J Youth Adolescence (2016) 45:195–210
DOI 10.1007/s10964-015-0265-5

EMPIRICAL RESEARCH

# Visible School Security Measures and Student Academic Performance, Attendance, and Postsecondary Aspirations

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Received: 1 December 2014 / Accepted: 21 February 2015 / Published online: 27 February 2015


**Abstract** Many U.S. schools use visible security measures (security cameras, metal detectors, security personnel) in an effort to keep schools safe and promote adolescents' academic success. This study examined how different patterns of visible security utilization were associated with U.S. middle and high school students' academic performance, attendance, and postsecondary educational aspirations. The data for this study came from two large national surveys—the School Crime Supplement to the National Crime Victimization Survey ($N = 38{,}707$ students; 51 % male, 77 % White, $M_{Age} = 14.72$) and the School Survey on Crime and Safety ($N = 10{,}340$ schools; average student composition of 50 % male, 57 % White). The results provided no evidence that visible security measures had consistent beneficial effects on adolescents' academic outcomes; some security utilization patterns had modest detrimental effects on adolescents' academic outcomes, particularly the heavy surveillance patterns observed in a small subset of high schools serving predominantly low socioeconomic students. The findings of this study provide no evidence that visible security measures have any sizeable effects on academic performance, attendance, or postsecondary aspirations among U.S. middle and high school students.

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**Keywords** Academic performance · Educational aspirations · Propensity scores · School attendance · School security · School surveillance

## Introduction

Schools play a central role in the psychosocial development of youth by providing ecological supports that can promote adolescents' cognitive, affective, and behavioral adjustment (Eccles and Roeser 2011). Adolescents spend most of their waking hours at school, and thus schools are expected to provide safe and healthy learning environments. Despite this expectation, many youth are exposed to aggression, violence, drugs, or other illegal activities at school. In 2011, approximately 7 % of high school students had been threatened or injured with a weapon, 33 % had been in a fight, 20 % had been bullied, and 26 % had been offered, given, or sold drugs on school property in the past year (Eaton et al. 2012). Adolescents' exposure to violent, aggressive, and drug-using behaviors are important developmental issues in their own right (Krug et al. 2002; World Health Organization 2007, 2009), but are particularly problematic given their strong association with academic problems and school failure (Cook et al. 2010; Lipsey and Derzon 1998; McEvoy and Welker 2000). Given that school success is one key indicator of thriving for positive youth development (Scales et al. 2000), it is crucial to understand what school contexts provide the most effective ecological supports for promoting academic success among adolescents.

One way that school administrators attempt to create safe and effective learning environments is to use visible security measures (e.g., metal detectors, security cameras, security personnel) that limit access to school buildings, limit weapon presence, increase student surveillance, or provide a means for reacting to crises (Addington 2009). Visible security measures are designed to decrease problematic student behavior and promote academic success by making schools safer. Yet there are concerns that visible security measures may negatively influence youth by promoting a culture of fear and creating negative expectancy effects (Goldstein et al. 2008; Mayer and Leone 1999). To date, no rigorous quantitative research studies have examined how visible security measures influence adolescents' academic success or whether any contextual characteristics may moderate those relationships. This study attempts to address this gap in the literature by examining whether visible security measures are associated with U.S. middle and high school students' attendance, academic performance, and postsecondary aspirations, and whether those relationships vary for different types of students or in different school contexts.

## Visible School Security Measures and Adolescents' Academic Success

As highlighted in ecological systems theory (Bronfenbrenner 1979), development occurs through dynamic, reciprocal, and complex interactions across multiple ecological contexts. Within this framework, it is imperative to situate human behavior within broader social contexts, and schools are one particularly salient developmental context during adolescence (Eccles and Roeser 2011). School safety is an important social issue that often gains prominence in the public following highly publicized school shootings (Addington 2009). In response, many schools have increased their use of visible security measures in an attempt to create safe and effective learning environments. Despite the considerable expenses associated with many security measures (Garcia 2003), these measures are often appealing given their perceived effectiveness in alleviating parental and student fear and promoting school safety (Brown 2005; Finn and McDevitt 2005).

The logic of using visible security measures to promote school safety implicitly relies on rational deterrence and routine activity theories of criminal behavior. Namely, visible security measures are expected to deter adolescents from engaging in problematic behaviors by increasing the perceived risk of apprehension and punishment. This deterrence hypothesis is based on a rational choice theory of behavior, whereby the likelihood of criminal offending is a function of the perceived costs and benefits associated with committing a crime (Becker 1968). Routine activity theory further suggests that the presence of motivated offenders, suitable targets, and a lack of capable guardians are necessary for a crime to occur (Cohen and Felson 1979). Visible security measures should therefore promote school safety by minimizing the presence of motivated offenders (via deterrence) and increasing the presence of capable guardians (either physical guardians such as security personnel or symbolic/virtual guardians such as security cameras). For most school administrators, the primary goal of using visible security measures is to deter adolescents' criminal or delinquent behavior; but a secondary goal is to promote adolescents' academic success. Namely, these visible security measures should have a beneficial effect on adolescents' academic success by creating safe and supportive learning environments designed to promote adolescents' healthy development. Adolescents who feel safe at school have higher attendance rates, better academic performance, and may experience fewer classroom disruptions from other students (Bowen and Bowen 1999; Card and Hodges 2008; Lacoe 2013; Milam et al. 2010).

The use of visible school security measures remains controversial, however, as some scholars have theorized that the increasing prevalence of visible security measures in schools has led to a culture of criminalization and fear, which may in turn lead to worse student behavior and negative school climates (Hirschfield 2008; Kupchik and Monahan 2006). The criminalization of school discipline may elicit negative expectancy or self-fulfilling prophecy effects among students, such that students labeled as criminal or suspect adjust their behaviors to align with those labels attributed to them (Warnick 2007; Watts and Erevelles 2004); several research studies lend support to this hypothesis (Kupchik 2010; Mayer and Leone 1999). In particular, non-violent student offenses that may be highly interpretable such as disorderly conduct or insubordination are often met with more severe punishment in schools with police (Kupchik 2010; Na and Gottfredson 2013; Theriot 2009). The criminalization perspective implies that visible security measures may have direct negative effects on adolescents' academic outcomes, given that youth may internalize negative expectancy effects arising from prison-like school settings drawing on penological rather than pedagogical procedures for dealing with students (Hirschfield 2008).

The deterrence and criminalization perspectives provide competing predictions regarding the effects of visible security measure on adolescents' academic success. These competing predictions suggest that visible security measures do not have consistent (positive or negative) effects on adolescents' academic success, but rather, these effects may be moderated by various school contexts and student characteristics. In particular, school size, the clarity and consistency of school rules, and student socio-demographic characteristics may moderate the effects of visible security measures. First, larger schools may have less social cohesion and greater organizational alienation (Lee et al. 1993), where the use of visible security measures may increase fear and mistrust and therefore be less effective in promoting adolescents' academic success. Second, the deterrence perspective implies that visible security measures should promote academic success by creating certainty that transgressions will be punished. Thus, visible security measures may be more effective in schools characterized by clear policies, policies perceived as equitable, and policies that incorporate input from the surrounding community. Finally, visible security measures may have a less positive effect on adolescents' academic success in schools with high proportions of groups that tend to report less favorable attitudes toward police such as minority students, socioeconomically disadvantaged, or female students (e.g., Hurst and Frank 2000). Large urban schools with higher proportions of minorities are likely to have more strict approaches to discipline regardless of the security measures they implement (Payne and Welch 2010; Welch and Payne 2010, 2012), and thus any effects of visible security measures may also be different in such schools. Indeed, security measures considered "exclusionary" (e.g., metal detectors) are more commonly found in schools with larger proportions of poor and non-White students (Kuphick and Ward 2014). In summary, the effects of visible security measures may vary according to school size, clarity and consistency of school policies, and the sex, racial, and socioeconomic status composition of students.

## Prior Research on the Academic Consequences of Visible School Security Measures

There is a notable lack of research examining the effects of visible school security measures on adolescents' academic success (Cook et al. 2010; Skiba and Peterson 2000). To date, we are unaware of any randomized controlled trials that have examined the effects of visible security measures on adolescents' academic outcomes, and few that have used quasi-experimental designs. Indeed, the limited research on this topic has largely focused on behavioral outcomes like arrests, weapon charges, and drug use (e.g., Jackson 2002; Na and Gottfredson 2013; Theriot 2009) with surprisingly little focus on adolescents' academic outcomes. One notable exception was a quasi-experimental evaluation of the New York City's Impact Schools program (Brady et al. 2007), which found that schools with an increased police presence fared worse than comparison schools on school attendance rates as well as the proportion of students reading at grade level, at grade level for math, taking the SAT, and dropping out of school. However, the authors noted that these negative program effects might have been due to the lack of baseline equivalence between the program and comparison schools, so it is unclear whether these findings accurately depict the effect of school security personnel on adolescents' academic success.

A few quasi-experimental and correlational studies have also examined the relationships between visible security measures and academic outcomes, but findings have been inconsistent (see Addington 2009; Fletcher et al. 2008; Hankin et al. 2011 for recent reviews). For instance, one study reporting findings from a national survey of 1,387 schools found that schools' level of security technology use was not correlated with student achievement levels (measured via state achievement percentiles; Coon 2004). In a more recent study, Peguero and Bracy (2015) found that students attending schools with more security measures tended to drop out at higher rates, but that this effect attenuated to no significance when also considering other aspects of school climate such as discipline, disorder, procedural justice, and student–teacher relationships. Another study examining school record data from a single county school system found that the introduction of school resource officers (SROs) had no discernable effect on adolescents' academic achievement (Rogers 2004). Finally, a study using statewide school records from Missouri reported no differences between schools with and without SROs in student attendance, graduation rates, or dropout rates; however, schools with SROs had higher cumulative ACT scores compared to schools without SROs (Link 2010). In summary, there is a relatively small body of research providing somewhat conflicting evidence regarding the overall effects of visible security measures on adolescents' academic outcomes. Indeed, most empirical studies have focused on the effects of visible security measures on adolescents' delinquency or victimization outcomes (e.g., Burrow and Apel 2008 Jackson 2002; Theriot 2009), with no examination of a crucial indicator of adolescent well-being—namely, success in school.

Nonetheless, prior research does highlight the potential variability in the types and patterns of visible security measures used by schools, such that it may be useful to conceptualize school security in terms of patterns or typologies (rather than the mere presence/absence of any single type of security measure). This conceptualization of security utilization patterns also recognizes that some visible school security measures, such as metal detectors, may be more exclusionary than others (Hirschfield 2010; Kupchik and Ward 2014), and that there could be cumulative effects of multiple security measures within a school (Bracy 2011; Fuentes 2011; Mayer and Leone 1999).

Given the lack of empirical research examining the direct effects of visible security measures on adolescents' academic outcomes, it is perhaps not surprising that, to date, no studies have examined whether any school context or student background characteristics moderate those relationships. Although prior research has documented relationships between school size, school policies, student socio-demographic characteristics, and students' academic and behavioral outcomes (e.g., Bosworth et al. 2011; Bowen and Bowen 1999; Bradshaw et al. 2009; Gottfredson et al. 2005; Milam et al. 2010), this literature has not explicitly addressed whether these contextual characteristics may moderate the effects of visible security measures on adolescents' academic success. Therefore, the sparse empirical literature on visible security measures and adolescents' academic success highlights clear gaps in our understanding of what school contexts provide the most effective ecological supports for promoting academic success among adolescents.

## The Current Study

This study sought to address identified gaps in the literature by examining whether and how schools' utilization patterns of security personnel, cameras, and metal detectors are associated with adolescents' academic outcomes. Despite the widespread use of these visible security measures in schools, to date, there is sparse and inconsistent evidence regarding their actual effectiveness in promoting academic success among students. Therefore, this study used data from two national surveys to address two broad research questions. First, are different utilization patterns of visible security measures in U.S. middle and high schools associated with adolescents' academic outcomes (i.e., academic performance, school attendance, and postsecondary aspirations)? Knowing whether visible security measures are associated with adolescents' academic success has important implications for understanding the ecological supports schools might provide for promoting positive youth development. Second, do school context characteristics (size, policies related to discipline and safety, parental or community involvement in school activities) or adolescent demographic characteristics (sex, race, socioeconomic status) moderate the relationships between security utilization patterns and academic outcomes? Although there is little prior research on this issue, competing theoretical perspectives suggest that the effects of visible security measures may not be consistently positive or negative, but rather, vary across different contexts.

## Method

### Sample

We used secondary data from two nationally representative surveys, analyzing data from the two samples separately but in parallel fashion to assess the consistency and generalizability of findings. The first sample came from the publicly available School Crime Supplement (SCS) to the National Crime Victimization Survey (NCVS). The Census Bureau for the Bureau of Justice Statistics and the National Center for Education Statistics collects the SCS, which is a cross-sectional survey of 12–18 year old students in the United States. The Census Bureau used a rotating panel design to select households for participation in the larger NCVS survey; in SCS survey years household members between the ages of 12–18 who had been enrolled in a primary or secondary education program in the past 6 months were also given an SCS survey (U.S. Department of Justice 2009). We used student-level response data from the SCS surveys collected in 2001, 2003, 2005, 2007, 2009, and 2011 (aggregated $N = 38{,}707$; $N_{2001} = 8{,}601$; $N_{2003} = 7{,}641$; $N_{2005} = 6{,}399$; $N_{2007} = 5{,}722$; $N_{2009} = 4{,}414$; $N_{2011} = 5{,}930$). Because the SCS surveys are cross-sectional, it is not possible to follow adolescents longitudinally over time.[1] Therefore, to maximize the analytic sample size, student data across these six SCS survey years were pooled into a common dataset and all analyses statistically controlled for survey year. Although it is possible that some of the student respondents were nested within the same schools, the de-identified nature of the data made it impossible to account for this clustering in the statistical analyses.

The second sample came from the restricted use School Survey on Crime and Safety (SSOCS). The SSOCS is a cross-sectional survey of principals and administrators of schools in the United States. The SSOCS uses a stratified sampling design based on the Common Core of Data to stratify on school level, locale, and enrollment size (Ruddy et al. 2010). We used school administrator-reported data from the SSOCS surveys collected in 2003–2004, 2005–2006, 2007–2008, and 2009–2010—thus covering a similar time-span and school level composition as the SCS surveys (aggregated $N = 10{,}340$; $N_{2003} = 2{,}680$; $N_{2005} = 2{,}630$; $N_{2007} = 2{,}460$; $N_{2009} = 2{,}570$). As with the SCS sample, the cross-sectional design of the SSOCS survey precluded any longitudinal analysis over time.[2] Therefore, we pooled cross-sectional data across the four survey years, and statistically controlled for survey year in all analyses.

### Measures

#### *Grades*

In the SCS, adolescents' academic performance was measured using a single student-reported item indicating grades

[1] Although it is possible for the same adolescent to have been interviewed across multiple data collection periods, the national sampling frame of the SCS surveys means the probability of such overlap is small and the de-identified nature of the data makes it impossible to discern whether the same students were surveyed in multiple years.

[2] Although the SSOCS surveys include Common Core of Data identification numbers that allow linkage of SSOCS respondents (i.e., schools) longitudinally over time, the national sampling frame of the SSOCS surveys means that the probability is quite small for any overlap of schools across survey years.

across all subjects in the current school year (ranging from 0 = *mostly F's* to 4 = *mostly A's*).

#### *Truancy*

In the SCS, truancy was measured using a single student-reported item indicating the number of days the adolescent skipped class in the past month (range 0–20 days).

#### *Postsecondary Aspirations*

In the SCS, postsecondary aspirations was measured with a single student-reported binary variable indicating whether the adolescent expected to attend school after high school (0 = *no*; 1 = *yes*).

#### *Percent of Students Scoring Below 15th Percentile*

In the SSOCS, school-level academic performance was measured using a single administrator-reported item indicating the percent of students in the school who scored below the 15th percentile on state standardized tests in the past year (range 0–100).

#### *Percent Daily Attendance*

In the SSOCS, school-level attendance was measured using a single administrator-reported item indicating the average percent daily attendance rate (range 0–100).

#### *School-Level Postsecondary Aspirations*

In the SSOCS, school-level postsecondary aspirations were measured using a single administrator-reported item indicating the percent of students in the school who were likely to go to college after high school (range 0–100).

#### *Visible Security Utilization Pattern*

In both the SCS and SSOCS data sources, visible security utilization patterns were measured with a nominal 8-category variable. This variable indexed the different possible combinations of security personnel, security cameras, and metal detectors used in schools (i.e., *none, cameras only, metal detectors only, metal detectors/cameras, security personnel only, security personnel/cameras, security personnel/metal detectors, cameras/metal detectors/security personnel*). Respondents in both surveys indicated the presence or absence of security personnel, cameras, and metal detectors in their school; as noted in the Introduction, we elected to focus on the 8-category utilization pattern (and not the presence/absence of any single security measure) given that these patterns are more representative of how security measures are used in school settings.

#### *School and Student Context Moderators*

In the SCS, the school and student context moderators were student sex (1 = *male*; 0 = *female*), student race (*White, Black, other*), yearly family income (log transformed for normality), and a mean scale measuring the clarity and consistency of school rules. The school rules scale was created by taking the average of five ordinal (*strongly agree, agree, disagree, strongly disagree*) items: "Everyone knows what the school rules are; If a school rule is broken, students know what kind of punishment will follow; The school rules are strictly enforced; The school rules are fair; The punishment for breaking school rules is the same no matter who you are" ($\alpha = .76$).

School context moderators in the SSOCS were percent of male students (range 0–100), percent of White students (range 0–100), percent of students receiving free/reduced price lunch (FRPL) (range 0–100), school enrollment size (range 10–5,100), and a scale measuring parental/community involvement in school. The parental/community involvement scale was created by taking the average of eight binary (agree, disagree) items: "Were any of the following community and outside groups involved in efforts to promote safe, disciplined, and drug-free schools… {Parents groups; Social service agencies; Juvenile justice agencies; Law enforcement agencies; Mental health agencies; Civic organizations/service clubs; Private corporations and business; Religious organizations}" ($\alpha = .74$).

### Data Analysis Procedures

We used ordinary least squares, logistic, and negative binomial regression models to predict the continuous, binary, and non-negative count outcomes (respectively). To test for moderation effects, we used multiplicative interaction terms estimated as the product of the security utilization pattern dummy indicators and the moderators listed in the Method section. We examined the effect of one moderator (e.g., student sex) at a time; because this involved seven interaction terms per moderator (one for each security pattern dummy indicator), we used a Wald test to examine whether the seven interaction terms for each moderator were jointly equal to zero. To adjust for the surveys' complex sampling designs, we used a Taylor series variance estimation method for the SCS (U.S. Department of Justice 2009), and a jackknife variance estimation method for the SSOCS (Ruddy et al. 2010). Given the large analytic sample sizes in both survey sources and the multiple statistical tests conducted, we assessed statistical significance at the $\alpha = .01$ level. We also estimated standardized mean difference effect sizes (Cohen's *d*) and odds ratios (*OR*) to convey the magnitude of any statistically significant effects.

### *Propensity Score Estimation*

Because this study involved secondary data analysis, it was not possible to randomly assign students/schools to different security utilization patterns. Therefore, we used propensity scores to balance respondents in schools using different security utilization patterns (Guo and Fraser 2010). Propensity score methods can be useful for reducing the impact of selection bias and confounding on estimated treatment effects in non-randomized observational studies by balancing groups on a wide range of observed baseline characteristics (Tanner-Smith and Lipsey 2014). The 'treatment' indicator in this study—security utilization pattern—was a nominal polytomous measure, so we used a generalized propensity score method appropriate for non-binary treatment indicators (Hirano and Imbens 2004; Imai and Van Dyk 2004). We estimated propensity scores as the predicted probability of respondents' observed school security utilization pattern based on a multinomial logistic regression model that included a wide range of potentially confounding characteristics, including measures of perceived and/or actual school safety (see Appendix). Propensity score balancing techniques commonly used for binary treatments (e.g., nearest neighbor matching, inverse propensity score weighting) were not feasible to implement given the large number of treatment categories and the complex sampling designs of the surveys. Therefore, we statistically controlled for the estimated propensity scores and their squared and cubed terms in all outcome models. Although this quasi-experimental research design does not permit causal inferences regarding the effects of security utilization patterns on adolescents' outcomes, it attempts to minimize the impact of selection bias and confounding on any observed treatment effects.[3]

### *Control Variables*

All outcome models statistically controlled for the estimated propensity scores (and their squared/cubed terms), and the student/school context moderators described above.

The models predicting student-reported outcomes from the SCS included the following control variables: student age, students' fear of being attacked or harmed in the school building or on school property (0 = *Never*; 1 = *Almost never/sometimes/most of the time*); urbanicity (0 = *No*; 1 = *Yes*); public school (0 = *No*; 1 = *Yes*); and survey year (range 1999–2011).

The models predicting school administrator-reported outcomes from the SSOCS included the following control variables: school level (0 = *Middle/mixed grade*; 1 = *High school*); urbanicity (0 = *No*; 1 = *Yes*); and survey year (range 2003–2010).

### *Missing Data*

We used multiple imputation (Graham 2009; Schafer and Graham 2002) to handle missing data. None of the key variables of interest were missing data on more than 19 % of cases. We created 20 imputed datasets based on all key variables of interest (i.e., school security measures, academic outcomes, student/school context characteristics, and all baseline covariates used in the propensity score estimation models). Pooled estimates and inferential statistics were calculated using Rubin's rules (1987).

## Results

### Descriptive Statistics

Table 1 presents descriptive statistics and bivariate correlations for the visible school security measures, academic outcomes, and student/school context moderators of interest; the results are shown separately for the two survey data sources. The pooled SCS sample across the 2001–2011 survey years included 38,707 students (51 % male, 77 % White, $M_{Age} = 14.72$, 91 % attending public schools). The majority of adolescents reported that their schools used security personnel (70 %) and security cameras (71 %); only 15 % reported metal detectors. The pooled SSOCS sample across the 2003–2010 survey years included 10,340 public schools (average student composition: 50 % male, 57 % White, 15 % high school only vs. middle or mixed grade span, $M_{Enrollment} = 590$, $M_{Student\text{–}teacher\ ratio} = 18.89$). Almost one-half of school administrators reported that their schools used security personnel (46 %) and security cameras (49 %); only 1 % reported using metal detectors.

As shown in Table 2, the most prevalent patterns of security utilization in the SCS student surveys were security cameras with personnel (42.5 %), security personnel only (16.5 %), cameras only (15.4 %), or no cameras/no metal detectors/no security personnel (14.8 %). The results were similar in the school administrator surveys, where the most prevalent patterns were no cameras/no metal detectors/no personnel (32.6 %), security cameras with personnel (26.5 %), cameras only (21.6 %), and security personnel only (18 %). Notably, in both the SCS and SSOCS, metal detectors were rare, and almost always used

[3] Indeed, this quasi-experimental design can minimize the impact of selection bias and confounding even more than simply using the baseline covariates as statistical controls in the regression models. This latter approach would not account for variability in the magnitude or direction of the effects of those covariates across the different security utilization patterns.

**Table 1** Descriptive statistics and bivariate correlations for visible security measures, academic outcomes, and school/student characteristics

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. No security measures | 1.0 | −.21 | – | – | −.24 | −.42 | – | −.07 | −.06 | .03 | .00 | .03 | .03 | −.01 | −.17 |
| 2. CAM | −.18 | 1.0 | – | – | −.22 | −.38 | – | −.06 | −.06 | .04 | .01 | −.01 | .12 | −.04 | −.08 |
| 3. MD | −.02 | −.02 | 1.0 | – | – | – | – | – | – | – | – | – | – | – | – |
| 4. CAM + MD | −.03 | −.03 | −.00 | 1.0 | – | – | – | – | – | – | – | – | – | – | – |
| 5. SP | −.20 | −.19 | −.03 | −.04 | 1.0 | −.43 | – | −.07 | .02 | .02 | −.02 | −.00 | −.09 | .02 | .02 |
| 6. CAM + SP | −.36 | −.35 | −.05 | −.06 | −.40 | 1.0 | – | −.12 | .03 | −.03 | .03 | −.02 | .01 | −.03 | .17 |
| 7. MD + SP | −.05 | −.05 | −.01 | −.01 | −.06 | −.11 | 1.0 | – | – | – | – | – | – | – | – |
| 8. CAM + MD + SP | −.12 | −.12 | −.02 | −.02 | −.14 | −.25 | −.04 | 1.0 | .15 | −.12 | −.05 | −.02 | −.19 | .16 | .04 |
| 9. Grades/Percent below 15th percentile | .04 | .04 | −.01 | .01 | −.03 | .00 | −.04 | −.05 | 1.0 | −.15 | −.34 | .03 | −.35 | .41 | .03 |
| 10. Truancy/Percent daily attendance | −.05 | −.02 | −.01 | .00 | −.01 | .05 | .01 | .02 | −.12 | 1.0 | .09 | .01 | .09 | −.11 | −.03 |
| 11. Postsecondary aspirations | .00 | −.01 | −.00 | −.02 | .01 | .00 | −.00 | −.00 | .24 | −.09 | 1.0 | −.01 | .28 | −.53 | .01 |
| 12. Male student/Percent male | .00 | .00 | .00 | .00 | −.01 | .00 | .00 | .00 | −.16 | .01 | −.08 | 1.0 | .03 | .01 | −.01 |
| 13. White student/Percent White | .07 | .09 | −.00 | −.00 | −.02 | −.00 | −.06 | −.16 | .07 | .00 | −.02 | .00 | 1.0 | −.67 | −.01 |
| 14. Family income (ln)/Percent FRPL | .04 | .05 | −.01 | −.02 | −.01 | .03 | −.08 | −.12 | .18 | −.01 | .10 | .01 | .22 | 1.0 | .02 |
| 15. School rules/Community involvement | .02 | .01 | −.00 | .01 | −.02 | −.01 | −.02 | .00 | .14 | −.09 | .08 | −.02 | .02 | .05 | 1.0 |
| SCS student reports ($N = 38{,}707$) | | | | | | | | | | | | | | | |
| M | .15 | .15 | .003 | .01 | .17 | .43 | .02 | .08 | 3.09 | .30 | .90 | .51 | .77 | 2.31 | 3.10 |
| SD | .36 | .35 | .05 | .08 | .38 | .49 | .13 | .28 | .84 | 1.26 | .29 | .50 | .40 | .50 | .45 |
| Range | 0–1 | 0–1 | 0–1 | 0–1 | 0–1 | 0–1 | 0–1 | 0–1 | 0–4 | 0–20 | 0–1 | 0–1 | 0–1 | 0–2.64 | 1–4 |
| SSOCS administrator reports ($N = 10{,}340$) | | | | | | | | | | | | | | | |
| M | .33 | .22 | .00 | .00 | .18 | .27 | 00 | .01 | 13.45 | 93.78 | 56.18 | 49.61 | 57.10 | 48.05 | .51 |
| SD | .39 | .37 | | | .40 | .13 | | .07 | 14.24 | 7.14 | 24.94 | 9.21 | 31.65 | 27.50 | .27 |
| Range | 0–1 | 0–1 | 0–1 | 0–1 | 0–1 | 0–1 | 0–1 | 0–1 | 0–100 | 0–100 | 0–100 | 0–100 | 0–100 | 0–100 | 0–1 |

Correlations below the diagonal are based on student reports from the SCS. Correlations above the diagonal are based on school administrator reports from the SSOCS

*SCS* school crime supplement, *SSOCS* school survey on crime and safety, *CAM* security cameras, *MD* metal detectors, *SP* security personnel, *FRPL* free/reduced price lunch

**Table 2** Unadjusted means and standard deviations for academic outcomes, by data source and visible security utilization pattern

| Data source; outcome | None | CAM | MD | CAM + MD | SP | CAM + SP | MD + SP | CAM + MD + SP |
|---|---|---|---|---|---|---|---|---|
| SCS student reports ($N$ = 38,707; % in category) | 14.8 | 15.4 | 0.3 | 0.6 | 16.5 | 42.5 | 1.5 | 8.4 |
| Grades | 3.17$^{abcd}$ (0.81) | 3.18$^{efgh}$ (0.84) | 3.00 (0.83) | 3.15$^{ij}$ (0.81) | 3.05$^{aekl}$ (0.88) | 3.09$^{bfmn}$ (0.85) | 2.85$^{cgikm}$ (0.87) | 2.97$^{dhjln}$ (0.85) |
| Truancy | 0.16$^{abcde}$ (0.89) | 0.24$^{afg}$ (0.91) | 0.22 (0.55) | 0.34 (1.87) | 0.27$^{bhi}$ (1.27) | 0.37$^{cfh}$ (1.47) | 0.41$^{d}$ (1.69) | 0.40$^{egi}$ (1.62) |
| Postsecondary aspirations | 0.90 (0.29) | 0.90 (0.29) | 0.88 (0.30) | 0.83$^{ab}$ (0.34) | 0.91$^{a}$ (0.29) | 0.90$^{b}$ (0.29) | 0.89 (0.31) | 0.90 (0.29) |
| SSOCS administrator reports ($N$ = 10,340; % in category) | 32.6 | 21.6 | 0.0 | 0.0 | 18.0 | 26.5 | 0.0 | 1.0 |
| Percent below 15th percentile | 12.00$^{abc}$ (12.90) | 12.38$^{def}$ (11.23) | – | – | 14.39$^{adg}$ (14.43) | 14.77$^{beh}$ (14.46) | – | 28.80$^{cfgh}$ (25.30) |
| Percent daily attendance | 93.91$^{a}$ (8.65) | 94.19$^{bc}$ (6.20) | – | – | 94.00$^{de}$ (6.36) | 93.38$^{bdf}$ (6.72) | – | 88.48$^{acef}$ (10.37) |
| School level postsecondary aspirations | 56.65 (25.78) | 56.70 (25.23) | – | – | 54.98 (25.49) | 56.22 (23.96) | – | 51.92 (27.22) |

Standard deviations shown in parentheses. Means and standard deviations are unadjusted for other control variables. Proportions across security pattern categories may not sum to 100 % due to rounding. Superscripts indicate significant contrasts in outcome means across visible security utilization patterns, at the $p < .01$ level

*SCS* school crime supplement, *SSOCS* school survey on crime and safety, *CAM* security cameras, *MD* metal detectors, *SP* security personnel

in tandem with security cameras and personnel. This highlights the importance of examining patterns of school security utilization, given that certain visible security measures (e.g., metal detectors) may rarely be used in isolation.

## Security Utilization Patterns and Academic Outcomes

### *Student-Reported Outcomes*

Table 2 presents unadjusted means and standard deviations for adolescents' academic outcomes across security utilization patterns. Table 3 presents predicted marginal means from the regression models examining the relationships between security utilization patterns and student-reported academic outcomes from the SCS surveys, after adjusting for all control variables (see Appendix for full regression models). Within each row of the table, superscripts denote significant contrasts in outcome levels across security utilization groups. The results indicated that adolescents attending schools with only security personnel reported significantly lower grades than those attending schools using no security measures [$b = -0.06$, 99 % CI (−0.10, −0.01), $d = -0.07$], or those using only security cameras [$b = -0.05$, 99 % CI (−0.11, −0.00), $d = -0.06$]. Both of these effects were quite small in magnitude, however, equivalent to a 0.05–0.06 difference in grades (on a 0–4 scale). As shown in Table 3, there was no evidence of any other differences in student-reported grades across the security utilization groups.

The results for the student-reported truancy outcome indicated that adolescents in schools using only security personnel reported significantly higher truancy than those attending schools using no security measures [$b = 0.31$, 99 % CI (0.02, 0.61), $d = 0.25$], or those only using cameras [$b = 0.30$, 99 % CI (0.03, 0.57), $d = 0.24$], but again, these effects were small in practical terms. Adolescents in schools using metal detectors with security personnel also reported higher truancy than those attending schools using no security measures [$b = 0.84$, 99 % CI (0.13, 1.56), $d = 0.67$], or those only using cameras [$b = 0.83$, 99 % CI (0.13, 1.54), $d = 0.66$]. The predicted truancy incidence rate was 0.43 for adolescents in schools using metal detectors with security personnel, 0.14 in schools using no security measures, and 0.23 in schools using only security cameras. As shown in Table 3, there was no other evidence of differences in student-reported truancy across the security utilization groups.

For the postsecondary aspirations outcome, adolescents in schools using only security personnel reported significantly higher odds of postsecondary aspirations relative to those attending schools with no security measures [$b = 0.28$, 99 % CI (0.06, 0.49), $OR = 1.32$], or cameras and metal detectors [$b = 0.79$, 99 % CI (0.01, 1.58), $OR = 2.20$]. Adolescents in schools using cameras and security personnel also reported

**Table 3** Predicted marginal means for academic outcomes, by data source and visible security utilization pattern

| Data source; outcome | None | CAM | MD | CAM + MD | SP | CAM + SP | MD + SP | CAM + MD + SP |
|---|---|---|---|---|---|---|---|---|
| SCS student reports ($N = 38{,}707$) | | | | | | | | |
| Grades | $3.17^{a}$ | $3.18^{b}$ | 3.00 | 3.14 | $3.04^{ab}$ | 3.09 | 2.84 | 2.96 |
| Truancy | $0.14^{ab}$ | $0.23^{cd}$ | 0.19 | 0.43 | $0.25^{ac}$ | 0.38 | $0.43^{bd}$ | 0.41 |
| Postsecondary aspirations | $0.90^{abc}$ | 0.90 | 0.89 | $0.82^{de}$ | $0.91^{ad}$ | $0.90^{b}$ | 0.88 | $0.90^{ce}$ |
| SSOCS administrator reports ($N = 10{,}340$) | | | | | | | | |
| Percent below 15th percentile | $11.49^{ab}$ | $11.55^{c}$ | – | – | $13.69^{d}$ | $14.27^{ae}$ | – | $29.27^{bcde}$ |
| Percent daily attendance | $93.90^{a}$ | $94.13^{b}$ | – | – | $93.84^{c}$ | $93.13^{d}$ | – | $88.15^{abcd}$ |
| School level postsecondary aspirations | 58.68 | 59.26 | – | – | 58.71 | 59.60 | – | 52.02 |

Marginal means are estimated from generalized linear models shown in Appendix. Superscripts indicate significant contrasts in outcome means across visible security utilization patterns, at the $p < .01$ level

*SCS* school crime supplement, *SSOCS* school survey on crime and safety, *CAM* security cameras, *MD* metal detectors, *SP* security personnel

significantly higher odds of postsecondary aspirations relative to those attending schools with no security measures [$b = 0.22$, 99 % CI (0.02, 0.43), $OR = 1.25$]. Finally, adolescents in schools using all three types of security patterns reported significantly higher odds of postsecondary aspirations relative to those attending schools with no security measures [$b = 0.31$, 99 % CI (0.01, 0.61), $OR = 1.36$], or cameras and metal detectors [$b = 0.83$, 99 % CI (0.06, 1.60), $OR = 2.29$]. These effects were all small in practical terms, however, given that the predicted probability of adolescents aspiring to attend postsecondary school ranged from 0.82 to 0.91 across all of the security utilization groups (see Table 3).

### *School Administrator-Reported Outcomes*

The bottom section of Table 3 presents predicted marginal means from the regression models examining the relationships between security utilization patterns and school administrator-reported outcomes from the SSOCS surveys (see Appendix for full regression models). The results indicated that schools using all three types of security measures fared worse in terms of academic performance relative to schools using all other security utilization patterns. For instance, the predicted percentage of students who scored below the 15th percentile was 29.27 % for school using all three types of security measures, versus 11.49 % for those using no security measures, 13.69 % for those using security personnel only, 11.55 % for those using cameras only, and 14.27 % for those using cameras and security personnel. As shown in Table 3, there were few other significant differences across security utilization patterns in terms of the percent of students scoring below the 15th percentile on state standardized tests.

The results were similar in terms of percent daily attendance rates, such that schools using cameras, metal detectors, and security personnel reported significantly lower attendance rates than schools using no security measures [$b = -4.32$, 99 % CI (−6.47, −2.17), $d = -0.30$], only cameras [$b = -4.58$, 99 % CI (−6.19, −2.80), $d = -0.32$], only security personnel [$b = -4.37$, 99 % CI (−5.96, −2.78), $d = -0.31$], or cameras and security personnel [$b = -4.21$, 99 % CI (−5.81, −2.60), $d = -0.30$]. These effects were small in practical terms, however; the predicted average daily attendance rate was 93.84 % for schools using only security personnel, 94.13 % for those using only cameras, 93.13 % for those using cameras and security personnel, and 88.15 % for those using all three types of security measures. There was no evidence of any other differences in percent daily attendance rates across visible security utilization groups.

Finally, as shown in the last row of Table 3, there was no evidence that school level postsecondary aspiration rates varied across schools in the different visible security utilization groups, with school level postsecondary aspiration rates ranging from 52 to 60 % across groups.

## Moderating Effects of Student and School Context Characteristics

### *Student-Reported Outcomes*

To examine whether student and school characteristics moderated the effects of visible security measures on academic outcomes, we replicated all regression models and added multiplicative interaction terms for each moderator, in turn (see Appendix for full model results). The results from the student-reported SCS surveys provided no evidence that adolescents' race, family income, or perceived clarity of school rules moderated the effects of visible security utilization patterns on adolescents' academic outcomes.

### *School Administrator-Reported Outcomes*

The results from the school administrator-reported SSOCS surveys also provided little evidence that any school characteristics moderated the effects of visible security measures on academic outcomes, with two notable exceptions (see Appendix for full model results). First, the effects of visible security utilization patterns on percent daily attendance rates varied according to the percent of students receiving FRPL (Wald $F = 3.27$, $p = .006$). Across all security utilization groups, attendance rates were lowest in schools with the most FRPL students, but this difference was magnified in the small group of schools using all three types of security measures. Within this group of schools, the predicted average daily attendance rate was 91 % when there were no students receiving FRPL, 89 % in schools where 40 % of students received FRPL, and 88 % in schools where 60 % of students received FRPL. Second, the percent of FRPL students in school moderated the effects of visible security patterns on school level postsecondary aspiration rates (Wald $F = 3.90$, $p = .002$). Across all security utilization groups, postsecondary aspirations were lowest in schools with the most FRPL students; but again, this difference was magnified in the group of schools using all three types of security measures. Thus, the results indicated that the combined use of surveillance cameras, metal detectors, and security personnel was associated with lower student attendance and lower postsecondary aspirations, particularly in schools with higher proportions of low socioeconomic students.

## Discussion

Schools are increasingly using visible school security measures such as cameras, metal detectors, and security personnel in an attempt to promote school safety and students' academic success. Although there has been increased federal funding for school security measures in recent years (The White House 2013), there is a notable lack of rigorous empirical research that has examined the effects of visible security measures on adolescents' academic success (Addington 2009; Fletcher et al. 2008; Hankin et al. 2011). Among the few studies that have examined how visible school security measures are associated with adolescents' academic success, findings have been inconsistent, including positive effects (Link 2010), negative effects (Brady et al. 2007), or no evidence of an effect (Coon 2004; Peguero and Bracy 2015; Rogers 2004). However, most prior research studies have focused on only one type of security measure at a time (e.g., security personnel), have failed to explore possible moderators of any observed effects, and/or used weak correlational research designs that do not permit causal inferences. We attempted to address these issues in the current study by examining whether visible security utilization patterns were associated with adolescents' academic outcomes and whether those effects varied across different school contexts or student characteristics. We triangulated findings from two large national surveys (one student-reported and one school administrator-reported), and used propensity score methods to control for baseline differences in schools using different visible security utilization patterns.

The results from student-reported surveys indicated that schools' visible security utilization patterns had minimal effect on adolescents' academic performance and postsecondary aspirations, but that truancy rates may be higher in schools using metal detectors with security personnel (versus those using none, or security cameras only). The results from the administrator-reported surveys further indicated that the small subset of schools using security cameras, security personnel, and metal detectors fared worse in terms of academic performance and attendance, particularly in schools with a large percentage of students receiving free and reduced-price lunches. Although findings across the two survey sources were not entirely convergent, taken together, they provide no evidence that visible security measures have consistent beneficial effects on adolescents' academic outcomes, and indeed, that certain security utilization patterns may have modest detrimental effects on academic outcomes (even after controlling for a range of other potential confounding variables). Overall, these results are consistent with prior evidence that visible security measures, particularly the presence of security personnel, may be negatively related to adolescents' academic performance and/or attendance (Brady et al. 2007). Although this study focused specifically on outcomes related to adolescents' academic outcomes, these results parallel recent findings that indicate visible security measures may also be related to worse student behavior outcomes such as delinquency and victimization (Na and Gottfredson 2013; Tanner-Smith et al. 2015)

In the administrator-reported survey data, most of the observed detrimental effects on adolescents' academic outcomes were driven by a small group of roughly 100 schools that utilized all three types of security measures. This may speak to the possibility of an additive phenomenon where the presence of multiple security measures is more than the sum of its parts; this hyper-securitized group of schools relies heavily on surveillance and security measures and may have begun to resemble and function like prisons where democracy is eroded and students are limited in their opportunities to meaningfully engage with their school (Addington 2009; Beger 2003; Fuentes 2011; Noguera 1995). In the current study, adolescents in this hyper-securitized group of schools had worse academic outcomes, and these detrimental effects were compounded in schools with higher rates of poverty. High schools in urban areas with large proportions of minority students are especially likely to utilize multiple security measures (Steinka-Fry et al. 2015); therefore, these hyper-securitized schools may want to devote special attention to context-specific policies and procedures that govern the use of school security measures, with particular emphasis on mitigating any detrimental effects on adolescents that may propagate the "school-to-prison pipeline."

It is noteworthy that although they are presumably from the same population of schools, the students and administrators in these survey samples reported somewhat different utilization patterns of visible security measures. It is possible that adolescents may not always recognize the presence of school security measures and report them as such. Indeed, some scholars suggest that the increasingly ubiquitous presence of security measures both in school and society more generally has led to a casual acceptance of security by young people (Kupchik 2010). Moreover, the proliferation of video recording devices in computers and mobile phones among other places may have led adolescents to perceive surveillance cameras as less invasive compared to several years ago, perhaps to the point where they do not consider them a notable part of a school's infrastructure.

Of course, the findings from the current study must be considered with its limitations. One limitation of this study was the lack of a true experimental design that might have permitted causal inferences about the effects of visible security utilization patterns on adolescents' academic success. Because it was not possible to randomly assign adolescents to schools using different security utilization patterns, the observed associations with adolescents' academic outcomes may be due to other confounding characteristics. Indeed, schools that use one or more visible security measures may be systematically different from those that do not, including differences such as historic problems with violence in that school or neighborhood, parental or community concerns about school violence, or other baseline risk levels. Although we attempted to control for these potential selection biases by using a rigorous quasi-experimental research design that employed generalized propensity scores based on a wide range of baseline characteristics (see Appendix), it is possible that other unmeasured baseline characteristics may have introduced selection bias. Despite this limitation, findings from this study provide at least an initial understanding of which patterns of security measures are most influential, and might be targeted in future intervention studies.

Another limitation of the current study was our inability to examine school-level contextual effects in the student-reported survey data, given that these publicly available data did not provide a school-level identifier. Future research studies should aim to collect data at both the student and school level, to permit more in-depth exploration of possible contextual effects associated with adolescents' experiences that are situated within school contexts. This is particularly important for advancing developmental systems perspectives (Lerner and Castellino 2002) of how development is shaped by adolescents' relations with the contexts in which they are embedded. Schools are an influential social context in the lives of adolescents (Eccles and Roeser 2009), and have the potential to provide ecological supports to promote adolescents' thriving and other positive psychosocial development (Debnam et al. 2013; Roeser et al. 2000; Wang and Dishion 2011). Thus, future research studies that employ multilevel and longitudinal research designs could advance an understanding of the ways in which the dynamic interactions between adolescents, peers, teachers, and school administrators explain the effects of visible security measures on adolescents' academic success. Recognizing that the perceptions and interpretations of school security measures reflect a dynamic and synergistic transaction between adolescents and their social environments should advance our understanding of how school contexts may influence student engagement (Lawson and Lawson 2013).

Finally, because the aims of this study were to examine possible direct effects (and moderators of those direct effects) of schools' visible security utilization patterns on adolescents' academic outcomes, we did not examine possible mediators of these relationships. Given our findings that visible security measures may have detrimental effects on adolescents' academic outcomes, future research is needed to explore the pathways by which these school characteristics inhibit positive youth development. Drawing on theories of ecological systems and positive youth development, these detrimental effects may be due to mismatches between adolescents' developmental needs and the school context. Future studies might therefore examine whether the associations between school security measures and academic success might be partially an effect of adolescents' perceptions of school safety, school equity, connectedness to school, or other measures of behavioral adjustment.

## Conclusions

Given the central role of schools in the psychosocial development of adolescents (Eccles and Roeser 2011), an important issue in the field of adolescent development is understanding what school contexts provide the most effective ecological supports for promoting youth's academic success. Schools are expected to provide adolescents with nurturing environments designed to promote healthy development and thriving. Visible security measures are one mechanism that schools may use in an effort to create safe and effective learning environments for youth. However, as noted in recent reviews (e.g., Cook et al. 2010), there is often a disturbing disconnect between research and school policy when it comes to schools' efforts to reduce adolescent problem behavior and promote student success. This study examined student- and school administrator-reported data from two large national surveys to examine whether and when school security utilization patterns were associated with students' academic outcomes. The study's results provided no evidence that security utilization patterns were associated with consistent beneficial effects on academic outcomes, and in fact, some security utilization patterns had detrimental effects on students' academic performance, attendance, and postsecondary aspirations. Findings from this study advance our understanding of how school environments designed to serve as ecological supports for adolescents may also be sources of risk for healthy adolescent development. Researchers and policymakers can use these findings to investigate other mechanisms for creating developmentally supportive school environments designed to promote adolescent thriving.

**Acknowledgments** The research reported here was supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305A120181 to Vanderbilt University. The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education. The authors would also like to thank Mark Lipsey and two peer reviewers for their comments on earlier drafts of the manuscript.

**Author Contributions** ETS conceived of the study, participated in its design and coordination and drafted the manuscript; BWF participated in the analysis and interpretation of the data and helped to draft the manuscript. All authors read and approved the final manuscript. All authors declare no conflicts of interest.

## Appendix

See Tables 4, 5, 6.

**Table 4** Variables used in propensity score models

| |
|---|
| *SCS student surveys* |
| Months student attended school, past 6 months |
| Grade in school |
| Student age |
| Student sex |
| Student race/ethnicity |
| Student employed |
| Bullying frequency at school |
| Saw students on drugs/alcohol at school |
| Amount of time it takes to get from home to school |
| Ride bus to school most of the time |
| Ride bus home from school most of the time |
| Parent age |
| Parent sex |
| Parent race/ethnicity |
| Parent marital status |
| Parent education level |
| Family income |
| Female headed household |
| Number of household units |
| Years lived in house |
| Family owns house |
| Household size |
| Number of children in family |
| Any vandalism against household |
| Dollar amount of damage from vandalism |
| Number of times something stolen/attempted stolen from household |
| Number of times household member attacked |
| Average scale of victimization attempts on household |
| Number of crime victimization incidents per person in family |
| School has locked entrance/exit doors during day |
| School uses locker checks |
| School has requirement that students wear badges or picture identification |
| Public school |
| Highest grade level offered in school |
| Students allowed to leave school grounds at lunch |
| Perceived clarity and consistency of school rules |
| Urban area |
| Geographic region |
| Metropolitan statistical area |
| Adult present during interview |
| Survey year |
| *SSOCS administrator surveys* |
| Provide two-way radios to staff |
| Use drug testing for students |
| Parent involvement in school discipline policies |
| Number of full time teachers |
| Provide an anonymous threat reporting system |
| Provide student counseling activities for students |
| Tobacco prohibited on school grounds |
| Number of full time special education teachers |
| Student–teacher ratio |
| Title I eligible |
| Percent urban land use in school zip code region |
| Population density in school zip code region |
| Size of school zip code region |
| Median household income in school zip code region |
| Gang related crime activity |
| Hate related crime activity |
| Parent involvement in school committees |
| School policies related to disaster preparedness |
| Percent English language learner students |
| Percent special education students |
| Regular school (vs. charter, religious) |
| School grade span |
| Urbanicity |
| School enrollment size |
| Percent free and reduced-price lunch students |
| Percent male students |
| Percent White students |
| Community involvement in school activities |
| Staff training activities |
| Student bullying frequency |
| Student racial/ethnic tensions |
| Factors limiting school efforts to reduce crime |
| Student verbal abuse of teachers |
| Classroom disorder |
| Student disrespect for teachers |
| Gang activity |
| Cult or extremist group activities |
| Written plan for bomb threats |
| Private school |
| Administrator years at current school |
| Crime levels in areas where students live |
| Provide lockers to students |
| Survey year |

**Table 5** Effects of visible security measures on academic outcomes, SCS student surveys (N = 38,707)

| | Grades | | | Truancy | | | Postsecondary aspirations | | |
|---|---|---|---|---|---|---|---|---|---|
| | *b* | 99 % CI | *p* | *b* | 99 % CI | *p* | *b* | 99 % CI | *p* |
| Visible security pattern | | | | | | | | | |
| None (ref) | – | | | – | | | – | | |
| CAM | −0.00 | (−0.05, 0.05) | .931 | 0.01 | (−0.28, 0.31) | .921 | 0.08 | (−0.15, 0.30) | .371 |
| MD | −0.06 | (−0.31, 0.20) | .542 | 0.32 | (−1.87, 2.52) | .696 | −0.16 | (−1.28, 0.96) | .706 |
| CAM + MD | 0.07 | (−0.11, 0.24) | .319 | 0.59 | (−0.46, 1.64) | .144 | −0.52 | (−1.27, 0.23) | .072 |
| SP | −0.06 | (−0.10, −0.01) | .003 | 0.31 | (0.02, 0.61) | .006 | 0.28 | (0.06, 0.49) | .001 |
| CAM + SP | −0.03 | (−0.08, 0.01) | .072 | 0.13 | (−0.16, 0.43) | .226 | 0.22 | (0.02, 0.43) | .005 |
| MD + SP | −0.11 | (−0.24, 0.02) | .027 | 0.84 | (0.13, 1.56) | .003 | 0.18 | (−0.36, 0.72) | .374 |
| CAM + MD + SP | −0.07 | (−0.14, 0.00) | .014 | 0.30 | (−0.05, 0.65) | .026 | 0.31 | (0.01, 0.61) | .007 |
| School rules | 0.21 | (0.17, 0.24) | <.001 | −0.79 | (−0.93, −0.65) | <.001 | 0.43 | (0.29, 0.57) | <.001 |
| Male | −0.26 | (−0.28, −0.24) | <.001 | 0.13 | (0.00, 0.25) | .009 | −0.53 | (−0.65, −0.41) | <.001 |
| White | 0.06 | (0.02, 0.10) | <.001 | 0.16 | (−0.03, 0.34) | .026 | −0.32 | (−0.49, −0.15) | <.001 |
| Student age | −0.01 | (−0.02, −0.00) | <.001 | 0.33 | (0.30, 0.37) | <.001 | −0.25 | (−0.28, −0.22) | <.001 |
| Family income (ln) | 0.27 | (0.24, 0.30) | <.001 | −0.16 | (−0.29, −0.02) | .004 | 0.62 | (0.52, 0.72) | <.001 |
| Perceived unsafety | −0.15 | (−0.18, −0.11) | <.001 | 0.26 | (0.08, 0.44) | <.001 | −0.36 | (−0.50, −0.22) | <.001 |
| Urban | −0.00 | (−0.04, 0.03) | .848 | 0.43 | (0.25, 0.61) | <.001 | 0.32 | (0.18, 0.46) | <.001 |
| Public school | −0.14 | (−0.18, −0.10) | <.001 | 0.24 | (−0.01, 0.48) | .013 | −0.30 | (−0.57, −0.04) | .003 |
| Survey year | 0.01 | (0.01, 0.02) | <.001 | 0.15 | (0.13, 0.17) | <.001 | 0.01 | (−0.01, 0.03) | .362 |
| PS | 0.46 | (−0.29, 1.21) | .113 | 0.54 | (−2.85, 3.94) | .676 | −0.44 | (−3.58, 2.69) | .710 |
| $PS^2$ | −1.37 | (−3.53, 0.79) | .099 | 1.56 | (−8.01, 11.12) | .671 | 0.66 | (−8.14, 9.46) | .844 |
| $PS^3$ | 1.14 | (−0.67, 2.95) | .101 | −2.56 | (−10.36, 5.23) | .391 | 0.26 | (−7.15, 7.67) | .927 |
| Moderator tests | | Wald *F* | *p* | | Wald *F* | *p* | | Wald *F* | *p* |
| School rules | | 0.62 | .735 | | 1.83 | .086 | | 1.29 | .258 |
| Male | | 0.53 | .809 | | 0.18 | .989 | | 0.33 | .941 |
| White | | 0.98 | .445 | | 0.23 | .976 | | 0.39 | .907 |
| Family income (ln) | | 2.16 | .041 | | 0.87 | .536 | | 0.96 | .461 |

Pooled estimates from generalized linear models that account for the complex survey design; based on 20 multiply imputed datasets. The results for grades outcome are unstandardized OLS regression coefficients. The results for truancy outcome are unstandardized coefficients from negative binomial regression models. The results for college attendance outcome are logit coefficients from logistic regression models

*SCS* school crime supplement, *CAM* security cameras, *MD* metal detectors, *SP* security personnel, *PS* estimated propensity score

**Table 6** Effects of visible security measures on academic outcomes, SSOCS administrator surveys (N = 10,340)

| | Percent below 15th percentile | | | Average daily attendance | | | Postsecondary aspirations | | |
|---|---|---|---|---|---|---|---|---|---|
| | *b* | 99 % CI | *p* | *b* | 99 % CI | *p* | *b* | 99 % CI | *p* |
| Visible security pattern | | | | | | | | | |
| None (ref) | – | | | – | | | – | | |
| CAM | 1.29 | (–0.03, 2.61) | .012 | 0.26 | (–0.66, 1.17) | .467 | –1.09 | (–3.59, 1.40) | .258 |
| SP | 0.80 | (–0.80, 2.40) | .196 | 0.23 | (–0.71, 1.16) | .532 | –0.35 | (–2.92, 2.22) | .727 |
| CAM + SP | 2.34 | (0.96, 3.72) | <.001 | –0.11 | (–0.93, 0.71) | .729 | –2.10 | (–4.28, 0.08) | .013 |
| CAM + MD + SP | 9.39 | (3.77, 15.01) | <.001 | –4.32 | (–6.47, –2.17) | <.001 | 2.29 | (–4.63, 9.21) | .394 |
| Enrollment | 0.00 | (–0.00, 0.00) | .771 | 0.00 | (–0.00, 0.00) | .172 | 0.00 | (–0.00, 0.00) | .669 |
| Student–teacher ratio | 0.02 | (–0.02, 0.07) | .167 | 0.01 | (–0.01, 0.03) | .225 | –0.08 | (–0.18, 0.01) | .021 |
| Comm. involvement | –0.54 | (–2.38, 1.30) | .449 | –0.20 | (–1.14, 0.74) | .580 | 2.02 | (–0.97, 5.01) | .082 |
| Percent male | 0.07 | (0.01, 0.13) | .001 | 0.01 | (–0.02, 0.03) | .504 | 0.01 | (–0.09, 0.11) | .869 |

**Table 6** continued

| | Percent below 15th percentile | | | Average daily attendance | | | Postsecondary aspirations | | |
|---|---|---|---|---|---|---|---|---|---|
| | *b* | 99 % CI | *p* | *b* | 99 % CI | *p* | *b* | 99 % CI | *p* |
| Percent White | –0.05 | (–0.08, –0.03) | <.001 | –0.00 | (–0.01, 0.01) | .940 | –0.09 | (–0.13, –0.05) | <.001 |
| High school | 2.40 | (1.34, 3.46) | <.001 | –1.80 | (–2.35, –1.25) | <.001 | 0.96 | (–0.78, 2.71) | .155 |
| Percent FRPL | 0.16 | (0.14, 0.19) | <.001 | –0.02 | (–0.04, –0.01) | <.001 | –0.56 | (–0.60, –0.52) | <.001 |
| Urban | 1.07 | (0.02, 2.12) | .009 | –0.43 | (–1.04, 0.18) | .071 | 5.19 | (3.43, 6.94) | <.001 |
| Survey year | –0.70 | (–0.92, –0.48) | <.001 | 0.06 | (–0.06, 0.18) | .228 | 1.64 | (1.27, 2.01) | <.001 |
| PS | 4.10 | (–19.74, 27.95) | .658 | –5.85 | (–17.98, 6.28) | .214 | –47.04 | (–86.98, –7.10) | .002 |
| $PS^2$ | –5.53 | (–62.62, 51.55) | .803 | 12.27 | (–19.93, 44.47) | .326 | 114.95 | (12.73, 217.17) | .004 |
| $PS^3$ | 1.55 | (–38.60, 41.70) | .921 | –7.95 | (–31.37, 15.48) | .382 | –80.78 | (–157.93, –3.64) | .007 |
| Moderator tests | | Wald *F* | *p* | | Wald *F* | *p* | | Wald *F* | *p* |
| Enrollment | | 0.55 | .735 | | 0.48 | .794 | | 0.86 | .507 |
| Comm. involvement | | 2.50 | .029 | | 1.84 | .102 | | 0.99 | .422 |
| Percent male | | 2.67 | .020 | | 2.41 | .034 | | 0.74 | .596 |
| Percent White | | 1.75 | .119 | | 2.70 | .019 | | 2.33 | .040 |
| Percent FRPL | | 2.16 | .056 | | 3.27 | .006 | | 3.90 | .002 |

Pooled estimates from generalized linear models that account for the complex survey design; based on 20 multiply imputed datasets. The results are unstandardized OLS regression coefficients

*SSOCS* school survey on crime and safety administrator sample, *CAM* security cameras, *MD* metal detectors, *SP* security personnel, *PS* estimated propensity score

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