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Essays in Labor Economics and Applied Microeconomics

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Doctor of Philosophy
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by

Yixin Chen

Committee in charge:

Professor Kelly Bedard, Chair
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June 2024

The Dissertation of Yixin Chen is approved.

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Essays in Labor Economics and Applied Microeconomics

I dedicate my dissertation to my parents who have supported me through these many years.

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Abstract

Essays in Labor Economics and Applied Microeconomics

by

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This dissertation contains three chapters in labor economics and applied microeconomics.

In Chapter 1, I provide the first empirical evidence on the effect of having a female officer in the primary unit on the discovery of domestic violence (DV) in physical abuse incidents. DV is a crime that usually has female victims and is often under-reported. This chapter studies the effect of having a female officer dispatched in the primary unit on the discovery of DV in physical abuse incidents in Milwaukee and Chicago. Using three-year calls for service data and conditional random assignment of officers in the dispatch process, the chapter finds that the existence of a female officer in the primary unit scales up the likelihood of discovering DV in physical abuse incidents by 10% in Milwaukee. Analysis of data from Chicago indicates a similar effect. These results indicate that female officers play an important role in discovering DV.

In Chapter 2, we study the effect of college basketball game days on sexual assault. Basketball games are an important part of college identity and social activities. This chapter studies the effect of college basketball game days on the probability of having local sexual assault reports. Using crime data from universities with top basketball programs and local law enforcement agencies, this chapter shows that home game days have little effect on the probability of sexual assault reports, while away game days scale up the probability by 14%. This finding is different from those found for football, which likely reflects differences in viewing and partying behavior across the two sports.

In Chapter 3, I study the relationship between school lunch and nutrition. School lunch is an important channel of students' nutrition intake. This chapter studies the potential mechanisms for effects of the Healthy, Hunger-Free Kids Act using metabolic analysis. Using data from the National Health and Nutrition Examination Survey, the chapter finds that this policy decreased the probability of having high total cholesterol by about 30% for students who usually eat school lunches. This result is largely driven by the significant decrease in the proportion of students with high LDL cholesterol and triglycerides. The results reported in the chapter show the powerful impact of this policy on adolescent health.

Contents

Chapter 1

Female Officers and the Discovery of Domestic Violence

1.1 Introduction

Domestic violence (DV) is a common yet under-reported gender-based crime. In DV incidents, victims are largely female and offenders are largely male. One of the most apparent forms of DV is physical abuse (United Nations, n.d.). There are approximately 2.5 to 4.5 million physical abuse incidents against women in the US each year (Rand & Rennison, 2005). DV has different interpretations. It is interpreted to be a way for a man to dominate his partner (Dobash & Dobash, 1979), to provide positive utility to some men (Tauchen et al., 1991; Aizer, 2010), and to be an unintentional outcome when an argument becomes out of control (Straus et al., 1980; Johnson, 2009). DV has adverse health outcomes in women's health systems that include the brain system, cardiovascular system, gastrointestinal system, immune and endocrine system, musculoskeletal system, and reproductive system (Black, 2011). Besides, DV has psychological impacts that parallel with the trauma of being taken hostage and subjected to torture (Dutton, 2000;

Herman, 2015). Also, DV has intergenerational effects that are transmitted from parents to children (Pollak, 2004).

Despite its severe health outcomes, psychological impacts, and intergenerational effects, DV frequently remains under-reported. By summarizing data from the National Crime Victimization Survey (NCVS), Reaves (2017) finds that nearly 50% of DV incidents remain unreported. Reasons for not reporting these incidents include social stigma (Devries et al., 2011), distrust of the institution (Belknap, 2010), fear of retaliation (Kishor & Johnson, 2005), lack of awareness (Casey et al., 2011), and financial barriers (Wolf et al., 2003). Under-reporting has detrimental consequences from various perspectives. It perpetuates such incidents and causes extended sufferings for victims. It also limits people's understanding of the actual magnitude of these incidents, which makes developing effective mitigation strategies difficult (Sahay, 2021).

Although under-reporting DV has detrimental consequences from various perspectives, the question of how to respond to incidents so that more DV can be discovered and reported remains mostly unsolved. One potential solution is to have female officers respond to physical abuse incidents in order to discover more DV incidents. As mentioned earlier, most victims of DV are female and physical abuse is one of the most apparent forms of DV. Given that female officers often express more empathy (Rabe-Hemp, 2008) and victims find female officers more favorable in these incidents (Lonsway et al., 2003), it is plausible that officers' gender may play a role in discovering DV related physical abuse.

This paper provides the first empirical evidence on the effect of dispatching female officers on discovering DV related physical abuse incidents using 911 calls for service data. A call for service is a primary way in which the public can solicit the assistance of police. However, the classification of the call may be inaccurate because of ambiguous information from callers and time pressure in the classification process (Simpson & Orosco, 2021). Therefore, it is likely that officers on the scene discover DV elements in physical abuse incidents and then reclassify the calls. Given that DV victims are predominantly female, female officers might be important for discovering these incidents.

This paper uses the calls for service data merged with officer characteristics data from the Milwaukee and Chicago Police Departments to study the effect of having a female officer dispatched in the primary unit on discovering DV related physical abuse incidents. The two cities are very different in sizes, populations, and police demographics. Both police departments provided three years of data from 2017 to 2019. In both police departments, there is a telecommunicator or call taker who picks up a 911 call, and a dispatcher who assigns available officers to the call. Calls are dispatched based on priority. This dispatch process indicates that the variation in whether there exists a female officer in the primary unit is as good as random conditional on district and time fixed effects. This conditional random assignment of officers in the police dispatch process overcomes issues arisen when there is nonrandom officer selection into situations (Hoekstra & Sloan, 2022).

Results indicate that the existence of a female officer in the primary unit improves the discovery of DV in physical abuse incidents by 10% in the Milwaukee Police Department. A positive effect is also found by analyzing data from the Chicago Police Department. Results show that the existence of a female officer in the primary unit scales up the discovery of DV in physical abuse incidents by 13%. These results support the notion that the empathy of female officers (Rabe-Hemp, 2008), along with victims' preferences for female officers (Lonsway et al., 2003), play a significant role in the enhanced discovery of DV in physical abuse incidents.

The paper explores two dimensions of heterogeneity. First, it considers heterogeneous effects by the timing of shifts. Results indicate that the significant increase in the probability of discovering DV related physical abuse when a female officer is present in the primary unit is mostly contributed by those working in the shift from 8 am-4 pm in both police departments. Second, it considers heterogeneous effects of having a more or less experienced female officer in the primary unit. Results from both police departments indicate that the significant increase in the probability of discovering DV related physical abuse in the presence of a female officer in the primary unit is mostly contributed by those with at least 10 years of experience.

This paper makes contributions to the economics of crime literature on DV by directly providing quantitative evidence of the effect of gender roles on the novel outcome of discovering DV related physical abuse incidents. Previous literature has studied the effects of arrests (Iyengar, 2009; Amaral et al., 2023), prosecution (Aizer & Dal Bo, 2009), unilateral divorce laws (Dee, 2003; Stevenson & Wolfers, 2006), gender wage gap (Aizer, 2010), unemployment (van den Berg & Tertilt, 2012), upset losses in football games (Card & Dahl, 2011), rainfall shocks (Sekhri & Storeygard, 2014), and female representation among officers in an area (Miller & Segal, 2019) on DV incidents. Specifically, Miller & Segal (2019) analyze data from the NCVS and Uniform Crime Reporting (UCR) program using OLS and IV approaches. Using responses to the questions on crime incidents and whether these incidents are reported to the police, the authors conclude that increasing female representation among officers in an area through affirmative action plans increases reports of DV. Using homicide data from the UCR program, they find a negative relationship between the previous year's female share of officers in the county and the current year's intimate partner homicide rates. The data from NCVS and UCR program do not the allow the authors to observe how people in the area know there are more female officers and how these police-civilian interactions take place. This paper fills in the gap by directly estimating the effect of female officers in calls for service. A key advantage of using calls for service data is that the existence of a female officer in the primary unit is conditionally random. This empirical strategy avoids problems generated by endogenous police-civilian interactions. The idea of using a different approach to solve this endogeneity issue is related to works by West (2018) who utilizes conditional random assignment of officers to traffic accidents to study racial bias in traffic citations, Weisburst (2022) who uses 911 call data to assess the individual police officers' value added, and Hoekstra & Sloan (2022) who use 911 call data to examine race and police use of force.

This paper also contributes to the literature that studies the effects of police staffing and policies. Previous literature has focused on the size of police forces (Levitt, 1997; Chalfin & McCrary, 2013), the adoption of information technology (Garicano & Heaton, 2010), and the use of DNA databases (Doleac, 2017). This paper considers another aspect of police staffing by studying the effects of officers' gender. The focus on officers' gender is related to Lonsway et al. (2003) who use survey data to describe advantages of hiring women in law enforcement agencies. Using survey data does not allow the authors to establish causal inferences on the effects of gender and it has issues with sampling error. This paper deals with sampling issues and estimates causal effects of female officers by using calls for service data. Moreover, the focus on officers' gender in this paper is broadly related to the literature on police demographics. Previously, studies have related officer race to arrests (Donohue III & Levitt, 2001), search (Antonovics & Knight, 2009), and use of force (Fryer Jr, 2019; Hoekstra & Sloan, 2022). The difference between this paper and that literature is that this paper considers the role of gender in interactions between police and victims while that literature mainly considers interactions between police and suspected offenders.

Furthermore, this paper contributes to the literature that studies the effects of female representation. The finding of an increased discovery of DV related physical abuse with female officer dispatched in this paper highlights the importance of female officers in the police force, a field traditionally dominated by male officers. As a result, this paper is related to studies on the effects of female representation. Previously, Chattopadhyay

& Duflo (2004) point out that women leaders in local government invest more in the public goods that are more closely linked to women's concerns. Iyer et al. (2012) find that an increase in female representation in local government increases reports of crimes against women. Matsa & Miller (2011) show that female representation on corporate boards influences the gender composition of the top management in companies. Matsa & Miller (2013) and Miller (2018) focus on the effects of gender quotas for corporate board seats on corporate decisions and find that there are fewer workforce reductions in these corporations. I'm unaware of any studies that examine the effects of female representation in primary units for calls for service on discovering DV incidents.

Results in this paper have policy implications for policing in the US. There have been controversies on the integration of female officers (Martin & Jurik, 2006). Opponents believe that since women are generally smaller and weaker than men, they are less capable at policing. They are concerned that there may also be lower standards for female officers in the hiring process, which lowers average officer quality (Miller & Segal, 2019). Contrary to these views, this paper provides evidence on the vital role that female officers play. Although there are only two cities in the analysis, results in this paper imply that DV can be under-reported when male officers are the only ones dispatched in the primary unit. The existence of a female officer in the primary unit is important for discovering DV in physical abuse incidents. Moreover, results in this paper show the importance of having a more experienced female officer in the primary unit. Given the role of experience, it is helpful to provide more training for police officers to enhance the discovery of DV in physical abuse incidents. Overall, results in this paper indicate that female officers are an indispensable part in the police force.

The rest of the paper proceeds as follows. Section 2 discusses the research design. Section 3 presents empirical analysis. Section 4 concludes.

1.2 Data

To obtain the data needed in this paper, I sent Freedom of Information Act (FOIA) requests to police departments in the top twenty cities in terms of homicide rate in the US.[1] Homicide is one of the most serious violent crimes. Cities ranked in the top in terms of homicide rate are more likely to incur other violent crimes such as physical abuse. These physical abuse incidents are the focus of this paper. Moreover, cities with higher violent crime rates are more likely to maintain database to record crimes in order to analyze crime patterns and better serve the community.

For the dataset in this paper, I need to be able to observe and link the gender of the police officer to 911 calls. Among the twenty police departments with FOIA requests sent, only the Milwaukee Police Department and Chicago Police Department provided the calls for service data and officer characteristics data that can be linked together from 2017-2019. The other 18 police departments did not provide the data needed in the paper.[2]

The background information of the two cities is introduced below. Milwaukee is the largest city in the state of Wisconsin with a population of about 570,000. There are seven police districts in this city. Like other law enforcement agencies in the US, it uses the computer aided dispatch system to record the call information such as type of incident, officer assigned, and dispatch time, as well as information on officer availability. When a civilian calls 911, the first available telecommunicator takes the call. A telecommunicator's responsibility includes ascertaining incident information, establishing incident

[1]The ranking of the homicide rate of cities in the US comes from `https://en.wikipedia.org/wiki/List_of_United_States_cities_by_crime_rate`.

[2]For the 18 police departments that did not provide the data needed in this paper, Indianapolis and Philadelphia Police Departments did not respond. Atlanta, Baltimore, Cleveland, Detroit, District of Columbia, Kansas City, Memphis, Mobile, New Orleans, Newark, Pittsburgh, and Tulsa Police Departments did not provide the calls for service data. Baton Rouge, Cincinnati, St. Louis, and Stockton Police Departments provided the calls for service data without information on officers dispatched to the call.

priority, and forwarding the incident for dispatch (National 911 Program, 2022). After the telecommunicator assigns the call to the appropriate district dispatcher, the dispatcher assigns available officers in the shift to the call based on call priority. I emailed officers in the police department and they confirmed that calls are dispatched based on priority. Chicago is the largest city in the state of Illinois and the third most populous city in the US. Its population is around 2.75 million. There are twenty-two police districts in the city. In this police department, call takers pick up 911 calls. Call takers gather information about the emergency and input it into the police computer aided dispatch system (Neusteter et al., 2019). According to the General Order G03-01-01 in the directive of the Chicago Police Department, the system automatically prioritizes each event, and then dispatchers assign available officers to the call based on call priority.

The empirical analysis uses calls for service data linked to officer characteristics data from the Milwaukee and Chicago Police Departments from 2017-2019. The calls for service data contains information on call created time and date, call dispatched time and date, original and final call type, officer dispatched, primary unit dispatched, and police district. The primary unit is generally the first unit to arrive on the scene. The time between call and dispatch represents call priority, since higher ranked calls are at the top of the dispatch queue. The officer characteristics data has information on officer race, gender, and date that the officer was first appointed at the police department. The linked calls for service data and officer characteristics data allow observation of dispatched officers and their characteristics for each of the call.

DV related physical abuse is any type of physical force against the intimate partner that causes injury or puts the person's health in danger (Office on Women's Health, 2021). Most police intervention of these incidents starts from emergency calls (HM Inspectorate of Constabulary, 2014). In the Milwaukee Police Department, there are nine call types that fall under DV related physical abuse. These calls have the suffix "DV" to differentiate themselves from others. For example, the police department records "battery cutting" and "battery cutting-DV" separately. Table 1.1a presents call types that belong to DV related physical abuse and their corresponding ones without the "DV" suffix. Observation of the data indicates that the final call type can be different from the original call type. About 50% of calls that are reclassified as DV related physical abuse come from call types related to physical abuse only. This implies that there are ambiguities in the original call type classification, as officers on the scene know more details about incidents than dispatchers who often have limited information. Similar to Hoekstra & Sloan (2022), this paper briefly introduces data related to the Chicago Police Department. In this police department, the call type that falls under DV related physical abuse is domestic battery. The corresponding physical abuse incidents without DV elements are classified as battery related. Table 1.1b presents the call type that belongs to DV related physical abuse and the corresponding ones without DV elements at the Chicago Police Department.

To study whether female officers are more likely to discover DV related physical abuse on the scene, the sample is restricted to call types related to physical abuse only as listed in the second column of Table 1.1a for the Milwaukee Police Department and the second column of Table 1.1b for the Chicago Police Department. For the Milwaukee Police Department, roughly 28% of the calls have one officer dispatched and roughly 71% of the calls have two officers dispatched in the primary unit in the sample. Characteristics of the officer with more years of experience in the primary unit are important, as less experienced officers often learn from more experienced ones. This echoes the accumulation of human capital with more knowledgeable coworkers (Herkenhoff et al., 2018). These officers with more years of experience in primary units are very familiar with the districts that they work at. Similar to Hoekstra & Sloan (2022), the analysis uses home district to proxy the district to which the officer responds to the most calls. To be more precise, it calculates the home districts for officers each month. By conducting a comparison of officers' home districts across months, results reveal that there is an 85% chance that these officers remain assigned to their home districts. This pattern corresponds to the community policing philosophy, which emphasizes long-term assignment of officers to specific areas in order to increase trust in police and improve community partnerships (U.S. Department of Justice, 2014). Column (1) of Table 2.2 presents summary statistics for incidents in the sample. These incidents receive speedy response. The time between call and dispatch is about 9 minutes on average. There is a 95% chance that the call is from the home district of the officer with more years of experience in the primary unit. About 21% of the primary units have female officers. Roughly 64% of the officers with more years of experience in primary units are white. On average, more experienced officers in primary units have worked for about 11 years. Column (2) of Table 2.2 presents summary statistics for incidents in the sample for the Chicago Police Department. The time between call and dispatch is about 5 minutes on average. There is a 97% chance that the call is from the home district that the more experienced officer in the primary unit responds to the most calls. The probability that there exists a female officer in the primary unit is around 32%. About 42% of the officers with more years of experience in primary units are white. On average, more experienced officers in primary units have worked for roughly 11 years.

The way that the dispatch process works in calls for service leads to conditional random assignment. In both police departments, there is a telecommunicator or call taker who picks up a 911 call, and a dispatcher who assigns available officers to the call. Calls are dispatched based on priority. The dispatcher does not have direct contact with the caller and only has limited information from the telecommunicator or call taker, which rules out that the dispatcher has extra information on specific needs of the caller (Amaral et al., 2023). Moreover, calls in the sample from both police departments receive speedy response. The way that the dispatch process works implies that conditional on district and time fixed effects, the variation in whether there exists a female officer in the primary unit is as good as random. As a result, the regression controls for district-by-year fixed effects in the baseline regression, and district-by-year-by-week-by-shift fixed effects in the preferred specification.[3]

To assess the validity of the design, the paper directly examines the correlation between call characteristics and whether there exists a female officer in the primary unit. Specifically, the assessment separately regresses time between call entry and call dispatch, and whether the call is from the home district of the officer with more years of experience in the primary unit on the existence of a female officer in the primary unit with district-by-year fixed effects and district-by-year-by-week-by-shift fixed effects. Since calls with higher priority are at the top of the dispatch queue, the first assessment checks whether primary units with female officers are dispatched to more or less urgent incidents using the following equation:

$$TimeBetween_{dct} = \alpha_0 + \alpha_1 I(\text{Female officer in primary unit})_{dct} + \theta_{dt} + \varepsilon_{dct}. \qquad (1.1)$$

$TimeBetween_{dct}$ represents the time between call entry and call dispatch for the call c from district d in time period t. $I(\text{Female officer in primary unit})_{dct}$ is an indicator variable that takes on a value of one if there exists a female officer in the primary unit for the call. θ_{dt} contains district and time fixed effects. In the first column of the regression table, it represents the district-by-year fixed effects. In the second column of the regression table, it represents the district-by-year-by-week-by-shift fixed effects. The standard error is clustered at the officer with more years of experience in the primary unit for the call for service. Table 1.3a shows results from the Milwaukee Police Department. Results in the table indicate there is no statistical significance for the coefficients. Moreover, results

[3]In district-by-year-by-week-by-shift fixed effects, shifts are defined as 8 am-4 pm, 4 pm-midnight, and midnight-8 am. Hoekstra & Sloan (2022) also define shifts in these three time periods.

from the Chicago Police Department in Table 1.3b also show there is no statistical significance for the coefficients. These results are consistent with the identifying assumption in the paper. The second assessment checks whether primary units with female officers are dispatched to districts where officers with more years of experience respond to the most calls using the following equation:

$$HomeDist_{dct} = \alpha_0 + \alpha_1 I(\text{Female officer in primary unit})_{dct} + \theta_{dt} + \varepsilon_{dct}. \tag{1.2}$$

$HomeDist_{dct}$ represents whether the call comes from the home district of the officer with more years of experience in the primary unit. Table 1.4a reports results from the Milwaukee Police Department. Results show there is no statistical significance for the coefficients. Table 1.4b reports results from the Chicago Police Department. The significant coefficients reported in Table 1.4b imply that primary units with female officers are roughly 0.3 percentage points less likely to be dispatched to calls from the home district of the officer with more years of experience in the primary unit. Given that 97% of the calls come from the home district of the officer with more years of experience in the primary unit, a deviation of 0.3 percentage points is negligible. The economic significance is very small. The lack of statistical and economic significance of the coefficients in the table are consistent with the identifying assumption in the paper. Hoekstra & Sloan (2022) also have similar issues and use this argument to justify the identifying assumption.

1.3 Empirical Analysis

1.3.1 Regression Model

The empirical analysis uses the regression below to estimate the effect of having a female officer in the primary unit on the probability of discovering DV related physical abuse. As discussed in the previous section, the identifying assumption is that conditional on district and time fixed effects, the variation in whether there exists a female officer in the primary unit is as good as random. The regression model incorporates the identifying assumption in the following equation:

$$Discover_{dct} = \beta_0 + \beta_1 I(\text{Female officer in primary unit})_{dct} + \theta_{dt} + \gamma X_c + \varepsilon_{dct}. \tag{1.3}$$

$Discover_{dct}$ is a binary variable equal to one when call c from district d in time period t is classified into DV related physical abuse in the final call type. X_c includes call controls that contain the time between call and dispatch, whether the call is from the home district of the officer with more years of experience in the primary unit, race of the officer with more years of experience in the primary unit, as well as fixed effects for the day of the week, original call type, and maximum years of experience for officers in the primary unit. An officer's home district is proxied by the district to which the officer responds to the most calls in a month. The standard error is also clustered at the officer with more years of experience in the primary unit for the call for service.

1.3.2 Main Results

Table 1.5a and Table 1.5b present regression results for the Milwaukee and Chicago Police Department correspondingly. Column (1) shows regression results with district-by-year fixed effects. Column (2) shows regression results with district-by-year-by-week-by-shift fixed effects and all call controls except whether the call is from the home district of the officer with more years of experience in the primary unit. The reason for having this column is because of the small effect found when regressing whether the call is from the home district of the officer with more years of experience in the primary unit on the existence of a female officer in the primary unit for the Chicago Police Department in Section 2. Column (3) shows regression results with district-by-year-by-week-by-shift fixed effects and all call controls.

Results from Table 1.5a for the Milwaukee Police Department show that there is a significant increase in the probability of discovering DV in physical abuse incidents when there exists a female officer in the primary unit across the specifications in the three columns, and the estimates remain similar. Results from the preferred specification in column (3) indicate that having a female officer in the primary unit increases the probability of discovering DV related physical abuse by about 0.3 percentage points. Given that 3% of the original call types are reported as DV related physical abuse in this city, having a female officer in the primary unit is 10% more likely to discover these incidents.

In addition to studying the effects of the existence of a female officer in a primary unit on the probability of discovering DV related physical abuse using three-year data from Milwaukee, the paper also studies the effects using three-year data from Chicago. Compared to Milwaukee, the population in Chicago is five times larger, the land size is three times larger, and the police demographics are very different. Table 1.5b shows regression results. Results from the preferred specifications in column (3) imply that having a female officer in the primary unit enhances the probability of discovering DV related physical abuse by 0.4 percentage points. Given that approximately 3% of the calls for service are classified as domestic battery initially in this city, having a female officer in the primary unit scales up the likelihood of discovering these incidents by 13%.

For robustness check, the analysis conducts a logit regression. Due to concerns that the logit estimator can have convergence issues when there are many fixed effects in the regression (Chamberlain, 1980), the logit regression controls for district-by-year fixed effects. Table A.1a and Table A.1b report the regression results in odds ratio for the Milwaukee and Chicago Police Department correspondingly. These results also imply a significant increase in the probability of discovering DV in physical abuse incidents when a female officer exists in the primary unit in both police departments.

According to previous literature, two potential channels can contribute to the increased discovery of DV related physical abuse when there exists a female officer in the primary unit. First, female officers have greater empathy and better communication skills (Rabe-Hemp, 2008). They also express more concerns, patience, and understanding than male officers when dealing with violence against women (Homant & Kennedy, 1985; Lonsway et al., 2003). The care and patience by female officers can be related to finding out more DV related physical abuse on the scene. Second, most victims of DV are female. They find female officers more helpful and favorable in these incidents (Lonsway et al., 2003). This echoes the notion of female officers helping women (Miller & Segal, 2019) and the notion of female role modelling in positions of authority (Athey et al., 2000; Keiser et al., 2002; Meier & Nicholson-Crotty, 2006; Carrell et al., 2010). So victims can be more willing to disclose incident details to female officers. As a result, it is reasonable that female officers are more likely to discover DV related physical abuse when they are dispatched to calls that may have ambiguity.

1.3.3 Heterogeneity Analysis on Timing of Shifts

This section considers the heterogeneity analysis of estimated effects by the timing of shifts. There is some evidence that people perform better during the day (Cho et al., 2020). This implies that people can have different levels of performance in different periods of the day. Therefore, the heterogeneity analysis in this section fits separate models for incidents in the three eight-hour shift windows to observe the performance of primary units that contain a female officer in each shift. Card & Dahl (2011) also use a similar approach for analysis related to the timing.

Table 1.6a and Table 1.6b show results for the Milwaukee and Chicago Police Department correspondingly. Results from Table 1.6a show that having a female officer in the primary unit increases the probability of discovering DV related physical abuse by about 0.5 percentage points in the 8 am-4 pm shift and 0.4 percentage points in the 4 pm-midnight shift. Given that roughly 3% of the original call types are classified as DV related physical abuse in the two shifts in Milwaukee, having a female officer in the primary unit enhances the likelihood of discovering these incidents by about 17% in the 8 am-4 pm shift and about 13% in the 4 pm-midnight shift. These results imply that the significant increase in the probability of discovering DV related physical abuse when there is a female officer in the primary unit in the main result is largely contributed by those working in the 8 am-4 pm shift. Moreover, results from Table 1.6b indicate that having a female officer in the primary unit enhances the probability of discovering DV related physical abuse by about 0.8 percentage points in the 8 am-4 pm shift. Given that approximately 2% of the original call types are classified as DV related physical abuse in this shift in Chicago, having a female officer in the primary unit increases the likelihood of discovering these incidents by about 40%. This result also shows that the significant increase in the probability of discovering DV related physical abuse in the presence of a female officer in the primary unit in the main result is mostly contributed by those working in the 8 am-4 pm shift.

1.3.4 Heterogeneity Analysis on Officer Experience

Moreover, the empirical analysis considers the heterogeneity of estimated effects of having a more or less experienced female officer in the primary unit on the probability of discovering DV related physical abuse. This is motivated by Ba et al. (2021) who find that more experienced officers are more effective at deterring violent crime and they are less likely to use force. Then, this heterogeneity analysis explores whether having a female officer with a minimum of 10 years of experience or one with less than 10 years of experience in the primary unit contributes to the significant increase in the probability of discovering DV in physical abuse incidents.

The regression considers the effects of having a more or less experienced female officer by further categorization. The cutoff for more or less experience is at 10 years, which approximates the average work experience for the more experienced officer in the primary unit in Table 2.2. The regression uses the following equation:

$$\begin{aligned} Discover_{dct} = \beta_0 + \beta_1 I(\text{Female officer} \geq 10 \text{ years of experience in primary unit})_{dct} + \\ \beta_2 I(\text{Female officer} < 10 \text{ years of experience in primary unit})_{dct} + \theta_{dt} + \gamma X_c + \varepsilon_{dct}. \end{aligned} \tag{1.4}$$

$I(\text{Female Officer} \geq 10 \text{ Years of Experience in Primary Unit})_{dct}$ is an indicator variable that equals to 1 if there exists a female officer with at least 10 years of experience in the primary unit. $I(\text{Female Officer} < 10 \text{ Years of Experience in Primary Unit})_{dct}$ is an indicator variable that equals to 1 when there exists a female officer with less than 10 years of experience in the primary unit. For simplicity, I drop incidents that have a female officer with at least 10 years of experience in the primary unit and a female officer with less than 10 years of experience in the primary unit at the same time. These incidents constitute about 0.3% in the sample for the Milwaukee Police Department and about 1.6% in the sample for the Chicago Police Department.

Table 1.7a and Table 1.7b present results from the Milwaukee and Chicago Police Department. Results from Table 1.7a show that compared to primary units with male officers only, there is a significant increase in the probability of discovering DV related physical abuse incidents when there exists a female officer with at least 10 years of experience in the Milwaukee Police Department. Results from Table 1.7b indicate that, in comparison to primary units that contain solely male officers, having either a female officer with a minimum of 10 years of experience or one with less than 10 years of experience in the primary unit significantly increases the probability of discovering DV related physical abuse incidents. The magnitude of the coefficient is larger in the presence of a female officer with at least 10 years of experience. These results indicate that the significant rise in the probability of discovering DV related physical abuse in the presence of a female officer in the primary unit in the main result is mostly contributed by those with at least 10 years of experience.

1.4 Conclusion

This paper examines the effects of having a female officer in the primary unit on the discovery of DV in physical abuse incidents. It exploits the as-good-as-random variation in the existence of a female officer in the primary unit in calls for service dispatch at the Milwaukee and Chicago Police Departments. Results provide strong evidence that female officers play an important role. Having a female officer in the primary unit scales up reports of DV in physical abuse incidents by 10% in the Milwaukee Police Department. Results from the Chicago Police Department also find positive effects. Estimates indicate that having a female officer in the primary unit scales up DV reports in physical abuse incidents by 13%. These results can be driven by empathy and concerns from female officers (Rabe-Hemp, 2008), as well as preferences for female officers from victims (Lonsway et al., 2003).

The paper also conducts two dimensions of heterogeneity analysis. First, it considers the heterogeneity of estimated effects by the timing of shifts. Results show that the significant increase in the probability of discovering DV related physical abuse when there exists a female officer in the primary unit is mostly contributed by those working in the shift from 8 am-4 pm in both police departments. Second, the paper considers the heterogeneity of estimated effects of having a more or less experienced female officer in the primary unit. Results from both police departments imply that the significant rise in the probability of discovering DV related physical abuse in the presence of a female officer in the primary unit is mostly contributed by those with at least 10 years of experience.

Overall, findings in this paper indicate that female officers play a vital role in discovering DV in physical abuse incidents. These findings have policy implications. The majority of police officers are male. Females are often considered to be less capable at policing (Miller & Segal, 2019). But results in this paper imply that when male officers are the only ones dispatched in the primary unit, DV may not be discovered and can be under-reported. Therefore, it is important to have a female officer in the primary unit so that more DV incidents can be discovered and reported in physical abuse incidents. Also, results in this paper indicate the importance of having a more experienced female officer in the primary unit. Given the role of experience, it is helpful to provide more training for police officers to enhance the discovery of DV in physical abuse incidents. Results in this paper further justify that female officers are an indispensable part in the police force.

1.5 Tables

Table 1.1: Call types for DV related physical abuse and physical abuse only

(a) Milwaukee

Call types for DV related physical abuse	Call types for physical abuse only
ABDUCTION-DV	ABDUCTION
BATTERY DV	BATTERY
BATTERY CUTTING-DV	BATTERY CUTTING
FIGHT-DV	FIGHT
HOSTAGE SIT-DV	HOSTAGE SITUATION
RECK USE OF W-DV	RECK USE OF WEAP
SHOTS FIRED-DV	SHOTS FIRED
SUBJ WITH GUN-DV	SUBJ WITH GUN
SUBJ W/WEAPON-DV	SUBJ WITH WEAPON

(b) Chicago

Call types for DV related physical abuse	Call types for physical abuse only
	BATTERY IP
	BATTERY JO
	BATTERY REPORT
DOMESTIC BATTERY	BATTERY VICTIM INJ.

Table 1.2: Summary statistics for calls in the sample

	Milwaukee	Chicago
Time between call and dispatch (in minutes)	9.450	5.023
	(26.658)	(13.013)
Call from home district of officer with more years of experience in primary unit	0.953	0.965
	(0.212)	(0.183)
Female officer in primary unit	0.214	0.316
	(0.410)	(0.465)
Black officer as officer with more years of experience in primary unit	0.173	0.196
	(0.378)	(0.397)
Hispanic officer as officer with more years of experience in primary unit	0.140	0.118
	(0.347)	(0.322)
White officer as officer with more years of experience in primary unit	0.642	0.422
	(0.479)	(0.494)
Max years of experience for the officer in primary unit	10.694	10.606
	(6.892)	(7.916)
Observations	102050	184189

This table reports the mean, standard deviation, and the number of observations for each variable. Officer home district is proxied by the district to which the officer responds to the most calls in a month. Standard deviations are in parentheses.

Table 1.3: Correlation between time between call entry and call dispatch and whether there exists a female officer in the primary unit

(a) Milwaukee

	(1)	(2)
Female officer in primary unit	0.508	0.322
	(0.415)	(0.414)
Observations	102050	102048
District-by-year FE	Yes	No
District-by-year-by-week-by-shift FE	No	Yes
Average time between call and dispatch (in minutes)	9.450	9.450

(b) Chicago

	(1)	(2)
Female officer in primary unit	-0.132	-0.0456
	(0.0861)	(0.0836)
Observations	184189	184040
District-by-year FE	Yes	No
District-by-year-by-week-by-shift FE	No	Yes
Average time between call and dispatch (in minutes)	5.023	5.023

This table reports the coefficient on *Female officer in primary unit* from separate regressions of time between call entry and call dispatch on a binary variable representing whether there exists a female officer in the primary unit dispatched. Standard errors are reported in parentheses and are clustered at the level of the officer in the primary unit with more years of experience.

Table 1.4: Correlation between whether the call comes from the home district of the officer with more years of experience in the primary unit and whether there exists a female officer in the primary unit

(a) Milwaukee

	(1)	(2)
Female officer in primary unit	-0.00932	-0.00896
	(0.00831)	(0.00783)
Observations	102050	102048
District-by-year FE	Yes	No
District-by-year-by-week-by-shift FE	No	Yes
Average probability of having a call from the home district of officer with more years of experience in primary unit	0.953	0.953

(b) Chicago

	(1)	(2)
Female officer in primary unit	-0.00324**	-0.00274*
	(0.00152)	(0.00150)
Observations	184189	184040
District-by-year FE	Yes	No
District-by-year-by-week-by-shift FE	No	Yes
Average probability of having a call from the home district of officer with more years of experience in primary unit	0.965	0.965

This table reports the coefficient on *Female officer in primary unit* from separate regressions of whether the call comes from the home district of the officer with more years of experience in the primary unit on a binary variable representing whether there exists a female officer in the primary unit dispatched. Standard errors are reported in parentheses and are clustered at the level of the officer in the primary unit with more years of experience.

Table 1.5: The effect of having a female officer in the primary unit on discovering DV related physical abuse

(a) Milwaukee

	(1)	(2)	(3)
Female officer in primary unit	0.00401**	0.00310*	0.00323*
	(0.00174)	(0.00170)	(0.00165)
Observations	102050	102045	102045
District-by-year FE	Yes	No	No
District-by-year-by-week-by-shift FE	No	Yes	Yes
Call controls except whether the call is from the home district of the officer with more years of experience in the primary unit	No	Yes	No
Call controls	No	No	Yes
Probability of having DV related physical abuse as the original call types	0.0301	0.0301	0.0301

(b) Chicago

	(1)	(2)	(3)
Female officer in primary unit	0.00567***	0.00450***	0.00426***
	(0.00131)	(0.00134)	(0.00133)
Observations	184189	184040	184040
District-by-year FE	Yes	No	No
District-by-year-by-week-by-shift FE	No	Yes	Yes
Call controls except whether the call is from the home district of the officer with more years of experience in the primary unit	No	Yes	No
Call controls	No	No	Yes
Probability of having DV related physical abuse as the original call type	0.0280	0.0280	0.0280

This table shows the effect of having a female officer in the primary unit on discovering DV related physical abuse. Call controls contain time between call and dispatch, whether the call is from the home district of the officer with more years of experience in the primary unit, race of the officer with more years of experience in the primary unit, as well as fixed effects for the day of the week, original call type, and max years of experience for the officer in the primary unit. Officer home district is proxied by the district to which the officer responds to the most calls in a month. Standard errors are reported in parentheses and are clustered at the level of the officer in the primary unit with more years of experience.

Table 1.6: The effect of having a female officer in the primary unit in different shifts on discovering DV related physical abuse

(a) Milwaukee

	(1)	(2)	(3)
	midnight-8 am	8 am-4 pm	4 pm-midnight
Female officer in primary unit	-0.00124	0.00478*	0.00444*
	(0.00343)	(0.00286)	(0.00245)
Observations	23038	31774	47233
District-by-year-by-week-by-shift FE	Yes	Yes	Yes
Call controls	Yes	Yes	Yes
Probability of having DV related physical abuse as the original call types in different shifts	0.0318	0.0269	0.0320

(b) Chicago

	(1)	(2)	(3)
	midnight-8 am	8 am-4 pm	4 pm-midnight
Female officer in primary unit	0.00319	0.00811***	0.00199
	(0.00269)	(0.00248)	(0.00183)
Observations	46191	54075	83771
District-by-year-by-week-by-shift FE	Yes	Yes	Yes
Call controls	Yes	Yes	Yes
Probability of having DV related physical abuse as the original call types in different shifts	0.0344	0.0241	0.0281

This table shows the effect of having a female officer in the primary unit in different shifts on discovering DV related physical abuse. Estimates are based on the same model as column (3) of Table 5 (including district-by-year-by-week-by-shift fixed effects and all call controls). Standard errors are reported in parentheses and are clustered at the level of the dispatched officer in the primary unit with more years of experience.

Table 1.7: The effect of having a female officer with a minimum of 10 years of experience or one with less than 10 years of experience in the primary unit on discovering DV related physical abuse

(a) Milwaukee

	(1)
Female officer $\geq$ 10 years of experience in primary unit	0.00507*
	(0.00293)
Female officer $<$ 10 years of experience in primary unit	0.00203
	(0.00203)
Observations	101730
District-by-year-by-week-by-shift FE	Yes
Call controls	Yes

(b) Chicago

	(1)
Female officer $\geq$ 10 years of experience in primary unit	0.00546**
	(0.00228)
Female officer $<$ 10 years of experience in primary unit	0.00371**
	(0.00156)
Observations	181054
District-by-year-by-week-by-shift FE	Yes
Call controls	Yes

This table shows the effect of having a female officer with more and fewer years of experience in the primary unit on discovering DV related physical abuse. Estimates are based on the similar model as column (3) of Table 5 (including district-by-year-by-week-by-shift fixed effects and all call controls). Incidents that have a female officer with ≥ 10 years of experiences in primary unit and a female officer with < 10 years of experience in primary unit at the same time are dropped. These incidents constitute about 0.3% in the sample for the Milwaukee Police Department and about 1.6% in the sample for the Chicago Police Department. Standard errors are reported in parentheses and are clustered at the level of the officer in the primary unit with more years of experience.

Chapter 2

College Basketball Game Day and Sexual Assault

2.1 Introduction

College basketball teams, especially top ones, draw enormous attention from the public. For example, Duke has sold out all basketball home games since 1990.[1] Even more people are watching college basketball games on TV. Coach Krzyzewski's last home game at Duke against the University of North Carolina at Chapel Hill had 3.98 million viewers on ESPN.[2]

The high frequency of games is a distinctive feature of college basketball. Teams play 30-40 games per season, depending on how far the team goes in the tournament.[3] In contrast, the college football season is only 12 games long.[4]

[1]Source: https://goduke.com/news/2022/3/3/mens-basketball-no-4-duke-faces-north-carolina-in-coach-ks-final-home-game.aspx

[2]Source: https://www.sportsmediawatch.com/2022/03/duke-unc-ratings-coach-k-finale-most-watched-game-college-basketball-season/

[3]Source: https://www.ncaa.com/news/basketball-men/article/2020-10-27/how-many-games-are-college-basketball-season

[4]Source: https://en.wikipedia.org/wiki/NCAA_Division_I_Football_Bowl_Subdivision

Due to the popularity and frequency of college basketball games, fan game day behavior might be of concern. Previous studies have found increases in the number of crime reports on football game days. Rees & Schnepel (2009) find a 9% increase in assaults and 18% increase in vandalism on college football home game days. Card & Dahl (2011) report a 10% increase in domestic violence for upset losses (defeats when a home team is expected to win by at least four points) in NFL games. Lindo et al. (2018) estimate that college football game days increase rape reports by 28% among college-aged victims.[5] College basketball games also draw enormous attention from the public and they take place at a high frequency. But to our best knowledge, no paper has studied these issues for college basketball.

This paper examines the effect of NCAA Division I basketball games by prominent teams on the probability of having sexual assault reports involving college-aged victims. The identifying assumption is that the timing of game days is as good as random conditional on agency fixed effects and time-varying controls. Utilizing crime data from the National Incident-Based Reporting System (NIBRS) and game results data from top Division I basketball teams between 2008 and 2019, we find that basketball home game days have little effect on the probability of having sexual assault reports among college-aged victims while basketball away game days scale up the probability by 14%. There is a significant difference in estimates for basketball home and away game days, and it can be explained by different watching patterns. Home game days bring people together at basketball arenas on campus, where there are often more police patrols due to special campus events. On basketball away game days, people are mostly dispersed off campus, where there are not as many police patrols as basketball home game days.

[5] All three papers use regressions that model count variables with the logit link function. Rees & Schnepel (2009) use the negative binomial regression model. Card & Dahl (2011) and Lindo et al. (2018) use the Poisson regression model. Results interpretation follows the incidence rate ratio, which is calculated as $e^{\beta} - 1$. Hence, these results have different measurement as results from the linear probability model, which will be discussed shortly.

Results from heterogeneity analysis by the location of police departments support this notion. The results indicate that increases of sexual assault reports on basketball away game days are concentrated in city police departments. Heterogeneity analysis by team prominence shows that the effect on basketball away game days is large and significant for more prominent teams. Further analysis of victim-offender relationship indicates that effects on basketball away game days are mainly driven by offenders outside family but known to victims, which is consistent with results from the Rape, Abuse & Incest National Network (RAINN) that most sexual assault victims know offenders. Also, results show that there is a significant increase for offenders over 24 years old on basketball away game days, which corresponds to the notion that these offenders are mostly non-student and thus they are not bounded by the student conduct code. The significant increase in white victims on basketball away game days is consistent with the mostly white student body for universities in the sample.

Our finding is different from those found for football, which likely reflects differences in viewing and partying behavior across the two sports. Football is more violent than basketball. People learn to behave more violently when watching violent behaviors (Bandura, 1973). Football games are usually associated with lots of partying and tailgating events, which increases sexual assaults (Lindo et al., 2018). Thus, it is reasonable to have smaller estimated effects for basketball than football.

Sexual assaults inflict high social costs. Using the estimated cost of $267,000 per offense (McCollister et al., 2010; Lindo et al., 2018), estimated social costs of sexual assaults induced by top basketball teams is almost $60 million in a basketball regular season each year.

The rest of the paper proceeds as follows. Section 2 discusses the data used in the paper. Section 3 introduces the econometric model. Section 4 provides analysis results. Section 5 discusses the implication of results and concludes.

2.2 Data

The empirical analysis uses crime data from the National Incident-Based Reporting System (NIBRS) concatenated by Kaplan (2021). According to the Institute for Social Research at the University of Michigan, NIBRS offers the academic community more comprehensive data than ever before for research.[6] The key advantage of NIBRS data is its detailed information on incidents such as the reporting agency, incident time, date, age and race of the victim, and the relationship between victim and offender. Two limitations of NIBRS data are that agencies voluntarily participate in NIBRS to report offenses and NIBRS only records crimes reported. The percentage of population covered by NIBRS was 30% as of 2012, and it has reached 66% as of 2022.[7] But similar to Cardazzi et al. (2022), an agency's willingness to participate in the NIBRS is unrelated to game days. The other limitation is that NIBRS only records crime reported and rape is an underreported crime. Kilpatrick et al. (2007) finds that only 12% of college-aged women who experience a rape report it to law enforcement. Nevertheless, Lindo et al. (2018) show that rapes reported are unrelated to game days. Hence, the two limitations do not bias results.

The analysis focuses on college-aged sexual assault victims who are between 17 and 24 years old. The inclusion of 17-year-olds considers the belief that freshmen at the beginning of a new academic year are vulnerable to sexual assault predators (Lindo et al., 2018). The inclusion of victims through 24 years old considers the statistic that 44% of first-time recipients for bachelor's degree finished their degree within 48 months of their initial post secondary enrollment, 23% finished within 49-60 months, and 9% finished within 61-72 months (Cataldi et al., 2011). The analysis includes rape, sodomy,

[6] Source: https://www.icpsr.umich.edu/web/pages/NACJD/NIBRS/

[7] Sources: https://ucr.fbi.gov/nibrs/2012/resources/nibrs-participation-by-state, https://bjs.ojp.gov/national-incident-based-reporting-system-nibrs

and sexual assault with an object in sexual assault incidents. According to NIBRS user manual, the three offenses are all sexual acts against another person without the consent.[8] Lindo et al. (2018) also use this age classification and sexual assault definition.

Data on sexual assault incidents comes from local police departments of prominent college basketball teams. The analysis focuses on universities with NCAA Division I basketball programs that rank in the top 50 based on the frequency of occurrence in the compiled Associated Press Poll (AP Poll) list from 2007-2008 season to 2019-2020 season.[9] Since game day effects can be observed not only on campus but also in the downtown area for spillovers, the analysis uses NIBRS data from university police departments and police departments located in the same city. The analysis excludes data from police departments in cities that have more than one university participating in the Division I basketball program to ensure that all incidents in a city are assigned to one college basketball team. Because most universities with basketball programs ranked in the top 50 in the compiled AP Poll list have football programs and Lindo et al. (2018) find a significant increase in sexual assault reports with college-aged victims on football game days, the analysis excludes universities without football programs so that universities in the analysis have similar sports culture. As a result, there are 44 police departments that correspond to 27 universities in the analysis. Table 2.1 records universities, their corresponding police departments, and years available in the NIBRS.[10]

The analysis uses NIBRS data on sexual assault incidents from the 44 police departments to generate agency-by-day level data on these incidents and links it to their

[8] Fondling is not included because it refers to fondling against child in NIBRS and thus it is not relevant to college-aged victims in the analysis. Source: `https://le.fbi.gov/file-repository/nibrs-user-manual.pdf/view`

[9] The AP Top 25 College Basketball Poll provides weekly rankings of the top 25 NCAA basketball teams. The ranking is compiled by polling 60+ sportswriters and broadcasters across the nation who closely follow college basketball games. Votes of the members in the AP Poll are also made public. Source: `https://apnews.com/hub/ap-top-25-college-basketball-poll`

[10] Since an agency may join the NIBRS in the middle of a year, the analysis only considers agencies that report data on any crimes in a month.

corresponding universities' game records.[11] To account for events that go from late night to early morning, a day is defined to be from 6:00 am to 5:59 am the next day. This adjustment utilizes incident date and time records in the NIBRS. The agency-by-day level data is then linked to basketball and football game records at their corresponding universities. As mentioned previously, football game days have significant effects on sexual assaults with college-aged victims (Lindo et al., 2018). The analysis takes it into consideration by controlling for football game days, which will be discussed in the next section. Data on college basketball and football games comes from `sportsbookreviewsonline.com`. The basketball game day data is cross checked with data from Benz (2022) and the football game day data is cross checked with data from `sports-reference.com/cfb/`. As college basketball games mostly take place in regular seasons and lots of games are cancelled in 2020 due to the COVID-19 pandemic, the analysis focuses on dates in regular seasons of college basketball from 2008-2019.[12] The appendix reports results using dates from other time periods.

Therefore, the sample in the main analysis has 43,820 observations. This includes 11,049 days with basketball games. Table 2.2 records reported sexual assault incidents per day based on the sample in the main analysis. Reported incidents per day with college-aged victims are almost the same as reported incidents per day with victims over 24 years old. This statistic indicates that lots of college-aged victims are involved. Further analysis on victims' race shows that these college-aged victims are largely white.

[11]NIBRS stores details of sexual assault incidents in different segments. The originating agency identifier, incident number, and incident date are used to link incident details in different segments. If the two incidents have the same linking variables, incident details are matched using the order of appearance in segments (administrative, offense, victim, and offender segments) unless there are differences in the number of segments and relationship of victim to offender. Around 40 incidents have the issue, which is about 0.1% out of all sexual assault incidents from 2008-2019 reported by the 44 police departments.

[12]The analysis drops bowl game days, as well as the day before and after, because these post-season games are not typical. This is the same as Lindo et al. (2018). Dates on NCAA basketball regular and post seasons come from Wikipedia.

2.3 Econometric Model

The econometric model estimates the effect of basketball game days on the probability of having one or more sexual assault incident reports. The identifying assumption is that the timing of game days is as good as random conditional on agency fixed effects and time-varying controls. Lindo et al. (2018) also use this identifying assumption to study the effect on college football game days. The choice of econometric model considers three characteristics of sample data. First, sexual assault is a rare event. About 95% of the agency-by-day level data in the sample records no sexual assault incident involving college-aged victim and about 4% records one incident. Hence, the econometric model uses regressions with binary dependent variables to study the effect of basketball game days on the probability of having one or more sexual assault incident reports involved with college-aged victims. Linear probability model and logit regression model are two candidates. Second, the sample uses incident reports from university police departments and police departments located in the same city to account for spillover effects. As a result, reports from the university and its corresponding city police department are likely to be correlated. Due to the small number of colleges for clusters, standard errors are generated with bootstraps to solve the within-group dependence issue (Cameron et al., 2008). Third, the econometric model includes agency fixed effects and a set of time-varying controls at different levels to control for unobserved variables, which will be introduced below. As nonlinear models with many fixed effects and bootstraps are usually computationally unstable and they can have convergence issues, the main specification adopts the linear probability model with bootstrapped standard errors. The appendix reports results from the logit regression model without bootstraps as a robustness check.

The baseline linear probability model that estimates the effect of basketball game days on the probability of having sexual assault incident reports involved with college-aged victims corresponds to the following equation:

$$R_{ijt} = \theta_i + \gamma X_t + \beta_1 B_{jt}^{h-1} + \beta_2 B_{jt}^{h} + \beta_3 B_{jt}^{h+1} + \beta_4 B_{jt}^{a-1} + \beta_5 B_{jt}^{a} + \beta_6 B_{jt}^{a+1} + \beta_7 F_{jt}^{h-1} + \beta_8 F_{jt}^{h} + \beta_9 F_{jt}^{h+1} + \beta_{10} F_{jt}^{a-1} + \beta_{11} F_{jt}^{a} + \beta_{12} F_{jt}^{a+1}. \quad (2.1)$$

R_{ijt} a binary variable that equals to 1 if there are sexual assault incident reports with college-aged victims at agency i for college j on day t. θ_i represents an agency fixed effect. X_t represents a set of time-varying controls which include day-of-week fixed effects, holiday controls, and year fixed effects.[13] B_{jt}^{h-1}, B_{jt}^{h}, B_{jt}^{h+1} represent the day before, the day of, and the day after basketball home game day t at college j correspondingly. B_{jt}^{a-1}, B_{jt}^{a}, B_{jt}^{a+1} represent the day before, the day of, and the day after basketball away game day t at college j correspondingly. F_{jt}^{h-1}, F_{jt}^{h}, F_{jt}^{h+1} represent the day before, the day of, and the day after football home game day t at college j correspondingly. F_{jt}^{a-1}, F_{jt}^{a}, F_{jt}^{a+1} represent the day before, the day of, and the day after football away game day t at college j correspondingly. The regression separately considers home and away game days to account for different watching patterns. It controls for football game days due to their significant impact on sexual assaults. One-day lag and lead from basketball and football game days consider spillover effects in the short run. Standard errors are bootstrapped 200 times because of a small number of clusters at the college level (Cameron et al., 2008; Bana et al., 2023).

The identifying assumption is that the timing of basketball game days is random, conditional on agency fixed effects and time-varying controls. In the regression, agency fixed effects account for differences in local characteristics such as culture and population. Day-of-week fixed effects control for changes across different days of the week. For

[13]Holiday controls include indicators for Christmas Eve, Christmas Day, New Year's Eve, New Year's Day, Halloween, Thanksgiving Day, Labor Day, Columbus Day, and Veterans Day.

example, Saturdays are more likely to associate with gatherings. Holiday controls consider different student availability on holidays. Year fixed effects control for changes in annual trends. The regression model progressively adds agency-by-month fixed effects, agency-by-week fixed effects, agency-by-year-by-month fixed effects, and agency-by-year-by-week fixed effects to control for changes over the course of the year. Interpretation of results uses the regression with day-of-week fixed effects, holiday controls, and agency-by-year-by-week fixed effects. With these controls, days in the week without basketball games are counterfactuals for days in the same week with basketball games.

2.4 Results

2.4.1 Main Results

Table 2.3 reports results from the linear probability model that estimates effects of basketball home and away games on the probability of sexual assault incidents involving college-aged victims during regular seasons from 2008 to 2019. Estimation in column (1) of Table 2.3 follows equation (1). Column (2)-(5) show results from models that progressively add agency-by-month fixed effects, agency-by-week fixed effects, agency-by-year-by-month fixed effects, and agency-by-year-by-week fixed effects. Estimates change little across different fixed effects specifications. As mentioned earlier, interpretation follows the regression with agency-by-year-by-week fixed effects in column (5). Results show that on basketball away game days, the probability of getting sexual assault reports involving college-aged victims increases by 0.7 percentage points. This is a 14% increase given that the sample mean is 5%. Basketball home game days have little effects on the probability of sexual assault reports. Hypothesis test on whether the coefficient of basketball home game day is the same as the coefficient of basketball away game day indicates that the equality hypothesis is rejected at the 5% significance level. The significant difference in estimates for basketball home and away games can be explained by different watching patterns. Basketball home games bring people together at basketball arenas on campus, where there are often more police patrols due to special campus events. On basketball away game days, people are largely dispersed off campus, where there are not as many police patrols as basketball home game days. As mentioned in Dau et al. (2021), police presence has significant crime preventative effects. So it is reasonable to have larger estimated effects on basketball away game days. Besides, results show that there is a significant increase in the probability of sexual assault reports the day after basketball away game days, compared to days not related to basketball or football games. Hypothesis test on whether the coefficient of basketball away game day equals the coefficient of the day after basketball away game day cannot be rejected. Phillips (1983) and Miller et al. (1991) also find people's behavior change days after a sporting event.

Moreover, Table 2.3 shows that compared to days not related to basketball or football games, there are more positive deviations related to the probability of sexual assault reports on football home and away game days than basketball home and away game days correspondingly. This can be attributed to differences in viewing and partying behavior across the two sports. Football games are more violent than basketball games. According to the social learning theory by Bandura (1973), people learn to behave violently when watching violent behaviors. Football games are often associated with lots of partying and tailgating, which intensifies sexual assault (Lindo et al., 2018). Therefore, it is reasonable to have smaller estimated effects for basketball than football.

The analysis conducts robustness checks for main results from two perspectives. First, the analysis adopts a logit regression without bootstrapped standard errors to relax the functional format assumption. Results are reported as odds ratios in Table B.1.[14] They

[14]By definition, odds represent the probability that an event will occur divided by the probability

have the same signs as those in column (5) of Table 2.3. Second, the analysis considers different time windows for estimation. Coefficients reported in Table B.2 are similar to those reported in column (5) of Table 2.3.

2.4.2 Heterogeneity Analysis

The analysis further considers the heterogeneity of estimated effects by the location of police departments, prominence of basketball teams, victim and offender characteristics, and emotional cues associated with wins and losses. Estimates follow the model with the richest specification in column (5) of Table 2.3. For brevity, tables in the heterogeneity analysis only report coefficients related to basketball game days.

Location of Police Departments

This subsection is motivated by previous results that find a significant increase in the probability of having sexual assault reports involving college-aged victims on basketball away game days and little effect on basketball home game days. This difference can be attributed to different watching patterns for basketball home and away games. Home games bring people together on campus. On away game days, people are mostly dispersed off campus. Incidents on campus fall under the jurisdiction of university police departments and incidents off campus fall under the jurisdiction of city police departments. As a result, this subsection further considers the heterogeneity of estimated effects by the location of police departments to find out which police departments contribute to the elevated effect on basketball away game days.

Column (1) of Table 2.4 considers the probability of having sexual assault reports with

that the event will not occur ($probability(success)/probability(failure)$) and odds ratio is defined to be $\frac{probability(success)A/probability(failure)A}{probability(success)B/probability(failure)B}$. Source:https://stats.oarc.ucla.edu/stata/webbooks/logistic/chapter1/logistic-regression-with-statachapter-1-introduction-to-logistic-regression-with-stata/

college-aged victims at city police departments and column (2) considers university police departments. Results indicate that the probability of sexual assault reports increases by 1.3 percentage points at city police departments on basketball away game days and there is little effect on sexual assault reports at university police departments on these days.

This result supports different watching patterns for basketball home and away game days, as well as incident locations covered by different jurisdictions of police departments. On basketball home game days, people are brought together at campus basketball arenas. On basketball away game days, people are mostly dispersed off campus. Also, university and city police departments have different jurisdictions. For example, the police department at Clemson University is responsible for properties on campus, non-campus buildings controlled by student organizations officially recognized by the institution, and non-campus buildings used for the institution's educational purposes.[15] Therefore, places such as off-campus residences not owned by the institution do not fall into the jurisdiction of university police departments while lots of sexual assault incidents happen there. In the main sample, about 70% of the sexual assault incidents occur at residences and almost all sexual assault incidents happened at residences are reported by city police departments. This is consistent with results from the Rape, Abuse & Incest National Network (RAINN) that most sexual assaults happen at or near home locations.[16] Other results in Table 2.4 provide insights on people's trajectory around basketball away game days. There are significant increases in the probability of sexual assault reports the day before basketball away game days at university police departments and the day after basketball away game days at city police departments. These results suggest that people mostly remain on campus the day before basketball away game days, participate in events off campus on basketball away game days, and still behave badly off campus the

[15] Source: https://www.clemson.edu/cusafety/cupd/reports-and-statistics/clery-act/geography.html

[16] Source: https://www.rainn.org/statistics/scope-problem

day after basketball away game days.

Hence, on basketball away game days, increases in sexual assault reports for college-aged victims are mostly contributed by city PD. There is very little increase in sexual assault reports at university police departments on those days.

Prominence of Basketball Teams

This subsection considers heterogeneous effects by the prominence of basketball teams. The motivation is that more people pay attention to basketball games by more prominent teams, so there can be large effects on the probability of sexual assault reports.

Column (1) of Table 2.5 studies effects on the probability of having sexual assault incident reports with college-aged victims for universities that are ranked in the top 25 of the compiled AP Poll list (introduced in the data section) and column (2) studies the effects for universities that are ranked 26-50 in the compiled AP Poll list. Results show that there is a large and significant increase in the probability of sexual assault reports for more prominent college basketball teams. The probability of sexual assault reports rises by 0.8 percentage points on basketball away game days for colleges ranked in the top 25 of the compiled AP Poll list. A similar effect is also observed the day after basketball away game days for these universities. Moreover, there is a significant decrease in the probability of sexual assault reports on basketball home game days for colleges ranked in the top 26-50 of the compiled AP Poll list. Since basketball teams at these schools are not as prominent, students may pay less attention to home games. With more police around on home game days, it is reasonable to have a decrease in sexual assault reports.

This result corresponds to the notion that prominent teams draw more attention from people, and thus there is a large and significant effect for more prominent teams.

Victim and Offender Characteristics

This subsection examines the heterogeneity of estimated effects by victim-offender relationship and characteristics of victims and offenders to further analyze who the victims and offenders are.

Table 2.6 and Table 2.7 focus on the relationship between victims and offenders. Table 2.6 shows estimated effects by whether offenders are known to victims. There is 0.7 percentage points increase in the probability of sexual assault reports for offenders known by victims on basketball away game days. The estimate for offenders unknown by victims on those days is close to zero. The significant increase for offenders known by victims on the day before and after basketball away game days as well as the significant decrease for offenders unknown by victims on the day before basketball away game days also support the result that people who already know each other are more likely to be together around basketball away game days. Further analysis explores the heterogeneity for offenders known by victims by considering whether offenders are within family. Table 2.7 shows that basketball away game days significantly increases the probability of sexual assault reports by 0.6 percentage points for offenders outside family but known to victims. The increase is also observed the day before and after basketball away game days. There is almost no effect for offenders within family. These results are consistent with results from RAINN that victims know offenders in most incidents and offenders are largely acquaintances instead of family members.[17]

Table 2.8 considers heterogeneous effects by offender age groups (17-20, 21-24, and over 24 years old).[18] The group for ages 17-20 contains college-aged offenders below the legal drinking age, the group for ages 21-24 contains college-aged offenders above the

[17]Source: `https://www.rainn.org/statistics/perpetrators-sexual-violence`

[18]Around 16% of offenses have missing offender age, which is similar to Lindo et al. (2018). Following their specification, the heterogeneity analysis here excludes these offenses.

legal drinking age, and the group for ages greater than 24 contains offenders that are not college-aged. Estimates show that the probability of sexual assault reports increases by 0.5 percentage points for offenders over 24 years old on basketball away game days. There is little effect for college-aged offenders on those days. Robustness checks that focus on offender ages 18-22 and 21-22 in Table B.3 also support this finding. Results in Table 2.8 correspond to the notion that students are bounded by the student conduct code and university disciplinary process, but people over 24 years old are mostly non-student and they are not disciplined by student conduct code. Therefore, there is a large and significant effect for offenders over 24 years old on basketball away game days. Moreover, Table 2.8 shows that there is a significant decrease in the probability of sexual assault reports for offenders over 24 years old on basketball home game days and the day before. These results are reasonable because there are usually more police patrols around basketball home game days for special campus events.

Table 2.9 studies heterogeneity by race of victim. Results imply that the probability of sexual assault reports by white college-aged victims rises by 0.6 percentage points on basketball away game days. The rise is also observed the day before and after basketball away game days. These results support the observation from Table 2.1 that students in these universities are predominantly white.

Table 2.10 shows results by victim ages 17-20, 21-24, and over 24. Table 2.11 reports results by race of offender. These results imply that effects on basketball away game days are not solely driven by a specific victim age group, nor by black or white offenders. The significant decrease in sexual assault reports for victims over 24 years old on the day before basketball home game days corresponds to the significant decrease for offenders over 24 years old on these days. The significant increase for white offenders on the day before basketball away game days corresponds to the significant increase in white victims on these days.

Emotional Cues Associated with Wins and Losses

Analysis in the paper has focused on effects of basketball game days on sexual assault incidents involving college-aged victims. This subsection considers whether emotional cues associated with wins and losses by college basketball teams affect sexual assault reports. It is motivated by Card & Dahl (2011) who find that emotional cues associated with wins and losses by professional football teams affect family violence. They show that upset losses by the local NFL team increase family violence by 10%. Following their specifications, this subsection defines an upset loss to be a loss when the team is expected to win by over three points and the definition of an upset win is similar.[19] Results from Table 2.12 indicate that there is little effect for upset wins, upset losses, and close losses by college basketball teams on sexual assault reports. Differences in research focus and sports offer explanations for differences in results. This paper focuses on college-aged sexual assault victims. Card & Dahl (2011) focus on family violence in a different age group. So the research focus is different. Moreover, the two papers study different sports at different professional levels. As mentioned earlier, basketball games are much more frequent than football games. Also, football is more violent than basketball, and people learn to behave violently by watching violent behaviors (Bandura, 1973). The professional level is another difference. This paper studies college basketball. Card & Dahl (2011) study professional football. Therefore, it is reasonable to have different results. Besides, estimates in Table 2.12 find that upset wins increase the probability of sexual assault reports the day before basketball game days. This result should be viewed with caution because pregame behaviors should not be affected by game outcomes. Lindo et al. (2018)

[19]Card & Dahl (2011) use pregame point spreads from Las Vegas bookmakers to measure expected game outcomes. This subsection follows their specification and uses pregame point spreads from `sportsbookreviewsonline.com` to obtain expected game outcomes. Games that are expected to be close are those with betting market spreads no more than three points because each offense play in basketball commonly yields at most three points.

also observe this phenomenon in their paper.

2.5 Discussion and Conclusion

This paper finds that the probability of getting sexual assault reports involving college-aged victims increases by roughly 0.7 percentage points on basketball away game days. This is a 14% increase given that the sample mean is 5%. There is little effect on basketball home game days. Further analysis of police departments' location shows that increases in sexual assault reports for college-aged victims on basketball away game days are concentrated in city police departments and incident locations are mostly at residences. There is little increase in sexual assault reports at university police departments on those days. These results support the notion of different watching patterns on basketball home and away game days. Basketball home game days bring people together at basketball arenas on campus, where there are often more police patrols due to special campus events. On basketball away game days, people are largely dispersed off campus, where there are not as many police patrols as basketball home game days. Moreover, heterogeneity analysis by the prominence of teams shows that the effect on basketball away game days is large and significant for more prominent teams. Furthermore, the paper conducts heterogeneity analysis of victims and offenders. The significant increase in offender outside family but known to victim on basketball away game days is consistent with results from RAINN that most sexual assault victims know offenders. The significant increase in offenders over 24 years old supports the point that they are mostly non-student and thus they are not bounded by the student conduct code. The significant increase in white victims on basketball away game days corresponds to the mostly white student body for universities in the sample. Results for basketball game days are different from results for football game days, which likely reflects differences in viewing and partying behavior across the two sports. Football games are more violent. By the social learning theory, people learn to behave violently when watching violent behaviors (Bandura, 1973). Football games are usually associated with lots of partying and tailgating, which intensifies sexual assault (Lindo et al., 2018). Hence, it is reasonable to have smaller estimated effects for basketball than football.

Results in the paper have policy implications. Sexual assaults incur high social costs. The estimated cost for one sexual assault incident is $267,000 in 2015 dollars (McCollister et al., 2010; Lindo et al., 2018). This implies that basketball games by top teams generate social costs of nearly $60 million in a basketball regular season each year.[20] The estimate is conservative because of price inflation and underreported nature of rapes. Kilpatrick et al. (2007) point out that only 12% of rapes among college-aged women are reported to law enforcement. Elevated sexual assault reports during basketball away game days instead of home game days imply that measures taken on home game days are effective to reduce sexual assault incidents. For example, the University of Washington Police Department staffs university athletic events with uniformed or plainclothes police officers.[21] Police presence has significant crime preventative effects (Dau et al., 2021). Therefore, a policy suggestion for basketball away game days is to have more police patrols in the city.

[20] Calculation follows $267,000 * 43,820 * 0.058/12 = 56,549,710$.

[21] Source: `http://police.uw.edu/aboutus/divisions/operations/specialops/`

2.6 Tables

Table 2.1: List of Division I basketball schools and their corresponding law-enforcement agencies in the analysis

School	Agencies (Years available in NIBRS from 2008 to 2019)
Baylor University	Waco Police Department (2018-2019)
Clemson University	Clemson Police Department (2008-2019) Clemson University Police (2008-2019)
University of Connecticut	University of Connecticut Police (2008-2019)
Duke University	Durham Police Department (2019)
Indiana University Bloomington	Bloomington Police (2019)
University of Iowa	Iowa City Police Department (2008-2019) University of Iowa Police (2008-2019)
Iowa State University	Ames Police Department (2008-2019) Iowa State University Police (2008-2019)
University of Kansas	Lawrence Police Department (2008-2014) University of Kansas Police Department (2008-2019)
Kansas State University	Kansas State University Police Department (2008-2019)
University of Kentucky	Lexington Division of Police (2010-2019) University of Kentucky Police Department (2008-2019)
University of Louisville	University of Louisville Police Department (2009-2019)
University of Memphis	Memphis Police Department (2008-2019) University of Memphis Police (2008-2019)
University of Michigan-Ann Arbor	Ann Arbor Police Department (2008-2019) University of Michigan of Public Safety Ann Arbor (2008-2019)
Michigan State University	East Lansing Police Department (2008-2019) Michigan State University Police Department (2008-2019)
University of Missouri	Columbia Police Department (2019)
University of North Carolina at Chapel Hill	Chapel Hill Police Department (2019) University of North Carolina-Chapel Hill Public (2019)
University of Notre Dame	South Bend Police Department (2018-2019)
Ohio State University-Columbus	Ohio State University Police Department (2008-2019) Columbus Police Department (2008-2019)
University of Oklahoma	Norman Police Department (2016-2019)

continued

Table 2.1: List of Division I basketball schools and their corresponding law-enforcement agencies in the analysis

School	Agencies (Years available in NIBRS from 2008 to 2019)
University of Oregon	Eugene Police Department (2013-2019) University of Oregon Police Department (2014-2019)
University of Tennessee	Knoxville Police Department (2008-2019) University of Tennessee at Knoxville Police (2008-2019)
University of Texas at Austin	Austin Police Department (2019) University of Texas-Austin Police (2019)
Texas A&M University	College Station Police Department (2018-2019) Texas A&M University Police Department (2019)
Texas Tech University	Lubbock Police Department (2017-2019) Texas Tech University Police Department (2017-2019)
University of Virginia	Charlottesville Police Department (2008-2019) University of Virginia Police Department (2008-2019)
West Virginia University	Morgantown Police Department (2008-2019) West Virginia University Police Department (2008-2019)
University of Wisconsin-Madison	Madison Police Department (2010-2019)

Note: While the table follows Lindo et al. (2018) to find law enforcement agencies for universities and agencies in the same city as the university, the table does not use Riley county police department for Kansas State University and Louisville metro police department for University of Louisville because they serve counties instead of cities. Also, the table uses Madison police department instead of Madison township police department for University of Wisconsin-Madison according to the university's address.

Table 2.2: Reported sexual assault incidents per day based on the sample in the main analysis (regular seasons of NCAA basketball from 2008 to 2019)

Sexual Assaults, victims ages 17-24	0.058
Sexual Assaults, victims ages 17-20	0.035
Sexual Assaults, victims ages 21-24	0.022
Sexual Assaults, victims ages >24	0.058
Sexual Assaults, victims ages 17-24, victim is black	0.020
Sexual Assaults, victims ages 17-24, victim is white	0.035

Table 2.3: Estimated effects of basketball and football home and away game days on the probability of sexual assault reports with college-aged victims

	(1)	(2)	(3)	(4)	(5)
Basketball day before home game	0.00295	0.00230	0.00219	0.00182	0.00165
	(0.00228)	(0.00296)	(0.00316)	(0.00319)	(0.00351)
Basketball home game day	-0.00304	-0.00368	-0.00342	-0.00386	-0.00338
	(0.00455)	(0.00310)	(0.00321)	(0.00326)	(0.00372)
Basketball day after home game	0.00240	0.00177	0.00200	0.00168	0.00251
	(0.00261)	(0.00289)	(0.00312)	(0.00314)	(0.00330)
Basketball day before away game	0.00382	0.00250	0.00254	0.00319	0.00373
	(0.00252)	(0.00360)	(0.00372)	(0.00385)	(0.00338)
Basketball away game day	0.00539*	0.00442	0.00422	0.00544	0.00657*
	(0.00310)	(0.00335)	(0.00333)	(0.00355)	(0.00376)
Basketball day after away game	0.00674***	0.00543	0.00526	0.00586*	0.00695*
	(0.00259)	(0.00331)	(0.00324)	(0.00341)	(0.00370)
Football day before home game	0.0102	0.0109	0.00956	0.0110	0.00547
	(0.0114)	(0.0137)	(0.0120)	(0.0111)	(0.0111)
Football home game day	0.0209	0.0222	0.0202*	0.0226*	0.0171
	(0.0145)	(0.0159)	(0.0120)	(0.0116)	(0.0126)
Football day after home game	0.00151	0.00241	0.00102	0.00265	-0.00200
	(0.00797)	(0.00859)	(0.00797)	(0.00840)	(0.00959)
Football day before away game	0.00470	0.00670	0.00619	0.00661	0.0100
	(0.0112)	(0.0118)	(0.0102)	(0.0107)	(0.0105)
Football away game day	0.0151*	0.0177	0.0177	0.0181*	0.0225*
	(0.00833)	(0.0125)	(0.0113)	(0.0109)	(0.0116)
Football day after away game	0.0155	0.0181*	0.0178*	0.0178*	0.0245**
	(0.00951)	(0.00992)	(0.00920)	(0.00976)	(0.0107)
Day-of-week fixed effects	Yes	Yes	Yes	Yes	Yes
Holiday controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	No	No
Agency fixed effects	Yes	No	No	No	No
Agency by month of year fixed effects	No	Yes	No	No	No
Agency by week of year fixed effects	No	No	Yes	No	No
Agency-by-year-by-month fixed effects	No	No	No	Yes	No
Agency-by-year-by-week fixed effects	No	No	No	No	Yes
Schools	27	27	27	27	27
Agencies	44	44	44	44	44
Observations	43820	43820	43820	43820	43820

Estimates in the table are coefficients from linear probability models that use daily data in regular seasons from 2008 to 2019 for law enforcement agencies in the NIBRS corresponding to Division I basketball schools that are ranked in the top 50 in the AP Poll frequency list from 2007-2008 season to 2019-2020 season and have football teams. The outcome variable is whether there are rape reports for college-aged victims (17-24 years old) at an agency on a day. Days are defined to be from 6:00 am to 5:59 am to consider spillovers in the early morning. Standard errors are bootstrapped 200 times.

Table 2.4: Estimated effects of basketball and football home and away game days on the probability of sexual assault reports with college-aged victims at city and university police departments

	(1) City PD	(2) University PD
Basketball day before home game	0.00371	-0.0000730
	(0.00724)	(0.00240)
Basketball home game day	-0.00604	-0.000674
	(0.00693)	(0.00251)
Basketball day after home game	0.00316	0.00198
	(0.00624)	(0.00228)
Basketball day before away game	0.00297	0.00467*
	(0.00721)	(0.00255)
Basketball away game day	0.0126*	0.00161
	(0.00753)	(0.00270)
Basketball day after away game	0.0173**	-0.00232
	(0.00764)	(0.00233)
Schools	24	20
Agencies	24	20
Observations	20758	23062

This table considers whether there are sexual assault reports involving college-aged victims in city and university police departments on a given day. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Table 2.5: Estimated effects of basketball and football home and away game days on the probability of sexual assault reports with college-aged victims by the prominence of basketball teams

	(1) Top 25	(2) Top 26-50
Basketball day before home game	0.00305	-0.000157
	(0.00440)	(0.00622)
Basketball home game day	0.00134	-0.0106*
	(0.00416)	(0.00580)
Basketball day after home game	-0.000515	0.00811
	(0.00414)	(0.00558)
Basketball day before away game	0.00538	0.00215
	(0.00453)	(0.00614)
Basketball away game day	0.00789*	0.00589
	(0.00466)	(0.00562)
Basketball day after away game	0.00792*	0.00622
	(0.00453)	(0.00687)
Schools	16	11
Agencies	26	18
Observations	27640	16180

This table considers reports of college-aged sexual assault victims from universities ranked in the top 25 and 26-50 based on the frequency of appearance in the AP Poll from 2007-2008 season to 2019-2020 season. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Table 2.6: Estimated effects of basketball and football home and away game days on the probability of sexual assault reports with college-aged victims by known and unknown offenders

	(1) Offender known by victim	(2) Offender unknown by victim
Basketball day before home game	0.000890	-0.00275
	(0.00287)	(0.00235)
Basketball home game day	-0.00255	-0.00309
	(0.00327)	(0.00217)
Basketball day after home game	0.000424	0.00142
	(0.00284)	(0.00208)
Basketball day before away game	0.00734**	-0.00522***
	(0.00314)	(0.00200)
Basketball away game day	0.00660**	0.000255
	(0.00321)	(0.00241)
Basketball day after away game	0.00654**	-0.00294
	(0.00301)	(0.00220)
Schools	27	27
Agencies	44	44
Observations	43820	43820

This table considers whether there are sexual assault reports from college-aged victims by offenders who are known and unknown to them. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Table 2.7: Estimated effects of basketball and football home and away game days on the probability of sexual assault reports with college-aged victims by known offenders within or outside family

	(1) Offender within family	(2) Offender outside family but known to victim
Basketball day before home game	0.000227	0.000482
	(0.000674)	(0.00285)
Basketball home game day	-0.000558	-0.00200
	(0.000671)	(0.00317)
Basketball day after home game	-0.000575	0.000820
	(0.000581)	(0.00283)
Basketball day before away game	0.000351	0.00688**
	(0.000671)	(0.00309)
Basketball away game day	0.0000892	0.00633**
	(0.000632)	(0.00313)
Basketball day after away game	0.00113	0.00544*
	(0.000882)	(0.00289)
Schools	27	27
Agencies	44	44
Observations	43820	43820

This table considers sexual assault reports from college-aged victims by known offenders, which include offenders within family and offenders outside family but known to victim. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Table 2.8: Estimated effects of home and away game days on the probability of sexual assault reports with college-aged victims by offender age groups

	(1) Offender ages 17-20	(2) Offender ages 21-24	(3) Offender ages >24
Basketball day before home game	-0.000399	0.000758	-0.00477**
	(0.00174)	(0.00163)	(0.00239)
Basketball home game day	0.000252	-0.00165	-0.00467*
	(0.00202)	(0.00165)	(0.00269)
Basketball day after home game	0.000449	0.000603	-0.00298
	(0.00173)	(0.00171)	(0.00245)
Basketball day before away game	0.00159	0.00229	-0.000911
	(0.00207)	(0.00207)	(0.00250)
Basketball away game day	0.000833	-0.00121	0.00478*
	(0.00192)	(0.00182)	(0.00276)
Basketball day after away game	0.000185	0.00162	0.00177
	(0.00180)	(0.00197)	(0.00256)
Schools	27	27	27
Agencies	44	44	44
Observations	43820	43820	43820

This table considers reports of college-aged sexual assault victims involving offenders of different ages. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Table 2.9: Estimated effects of home and away game days on the probability of sexual assault reports with college-aged victims by victim race

	(1) Black victim	(2) White victim
Basketball day before home game	-0.000960	0.00154
	(0.00223)	(0.00286)
Basketball home game day	-0.00140	-0.00274
	(0.00217)	(0.00308)
Basketball day after home game	-0.000422	0.00276
	(0.00211)	(0.00277)
Basketball day before away game	-0.00267	0.00624**
	(0.00205)	(0.00315)
Basketball away game day	0.00177	0.00552*
	(0.00230)	(0.00313)
Basketball day after away game	-0.000670	0.00677**
	(0.00217)	(0.00316)
Schools	27	27
Agencies	44	44
Observations	43820	43820

This table considers reports of college-aged sexual assault victims with different races. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Table 2.10: Estimated effects of home and away game days on the probability of sexual assault reports with college-aged victims in different age groups

	(1) Victim ages 17-20	(2) Victim ages 21-24	(3) Victim ages >24
Basketball day before home game	-0.000778	0.00238	-0.00769**
	(0.00295)	(0.00215)	(0.00312)
Basketball home game day	-0.00316	-0.00217	-0.00106
	(0.00301)	(0.00248)	(0.00327)
Basketball day after home game	0.00122	0.00149	-0.00202
	(0.00297)	(0.00224)	(0.00327)
Basketball day before away game	0.00110	0.00119	0.000232
	(0.00305)	(0.00230)	(0.00305)
Basketball away game day	0.00453	0.00307	0.00152
	(0.00308)	(0.00243)	(0.00333)
Basketball day after away game	0.00426	0.00279	-0.00428
	(0.00306)	(0.00268)	(0.00344)
Schools	27	27	27
Agencies	44	44	44
Observations	43820	43820	43820

This table considers reports of sexual assault victims in different age groups. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Table 2.11: Estimated effects of home and away game days on the probability of sexual assault reports with college-aged victims by offender race

	(1) Black offender	(2) White offender
Basketball day before home game	-0.0000476	-0.00193
	(0.00254)	(0.00227)
Basketball home game day	-0.00335	-0.00271
	(0.00234)	(0.00244)
Basketball day after home game	-0.00206	0.000662
	(0.00236)	(0.00229)
Basketball day before away game	-0.000726	0.00435*
	(0.00226)	(0.00256)
Basketball away game day	0.00247	0.00295
	(0.00237)	(0.00261)
Basketball day after away game	0.00270	0.00293
	(0.00238)	(0.00270)
Schools	27	27
Agencies	44	44
Observations	43820	43820

This table considers reports for college-aged sexual assault victims involving offenders of different races. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Table 2.12: Estimated effects of unexpected emotional shocks on the probability of getting sexual assault reports with college-aged victims

	(1)
Day before basketball game, expected to lose	0.998
	(0.00575)
Basketball game day, expected to lose	1.000
	(0.00630)
Day after basketball game, expected to lose	1.009
	(0.00599)
Day before basketball game, expected to be close	1.000
	(0.00683)
Basketball game day, expected to be close	1.009
	(0.00682)
Day after basketball game, expected to be close	0.997
	(0.00623)
Day before basketball game, expected to win	1.002
	(0.00361)
Basketball game day, expected to win	0.999
	(0.00324)
Day after basketball game, expected to win	1.005
	(0.00354)
Day before basketball game, expected to lose and won (upset win)	1.021*
	(0.0120)
Basketball game day, expected to lose and won (upset win)	0.992
	(0.00930)
Day after basketball game, expected to lose and won (upset win)	1.002
	(0.0105)
Day before basketball game, expected to be close and lost (close loss)	1.013

Table 2.12: Estimated effects of unexpected emotional shocks on the probability of getting sexual assault reports with college-aged victims (continued)

	(1)
	(0.00972)
Basketball game day, expected to be close and lost (close loss)	1.000
	(0.0103)
Day after basketball game, expected to be close and lost (close loss)	0.998
	(0.00909)
Day before basketball game, expected to win and lost (upset loss)	0.999
	(0.00716)
Basketball game day, expected to win and lost (upset loss)	1.006
	(0.00729)
Day after basketball game, expected to win and lost (upset loss)	0.997
	(0.00719)
Schools	27
Agencies	44
Observations	42524

Note: The estimates are based on a similar linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, and controls for football home and away game days as well as their one-day leads and lags). Games that are expected to be close are those with betting market spread no more than 3 points. For games with no betting information, the game day and the one-day lead and lag are dropped. Standard errors are bootstrapped 200 times.

Chapter 3

School Lunch and Nutrition

3.1 Introduction

Nutrition plays an important role in children's health and cognitive development. Children spend a substantial amount of time at school and consume a third to a half of daily calorie intake there (Schanzenbach, 2009). As a result, previous studies focus on effects of school meals on children's development. Schanzenbach (2009) points out that it is more likely for children who consume school lunches to be obese than those who eat brown bag lunches. While at the same time, Gordanier et al. (2020) and Schwartz & Rothbart (2020) find out that universal free meal programs have positive effects on students' academic performance.

In 2010, the Healthy, Hunger-Free Kids Act (HHFKA) was signed into law. This act aimed to increase the nutritional standards for school meals and combat childhood obesity. By July 2012, all schools enrolled in the National School Lunch Program (NSLP) were required to comply with the HHFKA. Changes to the NSLP by the HHFKA included increasing the availability of fruits, vegetables, whole grains, and fat-free and low-fat fluid milk (Food & Nutrition Service, 2012). The HHFKA improved the dietary quality of school lunches (Kinderknecht et al., 2020). Previous literature, Kenney et al. (2020) for example, has examined the impact of HHFKA on childhood obesity as measured by body mass index (BMI).

Although studying BMI is important, BMI provides an incomplete picture of health and the metabolic effects of diet. It does not consider the difference between fat and nonfat mass, and it does not consider changes in body composition over age (Rothman, 2008). Metabolic analysis, on the other hand, provides a more direct measure. Using fluid samples including blood samples, it investigates reactions that occurred in the body (Braga & Adamec, 2018; de Nava & Raja, 2022). Therefore, it provides a more complete and direct picture of health. To the best of my knowledge, no paper has studied the effects of HHFKA by the metabolic analysis. This paper adds to people's stock of knowledge on diet and health.

This paper explores the mechanism of effects by the HHFKA through the metabolic analysis. It focuses on obesity-related cardiometabolic parameters that include cholesterol levels, blood glucose levels, and blood pressure (Klop et al., 2013; Aung et al., 2020). The analysis uses data from the National Health and Nutrition Examination Survey (NHANES) for students aged 12 to 18 who consume school lunches five times per week. The results show that the probability of having high total cholesterol decreased by about 30% after the implementation of HHFKA. This result is largely driven by the significant decrease in the proportion of students with high LDL cholesterol and triglycerides. The analysis also explores two dimensions of heterogeneity for total cholesterol. First, I consider the heterogeneous effects by students' race. The results imply that there is a significant reduction in the probability of having high total cholesterol for Mexican American students. Second, I consider the heterogeneous effects by household reference person's education level. The results imply that there is a significant decrease in the probability of having high total cholesterol when the student's corresponding household reference person, usually a parent, did not graduate from high school. Moreover, analysis on glucose related lab results and blood pressure examination results indicates that the implementation of HHFKA had little effect on the probability of having high glycohemoglobin, high fasting plasma glucose, high two-hour oral glucose, and hypertension.

The results in this paper have policy implications. Diets play an important role for cholesterol levels (Stanford Medicine Children's Health, n.d.). Teens with high cholesterol levels are at higher risk for heart disease when they become adults (Stanford Medicine Children's Health, n.d.; National Heart, Lung, and Blood Institute, 2020). The results from this paper show that HHFKA was effective at decreasing the probability of having high cholesterol levels. These results demonstrate the importance of HHFKA to students' health. However, in recent years, there have been attempts to ease the HHFKA standards. Therefore, it is important to maintain the original standards in HHFKA.

The rest of the paper proceeds as follows. Section 2 describes the data in this paper. Section 3 presents empirical analysis. Section 4 concludes.

3.2 Data

To study whether HHFKA has effects on students through reactions that occur in the body, I need to be able to observe test results on cardiometabolic parameters related to obesity for students who eat school lunches in the pre-policy and post-policy period. These cardiometabolic parameters are cholesterol, glucose, and blood pressure related measures (Klop et al., 2013; Aung et al., 2020).

NHANES is a major program of the National Center for Health Statistics, which is part of the Centers for Disease Control and Prevention (CDC). This program examines a nationally representative sample to assess the health and nutritional status of people in the US (National Center for Health Statistics, 2023). It provides laboratory data that contains findings from blood samples. In addition, it provides information on the number of times a week a person gets school lunch, as well as demographic information such as age, gender, race, and family income. As a result, the empirical analysis uses data from NHANES.

As mentioned previously, the HHFKA was signed into law in 2010 and implemented in 2012. Therefore, the paper uses data from NHANES 2007-2008 and NHANES 2009-2010 as the pre-policy period. Data from NHANES 2013-2014 and NHANES 2015-2016 are for the post-policy period. Data from NHANES 2011-2012 are excluded from the analysis since this is a transition period.

The empirical analysis restricts the sample to students aged 12 to 18 who get school lunches five times per week at schools that serve school lunch. NHANES conducts laboratory tests of interest for students in this age group. Students who get school lunches five times per week are those who are most likely to be affected by the HHFKA. Thus, these students are the focus of this paper.

Table 3.1 shows summary statistics for student characteristics in the pre-policy and post-policy period. These characteristics are related to factors that increase obesity risk (Richardson et al., 2022).[1] The number of school breakfasts per week is also considered as it can have a confounding impact (Schanzenbach, 2009). Students with missing characteristics data are not included in the sample. Table 3.1 provides summary statistics for student characteristics in the pre-policy and post-policy period. There exists statistical difference for some covariates. For example, about 29% of students are non-hispanic white in the pre-policy period while about 23% are in the post-policy period. About 35% of students come from households with reference person, usually a parent, not graduating

[1] Richardson et al. (2022) use another dataset for analysis and they also consider birthweight, whether the family eats evening meal together in a typical week, and number of hours a day the child usually watches TV or videos on school days. These covariates are not available for all students aged 12-18 in the corresponding NHANES and thus they are not considered in the paper.

from high school in the pre-policy period. This ratio decreases to 28% in the post-policy period.

There are two concerns related to the data. First, students choose to eat school lunches, and thus there exists selection problem. However, according to U.S. News & World Report (2015), "of the over 30 million children who eat school lunch every day, more than 71.5 percent come from disadvantaged families." These students have less healthy diet behavior and they usually eat more fast food (Hastert & Babey, 2009). So the change in school lunch by the HHFKA is the primary source of change in their diet. Second, the results from Table 3.1 show that there exists covariate imbalance. The empirical analysis uses entropy balancing to address these concerns. Entropy balancing is a preprocessing technique to achieve covariate balance in observational studies with binary treatments (Hainmueller, 2012). It puts more weight to under-represented groups and less weight to over-represented group (Watson & Elliot, 2016). After the data is reweighted, it mimics a randomized experiment more closely (Athey & Imbens, 2017). Table 3.2 presents student characteristics in the pre- and post-policy period after entropy balancing. The table shows that student characteristics after weighting are similar in the two periods.

3.3 Empirical Analysis

3.3.1 Approach

The primary objective is to estimate the effects of the HHFKA by comparing the post-policy period to the pre-policy period for students aged 12 to 18 who get school lunches five times per week:

$$Y_{it} = \beta_0 + \beta_1 P_{it} + X_{it}. \tag{3.1}$$

Y_{it} is a binary variable that equals to 1 if the examination result is beyond the acceptable or the borderline range for person i. P_{it} is a binary variable that equals to 1 if the student eats school lunch five times per week in the post-policy period. X_{it} represents student characteristics, which include age, gender, race, household reference person's education level, whether family members receive income from wages and salaries last year, family income level compared to the federal poverty line, and number of school breakfast per week. As discussed in the previous section, the analysis uses entropy balancing to preprocess the data.

In the regression, year is not included in the control because of multicollinearity. There may be concerns that changes happening at the same time as the policy change also impact diet. However, this is unlikely to compromise identification. Students who eat school lunch five times per week do not bring lunch to school from home. They have less healthy diet behavior and they usually eat more fast food (Hastert & Babey, 2009). Liu et al. (2021) examine the trend in junk food consumption among US children over time and point out that the trend remains stable. Thus, it is unlikely to have a change that happens at the same time as the policy change that impacts diet.

3.3.2 Cholesterol Related Lab Results

Main Results

This subsection considers cholesterol related lab results, which are results on HDL cholesterol, LDL cholesterol, triglyceride, and total cholesterol. The measurements are introduced as follows: HDL cholesterol is also called the “good” cholesterol, which carries some of the cholesterol out of the bloodstream and prevents it from being deposited; LDL cholesterol is also called the “bad” cholesterol, which carries most of the body’s cholesterol and can lead to plaque buildup in arteries; triglycerides are a type of fats circulating in the bloodstream; total cholesterol is the sum of HDL, LDL, and 20% of the triglyceride level (CDC, 2023a; Cincinnati Children’s, 2022; Cleveland Clinic, 2022).

Cutoffs for each lab test to be beyond the acceptable or borderline range are listed as follows: less than 40mg/dl for HDL cholesterol, 130mg/dl or greater for LDL cholesterol, 130mg/dl or greater for triglyceride, and 200mg/dl or greater for total cholesterol (Cincinnati Children’s, 2022). Observations with missing test results are excluded from the analysis. In NHANES, LDL cholesterol and triglyceride are tested among people who are examined in the morning session.

Table 3.3 presents estimation results. The results show that the probability of having high LDL cholesterol and high triglyceride significantly decreased by about 6 percentage points. Also, the probability of having high total cholesterol reduced by 2 percentage points. Given that the probability of having high total cholesterol in the pre-policy period is around 7%, the implementation of HHFKA scaled down the likelihood of having high total cholesterol by approximately 30%.

Heterogeneity Analysis

This subsection considers heterogeneity of estimated effects by students’ race and household reference persons’ education levels. The outcome variable is whether the examination for total cholesterol is beyond its acceptable or borderline range. According to NHANES, the household reference person is the first household member at or above 18 years old who owns or rents the residence. By focusing on students’ race and household reference persons’ education levels, this analysis investigates students from which socioeconomic status are affected the most by the HHFKA.

Table 3.4 presents results for heterogeneity analysis on students' race. The results show that there is a significant decrease in the probability of having high total cholesterol for Mexican American students. Table 3.5 shows results for heterogeneity analysis on household reference persons' education levels. The results imply that there is a significant decrease in the probability of having high total cholesterol for students from families with the education level of household reference person, usually a parent, not graduating from high school.

3.3.3 Glucose Related Lab Results

This subsection discusses glucose related lab results on glycohemoglobin, fasting plasma glucose, and two-hour oral glucose. Glycohemoglobin reflects average plasma glucose in the past eight to twelve weeks (WHO, 2011). Fasting plasma glucose measures the blood sugar after not eating over night. Two-hour oral glucose measures the fasting blood sugar and two hours after the person drinks a liquid that has glucose (CDC, 2023b).

Cutoffs for each test to be beyond the acceptable or borderline range are listed as follows: 6.5% or higher for glycohemoglobin; 126mg/dl or above for fasting plasma glucose; 200mg/dl or above for two-hour oral glucose (CDC, 2023b). Observations with missing test results are excluded from the analysis. According to NHANES, fasting plasma glucose and two-hour oral glucose are tested among people who get examined in the morning session.

Table 3.6 presents estimation results. The results imply that HHFKA had little effects on the probability of having high glycohemoglobin, high fasting plasma glucose, and high two-hour oral glucose.

3.3.4 Blood Pressure Examination Results

This subsection discusses results on blood pressure related examination results. In blood pressure measurements, a systolic blood pressure indicates the pressure the blood is exerting against the artery walls during heart contraction, and a diastolic blood pressure indicates the pressure the blood is exerting against the artery walls when the heart is resting between contractions (American Heart Association, 2023). According to Whelton et al. (2018), if a person's systolic blood pressure is 130 mm Hg or higher or the diastolic blood pressure is 80 mm Hg or higher, then the person is considered to have hypertension.

NHANES obtains three consecutive blood pressure readings. When one measurement is interrupted or incomplete, it may obtain a fourth reading. The empirical analysis only considers observations with three blood pressure readings. It calculates the average systolic and diastolic blood pressure from the three readings and compare the averages to their corresponding cutoffs. If either of the averages is above the cutoff, then the student is considered to have hypertension.

Table 3.7 presents estimation results. The results show that HHFKA had little effect on the probability of having hypertension.

3.4 Conclusion

This paper studies the potential mechanisms for effects by the HHFKA. It compares cholesterol related lab results, glucose related lab results, and blood pressure examination results for students aged 12 to 18 who get school lunches five times per week in the pre-policy and post-policy period. The results imply that HHFKA decreased the likelihood of having high total cholesterol by approximately 30%. This result is largely driven by the significant decrease in the proportion of students with high LDL cholesterol and triglycerides. The analysis also explores two dimensions of heterogeneity for the measure of total cholesterol. First, I consider the heterogeneity analysis of estimated effects on students' race. The results indicate that there is a significant decrease in the probability of having high total cholesterol for Mexican American students. Second, I consider the heterogeneity analysis of estimated effects on household reference person's education level. The results imply that there is a significant decrease in the probability of having high total cholesterol with reference person's education below high school degree.

In recent years, there have been attempts to relax the HHFKA standards. Results in this paper demonstrate the importance of HHFKA to students' health. These results imply that HHFKA was effective at reducing the probability of having high cholesterol levels. Hence, it is important to keep the original standards in HHFKA and continue improving these standards for adolescent health.

3.5 Tables

Table 3.1: Summary statistics for student characteristics in the pre-policy and post-policy period

Variable	(1) Students from 2007-2008 and 2009-2010 sample	(2) Students from 2013-2014 and 2015-2016 sample	Difference
Male	0.553	0.559	0.006
	(0.497)	(0.497)	(0.020)
Age	14.469	14.456	-0.013
	(1.922)	(1.904)	(0.078)
Mexican American	0.275	0.245	-0.030*
	(0.447)	(0.430)	(0.018)
Other Hispanic	0.125	0.119	-0.005
	(0.330)	(0.324)	(0.013)
Non-Hispanic White	0.291	0.229	-0.062***
	(0.455)	(0.420)	(0.018)
Non-Hispanic Black	0.254	0.268	0.014
	(0.435)	(0.443)	(0.018)
Other Race - Including Multi-Racial	0.056	0.139	0.083***
	(0.229)	(0.346)	(0.012)
Household reference person below high school degree	0.354	0.283	-0.070***
	(0.478)	(0.451)	(0.019)
Household reference person with high school degree	0.243	0.237	-0.006
	(0.429)	(0.425)	(0.017)
Household reference person above high school degree	0.403	0.480	0.077***
	(0.491)	(0.500)	(0.020)
Family member receive income from wages and salaries last year	0.895	0.888	-0.007
	(0.307)	(0.315)	(0.013)
Family income below 135% of the federal poverty line	0.511	0.522	0.011
	(0.500)	(0.500)	(0.020)
Family income between 135% and 185% of the federal poverty line	0.126	0.136	0.009
	(0.332)	(0.343)	(0.014)
Family income above 185% of the federal poverty line	0.363	0.342	-0.021
	(0.481)	(0.475)	(0.020)
Number of school breakfast per week	2.230	2.444	0.214**
	(2.310)	(2.308)	(0.094)
Observations	1,171	1,224	2,395

Note: This table reports student characteristics in the sample in the pre-policy and post-policy period. The sample considers students who are between 12 and 18 years old and get school lunches five times a week. Data from NHANES 2007-2008 and NHANES 2009-2010 are in the pre-policy period. Data from NHANES 2013-2014 and NHANES 2015-2016 are in the post-policy period. Standard deviations are in parentheses.

Table 3.2: Summary statistics for student characteristics in the pre-policy and post-policy period after entropy balancing

Variable	(1) Students from 2007-2008 and 2009-2010 sample	(2) Students from 2013-2014 and 2015-2016 sample
Male	0.559	0.559
	(0.497)	(0.497)
Age	14.456	14.456
	(1.904)	(1.904)
Mexican American	0.245	0.245
	(0.430)	(0.430)
Other Hispanic	0.119	0.119
	(0.324)	(0.324)
Non-Hispanic White	0.229	0.229
	(0.420)	(0.420)
Non-Hispanic Black	0.268	0.268
	(0.443)	(0.443)
Household reference person below high school degree	0.283	0.284
	(0.451)	(0.451)
Household reference person with high school degree	0.237	0.237
	(0.425)	(0.425)
Family member receive income from wages and salaries last year	0.888	0.888
	(0.315)	(0.315)
Family income below 135% of the federal poverty line	0.522	0.522
	(0.500)	(0.500)
Family income between 135% and 185% of the federal poverty line	0.136	0.136
	(0.343)	(0.343)
Number of school breakfast per week	2.444	2.444
	(2.308)	(2.308)

Note: This table reports weighted student characteristics in the sample. The sample considers students who are between 12 and 18 years old and get school lunches five times a week. Data from NHANES 2007-2008 and NHANES 2009-2010 are in the pre-policy period. Data from NHANES 2013-2014 and NHANES 2015-2016 are in the post-policy period. Covariates *Other Race - Including Multi-Racial, Household reference person above high school degree, family income above 185% of the federal poverty line* are not included because of multicollinearity. Standard deviations are in parentheses.

Table 3.3: Estimated effects of the HHFKA using cholesterol related measures

	(1) High total cholesterol	(2) Low HDL cholesterol	(3) High LDL cholesterol	(4) High Triglyceride
Policychange	-0.0199*	-0.00652	-0.0569***	-0.0560***
	(0.0107)	(0.0154)	(0.0184)	(0.0213)
Observations	2160	2160	871	872

This table shows coefficients of *Policychange*. The outcome variable is whether the examination result is beyond its acceptable or borderline range. LDL cholesterol and triglyceride are tested among people who are examined in the morning session. Observations with missing test results are excluded from the analysis.

Table 3.4: Estimated effects of the HHFKA using the measure of total cholesterol in different races

	(1) Mexican American	(2) Other Hispanic	(3) Non-Hispanic White	(4) Non-Hispanic Black	(5) Other Race
Policychange	-0.0416**	-0.0186	-0.0105	-0.0121	-0.0107
	(0.0205)	(0.0210)	(0.0213)	(0.0198)	(0.0404)
Observations	585	272	561	534	208

This table shows coefficients of *Policychange* for students in different races. The outcome variable is whether the examination result for total cholesterol is beyond its acceptable or borderline range. Observations with missing test results are excluded from the analysis.

Table 3.5: Estimated effects of the HHFKA using the measure of total cholesterol in different education levels of the household reference person

	(1) Household reference person below high school degree	(2) Household reference person with high school degree	(3) Household reference person above high school degree
Policychange	-0.0298*	-0.0197	-0.0140
	(0.0181)	(0.0248)	(0.0152)
Observations	689	512	959

This table shows coefficients of *Policychange* for students from families with different education levels of the household reference person. According to NHANES, the household reference person is that first household member at or above 18 years old who owns or rents the residence. It characterizes the socioeconomic status of the households. The outcome variable is whether the examination result for total cholesterol is beyond its acceptable or borderline range. Observations with missing test results are excluded from the analysis.

Table 3.6: Estimated effects of the HHFKA using glucose related measures

	(1) High glycohemoglobin	(2) High fasting plasma glucose	(3) High two-hour oral glucose
Policychange	-0.00249	0.00779	0.00449
	(0.00308)	(0.00695)	(0.00591)
Observations	1891	900	721

This table shows coefficients of *Policychange*. The outcome variable is whether the examination result is beyond its acceptable and borderline range. Fasting plasma glucose and two-hour oral glucose are tested among people who are examined in the morning session and have a 9 hour fast. Observations with missing test results are excluded from the analysis.

Table 3.7: Estimated effects of the HHFKA using blood pressure

	(1)
	Hypertension
Policychange	-0.00120
	(0.00693)
Observations	2223

This table shows coefficients of *Policychange*. The outcome variable is whether the examination result is beyond its acceptable or borderline range. Only observations with three blood pressure readings are considered.

Appendix A

Appendix for "Female Officers and the Discovery of Domestic Violence"

Table A.1: The effect of having a female officer in the primary unit on discovering DV related physical abuse using logit regression

(a) Milwaukee

	(1)
Female officer in primary unit	1.105**
	(0.0468)
Observations	102050
District-by-year FE	Yes
District-by-year-by-week-by-shift FE	No
Call controls	No

(b) Chicago

	(1)
Female officer in primary unit	1.111***
	(0.0265)
Observations	184189
District-by-year FE	Yes
District-by-year-by-week-by-shift FE	No
Call controls	No

This table shows the effect of having a female officer in the primary unit on discovering DV related physical abuse using logit regression. Results are odds ratios. Standard errors are reported in parentheses and are clustered at the level of the dispatched officer in the primary unit with more years of experience.

Appendix B

Appendix for "College Basketball Game Day and Sexual Assault"

Table B.1: Estimated effects of basketball and football home and away game days on the probability of sexual assault reports with college-aged victims with the logit regression

	(1)
Basketball day before home game	1.041
	(0.0902)
Basketball home game day	0.918
	(0.0851)
Basketball day after home game	1.058
	(0.0942)
Basketball day before away game	1.090
	(0.105)
Basketball away game day	1.155
	(0.111)
Basketball day after away game	1.196*
	(0.116)
Football day before home game	1.122
	(0.263)
Football home game day	1.319
	(0.295)
Football day after home game	0.944
	(0.266)
Football day before away game	1.362
	(0.326)
Football away game day	1.676**
	(0.377)
Football day after away game	2.039***
	(0.503)
Schools	27
Agencies	41
Observations	9433

Estimates in the table are odds-ratios from the logit model with day-of-week fixed effects, holiday controls, and agency-by-year-by-week fixed effects. The table considers the same outcome (whether there are sexual assult reports involving college-aged victims at an agency on a given day). Note that while the same sample as Table 2.3 is used here, in the fixed effects logit regression Stata drops all positive or all negative outcomes.

Table B.2: Estimated effects of basketball home and away game days on the probability of having sexual assault reports with college-aged victims in different time periods

	(1) February and March in basketball regular seasons	(2) Omitting consecutive basketball game days in basketball regular seasons	(3) Basketball regular and post seasons
Basketball day before home game	0.00143	0.00183	0.00196
	(0.00633)	(0.00363)	(0.00359)
Basketball home game day	0.00104	-0.00300	-0.00330
	(0.00660)	(0.00357)	(0.00358)
Basketball day after home game	0.00425	0.00248	0.00223
	(0.00548)	(0.00329)	(0.00334)
Basketball day before away game	0.000328	0.00368	0.00326
	(0.00566)	(0.00325)	(0.00350)
Basketball away game day	0.00722	0.00743^{*}	0.00737^{**}
	(0.00644)	(0.00389)	(0.00359)
Basketball day after away game	0.00529	0.00676^{*}	0.00555
	(0.00624)	(0.00395)	(0.00369)
Football day before home game		0.00777	0.00568
		(0.0132)	(0.0115)
Football home game day		0.0218^{*}	0.0170
		(0.0129)	(0.0131)
Football day after home game		-0.00318	-0.00287
		(0.00983)	(0.00963)
Football day before away game		0.00917	0.0102
		(0.0113)	(0.0103)
Football away game day		0.0206^{*}	0.0224^{**}
		(0.0125)	(0.0111)
Football day after away game		0.0236^{**}	0.0237^{**}
		(0.00940)	(0.00998)
Schools	26	27	27
Agencies	41	44	44
Observations	14634	42543	51151

The estimates consider the same outcome (whether there are sexual assult reports involving college-aged victims at an agency on a given day) using the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls) with data in different time periods. Standard errors are bootstrapped 200 times. Column (1) does not have variables for football because there is no football game in the period.

Table B.3: Estimated effects of home and away game days on the probability of sexual assault reports with college-aged victims by different offender age groups

	(1) Offender ages 18-22	(2) Offender ages 21-22
Basketball day before home game	-0.000571	-0.000772
	(0.00219)	(0.00151)
Basketball home game day	-0.00284	-0.00208
	(0.00212)	(0.00130)
Basketball day after home game	-0.000344	-0.000208
	(0.00194)	(0.00130)
Basketball day before away game	0.00333	0.000851
	(0.00239)	(0.00166)
Basketball away game day	0.00169	-0.000333
	(0.00223)	(0.00162)
Basketball day after away game	0.00185	0.00103
	(0.00219)	(0.00172)
Schools	27	27
Agencies	44	44
Observations	43820	43820

This table considers sexual assault reports involving college-aged victims with offenders aged 18-22 and 21-22. The estimates are based on the same linear probability model as column (5) of Table 2.3 (including agency-by-year-by-week fixed effects, day-of-week fixed effects, holiday controls, controls for football home and away game days as well as their one-day leads and lags). Standard errors are bootstrapped 200 times.

Appendix C

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