

Preferences predict who commits crime among young men

Thomas Epper^{a,b,c,d}, Ernst Fehr^{d,e,1}, Kristoffer Balle Hvidberg^d, Claus Thustrup Kreiner^d, Søren Leth-Petersen^d, and Gregers Nytoft Rasmussen^d

^aCNRS, UMR 9221–Lille Economie Management (LEM), 59000 Lille, France; ^bIESEG School of Management, UMR 9221–Lille Economie Management (LEM), 59000 Lille, France; ^cUniversity of Lille, UMR 9221–Lille Economie Management (LEM), 59000 Lille, France; ^dCenter for Economic Behavior and Inequality, Department of Economics, University of Copenhagen, 1353 Copenhagen, Denmark; and ^eUBS Center for Economics in Society, Department of Economics, University of Zurich, 8006 Zurich, Switzerland

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Understanding who commits crime and why is a key topic in social science and important for the design of crime prevention policy. In theory, people who commit crime face different social and economic incentives for criminal activity than other people, or they evaluate the costs and benefits of crime differently because they have different preferences. Empirical evidence on the role of preferences is scarce. Theoretically, risk-tolerant, impatient, and self-interested people are more prone to commit crime than risk-averse, patient, and altruistic people. We test these predictions with a unique combination of data where we use incentivized experiments to elicit the preferences of young men and link these experimental data to their criminal records. In addition, our data allow us to control extensively for other characteristics such as cognitive skills, socioeconomic background, and self-control problems. We find that preferences are strongly associated with actual criminal behavior. Impatience and, in particular, risk tolerance are still strong predictors when we include the full battery of controls. Crime propensities are 8 to 10 percentage points higher for the most risk-tolerant individuals compared to the most risk averse. This effect is half the size of the effect of cognitive skills, which is known to be a very strong predictor of criminal behavior. Looking into different types of crime, we find that preferences significantly predict property offenses, while self-control problems significantly predict violent, drug, and sexual offenses.

crime | risk preference | time preference | self-control | altruism

In choice theory of crime, individuals trade off their benefits from criminal activity against the opportunity costs of legitimate activity and the risks of future costs due to apprehension and punishment (1–3). People can face different trade-offs, for instance, due to differences in how much they can otherwise earn in the labor market, or they can evaluate the trade-offs differently due to differences in preferences. A large empirical literature documents that variation in the trade-off people face predicts who commits crime (3–6). In contrast, little is known about the role of preferences.

Key preference parameters are risk tolerance and impatience. Intuitively, crime provides a benefit now but at the risk of a cost in the future which makes crime less attractive for people who dislike risk and care more about future well-being (3). Thus, more risk-tolerant and more impatient people are more prone to commit crime than others (see *SI Appendix, SI Text*, for a formal derivation in a basic model of criminal behavior). In standard choice theory, people are entirely driven by self-interest, but the theory can be extended to allow for altruistic motives or more sophisticated, other-regarding preferences (7–9). More altruistic people will commit less crime because they care about the costs they inflict on others.

In this paper, we ask whether preferences predict who commits crime among young men. We focus on young men (age 18 to 19) who are known to have much higher crime rates than women and

older people (3, 10, 11). To answer the question, we leverage a unique combination of data where we use incentivized experiments to elicit the preferences of young men in Denmark and link this experimental data to administrative records with information about all criminal offenses.

We examine the association between preferences and crime while also controlling for other differences across people that can explain criminal behavior. The link between experimental data and administrative records enables us to include an extraordinary rich set of relevant control variables. This includes school performance, area of residence, immigrant status, family size, birth order, parental socioeconomic status, criminal records of parents, and family stress as measured by parental divorce or unemployment. Moreover, when we collected the experimental data on preferences, we also asked about self-control which is known to be a strong predictor of crime (12–14). We use this information to control for behavioral factors other than risk, time, and social preferences. We also investigate the relation between preferences and different types of criminal offenses. Arguably, the hypothesis that cost-benefit considerations help explain crime seems more appropriate for property crimes than violent, drug, and sexual offenses where lack of self-control may be a more important driver.

Significance

Who commits crime? Theoretically, risk-tolerant and impatient people are more likely to commit crime because they care less about the risks of apprehension and punishment. By linking experimental data on risk tolerance and impatience of young men to administrative crime records, we find empirical support for this hypothesis. For example, crime rates are 8 to 10 percentage points higher for the most risk-tolerant people compared to the most risk averse. A theoretical implication is that those who are most prone to commit crime are also those who are least responsive to stricter law enforcement. Risk tolerance and impatience significantly predict property crime, while self-control is a stronger predictor of crimes of passion (violent, drug, and sexual offenses).

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¹To whom correspondence may be addressed. Email: ernst.fehr@econ.uzh.ch.

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This study links experimentally elicited risk, time, and social preferences to actual criminal behavior. We follow a large literature in experimental economics that elicits people's preferences using incentivized choice experiments, where participants receive payments according to their decisions in the experiment. This literature documents pervasive variation in preferences including that some people are more risk tolerant, impatient, and motivated by self-interest than others (15–17). Studies also show that these parameters are correlated with real-life behavior and outcomes in accordance with theoretical predictions, for example, savings, high school graduation, disciplinary referrals of school children, entrepreneurship, body mass index, and smoking (18–25). The number of participants in our elicitation experiment is large compared to previous studies, and the participants are sampled randomly from the population in contrast to many previous studies which are based on samples of students (26). A large population sample is important for our purpose because crime frequency is low and because students differ significantly from the population at large with respect to their crime propensity.

Most closely related to our work is a recent study that finds a significant relationship between patience and criminal offenses (27). The study uses a nonincentivized survey question to measure patience and demonstrates that this predicts crime. Interestingly, the authors find that the predictive power of patience is about one-third of the power of cognitive skills and that patience is most predictive of property crime, which is similar to our findings. Our study differs 1) by providing a more comprehensive and experimentally elicited set of preference measures that include risk preferences and social preferences and 2) by including a self-control measure in the set of predictors. This enables us to 1) show that risk tolerance is the strongest predictor of crime among the preference parameters and 2) document that risk and time preferences significantly predict property crime where self-control is not a significant predictor, whereas in the domain of violent, drug, and sexual offenses, self-control is a key predictor, while risk and time preferences are not significantly predictive.

Materials and Methods

Based on a random sample provided from population registries by Statistics Denmark, we conducted an online incentivized preference elicitation experiment among 18- to 19-year-old individuals in Denmark in 2018. We invited 13,799 individuals to participate, who all received a personalized letter from the University of Copenhagen inviting them to participate on a customized internet platform. The invitations were distributed through an electronic mailbox (Digital Post), which is the default way to receive mail from public authorities in Denmark. Previous research suggests that response rates are

higher when contacting a random sample of potential respondents in this way compared to sending out physical invitation letters (28). In our case, 39% of the invited individuals logged on to the platform.

For the elicitation of each preference parameter, the participants were presented a series of choice situations, resembling methods previously used in the literature. Before making decisions in these choice situations, participants watched an animated instruction video and completed a tutorial session. The choice situations were presented in random order. Each choice situation involved a monetary trade-off, and toward the end of the session, one choice situation was randomly selected to be paid out. The average payment to participants was DKK 250 (USD 40). After the random selection, participants typed their cell number, and the money was then transferred through Mobile Pay, a Danish app used for fast transfer of money.

We used a money-earlier-or-later task (25) with 16 choice situations to elicit time preferences. Fig. 1A shows a screen shot of one of the choice situations in the time preference task. In this choice situation, an individual could choose to get DKK 250 paid out in 8 wk or to save all or some of the money for later and receive the savings plus an interest rate of 2.4% in 16 wk. In this example, the individual chose to save DKK 100 corresponding to a savings rate of 40% (100/250). This gave a payout of DKK 150 in 8 wk and a payout of DKK 102.4 in 16 wk. The rate of return and the time profile varied across the choice situations (SI Appendix, Table S6). We compute the mean savings rate across the choice situations of each individual and then use this measure to rank people on a 1 to 100 scale, corresponding to their percentile positions in the distribution of elicited impatience. The degree of impatience may be computed in more sophisticated ways, e.g., by estimating a structural model, but as we show, this does not change the results since the rank position of an individual is quite robust to different ways of computing impatience from the experiment (SI Appendix, Table S4).

The elicitation of risk preferences is based on an investment task (29) with 15 choice situations. Fig. 1B shows a screen shot for one of the situations. Here an individual could choose to get DKK 250 with certainty or invest some or all of the money in a lottery which yielded an average rate of return of 6%, with the risk of a significant loss. In this example, the individual chose to keep DKK 50 and invest DKK 200 in the lottery, corresponding to an investment of 80% of the initial DKK 250 endowment. The investment gave DKK 80 (a loss) with a probability of 40% and DKK 300 (a win) with a probability of 60%. The outcome of the lottery and the sum of money earned were displayed afterward. If this situation was selected for payment, then the individual would receive the money within 24 h. The probability of winning and the expected rate of return varied across the choice situations (SI Appendix, Table S7). Similar to the measurement of impatience, we compute the mean investment of each individual across the choice situations and then use this measure to rank people, thereby obtaining their percentile positions in the distribution of risk tolerance.

The elicitation of altruism used 20 different choice situations with dictator games (30) that systematically varied the costs and benefits of giving as well as the resulting inequality (SI Appendix, Table S8). These dictator games enable us to construct an overall measure of altruism as well as decomposing this measure into behindness and aheadness aversion (8, 31). The overall

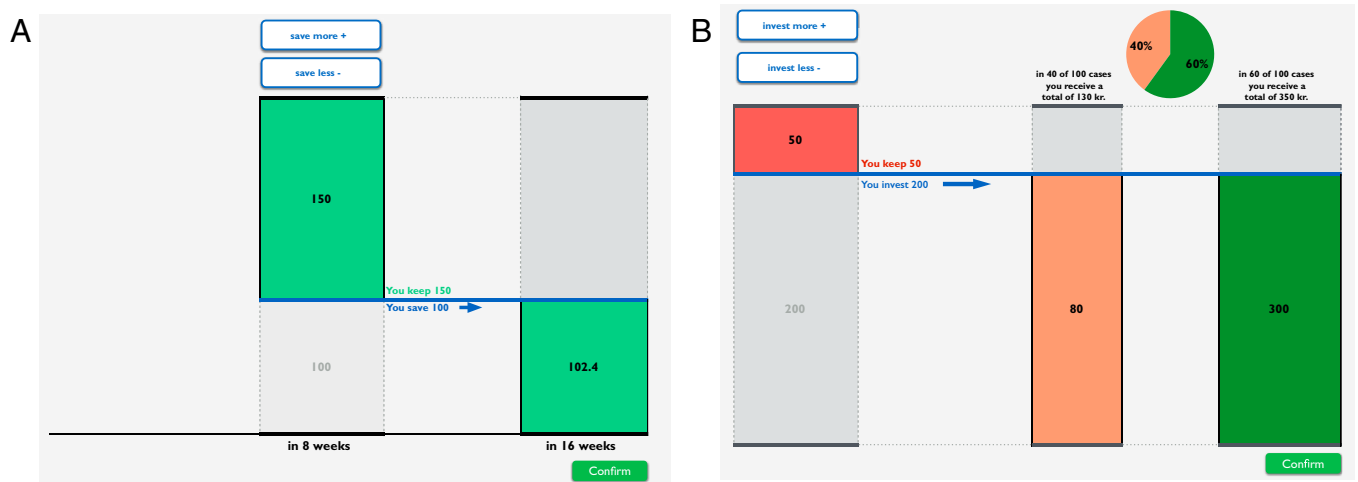


Fig. 1. Screenshots of online experiment eliciting time and risk preferences. (A) Time. (B) Risk.

measure of altruism is the money given to the other person as a share of what the individual could potentially give (the giving rate). As with the other preference measures, we compute the mean giving rate across the 20 choice situations and then use this measure to rank the individual relative to other participants. *SI Appendix, Fig. S1* shows a screenshot for one of the choice situations.

We also asked individuals about age and gender, which can be verified in the registers, and about their school grade point average (GPA), which is used in a few special cases where grades are not included in the register data. Most importantly, we also included a question about the self-assessed capacity to exercise self-control, which is known to be a strong predictor of crime. On average, participants spent 45 min from start to end.

We link the experimental data to administrative records that contain all criminal offenses as well as detailed background information about the individuals. Since crime is a low-frequency outcome, we define a person as criminal if he or she is convicted of a criminal offense committed during the age span 15 to 20. We exclude traffic offenses, which are common but mostly minor offenses that only involve small fines. We focus on the males in our sample who have much higher crime rates than females. The crime rate is 19% for the invited males compared to 3% for the invited females. More details on the crime data and the many background variables included are provided in *SI Appendix, SI Text. SI Appendix, Table S1* also includes summary statistics on the random sample of invited men and on the analysis sample of men who completed all experiments. In line with previous research inviting people to participate in surveys/experiments (25, 28), participants have somewhat different outcomes than nonparticipants, in particular lower crime rates. If we account for the differences between the participants and the population of 18-y-old men by reweighting the observations based on the propensity score estimated on observable characteristics, preferences play an even stronger role than in the main analysis (*SI Appendix, Table S5*, column 6).

The first screen on the internet platform informed the participants about the experiment, the use of the data, and how participants received the payments from the experiment. Participants were asked to give consent and continue to the experiment by clicking on a button on the screen.

Preferences and Criminal Offenses

Fig. 2 illustrates the bivariate relationship between individuals' preference parameters and their propensity to commit crimes. In all diagrams, the vertical axis shows the probability of being convicted of a crime. On the horizontal axis in Fig. 2*A*, we rank individuals according to their level of risk tolerance going from percentile 1 to 100 in the distribution of risk tolerance. Similarly, Fig. 2*B* ranks individuals according to their level of impatience, and Fig. 2*C* ranks individuals according to their level of altruism. The diagrams show a strong and almost linear relationship between each of the preference parameters and the propensity to commit crime. All relationships are statistically significant at the 1% level of significance.

Going from the most risk-averse individuals to the most risk-tolerant individuals is associated with a change in the crime propensity from 8 to 18%, and moving up 10 percentiles in the risk tolerance distribution is associated with a 1 percentage point increase in the crime propensity. The association with impatience is slightly weaker. In this case, moving up 10 percentiles is associated with a 0.8 percentage point increase in the crime propensity. Moving up 10 percentiles in the distribution of altruism is associated with a 0.9 percentage point decrease in the crime propensity.

Table 1 shows results from estimations of multivariate probit models. All three preference parameters are still strongly associated with crime when we move from the bivariate analysis in the graphs to the multivariate analysis in Table 1, second column. Table 1 reports the estimated marginal effects of a change in each of the preferences parameters, for given values of the other preference parameters, on the probability of having committed an offense. The marginal effects are of the same magnitude as the slopes in Fig. 2.

Table 1. Preferences and probability of having been convicted of an offense

	Probability of having been convicted of an offense committed at age 15 to 20							At age 19 to 20	
	Only preferences	Adding self-control	Adding GPA	Adding individual controls	Adding parental controls	Full set of controls	Flexible specification	Only preferences	Full set of controls
Risk tolerance	10.9*** (2.5)	10.1*** (2.4)	8.3*** (2.4)	8.3*** (2.4)	8.1*** (2.4)	7.9*** (2.4)	7.4* * (2.4)	7.4*** (2.2)	4.9* (2.0)
Impatience	8.9*** (2.5)	7.6** (2.5)	5.9* (2.5)	5.2* (2.5)	5.2* (2.5)	5.0* (2.4)	5.3* (2.4)	5.5* (2.1)	2.2 (2.0)
Altruism	-7.0** (2.4)	-6.9** (2.4)	-2.7 (2.5)	-2.5 (2.4)	-2.3 (2.4)	-2.5 (2.4)	-2.5 (2.4)	-5.3* (2.1)	-2.4 (2.1)
Self-control		-13.2*** (2.5)	-11.4*** (2.5)	-10.4*** (2.5)	-10.2*** (2.5)	-10.1*** (2.4)	Category indicators		-8.6*** (2.1)
GPA			-16.7*** (2.6)	-14.2*** (2.7)	-12.9*** (2.7)	-13.7*** (2.8)	Decile indicators		-9.7*** (2.4)
Parental income					-1.4 (2.7)	-1.6 (3.4)	Decile indicators		-0.3 (2.8)
Convicted parent (=1)					6.3** (2.1)	5.7** (2.2)	6.1** (2.2)		4.7* (1.9)
Observations	2,254	2,254	2,254	2,254	2,254	2,254	2,254	2,254	2,254
Individual controls				X	X	X	X		X
Parental controls						X	X		X

The table reports the marginal effects on the percentage share of respondents committing crime from estimated probit models. Risk tolerance, impatience, altruism, self-control, GPA, and parental income are all within cohort in sample rank. The eighth column includes flexible controls for self-control, GPA, and parental income instead of continuous measures. For self-control, we use category indicators; for GPA and parental income, we use dummies for each decile. Convicted parent is an indicator. Individual controls include regional fixed effects, large city indicator, immigrant and descendant status, a living with both parents indicator, an only child indicator, a first born indicator, and an indicator for misreported age or gender in the survey. Parental controls include educational level, age at child's birth, employment status, and unemployment history. 13.4% are convicted from age 15 to 20. 9.3% are convicted from age 19 to 20. Robust SEs are in parentheses. * $P < 0.05$, ** $P < 0.01$, and *** $P < 0.001$.

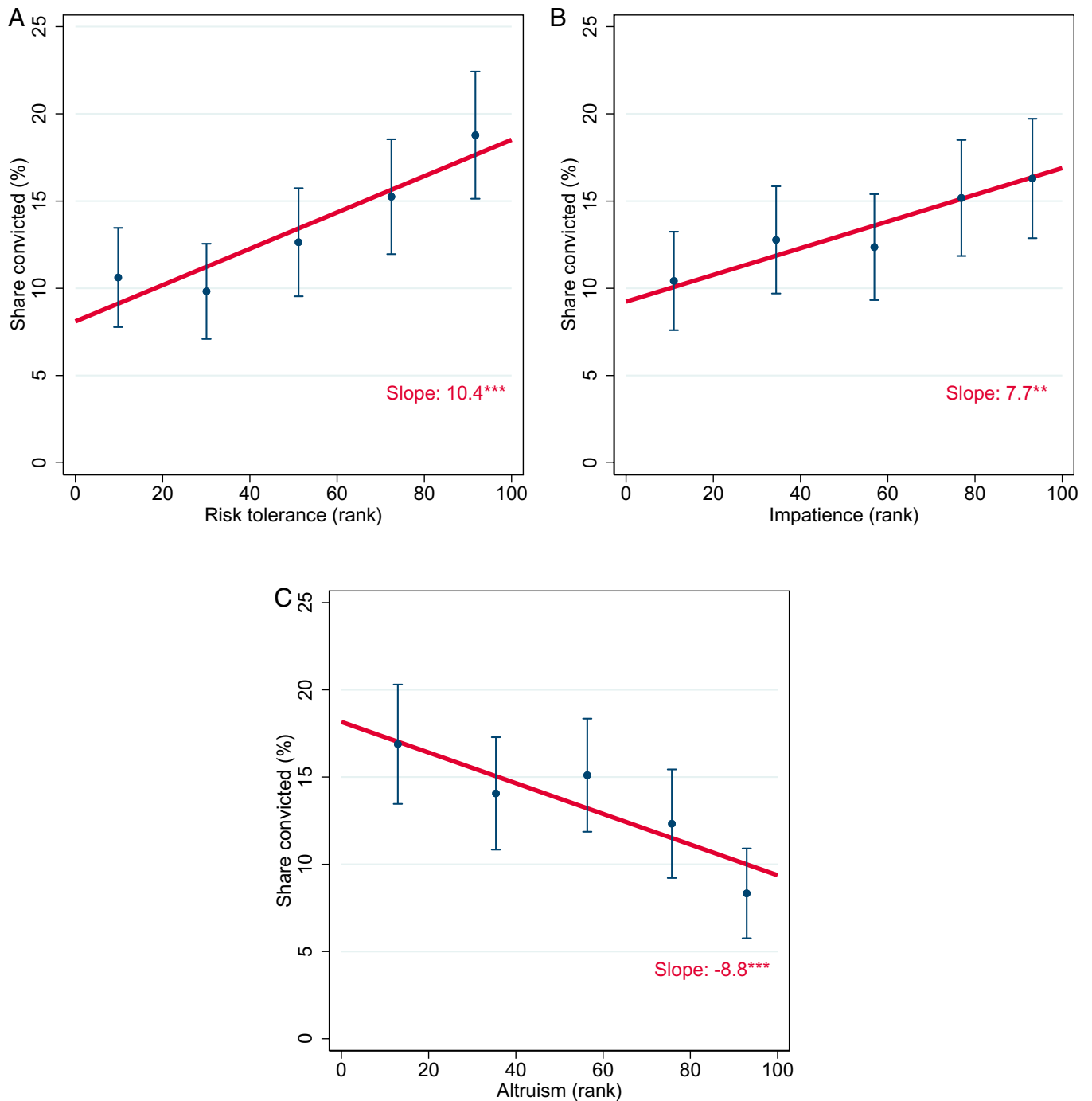


Fig. 2. Association between preferences and criminal offenses. The 95% confidence intervals are based on robust SEs. **** $P < 0.01$** and ***** $P < 0.001$** . (A) Risk tolerance. (B) Impatience. (C) Altruism.

In Table 1, third column, we move beyond the rational choice framework by including a measure of self-control. Self-control is known to be strongly associated with crime propensities (12–14). This is also the case in Table 1, third column. Importantly, the effects of the preference parameters are nearly unchanged. The effect of impatience is most affected, which is consistent with the intuitive idea that impatience and self-control are related concepts.

Cognitive skills are known to be strong predictors of criminal behavior (32, 33). One likely reason is that low-skilled individuals obtain lower wages in the labor market and, therefore, face lower opportunity costs of crime (4). Cognitive skills are also known to

be correlated with preferences (34) and are therefore potential confounders. *SI Appendix, Table S2* shows that all three preferences measures are correlated with cognitive skills measured in terms of individuals' GPAs at the end of compulsory schooling (age 15 to 16). The correlation between altruism and GPA is particularly pronounced with less skilled individuals being less altruistic on average.

In Table 1, fourth column, we include the individual's percentile rank position in the GPA distribution in the regression. As expected, this is a strong predictor of crime. Moving up 10 percentiles in the grade distribution is associated with a 1.7 percentage point decrease in the crime propensity conditional on

the other characteristics. Now, altruism is no longer significant, but the effects of risk tolerance and impatience are still large and significant. The effect of moving up 10 percentiles in the risk tolerance distribution or in the impatience distribution corresponds to about a half and one-third of the effect, respectively, of moving up 10 percentiles in the GPA distribution.

In Table 1, fifth column, we include a large set of additional variables that are likely predictive of crime, including region of residence, living in a large city, divorce of parents, immigrant status, having siblings, and birth order (35–39). This reduces the effect of impatience somewhat but has no impact on the effect of risk tolerance. In Table 1, sixth column, we include the percentile position of parents in the distribution of parental income. We also include information on whether parents have committed crime, which is known to be a strong predictor of criminal offenses of sons (40, 41). The position in the income distribution is, in isolation, strongly correlated with crime (*SI Appendix, Table S2*) but not when it is included together with the other variables in Table 1, sixth column. As expected, parental crime is strongly associated with the criminal propensity of sons. Most importantly, the effects of risk tolerance and impatience are almost unchanged when going from the fifth to sixth column in Table 1.

In Table 1, seventh column, we account for additional parental characteristics that are potentially important, including education, age at child birth, recent employment status, and unemployment history (42). This has nearly no impact on the estimated effects of interest. In total, Table 1, seventh column, includes 55 relevant controls beyond the three preference parameters (*SI Appendix, Table S3*).

Overall, school GPA is the strongest predictor of criminal behavior in Table 1, fourth through seventh columns. Across all the specifications, the effect of risk tolerance is significant at the 0.1% level, and its size is about one-half of the effect of school GPA. The effect of impatience is significant at the 5% level and is about one-third of the effect of school GPA.

Identifying the causal impact of preferences on crime propensities is a challenge since preferences are normally considered to be fixed individual characteristics, which makes it impossible to randomly assign preferences to people (25, 43). Following previous work, our analysis examines the association between preferences and crime while controlling for other differences across people that potentially confound the effects of preferences. Although we have an extraordinarily large control set, we cannot know for sure if we fully span all relevant heterogeneity across people. In Table 1, eighth column, we further show that the coefficients on risk tolerance and impatience are almost unchanged, if we allow for a more flexible regression specification with category indicators for self-control and decile indicators for GPA and parental income. *Additional Results and Robustness Checks* reports further results along these lines, including a bounding exercise showing that the effects of preferences are still large if we account for the possibility of unobservable selection effects. Another possibility is that we underestimate the true effects of preferences because we include mediators, i.e., controls that are themselves determined by preferences. For example, the very strong impact of school performance on crime can reflect differences in preferences, which are determinants of school effort and educational investments in theory of human capital (44). According to this view, the more sparse specification in Table 1, second column, may better capture the true effects of preferences.

To enhance the statistical power, we identify a person as criminal if having at least one offense in the age span 15 to 20. In Table 1, ninth and tenth columns, we investigate the predictive power of preferences for future crime by focusing on offenses committed at age 19 to 20, which is after the preference elicitation. The effects become smaller since the crime propensity over 2 y is lower, but importantly, the effect of risk tolerance is significant and still half as large as the effect of GPA.

Table 2 reports results from running the analysis separately for property offenses and violent, sexual, and drug offenses using the specification with all controls as in Table 1, seventh column. The estimates show that risk tolerance and impatience significantly predict property offenses but do not significantly predict violent, drug, and sexual offenses. Conversely, self-control does not significantly predict property offenses but is a significant predictor of violent, drug, and sexual offenses. These results suggest an intuitive separation of crime with property offenses explained well by preferences as hypothesized in the basic choice theory framework, while violent, drug, and sexual offenses are more related to self-control problems.

Additional Results and Robustness Checks

Here we report the conclusions from additional results and robustness checks shown in *SI Appendix*. In *SI Appendix, Table S4*, we include additional behavioral measures that can be computed from the experiments. For example, we compute a measure that indicates whether respondents are present-biased (45), which relates to the broader measure of self-control problems included in the analysis. This additional measure is insignificant. We also use the behavioral data from our social preference experiment to decompose our measure of altruism into a measure of “behindness aversion” and a measure of “aheadness aversion” (8). A behindness-averse person is willing to give up money in the experiment to reduce the amount the other person receives if this reduces disadvantageous inequality, i.e., the payoff advantage of the other person. An aheadness-averse person is willing to increase the other persons’ payoff in the domain of advantageous inequality, i.e., when the decision-maker has a payoff advantage over the other person. An individual can be behindness averse in the domain of disadvantageous inequality while simultaneously being aheadness averse in the domain of advantageous inequality. When we substitute these measures for the overall altruism measure, we find that crime is strongly associated with behindness aversion but not with aheadness aversion. As in the case with altruism, behindness aversion becomes insignificant when we control for GPA. Finally, we redo the main analysis but rank the participants in the preference distributions according to structural estimates of their preference parameters as is often done in the experimental literature (46, 47). This does not change the results.

In *SI Appendix, Table S5*, we report sensitivity results with respect to changes in variable measurement, sample selection, and empirical specification. It shows that the effects of the key

Table 2. Probability of having been convicted of different offenses

	Property offense		Violent, drug, or sexual offense	
Risk tolerance	3.21**	(1.06)	2.34	(1.31)
Impatience	2.16*	(0.96)	0.87	(1.38)
Altruism	−1.28	(0.98)	−1.33	(1.36)
Self-control	−1.47	(0.95)	−6.47***	(1.50)
GPA	−5.09***	(1.45)	−5.73***	(1.70)
Parental income	−1.19	(1.42)	−0.53	(1.77)
Convicted parent (=1)	1.18	(0.78)	1.62	(1.26)
Observations	2,254		2,254	
Mean outcome (%)	2.40		4.21	
Individual controls	X		X	
Parental controls	X		X	

The results correspond to Table 1, seventh column, but with two different outcomes: the probability of being convicted of a property offense and the probability of being convicted a violent, drug, or sexual offense committed at age 15 to 20. Robust SEs are in parentheses. * $P < 0.05$, ** $P < 0.01$, and *** $P < 0.001$.

preference parameters are unchanged if we only include math grades in GPA (*SI Appendix, Table S5*, column 2), which might be a better proxy for differences in cognitive skills. Similarly, the conclusions are the same if we estimate a linear probability model instead of a probit model (*SI Appendix, Table S5*, column 3), if we adjust for bias from unobservable selection using the Oster method (*SI Appendix, Table S5*, column 4) (48) or substitute the percentile rank variables with the corresponding z scores (*SI Appendix, Table S5*, column 5). The effects of interest are a little higher if we account for selection into the experiment by applying propensity score weighted regressions that account for observable differences between participants and nonparticipants (*SI Appendix, Table S5*, column 6). If we include women in the sample (*SI Appendix, Table S5*, column 7), the effect of risk preference falls somewhat, but both risk and time preferences are still significant. In the main analysis, if individual information does not exist on an explanatory variable, then this is captured by an indicator variable. If we instead remove respondents altogether when information is missing on one or more variables, then the main effects of interest fall somewhat, but the relative magnitudes of risk, impatience, self-control, and GPA are unchanged (*SI Appendix, Table S5*, column 8).

Concluding Remarks

Our results show that differences in preferences predict who commits crime. Risk tolerance, impatience, and altruism are all associated with the crime propensity. Impatience and, in particular, risk tolerance strongly predict crime when we control for an extensive set of background characteristics. The most risk-tolerant individuals have a crime propensity that is 8 to 10 percentage points higher than the least risk-tolerant individuals. This effect is half the size of the effect of cognitive skills, which is the best predictor of crime. Evidence on crime levels across countries does not place Denmark as very different from other countries (49). In that respect, there is no reason to believe that our results should be unique to Denmark.

One of the criminal justice system's key functions is deterrence of crime. The choice theory of crime implies that policy initiatives

that increase the certainty and severity of sanctions deter crime. However, a theoretical implication of our evidence on the importance of differences in preferences is that those who are most prone to commit crime are also those who are least responsive to increases in certainty and severity of sanctions (*SI Appendix, SI Text*). This might help explain the somewhat mixed evidence on the effectiveness of sanctions on deterrence (4).

We also find that variation in preferences significantly predicts property offenses but not crimes of passion such as violent, sexual, and drug offenses. Conversely, we find that self-control significantly predicts crimes of passion but not property crime. At a broader level, these findings, together with previous results (27, 50), suggest that the choice theory framework might be most relevant for understanding certain types of crime such as white-collar crime but not for other types of crime such as violence and sexual assaults where other behavioral parameters might be more appropriate.

Data Availability. Our empirical analysis combines experimental data and administrative register data linked together using social security numbers. The project was approved by the Danish Data Protection Agency under Agreement 2015-57-0125-0008 and was also approved by Statistics Denmark and the Internal Review Board at the Department of Economics, University of Copenhagen. Data and programs are stored in a separate directory at Statistics Denmark with project number 704856. The empirical analyses were carried out with the software Stata/MP 16.1 using the secure internet interface of Statistics Denmark. Individual-level data are subject to the European Union's General Data Protection Regulation. Due to privacy rules, the data may not be transferred to computers outside Statistics Denmark. Researchers interested in obtaining access to the data employed in this paper are required to submit a written application to gain approval from Statistics Denmark. Applications can be submitted by researchers who are affiliated with Danish institutions accepted by Statistics Denmark or by researchers outside of Denmark who collaborate with researchers affiliated with these institutions. We will assist in any way we can with this procedure.

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