# Abstract

The idea that some abilities might be enhanced by adversity is gaining traction. For example, research leveraging the hidden talents approach has uncovered a few specific abilities enhanced by exposure to particular forms of adversity in a given context. Yet, in order for a field to grow, we must not dig too deep, too fast. In this paper, we compliment adaptation-based research with principled exploration. To do so, we draw on the basic insights of adaptation-based research: 1) enhanced performance manifests within individuals and 2) reduced and enhanced performance can co-occur. Although commonly assumed, these assertions are rarely tested. To do so, a variety of ability measures are needed that examine relative performance differences. However, rather than using adaptive-logic to predict which abilities are enhanced or reduced, we develop statistical criteria to help interpret three different data patterns: reduced, enhanced, and intact performance. We use these criteria to analyze data from the Study of Early Childcare and Youth Development (SECCYD) to examine how adversity shapes within-person performance across 10 abilities in the Woodcock Johnson Cognitive and Achievement test batteries. Our goals are to document adversity-shaped cognitive profiles, identify possible drivers of reduced overall performance, map out sets of ‘intact’ abilities, and discover new enhanced abilities. We argue that principled exploration with clear criteria can help break new ground, re-map old territory, and fuel theory development. Our approach thus offers a valuable complement to the adaptive-logic approach that has dominated this emerging area of research to date.

# How does adversity relate to performance across different abilities in the same person?

Developmental science commonly asserts that adversity-exposure during development reduces cognitive performance—a claim founded on decades of empirical findings (Duncan et al., 2017; Farah et al., 2006; Fraley et al., 2013; Hackman et al., 2010; McLaughlin et al., 2019; Raby et al., 2015). In recent years, however, adaptation-based frameworks, rooted in the idea that adversity might enhance certain abilities, have complemented this work—and it is gaining traction (Ellis et al., 2017; Ellis et al., 2022; Frankenhuis, Young, et al., 2020; Frankenhuis & de Weerth, 2013; Frankenhuis & Nettle, 2020). Since its inception, the goal of adaptation-based frameworks has been to inspire a more well-rounded view of adversity and its influence on abilities—one that incorporates both the struggles and strengths of people from disadvantaged backgrounds (Frankenhuis & de Weerth, 2013). As it develops further, the core task of adaptation-based research is to “uncover a high-resolution map of specific cognitive abilities that are enhanced as a result of growing up under high-adversity conditions” (Ellis et al., 2017, p. 562). To uncover this map, researchers have used confirmatory study designs, which have gleaned useful insights. Yet, to cultivate growth in an emerging research program—where there is little known and much to learn—we must not dig too deep, too soon. Without complementary approaches, exclusive use of confirmatory designs can create tunnel vision and miss new insights (McIntosh, 2017; Roisman, 2021; Rozin, 2001; Scheel et al., 2021).

In this paper, we use a complementary approach to confirmatory research: principled exploration. To guide our exploration, we build on two basic insights from adaptation-based research: 1) enhanced performance manifests within individuals, and 2) reduced and enhanced performance can co-occur. The first insight implies we need designs and models that can tease apart both within- and between-person performance differences. The second suggests that, to map out more of the adversity-ability landscape, we must examine multiple abilities measured within the same person. Doing so will allow us to capture cognitive performance profiles that comprise three conceptual data patterns: reduced, intact, and enhanced performance. Past research has focused on reduced and enhanced performance on tests of single abilities. However, we know little about intact abilities, defined as cases where test performance is unrelated to adversity exposure. Thus, our goal is to document adversity-shaped cognitive performance profiles that include reduced, intact abilities, and enhanced test performance patterns.

# **Essential Features and Empirical Insights from Adaptation-based Frameworks**

Adaptation-based research has two essential features. First, it assumes development shapes the individual, and their abilities, to fit the local environment (Frankenhuis, Young, et al., 2020). Second, because environments differ in the challenges they pose (resource-scarcity versus violence exposure), development shapes abilities according to specific challenges. Thus, one’s abilities are thought to match the challenges of one’s lived experience. These features are useful guideposts for confirmatory hypothesis generation. Using them as building blocks, it is possible to construct an intuitive bridge between an ability and an environmental challenge. For example, a researcher might identify a specific challenge posed by a dimension of adversity (e.g., threats to safety in high-crime neighborhoods) and an ability needed to meet the challenge (e.g., enhanced threat detection).

This approach is appealing because it forces researchers to be specific and logically tie together challenges and abilities. It has also been successful in discovering a handful of adversity-enhanced abilities, especially in harsh and unpredictable environments. For example, past work has proposed that constantly changing environments (i.e., unpredictable environments) might shape the ability to track and respond to changing information. Using this logic, research build an intuitive bridge between changing environments and two abilities–attention-shifting and working memory updating—and some empirical data are consistent with this logic (Fields et al., 2021; Mittal et al., 2015; Nweze et al., 2021; Young et al., 2018). However, there are two limitations to this approach. First, previous studies are difficult to compare because they use different measures and designs. Second, the logic behind confirmatory hypotheses is easily flipped. For example, exposure to unpredictable environments is thought to reduce inhibition, or the ability to resist distractions. If opportunities are fleeting and threats are unpredictable, inhibition is costly because focusing on long-term goals might cause one to miss opportunities or fail to detect a threat. But we can also assert the exact opposite. For example, inhibition might be enhanced by unpredictable environments because attending to every possible opportunity or threat will derail most goal-directed actions. Thus, adaptive-logic can afford different or (in some cases) opposing hypotheses. This does not diminish the enterprise—empirical research is the ultimate arbiter—but there is a risk of becoming too focused on a particular corner of hypothesis space, when other regions would be just as reasonable to explore (REFS).

Adaptation-based research has also focused on testing content, or the notion that performance should improve when the testing content matches the lived experience of people exposed to adversity. For example, studies have examined relational memory, attention shifting, and working memory task performance using more ecologically relevant testing content (e.g., social dominance, real-world, and socioemotional stimuli) compared to neutral or abstract content. In some cases, ecologically relevant content appeared to equalize performance for people exposed to adversity, but this depends on the specific adversity measure and task (Frankenhuis, de Vries, et al., 2020; Rifkin-Graboi et al., 2021; Young et al., 2022). Yet, in other studies, conditions thought to be well-matched to the lived experience of those exposed to adversity actually lower performance. For example, youth from low socioeconomic backgrounds tend to score lower on math items about social relations, money, and food—items thought to be particularly relevant to lived experience—compared to other math items (Duquennois, 2022; Muskens, 2019).

In light of various caveats, this body of work has generated at least two empirical insights. First, although it is possible for adversity to enhance performance between individuals (e.g., low versus high adversity exposure), empirical findings suggest effects mostly occur within individuals (Fields et al., 2021; Frankenhuis, de Vries, et al., 2020; Young et al., 2022). Second, associations between specific types of adversity and enhanced performance appears to be context specific—enhancements depend on testing content, context, and ability type (Fields et al., 2021; Frankenhuis, de Vries, et al., 2020; Mittal et al., 2015; Nweze et al., 2021; Young et al., 2018; Young et al., 2022). Yet, adaptation-based studies have looked for abilities in an isolated and piecemeal fashion, in part, because confirmatory designs tend to narrow a study’s scope. This means we know little about how enhanced abilities relate to broader sets of ability measures.

# **Motivating Principled Exploration**

We believe that adaptation-based frameworks can provide useful guideposts. However, one should use shovels, not scalpels, when breaking new ground. Emerging research programs have yet to lay basic groundwork for testing theories, such as auxiliary assumptions or boundary conditions (Scheel et al., 2021). Our aim is to complement adaptation-based, confirmatory research with principled exploration (Flournoy et al., 2020; Rozin, 2001). We see two benefits of this approach. The first is to re-examine established patterns with a new lens. For example, both deficit- and adaptation-based perspectives assume that adversity should reduce performance on standard assessments of cognitive ability (Ellis et al., 2022; Frankenhuis, Young, et al., 2020; Hackman et al., 2010; McLaughlin et al., 2019; Ursache & Noble, 2016). Yet, these tests are often comprised of many different subtests, and individual tests may show unique patterns that diverge from widely used composite scores. The second is to feed theory with useful description. One reason why we know little about broad sets of abilities is that adaptive logic is yet to be developed for some abilities. However, the lack of such logic this does not imply the presence or absence of a functional link. A complementary approach is to explore, describe, and follow up associations between adversity and abilities to aid theory development. Therefore, we return to the map of cognitive abilities that might be shaped by adversity and ask “what territory needs exploration and which areas may need re-mapping?”.

To carefully examine and interpret data in a principled exploration, it is helpful to develop inferential criteria. For example, rather than using adaptive logic to predict which abilities are enhanced or reduced, we can ask what criteria are needed for evaluating and interpreting different data patterns. In addition, research typically focuses on reduced versus enhanced test performance, but performance on some tests might remain intact (unaffected) by exposure to adversity (Frankenhuis, Young, et al., 2020). We know little about the intact performance of people exposed to adversity. We also know little about the drivers of reduced performance on broad and generic measures of ability and achievement. For example, deficit approaches have collapsed many abilities into composites and find that adversity exposure is associated with reduced performance (Fraley et al., 2013; Raby et al., 2015). However, one possibility is that a smaller set of specific performance measures are driving effects. In total, there is still much to learn about how adversity shapes cognitive abilities. Principled exploration can complement confirmatory research in drawing this map, especially in the early stages of a new field.

# The Current Study

We conduct a principled exploration of how adversity relates to performance on a widely-used cognitive achievement battery using longitudinal, prospective data from the Study of Early Childcare and Youth Development (SECCYD). Drawing on the general insights of adaptation-based research, we employ a within-person performance design to explore performance across 10 abilities. This design allows us to assess how exposure to each measure of adversity is associated with relative performance differences across many abilities (see Figure 1). In other words, we can compare specific abilities (e.g., short-term memory performance) to overall performance (within-person average performance on all tests) to get a clear picture of how enhanced and reduced performance manifest in parallel within an individual.

We focus on adversity measures of two constructs: environmental harshness and unpredictability. We focus on these constructs because they feature often in adaptation-based research on cognitive abilities (Ellis et al., 2017; Ellis et al., 2022; Fields et al., 2021; Frankenhuis, Young, et al., 2020; Mittal et al., 2015; Young et al., 2018; Young et al., 2022). Conceptually, harshness is defined as external causes of mortality-morbidity and unpredictability is defined as random variation in harshness over space and time (Ellis et al., 2009). To measure harhness, studies typically use socioeconomic indices, such as income (Belsky et al., 2012; Doom et al., 2016, 2022; Hartman et al., 2018; Li et al., 2018; Simpson et al., 2012; Sung et al., 2016; Szepsenwol et al., 2015, 2019; Zhang et al., 2022). To measure unpredictability, studies have used a wide variety of approaches (see Young et al., 2020), including counting family transitions and computing variability in income scores (Belsky et al., 2012; Hartman et al., 2018; Li et al., 2018).

We use both previously-used (i.e., income for harshness; family transitions and income variability for unpredictability) and unexplored measures for both. Unexplored measures include neighborhood disadvantage (mean for harshness and variability for unpredictability). We leverage data from the 1990 Census about the broader ecological context, which has been used to measure the neighborhood context in the SECCYD previously (Bleil, Spieker, et al., 2021; Bleil, Appelhans, et al., 2021).

We outline two sets of criteria for evaluating results. First, our expectations change according to the conceptual framework. For example, from a traditional deficit perspective, we should expect negative overall effects of adversity. Performance on subtests should closely match the overall effect. In contrast, from an adaptation-based perspective, we expect an overall negative effect but performance on some subtests is either less reduced, intact, or even enhanced.

Our second set of criteria are statistical. Our modeling strategy allows us to quantify performance as a function of adversity in two ways. First, we can test whether the effect of adversity on each subtest is different from zero using a simple slopes test. A positive and negative effect suggests enhanced and reduced performance, respectively. Second, we compare subset performance (simple slope) against overall performance (main effect of adversity across all tests), which is measured by the interaction between subtest category and adversity. This interaction term indicates whether performance is significantly more negative, less negative, or even positive compared to overall performance. For both types of effects, we can determine if they are practically equivalent to either zero (simple effect) or overall performance (main effect). Subtest performance is intact when the effect of adversity on a subtest is practically equivalent to zero. Using these criteria, we position ourselves to identify the drivers of reduced overall cognitive performance, map out sets of ‘intact’ cognitive abilities, and discover (possible) enhancements.

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| Figure 1. Conceptual visualization of Woodcock Johnson statistical models. A) is the main effect of adversity on overall performance. B) is the main effect of a subtest, which reflects the average performance on a subtest. C) is the simple effect (slope) of adversity for a particular subtest. D) is the interaction effect that measures the difference between A and C. A significant simple effect means the C ≠ 0 and a significant interaction means A ≠ C. Put differently, when C is significant, it means that adversity is associated with performance on a subtest. When D is significant, it means that the association between adversity and a subtest (C) is different than the association between adversity and the overall effect (A). |

# Method

## Participants

Families were initially recruited for the NICHD SECCYD in 1991. A total of 1364 families met all the prescreening criteria, namely that mothers: were age 18 or older, did not plan to move, had a newborn without any known disabilities (and could leave the hospital within one week), had no history of substance abuse, could speak English, and lived within one hour driving distance from the research lab and were in a relatively safe neighborhood (NICHD ECCRN, 2005). More information about recruitment and selection procedures is available from the study (see <https://www.icpsr.umich.edu/web/ICPSR/series/00233>). The current analyses included participants with non-missing data on most predictors and outcome variables through age 15 (*N* = 1156).

## Measures

### **Cognitive Ability Test Battery**

We used the Woodcock-Johnson (WJ) Cognitive and Achievement standardized test battery to examine performance across 10 subtests (Woodcock et al., 1990; Woodcock, 1990). The SECCYD administered the WJ five times: in the 54 month, 1st grade, 3rd grade, 5th grade, and 15-year assessments.

There are two WJ test batteries, the cognitive and achievement tests. The WJ cognitive test includes the Memory for Names, Memory for Sentences, Verbal Analogies, Incomplete Words, and Picture Vocabulary subtests (described later). The WJ achievement battery includes Letter-Word Identification, Passage Comprehension, Calculations, Applied Problems, and Word Attack subtests (described later).

For all tests, we analyzed standard scores, which are equivalent to IQ scores (e.g., *M* = 100, *SD* = 15). Using standard scores for subtests puts all tests on the same scale to facilitate comparison (see Figure 2). For each subtest, we averaged standard scores over time to create one score per subtest, per participant. However, the specific set of subtests administered at each assessment varied (see Figure 2). For example, the Verbal Analogies test was measured at grade three and age 15 whereas Passage Comprehension was measured at grades 3, 5, and age 15 (see Table 1). Thus, to create overall scores for each subtest, we averaged over all time points available for each subtest (see <https://tinyurl.com/seccyd-wj-agg-dvs> for code).

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| ***Figure 2.*** WJ subtest standard scores across assessments. Different sets of subtests were administered at each asessment. Scores were averaged over assessments to create an overall subtest score. Vertical histograms reflect distributions of overall scores per subtest. Gray horizontal lines are sampe average scores for all subtests (e.g., overall WJ score). |

**Picture Vocabulary.** This subtest measures verbal comprehension and crystallized knowledge. The test contains 58 items requiring participants to view and name familiar and unfamiliar objects. The test was administered five times: at 54 months, grades 1, 3, 5, and at 15 years. Higher scores indicate more verbal comprehension and more crystallized knowledge.

**Verbal Analogies.** This subtest measures the ability to reason about analogies between relatively simple words. Although the words remain simple, relations between words increase in complexity of over the test items. The test contains 35 items and was assessed twice: at grades 3 and 5. Higher scores indicate more reasoning and more verbal/crystallized knowledge.

**Passage Comprehension.** This subtest test measures the ability to read a short passage and name an appropriate key word that is missing. The test contains 43 items and was administered three times: at grades 3, 5, and at age 15. Higher scores indicate more vocabulary, comprehension, and reading skill.

**Applied Problems.** This subtest contains a set of practical math problems. Participants must read and identify a strategy for solving the problem and execute simple arithmetic calculations. The test contains 60 items and was administered five times: at the 54-month, 1st, 3rd and 5th grade, and 15-year assessments. Higher scores indicate more practical math and problem-solving skill.

**Calculations.** This subtest required participants to solve traditional math problems containing addition, subtraction, multiplication, division, and different combinations of each. The test also includes some geometry and trigonometry problems. Some items require logarithmic operations and calculus. The test contains 58 items and was administered twice: at the 3rd and 5th grade assessments. Higher scores indicate more mathematical/quantitative skill.

**Memory for Names.** This subtest is an auditory-visual association test. It requires participants to learn a set of ‘space creatures’ and their names. After learning a set of creature-name pairs, participants are presented with nine creatures and must identify which were just shown and which were shown previously. The test difficulty is controlled by (decreasing) increasing the create-name pairs presented in each set. The test contains 72 items and was administered twice: at the 1st and 3rd grade assessments. Higher scores indicate more visual-auditory association and long-term memory skill.

**Incomplete Words.** This subtest measures the ability to listen to words containing missing phonemes and complete the word. The test contains 40 items and was administered twice: at the 54 month and 1st grade assessments. Higher scores indicate more auditory processing skill.

**Memory for Sentences.** This subtest measures the ability to listen to and remember words, phrases, and sentences. The words, phrases, and sentences are played on an audio tape and participants must recall as many as possible. The test contains 32 items and was administered three times: at the 54-month, 1st grade, and 3rd grade assessments. Higher scores indicate more short-term memory skill.

**Letter-word Identification.** This subtest measures reading and pronunciation ability. Participants must initially read letters and then words, which gradually increase in difficulty. The test contains 57 items and was administered four times: at the 54-month, 1st, 3rd, and 5th grade assessments. Higher scores indicate more verbal knowledge.

**Word Attack.** This subtest measures the ability to pronounce unfamiliar words. Participants must read aloud phonetically logical but nonsense or infrequent words. It contains 30 items and was administered twice: at the 1st and 3rd grade assessments. Higher scores indicate more auditory processing and linguistic structural analysis knowledge and skill.

| **Table 1. Bivariate correlations and descriptive statistics for WJ subtests.** | | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 1. Passage Comprehension | - |  |  |  |  |  |  |  |  |  |
| 2. Picture Vocab | 0.66\*\* | - |  |  |  |  |  |  |  |  |
| 3. Calculations | 0.75\*\* | 0.75\*\* | - |  |  |  |  |  |  |  |
| 4. Verbal Analogies | 0.66\*\* | 0.73\*\* | 0.76\*\* | - |  |  |  |  |  |  |
| 5. Letter-Word Pronunciation | 0.61\*\* | 0.56\*\* | 0.66\*\* | 0.64\*\* | - |  |  |  |  |  |
| 6. Short-Term Memory | 0.49\*\* | 0.43\*\* | 0.48\*\* | 0.51\*\* | 0.50\*\* | - |  |  |  |  |
| 7. Applied Problems | 0.45\*\* | 0.42\*\* | 0.47\*\* | 0.43\*\* | 0.35\*\* | 0.30\*\* | - |  |  |  |
| 8. Auditory Processing | 0.64\*\* | 0.63\*\* | 0.78\*\* | 0.71\*\* | 0.57\*\* | 0.47\*\* | 0.50\*\* | - |  |  |
| 9. Unfamilar Words | 0.48\*\* | 0.55\*\* | 0.67\*\* | 0.59\*\* | 0.47\*\* | 0.39\*\* | 0.43\*\* | 0.84\*\* | - |  |
| 10. Auditory-Visual Associations | 0.50\*\* | 0.58\*\* | 0.65\*\* | 0.76\*\* | 0.46\*\* | 0.43\*\* | 0.39\*\* | 0.65\*\* | 0.60\*\* | - |
| N | 1156 | 1064 | 1080 | 1155 | 1142 | 1092 | 1103 | 1154 | 1103 | 1075 |
| Mean | 102.64 | 111.08 | 108.63 | 107.91 | 97.04 | 96.21 | 105.39 | 106.94 | 106.84 | 112.10 |
| SD | 13.65 | 15.65 | 12.85 | 13.62 | 14.68 | 10.74 | 13.32 | 13.14 | 14.30 | 16.72 |
| Min | 31.50 | 50.00 | 42.00 | 33.50 | 45.00 | 39.00 | 46.00 | 30.00 | 54.00 | 12.00 |
| Median | 102.55 | 110.25 | 108.67 | 108.67 | 96.33 | 96.50 | 105.00 | 107.00 | 106.00 | 113.50 |
| Max | 147.00 | 156.00 | 146.00 | 149.00 | 144.00 | 128.00 | 162.00 | 150.00 | 152.00 | 178.50 |
| *Note: \* p* < .05, *\*\* p* < .01 | | | | | | | | | | |
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### Indicators of Harshness

We measured environmental harshness in two ways. First, following previous studies using data from the SECCYD, we used family income-to-needs ratio scores from 1, 6, 15, 24, 36, and 54-month assessments (Belsky et al., 2012; Hartman et al., 2018; Li et al., 2018; Sung et al., 2016; Zhang et al., 2022). We calculated a simple average of all income-to-needs scores across assessments to create an overall income-to-needs score (see <https://tinyurl.com/seccyd-wj-agg-income> for code). We reverse-scored income-to-needs mean scores to create a family income disadvantage score where higher values indicate more disadvantage.

Second, we used data from the 1990 Census about the broader economic and ecological context in a similar way to previous analyses of neighborhood-level socioeconomic conditions in the SECCYD (Bleil, Spieker, et al., 2021; Bleil, Appelhans, et al., 2021). Specifically, addresses were tracked for each participant over time. Each family address start and stop dates were recorded, geocoded, and linked to the 1990 decennial Census blocks. These blocks are the smallest Census-tracked geographical unit. For each Census block, sociodemographic data were extracted from the Census databases to measure neighborhood-level economic conditions for each participant. We extracted five variables: 1) percent of people living under the poverty line, 2) median household income, 3) Gini coefficients of income inequality based on income frequency data, 4) percent of unemployed individuals over 16 in the workforce, and 5) the percent of occupied houses that were being rented. These neighborhood variables were standardized and then averaged to create a neighborhood socioeconomic disadvantage score for each home a participant lived in. Next, we averaged these neighborhood scores over time (up until the 54-month assessment). Thus, if a participant lived in two homes between birth and the 54-month assessment, neighborhood-level variables would be standardized and averaged within the first and second Census block, and then averaged between them. These scores served as measures of neighborhood socioeconomic disadvantage where higher scores indicate higher rates of poverty, income-inequality, unemployment, lower education, and more rental housing (see <https://tinyurl.com/seccyd-wj-processing-census> for processing and <https://tinyurl.com/seccyd-wj-agg-census> for aggregation).

### **Indicators of Unpredictability**

Environmental unpredictability is notoriously hard to define and measure (Young et al., 2020). Studies leveraging data from the SECCYD have used two approaches. The first is track and count family transitions, including changes in paternal figures living in the home, parental job transitions, and residential changes (Belsky et al., 2012; Hartman et al., 2018). The second approach is to quantify variability in repeated measures of harshness indicators (e.g., computing variance in family income disadvantage across time). For example, Li and colleagues (2018) fit a linear model to each participants’ income-to-needs scores over time. Then, they computed the residual variance around participant-level linear trends in income-to-needs to create an income variability score. In the current study, we compute unpredictability scores using both approaches and extend the Li and colleagues (2018) approach to the neighborhood-level Census block data.

To calculate family transitions, we computed the number of paternal figure changes (father figures moving in and out of the home), mother and father (figure) job changes, and residential changes across 17 assessments from 1 to 54 months (Belsky et al., 2012; Hartman et al., 2018). After computing scores across time, we standardized each variable and averaged them together to compute an overall family transitions variable (see <https://tinyurl.com/seccyd-wj-agg-transitions> for code).

We calculated variability scores for both family income and neighborhood socioeconomic disadvantage. For, family income disadvantage scores, we computed a standard deviation of all income-to-needs scores for each participant from the 1, 6, 15, 24, 36, and 54-month assessments (see <https://tinyurl.com/seccyd-wj-agg-income> for code). For neighborhood socioeconomic disadvantage variability, we computed the standard deviation of neighborhood socioeconomic disadvantage scores (see Indicators of Harshness, above). If participants had only lived in one Census block from 1 to 54 months, their neighborhood socioeconomic disadvantage variability score was zero (see <https://tinyurl.com/seccyd-wj-agg-census> for code).

### **Control Variables**

We used a standard set of three control variables typically used in analyses of SECCYD data: 1) maternal education, 2) sex assigned at birth (1 = female), and 3) the race/ethnicity of each child coded as White/non-Hispanic = 0, otherwise = 1[[WF1]](#Xd8c3846978d47bdf5af6a8f09caf94b87f551a5) .

[[WF1]](#X8d324fc7bb1d799b5d36acc94a659546b34a12f)Some readers may criticize this choice. Perhaps we should motivate it or discuss it as a limitation later (adding a parenthetical here stating that we will do so).

| **Table 2. Bivariate correlations and descriptive statistics for adversity measures.** | | | | | |
| --- | --- | --- | --- | --- | --- |
| Variable | 1 | 2 | 3 | 4 | 5 |
| 1. Family Transitions | - |  |  |  |  |
| 2. Family Income Disadvantage | 0.34\*\* | - |  |  |  |
| 3. Family Income Variability | -0.11\*\* | -0.70\*\* | - |  |  |
| 4. Neigh. Socioeconomic Disadvantage | 0.25\*\* | 0.45\*\* | -0.24\*\* | - |  |
| 5. Neigh. Socioeconomic Variabibiliy | 0.44\*\* | 0.19\*\* | -0.06\* | 0.31\*\* | - |
| N | 1155 | 1154 | 1146 | 1139 | 1139 |
| Mean | 0.04 | -3.52 | 1.11 | -0.02 | 0.02 |
| SD | 0.71 | 2.68 | 1.17 | 0.74 | 0.80 |
| Min | -0.82 | -23.79 | 0.00 | -1.95 | -0.69 |
| Median | -0.15 | -2.87 | 0.82 | -0.10 | -0.11 |
| Max | 3.86 | -0.17 | 17.78 | 3.35 | 3.09 |
| *Note: \* p* < .05, *\*\* p* < .01 | | | | | |
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# Results

## Preregistration, Statistical Power, and Computational Reproducibility

We preregistered this study using a template for secondary data analysis (Akker et al., 2021). The preregistration document and its entire version history was tracked on GitHub (see <https://tinyurl.com/seccyd-wj-prereg> for the document and <https://tinyurl.com/seccyd-wj-prereg-history> for revision history).

We also conducted a power analysis as part of our preregistration (see <https://tinyurl.com/seccyd-wj-power> for write up and see <https://tinyurl.com/seccyd-wj-power-code> for code). In short, we used a simulation approach to conduct power analyses. Although we simulated adversity scores, we used the actual WJ test scores from SECCYD data used in this study. Simulations showed that, with a sample size of (*N* = 1156), the smallest interaction effect we can detect is = -.075 (or .075) with 90% power, if error is small. When error is larger, we can detect the same effect size with only 65% power. However, even with larger error, we can detect a = -.10 (or .10) with 83% power.

All relevant files (data processing, analysis code, manuscript etc.) for this project are tracked on GitHub (see <https://tinyurl.com/seccyd-wj>), including data needed to reproduce all results (see <https://tinyurl.com/seccyd-wj-data>). Raw data (data provided by SECCYD) is only available via Inter-university Consortium for Political and Social Research (ICPSR, see <https://www.icpsr.umich.edu/web/pages/>). However, documentation for the study is free to download (see <https://www.icpsr.umich.edu/web/ICPSR/studies/21940>), which contains lists of raw datasets and variables. For those who have access to raw SECCYD data, we provide a table of raw datasets and variables used in this project (see <https://tinyurl.com/seccyd-wj-data>).

We used R, Rstudio, and Quarto to process, analyze, and report results (Allaire, 2022; Posit team, 2023; R Core Team, 2023). For reading raw SECCYD data, used the haven and readxl R packages (Wickham et al., 2023; Wickham & Bryan, 2023). For data processing, visualizations, and table creation, we used the tidyverse, sjlabelled, ggdist, ggsci, and the patchwork R packages (Gohel & Skintzos, 2023; Kay, 2023; Lüdecke, 2022; Pedersen, 2022; Wickham et al., 2019; Xiao, 2023). For analyses, including mixed models, simple slopes, and equivalence tests, we used lme4, faux, ggeffects, marginaleffects, and the parameters R packages (Arel-Bundock, 2023; Bates et al., 2015; DeBruine, 2023; Lüdecke, 2018; Lüdecke et al., 2020).

## Data Analysis Strategy and Inferential Criteria

We used a mixed effects modeling approach to analyze how adversity relates to WJ performance. For our primary analyses, we ran one model per adversity variable. Each model contained sex assigned at birth, race/ethnicity, and maternal education as covariates. Adversity and covariates were standardized or recoded to center variables at zero.

To analyze and compare WJ subtest performance with overall WJ performance, we restructured the data so that each participant was represented by 10 rows, one for each WJ subtest score. Then, we created a sum-coded contrast variable for WJ subtests with 10 levels (one for each subtest). This type of contrast sets the model intercept to the grand mean (e.g., the mean of all subtest scores). To analyze the effects of adversity on test performance, we entered adversity as a main effect and the interaction between adversity and the contrast-coded subtest variable.

A model with this structure will contain a main effect for each covariate, a main effect of adversity, and an interaction term for each subtest (i.e., 10 interaction terms). The main effect of adversity reflects the association between adversity and overall WJ performance (e.g., within-person average of all subtests; see Figure 1). Interaction terms reflect the association between adversity and subtest performance *compared to the main effect of adversity* (see Figure 1). That is, they reflect the difference between the effect of adversity on overall performance and simple effects of adversity on subtest performance (see Figure 1). Whereas simple effects test whether an association between adversity and subtest performance is different from zero, interaction terms measure whether a simple effect is different from the main effect.

Using this modeling strategy, we compute three types of effect sizes: 1) the main effect of each adversity measure (tested in separate models), 2) the interaction effect between an adversity measure and subtest, and 3) the simple effect of adversity for each subtest. We do not have specific point or range predictions for the effect size types above. However, we decided a priori (see preregistration at <https://tinyurl.com/seccyd-wj-prereg>) to consider standardized regression coefficients (i.e., ’s) of .10 (or higher) and -.10 (or lower) as meaningful. For main effects, coefficients outside this range indicate that overall performance is meaningfully positive or negative across levels of adversity. For interactions, effect sizes outside these bounds indicate that associations between adversity and subtest performance are meaningfully more negative or more positive than overall performance. For simple effects, effects outside these bounds indicate that the effect of adversity on a specific subtest is meaningfully different from zero.

We are also interested in null effects. Specifically, we use equivalence testing to determine if a given effect is practically equivalent to a Range of Practical Significance (ROPE). We chose a ROPE falling between  = -.10 and  = .10 (Kruschke, 2018; Lakens et al., 2018). Although we report standardized coefficients, we converted our ROPE to the WJ standard score scale by multiplying the standard deviation of standard WJ scores (*SD* = 15) by .1. This means our ROPE was -1.5 to 1.5 for unstandardized coefficients.

To guide interpretation, we apply a set of inferential criteria for categorizing data patterns. We are interested in three data patterns: 1) enhanced performance, 2) reduced performance, and 3) intact performance. We infer ‘enhanced performance’ when main and simple effects are positive, statistically different from zero, and outside the ROPE. We infer ‘reduced performance’ when main and simple effects are negative, statistically different from zero, and outside the ROPE. We infer intact performance when a main or simple effect (and its confidence bounds) is practically equivalent to zero (i.e., falls inside the ROPE).

We use the same criteria for interaction terms with one difference. Because interaction terms test the difference between main and simple effects, they quantify relative performance patterns. For ‘enhanced relative performance’, interaction terms must be meaningfully positive (outside the ROPE) and statistically significant. For ‘reduced relative performance’, an interaction term must be meaningfully negative (outside the ROPE) and statistically significant. Interaction terms that are practically equivalent to zero reflect simple effects that closely resemble the main effect on overall performance. However, inferring ‘enhanced’, ‘reduced’, or ‘intact’ relative performance depends on the size and direction of the main effect. We are particularly interested in cases where a main effect is negative and interaction terms are positive. This may reflect ‘enhanced relative performance’ (e.g., meaningful and significant positive interactions), or ‘less reduced’ performance on a particular subtest in the context of an overall reduced pattern of performance.

## Primary Analyses

Our primary analyses examined how indicators of harshness and unpredictability were associated with WJ overall and subtest performance. We ran one mixed model per indicator for a total of five primary analyses (two for harshness and three for unpredictability).[[WF1]](#Xd8c3846978d47bdf5af6a8f09caf94b87f551a5)

[[WF1]](#X8d324fc7bb1d799b5d36acc94a659546b34a12f)Here we can add a note about whether or not we correct for multiple testing. We have yet to decide this. I’m not sure. If we don’t because we’re doing exploratory work and are not interpreting p-values as support for a ‘hypothesis’, it would be good to make this explicit for our readers.

All analyses controlled for the main effects of maternal education, race/ethnicity, and sex assigned at birth. Across all models, there were main effects for both maternal education and race/ethnicity. Lower maternal education and having a non-White racial/ethnic background was associated with lower WJ overall performance. No model contained effects for sex assigned at birth. Below we describe the effects of our primary analysis predictors (see Supplement Table 1). Primary analysis code can be found on GitHub (see <https://tinyurl.com/seccyd-wj-primary>).

### Indicators of Harshness

**Family Income Disadvantage (mean)**. Our mixed model analyzed the effect of family income disadvantage on overall compared with subtest WJ performance. There was a main effect of family income disadvantage such that a higher disadvantage was associated with lower overall WJ performance. Equivalence tests show that this overall main effect was meaningfully negative (outside the ROPE, see Figure 3).

Interaction effects between family income disadvantage and subtests revealed a more nuanced landscape of associations. The association between disadvantage and performance on Passage Completion, Calculations, Verbal Analogies, Letter-Word, Short-Term Memory, and Unfamiliar Words subtests did not differ from the overall main effect (see Figure 3). However, the association between disadvantage and performance on the Picture Vocabulary subtest was significantly and meaningfully more negative than the overall main effect (see Figure 3). Interestingly, the association between disadvantage and performance on the Auditory Processing, Unfamiliar Words, and Auditory-Visual Associations subtests were significantly more positive than the overall main effect (see Figure 3). However, equivalence tests suggest that the disadvantage and Unfamiliar Words performance association was inside the ROPE, and thus practically equivalent to the main effect. The association between disadvantage and Auditory Processing and Auditory-Visual performance were outside the ROPE.

Our simple effects analysis tested whether the associations between family income disadvantage and subtest performance was statistically different from zero and whether they were practically equivalent to the ROPE (see Figure 3). Analyses revealed that the association between family income disadvantage and each of the subtests where significantly and meaningfully negative, except for the Auditory Processing, Unfamiliar Words, and Auditory-Visual Associations subtests (see Figure 3). For these tests, the association between income disadvantage and test performance was not statistically different from zero and practically equivalent to the ROPE (see Figure 3).

Based on our inferential criteria, the main effect of family income disadvantage suggests that higher income disadvantage was associated with reduced overall performance. Simple effects also revealed mostly reduced performance on each subtest. However, for the Picture Vocabulary subtest, the income disadvantage-performance association was significantly and meaningfully more negative than the overall pattern, suggesting performance on this test was particularly reduced for income disadvantaged families. Interestingly, three subtests showed relative enhancement to the overall pattern of income disadvantage: Auditory Processing, Unfamiliar Words, and Auditory-Visual Associations subtests. Yet, only the associations between income disadvantage and the Auditory Processing and Auditory Visual Associations subtest performance were outside the ROPE. However, simple effects were not consistent with enhancement. Instead, simple effects revealed that the income disadvantage-performance associations between the Auditory Processing, Unfamiliar Words, and Auditory-Visual Associations were inside the ROPE, suggesting higher income disadvantage was associated with intact performance on these tests.

**Neighborhood Socioeconomic Disadvantage (Mean)**. Analyses revealed a main effect of neighborhood socioeconomic disadvantage such that a living in a high neighborhood socioeconomic disadvantage was associated with reduced overall WJ performance (see Figure 3). Equivalence tests show that this overall main effect was outside the ROPE.

Interaction effects between neighborhood socioeconomic disadvantage and subtest were varied. Associations between socioeconomic disadvantage and subtest performance on Passage Completion, Calculations, Letter-Word, and Short-Term Memory did not statistically differ from the overall main effect (see Figure 3). However, neighborhood socioeconomic disadvantage and subtest performance associations for the Picture Vocabulary, Verbal Analogies, and Applied Problems subtests were significantly more negative than the main effect (see Figure 3). However, equivalence tests showed that only the association between socioeconomic disadvantage and Verbal Analogies subtest performance was meaningfully more negative than the main effect. Similar to the family income disadvantage analysis, neighborhood socioeconomic disadvantage was associated with significantly more positive performance for the Auditory Processing and Auditory-Visual Associations compared to the overall main effect. Equivalence tests revealed that both associations were also meaningfully more positive, suggesting that performance on these tests were relatively enhanced (compared to the main effect) for participants living in socioeconomically disadvantaged neighborhoods (see Figure 3).

Simple effects revealed that higher neighborhood socioeconomic disadvantage was associated with statistically and meaningfully negative performance for all subtests except for the Auditory Processing and Auditory-Visual Associations subtests. Again, for these two subtests, performance among those living in socioeconomically disadvantaged neighborhoods was not statistically or meaningfully different from zero.

According to our inferential criteria, results suggest that the main effect of neighborhood socioeconomic disadvantage is consistent with reduced overall pattern of performance. For the Verbal Analogies subtest, high neighborhood socioeconomic disadvantage was associated with particularly reduced performance compared with the main effect. However, high neighborhood disadvantage and performance associations for the Auditory Processing and Auditory-Visual Associations subtests were consistent with relative enhancement. Similar to the family income disadvantage results, simple effects were not consistent with enhancement and instead revealed mostly reduced performance. For the Auditory Processing and Auditory-Visual Associations subtests, however, simple effects suggest that performance remained intact at higher levels of neighborhood socioeconomic disadvantage.

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| **Figure 3.** Results of models testing the effect of family and neighborhood economic disadvantage on WJ performance. The top and bottom rows depict family and neighborhood socioeconomic disadvantage, respectively. The left column plots the overall slope (thick black lines) against the subtest slopes across low to high socioeconomic disadvantage Unfaded and faded lines are practically inequivalent and equivalent to the overall slope, respectively. The middle and right columns show interaction and simple effects. Black horizontal lines are the main effect and zero for interactions and simple effects, respectively. The gray ribbon reflects the ROPE. Solid points indicate interactions and simple effects that are practically equivalent to the ROPE. Hollow points reflect interaction and simple effects that are outside the ROPE. Statistical significance for interactions (tested against the main effect) and simple effects (tested against zero) are flagged with significance stars. \*\*\* *p* < .001, \*\* *p* < .01, \* *p* < .05 |

### Indicators of Unpredictability

**Family Transitions**. Our analysis of family transitions revealed no main effect on overall WJ performance. The main effect also fell inside the ROPE range, suggesting that overall performance was not associated with exposure to more family transitions (see Figure 4).

Three interaction terms were statistically significant: Calculations (more negative), Auditory Processing (more positive), and Audio-Visual Associations (more positive). However, only the association between family transitions and performance on the Calculations was meaningfully different from the main effect (see Figure 4).

Simple effects showed that exposure to family transitions was not associated with subtest performance, except the Calculations and Applied Problems subtests. For Calculations, exposure to more family transitions was associated with significantly and meaningfully lower performance. For Applied Problems, more family transitions were associated with meaningfully lower performance, but this difference was not statistically different from zero (i.e., the association was not significant but was outside the ROPE).

Our inferential criteria suggest that exposure to family transitions was associated with intact overall WJ performance. Simple effects suggest that performance on most subtests was also largely intact among those exposed to family transitions. However, for the Calculations subtest, more family transitions were related to a pattern of reduced performance.

**Family Income Variability (*SD*).** Models unpacking the effect of family income variability on WJ overall and subtest performance yielded surprising results. Specifically, the directions of all effects were opposite to analyses using family income average scores. For subtests that showed reduced performance at high *mean* levels of family income disadvantage, we found enhanced performance at high levels of *variability* in family income. We believe such effects are driven by the fact that family income disadvantage mean and variability scores are strongly negatively related (*r* = -0.70), which has been reported before elsewhere (Li et al., 2018). That is, families experiencing more income disadvantage tended to experience less income variability. Put differently, richer families were more likely to experience income fluctuations.

This raises questions about using family income variability as an indicator of adversity. In most empirical cases, higher levels of harshness are associated with higher levels of unpredictability. Yet here, income variability and average income are correlated in the opposite direction. One possibility is that it matters how variability scores are computed over repeated measures of income. Thus, to unpack this issue, we conducted a set of secondary analyses that use different methods for computing variability over income-to-needs scores. We report analyses using different methods for quantifying variability in our Secondary Analyses (see <https://tinyurl.com/seccyd-wj-update1> for the update to our analysis plan).

**Neighborhood Socioeconomic Variability**. In contrast to family income variability, more neighborhood socioeconomic variability was related to higher average neighborhood socioeconomic disadvantage. That is, families living in more socioeconomically disadvantaged neighborhoods (more harsh) were more likely to experience variability in neighborhood economic disadvantage (more unpredictable) from one to 54 months (*r* = 0.31). Additionally, the associations between average and variability scores were moderate rather than strong (see Table 2).

There was no main effect of neighborhood socioeconomic variability on overall WJ scores (see Figure 4). There was only one significant interaction with subtest performance. High neighborhood socioeconomic variability was associated with higher Audio-Visual Associations performance compared to overall performance. However, this effect was inside the ROPE, suggesting it was not meaningfully different from the overall effect. In addition, simple effects showed that high neighborhood socioeconomic variability was not associated with performance on any subtest and all simple effects were inside the ROPE.

Based on our inferential criteria, high neighborhood socioeconomic variability was associated with intact performance for overall and individual subtest performance.

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| **Figure 4.** Results of models testing the effect of family transitions and neighborhood socioeconomic variability on WJ performance. The top and bottom rows reflect family transitions and neighborhood socioeconomic variability, respectively. The left column plots the overall slope (thick black lines) against the subtest slopes across low to high unpredictability. Unfaded and faded lines are practically inequivalent and equivalent to the overall slope, respectively. The middle and right columns show interaction and simple effects. Black horizontal lines are the main effect and zero for interactions and simple effects, respectively. The gray ribbon reflects the ROPE. Solid points indicate interactions and simple effects that are practically equivalent to the ROPE. Hollow points reflect interaction and simple effects that are outside the ROPE. Statistical significance for interactions (tested against the main effect) and simple effects (tested against zero) are flagged with significance stars. \*\*\* *p* < .001, \*\* *p* < .01, \* *p* < .05 |

## Secondary Analyses

Our primary analyses examining family income variability raised questions about its validity as an adversity measure. Our secondary analyses were designed to address this issue and explore different methods of computing variability scores (see <https://tinyurl.com/seccyd-wj-update1> for the secondary analysis plan).

We computed three types of variability scores over the income-to-needs data. The first was identical to our primary analyses; we computed a within-person standard deviation of income-to-needs from 1 to 54 months. Second, we computed residual standard deviations (Li et al., 2018). To do so, we fit a linear slope to each participant’s income-to-needs data, extracted residual scores, and computed the standard deviation of these residuals.

The last method computed percent change scores over each participant’s income-to-needs data. In time series analysis, percent change reflects how much a score changes relative to the previous time point and scales income accordingly. For example, if one’s income is $1,000 at one time point and increases to $1,500 at the next time point, their percent change score would be .50 or 50% ($500 increase is half of income at the first time point). The percent change score is always relative to the previous time point so if income increases another $500 at time point 3, the percent change score would be .33 or 33% ($500 is 1/3 of the second time point income of $1,500). For low income families, percent change scores can account for the fact that smaller income fluctuations have a larger impact: a family with a monthly income of $1,500 that loses $500 the next month (33% of their income) is impacted more than a family earning $5,000 a month (10% of their income). After computing percent change scores for each assessment, we averaged percent change scores to create a single percent change score per participant.

Simple and residual standard deviation family income scores were strongly related to both each other and to the average family income disadvantage (see Table 3). However, average percent change scores were only weakly related to income standard deviation and residual standard deviation scores. In addition, average percent change in income scores were weakly and positively related to mean family income disadvantage scores (*r* = 0.17, see Table 3). That is, families experiencing higher mean levels of income disadvantage also experienced larger average percent changes in income over time. This aligns with prior conceptual and empirical work that expects and finds that harsher environments tend to be more unpredictable (Belsky et al., 2012; Brumbach et al., 2009; Ellis et al., 2009; Simpson et al., 2012; Szepsenwol et al., 2015).

| **Table 3. Bivariate correlations and descriptive statistics for family income variability scores.** | | | | |
| --- | --- | --- | --- | --- |
| Variable | 1 | 2 | 3 | 4 |
| 1. Mean | - | 1146 | 1140 | 1146 |
| 2. Standard Deviation | -0.70\*\* | - | 1140 | 1146 |
| 3. Residual Standard Deviation | -0.67\*\* | 0.95\*\* | - | 1140 |
| 4. Average Percent Change | 0.17\*\* | 0.16\*\* | 0.19\*\* | - |
| N | 1154 | 1146 | 1140 | 1146 |
| Mean | -3.52 | 1.11 | 1.02 | 0.59 |
| SD | 2.68 | 1.17 | 1.10 | 0.83 |
| Min | -23.79 | 0.00 | 0.00 | 0.00 |
| Median | -2.87 | 0.82 | 0.74 | 0.35 |
| Max | -0.17 | 17.78 | 14.39 | 12.16 |
| *Note: \* p* < .05, *\*\* p* < .01 | | | | |
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After computing each type of family income variability scores, we ran three analyses with each as the primary predictor. We used the same modeling strategy, covariates, and inferential criteria as our primary analyses. Findings revealed similar patterns for both simple and residual standard deviation scores: more variability in family income was associated with enhanced performance, in contrast to the negative associations with average family income disadvantage (see Figure 5). Again, we believe this is an artifact of the relation between family income average and variability scores.

In contrast, however, average family percent change in income did not follow this pattern. Instead, higher percent changes in income were consistent with intact overall WJ test performance. The only subtest that differed from the overall effect was the Calculations subtest, which showed that higher percent changes in income was associated with a significant, but not meaningful, reduction in performance. Simple effects showed higher percent changes in income were associated with intact performance for all subtests except the Auditory Processing subtest, which was meaningfully more positive but not statistically different from zero.

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| **Figure 5.** Results of models testing the effect of different family income variability scores on WJ performance. The top, middle, and bottom rows reflect simple standard deviation, residual standard deviation, and average percent change in family income from one to 54 months. The left column plots the overall slope (thick black lines) against the subtest slopes across low to high variation in family income Unfaded and faded lines are practically inequivalent and equivalent to the overall slope, respectively. The middle and right columns show interaction and simple effects. Black horizontal lines are the main effect and zero for interactions and simple effects, respectively. The gray ribbon reflects the ROPE. Solid points indicate interactions and simple effects that are practically equivalent to the ROPE. Hollow points reflect interaction and simple effects that are outside the ROPE. Statistical significance for interactions (tested against the main effect) and simple effects (tested against zero) are flagged with significance stars. \*\*\* *p* < .001, \*\* *p* < .01, \* *p* < .05 |

# Discussion

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