Parental Personality and Child Skills Formation

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This paper studies the influence of parental personality on child development. I exploit detailed individual-level data from the PSID and its Child Development and Wellbeing Supplements on parental personality, children's skills, wages, and time-use decisions. Our empirical results suggest a systematic gap in cognitive and non-cognitive skills between children of parents with different personalities. This skills gap increases as children grow older and remains significant after accounting for traditional family attributes. To provide a rationale for these observed patterns, I estimate a life cycle model that incorporates parental personality and considers household decisions with endogenous formation for a child's cognitive and non-cognitive skills. In this framework, parental personality affects the monetary and time inputs in children as well as the type of interactions between parents and children. Our simulations suggest that most of the influence of personality on a child's skills is through its effect on the quality of parent-child interactions. Also, cash transfer policies that do not account for the productivity associated with parental personality can have unexpected, negative effects on child development.

Keywords: Child Development, Household Choices, Personality Traits
JEL Codes: D13, D91, J22, J24

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1. Introduction

Understanding the factors influencing child skill development is a key challenge across disciplines. Early life deficits and inequalities have lasting impacts, shaping outcomes throughout a person's life (Attanasio, Cattan, and Meghir, 2022). A large body of evidence demonstrates that differences in parental investments and the quality of parent-child interactions play a crucial role in early childhood development (Heckman and Mosso, 2014). Increasingly, studies recognize that parental personality may be a key factor influencing parenting behavior beyond traditional family characteristics such as parental education or socioeconomic status (Prinzie, de Haan, and Belsky, 2019). Evidence suggests that parental personality influences early childhood development more than parental cognitive skills (Cunha, Heckman, and Schennach, 2010). However, the underlying mechanisms driving this relationship remained largely unexplored. In what ways does parental personality influence child skills? To what extent does the personality of parents affect their investments in children? Does personality shape the type of interaction between parents and children?

The goal of this paper is to address these questions by examining the impact of parental personality on the formation of child skills throughout the developmental cycle. I quantify the mechanisms driving this relationship by combining descriptive analyses with a dynamic framework of household choices and endogenous skill formation. This empirical framework allows us to disentangle between different features of parental personality that influence household behavior and children's development.

I use data from couples and single parents collected through the Panel Study of Income Dynamics (PSID, 1997—2019 waves) and its supplements, the Child Development Supplement and the Wellbeing Supplement. These supplements provide not only detailed parental time-use surveys, test scores, and socioemotional scales taken at various stages of a child's development but also measures of parental personality based on the Big Five personality traits (Borghans et al., 2008). By applying clustering methods to this observed set of personality traits, I construct personality types rooted in developmental psychology theory, which are utilized throughout the analysis (Belsky, 1984).

In the first part of the paper, we present descriptive evidence on the links between parental personality, wages, labor supply decisions, and children's skills. I show that children of *emotionally stable* parents consistently perform better than children of *emotionally vulnerable* parents in both cognitive and non-cognitive skill measures. Our empirical findings reveal a systematic average gap in children's skills, ranging from 0.1 to 0.4 standard deviations. The average skills gap widens as children grow older and remains significant even after accounting for traditional family characteristics, such as parental education, household income, or parental health status. Our results also find strong links between parental personality and labor market outcomes, including hourly wage rates and labor supply (Flinn, Todd, and Zhang, 2018). This suggests that a parent's personality type can indirectly influence the monetary and time investments they make in their child through wage offers. Additionally, we find that some children exhibit higher ability scores when parents spend less time interacting with them. We observe that parental personality types differ in how much time they dedicate to active versus passive interactions with their children. This highlights that certain personality traits, such as neuroticism, may be associated with less responsive and engaged caregiving, dampening the quality of the parent-child interaction (Prinzie, de Haan, and Belsky, 2019).

Building on our descriptive findings, the second part of the paper introduces parental personality into a model where households make intertemporal decisions regarding labor supply, child-related expenditures, and time devoted to childcare. This framework acknowledges that the influence of parental personality on household choices is potentially intertwined with household preferences, technology, and constraints. The main idea of the model is that children's skills are exposed to their parents' personalities throughout the developmental process. Households value a child's cognitive and non-cognitive skills. These skills are produced through a household production function that depends on parental time spent on childcare, monetary investments in the child, and the child's past skill development. Parents are endowed with a stable personality type that impacts both their *labor market productivity* and *chilcare time productivity*. In the model, periodic wage offers evolve stochastically and are influenced by the parent's personality type. As a result, labor market returns to personality can potentially affect a child's skills as households adjust their time and budget allocations in response to wage changes. Additionally, the household production function flexibly adapts to the child's age and the parent's personality, indicating that different personality types can lead to variations in the productivity—or quality—of childcare time.

The model is estimated using the Simulated Method of Moments (e.g., Adda and Cooper (2003)). Given the tractable form of the household's dynamic problem, I leverage closed-form solutions to the first-order conditions for all choices during the estimation. The parametric structure of the household problem enables us to generate moment conditions that would identify both technology and preference parameters using detailed data on production outcomes, input demands, wages, and time allocation. I show that the model successfully replicates much of the observed heterogeneity in parental time use, child skill scores, wages, and non-labor income.

Consistent with the existing literature, our structural results suggest that time, money, and past skills all play significant roles in the development of both cognitive and non-cognitive skills, with childcare time being especially important during early childhood (Del Boca, Flinn, and Wiswall, 2014). Parental childcare time is particularly relevant for the development of socioemotional skills compared to cognitive abilities. Additionally, skills exhibit well-known properties such as self-reproductivity and the importance of non-cognitive skills in fostering cognitive development (Cunha, Heckman, and Schennach, 2010). Most importantly, the model highlights the significant role of parental personality in explaining child outcomes. In particular, it predicts that emotionally stable parents are substantially more productive—both in the labor market and in childcare—than emotionally vulnerable parents, which can have long-lasting dynamic effects on children's skill development. This aligns with the idea that developmentally supportive interactions are more frequently provided by psychologically healthy parents (Belsky, 1984; Prinzie et al., 2009).

In the final section of the paper, I simulate counterfactual scenarios aimed at improving overall skill levels and reducing inequalities among children of emotionally stable and vulnerable parents. First, I provide insight into the relevance of parental personality's labor market and childcare time productivities for child outcomes. Our simulations indicate that much of the skill inequality reproduced by the model can be attributed to differences in the quality of parent-child interactions among parents. When the gap in labor market productivity between parents is eliminated, net differences in the reallocation of time and budget across family types are relatively small. However, closing the gap in childcare time productivity leads to a substantial reduction in the average skills gap, partly driven by the reallocation of time by vulnerable *fathers*. Importantly, this significant decrease in inequality is accompanied by an increase in average skill levels.

Second, our model enables the study of traditional cash transfer policies, considering that household choices are influenced by the overall returns to personality. Specifically, I simulate a cash transfer equivalent to an annual increment of 2400 USD, which aligns with the full monetary amount provided by current subsidy programs in the US. Differences in the behavioral responses across parents imply a negative distributional effect on children's skills. For instance, emotionally vulnerable parents tend to allocate a larger fraction of the transfer to household consumption and less to child-related expenditures compared to emotionally stable parents. Additionally, while both types of families adjust their labor supply in response to the transfer, vulnerable parents are more inclined to reallocate hours to leisure rather than increasing time spent on childcare.

The main implication of this paper is to stress the important role that parental personality plays in child development. Our findings suggest that policies focused on improving parent-child interactions could be highly effective in equalizing opportunities for children, particularly for those whose parents exhibit personalities that may be less conducive to a *suitable* parenting. Relying solely on monetary aid to improve child outcomes could potentially have adverse effects for children of emotionally vulnerable parents. Furthermore, the paper highlights that involving fathers more actively in growth-promoting childcare activities, can potentially lead to reductions in skill inequality and improvements in overall developmental outcomes.

Contributions to the Literature—This paper contributes to three main strands of the literature: child development and skills formation, the economics of personality, and the quantification of policy effects on child outcomes.

Much of the research on child development and skill formation investigates the impact of parental investments and characteristics on children's human capital outcomes. This link has been explored through various approaches, such as reduced-form estimations of input demand—e.g., Todd and Wolpin (2003, 2007); Cunha and Heckman (2007, 2008); Cunha, Heckman, and Schennach (2010); Bernal and Keane (2010, 2011); Fiorini and Keane (2014); Agostinelli and Wiswall (2016); Bono et al. (2016); Agostinelli and Sorrenti (2021)—as well as experimental interventions—e.g., Heckman et al. (2010); Campbell et al. (2014); Gertler et al. (2014); Attanasio et al. (2014, 2020); Attanasio, Cattan, and Meghir (2022)—and structural models with endogenous input choices—e.g., Del Boca, Flinn, and Wiswall (2014, 2016); Del Boca et al. (2023); Mullins et al. (2015); Tartari (2015); Verriest (2018); Caucutt et al. (2020); Mullins (2022); Agostinelli et al. (2024). Factors influencing parenting decisions studied in this body of work include parental education (Lareau, 2018; Verriest, 2018), parental expectations (Akabayashi, 2006), parenting styles (Doepke and Zilibotti, 2017; Cobb-Clark, Salamanca, and Zhu, 2019; Doepke, Sorrenti, and Zilibotti, 2019), socioeconomic status (Kosse et al., 2020), incentives for child self-investment (Del Boca et al., 2023), and information frictions (Seror, 2022).

The main contribution of this paper is to delve deeper into the role of parental personality in child development. Our starting point builds on the seminal observation of Cunha, Heckman, and Schennach (2010) that maternal non-cognitive traits—such as self-esteem and locus of control—correlate more strongly with early childhood cognitive and non-cognitive outcomes than parental cognitive abilities. Our paper sheds light on the mechanisms by which parental personality impacts child outcomes. Extending the seminal single-skill model of Del Boca, Flinn, and Wiswall (2014), we integrate personality within a fully specified household model, allowing for the endogenous formation of both cognitive and non-cognitive skills.

Our empirical framework builds on the insights developed by the emerging literature on the economics of personality, which investigates the relationship between psychological traits or social skills and labor market outcomes, including worker productivity, job performance, labor supply, bargaining power, and job search behaviors (Heckman, Stixrud, and Urzua, 2006; Mueller and Plug, 2006; Borghans et al., 2008; Almlund et al., 2011; Fletcher, 2013; Heckman and Raut, 2016; Deming, 2017; Flinn, Todd, and Zhang, 2020; Todd and Zhang, 2020; Heckman, Jagelka, and Kautz, 2021; Aghion et al., 2024). More recently, this literature began to explore how personality influences family dynamics, such as marriage market outcomes, intrahousehold bargaining, household preferences, and home production (Lundberg, 2012; Dupuy and Galichon, 2014; Flinn, Todd, and Zhang, 2018; Fernández, 2023; Fernández and Kovaleva, 2024). Our paper contributes by explicitly linking personality traits to child skill formation in a parametric model that captures how labor market returns to personality shape household choices and child outcomes. Additionally, we emphasize the behavioral aspects of personality and how they affect parent-child interactions within households.

Finally, this paper contributes to the literature quantifying the effects of policy simulations on child outcomes (Dahl and Lochner, 2012; Bastian and Michelmore, 2018; Daruich, 2018; Verriest, 2018; Guner, Kaygusuz, and Ventura, 2020; Abbott, 2022; Mullins, 2022). Using our model, we evaluate the behavioral responses of households to policy interventions that modify key inputs in child development. We show that interventions targeting improved parent-child interactions emerge as the most effective policy for enhancing child outcomes when parental personality is taken into account. Additionally, we highlight the potential negative effects of cash transfer policies, similar to current subsidy programs in the United States such as the 2018 Child Tax Credit.

Structure of the Paper—The rest of this paper unfolds as follows. In Section 2, we introduce the sample used throughout the empirical analysis and structural estimation of the model. This section also presents key descriptive patterns in the data related to parental personality, time use, and child outcomes. In Section 3, we formally integrate parental personality within a model of household behavior with skills formation, introducing the necessary notation. Section 4 details the econometric implementation of our framework and characterizes the first-order conditions used in the model estimation. Section 5 discusses the identification arguments, which rely on the parametric structure of the model. Section 6 presents the estimation procedure, structural results, and fit of the model. In Section 7 we discuss the implications of our results for policy design by presenting several simulated counterfactuals. Section 8 concludes.

2. Data

The empirical section and the application of our structural model of household behavior will be based on information drawn from the PSID (Panel Study of Income Dynamics) core panel, merged with the Child Development Supplement (CDS) and Wellbeing Supplement (WS). The PSID began in 1968 with a representative sample of over 18000 individuals living in 5000 households in the United States (US), containing information about employment, income, and socio-demographic variables. Additionally, the CDS collects detailed information on children and adolescents in PSID families, for two cohorts of children in 1997 (CDS I) and 2014 (CDS IV). Each cohort of CDS children is followed over time and surveyed in 2002 (CDS II) and 2007 (CDS III), as well as in the 2019 wave (CDS V).[1] In 2015, the PSID was supplemented with the WS which collects information about the personality traits of all adults in the household.

2.1. Data on Parental Time, Child Outcomes, and Parental Personality

All the CDS waves administered the Woodcock-Johnson Revised Tests of Achievement including several tests measuring cognitive abilities (Duffy and Sastry, 2014). These tests are the Letter Word (LW) test, aimed to capture a child's symbolic learning and reading identification skills; the Applied Problems (AP) test, which assesses mathematics reasoning and knowledge; and the Passage Comprehension (PC) test, measuring reading comprehension, vocabulary, and sentence completion. In addition, the CDS also implemented scales related to the socioemotional skills of a child based on the Achenbach Behavior Problems Checklist (Peterson and Zill, 1986). These scales are the Behavior Problem Index (BPI), which was designed to gather information about the incidence and severity of child behavior problems through parental assessment of the child; and also, two derived subscales, the External Behavior Problems (EBP) and Internal Behavior Problems (IBP). The CDS collected aggregate raw scores on each test and scale.[2] The CDS waves also included time use diaries collecting detailed information on the child's whereabouts and activities and who else was present at each time, allowing me to construct empirical measures of parental childcare time. From this information, we can construct measures of active *vs.* passive interactions between parents and children.

In 2015, the WS collected information about the Big Five (B5) personality traits of adult individuals living in a household and who have been classified as a household head or spouse/partner. The B5 personality questionnaire was designed to summarize an individual's personality into five overarching dimensions: agreeableness, conscientiousness, emotional stability, openness to experiences, and extraversion (Goldberg, 1992).[3] As explained below, I will use personality types constructed based on the B5 traits throughout the analyses.

In the empirical evidence and estimation of the structural model, I use a sample of children included in either the first CDS panel (1997, 2002, and 2007) or the second CDS panel (2014 and 2019). The sample consists of 308 children of married or single parents (763 observations) for which there is: (i) valid information on their cognitive and non-cognitive skills; (ii) valid information on time use diaries; and (iii) valid information

[1] The third wave of the second CDS cohort gathered in 2020 is not included in the analysis, due to changes in the survey design because of the 2020 pandemic.

[2] Several of these tests and scales have been used extensively by the literature as empirical measures of cognitive and non-cognitive abilities (e.g., Cunha and Heckman (2008); Fiorini and Keane (2014); Mullins (2022); Agostinelli and Sorrenti (2021); Del Boca et al. (2023)).

[3] Other structural analyses of household behavior using this questionnaire include Dupuy and Galichon (2014); Flinn, Todd, and Zhang (2018); Todd and Zhang (2020); Fernández (2023).

on the personality of their parents. From the total number of children, 172 children correspond to households where both biological parents are present throughout the observed developmental period of their child.[4]

Table 1 provides descriptive statistics for the main variables. Panel A of the table shows key information in the PSID-CDS: child's initial age, parental childcare time, and raw scores for our available skill measures. Overall, mothers spend more weekly hours in childcare than fathers. CDS children from the cohort 1997–2007 scored slightly higher than children from the cohort 2014–2019. This is because the former group of children is older and tests scores are positively correlated with age (see Figure A2 in Appendix A). Panel B of Table 1, presents parental B5 personality traits. In line with the literature, we observe the largest differences across genders in emotional stability and conscientiousness (Flinn, Todd, and Zhang, 2021). We do not observe strong assortative mating in personality among couples (see Figure A1 in Appendix A). Finally, Panel C shows additional demographic and wage information on the parents. Fathers are older, more educated, earn more, and allocate more hours to the labor market than mothers.

2.2. Descriptive Evidence on Parental Personality and Child Skills

In this section, I present the reduced-form effect of parental personality on a child's skills. I also show suggestive evidence on the potential mechanisms of this effect, namely: a *labor market effect*, which is associated with labor market returns to personality potentially driving time use decisions of the parents; as well as a *childcare time effect*, related to the fact that the type of childcare time spent by parents vary by personality.

Parental Personality Types—We conduct our analyses using personality types throughout the paper.[5] These types are obtained by clustering the parents in our sample based on their B5 personality traits presented above. The full explanation of the clustering method is in Appendix B.1. As shown in Table 2, we obtain two personality types that summarize opposite configurations of the B5 traits. In the first personality type, labeled as *emotionally stable*, all five personalities load positively except for neuroticism. The opposite pattern is observed in the second personality type, labeled as *emotionally vulnerable*.[6] As shown

[4]We follow the literature modeling household behavior with CDS information and select one child per household (Del Boca, Flinn, and Wiswall, 2014). For sample homogeneity, I exclude households with three or more children, and for households with two children, I select the child with the most complete CDS information.

[5]The typological approach to personality has been widely used in psychology (Robins et al., 1996; Specht, Luhmann, and Geiser, 2014; Gerlach et al., 2018) and, more recently, in economics (Todd and Zhang, 2020; Fernández, 2023). By grouping individuals with similar values in several personalities, this approach offers insights into individual differences in the configuration of the B5 traits. Moreover, working with types instead of all five traits significantly reduces the computational burden in the structural estimation and allows for a much more credible identification.

[6]There have been several interpretations of personality types with opposing patterns, likewise our clusters.

TABLE 1. Summary Statistics

A. PSID-CDS: I-V	Mean	Std. Dev.	Min.	Max.
Child's age in 1997–2007	10.81	4.49	3.00	18.00
Child's age in 2014–2019	7.92	3.51	3.00	18.00
Mother's weekly childcare hours 1997−2002	41.44	22.86	0.00	109.50
Mother's weekly childcare hours 2014−2019	33.81	23.62	0.00	124.41
Father's weekly childcare hours 1997−2002	22.32	24.22	0.00	102.91
Father's weekly childcare hours 2014−2019	17.88	26.07	0.00	107.33
Letter Word score in 1997–2002	36.79	16.36	0.00	57.00
Letter Word score in 2014–2019	32.09	20.22	3.00	57.00
Applied Problems score in 1997–2002	32.16	12.77	0.00	58.00
Applied Problems score in 2014–2019	20.62	8.85	3.00	39.00
Passage Comprehension score in 1997–2002	25.35	7.34	0.00	42.00
Passage Comprehension score in 2014–2019	24.88	8.02	5.00	38.00
Behavior Problem Index in 1997–2002	7.77	5.75	0.00	27.00
Behavior Problem Index in 2014–2019	9.15	6.74	0.00	26.00
External Behavior Problems in 1997–2002	5.34	3.96	0.00	17.00
External Behavior Problems in 2014–2019	7.77	6.07	0.00	17.00
Internal Behavior Problems in 1997–2002	2.58	3.96	0.00	13.00
Internal Behavior Problems in 2014–2019	3.48	3.66	0.00	14.00
B. PSID-WB: 2015	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Mother's conscientiousness	8.17	1.51	5	14
Father's conscientiousness	7.90	1.42	4	12
Mother's extraversion	9.57	1.44	5	14
Father's extraversion	9.54	1.48	5	14
Mother's openness	9.10	1.66	5	14
Father's openness	9.00	1.84	5	15
Mother's emotional stability	11.34	2.20	5	15
Father's emotional stability	10.87	2.01	5	15
Mother's agreeableness	8.37	1.46	5	13
Father's agreeableness	8.81	1.58	5	13
C. PSID-Core: 1997−2019	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Mother's age	45.99	10.31	20.00	89.00
Father's age	48.37	9.86	21.00	86.00
Mother's education	13.72	2.17	3.00	17.00
Father's education	14.03	2.29	5.00	17.00
Mother's weekly work hours	29.77	18.63	0.00	100.00
Father's weekly work hours	42.03	15.35	0.00	112.00
Mother's hourly real wage	20.79	14.60	0.07	121.21
Father's hourly real wage	29.18	20.27	0.06	149.59

Notes: Sample size = 308 children (763 observations). Raw scores included. Parental work hours, wages, educational level, and age statistics are averaged over all CDS years, ranging from 1997 to 2019. Wages are in real terms (base year: 2010) and statistics do not include zero wages.

Individuals with positive loadings in all five traits have been labeled as resilient—someone adaptable under new environmental demands—as opposed to unresilient—individuals that are *emotionally vulnerable* to stress factors (Robins et al., 1996). This distinction was first introduced in developmental psychology by Block and Haan (1971) when theorizing about the dimensions of an individual's ego structure. See Donnellan and Robins (2010) and Oshio et al. (2018) for an overview. Moreover, high loadings in traits such as openness, emotional stability, and agreeableness are associated with *psychologically or emotionally stable* parents—capable of providing developmentally flexible and growth-promoting care (Prinzie et al., 2009). This was first introduced by Belsky (1984)'s process model. See Prinzie, de Haan, and Belsky (2019) for a recent review.

in Table B1 in Appendix B.2, our cluster solution is validated as it provides the best fit in several goodness-of-fit measures. Overall, our personality types correlate weakly with different demographic variables including income, education, and health (see Table B2 in the appendix). Given data constraints, I will assume that these personality types are exogenous and stable over time.[7]

TABLE 2. Personality Types

	Loadings	
Personality trait	**Type 1: Emotionally stable**	**Type 2: Emotionally vulnerable**
Extraversion	0.11	-0.06
Openness to experience	0.81	-0.39
Agreeableness	0.85	-0.41
Conscientiousness	0.46	-0.22
Neuroticism	-0.17	+0.08
Fraction of parents	59.1%	40.9%

Notes: Personality types were constructed by K-means clustering with hierarchical centroids as starting values for the algorithm (Lattin, Carroll, and Green, 2003). Details about the clustering algorithm are in Appendix B.1. Details about the cluster validation are in Appendix B.2.

Parental Personality and Child Outcomes—On average, children with a mother or father emotionally stable score higher than children with a mother or father emotionally vulnerable. Figure 1 presents the distribution of standardized scores of our available measures of a child's cognitive and non-cognitive skills, conditional on a mother's or a father's personality type. In all cases, the distribution of scores of children from stable parents is more skewed to the right than the distribution of scores of children from vulnerable mothers. In Appendix B, I present unconditional, conditional, and residualized significant estimates of the effect of parents' personality types on ability scores (see Table B3).

Next, we look at the differences in scores of children of parents of either personality type, excluding from the analysis the scores of children coming from mixed household types—for example, having an emotionally stable mother and an emotionally vulnerable father. Figure 2 presents these results with each bar corresponding to the average difference in standardized scores between the scores of children of *only* stable parents minus the scores of children of *only* vulnerable parents. We repeat this exercise across all ability measures and for two children's age categories—ages 3 to 11 and ages 12 to 18. Overall, we observe sizeable differences in standardized scores that range from slightly more than 0.1 standard deviations to more than 0.4 standard deviations.[8] These gaps in scores are

[7]There is suggestive evidence that personality traits remain relatively stable in adult ages over time (Cobb-Clark and Schurer, 2012; Fitzenberger et al., 2022). Although it is possible to observe within-situation changes in mood and feelings, the average personality does not vary drastically over time (Donnellan and Robins, 2010). In section B.3 of Appendix B, I show descriptive evidence on the stability of the personality of parents in my sample using available panel variation for the trait self-esteem.

[8]The magnitude of these differences in scores are similar to those found by the literature after computing

systematic across ability measures and over a child's age. The average gap in cognitive skills increases from 0.13 standard deviations to 0.27 standard deviations as the child ages. The average gap in non-cognitive skills, while slightly decreasing over time, remains sizable, dropping from 0.39 to 0.34 standard deviations. Importantly, after conditioning for family attributes potentially confounding these results—like parents' educational level, income, and health status—the observed mean gaps remain significant and sizeable (see Figure B3 in Appendix B).[9]

Parental Personality, Labor Supply, and Childcare Time—To gain insights on the potential reasons underlying the relationship presented above, I look at the effect of parental personality on several variables that could affect parental inputs in the child's developmental process. The results presented below, come from different specifications that condition on a dichotomous variable that takes the value of 1 if the parent is emotionally stable and 0 if the parent is emotionally vulnerable.

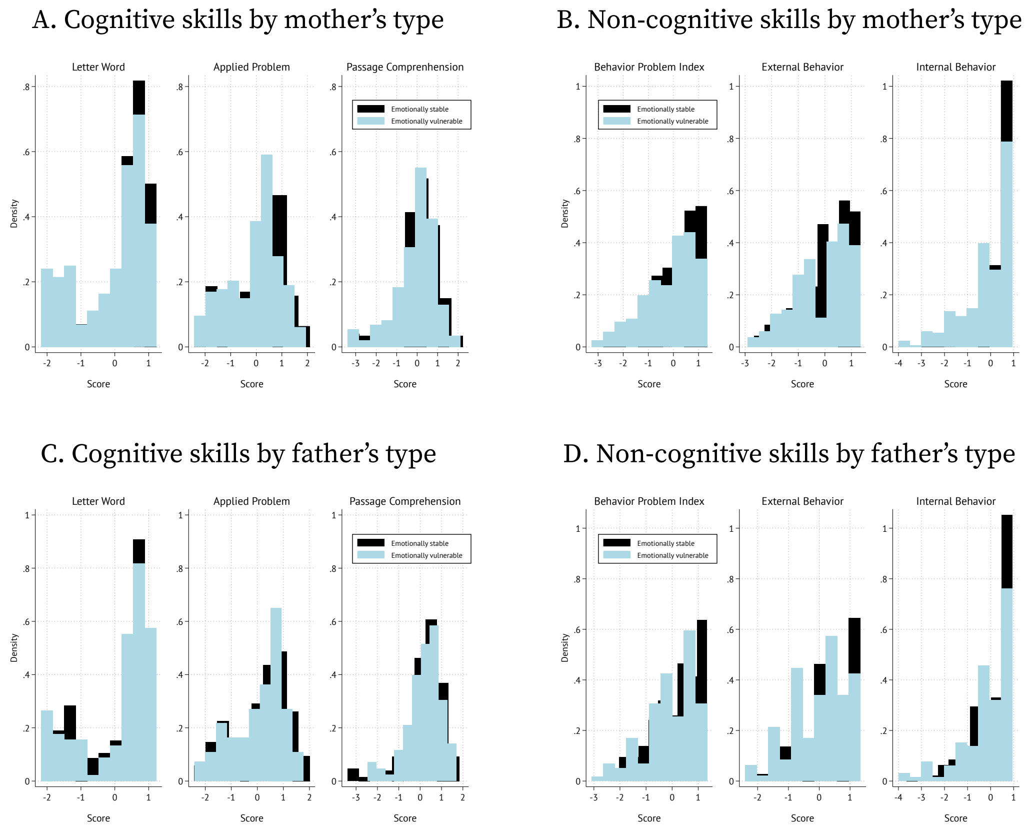
In Panel A of Figure 3, I show the conditional average effect—net of observables—of parents' personality types on log wages across different age categories of a parent's life cycle. We observe that emotionally stable parents, characterized by traits typically highly valued in the labor market—such as conscientiousness— are significantly correlated with higher wages across gender and over time. Labor market returns to personality may drive substitution between market work and childcare time. I explore this in the remaining panels of Figure 3. In Panel B, I present the conditional average effect of parents' personality types on three labor supply outcomes: the fraction of working full-time parents, the fraction of parents working part-time, and the fraction of parents not working.[10] Overall, both stable mothers and stable fathers are significantly more likely to spend more weekly hours working in the labor market than vulnerable parents. Also, we observe a greater sensitivity for fathers along the extensive margin—the choice of working or not. Along the intensive margin—transitioning between full-time and part-time work—, we observe significant results only for mothers. In Panel C, we observe the conditional

differences in standardized socres for education and income groups. See Heckman and Mosso (2014) for a review.

[9]Our results are in line with papers looking at the broad link between parental personality traits (or non-cognitive traits) and child outcomes. In the seminal contribution of Cunha, Heckman, and Schennach (2010), parental self-esteem and locus control are important traits in the production of a child's cognitive and non-cognitive skills. Other traits related to parental psychological distress, externalizing skills, and internalizing skills have shown to be relevant for a child's skills (Agostinelli and Wiswall, 2016; Del Bono, Kinsler, and Pavan, 2020; Attanasio, de Paula, and Toppeta, 2024). Our results are also consistent with papers looking at the specific link between some of the Big Five traits and child outcomes. Through positive parenting, higher levels of agreeableness, emotional stability, and openness to experience correlate with better child outcomes (Prinzie et al., 2009; Prinzie, de Haan, and Belsky, 2019; Atherton and Schofield, 2021; Breitkopf et al., 2024).

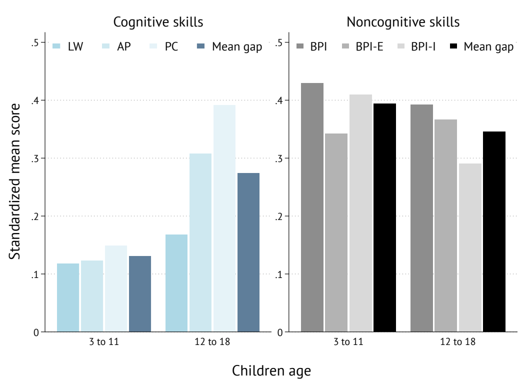
[10]Full-time work constitutes more than 30 hours per week, part-time work falls within the 10 to 30 hours per week range, and non-working encompasses anything less than 10 hours per week.

FIGURE 1. Distribution of a Child's Skills by Parents' Personality Types



Notes: This figure shows the histogram of standardized scores on available cognitive and non-cognitive skills measures, conditional on a parent's personality type.

FIGURE 2. Differences in a Child's Skills



Notes: This figure shows differences in the standardized scores of available measures associated with cognitive and non-cognitive skills. The difference is computed between the scores of children living only with stable parents minus the scores of children living only with vulnerable parents. **LW**: Letter Word; **AP**: Applied Problems; **PC**: Passage Comprehension; **BPI**: Behavior Problem Index; **BPI-E**: Externalizing Behavior; **BPI-I**: Internalizing Behavior.

average effect—net of observables—of parental personality on childcare active and passive time. Emotionally stable parents significantly spend less weekly hours with children than emotionally vulnerable parents. Stable mothers, on average, allocate fewer hours to passive time than vulnerable mothers, whereas stable fathers allocate fewer hours to active time than vulnerable fathers.[11]

Productivity Effects of Personality—Our results above suggest that there may be a *labor market productivity* effect of personality. Labor market returns to personality may impact the monetary resources devoted to children, implying a potential income effect. Additionally, the opportunity cost of childcare time may drive the substitution between market work time and hours spent with children, and thus the total time that parents spend with their kids.[12] Secondly, we might also have a *childcare time productivity* effect of personality. A child's skills could be also affected by the fact that stable and vulnerable parents may be more or less productive in childrearing activities, with everything else held constant. For example, even though vulnerable parents, on average, interact more hours with their kids, their children tend to perform worse both in cognitive and non-cognitive skills than children from stable parents.[13]

Generally, the influence of parental personality on household choices may be intertwined with household unobserved preferences, unobserved technology, and resource constraints, as shown in Figure 4. To disentangle between these mechanisms, I structurally model and estimate labor supply choices and parental investments jointly, as described in the following section.

3. Model

I now present a model of household choices, child development, and parental personality that provides a rationale for the descriptive facts presented in the previous section. This framework extends Del Boca, Flinn, and Wiswall (2014) by considering (1) households

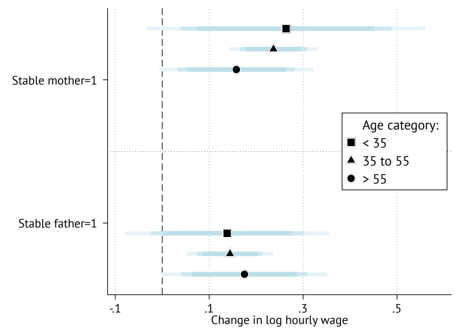
[11] This evidence is in line with papers looking at the role of certain traits in explaining labor market outcomes. Lower levels of neuroticism and higher levels of conscientiousness and openness to experience have proven to be correlated with higher hourly log wages, a larger probability of working in a white-collar position, and a larger duration in job spells (Todd and Zhang, 2020; Flinn, Todd, and Zhang, 2021). Labor supply changes and adjustments in childcare time of parents as a response to labor market dynamics have also been studied elsewhere—for example, in the context of household responses to welfare programs (Agostinelli and Sorrenti, 2021) or labor market returns to education (Verriest, 2018).

[12] For instance, Agostinelli and Sorrenti (2021) document household labor supply responses to US federal income support programs and its effect on child development due to a trade-off between the income effect and the substitution effect of the recipient working hours.

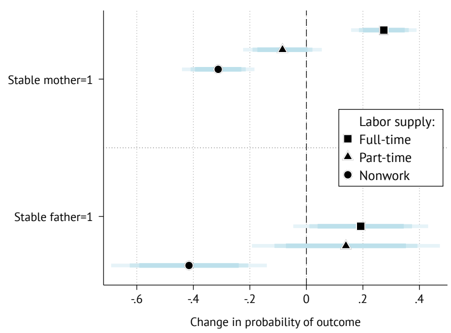
[13] There is support to the notion that parental skills can play a disequalizing role in child development as they enhance the productivity of investments, changing the parent-child interaction (Cunha, Heckman, and Schennach, 2010; Seror, 2022). For example, more educated parents, by engaging their children more, increase the formative value of investments such as sports or cultural activities (Lareau, 2018).

FIGURE 3. Parental Personality, Labor Market Outcomes, and Childcare Time

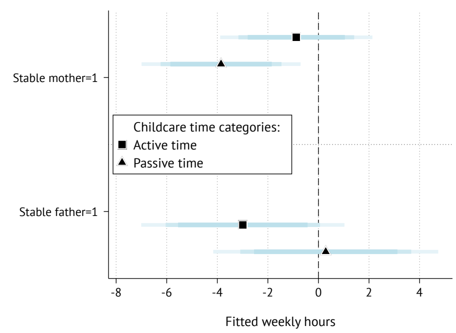
A. Log hourly wages



B. Labor supply decisions



C. Weekly childcare time

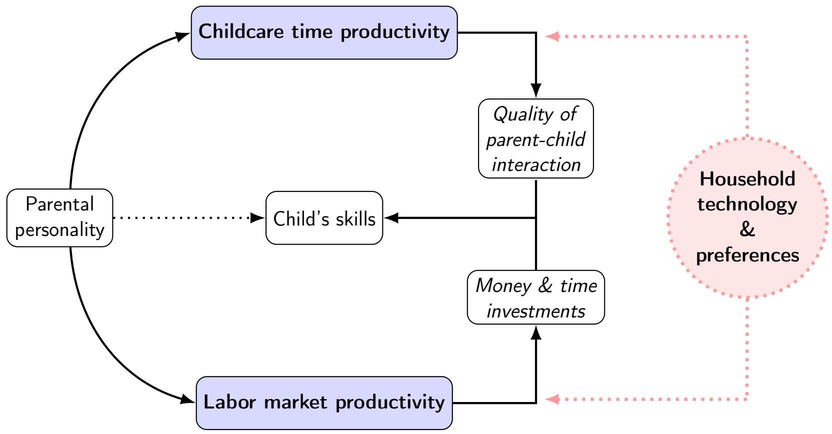


Notes: **Panel A** shows the residualized effect of personality types on log wages. First, we regress log hourly wages on parental education, parental age and its square, parental health, region fixed effects, and time fixed effects. Then, we get the residuals. **Panel B** shows the estimates of Probit regressions of labor market choices conditional on parental personality types, parental education, parental age, parental health, household income, parental religiosity, a child's birth weight, and a child's age. Finally, we regress the estimated residuals on a parent's personality type. **Panel C** shows the residualized effect of personality type on weekly childcare hours. First, we regress childcare hours on parental education, parental age, parental health, household income, an indicator of whether the parent is working full-time or not, and marital status. Then, we get the residuals. Finally, we regress the estimated residuals on a parent's personality type.

formed by couples or single individuals, (2) the dynamic production of both cognitive and non-cognitive skills, and (3) parental personality driving choices and outcomes over time.

Primitives—Households consist of married or single parents who spend resources producing a child's skills. Parents' gender is indexed by $i = \{1, 2\}$ and the marital status of the household (couples or singles) is indexed by $M \in \{C, S\}$. Parents are endowed with a personality that can be emotionally stable (E_s) or vulnerable (E_v). These personality types are exogenous and stable over time and denoted by $\rho_{i,\pi}$ with $\pi = \{E_s, E_v\}$. Time (t) is discrete and indexed by a child's developmental stage before entering adulthood ($t \in \{1, \ldots, 18\}$). In each period, parents spend their available time on leisure ($\ell_{i,t}$), market

FIGURE 4. Parental Personality and a Child's Skills



work ($h_{i,t}$), and childcare time ($\tau_{i,t}$). For each parent i, the time constraint thus equals:

$$\ell_{i,t} + h_{i,t} + \tau_{i,t} = H_{i,t}, \tag{1}$$

where $H_{i,t}$ are the total hours available an individual has, net of sleep time and personal care hours.

One unit of market work by parent i is associated with a wage defined by $w_{i,t}(\rho_{i,\pi})$, which is exogenous to the parent and assumed to be an explicit function of parent i's personality type (e.g., Flinn, Todd, and Zhang (2020)). Households also have exogenous non-labor income (I_t^M). The total income of households is allocated to a Hicksian composite good with a price that is normalized to one. I assume that the Hicksian composite good is used for household consumption (c_t^M) and children-related expenditures (e_t^M). This is translated in the following household budget constraints for singles and couples:

$$\begin{aligned} c_t^C + e_t^C &= w_{1,t}(\rho_{1,\pi})h_{1,t} + w_{2,t}(\rho_{2,\pi})h_{2,t} + I_t^C && \text{(couples)}, \\ c_t^S + e_t^S &= w_{i,t}(\rho_{i,\pi})h_{i,t} + I_t^S && \text{(singles)}. \end{aligned} \tag{2}$$

The allocation and size of a household's income depend on the preferences of the household, which are represented by the following time-invariant and instantaneous utility function:

$$\begin{aligned} u_t^C &= \nu_t^C(\ell_{1,t}, \ell_{2,t}, c_t^C, \theta_{k,t}^C, \theta_{q,t}^C; \boldsymbol{\alpha}^C) && \text{(couples)}, \\ u_t^S &= \nu_t^S(\ell_{i,t}, c_t^S, \theta_{k,t}^S, \theta_{q,t}^S; \boldsymbol{\alpha}^S) && \text{(singles)}, \end{aligned} \tag{3}$$

where $\boldsymbol{\alpha}^M$ is a vector of time-invariant preference parameters, and $\theta^M_{k,t}$ and $\theta^M_{q,t}$ represent a child's cognitive and non-cognitive abilities, respectively.

Every period, households produce a child's ability $\theta^M_{\mathcal{A},t}$ with $\mathcal{A} \in \{k, q\}$ with a technology of production defined by:

$$
\begin{aligned}
(4) \qquad & \theta^C_{\mathcal{A},t+1} = f^{\mathcal{A},C}_t\Big[\tau_{1,t}, \tau_{2,t}, e^C_t, \theta^C_{k,t}, \theta^C_{q,t}; \boldsymbol{\delta}^{\mathcal{A}}_t(\boldsymbol{\rho})\Big] && \text{(couples)},\\
& \theta^S_{\mathcal{A},t+1} = f^{\mathcal{A},S}_t\Big[\tau_{i,t}, e^S_t, \theta^S_{k,t}, \theta^S_{q,t}; \boldsymbol{\delta}^{\mathcal{A}}_t(\rho)\Big] && \text{(singles)},
\end{aligned}
$$

where the function $f^{\mathcal{A},M}_t$ is assumed to be twice continuously differentiable and increasing in all arguments (Cunha, Heckman, and Schennach, 2010). The stocks of current period skills and investments produce the next period's skills. Couples and singles may differ in their innate ability to raise kids, represented by the superscript associated with marital status in each production function (Tartari, 2015). The vector $\boldsymbol{\delta}$ collects time-variant productivity parameters associated with each input and specific to each skill. The personality of each parent ($\rho_{i,\pi}$) is embedded in the productivity of these investments allowing, e.g., for a potential relationship between parental personality and childcare time (Prinzie et al., 2009).

Parental Personality and Child's Skills—The model presented so far, parsimoniously integrates the reduced-form evidence presented in Section 2.2, by linking the personality type of fathers and mothers with three important inputs in the production of a child's skills: money investments, parental time, and the type of interaction between parents and children.

Returns to personality in the labor market may be associated with higher or lower earnings, everything else equal, which can potentially affect the monetary resources devoted to children (e^M_t). As labor market earnings require substantial time commitments from parents, the total resources to raise children may decrease as parents could substitute childcare time ($\tau_{i,t}$) for working hours ($h_{i,t}$). This channel may dampen a potential positive relationship between money and a child's skills. At the same time, parental personality may enhance the productivity of time investments differently—for example:

$$
(5) \qquad \left.\frac{\partial \theta^M_{\mathcal{A},t+1}}{\partial \tau_{i,t}}\right|_{\pi=E_s} \neq \left.\frac{\partial \theta^M_{\mathcal{A},t+1}}{\partial \tau_{i,t}}\right|_{\pi=E_v},
$$

which may mitigate a potentially negative relationship between less parental time and a child's skills (Heckman and Mosso, 2014).

Household Problem—The maximization of the following value functions gives the within-period household problem of resource allocation for couples and singles:

$$
\begin{aligned}
V_t^C(\boldsymbol{\Omega}_t^C) &= \max_{\substack{\tau_{1,t},\tau_{2,t},\\ h_{1,t},h_{2,t},e_t^C}} \left\{ u_t^C + \beta\, \mathbb{E}_{|\mathcal{I}_t^C}\left[V_{t+1}^C(\boldsymbol{\Omega}_{t+1}^C) \right] \right\} \qquad \text{(couples)}, \\
V_t^S(\boldsymbol{\Omega}_t^S) &= \max_{\tau_{3,t},h_{3,t},e_t^S} \left\{ u_t^S + \beta\, \mathbb{E}_{|\mathcal{I}_t^S}\left[V_{t+1}^S(\boldsymbol{\Omega}_{t+1}^S) \right] \right\} \qquad \text{(singles)},
\end{aligned} \tag{6}
$$

subject to the corresponding time constraints in (1), budget constraint in (2), and non-negativity constraints in all choice variables. The vector $\boldsymbol{\Omega}_t^M$ corresponds to all state variables at period t, with $\boldsymbol{\Omega}_1^M$ as the initial conditions of the dynamic problem, β as an exogenous and common to all households discount factor, and $\mathbb{E}_{|\mathcal{I}_t^M}$ denoting the conditional expectation operator with respect to the period t's information set of the household ($\mathcal{I}_t^M$).

In general, the dynamic nature of the technology of skills defined in (4) implies that at period $t = T+1$ the household has produced $\theta_{k,T+1}^M$ and $\theta_{q,T+1}^M$. I assume that the valuation by the household at $t = T+1$ is defined as a smooth function of a child's future skills:

$$
V_{T+1}^M(\boldsymbol{\Omega}_{T+1}^M) \equiv g_{T+1}(\theta_{k,T+1}^M, \theta_{q,T+1}^M), \tag{7}
$$

which captures the altruistic preference of couples and singles for their children's adult life (Del Boca, Flinn, and Wiswall, 2014). The continuation value for the dynamic problem can be thus written as:

$$
V_T^M(\boldsymbol{\Omega}_T^M) = \max_{\mathbf{a}_T^M} \left\{ u_T^M + \beta g_{T+1}(\theta_{k,T+1}^M, \theta_{q,T+1}^M) \right\} \tag{8}
$$

with $\mathbf{a}_T^C = (\tau_{1,T}, \tau_{2,T}, h_{1,T}, h_{2,T}, e_T^C)'$ and $\mathbf{a}_T^S = (\tau_{i,T}, h_{i,T}, e_T^S)'$. Equation (8) aims to capture the stream of future household utility received as a function of a child's end-of-childhood cognitive and non-cognitive skills.

Model Solution—The household optimal choices are observable functions of wages, non-labor income, a recursive component of a child's skills, and reduced-form parameters associated with preferences (α) and technology (δ). For a couple, the policy rules are given by:[14]

[14] In Section C.1 of Appendix C, I provide the full characterization of one-parent households' policy rules.

$$
\begin{aligned}
h_{1,t} &= h_{1,t}\Big[\mathbf{w}_t, I_t^C, g_{t+1}(\theta_{k,t+1}^C, \theta_{q,t+1}^C); \boldsymbol{\alpha}^C, \boldsymbol{\delta}_t\Big],\\
h_{2,t} &= h_{2,t}\Big[\mathbf{w}_t, I_t^C, g_{t+1}(\theta_{k,t+1}^C, \theta_{q,t+1}^C); \boldsymbol{\alpha}^C, \boldsymbol{\delta}_t\Big],\\
\tau_{1,t} &= \tau_{1,t}\Big[\mathbf{w}_t, I_t^C, g_{t+1}(\theta_{k,t+1}^C, \theta_{q,t+1}^C); \boldsymbol{\alpha}^C, \boldsymbol{\delta}_t\Big],\\
\tau_{2,t} &= \tau_{2,t}\Big[\mathbf{w}_t, I_t^C, g_{t+1}(\theta_{k,t+1}^C, \theta_{q,t+1}^C); \boldsymbol{\alpha}^C, \boldsymbol{\delta}_t\Big],\\
e_t^C &= e_t^C\Big[\mathbf{w}_t, I_t^C, g_{t+1}(\theta_{k,t+1}^C, \theta_{q,t+1}^C); \boldsymbol{\alpha}^C, \boldsymbol{\delta}_t\Big].
\end{aligned} \tag{9}
$$

As detailed in the following section, the parametric functional form for household preferences and technology allows us to get a closed-form expression for the set of policy functions in (9), which I leverage in the identification and estimation of the model.

4. Econometric Implementation

This section presents the parametric assumptions used for estimation and the resulting expressions for the model solution.

4.1. Parametric Assumptions

Flow Utility—In each period, the household utility function takes the following log-additively separable form:

$$
\begin{aligned}
u_t^C &= \alpha_1^C \ln(c_t^C) + \alpha_2^C \ln(\theta_{k,t}^C) + \alpha_3^C \ln(\theta_{q,t}^C) + \alpha_4^C \ln(\ell_{1,t}) + \alpha_5^C \ln(\ell_{2,t}) \qquad \text{(couples)},\\
u_t^S &= \alpha_1^S \ln(c_t^S) + \alpha_2^S \ln(\theta_{k,t}^S) + \alpha_3^S \ln(\theta_{q,t}^S) + \alpha_4^S \ln(\ell_{i,t}) \qquad \text{(singles)},
\end{aligned} \tag{10}
$$

where $\alpha_j^C > 0$ and $\sum_j \alpha_j^C = 1$ for all $j \in \{1, \ldots, 5\}$ and $\alpha_l^S > 0$ and $\sum_l \alpha_l^S = 1$ for all $l \in \{1, \ldots, 4\}$. These restrictions ensure that the utility is increasing in each argument and that the scale of the utility function is normalized. Preference parameters are allowed to vary heterogeneously between couples and single parents but remained fixed over time.

The estimated parameters that map into preference parameters are given by:

$$
\begin{aligned}
\alpha_j^C &= \frac{\exp(\lambda_j^C)}{1 + \sum_j \exp(\lambda_j^C)} \quad \text{and} \quad \alpha_5^C = \frac{1}{1 + \sum_j \exp(\lambda_j^C)} \quad \forall j = \{1,2,3,4\},\\
\alpha_l^S &= \frac{\exp(\lambda_l^S)}{1 + \sum_l \exp(\lambda_l^S)} \quad \text{and} \quad \alpha_4^S = \frac{1}{1 + \sum_l \exp(\lambda_l^S)} \quad \forall l = \{1,2,3\},
\end{aligned} \tag{11}
$$

where $\boldsymbol{\lambda}^C \sim N(\mu_{\lambda^C}, \Sigma_{\lambda^C})$ and $\boldsymbol{\lambda}^S \sim N(\mu_{\lambda^S}, \Sigma_{\lambda^S})$. Hence, although utility parameters are stable, we do allow heterogeneity in the household utility function with each utility parameter being drawn from a multivariate normal distribution characterized in terms of a vector μ_{λ^M} and covariance matrix Σ_{λ^M}.[15]

Valuation of Final Skills—The valuation by the household at $t = T+1$ is assumed to take the following form:

$$V^M_{T+1}(k^M_{T+1}, q^M_{T+1}) = \exp(\psi)\left[\alpha^M_2 \ln(\theta^M_{k,T+1}) + \alpha^M_3 \ln(\theta^M_{q,T+1})\right] \quad \forall M \in \{C, S\}, \tag{12}$$

where ψ is a parameter to be estimated, common to all households, and scales the terminal household valuation of child quality. This approach is computationally appealing because it avoids solving for the entire children's future life cycle as a function of their inherited skills (Agostinelli et al., 2024).[16]

Technology of Skills Formation—Period $t+1$ cognitive and non-cognitive skills are produced by the period t level of skills, parental childcare time, and monetary investments in the child. The evolution of a child's skill $\theta^M_{\mathcal{A},t}$ with $\mathcal{A} \in \{k, q\}$ is determined by a Cobb-Douglas production function, specified for a child of age t as: [17]

$$\begin{aligned} \theta^C_{\mathcal{A},t+1} &= R^{C,\mathcal{A}}_t \, \tau_{1,t}^{\delta^{\mathcal{A}}_{1,t}} \, \tau_{2,t}^{\delta^{\mathcal{A}}_{2,t}} \, e_t^{C,\delta^{\mathcal{A}}_3} \, \theta_{k,t}^{C,\delta^{\mathcal{A}}_4} \, \theta_{q,t}^{C,\delta^{\mathcal{A}}_5} \qquad &\text{(couples)}, \\ \theta^S_{\mathcal{A},t+1} &= R^{S,\mathcal{A}}_t \, \tau_{i,t}^{\delta^{\mathcal{A}}_{i,t}} \, e_t^{S,\delta^{\mathcal{A}}_3} \, \theta_{k,t}^{S,\delta^{\mathcal{A}}_4} \, \theta_{q,t}^{S,\delta^{\mathcal{A}}_5} \qquad &\text{(singles)}. \end{aligned} \tag{13}$$

All other exogenous, omitted, or residual inputs are captured in the total factor productivity (TFP) scaling parameter $R^{M,\mathcal{A}}_t$ with $M \in \{C, S\}$ which is time-variant and common across households:

[15] This parametrization follows a similar fashion as in Del Boca, Flinn, and Wiswall (2014, 2016); Del Boca et al. (2023) but introduces the possibility of heterogenous preferences between couples and singles.

[16] The additive form of the expression in brackets in equation (12) will become instrumental to obtain tractable, recursive closed-form expressions that are used in the estimation of the model, as detailed below.

[17] Although several studies have imposed a Cobb-Douglas technology before (Cunha and Heckman, 2008; Del Boca, Flinn, and Wiswall, 2014; Attanasio et al., 2020), restricting the elasticity of substitution to be one implies a particular form of complementarity between the stock of skills and parental investments. From an empirical perspective, previous studies have shown that the Cobb-Douglas specification cannot be rejected in data (Cunha, Heckman, and Schennach, 2010; Attanasio, Meghir, and Nix, 2020). From a computational perspective, allowing for the substitutability of different inputs can result in a highly nonlinear relationship between a child's skills and parental investments (Attanasio, Cattan, and Meghir, 2022). Recently, using a sample of households from the US, Mullins (2022) shows that the data cannot reject (1) a linear form for the investment equations, and (2) independence between investments and the current stock of skills.

$$R_t^{M,\mathcal{A}} = \exp(\kappa_0^{\mathcal{A}} + \omega_t^{\mathcal{A},M}) \quad \text{with} \quad \omega_t^{\mathcal{A},M} \overset{\text{i.i.d.}}{\sim} N(0, \sigma_{\omega_{\mathcal{A},M}}), \tag{14}$$

where the period-specific productivity shock $\omega_t^{\mathcal{A},M}$, identically and independently distributed over time and across households, correlates with the child living in a two-parent or single-parent household.

The amount of investments may differ between couples and singles but not the productivity of these investments.[18] Hence, the input-specific productivity parameters associated with each skill are defined by:

$$\begin{aligned} \delta_{i,t}^{\mathcal{A}} &= \exp(\kappa_{i,0}^{\mathcal{A}} + \kappa_{i,1}^{\mathcal{A}} t + \kappa_{i,2}^{\mathcal{A}} \rho_{i,\pi}), \\ \delta_j^{\mathcal{A}} &= \exp(\kappa_{j,0}^{\mathcal{A}}), \end{aligned} \tag{15}$$

for all $\mathcal{A} \in \{k, q\}$, $i \in \{1, 2\}$, $j \in \{3, 4, 5\}$, and $t = 1, \ldots, T$. The parametrization in (15) restricts the productivity of each input to be strictly positive (Heckman and Mosso, 2014). Moreover, the productivity of parental childcare time is assumed to be monotonic in a child's age (t) and directly affected by parental personality ($\rho_{i,\pi}$).[19]

Wages—The wage processes for couples and singles are exogenously given, defined by:

$$w_{i,t} = \exp(\mu_{i,t} + \epsilon_{i,t}) \tag{16}$$

where the idiosyncratic component $\epsilon_{i,t}$ makes this process to evolve stochastically in every period, with:

$$\begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \overset{\text{i.i.d.}}{\sim} N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{w_1} & \sigma_{w_2 w_1} \\ \sigma_{w_2 w_1} & \sigma_{w_2} \end{bmatrix} \right) \quad \text{and} \quad \epsilon_{i,t} \overset{\text{i.i.d.}}{\sim} N(0, \sigma_{w_i}). \tag{17}$$

[18] This assumption reduces significantly the number of parameters that are required to be estimated inside the model and is consistent with papers looking at the effect of marital status on child development (e.g., Tartari (2015)).

[19] Papers studying the implications of household choices in the US have consistently shown that parental time productivity decreases as the child ages (Del Boca, Flinn, and Wiswall, 2014, 2016; Del Boca et al., 2023). Moreover, we assume that $\delta_{i,t}^{\mathcal{A}}$ can be fairly interpreted as a proxy of the quality of time that parents and children spend together. For example, Verriest (2018) makes a similar interpretation of this parameter in a collective model with skills formation. Also, correlational evidence shows that parental personality—especially high levels of agreeableness and low levels of neuroticism—could drive growth-promoting parenting decisions regarding childcare time (Prinzie et al., 2009). Finally, the assumption that the productivity of the remaining inputs stays constant over a child's lifecycle is made purely for computational purposes. The model could be easily extended to allow for different types of heterogeneity in these productivities as well.

Hence, the random component of the intra-period log wage process is assumed to be independently distributed over time and across households which, in the case of couples, is allowed to be correlated between spouses.

The average of the period-specific log wage process is assumed to be an extended Mincer equation and deterministic based on the education, age, and personality of the parent:

$$\ln(\mu_{i,t}) = \mu_i^0 + \mu_i^1 \text{Educ}_{i,t} + \mu_i^2 \text{Age}_{i,t} + \mu_i^3 \text{Age}_{i,t}^2 + \mu_i^4 \rho_{i,\pi}, \tag{18}$$

with μ_i^4 corresponding to the returns in the labor market to personality type $\rho_{i,\pi}$ with $\pi \in \{E_s, E_v\}$.[20]

Non-labor Income—The non-labor income process for all households is exogenously given and defined by a truncated version of a latent process:

$$I_t^{M,latent} = \mu^I + \varepsilon_t^M \quad \text{with} \quad \varepsilon_t^M \overset{\text{i.i.d.}}{\sim} N(0, \sigma_{\varepsilon_M}), \tag{19}$$

with the actual non-labor income process given by: $I_t^M = \max\{0, I_t^{M,latent}\}$ for all t.

Measuring Child Skills—To measure children's abilities, I focus on the Letter Word (LW) score anchoring a child's cognitive skills and on the Behavior Problem Index (BPI) anchoring a child's non-cognitive skills.[21]

For child j at age t, I map observed scores ($\tilde{\theta}_{LW,j,t}$ and $\tilde{\theta}_{BPI,j,t}$), simulated latent ability on these scales ($\theta_{LW,j,t}$ and $\theta_{BPI,j,t}$), and a child's simulated ability in the model ($\theta_{k,j,t}$ and $\theta_{q,j,t}$) using Item Response Theory (IRT). This approach sets up a measurement model with intra-scale measurement error in ability measures that have a categorical (or dichotomous) nature (e.g., Lord and Novick (2008)).[22] As such, our measurement system maps continuous latent skills into a discrete score, allowing for measurement error. In each simulation of the model, we transform the simulated ability measures into simulated scores on the observed ability scales, which are then linked to observed raw scores in the estimation of moments. Refer to Appendix C.2 for a detailed explanation of the IRT

[20] Structural household models studying the implications of labor market returns to personality have followed similar approaches (Todd and Zhang, 2020; Fernández and Kovaleva, 2024).

[21] This is consistent with a bulk of papers using these two variables as empirical measures of cognitive and non-cognitive abilities (Cunha and Heckman, 2008; Del Boca, Flinn, and Wiswall, 2014, 2016; Fiorini and Keane, 2014; Verriest, 2018; Mullins, 2022; Del Boca et al., 2023). See Cunha, Nielsen, and Williams (2021) for a recent discussion on measuring skills. Moreover, in our sample, the LW and BPI are the ability measures for which we have the most completed set of records across households.

[22] Under continuous measures, previous studies have used linear or log linear measurement models (Cunha, Heckman, and Schennach, 2010; Cunha, Nielsen, and Williams, 2021).

approach and the child's skills estimation algorithm that we used.

4.2. Recursive Solution to the Household Problem

Given our parametric assumptions, all household choices can be expressed in closed-form recursive functions of wages, non-labor income, preference parameters, and productivity parameters. Describing the solution to the final period problem is instructive in understanding the recursive formulation of household decisions.

For a couple, the final-period problem boils down to the maximization of the following unconstrained program:

$$
\begin{aligned}
&V_T^C(\boldsymbol{\Omega}_T^C) = \\
&\max_{\substack{\tau_{1,T},\tau_{2,T},\\ h_{1,T},h_{2,T},e_T^C}} \Big\{ \alpha_1^C \ln\big(w_{1,T}h_{1,T} + w_{2,T}h_{2,T} + I_T^C - e_T^C\big) + \alpha_2^C \ln(\theta_{k,T}^C) + \alpha_3^C \ln(\theta_{q,T}^C) \\
&\qquad + \alpha_4^C \ln\big(112 - h_{1,T} - \tau_{1,T}\big) + \alpha_5^C \ln\big(112 - h_{2,T} - \tau_{2,T}\big) \\
&\qquad + \beta\psi\Big[\alpha_2^C\big(\ln R_T^{C,k} + \ln \tau_{1,T}^{\delta_{1,T}^k} + \ln \tau_{2,T}^{\delta_{2,T}^k} + \ln e_T^{C,\delta_{3,T}^k} + \ln \theta_{k,T}^{C,\delta_{4,T}^k} + \ln \theta_{q,T}^{C,\delta_{5,T}^k}\big) \\
&\qquad + \alpha_3^C\big(\ln R_t^{C,q} + \ln \tau_{1,T}^{\delta_{1,T}^q} + \ln \tau_{2,T}^{\delta_{2,T}^q} + \ln e_T^{C,\delta_{3,T}^q} + \ln \theta_{k,T}^{C,\delta_{4,T}^q} + \ln \theta_{q,T}^{C,\delta_{5,T}^q}\big)\Big]\Big\},
\end{aligned} \tag{20}
$$

with the vector of state variables for a couple defined by $\boldsymbol{\Omega}_T^C = (w_{1,T}, w_{2,T}, \epsilon_{1,T}, \epsilon_{2,T}, I_T^C, \varepsilon_T^C)'$.[23]

Let the marginal utility to the couple at period t of a child's log cognitive and log non-cognitive skills, respectively, be defined by:

$$
\eta_t^{C,k} \equiv \frac{\partial V_t^C(\boldsymbol{\Omega}_t^C)}{\partial \ln(\theta_{k,t}^C)} \quad \text{and} \quad \eta_t^{C,q} \equiv \frac{\partial V_t^C(\boldsymbol{\Omega}_t^C)}{\partial \ln(\theta_{q,t}^C)}. \tag{21}
$$

At $t = T$, we get that:

$$
\begin{aligned}
\eta_T^{C,k} &= \alpha_2^C + \beta(\eta_{T+1}^{C,k}\delta_{4,T}^k + \eta_{T+1}^{C,q}\delta_{4,T}^q), \\
\eta_T^{C,q} &= \alpha_3^C + \beta(\eta_{T+1}^{C,k}\delta_{5,T}^q + \eta_{T+1}^{C,q}\delta_{5,T}^q),
\end{aligned} \tag{22}
$$

[23] Throughout, we assume that the total hours available an individual can allocate to different activities is 112. We also assume that parental childcare time (τ) corresponds to active time spent with children (e.g., outdoor activities, playing, reading, or talking). Any passive time with children is embedded into a parent's leisure time. Also, the final-period problem for single households has a similar structure than the problem for couples. The main difference lies in having fewer household choices. See C.3 in Appendix C for the formulation and derivations of the problem for singles.

with $\eta^{C,k}_{T+1} = \psi\alpha^C_2$ and $\eta^{C,q}_{T+1} = \psi\alpha^C_3$, which are obtained from taking the corresponding partial derivatives of the valuation of the household in equation (12). In general, the variables $\eta^{M,k}_t$ and $\eta^{M,q}_t$ with $M \in \{C, S\}$ reflect both the present, per-period preferences for a child's skills and the discounted future value for the household of these produced skills.

The F.O.C. to the couple's problem at period T, are given by:

$$
\begin{aligned}
\tau_{1,T} &= \Big(112 - h_{1,T}\Big) \\
&\quad \times \left[\frac{\beta\delta^k_{1,T}\Big[(\alpha^C_2 + \beta\Psi(\delta^k_{4,T} + \delta^q_{4,T}))\Big] + \beta\delta^q_{1,T}\Big[(\alpha^C_3 + \beta\Psi(\delta^k_{5,T} + \delta^q_{5,T}))\Big]}{\alpha^C_4 + \beta\delta^k_{1,T}\Big[(\alpha^C_2 + \beta\Psi(\delta^k_{4,T} + \delta^q_{4,T}))\Big] + \beta\delta^q_{1,T}\Big[(\alpha^C_3 + \beta\Psi(\delta^k_{5,T} + \delta^q_{5,T}))\Big]} \right], \\
\tau_{2,T} &= \Big(112 - h_{2,T}\Big) \\
&\quad \times \left[\frac{\beta\delta^k_{2,T}\Big[(\alpha^C_2 + \beta\Psi(\delta^k_{4,T} + \delta^q_{4,T}))\Big] + \beta\delta^q_{2,T}\Big[(\alpha^C_3 + \beta\Psi(\delta^k_{5,T} + \delta^q_{5,T}))\Big]}{\alpha^C_5 + \beta\delta^k_{2,T}\Big[(\alpha^C_2 + \beta\Psi(\delta^k_{4,T} + \delta^q_{4,T}))\Big] + \beta\delta^q_{2,T}\Big[(\alpha^C_3 + \beta\Psi(\delta^k_{5,T} + \delta^q_{5,T}))\Big]} \right], \\
e^C_T &= \Big(w_{1,T}h_{1,T} + w_{2,T}h_{2,T} + I_T\Big) \\
&\quad \times \left[\frac{\beta\delta^k_{3,T}\Big[(\alpha^C_2 + \beta\Psi(\delta^k_{4,T} + \delta^q_{4,T}))\Big] + \beta\delta^q_{3,T}\Big[(\alpha^C_3 + \beta\Psi(\delta^k_{5,T} + \delta^q_{5,T}))\Big]}{\alpha^C_1 + \beta\delta^k_{2,T}\Big[(\alpha^C_2 + \beta\Psi(\delta^k_{4,T} + \delta^q_{4,T}))\Big] + \beta\delta^q_{2,T}\Big[(\alpha^C_3 + \beta\Psi(\delta^k_{5,T} + \delta^q_{5,T}))\Big]} \right], \\
h_{1,T} &= \frac{\alpha^C_1 w_{1,T}\Big(112 - \tau_{1,T}\Big) + \alpha^C_4\Big(e^C_T - I^C_T - w_{2,T}h_{2,T}\Big)}{\Big(\alpha^C_1 w_{1,T} + \alpha^C_4 w_{1,T}\Big)}, \\
h_{2,T} &= \frac{\alpha^C_1 w_{2,T}\Big(112 - \tau_{2,T}\Big) + \alpha^C_5\Big(e^C_T - I^C_T - w_{1,T}h_{1,T}\Big)}{\Big(\alpha^C_1 w_{2,T} + \alpha^C_5 w_{2,T}\Big)},
\end{aligned}
\tag{23}
$$

which anticipate us that the marginal utilities of a child's skills, represented by the time-invariant weights α^C_2 and α^C_3 and the discounted terms $\beta\psi(\delta^k_{4,T} + \delta^q_{4,T})$ and $\beta\psi(\delta^k_{5,T} + \delta^q_{5,T})$, will enter recursively over time in the household decisions. Using a recursive expression for the sequences $\{\eta^{C,k}_t\}^{T+1}_{t=1}$ and $\{\eta^{C,q}_t\}^{T+1}_{t=1}$, we can write for any period t the optimal household choices for childcare time and expenditures as conditional functions of spouses' labor supplies:[24]

[24]The derivation of the recursive sequences $\{\eta^{C,k}_t\}^{T+1}_{t=1}$ and $\{\eta^{C,q}_t\}^{T+1}_{t=1}$ is shown in Appendix C.4.

$$
\begin{aligned}
\hat{\tau}_{1,t} &= \left(112 - h_{1,t}\right)\frac{\zeta_{1,t}}{\alpha_4^C + \zeta_{1,t}}, \\
\hat{\tau}_{2,t} &= \left(112 - h_{2,t}\right)\frac{\zeta_{2,t}}{\alpha_5^C + \zeta_{2,t}}, \\
\hat{e}_t^C &= \left(w_{1,t}h_{1,t} + w_{2,t}h_{2,t} + I_t^C\right)\frac{\zeta_{3,t}}{\alpha_1^C + \zeta_{3,t}},
\end{aligned} \tag{24}
$$

where $\zeta_{l,t} = \beta(\delta_{l,t}^{k}\eta_{t+1}^{C,k} + \delta_{l,t}^{q}\eta_{t+1}^{C,q})$ for all $l \in \{1, 2, 3\}$.

Our parametric assumptions regarding preferences, technology, and the valuation of the household at $t = T+1$ of a child's cognitive a non-cognitive skills, allow us to extend the single-skill model of Del Boca, Flinn, and Wiswall (2014) to the case of multiple skills while maintaining a similar tractable recursive structure. Moreover, we can use the simplified expressions in (24), to get a form for the optimal labor supply decisions at period t as a function of wages, non-labor income, and the (recursive) marginal utilities for a child's skills:[25]

$$
\begin{aligned}
h_{1,t} &= \frac{w_{1,t}(\alpha_1^c + \zeta_{3,t}) - I_t^C(\alpha_4^C + \zeta_{1,t}) - w_{2,t}h_{2,t}(\alpha_4^C + \zeta_{1,t})}{w_{1,t}(\alpha_4^C + \alpha_1^c + \zeta_{1,t} + \zeta_{3,t})}, \\
h_{2,t} &= \frac{w_{2,t}(\alpha_1^c + \zeta_{3,t}) - I_t^C(\alpha_5^C + \zeta_{1,t}) - w_{1,t}h_{1,t}(\alpha_4^C + \zeta_{1,t})}{w_{2,t}(\alpha_5^C + \alpha_1^c + \zeta_{1,t} + \zeta_{3,t})}.
\end{aligned} \tag{25}
$$

Defining the following scalars:

$$
\begin{aligned}
a_{1,t}^C &\equiv \frac{w_{1,t}(\alpha_1^c + \zeta_{3,t}) - I_t^C(\alpha_4^C + \zeta_{1,t})}{w_{1,t}(\alpha_4^C + \alpha_1^c + \zeta_{1,t} + \zeta_{3,t})}, \\
b_{1,t}^C &\equiv \frac{w_{2,t}h_{2,t}(\alpha_4^C + \zeta_{1,t})}{w_{1,t}(\alpha_4^C + \alpha_1^c + \zeta_{1,t} + \zeta_{3,t})}, \\
a_{2,t}^C &\equiv \frac{w_{2,t}(\alpha_1^c + \zeta_{3,t}) - I_t^C(\alpha_5^C + \zeta_{1,t})}{w_{2,t}(\alpha_5^C + \alpha_1^c + \zeta_{1,t} + \zeta_{3,t})}, \\
b_{2,t}^C &\equiv \frac{w_{1,t}h_{1,t}(\alpha_4^C + \zeta_{1,t})}{w_{2,t}(\alpha_5^C + \alpha_1^c + \zeta_{1,t} + \zeta_{3,t})},
\end{aligned} \tag{26}
$$

the optimal labor supply choices for a couple at period t are given by:

[25] The full derivation of the optimal labor supplies is provided in Appendix C.5.

$$h^*_{1,t} = \frac{a^C_{1,t} - b^C_{1,t}a^C_{2,t}}{(1 - b^C_{1,t}b_{2,t})} \quad \text{and} \quad h^*_{2,t} = \frac{a^C_{2,t} - b^C_{2,t}a^C_{1,t}}{(1 - b^C_{1,t}b^C_{2,t})}. \tag{27}$$

The scalars obtained in (27), will define whether the household supplies time to the labor market or if the household is at a corner solution. From these optimal labor supplies, we get final expressions for the optimal choices for childcare time and household child-related expenditures which are used in estimating the model:

$$\begin{aligned}
\tau^*_{1,t} &= \left(112 - \frac{a^C_{1,t} - b^C_{1,t}a^C_{2,t}}{(1 - b^C_{1,t}b_{2,t})}\right)\frac{\zeta_{1,t}}{\alpha^C_4 + \zeta_{1,t}}, \\
\tau^*_{2,t} &= \left(112 - \frac{a^C_{2,t} - b^C_{2,t}a^C_{1,t}}{(1 - b^C_{1,t}b^C_{2,t})}\right)\frac{\zeta_{2,t}}{\alpha^C_5 + \zeta_{2,t}}, \\
e^{C*}_t &= \left(w_{1,t}\frac{a^C_{1,t} - b^C_{1,t}a^C_{2,t}}{(1 - b^C_{1,t}b_{2,t})} + w_{2,t}\frac{a^C_{2,t} - b^C_{2,t}a^C_{1,t}}{(1 - b^C_{1,t}b^C_{2,t})} + I^C_t\right)\frac{\zeta_{3,t}}{\alpha^C_1 + \zeta_{3,t}}.
\end{aligned} \tag{28}$$

5. Identification

In this section, I provide a discussion concerning the identification of specific parameters. The arguments sketched in this section allow for a parametric identification given the structure of the household problem, with the details presented in Appendix C.6. The identification arguments are given for the case of couples but can easily be extended to the case of single households. Additionally, at the end of this section, Table 3 summarizes the variation in data that would be used for identification.

Technology of Skills Formation—The first step for identifying technology parameters corresponds to addressing the fact that a child's skills do not have natural units (Agostinelli and Wiswall, 2016). We solve the indeterminacy problem by normalizing the location and scale parameters of the measurement system. Besides allowing for measurement error, our measurement system maps scores to latent ability and translates this ability into a probability.[26]

If outputs and all demand inputs are observed, estimating technology parameters is straightforward if the household choice inputs are not a function of any stochastic unobserved component. Given our parametric assumptions, a child's cognitive and non-cognitive skills at period $t+1$ can be written as:

[26] This method is discussed in Section 4, and the full details are provided in Appendix C.2.

$$
\begin{aligned}
\ln \theta^C_{k,t+1} &= \exp(\kappa^k_{1,0} + \kappa^k_{1,1} t + \kappa^k_{1,2} \rho_{1,\pi}) \ln \tau_{1,t} + \exp(\kappa^k_{2,0} + \kappa^k_{2,1} t + \kappa^k_{2,2} \rho_{2,\pi}) \ln \tau_{2,t} \\
&\quad + \exp(\kappa^k_{3,0}) \ln e^C_t + \exp(\kappa^k_{4,0}) \ln \theta^C_{k,t} + \exp(\kappa^k_{5,0}) \ln \theta^C_{q,t} \\
&\quad + \exp(\kappa^k_0) \exp(\omega^{k,C}_t), \\
\ln \theta^C_{q,t+1} &= \exp(\kappa^q_{1,0} + \kappa^q_{1,1} t + \kappa^q_{1,2} \rho_{1,\pi}) \ln \tau_{1,t} + \exp(\kappa^q_{2,0} + \kappa^q_{2,1} t + \kappa^q_{2,2} \rho_{2,\pi}) \ln \tau_{2,t} \\
&\quad + \exp(\kappa^q_{3,0}) \ln e^C_t + \exp(\kappa^q_{4,0}) \ln \theta^C_{k,t} + \exp(\kappa^q_{5,0}) \ln \theta^C_{q,t} \\
&\quad + \exp(\kappa^q_0) \exp(\omega^{q,C}_t).
\end{aligned} \tag{29}
$$

Moreover, under the Cobb-Douglas assumptions for preferences and technology, household choices are not directly related to $\theta^C_{k,t}$ and $\theta^C_{q,t}$. We also have that:

$$
\mathbb{E}(\omega^{k,C}_t | \tau_{1,t}, \tau_{2,t}, e^C_t, \theta^C_{k,t}, \theta^C_{q,t}) = 0 \quad \text{and} \quad \mathbb{E}(\omega^{q,C}_t | \tau_{1,t}, \tau_{2,t}, e^C_t, \theta^C_{k,t}, \theta^C_{q,t}) = 0 \quad \forall t, \tag{30}
$$

because the productivity shocks are independent of the household choices and current state variables. Finally, as unobserved productivity is assumed to be independently distributed over time for each couple, we have that $\omega^{k,C}_t \perp\!\!\!\perp \omega^{q,C}_t$ for all t. If all demand inputs are observed, the estimation of (29) can be done by OLS, yielding unbiased and consistent estimates, provided that not all couples choose the same values of investments for a given period.[27]

Like other studies estimating the technology of skills production with PSID-CDS data, we do not observe child expenditures. One approach for solving this is provided in Verriest (2018). The productivity of child expenditures can be identified by residual variation in child scores that is not explained by the variation in parental time investments and the stock of skills. Moreover, the *systematic* variation in child scores over time could be explained by the TFP process, which is the same for all couples and, therefore, cannot explain variation across households. Given our parametric assumptions on technology, none of the F.O.C in equation (23)—and therefore, none of the endogenous choices—depend on the TFP process. Although our technology is stochastic—through the inclusion of $\omega^{\mathcal{A},M}_t$—, we have assumed that shocks to a child's skills are mean-zero and additive in each period, which makes the solution to the problem identical to one with a deterministic TFP process. Hence, the residual growth rate in a child's scores and its variation *across* couples can only be explained by heterogeneity in child expenditures.

[27] Although our model is solved annually, the CDS data does not contain successive observations on child skills along with inputs. We accommodate for this during the estimation of technology parameters by collapsing the periods into three periods (early, middle, and late years in the child development process). Del Boca et al. (2023) shows that even without collapsing periods, identification could be achieved by using expected values for a sequence of inputs conditional on state variables.

Alternatively, one could rely on replacement functions.[28] For example, find a variable y_t^C that would be irrelevant for explaining a child's skills once time investments and the stock of past skills have been controlled for, that is:

$$(31) \quad \mathbb{E}(\theta^C_{\mathcal{A},t+1}|\tau_{1,t},\tau_{2,t},e^C_t,\theta^C_{k,t},\theta^C_{q,t},y^C_t) = \mathbb{E}(\theta^C_{\mathcal{A},t+1}|\tau_{1,t},\tau_{2,t},e^C_t,\theta^C_{k,t},\theta^C_{q,t}) \quad \forall \mathcal{A} \in \{k,q\}.$$

Moreover, we could assume that the correlation between child expenditures and the remaining observed inputs is zero once we partial out the variable y_t^C:

$$(32) \qquad \mathbb{E}(e^C_t|\tau_{1,t},\tau_{2,t},\theta^C_{k,t},\theta^C_{q,t},y^C_t) = \mathbb{E}(e^C_t|y^C_t).$$

Let the unobserved expenditures be defined as $e_t^C = \gamma_0 + \gamma_1 y_t^C + \tilde{\pi}_t$.[29] To get an estimable equation, we can replace e_t^C in both equations in (29) and, under the assumptions (31) and (32), get consistent estimates for all technology parameters from an OLS regression. For instance, Cunha, Heckman, and Schennach (2010) considers y_t^C to be lagged values of household income. Del Boca et al. (2023) also relies on the fact that unobserved expenditures are a function of household income (up to some unknown function of parameters). This pathway for identification would imply additional parametric assumptions that we detailed in Appendix C.6.[30]

Preferences—All expressions in the conditional demand system depend on preference and productivity parameters (see equation (28)). Therefore, conditional on having a consistent estimator of productivity parameters, we can invert the conditional demand system to obtain a unique value for preference parameters. As preference parameters are assumed to be time-invariant, we can exploit data for any given period on mothers' and fathers' time allocations to identify each parent's preferences for leisure and child's skills (and thus consumption).

[28] Wooldridge (2010) develop several pathways to omitted variables problem, including the one explained here which relies on exploiting information on a proxy variable for child expenditures. The parametric example we used from Cunha, Heckman, and Schennach (2010) relies on similar arguments.

[29] By definition, $\mathbb{E}(\tilde{\pi}_t) = 0$ and $Cov(y_t^C, \tilde{\pi}_t) = 0$. If the variable y_t^C is a good proxy for e_t^C, then we would expect that $\gamma_1 \neq 0$ (possibly $\gamma_1 > 0$) and $Cov(\tau_{1,t}, \tilde{\pi}_t) = 0$; $Cov(\tau_{2,t}, \tilde{\pi}_t) = 0$; $Cov(\theta^C_{k,t}, \tilde{\pi}_t) = 0$; $Cov(\theta^C_{q,t}, \tilde{\pi}_t) = 0$.

[30] In principle, nonparametric identification could also be achieved by assuming strict exogeneity between household observed inputs and unobserved productivity (including unobserved expenditures). Independence between observed time inputs and unobserved expenditures could be relaxed by using external sources of information regarding household expenditures (e.g., CEX or SIPP datasets). The household production and utility functions could be written as nonseparable, nonparametric functions. Assuming that $\omega_t^{\mathcal{A},M}$ is independent of $(\tau_{1,t}, \tau_{2,t}, \theta_{k,t}, \theta_{q,t}, e_t^C)$ for all t and strict monotonicity of the production and utility functions, we could identify these functions (after proper normalizations of $\omega_t^{\mathcal{A},M}$). This result follows from Matzkin (2003, 2013). Cunha, Heckman, and Schennach (2010) apply these arguments for their technology of skills formation.

We can write the constrained problem of a couple at period t as:

$$V_t^C(\mathbf{\Omega}_t^C) = \tag{33}$$
$$\max_{\substack{\tau_{1,t},\tau_{2,t},\\ h_{1,t},h_{2,t},e_t^C}} \left\{\alpha_1^C \ln c_t^C + \alpha_2^C \ln \theta_{k,t}^C + \alpha_3^C \theta_{q,t}^C + \alpha_4^C \ln \ell_{1,t} + \alpha_5^C \ln \ell_{2,t} + \beta \mathbb{E}_t\Big[V_{t+1}^C(\mathbf{\Omega}_{t+1}^C)\Big]\right\},$$

subject to $\ell_{1,t} + h_{1,t} + \tau_{1,t} = 112$; $\ell_{2,t} + h_{2,t} + \tau_{2,t} = 112$; and $c_t^C + e_t^C = w_{1,t}h_{1,t} + w_{2,t}h_{2,t} + I_t^C$, and where $\mathbf{\Omega}_t^C$ collects the state variables at period t. From the first-order conditions (F.O.C) to problem (33), it is easily shown that (the ratio of) spouses' preference for leisure can be identified from cross-section information on time-use allocations and wages:[31]

$$\begin{aligned} \frac{\alpha_1^C w_{1,t}\ell_{1,t}}{\alpha_4^C} &= \frac{\alpha_1^C w_{2,t}\ell_{2,t}}{\alpha_5^C}, \\ \frac{w_{1,t}\ell_{2,t}}{w_{2,t}\ell_{1,t}} &= \frac{\alpha_4^C}{\alpha_5^C}. \end{aligned} \tag{34}$$

For given values $\mathbf{x}$ of household observables $\mathbf{X}$, we can form the following conditional moment conditions:

$$\mathbb{E}\left(\frac{w_{1,t}\ell_{2,t}}{w_{2,t}\ell_{1,t}} \Big| \ \mathbf{X} = \mathbf{x}\right) = \mathbf{0}. \tag{35}$$

To identify the household weights for a child's skills, we can exploit the following expressions for time investments delivered by the structure of the model:[32]

$$\begin{aligned} \tau_{1,t} &= \frac{w_{2,t}\ell_{2,t}}{w_{1,t}}\frac{\alpha_4^C}{\alpha_5^C}\frac{\beta}{\alpha_5^C}(\alpha_2^C\delta_{1,t}^k + \alpha_3^C\delta_{1,t}^q), \\ \tau_{2,t} &= \frac{w_{1,t}\ell_{1,t}}{w_{2,t}}\frac{\alpha_5^C}{\alpha_4^C}\frac{\beta}{\alpha_5^C}(\alpha_2^C\delta_{2,t}^k + \alpha_3^C\delta_{2,t}^q), \end{aligned} \tag{36}$$

which, after rearranging, gives us the following expression for the ratio of spouses' child-care time decisions:

[31] Equation (C25) in Appendix C.6 provides the full set of equalities obtained from the F.O.C to problem (33).
[32] The set of equations in (C25) and (C28) lead to this result.

$$(37) \qquad \frac{w_{1,t}\tau_{1,t}}{w_{2,t}\tau_{2,t}} = \frac{(\alpha_2^C\delta_{1,t}^k + \alpha_3^C\delta_{1,t}^q)}{(\alpha_2^C\delta_{2,t}^k + \alpha_3^C\delta_{2,t}^q)} = \frac{\alpha_2^C(\delta_{1,t}^k + \frac{\alpha_3^C}{\alpha_2^C}\delta_{1,t}^q)}{\alpha_2^C(\delta_{2,t}^k + \frac{\alpha_3^C}{\alpha_2^C}\delta_{2,t}^q)} = \frac{(\delta_{1,t}^k + d\delta_{1,t}^q)}{(\delta_{2,t}^k + d\delta_{2,t}^q)},$$

where $d = \frac{\alpha_3^C}{\alpha_2^C}$. Equality (37) tells us that, conditional on having estimates for the productivity of spouses' time, we can identify the relative weight of non-cognitive skills compared to cognitive skills. The following moment conditions would allow us to identify technology parameters separately:

$$(38) \qquad \mathbb{E}\left(\frac{w_{1,t}\tau_{1,t}}{w_{2,t}\tau_{2,t}} \middle| \ \mathbf{X} = \mathbf{x}; \hat{\boldsymbol{\delta}}_t^k, \hat{\boldsymbol{\delta}}_t^q\right) = \mathbf{0}.$$

By construction, we could then identify a couple's preferences for household consumption, as we have defined that: $\alpha_1^C = 1 - \alpha_2^C - \alpha_3^C - \alpha_4^C - \alpha_5^C$. This would complete the identification of all time-invariant preference parameters.

Wages and Non-labor Income—Wages and non-labor income processes are exogenous to all household endogenous choices (and realized before choices are made), they will not affected by variations in time or budget allocations nor in the output of the production function. Moreover, given the distributional assumptions regarding the stochastic components of these processes and the fact that wages and non-labor income are uncorrelated, we can achieve the identification by exploiting cross-section or panel variation in wages and non-labor income.

TABLE 3. Identification of Parameters

Parameters	Symbol	Variation in data
Technology:		
Mother's time productivity, *intercept*	$\kappa^k_{10}, \kappa^q_{10}$	Panel variation in scores and mother's time by personality
Mother's time productivity, *slope*	$\kappa^k_{11}, \kappa^q_{11}$	Panel variation in scores and mother's time by personality
Mother's time productivity, *personality*	$\kappa^k_{12}, \kappa^q_{12}$	Panel variation in scores and mother's time by personality
Fathers's time productivity, *intercept*	$\kappa^k_{20}, \kappa^q_{20}$	Panel variation in scores and father's time by personality
Fathers's time productivity, *slope*	$\kappa^k_{21}, \kappa^q_{21}$	Panel variation in scores and father's time by personality
Fathers's time productivity, *personality*	$\kappa^k_{22}, \kappa^q_{22}$	Panel variation in scores and father's time by personality
Expenditures productivity	$\kappa^k_{30}, \kappa^q_{30}$	Residual variation in scores
Past cognitive skills productivity	$\kappa^k_{40}, \kappa^q_{40}$	Panel variation in scores
Past non-cognitive skills productivity	$\kappa^k_{50}, \kappa^q_{50}$	Panel variation in scores
TFP, *intercept*	$\kappa^k_{0}, \kappa^q_{0}$	Unconditional mean scores
TFP shock s.d., *couples*	σ_{ω_C}	Variance mean scores for couples
TFP shock s.d., *singles*	σ_{ω_S}	Variance mean scores for singles
Preferences:		
Consumption weight, *couples*	λ^C_1	Difference across gender in time allocations
Mother's leisure weight, *couples*	λ^C_2	Difference across gender in time allocations
Father's leisure weight, *couples*	λ^C_3	Difference across gender in time allocations
Cognitive skills weight, *couples*	λ^C_4	Difference across gender in time allocations
Consumption weight, *singles*	λ^S_1	Difference between couples and singles in time allocations
Household's leisure weight, *singles*	λ^S_2	Difference between couples and singles in time allocations
Cognitive skills weight, *singles*	λ^S_3	Difference between couples and singles in time allocations
Terminal value of a child's skills	ψ	Panel variation in time allocations and parental investments
Wages:		
Intercept	u^0_i	Cross-section variation on wages and labor supply
Returns to education	u^1_i	Cross-section variation on wages and labor supply
Returns to experience	u^2_i	Cross-section variation on wages and labor supply
Returns to experience sq.	u^3_i	Cross-section variation on wages and labor supply
Returns to personality	u^4_i	Cross-section variation on wages and labor supply
Wage shock s.d., *mothers*	σ_{ε_1}	Variance of wages and labor supply of mothers
Wage shock s.d., *fathers*	σ_{ε_2}	Variance of wages and labor supply of fathers
non-labor income:		
Intercept	u^I	Cross-section and panel variation on non-labor income
non-labor income shock s.d., *couples*	σ_{ε_C}	Cross-section and panel variation on non-labor income
non-labor income shock s.d., *singles*	σ_{ε_S}	Cross-section and panel variation on non-labor income

Notes: This table shows variation in observed data from PSID, CDS, and WB that could be potentially used for identification of model parameters.

6. Estimation

This section explains the estimation procedure, presents the structural estimates, and shows the overall fit of the model.

6.1. Estimation procedure

The estimation procedure consists of two steps. In the first step, I fix and estimate a subset of model parameters directly outside the model. This allows us to reduce the computation burden of the estimation of the full model. In the second step, I estimate the rest of the structural parameters via the Simulated Method of Moments (SMM) estimator (e.g., Adda and Cooper (2003)).

Parameters Exogenously Set—The subset of parameters fixed or estimated outside of the model are related to the household discount factor, non-labor income process, and a child's initial cognitive and non-cognitive skills:

- The annual discount factor (β) is set to be 0.95.
- The household non-labor income (I_t^M) is assumed to be a censored model, with i.i.d. error terms (ε_t^M), and independent of the wage process for all t. The mean (μ^I) and the variance (σ_{ε_M}) of the underlying distribution are estimated with cross-sectional PSID data from 1996 to 2018.
- The initial distribution of cognitive and non-cognitive skills from which the model starts its simulation is estimated directly from data on a child's LW and BPI scores. See Appendix C.2 in C for a detailed explanation of the estimation algorithm for a child's initial skills.

Parameters Structurally Estimated—I estimate the vector ($\boldsymbol{\Theta}$) of 52 remaining parameters "inside" the model by the SMM:

- Per-period utility of the couple—$v_t^C(\ell_{1,t}, \ell_{2,t}, c_t^C, \theta_{k,t}^C, \theta_{k,t}^C; \boldsymbol{\alpha}^C)$:
  $\mu_{\lambda_1^C}, \mu_{\lambda_2^C}, \mu_{\lambda_3^C}, \mu_{\lambda_4^C}, \sigma_{\lambda_1^C}, \sigma_{\lambda_2^C}, \sigma_{\lambda_3^C}, \rho^{\text{corr}}_{\lambda_1^C,\lambda_2^C}, \rho^{\text{corr}}_{\lambda_3^C,\lambda_2^C}, \rho^{\text{corr}}_{\lambda_1^C,\lambda_3^C}$
- Per-period utility of the single—$v_t^S(\ell_t, c_t, k_t, q_t; \boldsymbol{\alpha}^S)$:
  $\mu_{\lambda_1^S}, \mu_{\lambda_2^S}, \mu_{\lambda_3^S}, \sigma_{\lambda_1^S}, \sigma_{\lambda_2^S}, \rho^{\text{corr}}_{\lambda_1^S,\lambda_2^S}$
- Terminal condition of the household—$V_{T+1}(\theta_{k,T+1}^M, \theta_{q,T+1}^M)$:
  ψ

- Production function—$f_t^{\mathcal{A},M}\left(\boldsymbol{\tau}_t, e_t^M, \theta_{k,t}^M, \theta_{q,t}^M; \boldsymbol{\delta}(\boldsymbol{\rho})_t^{\mathcal{A},\tau_t}, \boldsymbol{\delta}_t^{\mathcal{A},-\tau_t}\right)$:
  $\kappa_{10}^k, \kappa_{11}^k, \kappa_{12}^k, \kappa_{10}^q, \kappa_{11}^q, \kappa_{12}^q, \kappa_{20}^k, \kappa_{21}^k, \kappa_{22}^k, \kappa_{20}^q, \kappa_{21}^q, \kappa_{22}^q, \kappa_{30}^k, \kappa_{40}^k, \kappa_{50}^k, \kappa_{30}^q, \kappa_{40}^q, \kappa_{50}^q$

- TFP process—$R_t^{M,\mathcal{A}}$:
  $\kappa_0^k, \kappa_0^q, \sigma_{\omega_{\mathcal{A},C}}, \sigma_{\omega_{\mathcal{A},S}}$

- Wage process—$(w_{1,t}, w_{2,t})$:
  $\mu_1^0, \mu_1^1, \mu_1^2, \mu_1^3, \mu_1^4, \mu_2^0, \mu_2^1, \mu_2^2, \mu_2^3, \mu_2^4, \sigma_{w_1}, \sigma_{w_2}, \sigma_{w_1 w_2}$

The wage process although exogenous, is estimated simultaneously with preferences and technology parameters to correct for the non-random selection of observed wages (Del Boca, Flinn, and Wiswall (2014) and Agostinelli et al. (2024)).

Simulated Method of Moments—The estimator requires solving and estimating the dynamic household problem to construct the set of empirical simulated moments analogous to the sample moments we observe in the data.

The estimation algorithm is as follows:

Step 1—For each household in the sample, the estimation process starts at period $t_j = (t_j^0 - 1)$, one year before the initial age at which the child j's skills ($\tilde{\theta}^M_{\mathcal{T},j,t_j^0}$ with $\mathcal{T} \in \{LW, BPI\}$) are observed for the first time.[33] Time-invariant cross-section heterogeneity in preferences and the TFP process is realized for the entire sample path. Income and wages are also determined after we draw time-variant heterogeneity from the distribution of shocks to wages and non-labor income. The model is solved analytically at $t_j = (t_j^0 - 1)$ yielding labor supply, expenditure, and childcare time decisions.

Step 2—At period $t = t_j^0$, we draw an initial skills level, $\theta^M_{\mathcal{A},j,t_j^0}$ with $\mathcal{A} \in \{k, q\}$, for the entire sample path using the algorithm in Appendix C.2. At this period, the solution of the full model starts since this is the first period for which we have data on a child's outcomes. The model is solved, yielding labor supply and investment choices.

Step 3—At period $t = (t_j^0 + 1)$, we use the data-generating process to simulate values for child skills and investment choices, which are not observed for this period. Drawing new realizations for wages and non-labor income, we can determine household

[33] The initial year depends on the CDS cohort the child belongs to. The first cohort of CDS children was surveyed for the first time in 1997 whereas the second cohort of CDS children was in 2014.

choices and a child' skills.

Step 4—Continuing like this for the remaining periods, we can generate the following sequence of variables:

$$\left\{\tau_{1,t}, \tau_{2,t}, h_{1,t}, h_{2,t}, e_t^C, e_t^S, w_{1,t}, w_{2,t}, I_t^C, I_t^S, \theta_{k,t+1}^C, \theta_{q,t+1}^C, \theta_{k,t+1}^S, \theta_{q,t+1}^S\right\}_{t=(t_j^0-1)}^T.$$

For each household, the process outlined above is repeated $\mathbb{S}$ times to have $\mathbb{S} \times \mathbb{N}$ sample paths, where $\mathbb{N}$ is the number of households in the sample.

Step 5—We use the simulated distributions from the previous step to compute the simulated counterparts ($\mathbb{M}^{sim}$) of the moments estimated in the data ($\mathbb{M}^{data}$). The SMM objective function is given by:

$$\hat{\boldsymbol{\Theta}}_{\mathbb{S},\mathbb{N}} = \arg\min_{\boldsymbol{\Theta}} (\mathbb{M}_{\mathbb{N}}^{data} - \mathbb{M}_{\mathbb{S}}^{sim}(\boldsymbol{\Theta}))' W_{\mathbb{N}} (\mathbb{M}_{\mathbb{N}}^{data} - \mathbb{M}_{\mathbb{S}}^{sim}(\boldsymbol{\Theta})),$$

with $W_{\mathbb{N}}$ being the inverse of the variance-covariance matrix of the empirical moments estimated through a bootstrap method. The optimal vector of parameters that minimizes the objective function is found using numerical methods.

Selected Moments—The estimator presented above uses all the information from the data moments jointly. However, our selected set of moments is chosen based on the identification discussion given in Section 5. The set of targeted moments includes the averages, standard deviations, and/or correlations of hourly wages, employment rates, parental active time investments, weekly hours of work in the labor market, and child scores on the LW and BPI. Some of these moments are categorized into a child's age categories, gender of the parent, marital status, and personality types.

6.2. Model Estimates

Preferences—Table 4 presents the estimates of preference parameters. Although preference parameters are stable over time, we introduce heterogeneity in preferences across households. I present the mean values for preference parameters across households, standard deviations, and correlation coefficients, which describe the moments of the parametric distribution assumed for preferences. In Panel A, I present the estimates for couples. Overall, couples put more weight on a mother's leisure time than on a father's leisure time. Couples' weight on household consumption is around 0.21, a bit lower than weights on a child's skills. Moreover, these households put slightly more weight on a child's cognitive skills than on non-cognitive skills. The estimated preference weights have a dispersion that ranges from 0.09 to 0.21 standard deviations. We estimate a fairly strong correlation between spouses' leisures. In Panel B, we observe the estimates for singles. There is a relatively large weight on household leisure as compared to household consumption. Overall, singles also value a child's skills more than any household commodity. In Panel C, I show the estimated parameter for a household's final valuation of a child's skills, which is common to all households. For instance, a household that is infinitely lived would have an implied final valuation of $1/(1-\beta) = 20$. Our estimate of 35.50 reflects the fact that households not only highly value the flow utility of a child's skills but also its terminal value. Most of the papers that estimate fully specified models using PSID-CDS data find similar results (Del Boca, Flinn, and Wiswall, 2014, 2016). Compared to these papers, our estimates suggest somewhat smaller weights for leisure and a larger overall estimated dispersion.

Technology of Skills Formation—Table 5 presents the estimates of technology parameters for the production function of cognitive and non-cognitive skills. Due to the exponential transformation function, the raw estimates relating to each input are difficult to interpret. Figure 5 shows the transformed estimates for the productivity of parental childcare time as a function of a child's age. Overall, we estimate a downward trend in the productivity of time as children grow older. Parental childcare time is more productive for producing non-cognitive skills than cognitive skills, in particular maternal childcare time. Mothers are more productive than fathers in producing both types of skills at all ages. Using PSID data on couples, Del Boca et al. (2023) also finds a decreasing pattern for the productivity of parental time as a function of age. From a sample of single mothers drawn from the same panel, Mullins (2022) also finds that for some periods—especially between ages 6 and 12—mothers' time input is significantly more relevant for producing non-cognitive skills than cognitive skills. Cunha, Heckman, and Schennach (2010) estimates a larger impact of maternal non-cognitive skills than maternal cognitive skills on children's outcomes in a sample of NLSY children.

Figure 6 shows the estimated productivity of parental time by personality types. In line with our intuition, emotionally stable parents are more productive in spending time with children than emotionally vulnerable parents in all cases. Differences between types are larger for mothers than for fathers. The fact that stable parents might be spending more quality time with children could help rationalize why children of emotionally vulnerable parents tend to perform worse on standardized scores than children of emotionally stable parents (as we saw in Figure 2). Correlational evidence from psychology suggests that parents loading low in neuroticism and high in agreeableness could provide better quality interactions with their children (Prinzie, de Haan, and Belsky, 2019).

TABLE 4. Preferences Parameters Estimates

	Estimate	S.E.
Panel A—Couples:		
Mother's leisure, *mean*	0.1392	(0.0176)
Mother's leisure, *s.d.*	0.2156	(0.0199)
Fathers's leisure, *mean*	0.0931	(0.0118)
Fathers's leisure, *s.d.*	0.0911	(0.0121)
Consumption, *mean*	0.2143	(0.0197)
Consumption, *s.d.*	0.1645	(0.0183)
Cognitive skills, *mean*	0.2998	(0.0250)
Cognitive skills, *s.d.*	0.1545	(0.0181)
non-cognitive skills, *mean*	0.2534	(0.0214)
non-cognitive skills, *s.d.*	0.1215	(0.0166)
Correlation leisures	0.3387	(0.1612)
Correlation consumption-leisure, *mothers*	0.2001	(0.1551)
Correlation consumption-leisure, *fathers*	-0.1531	(0.1449)
Panel B—Singles:		
Leisure, *mean*	0.3591	(0.0441)
Leisure, *s.d.*	0.1265	(0.0210)
Consumption, *mean*	0.1305	(0.0227)
Consumption, *s.d.*	0.1120	(0.0205)
Cognitive skills, *mean*	0.2763	(0.0388)
Cognitive skills, *s.d.*	0.1310	(0.0229)
non-cognitive skills, *mean*	0.2342	(0.0319)
non-cognitive skills, *s.d.*	0.1159	(0.0213)
Correlation consumption-leisure	0.2516	(0.1477)
Panel C—All households:		
Valuation final skills	30.5030	(0.1386)

Notes: Standard errors (S.E.) in parentheses are computed by bootstrap sampling from the estimated parameter distribution.

Finally, we also estimate that money investments are not as productive as other investments. Skills show self-productivity, and the stock of non-cognitive skills tends to be more relevant in producing cognitive skills than the other way around (Cunha, Heckman, and Schennach, 2010). We estimate that TFP is slightly larger for couples than for singles.

Wages and Non-labor Income—Table 6 presents the estimates of the wage and non-labor income processes. Wages are defined as a function of the education and age profile of the parent as well as of their personality type. Overall, we estimate standard concave wage

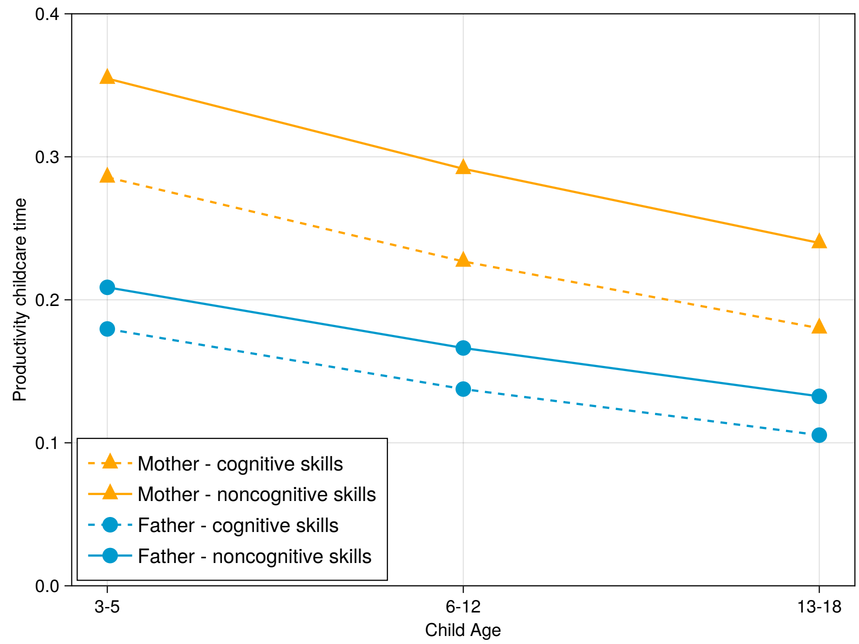
TABLE 5. Technology Parameters Estimates

	Estimate	S.E.
Panel A—Cognitive Skills:		
Mother's time, *intercept*	-1.6595	(0.0566)
Mother's time, *slope*	-0.2374	(0.0074)
Mother's time, *personality*	0.0903	(0.0251)
Father's time, *intercept*	-1.6960	(0.0564)
Father's time, *slope*	-0.2810	(0.0081)
Father's time, *personality*	0.0465	(0.0214)
Child expenditures	0.1804	(0.0041)
Past skills, *cognitive skills*	0.5978	(0.0127)
Past skills, *non-cognitive skills*	0.5296	(0.0119)
TFP, *couples*	0.7913	(0.0261)
TFP, *singles*	0.7577	(0.0258)
Panel B—non-cognitive Skills:		
Mother's time, *intercept*	-1.2612	(0.0304)
Mother's time, *slope*	-0.2253	(0.0072)
Mother's time, *personality*	0.0952	(0.0294)
Father's time, *intercept*	-1.6676	(0.0527)
Father's time, *slope*	-0.2478	(0.0077)
Father's time, *personality*	0.0564	(0.0322)
Child expenditures	0.1595	(0.0038)
Past skills, *cognitive skills*	0.4086	(0.0114)
Past skills, *non-cognitive skills*	0.8517	(0.0262)
TFP, *couples*	0.8187	(0.0272)
TFP, *singles*	0.7964	(0.0264)

Notes: Standard errors (S.E.) in parentheses are computed by bootstrap sampling from the estimated parameter distribution.

processes for both men and women with respect to age. We estimate returns to schooling of about 5.2% for women and 8.3% for men, which are within the range of previous estimates (e.g., Fletcher (2013)). The dispersion of the wage shock is slightly more volatile for mothers than for fathers. For couples, we estimate a relatively strong correlation in the dispersion of the innovation process. In line with our reduced-form results, our estimates also suggest that emotionally stable parents earn more than emotionally vulnerable parents, *ceteris paribus*, with the estimates ranging from 4.3% to 7.3%. In Section 2, we saw that emotionally stable parents are characterized by positive loadings in conscientiousness and negative loadings in neuroticism (see Table 2), two traits that the literature has shown to be particularly relevant for explaining earnings (Heckman, Jagelka, and Kautz, 2021).

FIGURE 5. Technology Parameters—Productivity of Childcare Time by Skills and Gender

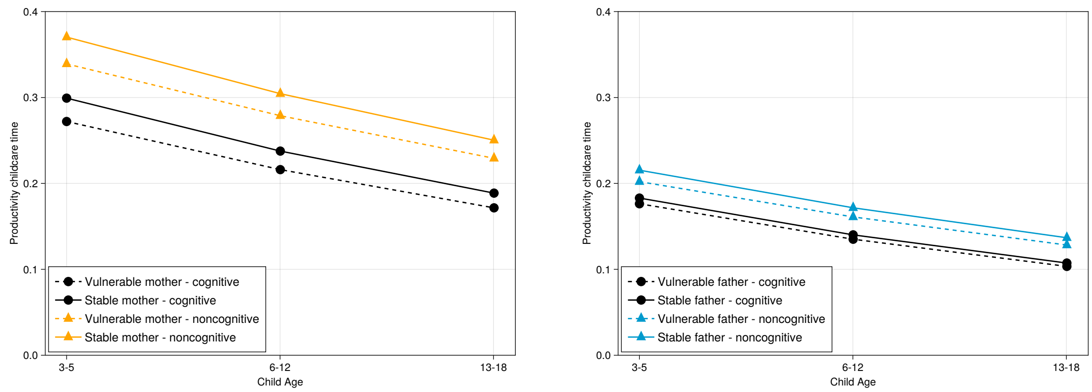


Notes: This figure presents the evolution of the productivity of parental childcare time over a child's age.

The effects of these traits on similar wage processes found elsewhere range from 2.5% to 6.8% (Flinn, Todd, and Zhang, 2018, 2021; Todd and Zhang, 2020). Returns to personality may have different implications in terms of income and substitution effects of working hours between stable and vulnerable parents. These results, together with the gap in the productivity of time between personality types presented above, help rationalize differences in scores between children of these two family types.

FIGURE 6. Technology Parameters—Productivity of Childcare Time by Personality Type

A. Time Productivity of Mothers B. Time Productivity of Fathers



Notes: This figure presents differences in the productivity of parental childcare time over a child's age between emotionally stable and vulnerable parents.

TABLE 6. Wage and non-labor Income Parameters Estimates

	Estimate	**S.E.**
Panel A—Wage Process:		
Intercept, *mother*	2.4386	(0.0551)
Returns to experience, *mother*	0.0677	(0.0021)
Returns to experience s.q., *mother*	-0.0004	(0.0004)
Returns to education, *mother*	0.0525	(0.0056)
Returns to personality, *mother*	0.0431	(0.0011)
Shock s.d., *mother*	0.5035	(0.0899)
Intercept, *father*	3.4828	(0.0709)
Returns to experience, *father*	0.0944	(0.0033)
Returns to experience s.q., *father*	-0.0002	(0.0001)
Returns to education, *father*	0.0833	(0.0078)
Returns to personality, *father*	0.0738	(0.0018)
Shock s.d., *father*	0.4001	(0.0650)
Correlation shocks, *couples*	0.3982	(0.1671)
Panel B—non-labor Income:		
Intercept	50.3703	(14.7229)
Shock s.d.	5.7934	(0.0357)

Notes: Standard errors (S.E.) in parentheses are computed by bootstrap sampling from the estimated parameter distribution.

6.3. Model Fit

In this subsection, I present the model fit for targeted moments associated with children's scores, labor supply, childcare time, and hourly wages conditional on personality type and gender. In Appendix D, I show related targeted moments conditional on marital status. At the end of this subsection, I present nontargeted moments on the gap in standardized mean scores between children of emotionally stable and emotionally vulnerable parents.

The model is able to predict relatively well the evolution of children's scores. Figure 7 shows the observed and simulated average scores for the Letter Word Test and the Behavior Problem Index across different child age categories. For both skills, the model slightly overpredicts scores at later ages. The estimated model is also able to capture relevant dynamics in parental labor supply. Figures 8 and 9 show, respectively, the actual and simulated mean employment rates and mean work hours by parents' gender, child's age categories, and personality types. The predicted values consider the overall trends over time in labor supply and the differences between emotionally stable and vulnerable parents. Figure 10 shows the observed and predicted moments for mean childcare hours by personality, gender, and a child's age categories. Although the model captures relatively well differences over time, we observe an overprediction in average hours in most of the cases. The fit of childcare time is relatively better in the case of singles and couples (see Figure D5). Finally, the model also captures well the observed heterogeneity in average wages between personality types across genders and marital status. Figure 11 shows the simulated and observed moments for hourly mean wages.

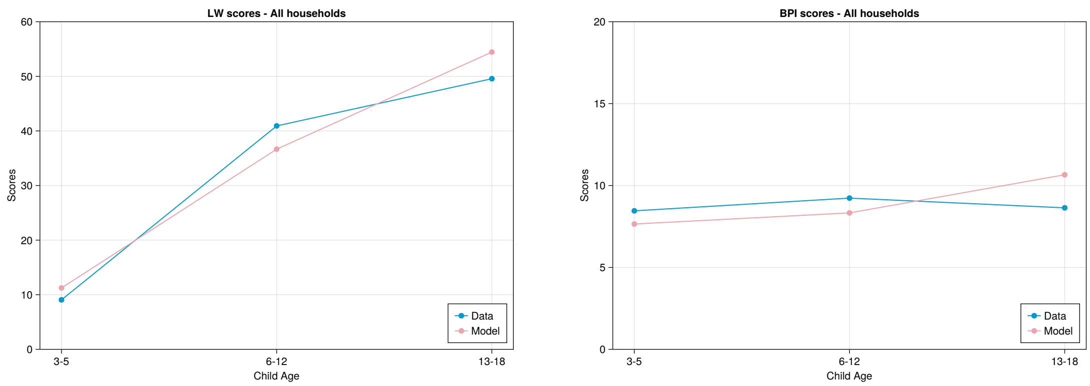
Another element of interest corresponds to the distribution of a child's skills across families. In Figure 12, we show the untargeted differences in standardized scores between children of stable parents and vulnerable parents conditional on a child's age and skill. Although we slightly overpredict the skills gap in general, the model is able to reproduce relevant features of the data, i.e., that children of stable parents perform better than children of vulnerable parents across skills and over time.

7. Policy Counterfactuals

In this section, I use the model estimates to quantify the implications of parental personality for policies aimed at improving child outcomes. Our empirical findings indicate that parental personality influences a child's skills through its effects on both labor market productivity and childcare time. I first provide insight into the significance of each channel for child outcomes. The model shows that a substantial portion of the skills gap between family types can be attributed to differences in the productivity of childcare time among parents. Eliminating the gap in the quality of parent-child interactions leads to a significant reduction in skill inequality and an overall increase in skill levels. Next, I examine the

FIGURE 7. Targeted Moments—Average Scores by Child Age Categories

A. Cognitive Skills (LW) B. non-cognitive Skills (BPI)



Notes: This figure shows the average score in cognitive (Letter Word Test) and non-cognitive skills (Behavior Problem Index) by child age categories observed in the data and predicted by the model.

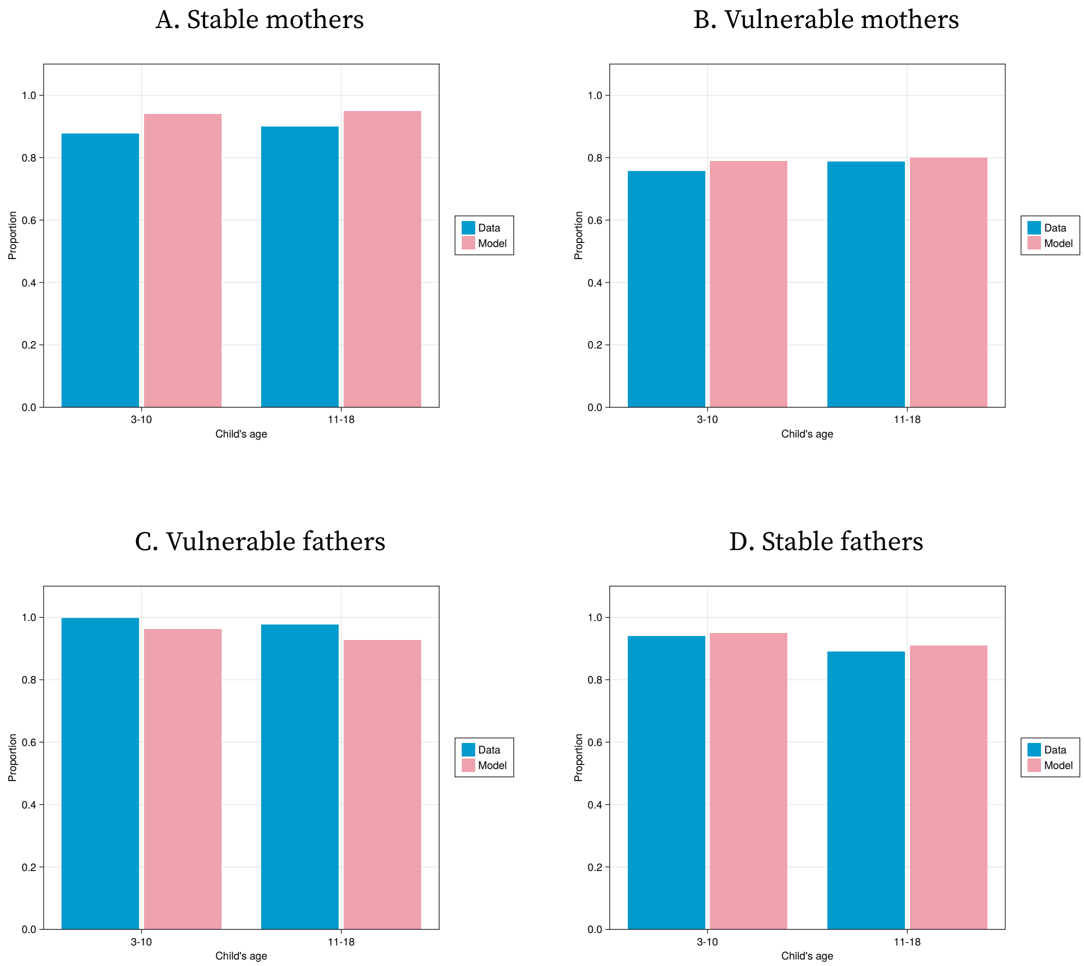
economic and behavioral responses following exogenous changes to household monetary inputs through permanent cash transfers (similar to the 2018 US Child Tax Credit). Our simulations suggest that existing policies could have unintended negative distributional effects on children's skills due to varied reallocations of budget and time among different families.

Labor Markert *vs.* Childcare Time Productivity—The first objective of our simulations is to understand the importance of the two channels through which personality affects child outcomes. I analyze household behavior after closing the gap in labor market and childcare time productivity between emotionally stable and vulnerable parents.

Column (1) of Table 7 shows the simulated results for the scenario where labor market incentives linked to personality are equalized. For both personality types, I remove the labor market premiums associated with personality and allow households to reoptimize their choices. All changes are expressed as the average fraction of a standard deviation relative to the baseline. Panels (A) and (B) present changes in children's skills averaged for ages 16 to 18 (the late developmental stage). The results indicate modest effects on average cognitive and non-cognitive skills. For example, closing the gap in labor market productivity results in a 0.02 standard deviation increase in non-cognitive skills, equivalent to a 0.06 overall increase over the entire period. The skills gap remains nearly unchanged before and after the adjustment.

To explore the behavioral mechanisms underlying this result, Panels (C) through (F) display changes in budget and time allocation for stable and vulnerable parents, averaged over a child's lifecycle. While stable and vulnerable parents smooth consumption differently, significant differences in time and financial allocations to children are not observed.

FIGURE 8. Targeted Moments—Employment Rates by Personality and Gender



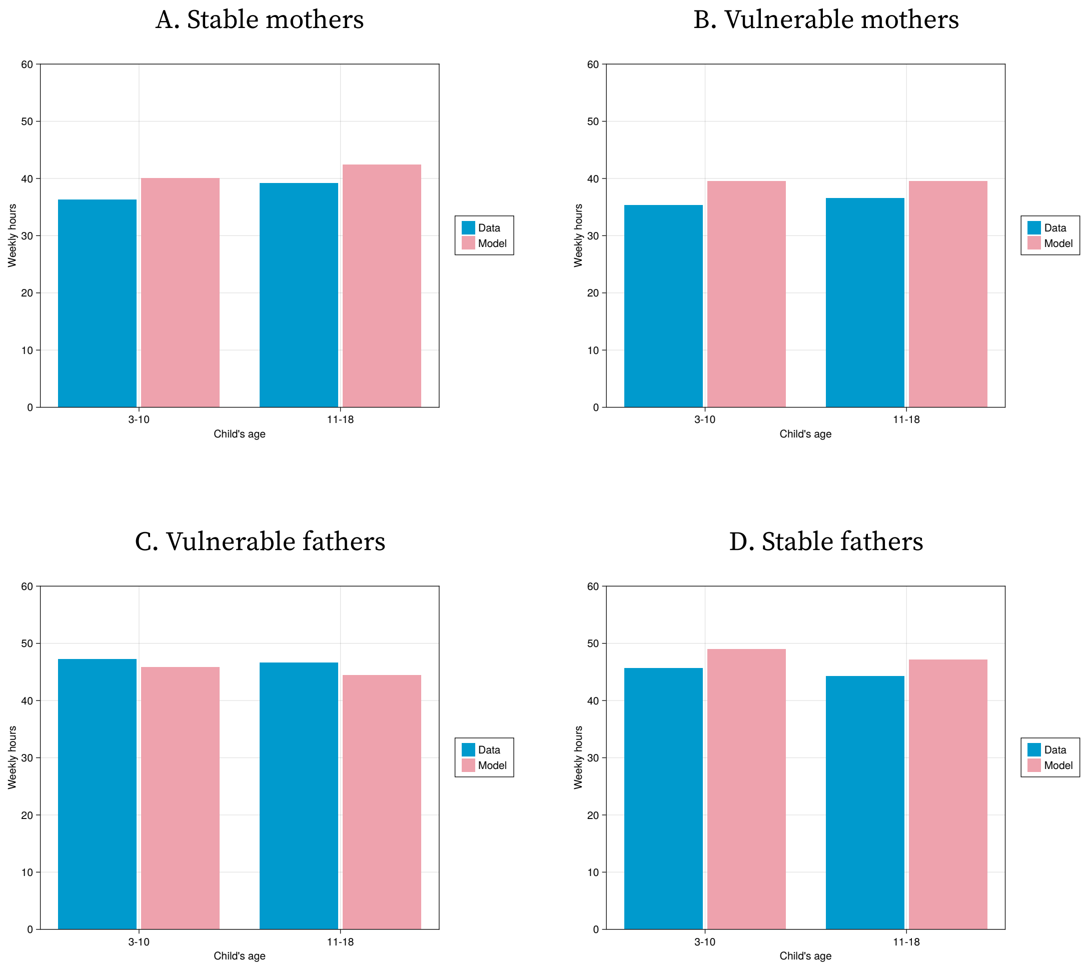
Notes: This figure shows the proportion of individuals employed in the labor market by personality types and gender observed in the data and predicted by the model.

After eliminating the wage premium linked to personality, vulnerable households allocate more time to labor market activities than stable households, but the net difference in childcare hours remains minimal. Additionally, positive income changes are primarily used for household consumption rather than child-related expenditures.

Column (2) of Table 7 presents the results for the scenario where the gap in childcare time productivity is closed, and vulnerable parents become as productive at home as stable parents. Panels (A) and (B) show similar increases in skill levels, with a 3.9% increase in the average skill level during the late developmental stage. The skills gap in cognitive and non-cognitive abilities narrows by 0.11 and 0.20 standard deviations, respectively, nearly closing the gap by later ages. This suggests that improvements in parental childcare productivity can have lasting, impactful effects on reducing skill disparities.

These results are largely driven by the behavioral shifts of vulnerable parents. Notably,

FIGURE 9. Targeted Moments—Mean Work Hours by Personality and Gender

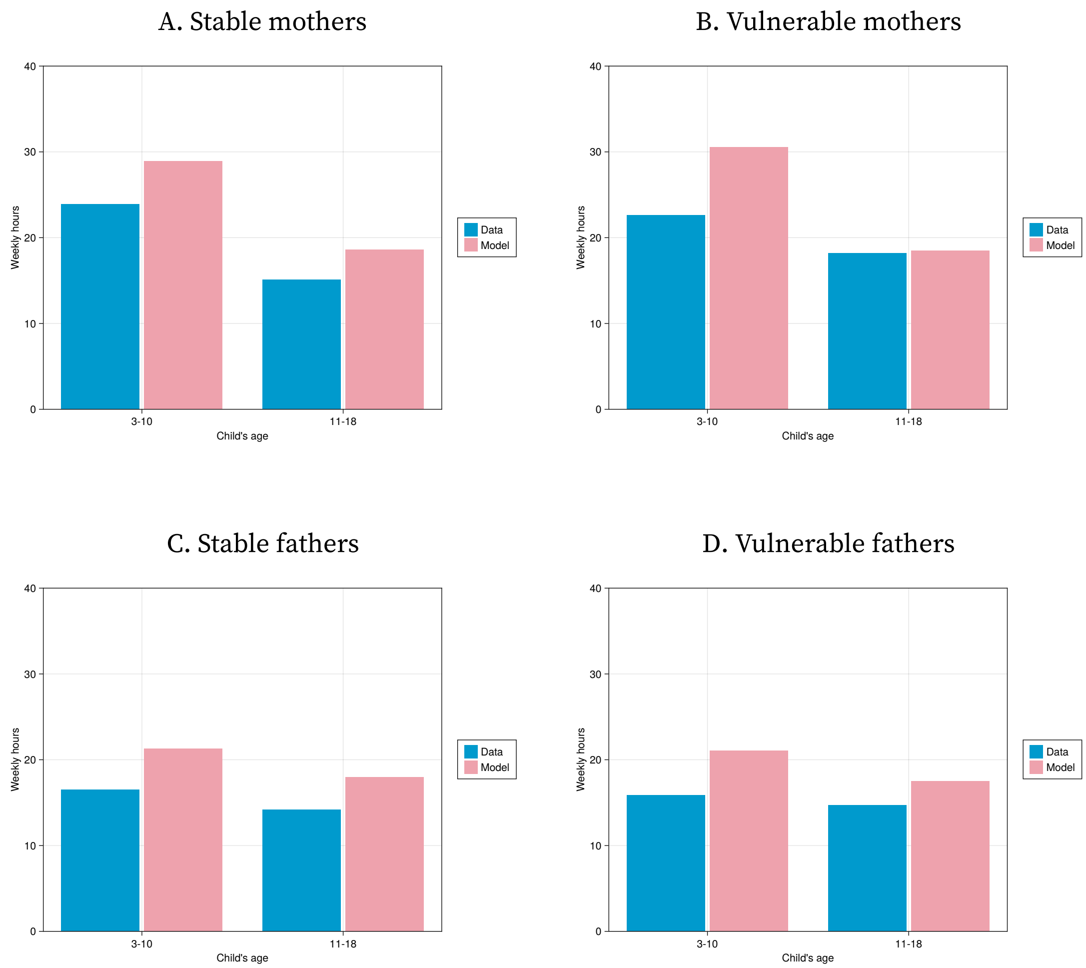


Notes: This figure shows the average weekly work hours in the labor market between fathers and mothers by personality types observed in the data and predicted by the model.

emotionally vulnerable *fathers* substitute market work and leisure for increased time with their children, raising average childcare hours by approximately 7% of a standard deviation annually. This time reallocation, coupled with the higher productivity of vulnerable *fathers*, explains the significant reduction in skill gaps.

Overall, the simulations highlight that parental personality, particularly its influence on childcare time productivity, plays a crucial role in shaping child skill development and reducing inequalities. One interpretation of parental childcare time productivity is the quality of parent-child interactions (e.g., Verriest (2018)). Our findings imply that policies designed to enhance these interactions could be effective in leveling opportunities for children of parents with less *suitabel* personality traits for parenting. This is especially significant given the emphasis in experimental literature on allocating public resources to parenting and mentoring programs that foster active engagement (Heckman and Mosso,

FIGURE 10. Targeted Moments—Mean Childcare Hours by Personality and Gender

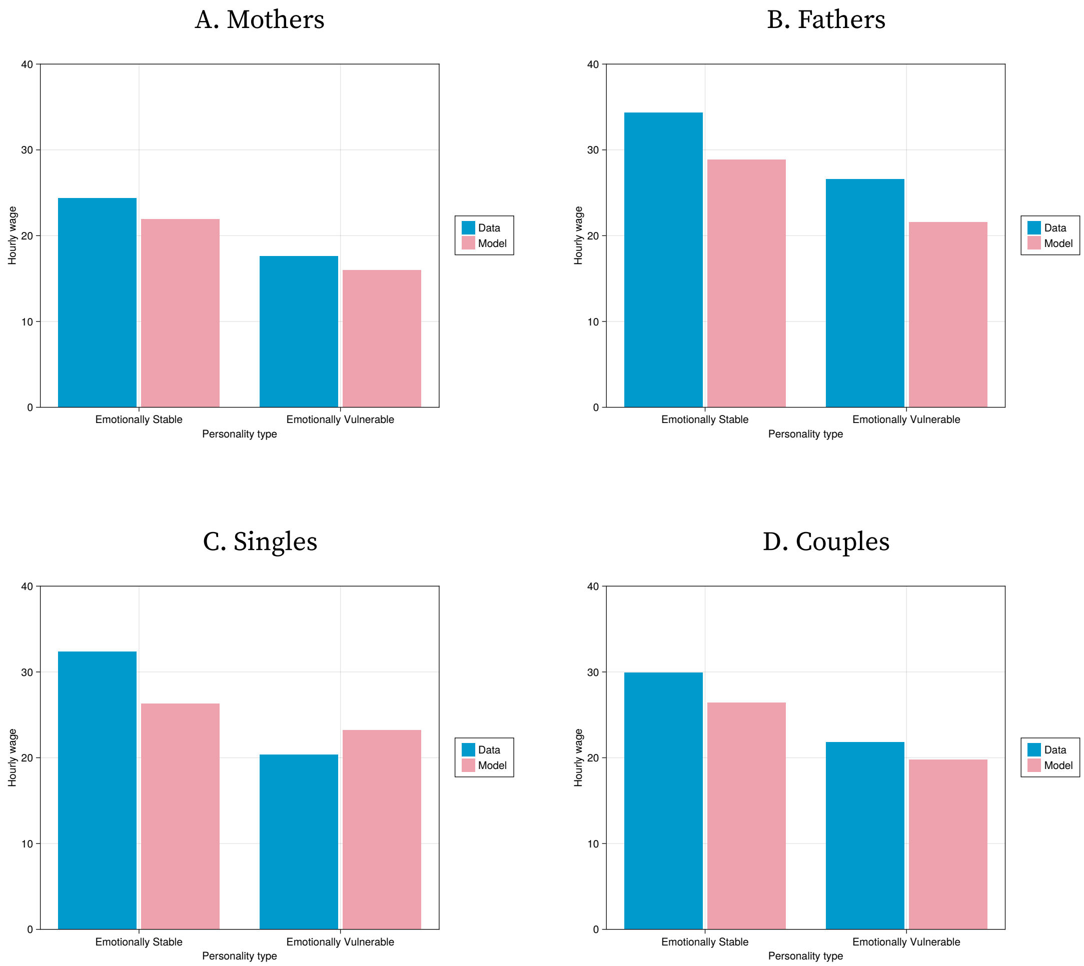


Notes: This figure shows the average weekly childcare hours between fathers and mothers by personality types observed in the data and predicted by the model.

2014; Attanasio, Cattan, and Meghir, 2022). For example, rather than fully eliminating the productivity gap in childcare time between parents (as simulated in Column (2) of Table 7), we explored the outcomes of a simulated intervention reflecting the average treatment effect of a successful program like the Jamaica Home Study (Grantham-McGregor et al., 2020).[34] In Column (3) of Table 7, the results show mean changes after reducing the

[34]The Jamaica Home Visit (JHV) program is a home-visiting parenting intervention that was first implemented in Jamaica in the 1970s. The goal was to build a rich relationship between parents and children by strengthening parenting skills through several home visits at regular intervals for an extended period. The home visitor introduces activities for the parent to perform with the child and discusses how these can be included in daily routines. Each activity addresses a separate developmental domain, related to cognitive, language, motor, and socioemotional skills. Many later interventions have replicated the JHV in other countries such as Bangladesh, China, Perú, Colombia, and India. Nowadays, the JHV is known as the Reach Up Early Childhood Parenting Program. For our simulations, we take as a benchmark the estimates in Grantham-McGregor et al. (2020), one recent implementation of this program. In this case, the program

FIGURE 11. Targeted Moments—Mean Hourly Wages by Personality and Gender



Notes: This figure shows the average hourly wage rate by personality types, gender, and marital status observed in the data and predicted by the model.

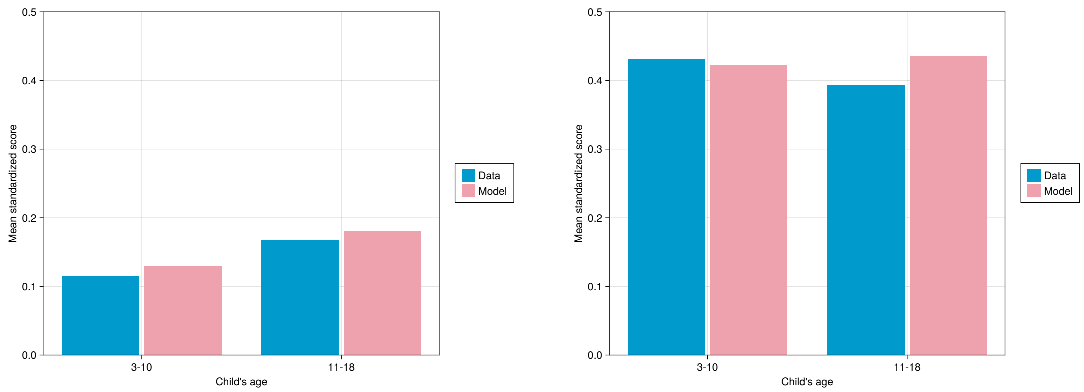
productivity gap in childcare time by approximately 0.3 standard deviations—mirroring the impact of the Jamaica Home Study program. Even when the productivity gap is only partially closed, we observe notable reductions in skill inequality accompanied by similar increases in average skill levels. Additionally, our results highlight the potential role that *fathers* can play in enhancing child outcomes, aligning with emerging research on paternal engagement in early childhood development (Evans and Jakiela, 2024). Historically, fathers have spent less time engaging in stimulating activities with their children compared to mothers, often leading to policies that underestimate their role in childrearing. However, our simulations indicate that with appropriate parenting tools, fathers could

had a positive effect on child outcomes accompanied by an increase of 0.3 standard deviations in "family care indicators" (e.g., the presence of toys and books and scales measuring the caregiver's involvement with children in various play activities) Attanasio, Cattan, and Meghir (2022) provides an in-depth review of this program and its several implementations.

FIGURE 12. Nontargeted Moments—Differences in a Child's Skills

A. Cognitive Skills

B. Non-cognitive Skills



Notes: This figure shows the average standardized skills gap between children of emotionally stable parents and children of emotionally vulnerable parents by child age categories observed in the data and predicted by the model.

effectively reallocate their time to include more interaction with their children, contributing positively to child skill development.

Simulated Cash Transfer—The second objective of our simulations is to assess how current cash transfer policies interact with the influence of parental personality, particularly its associations with labor market incentives and childcare behavior. Various cash transfer programs in the U.S. and globally aim to support working families by alleviating the high costs of raising children.[35] In this subsection, I evaluate the effects of an unrestricted lump sum cash transfer. Following standard modeling practices, I treat cash transfers as an increase in household non-labor income (Mullins, 2022). The simulated transfer amounts to an annual permanent increment of 2400 USD (approximately 50 USD per week), aligning with the full benefit of the 2018 Child Tax Credit and similar subsidy program (Verriest, 2018). After implementing the policy, households reoptimize their choices based on their preferences, technology, and constraints, which ultimately determine the portion of the transfer allocated to child-related expenditures. As with many U.S. cash assistance programs, it is assumed that households are aware of the transfer well in advance.

In Column (4) of Table 7, I show the results after the policy simulation. The findings show that a universal cash transfer leads to an average increase in non-cognitive and cognitive skills of 0.07 and 0.09 standard deviations, respectively, for children aged 16 to 18.[36] However, this increase in average skill levels is accompanied by a notable widening

[35]In the U.S., several governmental programs take the form of either monetary transfers or tax breaks to families—for example, the Child Tax Credit, Assistance to Families with Dependent Children, or Temporary Assistance of Needy Families.

[36]These magnitudes are within the range of estimates found in the literature that looks at the evaluation of

of the skills gap, approximately 0.06 standard deviations across skills (around 0.18 for the entire period). This result is explained by differences in how stable and vulnerable parents use the additional economic resources and adjust their time allocation. For example, emotionally stable parents are more likely to allocate a larger portion of the transfer to child-related expenditures compared to their emotionally vulnerable counterparts. Furthermore, while both types of families adjust their labor supply in response to the transfer, vulnerable parents are more inclined to reallocate time toward leisure rather than childcare. Overall, these results suggest that current cash transfer policies may inadvertently exacerbate skill inequalities due to the differential ways in which parental personality traits affect labor and childcare productivity.

similar cash transfers of subsidy programs in child outcomes. Dahl and Lochner (2012) find that an additional 1000 USD in annual household income from EITC expansions increments math and reading skills by 0.06 of a standard deviation. Akee et al. (2018) suggest that an increment of 3500 USD in annual household income lead to a 0.20 reduction of a standard deviation in behavioral problems. Mullins (2022) provides a more conservative view where incrementing household income by 1000 USD implied an increment in cognitive skills of a bit less than 0.02 of a standard deviation and an increment in non-cognitive skills of less than 0.01 of a standard deviation.

TABLE 7. Policy Counterfactuals

	Changes from baseline after:			
	(1) No gap in labor market productivity	(2) No gap in childcare time productivity	(3) ATE of parenting program	(4) Lump-sum cash transfer
(A) non-cognitive skills, ages 16–18:				
Skills levels	+0.020	+0.015	+0.010	+0.076
Skills gap	-0.004	-0.117	-0.070	+0.042
(B) Cognitive skills, ages 16–18:				
Skills levels	+0.013	+0.011	+0.012	+0.091
Skills gap	-0.018	-0.204	-0.138	+0.090
(C) Lifecycle budget constraint—*emotionally stables*				
non-labor income	+0.022	+0.021	+0.021	+0.101
Labor income	+0.011	+0.003	+0.003	-0.038
Consumption	+0.012	+0.004	+0.002	+0.041
Child expenditures.	+0.002	+0.002	+0.001	+0.028
(D) Lifecycle budget constraint—*emotionally vulnerables*				
non-labor income	+0.044	-0.002	-0.001	+0.097
Labor income	+0.009	-0.009	-0.006	-0.024
Consumption	+0.013	-0.008	-0.006	+0.065
Child expenditures.	+0.009	-0.009	-0.007	+0.012
(E) Lifecycle time constraint—*emotionally stables*				
Mother's labor supply	+0.079	+0.009	+0.011	-0.095
Fathers's labor supply	-0.063	+0.009	+0.002	+0.058
Mother's childcare time	-0.035	-0.005	-0.017	+0.054
Fathers's childcare time	+0.034	-0.011	-0.002	-0.025
Mother's leisure time	-0.031	+0.004	+0.001	+0.068
Fathers's leisure time	+0.033	+0.001	+0.010	-0.027
(F) Lifecycle time constraint—*emotionally vulnerables*				
Mother's labor supply	-0.118	-0.004	-0.008	+0.073
Fathers's labor supply	+0.116	-0.052	-0.030	-0.153
Mother's childcare time	+0.049	-0.005	+0.010	-0.028
Fathers's childcare time	-0.032	+0.071	+0.042	+0.051
Mother's leisure time	+0.057	-0.005	-0.001	-0.035
Fathers's leisure time	-0.056	-0.016	-0.013	+0.104

Notes: This table shows the behavioral responses after the implementation of counterfactual scenarios. **Column 1:** For either personality type, the labor market premium associated with personality in the wage process is turned off. **Column 2:** Vulnerable parents are made equally productive in childcare time as stable parents. **Column 3:** Vulnerable parents are made 0.3 standard deviations more productive in childcare time. **Column 4:** Annual household non-labor income of all households is increased permanently by 2400 USD. All changes are expressed as a fraction of a standard deviation. In Panel (A) and Panel (B), changes are averaged out over the age of 16 to 18. In the remaining panels, changes are averaged out over all periods.

8. Conclusion

In this paper, I study the mechanisms by which parental personality affects the formation of a child's cognitive and non-cognitive skills. I combine reduced-form analyses with the estimation of a structural life cycle model of household choices with endogenous skills formation.

Three key findings emerge from our empirical analysis. First, children of emotionally stable parents tend to outperform children of emotionally vulnerable parents in various measures of cognitive abilities and socioemotional skills. Second, the skills gap between these groups widens as children grow older and remains significant even after controlling for traditional family characteristics such as household income, parental education, and parental health status. Third, emotionally stable parents exhibit higher productivity both in the labor market (i.e., wages) and in childcare (i.e., time spent in active versus passive interactions).

I develop and estimate a structural dynamic model with endogenous production of a child's skills and household choices related to labor supply, consumption, and investments in children. Our results indicate that time inputs play a significant role in developing a child's skills, particularly for socioemotional development. Additionally, emotionally stable parents consistently spend more quality time with their children compared to emotionally vulnerable parents, a trend that persists throughout the child's developmental process. Our analysis also shows that the opportunity cost of time is higher for emotionally stable parents than for emotionally vulnerable parents, influencing the income and substitution effects on working hours.

We then use our model to disentangle the relevance between the labor market productivity and childcare time productivity of parental personality for children's skills. We also assess the implications of our findings for cash transfer policies. Our analysis reveals that much of the impact of parental personality on a child's skills stems from its effect on childcare time productivity. The results also show the potential role fathers can play in enhancing child outcomes. Emotionally vulnerable fathers, when provided with better parenting tools, tend to reallocate their time to include more quality interactions with their children. Furthermore, our simulations indicate that current cash transfer policies could unintentionally have adverse distributional effects on skills, driven by the significant influence of parental personality on household responses.

This study illustrates how combining a theoretical framework with empirical data can shed light on the importance of parental personality in child development by identifying key mechanisms at play. Policies aimed at improving the quality of parent-child interactions could be highly effective in equalizing opportunities for children raised by psychologically vulnerable parents.

While this paper addresses crucial aspects of the relationship between parental personality and skill formation, several questions remain for future research. First, this paper does not account for the effects of divorce or unstable marriages on child development. Integrating the current framework within a dynamic collective model where choices are made under limited commitment could be a promising approach (e.g., Fernández and Kovaleva (2024)) Second, is paper abstracts from the possibility of parental personality being endogenously influenced by a child's development, which could be investigated using richer datasets on parental traits (e.g., Todd and Zhang (2020)). Finally, like much of the child development literature, we assume that a child's scores are an adequate proxy for child welfare. This assumption could be tested using nonparametric revealed preference conditions and examining the intrahousehold production process (e.g., Cherchye et al. (2017)).

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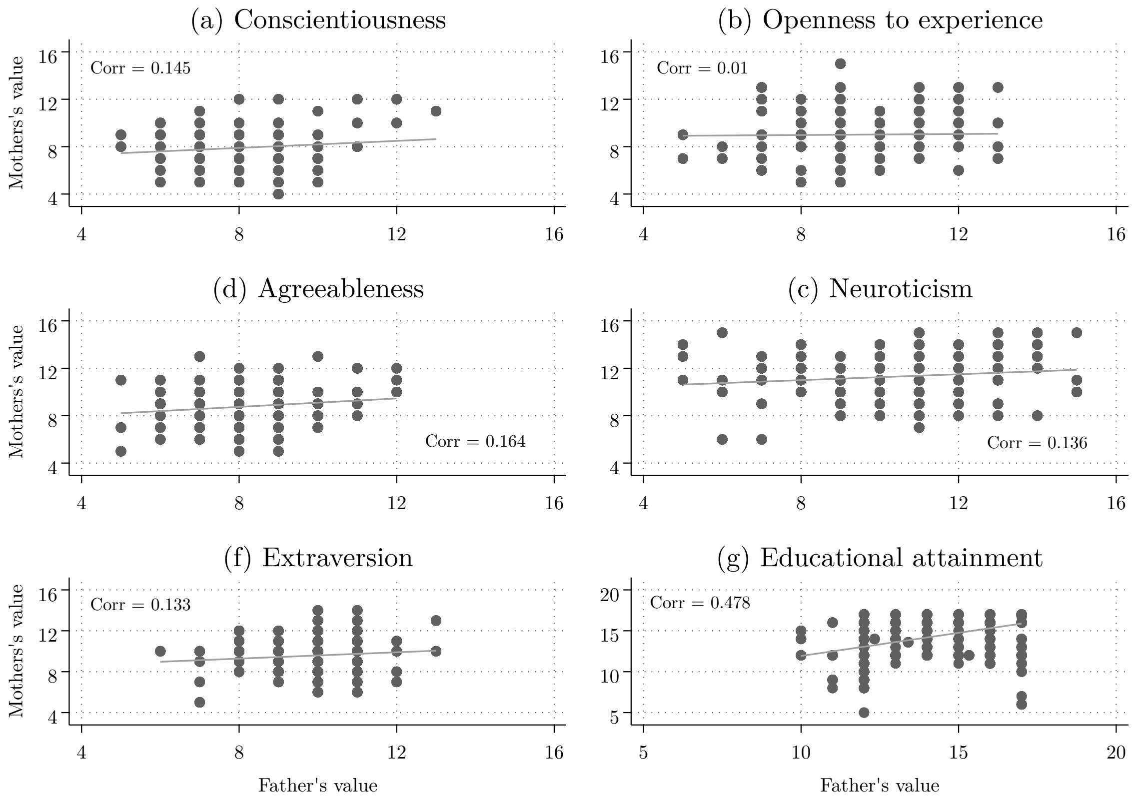
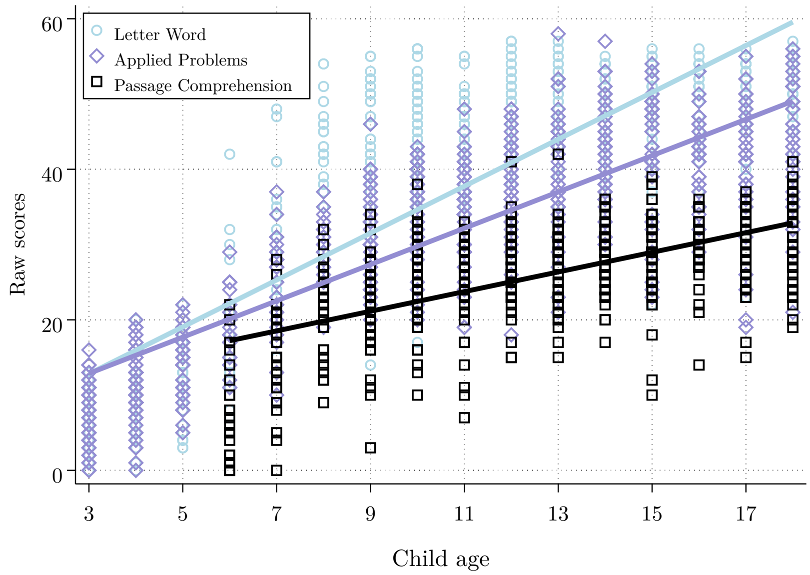
Appendix A. Data appendix

FIGURE A1. Assortative Mating in Personality Traits and Education



Notes: Subsample of married couples

FIGURE A2. Relationship Between Raw Scores and a Child's Age



Notes: This figure shows the positive relationship between the scores on tests measuring a child's cognitive ability and a child's age. The Letter Word and Applied Problems tests are first applied at age 3 whereas the Passage Comprehension test is applied from age 6 onwards.

Appendix B. Empirics appendix

B.1. Clustering Algorithm

I construct clusters using the K–means clustering method (Hartigan, 1975). The goal of this method is to split the sample into a predetermined number of non-overlapping groups so that within-cluster variation is as small as possible and between-cluster variance is maximal.

Let N_k be the number of observations in cluster k, i, j represent different observations, and assume to have p number of variables x. The within-cluster variation for cluster C_k is given by:

$$W(C_k) = \frac{1}{N_k} \sum_{i,j \in C_k} \sum_{l=1}^{p} (x_{il} - x_{jl})^2 = 2 \sum_{i \in C_k} \sum_{l=1}^{p} (x_{il} - \bar{x}_{kl})^2, \tag{B1}$$

with $\bar{x}_{kl} = \frac{1}{N_k} \sum_{i \in C_k} x_{il}$. The K–means method partitions observations in K groups so that $\sum_k W(C_k)$ is minimal.

In the K–means algorithm described below, we use as a starting point the solution of a hierarchical clustering method (Lattin, Carroll, and Green, 2003). This method starts by assigning each observation to its own cluster. In subsequent steps, clusters with the smallest distance are merged. The distance (D_{ij}) between two observations is given by the Euclidean distance:

$$D_{ij} = \Big(\sum_{k=1}^{p}(x_{ik} - x_{jk})^2\Big)^{1/2}. \tag{B2}$$

The following algorithm summarizes the method:

Step 1—Assign each observation to one of K clusters based on the resulting centroids of a hierarchical clustering.

Step 2—Iterate until the cluster assignments stop changing:
Compute the cluster centroid $\bar{\mathbf{x}}_k = (x_{k1}, \ldots, x_{kl}, \ldots, x_{kp})$. Assign each observation to the cluster whose centroid is closest (in terms of Euclidean distance).

Given initial centroids, the K–means algorithm converges to a local optimum.

B.2. Clusters Validation

In general, selecting a cluster solution is based on the interpretation that can be given to the chosen clusters and summary statistics trading-off between adequacy and complexity. In Table B1, I compare fit measures across several cluster solutions.

The pseudo–F statistic captures the trade-off between the number of clusters and within-cluster heterogeneity. A higher value in this statistic, suggests that the clusters are well-separated from each other (high between-cluster variance) and that the data points within each cluster are close to each other (low within-cluster variance). The hit rate provides the percentage of correct classified observations when verifying the generalizability of the cluster solution. Finally, the Adjusted Rand Index indicates how far the cluster solution is from a random classification of observations. For further information, Lattin, Carroll, and Green (2003). As shown in Table B1, the two cluster solution provides the better fit.

B.3. Stability of Personality—the Case of Self-Esteem

Given that we only observe cross-section variation in a parent's Big Five personality traits collected in the WB 2015 wave, we assume that parents' personality types remain fixed over time. To provide evidence for this assumption, we exploit panel data variation available for the personality trait *self-esteem*, collected in each CDS wave through the Rosenberg Self-Esteem scale (Rosenberg, 1965). A minimum score of 1 and a maximum score of 4 are

TABLE B1. Validation of Cluster Solution

Number of Clusters	**Pseudo–*F***	**Hit Rate**	**Adjusted Rand Index**
2	113.90	0.90	0.65
3	105.50	0.77	0.45
4	93.10	0.61	0.29

Notes: Cluster solutions were constructed by K-means clustering with hierarchical centroids. The pseudo–F statistic trade-offs between simplicity (number of clusters) and adequacy (within-cluster heterogeneity). The hit rate corresponds to the percentage of correct classification when verifying the generalizability of the cluster solution. The Adjusted Rand Index will be 0 in case of random classification and 1 in case of perfect agreement.

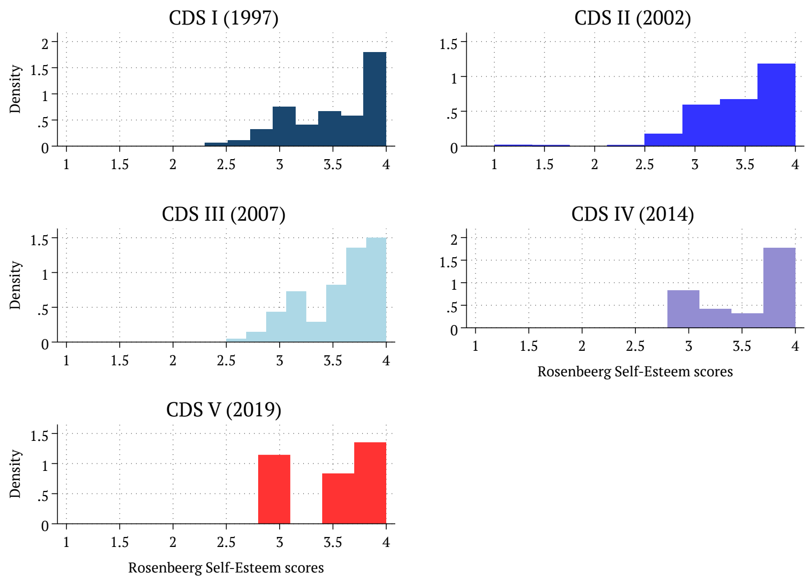
TABLE B2. Correlation Between Personality Types and Demographic Variables

Variable	**Stable mother**	**Stable father**
Educational level, *mothers*	0.16	0.04
Educational level, *fathers*	0.12	0.22
Age, *mothers*	0.01	-0.06
Age, *fathers*	0.05	-0.04
Health status, *mothers*	0.05	-0.10
Health status, *fathers*	-0.07	-0.14
Household income	0.08	0.15
Marital status (1 = singlehood)	-0.08	-0.01
Parental WARMTH Scale	0.09	0.07

This table shows the Pearson correlation coefficients between personality types and relevant variables. The correlation coefficients for the case of *emotionally vulnerable* parents correspond to the reverse signs. Overall, there is a weak correlation between personality types and relevant demographic variables.

possible to obtain after answering this scale. Figure B1 shows the distribution of scores across CDS waves.

FIGURE B1. Distribution of Rosenberg Self-Esteem scores

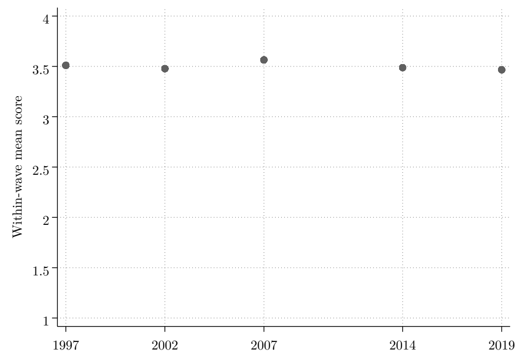


Notes: This figure shows the distribution of raw scores on the Rosenberg Self-Esteem Scale across CDS waves.

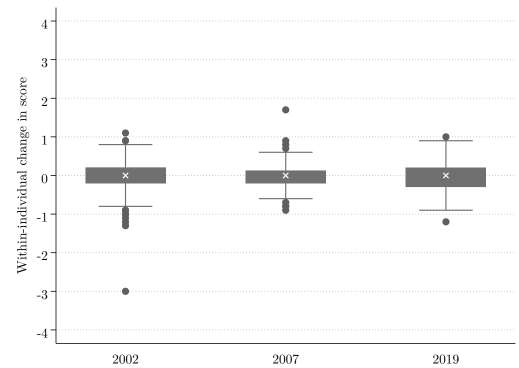
Panel A of Figure B2, which shows the within-CDS wave variation in mean self-esteem scores, presents evidence of a rather stable average score across time and between CDS cohorts, which is around 3.5 absolute points. Panel B of Figure B2, confirms the stability of self-esteem by presenting within-individual variation over time. For example, in the first boxplot, we present the distribution of individual changes in scores between 1997 and 2002. Overall, within-individual changes in scores are accumulated around 0 absolute scores. Although we cannot test the stability of self-esteem independent of having a child or not, we can check for the relationship between a child's initial test/scale score—measured as the score obtained in available ability measures when surveyed for the first time (i.e., either in 1997 or 2014)—and a parent's final self-esteem score—measured as the self-reported score in self-esteem at the last time surveyed (i.e., either in 2002, 2007, or 2019). Overall, there is a very small correlation between a child's initial score and a parent's final self-esteem, especially for measures associated with a child's cognitive skills.

FIGURE B2. Stability of Rosenberg Self-Esteem Scale over time

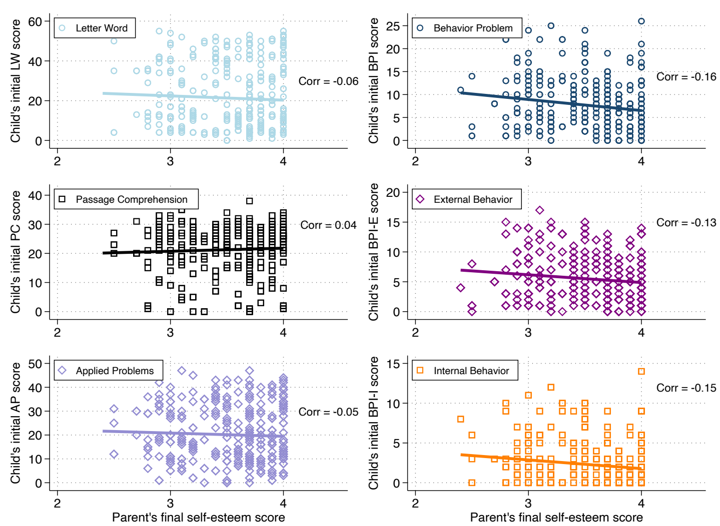
A. Average score by CDS wave



B. Distribution of within-individual changes over time



C. A child's initial skills and a parent's final self-esteem



Notes: This figure presents evidence of the stability of personality traits over time for parents of the two CDS cohorts of children. The first cohort of children was surveyed in 1997, 2002, and 2007; the second cohort of children was surveyed in 2014 and 2019. **Plot A**: average score for the Rosenberg Self-Esteem scale by each CDS wave. The maximum and minimum scores are 4 and 1, respectively. **Plot B**: distribution of changes in absolute scores over time for each parent. The white crosses represent the median of the distributions. **Plot C**: relationship between a child's initial ability score and a parent's final score in self-esteem.

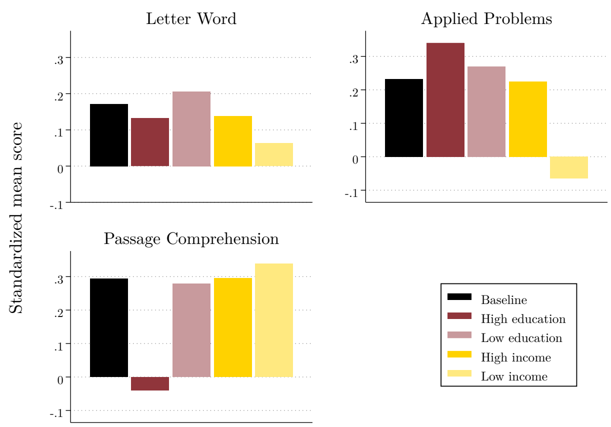
TABLE B3. OLS Estimates of Parental Personality Types on a Child's Skills

	Cognitive Skills			non-cognitive Skills		
	LW	AP	PC	BPI	BPI-E	BPI-I
A. Unconditional estimates						
$\mathbb{1}\left\{\text{stable mother} = 1\right\}$	2.28**	1.87**	1.22*	-1.76***	-0.96**	-0.77***
	(0.93)	(0.83)	(0.63)	(0.56)	(0.41)	(0.25)
Observations	746	743	594	746	695	746
$\mathbb{1}\left\{\text{stable father} = 1\right\}$	0.34	1.02	0.38	-1.21*	-0.63	-0.65*
	(1.24)	(1.11)	(0.76)	(0.51)	(0.39)	(0.36)
Observations	455	454	360	455	432	455
B. Conditional estimates						
$\mathbb{1}\left\{\text{stable mother} = 1\right\}$	1.19^{+}	0.84	0.92*	-1.86***	-0.99**	-0.788***
	(0.80)	(0.65)	(0.56)	(0.58)	(0.40)	(0.28)
Observations	654	651	533	654	603	654
$\mathbb{1}\left\{\text{stable father} = 1\right\}$	0.31	0.25	0.04	-1.25*	-0.51	-0.77**
	(1.21)	(0.94)	(0.73)	(0.57)	(0.52)	(0.33)
Observations	392	391	314	392	370	753
C. Residualized estimates						
$\mathbb{1}\left\{\text{stable mother} = 1\right\}$	1.10^{+}	0.77	0.84*	-1.72***	-0.90***	-0.81***
	(0.75)	(0.56)	(0.46)	(0.44)	(0.31)	(0.21)
Observations	654	651	533	654	603	654
$\mathbb{1}\left\{\text{stable father} = 1\right\}$	0.25	0.21	0.04	-1.09**	-0.44	-0.67**
	(1.07)	(0.82)	(0.60)	(0.56)	(0.39)	(0.29)
Observations	392	391	314	392	370	392

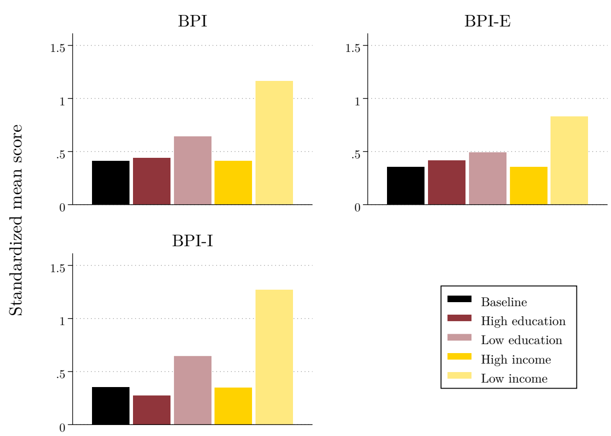
Notes: This table shows pooled OLS estimates of parental personality types on a child's cognitive and non-cognitive skills. This effect is captured by the indicator variable: $\mathbb{1}\left\{\text{parent mother} = 1\right\}$. Robust standards errors clustered at the child level in parentheses. **Panel A**: estimates of parents' personality type on a child's ability raw score. **Panel B**: estimates of parents' personality type on a child's ability raw score conditioning by the log of family income, parental education, parental marital status, parental age, parental health, parental labor supply, parental childcare time, a measure of parental warmth (the Warmth Scale), a measure of parental self-esteem (the Rosenberg Scale), a measure of home cognitive stimulation (the HOME index), a child's age, a child's sex, a child's race, and year fixed effects. **Panel C**: residualized estimates of parent's personality types on a child's ability raw scores. We first regress the observed scores on the same controls as in the conditional estimates except for a parent's personality type. Then, we get the residuals. Finally, we regress the residuals on parental personality. **LW**: Letter Word; **AP**: Applied Problems; **PC**: Passage Comprehension; **BPI**: Behavior Problem Index; **BPI-E**: Externalizing Behavior; **BPI-I**: Internalizing Behavior.
$^{+}$: p–value < 0.15; *: p–value < 0.10; ** : p–value < 0.05; *** : p–value <0.01.

FIGURE B3. Conditional Differences in a Child's Skills

A. Cognitive skills



B. Non-cognitive skills



Notes: This figure shows differences in standardized scores of available measures associated with cognitive and non-cognitive skills, conditional on parental education and labor income. The difference is computed between the scores of children living only with stable parents minus the scores of children living only vulnerable parents, for each educational or income category. **High education**: educational level above or equal to the percentile 75th. **Low education**: educational level below or equal to the percentile 25th. **High income**: household labor income above or equal to the percentile 75th. **Low income**: household labor income below or equal to the percentile 25th. **BPI**: Behavior Problem Index; **BPI-E**: Externalizing Behavior; **BPI-I**: Internalizing Behavior.

Appendix C. Mathematical appendix

C.1. Problem of Singles—Model Solution

As with couples, the optimal choices for a one-parent household are a set of policy rules depending on wages, non-labor income, a recursive component of a child's skills, and reduced-form preference and productivity parameters:

$$
\begin{aligned}
h_{i,t} &= h_{i,t}\Big[w_{i,t}, I_t^S, g_{t+1}(\theta_{k,t+1}^S, \theta_{q,t+1}^S); \boldsymbol{\alpha}^S, \delta_t\Big],\\
\tau_{i,t} &= \tau_{i,t}\Big[w_{i,t}, I_t^S, g_{t+1}(\theta_{k,t+1}^S, \theta_{q,t+1}^S); \boldsymbol{\alpha}^S, \delta_t\Big],\\
e_t^S &= e_t^S\Big[w_{i,t}, I_t^S, g_{t+1}(\theta_{k,t+1}^S, \theta_{q,t+1}^S); \boldsymbol{\alpha}^S, \delta_t\Big].
\end{aligned} \tag{C1}
$$

C.2. Measuring a Child's Skills

Let $x = \{1, \dots, N_{LW}\}$ and $y = \{1, \dots, N_{BPI}\}$ be the total number of individual items on the scales LW and BPI, respectively. The observed scores of the child j on these scales, $\tilde{\theta}_{LW,j,t}$ and $\tilde{\theta}_{BPI,j,t}$, are related to the child's abilities in these scales, $\theta_{LW,j,t}$ and $\theta_{BPI,j,t}$, by the functions $p_x(\theta_{LW,j,t})$ and $p_y(\theta_{BPI,j,t})$, respectively. These functions, called the Item Characteristic Curves (ICCs), give the probability that child j "succeeds" in answering an individual item given her level of latent ability $\theta_{\mathcal{T},j,t}$ with $\mathcal{T} \in \{LW, BPI\}$. These probabilities are a thus function of latent skills and are assumed to be non-decreasing in a child's skills.

A generic functional form for the ICCs can be expressed as:

$$
\begin{aligned}
p_x(\theta_{LW,j,t}; a_x, b_x) &= F(a_x(\theta_{LW,j,t} - b_x)),\\
p_y(\theta_{BPI,j,t}; c_y, d_y) &= F(c_y(\theta_{BPI,j,t} - d_y)),
\end{aligned} \tag{C2}
$$

where the parameters a_x and c_y represent the discriminatory power of individual items whereas parameters b_x and d_y represent the difficulty of individual items (Baker, 2001). Because probabilities are bounded between 0 and 1, the function $F(\cdot)$ is typically a variation of a cumulative logistic distribution—such as the two-parameter logistic model (Birnbaum, 1968):

$$
\begin{aligned}
p_x(\theta_{LW,j,t}; a_x, b_x) &= \frac{\exp(a_x(\theta_{LW,j,t} - b_x))}{1 + \exp(a_x(\theta_{LW,j,t} - b_x))},\\
p_y(\theta_{BPI,j,t}; c_y, d_y) &= \frac{\exp(c_y(\theta_{BPI,j,t} - d_y))}{1 + \exp(c_y(\theta_{BPI,j,t} - d_y))}.
\end{aligned} \tag{C3}
$$

For identification, we can assume that $a_x = 1$ and $b_x = 0$ for all $x = \{1, \ldots, N_{LW}\}$ and $c_y = 1$ and $d_y = 0$ for all $y = \{1, \ldots, N_{BPI}\}$, which give the following normalized ICCs:[37]

$$
\text{(C4)} \qquad \begin{aligned}
p_x(\theta_{LW,j,t}; a_x = 1, b_x = 0) &= \frac{\exp(\theta_{LW,j,t})}{1 + \exp(\theta_{LW,j,t})}, \\
p_y(\theta_{BPI,j,t}; c_y = 1, d_y = 0) &= \frac{\exp(\theta_{BPI,j,t})}{1 + \exp(\theta_{BPI,j,t})}.
\end{aligned}
$$

The latent skills in the model $\theta_{\mathcal{A},j,t}$ with $\mathcal{A} \in \{k, q\}$ may not be defined on the same scale as the latent estimated skills $\theta_{\mathcal{T},j,t}$ with $\mathcal{T} \in \{LW, BPI\}$. To transform a value of $\theta_{\mathcal{A},j,t}$ into a corresponding value of $\theta_{\mathcal{T},j,t}$ we assume the following continuous and strictly increasing function:

$$
\text{(C5)} \qquad \theta_{\mathcal{T},j,t} = \log(\theta_{\mathcal{A},j,t}) \Longleftrightarrow \theta_{\mathcal{A},j,t} = \exp(\theta_{\mathcal{T},j,t}).
$$

Under this assumption, we can write the normalized ICCs as:

$$
\text{(C6)} \qquad \begin{aligned}
p_x(\theta_{LW,j,t}; a_x = 1, b_x = 0) &= \frac{\theta_{k,j,t}}{1 + \theta_{k,j,t}}, \\
p_y(\theta_{BPI,j,t}; c_y = 1, d_y = 0) &= \frac{\theta_{q,j,t}}{1 + \theta_{q,j,t}}.
\end{aligned}
$$

These normalized ICCs can be inverted to obtain an expression for a child's skills in the model:

$$
\text{(C7)} \qquad \begin{aligned}
\theta_{k,j,t} &= \frac{p_x(\theta_{LW,j,t}; a_x = 1, b_x = 0)}{1 - p_x(\theta_{LW,j,t}; a_x = 1, b_x = 0)}, \\
\theta_{q,j,t} &= \frac{p_y(\theta_{BPI,j,t}; c_y = 1, d_y = 0)}{1 - p_y(\theta_{BPI,j,t}; c_y = 1, d_y = 0)}.
\end{aligned}
$$

Skills Estimation Algorithm— We use the following algorithm to estimate a child's skills. Initial skills are estimated following the approach of updating the "total ignorance" assumption in Del Boca, Flinn, and Wiswall (2014):

[37] Structural models of child development measuring a child's skills through IRT typically assume this; can be interpreted that a child with skills of unit 1 can succeed in an individual item with difficulty 0 and discriminatory 1 with 50% of probability (see Verriest (2018)).

Step 1—Prior distribution. At the initial condition, the functions p_x and p_y are assumed to follow a Beta random distribution with parameters $(1,1)$:

$$
\begin{aligned}
&p_x(\theta_{LW,j,initial}; a_x, b_x) \sim Beta(1,1), \\
&p_y(\theta_{BPI,j,initial}; c_y, d_y) \sim Beta(1,1).
\end{aligned} \tag{C8}
$$

Step 2—Posterior distribution. After observing the actual scores at the moment children were first surveyed in 1997 or 2014 ($\tilde{\theta}_{LW,j,t=survey}$ and $\tilde{\theta}_{BPI,j,t=survey}$), we update the prior scores:

$$
\begin{aligned}
p_x(\theta_{LW,j,initial}; a_x, b_x) &\sim Beta(1 + \tilde{\theta}_{LW,j,t=survey}, (N_{LW} - \tilde{\theta}_{LW,j,t=survey}) + 1), \\
p_y(\theta_{BPI,j,initial}; c_y, d_y) &\sim Beta(1 + \tilde{\theta}_{BPI,j,t=survey}, (N_{BPI} - \tilde{\theta}_{BPI,j,t=survey}) + 1),
\end{aligned} \tag{C8}
$$

which are estimated measures of $\theta_{LW,j,initial}$ and $\theta_{BPI,j,initial}$. These simulated scores are then mapped into skills in the model to obtain $\theta_{k,j,initial}$ and $\theta_{q,j,initial}$.

Step 3—In the remaining simulated paths, the estimated latent ability is assumed to follow a Binomial random distribution:

$$
\begin{aligned}
\theta_{LW,j,t} &\sim B(N_{LW}, p_x(\theta_{LW,j,t}; a_x = 1, b_x = 0)), \\
\theta_{BPI,j,t} &\sim B(N_{BPI}, p_y(\theta_{BPI,j,t}; c_y = 1, d_y = 0)),
\end{aligned} \tag{C9}
$$

which we can then invert to obtain the estimated latent skills in the model.

C.3. Problem of Singles—Econometric Implementation

The dynamic structure of the problem of one-adult households follows a simpler structure than the dynamic problem of couples, with fewer number of household choices.

At $t = T$, we have the following problem:

(C10)
$$V_T^S(\boldsymbol{\Omega}_T^S) =$$
$$\max_{\tau_{i,T},h_{i,T},e_T^S}\Big\{\alpha_1^S\ln\big(w_{i,T}h_{i,T}+I_T^S-e_T^S\big)+\alpha_2^S\ln(\theta_{k,T}^S)+\alpha_3^S\ln(\theta_{q,T}^S)\ +\ \alpha_4^S\ln\big(112-h_{i,T}+\tau_{i,T}\big)$$
$$+\ \beta\psi\Big[\alpha_2^S\big(\ln R_T^k+\ln\tau_{i,T}^{\delta_{i,T}^k}+\ln e_T^{S,\delta_{3,T}^k}+\ln\theta_{k,T}^{S,\delta_{4,T}^k}+\ln\theta_{q,T}^{S,\delta_{5,T}^k}\big)$$
$$+\ \alpha_3^S\big(\ln R_T^q+\ln\tau_{i,T}^{\delta_{i,T}^q}+\ln e_T^{S,\delta_{3,T}^q}+\ln\theta_{k,T}^{S,\delta_{4,T}^q}+\ln\theta_{q,T}^{S,\delta_{5,T}^q}\big)\Big]\Big\},$$

with the vector of state variables defined by $\boldsymbol{\Omega}_T^S = (w_{i,T}, \epsilon_{i,T}, I_T^S, \varepsilon_{i,T})'$. The marginal utility to the household at period t are defined by:

(C11)
$$\eta_t^{S,k} \equiv \frac{\partial V_t^S(\boldsymbol{\Omega}_t^S)}{\partial \ln\theta_{k,t}^S} \quad \text{and} \quad \eta_t^{S,q} \equiv \frac{\partial V_t^S(\boldsymbol{\Omega}_t^S)}{\partial \ln\theta_{q,t}^S}.$$

At $t = T$, we get that:

(C12)
$$\eta_T^{S,k} = \alpha_2^S + \beta(\eta_{T+1}^{S,k}\delta_{4,T}^k + \eta_{T+1}^{S,q}\delta_{4,T}^q),$$
$$\eta_T^{S,q} = \alpha_3^S + \beta(\eta_{T+1}^{S,k}\delta_{5,T}^q + \eta_{T+1}^{S,q}\delta_{5,T}^q),$$

with $\eta_{T+1}^{S,k} = \psi\alpha_2^S$ and $\eta_{T+1}^{S,q} = \psi\alpha_3^S$.

Similarly, as in the problem of a couple, we can use a recursive expression for the sequences $\{\eta_t^{S,k}\}_{t=1}^{T+1}$ and $\{\eta_t^{S,q}\}_{t=1}^{T+1}$ to write period t's optimal choices for childcare time and expenditures as conditional functions of the household labor supply:

(C13)
$$\hat{\tau}_{i,t} = \big(112 - h_{i,T}\big)\frac{\zeta_{1,t}}{\alpha_4^S + \zeta_{1,t}},$$
$$\hat{e}_t^S = \big(w_{i,T}h_{i,T} + I_T^S\big)\frac{\zeta_{2,t}}{\alpha_1^S + \zeta_{2,t}},$$

where $\zeta_{l,t} = \beta(\delta_{l,t}^k\eta_{t+1}^{S,k} + \delta_{l,t}^q\eta_{t+1}^{S,q})$ for all $l \in \{1, 2\}$. Working out the system of equations (C13) gives the optimal labor supply at period t:

$$h^*_{i,t} = \frac{w_{i,t}(\alpha^S_1 + \zeta_{2,t}) - I^S_t(\alpha^S_4 + \zeta_{1,t})}{w_{i,t}(\alpha^S_4 + \alpha^S_1 + \zeta_{1,t} + \zeta_{2,t})}. \tag{C14}$$

Finally, combining expressions (C13) and (C14) gives the optimal choices for childcare time and expenditures in single households.

C.4. Marginal Utility of a Child's Skills—Recursive Formulation

The recursive formulation for the marginal utility of children's skills presented here makes clear the transition from the (F.O.C) in equation (23) to the conditional solutions in equation (24).

Recall that the marginal utilities are defined as:

$$\eta^{M,k}_t \equiv \frac{\partial V^M_t(\mathbf{\Omega}^M_t)}{\partial \ln(\theta^M_{k,t})} \quad \text{and} \quad \eta^{M,q}_t \equiv \frac{\partial V^M_t(\mathbf{\Omega}^M_t)}{\partial \ln(\theta^M_{q,t})}, \tag{C15}$$

with $M \in \{C, S\}$. From these definitions, we can start formulating the recursive sequence. At $t = T + 1$, we have that:

$$\begin{aligned} V^M_{T+1}(\theta^M_{k,T+1}, \theta^M_{q,T+1}) &= \psi(\alpha^M_2 \ln \theta^M_{k,T+1} + \alpha^M_3 \ln \theta^M_{q,T+1}), \\ \eta^{M,k}_{T+1} &= \psi\alpha^M_2, \\ \eta^{M,q}_{T+1} &= \psi\alpha^M_3. \end{aligned} \tag{C16}$$

At period $t = T$, we have that:

$$\begin{aligned} &V^M_T(\mathbf{\Omega}^M_T) = u^M_T \\ &\quad + \beta\psi\Big[\alpha^C_2(\cdots + \delta^k_{4,T} \ln \theta^M_{k,T} + \delta^k_{5,T} \ln \theta^M_{q,T}) + \alpha^C_3(\cdots + \delta^q_{4,T} \ln \theta^M_{k,T} + \delta^q_{5,T} \ln \theta^M_{q,T})\Big], \\ &\eta^{M,k}_T = \alpha^M_2 + \beta(\eta^{M,k}_{T+1}\delta^k_{4,T} + \eta^{M,q}_{T+1}\delta^q_{4,T}), \\ &\eta^{M,q}_T = \alpha^M_3 + \beta(\eta^{M,q}_{T+1}\delta^k_{5,T} + \eta^{M,q}_{T+1}\delta^q_{5,T}). \end{aligned} \tag{C17}$$

At period $t = T - 1$, we have that:

(C18)

$$
\begin{aligned}
V^M_{T-1}(\boldsymbol{\Omega}^M_{T-1}) &= u^M_{T-1} + \beta\Bigg[\alpha^C_2(\cdots + \delta^k_{4,T-1}\ln\theta^M_{k,T-1} + \delta^k_{5,T-1}\ln\theta^M_{q,T-1}) \\
&+ \alpha^C_3(\cdots + \delta^q_{4,T-1}\ln\theta^M_{k,T-1} + \delta^q_{5,T-1}\ln\theta^M_{q,T-1}) + \beta\psi\Big[\alpha^C_2(\delta^k_{4,T}(\cdots + \delta^k_{4,T-1}\ln\theta^M_{k,T-1} + \delta^k_{5,T-1}\ln\theta^M_{q,T-1}) \\
&+ (\delta^k_{5,T}(\cdots + \delta^q_{4,T-1}\ln\theta^M_{k,T-1} + \delta^q_{5,T-1}\ln\theta^M_{q,T-1}) + \alpha^C_3(\delta^q_{4,T}(\cdots + \delta^k_{4,T-1}\ln\theta^M_{k,T-1} + \delta^k_{5,T-1}\ln\theta^M_{q,T-1})) \\
&+ (\delta^q_{5,T}(\cdots + \delta^q_{4,T-1}\ln\theta^M_{k,T-1} + \delta^q_{5,T-1}\ln\theta^M_{q,T-1})\Big]\Bigg],
\end{aligned}
$$

$$
\begin{aligned}
\eta^{M,k}_{T-1} &= \alpha^M_2 + \beta(\eta^{M,k}_T\delta^k_{4,T-1} + \eta^{M,q}_T\delta^q_{4,T-1}), \\
\eta^{M,q}_{T-1} &= \alpha^M_3 + \beta(\eta^{M,q}_T\delta^k_{5,T-1} + \eta^{M,q}_T\delta^q_{5,T-1}).
\end{aligned}
$$

Following similar steps, it is easily shown that at period t we have:

$$
\begin{aligned}
\eta^{M,k}_t &= \alpha^M_2 + \beta(\eta^{M,k}_{t+1}\delta^k_{4,t} + \eta^{M,q}_{t+1}\delta^q_{4,t}), \\
\eta^{M,q}_t &= \alpha^M_3 + \beta(\eta^{M,q}_{t+1}\delta^k_{5,t} + \eta^{M,q}_{t+1}\delta^q_{5,t}).
\end{aligned} \tag{C19}
$$

C.5. Optimal Labor Supplies—Derivation

This section provides the derivation of the optimal labor supply choice of spouse $i = 1$, which is homologous to the cases of the second spouse in a couple ($i = 2$) and single households ($i = 3$).

We can rewrite the F.O.C. associated with h_{1T} in the system of equations (23) in the main text as:

$$
h_{1,T}\left(\alpha^C_1 w_{1,T} + \alpha^C_4 w_{1,T}\right) = \alpha^C_1 w_{1,T}\left(112 - \tau_{1,T}\right) + \alpha^C_4\left(e^C_T - I^C_T - w_{2,T}h_{2,T}\right). \tag{C20}
$$

Plugging into (C20) the conditional household choices for childcare time ($\tau^*_{1,t}$) and expenditures (e^{C*}_t) from equation (24), we can write the right-hand-side (RHS) of equation (C20) as:

$$= \alpha_1^C w_{1,T}\Big(112 - \tau_{1,T}\Big) + \alpha_4^C\Big(e_T^C - I_T^C - w_{2,T}h_{2,T}\Big),$$

$$= \alpha_1^C w_{1,T}\Big[112 - (112 - h_{1,T})\frac{\zeta_{1,T}}{\alpha_4^C + \zeta_{1,T}}\Big]$$

(RHS C20)
$$+ \alpha_4^C\Big[\Big(w_{1,T}h_{1,T} + w_{2,T}h_{2,T} + I_T^C\Big)\frac{\zeta_{3,T}}{\alpha_1^C + \zeta_{3,T}} - I_T^C - w_{2,T}h_{2,T}\Big],$$

$$= 112(\frac{\alpha_4^C}{\alpha_4^C + \zeta_{1,T}})\alpha_1^C w_{1,T} + \alpha_1^C w_{1,T}h_{1,T}(\frac{\zeta_{1,T}}{\alpha_4^C + \zeta_{1,T}})$$

$$+ \alpha_4^C w_{1,T}h_{1,T}(\frac{\zeta_{3,T}}{\alpha_1^C + \zeta_{3,T}}) - (\frac{\zeta_{3,T}}{\alpha_1^C + \zeta_{3,T}})(I_T^C + w_{2,T}h_{2,T})\alpha_4^C.$$

Using the resulting expression, we can factorize terms and write the left-hand-side (LHS) of equation (C20) as:

(LHS C20)
$$= h_{1,T}\left[\Big(\alpha_1^C w_{1,T} + \alpha_4^C w_{1,T}\Big) - \alpha_1^C w_{1,T}(\frac{\zeta_{1,T}}{\alpha_4^C + \zeta_{1T}}) - \alpha_4^C w_{1,T}(\frac{\zeta_{3,T}}{\alpha_1^C + \zeta_{3,T}})\right],$$

$$= h_{1,T}\left[\alpha_1^C \alpha_4^C w_{1,T}\Big(\frac{1}{\alpha_1^C + \zeta_{3,T}} + \frac{1}{\alpha_4^C + \zeta_{1,T}}\Big)\right].$$

With the final expressions in (RHS C20) and (LHS C20), h_{1T} can be written as:

(C21)
$$h_{1,T} = \frac{112(\frac{\alpha_4^C}{\alpha_4^C+\zeta_{1,T}})\alpha_1^C w_{1,T} - (\frac{\zeta_{3,T}}{\alpha_1^C+\zeta_{3,T}})(I_T^C + w_{2,T}h_{2,T})\alpha_4^C}{\alpha_1^C\alpha_4^C w_{1,T}(\frac{\alpha_1^C+\alpha_4^C+\zeta_{3,T}}{(\alpha_1^C+\zeta_{3,T})(\alpha_4^C+\zeta_{1,T})})},$$

which, after simplifications, yields equation (25) in the main text:

(C22)
$$h_{1,T} = \frac{w_{1,T}(\alpha_1^C + \zeta_{3,T}) - I_T^C(\alpha_4^C + \zeta_{1,T}) - w_{2,T}h_{2,T}(\alpha_4^C + \zeta_{1,T})}{(\alpha_1^C + \zeta_{3,T})(\alpha_4^C + \zeta_{1,T})} w_{1,T}\Big(\frac{(\alpha_1^C + \zeta_{3,T})(\alpha_4^C + \zeta_{1,T})}{\alpha_1^C + \alpha_4^C + \zeta_{1,T} + \zeta_{3,T}}\Big),$$

$$= \frac{w_{1,T}(\alpha_1^c + \zeta_{3,T}) - I_T^C(\alpha_4^C + \zeta_{1,T}) - w_{2,T}h_{2,T}(\alpha_4^C + \zeta_{1,T})}{w_{1,T}(\alpha_4^C + \alpha_1^c + \zeta_{1,T} + \zeta_{3,T})}.$$

To facilitate the calculations, we can redefine $h_{1,T}$ in (C22) in terms of scalars $a_{1,T}^C$ and

$b^C_{1,T}$:

$$h_{1,T} = \frac{w_{1,T}(\alpha^c_1 + \zeta_{3,T}) - I^C_T(\alpha^C_4 + \zeta_{1,T})}{w_{1,T}(\alpha^C_4 + \alpha^c_1 + \zeta_{1,T} + \zeta_{3,T})} - \frac{w_{2,T}(\alpha^C_4 + \zeta_{1,T})}{w_{1,T}(\alpha^C_4 + \alpha^c_1 + \zeta_{1,T} + \zeta_{3,T})} h_{2,T},$$
$$h_{1,T} = a^C_{1,T} - b^C_{1,T} h_{2,T}, \tag{C23}$$

with the scalars defined as:

$$a^C_{1,T} \equiv \frac{w_{1,T}(\alpha^c_1 + \zeta_{3,T}) - I^C_t(\alpha^C_4 + \zeta_{1,T})}{w_{1,T}(\alpha^C_4 + \alpha^c_1 + \zeta_{1,T} + \zeta_{3,T})},$$
$$b^C_{1,T} \equiv \frac{w_{2,T} h_{2,T}(\alpha^C_4 + \zeta_{1,T})}{w_{1,T}(\alpha^C_4 + \alpha^c_1 + \zeta_{1,T} + \zeta_{3,T})}. \tag{C24}$$

Following similar steps for the optimal labor supply of $i = 2$ we yield that: $h_{2,T} = a^C_{2,T} - b^C_{2,T} h_{1,T}$. Using this result, we can write the following system of labor supplies:

$$h_{1,T} = a^C_{1,T} - b^C_{1,T} h_{2,T},$$
$$h_{2,T} = a^C_{2,T} - b^C_{2,T} h_{1,T}, \tag{C25}$$

which, after solving, gives the expressions for the optimal labor supplies in equation (27) in the main text.

C.6. Identification

As noted in the main text, the same structure of the identification arguments developed here would apply to the case of single households.

Replacement Functions—As the identification arguments sketched here suggest, allowing for time-variant unobserved heterogeneity could allow us to construct exclusion restrictions to identify the technology. The example worked out here is based on Cunha, Heckman, and Schennach (2010).

Let y^C_t be a variable available at period t. Let the productivity shocks be decomposed into two scalar components:

$$\omega^C_{k,t} = \tilde{\pi}^C_t + \tilde{\nu}^C_{k,t} \quad \text{and} \quad \omega^C_{q,t} = \tilde{\pi}^C_t + \tilde{\nu}^C_{q,t}, \tag{C26}$$

where $\tilde{\pi}^C_t$ is a shock independent over couples but not over time, affecting all technologies but potentially differing across technologies, and realized before choices are made. The component $\tilde{\nu}^C_{k,t}$ is independently identically distributed over time and exogenous to all other inputs (including y^C_t and e^C_t).

Moreover, we can augment our two production functions in equation (29) in the main text with the following equations:

$$
\begin{aligned}
e^C_t &= \gamma_0 + \gamma_1 y^C_t + \gamma_2 \tau_{1,t} + \gamma_3 \tau_{2,t} + \gamma_4 \theta_{k,t} + \gamma_5 \theta_{q,t} + \tilde{\pi}_t, \\
\ln y^C_t &= \tilde{\rho}_y \ln y^C_{t-1} + \tilde{\nu}_{y,t} \quad \text{with} \quad \tilde{\nu}_{y,t} \sim N(0, \sigma^2_y), \\
\tilde{\pi}_t &= \tilde{\rho}_{\tilde{\pi}} \tilde{\pi}_{t-1} + \tilde{\nu}_{\pi,t} \quad \text{with} \quad \tilde{\nu}_{\pi,t} \sim N(0, \sigma^2_\pi).
\end{aligned} \tag{C27}
$$

For identification, we further need to assume that:

$$
\begin{aligned}
&\tilde{\nu}_{y,t} \perp\!\!\!\perp (\theta^C_{k,t'}, \theta^C_{q,t'}, \tau_{1,t}, \tau_{2,t}, \tilde{\nu}_{y,t'}) && \forall t \neq t' \\
&\tilde{\nu}_{y,t} \perp\!\!\!\perp (y^C_{t'}, \tilde{\nu}_{k,t}, \tilde{\nu}_{q,t}) && \forall t > t' \\
&\tilde{\nu}_{\pi,t} \perp\!\!\!\perp (\theta^C_{k,t'}, \theta^C_{q,t'}, \tau_{1,t'}, \tau_{2,t'}, \tilde{\nu}_{k,t'}, \tilde{\nu}_{q,t'}) \\
&\pi \perp\!\!\!\perp (\theta^C_{k,1}, \theta^C_{q,1}, \tau_{1,1}, \tau_{2,1}, y^C_1)
\end{aligned} \tag{C28}
$$

Identification would follow from replacing the unobserved input by y^C_t in the outcome equation because $\tilde{\pi}_t$ and $\tilde{\nu}_{\mathcal{A},t}$ are now independent of all explanatory variables.

Auxiliary Conditions—The couples' problem at period t is given by:

$$
\begin{aligned}
&V^C_t(\boldsymbol{\Omega}^C_t) = \\
&\max_{\substack{\tau_{1,t},\tau_{2,t},\\ h_{1,t},h_{2,t},e^C_t}} \left\{ \alpha^C_1 \ln c^C_t + \alpha^C_2 \ln \theta^C_{k,t} + \alpha^C_3 \theta^C_{q,t} + \alpha^C_4 \ln \ell_{1,t} + \alpha^C_5 \ln \ell_{2,t} + \beta \mathbb{E}_t V^C_{t+1}(\boldsymbol{\Omega}^C_{t+1}) \right\},
\end{aligned} \tag{C29}
$$

subject to $\ell_{1,t} + h_{1,t} + \tau_{1,t} = 112$; $\ell_{2,t} + h_{2,t} + \tau_{2,t} = 112$; and $c^C_t + e^C_t = w_{1,t} h_{1,t} + w_{2,t} h_{2,t} + I^C_t$, and where $\boldsymbol{\Omega}^C_t$ collects the state variables at period t. Working out the first-order conditions (F.O.C), we get the following equalities:

$$
\begin{aligned}
\mu_1 &= \frac{\alpha^C_4}{\ell_{1,t}} = \mu_3 w_{1,t} = \beta \frac{\partial \mathbb{E}_t V^C_{t+1}(\boldsymbol{\Omega}^C_{t+1})}{\partial \tau_{1,t}}, \\
\mu_2 &= \frac{\alpha^C_5}{\ell_{2,t}} = \mu_3 w_{2,t} = \beta \frac{\partial \mathbb{E}_t V^C_{t+1}(\boldsymbol{\Omega}^C_{t+1})}{\partial \tau_{2,t}}, \\
\mu_3 &= \frac{\alpha^C_1}{c^C_t} = \beta \frac{\partial \mathbb{E}_t V^C_{t+1}(\boldsymbol{\Omega}^C_{t+1})}{\partial e^C_t},
\end{aligned} \tag{C30}
$$

where μ_1, μ_2, and μ_3 are the Lagrange multipliers of spouses' time and budget constraints. From (C30), we can obtain an equality for household consumption:

$$c_t^C = \frac{\alpha_1^C w_{1,t}\ell_{1,t}}{\alpha_4^C} = \frac{\alpha_1^C w_{2,t}\ell_{2,t}}{\alpha_5^C}, \tag{C31}$$

from which we can construct the conditional moment in equation (35) in the main text.

To identify some of the remaining preference parameters, we can use an expression for the partial derivative of $\mathbb{E}_t V_{t+1}^C(\boldsymbol{\Omega}_{t+1}^C)$ with respect to time and money investments in (C30), and rewrite the F.O.C. of the problem (C29) as:

$$\begin{aligned}
-\mu_1 + \beta\frac{1}{\tau_{1,t}}(\alpha_2^C\delta_{1,t}^k + \alpha_3^C\delta_{1,t}^q) &= 0,\\
-\mu_2 + \beta\frac{1}{\tau_{2,t}}(\alpha_2^C\delta_{2,t}^k + \alpha_3^C\delta_{2,t}^q) &= 0,\\
-\mu_3 + \beta\frac{1}{e_t}(\alpha_2^C\delta_{3,t}^k + \alpha_3^C\delta_{3,t}^q) &= 0.
\end{aligned} \tag{C32}$$

Using the definitions of the Lagrange multipliers μ_1 and μ_2, we can get the following expressions for time investments:

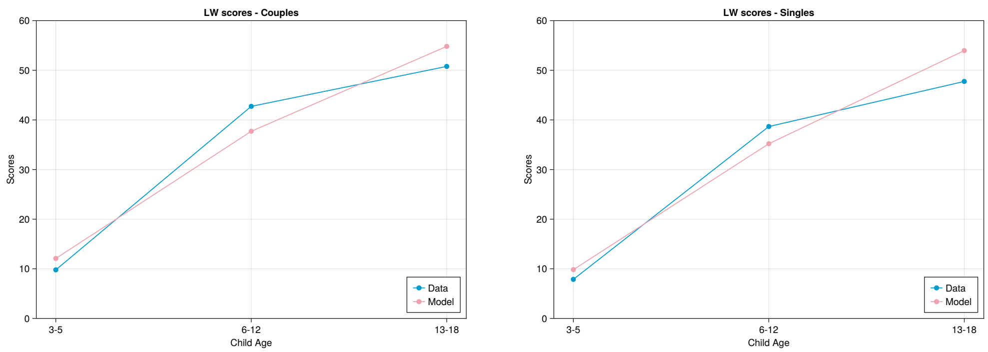
$$\begin{aligned}
\tau_{1,t} &= \frac{w_{2,t}\ell_{2,t}}{w_{1,t}}\frac{\alpha_4^C}{\alpha_5^C}\frac{\beta}{\alpha_5^C}(\alpha_2^C\delta_{1,t}^k + \alpha_3^C\delta_{1,t}^q),\\
\tau_{2,t} &= \frac{w_{1,t}\ell_{1,t}}{w_{2,t}}\frac{\alpha_5^C}{\alpha_4^C}\frac{\beta}{\alpha_5^C}(\alpha_2^C\delta_{2,t}^k + \alpha_3^C\delta_{2,t}^q),
\end{aligned} \tag{C33}$$

which are used to construct the moment condition in equation (38) in the main text.

Appendix D. Estimation appendix

FIGURE D1. Targeted Moments—Scores on the Letter Word Test by Marital Status

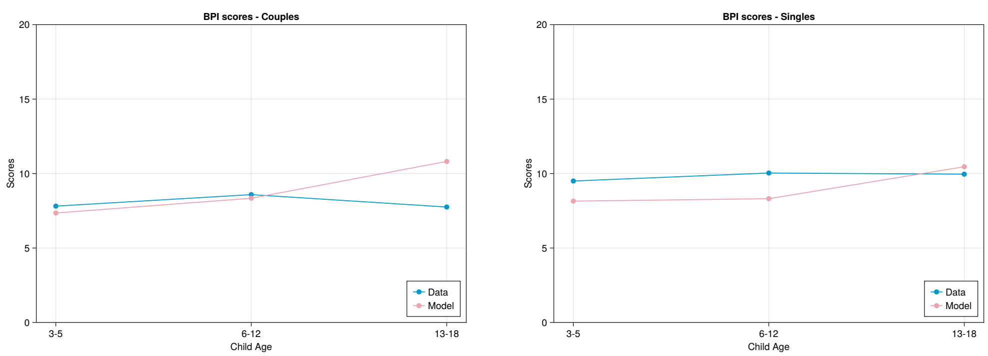
A. Only couples B. Only singles



Notes: This figure shows the average scores on the Letter Word Test (cognitive skills) by child age categories and marital status of the household.

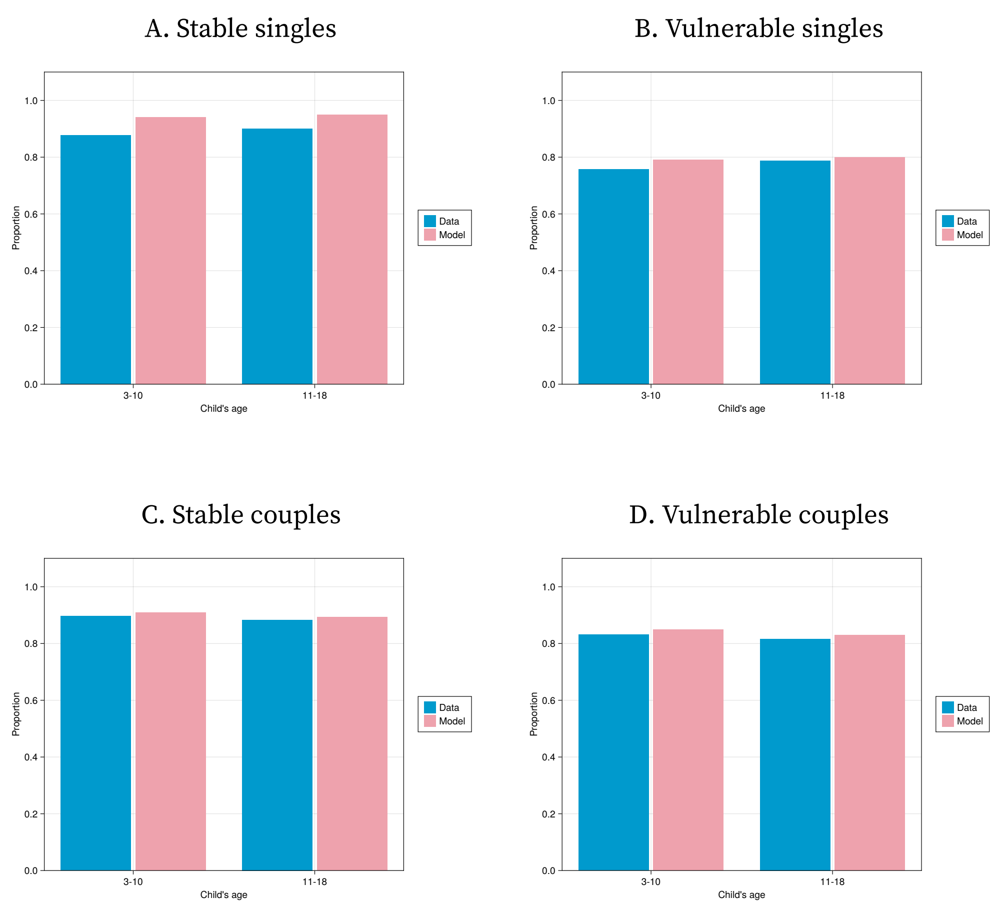
FIGURE D2. Targeted Moments—Scores on the Behavior Problem Index by Marital Status

A. Only couples B. Only singles



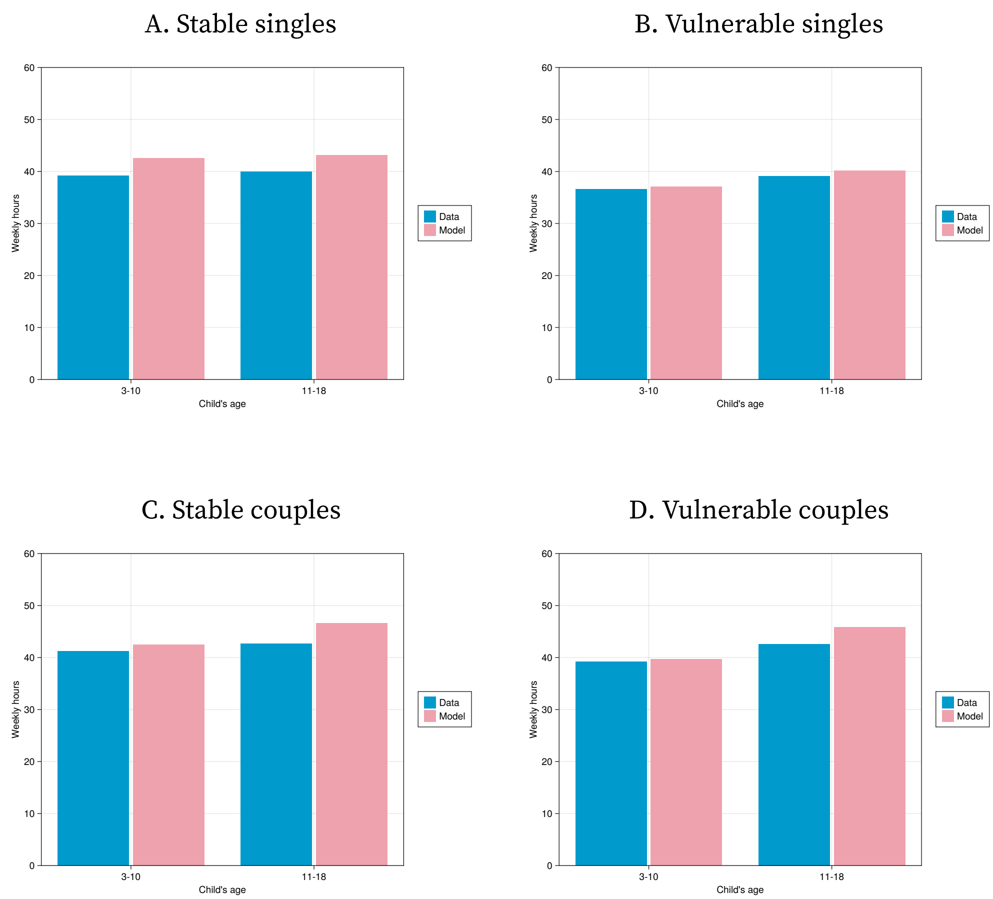
Notes: This figure shows the average scores on the Behavior Problem Index (non-cognitive skills) by child age categories and marital status of the household.

FIGURE D3. Targeted Moments—Employment Rates by Personality and Marital Status



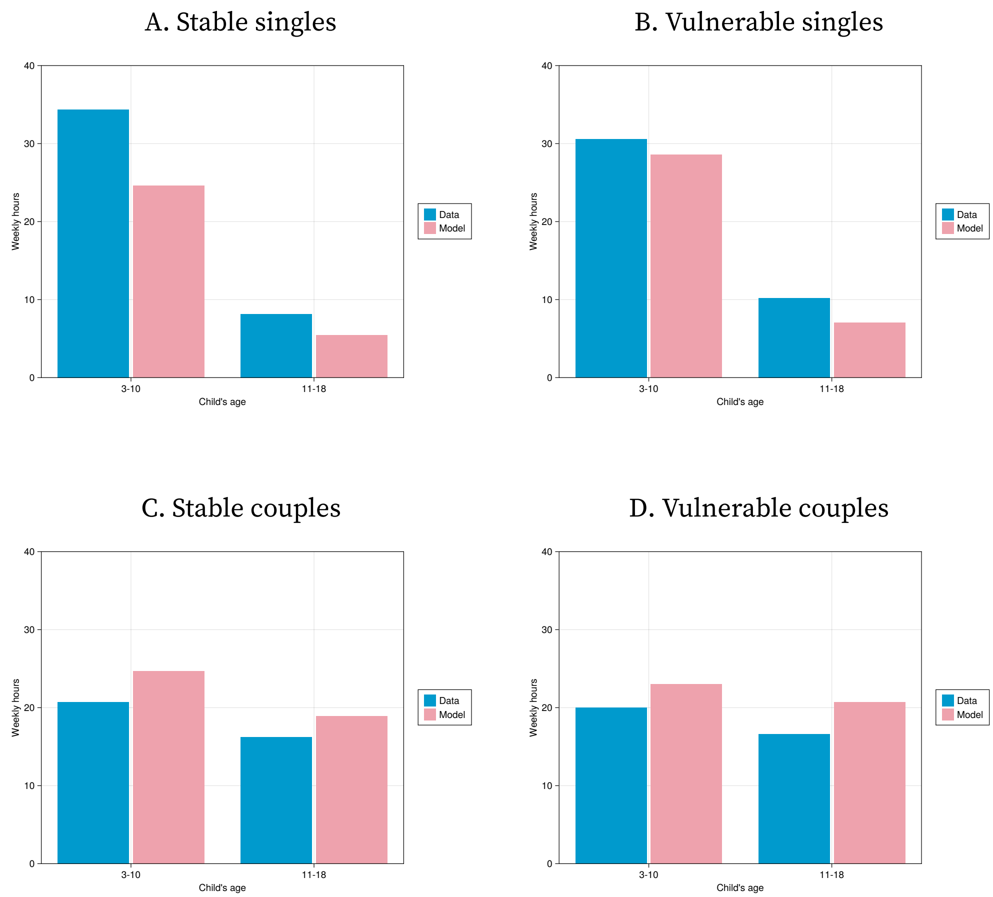
Notes: This figure shows the proportion of singles and couples employed in the labor market by personality types observed in the data and predicted by the model.

FIGURE D4. Targeted Moments—Mean Work Hours by Personality and Marital Status



Notes: This figure shows the average weekly work hours in the labor market between singles and couples by personality types observed in the data and predicted by the model.

FIGURE D5. Targeted Moments—Mean Childcare Hours by Personality and Marital Status



Notes: This figure shows the average weekly childcare hours between singles and couples by personality types observed in the data and predicted by the model.