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ORIGINAL PAPER

Confounding Bias in the Relationship Between Problem Gambling and Crime

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Abstract

Although the relationship between problem gambling and criminal behavior has been widely researched, concerns over the causal nature of this association remain. Some argue that problem gambling does not lead to crime; instead, the same background characteristics that predict problem gambling also predict criminal behavior. Yet, studies suggestive of a spurious association often rely on small, non-random, and cross-sectional samples; thus, the extent to which the findings are generalizable to the broader population is unknown. With this in mind, the present study uses data from The National Longitudinal Study of Adolescent to Adult Health and a series of propensity score weighting and matching techniques to examine the role of confounding bias in the relationship between problem gambling and criminal behavior in young adulthood. On the surface, results show a positive and significant relationship between problem gambling and a range of criminal behaviors. However, after statistically balancing differences in several background measures between problem gamblers and non-problem gamblers, such as low self-control, past substance use, and juvenile delinquency, we find no significant relationship between problem gambling and crime. These patterns are consistent across several propensity score weighting and matching algorithms. Our results therefore parallel those in support of the "generality of deviance" framework, whereby a similar set of covariates known to be associated with criminal behavior also predict problem gambling.

Keywords Problem gambling · Crime · Add health · Propensity score analysis

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Introduction

The relationship between problem gambling and criminal behavior has been examined extensively (see reviews by Adolphe et al. 2019; Banks 2017; Campbell and Marshall 2007). Most broadly, research shows that problem gambling is positively related to a range of criminogenic outcomes (Clark and Walker 2009; Grinols 2017; National Opinion Research Center 1999; Walker et al. 2010), including financially-motivated (Rudd and Thomas 2015) and violent (Laursen et al. 2016) crime. These patterns have been observed among general (e.g., Folino and Abait 2009) and incarcerated (e.g., Abbott et al. 2005; Turner et al. 2009) populations.

The extent to which problem gambling is linked to criminal behavior is grounded in Agnew's (1992, 2001) general strain theory, which contends that crime can be a coping mechanism in response to strains—or economic and noneconomic stressors that result in negative emotions (see reviews by Eitle and Taylor 2010; Greco and Curci 2017). As this relates to problem gambling, any financial, familial, or social-psychological strains resulting from gambling might increase one's desire for criminal behavior as a means to cope with such negative circumstances (Abbott and McKenna 2005; Adolphe et al. 2019; Blaszczynski and McConaghy 1994; Sakurai and Smith 2003; Turner et al. 2017). Indeed, among a sample of 332 male inmates in a Japanese prison, Yokotani et al. (2019) find that problem gambling increases unwanted gambling urges (i.e., strains), which, in turn, increases income-generating crimes. Moreover, based on their analysis of 90 convicted men with pathological gambling and/or antisocial personality disorders, Pastwa-Wojciechowska (2011: 675) concludes, "the crimes committed by persons who gamble result from the[ir] personal and financial problems."

Yet, despite the theoretically sound relationship between problem gambling and criminal behavior, and the extensive number of studies showing a positive association between the two, questions regarding causality remain (Adolphe et al. 2019). For instance, some contend that offending precedes problem gambling (Abbott and McKenna 2005; Jun et al. 2019). Alternatively, as Perrone et al. (2013) note, the association between problem gambling and involvement in crime may be co-symptomatic, wherein common underlying factors might account for both gambling and crime. In other words, problem gamblers may already be prone to criminal behavior because the background characteristics that predict problem gambling also predict crime.

Indeed, research using national surveys shows that men, young adults, racial and ethnic minorities, and socioeconomically disadvantaged populations report more problem gambling behaviors compared to their respective counterparts (Welte et al. 2011, 2017). Importantly, each of these sociodemographic characteristics is also a correlate of criminality (DeLisi and Vaughn 2016; Sumter et al. 2018). Traits such as low self-control (e.g., impulsivity and irrational decision-making) and depression are also associated with both problem gambling (Bergen et al. 2012; Welte et al. 2017) and crime (DeLisi and Vaughn 2016; Gottfredson and Hirschi 1990). Furthermore, social environmental factors, such as affiliating with delinquent peers and low attachment to parents and school, are related to problem gambling (Dowling et al. 2017; Magoon and Ingersoll 2006; McComb and Sabiston 2010; Welte et al. 2017) and crime (Akers 1973; Gottfredson 2006; Haynie and Osgood 2005; Hoeve et al. 2012). Employment during adolescence and poor academic performance are also associated with both problem gambling (Canale et al. 2016; Ladouceur et al. 1999; Winters et al. 1993) and criminal behavior (Katsiyannis et al. 2008; Uggen and Wakefield 2008). Additionally, studies suggest that religiosity and involvement in religious activities are negatively associated with both problem gambling (Hoffmann 2000; Welte et al. 2017) and crime (Baier and Wright 2001; Miller and Vuolo 2018). Finally, substance abuse and being arrested are related to problem gambling (Barnes et al. 2015; Ladouceur et al. 1999; Martins et al. 2014; Winters et al. 1993; Zhai et al. 2020) as well as subsequent criminality (Bernburg and Krohn 2003; D'Amico et al. 2008).

In light of these common correlates, research has examined whether some of the aforementioned characteristics do in fact account for the relationship between gambling and crime. For instance, Mishra et al. (2011), using a sample of 180 male students, find that controlling for traits indicative of low self-control accounts for a significant proportion of the relationship between problem gambling and criminal behavior. Moreover, Vitaro et al.'s (2001) examination of 717 adolescent males suggests that earlier delinquency and substance use account for the association between problem gambling and subsequent delinquency. These findings have led some researchers to conclude that the relationship between problem gambling and crime is merely a product of shared predictors that fall under the "generality of deviance" umbrella (Hirschi and Gottfredson 1994; Jones and Quisenberry 2004; Osgood et al. 1988).

Past studies supporting the "generality of deviance" framework have provided valuable insight into the causal association between problem gambling and criminal behavior. Yet, given the relatively small, and sometimes non-random nature of the samples used in these studies, the conclusions are not generalizable to the broader population (Mishra et al. 2017). Moreover, findings from existing studies are often cross-sectional (e.g., Mishra et al. 2011), meaning that issues of temporal ordering persist. With this in mind, the present study assesses the role of confounding bias in the relationship between problem gambling and criminal behavior using a nationally representative, longitudinal sample. We also employ a series of propensity score weighting and matching techniques to account for pre-existing differences in several background characteristics between problem gamblers and non-problem gamblers (e.g., sociodemographic characteristics, low self-control, delinquent peers, parental attachment, and substance use) that may explain the relationship between problem gambling and crime.

Method

Participants

We use data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), which began in 1994–1995, when over 90,000 middle and high school students from 80 schools completed an in-school questionnaire. Approximately 21,000 adolescents were selected for in-home interviews (Wave I). One year later, 14,838 of the original in-home respondents were re-interviewed (Wave II). In 2001–2002, when respondents were ages 18 to 26 years, 15,197 respondents were interviewed again (Wave III). In 2008–2009, 15,701 of the original Wave I respondents were re-interviewed (Wave IV). Although higher response rates were observed for female, white, and native-born respondents at Wave IV, the non-response bias is negligible, and Wave IV respondents represent the Wave I sample (see Brownstein et al. 2010).[1]

[1] For more information about the Add Health data, see https://www.cpc.unc.edu/projects/addhealth.

Our analysis includes 12,227 respondents from Waves I, III, and IV. The majority of covariates have minimal missing data (i.e., less than 1%), with the smallest amount of missing data on our measures of juvenile arrest and religious activities. Some exceptions are the measures of public assistance and low self-control, where approximately 13% and 16% are missing, respectively. Testing for the missing completely at random assumption (see Little 1988) and assessing the potential role of data that are not missing at random (see Yuan 2014) suggest that our data satisfy the missing at random assumption. We therefore use multiple imputation to address missing data, and results from 10 imputed datasets are combined following Rubin's (1987) method that accounts for variation within and between imputations.[2]

Measures and Covariates

Dependent Variables: Crime Types (Wave IV)

Respondents reported whether and how often (in the past 12 months) they engaged in criminal behavior, including deliberately damaging property, stealing, using a weapon to get something from someone, selling drugs, and getting into fights. We use this information to create three dependent variables. We first create a binary measure of *overall crime*, which is coded as (1) for those who reported involvement in any criminal acts and (0) for those who reported no involvement. We also create an indicator of financial or *instrumental crime*, which is coded as (1) for those who reported engaging in crimes with a financial motive, including stealing, selling stolen property, deliberately writing bad checks, or using someone else's credit card without their knowledge (referencing those who reported no involvement in instrumental crime). Finally, we create a binary measure indicating involvement in *violent crime* (coded as (1)), including fighting, hurting someone badly enough that they needed medical care, and shooting or stabbing someone (referencing no involvement in violent crime, which is coded as (0)).[3]

Independent Variable: Problem Gambling (Wave III)

Add Health asked eight gambling-related questions that were developed based on those used in clinical diagnostic tools (e.g., DSM-IV-TR; the South Oak Gambling Screen) for assessing problem-gambling (Clark et al. 2013; Jun et al. 2019; see also Feigelman et al. (2006) for a discussion of the gambling-related questions used in Add Health). First, all respondents answered three questions about their lifetime gambling participation (i.e., whether they ever (1) bought lottery tickets; (2) played casino tables or video games for

[2] Coefficients (i.e., $\bar{\beta}$) from the imputed datasets are combined as follows: $\bar{\beta} = \frac{\sum_{i=1}^{m} \beta_i}{m}$, where β_i is the coefficient for the respective covariate i for each imputed dataset, and m is the number of imputed datasets. Standard errors for the combined estimates are based on the combination of within- and between-imputation variance: $Variance_{within} = \frac{\sum_{i=1}^{m} SE_i^2}{m}$ and $Variance_{between} = \frac{\sum_{i=1}^{m} (\beta_i - \bar{\beta})^2}{m-1}$, where m is the number of imputed datasets, SE_i is the standard error of the respective covariate i, β_i is the parameter estimate of the respective covariate for each imputed dataset, and $\bar{\beta}$ is the average of the parameter estimates across all of the imputed datasets. The standard error for the combined estimate (i.e., $\bar{\beta}$) is as follows: $SE_{\bar{\beta}} = \sqrt{Variance_{within} + Variance_{between} + \frac{Variance_{between}}{M}}$, where m is again the number of imputed datasets.

[3] Supplemental analyses (available upon request) examined alternative operationalization strategies, such as crime counts and frequency measures, and the results were substantively similar to those presented here.

money; or (3) played any other games, such as cards or bingo, for money, or bet on horse races or sporting events, or taken part in any other kinds of gambling for money). Among those who reported ever gambling, respondents answered one question that asked about the largest amount of money they had ever lost from gambling in a single year. From there, respondents who reported ever being behind by more than \$500 in a given year were asked the remaining four questions tapping additional gambling problems (i.e., whether (1) they ever experienced a period of two or more weeks spending a lot of time thinking about/planning gambling; (2) they ever gambled to relieve uncomfortable feelings; (3) they ever lost money gambling and returned to get even; or (4) gambling ever caused serious or repeated relationship problems).

Approximately 3% (i.e., 422 respondents) of our sample reported ever being behind by more than \$500 in a given year, and these respondents were asked the four follow-up questions related to other gambling problems. The prevalence of additional gambling problems was sparse, as only about half of the 422 respondents answered affirmatively to experiencing at least one of the four other gambling problems. Thus, in order to retain the largest number of respondents exhibiting problem gambling behaviors, we code *problem gamblers* as (1) for those who reported being behind by more than \$500 in a given year, referencing those who either did not report any gambling participation or who had never been behind by more than \$500 in any given year (coded as (0)).

To ensure that our indicator of problem gambling was not masking variation in the overall pattern of results, we conducted several sensitivity analyses utilizing alternative measures for problem gambling (see Uecker and Stokes 2016). These included four measures indicating whether respondents were ever behind by \$500 over a year *and* (1) experienced a two week period thinking about gambling; (2) gambled to relieve uncomfortable feelings; (3) returned to gambling to get even; or (4) experienced serious relationship problems due to gambling. We also used these problem gambling indicators to create measures assessing the number of gambling problems reported by respondents. Across all of these operationalization strategies, the results from these sensitivity analyses (available upon request) were identical to those presented here.

Covariates: Background Controls (Wave I)

Demographic measures include self-reported gender (1 = *male*; 0 = female), race/ethnicity (dichotomous indicators for non-Hispanic *White*, non-Hispanic *Black*, *Hispanic*, non-Hispanic *Asian*, and non-Hispanic *other race*), and *age*. Familial background controls for socioeconomic disadvantage include a binary indicator for whether respondents *lived with both biological parents* during adolescence (1 = lived with both parents; 0 = lived in any other family structure). Additionally, family *socioeconomic status* ranges from 1 to 10 and is based on a combination of parents' educational attainment and occupational status (see Ford et al. 1999). *Neighborhood disadvantage* is the average of four census tract measures, including the percentage of adults unemployed, families below poverty, households receiving public assistance, and households headed by a single mother (Cronbach's $\alpha = 0.931$). Moreover, a dichotomous control for parents' receipt of *public assistance* such as welfare is also included (1 = received public assistance; 0 = otherwise).

Delinquency is a count (ranging from 0 to 9) of respondents' involvement in nine different behaviors in the past year (e.g., stealing, getting into physical fights, selling drugs, using a weapon to get something from someone). *Delinquent peers* is a count (ranging from 0 to 9) of how many of the respondents' three best friends smoked cigarettes daily, smoked pot monthly, or drank alcohol monthly (Cronbach's $\alpha = 0.758$). *Drug use* is a count (ranging from 0 to 5) of respondents' use of (1) marijuana, (2) cocaine, (3) inhalants, (4) intravenous drugs, or (5) other illegal drugs in the 30 days preceding the interview. *Juvenile arrest* is based on retrospective questions from Wave IV and indicates whether respondents ever experienced an arrest before their 18^{th} birthday (1 = juvenile arrest; 0 = otherwise).

We control for respondents' most recent grade point average (*GPA*), which is the average of respondents' self-reported grades in English, history, math, and science. We also control for Add Health Picture Vocabulary Test Scores (*AHPVT*; ranging from 14 to 146), which is a 78-item abbreviated version of the Peabody Picture Vocabulary Test-revised. *School attachment* (ranging from 1 to 5) assesses respondents' average level of agreement that they feel close to people at their school, feel a part of their school, and are happy to be at their school (Cronbach's $\alpha = 0.775$; see Johnson et al. 2006). *Parental attachment* is a count (ranging from 0 to 6) of whether respondents (1) talked about schoolwork or grades, (2) worked on a project for school, or (3) talked about other school-related topics with each of their parents in the past four weeks (Cronbach's $\alpha = 0.709$). Following Beaver et al. (2009), *low self-control* is a sum of 23 items that assess respondents' impulsivity and decision-making processes (e.g., "you usually go with your "gut feeling" without thinking too much about the consequences of each alternative;" "when making decisions, you generally use a systematic method for judging and comparing alternatives;" Cronbach's $\alpha = 0.765$). We also control for whether adolescents *work 20+ hours* per week (1 = work 20+ hours; 0 = otherwise). *Depression* in the past week is a summed scale of the frequency (never or rarely to most of the time or all of the time) of experiencing ten indicators from the Center for Epidemiological Studies Depression Scale, such as "you felt that you could not shake off the blues" and "you felt sad" (Cronbach's $\alpha = 0.685$). Finally, we include several dichotomous measures assessing *religious importance* (1 = religion is very important; 0 = otherwise), weekly *religious service attendance* in the past year (1 = attend religious services weekly or more; 0 = otherwise), daily *prayer* (1 = pray daily; 0 = otherwise), and weekly *youth group participation* in the past year (1 = participate in youth group activities, Bible classes, or choir weekly or more; 0 = otherwise). All descriptive statistics (i.e., mean, standard deviation, and minimum and maximum values) are presented in Table 1.

Analytic Strategy

Propensity score methods are used to statistically balance differences in background characteristics between problem gamblers (the treatment group) and non-problem gamblers (the control group) so that we may better assess the direct relationship between problem gambling and criminal behavior, net of confounding bias (Guo and Fraser 2015). This is accomplished by first regressing our binary indicator of problem gambling on the set of background controls via logistic regression analysis and retaining the predicted probabilities. The predicted probabilities—or propensity scores—range from 0 to 1, where higher values reflect a higher likelihood that a respondent reports problem gambling behaviors.[4]

[4] We restrict our analytic sample to those who fall within the region of common support (i.e., the range of propensity scores where problem gamblers and non-problem gamblers overlap). Following this restriction, there are 421 treated respondents and 11,260 controlled respondents.

Table 1 Weighted descritpive statistics for crime types, problem gambler, and all covariates

Variable	Mean/percentage	SD	Minimum	Maximum
Dependent variables				
Overall crime (%)	14.356	–	0	100
Instrumental crime (%)	11.109	–	0	100
Violent crime (%)	4.347	–	0	100
Independent variable				
Problem gambler (%)	3.451	–	0	100
Covariates				
Male (%)	49.067	–	0	100
White (%)	68.384	–	0	100
Black (%)	14.935	–	0	100
Hispanic (%)	11.633	–	0	100
Asian (%)	3.505	–	0	100
Other race (%)	1.551	–	0	100
Age	15.393	1.821	11	21
Lived with both biological parents (%)	58.121	–	0	100
Socioeconomic status (%)	6.094	2.603	1	10
Neighborhood disadvantage (%)	8.68	6.511	0	51.626
Public assistance (%)	9.001	–	0	100
Delinquency	1.27	1.684	0	9
Delinquent peers	2.50	2.652	0	9
Drug use	0.21	0.563	0	5
Juvenile arrest (%)	4.985	–	0	100
GPA	2.75	0.862	1	4
AHPVT	101.77	14.314	14	146
School attachment	3.74	0.880	1	5
Parental attachment	2.01	1.706	0	6
Low self-control	47.48	8.362	18	92
Work 20 + hours (%)	12.686	–	0	100
Depression	6.62	3.492	0	24
Religious importance (%)	40.558	–	0	100
Religious service attendance (%)	37.905	–	0	100
Prayer (%)	39.914	–	0	100
Youth group participation (%)	20.829	–	0	100
Sample size				12,227

GPA grade point average, *AHPVT* add health picture vocabulary test, *SD* Standard deviation

Using the propensity scores, we then weight controlled respondents in a manner so that they look statistically similar to treated respondents, so as to estimate the average treatment effect on the treated (ATT). That is, treated respondents receive a weight equivalent to:

$$\text{Problem Gambler} = 1$$

whereas controlled respondents receive a weight equivalent to:

$$\text{Non - Problem Gambler} = \frac{p(\text{Problem Gambler})}{1 - p(\text{Problem Gambler})}$$

where p is the predicted probability generated from the logistic regression analysis. We assess whether differences in the background controls in our unweighted and weighted samples are balanced with the weights by examining the standardized differences in the means and proportions between treated and controlled respondents. A standardized difference greater than |0.10| suggests imbalance (Austin 2009). Once balance is achieved, we examine the relationship between problem gambling and criminal behavior in our weighted sample.

In addition to propensity score weighting, we also utilize propensity score matching. Rather than creating a counterfactual sample with weights, we instead match treated respondents with controlled respondents who have a similar propensity for problem gambling. We then re-examine the relationships between problem gambling and criminal behavior within our matched sample. Our results conclude by testing the robustness of our findings via alternative propensity score matching algorithms. The propensity score weighting analysis was conducted in SAS 9.4 (Lanehart et al. 2012), and the propensity score matching analyses were conducted in Stata 15 via the "psmatch2" procedure (Leuven and Sianesi 2003).

Results

Table 2 shows the means and proportions of all background controls by problem gambling status in the unweighted and weighted samples. As expected in the unweighted sample, problem gamblers differ considerably on a number of background controls compared to non-problem gamblers. For instance, problem gamblers report more delinquency, delinquent peers, and drug use. After applying the propensity score weights, however, all differences in the background controls between problem gamblers and non-problem gamblers are balanced, as evidenced by the standardized differences falling below |0.10| in the weighted sample.

Table 3 shows the coefficients from several logistic regression analyses, where problem gambling is used to predict criminal behavior. Coefficients can be exponentiated (i.e., $exp(b_k)$) in order to obtain the odds ratios. The first set of coefficients shows the estimates associated with problem gambling in the unweighted sample, which are all positive and statistically significant ($p < 0.001$). That is, in the unweighted sample, problem gambling increases the odds of overall crime, instrumental crime, and violent crime by a factor of 2.108, 2.029, and 2.522, respectively. In the weighted sample, however, all of the estimates associated with problem gambling are not only attenuated in size, but they all fall out of statistical significance. That is, after accounting for differences in the background characteristics between problem gamblers and non-problem gamblers, the crime-inducing effects of problem gambling are null.

To further investigate the role of confounding bias in the association between problem gambling and crime, a one-to-one nearest neighbor matching algorithm (without replacement) is used in the following analysis. A caliper of 0.01 is used in the matching procedure, meaning problem gamblers are matched with a non-problem gambler whose propensity score deviates by no more than 0.01 from their match. All treated respondents are successfully matched with a controlled respondent. The bivariate associations shown in Table 4

Table 2 Bivariate statistics and standardized differences in background characteristics between problem gamblers and non-problem gamblers

Variable	Unweighted sample			Weighted sample		
	Problem gambler	Non-problem gambler	|Std. Diff.|	Problem gambler	Non-problem gambler	|Std. Diff.|
Male (%)	85.178	47.716	0.864	85.123	85.563	0.012
White (%)	69.490	68.342	0.025	69.376	69.115	0.006
Black (%)	13.664	14.983	0.038	13.715	13.626	0.003
Hispanic (%)	8.829	11.738	0.096	8.862	8.739	0.004
Asian (%)	6.290	3.401	0.135	6.314	6.222	0.004
Other race (%)	2.273	1.524	0.055	2.281	2.298	0.001
Age	16.097	15.367	0.425	16.086	16.128	0.024
Lived with both biological parents (%)	48.415	58.484	0.203	48.595	48.190	0.008
Socioeconomic status	6.033	6.096	0.024	6.031	6.013	0.007
Neighborhood disadvantage (%)	8.687	8.677	0.002	8.684	8.708	0.004
Public assistance (%)	10.150	8.958	0.041	10.187	10.414	0.007
Delinquency	2.176	1.233	0.490	2.155	2.191	0.017
Delinquent peers	4.091	2.443	0.607	4.073	4.156	0.028
Drug use	0.491	0.200	0.402	0.485	0.500	0.017
Juvenile arrest (%)	13.090	4.682	0.299	12.767	12.724	0.001
GPA	2.434	2.757	0.374	2.437	2.417	0.022
AHPVT	100.454	101.824	0.102	100.452	100.231	0.016
School attachment	3.625	3.743	0.127	3.627	3.627	0.000
Parental attachment	1.682	2.026	0.210	1.688	1.666	0.013
Low self-control	50.329	47.378	0.321	50.284	50.390	0.011
Work 20 + hours (%)	28.065	12.111	0.406	27.797	28.468	0.015
Depression	7.106	6.598	0.136	7.110	7.147	0.010
Religious importance (%)	28.519	41.009	0.265	28.625	28.327	0.007
Religious service attendance (%)	21.069	38.535	0.389	21.148	20.719	0.011
Prayer (%)	27.344	40.384	0.278	27.446	27.308	0.003

Table 2 (continued)

Variable	Unweighted sample			Weighted sample		
	Problem gambler	Non-problem gambler	|Std. Diff.|	Problem gambler	Non-problem gambler	|Std. Diff.|
Youth group Participation (%)	12.271	21.150	0.240	12.316	12.134	0.006
Sample size	422	11,805		421	11,260	

GPA grade point average, *AHPVT* add health picture vocabulary test. Weighted sample excludes one treated respondent (i.e., problem-gambler) and 545 controlled respondents (i.e., non-problem gamblers) who fell out of the region of common support. A standardized difference below |0.10| suggests the difference in a respective background control is balanced

Table 3 Logistic regression estimates of problem gambling on crime types: propensity score weighting

Outcome measures	Unweighted			Weighted		
	b	SE	*Z*-value	*b*	SE	*Z*-value
Overall crime	0.746	0.144	5.161*	0.221	0.152	1.457
Instrumental crime	0.708	0.166	4.269*	0.257	0.174	1.477
Violent crime	0.925	0.238	3.891*	0.241	0.254	0.945

SE refers to standard error. Propensity scores for weights estimated via a logistic regression model predicting problem gambling. All covariates shown in Table 1 (as well as the Add Health sampling weights) were used in the estimation of propensity scores. Coefficients in the weighted sample represent average treatment effects on the treated (ATT)

*$p<0.001$ (two-tailed test)

suggest that this matching procedure results in sufficient balance in the background controls between problem gamblers and non-problem gamblers, as all of the standardized differences are below |0.10|.

Table 5 reports the coefficients from logistic regression analyses, where problem gambling is used to predict the odds of criminal behavior in young adulthood in the matched sample. For ease of comparison, we repeat the estimates from these associations in the original, unmatched sample in Table 5, which are all positive and significantly associated with increases in the odds of offending. Once again, however, these associations are no longer statistically significant after we account for pre-existing differences between problem and non-problem gamblers in our matched sample.

To further aid interpretation, Fig. 1 presents the predicted probabilities for each of the crime outcomes for problem gamblers and non-problem gamblers in both the unmatched and matched samples. The predicted probabilities for all of the crime outcomes are significantly higher for problem gamblers in the unmatched sample; however, there are no significant differences observed in the matched sample.

As a final assessment, Table 6 reports the logistic regression coefficients associated with problem gambling using three additional propensity score matching algorithms. The first employs one-to-one nearest neighbor matching with replacement, wherein controlled respondents can be used in more than one match. The second uses a one-to-three nearest neighbor matching algorithm, which matches each problem gambler with three non-problem gamblers. The third matching algorithm utilizes a kernel-based matching estimator, which matches all problem gamblers with their closest controlled match but gives greater weight to closer matches and less weight to more distant matches. Across all of the various matching algorithms and outcomes, problem gambling is not significantly associated with criminal behavior.

Discussion and Conclusions

Using a longitudinal, nationally representative dataset and several propensity score weighting and matching techniques, this study examined the role of confounding bias in the relationship between problem gambling and criminal behavior in young adulthood. Consistent with the wealth of prior research, we initially observed a positive and

Table 4 Bivariate statistics and standardized differences in background characteristics between problem gamblers and non-problem gamblers in the matched sample (N = 421 matched pairs)

Variable	Problem gambler	Non-problem gambler	|Std. Diff.|
Male (%)	85.123	85.621	0.014
White (%)	69.376	69.717	0.007
Black (%)	13.715	13.204	0.015
Hispanic (%)	8.862	9.308	0.016
Asian (%)	6.314	5.862	0.019
Other race (%)	2.281	1.890	0.027
Age	16.086	15.997	0.052
Lived with both biological parents	0.486	0.503	0.034
Socioeconomic status	6.031	5.962	0.027
Neighborhood disadvantage (%)	8.684	8.544	0.021
Public assistance (%)	10.187	10.151	0.001
Delinquency	2.155	2.036	0.055
Delinquent peers	4.073	3.969	0.036
Drug use	0.485	0.441	0.053
Juvenile arrest (%)	12.767	10.691	0.065
GPA	2.437	2.425	0.013
AHPVT	100.452	100.496	0.003
School attachment	3.627	3.631	0.003
Parental attachment	1.688	1.704	0.010
Low self-control	50.284	49.837	0.048
Work 20 + hours (%)	27.797	26.116	0.038
Depression	7.110	6.941	0.045
Religious importance (%)	28.625	29.311	0.015
Religious service attendance (%)	21.148	23.984	0.068
Prayer (%)	27.446	27.976	0.012
Youth group participation (%)	12.316	12.508	0.006

GPA grade point average, *AHPVT* add health picture vocabulary test. Matched sample was generated using one-to-one nearest-neighbor matching without replacement. A Caliper of 0.01 was specified during the matching procedure. A standardized difference below |0.10| suggests the difference in a respective background control is balanced

statistically significant relationship between problem gambling and crime. However, once we accounted for the pre-existing differences between problem gamblers and non-problem gamblers, we found no meaningful association between problem gambling and crime.

Scholars have long debated the causal association between problem gambling and crime (Adolphe et al. 2019). Whereas some suggest that gambling is a precursor to crime (Clark and Walker 2009; Laursen et al. 2016), others suggest that crime is a precursor to problem gambling (Abbott and McKenna 2005; Jun et al. 2019). Further, some contend that problem gambling and crime are merely different manifestations of a common set of characteristics that underlie the “generality of deviance” (Barnes et al. 2005; Jones and Quisenberry 2004; Mishra et al. 2011, 2017). Our results parallel the latter, as problem gamblers exhibited social-psychological and behavioral characteristics that criminological research

Table 5 Logistic regression estimates of problem gambling on crime types: propensity score matching

Outcome measures	Unmatched			Matched		
	b	SE	*Z*-value	*b*	SE	*Z*-value
Overall crime	0.746	0.144	5.161*	0.306	0.299	1.024
Instrumental crime	0.708	0.166	4.269*	0.327	0.356	0.919
Violent crime	0.925	0.238	3.891*	0.393	0.435	0.903

Matched sample was generated using one-to-one nearest-neighbor matching without replacement. A caliper of 0.01 was specified. Propensity scores estimated via a logistic regression model predicting problem gambling. All covariates shown in Table 1 (as well as the Add Health sampling weights) were used in the estimation of propensity scores. Matched sample include 421 matched pairs. Coefficients for the matched sample represent the average treatment effects on the treated (ATT). Bootstrapped standard errors (SE) for coefficients in the matched sample were estimated across 1000 repetitions

*$p < 0.001$ (two-tailed test)

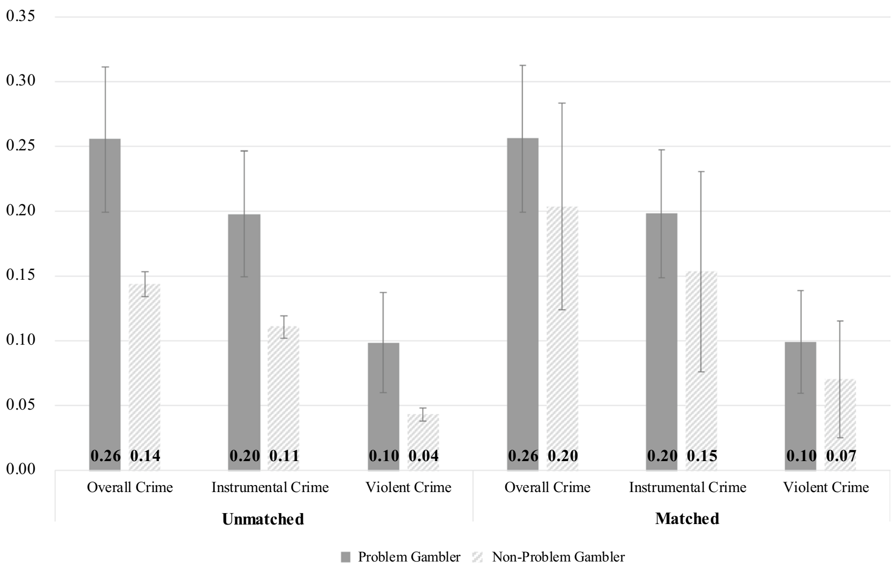

Fig. 1 Predicted Probabilities of Crime by Problem Gambling Status in the Unmatched and Matched Samples

has long speculated to be associated with crime (e.g., Akers 1973; Gottfredson and Hirschi 1990).

The implications of our findings suggest that curtailing problem gambling, and the criminogenic consequences that may arise from problem gambling, involves implementing early prevention/intervention efforts targeted at those with a propensity for general deviance. That is, it may be effective to implement strategies aimed at reducing risky behavior in general, as opposed to strategies specific to gambling behaviors (Mishra et al. 2011, 2017; Stinchfield 2004). For example, treatment and prevention programs can attempt to strengthen mental health and decision-making abilities in at-risk youth and young adults

Table 6 Logistic regression estimates of problem gambling predicting crime types: alternative propensity score matching techniques

Matching algorithm	Problem gambling estimates		
	b	SE	*Z*-value
Overall crime			
1-to-1 nearest neighbor with replacement (caliper: 0.01)	0.355	0.338	1.049
l-to-3 nearest neighbor with replacement (caliper: 0.01)	0.269	0.239	1.125
Kernel-based matching (bandwidth: 0.01)	0.257	0.162	1.584
Instrumental crime			
1-to-1 nearest neighbor with replacement (caliper: 0.01)	0.389	0.393	0.989
l-to-3 nearest neighbor with replacement (caliper: 0.01)	0.304	0.276	1.101
Kernel-based matching (bandwidth: 0.01)	0.286	0.175	1.641
Violent crime			
1-to-1 nearest neighbor with replacement (caliper: 0.01)	0.461	0.451	1.022
l-to-3 nearest neighbor with replacement (caliper: 0.01)	0.340	0.321	1.059
Kernel-based matching (bandwidth: 0.01)	0.319	0.248	1.288

Propensity scores estimated via a logistic regression model predicting problem-gambling. All covariates shown in Table 1 (as well as the Add Health sampling weights) were used in the estimation of propensity scores. Coefficients represent the average treatment effect on the treated (ATT). Bootstrapped standard errors (SE) for coefficients were estimated across 1000 repetitions

(Na and Paternoster 2012). In addition, policies can further seek to provide opportunities to engage in structured activities that encourage school and adult interaction with at-risk youth, such as having after-school programs and activities (Nofziger and Rosen 2016). Moreover, such programs could target high-risk areas, such as more disadvantaged neighborhoods or neighborhoods with high concentrations of gambling (Welte et al. 2017). Criminologists have suggested that early intervention among those with behavioral problems, such as those mentioned above, can reduce the likelihood of involvement in crime over the life course (Moffitt 1993). Given the overlapping predictors of problem gambling and crime, such practices may simultaneously reduce a variety of problem behaviors (Barnes et al. 2005; Vitaro et al. 2001).

Although it is relatively uncommon among existing studies on problem gambling (see Gainsbury et al. 2016), we relied on propensity score methods since these quasi-experimental analyses improve our assessment of the direct effects of problem gambling on crime net of potential confounders. Indeed, randomized controlled trials are the gold standard insofar as treatment effects are concerned (Austin 2011). Yet, in the social and behavioral sciences, where assigning “treatments” like problem gambling is impractical, the estimation of such effects can be difficult. As our results show, propensity score methods share many of the appealing aspects of randomized controlled trials, and future studies examining the consequences associated with problem gambling may benefit from implementing such methods.

Some study limitations should be noted. First, because Add Health is a school-based sample, it is plausible that those most susceptible to gambling and criminal behavior (e.g., dropouts or absentees) in young adulthood are missing. Moreover, although the prevalence (3.451%) of problem gambling based on our operationalization (i.e., ever being behind by more than $500 in a given year due to gambling) is close to the national average (Welte et al. 2015), we recognize that our measure is fairly broad. As aforementioned, sensitivity analyses using alternative definitions of problem gambling confirm the patterns presented here. Moreover, Uecker and Stokes (2016), also using Add Health, examined several different operationalization strategies for problem gambling and found that the indicator for being behind by $500 had the greatest influence on the results. Thus, we are confident that our approach to distinguish problem gamblers from non-problem gamblers was sufficient; however, we do encourage future research to test the robustness of these findings with other data.

Notwithstanding these limitations, our use of a nationally representative, longitudinal U.S. sample, along with propensity score methods, make this study an important contribution to the broader literature on the relationship between problem gambling and criminal behavior. Given the stark differences in crime between problem gamblers and non-problem gamblers in our original sample, coupled with the insignificant differences in our propensity score weighted and matched samples, our results suggest that problem gambling is part of a larger—and more general—set of behaviors that predict both gambling and subsequent crime. It is hoped that these findings shed light on the long-standing debate regarding the causal link between problem gambling and criminal behavior.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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