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Publication Date

2020-11-05

DOI

<https://doi.org/10.26085/C3WC7S>

Series Name: WPS
Paper No.: 125
Issue Date: 9 Jul 2020

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Recommended Citation:

Baird, Sarah; Muz, Jennifer; Panlilio, Raphael; Smith, Stephanie; Wydick, Bruce (2020): Identifying Psychological Trauma among Syrian Refugee Children for Early Intervention: Analyzing Digitized Drawings using Machine Learning. CEGA Working Paper Series No. WPS-125. Center for Effective Global Action. University of California, Berkeley. Text. <https://doi.org/10.26085/C3WC7S>

Identifying Psychological Trauma among Syrian Refugee Children for Early Intervention: Analyzing Digitized Drawings using Machine Learning¹

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Keywords: Refugees, Syrian Conflict, Lasso Regression, Psychological Trauma,
Children and Adolescence, Drawings

May 2020

Abstract: Nearly 5.6 million Syrian refugees were displaced by the country's civil war, of which 50% percent are children. Given the heightened risks of psychological distress for this population it is critical to efficiently and accurately assess well-being for this population for intervention. A digital analysis of features in children's drawings potentially represents a rapid, cost-effective, and non-invasive method for collecting individual and aggregate data on children's mental health. Using data collected from free drawings and self-portraits from over 2,500 Syrian refugee children in Jordan across two distinct datasets, we use regression and Lasso machine-learning techniques to understand the relationship between exposure to violence and different measures of psychological trauma. Our results suggest that individual drawing characteristics are strongly correlated with validated measures of psychological trauma and past exposure to violence, with child mental health declining with increased exposure to violence and improving with resettlement in host communities. These results serve as a proof-of-concept for the potential use of children's drawings as a diagnostic tool in human crisis settings.

¹ We would like to thank officials from the UNHCR for assistance with fieldwork, as well as Felipe Rodriguez and Mindset for help with logistics and data collection, Judith Fan for helpful support and input on the project, and seminar participants and faculty at the University of San Francisco for helpful comments on the research. We also thank Crystal Lim for assisting with analysis. The GAGE program is funded by UK aid from the UK Department for International Development (DFID). The views expressed and information contained within are not endorsed by DFID, which accepts no responsibility for such views or information or for any reliance placed on them.

1. Introduction

In every part of the world, displaced persons and refugees experience multiple forms of traumas and stresses, loss and isolation, persecution, uprooting, and exposure to violence. The cumulative trauma that is part of the refugee experience can lead to long-term impacts on mental health, including higher rates of anxiety, depression, and post-traumatic stress disorder (PTSD) compared to non-refugee populations (Williams et al., 1991; Thabet and Vostanis, 2004; Punamäki et al., 2001; Bronstein and Montgomery, 2011; Carswell, Blackburn, and Barker 2011; Giordano et al., 2019; Alemi et al., 2014). Psychological trauma is harmful in its own right, but also can initiate a feedback loop with diminished economic participation and activity that can fuel poverty traps (Fehr and Haushofer, 2014; de Quidt and Haushofer, 2016).

Children and adolescents are especially vulnerable to the negative impacts of continual exposure to violence because they are at a crucial period for developing and maintaining emotional habits critical for mental well-being (Breslau et al., 1999). Late childhood and early adolescence are times of intensified emotional distress, with half of all mental illnesses beginning by age 14 years, and mental disorders the leading cause of years lost because of disability in adolescence (Patel et al. 2007; Gore et al. 2011; WHO, 2014; Das et al. 2016). Poor mental health for young people is in itself a global health priority (Patel, 2013) but also matters for long-term human capital accumulation due to associations with factors such as increased risky decision making (Di Clemente et al. 2001; Fishbein et al. 2006) and lower educational attainment (Currie and Stabile 2006; Fletcher and Wolfe 2008). For refugee children and adolescents there are a number of factors that heighten these risks of psychological distress including exposure to violence, forced displacement, and socioeconomic conditions.

The psychological well-being of refugee children and its future consequences is of global importance. More than 31 million children were displaced as of the end of 2017, accounting for over 50% of the displaced population, compared to less than one-third of the overall population. Of the over 6.6 million displaced Syrians, 52% are children (UNICEF 2018). Evidence suggests that exposure to past and ongoing traumatic events, as well as complexities of navigating the post-migration environment, are the two key sets of factors shaping the mental health and resilience of refugee children (Fazel and Betancourt 2018). Thus, given that mental health resources are extremely limited in these contexts, creative methods are needed to identify those most at need. As Fazel and Betancourt (2018) note “within the development of preventive interventions, it might

be that focusing on high-risk populations of refugee children would have the greatest potential impact.”

This research aims to contribute to the literature on mental health measurement and policy response by using conventional econometric and machine-learning methods to explore the use of digitized children’s drawings as a predictor of past psychological trauma induced by forced displacement. The central contribution of our research to the literature is methodological. Children’s drawings, discussed in more detail in Section 2.2, have been used in clinical practice for many decades, but they have only recently become used in large-scale data analytics. Glewwe et al. (2018), for example, used drawing features in a large dataset, seeking to exploit the correlations inherent in the drawings to measure causal changes in psychology from a development intervention (international child sponsorship). This research builds on this work and represents an early foray into using modern analytical tools to obtain measures of psychological well-being within large populations of children in low resource settings. The first part of our work here is similar to Glewwe et al. (2018) in that, using historical correlations as a guide, we try to answer questions about the effectiveness of a policy, specifically whether refugee reintegration into a host country improves psychological well-being of children relative to sheltering in refugee camps. However, the remaining balance of this work is perhaps more aligned with previous research that has used children’s drawings for the purpose of updating probabilities over the presence of psychological trauma in individual children. Our contribution here is to utilize machine-learning and regularization methods to reduce the number of drawing features to a smaller set of characteristics with the lowest mean square error in predicting responses from standard psychology questionnaires and known previous exposure to violence.

If strong predictive correlations between drawing feature characteristics and different types of psychological trauma can be obtained through simple drawing exercises, it would be advantageous on three accounts. First, children’s drawings can be obtained quickly, even in a refugee or crisis setting. Second, children’s drawing exercises are relatively inexpensive to administer, even among large populations and in contexts where logistics are difficult. Third, drawing exercises are a non-invasive instrument that can be administered to children in refugee and disaster settings with little fear of augmenting current levels of trauma. They can reveal information about mental health that may be difficult or distressing to the child if obtained by clinicians or researchers using verbal questioning approaches commonly implemented in the psychoanalysis of adults (Koppitz, 1968, 1984). Farokhi and Hashemi (2011) argue that children

use drawings to identify themselves with the world around them and express their feelings in ways that are often difficult verbally. It is often in their drawings that children express their interpretations and understanding of both their feelings and the world around them.

If drawing features are strongly correlated with psychological disorders such as anxiety, depression, and PTSD, they would have the potential for use as a rapid, cost-effective, and non-invasive method to 1) flag individual children with the highest probability of psychological trauma for early treatment; 2) obtain relative measures of children's aggregate psychological health across refugee or disaster areas; and 3) monitor changes in children's aggregate psychological health in a single area over time. With respect to the economics of information collection, they represent a potentially efficient and innovative instrument to gather critical data on at-risk children and larger groups of children in crisis settings.

We use two data sets of children's drawings for our analysis. The first comes from a survey of Syrian refugee families in Jordan collected by University of San Francisco (USF) researchers in 2016, containing drawings from 1,231 children, aged 5-12. In the USF dataset, 707 of the children in the sample lived in the Zaatari refugee camp and 524 were members of Syrian families that had been re-integrated into society in a number of major cities. This USF dataset is more limited in that, while it does contain data on basic household covariates, it does not contain any additional mental health assessments besides the projective drawing exercise. Our second source of data was also obtained in Jordan among Syrian refugees as part of data collected by the Gender and Adolescence: Global Evidence (GAGE)² program. The GAGE data we utilize for this analysis comes from a sample of 1,289 Syrian refugee children³ aged 10-12 from the Azraq and Zaatari refugee camps as well as from host communities in Amman, Irbid, Jerash, Mafraq and Zarqa. It contains drawing data, psychological data from the General Health Questionnaire-12 (GHQ-12), as well as key data on household covariates. We are able to proxy for exposure to violence using data from the Syrian Revolution Martyr Database (SRMD), an often-cited and reliable source of casualty data from the Syrian civil war. The SRMD counts the number of battle-related deaths that have occurred within each governorate in Syria from 2011 to 2016, and we are able to match this

² GAGE is a 9-year DFID-funded longitudinal research program exploring the wellbeing of 20,000 adolescents across the course of adolescence (10-19 years) in six LMICs hosted by the Overseas Development Institute in London, and with research partners in each focal country. For more details see www.gage.odi.org.

³ The study sample could also be referred to as very young adolescents, but for consistency with the USF data and ease of discussion we refer to them as children in this paper.

data with the year and governorate from which Syrian households in our survey fled during different points of the war.

Using the USF dataset, our estimations suggest that our drawing-feature PTSD index increases among child refugees with high-level exposure to violence, and our drawing-feature depression index appears to dissipate more quickly among children who transition from refugee camps and assimilate into Jordanian society. As a check on these findings, we carry out the same estimations on a completely different set of children using the GAGE data, and we find remarkably similar results, where exposure to violence point-estimates on a PTSD index made from free-drawings are very similar, and we see a drawings-based anxiety/depression index increasing with exposure to violence and decreasing with assimilation into Jordanian society.

Using our GAGE dataset, we apply k -fold cross-validated LASSO (Least Absolute Selection and Shrinkage Estimator) and find significant correlations between children's drawing features historically linked with anxiety, and depression and responses indicating anxiety and depression in the GHQ-12 questionnaire. Finally, across both datasets, we find penalized drawing features retained using LASSO that significantly predict past exposure to violence, including children's depiction of monster figures, aggressive action figures, and drawing in a single color. We find modest consistency between our two datasets in the LASSO-retained variables, but where the retained drawing features differ, in most (but not all) cases they are consistent with feature-disorder correlations from previous research.

Our paper proceeds as follows: Section 2 provides additional literature on psychological impacts of refugee status and the role of children's drawings. Section 3 presents empirical results that utilize historical correlations of drawing features with psychological phenomena to create dependent variable indices that we use to estimate OLS effects on psychological well-being from exposure to violence and assimilation status. In Section 4 we introduce our GAGE data set, first replicating the analysis from Section 2 with this independent dataset, and then utilizing a LASSO machine-learning framework that allows us to test for the significance of correlations between drawing features and established measures of anxiety and depression obtained through the GHQ-12. In Section 5 we use both sets of data in a LASSO framework to ascertain whether certain features of children's drawings can be used to predict past exposure to violence. Section 6 concludes and summarizes the main findings from our research.

2. Literature Review

2.1 Psychological Impacts of Refugee Status

Our work contributes to a literature that seeks to understand the short- and long-term effects of exposure to violence and civil war, especially in low and middle-income countries. Previous work has found that psychological impacts from forced displacement and exposure to violence often result in decreased cognitive ability and increases in psychosocial impairments (Punamäki et al., 2010). Psychological distress among children of refugee families may originate from a number of factors common to refugee status. Some research highlights impacts from the fragmentation of community ties (Elbedour et al., 1993). Other work has identified psychological trauma principally from direct exposure to violence and the instability of post-migration experiences (Alemi et al., 2014; Bronstein and Montgomery, 2011). Regardless of the specific mediating variables, a strong consensus exists in the literature that exposure to the stressors of war and civil conflict provoke elevated levels of anxiety, depression, and PTSD (Alemi et al., 2014; Justino, 2010; Thabet and Vostanis, 2004).

Not surprisingly, the evidence for psychological disorders among children from civil conflict and refugee status extends across geography and culture. Savin et al. (1996) present clinical evidence of dramatically elevated levels of PTSD among a sample of Cambodian refugees. Dyregrov et al. (2000) study psychological trauma from the Rwandan genocide among 3,030 children and adolescents, finding that approximately two-thirds displayed symptoms of PTSD. Palestinian children in the Gaza Strip who were exposed to chronic traumatic experiences showed varying degrees of PTSD in the forms of intrusive thoughts, feelings of sadness and nervousness, increases in aggressive behavior and inability to focus in school (Altawil et al., 2008).

Psychological disorders tend to cluster within refugee households that have experienced trauma, both because of shared traumatic experience but also because disorders such as anxiety and depression easily spread from parents to children (Sack et al., 1994). Among children, psychosocial impacts among refugees manifest in a variety of emotional symptoms, social behavioral disorders, and academic behavioral disorders (Ellis et al., 2019; Trentacosta et al., 2016; Nader et al., 1993; Altawil et al., 2008). These impacts are often exacerbated in refugee contexts from poor access to health and educational services, and separation from home communities, familiar environments, and families (Santa Barbara, 2006).

Generally, research indicates that psychological impacts increase in proportion to the duration of trauma (Altawil et al., 2008; Kaysen et al., 2003; Nader et al., 1993). Victims of chronic and prolonged trauma have also been found to exhibit lower rates of recovery and responsiveness to interventions (Famularo et al., 1996; Terr, 1991). In a sample of Cambodian refugees resettled in the United States, Sack et al., (1993) provide some evidence that resettlement and assimilation of refugees in host countries mitigates anxiety, depression, and PTSD, however here it is difficult to generalize from the specific Cambodia to U.S. assimilation, as well as disentangle selection effects from causal effects.

Children and adolescents are at particular risk as refugees (Thabet et al. 2004), and the trauma from forced displacement and war experienced as a child can have lasting impacts into adulthood. Savin et al.'s (1996) study of Khmer refugees who fled Cambodia as children found that 39% met the diagnostic criteria for PTSD 6-10 years after displacement. Exposure to violence and other traumatic events have been found to impact educational outcomes through a number of different channels, such as excessive absenteeism, higher dropout rates, and lower performance (Fry et al., 2018), as well as through formations of behavioral disorders that interfere with their ability to learn (Morton, 2018). At early stages of growth, these effects, as well as the physical effects from malnutrition and other hardships accompanying refugee status, result in an increased vulnerability to future risk and diminished health, education, and labor market outcomes (Currie and Vogl, 2013; Alderman et al., 2006; Smith et al., 2001).

2.2 Children's Drawings as Indicators of Psychological Phenomena

Clinical psychology has established a rich literature that studies the use of children's drawings to help diagnose different types of psychological phenomena in children. The seminal work in this area is that of Koppitz (1968), who pioneered some of the early correlations between drawing features and different psychological disorders. Many of these have been confirmed in subsequent decades by work such as Wadeson (1971), Klepsch and Logie (1982), Di Leo (1983), Koppitz (1984), Thomas and Silk (1990), Peterson and Hardin (1997), Furth (2002), Skybo et al., (2007), Farokhi and Hashemi (2011), and Vass (2012). Over time, this body of work has revealed some consistent correlations between drawing features and diagnosed disorders. In children's free drawings, for example, the drawing of symbols or memories of trauma is highly correlated with diagnosed PTSD (Tibbets, 2013), as is the drawing of aggressive action figures (Magwaza et al., 1993), poor figural integration, (Tibbets, 2013), and tiny human figures (Skybo, 2007 and Tibets,

2013). In self-portraits, the dark shading of face or body is correlated with both anxiety and depression (e.g. Farokhi and Hashemi, 2011; Skybo 2007), as is the choice of dark over light colors for drawings (Koppitz, 1968; Wadeson, 1971). A self-portrait drawn with a smile or drawn in cheery or light colors is negatively correlated with anxiety (Wadeson, 1971; Furth, 2002), and a monster figure is correlated with PTSD (Peterson and Hardin, 1997; Tibets, 2013).

3. Refugee Status and Psychological Well-being

In our first empirical section we identify drawing features that have historically been found in the literature to correlate with measures of anxiety, depression, and PTSD. Under the assumption that drawing features are also able to capture these phenomena within our population of Syrian refugee children, we then use these indices as *dependent* variables in regressions on 1) household exposure to violence, and 2) household reintegration status. In subsequent sections we will relax this assumption so that a vector of children’s drawing features will be used as *independent* variables, testing their validity in predicting psychological trauma and exposure to violence using machine learning exercises and comparing our results with the historical correlations found in the literature.

3.1 USF Data Set Collection

For this exercise, we use information from the USF dataset obtained in 2016 from Syrian refugee families in the Jordanian cities of Amman, Irbid, Zarqa, Wadi Al-Seer, Ramtha, Sweileh, Mafraq, and Jerash and in the Zaatari refugee camp near the Syrian border.⁴ The dataset included 1,231 children aged 5-12. The drawing exercise was implemented in the following way: Permission for the child to participate in the drawing exercise was requested from the parent, guardian, or host organization. After permission was granted, subject children were provided with a box of twenty-four colored pencils and two sheets of paper. The children were then asked to draw two types of pictures. First, the child was instructed by a member of the research team to “Draw a picture of yourself” and secondly to “Draw a picture of whatever you feel like.”^{5,6}

⁴ Human subjects approval: University of San Francisco Institutional Review Board for the Protection of Human Subjects (IRBPHSIRB) Protocol #669.

⁵ Because Syrian children in the USF dataset were asked to draw both the self-portrait as well as the free drawing, these data are analyzed separately from children in the GAGE data set, who drew only the free drawings.

⁶ In conducting the drawing exercises, we clarified the following stipulations to everyone involved: The decision to draw was up to the child, and if requested, the child was given permission to draw in an area where he or she felt most comfortable. No prompt or suggestion was to be given to the child on how or what to draw. All drawings were to be done only by the child, and all children were to perform the drawing exercise free from distraction or criticism. After all the drawings and information were completed and collected, the exercise concluded. Generally, the drawing

Along with the drawings, we use data gathered from the parent, guardian, host organization, and participants themselves on basic socioeconomic and familial information: age and gender of the child, city of residence of the child's household in Syria, date of arrival in Jordan, the father's occupation in Syria, family size, and the number and gender of siblings.

Based on the review of the literature on the psychological analysis of self-portrait and free drawings, the drawing indicators of interest were trimmed down to eighteen indicators historically correlated with symptoms of anxiety, depression, and PTSD. Out of these indicators, nine were categorized as indicators for anxiety, nine were categorized as indicators for depression, and seven were categorized as indicators for PTSD. All drawing indicators were chosen before the analysis of the drawings. After analysis began, no drawing characteristics were added, removed, or modified. Table 1 summarizes the list of children's drawing indicators for anxiety, depression, and PTSD used in the analysis.⁷

Merging the SRMD battle deaths data⁸, which counts the number of battle-related deaths in each governorate in Syria from 2011 to 2016, with the information on date of arrival and city of origin collected from respondents, we generated a variable for the average number of battle-related deaths that occurred within a respondent's governorate of origin in the years prior to the respondent's flight from Syria to Jordan. In the USF dataset, only 293 out of the 1,231 children experienced zero battlefield deaths in their governorate prior to leaving Syria, the remainder of whom experienced an average of 40,940 total deaths, indicating high levels of exposure to violence. We code exposure to violence equal to 1 if this number is greater than zero, and zero otherwise.⁹ Children were coded as a 1 for "Reintegrated" if the refugee household had taken up residence in Jordanian society outside of a refugee camp, and zero if the child's family resided in a refugee camp. Table 2 provides summary statistics of children and household characteristics as well as outcome variables.

exercise would last between fifteen to thirty minutes.

⁷ A more extensive list of drawing features for other measures of psychological health and disorder such as agency, aggression, insecurity, and shyness, are given in Glewwe et al. (2018).

⁸ The SRMD battle deaths data can be found at <http://syriansshuhada.com>.

⁹ We also code four children for whom exposure was significantly lower than all others with battle-field death exposure. These four children experienced less than 700 deaths per year in the child's governorate, or about half of the total of the next highest average per year.

3.2 Model Estimation

We estimate the model

$$y_i = \alpha + \mathbf{X}'\boldsymbol{\tau} + \mathbf{Z}'\boldsymbol{\beta} + \epsilon_i, \quad (1)$$

where the y_i are standardized indices of anxiety, depression, and PTSD; \mathbf{X} is vector of refugee experiences that includes exposure to violence, assimilation status, or both; \mathbf{Z} is a vector of household and child characteristics that includes gender, family size, father's occupation in Syria, a dummy variable for urban family (in Syria), size of city of origin; α is the intercept; and ϵ_i is the error term. For our index creation, we use the method of Anderson (2008), where each variable v in index j receives a weight such that $\bar{s}_{vj} = (\mathbf{1}'\boldsymbol{\Sigma}^{-1}\mathbf{1})^{-1}(\mathbf{1}'\boldsymbol{\Sigma}^{-1}\mathbf{z}_{ij})$, where $\mathbf{1}$ is an $m \times 1$ column vector of ones, $\boldsymbol{\Sigma}^{-1}$ is the $m \times m$ inverted covariance matrix, and \mathbf{z}_{ij} is the $m \times 1$ vector of outcomes in index j for individual i . Following Abadie et al., (2017), we cluster our standard errors at the level of treatment, which we identify in our data as occurring at the governorate/flight-year level since this captures the intensity of the violence inflicted on families, creating substantial scope for clustered correlation of residuals.

3.3 Results and Causal Inference

Our estimations in Table 3 show higher levels of anxiety, depression, and especially PTSD among children with high exposure to violence based on indices of these phenomena created solely from their drawing features. Columns (1)-(3) display effects on these disorders from our exposure to violence measure, columns (4)-(6) show effects of assimilation into Jordanian society (our reintegration variable) and columns (7)-(9) include both of these measures simultaneously in order to examine the degree to which reintegration is able to mitigate psychological trauma as measured by our three drawings-based indices.

The coefficient on exposure to violence is positive on all estimations except for column (8) in its effect on depression, where it is slightly negative and insignificant. Coefficients on exposure to violence for our regressions using the drawing-feature-based anxiety and depression indices are very small and range from 0.01σ to 0.02σ and are insignificant. The coefficients measuring the effect of exposure to violence on the drawings-based PTSD index in columns (3) and (9) are much larger and statistically significant (0.14σ , $p < 0.01$, and 0.12σ , $p < 0.05$, respectively).

Columns (4), (5), and (6) show indices for anxiety, depression, and PTSD to be lower for children in reintegrated families. The coefficient on reintegration is -0.11σ ($p = 0.17$) for anxiety, 0.17σ ($p < 0.01$) for depression, and 0.10σ ($p < 0.05$) for PTSD, respectively; they change little

when reintegration is included with exposure to violence in columns (7)-(9). Children from reintegrated households thus appear to display significantly lower levels of depression and PTSD as reflected by drawing-features indices created from the historical correlations with these phenomena.

That measures of anxiety, depression, and PTSD taken solely from features of children's drawings appear to be strongly correlated--with the expected signs--to past exposure to violence and reintegration into mainstream society would seem to portend well for the use of drawing features as an analytical tool. But from a policy standpoint, how strongly can we make causal inferences from our exposure to violence and reintegration variables? We believe the strongest causal case can be made for exposure to violence as it is difficult to identify a potential confounder between individual children's baseline level of psychological health and the idiosyncratic geo-temporal dispersion of violence in civil conflict.

Perhaps somewhat more difficult is the relationship between our reintegration variable and psychological outcomes, yet here we also find a significant case for causality, at least through controlling for the most likely sources of endogeneity. One might think that households reintegrated into the host country sooner might be wealthier, white-collar households, having other characteristics that might be correlated with the ability to shelter children from the worst aspects of violence. But it is clear from Table 2 that, if anything, white-collar households make up a higher percentage of the Syrian refugee families remaining in refugee camps than among the families reintegrated into Jordanian society. At least based on observable characteristics such as rural/urban status in their home country, profession, family size and age of children, the two groups are remarkably similar.

We test for Oster (2019) bounds where in Table 3 our estimate of delta is negative for reintegration, meaning that when these observable covariates are added to the regression, the coefficient on reintegration becomes *larger* rather than smaller. Oster (2019) argues that if treatment coefficients become larger by adding observables, there is reason expect the same if were possible to include unobservables in the regression. With all of the normal caveats, we interpret these results in tandem with previous similar findings (e.g. Sack et al., 1993) as contributing to a body of evidence suggesting that household reintegration may be beneficial to children's psychological health relative to a counterfactual of refugee camp status.

4. Consistency of Drawing Features and Survey Questions

In the previous section, we assumed the validity of historical correlations of drawing features with psychological phenomena to estimate changes in children’s psychology from exposure to violence and refugee integration into the society of the host country. In this section, we first show whether the findings on exposure to violence and refugee reintegration replicate in the GAGE data. Then, we relax the assumption that these drawing features are valid measures of psychosocial well-being and test the extent to which children’s drawing features most accurately predict psychological phenomena measured from direct questionnaires.

4.1 GAGE Dataset Collection

In these estimations we use the data collected by the Gender and Adolescence: Global Evidence (GAGE) program.¹⁰ Starting in 2018, GAGE began collecting data from vulnerable adolescents in Jordan. Here we use data from 1,249 children aged 10-12 from the Zaatari and Azraq refugee camps as well as host communities across multiple governorates of Jordan. Detailed household level information was collected from each participant including age, gender, family size, asset decile, location of origin in Syria and the date of displacement. The children of this study were asked to participate in a free drawing exercise where they were asked to “Draw what you feel like.”

The GAGE dataset differs from the USF dataset in that children did not draw self-portraits in this wave of the GAGE data. This left us with a smaller set of drawing codes (see Table 1 for an indicator of the set of codes used with the GAGE data). Figure 1 illustrates how these codes were applied to drawings using four drawings from the GAGE sample. Unlike the USF dataset, the respondents were also asked to participate in mental health measurements. The main measurement used is the GHQ-12 developed by Goldberg and Blackwell (1970) and Goldberg and Williams (1988). The GHQ-12 was developed as a screening instrument to detect individuals who have the common mental health problems of anxiety, depression, and social withdrawal (Jackson, 2007). Each item is rated on a 4-point scale, and we utilize binary scoring with summed scores ranging from 0 to 12 and higher scores indicative of increased psychological distress. Summary statistics for the GAGE dataset are in Table 4, shown overall, and separated by host and camp.

¹⁰ The GAGE research program was approved by the George Washington University Committee on Human Research, Institutional Review Board (071721) and the ODI Research Ethics Committee (02438). In Jordan, we received permission from the UNHCR’s National Protection Working Group, the Ministry of Interior, and the Department of Statistics.

The average score on the GHQ-12 is 1.9 out of 12, with 27% of adolescents in camps and 31% in host showing signs of psychological distress.

There are a few other features of note between the two datasets: The participants of the GAGE data collection are on average slightly older and have lived in Jordan a year longer than the USF participants, the latter mainly due to the timing of the two surveys. Another difference is that 36% of participants from the GAGE dataset live in a refugee camp, while 57% of participants from the USF dataset live in a refugee camp, as opposed to living in a host community.

When looking at the summary statistics for the drawing characteristics, shown in Table 2, the biggest differences in presence of indicators come from ‘Lack of concern with integrating background’ (39% vs. 13%), ‘Drawn in a single color’ (10% vs. 20%) ‘Drawn in light colors’ (54% vs. 15%) and ‘Symbol of hope’ (43% vs. 60%). Excluding indicators that were not used across both datasets, all other indicators are in close proportion to one another.

4.2 Exposure to Violence and Reintegration

Before turning to the GHQ-12, we first re-estimate Equation 1 using the GAGE data. We follow the same procedure as in Section 3.2 creating indices of PTSD and anxiety/depression. As we only have free drawings the set of measures for PTSD is the same, but we have a smaller set of measures for anxiety and depression so combine them into one index. The covariates included in analysis with the GAGE data are similar and include age, gender, household size, an indicator for asset decile, and number of years spent in Jordan since flight from Syria. We use a slight variant to the USF measure on exposure to violence in the GAGE data given the distribution of exposure to violence in this sample. We construct the measure by standardizing the logged value of cumulative martyr deaths that occurred in the governorate of origin from 2011 up until the beginning of the year that the household left for Jordan. Then an indicator equal to 1 if that value is greater than zero is generated, which in practice takes on a value of one if the HH was exposed to more than 2000 martyr deaths total

Table 4 shows the GAGE results on the impact of exposure to violence and reintegration on the indices of anxiety/depression and PTSD constructed from the drawings. The results using the GAGE data suggest exposure to violence increases the anxiety/depression index by 0.098σ ($p < 0.05$) and the index of PTSD by 0.11σ ($p < 0.10$), the latter with a magnitude similar to the 0.14σ we find in the USF data. Also similar in magnitude to the USF data, reintegration has the expected sign in both cases, but is only significant for anxiety/depression (-0.187 , $p < 0.01$). The sign of the

coefficient always suggests a positive association with violence and a negative association with reintegration. The remarkably similar results across two unique datasets provides initial suggestive evidence that the indices constructed from children’s drawings appear to be capturing meaningful psychological phenomena. However, in creating these indices from historical correlations in the clinical psychology literature, we have assumed their validity as measures of psychological phenomena. We now relax this assumption and test the correlation of drawing features with standard psychological questions in the GAGE data from the GHQ-12.

4.3 LASSO Estimation

Machine learning techniques have been increasingly used in recent years by economists for a number of purposes, including for prediction (Athey and Imbens, 2019). Here we use the Least Absolute Shrinkage and Selection Operator (LASSO) regression analysis method (Tibshirani 1996). Machine learning techniques typically use regularization methods to prune the number of variables within a model. LASSO minimizes the residual sum of squares subject to a constraint on the absolute size of the estimated coefficients. This shrinks some coefficients and sets others to zero, creating a basis for model selection. The objective function of the LASSO is the following:

$$\underset{\hat{\beta}_0, \hat{\beta}_j}{\operatorname{argmin}} \sum_{i=1}^N (y_i - \beta_0 - \sum_{j=1}^J \beta_j x_{ij})^2 \quad \text{subject to} \quad \sum_{j=1}^J |\beta_j| \leq \lambda. \quad (2)$$

where $\lambda \geq 0$ is a tuning parameter that determines the strength of the L1 penalty and thus controls the amount of shrinkage and selection that is applied to the model. With $\lambda = 0$, no coefficients are eliminated and results match those of OLS. As λ increases, a greater number of coefficients are set to zero and are implicitly removed from the model. We use LASSO with a k -fold cross-validation where we set $k = 10$. Cross-validation in each of the k folds assess the out-of-sample prediction performance of the estimator. With k -fold cross-validation, the data is divided into k groups of approximately equal size, where $n(k)$ denotes the number of observations in the k^{th} data partition. The first fold is treated as the validation dataset and the remaining $k - 1$ folds function as the training data, repeated sequentially for iterations 2 through k for a given value of λ . Across a large number of values of λ , LASSO computes the mean-squared prediction error, where the model chooses the final penalty parameter λ that results in the lowest MSPE across all of the k folds, specifically LASSO chooses

$$\min_{\lambda} CV = \frac{1}{k} \sum_{f=1}^k MSPE_{(k,\lambda)}, \quad \text{where} \quad MSPE_{(f,\lambda)} = \frac{1}{n_1} \sum_{i=1}^{n_1} (y_i - x_i' \hat{\beta}_{(1,\lambda)})^2 \quad \text{for each fold } f. \quad (3)$$

to create an optimal out-of-sample prediction performance.

We implement the k -fold cross-validation LASSO machine-learning routine in the context of the following linear probability model:

$$Y_i = \beta_0 + \mathbf{X}'\boldsymbol{\gamma} + \mathbf{D}'\boldsymbol{\beta} + e_i \quad (4)$$

where Y_i represents a measure of psychological well-being for individual i , β_0 is a non-penalized constant, \mathbf{X} is a vector of non-penalized demographic controls that include age, gender, household size, an indicator for asset decile, an indicator for living in host community, and number of years spent in Jordan since flight from Syria, and \mathbf{D} represents a vector of penalized drawing features obtained from children of Syrian refugee households.

Results from the model give insight into the following questions: Which drawing indicator(s) serve as the best predictors of psychological distress among children of refugee families? To what extent do historically identified features of children's drawings correlate with the measures of psychological phenomena obtained through standard survey questions for anxiety, depression, and PTSD?

4.4 Results

Table 6 shows results from the LASSO estimation to determine the relative predictive power of drawing indicators for psychological distress as measured by a binary indicator from our GHQ-12 responses.¹¹ Table 6 shows the variables selected as a result of the LASSO, as well as the post-estimated OLS coefficient results.¹² Because of the tradeoff between variance and bias when using penalized estimation, the resulting standard errors do not provide significant hypothesis interpretation. However, in order to provide a general assessment of the variance of the estimates, robust standard errors from the OLS regressions are shown in column (2). At a lambda value of 40.066, four characteristics were retained by the LASSO and six were shrunk to zero. We did not subject the six control variables (age, indicator for female, household size, years spent in Jordan, asset decile and an indicator for host) to LASSO penalization and therefore they are always included in the model.

¹¹ We use a binary indicator for psychological distress; however, results are qualitatively similar if the continuous GHQ-12 is used.

¹² Post-LASSO OLS coefficients are obtained by running an OLS estimation using variables retained by the LASSO. Post-LASSO OLS coefficients are useful in that they give the conditional correlations inherent in the reduced model. However, standard errors and p -values cannot be interpreted in the standard manner as they represent coefficients that have been retained through a data-mining process and where some coefficients which may be true elements of the data-generating process may not have been retained. Confidence intervals will thus be biased to the extent that these non-retained variables are correlated with the LASSO-retained variables.

The first column in Table 6 displays the coefficients that were obtained when taking the λ penalty function into account. The second column displays the post-LASSO OLS estimations and standard errors which are obtained by running a standard OLS regression on the LASSO-retained variables. LASSO results indicate that the use of a political slogan or political imagery in a drawing is the strongest predictor of psychological distress in a child refugee. The corresponding OLS coefficient can be interpreted in the following way: The presence of a political slogan or political imagery in a child’s drawing is associated with a 0.158 probability increase in the child suffering from psychological distress. This is followed by these characteristics: drawn in a single color (0.081 probability increase), lack of details (0.073 probability increase), and lack of concern with integrating background (0.047 probability increase). We find it especially notable that all selected drawing features selected by the LASSO algorithm and their signs are consistent with historical correlations in the clinical psychology literature as indicators of anxiety, depression, or PTSD.

5. Drawing Features as Predictors of Exposure to Violence

While in the previous section we used children’s drawing features within a LASSO model to predict psychological phenomena as measured through standard questionnaires, this section we carry out a similar routine to predict exposure to violence among refugee children. Here we are able to utilize both the USF and GAGE datasets, which both contain information on exposure to violence from the Syrian Revolution Martyr Database (SRMD) and look for consistency in findings across the two datasets.¹³ It is important to note that the USF dataset contains more characteristics since it includes the self-portrait as well as the free drawing.

The key questions here are whether drawing features exhibit predictive power for past exposure to violence, whether the findings are consistent with both common sense and the historical correlations established in the psychology literature, and finally whether we see similarity in results across the two datasets. We view this exercise as particularly relevant as a proof-of-concept for a new approach to assessing mental health within crisis settings. If machine-learning techniques are able to consistently identify key features of children’s drawings as early predictors of psychological trauma, children’s drawings could be used as a quick, non-invasive,

¹³ We decided against pooling the datasets given the differences in covariates.

and cost-effective first-pass for mental health assessment across a large population of children for identifying those with the highest probability or highest level of psychological trauma.

5.2 Results

Table 7 presents the findings investigating what drawing characteristics are associated with past exposure to violence. First, looking at the USF dataset in columns (1) and (2) we see that three characteristics from the self-portraits and one from the free drawings is a significant predictor of past exposure to violence. For self-portraits, the following variables similarly align with the literature and predict higher exposure to violence: both “sketchy or broken lines” and “faint lines” are associated with increased probability of exposure to violence by 0.054 percentage points. However, the sign we find on “shading of the face or body” is opposite to what we would expect from the literature, suggesting a decreased probability of violence exposure (-0.097). The drawing feature that has the largest coefficient on predicting Exposure to Violence is the drawing of “aggressive action figures,” associated with a 0.164 percentage point increase in probability of past exposure to violence and strongly consistent with the clinical psychology literature.

When we turn to the GAGE data we once again see the strong predictive power of “aggressive action figures,” with the presence of an aggressive action figure in the drawing associated with a 0.309 increase in the probability of past exposure to violence. The consistency of this result across the two datasets suggests that this may be an important feature for identifying at risk children and of future research. Although unexpectedly, there is a negative association between drawings of symbols of memories of trauma (-0.187) and exposure to violence, we see other features of free drawings retained by LASSO in the GAGE data that align strongly with the clinical psychology literature: “monster picture” is associated with an increased likelihood of exposure to violence by 0.224 percentage points, “drawing in a single color” is associated with an increased likelihood of exposure to violence by 0.046 percentage points, and “lack of details” is associated with a 0.025 percentage point increase in exposure to violence.

These results present preliminary evidence that children’s drawings analyzed in large datasets may be useful in predicting exposure to violence, which here we use as a proxy for manifesting psychological trauma. Furthermore, we find that basic machine learning techniques, such as LASSO, appear to do a reasonable job of selecting key features of drawings that, a priori, we would expect might be correlated with psychological trauma among refugee children. Out of the nine selected terms, seven go in the expected direction, and one in particular stands out as

consistent across the two distinct datasets, the presence of aggressive action figures in a child's free drawing. Many children in refugee settings may have been exposed to violence, and so, in practice, we might think the presence of an aggressive action figure in a child's free drawing flags individual children as either being exposed to greater amounts of violence or as being more deeply traumatized by the level of violence to which she has been exposed. In either case, the coefficient on the feature that we estimate is large enough that it may warrant prioritizing refugee children manifesting this feature in a drawing for early attention.

6. Summary and Conclusion

Our research uses traditional econometric and machine-learning tools to explore the use of children's drawings as a rapid, cost-effective, and non-invasive method for obtaining information on the mental health of children in refugee and disaster settings. If the analysis of large datasets were to reveal significant correlations between specific features of children's drawings and different facets of mental health in children, they might be used to flag individual children for early attention in refugee settings, measure differences in aggregate mental health between refugee settings, and monitor the mental health of a single crisis population over time.

We view this work as a preliminary step in an exploration that combines psychological and machine-learning tools that allow practitioners to better serve refugee and crisis populations, and as such see four main conclusions from this research:

1. Across two distinct datasets, Syrian refugee children with high exposure to violence show higher levels of PTSD, anxiety and depression created from indices based solely from their drawing features historically linked to these disorders in the clinical psychology literature. Our drawing-based indices show increases in PTSD of approximately 0.13σ in the USF dataset and 0.11σ in the GAGE dataset from exposure to high levels of battlefield deaths before a child's family fled from Syria to Jordan. The GAGE data also show a significant increase in anxiety and depression of about 0.10σ .
2. Results from both datasets suggest that refugee children who have been reintegrated into mainstream society of a host country (Jordan) manifest lower levels of PTSD, anxiety and depression than children remaining in refugee camps. While our case for a causal relationship is slightly less strong as the effect of exposure to violence, we find this result controlling for the most important observables that we believe could influence selection

into reintegration and show robustness to Oster bounds tests. This result points to the possible beneficial role of reintegration on the psychological health of refugee children.

3. Our third main finding is that historical correlations found in clinical psychology between features in children’s drawings and psychological disorders appear to be operative in the Syrian refugee setting. Unlike our two previous findings which relied on the assumption that the historically identified drawing characteristics were valid measures of psychological trauma, here we explicitly test this assumption using the GAGE data, which includes a measure of the GHQ-12, a validated measure of psychological well-being. Using LASSO machine learning techniques, we find drawing features to predict children’s responses to GHQ-12 questions. All LASSO-selected features sign in the expected direction, providing optimism for children’s drawings as a valid information tool when assessing the psychological well-being of a child.
4. Finally, we find that machine-learning techniques such as LASSO can be used to predict likely triggers of PTSD, such as past exposure to violence. Using *k*-fold validation, LASSO identifies one consistent feature of children’s drawings—the presence of aggressive action figures—to strongly predict past exposure to violence. With the USF data we also find a number of other features of self-portraits associated with increased violence including body shading, and broken and faint lines. In the GAGE data, we find some consistency with the GHQ-12 results, with both lack of details and drawn in a single color also positively associated with past exposure to violence.

While we find these results compelling as a proof-of-concept for the potential use of children’s drawings as a diagnostic tool in human crisis settings, we also note several important limitations and caveats to this research. First, while the two datasets are similar in that they both look at Syrian refugee children in Jordan, they have a number of important differences that complicate comparisons and limit the ability to pool the data. These include the lack of self-portrait in the GAGE data, the lack of mental health measure in the USF data, and different age and location profiles. Second, while most of our correlations involving drawing features are consistent with the historical clinical literature, we also find that some are not. Likewise, while we do find broad similarities in results between our two datasets, they are by no means consistent in every instance.

While we present evidence that children's drawing feature characteristics manifest inward facets of psychological health and disorder in children, they are noisy signals. This has several implications for both research and practice. With respect to the latter, it means that for diagnosing and treating individual children, drawing features must be used merely as one tool in the context of a counseling relationship. This is something the clinical psychology literature has always emphasized (Koppitz, 1968, 1984), and new innovations in machine learning do not alter historical best practices in this regard. With respect to research, it implies the need for even larger datasets in more firmly establishing correlations between drawing-features and specific psychological phenomena. While our results do seem to conform with many of the correlations found in the historical clinical psychology literature as well as newer results in economics such as Glewwe et al. (2018), questions remain with respect to the external validity of specific drawing features across refugee and crisis settings. Future work using algorithms to code certain features as well as crowdsourcing for coding to ensure high consistency and inter-rater reliability could improve future analysis. We hope that this initial work is able to create a basis for this and other exciting future research.

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Table 1: Drawing Indicators for Anxiety, Depression, and PTSD for USF and GAGE Datasets

Drawing Indicator	USF Mean (s.d.)	GAGE Mean (s.d.)	Anxiety	Depression	PTSD	Sources
<i>Shading of Face or Body</i>	0.211 (0.408)	N/A	1	1	0	Farokhi and Hashemi (2011), Skybo (2007), di Leo (1983), Klepsch and Logie (1982), Johnson (1971)
<i>Missing Nose or Mouth</i>	0.098 (0.297)	N/A	1	1	0	Klepsch and Logie (1982), di Leo (1983), Skybo (2007), Dolidze (2013)
<i>Frowning or Crying</i>	0.069 (0.253)	N/A	1	1	0	Furth (2002)
<i>Drawn in Dark Colors</i>	0.155 (0.362)	0.210 (0.407)	1	1	0	Wadeson (1971)
<i>Drawn in Single Color</i>	0.199 (0.399)	0.101 (0.301)	1	1	0	Wadeson (1971)
<i>Poor Figural Integration</i>	0.485 (0.500)	N/A	1	1	1	Tibbets (2013)
<i>Smiling (Low Anxiety)</i>	0.601 (0.490)	N/A	-1	0	0	Furth (2002)
<i>Drawn in Light or Cheery Colors</i>	0.154 (0.361)	0.535 (0.499)	-1	0	0	Wadeson (1971)
<i>Sketchy, Broken Lines</i>	0.235 (0.424)	N/A	1	0	0	Di Leo (1983), Klepsch and Logie (1982)
<i>Tiny Figure</i>	0.145 (0.352)	N/A	0	1	1	Skybo (2007), Tibbets (2013)
<i>Faint lines</i>	0.098 (0.297)	N/A	0	1	0	Farokhi and Hashemi (2011)

Table 1 Continued: Drawing Indicators for Anxiety, Depression, and PTSD for USF and GAGE Datasets

<i>Tiny Head</i>	0.094 (0.292)	N/A	0	1	0	Koppitz (1968), Di Leo (1983)
<i>Lack of Details</i>	0.303 (0.460)	0.215 (0.411)	0	0	1	Tibbets (2013)
<i>Political Slogans or Imagery</i>	0.024 (0.153)	0.046 (0.211)	0	0	1	Tibbets (2013)
<i>Focus on Symbols or Memories of Trauma</i>	0.080 (0.271)	0.022 (0.145)	0	0	1	Tibbets (2013)
<i>Lack of Concern with Integrating Background</i>	0.131 (0.338)	0.387 (0.487)	0	0	1	(Tibbets, 2013)
<i>Monster Pictures</i>	0.053 (0.224)	0.009 (0.093)	0	0	1	Peterson and Hardin (1997); Tibbets (2013)
<i>Aggressive Action Figures</i>	0.018 (0.133)	0.008 (0.089)	0	0	1	Magwaza et al. (1993)

Table 2: USF Data, Summary Statistics
Means with Standard Deviations in Parentheses

Covariates	Refugee Camp	Reintegrated	Total
Age	8.864 (1.954)	8.628 (2.037)	8.764 (1.992)
Gender (1 if female)	0.607 (0.489)	0.529 (0.499)	0.574 (0.495)
Family Size	7.035 (1.989)	6.908 (1.793)	6.981 (1.909)
Years in Jordan (as of 2016)	3.057 (0.638)	2.948 (0.654)	3.011 (0.647)
Parental Occupation (Agriculture)	0.052 (0.223)	0.034 (0.182)	0.045 (0.207)
Parental Occupation (Blue Collar)	0.525 (0.500)	0.452 (0.498)	0.494 (0.500)
Parental Occupation (White Collar)	0.0424 (0.202)	0.023 (0.150)	0.034 (0.182)
Urban/Rural (1 if urban)	0.676 (0.468)	0.643 (0.480)	0.662 (0.473)
Population Size (0 if less than 50,000; 1 if between 50,000 and 1,000,000; 2 if greater than 1,000,000)	0.975 (0.496)	0.905 (0.389)	0.945 (0.455)
Outcome Variables:			
Anxiety	0.020 (1.025)	-0.027 (0.965)	0.000 (1.000)
Depression	0.036 (1.042)	-0.048 (0.940)	0.000 (1.00)
PTSD	0.015 (0.975)	-0.020 (1.033)	0.000 (1.000)
Observations	707	524	1,231

Notes: Summary statistics of key variables of interest for the USF data.

Table 3: OLS Regressions on impact of violence and reintegration on Anxiety, Depression and PTSD (USF Data)
Means with Standard Error in Parentheses

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Anxiety	Depression	PTSD	Anxiety	Depression	PTSD	Anxiety	Depression	PTSD
Exposure to Violence	0.021 (0.030)	0.009 (0.044)	0.136*** (0.048)	-	-	-	0.003 (0.028)	-0.018 (0.039)	0.122** (0.048)
Reintegration	-	-	-	-0.112 (0.079)	-0.166*** (0.057)	-0.098** (0.036)	-0.111 (0.080)	-0.167*** (0.059)	-0.087** (0.035)
Age	-0.083*** (0.015)	-0.084*** (0.015)	-0.069*** (0.020)	-0.084*** (0.015)	-0.086*** (0.015)	-0.071*** (0.019)	-0.084*** (0.015)	-0.087*** (0.015)	-0.070*** (0.019)
Gender (1 if female)	-0.554*** (0.053)	-0.462*** (0.054)	-0.432*** (0.064)	-0.562*** (0.051)	-0.477*** (0.052)	-0.429*** (0.064)	-0.563*** (0.051)	-0.475*** (0.053)	-0.439*** (0.064)
Urban/Rural (1 if urban)	0.103 (0.061)	0.121* (0.061)	0.074 (0.075)	0.112** (0.054)	0.125*** (0.044)	0.131* (0.076)	0.110** (0.052)	0.133** (0.052)	0.080 (0.070)
Parental Occupation (Agriculture=1)	0.114 (0.134)	-0.003 (0.139)	-0.146 (0.144)	0.103 (0.137)	-0.028 (0.143)	-0.117 (0.148)	0.102 (0.139)	-0.022 (0.137)	-0.156 (0.145)
Parental Occupation (Blue Collar=1)	-0.045 (0.078)	-0.107 (0.109)	-0.084 (0.072)	-0.053 (0.067)	-0.122 (0.095)	-0.067 (0.074)	-0.054 (0.070)	-0.119 (0.101)	-0.090 (0.070)
Parental Occupation (White Collar=1)	0.003 (0.169)	-0.140 (0.110)	-0.277** (0.111)	-0.018 (0.164)	-0.173 (0.107)	-0.278** (0.115)	-0.018 (0.164)	-0.171 (0.107)	-0.293** (0.111)
Family Size	-0.005 (0.016)	-0.002 (0.019)	-0.002 (0.014)	-0.007 (0.014)	-0.004 (0.017)	-0.008 (0.014)	-0.007 (0.014)	-0.005 (0.016)	-0.003 (0.014)
Population Size (50,000 to 1,000,000=1)	0.055 (0.056)	0.145** (0.061)	0.106 (0.082)	0.062 (0.049)	0.154*** (0.046)	0.120 (0.081)	0.062 (0.050)	0.155*** (0.046)	0.112 (0.080)
Population Size (Greater > 1,000,000=1)	0.139* (0.073)	0.190* (0.110)	0.158 (0.115)	0.123* (0.063)	0.156* (0.081)	0.196* (0.109)	0.121* (0.065)	0.164* (0.094)	0.145 (0.112)
Years in Jordan	0.019 (0.041)	-0.046 (0.032)	0.008 (0.050)	0.012 (0.038)	-0.056* (0.029)	0.005 (0.051)	0.012 (0.038)	-0.056* (0.030)	0.003 (0.048)
Constant	0.937*** (0.208)	1.039*** (0.214)	0.676** (0.328)	1.049*** (0.162)	1.192*** (0.193)	0.846** (0.341)	1.047*** (0.159)	1.205*** (0.179)	0.762** (0.308)
Observations	1,231	1,231	1,231	1,231	1,231	1,231	1,231	1,231	1,231
R-squared	0.106	0.088	0.070	0.108	0.094	0.070	0.108	0.094	0.072
Oster's Delta	0.05	0.03	0.20	-0.21	-0.21	-0.12	-0.21	-0.21	-0.13

Notes: Robust standard errors clustered at the governorate/flight-year level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4: GAGE Data, Summary Statistics on Covariates, Mental Health, and Exposure to Conflict

	Mean (s.d.)		
	Camp	Host	Overall
<i>Covariates</i>			
Age	11.081 (0.809)	11.225 (0.758)	11.174 (0.779)
=1 if Female	0.527 (0.500)	0.491 (0.500)	0.504 (0.500)
Household Size	7.573 (2.187)	7.051 (2.355)	7.233 (2.310)
Years in Jordan	4.839 (1.482)	4.628 (1.977)	4.696 (1.834)
Asset Decile (1-10, higher indicates more assets)	5.442 (2.755)	4.205 (1.638)	4.647 (2.744)
<i>Mental Health and Exposure to Conflict</i>			
GHQ-12 (0-12, higher indicates increased psychological distress)	1.817 (2.007)	2.011 (1.987)	1.942 (1.995)
=1 if Suffers from Psychological Distress (GHQ-12 \geq 3)	0.271 (0.445)	0.334 (0.472)	0.311 (0.463)
Index for Likelihood of PTSD (from drawings)	-0.020 (0.953)	0.011 (1.0254)	0.000 (1.000)
Index for Likelihood of Anxiety/Depression (from drawings)	0.081 (1.260)	-0.045 (0.983)	0.000 (1.000)
Exposure to Conflict	0.837 (0.370)	0.735 (0.442)	0.767 (0.433)
Sample Size	446	803	1,249

Notes: Summary statistics for the GAGE sample of Syrian refugee children aged 10-12 who live in camp or host community in Jordan.

Table 5: OLS Regressions on impact of violence and reintegration on Anxiety, Depression and PTSD (GAGE Data) Means with Standard Error in Parentheses

	Anxiety\ Depression	PTSD	Anxiety\ Depression	PTSD	Anxiety\ Depression	PTSD
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to Violence	0.098** (0.044)	0.111* (0.064)			0.072 (0.048)	0.105 (0.063)
=1 if Live in Host Community (re-integration)			-0.187*** (0.051)	-0.044 (0.066)	-0.179*** (0.051)	-0.039 (0.065)
Age	0.048 (0.055)	0.092*** (0.031)	0.064 (0.055)	0.094*** (0.033)	0.061 (0.056)	0.095*** (0.033)
=1 if Female	-0.329*** (0.054)	- 0.469*** (0.075)	-0.321*** (0.052)	- 0.483*** (0.078)	-0.329*** (0.052)	- 0.469*** (0.076)
Household Size	-0.021 (0.013)	-0.001 (0.011)	-0.026* (0.013)	-0.006 (0.012)	-0.025* (0.013)	-0.002 (0.011)
Years in Jordan	-0.001 (0.019)	-0.008 (0.016)	-0.008 (0.017)	-0.017 (0.015)	-0.004 (0.018)	-0.008 (0.016)
Asset Decile (1-10, higher indicates more assets)	0.003 (0.012)	-0.013 (0.009)	-0.004 (0.012)	-0.016* (0.008)	-0.004 (0.012)	-0.015* (0.009)
Sample Size	1091	1091	1091	1091	1091	1091

Notes: OLS regressions with Robust standard errors clustered at the governorate/flight-year level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 6: Predictors of Psychological Distress (GHQ-12 \geq 3), GAGE Data

	Lasso Coefficient	Post-est OLS coefficient (s.e.)
	(1)	(2)
<i>Selected Terms</i>		
Lack of Details (PTSD)	0.037	0.073*** (0.027)
Lack of Concern with Integrating Background (PTSD)	0.021	0.047 (0.035)
Political Slogans or Imagery (PTSD)	0.061	0.158** (0.062)
Drawn in a Single Color (Anxiety/Depression)	0.036	0.081 (0.064)
<i>Non-Penalized Terms</i>		
Age	-0.004	-0.008 (0.020)
=1 if Female	0.020	0.035 (0.028)
Household Size	0.014	0.013 (0.009)
Years in Jordan	0.007	0.008 (0.007)
Asset Decile (1-10, higher indicates more assets)	-0.006	-0.006 (0.007)
=1 if Host Community	0.051	0.057** (0.028)
Sample Size	1087	1087

Notes: Column (1) of this table shows results from a LASSO model with a k fold cross-validation where we set k =10. Sample size is 1,249. Lambda is 40.066. Non selected terms are: focus on symbols or memories of trauma, monster pictures, aggressive action figures, drawing in dark colors, drawn in a single color, and drawn in light colors. Column (2) shows the coefficient and standard error using OLS with robust standard errors, restricted to the selected and non-penalized terms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Predictors of Exposure to Conflict, GAGE and USF Data

	USF Dataset		GAGE Dataset	
	Lasso Coefficient	Post-est OLS coefficient (s.e.)	Lasso Coefficient	Post-est OLS coefficient (s.e.)
	(1)	(2)	(3)	(4)
<i>Selected Terms</i>				
Shading Face or Body (Anxiety/Depression)	-0.052	-0.097*** (0.020)		
Sketchy or Broken Lines (Anxiety)	0.023	0.054** (0.021)		
Faint Lines (Depression)	0.028	0.054 (0.038)		
Aggressive Action Figure(s) (PTSD)	0.074	0.164*** (0.046)	0.126	0.309** (0.154)
Lack of Details (PTSD)			0.001	0.025 (0.024)
Focus on Symbols or Memories of Trauma (PTSD)			-0.08	-0.187** (0.091)
Monster Pictures (PTSD)			0.109	0.224** (0.119)
Drawn in a Single Color (Anxiety/Depression)			0.019	0.046* (0.024)
Sample Size	1,210	1,210	1,091	1,091
Lamda	0.332		22.715	

Notes: Columns (1) and (3) of this table shows results from LASSO models with a k fold cross-validation where we set k =10. Columns (2) and (4) show the coefficient and standard error using OLS with robust standard errors clustered at the governorate/flight-year level, restricted to the selected and non-penalized terms. Columns (1) and (2) use the USF dataset and columns (3) and (4) use the GAGE dataset.. Non selected terms in column (1) are: missing nose or mouth, frowning or crying, drawing in dark color(s), drawing in single color, poor figural integration, smiling, drawn in light or cherry colors, tiny figure, tiny head, lack of details, symbols or memories of trauma, poor integration of background, monster figure and political symbols or slogans. Non selected terms in column (3) are: lack of concern with integrating background, political slogans or imagery. drawn in dark color(s) and drawn in light colors. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Drawing indicators of PTSD, anxiety, and depression in the GAGE dataset

