Intimate Partner Violence and Children's Human Capital

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Abstract

This paper studies how exposure to Intimate Partner Violence (IPV) affects the accumulation of cognitive and socio-emotional skills of young children. We use a dynamic latent factor model and estimate the joint dynamic process of IPV exposure, parental investment, mother's mental health and child skill development, allowing for static and dynamic complementarities between all inputs. We allow for both a *direct* effect of IPV —through the witnessing of abuse— and *indirect* effects —via changes in parental investment and mother's mental health. We find that the negative effect of IPV manifests earlier in childhood for socio-emotional skills whereas the long term effect is more persistent for cognitive skills. When decomposing the total effect into direct and indirect effects we find that for cognitive skills the direct effects play a relatively larger role, while for socio-emotional skills the indirect effects dominate. Finally, our results suggest that while early childhood interventions that target parental investment and mother's mental health can be effective in offsetting the immediate negative effects of IPV, in absence of follow-up the benefits will fade-out as the child ages.

Keywords: Intimate partner violence, skill development, investment, mental health.
JEL Classification: I14, I24, J12

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1 Introduction

Intimate partner violence (IPV) is the most common form of violence worldwide. IPV is a gendered problem, whereby most victims of IPV are women (Oram et al., 2022).[1] Globally, one third of women have experienced physical and/or sexual violence from an intimate partner at some time in their life as reported in 2019, with large variability across countries, 29% in the UK and 35% in the US, to reach levels as high as 80% in countries such as Pakistan and Guinea (OECD, 2022)

Besides the indubitable and widely documented adverse impact of IPV on women's physical and mental health (Graham-Bermann and Miller, 2013; Pico-Alfonso et al., 2006), children exposed to IPV are also increasingly recognized as victims in their own right, although evidence documenting such consequences for children is still limited. Growing up in a stressful home environment hampers the development of children human capital (Currie and Tekin, 2012; Moroni et al., 2019; Schurer et al., 2019). Witnessing a mother being abused by her partner might represent a grave stress factor for the child and imply some form of maltreatment (Wathen and MacMillan, 2013) or neglect, potentially hindering child development. The harm to children exposed to IPV may be both direct through the witnessing of abuse, or indirect by affecting the parental investment and mother's mental health.

This paper contributes to the highly influential and rapidly growing economic literature studying the importance of early childhood conditions for development (Attanasio et al., 2020a, 2022; Cunha and Heckman, 2007, 2008) by studying how exposure to IPV affects the accumulation of socio-emotional and cognitive skills of young children, accounting for both dynamic effects and relationships between skills and mother-child interactions and maternal mental health.

We exploit the Avon Longitudinal Study of Parents and Children (ALSPAC), an internationally unique UK longitudinal cohort data resource containing (i) annual indicators of the incidence of IPV; (ii) high frequency and reliable measures of children's cognitive and socio-emotional skills; (iii) extremely detailed set of information on parental investment as well as mother's mental health. We use a dynamic latent factor structure to

[1]IPV are also experienced by other groups, including sexual and gender minorities, people with disabilities, migrants, and people from marginalised ethnic or Indigenous groups.

study the process of early stage cognitive and socio-emotional skill formation allowing for the effects of exposure to IPV. Combining and augmenting the most recent advances to study the technology of human capital formation (Agostinelli and Wiswall, 2016a,b; Attanasio et al., 2020b; Aucejo and James, 2021; Cunha et al., 2010; Del Bono et al., 2020; Freyberger, 2021), we estimate the joint dynamic process of IPV exposure, parental investment, mother's mental health and child skill development, allowing for static and dynamic complementarities between all inputs.

Despite the raise in awareness and the willingness of reporting IPV to the police, IPV remains an hidden crime with only 1 out of 5 victims filing a report of abuse to the police against the perpetrator (Office for National Statistics - Crime Survey for England and Wales -CSEW). The self-reported nature of IPV in our data addresses the problem characterizing the administrative records such as police reports, typically underestimating the actual incidence of abuse within the household. Being a long and representative panel in a large general population with repeated information on the individual incidence of IPV, mental health and other outcomes for victim mothers and their children, our data ALSPAC is a unique data resource perfectly suited for studying the dynamics of and interactions in the relationship between children's exposure to IPV and their socio-emotional and cognitive development.

To estimate the model we follow and adapt the estimation procedure of Aucejo and James (2021) that proceeds in two steps. In the first step, we utilise a measurement system that describes the relationship between unobserved skills and the measures of skills that we observe in the data to nonparametrically recover the distribution of latent skills. Then, in a second step we estimate the parameters of the production technologies using draws from the distribution of the skills obtained during the first step. We impose parsimonious restrictions that allow us to separately identify the parameters of the measurement system, for each age, separately from the parameters of the skill production technologies.

Combining the richness of our data with a powerful estimation technique, the focus of this paper is on the dynamics of the accumulation of skills and how these change with IPV exposure, by studying how skills co-evolve and what is the role of mother-child interactions and mother's mental health in this process. More specifically we ask three main questions: (i) What are the *total effects* of children's exposure to IPV on their development of cognitive and socio-emotional skills? (ii) What are the *direct effects* of IPV and the *indirect effects* generated by the change in parental investment and mother's mental health as a response to IPV? (iii) What interactions between skills, and between skills and parental investment and mother's mental health, shape the dynamic effects of IPV on children's development of socio-emotional and cognitive skills over their early life years?

Our analysis produces three sets of results. First, we find a negative *total effect* of IPV on both cognitive and socio-emotional skills. For socio-emotional skills the negative effect of IPV starts from the early years and persists throughout the periods, increasingly substantially for children that are exposed to IPV in all development periods. For cognitive skills, the negative effect of IPV appears later in childhood but it is larger and remains persistent over periods. This suggests that while the effect of IPV exposure appears to be more immediate for socio-emotional skill development, the long term effect appears to be more consequential for the development of cognitive skills. This result in effect casts exposure to IPV as a form of harmful maltreatment.

Second, looking into the *direct* and *indirect effects*, we find interesting differences between cognitive and socio-emotional skills. We decompose the total effect into direct and indirect effects through parental investment and mother's mental health. For cognitive skills, we find that all channels play a role in explaining the total negative effect of IPV exposure, however, the indirect effects, via mother's mental health and via parental investment, are smaller in comparison to the direct effect. For socio-emotional skills, the indirect effects of IPV exposure, particularly via changes in mother's mental health, are the largest determinant of the gap relative to the direct effect.

Third, we confirm the evidence that there is a strong dynamic complementarity between cognitive and socio-emotional skills in the production of both skills. In addition, we document the evolution of skills as a function of the parental investment and mother's mental health and their marginal products depending on different paths of IPV exposure. In general, it seems that parental investment matters more for the development of cognitive skills whereby mother's mental health matters more for the development of socio-emotional skills. Despite this apparent difference between the two skills, looking at the different paths of IPV exposure and its relationship with the parental inputs, we find similar results in terms of optimal policy intervention. For both skills we find that policies attempting to increase mother's mental health and/or parental investment for children exposed to IPV in order to offset the negative effects of IPV would be more efficient if they are introduced earlier in the development process, howvever, in absence of follow-up the benefits of the interventions will fade-out as the child ages.

Our paper enhances the understanding of the consequences of IPV exposure for victims and their children. Such evidence has been largely documented across multiple disciplines, including sociology (Black, 2012), criminology (Dobash and Dobash, 2001) and developmental psychology (Vu et al., 2016). However, this research is limited to small and non representative samples and do not provide a full picture of the dynamics in the relationships.

With IPV strongly rooted in ongoing gender inequality and amplified by other sources of inequalities (Aizer, 2010), the economic literature has been motivated to contribute to the understanding of the relationship between IPV exposure and mothers and children's outcomes.[2] Most of these economic studies focused on children health with shocks to IPV occurred during pregnancy (Aizer, 2011; Currie et al., 2018; Jofre-Bonet et al., 2016) or child mortality (Rawlings and Siddique, 2018).[3] The paper most closely linked to ours is Bhuller et al. (2021), which estimates the effect of reporting domestic violence to the police on the mental health and well-being of mothers and their children by using administrative records from police reports in Norway.

Our paper contributes to the existing evidence by adding the dynamic perspective as well as the intertwined relationship between children cognitive and socio-emotional skills, IPV exposure, parental investment and mother's mental health, by using a large representative data of self reported measures of IPV therefore uncovering part of the

[2]The economic literature started contributing to the topic during the last decade by investigating the determinants of IPV. These determinants include: (i) economic factors such as unemployment and cash transfers (Anderberg et al., 2018; Bhalotra et al., 2021; Heath et al., 2020; Hidrobo et al., 2016; Roy et al., 2019) (ii) cultural and institutional factors such as bargaining power, family structure and law enforcement (Aizer, 2010; Amaral et al., 2021; Menon, 2020; Miller and Segal, 2019; Tur-Prats, 2019) (iii) health factors (Papageorge et al., 2021) (iv) restrictions of individual behavior such as legal drinking age and lockdown during COVID-19 (Anderberg et al., 2022; Bhalotra et al., 2022; Chalfin et al., 2022; Miller et al., 2022). Much more limited is the research on the consequences of IPV for women decisions such as divorce and employment (Anderberg et al., 2018; Gedikli et al., 2023).

[3]Notably, there is also evidence on the societal cost of IPV with evidence provided on the spillover effect of IPV on children's classroom peers' test scores, school outcomes and earnings (Carrell and Hoekstra, 2012; Carrell et al., 2018; Carrell and Hoekstra, 2010)

actual abuse occurring within the household that is often hidden in the administrative data.[4]

The remainder of the paper is organized as follows. We first describe the ALSPAC data in Section 2. Our model of skill developmnent and our estimation procedure is introduced in Section 3. We present our main results in Section 4, and conduct counterfactual policy simulations in section 5. Finally, we conclude in Section 6.

2 Data: ALSPAC

2.1 Description of the general data

The Avon Longitudinal Study of Parents and Children (ALSPAC) is a UK child development cohort study conducted in the former England county of Avon. The ALSPAC was designed to sample pregnant women with estimated delivery dates between April 1991 and December 1992.[5] The study is structured in different questionnaires and includes detailed information about the mother ('mother-based' questionnaires) and the study child ('child-based' questionnaires), therefore providing a rich description of the home environment in which the child grows up.[6] The ALSPAC is an exceptional data resource perfectly suited to study the relationship between IPV and child development. This is because it includes repeated information about mothers' experience with IPV from child birth and high-quality and repeated measures of children's cognitive and socio-emotional skills as well as measures of parental investment and mothers' mental health.

2.2 Mother's and child's demographic characteristics

The original sample of ALSPAC includes 14,541 observations. In order to retain a balanced sample of observations across periods we make a sample selection and exclude (i)

[4]The first attempt of such investigation of this relationship —although neglecting the dynamic component— has been provided by Anderberg and Moroni (2020)

[5]See the study website for details of all the data and questions that were collected by the study http://www.bristol.ac.uk/alspac/researchers/our-data/

[6]Moreover, a 'partner-based questionnaires' and externally matched health data collected in 'clinics' are also available (Boyd et al., 2013).

twins and triplets (199 observations) and observations with missing information on (ii) mother's age and/or qualification (1,630 observations), (iii) the first post-birth mother-based questionnaire (1,412 observations), (iv) abuse, birth, and/or partnership status (1,371 women) and any observations after the first missing observations, (v) cognitive or socio-emotional skills (6,228 observations), parental investment (424 observations) and mother's mental health (270 observations). Our estimation sample includes 3,007 mothers who are observed over three development periods.

Table 1 reports the mean and standard deviation of the demographics characteristics of the child at birth and the mother at baseline - measured when the mother is 32 weeks pregnant. The average birth weight of the ALSPAC study child is 3.5 kg with an average gestation period of 39.6 weeks; half of the sample are girls and the parity is 0.73. The average of mothers' age at baseline is 28.7, and almost all of them (97 per cent) lived with a partner. 17% of mothers have 'Low' academic qualification, 38% have 'medium' academic qualification and 45% have 'high' academic qualification.[7]

With its longitudinal structure, the ALSPAC data includes information from pregnancy to when the child is age 7. In this paper we focus on early childhood and restrict our attention up to when the child is approximately aged 5 years old[8]. In Figure 1 we present the longitudinal structure of the data and highlight the three developmental periods that we consider from birth until the child is aged approximately 5 years old.

The IPV measures are included in the mother based questionnaire administered when the child is 8, 21, 33, and 47 months old respectively, while the measures of child skills and parental investments are included in the child based questionnaire.[9] We observe measures of skills and investments first when the child is below 6 months of age, second when the child is between 21 to 30 months, third when the child is between 33 and 42 months,

[7]'Low' academic qualification corresponds to either no academic qualification, a CSE, or a low GCSE (grades D to G). 'Medium' academic qualification corresponds to an O-level or a high GCSE (grades A-C). 'High' academic qualification corresponds to an A-level, undergraduate, or postgraduate degrees.

[8]Previous literature has largely shown that the early years of life are fundamental for the development of later skills. See for example XXXX. Until age 5, ALSPAC includes the complete set of information in terms of children's skills and other inputs measures

[9]The measure of abuse reported at 8 months refer to the period since child birth. The later measures of abuse refer to time period since the previous questionnaire occurred. The data also includes information on episodes of abuse that occurred during pregnancy. We use this additional information in a robustness analysis.

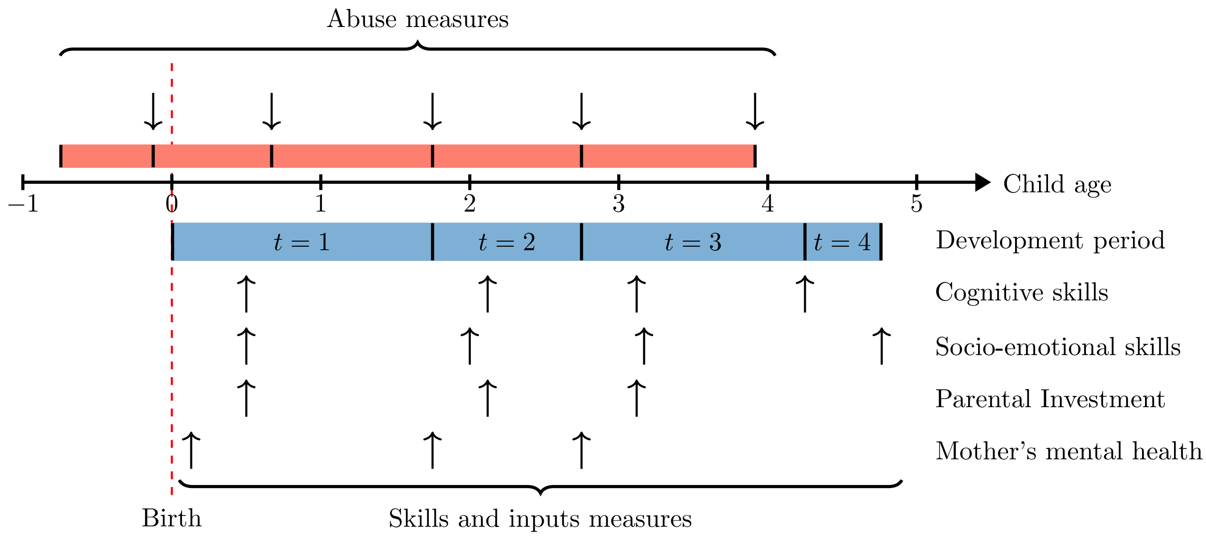
Table 1: Descriptive statistics of the mother and child's baseline characteristics

	(1) mean	(2) sd
a) Child at birth		
Birth weight (kg)	3.47	0.50
Gestation period (weeks)	39.62	1.55
Child is female	0.50	0.50
Birth parity	0.73	0.86
b) Mother at baseline		
Mother's age	28.70	4.21
Partner present	0.97	0.16
Medium academic qual.	0.38	0.49
High academic qual.	0.45	0.50
N	3,007	

Source: ALSPAC data.
Notes: The estimation sample includes women and their ALSPAC study-child. The table reports information on the birth of the ALSPAC study child and the mother at baseline (32 weeks pregnant).

lastly, our final observation of skill measures occurs between 45 and 57 months. Finally, information on mother's mental health is included in the mother based questionnaires, and is reported when the child is 8 weeks old, and 21 and 33 months old respectively. Figure 1 shows the relative timings of observation for each of the inputs that we consider in the skill production process, and also the respective timings of the skill measures. As shown in the figure, we aggregate all observations of measures into three distinct developmental periods, denoted by $t \in \{1, 2, 3\}$, and subsequently refer to $t = 4$ measures of skills as terminal skill measures. Specifically, the timing of the skills, parental investment and mother's mental health measures are indicated by the up-facing arrows shown below the timeline. Moreover, the timing of the abuse questionnaires are indicated by the down-facing arrows above the timeline, while the red block-segments indicate the time horizon to which the abuse questionnaire refers.

Figure 1: Timeline of inputs and abuse measures



Source: ALSPAC data.
Notes:

2.3 IPV: Measures of Abuse

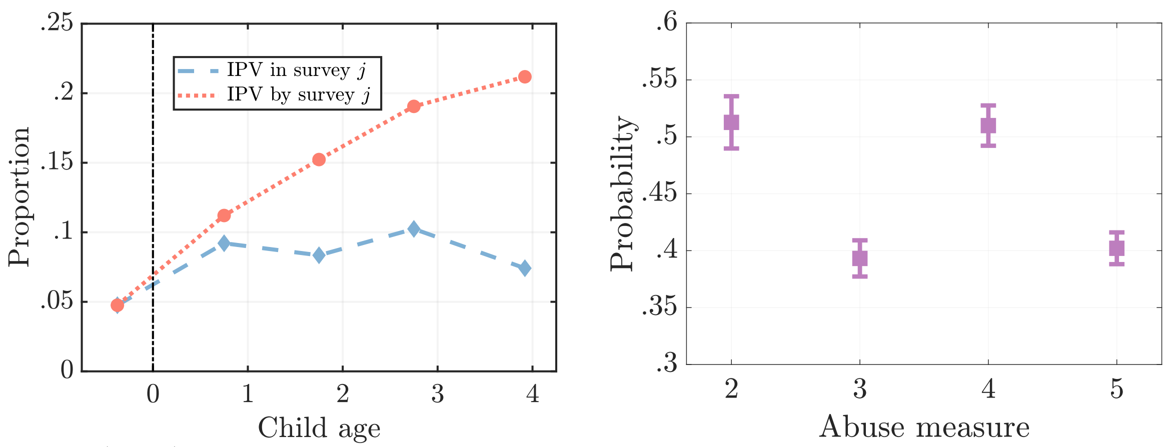
The mother-based questionnaires includes (roughly) annual questions on IPV exposure (See Figure 1 for details.). For the construction of our indicator of abuse we use the answer of two questions: 'Your partner was physically cruel to you' and 'Your partner was emotionally cruel to you'. As physical abuse occurs almost always in combination with emotional abuse, we construct a single indicator of 'any partner abuse' combining physical and emotional abuse. For the 3,007 ALSPAC mothers observed over 4 periods we have a total of 12,028 observations measuring IPV incidence. Among them, the average incidence of any abuse is 20.7 per cent, that is relatively close to the incidence of IPV for individuals in the UK experienced at some point in their life (29%, OECD 2022). Figure 2 illustrates the dynamics of IPV by showing (i) any IPV at and by time t in Panel (a) and (ii) the persistence of abuse in Panel (b).

The incidence of abuse in Panel (a) indicates that IPV experience sharply increases after birth and then slowly declines. The abuse by time t increases gradually up to 21.1% in the last period. This figure already shows that IPV incidence is highly persistent over time and suggests that it is often the same mothers being abused multiple times.

This finding is confirmed by the very strong persistence of abuse over time as illustrated in Panel (b). The figure reports the coefficients from regressing the abuse indicator in the current survey wave on the corresponding indicator of abuse in the previous survey wave. The figure shows that a woman who reported abuse in the previous survey is, on average, around 45 percentage points more likely to report abuse in the current period than is a woman who did not report any abuse in the previous period.

Figure 2: Description of IPV dynamics

(a) Abuse incidence (b) Abuse persistence



Source: ALSPAC data.
Notes: Panel (a) shows the incidence of any IPV at and by survey (j) relative to the birth of the ALSPAC child (vertical dashed line). Panel (b) illustrates the persistence of abuse, i.e. the probability of observing abuse in the survey wave (j) conditional on having being a victim of abuse in the previous survey ($j-1$).

2.4 Child's cognitive and socio-emotional skills

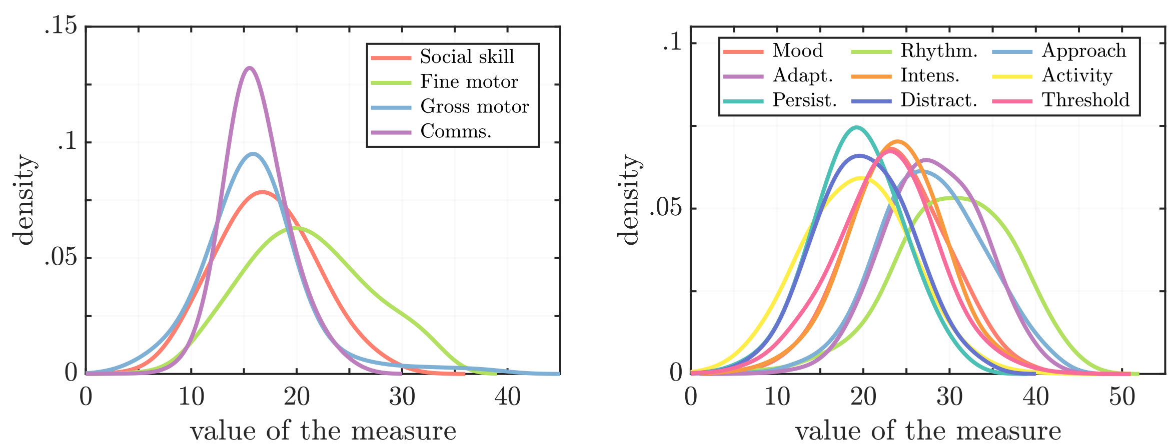
The ALSPAC contains various measures of cognitive skills across the four periods considered in this paper. In the first period we use a battery of questions from the Denver Developmental Screening Test (DDST) which includes four different categories: fine motor skills, gross motor skills, communication and social skills (Frankenburg and Dodds, 1967). These are measured when the child is 6 months. At that stage of childhood these can be considered cognitive skills. The distribution of these measures are shown in Figure 3, Panel (a).

For the following periods, the data includes age-appropriate versions of MacArthur–Bates Communicative Development Inventories (CDIs) and therefore we integrate the set of cognitive skills measures available since the first period with these additional ones including vocabulary, gestures, and grammar (Fenson et al., 2007).

There is also a large set of socio-emotional skills measures available in the four periods. In the first period we use a battery of questions from the Carey Infant Temperament (CIT) questionnaire measuring activity, rhythmicity, approach, adaptability, intensity, mood, persistence, and distractibility (Carey and McDevitt, 1977). These are measured when the child is 6 months ($t = 1$) and 24 months ($t = 2$). The distribution of these measures when the child is 6 months are shown in Figure 3, Panel (b). In the last two periods (38 months and 57 months, respectively $t = 3$ and $t = 4$) the ALSPAC data includes measures from the emotionality activity sociability (EAS) Temperament Survey used to assess temperament in children. The survey consists of 20 items where each temperament domain (Emotionality, Activity, Sociability, and Impulsivity) are represented, respectively, by five items (Bould et al., 2013).

Figure 3: Distribution of the cognitive and socio-emotional measures

(a) Cognitive measures (b) Socio-emotional measures



Source: ALSPAC data.
Notes: Panel (a) shows the distribution of the cognitive skills measures in period 1. Panel (b) shows the distribution of the socio-emotional skills measures in period 1.

2.5 Parental Investment

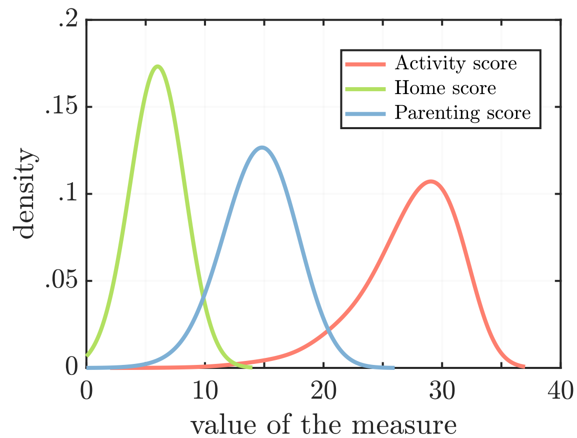
The data is also very rich in providing other information on the home environment, in particular about parental investment. We use three sources of information that are available for each of the four periods although adjusting the activities depending on the age of the child. These are (i) parenting score, (ii) activity score and (iii) home score. The distributions of each of the scores in the first period are shown in Figure 4.

The parenting score is an index constructed on the basis of the mother's report on how often she does the following activities with the child: (i) plays with the child; (ii) sings to child; (iii) shows child picture books; (iv) plays with toys together; (v) cuddles child; (vi) physically plays with child; (vi) takes child for walk; (vii) teaches child—with some questions changing over time to adapt to the child growing up.

The activity score is an index constructed on the basis of the child activities that includes the number of times the child is taken to (i) local shops, (ii) department store (iii) supermarket (iv) park (v) friends and family.

The home score is an index constructed on the basis of the items the child has at home including (i) cuddly toys, (ii) push/pull toys (iii) co-ordination toys (iv) walker (v) baby bouncer (vi) number of books.

Figure 4: Distribution of the parental investment measures

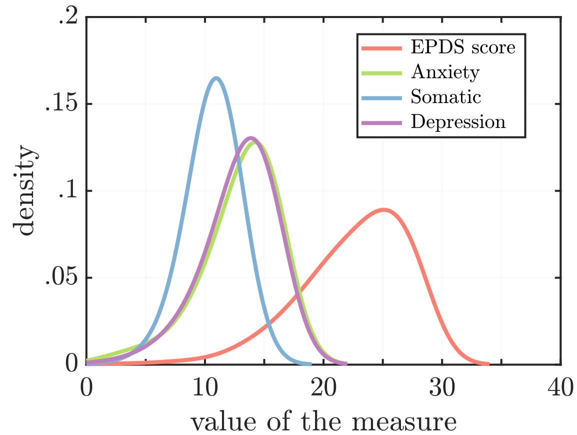


Source: ALSPAC data.
Notes: The figure shows the distribution of the parental investment measures in period 1.

2.6 Mother's mental health

Mother's mental health problems are measured with the Edinburgh Postnatal Depression Scale (EPDS), constructed on the basis of questions on mother's symptoms of depression and anxiety, typically characterizing the period after birth (Cox and Holden, 2003) as well as measures of the Crown Crisp Experiencial Index (CCEI) (Crown and Crisp, 1979) which includes specific scores of anxiety, depression and somatic symptoms. These measures are available for each development period, $t \in \{1, 2, 3\}$. The distributions of each of the scores in period 1 are shown in Figure 5.

Figure 5: Distribution of the mother's mental health measures



Source: ALSPAC data.
Notes: The figure shows the distribution of the mother's mental health measures in period 1.

3 The formation and evolution of skills

To describe the formation and evolution of cognitive and socio-emotional skills throughout early childhood, including different mechanisms through which exposure to IPV affects the development process, we use a modified dynamic latent factor model based on the seminal contribution of Cunha et al. (2010).[10] The latent factor model is a natural choice for our setting, firstly because it allows us to fully utilise the richness of the ALSPAC data that contains numerous measures of cognitive and socio-emotional skills for each development period that we observe. However, the model is also flexible as it allows for skills to be self-producing, but also includes cross-effects between skills and dynamic complementarities with respect to other inputs. These features are important for our setting because they allow us to understand how IPV exposure in early childhood perpetuates into the development of future skills, and to quantify the relative contributions of the mechanisms that are driving the overall effect.

Our approach modifies the Cunha et al. (2010) model in several ways and we estimate the model following recent contributions by Attanasio et al. (2020b) and Aucejo and

[10]the dynamic latent approach has been extended and applied in multiple recent applications of child human captial development including Attanasio et al. (2020a), Attanasio et al. (2020b), Attanasio et al. (2022), Aucejo and James (2021), Del Bono et al. (2020)

James (2021). First, we estimate a production technology of skill formation that takes a transcendental logarithmic (translog) functional form, containing four distinct inputs, discussed originally by Christensen et al. (1973). With the exception of Agostinelli and Wiswall (2016a), Agostinelli and Wiswall (2016b), and Del Bono et al. (2020), translog technologies have not been widely considered within the child skill development literature. However, the benefit of the translog technology is that it removes the restrictive substitution and transformation patterns imposed by constant elasticities of substitution (CES) technologies.[11] In addition, Del Bono et al. (2020) show that for translog technologies, properly anchored treatment effect estimates remain invariant to location and scale normalisations of the underlying measures while the same property does not hold for CES technologies. These features make the translog technology more suitable for our context. Secondly, within the translog production technologies we also estimate a return to scale parameter, relaxing the assumption of constant returns to scale, and we include a linear total factor productivity (TFP) equation that describes the effects of background characteristics and background demographics on the development of next period skills.[12] The TFP equation captures development that is not characterised by the inputs themselves and, importantly for our setting, it also provides a direct mechanism through which exposure to IPV can affect the development of next period skills. Thirdly, following Attanasio et al. (2020b) we model the parental investment and mother's mental health inputs as linear reduced-form equations. In absence of additional information on parental beliefs about the returns of their investments or the assumption that parents have perfect information regarding the structure of the production technologies, this approach provides a parsimonious way to model these inputs that is consistent with a more general structural model Attanasio et al. (2020b). However, the equations for parental investment and mother's mental health inputs also serve an additional function within the model because we allow IPV to enter these equations directly, which in-turn provides crucial indirect mechanisms through which IPV affects the production of next period skills. Finally, we jointly estimate the full model for all development periods by augmenting the two-step estimation procedure introduced by Aucejo and James (2021) to our setting.

[11] Attanasio et al. (2017) and Aucejo and James (2021) relax this restriction by estimating nested-CES production technologies.

[12] Agostinelli and Wiswall (2016b) and Freyberger (2021) outline the location and scale restrictions required in order to identify a TFP term.

3.1 The model

The frequency of the ALSPAC data allows us to characterise skill development throughout early-childhood from when the child is born, through three subsequent development periods, until the child is approximately 4 years old. Each period is indexed by t, where $t \in \{1,2,3,4\}$, and t corresponds to a unique point of observation within the ALSPAC data. At the beginning of each period t, the data contains multiple noisy measures of the child's cognitive (c), and socio-emotional (e) skills, and also of key inputs that include parental investment (I), and mother's mental health (mh). We use the notation $\theta^k_{i,t}$, $k \in \{c, e, I, mh\}$ to denote child i's skills and inputs respectively, in period t, where $\theta^k_{i,t} > 0$, and the notation $\Theta_{i,t}$ denotes the vector of child i's period t skills and inputs.

3.2 Skill production technologies

We assume that next period cognitive and socio-emotional skills, $\theta^k_{i,t+1}$ $k \in \{c, e\}$, develop via a trans-log production technology that depends on both current skills and current inputs:[13]

$$\ln \theta^k_{t+1} = \alpha^k_t + \gamma^k_{X,t} X_t + \gamma^k_{IPV,t} IPV_t + \beta^k_t \big(\gamma^k_{c,t} \ln \theta^c_t + \gamma^k_{e,t} \ln \theta^e_t + \gamma^k_{I,t} \ln \theta^I_t + \gamma^k_{mh,t} \ln \theta^{mh}_t + \frac{1}{2} \sum_q \sum_r \gamma^k_{qr,t} \ln \theta^q_t \ln \theta^r_t \big) + \eta^k_{\theta,t}, \quad k \in \{c, e\}, \quad q, r \in \{c, e, mh, I\} \tag{1}$$

where α^k_t and $\beta^k_t > 0$ are the location and scale parameters, respectively, for the production technology and $\eta^k_{\theta,t}$ is an unobserved production technology shock that is independent across skills $k \in \{c, e\}$ and periods t. The set of parameters $\left\{ \gamma^k_{c,t}, \gamma^k_{e,t}, \gamma^k_{,mh,t}, \gamma^k_{I,t}, \gamma^k_{qr,t} \right\}$ for $k \in \{c, e\}$ correspond to the elasticities of next period skills ($\theta^k_{t+1},\ k \in \{c, e\}$) with respect to current period skills ($\theta^k_t,\ k \in \{c, e\}$), parental investment ($\theta^I_t$), and mother's mental health (θ^{mh}_t). Our specification for the skill production technology models TFP in a reduced-form way that varies by individual i, by period t, and skill k. Within the TFP equation of the production technology we include IPV_t which is a dummy variable that is equal to 1 if the child is exposed to IPV during period t. The inclusion of the

[13] For brevity we have removed the i subscript.

IPV variable within the TFP equation captures the *direct effect* of IPV exposure on the production of next period skills, where its presence can shift the baseline level of next period skills relative to those that are not exposed. Finally, we also include X_t within the TFP equation which is a matrix of baseline birth characteristics and background demographic controls.

3.3 Parental investment and mother's mental health

As we do not have information on parental beliefs regarding the returns of their investments, and want to avoid making strong assumptions about parents knowledge of the production technologies, we follow Attanasio et al. (2020b) and estimate a separate reduced-form investment equation with the following empirical specification:

$$\ln \theta_t^I = \delta_{0,t}^I + \delta_{1,t}^I \ln \theta_t^c + \delta_{2,t}^I \ln \theta_t^e + \delta_{3,t}^I \ln \theta_t^{mh} + \delta_{4,t} \ln Y_t + \delta_{5,t}^I IPV_t + \delta_{X,t}^I X_t + \eta_t^I \quad (2)$$

where η_t^I is an unobserved investment shock. Our assumption is therefore that parental investment depends on current skills ($\theta_t^k,\ k \in \{c, e\}$), mother's mental health (θ_t^{mh}), household income (Y_t), and baseline birth characteristics and demographic controls (X_t). In addition, a key contribution of this paper is that we also allow parental investment to depend directly on IPV that occurred during period t. In the first instance this allows the model to capture differences in investment behaviour that can be attributed to different paths of exposure to IPV. However, it also captures an indirect mechanism through which exposure to IPV can affect the development of next period skills - via parental investment. Following similar reasoning and to account for another indirect channel through which IPV affects the development of skills, we also estimate a separate reduced form equation for mother's mental health in each period t, with the following empirical specification:

$$\ln \theta_t^{mh} = \delta_{0,t}^{mh} + \delta_{1,t}^{mh} \ln \theta_t^c + \delta_{2,t}^{mh} \ln \theta_t^e + \delta_{3,t}^{mh} \ln \theta_{t-1}^I + \delta_{4,t}^{mh} \ln Y_t + \delta_{5,t}^{mh} IPV_t + \delta_{X,t}^{mh} X_t + \eta_t^{mh} \quad (3)$$

where η_t^{mh} is the unobserved shock to mother's mental health. Here we assume that mother's mental health depends on current period cognitive and socio-emotional skills ($\theta_t^k,\ k \in \{c,e\}$), lagged parental investment (θ_{t-1}^I), household income (Y_t), and baseline birth characteristics and demographic controls (X_t).[14] Exposure to IPV during period t also enters the equation for mother's mental health directly, allowing the model to capture the significant detrimental effects that IPV exhibits on the mental health of the victim mothers. However, modelling mother's mental health in this way also generates further consequences for the development of next-period skills. The first is that because mother's mental health enters the production technologies directly (equation 1), this provides an additional indirect mechanism through which IPV exposure affects child skill development - via differences in mother's mental health. However, the second consequence is that because parental investment is itself affected by mother's mental health (equation 2), the model also takes into account how the effect of IPV on mother's mental health spills over into parental investment, and creates an additional indirect mechanism through which IPV affects skill development.

A major concern with modelling the production technology inputs in a reduced-form way is that shocks to skill development $\eta_{\theta,t}^k$ could themselves be correlated with shocks to parental investment η_t^I and mother's mental health η_t^{mh}. This is plausible if, for example, parents consider shocks to child's skills when they take their investment decisions. If this is true, then the production technology inputs are endogenous. To address this concern we follow Attanasio et al. (2020b) and use a control function approach. Specifically, we use our measure of household income Y_t as the excluded instrument. We therefore include the household income measure only in the reduced-form equations and exclude it from the production technologies. We then use the estimated residuals from the reduced-form equations as additional regressors in the TFP equation of the production technologies. Given that we control for baseline birth characteristics and demographic background characteristics of the child and the household, our identification assumption is that the household income measure Y_t is conditionally exogenous. Exogeneity of the inputs implies that the coefficients on the residual terms are equal to zero, we indeed test this hypothesis and show that this is not the case.

[14] we use lagged parental investment due to differences in timing of the input measures in the ALSPAC data. Specifically, mother's mental health is measured prior to the observation of the parental investment measures.

3.4 Measurement System

An additional concern for the estimation of the production technology parameters and the reduced-form equations for investment and mother's mental health is that the skills and inputs are not observed directly in the data. The factor model approach addresses this concern by backing-out the latent skills and inputs from the rich set of measures that are observed in the data. However, in order to obtain results that have an interpretable scale and to ensure comparability across development periods, factor models require additional restrictions related to the measures that are contained within the data (Agostinelli and Wiswall (2016b), Freyberger (2021)). A key feature of the ALSPAC data is that it is rich enough for us to address these issues in a parsimonious way because in each development period t, we observe multiple measures of skills and inputs, however, crucially we observe at least one repeat measure in every development period. Formally, for all latent skills and inputs within the model, Θ_t, we assume a log-linear measurement system between Θ_t and the measures of Θ_t that we observe in the data. Specifically, in each period t there are M_t^k measures of θ_t^k, and we use $Z_{t,m}^k$ to denote measure m of θ_t^k, where $m = 1, 2, \ldots, M_t^k,\ k \in \{c, e, I, mh\}$:

$$Z_{t,m}^k = \mu_{t,m}^k + \lambda_{t,m}^k \ln \theta_t^k + \varepsilon_{t,m}^k, \quad k \in \{c, e, I, mh\} \tag{4}$$

$\mu_{t,m}^k$ and $\lambda_{t,m}^k$ are the location and scale parameters for measure m in period t and $\varepsilon_{t,m}^k$ is the mean-zero measurement errors that is independent across measures and $k \in \{c, e, I, mh\}$. As mentioned above, identification of the factor model requires further restrictions on the measurement system via location and scale normalisations. We set the location and scale of each factor by normalising the location parameter, μ_t^k, equal to 0 and the scale parameter, λ_r^k equal to 1 for the repeat measures that we observe in each period within the ALSPAC data. For cognitive skills, the repeat measure is the child's gross motor score, for socio-emotional skills it is the child's hyperactivity score, for parental investment the repeat measure is the home score, and finally for mother's mental health the repeat measure is the mother's Edinburgh post-natal depression score. Normalising in this way satisfies the restrictions and provides the factors with an interpretable scale that is comparable across all development periods. Finally, we use a dedicated measurement system in each period, where the measures load only onto a single factor, and where we have at least three measures for each factor.[15]

3.5 Estimation Procedure

To estimate the model we follow the two-step estimation procedure of Aucejo and James (2021). This procedure is preferable for our setting, firstly because it can handle noncontinuous variables within the measurement system that are common in the ALSPAC data. Secondly, the procedure is easily able to accommodate binary and discrete variables, such as exposure to IPV, as it only requires modelling of the latent factors.[16] In summary, the estimation procedure proceeds as follows in two steps, in the first step, it uses the measurement system to nonparametrically recover the distribution of latent skills. Then, in a second step the procedure estimates the parameters of the production technologies using draws from the distribution of the factors that were obtained during the first step.

We now briefly outline the estimation procedure from Aucejo and James (2021) in full, adapted to our framework that includes translog production technologies and reduced-form equations for parental investment and mother's mental health. First we use $\theta \in \{\Theta_1, \Theta_2, \ldots, \theta_4\}$ to denote a realisation of the latent skills and production technology inputs, then, conditional on θ, the probability of the observed measures is: $p(Z_i|\theta) = \prod_{t=1}^{T} Pr(Z_{i,t}|\theta)$. Second, note that the probabilities $p(Z_i|\theta)$ are conditionally independent, and that the conditional distribution for θ is generated by the translog production technologies. Next, let $F(\theta|X_i, IPV_i)$ be the conditional probability for θ, based on the translog production technologies (equation 1) and reduced-form investment and mother's mental health equations (equations 2 and 3), where X_i are the baseline birth characteristics and background demographics within the TFP equation, and IPV_i is a vector outlining child i's full path of IPV exposure across all development periods. Because the production technology shocks, $\eta^k_{\theta,t}$, are i.i.d., the joint probability can be expressed as the product of marginal probabilities, where $f(\theta^k_i|\cdot)$ is the marginal distribution of log skill θ^k_t

[15] A full list of the measures that we use in each development period and the respetive normalisations that we impose can be found in appendix **??**

[16] For example, an alternative approach is the estimation procedure introduced by Attanasio et al. (2020b), to implement their procedure would however require fitting a mixture distribution to binary and discrete characteristics, including IPV.

in period t:

$$F(\theta|X_i, IPV_i) = f(\theta_4^e|\Theta_3, X_{i,4}, IPV_{i,4}) \cdot f(\theta_4^c|\Theta_3, X_{i,4}, IPV_{i,4}) \cdot \ldots \cdot f(\theta_1^c|X_{i,1}, IPV_{i,1}) \quad (5)$$

If we let Ψ denote the parameters of the model, the log likelihood function LL(Ψ) is then defined as the sum of the integrated likelihood for n individuals, where the integrated likelihood is the product of the conditional probability of observed measures $p(Z_i|\theta)$ and the joint distribution of latent skills $f(\theta|X_i, IPV_i)$:

$$\mathrm{LL}(\Psi) = \sum_{i=1}^{n} \ln \left[\int_\theta p(Z_i|\theta) \cdot f(\theta|X_i, IPV_i) d\theta \right] \quad (6)$$

Aucejo and James (2021) propose a two-step estimation procedure as an alternative to maximising equation (4) directly. In the first stage, the unconditional distribution of log skills and production technology inputs $p(\theta)$ and parameters of the measurement system are estimated:

$$LL_{\text{first stage}} = \sum_{i=1}^{n} \ln \left[\int_\theta p(Z_i|\theta) p(\theta) d\theta \right] \quad (7)$$

Then, in the second stage, an individual-specific conditional distribution $h(\theta|Z_i)$ is constructed based on observed measures and using bayes's rule. Finally, the parameters of the production function are estimated using maximum likelihood by integrating over the densities:

$$LL_{\text{second stage}} = \sum_j \int_\theta \ln \left[f(\theta|X_i, IPV_i) \right] h(\theta|Z_i) d\theta \quad (8)$$

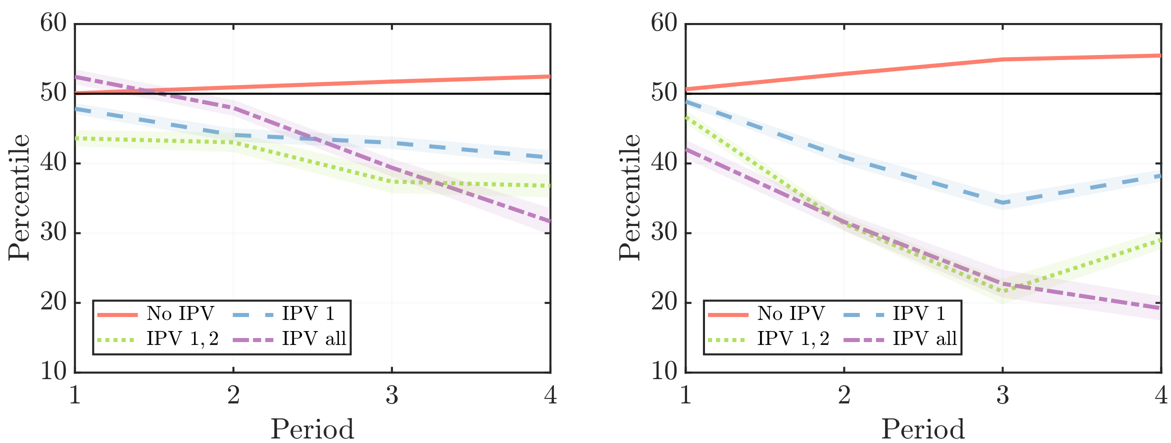
To obtain standard errors and confidence intervals for all parameter estimates, we compute 200 bootstrap replications over both estimation steps.

4 Results

4.1 The evolution of skills & exposure to IPV

We begin by highlighting how differing paths of exposure to intimate partner violence affect the development of cognitive (θ_t^c) and socio-emotional skills (θ_t^e). Taking as given the joint distribution of latent skills and inputs, recovered during step 1 of the estimation, we simulate skills across all periods, using the production technologies, for four distinct paths of IPV exposure.[17] The paths that we consider vary by increased levels of cumulative exposure to IPV with children that are never exposed to IPV as the baseline comparison group, results are shown in Figure 6.

Figure 6: Evolution of skills by differing paths of exposure to IPV



(a) Cognitive skills (θ_t^c) (b) Socio-emotional skills (θ_t^e)

Figure 6 plots the percentile in the distribution of skills for the median child with path of IPV exposure p, in period t, for skill k.[18] The figure shows that exposure to IPV creates quantitatively large percentile gaps in the skill distribution, for both skills, with the striking feature that the skill gaps materialise immediately - when the child is just 6 months old. For example, by the end period 1, children that are never exposed to IPV (solid red line) are 7 percentiles higher in the distribution of cognition than children exposed to IPV only in period 1 (dashed blue line), 8 percentiles higher than children exposed to IPV in periods 1 and 2 (dotted green line), and 4 percentiles higher than children exposed to IPV in all periods (dash-dotted purple line). With corresponding gaps for socio-emotional skills that are more pronounced at 12, 21, and 21 percentiles respectively.

[17] Appendix Figure A2 reports the model fit for both skills, showing that the model predicts the evolution of latent skills well for both skills in all estimation periods.

[18] Specifically, Figure 6 plots the value: $P[\text{median}(\theta^k_{t,p})] = \left(\frac{\sum_{i=1}^{N_{t,p}} \mathcal{I}[\theta^k_{i,t,p} < \text{median}(\theta^k_{t,p})]}{N_{t,p}}\right) \times 100, \quad k \in \{c, e\}$ where $\mathcal{I}(\cdot)$ is an indicator function, and $N_{t,p}$ is the total number of children with path of IPV exposure p at time t. The respective shaded areas in the figure represent 95% confidence intervals for each path from 100 bootstrap replications.

The second feature of Figure 6 is that percentile gaps are monotonically increasing in cumulative IPV exposure, with the consequence that children exposed to IPV in all periods are 20 (36) percentiles lower in the distribution of cognitive (socio-emotional) skills by the end of period 3. The importance becomes more apparent when noting that the end of period 3 corresponds to children that are aged 4 to 5 years old, meaning that persistent exposure to IPV appears to create significant disadvantages for children prior to and upon entry to the formal schooling system.

Notably, Figure 6 also shows that skill percentile gaps persist into periods where the child is no longer exposed to IPV, with scarce evidence of catch-up. For example, children that are exposed to IPV only in period 1 (blue dashed line) are 11 (18) percentiles lower in the distribution of cognitive (socio-emotional) skills by the end of period 3, despite having two subsequent periods of non-exposure. The persistence of skill percentile gaps into periods of non-exposure provides descriptive evidence that the consequences of IPV exposure are long-lasting, well beyond the period of exposure itself, and that in absence of intervention gaps are unlikely to close.

4.2 Skill production technologies, parental investment & mother's mental health

We now discuss the estimates of the skill production technologies and the equations for investment and mother's mental health that determine the dynamics of the skill development documented in Figure 6.

4.2.1 Parental investment & mother's mental health

While the production technologies ultimately determine the evolution of skills shown in Figure 6, parental investment and mother's mental health represent two key production technology inputs, reflecting parent's choices and behaviour, that are themselves a function of IPV. It is therefore crucial to understand these processes, firstly, because they likely represent an important mechanism through which IPV generates skill percentile gaps - we will show that this is indeed the case - and secondly, because understanding these processes facilitates the creation of interventions designed to offset the skill percentile gaps observed in Figure 6 - we will precisely demonstrate this in Section 5.

Table 2 reports estimates for the investment (equation 2) and mother's mental health (equation 3) equations, for each development period, with 90% bootstrap confidence intervals in parentheses. Note that we do not include lagged parental investment in the equation for mother's mental health at $t = 1$ because no such measures are available in the data.[19]

Table 2: Parental investment, mother's mental health, and IPV exposure

	(1)	(2)	(3)	(4)	(5)	(6)
	parental investment (θ_t^I)			mother's mental health (θ_t^{mh})		
	$t = 1$	$t = 2$	$t = 3$	$t = 1$	$t = 2$	$t = 3$
a) intimate partner violence						
exp. to IPV$_t$	0.00	0.01	-0.00	-0.63	-0.71	-0.59
	[-0.05, 0.05]	[-0.04, 0.05]	[-0.09, 0.08]	[-0.72, -0.53]	[-0.82, -0.61]	[-0.69, -0.50]
b) Prod. function inputs (Θ_t)						
cog$_t$	0.50	0.33	0.29	-0.02	0.01	0.00
	[0.37, 0.62]	[0.22, 0.44]	[0.23, 0.34]	[-0.08, 0.03]	[-0.09, 0.12]	[-0.05, 0.05]
socio-emo$_t$	0.07	-0.06	0.07	0.26	0.28	0.33
	[0.00, 0.15]	[-0.10, -0.01]	[-0.00, 0.15]	[0.22, 0.31]	[0.23, 0.32]	[0.28, 0.38]
mmh$_t$	0.07	0.07	0.02	-	-	-
	[0.02, 0.12]	[0.04, 0.11]	[-0.02, 0.06]			
inv$_{t-1}$	-	-	-	-	0.04	0.18
					[-0.07, 0.15]	[0.08, 0.29]

Notes:

Panel (a) in the table shows the direct effect of IPV, with the estimates pointing to substantial differences across inputs. Parental investment does not appear to be directly affected by within-period IPV, while conversely, there are significant direct impacts on mother's mental health. The coefficient implies that mothers, on average, experience at least 60% lower values of the mental health factor for periods where they are a victim, corresponding to a fall of () percentiles in the within-period distribution of mental health. While this represents a considerable negative shock to mother's mental health, panel (b) highlights that this direct effect is also compounded via the effect of mother's mental

[19] Full parameter estimates are shown in Appendix Table B1. Following Attanasio et al. (2020b), we use income as the excluded instrument to estimate the effect of investment and mother's mental health in the skill production technologies. The coefficients on income are positive and significant for both inputs in all but the final period for investment and the final period for mother's mental health.

health on current period parental investment. Specifically, the coefficients on mother's mental health are positive and significant for parental investment in all but the final period, indicating that mother's with higher values of the mental health factor invest more in their children. In section 4.3 we will decompose the relative importance of both the investment and mother's mental health channels when evaluating the impact of IPV on the development of next period skills.

Panel (b) also shows that child skills are an important determinant of parental investment and mother's mental health. The coefficients on cognitive skills are positive and significant for investment in all periods, while the coefficients on socio-emotional skills are positive and significant for mother's mental health in all periods. Implying that parents invest more in children with higher cognition, but also that mother's have increased mental health when their child has higher levels of socio-emotional skills.

4.2.2 Skill production technologies

We now discuss the production technologies for cognitive and socio-emotional skills (equation 1). The technologies determine the evolution of skills over time, allowing for complementarities between inputs, and both direct and indirect effects of IPV exposure. Table 3 reports the estimated marginal effects for each input in the full model where we allow inputs to be endogenous.[20] Panel (a) shows effects for the production of cognitive skills, while panel (b) shows corresponding estimates for socio-emotional skills, both evaluated for a "representative" child and with 90% bootstrap confidence intervals in parentheses.[21] The marginal effects have a simple closed-form that depends on both the parameters of the model and production technology inputs, and also carries an intuitive interpretation.[22]

The marginal effects in Table 3 help to capture three main findings regarding the structure and dynamics of the skill accumulation process, that are consistent with recent production technology estimates (Cunha et al. (2010), Attanasio et al. (2020b) and

[20]Full tables containing all estimated parameters are included in appendix tables B2 and B3, where columns 1-3 report estimates when inputs are assumed to be exogenous, and columns 4-6 report corresponding estimates for the full model where we allow inputs to be endogenous.

[21]In Table 3 the representative child corresponds to a child with median levels of all inputs Θ_t and baseline demographics X_t

[22]see appendix Appendix A: for a full derivation of the marginal effects

Table 3: Marginal effects of production function inputs (Θ_t)

	(1)	(2)	(3)
a) Cognitive skills (θ_t^c)	$t=2$	$t=3$	$t=4$
cognitive skills (θ_{t-1}^c)	0.76	0.71	0.49
	[0.66, 0.85]	[0.50, 0.92]	[0.33, 0.65]
socio-emotional skills (θ_{t-1}^e)	0.09	0.11	0.21
	[-0.01, 0.18]	[0.01, 0.21]	[0.11, 0.31]
parental inv. (θ_{t-1}^I)	0.37	0.56	0.69
	[0.26, 0.48]	[0.17, 0.96]	[0.40, 0.98]
mother's mental health (θ_{t-1}^{mh})	0.14	0.04	0.22
	[0.04, 0.24]	[-0.08, 0.16]	[0.10, 0.33]
b) Socio-emotional skills (θ_t^e)	$t=2$	$t=3$	$t=4$
cognitive skills (θ_{t-1}^c)	0.13	0.13	0.06
	[0.07, 0.19]	[0.02, 0.23]	[-0.03, 0.15]
socio-emotional skills (θ_{t-1}^e)	0.62	0.52	0.49
	[0.51, 0.74]	[0.40, 0.63]	[0.38, 0.59]
parental inv. (θ_{t-1}^I)	0.03	0.03	-0.00
	[-0.35, 0.41]	[-0.20, 0.25]	[-0.17, 0.17]
mother's mental health (θ_{t-1}^{mh})	0.22	0.32	0.66
	[0.07, 0.37]	[0.16, 0.48]	[0.48, 0.84]

Notes:

Aucejo and James (2021)). The first feature is self-productivity of skills at all ages. The estimates suggest that a 1 log unit increase in current cognitive (socio-emotional) skills at $t = 1$ would increase next period cognitive (socio-emotional) skills by 0.76 (0.62) log units, with comparable magnitudes in other periods. The second feature is the presence of complementarities between skills whereby both skills play an important role in the production of the other. For example, panel b) shows that a 1 log unit increase in cognition at $t = 1$ would increase next period socio-emotional skills by 0.13 log units. The impact of cognition on socio-emotional skills appears to decrease with child age, while the opposite appears to be true for the impact of socio-emotional skills on cognition. The third feature relates to the parental investment and mother's mental health inputs. For cognitive skills, the marginal effect of parental investment is positive, significant, and appears to be increasing with child age. As investment is negatively impacted by IPV, this firstly points to how IPV indirectly affects the development of next period skills. However, since parental investment is increasing in current cognition (see Table 2), the marginal effects also point to dynamic complementarity with respect to investment in the production of cognitive skills - an additional mechanism through which the effect of IPV operates. Panel a) also suggests similar findings with respect to the mother's mental health input, although they are quantitatively smaller in magnitude. For socio-emotional skills, interestingly, the findings are reversed. Panel b) highlights no significant marginal effects of parental investment for the production of socio-emotional skills. However, for mother's mental health the marginal effects are positive, significant and indicate dynamic complementarity in the production of socio-emotional skills. This is indicative that the indirect effect of IPV on socio-emotional skills primarily operates via the shock that IPV imposes on mother's mental health - an implication that we test in section 4.3.

The presence of dynamic complementarities are important because they provide a mechanism through which IPV exposure indirectly affects the production of skills in addition to first-order effects of reduced levels of investment and mother's mental health inputs. The intuition is that while IPV in period t reduces mother's mental health and parental investment, with both channels leading to a reduction in the level of skills at $t+1$. Dynamic complementarity also implies that the reduction in skills at $t+1$ reduces the productivity of investment and the benefits of mother's mental health at $t+1$. The main consequence is that dynamic complementarities therefore help to perpetuate percentile gaps in the skill distribution that materialise due to IPV, and also why gaps that we observe in Figure 6 persist into periods of non-IPV. In section 4.3 we label this as the "prior effect" of IPV exposure and quantify the extent to which it contributes to overall skill percentile gaps in each period.

The final estimates that we consider are the direct effects of IPV exposure within the production technologies.[23] The coefficients are negative with magnitudes suggesting the direct effect of IPV exposure decreases next period skills by around 3 percent. However, the direct effects are insignificant in all periods, indicating that the variation in skill dynamics is primarily attributed to the indirect channels - this is an additional implication that we will test in section 4.3.

Lastly, we discuss the coefficients of the investment and mother's mental health resid-

[23]See panel (a) of Appendix Tables B2 and B3.

uals[24]. For both skills, both sets of coefficients are either negative or insignificant, consistent with the idea that parents react and try to compensate for negative shocks to development via these inputs. It also suggests that the coefficients on investment and mothers mental health inputs should be smaller when they are assumed to be exogenous, Appendix Tables B2 and B3 confirm that this is indeed the case. The key implication is that when we assume these inputs to be exogenous, we underestimate the impact of the inputs themselves, and consequently underestimate the true extent of exposure to IPV on skill development.

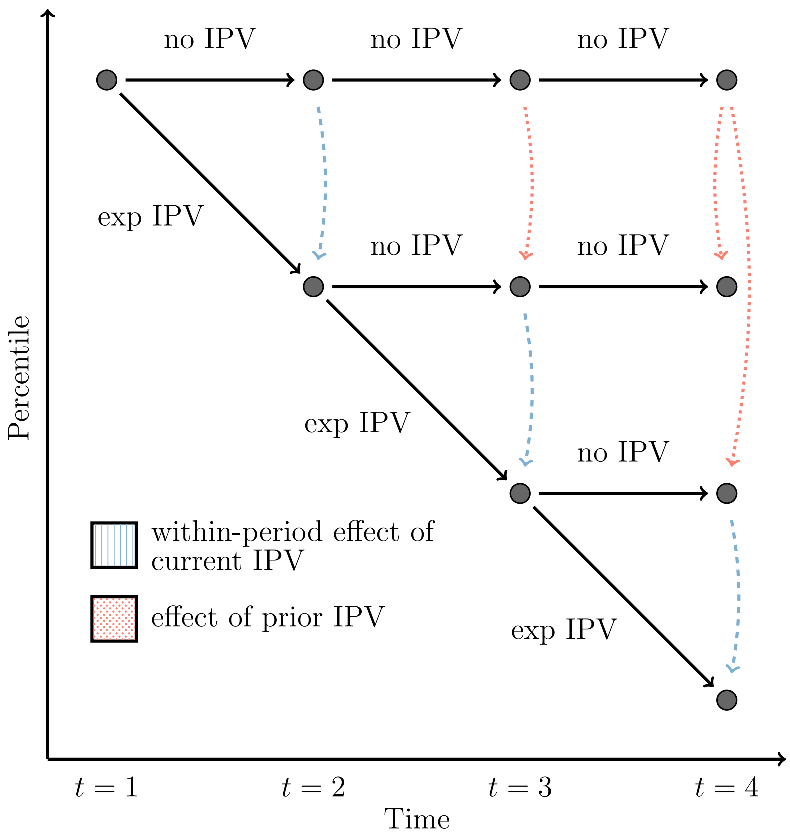
4.3 Decomposition exercise

While Figure 6 shows that IPV during early childhood is detrimental for the development of both skills, it fails to highlight the different mechanisms that determine the observed percentile gaps. For example, it could be that children with different paths of IPV exposure receive different levels of inputs, independent of the path of exposure that they are facing. If this is true, then in Figure 6 we are unable to disentangle these effects and their relative contributions to the percentile gaps.

To address this concern, we now consider skill development for a representative child and perform a decomposition exercise. Specifically, we consider a child endowed with median levels of skills and all other inputs. We then simulate forward the child's future skills, changing only their path of IPV exposure, for all paths shown in Figure 6. In the first instance, this allows us to isolate the overall effect of each path on the production of skills, relative to the no-IPV baseline, since variation in next-period skills is attributable *only* to the path of IPV exposure that the child faces. Secondly, by comparing percentile gaps across paths we can separately identify the effect of current IPV from the effect of prior IPV on the production of next-period skills. Disentangling these effects is relevant because for example, if the effect of prior IPV is relatively large, it suggests that percentile gaps will persist into periods of non-exposure, even if current IPV were removed. Table 4 below provides a visual representation of the exercise and the simulated percentile gaps, relative to the no-IPV baseline, for each skill and for each path of IPV exposure.

[24]see panel (f) of appendix tables B2 and B3.

Table 4: Decomposition exercise: percentile gaps due to different paths of IPV exposure



	(1)	(2)	(3)
a) Cognitive skills (θ_t^c)			
	Percentile difference at time t		
	$t = 2$	$t = 3$	$t = 4$
i) IPV at $t = 1$	-5.98	-5.74	-3.90
	[-6.57, -5.39]	[-6.15, -5.33]	[-4.19, -3.61]
ii) IPV at $t = 1$ & 2	-	-8.34	-9.24
	-	[-9.37, -7.30]	[-10.04, -8.44]
iii) IPV in all t	-	-	-17.46
	-	-	[-18.97, -15.95]
b) Socio-emotional skills (θ_t^e)			
	Percentile difference at time t		
	$t = 1$	$t = 2$	$t = 3$
i) IPV at $t = 1$	-16.17	-9.91	-5.67
	[-16.87, -15.47]	[-10.46, -9.37]	[-5.99, -5.35]
ii) IPV at $t = 1$ & 2	-	-30.30	-17.49
	-	[-31.46, -29.13]	[-18.21, -16.77]
iii) IPV in all t	-	-	-35.55
	-	-	[-36.84, -34.26]

Notes:

First, consider percentile gaps in period $t = 2$, shown in column 1 of Table 4. The gap that we observe is attributable only to IPV that occurred during period $t = 1$. This is the *within-period effect* of IPV at $t = 1$, represented by the blue dashed line between points at $t = 2$. The effect size is 5.98 (16.17) percentiles for cognitive (socio-emotional) skills, indicating that exposure to IPV during the first six months of childhood significantly impacts both skills, and is particularly detrimental for the development of socio-emotional skills.

Next, column 2 shows that an additional period of exposure in $t = 2$ leads to a larger, 8.34 (30.30) percentile gap in the distribution of cognitive (socio-emotional) skills in $t = 3$. However, the column also implies that if the same child had not experienced IPV at $t = 2$, there would remain a gap of 5.74 (9.91) percentiles at $t = 3$. This is due to the *effect of prior IPV* experienced at $t = 1$, represented by the red dotted line between points at $t = 3$. The difference between these paths, 2.60 (20.39) percentiles, identifies the within-period effect of IPV at $t = 2$, and is represented by the blue dashed line between points at $t = 3$. Here, the exercise highlights how the consequences of a single period of IPV are indeed long-lasting, via the prior effect, and perpetuate into future periods. For the path with an additional period of exposure in $t = 2$, more than half of the subsequent percentile gap in $t = 3$ cognition is due to IPV experienced one period earlier. While for the path of non-exposure in $t = 2$, IPV experienced previously slows the skill accumulation process to such an extent that a significant gap remains for both skills at $t = 3$. The implication therefore is that early prevention of IPV is imperative, and that preventing only future IPV is insufficient to fully offset skill percentile gaps.

Finally, column 3 shows that three consecutive periods of exposure generates an even larger, 17.46 (35.55) percentile gap in the distribution of cognitive (socio-emotional) skills at period $t = 4$ demonstrating that, for both skills, gaps are increasing in cumulative exposure, and also that the magnitude of the effects are larger for socio-emotional skills. In addition, column 3 shows that the gap would have been 9.24 (17.49) percentiles if the child had instead been exposed to IPV only in periods $t = 1$ and $t = 2$. This is the effect of prior IPV, experienced during periods $t = 1$ and $t = 2$, represented by the longer red dotted line between points at $t = 4$, and the difference, 8.22 (18.06) percentiles, identifies the within-period effect of IPV at $t = 3$, shown by the blue dashed line between points at $t = 4$. Similarly, if the child had instead been exposed to IPV only in $t = 1$, column

3 shows that the corresponding gap at $t = 4$ would have been 3.90 (5.67) percentiles, this is the effect of prior IPV, experienced during $t = 1$, shown by the smaller red dotted line at $t = 4$. The difference between prior effects, 5.34 (11.82) percentiles, is therefore attributable specifically to IPV that occurred during $t = 2$.

Overall, the exercise demonstrates that both current and prior effects of IPV have a significant role in explaining the percentile gaps that we observe between children with different paths of cumulative exposure to IPV. Notably, column 3 shows how just a single period of exposure at $t = 1$ perpetuates, through the prior effect, into a significant percentile gap at the end of the sample period. Moreover, the exercise suggests that for paths with multiple periods of IPV exposure, the effect of current IPV is relatively smaller than the effects of prior IPV for the production of next-period cognitive skills. For socio-emotional skills however, the effect of current IPV is larger, indicating firstly that socio-emotional skills are more receptive to the shock that IPV introduces, but also that the effect of the shock is less persistent for socio-emotional skills. The consequence is that, for socio-emotional skills, interventions should require a larger shift in inputs in order to offset the observed percentile gaps; we will explore this more precisely in section 5.

However, while the exercise suggests that intervention is required, it is currently silent regarding the inputs that interventions should target and their potential effectiveness. To address this, we note that when a child is exposed to IPV, the within-period effect aggregates the effect of the different mechanisms through which IPV affects skill production in the model. This includes both the direct mechanism, where exposure shifts TFP within the production technologies, and the indirect mechanisms, where IPV changes parental investment behavior and mother's mental health. Therefore, in addition to the exercise performed above, for each percentile gap attributed to the within-period effect of IPV, we can further decompose and identify the relative contributions of each mechanism to the gap. To achieve this, we consider the evolution of skills for the representative child that is exposed to IPV in every development period. As show in Table 4, this child experiences a within-period effect of IPV in each period, and also experiences the prior effect of IPV in period $t = 2$ and in period $t = 3$. Therefore, in Table 5 below, we quantify the relative contribution of these effects to the overall gap in each period, for both skills, and further decompose the within-period effect, documenting the contribution of each mechanism.

Table 5: Decomposing exercise: further decomposing the within-period and prior effects of IPV exposure

	(1)	(2)	(3)	(4)	(5)	(6)
	Percentile difference at time t					
	Cognitive skills (θ_t^c)			Socio-emotional skills (θ_t^e)		
	$t=2$	$t=3$	$t=4$	$t=2$	$t=3$	$t=4$
a) Total effect	-5.98	-8.34	-17.46	-16.17	-30.30	-35.55
	[-6.57, -5.39]	[-9.37, -7.30]	[-18.97, -15.95]	[-16.87, -15.47]	[-31.46, -29.13]	[-36.84, -34.26]
(i) % due to current IPV	100	31.21	47.10	100	67.29	50.80
	-	[25.90,36.51]	[42.82,51.37]	-	[64.74,69.84]	[49.18,52.41]
(ii) % due to prior IPV	0	68.79	52.90	0	32.71	49.20
	-	[63.49, 74.10]	[48.63, 57.18]	-	[30.16, 35.26]	[47.59, 50.82]
b) effect of current exp. to IPV	-5.98	-2.60	-8.22	-16.17	-20.39	-18.06
	[-6.57, -5.39]	[-3.23, -1.98]	[-8.93, -7.51]	[-16.87, -15.47]	[-21.01, -19.76]	[-18.63, -17.48]
(i) % due to direct effect	44.89	52.01	4.44	23.50	13.74	0.00
	[39.64, 50.15]	[46.75, 57.26]	[-0.82, 9.69]	[19.44, 27.55]	[9.68, 17.80]	[-4.06, 4.06]
(ii) % due to Δ in inv	20.44	42.61	86.06	0.96	1.75	12.74
	[15.53, 25.35]	[37.70, 47.51]	[81.15, 90.96]	[-1.02, 2.94]	[-0.23, 3.73]	[10.76, 14.72]
(iii) % due to Δ in mmh	34.66	5.39	9.51	75.54	84.51	87.26
	[31.93, 37.40]	[2.66, 8.12]	[6.78, 12.24]	[70.71, 80.37]	[79.68, 89.34]	[82.43, 92.09]
c) effect of prior exp. to IPV	-	-5.74	-9.24	-	-9.91	-17.49
	-	[-6.15, -5.33]	[-10.04, -8.44]	-	[-10.46, -9.37]	[-18.21, -16.77]
(i) % due to IPV at t = 1	-	100	42.21	-	100	32.41
	-	-	[38.97, 45.46]	-	-	[30.08, 34.75]
(ii) % due to IPV at t = 2	-	0	57.79	-	0	67.59
	-	-	[54.54, 61.03]	-	-	[65.25, 69.92]

Notes:

Firstly, panel a) in Table 5 reiterates the above observation that when a prior effect is present, it accounts for more than half of the overall gap for cognitive skills, while the within-period effect dominates for socio-emotional skills.

Then, panel b) proceeds to show the decomposition of the within-period effect, for both skills, in each period. The first row documents the percentile gap that is attributed to the within-period effect in period t. Consistent with the previous exercise in Table 4, the percentile gap in period $t = 2$ cognition is attributed only to the within-period effect and is 5.98 percentiles in magnitude. Subsequent rows show that 44.9% of the effect is due to the direct mechanism, 20.4% is due to changes in parental investment, and 34.7% is due to changes in mother's mental health. Overall, for cognitive skills, the decomposition of the within-period effect suggests that each mechanism contributes significantly in each development period. However, as the child ages, the direct channel and changes in mother's mental health begin to contribute less, while changes in parental investment become more consequential, determining 86% of the within-period effect at $t = 4$. Interestingly, for socio-emotional skills, the direct channel also contributes relatively less as the child ages, however, the majority of the within-period effect is instead determined by changes in mother's mental health, contributing at least 75% of the effect in each period. This result is noteworthy for two key reasons. The first is that, although the within-period effect creates significant and quantitatively important percentile gaps in each period, the mechanisms driving the gaps are different for each skill. Second, the result implies that when proposing policy interventions, targeting a specific input may be ineffective in offsetting percentile gaps for both skills, an implication that we explore further in section ().

Finally, panel c) of Table 5 shows how previous periods of exposure contribute to the realised prior effect in period t. Here, the decomposition is meaningful for the percentile gaps that are observed at $t = 4$, observed following three subsequent periods of exposure to IPV. Panel c) shows that for the 9.24 percentile gap at $t = 4$, attributed to the prior effect of IPV, 42% is due to IPV that occurred during $t = 1$, while the remainder, 58%, is due to IPV that occurred during $t = 2$. The observations for socio-emotional skills are similar, again emphasising that the consequences of just a single period of IPV are long-lasting, where a significant proportion of the overall gap for both skills at $t = 4$ is due to IPV experienced two periods earlier. This reiterates the previous statement that early prevention of IPV is imperative, but also highlights how the effects of early interventions will perpetuate into the development of future skills. In the next section, we proceed to evaluate the effectiveness of different timing and targeting of potential interventions, with the main policy goal of offsetting the observed percentile gaps.

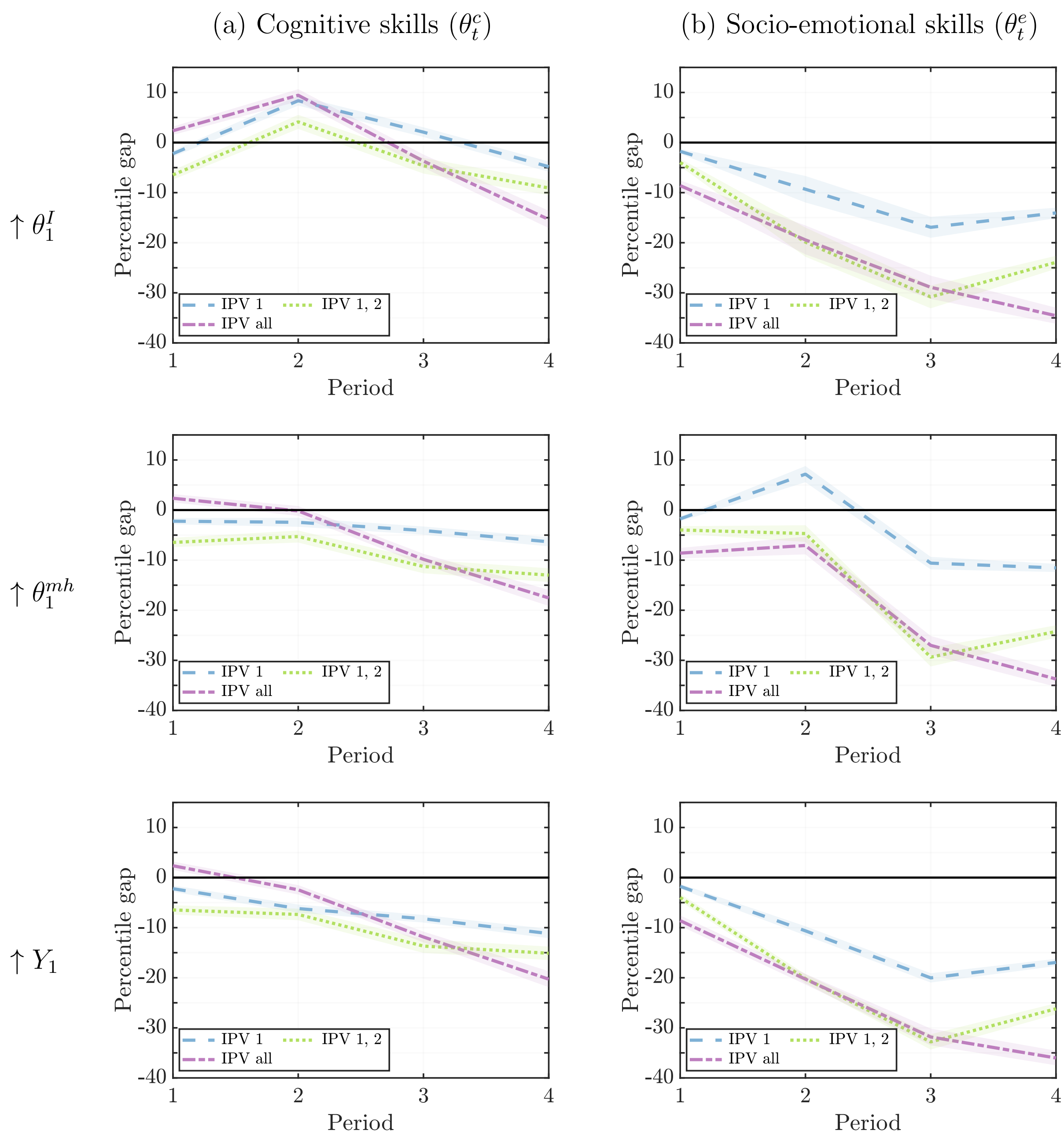
5 Policy counterfactuals

The decomposition exercise documented that early childhood exposure to IPV creates significant negative consequences for the development of skills. In particular, the exercise highlighted that the consequences materialise due to different mechanisms for each skill and that the effects of exposure to IPV are long-lasting, with important implications for the design and implementation of policy interventions. In this section, we formally test these implications by using the model to simulate child outcomes for scenarios that corresponding to potential real world interventions.

5.1 Impulse response simulations

First we consider the timing of potential interventions. Since the production technologies exhibit self-complementarity with respect to skills, and dynamic-complementarities with respect to other inputs, the implication is that early interventions should be more effective as the shock induced by the intervention will persist into periods beyond the period of the intervention itself (Cunha et al. (2010), Attanasio et al. (2020b)). However, what remains unclear is how the benefits of an intervention materialise when the child is simultaneously and subsequently exposed to IPV. For example, are the benefits sufficiently large to offset the negative impacts of IPV, or instead, are the benefits crowded out? We test this by simulating the impact of a 1 standard deviation shock to different inputs, targeting children with differing paths of exposure to IPV, and implementing the shock in the initial development period, $t = 1$. Specifically, we consider shocks to parental investment (θ_1^I) and mother's mental health (θ_t^{mh}), inputs that are themselves affected by IPV, while comparing this to an alternative policy that transfers income (Y_1) to the households that experience IPV, the results are shown below in Figure 7.

Figure 7: Impulse response simulations: 1 s.d. shock to input k during period $t = 1$



In Figure 7, column (a) corresponds to the resulting impulse response simulations for cognitive skills, while column (b) shows corresponding simulations for socio-emotional skills. Each row represents the set of simulations for the specific input that is targeted via the intervention. Specifically, the first row of Figure 7 corresponds to a 1 standard deviation increase to parental investment (θ_1^I), the second row represents a 1 standard deviation improvement in mother's mental health (θ_t^{mh}), and the final row is a 1 standard deviation increase in household income (Y_1). In each sub-figure we plot the percentile gap in the skill distribution (y-axis), calculated relative to the group that are never exposed to IPV, for each period (x-axis), and for the same paths of exposure to IPV that were highlighted in Figure 6. The blue dashed line plots the percentile gap for children that are exposed to IPV only in period $t = 1$, the green dotted line represents children exposed to IPV in periods $t = 1$ and $t = 2$, while the purple dashed-dotted line corresponds to children that are exposed to IPV in all development periods.

Firstly, consistent with the relative marginal effects of each input, shown in Table 3, the impulse response simulations generate interesting differences across skills. For cognitive skills, as expected, the shock to parental investment has the largest initial impact and is sufficiently large to offset the percentile gaps, for all paths, in the distribution of $t = 2$ cognitive skills, while shocks to mother's mental health have a much smaller effect, with gaps remaining for the paths with the highest levels of cumulative exposure. Therefore, the simulations suggest that if the policy goal is to close cognitive skill gaps, interventions that prioritise increases in parental investment should be more productive. For socio-emotional skills however, it is instead the shock to mother's mental health with the largest initial impact, although the effect is only enough to offset the gap for the children with the lowest level of cumulative exposure. Moreover, shocks to parental investment have a minimal impact on $t = 2$ socio-emotional skills, for all paths that we consider. Here, the implication is that if the goal is to instead close socio-emotional skill gaps, such an intervention should prioritise improvements in mother's mental health. Surprisingly, the final row shows that shocks to household income do not appear to close or indeed shift the $t = 2$ percentile gaps for any path of exposure, and for either cognitive or socio-emotional skills.

Secondly, although the simulations suggest that targeting specific inputs at $t = 1$ can be productive for eliminating gaps at $t = 2$, the more salient observation is that, irrespective of the input that is targeted by the intervention, percentile gaps remain in the distribution of $t = 4$ skills for both skills, and for children on all paths of exposure that we consider. The implication is that for each intervention evaluated, the benefits have been completely absorbed by simultaneous and subsequent exposure to IPV. It is important to note however that this does not suggest interventions will be ineffective in offsetting the consequences of exposure to IPV. Instead, the results of the simulations highlight that if we are unable to identify and remove the source of current and future IPV, offsetting the long-term consequences will require interventions that not only improve outcomes in the initial period, but that are also compounded by follow-up interventions.

5.2 Optimal policy interventions

To further demonstrate the need for follow-ups and the effectiveness of targeting specific inputs, we perform a final exercise where, instead of increasing each input by one standard deviation arbitrarily, we now consider the problem of the social planner. Specifically, we assume that the objective for the social planner is to offset the $t = 4$ skill percentile gaps, shown in figure 6, through a sequence of interventions that target the same input in each development period. To achieve this, the planner takes as given the initial joint-distribution of skills and inputs (Θ_1, X_1), the skill production technologies, and the equations for parental investment and mother's mental health. Then, conditional on this information, the planner solves for the optimal sequence of transfers $\{\tau_t^p\}_{t=1}^3$ to the intervention input considered, to minimise the distance between the $t = 4$ skill percentile of the median child that is never exposed to IPV, and the corresponding percentile for the median child with path of exposure p[25]. As in the previous exercise, the inputs that we consider for the sequence of interventions are parental investment, mother's mental health, and household income. We also constrain the size of the optimal transfer for parental investment and mother's mental health to be less than the corresponding within-period maximum in order to ensure a baseline level of feasibility for the proposed interventions, the results for cognitive skills are shown in table 6 below.

In Table 6, the initial three columns in the table distinguish the optimal transfers by path of exposure p, while each row corresponds to the amount of the transfer that should be introduced in development period t. The final three columns of the table shown the corresponding 10^{th}, 50^{th}, and 90^{th} percentiles for the period t distribution of the targeted input. Finally, panel a) in the table considers the optimal sequence of transfers to parental investment designed to offset cognitive skill percentile gaps, while panel b) shows corresponding results for improvements to mother's mental health, and panel c) shows results for transfers to household income. For example, panel a) suggests

[25] see appendix Appendix A: for a full derivation of the social planner's optimisation problem

Table 6: Optimal policy interventions - cognitive skills (θ_t^c)

	Path of IPV exposure			Percentile of input		
a) Intervention to parental investment (θ_t^I)						
	IPV at $t=1$	IPV at $t=1,2$	IPV in all t	10^{th}	50^{th}	90^{th}
$t=1$	1.01	1.89	3.33	26.20	29.29	32.19
	[0.00, 2.43]	[0.50, 3.28]	[1.03, 5.64]			
$t=2$	0.51	0.59	0.85	23.57	26.63	29.46
	[0.00, 1.71]	[0.00, 1.58]	[0.00, 1.99]			
$t=3$	0.23	0.26	0.33	21.85	25.13	28.22
	[0.08, 0.39]	[0.00, 0.85]	[0.00, 1.99]			
b) Intervention to mother's mental health (θ_t^{mh})						
	IPV at $t=1$	IPV at $t=1,2$	IPV in all t	10^{th}	50^{th}	90^{th}
$t=1$	1.89	3.49	5.02	9.51	13.80	15.40
	[1.26, 2.51]	[2.76, 4.21]	[4.30, 5.73]			
$t=2$	0.53	1.27	1.38	9.44	11.99	12.91
	[0.10, 0.95]	[0.85, 1.69]	[1.09, 1.68]			
$t=3$	0.39	0.65	0.78	9.18	11.73	12.97
	[0.17, 0.60]	[0.47, 0.83]	[0.63, 0.93]			
c) Transfer to household income (Y_t)						
	IPV at $t=1$	IPV at $t=1,2$	IPV in all t	10^{th}	50^{th}	90^{th}
$t=1$	782.7	3,352.6	502.7	1,750.1	2,518.7	3,850.3
	[767.5, 797.9]	[3,287.3, 3,417.9]	[492.9, 512.5]			
$t=2$	247.0	354.5	1,786.3	1,714.8	2,476.8	3,833.7
	[242.2, 251.8]	[347.6, 361.4]	[1,751.6, 1,821.1]			
$t=3$	557.7	821.6	841.3	1,714.0	2,467.0	3,829.3
	[546.8, 568.5]	[805.5, 837.6]	[824.9, 857.6]			

Notes:

that for children that are exposed to IPV in all periods, the optimal sequence of transfers to parental investment to offset cognitive skill percentile gaps at $t = 4$, is 3.33 units in $t = 1$, 0.85 units in $t = 2$, and 0.33 units in $t = 3$.

For cognitive skills, the results of the exercise showcase three of the key implications discussed throughout the paper, the first being the importance of early interventions. Specifically, the optimal sequence of transfers to parental investment and to mother's mental health suggest that the largest transfer should occur during the initial development period, for each path of exposure to IPV that we consider. In addition, subsequent transfers are decreasing with t, where transfers in the final period are, at most, 25% as large as the corresponding transfer in the initial period. Importantly, this result is not driven by issues related to the scale of the inputs, as the structure of the measurement system ensures that the input scale is consistent across periods. Lastly, the relative size of the optimal transfers are increasing in cumulative exposure to IPV, highlighting that higher levels of exposure to IPV are more costly to offset.

The second implication is the importance of follow-up interventions to facilitate and compound the effects of early interventions. In the previous exercise we showed that, in absence of follow-up, the benefits of early interventions are absorbed by current and future exposure to IPV. Here, the optimal sequence of transfers reiterates this finding where, for each path of IPV exposure and for each intervention that we consider, the optimal value of the transfer is positive in every development period. This is particularly salient for the group that are exposed to IPV only in during $t = 1$, where the exercise highlights that, despite facing two subsequent periods of non-exposure, follow-up interventions are still required to counteract the long-lasting effect that the initial period of exposure to IPV generates.

The final implication relates to the targeting of interventions. While the exercise shows that offsetting the $t = 4$ percentile gaps for cognitive skills can be achieved by a sequence of transfers to any of parental investment, mother's mental health, or household income, the exercise also highlights that there are efficiency gains to be obtained via targeting. For example, for cognitive skills, targeting mother's mental health would be relatively more costly, in terms of the magnitude of change that is required, relative to targeting parental investment or a household income transfer.

Finally, for socio-emotional skills the results of the exercise are shown below in Table 7. The patterns also reiterate the three key implications discussed above in relation to timing, targeting and follow-up. However, the major difference is that for socio-emotional skills the exercise further showcases the importance of policy targeting. Specifically, the results of the exercise show that a transfers to household income would be a highly inefficient policy if the goal is to offset socio-emotional skill gaps. This is because the marginal effects of the transfer on the socio-emotional skill percentile gap is so small, that in order to have any meaningful effect requires transfer sizes so large that they would be unrealistic to suggest for implementation. In contrast, the results also show highlight that targeting mother's mental health would be the most effective, in terms of the magnitude of change

Table 7: Optimal policy interventions - socio-emotional skills (θ_t^e)

	Path of IPV exposure			Percentile of input		
a) Intervention to parental investment (θ_t^I)						
	IPV at $t=1$	IPV at $t=1,2$	IPV in all t	10^{th}	50^{th}	90^{th}
$t=1$	20.31	26.58	19.51	26.20	29.29	32.19
	[17.64,22.98]	[23.66,29.50]	[15.98,23.04]			
$t=2$	20.88	21.70	17.48	23.57	26.63	29.46
	[18.82,22.95]	[18.90,24.49]	[14.32,20.64]			
$t=3$	9.37	9.61	7.81	21.85	25.13	28.22
	[7.46,11.27]	[7.68,11.54]	[5.24,20.64]			
b) Intervention to mother's mental health (θ_t^{mh})						
	IPV at $t=1$	IPV at $t=1,2$	IPV in all t	10^{th}	50^{th}	90^{th}
$t=1$	2.14	3.81	5.45	9.51	13.80	15.40
	[1.86, 2.41]	[3.35, 4.27]	[4.99, 5.90]			
$t=2$	0.91	1.47	2.31	9.44	11.99	12.91
	[0.85, 0.98]	[1.35, 1.60]	[2.16, 2.46]			
$t=3$	0.15	0.47	0.62	9.18	11.73	12.97
	[0.14, 0.17]	[0.43, 0.51]	[0.56, 0.67]			
c) Transfer to household income (Y_t)						
	IPV at $t=1$	IPV at $t=1,2$	IPV in all t	10^{th}	50^{th}	90^{th}
$t=1$	752.8	18,308.8	1,227,568.5	1,750.1	2,518.7	3,850.3
	[738.2, 767.5]	[17,951.9, 18,665.7]	[1,203,627.8, 1,251,509.2]			
$t=2$	3,461.1	119,959.8	863,293.8	1,714.8	2,476.8	3,833.7
	[3,393.6, 3,528.5]	[117,620.3, 122,299.3]	[846,457.3, 880,130.3]			
$t=3$	1,240.3	10,626.3	30,890.1	1,714.0	2,467.0	3,829.3
	[1,216.1, 1,264.5]	[10,419.1, 10,833.4]	[30,287.7, 31,492.4]			

Notes:

required, to offset socio-emotional skill percentile gaps.

6 Conclusion

This paper studies how exposure to Intimate Partner Violence (IPV) shapes the accumulation of cognitive and socio-emotional skills of young children. We use the Avon Longitudinal Study of Parents and Children (ALSPAC), an internationally unique UK longitudinal cohort data resource containing annual indicators of the incidence of IPV and rich measures of children's cognitive and socio-emotional skills and the home environment to estimate the joint dynamic process of IPV exposure, parental investment, mother's mental health and child skill development, allowing for static and dynamic complementarities between all inputs in a dynamic latent factor structure.

Combining the richness of our data with a powerful estimation technique, this paper is able to document the dynamics of the accumulation of skills and how these change with IPV exposure, by studying how skills co-evolve and what is the role of parental investment and mother's mental health in this process. We allow for both a *direct* effect of IPV —through the witnessing of abuse— and *indirect* effects —via changes in parental investment and mother's mental health. We find that, for socio-emotional skills the negative effect of IPV appears earlier in childhood, whereas for cognitive skills the effect appears later but the long term effect is more persistent. When decomposing the total effect of IPV on cognitve and socio-emotional skills into the direct and indirect effects, we find that for cognitive skills the direct effect have a relative larger role and that the indirect effects are determined by changes in parental investment, while we find the opposite for socio-emotional skills, whereby the negative effect of IPV on socio-emotional skills is largely driven by the changes in mother's mental health. Finally, the differences in the marginal products of parental investment and mother's mental health across children's skills distribution and over different paths of IPV exposure reveals that policies targeting parental investment and mother's mental health in order to offset the effect of IPV would be more effective if implemented in early childhood, but that they would also require follow-ups to be truly effective.

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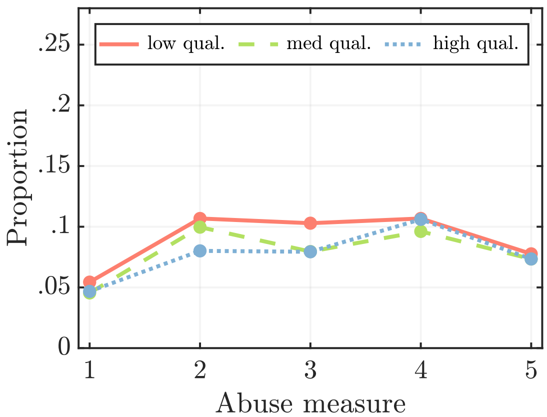
Appendix A: Additional Results

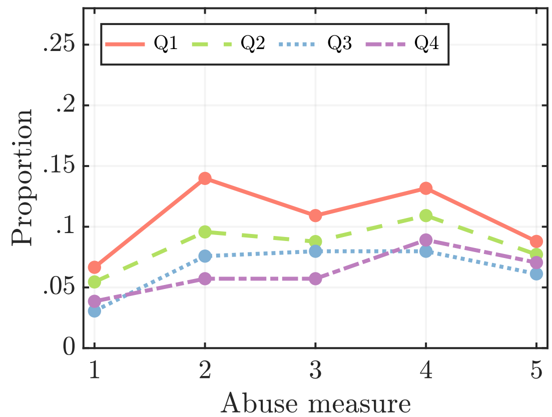
Appendix B: Additional Figures

Figure A1: IPV Incidence rates by mother and household characteristics

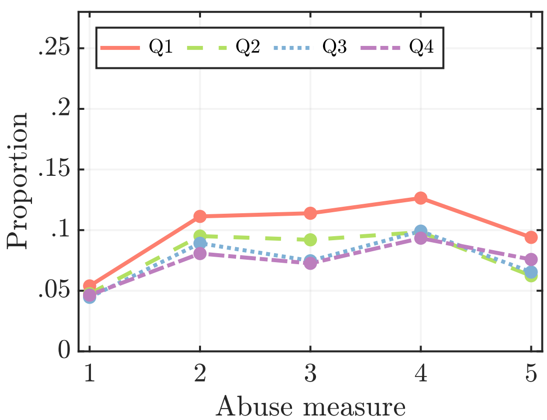
(a) Mother's education



(b) Household income (Y_t)



(c) Parental investment (θ_t^I)



(d) Mother's mental health (θ_t^{mh})

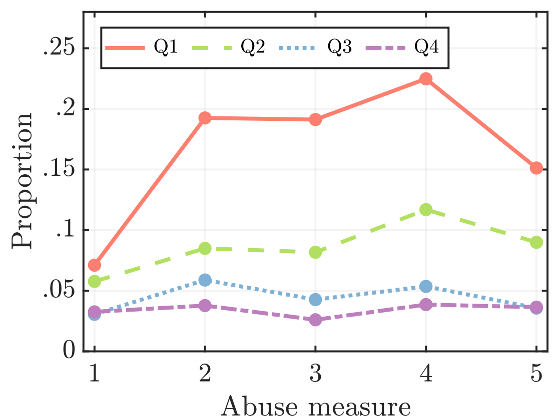
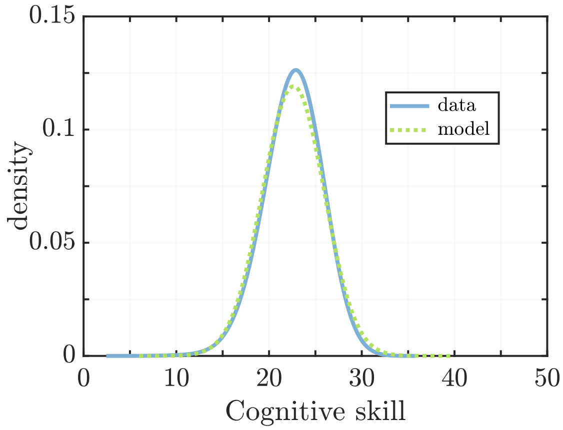
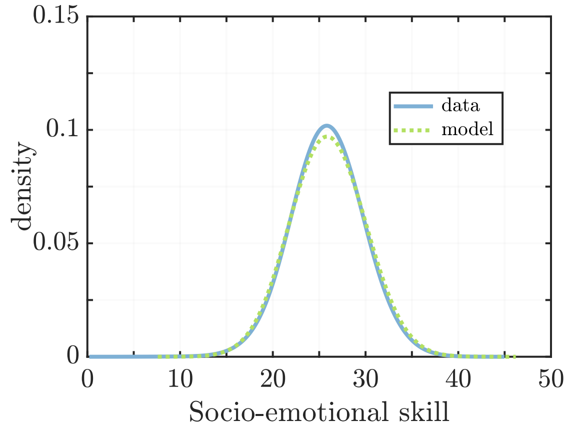


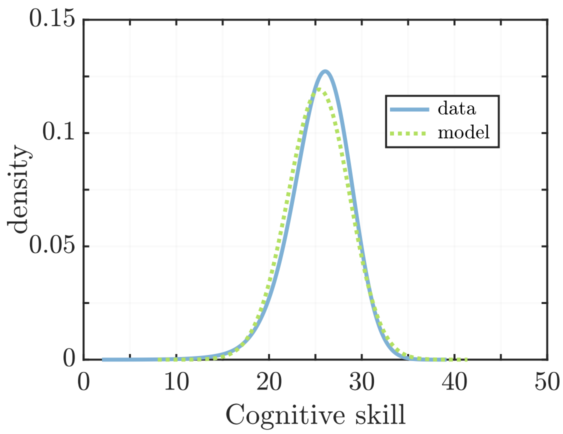
Figure A2: Model Fit: distributions of cognitive and socio-emotional skills



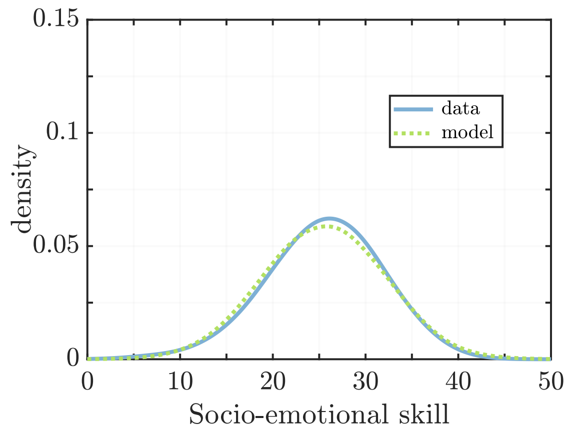
(a) Cognitive skills (θ_t^c): $t = 2$



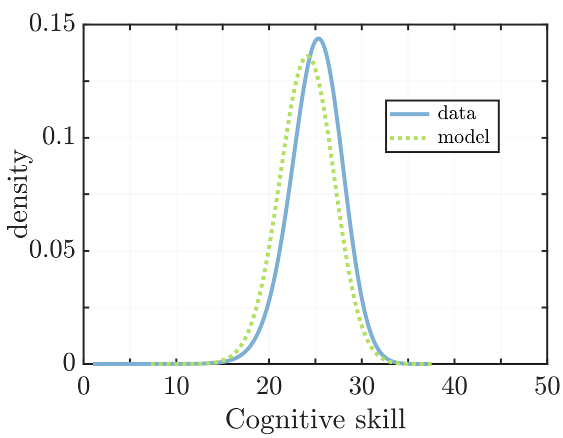
(b) Socio-emotional skills (θ_t^e): $t = 2$



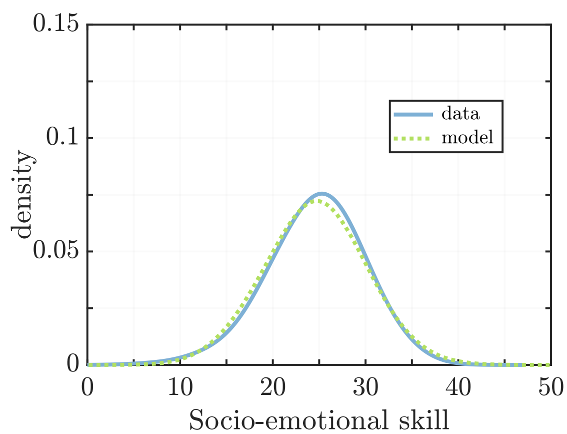
(c) Cognitive skills (θ_t^c): $t = 3$



(d) Socio-emotional skills (θ_t^e): $t = 3$



(e) Cognitive skill (θ_t^c): $t = 4$



(f) Socio-emotional skill (θ_t^e): $t = 4$

Appendix C: Additional Tables

Table B1: Parental Investment & Mother's Mental Health Equations

	(1)	(2)	(3)	(4)	(5)	(6)
	parental investment (θ_t^I)			mother's mental health (θ_t^{mh})		
	$t=1$	$t=2$	$t=3$	$t=1$	$t=2$	$t=3$
a) intimate partner violence						
exp. to IPV$_t$	0.00	0.01	-0.00	-0.63	-0.71	-0.59
	[-0.05, 0.05]	[-0.04, 0.05]	[-0.09, 0.08]	[-0.72, -0.53]	[-0.82, -0.61]	[-0.69, -0.50]
b) Prod. function inputs (Θ_t)						
cog$_t$	0.50	0.33	0.29	-0.02	0.01	0.00
	[0.37, 0.62]	[0.22, 0.44]	[0.23, 0.34]	[-0.08, 0.03]	[-0.09, 0.12]	[-0.05, 0.05]
socio-emo$_t$	0.07	-0.06	0.07	0.26	0.28	0.33
	[0.00, 0.15]	[-0.10, -0.01]	[-0.00, 0.15]	[0.22, 0.31]	[0.23, 0.32]	[0.28, 0.38]
mmh$_t$	0.07	0.07	0.02	-	-	-
	[0.02, 0.12]	[0.04, 0.11]	[-0.02, 0.06]			
inv$_{t-1}$	-	-	-	-	0.04	0.18
					[-0.07, 0.15]	[0.08, 0.29]
c) Demographics & background characteristics (X_t)						
Income	0.07	0.05	0.08	-0.02	0.10	0.14
	[0.00, 0.13]	[0.00, 0.09]	[-0.01, 0.16]	[-0.13, 0.09]	[0.01, 0.20]	[0.04, 0.24]
Partner	-0.11	-0.11	-0.25	-0.03	0.31	0.28
	[-0.22, -0.01]	[-0.19, -0.04]	[-0.35, -0.15]	[-0.22, 0.17]	[0.15, 0.48]	[0.13, 0.42]
Birth parity	-0.05	-0.06	-0.09	-0.04	-0.04	-0.01
	[-0.07, -0.03]	[-0.09, -0.04]	[-0.12, -0.06]	[-0.07, -0.01]	[-0.07, -0.01]	[-0.04, 0.01]
Birthweight	0.01	0.05	0.07	0.08	0.09	0.19
	[-0.09, 0.11]	[-0.04, 0.14]	[-0.08, 0.22]	[-0.10, 0.26]	[-0.09, 0.26]	[0.00, 0.39]
Gest. period	-0.23	-0.16	-0.04	0.32	0.35	0.71
	[-0.65, 0.20]	[-0.51, 0.20]	[-0.70, 0.62]	[-0.36, 1.00]	[-0.33, 1.03]	[0.02, 1.40]
Female	-0.03	0.06	0.06	-0.02	0.01	-0.05
	[-0.08, 0.01]	[0.03, 0.09]	[0.02, 0.10]	[-0.07, 0.03]	[-0.04, 0.06]	[-0.10, 0.00]
Middle edu.	0.06	0.04	0.04	0.01	0.01	0.05
	[0.02, 0.09]	[0.00, 0.08]	[-0.02, 0.10]	[-0.07, 0.09]	[-0.07, 0.08]	[-0.03, 0.14]
High edu.	0.16	0.13	0.16	0.02	-0.05	-0.00
	[0.11, 0.21]	[0.09, 0.17]	[0.09, 0.23]	[-0.06, 0.10]	[-0.13, 0.02]	[-0.09, 0.09]
cons.	1.23	0.88	0.16	-1.06	-1.84	-3.49
	[-0.26, 2.73]	[-0.38, 2.14]	[-2.19, 2.52]	[-3.48, 1.36]	[-4.27, 0.59]	[-5.95, -1.03]

Notes: This table shows parameter estimates for parental investment (θ_t^I) [columns (1)-(3)] & mother's mental health (θ_t^{mh}) [columns (4)-(6)] for each period t. All variables are in logs except for the binary dummy variables: partner, female, middle edu., and high edu.. 90% confidence intervals in square brackets are computed using 100 bootstrap replications.

Table B2: Production Function Parameter Estimates - Cognitive Skills (θ_t^c)

	(1)	(2)	(3)	(4)	(5)	(6)
	Production of Cognitive Skills (θ_t^c)					
	Baseline			with endogenous inv. & mmh.		
	$t=2$	$t=3$	$t=4$	$t=2$	$t=3$	$t=4$
a) intimate partner violence						
exp. to IPV_t	-0.00	-0.00	-0.04	-0.03	-0.03	-0.03
	[-0.06, 0.05]	[-0.07, 0.07]	[-0.12, 0.04]	[-0.09, 0.03]	[-0.11, 0.05]	[-0.12, 0.06]
b) lag cognitive skills (θ_{t-1}^c)						
cog_{t-1}	0.60	0.53	0.43	0.53	0.52	0.32
	[0.51, 0.69]	[0.44, 0.63]	[0.29, 0.56]	[0.45, 0.62]	[0.28, 0.77]	[0.11, 0.54]
cog_{t-1}^2	-0.15	-0.12	-0.10	-0.09	-0.17	-0.13
	[-0.22, -0.09]	[-0.20, -0.05]	[-0.21, 0.01]	[-0.15, -0.03]	[-0.29, -0.05]	[-0.24, -0.03]
$\text{cog}_{t-1} \times \text{socio-emo}_{t-1}$	0.01	0.06	0.03	0.01	0.03	-0.01
	[-0.06, 0.08]	[-0.01, 0.14]	[-0.06, 0.13]	[-0.06, 0.07]	[-0.07, 0.13]	[-0.11, 0.10]
$\text{cog}_{t-1} \times \text{inv}_{t-1}$	0.05	0.10	0.08	0.05	0.01	-0.02
	[-0.03, 0.14]	[0.01, 0.18]	[-0.03, 0.20]	[-0.03, 0.14]	[-0.16, 0.17]	[-0.16, 0.12]
$\text{cog}_{t-1} \times \text{mmh}_{t-1}$	-0.01	0.03	-0.06	0.00	-0.01	-0.18
	[-0.08, 0.06]	[-0.04, 0.10]	[-0.15, 0.03]	[-0.07, 0.07]	[-0.10, 0.08]	[-0.29, -0.07]
c) lag socio-emotional skills (θ_{t-1}^e)						
socio-emo_{t-1}	0.02	0.17	0.15	0.04	0.16	0.08
	[-0.06, 0.09]	[0.11, 0.23]	[0.07, 0.23]	[-0.02, 0.11]	[0.07, 0.24]	[-0.02, 0.19]
socio-emo_{t-1}^2	-0.01	-0.11	-0.08	-0.02	-0.05	-0.02
	[-0.07, 0.05]	[-0.17, -0.04]	[-0.17, 0.01]	[-0.07, 0.03]	[-0.11, 0.01]	[-0.09, 0.05]
$\text{socio-emo}_{t-1} \times \text{inv}_{t-1}$	-0.03	0.02	0.03	-0.01	-0.03	0.01
	[-0.08, 0.03]	[-0.06, 0.10]	[-0.09, 0.14]	[-0.07, 0.05]	[-0.12, 0.06]	[-0.10, 0.12]
$\text{socio-emo}_{t-1} \times \text{mmh}_{t-1}$	0.04	-0.01	0.00	0.01	-0.05	-0.02
	[-0.02, 0.10]	[-0.07, 0.05]	[-0.06, 0.07]	[-0.05, 0.07]	[-0.12, 0.03]	[-0.10, 0.05]
d) lag parental investment (θ_{t-1}^I)						
inv_{t-1}	0.37	0.30	0.34	0.38	0.57	0.70
	[0.25, 0.49]	[0.19, 0.42]	[0.16, 0.52]	[0.26, 0.49]	[0.17, 0.98]	[0.40, 0.99]
inv_{t-1}^2	-0.05	-0.06	-0.04	-0.03	0.00	0.04
	[-0.13, 0.02]	[-0.15, 0.03]	[-0.13, 0.06]	[-0.12, 0.06]	[-0.10, 0.11]	[-0.07, 0.14]
$\text{inv}_{t-1} \times \text{mmh}_{t-1}$	0.14	0.02	-0.00	0.11	-0.04	-0.05
	[0.05, 0.22]	[-0.08, 0.12]	[-0.11, 0.10]	[0.02, 0.20]	[-0.17, 0.08]	[-0.18, 0.07]
e) lag mother's mental health (θ_{t-1}^{mh})						
mmh_{t-1}	0.01	0.05	0.14	-0.01	0.02	0.18
	[-0.05, 0.08]	[-0.01, 0.10]	[0.06, 0.22]	[-0.08, 0.05]	[-0.07, 0.12]	[0.08, 0.29]
mmh_{t-1}^2	0.02	0.02	0.08	0.03	0.04	0.11
	[-0.02, 0.05]	[-0.01, 0.05]	[0.04, 0.12]	[-0.01, 0.07]	[-0.00, 0.08]	[0.06, 0.15]
f) test of exogeneity & prod. shocks						
inv. residual_t	-	-	-	-0.03	-0.54	-0.44
	-	-	-	[-0.08, 0.03]	[-0.95, -0.14]	[-0.64, -0.24]
mmh. residual_t	-	-	-	0.05	0.04	-0.04
	-	-	-	[0.01, 0.09]	[-0.04, 0.13]	[-0.12, 0.03]
sd. of shock_t	0.25	0.43	0.46	0.24	0.39	0.42
	[0.20, 0.30]	[0.38, 0.49]	[0.38, 0.54]	[0.19, 0.30]	[0.32, 0.45]	[0.33, 0.50]

Notes:

Table B3: Production Function Parameter Estimates - Socio-emotional Skills (θ_t^e)

	(1)	(2)	(3)	(4)	(5)	(6)
	Production of Socio-emotional Skills (θ_t^e)					
	Baseline			with endogenous inv. & mmh.		
	$t=2$	$t=3$	$t=4$	$t=2$	$t=3$	$t=4$
a) intimate partner violence						
exp. to IPV$_t$	-0.00	-0.02	-0.04	-0.04	-0.04	0.04
	[-0.06, 0.05]	[-0.10, 0.06]	[-0.14, 0.06]	[-0.14, 0.05]	[-0.13, 0.06]	[-0.06, 0.14]
b) lag cognitive skills (θ_{t-1}^c)						
cog$_{t-1}$	0.17	0.14	0.12	0.11	0.10	0.05
	[0.08, 0.26]	[0.02, 0.25]	[0.02, 0.22]	[-0.10, 0.31]	[-0.04, 0.24]	[-0.05, 0.15]
cog$_{t-1}^2$	-0.03	-0.07	-0.06	0.02	-0.02	-0.04
	[-0.09, 0.03]	[-0.15, 0.02]	[-0.15, 0.02]	[-0.03, 0.08]	[-0.12, 0.07]	[-0.11, 0.04]
cog$_{t-1}$ × socio-emo$_{t-1}$	-0.01	0.02	0.06	-0.00	0.00	0.03
	[-0.08, 0.06]	[-0.07, 0.10]	[-0.03, 0.15]	[-0.06, 0.06]	[-0.09, 0.09]	[-0.07, 0.13]
cog$_{t-1}$ × inv$_{t-1}$	0.05	0.04	0.04	0.04	0.03	0.03
	[-0.04, 0.13]	[-0.06, 0.14]	[-0.07, 0.16]	[-0.03, 0.11]	[-0.09, 0.15]	[-0.08, 0.15]
cog$_{t-1}$ × mmh$_{t-1}$	-0.02	0.02	0.06	-0.01	0.01	0.03
	[-0.11, 0.08]	[-0.12, 0.16]	[-0.07, 0.19]	[-0.09, 0.07]	[-0.13, 0.15]	[-0.09, 0.16]
c) lag socio-emotional skills (θ_{t-1}^e)						
socio-emo$_{t-1}$	0.47	0.35	0.27	0.42	0.36	0.25
	[0.40, 0.53]	[0.26, 0.44]	[0.19, 0.35]	[0.34, 0.51]	[0.26, 0.47]	[0.16, 0.34]
socio-emo$_{t-1}^2$	-0.05	-0.03	-0.03	-0.02	-0.01	-0.01
	[-0.10, 0.01]	[-0.08, 0.02]	[-0.09, 0.03]	[-0.07, 0.02]	[-0.07, 0.04]	[-0.06, 0.04]
socio-emo$_{t-1}$ × inv$_{t-1}$	0.08	-0.00	-0.06	0.12	0.02	-0.05
	[-0.04, 0.20]	[-0.10, 0.10]	[-0.16, 0.04]	[0.01, 0.23]	[-0.08, 0.13]	[-0.15, 0.05]
socio-emo$_{t-1}$ × mmh$_{t-1}$	0.03	0.11	0.10	0.01	0.09	0.08
	[-0.03, 0.09]	[0.04, 0.19]	[0.03, 0.18]	[-0.05, 0.07]	[0.01, 0.17]	[0.00, 0.16]
d) lag parental investment (θ_{t-1}^I)						
inv$_{t-1}$	0.04	0.08	0.06	0.07	0.09	0.03
	[-0.06, 0.14]	[-0.05, 0.21]	[-0.07, 0.19]	[-0.30, 0.44]	[-0.12, 0.31]	[-0.15, 0.21]
inv$_{t-1}^2$	-0.06	-0.01	-0.04	-0.02	-0.03	-0.04
	[-0.12, 0.01]	[-0.11, 0.08]	[-0.13, 0.06]	[-0.08, 0.04]	[-0.13, 0.07]	[-0.14, 0.06]
inv$_{t-1}$ × mmh$_{t-1}$	-0.05	-0.18	-0.19	-0.02	-0.18	-0.14
	[-0.18, 0.08]	[-0.37, 0.02]	[-0.38, -0.01]	[-0.14, 0.09]	[-0.38, 0.03]	[-0.32, 0.03]
e) lag mother's mental health (θ_{t-1}^{mh})						
mmh$_{t-1}$	0.29	0.44	0.53	0.22	0.42	0.64
	[0.19, 0.39]	[0.28, 0.60]	[0.38, 0.68]	[0.06, 0.39]	[0.23, 0.62]	[0.46, 0.82]
mmh$_{t-1}^2$	0.08	0.10	0.13	0.07	0.11	0.12
	[0.04, 0.11]	[0.05, 0.16]	[0.08, 0.18]	[0.04, 0.10]	[0.05, 0.16]	[0.07, 0.17]
f) test of exogeneity & prod. shocks						
inv. residual$_t$	-	-	-	-0.04	0.05	0.02
	-	-	-	[-0.39, 0.32]	[-0.23, 0.34]	[-0.11, 0.16]
mmh. residual$_t$	-	-	-	0.04	0.02	-0.30
	-	-	-	[-0.08, 0.16]	[-0.06, 0.10]	[-0.38, -0.21]
sd. of shock$_t$	0.40	0.47	0.55	0.40	0.47	0.51
	[0.35, 0.45]	[0.31, 0.62]	[0.41, 0.68]	[0.35, 0.44]	[0.31, 0.62]	[0.38, 0.64]

Notes: