Do Behaviors and Attitudes Affect Whether a Child is Arrested? A Consideration of Evidence From the Panel Study of Income Dynamics

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Introduction

Behaviors and attitudes are two important factors that can help determine an individual's life outcomes. A great deal of research has been devoted to assessing the causes of behavior and attitude problems as well as their outcomes. Never have the behavioral and attitudinal scales devised by developmental psychologists been used as predictors of arrest outcomes. This paper attempts to fill that void. This study utilizes two scales created by developmental psychologists to examine which behaviors and attitudes are most likely to lead to the arrest of a child. Using data from the 2005 Child Transition to Adulthood data set within the Child Development Study, I find one behavioral subscale and one attitudinal subscale that are strong predictors of arrest.

Sample Characteristics

The sample, taken from the 2005 Transition to Adulthood study, contains 724 children, of which 91 have been arrested once and 49 have been arrested multiple times. This means that 19.3 percent of the sample has been arrested at least once. The high percentage of children arrested makes for a robust study with many data points. The data set also includes information about the age of each respondent when he or she was first arrested, under the heading "Age at First Arrest" for multiple offenders and "Age at Only Arrest" for one-time offenders. On average, multiple offenders have been arrested for the first time at an earlier age than one-time offenders. The mean "age at first arrest" for one-time offenders is 17.3 and that of multiple offenders is 15.0 years. Throughout this study, I will not consider the demographic or regional characteristics of my sample. I will leave it to further research to add to the complexity

It is tempting to conclude that children who are poorly behaved are more likely to be arrested earlier in life. Factors that make bad behavior at a young age more likely such as parental involvement, peer effects, and neighborhood effects, are likely to contribute to the intensification of those bad behaviors later in childhood. It is equally plausible, however, that a child whose first arrest is for a serious crime will be monitored extremely carefully by a primary caregiver or a corrections officer that the child will simply not have the opportunity to commit another crime. A "monitoring effect" would decrease the probability of a second arrest. Also plausible is that a minor offense committed by a teenager, though leading to arrest, will not incur the same monitoring and deterrent effect on other crimes as a serious crime. As a result, the first arrest would not change the likelihood that the offender is arrested again.

The 2005 Transition to Adulthood study reports the number of times each child in the study has been arrested and includes information on the type of crime for which each child was arrested. I will use these data to assess the validity of the "monitoring" hypothesis by comparing the "type of arrest" data for single and multiple offenders. Fifteen different categories of offense are included, along with one catch-all for "Other" and another for "Don't Know." Because the categories are not easily divisible into "serious" and "minor" offenses, I will the consider the data as it is presented in the PSID without making any further categorizations. Figures 1 and 2 show the breakdown of the type of arrest for the single and multiple offenders, respectively. Table 1 gives the specific percentages of all of the "type of arrest" data.

It is apparent from the table and distributions that there is little difference in the types of crime for which single and multiple offenders are arrested. The "Robbery and Theft" category is the only specific crime type for which single offenders were arrested much more often. This type of offense is likely to be minor, indicating that the children only arrested once were picked up for

more mundane crimes than their counterparts with multiple arrests. Many more of the multiple offenders are in the "Other" category. It is difficult to draw conclusions about the meaning of this difference since the PSID is unclear as to what that category includes. One possibility is that "Other" captures arrests for crimes that involve more than one of the categories given, such as an assault committed during a robbery. If this is the case, the shift is an indication that multiple offenders commit much more serious offenses early on.

Another interesting exercise is to compare the arrest type for the first and most recent arrest of the children who have been arrested multiple times. Did the children commit "worse" crimes on their most recent arrest? Figure 3 shows the data in pie-chart form and Table 2 gives specific numbers. An 11.5 percent increase in drug offenses, combined with a slight rise in weapons offenses and declines in traffic offenses and burglaries indicates that one's second arrest is more likely to be for a more serious offense. Because the specifics of each arrest are unknown it is difficult to conclude whether the types of arrest became more or less serious. Though it appears this may be the case, I will draw any hasty conclusions. A replication of this analysis with more specific offense-type data would provide clearer results.

Comparisons of the characteristics of the children who have been arrested zero, one, or multiple times can help explain what behaviors and attitudes correlate with arrests. I will use two scales favored by developmental psychologists, the Behavior Problems Index and the Languishing/Flourishing Scale, to analyze this question. Both of these scales were collected as part of the Transition to Adulthood study, allowing me to have comprehensive data on each scale for each offender discussed earlier. In the remainder of the paper, I will use regression analysis to determine the strength of the relationship between each subscale and several different dependent variables.

Dependent Variables of Interest

First, I constructed a variable called "Binomial Arrest." Binomial Arrest takes a value of 1 if a particular child has been arrested and has a value of 0 if the child has never been arrested. This variable places the children with multiple arrests in the same category as those only arrested once. I believe that it takes a certain level of bad behavior to be arrested even once, and the children who have been arrested once and arrested multiple times can be considered, overall, to be quite similar. The creation of this binomial response variable allows me to use regression analysis to gauge the probability a child is arrest instead of just each variable's effect on the expected number of arrests for a child.

The 2005 data also contain a variable called "Arrested Once or More" that indicates whether a child has been arrested zero, once, or multiple times. In order to conduct a complete regression analysis, I simplify this scale by assuming that the children arrested multiple times have been only arrested twice and create the variable I will refer to as "Number of Arrests." There are 51 children in 2005 TA study that have been arrested multiple times. The relatively young ages of the participants (all are under 25) make it unlikely that a high proportion has been arrested more than two times, meaning that this assumption will probably not affect the validity of my results. If anything, the adjustment will cause an underestimate of the parameters of interest, since there are arrests that have happened but are not counted due to my simplification.

The 2005 TA study also contains variables known as "Age at Only Arrest" and "Age at First Arrest." The former applies to children who have only been arrested once and the latter is for the first arrest of those who have been detained multiple times. I combine these to create a composite "Age at First Arrest" variable which gives the age at the first arrest of all children who

have been arrested, regardless of how many times they have been arrested. This response variable will be useful in my attempts to discern whether the behaviors captured by the independent variables have any effect on how young a child will be arrested.

Independent Variables of Interest

All three of these response variables will be used in conjunction with the two measures of behavior that are popular with developmental psychologists: the Behavior Problems Index and the Languishing/Flourishing Scale. The Languishing/Flourishing scale (and its subscales) will be discussed in detail later in this paper. The Behavioral Problems Index (BPI), was conceived by developmental psychologists to assess "the incidence and severity of behavioral problems among children" (CDS User Guide). Three measures were reported in the 1997 and 2002 Child Development Studies. External BPI reflects the degree to which a child displays aggressive behavior. Internal BPI reflects the frequency of sad or withdrawn behaviors, a set of behaviors that would cause concern, though perhaps not as much as the the aggressive behaviors captured by External BPI. The Total BPI category is the average of these two measures. I will not analyze Total BPI scores because the two subscales used separately provide a more detailed look at which type of behaviors lead to arrest.

Many psychologists have attempted to ascertain specific causes of high Behavior Problems Index scores. Carlson and Corcoran (2001) find strong links between family income, quality of the home environment, and mother's psychological functioning play large roles in determine a child's behavior problems. Brand and Brinich (1999) find that placement in foster care and being adopted by nonrelatives correlate strongly with higher Total BPI scores. In this

study I will put aside the potential causes of high BPI scores and focus on their relationship to arrest outcomes.

Descriptives of the BPI subscales and all other variables are included in Table 3. Note that Behavior Problems Index scores from 1997 were used, as only a handful of participants were not assigned scores in this year while the data for the 2002 BPI is less complete. Since the number of observations is at a premium, I believe that using the 1997 BPI scores is the best course of action.

Number of Arrests and the BPI Subscales

There are three regressions estimated using Number of Arrests as the dependent variable: one with the 1997 External BPI score as the sole explanatory variable, one with the 1997 Internal BPI score as the sole explanatory variable, and a third with both included (Models I, II, and III, respectively). The results are reported in Table 4. Both External and Internal BPI appear to be strongly correlated with the number of arrests when they are the sole regressors. These results tell us that each additional point increase in External BPI generates an increase in the expected number of arrests for a given child of .02. According to the model, a child with the maximum score of 15 would be estimated to have been arrested .46 times. The regression with Internal BPI as the only regressor suggests its impact is also strong. Each point increase in Internal score is estimated to cause an increase in the number of arrests of .01, with a person having the maximum score only being expected to be arrested .38 times. There are two key differences in these single regressor estimates. The standard error of the External-only model is lower than that of the Internal-only model and the R-squared value of the External regression is nearly ten times

that of the Internal regression. This indicates that the model with only External BPI better fits the data.

A regression of both External and Internal BPI on Number of Arrests shows that the estimated effect of External BPI stays almost exactly the same (.03) while the coefficient on Internal BPI becomes negative and extremely small in magnitude (-.02). This indicates that the positive relationship between Internal BPI and the number of arrests estimated in the regression with Internal BPI as the only predictor was the result of omitted variable bias and that an increase in Internal BPI will lead to a decrease the number of arrests. This estimate implies that students with withdrawn behavior will have fewer arrests than those who do not: an intuitive result. To confirm the presence of an omitted variable bias, I regressed Internal BPI on External BPI. The results, reported in Table 7, show a positive correlation between the two, and is convincing evidence that the estimate of a strong effect from the model with Internal BPI as the only regressor was simply a result of the correlation between Internal BPI and the true predictor of Number of Arrests, External BPI. One with higher Internal BPI scores is likely to exhibit brooding behaviors and is likely to be less active. Less activity means a child is less likely to perpetrate a crime, while more activity correlates strongly with arrests.

The strong correlation between Internal and External BPI deserves examination. One would think that a child who exhibits aggressive behaviors would be less likely to demonstrate the withdrawn behaviors that lead to a high Internal BPI score. One reason for this correlation could be that children who act out are monitored more closely. If a child exhibits the kind of abnormal behavior that would cause a high score on one of the scales, the primary caregiver may be more apt to consider more behaviors to be “bad” than he or she otherwise would. Another possibility is that children who are poorly behaved in one way are also poorly behaved in other

ways. Children may not fit tidily into categories of "aggressive kids" and "withdrawn kids" but rather simply "well-behaved kids" and "poorly-behaved kids." This categorization does not contradict the strong influence of External BPI on the number of arrests. It implies that poorly behaved children tend to display both extremes of behavior, but it is only the aggressive behaviors that have a strong influence on the child's being arrested.

The latter conjecture can be tested by looking for the interaction between the two BPI scores. If an interaction effect is present, this means that having two high scores is more important than having a high score on either subscale by itself. An interaction term allows for a separation of the effect of changes in both Internal and External scores from the effect of changes in each score individually. The interaction term is simply the product of the two BPI subscales for each child. I included this term along with both BPI scales in a regression on Number of Arrests (Table 4, Model IV). The positive estimated coefficient of the interaction term, though not statistically significant, implies a positive interaction between the interaction term and the Number of Arrests. In all subsequent regressions that include the interaction term, its estimated coefficient of that term is positive. This provides moderate support to the hypothesis that higher levels of both Internal and External BPI contribute to the number of arrests a child will have.

The Binomial Arrest Variable and the External and Internal BPI subscales

I turn next to the dependent variable "Binomial Arrest." Since an omitted variable bias was present in the regressions with Number of Arrests as the dependent variable, I decided to only examine a model that includes Internal BPI, External BPI, and the interaction term as regressors in order to avoid the biased estimates of the single-regressor estimates above.

I initially assumed a linear relationship between each of the BPI subscales and the Binomial Arrest variable. The direction of each estimated effect is consistent with the results of the model with Number of Arrests as the dependent variable. According to the estimates, a ten point swing in External BPI score results in roughly a 2 percent increase in the probability of arrest. This effect may seem trivial, but considering the vast array of random factors that contribute to a person's being arrested, a two percent jump on the basis of a change in behavior is still a considerable margin. A summary of the binomial arrest variable (see Table 3) shows that the overall probability of arrest is .19 for the entire sample, a probability that is surprisingly high.

There is no clear-cut justification for use of only a linear probability model other than the ease with which it is interpreted. For this reason, I re-estimated the previous regressions using both logit and probit models to allow for a non-linear relationship between the BPI scores and arrest. Results for the probit and logit regressions are reported in Table 5. The signs of the estimated coefficients in the logit and probit models are consistent with the estimates of the Linear Probability Model. I used the estimates from Models III, VIII, and IX in the logit and LPM functional forms to calculate the percent change in the probability of arrest caused by a one sample standard deviation change in a given explanatory variable. The calculations are made assuming all other explanatory variables are at their sample mean values. These results are reported in Table 9. The estimated percent changes in the probability of arrest differ greatly across functional form all explanatory variables. There is no theoretical justification for this difference, nor is there any strong theoretical reason why either probit, logit, or an LPM should be considered more ideal in this situation. One important similarity stands out: the signs of the percentage changes are the same across functional form, showing that the general effect on the probability of arrest remains the same for each explanatory variable.

Age at First Arrest and the BPI Subscales

If External BPI has a meaningful effect on whether a child is arrested (as it appears to in the regressions on Binomial Arrest and Number of Arrests), the aggressive behaviors reflected in a high External BPI score may also lead him or her to be arrested at an earlier age. Using the Age at First Arrest dependent variable restricts the sample to only those children who have been arrested once or more, since including the zeros from those never arrested would obscure any meaningful effects. Within this restricted sample, I hypothesize that higher BPI scores on each scale will lead to a lower Age at First Arrest. Since a higher External score is correlated with a higher probability of arrest in all functional form considered earlier, it seems logical that this higher probability of arrest will lead to arrest at a younger age for children with higher External scores.

Just as there was omitted variable bias in the single-regressor estimates with Number of Arrests as the dependent variable, the estimated coefficients for Internal and External BPI would be biased if such a model were used in these estimations. The correlation between the two BPI scales is almost exactly as strong within the subset of arrested children as it is for the entire sample, and omitted variable bias would be present in single-regressor models. For that reason, I will not include results from the single-regressor models in this analysis.

Reported in Table 6 are the results from the two-regressor model. The estimated coefficient of External BPI is negative, supporting my hypothesis that more aggressive children would be expected to be arrested at a younger age than non-aggressive children. The model predicts a child with the maximum External score will be arrested .56 years earlier than a child with the mean external score, *ceteris paribus*. The coefficient of the Internal score is not as large

as that of the External score and is actually positive, indicating that as a child's withdrawn behaviors increase in frequency, the age of the child when first arrested will increase. This is consistent with intuition, since children who exhibit brooding behaviors are likley to be less impulsive than then kids with high External scores and will probably take more time considering a criminal act. In both cases, however, the standard errors are so high that neither estimate should be considered conclusive.

The Languishing/Flourishing Scale

The Languishing/Flourishing Scale (hereafter LF) is slightly more complicated than the Behavior Problems Index. The total score is based on the scores in three subscales that attempt to capture emotional, social, and psychological well-being separately. Each subscale is the average response to a subset of several separate TA questions which are listed in Appendix 1. Though I will leave it to the reader to peruse the specifics of each subscale, general descriptions of each subscale are straightforward. "Emotional Well-Being" captures the happiness and satisfaction or the respondent, "Social Well-Being" reflects feelings of community and content with society, and "Psychological Well-Being" shows the respondent's self-confidence and competence dealing with relationships. In each subscale, as with the total score, a higher score reflects "flourishing" while lower scores indicate a child who is "languishing." A child with high scores in a given subset is likely to be more content, stable, and well-adjusted than a child with lower scores. Howell (2009) shows in a study of undergraduate students that those who are classified as flourishing were more likely to have good grades and high self-esteem. This implies that scores that indicate that a child is "Flourishing" will correlate to a smaller number of arrests.

Descriptives of the subscales are given in Table 3. Each subscale provides a more specific look at the child's emotional makeup so I will test all three subscales' predictive power of arrest separately. The LF data reported was collected in 2005.

LF Scales and Number of Arrests

I used the LF subscales as predictors of Number of Arrests in single-regressor models that look at each LF scale's correlation to the dependent variable separately. Results are presented in Table 4. Since higher scores indicate better mental health, it is no surprise that all estimates in the single-regressor models predict negative relationships between subscale scores and the number of arrests. Though the model with only Emotional LF has the largest magnitude, the model with Social LF as the sole regressor has the smallest standard error and the highest R-squared value.

There could be an omitted variable bias present in these simple estimates since children who have mental health issues in one domain of the LF will probably suffer lower scores in other domains. For example, a child who has low self esteem (which would be reflected in a low Psychological LF score) probably also does not feel as though he or she fits in to society very well, and would consequently suffer from lower Social LF scores.

Next I included all three subscales as explanatory variables in a regression on the number of arrests (Model VIII) to see if omitted variable bias may be present in the earlier estimates. The estimated effects of emotional and psychological well-being, though they still indicate that more positive feelings lead to fewer arrests, are much smaller in magnitude than previously estimated with the one-regressor models. The one scale whose estimate retains strong predictive power and statistical significance is the Social LF subscale. This finding indicates that the attitudes captured

by the Social LF subscale play an important role in influencing the number of arrests. For example, a child scoring the maximum of 6 on the subscale being is predicted to be arrested .38 fewer times than a child scoring a 1. The magnitude of the estimated coefficient on the Emotional term is also noteworthy. Though a large standard error prevents it from having statistical significance, the practical significance of such a large point estimate is important. According to the results, one would expect a child with the maximum score on the Emotional subscale to be arrested .24 fewer times than a child with the minimum score.

The strong effects of social well-being are puzzling at first. It is odd that only one of the LF subscales serves as a statistically significant predictor of the number of arrests. In a comprehensive study of the history of homicide in the United States, Roth (2009) finds four variables that correlate strongly with homicide rates in the US and Western Europe for the past four centuries. One of these variables is "the belief that the social hierarchy is legitimate, that one's position in society is or can be satisfactory and that one can command the respect of others without resorting to violence." This variable is eerily similar to the attitudes captured by Social Well-Being subscale, which measures (among other things) "frequency of feeling something to contribute to society," "frequency of feeling of belonging to the community," and "frequency of feeling way society works makes sense." If these variables are correlated with homicide, they should also be good predictors of other crimes. Roth's historical findings give my results from the LF regressions a stronger underpinning.

LF Subscales and Binomial Arrest

All three subscales are used as regressors, as I have assumed that the omitted variable bias that skewed the results of the single-regressor estimates from the "number of arrests" section

would also plague this model. The regression results show that under a linear probability model, Social LF is the still strongest predictor or arrest. Assuming a score of 6 on the other two subscales, the model predicts that a child with a score of 6 on the Social subscale only has only a 1.8 percent probability of arrest while a child with the worst score on the subscale (a 1) has a probability of arrest of 28 percent. In all, the model predicts a 5.25 percent decline in the probability of arrest for every one percent increase in Social LF score, the estimate of the highest magnitude and the only one with statistical significance at the 99% level. This is clear evidence that Social LF is the best predictor of arrest out of all of the LF subscales.

Just as with the regressions involving the BPI scores as independent variables, it is not obvious that this data should follow a linear relationship. For this reason, I also ran identical regressions using logit and probit models. As is evident in Table 9, the percentage change in the probability of arrest that results from a one sample standard deviation change in each explanatory variable varies widely between using a Linear Probability and logit models. This was the result for the estimates using the BPI scores as well. I am unable to explain this wide variation, nor is there one functional form that should fit this data more closely. Across functional forms the directions of the estimates almost always remain the same, an result that suggests that though estimates may differ in magnitudes, general effects have solid empirical support.

LF Subscales and Age at First Arrest

The previous exercises involving "Number of Arrests" and "Binomial Arrest" showed Social LF to be the strongest predictor of arrest. Next, I will consider the effect of the LF subscales on the "Age at First Arrest" dependent variable. One would predict positive coefficients for all of the variables, since a child whose "flourishing" on a given subscale would

be less likely to act horribly when young. Regressions were run on each subscale separately and also on all three at once. Results are reported in Table 6. The Psychological subscale has a negative relationship in both regressions, indicating that a lack of self-confidence actually leads children to commit their first offense later in life. Perhaps this is because they doubt that they will be able to successfully perpetrate the crime. The LF subscales' predictive power seems to be weak, however, and none of the estimates are statistically significant.

The Relationship Between LF and BPI

It is apparent that the Languishing/Flourishing scale and the Behavior Problems index (specifically the Social LF and the External BPI) provide good clues about whether or not a child will be arrested. How do these measures relate to each other? Intuitively, it is easy to see that there would be a link between the two. A child who has low esteem and a low Psychological LF score seems likely to exhibit withdrawn or brooding behaviors that would result in a high Internal BPI score. After regressing Social LF on External BPI, it seems any such relationship is weak (Table 8) . The estimated coefficient on External BPI predicts an increase in Social LF of only .625 points for a child whose External BPI score were to shrink from the maximum of 15 to the minimum of 1. That these two predictors are not correlated strongly indicates that the unique behaviors captured by each are both important determinants of a child's arrest outcomes. A correlation matrix is presented in Table 10. As expected, the matrix shows that as attitudes improve (as represented by a higher BPI score), so will behaviors (as represented by a lower BPI scores).

In the regressions involving Model IX (reported in Tables 4, 5, and 6) I include all of the explanatory variables discussed throughout the paper. Though in a few cases they are no longer

statistically significant, the predictive power of External BPI and Social LF is still considerable in magnitude.

The dates when the data was collected are important. The LF scores were collected roughly eight years after the BPI scores used in this sample were collected. Ideally, these data would have been collected at the same time in order to provide the most consistent snapshot of the behavior and attitudes of a child at the time of the study. Unfortunately, the gaps between collection dates in the Transition to Adulthood study and the need to include as many data points as possible forced me to conduct the analysis as I did.

Conclusions

This analysis has identified two robust predictors of arrest: External BPI and Social LF scores. Children with poor scores on these measures are more likely to be arrested, more likely to have more arrests, and will likely be arrested at a younger age. This finding supports the use of both the Behavior Problems Index and the Languishing/Flourishing scale to assess the mental health and well-being of children. The fact that certain subscales of each measure are good predictors of arrest means that the scales do a good job of capturing the behaviors and attitudes they seek to capture. For parents and teachers, the findings provide a useful way to identify if a child is more at risk of arrest so that action can be taken to monitor and assist such children.

Further research should examine the effects of such monitoring on a child's arrest outcome. Exhibiting poor behaviors and attitudes when young will often lead to greater supervision, but the effect of such supervision is ambiguous. In some cases, stronger parental or teacher involvement and participation could cut down on a child's illegal activities. In other cases, students would rebel in the face of such supervision and commit progressively worse

criminal offenses. Further study should also attempt to use data from LF and BPI data that was collected within a closer timeframe than the data considered here.

Though they are strong predictors of arrest outcomes, the behaviors and attitudes captured by the External BPI and Social LF scores are unlikely to be totally innate. Neighborhood and peer effects are crucial to the development of behaviors and attitudes, as well as factors like being adopted and one's mother's psychological functioning. Further study should give careful consideration as to the causes of negative behaviors and attitudes as well as include demographic factors in an analysis of the arrest data. If researchers can better understand the roots of the behaviors and attitudes that correlate strongly with arrests, parents, primary caregivers, and teachers can focus their attention more closely to those children who are at the highest risk of being arrested, and lead them towards a more productive path.

References

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Figure 1.

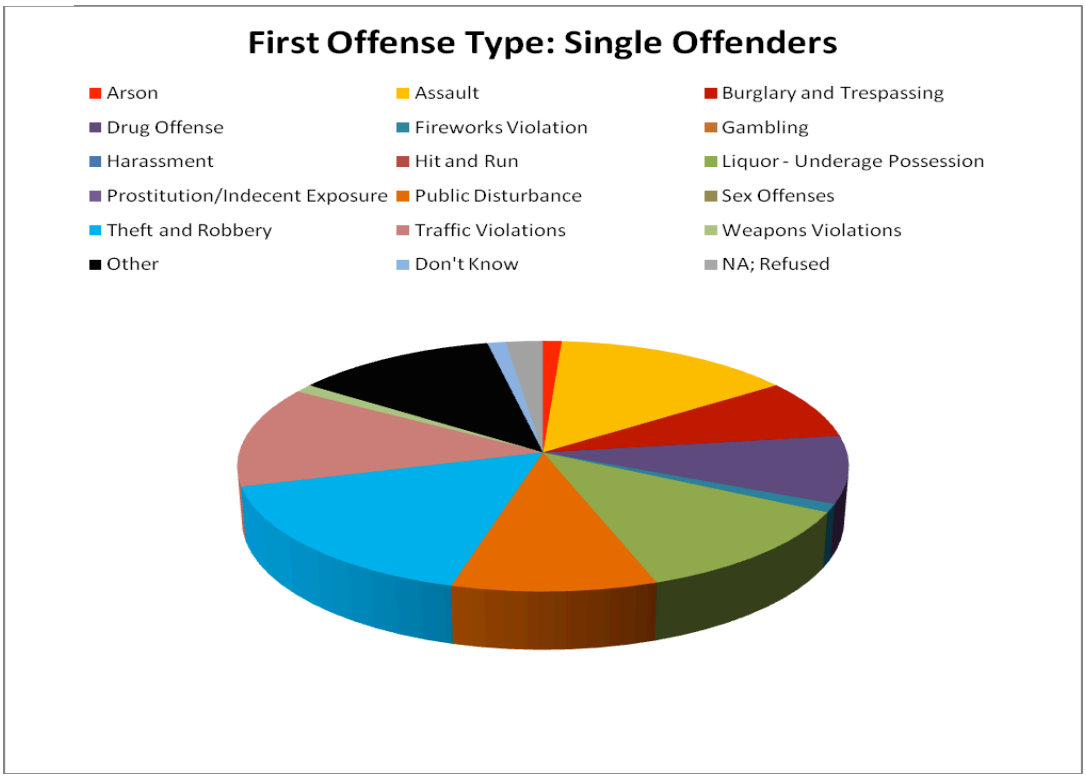

Figure 2.

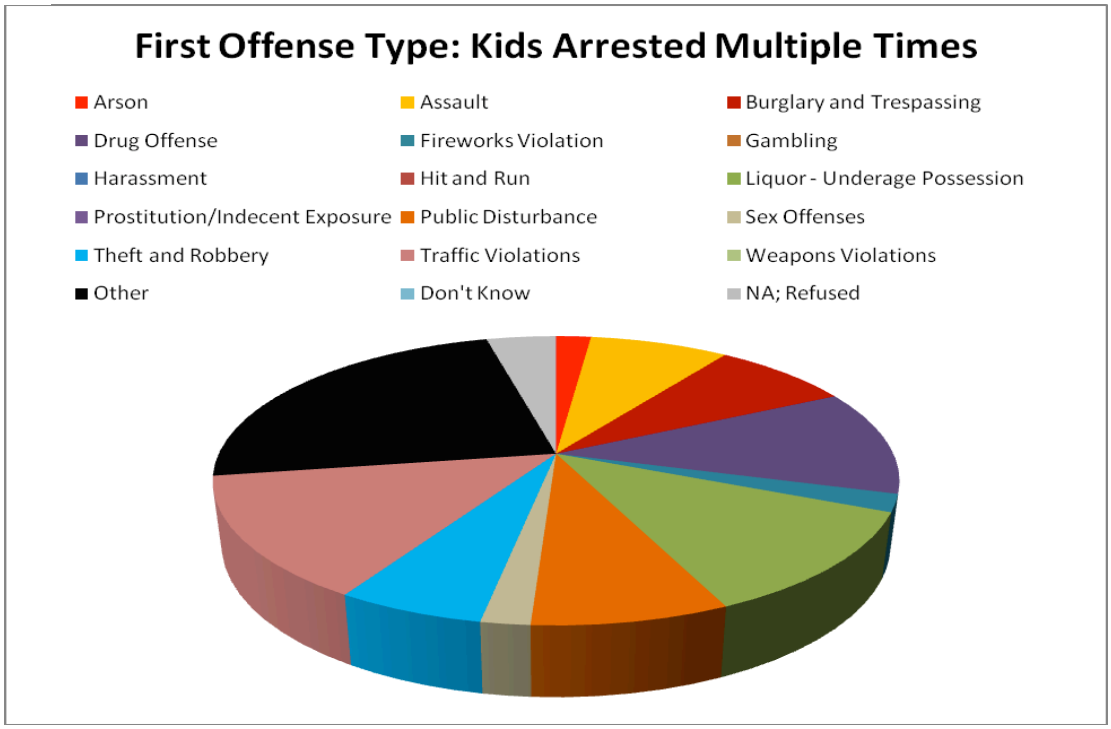

Figure 3.

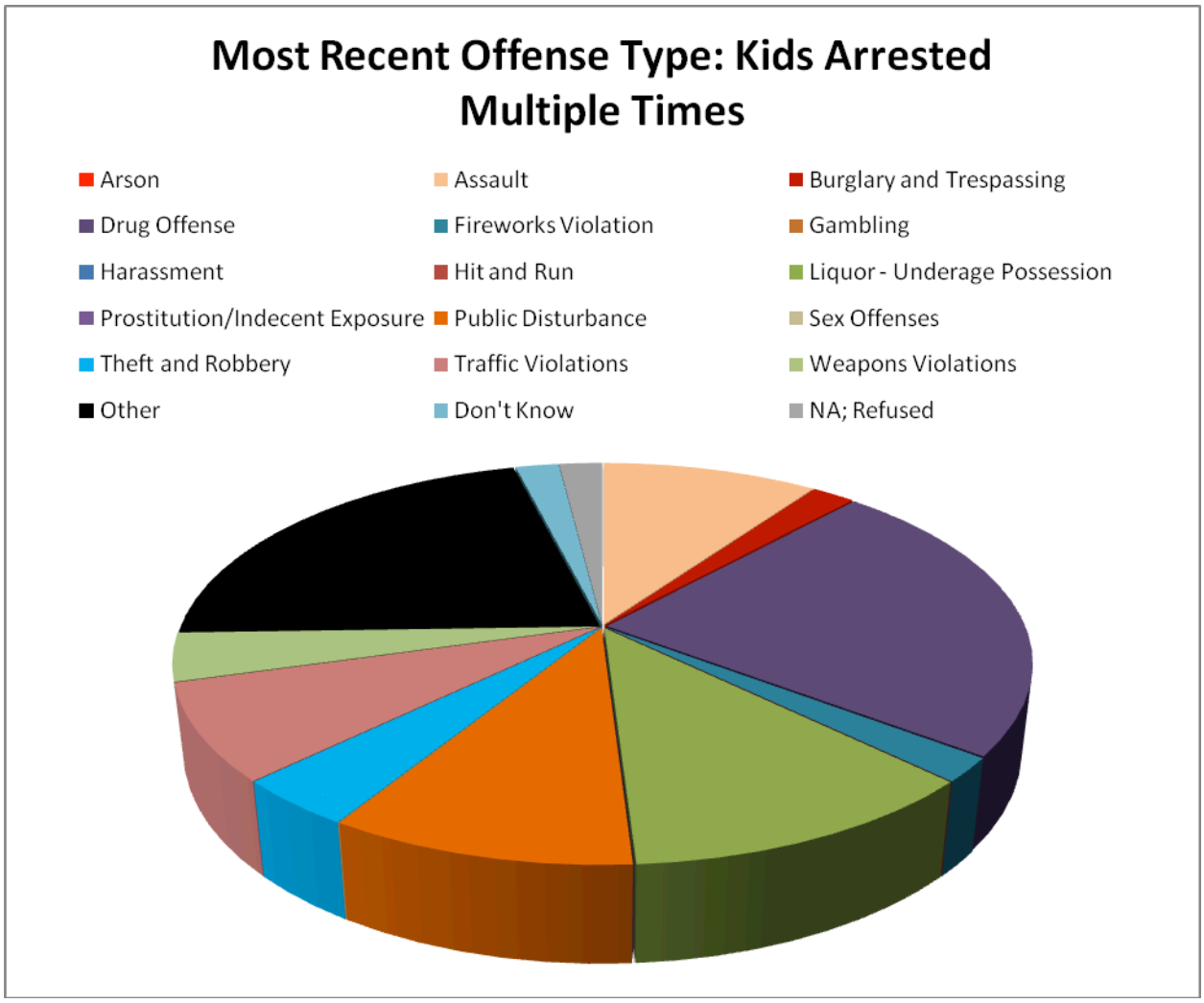
Most Recent Offense Type: Kids Arrested Multiple Times
Arson
Assault
Burglary and Trespassing
Drug Offense
Fireworks Violation
Gambling
Harassment
Hit and Run
Liquor - Underage Possession
Prostitution/Indecent Exposure
Public Disturbance
Sex Offenses
Theft and Robbery
Traffic Violations
Weapons Violations
Other
Don't Know
NA; Refused

Table 1	Single Offenders	Percentage	Multiple Offenders	Percentage	%Single-%Multiple
Arson	1	1.09%	1	1.92%	-0.84%
Assault	13	14.13%	4	7.69%	6.44%
Burglary and Trespassing	7	7.61%	4	7.69%	-0.08%
Drug Offense	8	8.70%	6	11.54%	-2.84%
Fireworks Violation	1	1.09%	1	1.92%	-0.84%
Gambling	0	0.00%	0	0.00%	0.00%
Harassment	0	0.00%	0	0.00%	0.00%
Hit and Run	0	0.00%	0	0.00%	0.00%
Liquor - Underage Possession	11	11.96%	6	11.54%	0.42%
Prostitution/Indecent Exposure	0	0.00%	0	0.00%	0.00%
Public Disturbance	9	9.78%	4	7.69%	2.09%
Sex Offenses	0	0.00%	1	1.92%	-1.92%
Theft and Robbery	15	16.30%	3	5.77%	10.54%
Traffic Violations	12	13.04%	7	13.46%	-0.42%
Weapons Violations	1	1.09%	0	0.00%	1.09%
Other	11	11.96%	12	23.08%	-11.12%
Don't Know	1	1.09%	0	0.00%	1.09%
NA; Refused	2	2.17%	3	5.77%	-3.60%
Sum	92	100.00%	52	100.00%	0.00%

Table 2	Multiple Offenders	Percentage	Multiple Offenders	Percentage	Percentage Difference (Last-First)
Arson	1	1.92%	0	0.00%	-1.92%
Assault	4	7.69%	5	9.62%	1.92%
Burglary and Trespassing	4	7.69%	1	1.92%	-5.77%
Drug Offense	6	11.54%	12	23.08%	11.54%
Fireworks Violation	1	1.92%	1	1.92%	0.00%
Gambling	0	0.00%	0	0.00%	0.00%
Harassment	0	0.00%	0	0.00%	0.00%
Hit and Run	0	0.00%	0	0.00%	0.00%
Liquor - Underage Possession	6	11.54%	6	11.54%	0.00%
Prostitution/Indecent Exposure	0	0.00%	0	0.00%	0.00%
Public Disturbance	4	7.69%	5	9.62%	1.92%
Sex Offenses	1	1.92%	0	0.00%	-1.92%
Theft and Robbery	3	5.77%	2	3.85%	-1.92%
Traffic Violations	7	13.46%	4	7.69%	-5.77%
Weapons Violations	0	0.00%	2	3.85%	3.85%

Other	12	23.08%	11	21.15%	-1.92%
Don't Know	0	0.00%	1	1.92%	1.92%
NA; Refused	3	5.77%	1	1.92%	-3.85%
Sum	52	100.00%	52	100.00%	0.00%

Table 3

Descriptives for Entire Sample

	External BPI	Internal BPI	Interaction Term	Number of Arrests	Bin. Arrest	Age First Arrest	Emotional LF	Social LF	Psych LF
Observations	724	724	724	724	724		724	724	724
Mean	5.347	2.949	23.402	0.261	0.193		5.019	3.417	5.068
Std. Deviation	3.872	2.879	33.81	0.573	0.395		0.938	1.275	0.932
Min	0	0	0	0	0		1	1	2
Max	15	13	195	2	1		6	6	6
Descriptives for Kids Arrested Once or More									
Observations	140	140	140	140	140	140	140	140	140
Mean	6.414	3.243	29.335	1.35	1	16.729	4.693	2.85	4.786
Std. Deviation	4.111	3.109	38.695	0.479	0	2.606	1.21	1.297	1.065
Min	0	0	0	1	1	9	1	1	2
Max	15	15	195	2	1	21	6	6	6

Reporting: Coefficient (Std. Error), *=99% Level of Significance, **=95% Level of Significance

Model Explanations

I. External BPI only

II. Internal BPI only

III. External and Internal BPI

IV. External, Internal, and Interaction Term

V. Emotional LF only

VI. Social LF only

VII. Psychological LF only

VIII. All LF scales

IX. All LF, both BPI subscales, and Interaction Term

Table 4 Dependent Variable: Number of Arrests

	Model								
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
External	.021* (.005)		.029* (.007)	.026* (.009)					.022** (.009)
Internal		.010 (.005)	-.017 (.010)	-.025 (.017)					-.031 (.017)
Interaction Term				.001 (.002)					.001 (.001)
Emotional LF					-.100* (.022)			-.048 (.028)	-.041 (.028)
Social LF						-.093* (.016)		-.073* (.020)	-.068 (.019)
Psychological LF							-.081* (.023)	-.004 (.028)	-.013 (.028)
R^2	.020	.0036	0.024	.024	.027	.042	.017	.0474	.0659

Reporting: Coefficient (Std. Error), *=99% Level of Significance, **=95% Level of Significance

Model Explanations

I. External BPI only

II. Internal BPI only

III. External and Internal BPI

IV. External, Internal, and Interaction Term

V. Emotional LF only

VI. Social LF only

VII. Psychological LF only

VIII. All LF scales

IX. All LF, both BPI subscales, and Interaction Term

Table 5 - Dependent Variable: Binomial Arrest

	Model											
	IV (BPM)	**IV (Probit)**	**IV (Logit)**	**V (LPM)**	**VI (LPM)**	**VII (LPM)**	**VIII (LPM)**	**VIII (Probit)**	**VIII (Logit)**	**IX (LPM)**	**IX (Logit)**	**IX (Probit)**
External	.018 (.007)	.064 (.024)	.113 (.041)							-.034 (.091)	.096** (.043)	.054** (.024)
Internal	-.014 (.012)	-.048 (.045)	-.086 (.083)							.026 (.193)	-.116 (.086)	-.063 (.466)
Interaction Term	.0004 (.001)	.001 (.005)	.002 (.008)							-.004 (.019)	.004 (.008)	.002 (.004)
Emotional LF				-.072* (.554)			-.031 (.018)	-.086 (.068)	-.160 (.117)	-.265 (.254)	-.133 (.118)	-.066 (.069)
Social LF					-.068* (.011)		-.052* (.013)	-.205* (.053)	-.374* (.095)	-.140 (.213)	-.359* (.096)	-.200* (.053)
Psychological LF						-.063* (.015)	-.009 (.019)	-.039 (.069)	-.057 (.121)	-.447 (.261)	-.078 (.122)	-.056 (.07)
R^2	.017	.021	.021	.029	.048	.022	.053	.002		0.063	0.07	0.068

Reporting: Coefficient (Std. Error), *=99% Level of Significance, **=95% Level of Significance

Table 6 - Dependent Variable: Age at First Arrest

	Model						
	III	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
External	-.066 (.072)	-.033 (.091)					-.034 (.091)
Internal	-.039 (.025)	.111 (.186)					.026 (.193)
Interaction Term		-.012 (.018)					-.004 (.019)
Emotional LF			.178 (.183)			.318 (238)	.265 (.254)
Social LF				.125 (.170)		.129 (.211)	.140 (.213
Psychological LF					-.191 (.208)	-.458 (.251)	-.447 (.261)
R^2	.009	.011	.007	.004	.006	.031	.037

Reporting: Coefficient (Std. Error), *=99% Level of Significance, **=95% Level of Significance

Table 7 - Dependent Variable: External BPI

Independent Variables	Coefficient	Std Error	p-value
Internal BPI	0.922	0.036	0.000
Constant	2.630		
$\mathbf{R^2}$=.469			

Table 8 - Dependent Variable: Social LF

Independent Variables	Coefficient	Std Error	p-value
External BPI	-0.042	0.012	0.001
Constant	3.641		
$\mathbf{R^2}$=.0161			

Table 9	Model					
Explanatory Variable	**III (Logit)**	**III (LPM)**	**VIII (Logit)**	**VIII (LPM)**	**IX (Logit)**	**IX (LPM)**
Exernal BPI	12.00%	6.96%			44.8%	-13.17%
Internal BPI	-8.30%	4.03%			-28.4%	7.49%
Interaction Term	0.02%	0.03%			15.8%	-13.52%
Emotional LF			-14.80%	-2.91%	-11.7%	-24.86%
Social LF			-31.20%	-6.63%	-36.7%	-17.85%
Psychological LF			-5.60%	-0.84%	7.0%	-41.67%

Table 10 **Correlation Matrix**

Variable	External BPI	Internal BPI	Interaction Term	Emotional LF	Social LF	Psychological LF
External BPI	1.000					
Internal BPI	0.684	1.000				
Interaction Term	0.814	.899	1.000			
Emotional LF	-.140	-.122	-.118	1.000		
Social LF	-.127	-.112	-.105	.496	1.000	
Psychological LF	-.067	-.112	-.072	.532	.506	1.000

Appendix 1: Descriptions of LF Subscales

The Following are the descriptions of each scale as given on the PSID website Data Center (http://psidonline.isr.umich.edu/data/Default.aspx)

A050935 "SUBSCALE: EMOTIONAL WB"

Emotional Well-being

Var Index

This scale is a subscale of the Languishing/Flourishing Scale (TA050934). It is the average of all responses to the following questions:

TA050888 M1. Frequency of Happiness in Last Month

TA050889 M2. Frequency of Interest in Life in Last Month

TA050890 M3. Frequency of Feeling Satisfied in Last Month

TA050936 "SUBSCALE: SOCIAL WB"

Social Well-being

Var Index

This scale is a subscale of the Languishing/Flourishing Scale (TA050934). It is the average of all responses to the following questions:

TA050891 M4. Frequency of Feeling Something to Contribute to Society

TA050892 M5. Frequency of Feeling Belonging to the Community

TA050893 M6. Frequency of Feeling Society Getting Better

TA050894 M7. Frequency of Feeling People Basically Good

TA050895 M8. Frequency of Feeling Way Society Works Makes Sense

TA050937 "SUBSCALE: PSYCHOLOGICAL WB"

Psychological Well-being

Var Index

This scale is a subscale of the Languishing/Flourishing Scale (TA050934). It is the

average of all responses to the following questions:

TA050896 M9. Frequency of Feeling Good at Managing Daily Responsibility

TA050897 M10. Frequency of Feeling Has Trusting Relationships with Others

TA050898 M11. Frequency of Feeling Challenged to Grow

TA050899 M12. Frequency of Feeling Confident of Own Ideas

TA050900 M13. Frequency of Feeling Liked Own Personality

TA050901 M14. Frequency of Feeling Life Had Direction

Responses to every question are recorded on a 1-6 scale, with responses of 8 and 9 corresponding to "Don't Know" and "NA; Refused," respectively. All are "in the last month, how often did you feel…"

1 – Never

2 – About once a week

3 – Once or twice a week

4 – Two or three times a week

5 – Almost every day

6 – Every day