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ARC Centre of Excellence for Children and Families over the Life Course

The Risk and Time Preferences of Young Truants and Their Parents

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NON-TECHNICAL SUMMARY

Truancy is a costly social problem. Approximately 10–15% of students across a range of countries are classified as chronically absent from school. School absences are both predictors and symptoms of poor academic outcomes, decreased psychological well-being, illegal substances abuse, and antisocial or criminal behavior. Lowering truancy rates requires that we understand what drives students to regularly miss school without reasonable grounds.

Economic theory predicts that truancy rates will be higher for more impatient, present-biased and/or risk-taking individuals. Previous research strongly suggests that adolescents' preferences shape their behavior and success at school. Interestingly, although parents are believed to play a large role in their children's decision-making, the link between parental preferences and school outcomes has not been studied.

We take advantage of a unique randomized intervention of anti-truancy policy-school partnership program to study the role of preferences of parents and adolescents in school attendance decisions. In the program we study, the Ability School Engagement Program (ASEP), police and local schools in Queensland, Australia came together in a structured partnership to better engage truanting young people in school and reduce anti-social behavior. 102 families were randomly assigned to either ASEP or the business-as-usual control condition, and ASEP was previously shown to reduce truancy rates by approximately 6 percentage points or 25%. Our objective is to analyze whether time and risk preferences are related to adolescents' propensity to be truant, whether the intervention impacted more malleable preferences, and whether preference measures may be used to identify subgroups of participants who benefitted more from the intervention.

We make an important contribution in focusing directly on young people with excessively high truancy rates living in an area characterized by significant socioeconomic disadvantage and high crime rates. Although such students are frequently the target of initiatives to raise school engagement, they are seldom captured in empirical research measuring economic preferences. This paper utilizes a sample of truanting adolescents from households who are often underrepresented in experimental studies and especially difficult to locate in longitudinal follow-up. Indeed, it took us over one year to locate the 100 participating families for the follow-up study. Therefore, our study is unique in both the longitudinal nature of the randomized trial and the embedded use of an incentivized risk and time preference elicitation. Additionally, we estimate the preferences of both adolescents and their parents in an incentive-compatible way, ensuring that the decisions that the participants make have real consequences.

Our results indicate that the intervention improved self-control in parents, though we find no evidence of it affecting the preferences of truanting adolescents nor the time and risk preferences of the parents. We also find the intervention is most effective for students with more risk averse parents. Whilst the small sample size remains a limitation, ASEP shows promise as an intervention that fosters increased school attendance especially among risk averse parents.

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Abstract

We use an incentivized experiment to measure the risk and time preferences of truant adolescents and their parents. We find that adolescent preferences do not predict school attendance and that a unique police-school partnership program targeting school absences was most effective in reducing the truancy of adolescents with relatively risk-averse parents.

Keywords: adolescent preferences; time preferences; risk preferences; RCT; truancy

1. Introduction

Truancy is a costly social problem. Approximately 10–15% of students across a range of countries are classified as chronically absent from school (Vaughn et al. 2013). School absences are both predictors and symptoms of poor academic outcomes (Coelho et al. 2015), decreased psychological well-being (Dembo et al. 2012), illegal substances abuse (Henry and Huizinga 2007), and antisocial or criminal behavior (Rocque et al. 2017). Lowering truancy rates requires that we understand what drives students to regularly miss school without reasonable grounds.

Economic theory predicts that truancy rates will be higher for more impatient, present-biased and/or risk-taking individuals, though to date this relationship has not been empirically examined. Previous research examining economic preferences and students' behavior at school focuses on good conduct or disciplinary referrals. Both are likely to be closely related to truancy; troublemakers may skip school more frequently and also receive more disciplinary referrals when they do attend school. Castillo et al. (2011) estimate that a one standard deviation increase in discount rate is associated with a 14% increase in disciplinary referrals, though because their discount rate measures were not adjusted for the curvature of the utility function, the effect of the discount rate is confounded with risk aversion (Andersen et al. 2008).

Experimentally measured risk and time preferences have also been linked to students' health and educational outcomes. Impatient adolescents are more likely to violate their schools' code of conduct, but there appears to be no relationship between misbehavior and risk preferences (Sutter et al. 2013). Castillo et al. (2017) find that more impatient young people are also less likely to graduate from high school.

Taken together, this evidence strongly suggests that adolescents' preferences shape their behavior and success at school. Interestingly, although parents are believed to play a large role in their children's decision-making, the link between parental preferences and school outcomes has not been studied. Moreover, previous research has not directly focused on the relationship between preferences and truancy rates.

Our objective is to analyze whether time and risk preferences are related to adolescents' propensity to be truant. We make an important contribution in focusing directly on young people with excessively high truancy rates living in an area characterized by significant socioeconomic disadvantage and high crime rates. Although such students are frequently the target of initiatives to raise school engagement, they are seldom captured in empirical research measuring economic preferences. Our study provides a unique opportunity to learn whether the truancy decisions of disadvantaged students are linked to their time and risk preferences and to understand the degree to which the success of anti-truancy interventions itself depends on students' or parents' preferences. Importantly, we estimate the preferences of both adolescents and their parents in an incentive-compatible way ensuring that the decisions that the participants make have real consequences.

2. The Experiment

2.1 The Ability School Engagement Program

Alarmed by high rates of truancy, police and local schools in Queensland, Australia came together in a structured partnership – the Ability School Engagement Program (ASEP) – to better engage truanting young people in school and reduce anti-social behavior. Specifically, school representatives and police met with young people and their parents to communicate parents' legal obligations to ensure their children attend school.

A distinguishing feature of ASEP is that the engagement with parents and truants was in a carefully scripted face-to-face family (rather than parent-only) focused forum. Families assigned to ASEP attended a facilitated conference which concluded with the development of a youth-focused Action Plan. The truant, their parent(s), school and uniformed police representatives, and relevant supporters also participated in the conference. A police officer monitored the execution of the Action Plan for six months following the initial conference.

Families with students aged 10-16 with less than 85% attendance over the previous three school terms were eligible to participate in the trial. Between 2011 and 2013, a total of 217 families were classified as eligible; 102 were contactable and consented to participate. These 102 families were randomly assigned to either ASEP or the business-as-usual control condition (see appendix). Using these trial data, ASEP was previously shown to reduce truancy rates by approximately 6 percentage points or 25% (Mazerolle et al. 2017).

Our primary outcome variable, the absence rate, comes from the Queensland Education Department's administrative database. For each student, absences were calculated as a proportion of all school days missed and measured over a period of three terms (30 teaching weeks) preceding the random assignment (*pre*-absence rates) and three terms following the initial conference (*post*-absence rates).

2.2 Measuring Economic Preferences

Preferences were measured during the two-year post randomization follow-up of the trial between October 2014 and January 2017. We measured risk attitudes, impatience and present bias for each adolescent and a parent using the double multiple price listing (Andersen et al. 2008) (see the appendix). Participants were incentivized to respond truthfully by paying cash based upon the choice from one of questions, chosen randomly.

We quantify an individual's risk attitude as the proportion of questions selected as the risky lottery instead of the sure payment and an individual's patience by calculating the proportion of questions selected as representing the desire to wait for the later, larger reward. To identify whether our participants show present bias, we calculated the difference between the proportion of times that they selected the sooner option when it was available now and the proportion of times that they selected the sooner option when it was to be delivered in one month.

3. Results

3.1 Data

Of the 102 families participating in the trial, we secured both parental and adolescent preference data from 82. Eight families provided either adolescents' or parents' preferences (Figure A.1). Attritors did not differ in characteristics from nonattritors, and attrition was not differentiated by treatment status (Table A.1). Table 1 summarizes the characteristics of the 90 families included in our analysis.

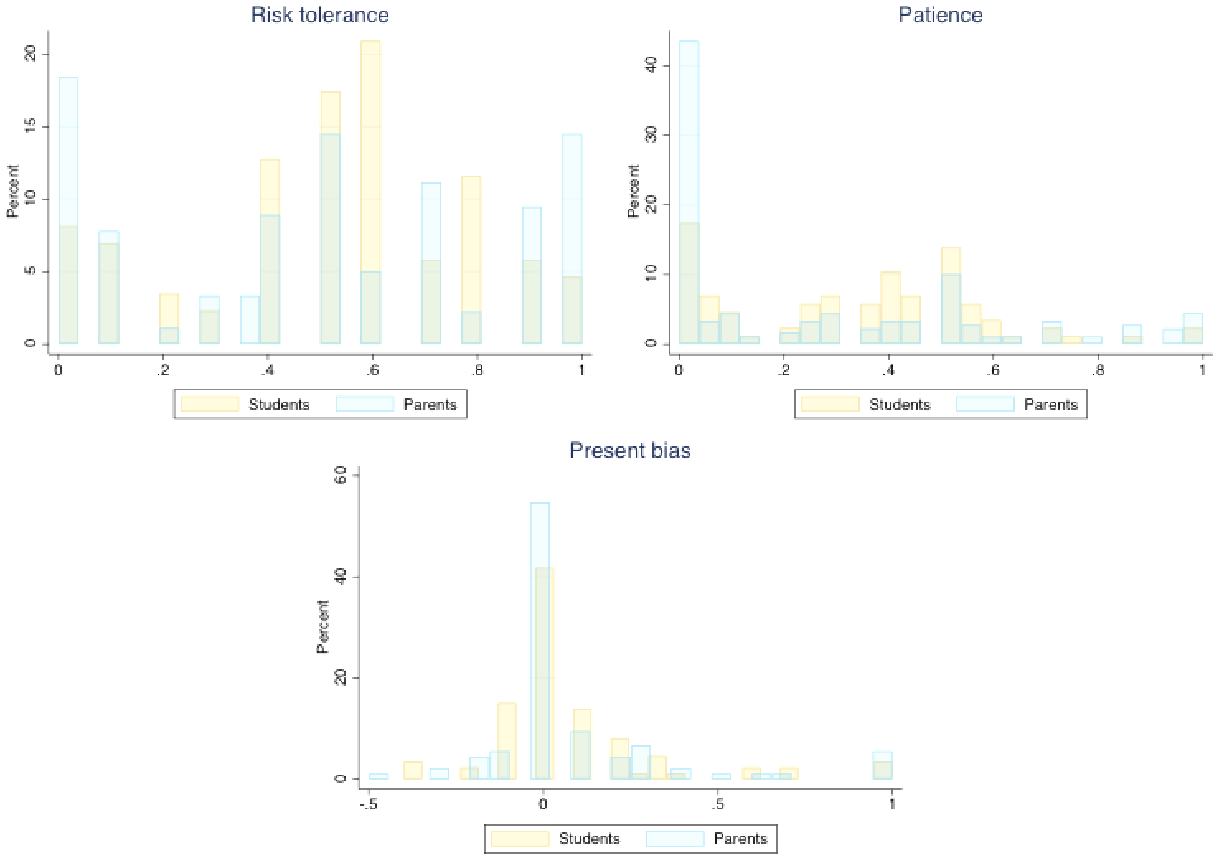
Table 1: Descriptive statistics and balance

	Baseline Sample				
	(1) Control Mean	(2) (st.dev.)	(3) T-C Diff	(4) p-val	(5) N
Student's age (at recruitment)	13.11	(2.2)	0.21	0.64	90
Student gender (1=Female)	0.45	(0.5)	0.05	0.67	90
Indigenous background	0.09	(0.3)	0.04	0.56	90
Parent's age (at recruitment)	42.37	(7.1)	−1.04	0.55	83
Parent gender (1=Female)	0.91	(0.3)	0.05	0.37	90
Parent is biological parent	0.93	(0.3)	0.01	0.88	85
Single parent	0.55	(0.5)	−0.02	0.82	90
Parent's income (100s AUD/pw)	8.51	(5.5)	−2.31	0.06*	86
Parent highest degree: Uni	0.12	(0.3)	−0.07	0.21	89
Parent highest degree: Trade diploma	0.28	(0.5)	−0.08	0.36	89
Parent highest degree: High school	0.30	(0.5)	0.02	0.81	89
Parent highest degree: Less than high school	0.37	(0.5)	0.06	0.55	89
Absence rate (pre-intervention)	25.30	(11.8)	2.29	0.43	90
School size (# students, in 100s)	11.19	(7.6)	−1.20	0.44	90
School level (1=High school, 0=Primary)	0.55	(0.5)	0.08	0.42	90
Joint test (p-value)				0.41	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We observe a wide distribution of risk preferences in our sample, illustrated in Figure 1. Many of our participants choose to wait for the larger reward and a majority of the participants do not display present bias, a common finding when transaction costs are equalized for all payment dates (Sutter et al. 2013). Unpaired t-tests confirm that adolescents do not significantly differ in their preferences from parents.

Figure 1: Distribution of preferences by respondent type



Previous research has found that parent's and children's time and risk preferences tend to be moderately correlated (Alan et al. 2017; Brown and van der Pol 2015; Kosse and Pfeiffer 2012). Our correlation coefficients are similar in magnitude to those typically found in the literature, however only patience is statistically significant (Table 2). We also find that, consistent with theory, risk tolerance and patience are strongly correlated in both parent and adolescent samples.

Table 2: Intergenerational correlations of preferences

				Adolescent Preferences			Parent Preferences		
				(1)	(2)	(3)	(4)	(5)	(6)
				Risk	Patience	Present bias	Risk	Patience	Present bias
Adolescent preferences	(1)	Risk	*ρ*	1.000					
			p						
			N	*86*					
	(2)	Patience	*ρ*	**0.215**	1.000				
			p	**0.047**					
			N	*86*	*86*				
	(3)	Present bias	*ρ*	-0.088	0.091	1.000			
			p	0.423	0.404				
			N	*86*	*86*	*86*			
Parent preferences	(4)	Risk	*ρ*	0.097	0.166	-0.021	1.000		
			p	0.388	0.135	0.854			
			N	*82*	*82*	*82*	*86*		
	(5)	Patience	*ρ*	0.079	**0.245**	0.041	**0.255**	1.000	
			p	0.483	**0.027**	0.714	**0.018**		
			N	*82*	*82*	*82*	*86*	*86*	
	(6)	Present bias	*ρ*	0.081	-0.010	-0.086	-0.036	0.202	1.000
			p	0.469	0.928	0.442	0.739	0.062	
			N	*82*	*82*	*82*	*86*	*86*	*86*

3.2 The Impact of the Treatment on Preferences

We test whether the intervention impacted economic preferences. Previous research indicates risk and time preference are relatively stable over time, while self-control is more malleable (Jamison, Karlan, and Zinman 2012). One component of the ASEP intervention involved creating an Action Plan, effectively a goal-setting task which is a common approach used to improve self-control.

We find that adolescents participating in ASEP do not differ from the controls in any measured preference; however, parents in the intervention become significantly less present biased, exhibiting greater self-control (see Figure 2 and Table 3). Estimates corrected for attrition are nearly identical (Table A.2).

Figure 2: Distributions of preferences by treatment arm

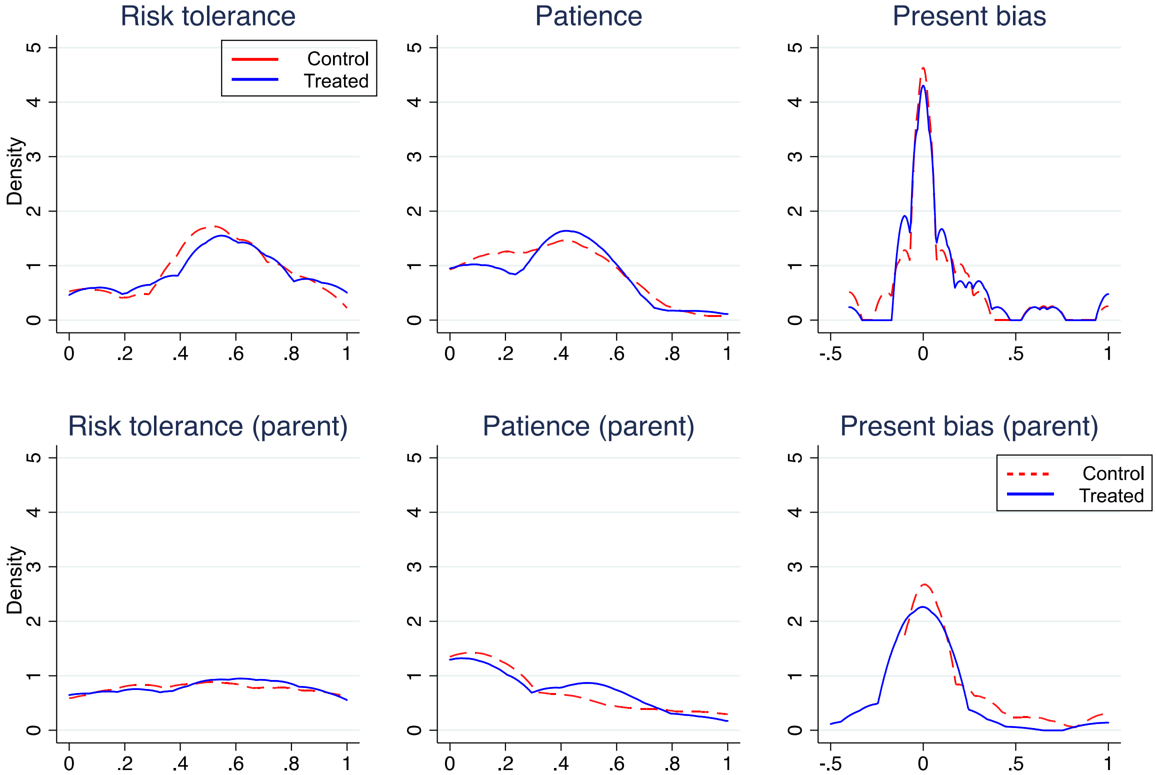


Table 3: Impact of intervention on preferences of adolescents and parents

	Adolescent Prefs.			Parental Prefs.		
	(1) Risk tolerance	(2) Patience	(3) Present bias	(4) Risk tolerance	(5) Patience	(6) Present bias
Treated	0.024	−0.016	0.048	−0.004	−0.005	−0.139**
	(0.059)	(0.050)	(0.056)	(0.076)	(0.067)	(0.061)
Observations	86	86	86	86	86	86
Control mean	0.00	0.00	0.00	0.00	0.00	0.00
Control s.d.	0.26	0.24	0.25	0.36	0.33	0.30

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Dependent variables are listed across the top of the table. Estimates produced by OLS, without any adjustment for baseline covariates.

3.3 Heterogeneity by Economic Preferences

We investigate whether the effectiveness of the intervention on attendance relates to parental risk tolerance or patience (Table 4). If risk and time preference are stable (as previous literature suggests, see Jamison et al. (2012)) and unaffected by treatment (as we demonstrate above), our *ex post* measures can serve as proxies for these preferences at baseline.

We find that the absence rates of participants in the intervention decreased more in response to the intervention if they have more risk averse parents (columns 1 and 2). These results are robust to controlling for basic demographics, patience, and present bias (columns 7 and 8). In contrast, we find no evidence of heterogeneous treatment effects by parental patience (columns 3 and 4).

While absence rates also fell more in response to the intervention for participants with less present-biased (self-controlled) parents (columns 5 and 6), this result is confounded with the effect of the intervention on parental self-control. However, parental present-bias does not appear to mediate the reduction in absences since estimates of the treatment effect are not attenuated after controlling for the mediator.

Finally, we investigated, but found no relationship between treatment effectiveness and adolescents' preferences (Table A.3). There are potentially several reasons for this. It is possible that the intervention was more effective in changing parental attitudes towards schooling (Mazerolle 2014) or that the decision to attend school is largely guided by the parent.

Table 4: Treatment effect heterogeneity by parental preferences

	Dependent variable: School absence rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	−4.49 (3.58)	−5.59 (3.68)	−4.35 (3.68)	−5.48 (3.79)	−5.05 (3.72)	−6.74* (3.81)	−5.05 (3.73)	−6.53* (3.90)
Treated × Risk (par)	21.3** (10.5)	20.5* (11.3)					19.9* (10.9)	19.4 (11.8)
Risk tolerance (parent)	−13.4* (7.17)	−12.4 (7.67)					−12.1 (7.51)	−11.4 (8.20)
Treated × Patience (par)			13.4 (11.5)	9.68 (12.5)			3.54 (12.1)	−1.54 (13.4)
Patience (parent)			−7.18 (8.05)	−5.24 (8.41)			−0.92 (8.93)	3.87 (9.81)
Treated × Present bias (par)					24.4* (13.1)	30.5** (14.1)	26.3* (13.7)	31.4** (14.8)
Present bias (parent)					−14.3 (8.71)	−21.0** (9.53)	−13.9 (9.29)	−20.8* (10.7)
Treated × Absence rate(pre)		−0.48 (0.31)		−0.53* (0.31)		−0.63** (0.30)		−0.58* (0.32)
Absence rate (pre-intervention)	0.77*** (0.13)	1.06*** (0.25)	0.80*** (0.13)	1.15*** (0.24)	0.84*** (0.13)	1.27*** (0.24)	0.76*** (0.14)	1.17*** (0.26)
Observations	84	84	84	84	84	84	84	84
Demographic controls	–	Yes	–	Yes	–	Yes	–	Yes
Demo. × Treated	–	Yes	–	Yes	–	Yes	–	–

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: All specifications control for decision error, measured as the number of switches for each preference parameter. Demographic controls include gender and age of student, parental education, gender, and if the parent is a single parent.

4. Conclusion

We find that ASEP improved self-control in parents, though we find no evidence of it affecting the preferences of truanting adolescents. We also find the intervention is most effective for students with more risk averse parents. Our study is based upon a unique sample of truanting adolescents from disadvantaged households who are often underrepresented in experimental studies and especially difficult to locate in longitudinal follow up studies. Our results from the ASEP trial are therefore unique in both the longitudinal nature of the randomized trial and the embedded use of an incentivized risk and time preference study. Whilst the small sample size remains a limitation, ASEP shows promise as an intervention that fosters increased school attendance especially among risk averse parents.

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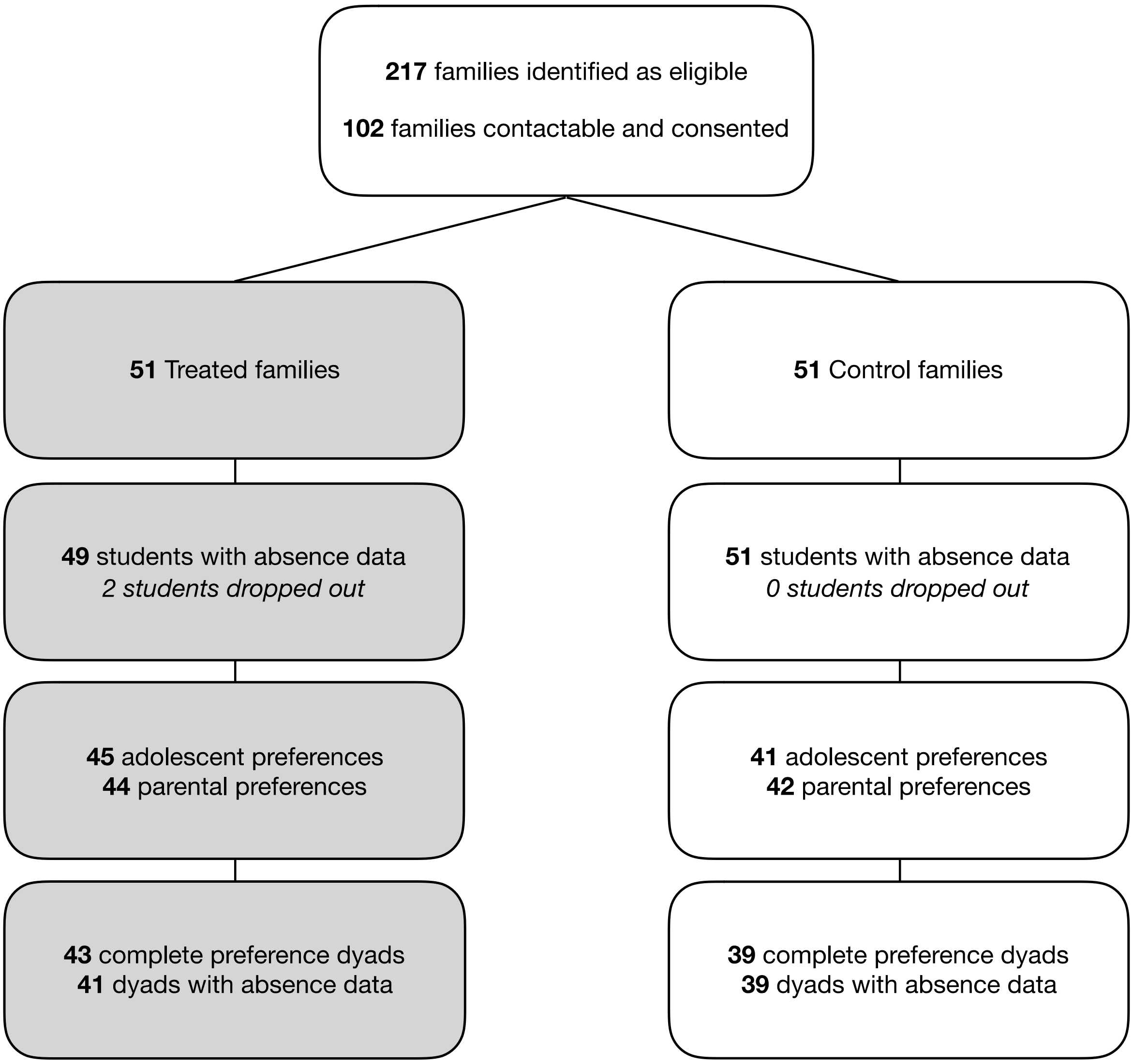
Appendix

Figure A.1: Sample Sizes



Description of business-as-usual (prior to ASEP)

At the time that the program was developed, schools were responsible for implementing the Education (General Provisions) Act 2006 (QLD) that explicitly applied a four-stage escalation process for school nonattendance. When the school identified unexplained or unsatisfactory absences or patterns of absences (Queensland Government 2016), the school principal was required to send a letter to the parent or guardian of the truanting student, explaining parental responsibilities for making sure their truanting child attends school (stage 1). If truancy continued, the principal would initiate a formal meeting with parents (stage 2), escalating to a formal warning of prosecution notice to parents (stage 3) and lastly (stage 4), initiation of prosecution procedures by the Chief Executive of the Department of Education and Training with a penalty of $AU660 for a first offense and $AU1320 for a second or subsequent offense.

Measuring preferences

Risk preferences were measured using a set of ten questions in which individuals selected between a payment of $15 for sure and a lottery that with equal likelihood paid nothing or a reward that changed from question to question and ranged from $15 to $86. To measure time preferences, we asked our participants to choose whether they would like to receive $40 sooner or wait three months longer to receive a larger amount (which ranging between $43 and $81).

After an individual finished the task, they chose a chip from a bag of 30 numbered poker chips to determine which choices they would be paid for. If a question from the risk assessment list was chosen for payment, they would receive the payment in cash at the end of the session. If a question from the time preference assessment list was chosen for payment, they would receive the payment mailed on the specified date using Express Post service that guarantees the next business day delivery. Tasks were completed in private with neither the experimenter nor other family members observing individual choices.

Figure A.2: Subject decision sheet

Question number					
1	☐	$15 for sure	*or*	☐	50% chance of $15
2	☐	$15 for sure	*or*	☐	50% chance of $24
3	☐	$15 for sure	*or*	☐	50% chance of $27
4	☐	$15 for sure	*or*	☐	50% chance of $34
5	☐	$15 for sure	*or*	☐	50% chance of $38
6	☐	$15 for sure	*or*	☐	50% chance of $46
7	☐	$15 for sure	*or*	☐	50% chance of $57
8	☐	$15 for sure	*or*	☐	50% chance of $63
9	☐	$15 for sure	*or*	☐	50% chance of $77
10	☐	$15 for sure	*or*	☐	50% chance of $86

Question number					
11	☐	$40 today	*or*	☐	$43 in 3 months (90 days)
12	☐	$40 today	*or*	☐	$46 in 3 months (90 days)
13	☐	$40 today	*or*	☐	$48 in 3 months (90 days)
14	☐	$40 today	*or*	☐	$51 in 3 months (90 days)
15	☐	$40 today	*or*	☐	$56 in 3 months (90 days)
16	☐	$40 today	*or*	☐	$61 in 3 months (90 days)
17	☐	$40 today	*or*	☐	$66 in 3 months (90 days)
18	☐	$40 today	*or*	☐	$71 in 3 months (90 days)
19	☐	$40 today	*or*	☐	$76 in 3 months (90 days)
20	☐	$40 today	*or*	☐	$81 in 3 months (90 days)
21	☐	$40 in 1 month (30 days)	*or*	☐	$43 in 4 months (120 days)
22	☐	$40 in 1 month (30 days)	*or*	☐	$46 in 4 months (120 days)
23	☐	$40 in 1 month (30 days)	*or*	☐	$48 in 4 months (120 days)
24	☐	$40 in 1 month (30 days)	*or*	☐	$51 in 4 months (120 days)
25	☐	$40 in 1 month (30 days)	*or*	☐	$56 in 4 months (120 days)
26	☐	$40 in 1 month (30 days)	*or*	☐	$61 in 4 months (120 days)
27	☐	$40 in 1 month (30 days)	*or*	☐	$66 in 4 months (120 days)
28	☐	$40 in 1 month (30 days)	*or*	☐	$71 in 4 months (120 days)
29	☐	$40 in 1 month (30 days)	*or*	☐	$76 in 4 months (120 days)
30	☐	$40 in 1 month (30 days)	*or*	☐	$81 in 4 months (120 days)

Figure A.3: Distribution of post-intervention absence rates by intervention arm

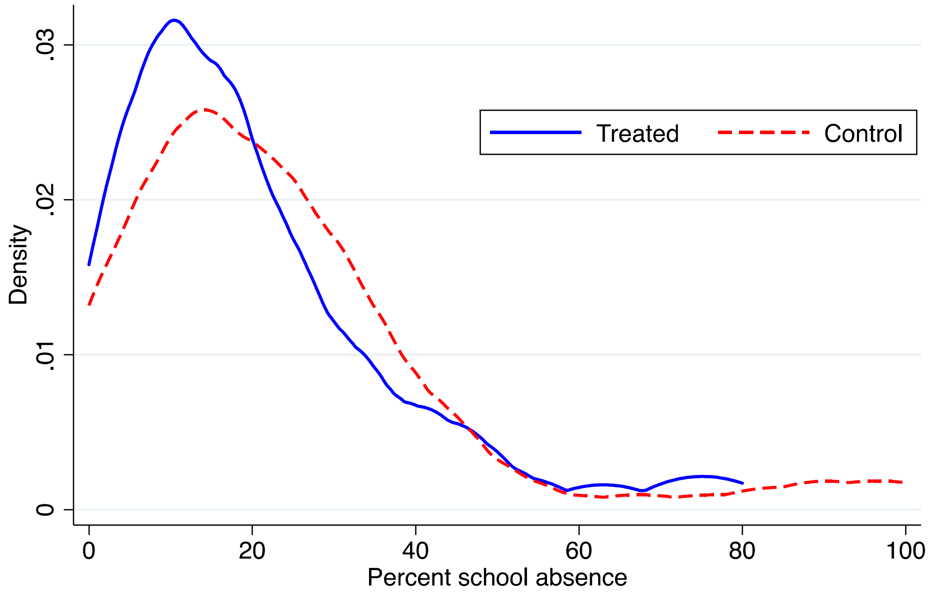


Table A.1: Characteristics of attrition

	Baseline Characteristics for Followup vs Attrition (LTFU) Samples				
	(1) Followup sample (N=90) Mean	(2) LTFU sample (N=12) Mean	(3) Difference (1) - (2)	(4) (s.e.)	(5) p-val
Student's age (at recruitment)	13.22	13.00	0.22	(0.68)	0.74
Student gender (1=Female)	0.48	0.42	0.06	(0.15)	0.69
Indigenous background	0.11	0.17	−0.06	(0.10)	0.58
Parent's age (at recruitment)	41.81	39.55	2.26	(2.44)	0.36
Parent gender (1=Female)	0.93	0.92	0.02	(0.08)	0.83
Parent is biological parent	0.93	1.00	−0.07	(0.07)	0.35
Single parent	0.53	0.58	−0.05	(0.15)	0.75
Parent's income (100s AUD/pw)	7.35	11.00	−3.65	(3.35)	0.28
Parent highest degree: Uni	0.08	0.08	−0.00	(0.08)	0.96
Parent highest degree: Trade diploma	0.24	0.42	−0.18	(0.13)	0.18
Parent highest degree: High school	0.31	0.08	0.23	(0.14)	0.10*
Parent highest degree: Less than high school	0.40	0.42	−0.01	(0.15)	0.94
Absence rate (pre-intervention)	26.47	25.26	1.21	(4.13)	0.77
School size (# students, in 100s)	10.57	9.41	1.17	(2.31)	0.62
School level (1=High school, 0=Primary)	0.59	0.50	0.09	(0.15)	0.56
Joint test (p-value)				0.55	

Difference in followup rate
Treatment-Control = 0.04
$p = 0.54$

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Table presents characteristics of the preference study followup and trial participants who were lost to followup (LTFU) for the preference study. Columns 1 and 2 present means by the sample with preference data and those who were not located, respectively. Column 3 presents the difference in means between the two samples, column 4 the standard error of the difference, and column 5 the associated p-value. The p-value of the joint test of whether baseline characteristics of the two samples differed is presented in the bottom row.

Table A.2: Attrition-corrected treatment effects on preferences

	Adolescent Prefs.			Parental Prefs.		
	(1) Risk tolerance	(2) Patience	(3) Present bias	(4) Risk tolerance	(5) Patience	(6) Present bias
Treated	0.030	−0.003	0.061	0.013	0.012	−0.141**
	(0.058)	(0.052)	(0.060)	(0.076)	(0.069)	(0.063)
Observations	84	84	84	84	84	84
Control mean	0.00	0.00	0.00	0.00	0.00	0.00
Control s.d.	0.26	0.24	0.25	0.36	0.33	0.30

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Dependent variables are listed across the top of the table. Estimates produced by OLS, regressing dependent variables on an indicator for whether the individual was part of the intervention arm ("Treated"). Estimate are presented without any additional adjustment for baseline covariates, but corrected for attrition using Inverse Probability Weighting where the weights are calculated as the inverse of probability of that the participant is observed in the preference study conditional on baseline demographics (gender and age of student and parent, parental education, income, if the parent is a single parent, pre- and post-intervention absence rates, and a treatment dummy) estimated by Probit. N=86 in the unweighted estimation. Two observations are lost due to inclusion of post-intervention absence rates (estimates similar using pre-intervention rates only).

Table A.3: Heterogeneity by student preferences

	Dependent variable: School absence rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	−4.76	−6.10	−4.88	−6.17	−4.90	−6.51*	−5.18	−6.48
	(3.57)	(3.76)	(3.59)	(3.79)	(3.59)	(3.81)	(3.75)	(4.10)
Treated × Risk tolerance	3.31	7.08					5.93	8.76
	(13.7)	(15.4)					(15.7)	(18.3)
Risk tolerance	−8.01	−12.5					−9.53	−12.6
	(10.1)	(11.9)					(10.5)	(12.6)
Treated × Patience			−0.25	−5.56			−0.046	−6.10
			(15.0)	(16.2)			(16.4)	(18.7)
Patience			−2.41	−0.46			−1.87	1.47
			(10.8)	(11.5)			(11.3)	(12.3)
Treated × Present bias					−9.00	−11.0	−11.4	−12.4
					(14.2)	(16.8)	(15.4)	(18.8)
Present bias					3.46	9.95	5.85	10.6
					(10.3)	(13.2)	(11.2)	(14.5)
Treated × Absence rate(pre)		−0.53*		−0.48		−0.53		−0.54
		(0.31)		(0.31)		(0.32)		(0.35)
Absence rate (pre-intervention)	0.82***	1.17***	0.81***	1.14***	0.83***	1.19***	0.85***	1.22***
	(0.13)	(0.25)	(0.13)	(0.25)	(0.13)	(0.26)	(0.14)	(0.27)
Observations	84	84	84	84	84	84	84	84
Demographic controls	–	Yes	–	Yes	–	Yes	–	Yes
Demo. × Treated	–	Yes	–	Yes	–	Yes	–	–

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: All specifications control for decision error, measured as the number of switches for each preference parameter. Demographic controls include gender and age of student, parental education, gender, and if the parent is a single parent.