1.85	-0.35	-5.38***
	(0.68)	(1.97)	(0.97)	(1.16)
Hispanic	-2.86***	-0.16	-0.93	-7.07*
	(0.85)	(1.56)	(1.12)	(3.14)
Other	-2.77*	-6.35	-0.14	-3.59
	(1.35)	(7.80)	(1.51)	(2.64)
Age				
Juvenile	4.57**	4.80	2.58	0.95
	(1.69)	(3.06)	(1.88)	(5.84)
Elderly	-2.28	-3.56	-1.94	-0.23
	(2.21)	(4.45)	(2.57)	(4.94)
Sex	-1.43*	-2.51	-2.56**	0.38
	(0.73)	(1.92)	(0.84)	(1.37)
Unknown	-1.77	-4.93	-2.79	0.29
	(1.74)	(7.38)	(1.99)	(3.03)
Interactions				
Juvenile x Male	-1.81	4.53	-0.24	1.29
	(1.91)	(4.14)	(2.08)	(6.17)
Juvenile x Unknown	0.87	1.33	-2.48	6.45
	(3.06)	(9.23)	(4.10)	(7.12)
Elderly x Male	5.84*	2.70	1.77	9.75
·	(2.69)	(6.16)	(3.17)	(5.63)
Constant	5.85***	5.82*	4.65***	4.39*
	(1.00)	(2.32)	(1.25)	(2.00)
R-sqr	0.06	0.2	0.06	0.11
dfres	950	107	438	375
BIC	6562.9	878.2	2891.3	2805.9

* p<0.05, ** p<0.01, *** p<0.001

$\begin{tabular}{ c c c c c c c } \hline Full Sample & San Antonio & Chicago & Philadelphia \\ \hline b/sc & b/sc & b/sc & b/sc \\ \hline Season (fall = ref) & & & & & & & & & & & & & & & & & & &$					
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Winter -0.9 (0.68) -0.44 (1.95) -1.56 (0.80) -0.74 (1.27)Shooting (ref=yes) 0.48 (0.57) -0.75 (1.44) -0.16 (0.63) $2.79*$ (1.25)Race/Ethnicity (ref = white) -0.75 (0.57) -0.16 (1.44) $2.79*$ (0.63) -0.75 (1.25)Back -1.03 (1.52) -3.58 (3.70) -0.56 (2.11) 1.65 (3.01)Hispanic 1.4 (1.99) 1.37 (3.02) -1.74 (2.67) 4.79 (8.54)Other -1.57 (2.47) -4.64 (7.62) -1.52 (2.82) 1.29 (4.81)Sex -0.86 (4.53) -1.09 (2.21) -3.02 (2.84) $7.18*$ (2.84)Unknown -0.86 (4.53) -1.09 (5.48) -0.74 (4.35) 0.49 (9.07)Interactions -2.90 (1.69) 2.39 (3.43) 0.34 (3.23) $-7.92*$ (1.69)Black # Male (4.80) -2.90 (9.44) 2.39 (4.76) 0.34 (9.43)Interactions -2.90 (2.39) 0.34 (3.48) $-7.92*$ (9.03)Black # Male (4.80) -2.90 (3.48) 2.39 (9.12)Hispanic # Male (5.68) -1.79 (1.04) -1.322 (2.20)Hispanic # Unknown (6.85) -1.24 0 1.84 (4.59)	Summer				
$ \begin{array}{c cccc} (0.68) & (1.95) & (0.80) & (1.27) \\ \hline \mbox{Shooting (ref=yes)} & 0.48 & -0.75 & -0.16 & 2.79* \\ (0.57) & (1.44) & (0.63) & (1.25) \\ \hline \mbox{Racc/Ethnicity (ref = white)} \\ \hline \mbox{Black} & -1.03 & -3.58 & -0.56 & 1.65 \\ (1.52) & (3.70) & (2.11) & (3.01) \\ \hline \mbox{Hispanic} & 1.4 & 1.37 & -1.74 & 4.79 \\ (1.99) & (3.02) & (2.67) & (8.54) \\ \hline \mbox{Other} & -1.57 & -4.64 & -1.52 & 1.29 \\ (2.47) & (7.62) & (2.82) & (4.81) \\ \hline \mbox{Sex} & & & & & \\ \hline \mbox{Male} & 1.36 & -1.09 & -3.02 & 7.18* \\ (1.49) & (2.70) & (2.21) & (2.84) \\ \hline \mbox{Unknown} & -0.86 & -4.79 & -0.74 & 0.49 \\ (4.53) & (5.48) & (4.35) & (9.07) \\ \hline \mbox{Interactions} & & & & \\ \hline \mbox{Black \# Male} & -2.90 & 2.39 & 0.34 & -7.92* \\ (1.69) & (4.35) & (2.36) & (3.23) \\ \hline \mbox{Black \# Male} & -5.04* & -1.79 & 1.04 & -13.22 \\ (2.20) & (3.48) & (2.93) & (9.12) \\ \hline \mbox{Hispanic \# Male} & -5.04* & -1.79 & 1.04 & -13.22 \\ (2.20) & (3.48) & (2.93) & (9.12) \\ \hline \mbox{Hispanic \# Male} & -1.16 & 0 & 0 & 0 \\ (6.85) & (.) & (.) & (.) \\ \hline \mbox{Other \# Male} & -1.24 & 0 & 1.84 & -4.59 \\ \hline \end{tabular}$. ,	· · · ·	· · · ·	
Shooting (ref=yes) 0.48 -0.75 -0.16 $2.79*$ Race/Ethnicity (ref = white) Black -1.03 -3.58 -0.56 1.65 Black -1.03 -3.58 -0.56 1.65 Hispanic 1.4 1.37 -1.74 4.79 Other -1.57 -4.64 -1.52 1.29 Other -1.57 -4.64 -1.52 1.29 Other -1.57 -4.64 -1.52 1.29 Other -0.86 -1.09 -3.02 $7.18*$ Male 1.36 -1.09 -3.02 $7.18*$ Unknown -0.86 -4.79 -0.74 0.49 (4.53) (5.48) (4.35) (9.07) Interactions Black # Male -2.90 2.39 0.34 $-7.92*$ Black # Male -2.90 2.39 0.34 $-7.92*$ (1.69) (4.35) (2.36) (3.23) 1.03 Black # Male -2.90 2.39 0.34	Winter				
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Hispanic # Unknown-1.16000(6.85)(.)(.)(.)(.)Other # Male-1.2401.84-4.59	Hispanic # Male		· /	· /	· /
Hispanic # Unknown-1.16000(6.85)(.)(.)(.)(.)Other # Male-1.2401.84-4.59	-	(2.20)	(3.48)	(2.93)	(9.12)
Other # Male -1.24 0 1.84 -4.59	Hispanic # Unknown	. ,			0
Other # Male -1.24 0 1.84 -4.59		(6.85)	(.)	(.)	(.)
(3.00) (.) (3.39) (5.85)	Other # Male	-1.24			
		(3.00)	(.)	(3.39)	(5.85)

Table D2: Race and Gender Interaction

Age (adult = ref)

Juvenile	3.31***	7.39***	2.27**	2.85
	(0.76)	(2.04)	(0.80)	(1.72)
Elderly	1.99	-1.54	-0.76	8.50**
	(1.29)	(3.16)	(1.48)	(2.56)
Constant	3.63*	4.53	5.01*	-1.79
	(1.43)	(2.58)	-2.03	(2.95)
R-sqr	0.06	0.2	0.06	0.12
dfres	948	107	437	374
BIC	6577.5	878.3	2897.5	2809.3

* p<0.05, ** p<0.01, *** p<0.001

Appendix E: Materials for Vignette Construction

Appendix E: Inspiration Articles and Developed Vignettes

Article 1: 2 drivers in Minn., N. Dakota cross centerline; 4 left dead

Two vehicles crossed the centerlines of roadways in Minnesota and North Dakota, causing crashes and killing four people.

Three people in a van were killed when a 16-year-old girl driving an SUV crossed the centerline late at night on a road west of Fargo and struck the van head-on. The teen driver and two other passengers in the cargo van were injured in the collision that occurred about 11:35 p.m. Friday on Cass County Road 10 about 40 miles west of Fargo, according to the North Dakota Highway Patrol.

Traffic was rerouted for about five hours as law enforcement collected evidence and cleared the debris from the crash involving a Lincoln Aviator and Ford Econoline van that blocked the road. The van's driver, Matthew Wipf, 40, of Tower City, N.D., was killed along with two of his passengers: Kathy Wipf, 43, also of Tower City, and Dorothy Decker, 46, of Ipswich, S.D., according to the patrol. Both women were in the rear seat.

Two others in the van were injured: Henry Decker, 50, who was in the front passenger seat, and Heidi Hoffer, 35, who was in the rear seat. Both were also from Ipswich. The teen driving the SUV was identified as Sophia Weshnevski of Buffalo, N.D. She was taken by air ambulance to a Fargo hospital with serious injuries, the patrol said.

In the other crash, a driver with a history of drinking and driving was jailed, accused of a felony, after he crossed the centerline on an Otsego road and triggered a four-vehicle crash that left another motorist dead, authorities said Brandon D. Pedrys, 26, of Elk River, is suspected of criminal vehicular operation in connection with the death Friday of a driver who was struck head-on on County Road 39 near NE. Page Avenue, according to the Wright County Sheriff's Office. Sharon Veiman, 62, of Anoka, died at the scene.

In less than eight years, Pedrys has been convicted twice for drunken driving, once for drinking and driving under age 21, twice for underage drinking and once for drug possession.

Article 2:

Suspect, 19, charged in fatal crash

A 19-year-old St. Paul man has been charged with felony drunken driving for striking another car last week and killing the other driver, according to charges.

Jose O. Vasquez-Guillen was charged Wednesday in Ramsey County District Court with Criminal vehicular homicide in connection with the crash on April 3 south of the St. Paul Downtown Airport. Mark J. O'Gara, 52, of St. Paul, died at the scene.

Two days after the crash, Vasquez-Guillen, who had previously been ordered deported, left the Ramsey County jail and was arrested by U.S. Immigration and Customs Enforcement (ICE). He remains in federal custody in the Sherburne County jail.

Vasquez-Guillen, a citizen of El Salvador, entered the country illegally at age 15 in January 2016, and a federal judge seven months later in Dallas ordered him deported, ICE spokesman Shawn Neudauer said Thursday. The deportation order came after Vasquez-Guillen failed to appear for his immigration hearing.

The charges say that Vasquez-Guillen's blood-alcohol content about two hours after the crash was 0.149, well above the legal limit for anyone 21 and older to drive in Minnesota. O'Gara leaves behind a wife, 10 children and six grandchildren.

Developed Vignettes (Control, DUI, Immigration)

3 Struck and Killed in Crash

Three people in a van were killed when a 26-year-old man driving an SUV crossed the centerline late last night striking the van head-on. The driver sustained minor injuries in the collision that occurred at about 11:35 p.m. Friday night and was later taken into custody.

The van's driver, a 50-year-old man, was pronounced dead at the scene. Two women, the driver's wife and her sister, were taken to the hospital in critical condition where they passed away early this morning. They leave behind 2 children and 4 grandchildren.

3 Struck and killed in crash

Three people in a van were killed when a 26-year-old man driving an SUV crossed the centerline late last night striking the van head-on. The SUV driver, who had previously been jailed for drinking and driving, sustained minor injuries in the collision that occurred at about 11:35 p.m. Friday night and was later taken into custody. The charges say that the driver's blood-alcohol content about two hours after the crash was 0.2, well above the legal limit in Minnesota.

The van's driver, a 50-year-old man, was pronounced dead at the scene. Two women, the driver's wife and her sister, were taken to the hospital in critical condition where they passed away early this morning. They leave behind 2 children and 4 grandchildren.

3 Struck and killed in crash

Three people in a van were killed when a 26-year-old man driving an SUV crossed the centerline late last night striking the van head-on. The SUV driver, who had recently been ordered to be deported, sustained minor injuries in the collision that occurred about 11:35 p.m. Friday night and was later taken into custody.

He was found to have entered the United States illegally at age 16 and was ordered to be deported after missing an immigration hearing. He was arrested by ICE agents shortly after leaving the Ramsey County Jail.

The van's driver, a 50-year-old man, was pronounced dead at the scene. Two women, the driver's wife and her sister, were taken to the hospital in critical condition where they passed away early this morning. They leave behind 2 children and 4 grandchildren.

Table F1: Participant Descriptives		
	N	%
Age 15 to 19 20 to 29 30 to 39 40 to 49 50 to 54 55 or older	4 63 64 35 12 13	2.09 32.98 33.51 18.32 6.28 6.81
Gender Female Male Other	83 107 1	43.46 56.02 0.52
Race Asian Black or African American White or Caucasian Other	10 10 164 6	5.26 5.26 86.32 3.14
Hispanic Ethnicity No Yes	184 5	97.35 2.65
Education Less than high school diploma High school diploma/GED Some college/vocational school Bachelor's degree Post-baccalaureate degree	3 17 62 87 22	1.57 8.9 32.46 45.55 11.52
Income Less than 10,000 10,000 to 14,999 15,000 to 24,999 25,000 to 34,999 35,000 to 49,999 50,000 to 74,999 75,000 to 99,999	17 9 18 13 39 44 33	8.99 4.76 9.52 6.88 20.63 23.28 17.46
100,000 or more	16	8.47

Table F1: Participant Descriptives

N=189-191 due to non-response

Appendix G: Full Regressions

Table G1: Full Regression Models

Variables	Control	DUI	Immigrant
Political Views	-0.01	-0.02+	-0.04**
	(0.02)	(0.01)	(0.02)
Income			
Less than 10,000	-0.13	-1.18	-1.63
	(5.26)	(1.21)	(2.89)
15,000 to 24,999	0.14	-3.63	-1.07
	(5.31)	(1.50)	(2.26)
25,000 to 34,999	4.09	-2.06	-0.10
	(5.25)	(1.87)	(2.05)
35,000 to 49,999	0.08	-0.10	1.10
	(5.27)	(1.18)	(1.97)
50,000 to 74,999	0.58	0.30	-0.09
	(5.27)	(1.23)	(1.98)
75,000 to 99,999	1.73	-1.59	1.84
	(5.25)	(1.28)	(2.10)
100,000 to 149,999	-3.78	0.96	1.61
	(6.72)	(1.52)	(2.24)
200,000 or more	-0.79	-0.28	3.58
	(7.58)	(1.43)	(2.68)
Education			
High school/GED	-0.03	1.68	3.41
	(2.36)	(0.72)	(1.82)
Less than HS	0.50	-	-
	(3.56)	-	-
Post-baccalaureate	-1.09	-1.26	0.87
	(2.67)	(0.59)	(1.42)
Some college	-0.91	0.17	1.60
	(1.32)	(0.50)	(1.03)
Gender			
Male	-1.03	-0.43	-0.56
	(1.22)	(0.41)	(0.94)
Trans/gender non-conforming	1.76	-	-
	(4.93)	-	-
Race			
Asian	-1.93	-	-
	(4.78)	-	-
Black	-4.07	2.09	4.01
	(5.38)	(1.95)	(2.42)
White	-5.06	0.51	1.05
	(4.52)	(1.36)	(1.92)
American Indian/Alaskan Native	-	4.46	4.89
	-	(1.94)	(3.77)

	Other	_	-3.94	3.61
		-	(1.94)	(4.01)
		5.24	0.62	0.42
Hispanic		5.24	0.62	-0.42
		(3.82)	(1.61)	(2.56)
Age	••	A 4 F	1.00	1.10
	20 to 24	-2.17	1.29	-1.48
		(3.64)	(1.26)	(3.84)
	25 to 29	-3.36	0.90	0.46
		(3.82)	(1.16)	(3.86)
	30 to 34	-0.18	0.06	-2.20
		(3.61)	(1.20)	(3.95)
	35 to 39	-1.03	0.93	-1.38
		(3.63)	(1.21)	(4.04)
	40 to 44	-2.96	0.95	0.08
		(3.82)	(1.26)	(4.08)
	45 to 49	-6.04	0.50	-1.84
		(5.20)	(1.22)	(4.03)
	50 to 54	2.26	0.05	0.61
		(4.29)	(1.44)	(3.98)
	55 to 59	1.41	0.94	-0.22
		(5.37)	(1.74)	(4.17)
	60 to 64	-1.27	0.40	1.23
		(5.14)	(2.20)	(4.63)
	70 to 74	-	-	-0.89
		-	-	(4.38)
Constant		12.02	9.54	8.40
Constant		(7.82)	(1.67)	(3.20)
		(7.62)	(1.07)	(3.20)
# of Observations		54	60	73

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Appendix H: Pilot Survey Question Wording

Imagine you have all the resources you need to buy a home. The text below describes a home that is currently for sale. You are given information about the house and the surrounding neighborhood. Carefully read and consider the information before answering the questions

How much money do you think this home costs? Give your answer in US dollars.

How confident are you in this number?

Would you buy this home?

Appendix I: Pilot Survey House Combinations (Houses 1 – 5 in order)

Figure I1: Feature Combinations

Number of Bedrooms: 4 Number of Bathrooms: 3 Description: This house is furnished in a Modern style. The house itself is in new-build condition. Crime: High Foreclosure: High School Districts: Average Amount of Restaurants/Shopping Nearby: Below Average Average Neighborhood Home Value: Mid-Priced

Number of Bedrooms: 3 Number of Bathrooms: 1 Description: This house is furnished in a Classic style. The house itself is in renovated condition. Crime: High Foreclosure: Low School Districts: Above average Amount of Restaurants/Shopping Nearby: Average Average Neighborhood Home Value: Low-priced

Number of Bedrooms: 3 Number of Bathrooms: 2 Description: This house is furnished in a classic style. The house itself is in vintage condition. Crime: Moderate Foreclosure: Moderate School Districts: Below Average Amount of Restaurants/Shopping Nearby: Average Average Neighborhood Home Value: High-priced

Number of Bedrooms: 2 Number of Bathrooms: 1 Description: This house is furnished in a Modern style. The house itself is in renovated condition. Crime: Low Foreclosure: Moderate School Districts: Average Amount of Restaurants/Shopping Nearby: Above Average Average Neighborhood Home Value: High-priced

Number of Bedrooms: 3 Number of Bathrooms: 2 Description: This house is furnished in a classic style. The house itself is in new-build condition. Crime: Moderate Foreclosure: High School Districts: Above Average Amount of Restaurants/Shopping Nearby: Below Average Average Neighborhood Home Value: Low-Priced

Appendix J: Sample Graphics from Main Survey

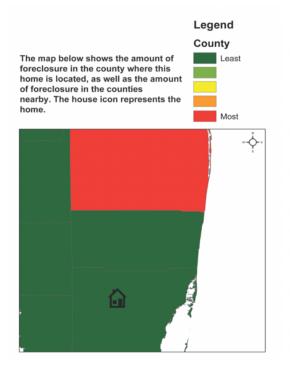
Figure J1: Sample Graphics, Main Sample

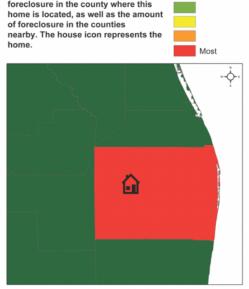
Sample images from main survey (described clockwise). General description, interior photos, foreclosure map,

crime map.



This home is a single-family home. It has 3 bedrooms and 2 bathrooms. It is 1944 square feet.







County

Least

The map below shows the amount of foreclosure in the county where this

Kat Albrecht

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Education	
Ph.D. 2021	Sociology, Northwestern University Committee: Andy Papachristos, Laura Beth Nielsen, Bob Nelson Dissertation: Data Distortions and the Quantification of Fear
J.D. 2021	Pritzker School of Law, Northwestern University
M.A. 2018	Sociology, Northwestern University Committee: John Hagan & Laura Beth Nielsen
B.S. 2016	Sociology, University of Minnesota, Summa Cum Laude Honors Thesis: Newsworthiness in Minnesota Homicide Winner of Undergraduate Thesis Award

Academic Positions

Upcoming	Assistant Professor of Criminology & Criminal Justice Andrew Young School of Policy Studies, Georgia State University <i>Beginning 9 Aug. 2021</i>
Refereed	Articles
Accepted	Filip, Kaitlyn and Kat Albrecht. Including but Not Limited To, Personal Injury, Disability and Death: The Problems of University Liability Waivers for COVID- 19 Protections. <i>Kansas Journal of Law and Public Policy</i> .
Accepted	Hawilo, Maria, Kat Albrecht, Meredith Rountree, and Tom Geraghty. "How Culture Impacts Courtrooms." <i>Journal of Criminal Law and Criminal Justice</i> .
Proposal Accepted	Burns, Andrew and Kat Albrecht. "Seeing the Shadow Users: How Covid-19 is Worsening the Opioid Epidemic." <i>The Russell Sage Foundation Journal of the</i> <i>Social Sciences issue on</i> The Social and Political Impact of COVID-19 in the US.
2020	Albrecht, Kat, and Brian Citro. "Data Control and Surveillance in the Global TB Response: A Human Rights Analysis." 2(1) <i>Law, Technology and Humans</i> 107.
2019	Weinberg, Jill D., Laura Beth Nielsen, and Kat Albrecht. "The Deserving Worker: Decisions about Workplace Accommodation by Judges and Laypeople." 41(3) <i>Law & Policy</i> 286-309.

2017 Pah, Adam., John Hagan, Andrew Jennings, Aditya Jain, Kat Albrecht, Adam Hockenberry, and Luis. Amaral. "Economic Insecurity and the Rise in Gun Violence at US Schools." 1(2) *Nature Human Behaviour* 1-6.

Refereed Chapters

Forthcoming	Albrecht, Kat. Social Media: Harmful or Helpful? Anthology Chapter in <u>Surveillance and Social Justice</u> . Edited by Mike Kent and Leanne Mcrea. Forthcoming.
2018	Schoenfeld, Heather, Rachel M. Durso, and Kat Albrecht. "Maximizing Charges: Overcriminalization and Prosecutorial Practices During the Crime Decline." In <i>After Imprisonment;</i> Austin D. Sarat <i>Ed.</i> (Emerald Publishing Limited).

Other Writing

2021	Albrecht, Kat. Review of Appearance Bias and Crime, by Bonnie Berry, <i>Contemporary Sociology</i> .
2020	Albrecht, Kat. Data Transparency & the Disparate Impact of the Felony Murder Rule. <i>Duke Center for Firearms Law Online</i> .
2020	Citro, Brian and Kat Albrecht. 2020. "Data Control and Surveillance in the Covid- 19 Response." <i>Northwestern University Law Review Online</i> .

Works in Progress (Full Manuscripts Available)

Albrecht, Kat, Laura Beth Nielsen, and Lydia Wuorinen. Law Misunderstood: Undergraduates' Analysis of Campus Title IX Policies (R&R).

Stallings, Carrie and Kat Albrecht. The Law of the Land: Disparity in Native American Arrest.

Redbird, Beth and Kat Albrecht. Quantifying Disparity: Developing New Measures of Racial Disparity in Arrest.

Open-source tool: <u>Racial Disparities in Police Arrests Map: A Policy Tool.</u> Working Paper: <u>Racial Disparity in Arrests Increased as Crime Declined</u>. (WP-20-28). IPR.

Fellowships

1	
2020 - 2022	Social Networks & Health Fellow, Duke University via NIH grant
	"Co-Presence and Drug Overdose Networks in Small-Town Ohio"
2020 - 2021	Global Impacts Fellow, Buffett Institute, (stipend + tuition)
	"Put a Tracker on it: Fear, Surveillance, and International Human Rights Law"
2019 - 2020	Research Affiliate, Duke Center for Firearms Law (\$7,500)
	"Data Transparency & the Disparate Impact of the Felony Murder Rule"
2018 - 2020	Law and Sciences Fellow, Pritzker School of Law (tuition)

Grants and Awards

- 2021 Sociology Department Research Grant, Northwestern University (\$500)
- 2020 ACJS Doctoral Summit, Academy of Criminal Justice Sciences
- 2020 MacArthur Summer Research Grant, with Laura Beth Nielsen, NU (\$1,000)
- 2020 ASA Methods Section Travel Award (\$450)
- 2019 Fiction Research Award, with Kaitlyn Filip, Sisters in Crime (\$500)
- 2018 Richard R. Block Award, Homicide Research Working Group (\$500)
- 2018 Alumni Grant Award, with B. Redbird, Northwestern University (\$5,000)
- 2018 Graduate Research Grant, Northwestern University (\$2,400)
- 2017 Russell Sage Foundation, with Maria Rodriguez (\$2,500)
- 2017 MacArthur Summer Research Grant, with John Hagan, Northwestern Univ. (\$1,200)
- 2016 Northwestern University Quantitative Fellowship (\$2,500)
- 2016 Talle Family Scholar 2015-2016, University of Minnesota College of Liberal Arts

Summer Institute in Computational Social Science Chicago, Alfred P. Sloan Foundation

Website: <u>The Summer Institutes in Computational Social Science</u> Chicago Location: <u>SICSS Chicago</u>

- 2021 Lead Organizer, Summer Institute in Computational Social Science Chicago (\$8,200)*
- 2020 Lead Organizer, Summer Institute in Computational Social Science Chicago (\$15,500)**
- 2020 TGS Co-Sponsorship Grant, NU (\$1,000)** un-used due to Covid-19
- 2019 Lead Organizer, Summer Institute in Computational Social Science Chicago (\$15,500)
- 2018 Co-organizer, Summer Institute in Computational Social Science Chicago (\$15,500)

Additional financial support from The Kellogg School of Management, The Northwestern Institute on Complex Systems, The Community Data Science Collective, and The Science of Networks in Communities research group.

* Change in funding amount due to running a fully virtual institute during Covid-19

Teaching

2020 - 2021	Searle Teaching Certificate Program
2020	Instructor of Record, Northwestern University Winner of Robert F. Winch Award for Outstanding Grad Student Instructor Law and Society, Sociology of Fear
2016 – Present	Teaching Assistant, Northwestern University Winner of Robert F. Winch Award for Outstanding Grad Student TA
	Undergraduate/Graduate Courses: Law and Society; Social Inequality - Race, Class, & Power; Introduction to Python Programming; School Policy
	MBA Courses: Social Dynamics & Network Analysis; Human & Machine Intelligence
	Executive MBA Courses: Leadership

2013 – 2016 Teaching Assistant, University of Minnesota *Winner of Outstanding Undergrad TA Award* Undergraduate/Graduate Courses: Sociological Research Methods; Sociology of Killing; Sociology of Race, Class, and Gender

Original Databases and Policy Tools

2020 Quantifying Disparity: Racial Disparities in Police Arrests

Redbird, Beth, and Kat Albrecht. 2019. <u>"Measuring Racial Disparities in</u> Local and County Police Arrests." *Working Paper*, Institute for Policy Research, Northwestern University.

This dataset and related measures are created from a rigorous combination of several streams of institutional data. The data comes from FBI records of nationwide arrests, reported by 13,917 police agencies, including 2,908 county and 11,009 municipal police, from 1999 through 2015. The data has been translated into an interactive map (and accompanying Github) with two measures for disparity in arrest. The first is an Arrest Risk Ratio measure of racial differences which considers population size. The second is an Arrest Residual measure of racial differences which considers population size and factors that affect crime rates.

Open-source tool: <u>Racial Disparities in Police Arrests Map: A Policy Tool.</u> Working Paper: <u>Racial Disparity in Arrests Increased as Crime Declined</u>. (WP-20-28). IPR. Working Paper: <u>Measuring Racial Disparity in Local and County Arrests</u>. (WP-20-27). IPR.

2017 Gun Violence at US Schools

Pah, Adam., John Hagan, Andrew Jennings, Aditya Jain, Kat Albrecht, Adam Hockenberry, and Luis. Amaral. "Economic Insecurity and the Rise in Gun Violence at US Schools." 1(2) *Nature Human Behaviour* 1-6.

Frequent school shootings are a unique US phenomenon that has defied understanding. Uncovering the etiology of this problem is hampered by the lack of an established dataset. Here we assemble a carefully curated dataset for the period 1990–2013 that is built upon an exhaustive review of existing data and original sources.

Data: <u>Gun Violence at US Schools</u> Interactive map: <u>Interactive Gun Violence Map</u>

Selected Research/ Computational Consulting Experience

2018 – Present	The Northwestern Neighborhood & Network Initiative
2016 - Present	American Bar Foundation

2020 - Present	McComas Legal
2020	Golden Set Analytics
2020	Fong Legal
2019 - 2020	International Human Rights Clinic, Bluhm Legal Clinic
2018 - 2019	Northwestern Research Computing
2018	Karen Decrow Project (archival)
2017 - 2018	Institution of Population Research, Northwestern University
2017 - 2018	Safford Legal
2016 - 2018	Data Science Initiative, Northwestern University
2013 - 2016	University of Minnesota Pediatrics
2015 - 2016	Food Protection and Defense Center
Summer 2015	NSF REU, University of Texas at Austin

Experience in Criminal Justice

2020 – Present	Life without the Possibility of Parole Project with McComas Legal Data Science Consultant, Co-author
	This project began as a consultancy to provide statistical evidence on Life Without the Possibility of Parole (LWOP) to be used for specific litigation. It has grown into a data transparency project where we are submitting memos and letters to DAs and others, petitioning for large amounts of data, and creating public facing resources to understand bias in LWOP for young offenders. We are currently writing up scholarly our findings in the format of a law review article.
	Outputs: Legal memorandums, statistical reports, ongoing law review article
2015 - 2019	Child Pornography Initiative with Hennepin County Sex Offender Unit Research Intern, Research Consultant, Co-author
	Created and coded a database of all child pornography offenders from Adult Supervision in Hennepin County, MN with unit chief Hanna O'Neil. Transitioned to supervising other members of the research team and acting as a research consultant. Following data compilation, statistical analysis is being used to generate practitioner reports and a peer-reviewable journal article.
	Outputs: Database, practitioner reports, ongoing peer-review journal article
2013 - 2014	Center for Homicide Research, Minneapolis, MN Research Intern
	Coded and maintained databases of Minnesota Homicides. Edited and authored technical reports about homicide.
	Outputs: Databases, Technical reports

Invited Talks

2021 Albrecht, Kat. 2021. Pre-Conference Workshop on Computational Criminology at American Criminological Society Annual Meeting 2021.

2020	Redbird, Beth and Kat Albrecht. 2020. <i>Racial Disparity in Arrests Increases as Crime Rates Decline</i> . One Book Northwestern.
2020	Albrecht, Kat. 2020. Sociology of Fear. Unite the World with Africa Foundation.
2020	Albrecht, Kat. 2020. <i>Data Distortions and the Felony Murder Rule</i> . Duke Firearms Law Symposium.
2019	Albrecht, Kat 2019. <i>Machine Learning and Data Driven Law</i> . Institute for Future Law Practice.
2019	Albrecht, Kat. 2019. Computational Techniques to Study Homicide. Homicide Research Working Group Annual Meeting.
2018	Albrecht, Kat. 2018. Fundamental Data Science to Investigate Social Problems. Northwestern Institute on Complex Systems, Data Science Hack Nights.

Selected Conference Presentations

2021	Stallings, Carrie and Kat Albrecht. False Equivalence: Reductionist Assumptions about Disparity in Native American Arrest. The Newberry Consortium for American Indian Studies. Accepted forthcoming.
2020	Albrecht, Kat and Andrew Burns. Co-Presence Networks in Drug Overdose. The Criminology Consortium.
2020	Albrecht, Kat and Brian Citro. <i>Data Surveillance, TB & Human Rights Law.</i> 51st Union World conference on Lung Health.
2020	Albrecht, Kat, Laura Beth Nielsen, and Lydia Wuorinen. Law's Failure: Title IX Policies, Managerialized Rights, and Undergraduate Understanding. Law and Society National Meeting.
2020	Albrecht, Kat. Crime Doesn't Matter: Dynamic Longitudinal Measures of Legal Cynicism in Chicago. American Sociological Association.
2020	Burns, Andrew and Kat Albrecht. <i>Getting Jumped in Vacationland: The Complicated Rhetoric and Realities of Assault in a Small Town</i> . American Sociological Association.
2019	Albrecht, Kat. Comparative Methodology in Newsworthiness Research. American Society of Criminology Annual Meeting.
2019	Albrecht, Kat. <i>Modelling Gun Violence in Schools</i> . American Sociological Association.

2018	Albrecht, Kat. <i>The Aspiration v. Attainment Gap: Gun Violence in Schools.</i> American Society of Criminology Annual Meeting.
2018	Albrecht, Kat. <i>Redefining Crime Categories</i> . American Society of Criminology Conference.
2018	Albrecht, Kat. <i>Prosecutorial Bias in Dyadic Homicide Sentencing</i> . Law and Society National Meeting.
2018	Albrecht, Kat. Big Data Approaches to Homicide Research. Homicide Research Working Group Annual Meeting.
2017	Albrecht, Kat. <i>Racial Disparity in Arrest Rates</i> . American Sociological Association Annual Meeting, Section on Race and Policing.
2017	Albrecht, Kat. <i>Process Models of Homicide</i> . Homicide Research Working Group Annual Meeting.

Affiliations/Institutes

Covid-19 Social Change Lab
Law and Society Association
American Sociology Association
Sections: Methodology; Law; & Crime, Law, and Deviance; Drugs, Alcohol
& Tobacco
Graduate Fellow in Legal Studies
Amaral Complex Systems Lab, Northwestern University
Homicide Research Working Group
American Society of Criminology
Princeton Summer Institute in Computational Social Science
University of Minnesota Sociological Association, President

Related Service

Reviewer: Network Science; PlosOne; Crime, Law, and Social Change; Homicide Studies; Social Problems; Contemporary Sociology, Northwestern University Law Review

Grant Reviewer: Sloan Foundation

2020 - 2021	Society for the Study of Social Problems Local Arrangements Committee
2020 - 2021	Crime, Law, and Deviance Workshop Student Coordinator
2019 - 2021	American Sociological Association, Methodology Section Elected Student Representative, Co-organizer for Mid-Year Meeting 2020

2018 - 2021	Homicide Research Working Group Richard R. Block Awards Committee
2017 - 2021	Graduate Women Across Northwestern Service Chair, Academic Liaison
2017 - 2018	Applied Quantitative Methods Workshop Student Coordinator
2017 - 2018	Graduates Mentoring Undergraduates Graduate Student Mentor

Languages/Software
Python, STATA, SPSS, Q/GIS, LaTeX, Qualtrics, RedCap, Git, basic R